Dynamic Allocation Models for Hospital Emergency Resources in Emergencies (Postprint)

Authors: Wan Zhiyuan, Liu Qinming, Ye Chunming, Liu Wenyi

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Abstract

To address the problem of supply-demand imbalance for emergency resources in hospitals during emergencies, this study investigates a dynamic allocation model for hospital emergency resources. Considering that the increasing number of patients and the evolution of their injuries lead to relative scarcity of hospital emergency resource supply, the changes in patient demand are modeled as a Markov decision process based on sequential decision theory, thereby establishing a dynamic allocation model for hospital emergency resources. The model is solved using a basic particle swarm optimization algorithm, and analysis is performed through a case study of hospital rescue operations following an earthquake. The case study demonstrates that the Markov decision process can dynamically satisfy the needs of patients in different states as injuries evolve, achieving optimal overall resource utilization in emergency rescue.

Full Text

Preamble

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Research on Hospital Emergency Resource Dynamic Allocation Model Under Emergencies

Wan Zhiyuan, Liu Qinming†, Ye Chunming, Liu Wenyi
(Business School, University of Shanghai for Science & Technology, Shanghai 200093, China)

Abstract: This paper investigates the dynamic allocation model for hospital emergency resources to address the supply-demand imbalance during emergencies. Considering that increased patient volume and evolving injury conditions lead to relative scarcity of emergency resources, we design patient demand changes as a Markov decision process based on sequential decision theory and establish a dynamic allocation model for hospital emergency resources. The model is solved using a basic particle swarm optimization algorithm and analyzed through a hospital rescue case following an earthquake. The case study demonstrates that the Markov decision process can dynamically meet the needs of patients in different states as injuries evolve, optimizing overall resource utilization in emergency rescue operations.

Keywords: emergencies; resource allocation; evolution of injuries; sequential decision-making; Markov process

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0 Introduction

Medical emergency response constitutes a core issue in emergency management and decision-making during 突发事件. Hospitals serve as critical rescue sites, and timely supply of emergency service resources effectively guarantees improved treatment rates. Emergencies are characterized by continuous evolution, multi-stage progression, and uncertainty, necessitating scientific emergency decision-making throughout rescue operations.

Chen et al. [1] abstracted emergency decision-making for major incidents into a multi-objective optimization model based on multi-attribute decision theory. Botega et al. [2] argued that Situation Awareness (SAW) represents a concept widely disseminated in critical decision-making application domains, such as emergency dispatch systems, where situational evolution and development trends in emergencies constitute dynamic change problems. Zheng et al. [3] constructed a continuous emergency resource scheduling model based on earliest emergency response time, incorporating characteristics of multi-point rescue in emergency systems where resource consumption rates are non-negative integrable functions. Decision-makers often face preference shift issues when making decisions about emergencies in complex environments; Xu et al. [4] proposed a novel large-group risk-based dynamic emergency decision-making method. Zhang [5] applied conflict management principles to develop an optimal decision model representing maximum stakeholder interests under game theory guidance. Emergency decision-making problems exhibit typical complex system characteristics; Wang et al. [6] analyzed differences between traditional and emergency decision-making problems, proposing a "cross-domain simulation-based emergency decision-making method" for emergencies. To better enable dynamic adjustment of emergency plans during 突发事件, Jiang et al. [7] constructed a risk decision-making method based on risk assessment. Luscombe et al. [8, 9] proposed a dynamic scheduling framework providing real-time support for managing scarce resources in emergency departments.

Liu et al. [10, 11] studied shortest path problems in emergency scheduling, establishing a multi-period fuzzy optimization model for multi-mode emergency material supply under 突发事件 based on demand splitting strategies. During emergency operations, emergency material supply and distribution operate in complex real-world environments characterized by uncertain demand at different disaster sites, inconsistent demand levels, and dynamic transportation routes; Tian et al. [12, 13] analyzed these issues using dynamic fuzzy logic, providing new ideas and theoretical methods for dynamic emergency decision-making during 突发事件. Due to social changes and increased public demand, ambulance call volumes continue rising, leading to increased costs and personnel shortages. Mould-Millman et al. [14, 15] studied dynamic data-driven emergency medical service decision support systems, providing a means for pre-hospital emergency care resources and expertise.

Current research on hospital emergency resource allocation optimization remains limited, with most studies relying on pre-established static emergency plans or experience-based strategies. Therefore, this paper investigates the dynamic allocation model for hospital emergency resources to address supply-demand imbalance during 突发事件.

1.1 Markov Decision Process Based on Injury State Evolution Under Sequential Decision Theory

In statistical decision-making problems, rather than pre-determining sample size, samples are taken sequentially until sufficient information enables appropriate decision-making. This process is called sequential analysis. In this paper, based on observed system information at each stage, an action is selected from the available action set to make a decision. The system' s next state is random, and this state transition probability exhibits the Markov property. For such decision systems with non-aftereffect state transitions, the corresponding sequential analysis decision process is called a Markov decision process. Among existing prediction models, this decision process is simpler and provides a quantifiable scheme for system state evolution trends, making it suitable for mathematical modeling in this context. Therefore, we apply it to emergency resource decision allocation in hospitals during 突发事件.

After an emergency occurs, patients transported to hospitals create demand for emergency resources, increasing pressure on timely medical service resource supply. Emergency management in hospitals requires rapid mobilization of all emergency resources within a short timeframe. Let J denote the set of patients j, $J = \{1, 2, 3, \dots, j_{\max}\}$. Let K denote the set of emergency resources k in hospitals during 突发事件, $K = \{1, 2, 3, \dots, k_{\max}\}$. We design the hospital emergency resource allocation problem as a dynamic multi-stage decision problem, with stages represented by set T, $T = \{1, 2, 3, \dots, t_{\max}\}$.

In the realistic environment of supply-demand imbalance for emergency resources, a patient' s demand is considered "satisfied" at a given stage if their emergency resource request is fully allocated. Resource demand correlates with patient injury conditions. At each decision stage, we must decide whether to satisfy each patient' s emergency resource demand immediately or defer it to the next stage. Thus, this paper' s hospital emergency decision framework is dynamic: "satisfy patient demand now & satisfy patient demand in the future," contrasting with traditional static frameworks of "satisfy patient demand now & do not satisfy patient demand now."

Let the decision variable Z_{tjk} represent whether to satisfy patient j' s demand for resource k at stage t:

$$Z_{tjk} = \begin{cases} 1 & \text{if patient demand is satisfied at stage } t \\ 0 & \text{otherwise} \end{cases}$$

Due to varying and uncertain patient demands, demand state transitions between adjacent stages are random, depending only on current and future demand state changes. Thus, Z_{tjk} is essentially a random variable. If the demand state at a certain stage is θ, the probability that the demand state becomes θ' after one stage of injury evolution is $R_{jk}(\theta, \theta')$, representing the state transition probability. The patient demand state transition probability matrix is R_{jk}, which is an upper triangular matrix with all elements below the diagonal equal to 0:

$$R_{jk} = \begin{pmatrix} R_{jk}(\theta_1, \theta_1) & R_{jk}(\theta_1, \theta_2) & \cdots & R_{jk}(\theta_1, \theta_{\max}) \\ 0 & R_{jk}(\theta_2, \theta_2) & \cdots & R_{jk}(\theta_2, \theta_{\max}) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R_{jk}(\theta_{\max}, \theta_{\max}) \end{pmatrix}$$

When patient demands are not fully satisfied, the demand state value evolving naturally according to injury trends is called the "natural value," denoted as G_{tjk}. The sequence of "natural values" generated at different stages, $\{G_{tjk}\}$, forms a Markov chain. Its next-stage "natural value" depends only on the current patient demand state, independent of previous demand states. The expected "natural value" at stage t for patient j' s demand for resource k is:

$$E[G_{t+1,jk}] = \sum_{\theta'} R_{jk}(\theta, \theta') \cdot G_{tjk}$$

Patient injuries and resource demands vary across stages. Decision-makers' choices at a given stage affect subsequent decision processes, constituting a typical dynamic programming problem.

Let the demand state set be $\Theta = \{\theta_1, \theta_2, \dots, \theta_{\max}\}$. Since patient demand state values are non-negative integers, $E[G_{t+1,jk}]$ may not coincide with demand state value points, i.e., $E[G_{t+1,jk}] \neq G_{t+1,jk}$. The two values only become equal when the adjacent time interval L approaches 0:

$$\lim_{L\to 0} E[G_{t+1,jk}] = G_{t+1,jk}$$

The state value reflects the scale of emergency resource demand and the urgency of meeting demands directly related to patient injury severity. A value of 1 indicates mild injury; larger values indicate more severe injuries, greater demand, and higher priority for satisfaction. Obviously, patient injury states vary due to hospital service levels, service environments, and patient characteristics such as age, gender, physical condition, and particularly stage (time).

To reflect this phenomenon, we design parameter G_{tjk} to represent patient j' s demand state for resource k at stage t. For example, $G_{1jk} = 2$ indicates that at stage 1, patient j' s demand state for resource k is 2. This state has the following properties:

Property 1: When patient demand is not fully satisfied, the demand state is a monotonically non-decreasing function.

Proof: Assuming all patient demands can only be satisfied by emergency service resources provided by decision-makers, and based on injury evolution trends, demand can only increase or remain constant over time when not fully satisfied, never decrease. When $L \to 0$, state values are continuous, and $E[G_{t+1,jk}]$ ranges over all points in $[G_{tjk}, G_{tjk}^{\max}]$. Therefore, $E[G_{t+1,jk}]$ must coincide with demand state value points. However, continuous decision problems are difficult to solve. To enable equality, we convert continuous decisions to discrete decisions by rounding the right side of the equation, obtaining the patient demand state transition formula between adjacent time "natural values" :

$$G_{t+1,jk} = \text{round}\left(\sum_{\theta} R_{jk}(\theta, \theta') \cdot G_{tjk}\right)$$

where round(x) denotes stochastic rounding of x as shown in Equation (7), which allows x to take the integer value closest to itself:

$$\text{round}(x) = \begin{cases} \lfloor x \rfloor & \text{if rand} \geq x - \lfloor x \rfloor \\ \lfloor x \rfloor + 1 & \text{otherwise} \end{cases}$$

where rand is a random number in $[0, 1]$, and $\lfloor x \rfloor$ is the integer part of x.

In addition to Equation (6), an initial value must be specified:

$$G_{0jk} = \theta_0$$

Property 2: Changes in patient demand state are random.

Property 3: If patient demand is fully satisfied at a certain stage, the demand state value returns to the initial demand value and then restarts the evolution process.

When patient demand may be fully satisfied, the natural evolution process of demand state is disturbed. We call this changed value the "interference value," denoted as $\hat{G}_{tjk}$. Incorporating the impact of interference behavior on patient demand state transition into Equations (6) and (8), we obtain the state transition equation between adjacent time "interference values" :

$$\hat{G}_{tjk} = \begin{cases} \theta_0 & \text{if } Z_{tjk} = 1 \\ \text{round}\left(\sum_\theta R_{jk}(\theta, \theta') \cdot \hat{G}_{t-1,jk}\right) & \text{otherwise} \end{cases}$$

After calculating the "interference values" of patient demand states at each stage, we must determine patient demand values. Patient demand is proportional to demand state. Let μ_{jk} be a weight factor comprehensively determined by patient age, gender, injury severity, physical condition, etc. Then patient j' s demand for resource k at stage t is:

$$d_{tjk} = \mu_{jk} \cdot \hat{G}_{tjk}$$

Since different patients have varying demand quantities, we normalize emergency resources using Equation (12) to obtain a unified demand value S_{tjk}:

$$S_{tjk} = \frac{d_{tjk} - d_{jk}^{\min}}{d_{jk}^{\max} - d_{jk}^{\min}}$$

where $d_{jk}^{\max}$ and $d_{jk}^{\min}$ represent the maximum and minimum emergency resource demands of patient j for resource k, respectively. Equation (13) ensures that the total satisfied demand across all stages does not exceed actual hospital emergency resource supply, where C_{tk} denotes the supply upper limit for resource k at stage t:

$$\sum_{j \in J} Z_{tjk} \cdot S_{tjk} \leq C_{tk}, \quad \forall t \in T, k \in K$$

1.2 Establishment of Hospital Emergency Resource Dynamic Allocation Model

Hospital emergency resources during 突发事件 refer to the totality of all resources that can be rapidly mobilized or actively responded to in hospital emergency management, including human and material resources. Human resources primarily comprise decision-makers, medical experts, medical consultants, and logistics support staff. Material resources mainly include infrastructure, medical technology equipment, emergency supplies, and medicines. Hospital emergency management and decision-making differ from general resource scheduling, with the primary principle being fastest satisfaction of patient resource demands, where timeliness clearly outweighs cost considerations.

Hospital emergency service resource allocation is not a single-stage task; it requires dynamic, multi-stage allocation based on actual situation changes and previous stage effects until rescue completion. The random, dynamic nature of 突发事件 determines that emergency management resource allocation is a dynamic multi-stage process. Resources always appear relatively scarce compared to large patient demands, requiring decision-makers to allocate limited, relatively scarce resources rationally to achieve rescue objectives with minimal resource consumption.

This paper treats hospital decision-makers as the model' s decision agents, with patients transported to hospitals after 突发事件 as the decision objects, and key hospital resources as doctors and nurses. The model's decision process primarily involves dynamic, multi-stage demand satisfaction of doctors and nurses for patients. The objective function is:

$$\min \sum_{t\in T}\sum_{j\in J}\sum_{k\in K} S_{tjk}$$

where S_{tjk} represents patient j's demand for resource k at stage t. Since demand evolution is closely related to decision-makers' satisfaction strategies, a rapid, timely, and effective satisfaction strategy can maximally delay demand evolution. This paper minimizes the total demand across all stages and all patients.

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2 Model Solving

Given that the hospital emergency resource allocation model operates during 突发事件, solution time requirements are stringent. Particle swarm optimization (PSO) is an evolutionary algorithm similar to simulated annealing. Starting from random solutions, it iteratively seeks optimal solutions, evaluates solution quality through fitness functions, and converges to global optima. Compared with genetic algorithms, PSO has simpler rules without crossover and mutation operations, faster computation speed, and finds global optima by tracking currently searched optimal values. It is insensitive to population size and suitable for numerous optimization problems due to its easy implementation, fast convergence, and high precision.

The algorithm is described as follows: In an M-dimensional space, there are I particles with maximum evolution generation $n_{\max}$. The position of particle i at generation n is $X_i^n = \{X_{i1}^n, X_{i2}^n, \dots, X_{iM}^n\}$. During computation, particles correspond to fitness functions associated with the objective function. The individual optimal position of particle i during operation is $P_i^n = \{P_{i1}^n, P_{i2}^n, \dots, P_{iM}^n\}$, and the global optimal position of all particles is $P_g^n = \{P_{g1}^n, P_{g2}^n, \dots, P_{gM}^n\}$.

2.1 Particle Position and Velocity Update

This paper addresses a discrete space optimization problem. Since decision variable Z_{tjk} is integer, particle dimension is set to $M = j_{\max} \times t_{\max}$. Let X_{ijt}^n denote the element in row j and column t of position matrix X_i^n for particle i at generation n. Similarly, elements of particle velocity, individual optimal position, and global optimal position matrices are denoted as V_{ijt}^n, P_{ijt}^n, and P_{gjt}^n, respectively.

To ensure particle initial and updated positions correspond to objective function values, initial position and velocity are designed as:

$$X_{ijt}^0 = \begin{cases} 1 & \text{if rand} < 0.5 \\ 0 & \text{otherwise} \end{cases}$$

$$V_{ijt}^0 = \text{rand}$$

Particle velocity update formula is:

$$V_{ijt}^{n+1} = w \cdot V_{ijt}^n + c_1 \cdot \text{rand} \cdot (P_{ijt}^n - X_{ijt}^n) + c_2 \cdot \text{rand} \cdot (P_{gjt}^n - X_{ijt}^n)$$

where w is inertia weight, and c_1, c_2 are learning factors.

Since velocities must map to the $[0, 1]$ interval, updated velocities are converted to probabilities of position taking value 1 using the sigmoid function:

$$S(V_{ijt}^{n+1}) = \frac{1}{1 + e^{-V_{ijt}^{n+1}}}$$

Particle position update formula is then:

$$X_{ijt}^{n+1} = \begin{cases} 1 & \text{if rand} < S(V_{ijt}^{n+1}) \\ 0 & \text{otherwise} \end{cases}$$

In addition to constraints (1)-(10), two more constraints are needed. Inequality constraint (13) is incorporated into the original objective function as a penalty term:

$$\min \sum_{t\in T}\sum_{j\in J}\sum_{k\in K} S_{tjk} + \sum_{t\in T}\sum_{k\in K} \min\left(0, C_{tk} - \sum_{j\in J} Z_{tjk}\cdot S_{tjk}\right)$$

The fitness function for particle i at generation n is denoted as Fit_i^n.

2.2 Algorithm Steps

The PSO algorithm for solving the hospital emergency resource decision problem proceeds as follows:

a) Initialize parameters and population.

b) Initialize and update particle positions using the position formula, and initialize and update particle velocities using the velocity formula.

c) Calculate fitness values using Equation (19).

d) Compute individual optimal values and positions, and global optimal value and position.

e) Compare current generation n with maximum generation $n_{\max}$: if $n \neq n_{\max}$, increment $n = n + 1$ and return to step b); if $n = n_{\max}$, proceed to step f).

f) Terminate computation and output global optimal value and position.

3.1 Example Description

Consider a natural disaster where a hospital emergency rescue process involves j patients urgently needing k types of medical resources. Patient demands for emergency resources (primarily doctors and nurses) evolve dynamically. Assume three demand states. Comparison tables of injury severity versus demand states, demand state transition probability matrices, and baseline demand data are shown in through . Assume hospital emergency resource reserves supply 5 doctors and 5 nurses per stage during allocation.

3.2 Example Analysis

The model was programmed and solved using MATLAB R2017a on a computer with 3.4 GHz CPU and 4 GB RAM. Parameters were set as: population size = 200, maximum generations = 200, inertia weight = 0.7298, and both learning factors = 1.49445. Running the program 20 times consecutively yielded solution times between 13.40212 and 13.82192 seconds, demonstrating high stability in both results and computation time. The fitness function variation curve is shown in [Figure 1: see original paper].

compares injury severity with demand states. presents patient demand state transition probability matrices for doctors and nurses. shows patient baseline demands (unit: persons) and state initial values.

Optimal demand satisfaction strategies are shown in . Due to insufficient emergency resource supply, not all patient demands can be fully satisfied at each stage, requiring selective satisfaction. Patients 3, 4, and 5 receive satisfaction opportunities more frequently than the other three patients. [Figure 2: see original paper] illustrates the rationale.

In [Figure 2: see original paper], blue curves represent "natural value" variation without demand satisfaction strategy interference, reflecting the Markov process of demand state evolution. Clearly, patients 2, 4, and 5 have more urgent resource demands, likely due to larger baseline demands compared to the other three patients. The demand satisfaction strategy should prioritize these high-demand patients, which confirms.

The satisfaction strategy proves more effective for patients 2, 4, and 5 in two ways:

a) The strategy significantly reduces total resource demand. The area between blue and orange curves in [Figure 2: see original paper] represents the demand reduction achieved by the satisfaction strategy. This area is larger for patients 2, 4, and 5.

b) The strategy flattens demand variation curves. Orange curves represent "interference value" variation under satisfaction strategy influence. All "interference value" curves show smoother overall trends.

In summary, the proposed Markov decision method can dynamically formulate appropriate demand satisfaction strategies, maintaining stable overall demand trends and minimizing total demand levels. Under resource scarcity during 突发事件, the method prioritizes patients with faster demand evolution and larger baseline demands as rescue targets, dynamically adjusting satisfaction strategies over time to balance fairness and efficiency in emergency resource allocation from a holistic rescue planning perspective. The Markov process effectively demonstrates demand state evolution patterns.

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4 Conclusion

This paper investigates the dynamic allocation model for hospital emergency resources to address supply-demand imbalance during 突发事件. Considering increased patient volume and evolving injury conditions that lead to relative resource scarcity, we design patient demand changes as a Markov decision process based on sequential decision theory and establish a dynamic allocation model. The main innovation lies in designing a decision process that conforms to demand evolution patterns caused by injury progression during 突发事件, proposing optimal strategies for patient demand satisfaction, and analyzing a hospital rescue case following an earthquake. The case study demonstrates that the Markov decision process can dynamically meet patient needs across different states as injuries evolve, optimizing overall resource utilization in emergency rescue.

The model remains somewhat idealized; real-world hospital emergency decision-making faces more complex situations with additional factors. Future research directions include investigating more complex multi-type medical emergency resource allocation networks and developing superior solution algorithms.

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Note: Figure translations are in progress. See original paper for figures.