Simulation Research of First-Aid Treatment on Combat Casualty

Xinyi Li, Yilin Dong, Jingyi Lu

University of Victoria

CSC 446

Kui Wu

April 2023

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1.0 Problem Description

Simulation research of wartime first aid holds paramount importance in reducing casualties, securing victories, and ultimately achieving the political objectives behind a war. By creating virtual environments and scenarios that mirror real-life combat situations, researchers can explore various medical interventions and their potential impacts on injured soldiers, leading to the development of more effective first aid protocols. Furthermore, these simulation research provide invaluable data for the design and optimization of medical equipment and supplies, ensuring that soldiers have access to the best possible care, even in the most adverse conditions. The superiority of simulation research is particularly evident when faced with the limitation of insufficient sources of data for peacetime research, as these simulations allow for the examination of a wide range of scenarios without the need for actual conflict.

The pursuit of effective wartime first aid through simulation research serves the immediate needs of soldiers in combat and plays a crucial role in the overall success of military operations. The advancements in medical techniques, equipment, and training derived from these research directly contribute to the well-being and preparedness of the military force. As a result, nations can better protect their interests, project their power, and secure their objectives, ultimately bolstering their strategic position in the global landscape.

2.0 Casualty and First-Aid Model

To conduct a battle wound first aid simulation study, it is necessary to simulate the arrival, queuing, and treatment of casualties with a simplified but consistent model that matches the actual battlefield and troop situation. We know that the modern battlefield is rapidly changing and the flexibility of the model allows us to evaluate the treatment of casualties and the stability of the first aid system under different battlefield conditions. First, we need to formulate some assumptions to aid in the development of our simplified model.

2.1 Assumptions for Casualty Modeling

For casualties, we know that there is a certain pattern of arrival based on other studies in similar fields (LONG & WU, 2018), and we make the following assumptions: it is assumed that the arrival generation of casualties obeys a Poisson distribution and the arrival interval of casualties obeys an exponential distribution (LONG & WU, 2018). In practice, the Chinese People's Liberation Army classifies casualties into four categories based on respiration, circulation, and consciousness (LONG & WU, 2018). For convenience, we divided the casualties into two categories: lightly wounded and seriously wounded (LONG & WU, 2018).

2.2 First-Aid Assumptions

Assume that there are two emergency teams that specialize in dealing with minor and major injuries. During the queuing process, we assume that minor and major casualties will receive first aid at the corresponding emergency team upon arrival according to their first-come-first-served status. However, when an emergency team becomes available, we can allow the casualty to be served on a team other than the one they belong to.

In addition, if the queue for a seriously injured person is too long, the seriously injured person will be able to jump the queue to be the first to receive first aid in a first aid team earlier. The details of how this is done in practice will be explained in a later section.

3.0 Simulation Goals & Parameter

In this comprehensive simulation study, we examined emergency care for the wounded in PLA's field hospitals during wartime to better understand their operational capabilities and limitations. By setting most parameters statically, we ensured consistency and reliability in our analysis, focusing on parameters such as the occurrence rate of Class A and Class B casualties and the total number of casualties. The insights gained from this study will help identify areas for improvement in field hospitals, enhancing force building and readiness.

3.1 Simulation Goal

We conducted a comprehensive simulation study of emergency care for the wounded in PLA field hospitals during wartime. This study is critical to understanding the operational capabilities and limitations of field hospitals in providing emergency medical services during military conflict. Through this study, we have assessed the treatment capabilities and limitations of field hospitals and will help identify areas for improvement or modification. By improving the overall efficiency of field hospitals, force building and readiness will be enhanced.

3.2 Parameter

In our simulation studies, most parameters were set statically based on the values defined in the previous sections to ensure consistency and reliability of the analysis. The parameters used in the study are as follows. The λ_A and λ_B parameters for the Class A casualty index distribution represent the occurrence of Class A casualties (lighter injuries) and Class B casualties (heavier injuries) in wartime.The total number of casualties in the simulation is another key parameter for static settings. By setting a static value for this parameter, we can simulate a consistent scenario that allows us to analyze the effectiveness of field hospitals in different situations. We set several static values for rescue time so that we can analyze the impact of different rescue times on the overall outcome.

4.0 Methodology

We set up the simulation by dividing the casualties into lightly injured and seriously injured. These two groups of casualties will be sent to the serious injury group and the medical groups to get in line. We will detect and reassign them to the critically injured group and the medical group based on their waiting time and available medical resources. The parameters are set according to the information on the reference material we have consulted.

4.1 How our model is being simulated?

We generate a type A casualty and a type B casualty and put them into their respective first-come, first-served queues.

For type A casualties, if the type A medical team is available then they will be treated in the typeA medical team, if not then they will enter the queue first and after waiting for more than an hour will check if the queue for type B casualties is empty and if it is then they will enter the medical queue for type B casualties. If it is not empty, if the casualty has waited for another hour, he/she will be inserted into the queue for type B casualties.

For type B casualties, if the type B medical team is free then receive treatment in the type B medical team, if not then check if the type A queue is free first, if the type A medical team is free then receive treatment in the type A medical team, otherwise continue to queue in the type B casualty queue until treatment is received.

4.2 How did we set up the simulations?

We set up the casualty handling process based on the reference material and based on the process we wrote a python program including the following functions:

- Generate typeA casualties
- Generate typeB casualties
- Generate the arrival interval
- Simulate the arrival process
- Simulate the queuing process
- Simulate the treatment process
- Aggregate and output the statistics

With this program, we simulate the model we have built and obtain the data, the processing of which will be described in detail later on.

4.3 How did we collect the stats?

We collect statistics based on the output of the analogue. The simulation produces a series of numbers and we save the statistics collected each time to a CSV file. We then used Microsoft Excel to process the csv file, using the output to generate graphs, charts and figures. We ran the simulation multiple times with a different seed each time. We recorded the mean, variance and confidence level for each round. Afterwards we calculated the mean, variance and confidence of the mean. We plotted the graphs based on the average of the 5 rounds of simulations.

5.0 Analysis

We have read the references and, based on them, we have used a Python program to examine the performance of field hospitals under diverse battlefield conditions, based on queuing theory. We examined not only the performance of the PLA's usual field hospital formations under normal operational conditions, as derived from the PLA's past operational records, but also the reliability of field hospitals under extreme conditions, with a high concentration of casualties, according to the references. The field hospital's resilience was tested under simulated operational conditions.

5.1 Result For 7 Different Lambdas in 8 Hours

Using the hourly arrival rates of severely and lightly wounded as parameters, we first tested the field hospital's performance in conventional battlefield situations for each of the seven, ($\lambda A = 1$, $\lambda B = 1$), ($\lambda A = 2$, $\lambda B = 2$), ($\lambda A = 3$, $\lambda B = 3$), ($\lambda A = 4$, $\lambda B = 4$), ($\lambda A = 5$, $\lambda B = 5$), ($\lambda A = 6$, $\lambda B = 6$), ($\lambda A = 7$, $\lambda B = 7$) conditions, and to avoid extreme results for individual special cases, for each (λA , λB), we used five different random seeds and averaged the results. Once we had produced our results, the data were further processed using digital office tools to produce more data, and images and tables were produced. We came up with the following results:

λA, λB	1， 1	2， 2	3， 3	4， 4	5， 5	6， 6	7， 7
Random Seed 1	17.7	31.3	60.4	222.8	304.6	404.0	438.5
Random Seed 2	0.0	22.0	40.0	44.9	196.3	263.8	296.0
Random Seed 3	16.7	45.0	61.4	81.9	160.1	276.2	358.0
Random Seed 4	45.8	62.3	65.7	166.7	236.6	314.7	490.7
Random Seed 5	0.0	15.1	35.4	116.4	155.7	243.0	320.0
Avg Waiting of A	16.04	35.14	52.56	126.55	210.66	300.35	380.65

Table 1

λA, λB	1， 1	2， 2	3， 3	4， 4	5， 5	6， 6	7， 7
Random Seed 1	376.7	878.4	1240.6	1969.2	2550.3	3012.8	3371.0
Random Seed 2	330.6	455.6	900.2	1425.2	2280.1	2595.1	2880.1
Random Seed 3	382.6	473.9	425.9	1474.4	873.6	2283.0	2762.5
Random Seed 4	361.6	795.8	555.5	1830.4	1095.3	1275.3	3450.2
Random Seed 5	257.0	378.5	616.5	1373.6	1848.9	2310.8	2803.5
Avg Service Time	341.72	596.44	747.75	1614.56	1729.65	2295.37	3053.46

Table 2

λA, λB	1， 1	2， 2	3， 3	4， 4	5， 5	6， 6	7， 7
Random Seed 1	18	41	50	69	85	100	110
Random Seed 2	14	25	43	59	80	88	99
Random Seed 3	20	26	43	58	66	77	92
Random Seed 4	19	37	53	68	84	88	111
Random Seed 5	7	15	39	52	65	80	94
Avg Total Patients	15.60	28.80	45.60	61.20	76.00	86.60	101.20

Table 3

LambdaA, LambdaB	1， 1	2， 2	3， 3	4， 4	5， 5	6， 6	7， 7
Avg Waiting of A	16.0	35.1	52.6	126.5	210.7	300.3	380.6
Service Time	341.7	596.4	747.7	1614.6	1729.6	2295.4	3053.5
Total Patients	15.60	28.80	45.60	61.20	76.00	86.60	101.20

Table 4

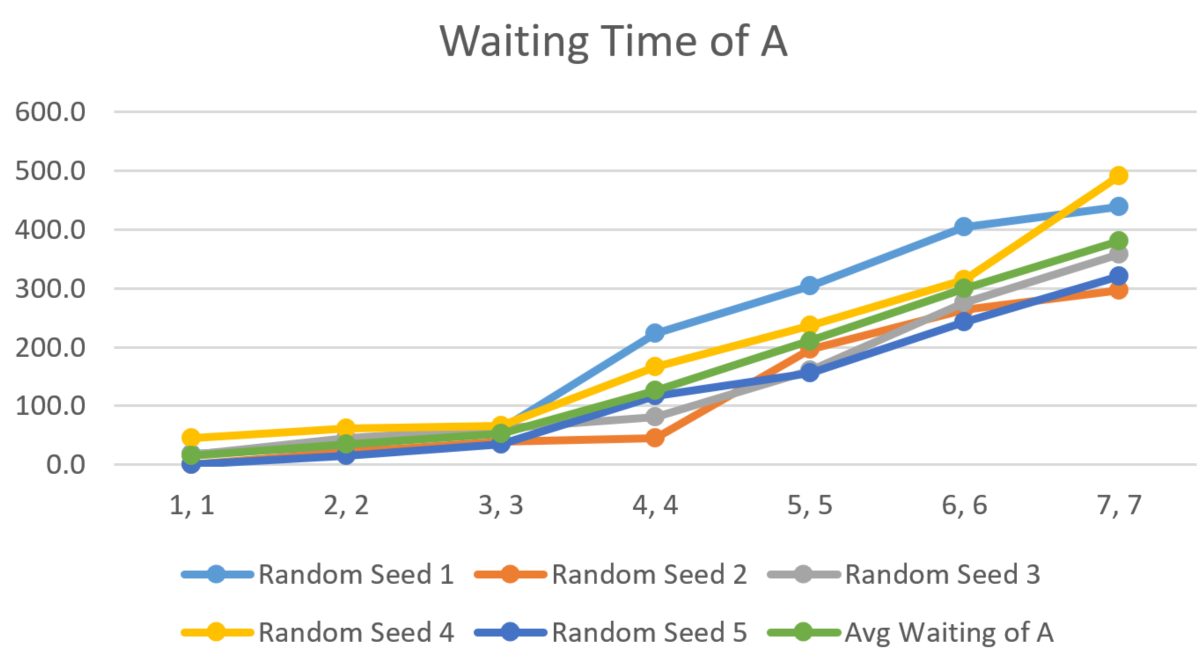

Figure 1

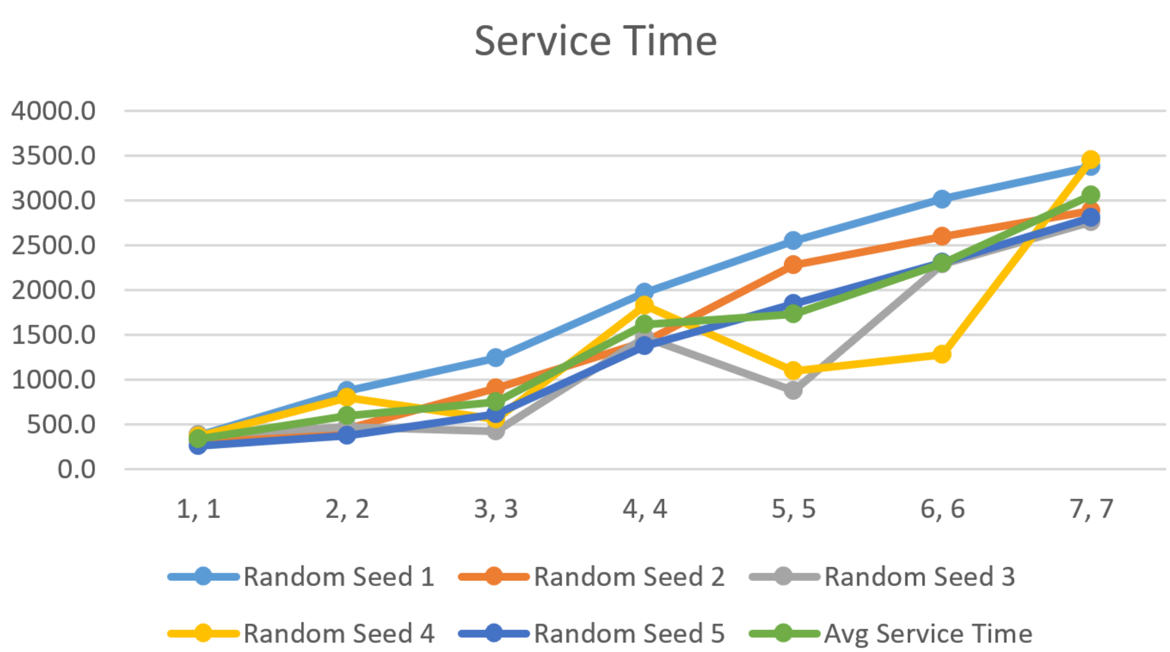

Figure 2

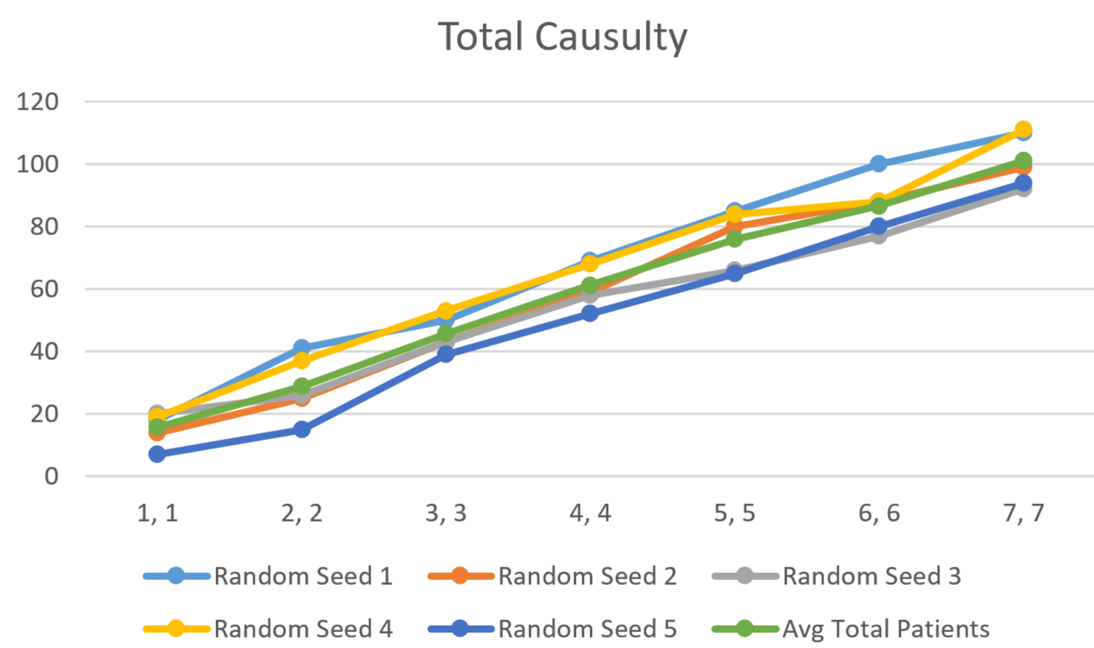

Figure 3

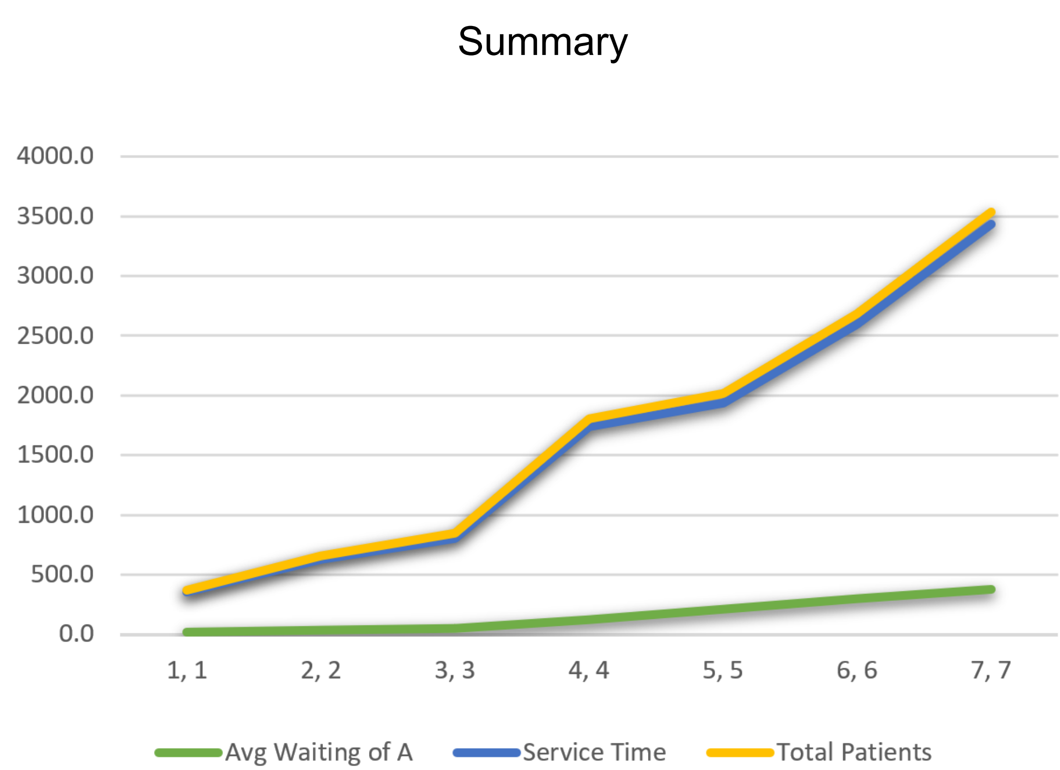

Figure 4

5.2 Analysis For 7 Different Lambdas in 8 Hours

Our four tables are based on the premise that the arrival rate of type A casualties is the same as that of type B casualties. We ran a simulation with each of the five seeds and averaged them separately. As seen in Table 3, λA and λB are essentially accurate as the arrival rates for A and B. As seen in Figure 3, the arrival of the casualty is perhaps increasing linearly with the sum of λA and λB.

According to Table 1, as the arrival rate increases, so does the number of casualties we have. Then the number of casualties we need to assist also rises. But because the size of our field hospitals is based strictly on the literature, it does not increase accordingly. Therefore, the waiting time for category A casualties increases as the arrival rate rises, and we can reach a similar conclusion with Figure 1.

We can see from Table 2 that as the arrival rate rises, the total field hospital service time rises by the same amount. So when the arrival rate increases our average waiting time and average service time increases. Combined with Figure 2, we can draw a similar conclusion. This shows that the efficiency of our field medical unit decreases as the arrival rate increases. This shows that the model in the literature is not able to handle extreme situations where there are too many people. The model in the literature is only applicable to small arrival rates.

5.3 Statistics For Extra Large Sample Size

We used this model to simulate an extreme scenario of a large influx of casualties into a medical department under unconventional warfare conditions. We set the arrival rates for light and serious casualties to 5000 per hour respectively. In this scenario, 5,000 light casualties and 5,000 serious casualties enter the medical unit every hour. This allows us to observe the efficiency and availability of the medical unit under these conditions. Although there is no such reference to large arrival rates in the literature, we used such a sample to test the "test with a large sample" proposed in the class.

In these tests we learned that the models in the literature are not capable of handling such a large number of samples. We can say that in this case it is an unstable system. When there is an influx of casualties into the medical department, the department is simply unable to provide effective care. There will be a large number of casualties waiting for weeks, months or even almost a year and missing out on treatment (deterioration or self-healing?). The result is that when a large number of injured people wait for weeks, months or even almost a year, they miss out on treatment (deterioration or self-healing?). The result is that the field hospital is unable to deal with the influx of casualties.

	type	arrival_time	id	care_giver	leaving_time
1	B	0.006180903	1	light	30.0061809
2	B	0.012361806	2	heavy	40.01236181
3	A	0.044002208	4	light	75.0061809
4	A	0.014280852	1	heavy	75.01236181
5	A	15.03841583	1265	heavy	110.0123618
6	A	0.081561095	6	light	120.0061809
7	A	50.01295998	4188	heavy	145.0123618
8	A	0.084854222	3	light	165.0061809
9	A	85.02765866	7154	heavy	180.0123618
10	A	0.088595664	8	light	210.0061809
11	A	120.0169638	10077	heavy	215.0123618
12	A	155.0148889	13054	heavy	250.0123618
13	A	0.109109995	10	light	255.0061809
14	A	190.0450682	15962	heavy	285.0123618
15	A	0.119942765	5	light	300.0061809
16	A	225.043883	18882	heavy	320.0123618
17	A	0.1429007	12	light	345.0061809
18	A	260.0178067	21867	heavy	355.0123618
19	A	0.184035076	14	light	390.0061809
20	A	295.0177612	24925	heavy	390.0123618
21	A	330.0206584	27883	heavy	425.0123618
22	A	0.18521399	7	light	435.0061809
23	A	365.0150019	30406	heavy	460.0123618
24	A	0.209773244	16	light	480.0061809
25	A	400.0210387	33655	heavy	495.0123618
⋮	⋮	⋮	⋮	⋮	⋮
80333	B	479.6614977	40156	light	3011940.006
80334	B	479.6710146	40158	light	3011970.006
80335	B	479.6718884	40160	light	3012000.006
80336	B	479.6724729	40157	light	3012030.006
80337	B	479.6734106	40159	light	3012060.006
80338	B	479.6971708	40162	light	3012090.006
80339	B	479.7510323	40164	light	3012120.006
80340	B	479.7530859	40161	light	3012150.006
80341	B	479.7556992	40163	light	3012180.006
80342	B	479.7570848	40166	light	3012210.006
80343	B	479.817398	40168	light	3012240.006
80344	B	479.8467592	40165	light	3012270.006
80345	B	479.8554635	40167	light	3012300.006
80346	B	479.8620647	40170	light	3012330.006
80347	B	479.9349851	40169	light	3012360.006

Figure 5

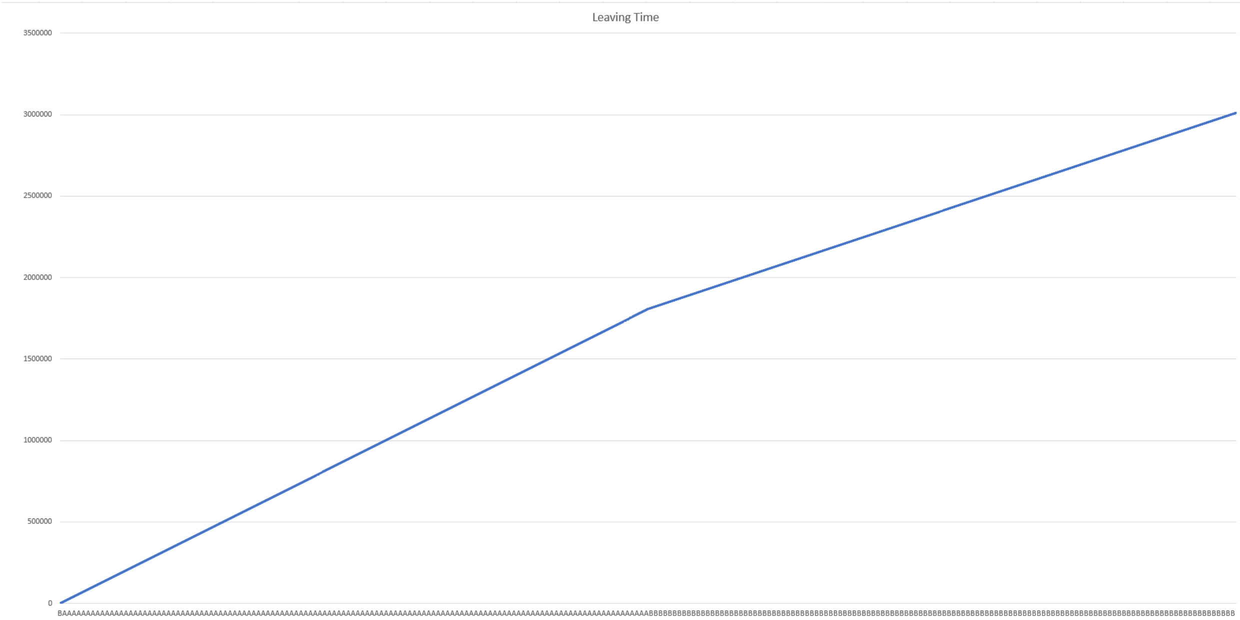
Leaving Time
3500000
3000000
2500000
2000000
1500000
1000000
500000
0

Table 5

6.0 Conclusion

In this simulated field hospital casualty emergency simulation experiment, by changing the arrival rate of different types of casualty types, we simulated the possible queueing and processing of field hospitals under different battlefields, and for the analysis and summary of the simulation results, we can come up with the best casualty arrangement strategy to cope with extreme battle damage situations. We can find that in most simulations, the whole system tends to be unstable when the number of casualties reaches a certain threshold. We can conclude that we may not be able to stabilize all casualties under the current treatment strategy.
In conclusion, Our simulation suggested 1 serving slot for both light type injury and serious injury could be very unstable and result in unacceptable waiting time.

6.1 Experience in learning

Towards the end of the project, we found ways to automate our data processing, table generation and chart generation. Even if we only automated the data generation, data processing and calculations in the second half of the project, our efficiency was greatly improved. In the future, we will draw more on our computer knowledge to fully automate the office and reduce the need for human resources, thus reducing research costs.

6.2 Results and Analysis Summary

Sample Run 3-3-5

95% Confidence Interval: 35.3 ± 14.7

Sample Run 1-1-4

95% Confidence Interval: 45.8 ± 16.7

Sample Run 5-5-3

95% Confidence Interval: 160 ± 35.6

Simulation analysis results above suggest How continuous growing is happening with bigger and bigger casualties.

6.3 Reflection and Summary

Through this project, we have tested in practice what we have learned in CSC 446. We were able to gain a good understanding of the importance of simulation studies through a project that was integrated into real life situations. It has stimulated our interest in simulation research as a field of study.

The downside is that we were limited by various objective conditions and did not have access to more detailed information on how the simulations in the study were implemented in the references, resulting in a degree of difference between our results and those in the references. We were also constrained by limited time resources, human resources and computing power to try more combinations than those tried in the references. In future research, we will attempt to address these issues.

Overall, as a first team attempt at a project, we have gained a lot. This project has been a great opportunity to develop our leadership, teamwork, project planning and practical skills. We are confident that we will be able to complete our next project better and more efficiently in the future.

Reference

LONG Yun, WU Songlin. A Modeling Simulation Research Based on the Queuing Theory of Giving First Aid Treatment to the Sick and Wounded Men During Wartime [J]. Journal of Chongqing University of Technology (NaturalScience), 2018 (9): 194-100.