1.0 Introduction

Long waits have become a staple of the Canadian healthcare system. In the past two decades, they have increased 198% [1]. The lack of accessibility introduces a challenge that impacts patient experience and contributes to hospital congestion. Patients requiring rehabilitation after acute care often face delays due to limited rehab bed capacity, prolonging their hospital stays and blocking new admissions to acute care.

Using Simio, a base model of the hospital's acute and rehabilitation care system was developed to estimate performance measures, including waiting times, queue lengths, and bed utilization, under the current First-Come, First-Served (FCFS) admission policy. Estimated distributions along with corresponding parameters for arrivals, treatment times, and rehabilitation durations were found through input modelling which are mentioned in this report.

Building on this, we have conducted a scenario analysis to identify an optimal priority order for admitting patients to rehabilitation units 3 and 4. The analysis evaluates various prioritization scenarios to minimize total long-run average waiting times, providing insights to improve resource utilization and patient care efficiency, which are discussed later in detail.

2.0 Input Modelling

This section outlines how the appropriate distributions were obtained along with the corresponding parameters for the provided datasets and the tests that were performed to verify them.

2.1 Arrivals

To estimate a distribution for the arrival data, the number of arrivals was fitted to various distributions such as exponential, gamma and normal and their respective QQ plots (see Figure 1) were generated. However, all of these distributions are continuous and fail to account for the discrete nature of the arrival data (see Appendix C). Therefore, it was fitted to a Poisson distribution which could better account for the discrete data points (see Figure 2) and a corresponding QQ plot was generated. The estimated mean parameter found had a value of 0.53167. A Chi-squared test was also performed to verify this result.

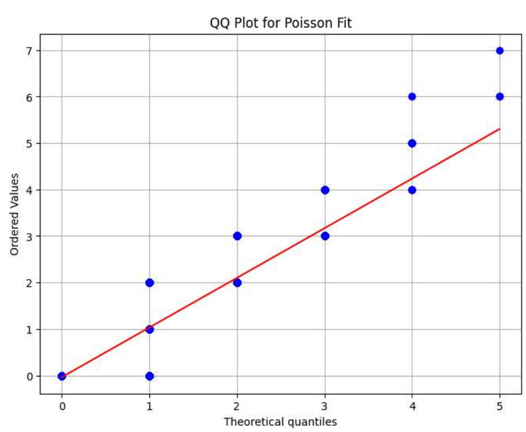


Figure 1. QQ Plot for Poisson fit

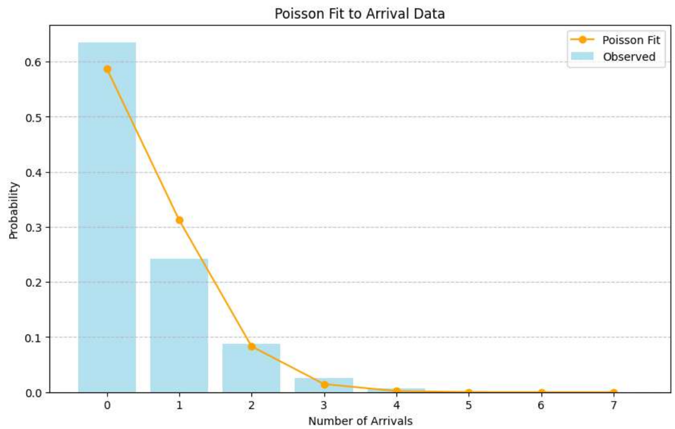


Figure 2. Fitting Arrival data to Poisson distribution

2.2 Treatment Times

To estimate the distribution of the treatment times, the data was separated by patient type and all negative and null data was removed. Then the histogram for the medicine treatment and neuro/MSK treatment was plotted (see Figures 3, 4). Visual analysis of the graphs indicated the distribution was non-negative and asymmetrical. To make an accurate estimate, both of the treatment times were fitted to exponential, gamma and log-normal distributions and their respective QQ plots were generated from the plots (see Figure 5,6), it can be seen that the data for medicine treatment fits the exponential distribution the best and the neuro treatment fits both the gamma and exponential distributions. For the neurological conditions treatment time, a gamma distribution was chosen due to its higher flexibility in capturing the shape of the data. A Kolmogorov-Smirnov goodness of fit test was then conducted to further confirm the hypothesis. For both treatment times, the p-value was 1 which is higher than the assumed significance value of 0.05, failing to reject the hypothesis. Therefore, the estimated distribution for the medicine treatment time is exponential with an estimated mean of 4.87. Neuro/MSK treatment time is fit to the gamma distribution, with the shape 1.01 and the scale 5.05.

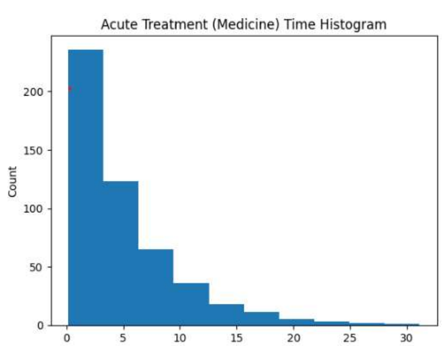


Figure 3. Histogram for Medicine

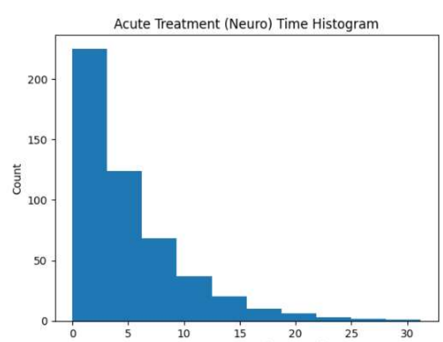


Figure 4. Histogram for Neuro/MSK

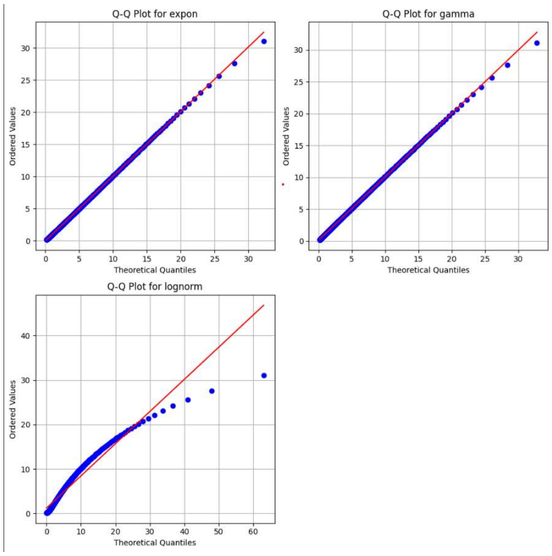


Figure 5. QQ Plots for Medicine

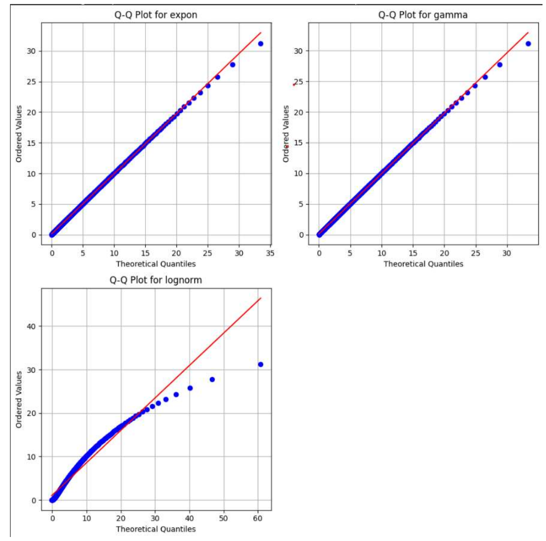


Figure 6. QQ Plots for Neuro/MSK

2.3 Rehabilitation Times

Similarly, to estimate the distribution of medically complex and stroke rehabilitation times, the data was segregated by patient type, and all negative and null data were removed. The histogram of stroke and medically complex rehabilitation data, as seen in Figure 7, is continuous, non-negative, and asymmetric.

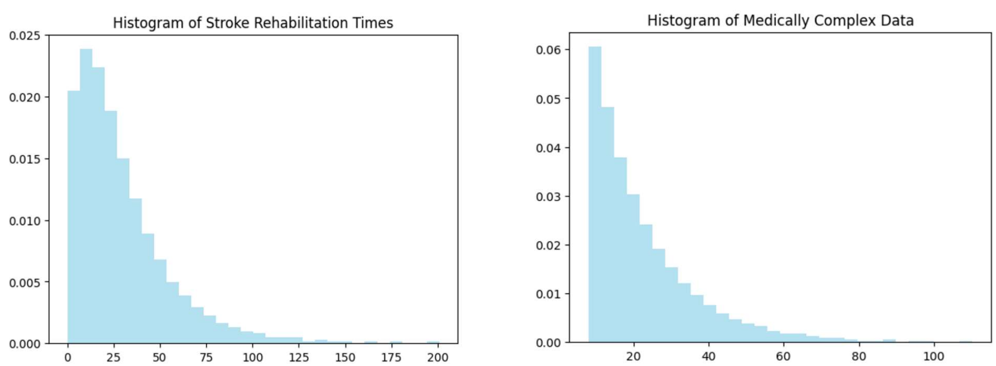


Figure 7. Histogram of Stroke Rehabilitation Data (left) and Medically Complex (right)

To make an accurate estimate, the rehabilitation time was fitted to exponential, gamma and log-normal distributions and their respective QQ plots were generated for both medically complex and stroke groups (see Figures 8 & 9). From the plots, it can be seen that the data for both groups fit the best with exponential distribution and to further confirm the hypothesis, a goodness of fit test was conducted using the Kolmogorov-Smirnov Test. For both the medically complex and stroke rehabilitation times, the p-value was 1 which is higher than the significance value 0.05, indicating failure to reject the hypothesis. Therefore the estimated distributions for both medically complex and stroke rehabilitation time are exponentially distributed. The estimated mean parameter for medically complex rehabilitation time distribution is 14.72 and the estimated mean parameter for stroke rehabilitation time distribution is 29.67.

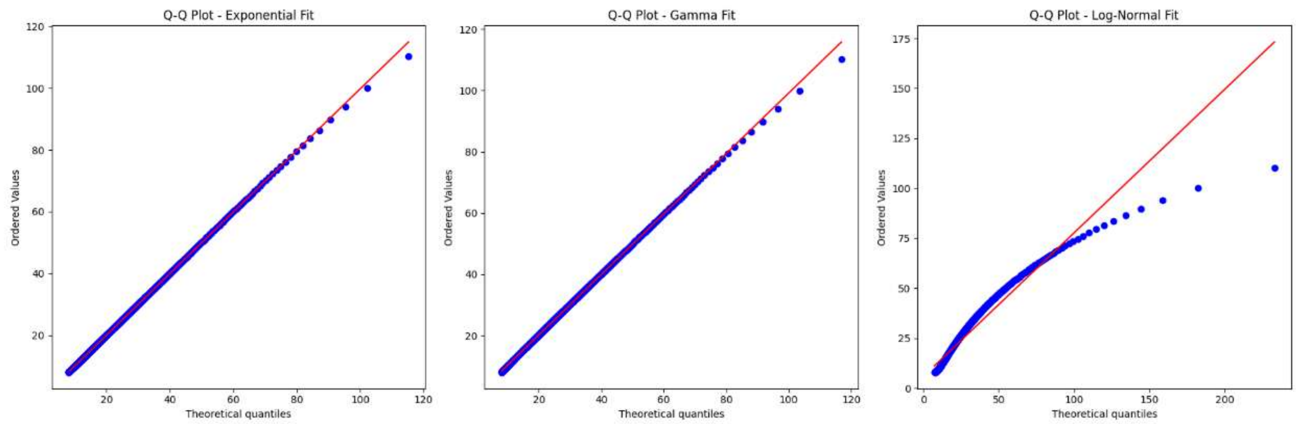


Figure 8. QQ Plots for Medically Complex data

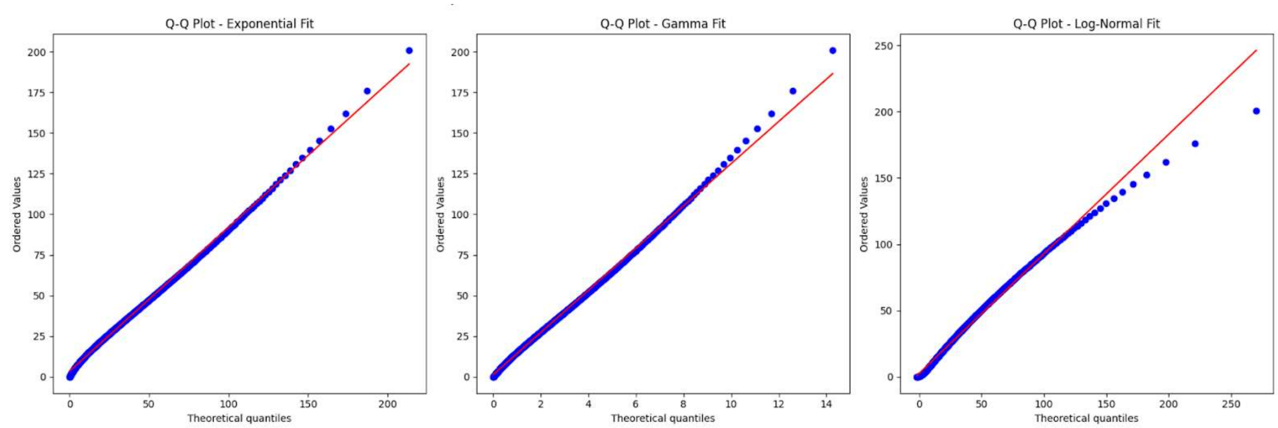


Figure 9. QQ Plot of Stroke Rehabilitation times

3.0 The Base Model

This section explains the logic of the simulation base model, the selection of the warm-up period, number of replications for the experiments, and provides its estimated performance measures.

3.1 Logic

Using the estimated distributions from Section 2.0, model entities were mapped to a data table shown in Figure 10. This allowed the model to probabilistically produce patient types according to their weights, reference entity priorities, and rehabilitation time distributions. Patient types belonging to rehabilitation wards 3 and 4 were assigned reference variables to allow for easier comparisons in section 4.0, in this section priorities were given a default value of one.

	patient Type	Priority	RehabTime (Days)	Pt Mix
1	StrokePT	Stroke_Priority	Random.Exponential(29.67)	4.5
2	BrainDysPt	Brain_Dys_Prio...	Random.Gamma(48.6, 0.45)	2.5
3	CardiacPT	Cardiac_Priority	Random.Gamma(16.81, 0.79)	1.5
4	MedCompPT	1	Random.Exponential(14.72)	7.5
5	NeuroPT	Neuro_Priority	Random.Lognormal(2.53 , 0.73)	1.5
6	SpinalCordPt	SpinalCord_Prio...	Random.Exponential(0.05)	2
7	NoRehabPT	1	0	75
8	OrthoPT	1	Random.Lognormal(3.01 , 0.51)	5.5

Figure 10. Mapping Table of Entity Properties

The base model seen in Figure 11, models the flow of patients through the wards of the hospital. The path from the emergency waiting room to acute wards 1 and 2 were probabilistically weighted 72 and 28 respectively. Patients will wait in the input queues of both acute wards until there is capacity. Once admitted, the duration of stay is generated by the acute ward. After processing, if the patient does not need rehabilitation they are immediately discharged. Otherwise, they will continue to take up capacity in the acute wards until the correct rehabilitation ward has capacity. Rehabilitation wards are selectively assigned by patient type to the remaining patients. Where processing time is determined by entity type. Once the duration of rehabilitation is over the patients can be discharged.

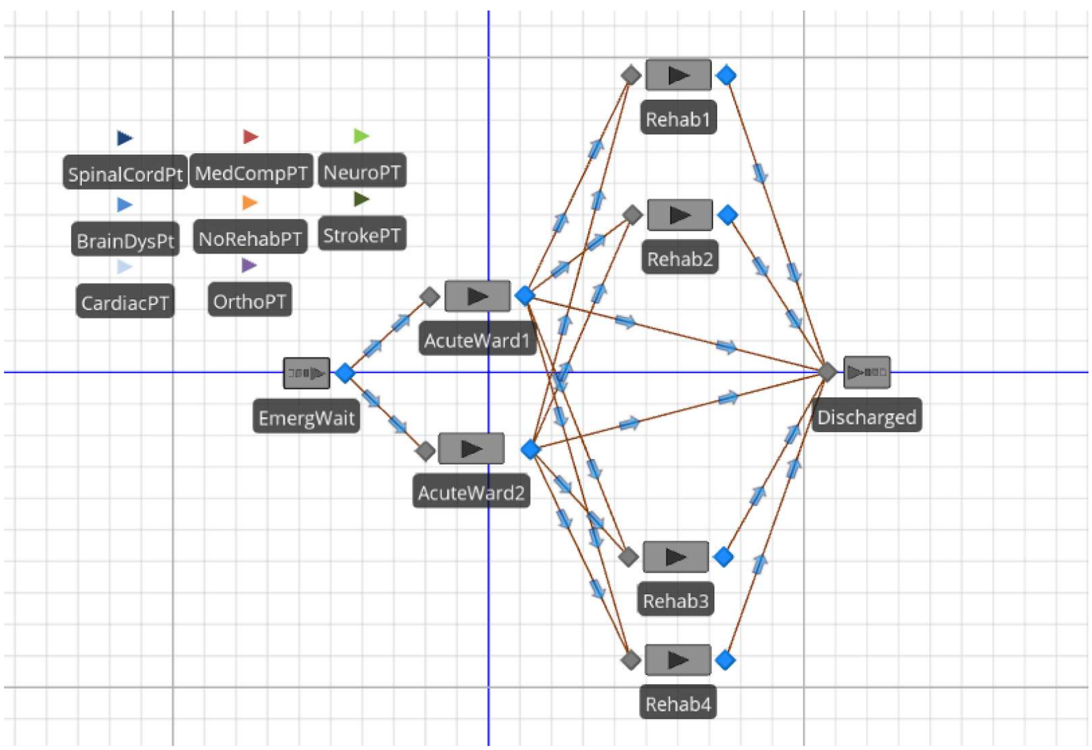


Figure 11. Simio Model

To estimate the warm-up period, the simulation was run for 1000 hours and it was observed. In Figure 12 the fluctuations in the number of patients (NIS) in the system started to stabilize growing upwards at the 4th 8:00 PM mark. At approximately 552 hours from when the simulation started, the NIS average plateaus indicate a good selection for the warm-up period. While there were still fluctuations remaining throughout the rest of the graph, this number was chosen to avoid being too conservative.

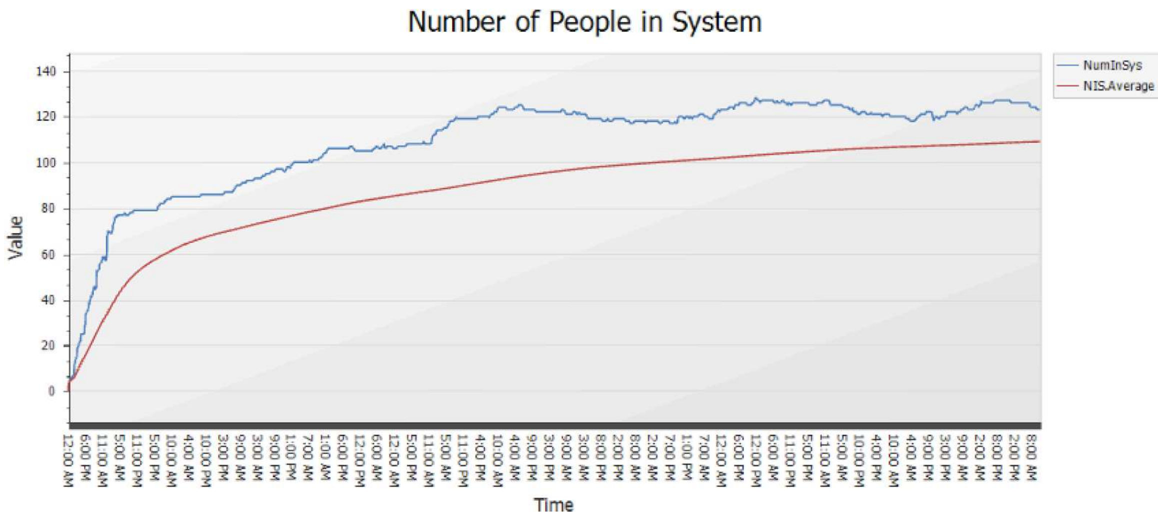


Figure 12. Number of people in the system over 4000 hours

Moreover, 20 replications were chosen since the confidence interval was much larger with just 10 replications, the half-width being 1.55. With 20 replications, the half-width was down to 0.74. While further replications did not significantly improve the half-width confidence interval.

3.2 Design of Experiments

Simio automatically tracks certain statistics such as average waiting times, and bed utilization of wards, however, other values need to be manually obtained. State statistics were defined to obtain a long-run proportion of blocked beds, and the number in the queue of both acute wards. To obtain the queue length, the state variable was incremented at the entrance of the acute ward queue and decremented right before processing, when the processing server has determined that there is capacity for the entity. For blocked beds, the state variable was incremented after processing and decremented once the patient had departed the acute ward if capacity was available. Long-time waiting averages were defined by tally statistics that started to record the time when processing was complete, once they entered the rehabilitation wards processes were assigned to take down the time difference by patient type.

3.3 Performance Measures

The estimates of the performance measures of the system are noted from the results table as follows, along with the corresponding half-widths are seen in Figures 13-17:

						Scenario2			
Object Type	Object N...	Data Source	Category	Data Item	Statistic	Average	Minimum	Maximum	Half Width
Server	AcuteWard1	InputBuffer	HoldingTime	TimeInStation	Average (Hours)	432.7647	387.6012	467.8102	10.7638
	AcuteWard2	InputBuffer	HoldingTime	TimeInStation	Average (Hours)	407.8570	337.6449	468.3295	15.7919

Figure 13. Long-run average waiting times for acute wards

Object Type	Object Name	Data Source	Category	Data Item	Statistic	Scenario2 Average	Minimum	Maximum	Half Width
Model	Model	AcuteQueueLen_W2	UserSpecified	StateValue	Average	239.6300	211.0091	275.1434	8.4507
		AcuteQueueLen_W1	UserSpecified	StateValue	Average	649.9096	586.1955	698.3277	15.7674

Figure 14. queue lengths for both acute wards.

Object Type	Object Name	Data Source	Category	Data Item	Statistic	Scenario2 Average	Minimum	Maximum	Half Width
Model	Model	RehabBedWaitTime_Stroke	UserSpecified	TallyValue	Average (Hours)	27.8015	0.0000	168.5518	18.4814
		RehabBedWaitTime_SCD	UserSpecified	TallyValue	Average (Hours)	1.0925	0.0000	15.8125	1.7062
		RehabBedWaitTime_Ortho	UserSpecified	TallyValue	Average (Hours)	32.5519	0.0000	143.6417	19.5630
		RehabBedWaitTime_Neuro	UserSpecified	TallyValue	Average (Hours)	22.9457	0.0000	65.7583	9.8311
		RehabBedWaitTime_MC	UserSpecified	TallyValue	Average (Hours)	0.4610	0.0000	8.8357	0.9230
		RehabBedWaitTime_Cardiac	UserSpecified	TallyValue	Average (Hours)	1.0608	0.0000	12.2935	1.4270
		RehabBedWaitTime_BD	UserSpecified	TallyValue	Average (Hours)	0.9230	0.0000	14.6905	1.5413

Figure 15. Long-run average waiting times of 7 rehabilitation groups

Object Type	Object Name	Data Source	Category	Data Item	Statistic	Scenario2 Average	Minimum	Maximum	Half Width
Server	Rehab4	[Resource]	Capacity	UnitsScheduled	Average	17.0000	17.0000	17.0000	0.0000
				UnitsUtilized	Average	9.2606	6.4791	12.2968	0.7251
	Rehab3	[Resource]	Capacity	UnitsScheduled	Average	20.0000	20.0000	20.0000	0.0000
				UnitsUtilized	Average	14.1372	9.3851	17.0838	0.9263
	Rehab2	[Resource]	Capacity	UnitsScheduled	Average	19.0000	19.0000	19.0000	0.0000
				UnitsUtilized	Average	13.9903	10.8345	16.6183	0.7562
	Rehab1	[Resource]	Capacity	UnitsScheduled	Average	26.0000	26.0000	26.0000	0.0000
				UnitsUtilized	Average	13.0193	10.6165	17.8728	0.9643
	AcuteWard2	[Resource]	Capacity	UnitsScheduled	Average	24.0000	24.0000	24.0000	0.0000
				UnitsUtilized	Average	22.6530	20.6198	23.5563	0.3652
	AcuteWard1	[Resource]	Capacity	UnitsScheduled	Average	53.0000	53.0000	53.0000	0.0000
				UnitsUtilized	Average	50.3368	45.7526	52.0153	0.6906

Figure 16. Long-run average bed utilization of acute wards and rehabilitation units.

Object Type	Object Name	Data Source	Category	Data Item	Statistic	Scenario2 Average	Minimum	Maximum	Half Width
Model	Model	BlockedAcuteBeds	UserSpecified	StateValue	Average	68.5551	45.8540	94.3259	5.6542

Figure 17. The long-run proportion of blocked beds for both acute wards.

4.0 Scenario Analysis

This section describes the process behind scenario analysis, including the controls of the experiments, the combinations tested, the results and the discussion.

4.1 Comparing multiple scenarios

To compare alternative policies, reference variables were initialized to allow for easy comparison of scenario statistics. The ranking rule in wards 3 and 4 was changed from FCFS to a priority by weighting, with the smallest numbers holding the highest ranking. Then several combinations of priorities in both wards were tested.

4.1.1 Explanation

Scenarios would be ranked on their wait time for each patient type, rehab unit 3 and 4 utilization, length of the queue and the number of blocked beds for each unit. Combinations of different scenarios were made by prioritizing different patient types (Stroke, Neurological Conditions, Brain Dysfunction, Spinal Cord Dysfunction and Cardiac) resulting in 21 combinations in total as seen in Figure 18.

Scenario		Replications		Controls				
Name	Status	Required	Completed	Neuro_Priority	Stroke_Priority	Brain_Dys_Priority	Cardiac_Priority	SpinalCord_Priority
Scenario1	Idle	20	20 of 20	1	1	1	1	1
Scenario2	Idle	20	20 of 20	1	2	1	1	1
Scenario3	Idle	20	20 of 20	2	1	1	1	1
Scenario4	Idle	20	20 of 20	1	1	1	2	3
Scenario5	Idle	20	20 of 20	1	1	1	3	2
Scenario6	Idle	20	20 of 20	1	1	2	1	3
Scenario7	Idle	20	20 of 20	1	1	2	3	1
Scenario8	Idle	20	20 of 20	1	1	3	1	2
Scenario9	Idle	20	20 of 20	1	1	3	2	1
Scenario10	Idle	20	20 of 20	1	2	1	2	3
Scenario11	Idle	20	20 of 20	1	2	1	3	2
Scenario12	Idle	20	20 of 20	1	2	2	1	3
Scenario13	Idle	20	20 of 20	1	2	2	3	1
Scenario14	Idle	20	20 of 20	1	2	3	1	2
Scenario15	Idle	20	20 of 20	1	2	3	2	1
Scenario16	Idle	20	20 of 20	2	1	1	2	3
Scenario17	Idle	20	20 of 20	2	1	1	3	2
Scenario18	Idle	20	20 of 20	2	1	2	1	3
Scenario19	Idle	20	20 of 20	2	1	2	3	1
Scenario20	Idle	20	20 of 20	2	1	3	1	2
Scenario21	Idle	20	20 of 20	2	1	3	2	1

Figure 18. Scenario Combinations of Rehab Units 3 and 4

4.1.2 Results

After the base model was altered as mentioned above, all possible scenarios were run and their values were recorded in Appendix A and B. For rehabilitation ward 3 utilization, the scenarios that have better utilization than the base case are scenarios 4, 9, 10, and 15. Scenario 4 has the highest mean of 87. 39. All the scenarios in unit 4 utilization have better means than the base case with scenario 11 having the highest mean of 65.60. Almost all of the scenarios for acute ward 1 and 2 have reduced queue lengths compared to the base case with scenario 13 having the lowest queue length for ward 1 and scenario 12 having the lowest queue length for ward 2. Additionally, the lowest number of blocked beds is achieved by scenario 17. To find the optimal scenario that would reduce the waiting time, the utilizations in unit 3 that are better than the base case will be used as the benchmark (see Table 1). Since scenarios 4, 9,10, and 15 have the best utilization means, the values in the other metrics (queue length and blocked beds) will be used and whichever scenario has the best combination will be the optimal scenario. The highlighted values of each metric are the ones in each scenario that are higher or lower than the base case, to see how many requirements each scenario meets and only scenario 10 meets all of the requirements. Therefore scenario 10 is the optimal scenario since the utilization for both rehabilitation units 3 and 4 are higher than the base case, the queue length for acute wards 1 and 2 are lower than the base case respectively, and the blocked beds for this scenario are lower than the base case. The optimal priority order should be given to neuro and then stroke for rehab unit 3 and brain dysfunction, cardiac and then spinal cord dysfunction for rehab unit 4 to minimize the total long-run average waiting time of patients.

Table 1: Table of Metrics and Scenarios

	Rehab3_util	Rehab4_util	AcuteW1Len	AcuteW2Len	Blocked Beds
Base Case	**87.1967**	**65.0787**	**882.568**	**325.764**	**91.593**
Scenario 4	**87.3882**	**65.1404**	**882.59**	**325.21**	**90.945**
Scenario 9	**87.3035**	**65.1085**	**881.793**	**325.702**	**91.6408**
Scenario 10	**87.3246**	**65.5351**	**882.036**	**323.334**	**91.2251**
Scenario 15	**87.2399**	**65.588**	**881.447**	**323.853**	**91.925**

4.2 Trade-offs Analysis

The chosen solution has a priority order whereas the baseline model does not. The main trade-off is that people do not get treated on an FCFS basis but rather based on what group they belong to but the wait time is reduced. Moreover, assumptions made are that the severity of the patient's illness is not considered. Groups such as neuro and brain dysfunction will benefit the most because they are the number one priority and face shorter wait times. Whereas the other groups; stroke, cardiac, and spinal cord do not benefit as they are prioritized secondary and face longer wait times. This system is not fair to everyone individually, however, holistically more people get access to care and the average wait time is lower. This is better than the FCFS model due to lower accessibility and longer wait times. Although it is not completely fair, more people get access to care which justifies the patient increase in waiting time for certain rehab groups.

5.0 Discussion

Scenario 10 was identified to be the best solution when compared to the base model and other alternative policies. This report recommends hospitals to prioritize patients in the rehabilitation group for neurological conditions followed by stroke for rehab unit 3 and brain dysfunction, cardiac, and then spinal cord dysfunction so that they can treat as many patients as possible and as quickly as possible. Additionally, since prioritizing one group could cause other groups to have increased wait time, beds could be redistributed across the wards to increase bed utilization.

References

[1] “Waiting your turn,” Google.com, 2023. https://www.google.com/url?q=https://www.fraserinstitute.org/studies/waiting-your-turn-wait-times-for-health-care-in-canada-2023&sa=D&source=docs&ust=1733365860278291&usg=AOvVaw0uALrkCoQNSm76LfHWofCa (accessed Dec. 05, 2024).

Attribution Table

By signing below, you are confirming that all group members contributed to all parts of the project including developing the model, analyzing data for input modelling, and writing the report, and that the contributions were balanced and based on mutual agreement. Note that making fraudulent claims in an attribution table displays intent to deceive and is a serious academic offence.

If you have any concerns regarding the contribution of your team members, you are advised to contact the course instructor as soon as possible so that the disagreement can be resolved. If at the time of submission there are irreconcilable disagreements that are preventing all team members from signing the attribution table, each team member must write a letter (max 300 words) explaining their position on the disagreement. The instructor will then decide based on the statements.

Student Name	**Signature**
Anna Wang	
Anoushka Paul	
Naeer Khan	

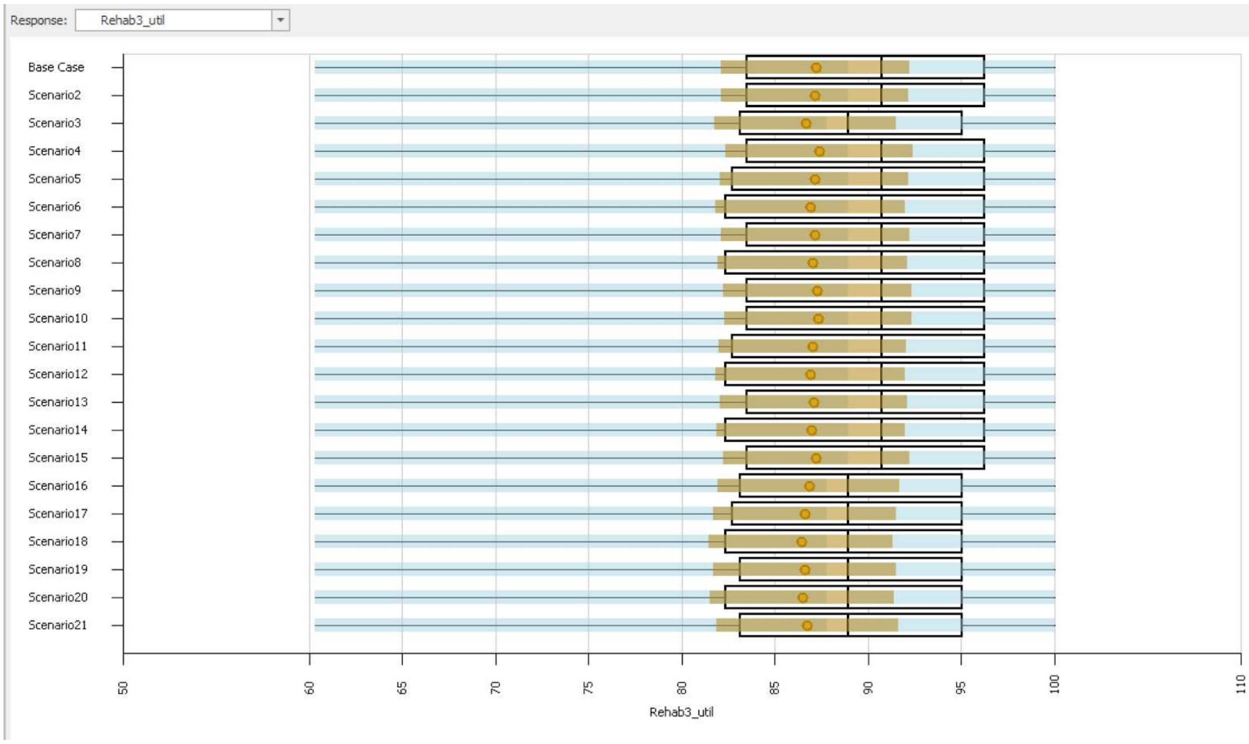
The Appendix

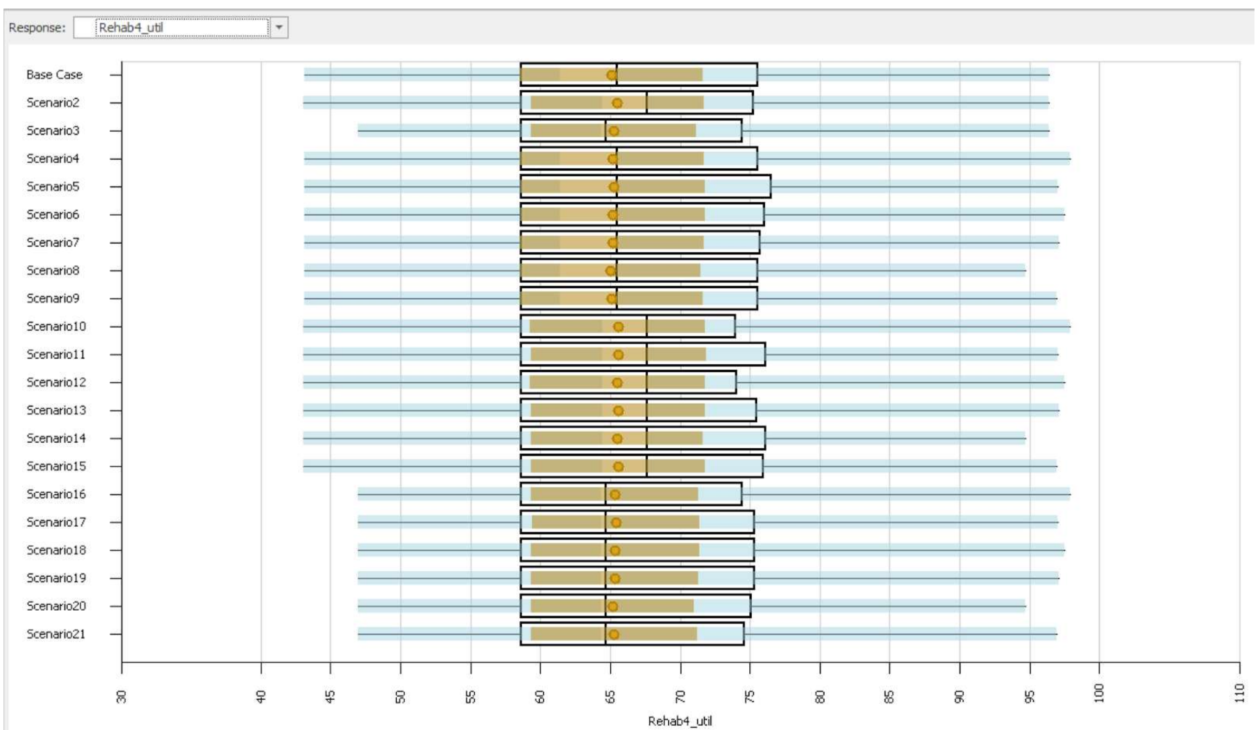
Appendix A : All Scenario Statistics

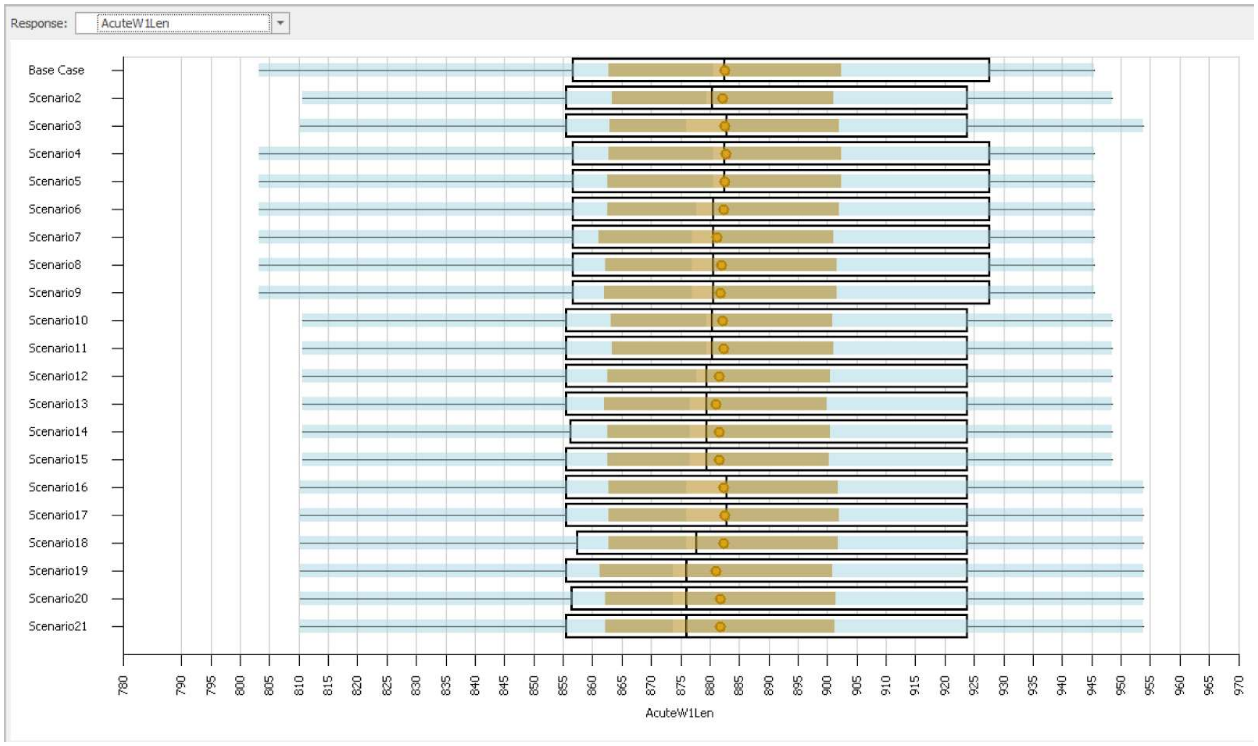
Design | Response Results | Pivot Grid | Reports | Dashboard Reports | Input Analysis

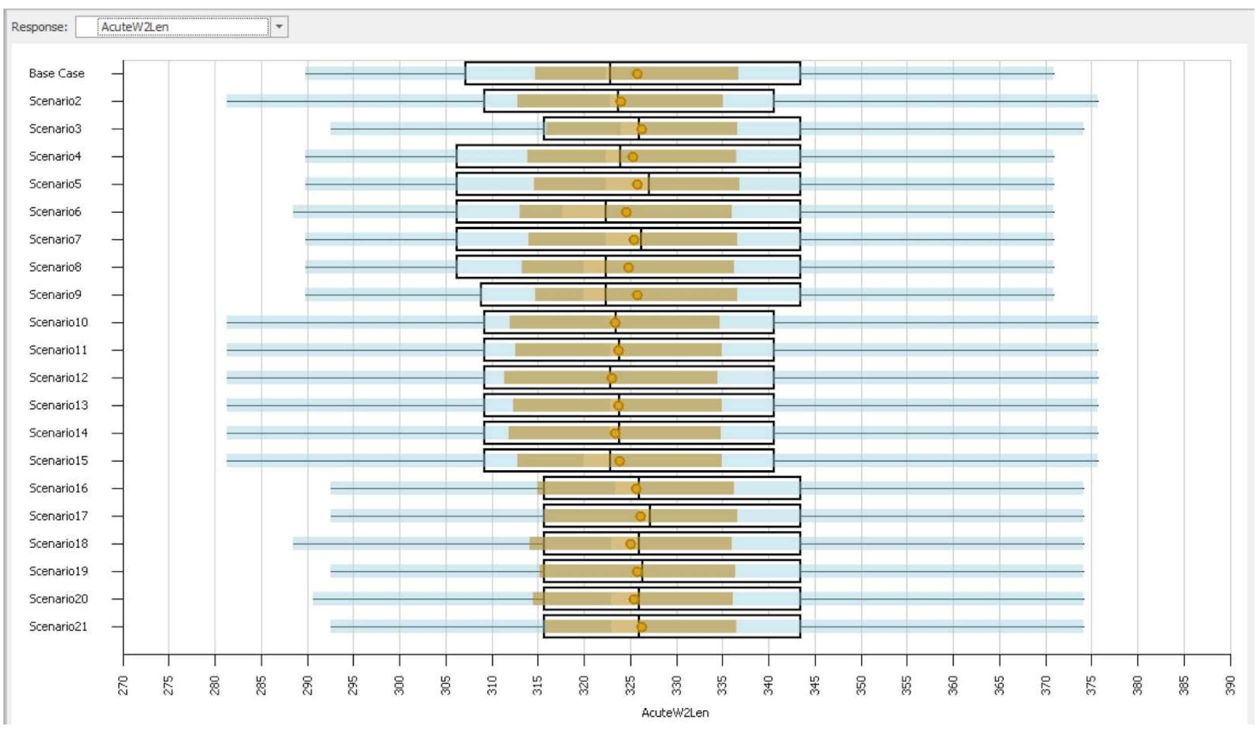
Scenario			Responses				
	Name	Status	Rehab3_util	Rehab4_util	AcuteW1Len	AcuteW2Len	BlockedBeds
☑	Base Case	Comple...	87.1967	65.0787	882.568	325.764	91.593
☑	Scenario2	Comple...	87.1331	65.5257	882.161	323.954	91.9676
☑	Scenario3	Comple...	86.6525	65.2332	882.495	326.278	91.2262
☑	Scenario4	Comple...	87.3882	65.1404	882.59	325.21	90.945
☑	Scenario5	Comple...	87.1357	65.228	882.485	325.703	91.0947
☑	Scenario6	Comple...	86.8971	65.1918	882.278	324.545	91.0112
☑	Scenario7	Comple...	87.1739	65.1587	881.119	325.346	91.9717
☑	Scenario8	Comple...	87.0323	65.0247	881.911	324.793	91.6356
☑	Scenario9	Comple...	87.3035	65.1085	881.793	325.702	91.6408
☑	Scenario10	Comple...	87.3246	65.5351	882.036	323.334	91.2251
☑	Scenario11	Comple...	87.0591	65.6011	882.232	323.753	91.4686
☑	Scenario12	Comple...	86.9043	65.5212	881.539	322.969	91.4686
☑	Scenario13	Comple...	87.1103	65.5739	880.988	323.656	92.3258
☑	Scenario14	Comple...	86.9659	65.4861	881.501	323.339	92.1747
☑	Scenario15	Comple...	87.2399	65.588	881.447	323.853	91.925
☑	Scenario16	Comple...	86.844	65.3077	882.328	325.638	90.5445
☑	Scenario17	Comple...	86.5915	65.4026	882.426	326.147	90.6484
☑	Scenario18	Comple...	86.4238	65.362	882.25	325.089	90.7218
☑	Scenario19	Comple...	86.6297	65.3357	880.998	325.805	91.5384
☑	Scenario20	Comple...	86.4881	65.1817	881.786	325.334	91.2432
☑	Scenario21	Comple...	86.7593	65.2663	881.722	326.18	91.197
☐	Scenario22	Idle					

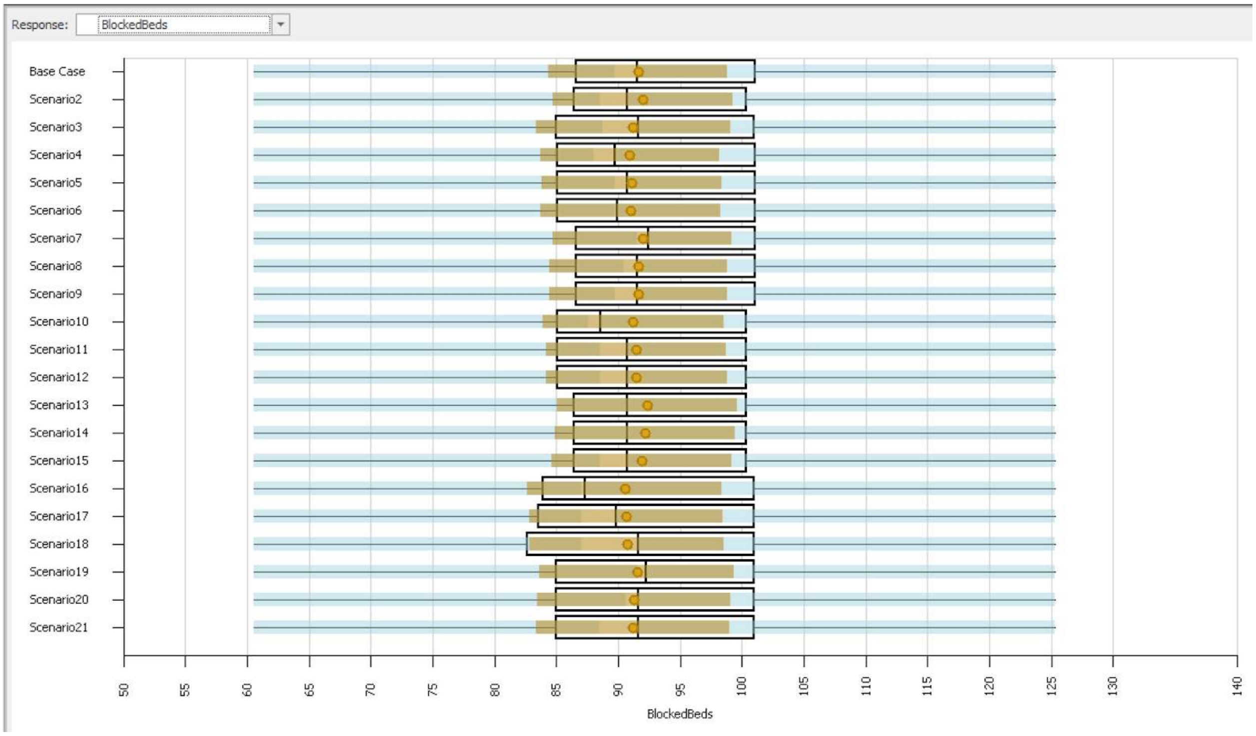
Appendix B: Optimization through Scenario Analysis






Response: AcuteW1Len
Base Case
Scenario2
Scenario3
Scenario4
Scenario5
Scenario6
Scenario7
Scenario8
Scenario9
Scenario10
Scenario11
Scenario12
Scenario13
Scenario14
Scenario15
Scenario16
Scenario17
Scenario18
Scenario19
Scenario20
Scenario21
780 790 795 800 805 810 815 820 825 830 835 840 845 850 855 860 865 870 875 880 885 890 895 900 905 910 915 920 925 930 935 940 945 950 955 960 965 970
AcuteW1Len


Response: AcuteW2Len
Base Case
Scenario2
Scenario3
Scenario4
Scenario5
Scenario6
Scenario7
Scenario8
Scenario9
Scenario10
Scenario11
Scenario12
Scenario13
Scenario14
Scenario15
Scenario16
Scenario17
Scenario18
Scenario19
Scenario20
Scenario21
270 275 280 285 290 295 300 305 310 315 320 325 330 335 340 345 350 355 360 365 370 375 380 385 390
AcuteW2Len



Appendix C: Fitting Arrival data to continuous distributions