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ORIGINAL RESEARCH

Network reliability analysis on casualty rescue for natural disaster evaluation

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Abstract

Casualty rescue is always a critical issue in emergency departments when the buildings collapsing, bridges or roads damaged happen in the earthquakes. However, previous studies essentially considered such a problem by assuming fixed travel time for the ambulance. This paper aims to involve road failure during the earthquake by considering the stochastic durations for each road. The probability that the casualty can be successfully rescued to the casualty collection point (CCP) provides further medical treatment for the casualties. Such a probability is named network reliability which is defined as the probability that the number of casualties can be successfully transported to the CCP in a given rescue time. To evaluate the network reliability, the data transformation procedure is firstly developed to convert the road data into duration probability table, which addresses the travel time and corresponding probability of each road. Second, the multi-state rescue network is established, and an algorithm is constructed to obtain all upper bound vectors meeting the demand and time constraint. The network reliability can be computed by obtained upper bound vectors using the recursive sum disjoint product method. An example of a real earthquake disaster in Tainan City, Taiwan is adopted to demonstrate the practicality of the proposed algorithm. Finally, the experimental results with different number of ambulances and times can provide the commander decision recommendations for immediate emergency responses.

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1 Introduction

In recent years, weather anomalies have become more and more serious and the number of people injured in natural disasters has gradually increased. Major natural disasters in Taiwan, such as the 921 earthquakes on September 21, 1999 (Sheu, 2014), caused 2455 deaths, more than 8000 injuries and damaged more than 38,000 buildings. In such a disaster, the difficulty of rescue has increased greatly, and several decision-making problems are arising one after another. It is necessary and also be a challenge for the rescue commander to grasp the situation in a very short time and make further immediate decisions. In a rescue operation, the route of the ambulance to transport the casualties is an important issue since the survival rate of the casualties is greatly influenced by the priority of the routes and the allocation of ambulances. When the disaster occurs, the victim needs to be transported to the casualty collection point (CCP) firstly for further disposal. Rescue efficiency can be described as the performance of the whole rescue process and needs to be improved first. In limited rescue time, knowing whether the casualties can be successfully transported to the CCP is important. Therefore, network reliability is adopted in this paper to demonstrate rescue efficiency, which is defined as the probability that the number of casualties can be successfully rescued to the CCP in the rescue time.

Network analysis is an applicable approach to be utilized for performance evaluation for real world systems. The whole rescue operation can be modeled as a network for the commander to easily understand the overall process. In this paper, the AOA (activity-on-arrow) diagram is utilized to investigate the rescue operation in which each arc is a road for ambulance transportation, and a node is termed a connection between two roads. For each route of ambulance, the travel time is concerned to evaluate the efficiency of the rescue. The decision of resources, such as the number of ambulances assigned to each location and even their corresponding route, becomes hard to evaluate for the commander, and thus influence the rescue efficiency. However, the travel time in the previous studies (Dulebenets et al., 2019; Wang et al., 2016a, b) is regarded as fixed value and it is difficult to reflect the reality in rescue operation due to the difficulty in describing the damage on each road in a disaster situation. For instance, travel time becomes more difficult to assess owing to collapse of buildings and roads or power outages in the traffic system.

Considering the disaster situation, the rescue duration (the travel time of the ambulance on each road) is regarded as a random integer variable to represent the uncertainty of the rescue process. Thus, such a rescue operation can be modeled as multi-state rescue network (MSRN) to consider the uncertain duration of each arc under earthquake damage. The transferred procedure is presented to establish the duration probability table. The stochastic travel time in such a table can be obtained to allow the commander to easily understand the damage in the rescue system. In such an MSRN, the minimal path approach (MP) (Bai et al., 2015; Burgelman & Vanhoucke, 2019; Forghani-elahabad & Bonani, 2017; Lin & Huang, 2013) is adopted as the rescue route for the ambulance, where MP is defined as an order sequence of arcs from the source node to the sink node without cycle. The MP concept can be used to obtain the upper bound vector, which is a maximal duration vector satisfying both demand (the number of casualties must be saved in affected area) and time constraints. In such an upper bound vector, the travel time which increases in at least one road would lead to the rescue operation failing because all casualties cannot be sent to the CCP. The current duration vector is called feasible when the ambulances are able to transport the demand to the CCP under time constraint through this duration vector, and all feasible duration vectors are contained in the upper bound vectors. Because it is NP-hard to calculate the network reliability in an MSRN (Ball, 1986), one efficient method is to obtain all upper bound vectors in terms of MP for network reliability evaluation.

Considering the road damage after an earthquake, we model the rescue operation as an MSRN. The stochastic travel time of each arc can be established to a duration probability table. The network reliability is further adopted to evaluate the efficiency of the rescue operation. The rescue commander can easily realize the emergency and make intelligent decisions for determining the ambulance allocation or rescue time. The remainder of this paper is organized into the following sections. The relevant literature is summarized in Sect. 2. Section 3 introduces the evaluation process of the network reliability, including the duration probability table and the upper bound vector search approach. An algorithm for calculating network reliability based on the upper bound vectors is proposed in Sect. 4. In Sect. 5, an illustrative example and further experimental results in the Shanshang district are presented. Finally, a conclusion is presented in Sect. 6.

2 Literature review

In disaster response activities, numerous decision issues need to be taken into account, such as distribution planning (Ghasemi et al., 2020), evacuation planning (Ghasemi et al., 2020; Wang et al., 2016a, b; Yi & Özdamar, 2007) and location allocation problem (Caunhye et al., 2015; Liu et al., 2019; Oksuz & Satoglu, 2020; Wang et al., 2016a, b). For ambulance rescue, the rescue routing problem is a critical issue in emergencies, including vehicle dispatching, route planning, and resource allocation, etc. Due to the importance of rescue efficiency, several optimization models (Dulebenets et al., 2019; Lim et al., 2015; Rambha et al., 2021; Shahparvari & Abbasi, 2017; Wang et al., 2016a, b, 2021) are presented to solve this problem. Different objective functions demonstrate different practical problems and lead to consider diverse properties. For instance, the efficiency of the rescue operation must be maximized when considering the order within rescue plans. Liu et al. (2020) coordinated the post-disaster search and rescue factors to represent the efficiency by using the extended data envelopment analysis model. Shahparvari and Abbasi (2017) also used a greedy algorithm to maximize the evacuation efficiency considering the time and evacuee population. Minimizing travel time or cost is also the most common objective in the rescue routing problem (Feng et al., 2017; Rambha et al., 2021). The previous studies on the optimized routing problem are summarized in Table 1. However, since the disaster would damage the road or buildings, the uncertainty of the rescue process, such as building or road collapsing and the traffic under disaster, is need to be studied in rescue operations. Therefore, the stochastic travel time of each arc is considered in this paper. Compared with previous research, the travel time in this study can present the traffic in disaster with multiple states rather than a fixed value, and the more real situation can be presented by the proposed method.

From the transportation management view, reliability is an important issue for the manager to measure the service level and system performance. Kim and Song (2018) proposed an integrated accessibility and reliability indicators that considers both metrics in combination to assess the performance and vulnerability of the public transportation. Zhang et al. (2019) also modeled the railway system to calculate five reliabilities, including the time reliability,

Table 1 The routing problems in previous studies

References	Problem	Objective	Method	Situation
Lim et al. (2015)	Decision of evacuation routes	Minimizing the jam density of the rescue route	Mixed integer programming	–
Wang et al. (2016a, b)	Shelter allocation and emergency routing problems	Maximizes the total reliability of routes connection	Nominated Sorting Genetic Algorithm (NSGA)	Floods
Wang et al., (2016a, b)	Finding the priori evacuation plans	Minimum expected total evacuation time	Heuristic algorithm combining the Lagrangian relaxation-based approach K-shortest path techniques	Floods
Shahparvari and Abbasi (2017)	Determine the required vehicles and routes in evacuee population	Maximized efficiency of an evacuation	Greedy algorithm	Wildfire
Dulebenets et al. (2019)	Assign individuals to emergency shelters through evacuation routes	Minimize the total travel time of individuals leaving an evacuation zone	The mixed-integer programming model The Most Urgent Evacuee heuristic	Hurricanes
Rambha et al. (2021)	Optimal number of patients of different types and the rescue vehicles	Minimize a linear combination of risk and cost associated	Stochastic optimization formulation	Hurricanes
Wang et al. (2021)	Evaluation of evacuation route on offshore platform	Reliability prediction model of emergency evacuation	K2 structure learning algorithm Bayesian estimation method Junction tree reasoning engine Markov method	Disaster on offshore platform
Feng et al. (2017)	Optimize resource allocation under limited medical resources	Minimize the average length of stay of patients and medical resource waste costs	Multi-objective simulation optimization algorithm Non-dominated sorting genetic algorithm II	–
Liu et al. (2020	Optimal rescue route	Maximizing the total rescue efficiency	Data envelopment analysis model Integer programing model	Earthquake

the average time for transportation chain, reserve time, buffer time and tolerable time boundary, for the railway container chain evaluation. Rahnamay-Naeini et al. (2011) presented a stochastic model to facilitate the spatially inhomogeneous and correlated link failures in communication networks. The vulnerabilities can be assessed in terms of network reliability in the stress-event centers. However, no previous research has taken into account the possibility of successfully rescuing the casualties in the routing problem. In addition, the multiple states at each component are not considered. More comprehensive stochastic factors are thus considered in terms of stochastic travel time for ambulance transporting in this study. We also develop network reliability as the indicator to redefine as rescue efficiency, which can systematically represent the efficiency of rescue operation.

This paper aims to propose an algorithm to efficiently evaluate the reliability in terms of network approach. Such a reliability named network reliability is widely applied in practical systems, such as supply chain (Huang, 2019, 2020a), computer system (Huang et al., 2020a, b; Lin et al., 2019a, b, c, d, e, 2022) project management (Huang et al., 2020a, b; Lin et al., 2017), and transportation system (Lin et al., 2019a, b; Yeh et al., 2021, 2022) In the previous works, MP method is commonly applied to efficiently calculate the network reliability (Bai et al., 2015; Lin, 2008; Lin & Huang, 2020). In terms of MP, several papers are devoted to calculate the network reliability by searching all upper bound vectors (Lin et al., 2017, 2019a, b, c, d, e). Note that, the upper bound vectors are the maximal duration vectors to satisfy D and T. In traffic application, Yeh et al. (2022) evaluated the rail transport network reliability considering the train arrival delay. Lin et al., (2019a, b, c, d, e) calculated the network reliability for intermodal logistics system considering the spoilage and time. Lin et al. (2019a) also applied such an index to the air transportation network to assess the probability of meeting multiple travel demands. However, the above works are lack for considering the damage of arc in a disaster situation, and also cannot evaluate the travel time of each arc for the rescue vehicles. In this paper, the stochastic travel time is concerned to construct the MSRN. The network reliability of an MSRN is further calculated to evaluate the possibility of rescue by ambulance.

To our best knowledge, there is no research for calculating the network reliability in rescue operation. The comparison table for these studies in the reliability problem is presented in Table 2. The uncertainty for the ambulance transporting under disaster is not considered and the probability of successfully rescue the casualties in a given time is not calculated in the previous studies. In this paper, the proposed algorithm is decomposed into two parts: The duration probability table is established to represent the damage of every arc from the earthquake. Second, the approach for searching all upper bound vectors is proposed to efficiently calculate the network reliability. The efficiency of the rescue operation can be evaluated by the network reliability to provide the decision suggestions.

3 Network reliability evaluation for multi-state rescue network

This section builds the MSRN to evaluate the network reliability and proposes a transformation procedure to obtain the duration probability table. Three stages are included in this section. First, the stochastic jam density is introduced to represent the damage of each road. Second, the Underwood model is applied to establish the duration probability table in terms of travel time. In the last phase, an efficient method is announced to search all upper bound vectors in a given rescue time. The flow chart of the whole method is shown in Fig. 1.

Table 2 Comparison of the reliability problem in transportation system

References	Problem	Definition of the reliability	Stochastic factor	Situation
Kim and Song (2018)	Evaluate the resilience and vulnerability of a spatially networked system	The probability that passengers using transit systems can reach destinations without failure or delay through routes available in the network	–	–
Zhang et al. (2019)	Built the railway container chain evaluation model	The probability of the goods that can be transported in specified distribution within expected travel time by railway	–	–
Rahnamay-Naeini et al. (2011)	Facilitate the spatially inhomogeneous and correlated link failures in communication networks	The probability of failures for an arbitrary collection of links with spatially correlated centers	Multiple sets of correlated link failures	Natural disaster
Yeh et al. (2022)	Evaluate the capacity of the rail transport network to determine the number of passengers in the tour group that can be served	The probability that the passenger groups can successfully depart from a source station for a sink station	Available train's loading capacity	–
Lin et al. (2019a, b, c, d, e)	Develop the delivery performance index to evaluate an intermodal logistics network	The probability that the intermodal logistics network can successfully deliver sufficient amount of commodity to meet market demand under the time and delivery spoilage constraints	The capacity of carriers on routes	–
Lin et al. (2019a)	Evaluate the reliability of an air transportation system considering practical properties from the perspective of travel agency	The probability that a set of demands can be carried successfully under constraints of time and number of stopovers	The number of available seats on each flight	–

Table 2 (continued)

References	Problem	Definition of the reliability	Stochastic factor	Situation
This study	Evaluate the probability to transport all casualty under uncertain disaster situation	The probability that the number of casualties can be successfully transported to the CCP in a given rescue time	The travel time of the ambulance	Natural disaster

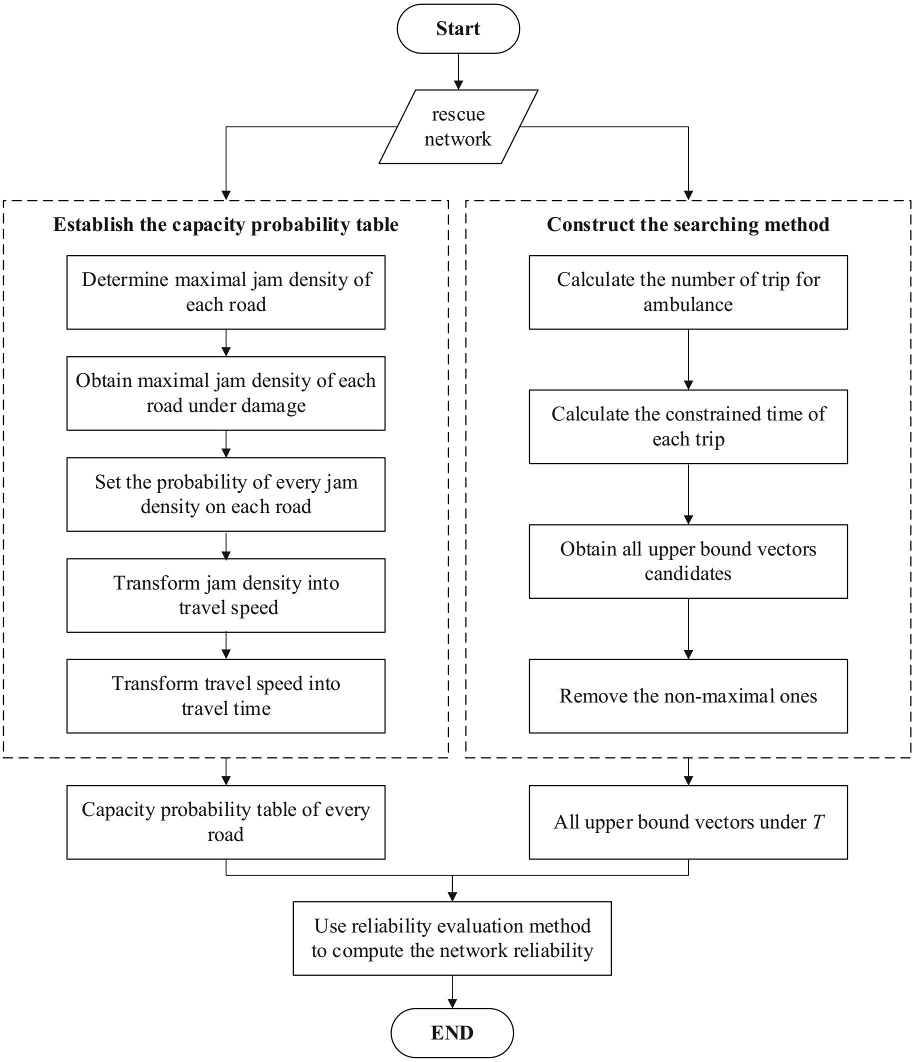

Fig. 1 Flow chart of the proposed approach

3.1 Jam densities for each road

Let $\boldsymbol{G} \equiv (\mathbf{A}, \mathbf{M})$ denote an MSRN with the affected area s to the CCP t. $\mathbf{A} = \{a_i \mid i = 1, 2, \ldots, n\}$ is the set of arcs, $\mathbf{M} = \{M_i \mid i = 1, 2, \ldots, n\}$ with M_i being the maximal duration of a_i. Each a_i represents the travel time through this road and displays several durations to reflect the damage in an earthquake situation. In this paper, the $\boldsymbol{G}$ should satisfy the following assumptions:

(1) The duration of each a_i takes integer values with a given probability distribution which is derived from historical data.
(2) The duration of different a_i is statistically independent.

The concept of MP is adopted in this paper to represent the route of the ambulance. Under a MSRN, MP$_j$ is jth MP for $j = 1, 2, \ldots, L$. Traffic affected by the earthquake level and the traffic time for ambulance rescue becomes hard to evaluate. The travel time of each arc is thus regarded as a random variable in this paper. For each arc a_i, the duration is defined as the travel time and may be affected by the probability of the road failure f_i and width w_i. Road failure f_i reflects the probability and damage level in the earthquake situation. Therefore, the jam density of each arc may be changed by the different f_i and w_i. The following presents the procedures for transforming the information of each arc, including the road failure and width, into a duration probability table to represent the road damage after an earthquake.

To obtain the travel time of each arc, the jam density should be first computed. The width can greatly influence the jam density of each arc. A vector $W = (w_1, w_2, \ldots, w_n)$ represents the width for every a_i. The value u_w is the minimal width range, $d_{\max}$ is the unit of the maximal jam density, and λ_1 is the adjusted ratio of jam density. The above parameters are pre-set based on the damage level or historical data. For each a_i, the maximal jam density k_i^1 can be obtained by the corresponding width and defined parameters λ_1, u_w and $d_{\max}$ via

$$k_i^1 = \begin{cases} d_{\max} + \lambda_1 \left\lfloor \frac{w_i}{u_w} \right\rfloor, & \text{if } w_i \geq u_w \\ d_{\max}, & \text{if } w_i \leq u_w \end{cases} \quad \text{for all } i \tag{1}$$

To reflect the uncertainty of the earthquake that damages the road, two extended maximal jam densities are carried out in this study. That is, there are three maximal jam densities for each road and the value of the other two would be lower than the original one to describe the damage on each road. $F = (f_1, f_2, \ldots, f_n)$ is a road failure vector to typify the probability and damage classification. The parameter δ_1, δ_2, and δ_3, are thresholds for classifying damages by width. λ_2 is the parameter to represent the damage level of every arc and δ_1, δ_2, and δ_3 are the parameters for damage classification. The defined parameters are obtained by the historical data or based on the intensity of earthquake. Two maximal jam density for each arc under damage can be obtained to reflect different damage states, including moderate k_i^2 and severe k_i^3.

$$k_i^2 = \begin{cases} [1 - (\lambda_2)^2]k_i^1, & \text{if} \delta_2 \leq f_i \leq \delta_1 \\ [1 - (\lambda_2)^3]k_i^1, & \text{if } \delta_3 \leq f_i \leq \delta_2 \\ [1 - (\lambda_2)^4]k_i^1, & \text{if } 0 \leq f_i \leq \delta_3 \end{cases} \quad \text{for all } i, \tag{2}$$

$$k_i^3 = \begin{cases} [1 - \lambda_2]k_i^1, & \text{if } \delta_2 \leq f_i \leq \delta_1 \\ [1 - (\lambda_2)^2]k_i^1, & \text{if } \delta_3 \leq f_i \leq \delta_2 \\ [1 - (\lambda_2)^3]k_i^1, & \text{if } 0 \leq f_i \leq \delta_3 \end{cases} \quad \text{for all } i. \tag{3}$$

Noted that, $k_i^1 \geq k_i^2 \geq k_i^3$ and two maximal jam densities, k_i^2 and k_i^3 are calculated from k_i^1 and λ_2. The parameter λ_2 is presented as the ratio of density declining and δ is adopted in

Eqs. (2) and (3) to classify the level of damage on each road. There are three jam densities to reflect the earthquake effect for every a_i. The probability for each jam density is given as p_i^1, p_i^2 and p_i^3.

$$\begin{aligned} p_i^1 &= 1 - f_i \\ p_i^2 &= p_i^3 = \tfrac{1}{2} f_i \end{aligned} \quad \text{for all } \ i. \tag{4}$$

The probabilities for three densities are obtained from the road failure f_i and the portion of the probability for three states can be adjusted according to different situation. The stochastic maximal jam density and corresponding probability can be obtained by Eqs. (1)–(4).

3.2 Establishment of the duration probability table

Underwood model (Underwood, 1961) is an exponential form and satisfies the properties of speed-density relationships, which is straightforward and easy to explain the vehicle behavior. For each road, given the free-flow speed v_f, the average density k, and the multiple jam density k_i^s obtained from Sect. 3.1, the travel speed v_i^s can be calculated as

$$v_i^s = v_f \exp\left(-\frac{k}{k_i^s}\right) \quad \text{for all } \ i \text{ and } s = 1, 2, 3. \tag{5}$$

Equation (5) is able to describe the travel speed of each arc where $0 \le v_i^s \le v_f$. Average density k is the current number of vehicles per kilometer and would be determined by the width of the road. Corresponding to three jam densities of every a_i, three travel speed values v_i^s would be further transformed to represent the travel speed considering the earthquake damage, respectively. The higher maximal jam density means fewer traffic jams. Thus, the travel speed would decrease in an earthquake situation by decreasing maximal jam density. A vector $L = (l_1, l_2, \ldots, l_n)$ is depicted the length of a_i. The travel time t_i^s under three damage scenarios can be derived by the travel speed as follows,

$$t_i^s = \frac{l_i}{v_i^s} \quad \text{for all } i \text{ and } s = 1, 2, 3. \tag{6}$$

Via the transform steps above, the duration probability table is established by the F, W and L. The route status of ambulance can be reflected by multiple jam densities on each road. Table 3 shows the stochastic durations to represent the possible damage for each a_i. The travel time of each route MP_j can be further estimated and adopted to calculate the network reliability.

Table 3 Duration probability table example

Situation	Jam density	Probability
No injury	t_i^1	p_i^1
Moderate damage	t_i^2	p_i^2
Severe damage	t_i^3	p_i^3

3.3 Calculation of network reliability in terms of upper bound vectors

Let $X = (x_1, x_2, \ldots, x_n)$ be a duration vector where x_i is the current duration of a_i. A simple way to calculate the network reliability $\mathrm{R}_{D,\,T}$ is to enumerate all X such that $X \in \mathbf{\Omega}$ and sum up their corresponding probabilities where $\mathbf{\Omega}$ is the set of feasible duration vectors to satisfy both the demand D and time constraint T. However, it is a time-consumed method when the scale of system becomes bigger. One effective method to calculate the network reliability is obtaining all upper bound vectors in terms of MP. Suppose there are o upper bound vectors: $X_1, X_2, \ldots, X_o$, then the network reliability $R_{D,\,T}$ for the given D and T can be efficiently calculated as

$$R_{D,T} = \Pr\{\mathbf{W}\} = \Pr\left\{\bigcup_{i=1,2,\ldots,o} \{ X|X \le X_i \} \right\}. \tag{7}$$

Such a reliability can be calculated by the inclusion–exclusion principle, the state-space decomposition algorithm or the recursive sum of disjoint product (RSDP) (Zuo et al., 2007). Zuo et al. (2007) indicated that RSDP is an efficient method to calculate the network reliability for larger systems. Hence, the RSDP method is adopted in this paper. Noted that, RSDP is a recursive algorithm based on the concept of sum of disjoint principle (SDP) for the evaluation of network reliability. From the SDP principle, the network reliability is calculated from the summation of divided o terms. The network reliability can be rewritten as

$$\mathrm{TM}_i = \Pr(X \le X_i) - \Pr\left(\bigcup_{j=1}^{i-1} \{X \le \max(X_j, X_i)\}\right) \quad \text{for} \quad i = 1, 2, \ldots, o, \tag{8}$$

$$R_{D,\,T} = \mathrm{PrU}(X_1, X_2, \ldots, X_o) = \sum_{i=1}^{o} \mathrm{TM}_i. \tag{9}$$

PrU(•) in Eq. (9) is the recursive function where TM_i is the ith term in the SDP calculation. In order to efficiently calculate the network reliability, the most important issue is to find all upper bound vectors that meet the demand D. The number of casualties each ambulance can transport depends on the severity of the injury. We suppose that one severe casualty or u_a slight casualties would be carried by one ambulance. Ambulances must transport casualties back and forth on given routes. The value u_a is set as the number of slight casualties in an ambulance for each trip. Given the number of casualties d_{slight}, d_{serious} and ambulance c in MSRN, the number of trips γ for every ambulance can be thus obtained via

$$\gamma = \left\lceil \frac{\lceil d_{\text{slight}}/u_a \rceil + d_{\text{serious}}}{c} \right\rceil \times 2 - 1. \tag{10}$$

By using the ceiling function to obtain the number of trips for ambulance, it is ensured that all casualties are transported to the CCP in enough trips. For example, there are 8 casualties and 3 ambulances, the trips for every ambulance $\gamma = 8/3 \times 2 - 1 = 5$ derived by Eq. (10). Note that the number of slight casualties that one ambulance can carry u_a is depended on different situations. Practically, u_a is larger than one since the slight casualty do not need that much space of ambulance. The average rescue time of each trip t can be calculated from T and γ by

$$t = \left\lfloor \frac{T}{\gamma} \right\rfloor. \tag{11}$$

To generate the upper bound vector candidates, each route for the ambulance should satisfy the given time for each trip. For each MP, the maximal travel time of the passing road can be generated by Eq. (11). Due to the assumption, the floor function is adopted to ensure the average time of each trip for ambulance not exceed the rescue time constraints. Note that, for the same path, the travel time of the unpassed road is set as its maximal travel time. The pseudo upper bound vector candidates $Z = (z_1, z_2, \ldots, z_n)$ can be obtained as follows.

$$z_i = \begin{cases} \sum\limits_{a_i \in \mathrm{MP}_j} z_i = t, & \text{if } z_i \in \mathrm{MP}_j \\ t_i^3, & \text{if } z_i \notin \mathrm{MP}_j \end{cases} \quad \text{for all } i \text{ and } j = 1, 2, ..., L,$$
$$t_i^1 \leq z_i, \quad \text{for all } i. \tag{12}$$

Suppose that there are v pseudo upper bound vectors: $Z_1, Z_2, \ldots, Z_v$. A group of $X = (x_1, x_2, \ldots, x_n)$ are transformed from those Z as follows,

$$x_i = \begin{cases} t_i^3, & \text{if } t_i^3 \leq z_i \\ t_i^2, & \text{if } t_i^2 \leq z_i < t_i^3 \\ t_i^1, & \text{if } t_i^1 \leq z_i < t_i^2 \end{cases}, \quad \text{for all } i. \tag{13}$$

Those X transformed by Eq. (13) are upper bound vector candidates. Then compare every candidate with each other to remove the non-maximal ones and the remainders are upper bound vectors. Suppose v upper bound vector candidates are obtained, the set $\Omega_{\max}$ is obtained as follows.

Input: $\boldsymbol{\Omega} = \{X_1, X_2, \ldots, X_v\}$

```
3.1:  Set Ωmax = ∅, I = ∅.
3.2:  FOR j = 1 to v and j ∉ I
3.3:  FOR k = j + 1 to v and k ∉ I
3.4:  IF Xj < Xk          //Xj is not belonged to Ωmax.
3.5:  I = I ∪ {j}.
      BREAK               //Next j
3.6:  ELSE IF Xj ≥ Xk     //Xk is not belonged to Ωmax.
3.7:  I = I ∪ {k}.
      END IF
      END FOR
3.8:  Ωmax ← Ωmax ∪ Xj.
      END FOR
```

Output: $\boldsymbol{\Omega}_{\max} = \{X_1, X_2, \ldots X_o\}$

4 Proposed algorithm

Combining establishment of the duration probability table and the obtained upper bound vectors, a novel algorithm is proposed for network reliability evaluation. Given all MP, all upper bound vectors are educed from the following algorithm.

INPUT: $d_{\text{slight}}, d_{\text{severe}}, c, T$

Step 1: For each arc, do the following steps to obtain the jam density, travel time and corresponding probability

1.1 Obtain all jam densities for every arc under three scenarios by Eqs. (14)−(16),

$$k_i^1 = \begin{cases} d_{\max} + \lambda_1 \left\lfloor \frac{w_i}{u_w} \right\rfloor, & \text{if } w_i \geq u_w \\ d_{\max}, & \text{if } w_i \leq u_w \end{cases} \quad \text{for all } i, \tag{14}$$

$$k_i^2 = \begin{cases} [1-(\lambda_2)^2]k_i^1, & \text{if } \delta_2 \leq f_i \leq \delta_1 \\ [1-(\lambda_2)^3]k_i^1, & \text{if } \delta_3 \leq f_i \leq \delta_2 \\ [1-(\lambda_2)^4]k_i^1, & \text{if } 0 \leq f_i \leq \delta_3 \end{cases} \quad \text{for all } i, \tag{15}$$

and

$$k_i^3 = \begin{cases} [1-\lambda_2]k_i^1, & \text{if } \delta_2 \leq f_i \leq \delta_1 \\ [1-(\lambda_2)^2]k_i^1, & \text{if } \delta_3 \leq f_i \leq \delta_2 \\ [1-(\lambda_2)^3]k_i^1, & \text{if } 0 \leq f_i \leq \delta_3 \end{cases} \quad \text{for all } i. \tag{16}$$

1.2 Calculate the corresponding probability for every jam density by Eq. (17).

$$\begin{array}{l} p_i^1 = 1 - f_i \\ p_i^2 = p_i^3 = \frac{1}{2} f_i \end{array} \quad \text{for all } i. \tag{17}$$

1.3 Transform the jam density into travel speed by Eq. (18).

$$v_i^s = v_f \exp\left(-\frac{k}{k_i^s}\right) \quad \text{for all } i \text{ and } s = 1, 2, 3. \tag{18}$$

1.4 Transform the travel speed into travel time by Eq. (19).

$$t_i^s = \frac{l_i}{v_i^s} \quad \text{for all } i \text{ and } s = 1, 2, 3. \tag{19}$$

Step 2: Calculate the average rescue time in terms of c and T by Eqs. (20) *and* (21)

$$\gamma = \left\lceil \frac{\lceil d_{\text{slight}}/u_a \rceil + d_{\text{serious}}}{c} \right\rceil \times 2 - 1, \tag{20}$$

$$t = \left\lfloor \frac{T}{\gamma} \right\rfloor. \tag{21}$$

Step 3: Obtain upper bounds vector candidate Ω by

$$z_i = \begin{cases} \sum\limits_{a_i \in \mathrm{MP}_j} z_i = t, & \text{if } z_i \in \mathrm{MP}_j \\ t_i^3, & \text{if } z_i \notin \mathrm{MP}_j \end{cases}, \quad \text{for all } i \text{ and } j = 1, 2, ..., L, \tag{22}$$
$$t_i^1 \leq z_i, \quad \text{for all } i.$$

and

$$x_i = \begin{cases} t_i^3, & \text{if } t_i^3 \leq z_i \\ t_i^2, & \text{if } t_i^2 \leq z_i < t_i^3 \\ t_i^1, & \text{if } t_i^1 \leq z_i < t_i^2 \end{cases}, \quad \text{for all } i. \tag{23}$$

Step 4: Suppose the result of step 3 is: $\mathbf{X_1}, \mathbf{X_2}, \ldots, \mathbf{X}_v$. Remove the non-maximal ones to obtain all upper bound vectors $\mathbf{\Omega_{max}}$

4.1:	Set $\mathbf{\Omega_{max}}=\varnothing$, $I=\varnothing$.
4.2:	**FOR** $j = 1$ to v and $j \notin I$
4.3:	**FOR** $k = j + 1$ to v and $k \notin I$
4.4:	**IF** $X_j < X_k$ //X_j is not belonged to $\mathbf{\Omega_{max}}$.
4.5:	$I = I \cup \{j\}$.
	BREAK //Next j
4.6:	**ELSE IF** $X_j \geq X_k$ //X_k is not belonged to $\mathbf{\Omega_{max}}$.
4.7:	$I = I \cup \{k\}$.
	END IF
	END FOR
4.8:	$\mathbf{\Omega_{max}} \leftarrow \mathbf{\Omega_{max}} \cup X_j$.
	END FOR

Step 5: Suppose the result of step 4 is: X_1, X_2, …, X_o. Derive network reliability by the RSDP method

$$\mathrm{TM}_i = \Pr(X \leq X_i) - \Pr\left(\bigcup_{j=1}^{i-1}\{X \leq \max(X_j, X_i)\}\right), \tag{24}$$

$$R_{D,T} = \mathrm{PrU}(X_1, X_2, \ldots, X_o) = \sum_{i=1}^{o}\mathrm{TM}_i. \tag{25}$$

Output: $R_{D,T}$

5 Illustrative example

In order to demonstrate the practicality of the proposed approach in disaster evaluation, the earthquake in Tainan City is discussed as the case study. Taiwan Earthquake impact Research and Information Application platform (TERIA) is an assessment application tool to analyze the impact of the earthquake. Information about damage, including roads, bridges, and buildings, can be easily presented by the 500 m × 500 m grid on Taiwan's map. An earthquake data in Tainan City, Taiwan is collected by TERIA to reappear the earthquake on February 11, 2017. For disaster management, rescue efficiency is difficult to evaluate, which is influenced the commander to make the decision. For example, ambulance allocation is a critical issue due to limited hospital resources in the emergency. The commander must decide the allocation of the ambulance to increase the survival rate of the casualty. The quantitative indicator is therefore becoming a useful method to help the commander understand the whole rescue situation. Based on data from the TERIA and the Geographic Information System (GIS), the number of casualties and the road distribution of the Shanshang district are presented in Fig. 2. For each grid in the Shanshang district, a different color represents a different number of casualties. The circled place is the case discussed in this paper.

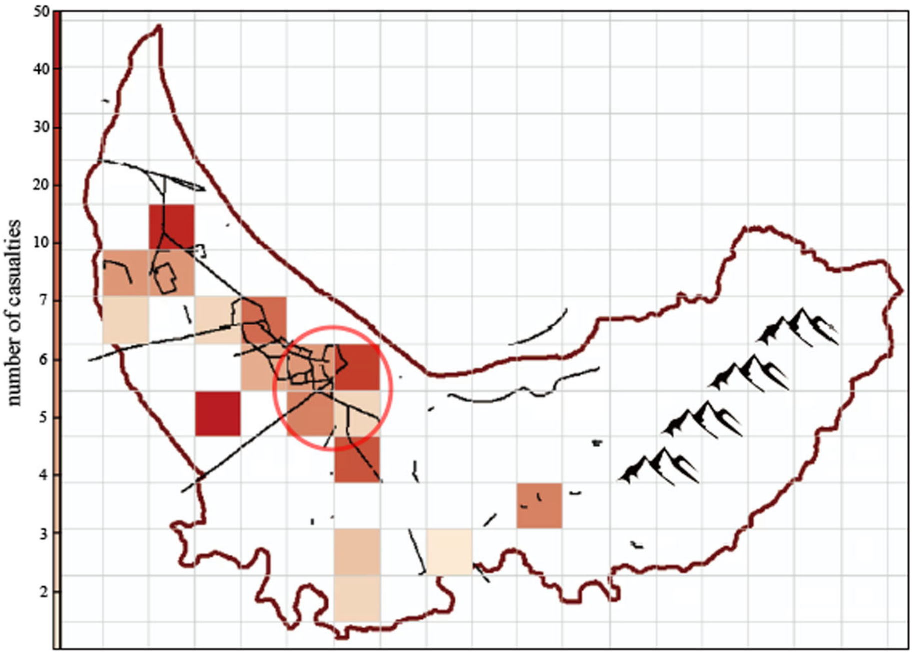

Fig. 2 The casualty allocation and road distribution of Shanshang district

5.1 Road information and network topology

In an earthquake situation, the government is the commander in the rescue operation, and the statistical data would be compiled to the TERIA. In TERIA, the disaster environment would be established from historical data to evaluate the disaster condition. The related information, such as road information and casualty distribution can also be obtained from TERIA. The damage parameter after disaster are able to be collected by TERIA for rescue evaluation. Otherwise, network reliability is the useful information that we want to calculate from the above data and provide to the leader. In this example, the area discussed is marked in Fig. 2 and the route network is set as Fig. 3. According to the historical data in this case from TERIA, there are a total of 4 casualties ($d_{\text{slight}} = 3$, $d_{\text{serious}} = 1$) that must be sent to the CCP with $T = 385$ and $c = 1$. The relevant data of the MSRN in Shanshang district are listed in Table 4. The input variable data, the width, length, and probability of road failure were obtained by TERIA. The other parameters are pre-set with $v_f = 30$, $k = 115$, $u_a = 3$, $u_w = 7$, $\lambda_1 = d_{\max} = 100$, $\lambda_2 = \delta_1 = 0.5$, $\delta_2 = 0.4$, and $\delta_3 = 0.25$ from historical data. These parameters can be adjusted by different situations and the parameter combination in this case is referred to the Regional Disaster Prevention and Rescue Plan in Tainan City, Taiwan and TERIA. Take λ_2 for instance in this real case, the road would be reduced to one-half of the travel area in severe state and thus λ_2 is set as 0.5.

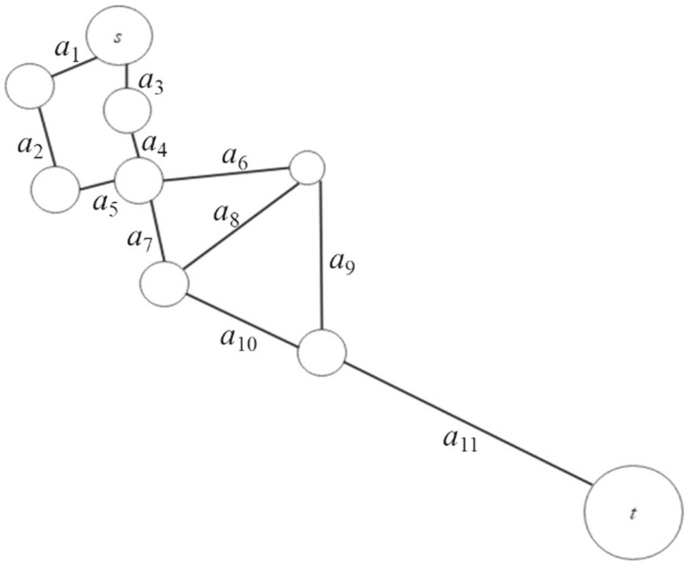

Fig. 3 The network topology in Shanshang district

Table 4 Road information in Shanshang district

Arc	Length l_i (m)	Width w_i (m)	Road failure *fi*
a_1	92.598	11	0.005238
a_2	118.583	9	0.005238
a_3	71.278	19	0.000192
a_4	63.362	20	0.000192
a_5	73.231	9	0.005238
a_6	165.481	11	0.005238
a_7	11.196	19	0.000192
a_8	123.725	12	0.000192
a_9	196.414	9	0.005238
a_{10}	169.115	18	0.000192
a_{11}	183.575	17	0.000192

5.2 Experimental results

The proposed algorithm is programmed with Python programming language and executed on a personal computer with Core™ I9-9900 and 16-gigabytes RAM. We demonstrate the rescue operation with 2 MP to transport the casualties to the CCP. According to Sect. 4, the network reliability calculation is performed by the following steps.

Step 1: Take $\mathbf{a_1}$ for example, do the following steps to obtain the travel time and probability

1.1 Obtain all jam densities under three scenarios by Eqs. (14)−(16).

$$k_1^1 = 100 + 100 \times \left\lfloor \frac{8}{7} \right\rfloor = 200,$$
$$k_1^2 = [1 - (0.5)^4] \times 200 = 187.5,$$
$$k_1^3 = [1 - (0.5)^3] \times 200 = 175.$$

1.2 Calculate the corresponding probability for every jam density by Eq. (17).

$$p_1^1 = 1 - 0.25 = 0.75,$$
$$p_1^2 = p_1^3 = 0.125.$$

1.3 Transform the jam density into travel speed by Eq. (18).

$$v_1^1 = 30 \times \exp\left(-\frac{115}{200}\right) = 16.88,$$
$$v_1^2 = 30 \times \exp\left(-\frac{115}{187.5}\right) = 16.25,$$
$$v_1^3 = 30 \times \exp\left(-\frac{115}{175}\right) = 15.55.$$

1.4 Transform the travel speed into travel time by Eq. (19).

$$t_1^1 = \frac{0.093}{16.88} = 0.0055\,(\mathrm{h}),$$
$$t_1^2 = \frac{0.093}{16.25} = 0.0057\,(\mathrm{h}),$$
$$t_1^3 = \frac{0.093}{15.55} = 0.006\,(\mathrm{h}).$$

Through ***Step 1***, the duration probability of every arc can be calculated and presented in Table 5. Note that the unit of the travel time obtained from *step 1.4* is hour. In this case, the unit of travel time is changed to second.

Step 2: Calculate the average rescue time in terms of c and T by Eqs. (20) and (21)

$$\gamma = \left\lceil \frac{\lceil 3/3 \rceil + 1}{1} \right\rceil \times 2 - 1 = 3,$$
$$t = \left\lfloor \frac{385}{3} \right\rfloor = 128.$$

Steps 3 and 4: Obtain upper bounds vector candidate $\boldsymbol{\Omega}$

Given MP_1, MP_2 and MP_3 as routes for this case shown in Table 6, the upper bound vector candidates $\boldsymbol{\Omega}$ are obtained through Eqs. (22) and (23) and shown in Table 7.

Take MP_1 for example, 6 upper bound vector candidates are generated by utilizing Eqs. (22) and (23). Since the minimal travel time of MP_3 is 135 which is more than the average travel time for each trip from *Step 2*, no solution can be obtained from Eqs. (22) and (23) in terms of MP_3. After further checking, no vector has been removed and thus there are 7 upper bound vectors in $\boldsymbol{\Omega}_{\mathbf{max}} = \{(20, 26, 14, 11, 16, 39, 2, 29, 46, 30, 34), (20, 26, 14, 11, 16, 39,$

Table 5 Duration probability table

a_i	Travel time (s)	Probability	a_i	Travel time (s)	Probability
a_1	20	0.750	a_7	2	0.750
	21	0.125		3	0.250
	22	0.125	a_8	27	0.750
a_2	26	0.750		28	0.125
	27	0.125		29	0.125
	28	0.125	a_9	42	0.750
a_3	13	0.875		44	0.125
	14	0.125		46	0.125
a_4	11	1.000	a_{10}	30	0.750
a_5	16	0.750		31	0.125
	17	0.250		32	0.125
a_6	36	0.750	a_{11}	33	0.750
	37	0.125		34	0.125
	39	0.125		35	0.125

Table 6 Travel time of the rescue routes

MP_j	Minimal travel time	Maximal travel time
$\mathrm{MP}_1 = (a_1, a_2, a_5, a_7, a_{10}, a_{11})$	127	137
$\mathrm{MP}_2 = (a_3, a_4, a_7, a_8, a_9, a_{11})$	128	138
$\mathrm{MP}_3 = (a_3, a_4, a_6, a_9, a_{11})$	135	145

Table 7 The results of *Step 3* for MP_1, MP_2 and MP_3

MP_j	Upper bound vector candidates
MP_1	$X_1 = (20, 26, 14, 11, 16, 39, 2, 29, 46, 30, 34)$
	$X_2 = (20, 26, 14, 11, 16, 39, 2, 29, 46, 31, 33)$
	$X_3 = (20, 26, 14, 11, 16, 39, 3, 29, 46, 30, 33)$
	$X_4 = (20, 26, 14, 11, 17, 39, 2, 29, 46, 30, 33)$
	$X_5 = (20, 27, 14, 11, 16, 39, 2, 29, 46, 30, 33)$
	$X_6 = (21, 26, 14, 11, 16, 39, 2, 29, 46, 30, 33)$
MP_2	$X_7 = (22, 28, 13, 11, 17, 39, 2, 27, 42, 32, 33)$
MP_3	–

2, 29, 46, 31, 33), (20, 26, 14, 11, 16, 39, 3, 29, 46, 30, 33), (20, 26, 14, 11, 17, 39, 2, 29, 46, 30, 33), (20, 27, 14, 11, 16, 39, 2, 29, 46, 30, 33), (21, 26, 14, 11, 16, 39, 2, 29, 46, 30, 33), (22, 28, 13, 11, 17, 39, 2, 27, 42, 32, 33)}.

Step 5: Derive network reliability by the RSDP method

After obtaining all upper bound vectors, we suppose that $\text{TM}_1 = \Pr(X \le X_1)$, $\text{TM}_2 = \Pr(X \le X_2) - \Pr(\bigcup_{j=1}^{2-1} \{X \le \max(X_j, X_i)\})$ and so on. Then the network reliability $R_{D,\,T} = \sum_{i=1}^{7} \text{TM}_i = 0.5315$ which means that we gave the possibility of 0.5315 to rescue a total of 4 casualties to the CCP in MSRN.

The experimental results with different T and number of MP are shown in Table 8. The network reliability would be increased with larger T or number of MP, and so is the CPU time. The commander could evaluate the probability of successfully rescuing for different situations and easily decide the rescue time or allocation of ambulances according to Table 8. Take $T = 394$ for example, network reliability would not increase when the number of routes increases from 2 to 3. The commander can assign the ambulance on these two routes when the given rescue time is 394. Furthermore, the suggestion for estimating the rescue time can also be provided under fixed number of routes, so that rescue resources are allocated more efficiently and also the probability of rescue can be improved.

6 Conclusions

This paper aims to propose an algorithm to evaluate the network reliability for the rescue operation. For the ambulance, each road would be damaged after the earthquake and cause the travel time of the route to become difficult to estimate. Therefore, the travel time of each arc is regarded as the random variable that represents the damage to every road. The duration probability table is then established by the proposed method mentioned in Sect. 3.2. Network reliability would be further calculated in terms of upper bound vectors. Through the experimental results, the commander can measure the rescue efficiency under given resources, such as the number of ambulances. The conclusions of this paper are summarized as follows:

1. The rescue operation can be modeled as MSRN and the travel time of each arc is regarded as stochastic.
2. The duration probability table is established to represent the damage to all arcs. For each ambulance, the travel time of each arc can be evaluated in earthquake situations.
3. Network reliability can be calculated in terms of all upper bound vectors by the RSDP method. This paper provides the commander with a quantitative indicator to easily evaluate rescue efficiency.
4. Different T and number of ambulances result in different probabilities of successful rescue which is network reliability. Reliable recommends would be provided to the decision maker by the experimental results in Table 8.

Future research may consider more casualties from multiple areas transported to the CCP. Furthermore, the rescue process from the CCP to the hospital is also an important issue that can be involved. Researchers can concentrate on several factors, such as the number of usable ambulances or the cost on rescue operation, and may be considered to make the rescue plan more complete.

Table 8 Experimental results

T	j	Network reliability	CPU time (s)
382	1	0.1780	0.0089
	1, 2	0.1780	0.0170
	1, 2, 3	0.1780	0.0219
	1, 2, 3, 4	0.1780	0.0439
	1, 2, 3, 4, 5	0.1780	0.0568
385	1	0.4153	0.0199
	1, 2	0.5315	0.0249
	1, 2, 3	0.5315	0.0339
	1, 2, 3, 4	0.5315	0.0508
	1, 2, 3, 4, 5	0.5315	0.0818
388	1	0.6625	0.0269
	1, 2	0.7868	0.0788
	1, 2, 3	0.7868	0.0907
	1, 2, 3, 4	0.7868	0.1057
	1, 2, 3, 4, 5	0.7868	0.1137
391	1	0.8372	0.1037
	1, 2	0.9270	0.6174
	1, 2, 3	0.9270	0.6154
	1, 2, 3, 4	0.9270	0.6453
	1, 2, 3, 4, 5	0.9270	0.6772
394	1	0.9351	0.3211
	1, 2	0.9804	2.2072
	1, 2, 3	0.9804	2.1921
	1, 2, 3, 4	0.9804	2.3778
	1, 2, 3, 4, 5	0.9804	2.3038
397	1	0.9789	0.4817
	1, 2	0.9957	3.4897
	1, 2, 3	0.9957	3.4996
	1, 2, 3, 4	0.9957	3.6154
	1, 2, 3, 4, 5	0.9957	3.6393
400	1	0.9944	0.4149
	1, 2	0.9993	2.5841
	1, 2, 3	0.9993	2.5392
	1, 2, 3, 4	0.9993	2.6270
	1, 2, 3, 4, 5	0.9993	2.6938
403	1	0.9989	0.2563
	1, 2	1.0000	1.0233
	1, 2, 3	1.0000	1.0741
	1, 2, 3, 4	1.0000	1.0563
	1, 2, 3, 4, 5	1.0000	1.0691

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Declarations

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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