Intracountry Disaster Relief Simulation

DATA 604: Simulation & Modeling

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1 Abstract

Disasters exact an extreme toll on lives and on economic well-being. Research into key aspects of disaster management is increasing. This study looks specifically at the domain of humanitarian logistics and more specifically, at intra-country relief logistics to the last mile, that point of transitioning aid to people affected by disasters. By identifying the key business processes, the authors present a model of supply logistics using computer based simulation software. The simulation enables experiments to investigate the value of establishing strategic supply chain agreements with vendors. The modeling of various supply chain choices are carried through to understand the impact on moving relief aid through the pipeline and on understanding the capabilities to service more beneficiaries in an efficient manner. The simulation model also enables research into the impact of access restrictions to distribution sites and the concerns on reliability of vehicle transfers in the supply chain process. Suggestions are given on natural extensions to the model and facilitating this intent, a public GitHub repository is made available for additional research.

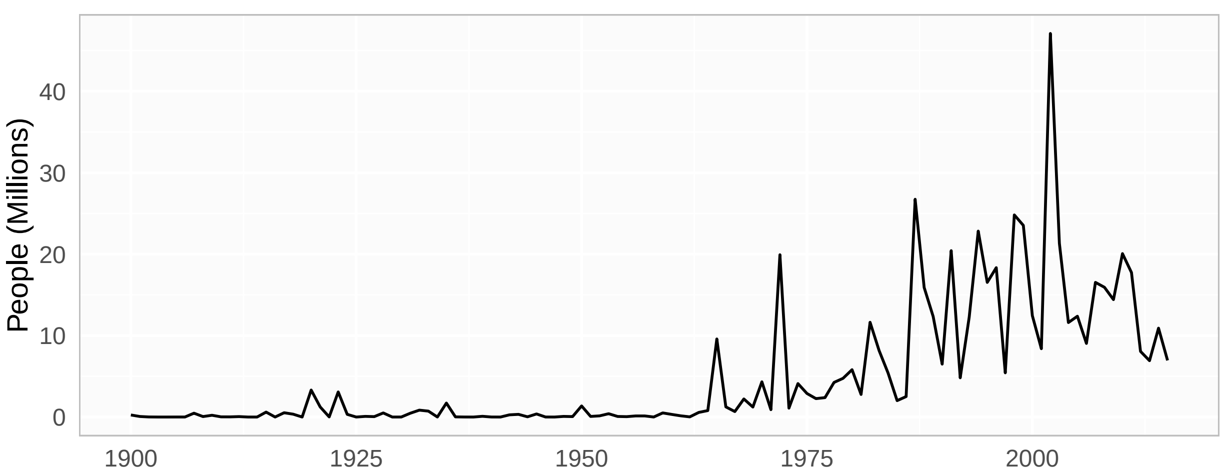
2 Keywords

humanitarian aid, logistics, disaster relief, simulation

3 Literature Review

The number of disasters witnessed over time appear to be increasing in terms of frequency and impact. Figure 1 for example, depicts the average number of people killed or adversely impacted (i.e. made homeless, injured or economically affected) due to natural disasters from the year 1900 to date. This information is based on disaster data pertaining to *notable* events in each year (EM-Dat, 2016).

Figure 1: Average Numbers Killed or Affected By Major Disasters in Given Year



While there are fluctuations from year to year, there is a clear trend showing a growth in the numbers or people who are affected or killed by disasters over time.

Responding to these types of disasters is a highly complex process. Often multiple stakeholders will be engaged, working under stressful environments with severe time pressure and significant uncertainty with respect to whether they can work to save lives.

In this context, we are beginning to see an increase in the amount of research into models and systems that can potentially help humanitarian workers make informed decisions. For example Kung et al (Kung, Chen, and Ku, 2012) present three prediction models and an inference engine using linear regression, multivariate analysis and back propagation networks to assess potential debris flows resulting from earthquakes. In another example, Rottkemper et al (Rottkemper, Fisher, and Blecken, 2012) present a mixed-integer programming model for an integrated relocation and distribution planning solution designed to minimize both operational costs and unmet demand for relief items.

Within the *logistics* aspects of emergency management, Ozdamar et al (Ozdamar, Ekinci, and Kucukyazici, 2004) present a model to complement decision support systems related to logistics planning following a disaster. The study contrasts various algorithmic approaches to solving for multi-period, multi-commodity network flow problems coupled with a vehicle routing problem.

Ozdamar et al's study helps to designate routing decisions for vehicles. The authors also note that the resolution to the various optimization choices are NP-hard. They suggest heuristic methodologies be applied to find solutions to large scale problems. Building on this recommendation, the current study, aims to understand the dynamics of in-country humanitarian logistics problems via simulations.

In running the simulation, we present a model of a simplified humanitarian logistics chain for the purpose of understanding the behaviour of the system and for evaluating certain strategies. We modelled key aspects of the humanitarian logistics chain using computer simulation software (Simio v8.136.13435). The intent is to understand the realities of moving humanitarian aid, particularly to the last mile of distributions (something that has not garnered as much research in the literature).

4 Methodology

4.1 Structure

The basic objective of a logistics system is to deliver the appropriate supplies, in good condition, in the quantities required, and at the places and time they are needed. Some emergencies generate a limited need for very rapid and very specific deliveries of supplies, commodities and resources from outside the affected area (i.e. outside the affected country). This process entails the implementation of an international humanitarian logistics chain (IHLC) as depicted in the following chart.

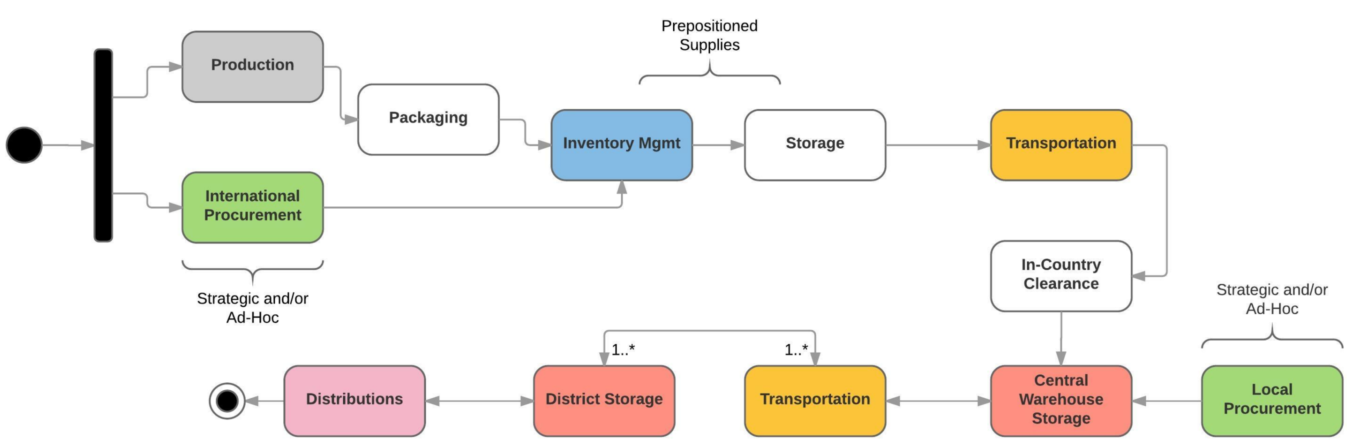


Fig 2: The International Humanitarian Logistics Chain

The IHLC is an involved process adding significant complexity to the movement of relief resources - see '(Bastian, Griffin, Spero, and Fulton, 2015) for an example of modelling an international logistics chain.

While international humanitarian logistics is a complex process, it is also important to note that the majority of relief logistic operations never actually receive international attention. With this reality in mind, and in an effort to simplify the modelling of the logistic chain, this project will consider the simulation needs of a in-country based logistic chain. The simplification of the model is shown in Figure 3.

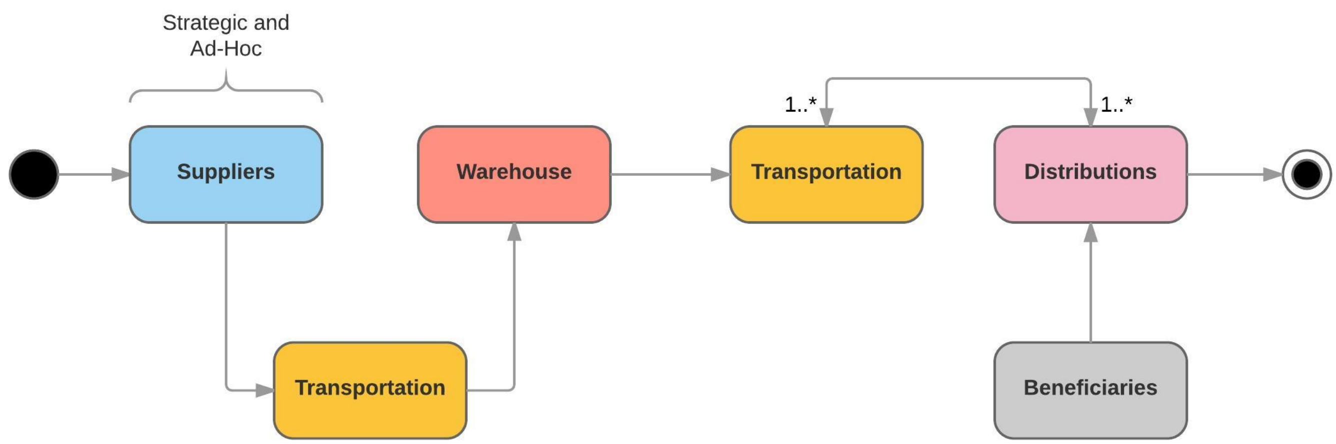


Fig 3: The Simplified Humanitarian Logistics Chain

Key entities are readily recognized from Figure 3. A short description follows on each entity that is modelled.

4.1.1 Supplier

A Supplier entity is included in the simulation model. This entity is the source of ReliefSupplies. The Supplier entity is used, through design of experiments, to simulate the reliability of suppliers. We do this by modelling three categories of supplier: Partner (Preferential Supplier, representing the establishment of strategic supply chain partnership agreements with a given supplier such as commitments on the frequency of supplies by a given time, agreement on price points etc.), an Adhoc Supplier (representing local suppliers that aid agencies establish at the onset of a disaster but without any formal supplier partnership agreement being established), and a Midlevel supplier (representing known suppliers ahead of the disaster but who have not entered into a strategic agreement with the given aid agency).

The inter-arrival times for relief supplies produced by these entities differs based on the construct of reliability. Note that the inter-arrival times are modelled as Random Normal events with mean arrival time of supplies being faster for Partner Suppliers, followed by Midlevel suppliers and finally Ad-hoc suppliers. The normal distribution was selected under an assumption that production of supplies would likely be based on known manufacturing processes. This is noted as a uncorroborated assumption and would require comparisons of the simulation results to real-world supplier data under the context of emergencies.

It should also be noted that the entity was also modelled on an assumption of infinite supply under the constraint of the inter-arrival time capability of the supplier, and continuous demand driven by the anticipation of a disaster and then the disaster itself. This assumption was felt to be appropriate given the fact that the simulation is modelling the rapid onset and response to a disaster wherein estimating affected beneficiary numbers is very hard to achieve up front. Consequently modelling a continuous supply of relief items, is considered a fair reflection of the real-world reality of an aid agency establishing a supply chain for relief items.

The following variables (Referenced Properties) were created to facilitate the study:

- The time to deliver a shipment of supplies: *SupplierTravelTimeToWarehouse*.
- The maximum number of relief supplies which the supplier will provide: *SupplierMaximumArrivals*

- The time between produced relief supplies available for movement to the warehouse: *SupplierReliefSuppliesInterarrivalTime*

The delivery vehicle, SupplierVehicle, was set to require a full load prior to departing for the Warehouse.

- The capacity of the SupplierVehicle: *SupplierVehicleCapacity*

4.1.2 Warehouse

A Warehouse entity was added to store disaster relief supplies in preparation for a disaster. This warehouse acted as the central hub for the aid agency to supply distribution sites during disasters (i.e. no secondary level warehouses were modelled).

The Warehouse entity was modelled as a server which processes incoming ReliefSupplies and stores them in a ready state for movement to a DistributionSite.

The following variables were created to facilitate design of experiments:

- The storage capacity of the warehouse: *WarehouseStorageCapacity*

The delivery vehicle, WarehouseVehicle, was set to require a full load prior to departing for a distribution site. A capacity of 1000 units was defined on these vehicles. Given the need to control against the risk of transportation being hijacked while on route (losing supplies) and the fact that these vehicles need to access smaller roads, the warehouse to distribution sites are modelled with a smaller load carrying capacity compared to the SupplierVehicle. The WarehouseVehicle was also designed to have periodic failures (details to follow).

- The capacity of the WarehouseVehicle: *WarehouseVehicleCapacity*
- The frequency of failure: *WarehouseVehicleUptimeBetweenFailures*

The selection weight on the paths from the Warehouse to the Distribution Sites were set to dynamically adjust based on the number of Beneficiaries waiting for Relief Supplies.

4.1.3 Distribution Sites

Two distribution sites are included in the simulation and are modelled as combiners which match Relief Supplies to Beneficiaries.

The following variable was created to facilitate design of experiments:

- The processing time needed to provide a ReliefSupply item to a ReliefBeneficiary: *DistSiteProcessingTime*

Typically this is a fast process, especially with pre-packed relief supplies as would be expected in the scenario being simulated. A Random Exponential with a mean of 1 minute was used to process individuals through the handover of supplies from aid worker to beneficiary.

4.1.4 Relief Beneficiaries

The Beneficiaries represent entities who are affected by the disaster and require ReliefSupplies. Two separate sources were included in the model to simulate separate points from which beneficiaries would origination for each distribution site.

The following variables were created to facilitate design of experiments:

- The interarrival time of the ReliefBeneficiaries: *ReliefBeneficiaryInterarrivalTime*

- The maximum number of ReliefBeneficiaries from a given source: *DisasterVictimMaximumArrivals*

Note that the inter-arrival times of beneficiaries was modelled as a Random Exponential event (inter arrival was set at every 2.5 minutes).

The rational for this is given as follows:

- Field experience of one of the researchers where the process of registrations and verification of people has been clocked with an average of 2-3 minutes per beneficiary.
- The exponential function is widely used to model arrivals that are completely random. As this simulation is concerned with rapid onset emergencies, the arrival of beneficiaries will be completely random (contrasted to distributions that are more organized ahead of time with the affected communities after weeks or months following the disaster).
- Research from studies looking at arrival times at emergency departments reference the highly random nature of arrivals. Many use forms of exponential family of distributions (such as Weibull)
- Note that this simulation assumes that the source of arrivals are unlimited (given the reference to rapid onset and immediate response). Any queue of beneficiaries to be modelled, was done so in an infinite manner.
- The exponential nature makes intuitive sense, given that we would expect the number of arrivals to taper off as time progresses (people will come to a distribution site, but as time passes - people know that the distributions are likely closed or the "noise" about a distribution happening in a certain location will likely taper off).

4.1.5 Disaster

The "Disaster" is set to begin at a designated time into the simulation. This gives some time to prestage relief supplies through the warehouse (priming the pump).

The following variables were created to facilitate design of experiments:

- The amount of time between simulation start and onset of the disaster: *DisasterTimeOffset*

4.2 Measured Outcomes

4.2.1 Average Beneficiary Time in System

Measured in hours, this response is an important indicator of the performance of the system. Fewer hours spent in the system are considered to be better outcomes as people should be looking after their families, rebuilding homes etc rather than queuing for relief items.

4.2.2 Relief Supplies Distributed

How many relief supplies were distributed?

4.2.3 Unsatisfied Beneficiaries

This was defined as the number of beneficiaries who had yet to receive relief items at the conclusion of the simulation. Naturally, we wanted this response to be zero (0) throughout all simulations.

4.2.4 Maximum Distribution Site 1 Time Waiting

Measured in hours, this response helped us understand the degree of the worst case scenario for distribution site 1 beneficiaries in need of relief supplies.

4.2.5 Maximum Distribution Site 2 Time Waiting

Measured in hours, this response helped us understand the degree of the worst case scenario for distribution site 2 beneficiaries in need of relief supplies.

4.3 Design of Experiments

A variety of experiments were performed in the context of the simulation. The following table lists the baseline values for the control variables. Each of the experiments modifies a single variable and recorded an outcome of interest, as described in the following subsections.

Table 1: Simulation Control Variables

Name	Value	Units
DisasterTimeOffset	3	Days
DisasterVictimMaximumArrivals (per Dist Site)	10000	Beneficiaries
DistSiteProcessingTime	Random.Exponential(1)	Minutes
Entry2DistSitePath	TimePathToDistSite2	Path Name
ReliefBeneficiaryInterarrivalTime	Random.Exponential(2.5)	Minutes
SupplierMaximumArrivals	Infinity	Relief Supply Items
SupplierReliefSuppliesInterarrivalTime	Random.Normal(1, 0.1)	Minutes
SupplierTravelTimeToWarehouse	Random.Normal(6,0.5)	Hours
SupplierVehicleCapacity	5000	Relief Supply Items
WarehouseStorageCapacity	Infinity	Relief Supply Items
WarehouseTravelTimeToDistributionSite1	Random.Normal(6,0.5)	Hours
WarehouseTravelTimeToDistributionSite2	Random.Normal(6,0.5)	Hours
WarehouseVehicleCapacity	1000	Relief Supply Items
WarehouseVehicleUptimeBetweenFailures	Random.Exponential(100)	Hours

4.3.1 Supplier: Partner vs Ad Hoc

How does a dedicated supplier whose production time is lower (more units of production are committed to our orders, which can be thought of as being a more reliable supplier), versus an ad hoc supplier whose production time is longer, affect the measured outcomes?

The following table shows key parameters (control variables) for this scenario:

Name	ReliefSuppliesInterarrivalTime
Adhoc Supplier	Random.Normal(4, 0.1)
Midlevel Supplier	Random.Normal(2.5, 0.1)
Partner Supplier (Baseline)	Random.Normal(1, 0.1)

4.3.2 Distribution Site: Level of Access

How does the level of access to distribution sites, modelled as travel time between the warehouse and distribution site 1, affect outcomes?

Name	WarehouseTravelTimeToDistSite1
Partner Supplier (Baseline)	Random.Normal(6,0.5)
Midlevel Access to Dist Site 1	Random.Normal(4,0.5)
Quick Access to Dist Site 1	Random.Normal(2,0.5)

4.3.3 Warehouse Vehicle: Propensity for Failure

How does the likelihood of the warehouse delivery vehicle failing, affect outcomes?

Name	WarehouseVehicleUptimeBetweenFailures
Partner Supplier (Baseline)	Random.Exponential(100)
Warehouse Vehicle Midlevel Failures	Random.Exponential(50)
Warehouse Vehicle No Failures	Infinity

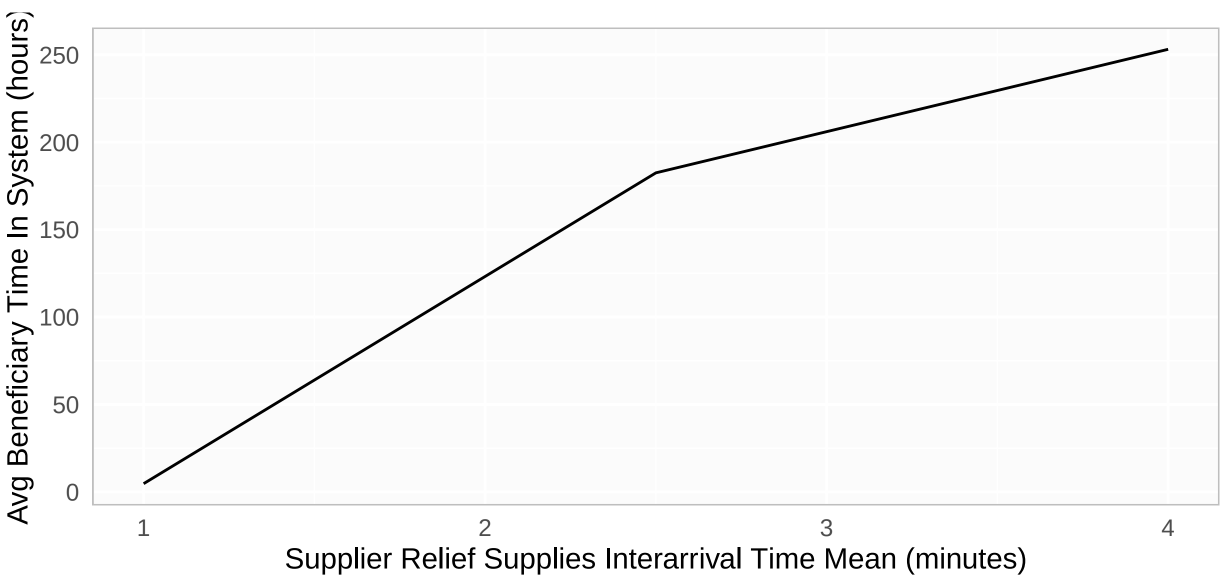
4.3.4 Distribution Site Closure

How does a distribution site closure affect outcomes?

Name	Entry2DistSitePath
Partner Supplier (Baseline)	TimePathToDistSite2
Distribution Site 2 Closed	TimePathToDistSite1

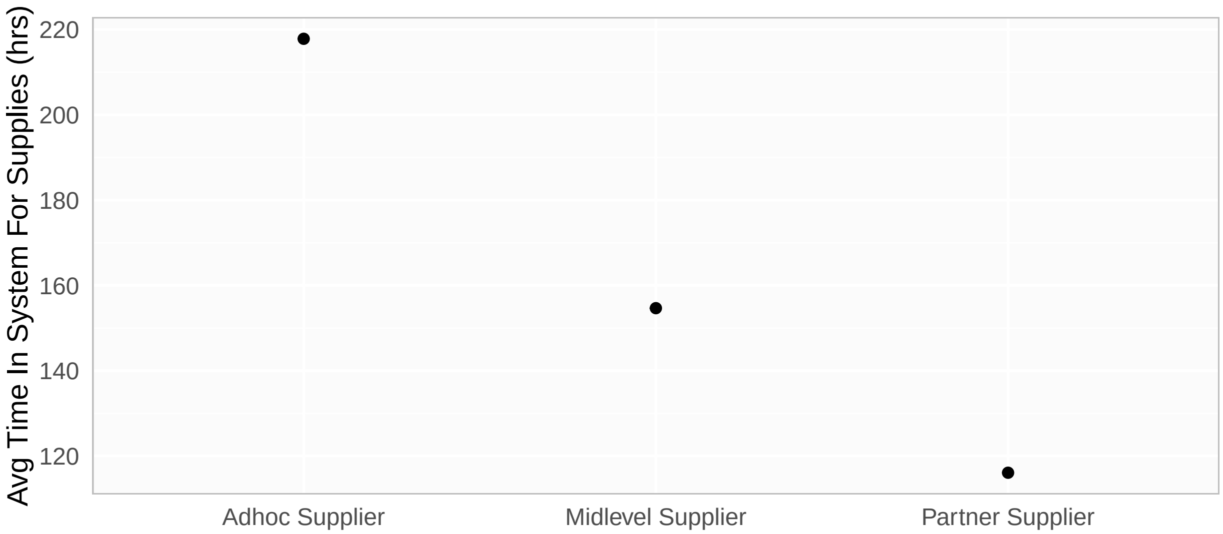
5 Results

5.1 Supplier: Partner vs Ad Hoc



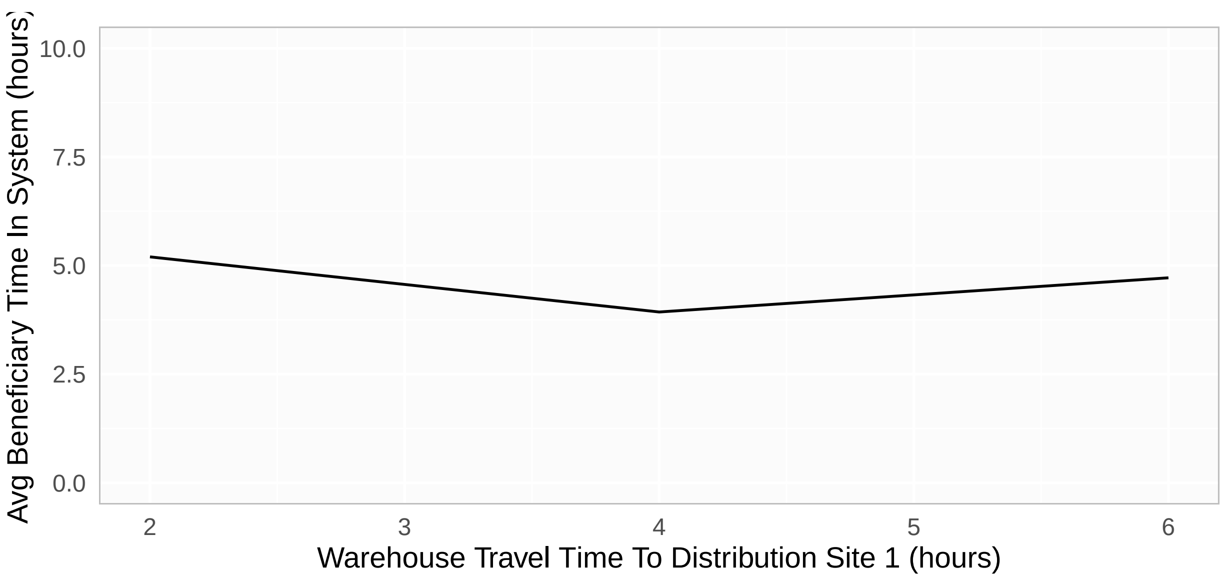
These simulated results are consistent with what we would expect in the real world. The investment in establishing strategic agreements with suppliers ahead of time (i.e. forming Strategic Partnerships) were modelled with a higher "average reliability" in providing the aid agency with supplies (i.e. a faster average inter-arrival of supplies). These forms of partnerships clearly had a positive impacted in reducing the average time in system for beneficiaries further down the chain (at distribution sites).

The worst performer was the Adhoc supplier relationship, wherein the average beneficiary time can be seen to grow to over 250 hours (inconsistent supplies meaning that many beneficiaries were kept waiting within the system until the pipeline was sufficient to feed the supply needs at the distribution sites). Note that the model did not 'open' or 'close' distributions based on set operating hours, and as such waiting time accumulated on a 24 hour basis. Perhaps this is slightly artificial, however it does indicate the impact of unreliable partners further up the supply chain.



The importance of pre-establishing strategic supplier relationships is further corroborated in the simulation by looking at the length of time supplies remain within the system. The ideal scenario would be to have a 'just-in' time supply chain thereby minimizing warehouse costs while fully meeting beneficiary needs. This is especially true for perishable relief items such as food or medicines. As can be seen in the figure above, the more established a relationship with the supplier, the less time it took for supplies to remain within the system.

5.2 Restricted Access to Distribution Site from Warehouse

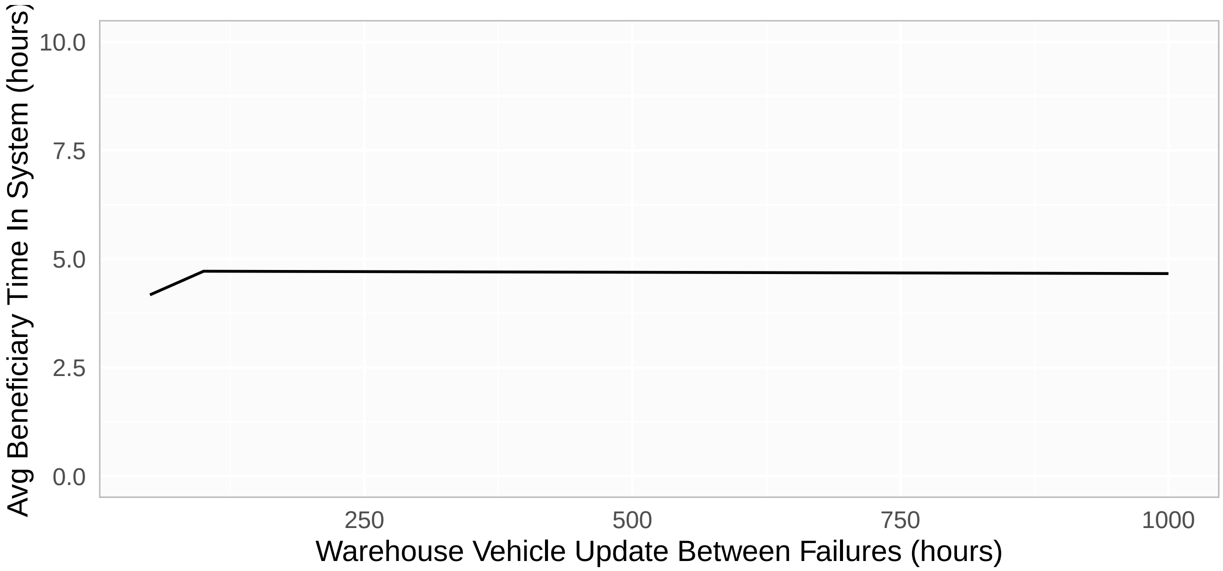


An average wait time by beneficiaries of 5 hours is noted when access to a distribution site is easier (modelled as quicker time to gain access to the distribution site). Interestingly we see that the model suggests that an optimal time (in terms of reduced beneficiary wait time at the distribution points) to reach/gain access to the distribution site is approximately 4 hours, after which the average wait time for beneficiaries begins to increase again.

It is suggested that the simulation is identifying a phenomenon associated with the arrival and queuing times of beneficiaries at a distribution site in conjunction with the capacity to serve the queue based on incoming supplies. One hypothesis is that at the 4 hour mark, sufficient numbers of beneficiaries have accumulated to effectively service people more quickly with all available supplies arriving on the truck. Quicker arrival times of trucks to the sites may imply that few people have accumulated in the queues. Moreover longer access times of the vehicles may mean that the buffer queue of beneficiaries is not being cleared in the most optimal manner (Note that the capacity of the trucks from the warehouse to the distribution sites are limited to carrying 1000 units per trip).

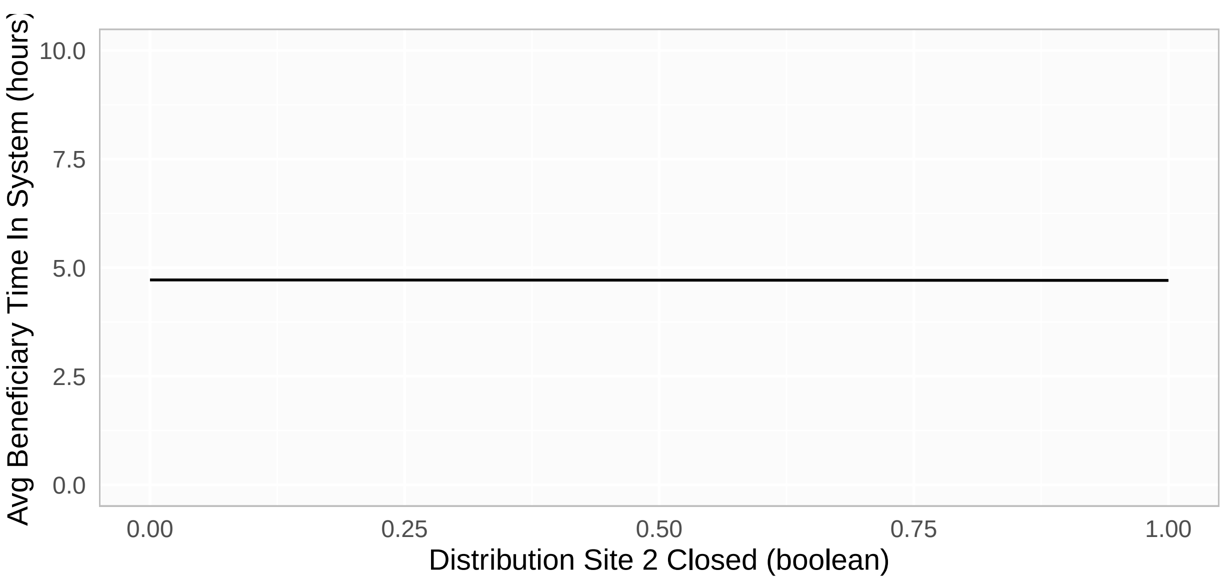
5.3 Warehouse Vehicle Failures

The warehouse vehicle failures yielded interesting results. It appears the difference between a 100 hour exponential mean and no failures is negligible. Strangely, the outcome of average beneficiaries time in system reduces for the mean failure rate of 50 uptime hours between failures. The confidence interval for these values reveals that an overlap suggesting an insignificant difference.

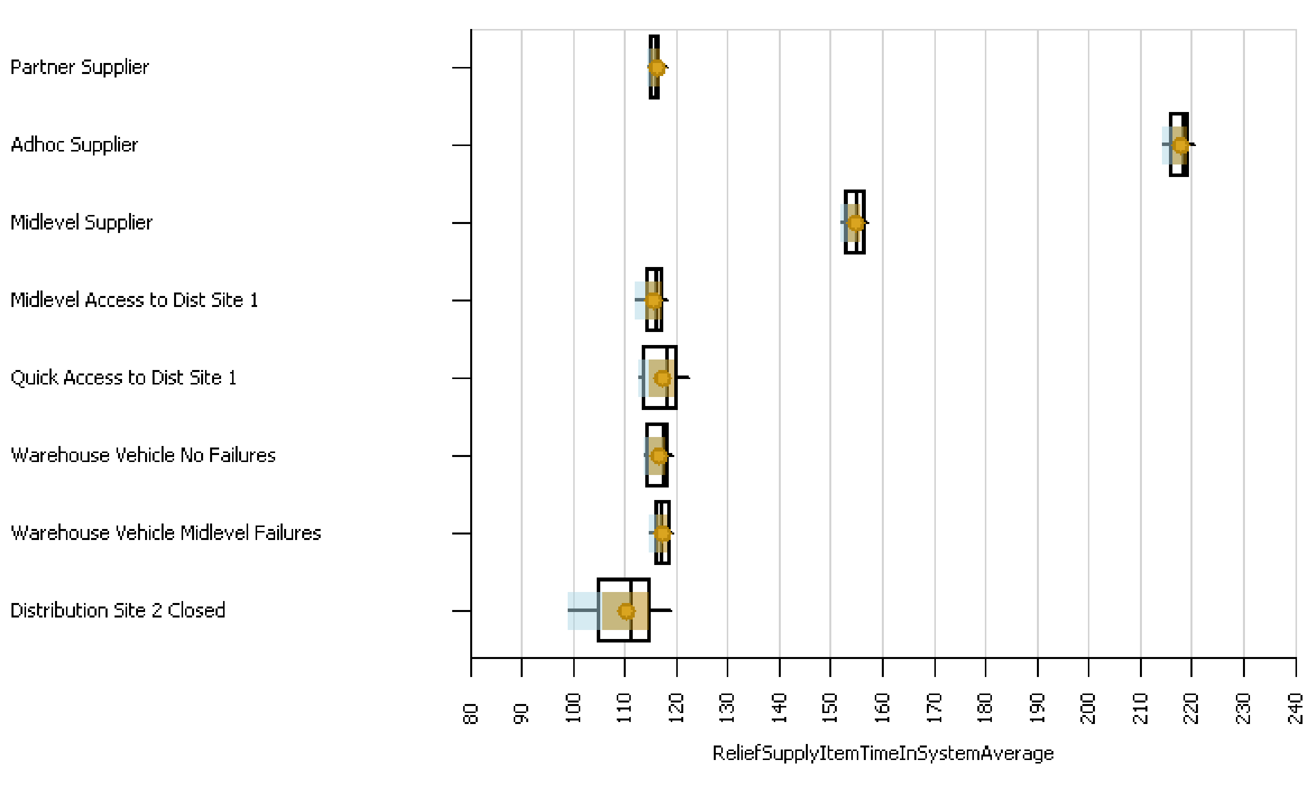


5.4 Distribution Site Closure

The distribution site closure did not have much of an effect on the primary outcome, average beneficiaries time in system. This requires further investigation but could indicate the travel time for the extra beneficiaries was too low. Additionally, it seems the capacity of the relief distribution system (as modelled) has sufficient head room to take on the additional demand at a single distribution site.



While the average beneficiary time in the system when distribution site 2 was closed, did not substantially differ from other experimental scenarios (with the exception of the noted differences when supplier was not equal to a Partner supplier), it was noted that the length of time for supplies to move through the system was slightly quicker when site 2 was closed. The range is seen to be lower under this scenario:



All Scenarios - Relief Supplies Time In System

Note that the average travel time between warehouses and distribution sites was the same (6 hours, with standard deviation of 30 minutes). Further, there is only one truck servicing both distribution sites. It is unclear as to why supplies appeared to move more quickly through the system in this scenario. One hypothesis is that when site 2 was closed, the queue of beneficiaries at site 1 filled up quicker and the numbers where therefore greater when distributing supplies following the arrival of the truck. In essence, the simulation may indicate that closing site 2, presented an opportunity to serve more people in a single truck-load of relief items thereby reducing the time for supplies to be in the system. The average wait time of beneficiaries would not have differed as the number of people entering the simulation did not change.

6 Suggestions for future work

The current study provides a good indication of in-country supply chain dynamics down to the last mile of distributions to beneficiaries. The underlying assumptions associated with production frequencies based on supplier type, the expected inter-delivery times of supplies, and the arrival behaviour of beneficiaries were estimated using domain knowledge experience and some limited field data. However much of this needs to be supplemented with experiments and production time observations at a broader scale.

It is also acknowledged that the context of the disaster will impact results. For example, disasters significantly affecting transportation infrastructure, would necessitate modelling different modes of delivery (such as aerial) instead of land-based vehicles. Future work may also look to adding an aspect of disaster intensity and disaster frequency as additions to the simulation.

Further, adding a financial analysis component to the the models to provide a cost quantification metrics would be a natural extension. For example to generate cost-benefit analysis of the different modes of reliable suppliers. This could be extended to include the opportunity costs of wait times for beneficiaries.

Quantifying supplies would help in finding optimal solutions in terms of the amount of stock to preposition, versus time to deliver relief (efficiency) and also to compare against wastage (spoiled supplies).

Finally, future work may wish to consider growing the entities to encompass more complexity associated with local supply chain systems. For example, modelling a greater number of warehouse centres (possibly modelling the movement from an in-country central warehouse to district level warehouses that hold supplies prior to running pre-planned distributions). The notion of security and risk may consequently be built into such extended models, as the security risks at district level warehouses are typically higher than those at central warehouses.

7 Summary

The simulation model developed in this study is focused on an in-country disaster relief scenario. The model is capable of more experiments than were executed given the variables and capabilities of Simio, but those experiments which were performed show that supplier capability and commitment can have a significant impact on beneficiary outcomes. Additionally, depending on supply chain capability and other factors, more distribution sites may actually degrade overall beneficiairy outcomes. Opening an additionaly distribution site should be considered carefully against the impact to existing sites.

All materials related to this study including the actual Simio simulation model are shared on GitHub under our DisasterReliefSim repository (Dittenhafer and Narhan, 2016).

8 References

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9 Appendix: Response Data

Table 6: Supplier: Partner vs Ad Hoc Responses

Scenario	Response	Mean	95% CI Lwr	95% CI Upr
Partner Supplier	ReliefSupplyItemTimeInSystemAverage	116.067162	115.254999	116.879324
Partner Supplier	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Partner Supplier	UnsatisfiedBeneficiaries	0.000000	0.000000	0.000000
Partner Supplier	ReliefSuppliesDistributed	20000.000000	20000.000000	20000.000000
Partner Supplier	MaxDistSite2TimeWaiting	36.100330	28.513714	43.686947
Partner Supplier	MaxDistSite1TimeWaiting	35.754016	31.111059	40.396974
Partner Supplier	AvgBeneficiaryTimeInSystem	4.717122	4.162509	5.271735
Adhoc Supplier	ReliefSupplyItemTimeInSystemAverage	217.834869	216.337952	219.331786
Adhoc Supplier	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Adhoc Supplier	UnsatisfiedBeneficiaries	15000.000000	15000.000000	15000.000000
Adhoc Supplier	ReliefSuppliesDistributed	5000.000000	5000.000000	5000.000000
Adhoc Supplier	MaxDistSite2TimeWaiting	289.963402	277.515510	302.411295
Adhoc Supplier	MaxDistSite1TimeWaiting	291.130365	279.314909	302.945821

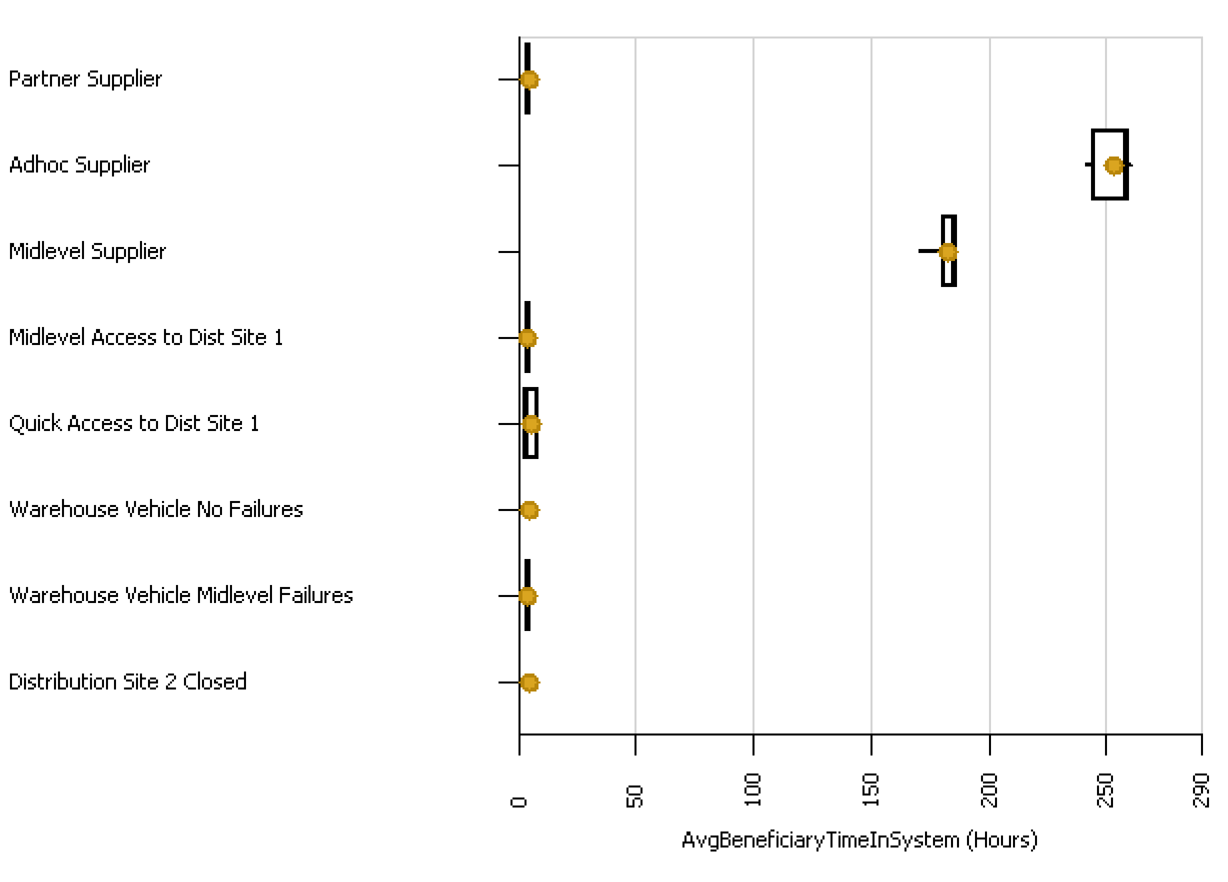
Scenario	Response	Mean	95% CI Lwr	95% CI Upr
Adhoc Supplier	AvgBeneficiaryTimeInSystem	253.084095	247.417765	258.750425
Midlevel Supplier	ReliefSupplyItemTimeInSystemAverage	154.665275	153.364968	155.965583
Midlevel Supplier	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Midlevel Supplier	UnsatisfiedBeneficiaries	10055.300000	9986.644543	10123.955458
Midlevel Supplier	ReliefSuppliesDistributed	9944.700000	9876.044542	10013.355457
Midlevel Supplier	MaxDistSite2TimeWaiting	243.629077	216.651744	270.606411
Midlevel Supplier	MaxDistSite1TimeWaiting	283.182952	257.416530	308.949375
Midlevel Supplier	AvgBeneficiaryTimeInSystem	182.449092	178.851824	186.046360

Table 7: Warehouse Access to Distribution Site Responses

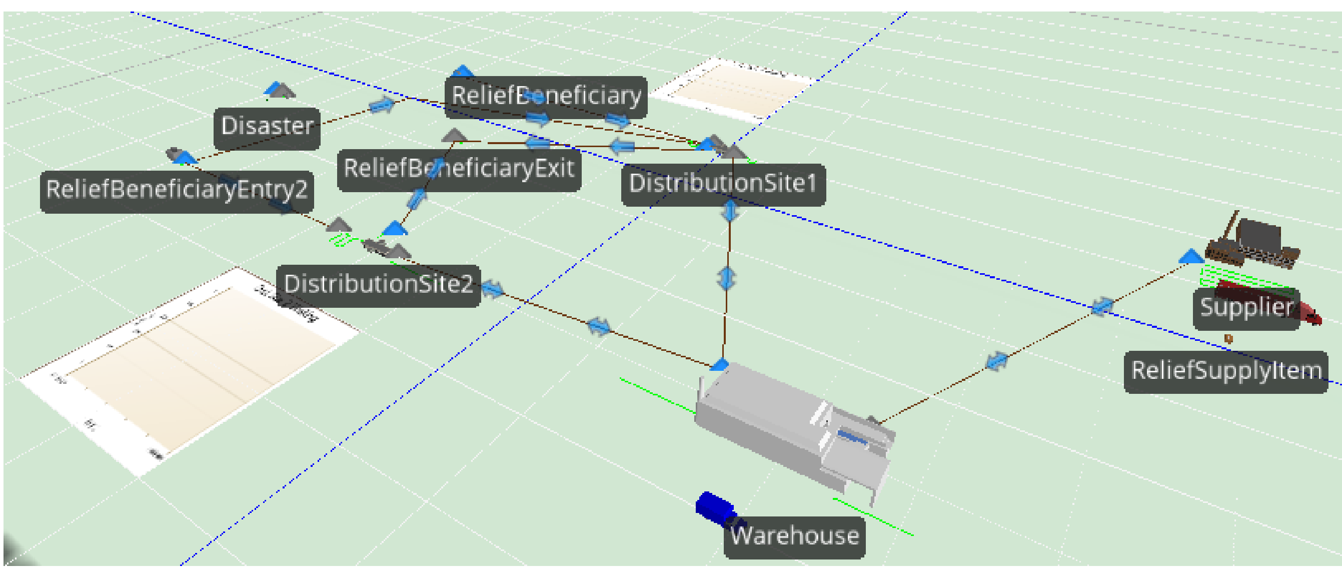
Scenario	Response	Mean	95% CI Lwr	95% CI Upr
Partner Supplier	ReliefSupplyItemTimeInSystemAverage	116.067162	115.254999	116.879324
Partner Supplier	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Partner Supplier	UnsatisfiedBeneficiaries	0.000000	0.000000	0.000000
Partner Supplier	ReliefSuppliesDistributed	20000.000000	20000.000000	20000.000000
Partner Supplier	MaxDistSite2TimeWaiting	36.100330	28.513714	43.686947
Partner Supplier	MaxDistSite1TimeWaiting	35.754016	31.111059	40.396974
Partner Supplier	AvgBeneficiaryTimeInSystem	4.717122	4.162509	5.271735
Midlevel Access to Dist Site 1	ReliefSupplyItemTimeInSystemAverage	115.639422	114.160935	117.117909
Midlevel Access to Dist Site 1	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Midlevel Access to Dist Site 1	UnsatisfiedBeneficiaries	0.000000	0.000000	0.000000
Midlevel Access to Dist Site 1	ReliefSuppliesDistributed	20000.000000	20000.000000	20000.000000
Midlevel Access to Dist Site 1	MaxDistSite2TimeWaiting	33.744925	29.221874	38.267975
Midlevel Access to Dist Site 1	MaxDistSite1TimeWaiting	33.066987	28.029844	38.104129
Midlevel Access to Dist Site 1	AvgBeneficiaryTimeInSystem	3.930074	3.464660	4.395489
Quick Access to Dist Site 1	ReliefSupplyItemTimeInSystemAverage	117.234860	114.722353	119.747368
Quick Access to Dist Site 1	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Quick Access to Dist Site 1	UnsatisfiedBeneficiaries	0.000000	0.000000	0.000000
Quick Access to Dist Site 1	ReliefSuppliesDistributed	20000.000000	20000.000000	20000.000000
Quick Access to Dist Site 1	MaxDistSite2TimeWaiting	46.082564	32.603982	59.561145
Quick Access to Dist Site 1	MaxDistSite1TimeWaiting	30.134080	24.634148	35.634013
Quick Access to Dist Site 1	AvgBeneficiaryTimeInSystem	5.199038	3.472673	6.925403

Table 8: Distribution Site Closure Responses

Scenario	Response	Mean	95% CI Lwr	95% CI Upr
Partner Supplier	ReliefSupplyItemTimeInSystemAverage	116.067162	115.254999	116.879324
Partner Supplier	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Partner Supplier	UnsatisfiedBeneficiaries	0.000000	0.000000	0.000000
Partner Supplier	ReliefSuppliesDistributed	20000.000000	20000.000000	20000.000000
Partner Supplier	MaxDistSite2TimeWaiting	36.100330	28.513714	43.686947
Partner Supplier	MaxDistSite1TimeWaiting	35.754016	31.111059	40.396974
Partner Supplier	AvgBeneficiaryTimeInSystem	4.717122	4.162509	5.271735
Distribution Site 2 Closed	ReliefSupplyItemTimeInSystemAverage	110.239356	105.740389	114.738322
Distribution Site 2 Closed	ReliefBeneficiaryNumberCreated	20000.000000	20000.000000	20000.000000
Distribution Site 2 Closed	UnsatisfiedBeneficiaries	0.000000	0.000000	0.000000
Distribution Site 2 Closed	ReliefSuppliesDistributed	20000.000000	20000.000000	20000.000000
Distribution Site 2 Closed	MaxDistSite2TimeWaiting	NaN	NaN	NaN
Distribution Site 2 Closed	MaxDistSite1TimeWaiting	26.806034	26.162973	27.449094
Distribution Site 2 Closed	AvgBeneficiaryTimeInSystem	4.706345	4.175804	5.236886



All Scenarios - Average Beneficiaries Time In System



Simio Simulation Model - 3D