Front. Eng. Manag. 2017, 4(2): 221–228
DOI 10.15302/J-FEM-2017020

RESEARCH ARTICLE

Ke WANG, Yixin LIANG, Lindu ZHAO

Multi-stage emergency medicine logistics system optimization based on survival probability

Abstract Using sudden cardiac deaths as an example and maximizing survival rate as the goal, this paper studies the influence of multi-stage medical logistics system optimization on the survival rate of sudden illness. A distribution model of survival is built, drone and ambulance arrival probability over time are discussed, a formula is proposed for maximum possible survival rate based on the probability of emergency medical logistics reaching the patient, and the results are analyzed using empirical data fitting distribution and numerical experiments performed with the model. The model is discussed as a reference point for management decision making by changing model parameters. Results show that compared to using current ambulance vehicles, ambulance drones delivering medical equipment for first aid on-site in emergencies can significantly increase survival rate, and the effect of collaborative multi-stage logistics optimization is better than that of any single stage logistics response optimization. Simulation results show that the medical rescue logistics service radius, speed, loading capacity and performance of ambulance drones impact the probability of survival, and there is an optimal service radius depending on the shape of probability distribution, which provides new information for management decisions.

Keywords emergency medicine logistics, ambulance drone, survival probability, critical illness

1 Introduction

When experiencing a critical illness such as cardiac arrest (also called sudden cardiac death, SCD), a patient's health deteriorates rapidly, the probability of their survival depends on the emergency medical logistics system delivering essential medical equipment or the patient.

Using SCD as an example, surveys show that the incidence of cardiac arrest in China ranks first in the world: More than 54 million people suffer SCD every year, that is, more than 1 person is affected per minute (Hua et al., 2009). Additionally, 80%–90% of cardiac arrest cases are caused by ventricular fibrillation. Early electric shock defibrillation is the key to patient survival, defibrillation for delay of every 1 min reduces the survival rate of patients by 7%–10% (Merghani et al., 2013). In the first few minutes of cardiac arrest, defibrillation improves survival rates by 50%; 10 min after defibrillation, there is little chance of survival; and >12 min after ventricular fibrillation, the survival rate is < 5% (Weisfeldt et al., 2010; Nielsen et al., 2013). Essentially, saving time is saving life.

The emergency medical logistics system is divided into several stages. In the basic life support stage, equipment such as AED (automated external defibrillator) should be delivered for first aid; in the advanced life support stage, patients should be transferred to a hospital by ambulance. There are life maintenance stages between these two stages. A report from the Paris Sudden Death Expertise Centre (SDEC), showed that most cases of 3670 sudden cardiac arrests occurred at home (72%), with bystanders present in 81% of the cases. Cardiopulmonary resuscitation (CPR) was performed in only 42% of the cases, only 34% of the cases were admitted alive at the hospital, and only 7% were discharged alive (European Society of Cardiology, 2013). A similar survey of 4619 SCD cases in Shenzhen city, China, reported that only 143 cases (3%) were admitted alive at the hospital, and ultimately, only 0.6 per thousand, less than 1 per thousand were discharged alive (MedSci, 2013). Gu et al. (2016) reviewed 57 articles, 29269 pre-hospital cardiac arrests to study the heart recovery rate by meta-analysis, concluded that providing first-aid equipment is the key factor to increase the survival rate. Lack of first-aid medical equipment delivery is a

Received March 30, 2017; accepted May 24, 2017

Ke WANG, Yixin LIANG, Lindu ZHAO (✉)
School of Economics and Management, Southeast University, Nanjing 210096, China
E-mail: ldzhao@seu.edu.cn

bottleneck in the development of pre-hospital care in China (He et al., 2016).

In the real world, ambulance response time is limited by traffic jams, and medical resources are relatively insufficient. Even France and Germany, equipped with first-aid helicopters, often miss the best time to rescue, arriving after 12 min±7 min at the scene of the emergency for cardiac arrest situations. With ambient intelligence technologies and remote-controlled drone (unmanned aerial vehicle, UAV) technology development, ambulance drones began to appear in medical care areas. Olshansky (2016) suggested developing and advancing new technologies and approaches, such as drone delivery of AED to sites of arrest rather than attempting to anticipate such sites and prepopulate with installed AEDs.

Research shows that traditional AED first aid efficiency optimization results can achieve only 10% survival rates, while medical logistics by drone can reduce geographic and traffic restrictions (Capucci et al., 2016). An ambulance drone prototype unveiled in Holland illustrates the function in detail. It can fly at speeds of up to 100 km/h, delivering a defibrillator to a patient within a 12 km^2 zone within a minute, increasing the chance of survival from 8% to 80%, and be expected to become a “flying medical toolbox” able to carry an oxygen mask to a person trapped in a fire or an insulin injection to a diabetes sufferer.

In regard to optimization of emergency medical services (EMS), Budge et al. (2010) studied the empirical distribution of ambulance response time; the relationship of time of arrival of EMS and survival from out-of-hospital ventricular fibrillation cardiac arrest was also analyzed (Gold et al., 2010), and there was research on ambulance optimization under cost constraint (Maxwell et al., 2014). A rural area dynamic ambulance management model was built as a solution (Van Barneveld et al., 2017). Only a little literature has been found on vehicle mix decisions in emergency medical service systems, and none involved drones (Chong et al., 2015). Travel time forecasting and dynamic routes design for emergency vehicles has been studied (Musolino et al., 2013).

Medical drones have entered the stage of both theoretical research and practical exploration. The requirements and feasibility to use UAVs for medical product transport was discussed (Thiels et al., 2015). Advantages of drones for cost and vaccine accessibility was analyzed, the economic and operational value of using drones to transport vaccines in low- and middle-income countries was proved (Haidari et al., 2016). A decision support system was proposed for coordinated disaster relief distribution; humanitarian goods (including medicines) can be distributed using both UAVs and SUVs (sport utility vehicles) (Fikar et al., 2016).

In summary, previous literature on emergency medical logistics for critical diseases such as cardiac arrest, focused on single traditional transport vehicles; the optimization goals are mainly to reduce costs, improve efficiency, and rarely consider the probability of survival. The few studies involving ambulance drone are limited on qualitative analysis and there is no research on the different stages of logistics optimization of emergencies considering both drone and ambulance.

The primary contributions of this paper are as follows: The models we propose to describe the impact of multistage emergency medical logistics optimization on SCD survival probability have not been well studied, especially considering the emergency drone. First, we build a model of the survival probability distribution over time in cardiac arrest and a probability distribution model of logistics arrival at different stages. Next, we analyze the survival probability of delivering first-aid medical equipment such as AED with an ambulance drone, and compare it with single stage logistics. Last, we discuss the meaning of the parameters for management, and offer advice for logistics decision making.

2 Problem description and hypothesis

2.1 Problem description

The present medical emergency logistics system is composed mostly of ambulances. When cardiac arrest occurs, patient survival rate drops rapidly. First, bystanders or attendants will call for an ambulance and wait for rescue, and after overcoming traffic congestion in the city or country roads in the countryside, the ambulance will arrive at the scene, usually later than the effective rescue time. With the development of telemedicine, an emergency center can quickly determine the patient’s geographical location and exchange information through a home ambient intelligence terminal. The emergency center supported by telemedicine can schedule appropriate logistics tools to deliver first aid equipment according to the patient’s rescue needs. In the earliest stage, a small volume of equipment such as an AED could be carried by an ambulance drone to the scene for bystander rescue. Bystanders or attendants could receive this first-aid medical equipment for simple and effective early treatment in the basic life support stage. At the same time, the emergency center could schedule an ambulance providing more equipment (oxygen, injections, and so on) for the next advanced life support stage. During the different stages, the patient’s survival probability will improve if the medical logistics arrive on time.

2.2 Research hypotheses

1) Based on previous research (Hansen et al., 2015), survival P_s (probability of survive) with time can be fitted by a linear probability distribution model, that is, Ps is the

linear function of time t;

2) In each stage, the probability of emergency medicine logistics arriving, P_d (probability of drone) and P_a (probability of ambulance) obey the normal distribution with time;

3) When first aid medical equipment delivered by ambulance drone arrives at the scene, that is, when $P_d \geqslant P_s$, the survival rate of patients with a declining trend will be improved, the speed of decline will be slower but still downward;

4) When advanced life support delivered by ambulance arrives, when $P_a \geqslant P_s$, survival rate will no longer decline and will remain the same until hospital treatment.

3 Model

3.1 Survival probability distribution model

According to the hypothesis, the distribution model of patient survival probability Ps over time t is

$$f_s(t) = M - kt, \tag{1}$$

where parameter M represents the max survival probability when SCD happen, parameter k represents the declining survival rate per 1-min delay in responding to the deterioration of health.

3.2 Ambulance drone arrival time probability distribution model

According to the hypothesis, ambulance drone delivering first-aid medical equipment arrives at the scene with probability P_d, and the probability density function over time t, $f_d(t)$, is:

$$f_d(t) = \frac{1}{\sigma_1\sqrt{2\pi}} e^{-\frac{(t-\mu_1)^2}{2\sigma_1^2}}, \ t \geqslant 0, \tag{2}$$

where parameter μ_1 represents the mean travel time of the ambulance drone, standard deviation σ_1 represents the time fluctuations and variety of transport distances around the radius.

3.3 Ambulance arrival time probability distribution model

According to the hypothesis, the ambulance arrival in probability P_a over time t density function, $f_a(t)$, is:

$$f_a(t) = \frac{1}{\sigma_2\sqrt{2\pi}} e^{-\frac{(t-\mu_2)^2}{2\sigma_2^2}}, \ t \geqslant 0, \tag{3}$$

where parameter μ_2 represents the mean travel time of the ambulance, standard deviation σ_2 represents the time fluctuations and variety of transport distances.

3.4 Survival rates in patients

Based on simultaneous equations, Eqs. (1) and (2), if there is an intersection point of the two probability distributions, then use the maximum value Max(P_{sd}), which represents the max survival probability improved by drone, and introduce the improved coefficient r.

$$f_{sd}(t) = M - (1-r)kt. \tag{4}$$

Use the maximum value Max(P_{sda}), that is, the max survival probability improved by drone and then by ambulance, when there is an intersection point of simultaneous equations, Eqs. (4) and (3).

$$f_{sda}(t) = \mathrm{Max}(P_{sda}). \tag{5}$$

Based on simultaneous equations, Eqs. (5) and (3), according to the properties of the normal distribution, the survival rates in patients can be described by the mean value of maximum probability $\overline{\mathrm{Max}(P_{sda})}$ and cumulative probability P_L^r.

$$P_L = P_L^r \cdot \overline{\mathrm{Max}(P_{sda})}. \tag{6}$$

For visual comparison and analysis, we use empirical data to simulate calculation.

4 Data and results

4.1 Survival probability distribution

In addition to (Merghani et al., 2013) where survival rates in patients declined 7%–10% for every 1-min delay in defibrillation, Huang (2014) studied the correlation of the cardio-pulmonary defibrillation resuscitation time window and the success rate of recovery. Patients were divided into five groups, < 1 min group, 1–3 min group, 3–6 min group, 6–8 min group, and >8 min group; corresponding defibrillation success rates were 91.67%, 66.67%, 54.55%, 31.58%, 11.11%. A survival time distribution model can be set up based on this data, intermediate values were used for four groups in front of them, average ambulance arrival time of 10 min was used for the >8 min Group (He et al., 2015).

Empirical data distribution can be fitted by Matlab Toolbox, expressed as linear Eq. (7).

$$P_s = 0.9 - 0.08t. \tag{7}$$

Goodness of fit results: SSE: 0.009188, R-square: 0.9763, adjusted R-square: 0.9684, RMSE (root-mean-square error): 0.05534.

Figure 1 shows that the model fitting effect is good.

4.2 Ambulance drone arrival time probability distribution

At present, data are lacking for an ambulance drone arrival

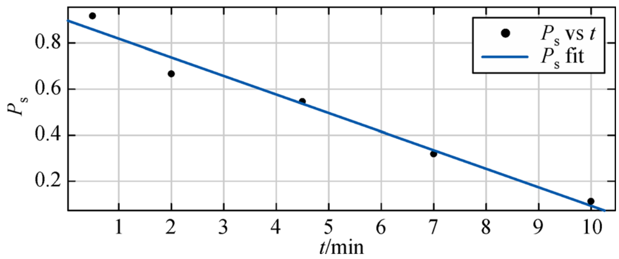

Fig. 1 Survival curve fitting

probability distribution. An ambulance drone can deliver a defibrillator to a patient in a 12 km^2 (4.6 mile^2) zone within a minute. If the period before arrival, or call response time is divided into start time and flight time, the mean time of flight can be preset at 1 min. Start time from emergency call to vehicle dispatching can be reduced to 1 min with standard deviation 0.11 as shown in practice based on established monitoring on-line systems, command software environments and other information technologies such as telemedicine (He et al., 2015). Assuming both ambulance drone response time and flight times are subject to (1, 0.11) normal distribution. Video information shows that it takes 2 min from an emergency call to ambulance drone arrival at a patient site. Therefore, the normal distribution of the ambulance drone is pre-set (2, 0.22), that is, $\mu_1 = 2$ min, $\sigma_1 = 0.22$ min.

4.3 Ambulance arrival time probability distribution

Results of research show that hospital emergency response rate in basic level hospitals can be improved by application of quality control circles. Ambulance response time before optimization has a normal distribution with mean 16 min and standard deviation 0.42 min. The distribution after optimization has mean 10 min and standard deviation 0.52 min (He et al., 2015). The impact of optimization will be researched later. The distribution of the ambulance is pre-set based on previous research, $\mu_2 = 16$ min, $\sigma_2 = 0.42$ min.

According to the literature, the improvement coefficient r is 0.5 (Weisfeldt et al., 2010; Nielsen et al., 2013).

4.4 Results

According to Eqs. (1)–(7) and combined with the properties of the normal distribution model results that can be obtained by Matlab:

$$\mathrm{Max}(P_{\mathrm{sd}}) = 0.76(t),\ t = 1.71\ \mathrm{min},$$

$$\overline{\mathrm{Max}(P_{\mathrm{sda}})} = \mathrm{Max}(P_{\mathrm{sda}}) = 0.22,\ t = 15.25\ \mathrm{min},$$

$$P_{\mathrm{L}}^{\mathrm{r}} = 0.40,\ P_{\mathrm{L}} = P_{\mathrm{L}}^{\mathrm{r}} \cdot \mathrm{Max}(P_{\mathrm{sda}}) = 0.09.$$

Survival rate improvement by the ambulance drone is shown by the shaded area in Fig. 2.

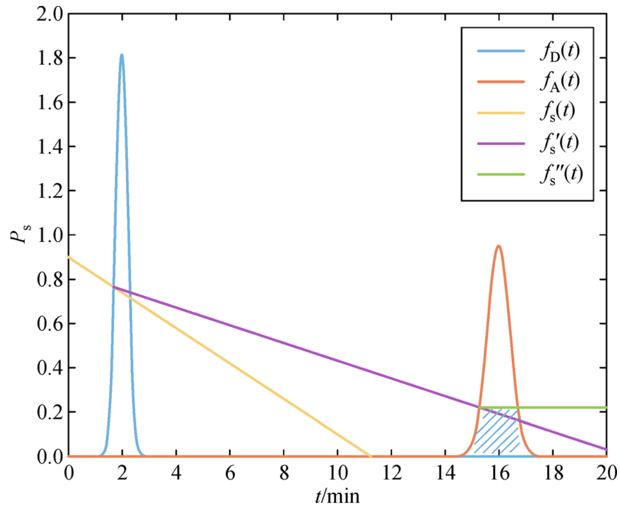

Fig. 2 Survival rate improvement by the ambulance drone

4.5 Results analysis

From Fig. 2, there is no intersection point between $f_s(t)$ and $f_a(t)$ before the application of the ambulance drone; when the ambulance arrived, the patient's survival rate was already near zero. With AED delivered by an ambulance drone, rapid defibrillation can gain valuable maintenance time before the hospital, but survival rates are still falling. From the average and standard deviation of ambulance arrival time, the maximum survival rate for patients can attain 9%, which is much more than the current $< 1\%$ and significant improvement. If the ambulance did not arrive in time, patients have no chance to live. Figure 2 prompt model parameters have significant impacts on $P_{\mathrm{L}}^{\mathrm{r}}$; it is necessary to discuss the practical meaning of different parameters.

5 Model parameters analysis

5.1 Improve logistics efficiency, shorten arrival time μ, no change in the parameter σ

When the ambulance drone average response time $\mu_1 = 2$ min, there is no more space to optimize in practice; therefore, only μ_2 will be observed without changing μ_1. As mentioned before, the ambulance response time in basic level hospitals can be shortened to 10 min, densely populated areas in a developed country coupled with a manned helicopter can attain 5 min. Therefore, μ_2 is assigned 5 and 10 min, results are visible in Table 1 and Fig. 3.

Table 1 Survive rate optimization results of different μ_2 Assignment

Average time, μ_2 /min	Lack of ambulance drone		Application of ambulance drone	
	Max(P_{sa})	P_L	Max(P_{sda})	P_L
16	Near 0	Near 0	0.22	0.09
10	0.16	0.02	0.45	0.31
5	0.54	0.35	0.64	0.55

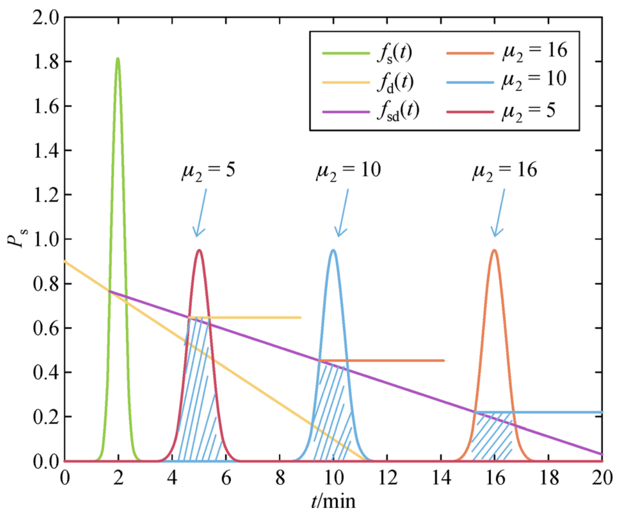

Fig. 3 Survive rate optimization results of different μ_2 assignment

Analysis:

1) The parameter adjustment results after further verification show that after the application of an ambulance drone, response time was shortened by 5 min, and the maximum survival rate can be increased to 55%. The maximum survival rate can be increased to only 35% without the application of an ambulance drone. The effect of collaborative multi-stage logistics optimization is better (at least 20%) than that of ambulance response optimization only.

2) Without the application of an ambulance drone, there is little improvement in maximum survive rate even if the ambulance response time can be shortened from 15 to 10 min. When the response time is $\leqslant$10 min, the maximum survival rate can improve significantly with shorter response time, but considering the emergency medical resource constraints and the traffic status in China, it is very difficult for ambulance response time to achieve $\leqslant$5 min.

3) There is a high need for efficient collaboration between ambulance drones and ambulance aerial vehicles as two phases of logistics, where unmanned drones for basic life support can improve the survive rate curve and aerial vehicles as advanced life support ambulances determines the final survival rate. The special use of ambulance drones with telemedicine will also greatly enhance the efficiency of ambulance first aid.

5.2 Optimized logistics response time, maintain the same μ, increase σ

Ambulance response times vary in different areas, performance from the grass-roots hospital can be optimized to $\mu_2 = 10$ min, $\sigma = 0.52$ min. The average first-aid response capacity of ambulances in Beijing average traveling time = 11.5 min, with a standard deviation of up to 6.52 min (Chen and Ma, 2008). The furthest distance in Chaoyang district can be up to 62 km with a big difference in traveling time; therefore, it is necessary to study parameter impact on survival rates. Based on $\mu_1 = 2$ min, $\mu_2 = 10$ min as a benchmark, ambulance unmanned aerial vehicles and an ambulance were compared.

5.2.1 Adjust ambulance drone σ_1

With the assignment of an ambulance drone σ_1, $\sigma_1 =$ 0.22 min, $\sigma_1 = 0.53$ min, $\sigma_1 = 1$ min. The effect is shown in Fig. 4.

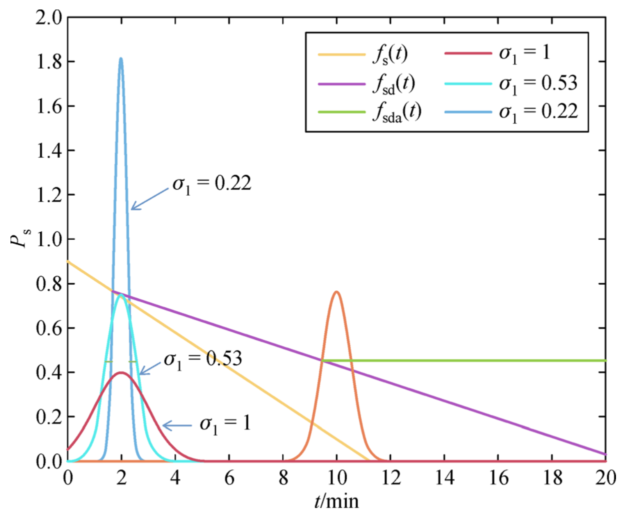

Fig. 4 Different σ_1 assignment

1) From Fig. 4, increasing σ_1 does not improve the maximum survival rate, but when σ_1 increases to a certain extent, as in the figure, when σ_1 >0.53 min, an ambulance drone is unable to improve the survival rate of patients.

2) As the average fluctuation degree of arrival time, σ_1 can reflect the rescue radius. In this case, based on 0.53 min

as the maximum standard deviation, the rescue radius can be estimated to not exceed 4 km.

3) It should also be noted that the reduced ambulance drone rescue radius does not significantly increase the maximum survival rate; an ambulance drone is characterized by faster reaction time and delivery speed, which are a great advantage in traffic-clogged cities and inaccessible rural areas with a distance of 2–4 km.

5.2.2 Adjust the ambulance σ_2

With the assignment of an ambulance $\sigma_2 = 0.52$ min, $\sigma_2 = 0.9$ min, $\sigma_2 = 3$ min, $\sigma_2 = 6$ min, the effect is shown in Fig. 5.

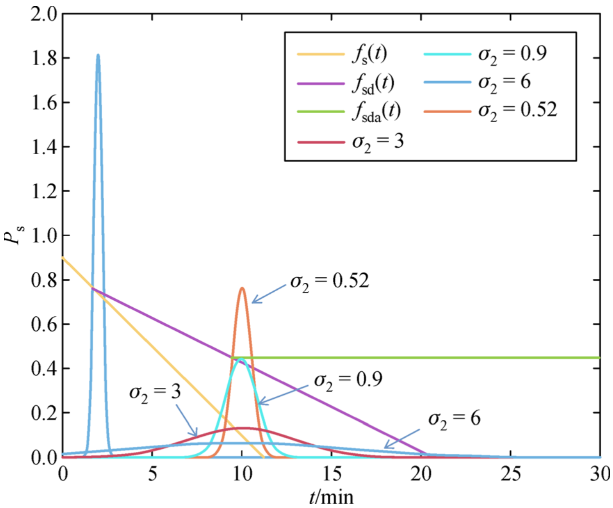

Fig. 5 Different σ_2 assignment

1) In Fig. 5, with the absence of an ambulance drone, moderate increases of σ_2 can effectively increase the maximum survival rate, but when σ_2 increased to a certain extent, the survival rate of patients in the point in time Max (P_{sa}) and the maximum survival rate began to decline. Even with ambulance drone transport, such as $\sigma_2 > 6$ min, the probability of loss can occur.

2) If first aid ambulance drones took part in delivering medical equipment, extending maintenance time greatly, the resource limitation of ambulance transport mileage will increase.

3) In this case, taking into account the first phase of ambulance drone delivery, the standard deviation of the ambulance can be increased to 0.9, which means the rescue radius could be expanded to 11 km according to an average speed of 60 km/h.

4) The problem of service radius setting has been plaguing researchers and practitioners planning resource location and scheduling. The general consensus is that a smaller rescue radius and standard deviation are the better plan, but how much is reasonable lacks quantitative reference. The results of this paper show that mean time and standard deviation based on survival rate can be used to set a new reference for service radius parameters, which can determine the radius to improve ambulance mobility and coverage.

5.3 Adjust improvement coefficient r

Assigns values to ambulances, $r = 0.3$, $r = 0.5$, $r = 0.8$, The effect is shown in Fig. 6.

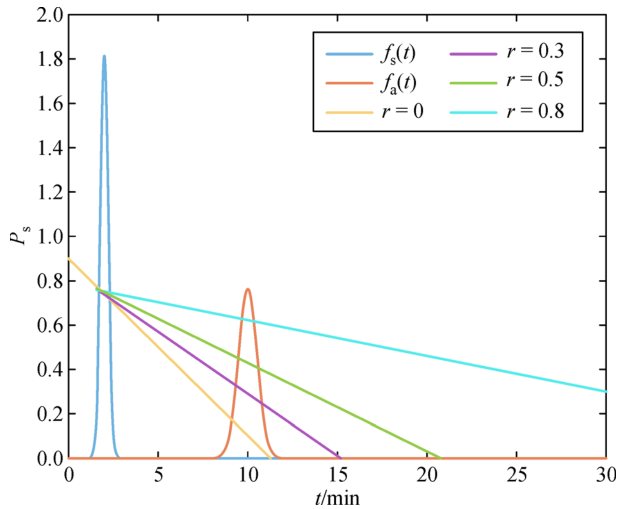

Fig. 6 Different r assignment

1) Improvement coefficients r can reflect the size of the ambulance drone's capacity and information exchanging performance, obviously an ambulance drone delivering more first-aid medical equipment such as AED, oxygen mask, blood bags and others at the same time, especially driven by telemedicine will improve survival rates more efficiently.

2) There is a possibility for young adult sudden death. The survival probability will sharply rise with timely site rescue and defibrillation, whether an ambulance arrives in the second stage is not important, as site vehicles can transport patients to a hospital for further treatment before an ambulance arrives, effectively saving ambulance resources and promoting life.

3) Figure 6 also shows that an ambulance drone must recognize the health condition quickly and effectively and be equipped with the appropriate medical equipment for improvement.

The effects of these parameters on the results of the model verify the effectiveness and practicality of research methods, and provide more reference for management decisions.

6 Conclusions

This paper studied the influence of multi-stage first-aid medical logistics optimization on survival of patients with medical emergencies in consideration of improvement by the application of ambulance drones on emergency medical logistics performance for patients with cardiac arrest. Distribution models of the patients' survival probability, ambulance drone arrival and ambulance arrival over time were constructed. Using patients' maximum health and safety as the goal, that is, maximizing the survival rate, we proposed formulas for patients' maximum possible survival rate with various logistics arrival probabilities. The results calculated by empirical data fitting the distribution model show the improvement of ambulance drones on the maximum survival rate from the existing emergency response time. The influence of changes to model parameters on maximum survival rate and reference values for management decision are discussed. Studies have shown that introducing ambulance drones, by slowing down the speed of decline of patient survival rate in the first aid stage, gain valuable time while victims are waiting for ambulance arrival to provide advanced life support, and can increase the maximum survival rate by optimizing ambulance response efficiency at the same time. The parameters of the model provide new references for actual management decision-making, maximize survival based on logistics response time probability distribution parameters, and help policy makers set a reasonable scope of rescue radius.

As ambulance drone involved in first aid medical equipment distribution is still at the initial stage of exploration and data of actual experiences are not available. This paper made theoretical assumptions based on device properties. To provide better decision making for severe medical emergency logistics, this study uses practice survey data from domestic hospital workers in China. Although the paper does not focus on an actual probability distribution model of survival rates and logistics, future study can precisely fit the curve and describe the trend based on actual data accumulated. After application of ambulance drones on site, how to coordinate schedules with ambulances and other medical resources and optimize costs under budget constraints merit further study.

Acknowledgements This work was partially supported by the National Natural Science Foundation of China (Grant No. 71390333), the National Key Technology R&D Program of China during the 12th Five-Year Plan Period (Grant No. 2013BAD19B05).

References

Budge S, Ingolfsson A, Zerom D (2010). Empirical analysis of ambulance travel times: The case of Calgary emergency medical services. Management Science, 56(4): 716–723

Capucci A, Aschieri D, Guerra F, Pelizzoni V, Nani S, Villani G Q, Bardy G H (2016). Community-based automated external defibrillator only resuscitation for out-of-hospital cardiac arrest patients. American Heart Journal, 172: 192–200

Chen H, Zhang J J, Jun M A, Zhao Y C (2008). The survey on the capacity of reaction for emergency in Beijing. Academic Journal of PLA Postgraduate Medical School, 29(5): 392–393 (in Chinese)

Chong K, Henderson S G, Lewis M E (2016). The vehicle mix decision in emergency medical service systems. Manufacturing & Service Operations Management: M & SOM, 18(3): 347–360

European Society of Cardiology (2013). Out-of-hospital cardiac arrest survival just 7 percent. Science Daily. https://www.sciencedaily.com/releases/2013/09/130901154147.htm, 2017-3-30

Fikar C, Gronalt M, Hirsch P (2016). A decision support system for coordinated disaster relief distribution. Expert Systems with Applications, 57: 104–116

Gold L S, Fahrenbruch C E, Rea T D, Eisenberg M S (2010). The relationship between time to arrival of emergency medical services (EMS) and survival from out-of-hospital ventricular fibrillation cardiac arrest. Resuscitation, 81(5): 622–625

Gu M, Li Z H, He Z J, Zhao Z W, Liu S Q (2016). A meta-analysis of the success rates of heartbeat restoration within the platinum 10 min among outpatients suffering from sudden cardiac arrest in China. Military Medical Research, 3: 6

Haidari L A, Brown S T, Ferguson M, Bancroft E, Spiker M, Wilcox A, Ambikapathi R, Sampath V, Connor D L, Lee B Y (2016). The economic and operational value of using drones to transport vaccines. Vaccine, 34(34): 4062–4067

Hansen C M, Kragholm K, Granger C B, Pearson D A, Tyson C, Monk L, Corbett C, Nelson R D, Dupre M E, Fosbøl E L, Strauss B, Fordyce C B, McNally B, Jollis J G (2015). The role of bystanders, first responders, and emergency medical service providers in timely defibrillation and related outcomes after out-of-hospital cardiac arrest: Results from a statewide registry. Resuscitation, 96: 303–309

He M J, Xu L L, Mindy D (2016). Status of pre-hospital emergency medical service in China and abroad. Journal of Nursing Management, 16(1): 24–26 (in Chinese)

He S F, Huang Y, LI Q (2015). Application of quality control circle in the improvement of hospital emergency response rate in basic level hospitals. Nursing Practice and Research, 12(9): 148–150 (in Chinese)

Hua W, Zhang L F, Wu Y F, Liu X Q, Guo D S, Zhou H L, Gou Z P, Zhao L C, Niu H X, Chen K P, Mai J Z, Chu L N, Zhang S (2009). Incidence of sudden cardiac death in China. Journal of the American College of Cardiology, 54(12): 1110–1118

Huang Q (2014). Correlation analysis between emergency cardiopulmonary resuscitation time window and the success rate of resuscitation. Chinese Journal of Medicinal Guide, 16(1): 62–63

Maxwell M S, Ni E C, Tong C, Henderson S G, Topaloglu H, Hunter S R (2014). A bound on the performance of an optimal ambulance redeployment policy. Operations Research, 62(5): 1014–1027

MedSci (2013). Shenzhen sudden cardiac death patients survival rates less than 1 per thousand. http://www.medsci.cn/article/show_article.do?id = ddb71891830-2, 2017-3-30 (in Chinese)

Merghani A, Narain R, Sharma S (2013). Sudden cardiac death: Detecting the warning signs. Clinical Medicine, 13(6): 614–617

Musolino G, Polimeni A, Rindone C, Vitetta A (2013). Travel time forecasting and dynamic routes design for emergency vehicles. Procedia: Social and Behavioral Sciences, 87: 193–202

Nielsen A M, Folke F, Lippert F K, Rasmussen L S (2013). Use and benefits of public access defibrillation in a nation-wide network. Resuscitation, 84(4): 430–434

Olshansky B (2016). Automatic external defibrillator-only resuscitation in cardiac arrest? The approach may be shocking! American Heart Journal, 172: 182–184

Thiels C A, Aho J M, Zietlow S P, Jenkins D H (2015). Use of unmanned aerial vehicles for medical product transport. Air Medical Journal, 34 (2): 104–108

Van Barneveld T C, Bhulai S, Rd V D M (2017). A dynamic ambulance management model for rural areas: Computing redeployment actions for relevant performance measures. Health Care Management Science, 20(2): 165–186

Weisfeldt M L, Sitlani C M, Ornato J P, Rea T, Aufderheide T P, Davis D, Dreyer J, Hess E P, Jui J, Maloney J, Sopko G, Powell J, Nichol G, Morrison L J (2010). Survival after application of automatic external defibrillators before arrival of the emergency medical system. Journal of the American College of Cardiology, 55(16): 1713–1720