Analyzing and modeling Mass Casualty Events in hospitals – An operational view via fluid models

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14.3.12

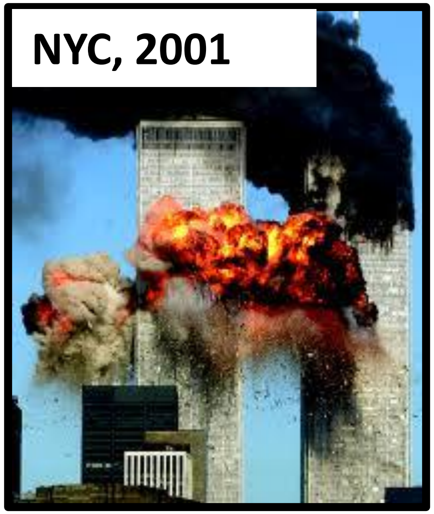
Mass Casualty Event

An unusual event in which the number of casualties exceeds the capacity for taking care of them.

The main challenges of MCEs are organizational and logistic problems, rather than trauma care problems [1].

Classification:

1. **Scale**
2. **Cause:** Human-Made events\ Natural disasters.
3. **Type:** Conventional \ Unconventional.
4. **Arrival rate of casualties**: sudden or sustained impact [2].



NYC, 2001

Madrid, 2004

Oklahoma City, 1995

Turkey, 2011

Rio De Janeiro, 2011

London, 2005

Argentina, 1994

Indian Ocean, 2004

Japan, 2011

Turkey, 1999

Haiti, 2010

Pakistan, 2010

Agenda

- Literature Review
- Problem Definition and Objectives
- **Choosing a Fluid Model**
  - First Fluid Model
  - Second Fluid Model
- **Optimization Problem**
  - Optimal Solution
  - Greedy Problem
  - Insights and Proof
  - Minimal time window for resource allocation
- Summary and Conclusions

Literature Review

Mass Casualty Events

Clinical Research

Hirsberg et al, 2001 [3]

Aylwin et al, 2005 [4]

Hirsberg et al, 2005 [5]

Einav et al, 2006 [6]

Kosashvili et al, 2009 [7]

Social Research

Hughes et al, 1991 [8]

Stratton et al, 1996 [9]

Merin et al, 2010 [10]

Operational Research

Mitigation

Atencia et al, 2004 [11]

Dudin et al, 2004 [12]

Preparedness

Dudin et al, 1999 [13]

Gregory et al, 2000 [14]

Response

Recovery

Bryson et al, 2002 [15]

Literature Review

MCE → OR → Preparedness & Response

Mathematical Models:

Setting priority assignment and scheduling casualties in MCEs

E.U. Jacobson, Nilay Tank Argon, Serhan Ziya, 2011, Priority Assignment in Emergency Response, Forthcoming OR [17].

N. T. Argon, S. Ziya, and R. Righter, 2008, Scheduling impatient jobs in a clearing system within sights on patient triage in mass casualty incidents. Probability In The Engineering And Informational Sciences [18].

Planning the transportation, Supply and Evacuation from disaster-affected areas in MCEs

Oh, S.C., Haghani, A., 1997. Testing and evaluation of a multi-commodity multi-modal network flow model for disaster relief management. Journal of Advanced Transportation. [19].

Barbarosoglu, G., Arda, Y., 2004. A two-stage stochastic programming framework for transportation planning in disaster response. Journal of the Operational Research Society. [20].

Sherali, H.D., Carter, T.B., Hobeika, A.G., 1991. A location allocation model and algorithm for evacuation planning under hurricane flood conditions. Transportation Research Part B-Methodological. [21].

Literature Review

MCE → OR → Preparedness & Response

Simulation:

Evaluate the realistic hospital capacity in MCEs

Hirshberg A, Holcomb JB, Mattox KL. Hospital trauma care in multiple-casualty incidents: a critical view. Ann Emerg Med. 2001; 37:647– 652. [3].

Prediction of Waiting time in MCEs

Paul, J.A., George, S.K., Yi, P., and Lin, L., 2006. Transient modelling in simulation of hospital operations for emergency response. Prehospital and Disaster Medicine,21 (4), 223–236. [22].

Quantify the relation between casualty load & trauma care level

Hirshberg A, Scott BG, Granchi T, Wall MJ Jr, Mattox KL, Stein M. How does casualty load affect trauma care in urban bombing incidents? A quantitative analysis. J Trauma. 2005;58:686–693.[5].

Hirshberg A, Frykberg ER, Mattox KL; Stein M. Triage and Trauma Workload in Mass Casualty: A Computer Model. Journal of Trauma-Injury Infection & Critical Care: November 2010 - Volume 69 - Issue 5 - pp 1074-1082.[23].

Defining the optimal staff profile of trauma teams in MCEs

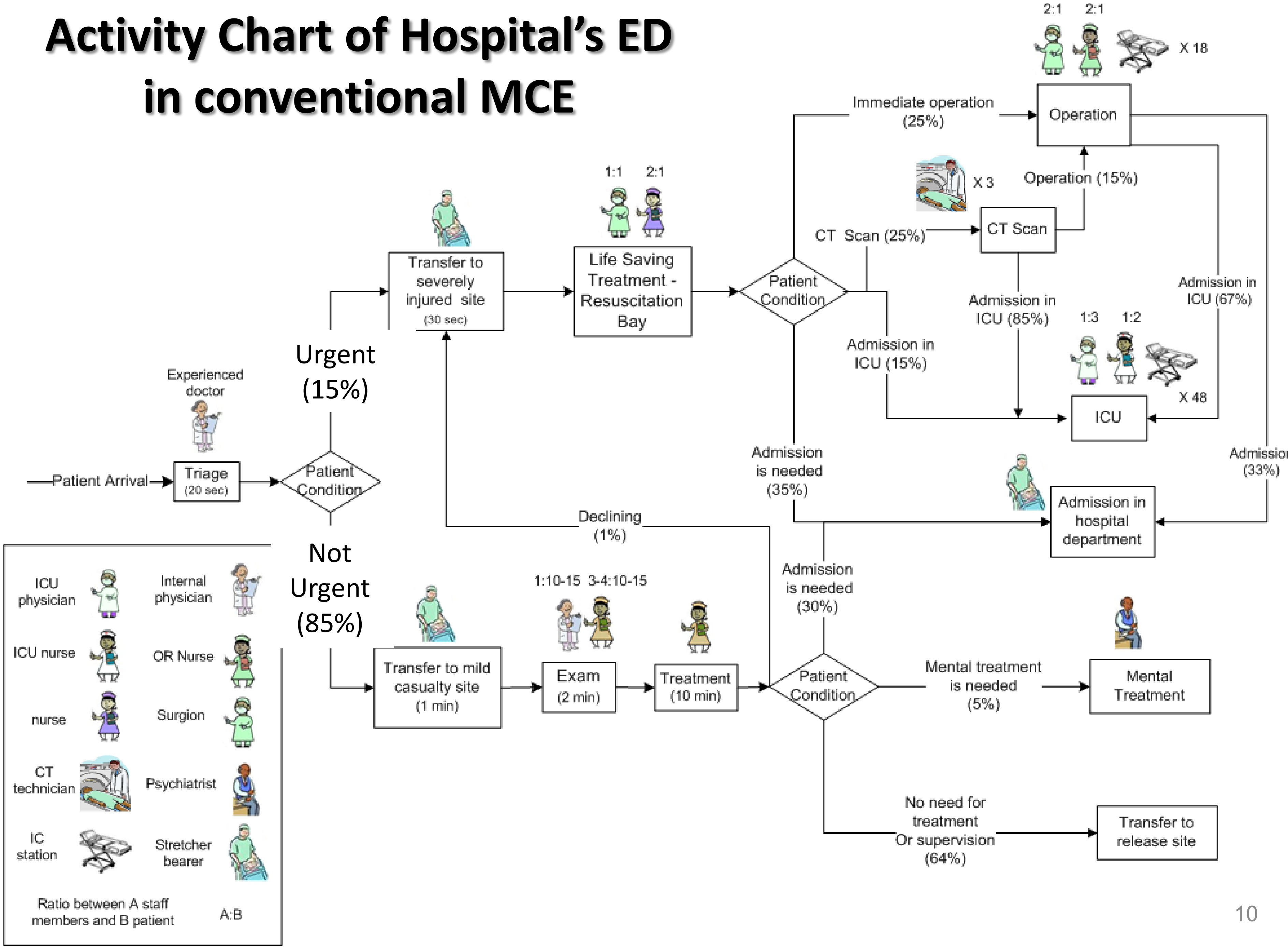
Hirshberg A, Stein M, Walden R. Surgical resource utilization in urban terrorist bombing: a computer simulation. J Trauma. 1999;47:545–550. [24].

Objectives:

1. Develop a mathematical (fluid) model for a hospital's Emergency Department (ED) during MCEs.

2. Determine the optimal policy for resource allocations.

Activity Chart of Hospital's ED in conventional MCE



Choosing a Model - Fluid Model

Stochastic
Discrete
Arrivals

↓ In large overloaded systems

Deterministic
Continuous
Model

Where customers are modeled by Fluid Continuous Flow

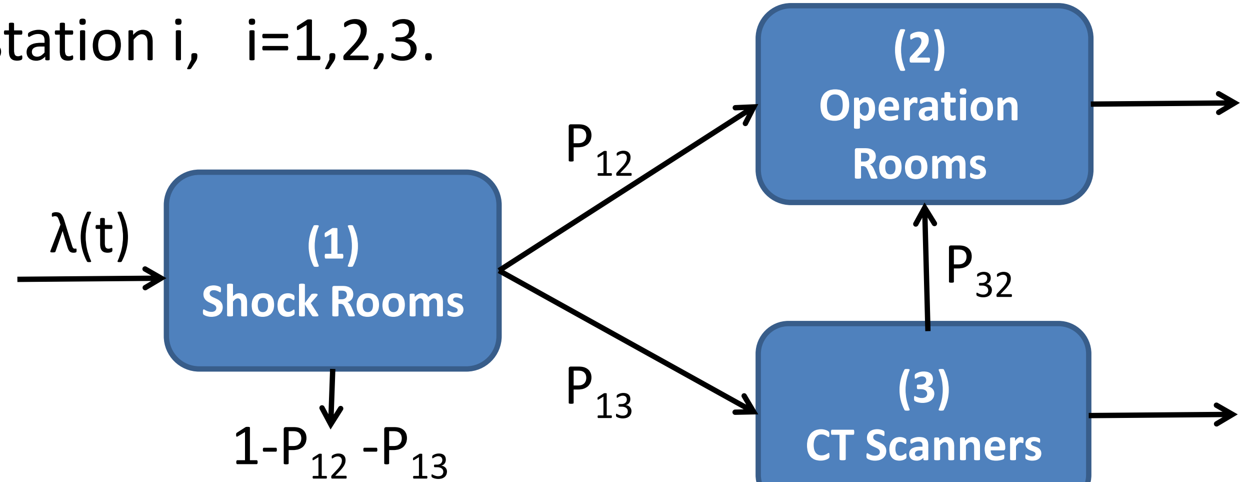
Choosing a Fluid Model

First Fluid Model

$Q_i(t)$ – Total number of casualties in station i at time t,   i=1,2,3.

$N_i(t)$ – Number of Surgeons in station i at time t, i=1,2.

μ_i – Treatment Rate in station i,   i=1,2,3.



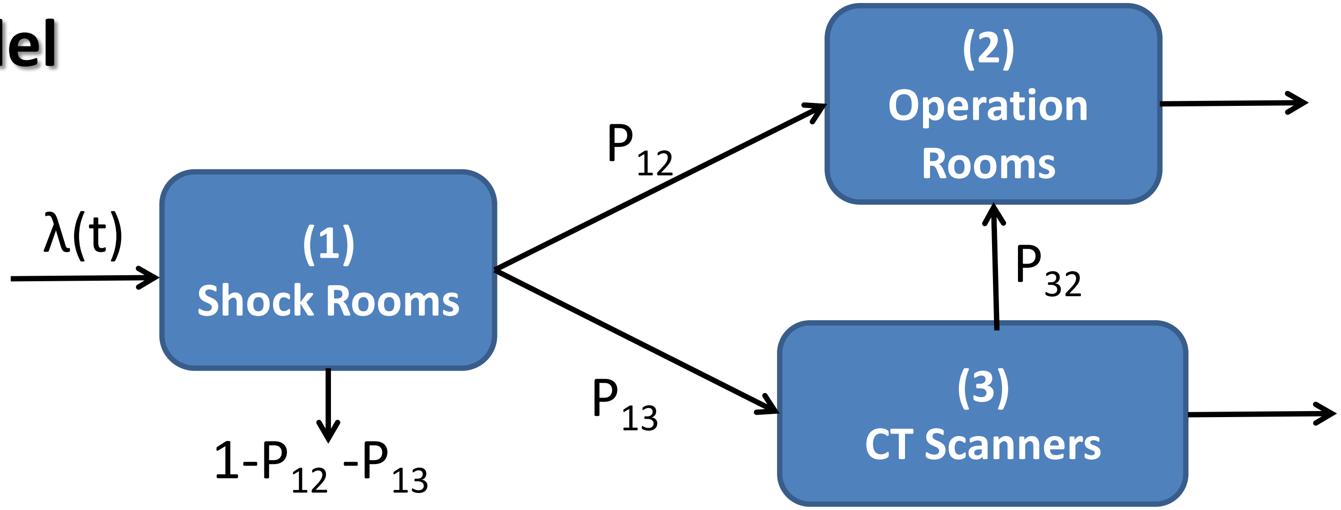
First station:

$$\dot{Q}_1(t) = \underbrace{\lambda(t)}_{\text{Entrance}} - \underbrace{\mu_1[Q_1(t) \wedge N_1(t)]}_{\text{Exit}}$$

$$[A \wedge B] = \min(A, B)$$

Choosing a Fluid Model

First Fluid Model



Three stations:

$$\dot{Q}_1(t) = \lambda(t) - \mu_1[Q_1(t) \wedge N_1(t)]$$

$$\dot{Q}_2(t) = p_{12}\mu_1[Q_1(t) \wedge N_1(t)] + p_{32}\mu_3[Q_3(t) \wedge N_3(t)] - \mu_2[Q_2(t) \wedge N_2(t)]$$

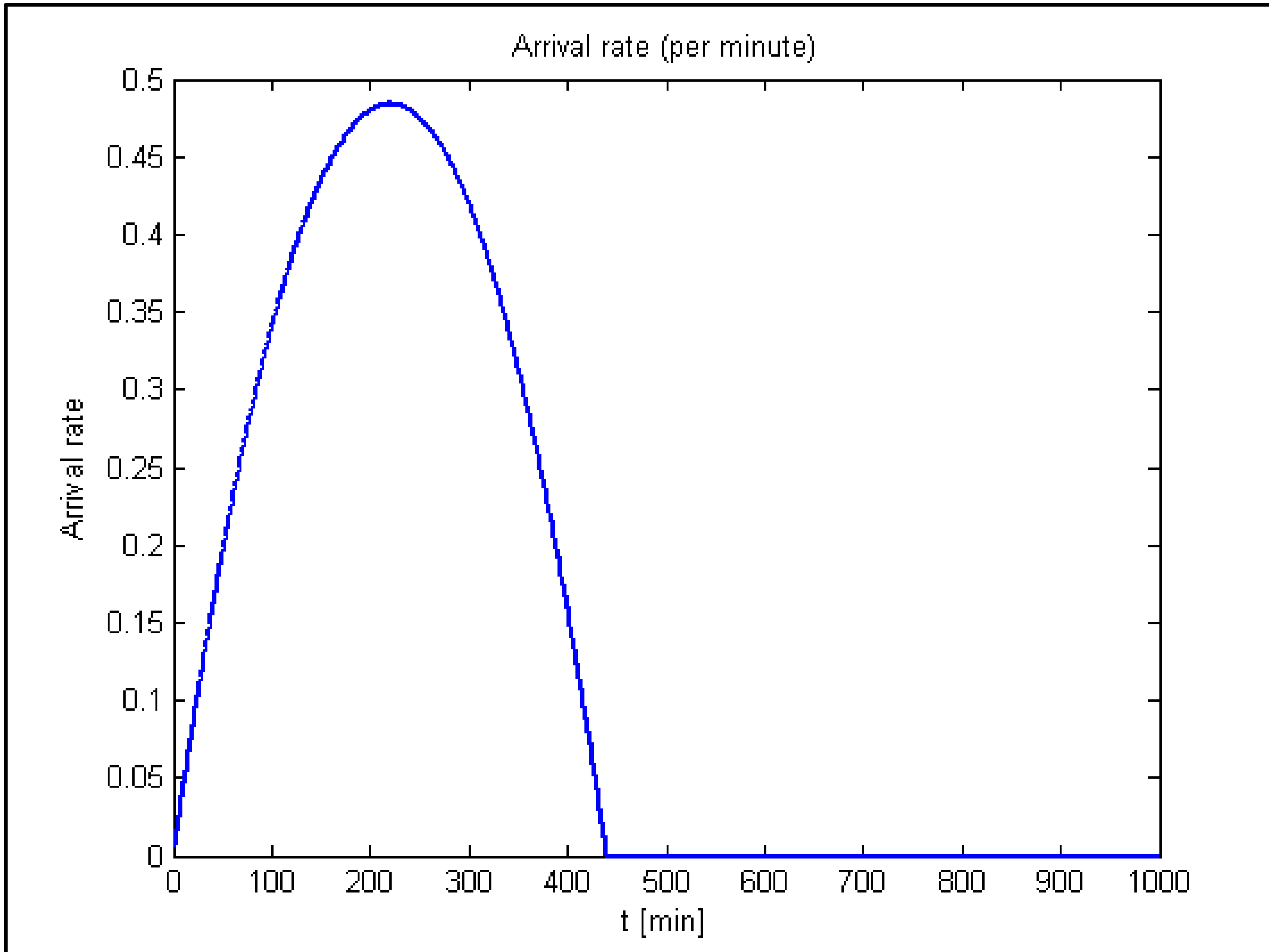
$$\dot{Q}_3(t) = p_{13}\mu_1[Q_1(t) \wedge N_1(t)] - \mu_3[Q_3(t) \wedge N_3(t)]$$

Queue Length: $L_{qi}(t) = [Q_i(t) - N_i(t)]^+$

$[A]^+ = \max(A, 0)$

Choosing a Fluid Model

First Scenario – Quadratic Arrival Rate

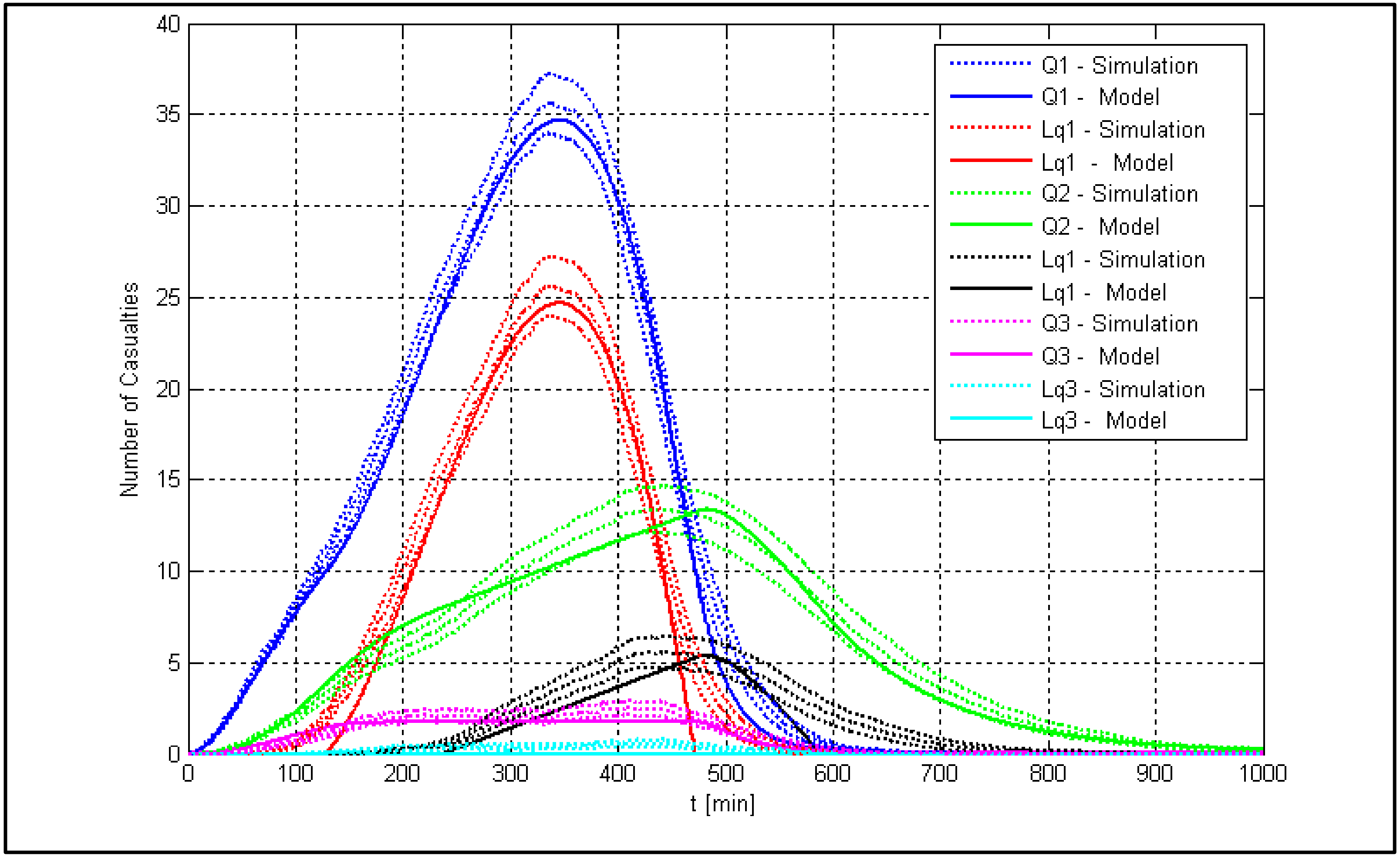


μ_1=1/30, μ_2=1/100, μ_3=1/20, p_{12} = 0.25, p_{13}=0.25, p_{32}=0.15 N_1=10, N_2=5, N_3=3

Choosing a Fluid Model

Total Number of Casualties

First Fluid Model vs. Simulation (quadratic arrival rate)



μ_1=1/30, μ_2=1/100, μ_3=1/20, p_{12} = 0.25, p_{13}=0.25, p_{32}=0.15 N_1=10, N_2=5, N_3=3

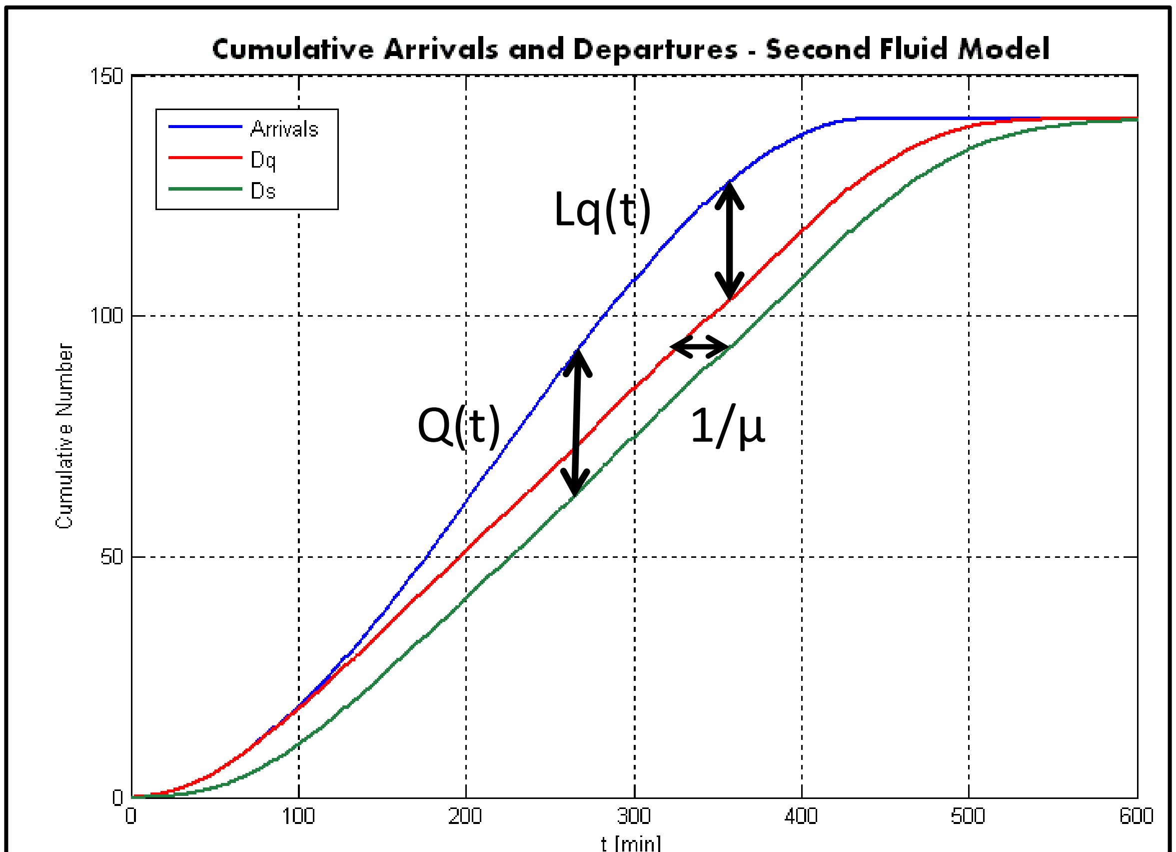
Choosing a Fluid Model

Second Fluid Model (long service time, Hall, 1991 [25])

$A_i(t)$ – Cumulative arrivals to station i until time t, i=1,2,3.

$Ds_i(t)$ – Cumulative Departures from Station i until time t, i=1,2,3.

$Dq_i(t)$ – Cumulative Departures from Queue i until time t, i=1,2,3



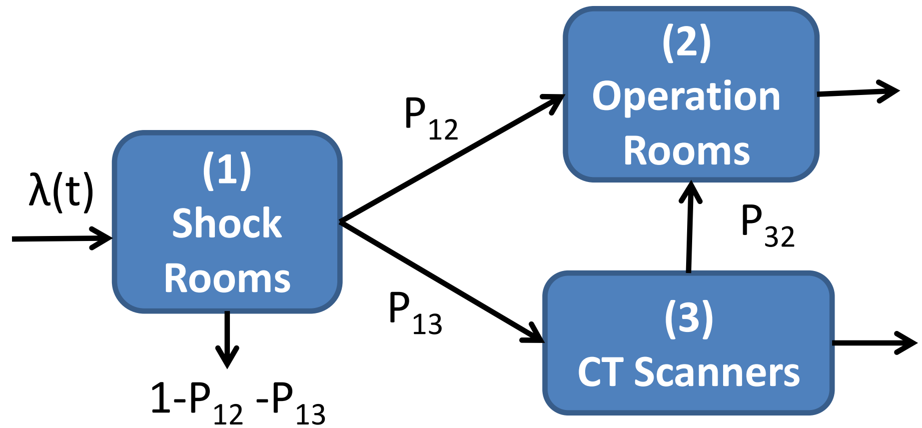
One station:

$$Ds(t + \frac{1}{\mu}) = Dq(t)$$

$$Dq(t) = \min(\underbrace{A(t)}_{\text{No Queue}},\ \underbrace{Ds(t) + N}_{\text{Queue}})$$

Choosing a Fluid Model

Second Fluid Model- Three stations:



#1

$$Ds_1(t+\frac{1}{\mu_1}) = Dq_1(t)$$

$$Dq_1(t) = \min(A(t),\ Ds_1(t)+N_1)$$

#2

$$Ds_2(t+\frac{1}{\mu_2}) = Dq_2(t)$$

$$Dq_2(t) = \min(\underbrace{p_{12}Ds_1(t)+p_{23}Ds_3(t)}_{A_2(t)},\ Ds_2(t)+N_2)$$

#3

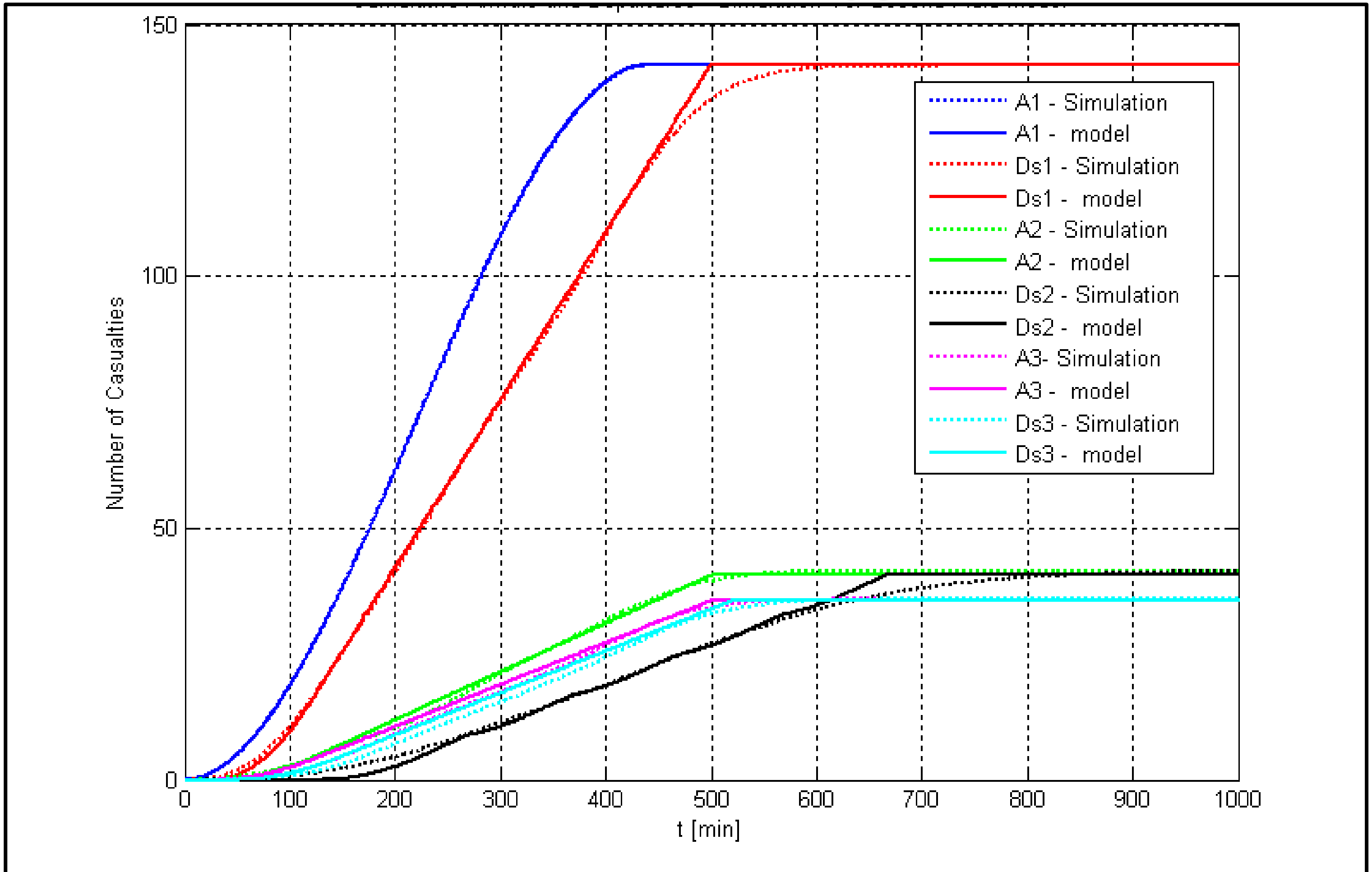
$$Ds_3(t+\frac{1}{\mu_3}) = Dq_3(t)$$

$$Dq_3(t) = \min(\underbrace{p_{13}Ds_3(t)}_{A_3(t)},\ Ds_3(t)+N_3)$$

Choosing a Fluid Model

Cumulative Arrival & Departures

Second Fluid Model vs. Simulation (quadratic arrival rate)

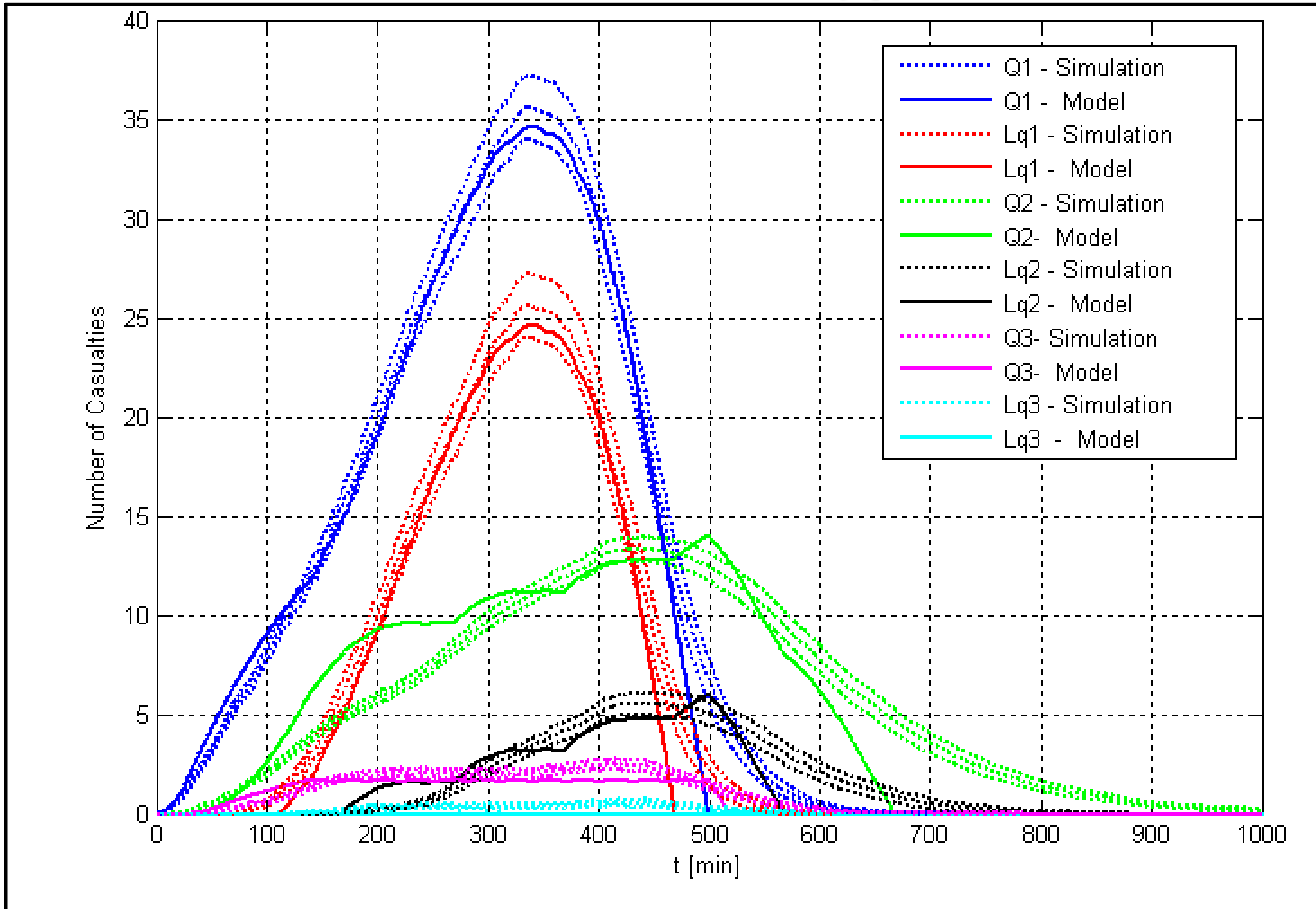


μ_1=1/30, μ_2=1/100, μ_3=1/20, p_{12} = 0.25, p_{13}=0.25, p_{32}=0.15 N_1=10, N_2=5, N_3=3

Choosing a Fluid Model

Total Number of Casualties

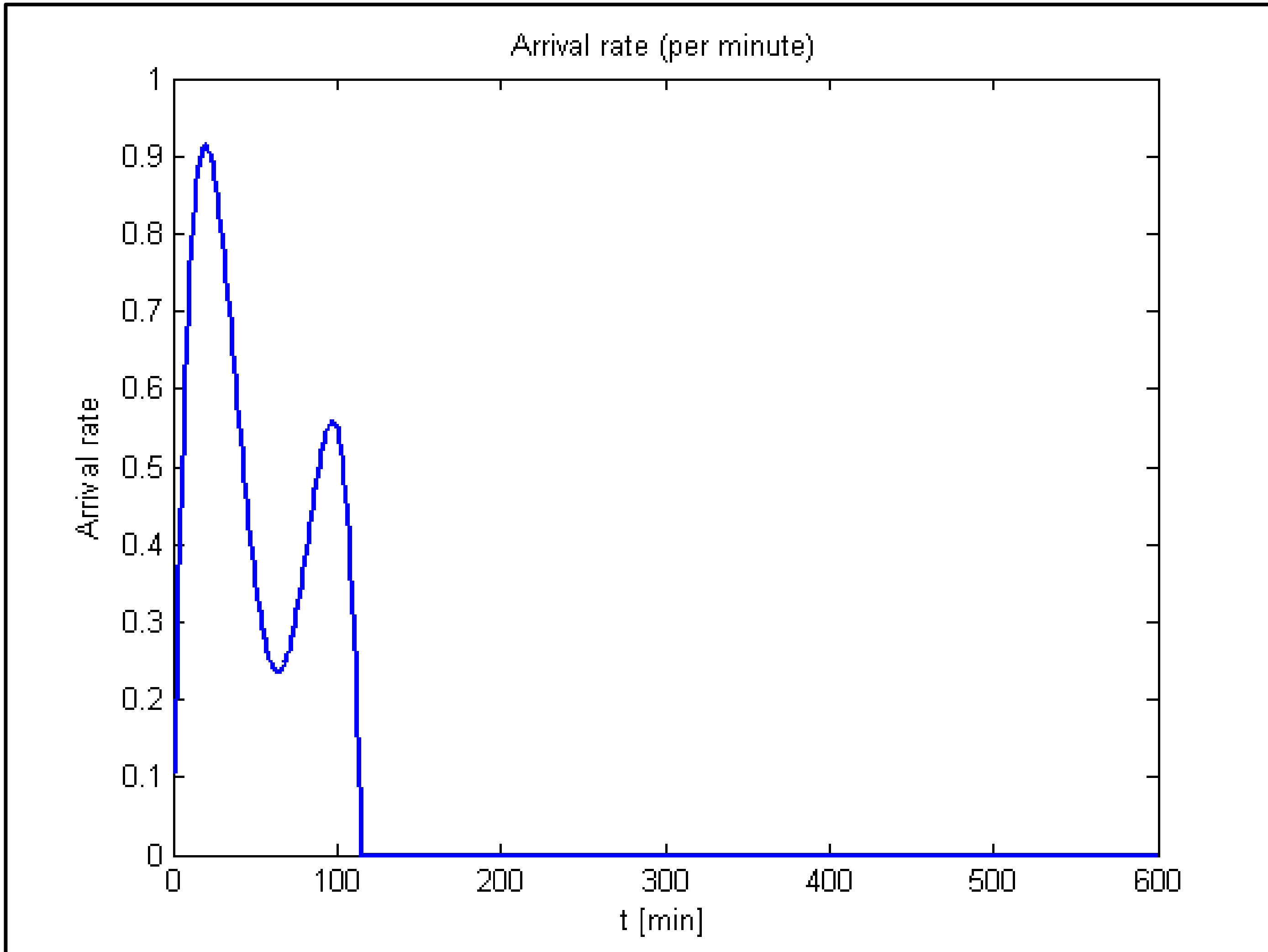
Second Fluid Model vs. Simulation (quadratic arrival rate)



$\mu_1=1/30$, $\mu_2=1/100$, $\mu_3=1/20$, $p_{12} = 0.25$, $p_{13}=0.25$, $p_{32}=0.15$ $N_1=10$, $N_2=5$, $N_3=3$

Choosing a Fluid Model

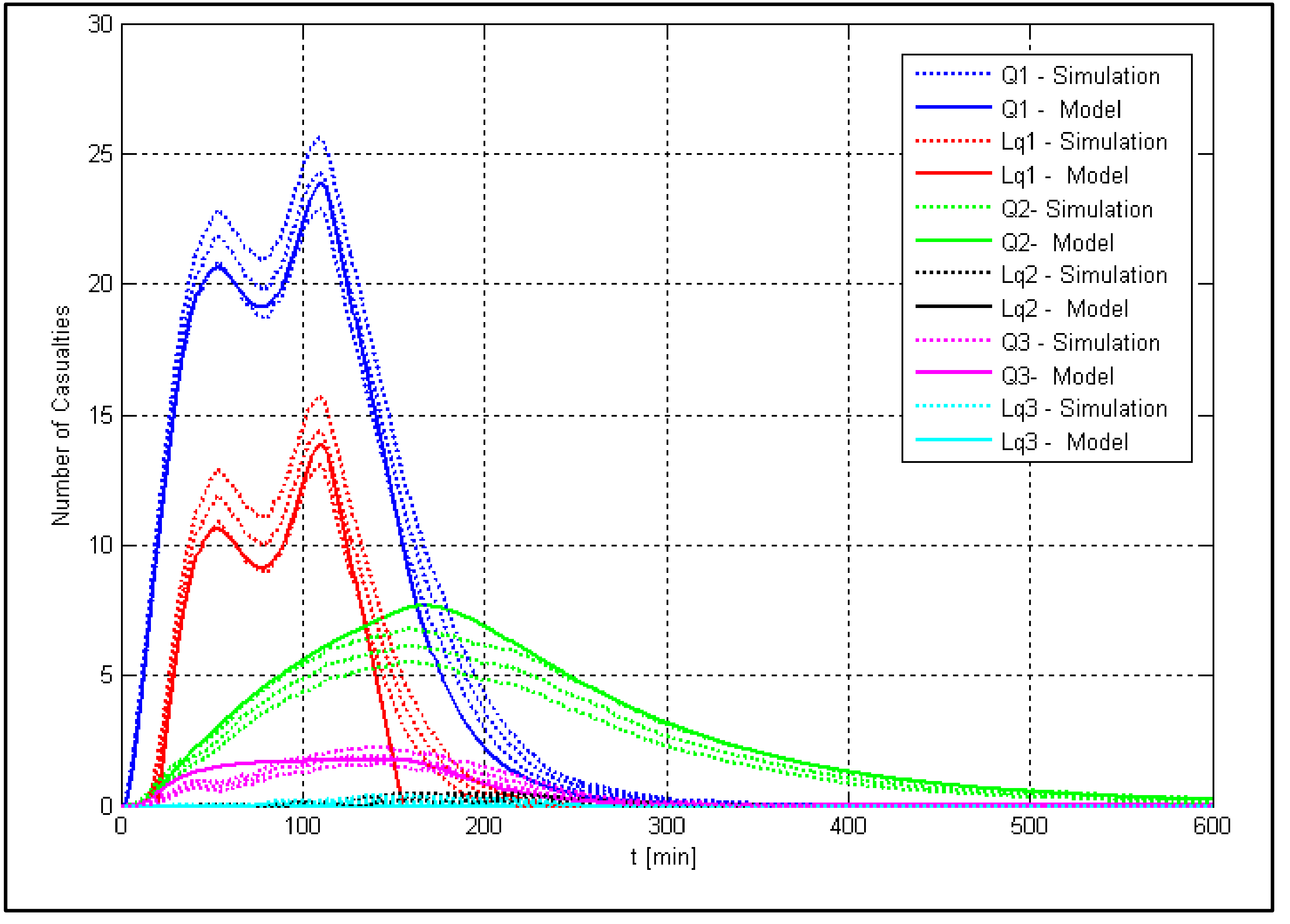
Second Scenario



μ_1=1/30, μ_2=1/100, μ_3=1/20, p12 = 0.25, p13=0.25, p32=0.15 N_1=10, N_2=8, N_3=3

Choosing a Fluid Model

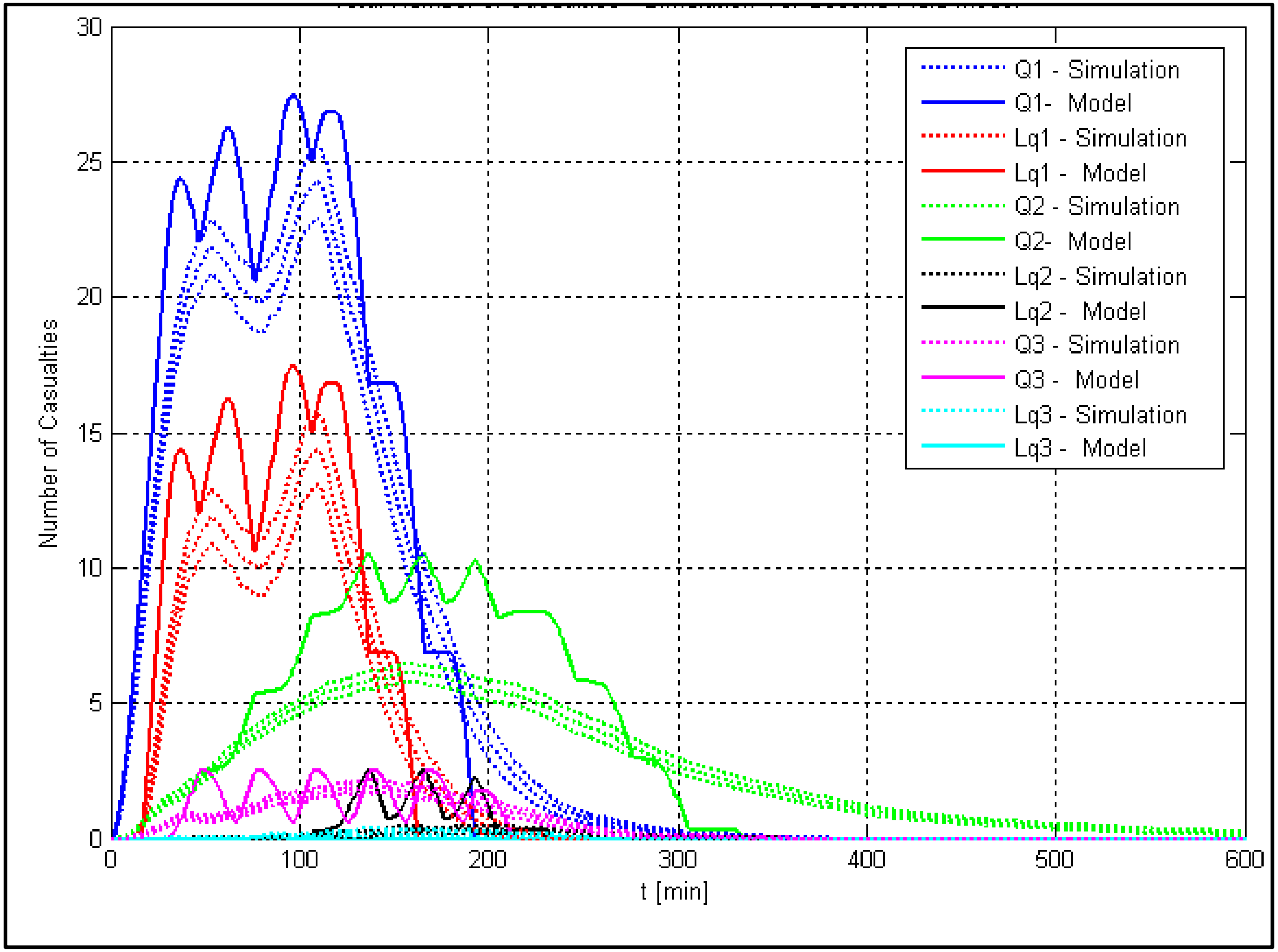
Total Number of Casualties - First Fluid Model vs. Simulation



μ_1=1/30, μ_2=1/100, μ_3=1/20, p12 = 0.25, p13=0.25, p32=0.15 N_1=10, N_2=8, N_3=3

Choosing a Fluid Model

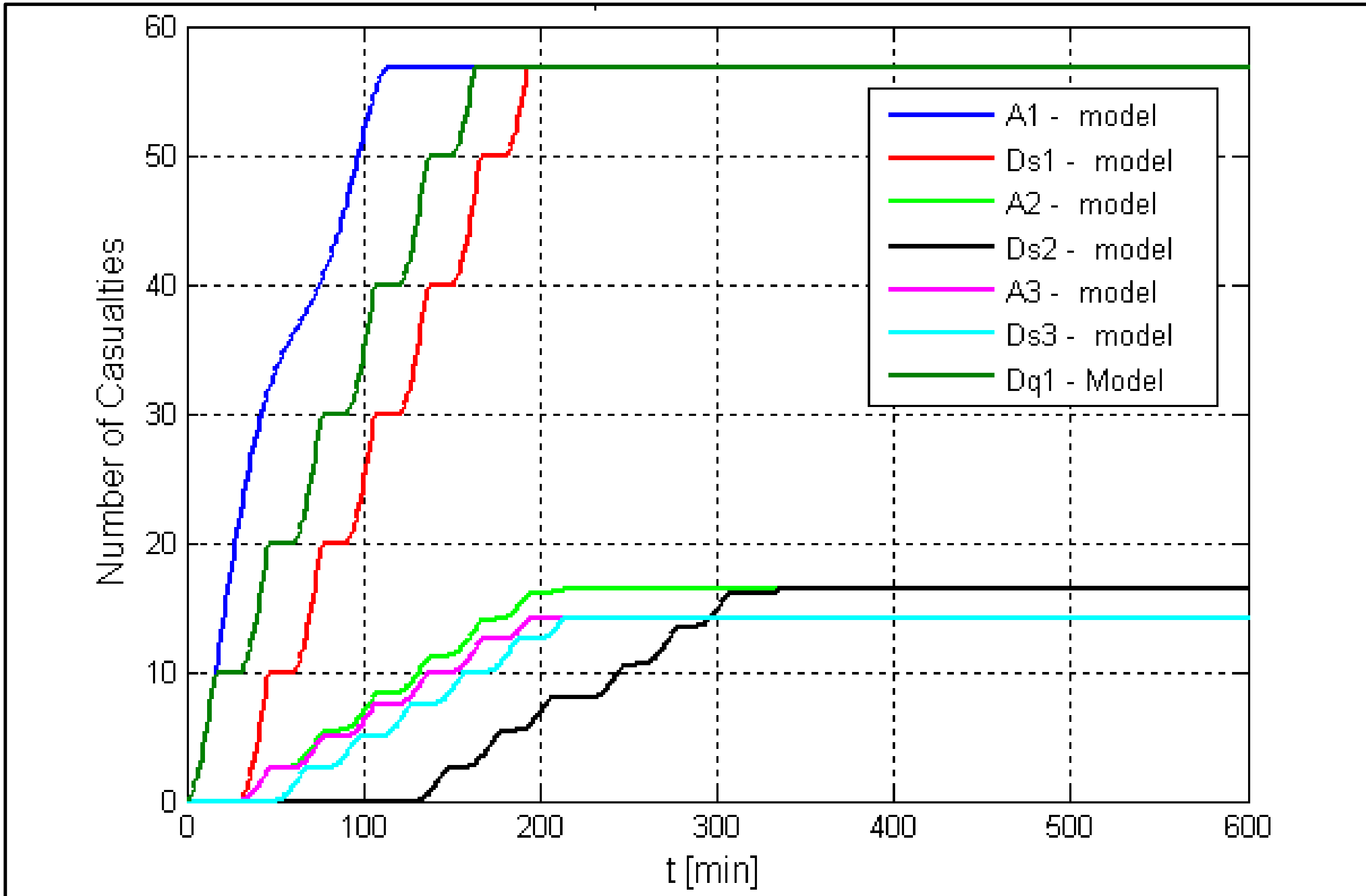
Total Number of Casualties – Second Fluid Model vs. Simulation



μ_1=1/30, μ_2=1/100, μ_3=1/20, p12 = 0.25, p13=0.25, p32=0.15 N_1=10, N_2=8, N_3=3

Choosing a Fluid Model

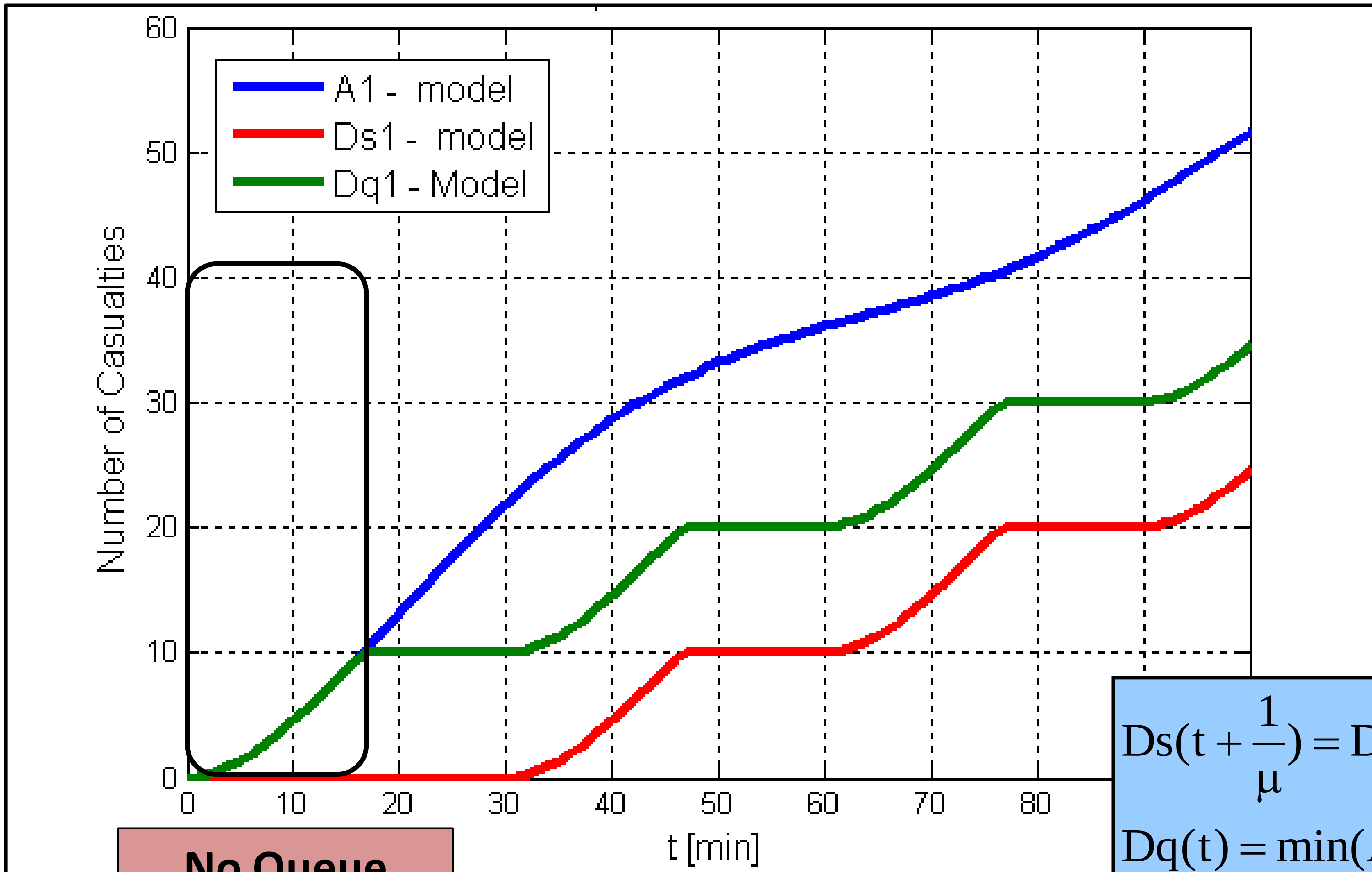
Cumulative Arrivals & Departures - Second Fluid Model



μ_1=1/30, μ_2=1/100, μ_3=1/20, p12 = 0.25, p13=0.25, p32=0.15 N_1=10, N_2=8, N_3=3

Choosing a Fluid Model

Cumulative Arrivals & Departures - Second Fluid Model



μ_1=1/30
N_1=10

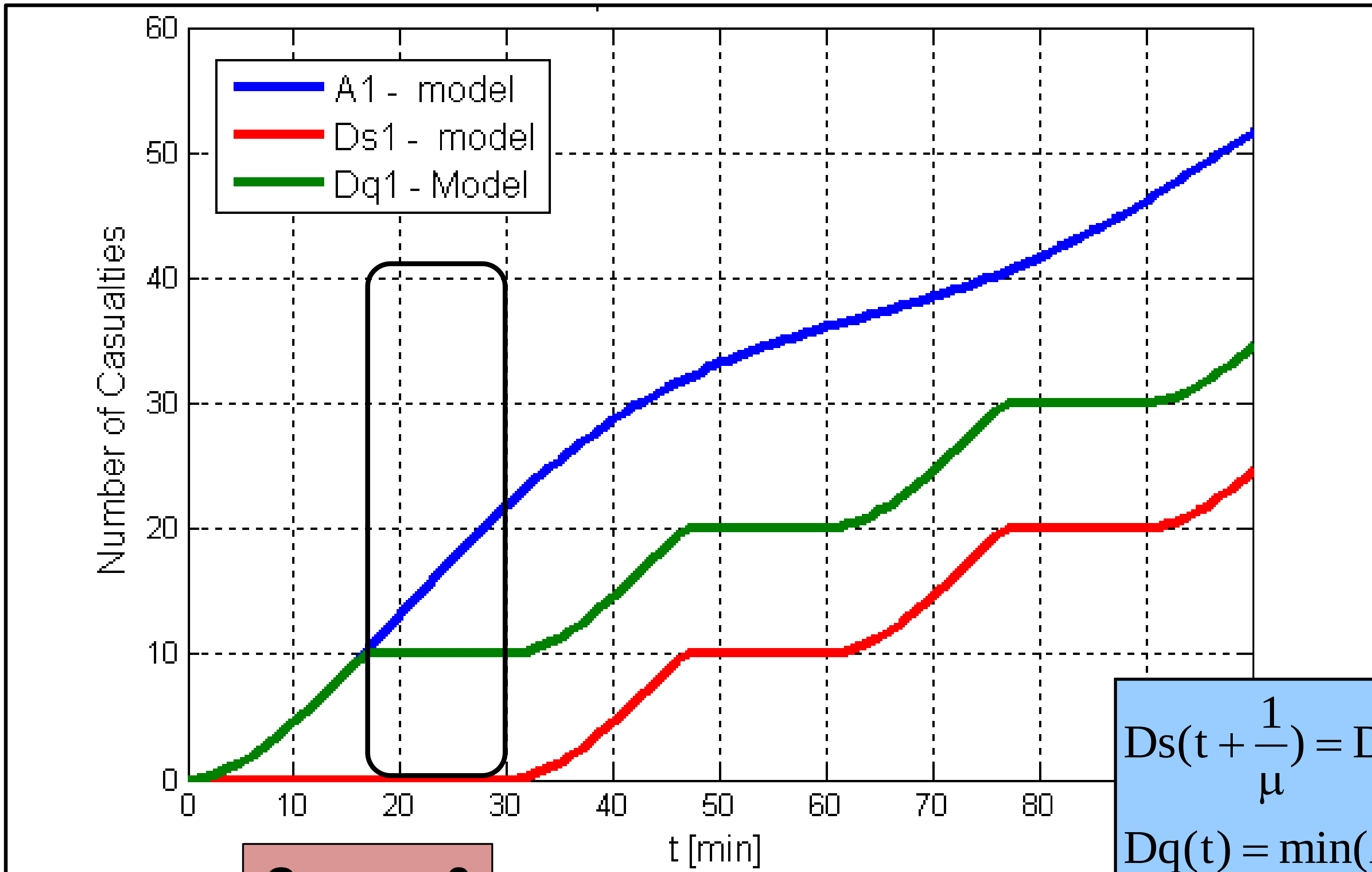
No Queue
Dq(t) = A(t)
Ds(t) =0

$$Ds(t+\frac{1}{\mu}) = Dq(t)$$

$$Dq(t) = \min(\underbrace{A(t)}_{\text{No Queue}},\ \underbrace{Ds(t)+N}_{\text{Queue}})$$

Choosing a Fluid Model

Cumulative Arrivals & Departures - Second Fluid Model



μ_1=1/30
N_1=10

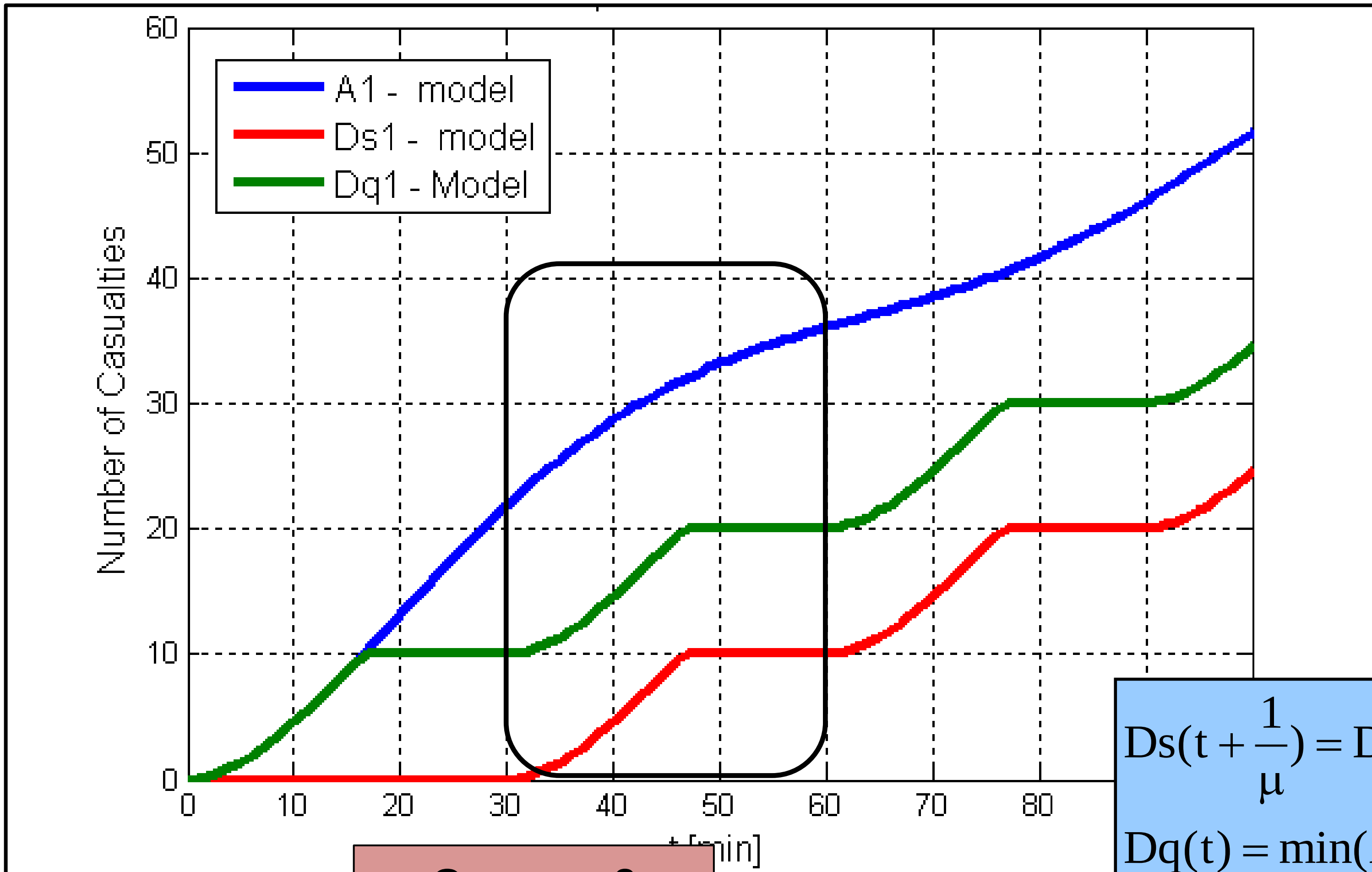
$$Ds\left(t+\frac{1}{\mu}\right) = Dq(t)$$

$$Dq(t) = \min(\underbrace{A(t)}_{\text{No Queue}},\ \underbrace{Ds(t)+N}_{\text{Queue}})$$

Queue > 0
Dq(t) = N
Ds(t) =0

Choosing a Fluid Model

Cumulative Arrivals & Departures - Second Fluid Model



μ_1=1/30
N_1=10

Queue > 0
Ds(t+1/μ)=Dq(t)
Dq(t) =Ds(t) +N

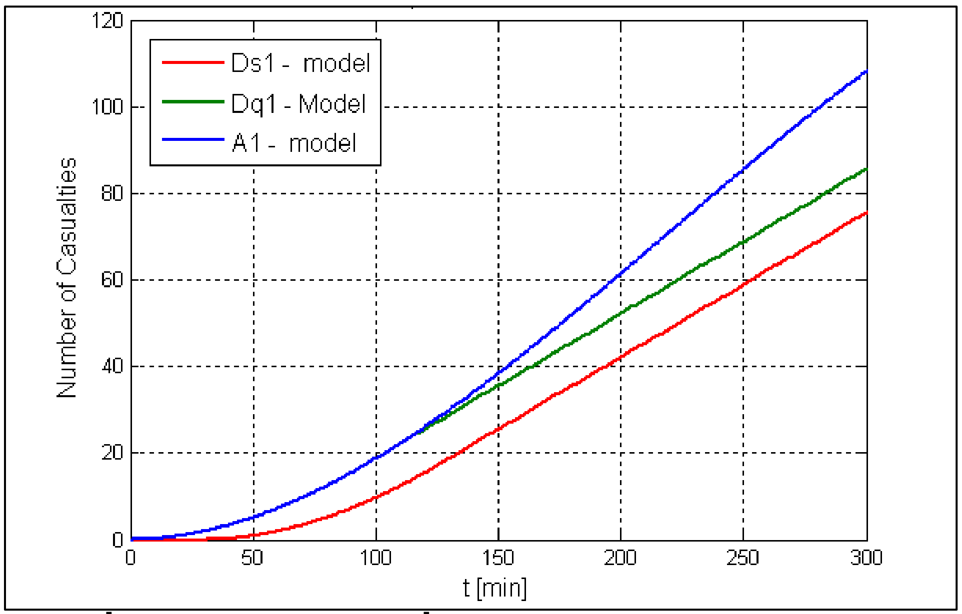
$$Ds(t + \frac{1}{\mu}) = Dq(t)$$

$$Dq(t) = \min(\underbrace{A(t)}_{\text{No Queue}},\ \underbrace{Ds(t) + N}_{\text{Queue}})$$

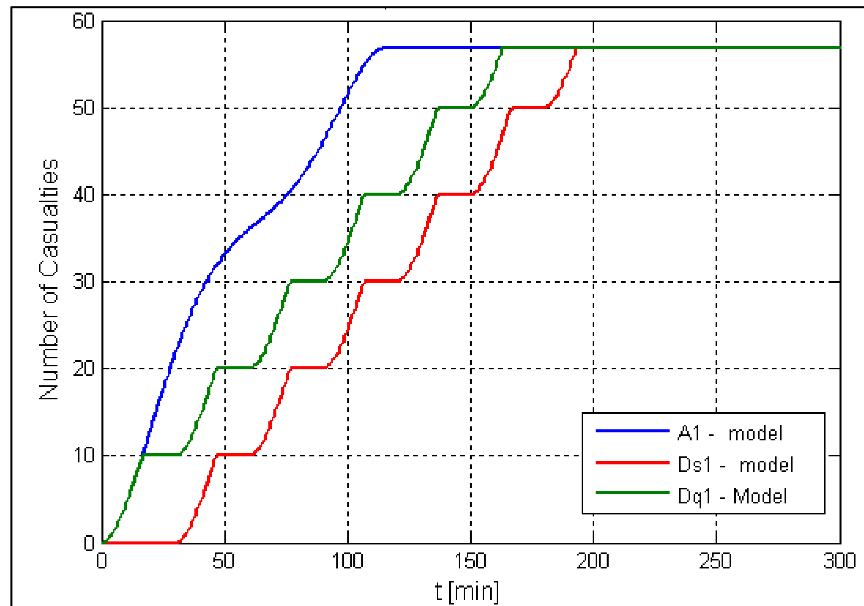
Choosing a Fluid Model

Second Fluid Model - Cumulative Arrivals & Departures

First Scenario



Second Scenario



No Queue

No Queue

A(t)=N when t<1/μ

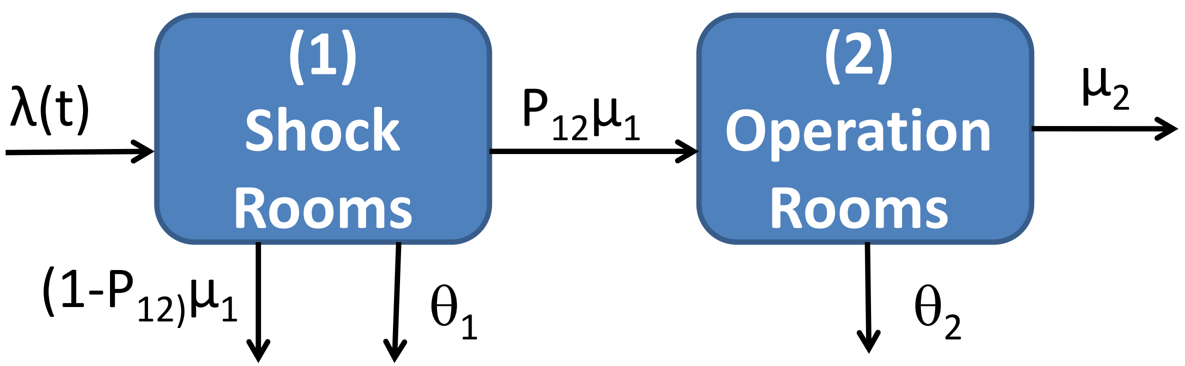
Queue > 0 before one service time

Optimization Problem

The main goal of the hospital's emergency response in MCEs is to **reduce mortality of casualties** [3]

We model mortalities as abandons, which can occur while waiting or while receiving treatment.

θ_i – Mortality rate from station i, i=1,2.



Optimization Problem

Continuous time

$$\underset{N_1(t),\,N_2(t)}{\mathrm{Min}} \quad \int_0^T [\theta_1 Q_1(t) + \theta_2 Q_2(t)]\, dt$$

s.t.

$$\dot{Q}_1(t) = \lambda(t) - \mu_1(Q_1(t) \wedge N_1(t)) - \theta_1 Q_1(t)$$

$$\dot{Q}_2(t) = p_{12}\mu_1(Q_1(t) \wedge N_1(t)) - \mu_2(Q_2(t) \wedge N_2(t)) - \theta_2 Q_2(t)$$

$$N_1(t) + N_2(t) \le N$$

$$N_1(t) \ge 0, \quad N_2(t) \ge 0$$

$$Q_1(t) \ge 0, \quad Q_2(t) \ge 0$$

$$Q_1(0) = Q_2(0) = 0$$

Optimization Problem

Discrete time

$$\min_{N_1(t),\, N_2(t)} \sum_{t=0}^{T-1} [\theta_1 Q_1(t+1) + \theta_2 Q_2(t+1)]$$

s.t.

$$Q_1(t+1) = Q_1(t) + \lambda(t) - \mu_1(Q_1(t) \wedge N_1(t)) - \theta_1 \cdot Q_1(t)$$

$$Q_2(t+1) = Q_2(t) + p_{12}\mu_1(Q_1(t) \wedge N_1(t)) - \mu_2(Q_2(t) \wedge N_2(t)) - \theta_2 \cdot Q_2(t)$$

$$N_1(t) + N_2(t) \le N$$

$$N_1(t) \ge 0, \quad N_2(t) \ge 0$$

$$Q_1(t) \ge 0, \quad Q_2(t) \ge 0$$

$$Q_1(0) = 0, \quad Q_2(0) = 0$$

Replacing $N_i(t) \wedge Q_i(t)$ with $N_i(t)$ and adding the constraints $N_i(t) \le Q_i(t)$ **will not affect the objective function**

Optimization Problem

Discrete time

$$\underset{N_1(t),\, N_2(t)}{\text{Min}} \quad \sum_{t=0}^{T-1} [\theta_1 Q_1(t+1) + \theta_2 Q_2(t+1)]$$

s.t.

$$Q_1(t+1) = Q_1(t) + \lambda(t) - \mu_1 N_1(t) - \theta_1 \cdot Q_1(t)$$

$$Q_2(t+1) = Q_2(t) + p_{12}\mu_1 N_1(t) - \mu_2 N_2(t) - \theta_2 \cdot Q_2(t)$$

$$N_1(t) + N_2(t) \le N$$

$$N_1(t) \le Q_1(t)$$

$$N_2(t) \le Q_2(t)$$

$$N_1(t) \ge 0, \quad N_2(t) \ge 0$$

$$Q_1(t) \ge 0, \quad Q_2(t) \ge 0$$

$$Q_1(0) = 0, \quad Q_2(0) = 0$$

Optimization Problem

Linear Programming Problem

$$\underset{N_1(t),\, N_2(t)}{\text{Min}} \quad \sum_{t=1}^{T-1} \{ N_1(t)\mu_1[(1-\theta_1)^{T-t} - 1 - p_{12}[(1-\theta_2)^{T-t} - 1]] + N_2(t)\mu_2[(1-\theta_2)^{T-t} - 1]\}$$

s.t.

$$N_1(1) = 0$$

$$\mu_1 N_1(1) + N_1(2) \le \lambda(1)$$

$$(1-\theta_1)\mu_1 N_1(1) + \mu_1 N_1(2) + N_1(3) \le (1-\theta_1)\lambda(1) + \lambda(2)$$

$$\vdots$$

$$(1-\theta_1)^{T-3}\mu_1 N_1(1) + (1-\theta_1)^{T-4}\mu_1 N_1(2) + \cdots + N_1(T-1) \le (1-\theta_1)^{T-3}\lambda(1) + (1-\theta_1)^{T-4}\lambda(2) + \cdots + \lambda(T-1)$$

$$N_2(1) = 0$$

$$\mu_2 N_2(1) - p_{12}\mu_1 N_1(1) + N_2(2) \le 0$$

$$(1-\theta_2)\mu_2 N_2(1) - (1-\theta_2)p_{12}\mu_1 N_1(1) + \mu_2 N_2(2) - p_{12}\mu_1 N_1(2) + N_2(3) \le 0$$

$$\vdots$$

$$(1-\theta_2)^{T-3}\mu_2 N_2(1) + (1-\theta_2)^{T-3}p_{12}\mu_1 N_1(1) + (1-\theta_2)^{T-4}\mu_2 N_2(2) - (1-\theta_2)^{T-4}p_{12}\mu_1 N_1(2) + \cdots$$

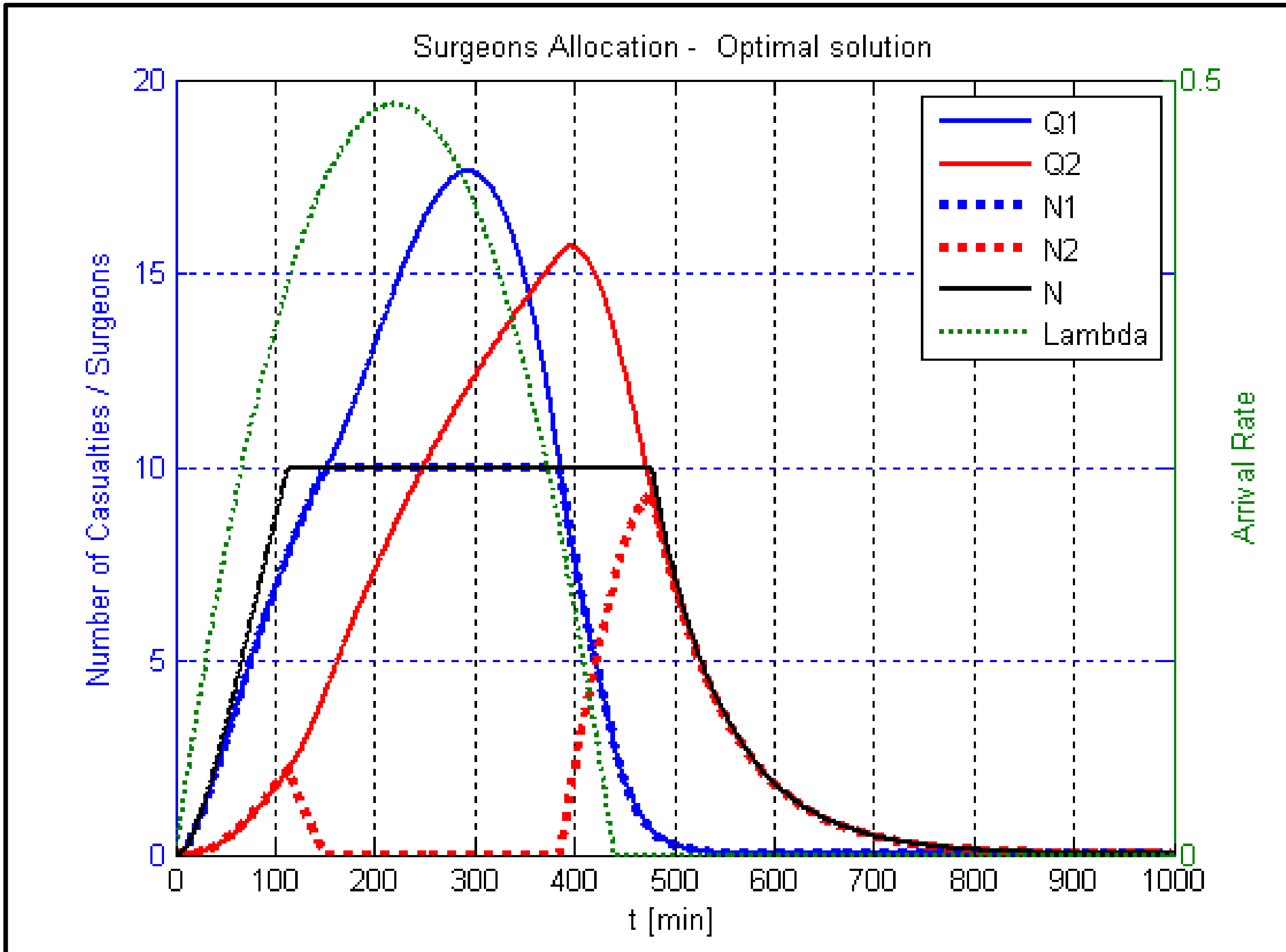
$$\cdots + \mu_2 N_2(T-2) - p_{12}\mu_1 N_1(T-2) + N_2(T-1) \le 0$$

$$N_1(t) + N_2(t) \le N$$

$$N_1(t),\ N_2(t) \ge 0$$

Optimization Problem

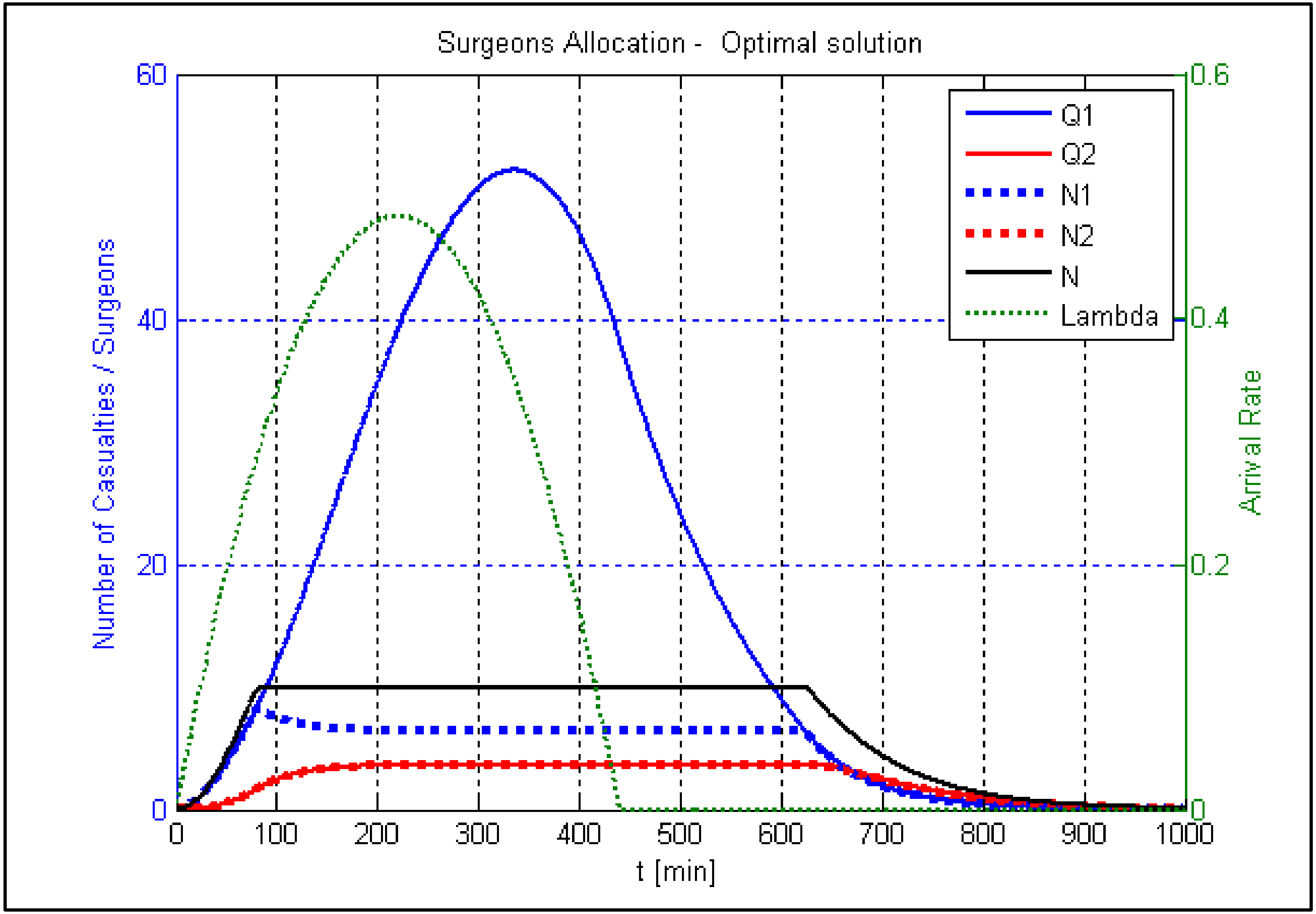
First Example – priority is given to Station 1



μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/300, p12 = 0.25, N=10

Optimization Problem

Second Example – priority is given to Station 2

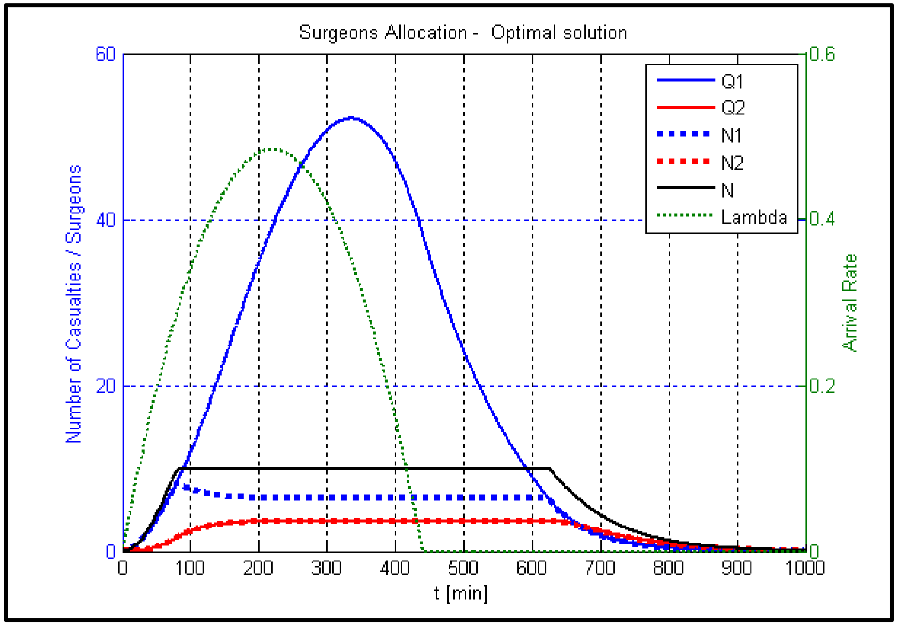


μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/180, p12 = 0.9, N=10

Optimization Problem

Second Example – priority is given to Station 2

$$\underbrace{p_{12} \cdot \mu_1 \cdot N_1(t)}_{\text{Entrance Rate to Station 2}} = \underbrace{(\mu_2 + \theta_2) \cdot N_2(t)}_{\text{Exit Rate from Station 2}}$$



When the system is overloaded:

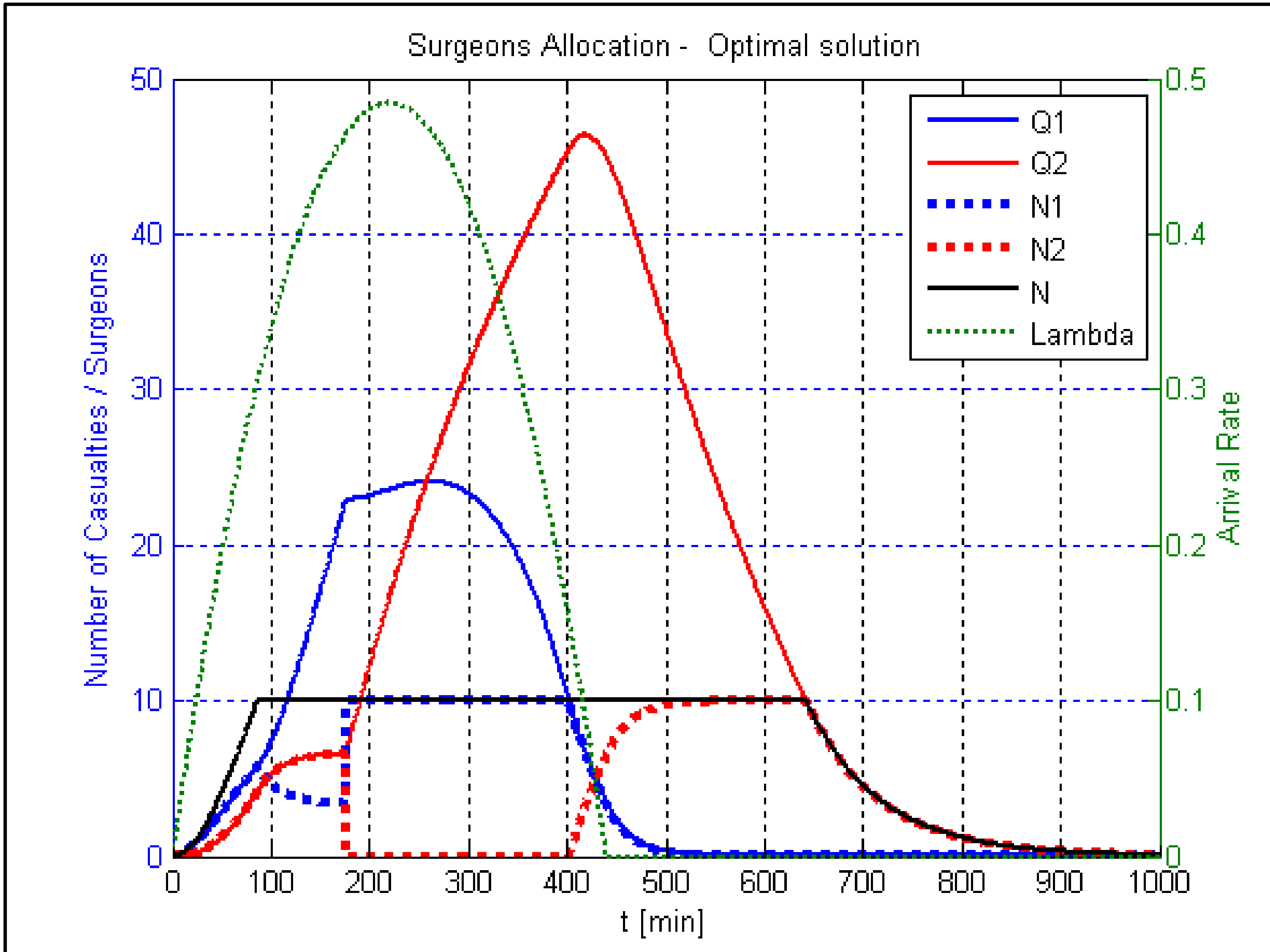
$$R_1 N_1(t) + R_2 N_2(t) = N \quad \Rightarrow \quad N_1(t) = \frac{N - R_2 N_2(t)}{R_1}$$

$$\boxed{N_1(t) = \frac{N(\mu_2 + \theta_2)}{R_1(\mu_2 + \theta_2) + R_2 \cdot p_{12} \cdot \mu_1}}$$

$$\boxed{N_2(t) = \frac{N \cdot p_{12} \cdot \mu_1}{R_1(\mu_2 + \theta_2) + R_2 \cdot p_{12} \cdot \mu_1}}$$

Optimization Problem

Third Example – priority is switching



μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/300, p12 = 0.8, N=10

Greedy Optimization Problem

Objective: Determine surgeons allocation every minute,

in order to minimize the mortality in the next minute.

For every $t \in [0, T\text{-}1]$:

$$\min_{N_1(t),\, N_2(t)} \quad \theta_1 Q_1(t+1) + \theta_2 Q_2(t+1)$$

s.t.

$$Q_1(t+1) = Q_1(t) + \lambda(t) - \mu_1 (Q_1(t) \wedge N_1(t)) - \theta_1 \cdot Q_1(t)$$

$$Q_2(t+1) = Q_2(t) + p_{12} \cdot \mu_1 (Q_1(t) \wedge N_1(t)) - \mu_2 (Q_2(t) \wedge N_2(t)) - \theta_2 \cdot Q_2(t)$$

$$N_1(t) + N_2(t) \le N$$

$$N_1(t), \;\; N_2(t), \;\; Q_1(t+1), \;\; Q_2(t+1) \ge 0$$

$$Q_1(0) = 0, \quad Q_2(0) = 0$$

Greedy Optimization Problem

$$\max_{N_1(t),\, N_2(t)} \; [\theta_1 - \theta_2 p_{12}]\mu_1 N_1(t) + \theta_2 \mu_2 N_2(t)$$

s.t.

$$N_1(t) + N_2(t) \le N$$

$$N_1(t) \le Q_1(t), \; N_2(t) \le Q_2(t)$$

$$N_1(t), \; N_2(t) \ge 0$$

A two variables LP problem

According to the **continuous Knapsack Problem:**

If $[\theta_1 - \theta_2 p_{12}]\mu_1 > \theta_2 \mu_2$ → Priority is given to station 1

$N_1(t) = \min(Q_1(t), N)$

$N_2(t) = \min(Q_2(t), N - N_1(t))$

If $[\theta_1 - \theta_2 p_{12}]\mu_1 < \theta_2 \mu_2$ → Priority is given to station 2

$N_1(t) = \min(Q_1(t), N - N_2(t))$

$N_2(t) = \min(Q_2(t), N)$

If $[\theta_1 - \theta_2 p_{12}]\mu_1 = \theta_2 \mu_2$ → No Difference

Greedy Optimization Problem

$$\max_{N_1(t),\, N_2(t)} \quad [\theta_1 - \theta_2 p_{12}]\mu_1 N_1(t) + \theta_2 \mu_2 N_2(t)$$

s.t.

$$R_1 N_1(t) + R_2 N_2(t) \le N$$

$$N_1(t) \le Q_1(t),\ N_2(t) \le Q_2(t)$$

$$N_1(t),\ \ N_2(t) \ge 0$$

Generalization for any R_1 and R_2

According to the **continuous Knapsack Problem:**

If $\dfrac{[\theta_1 - \theta_2 p_{12}]\mu_1}{R_1} > \dfrac{\theta_2 \mu_2}{R_2}$ → Priority is given to station 1

$N_1(t) = \min(Q_1(t), N)$

$N_2(t) = \min(Q_2(t), (N-R_1N_1(t))/R_2)$

If $\dfrac{[\theta_1 - \theta_2 p_{12}]\mu_1}{R_1} < \dfrac{\theta_2 \mu_2}{R_2}$ → Priority is given to station 2

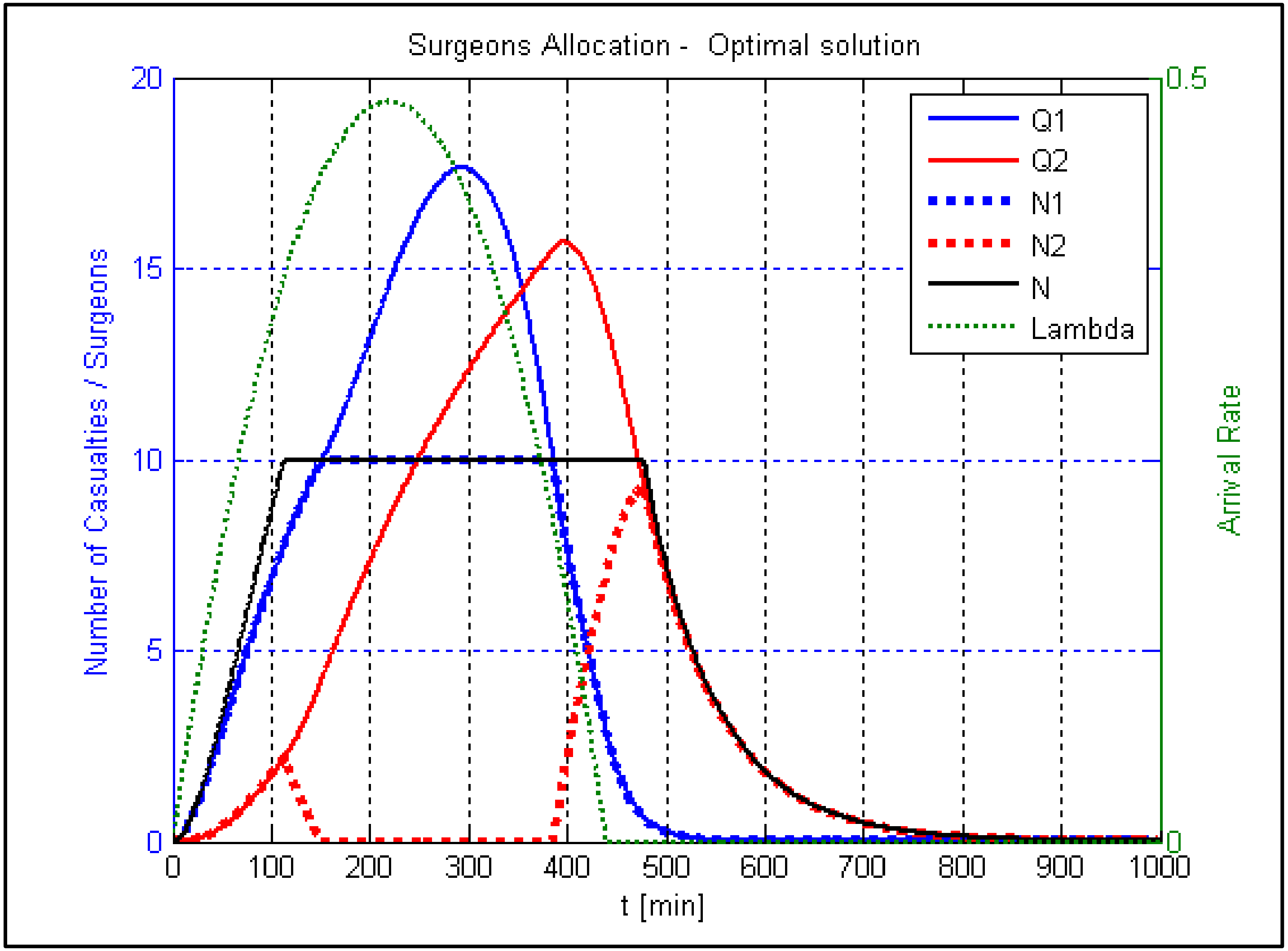
$N_1(t) = \min(Q_1(t), (N- R_2 N_2(t))/R_1)$

$N_2(t) = \min(Q_2(t), N)$

Greedy Optimization Problem

First Example – priority is given to Station 1

$$\boxed{[\theta_1 - \theta_2 p_{12}]\mu_1 > \theta_2 \mu_2}$$

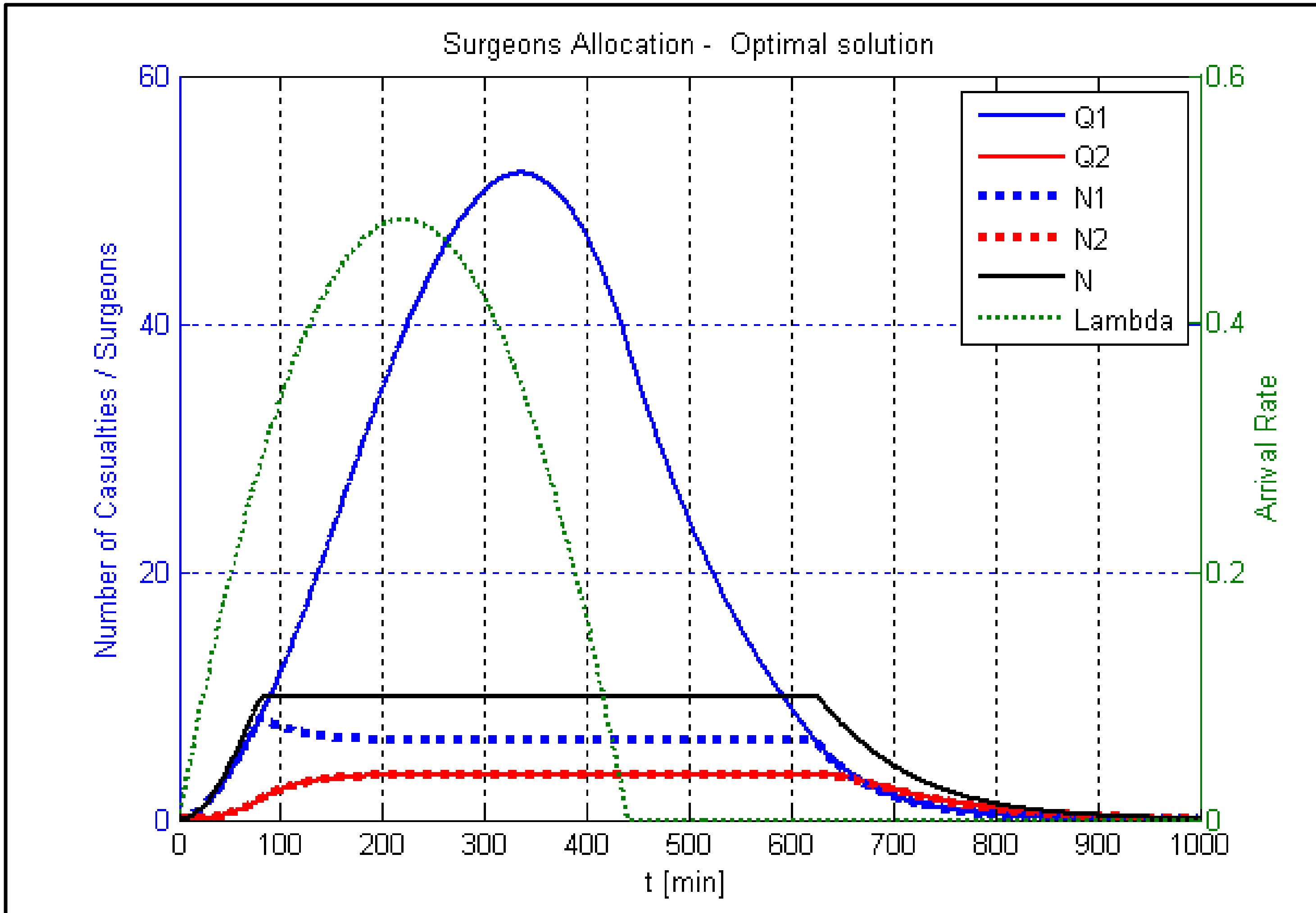


μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/300, p12 = 0.25, N=10

Greedy Optimization Problem

Second Example – priority is given to Station 2

$$\boxed{[\theta_1 - \theta_2 p_{12}]\mu_1 < \theta_2 \mu_2}$$

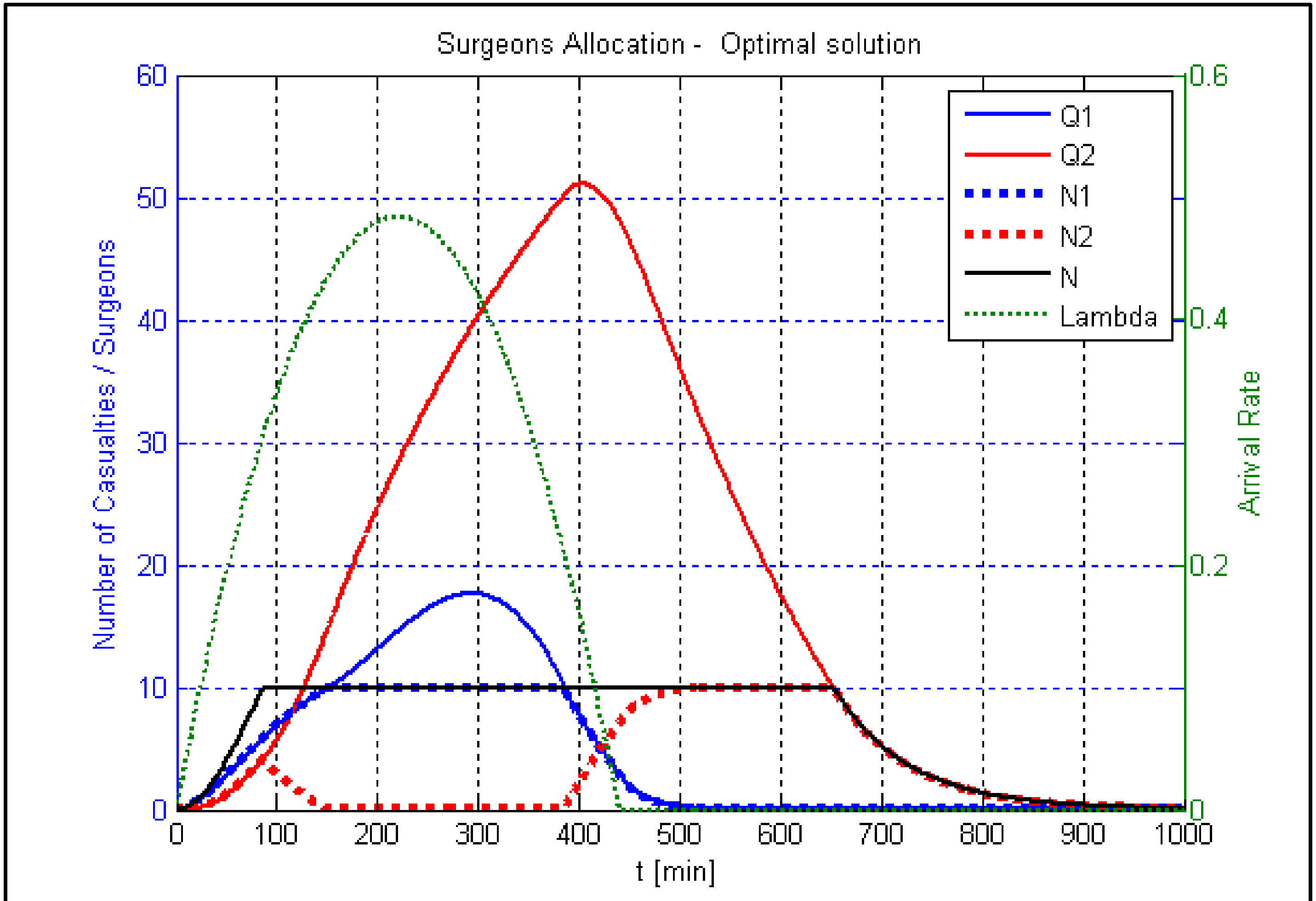


μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/180, p12 = 0.9, N=10

Greedy Optimization Problem

Third Example – priority is given to Station 1 (<u>not</u> switching)

$$\boxed{[\theta_1 - \theta_2 p_{12}]\mu_1 > \theta_2 \mu_2}$$



μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/300, p12 = 0.8, N=10

Optimal vs. Greedy Solution

1. **When $\theta_1=\theta_2$ Greedy solution is optimal.**

Proof

2. Greedy solution can be predicted by the problem parameters.
3. If station 1 gets priority when $\theta_1=\theta_2$ then when $\theta_1 > \theta_2$ station 1 will still get priority.
4. If station 2 gets priority when $\theta_1=\theta_2$ then when $\theta_1 < \theta_2$ station 2 will still get priority

Minimal Time Window for Resource Allocation

- Allocation can be changed every S minutes.
- $N_1(t)$, $N_2(t)$ remain constant for S minutes:

  for example, if S= 30:

  - $N_1(0) = N_1(1)= N_1(2)=\ldots= N_1(29)$
  - $N_2(0) = N_2(1)= N_2(2)=\ldots= N_2(29)$

- The constraint $N_i(t) \le Q_i(t)$ cannot be added.
- Auxiliary variables $Z_i(t)$ replace the statement $N_i(t) \wedge Q_i(t)$

  and the following constraints are added for i=1,2:

$$Z_i(t) \le Q_i(t)$$
$$Z_i(t) \le N_i(t)$$

Minimal Time Window for Resource Allocation

$$\min_{N_1(t),\, N_2(t)} \sum_{t=0}^{T-1} [\theta_1 Q_1(t+1) + \theta_2 Q_2(t+1)]$$

s.t.

$$Q_1(t+1) = Q_1(t) + \lambda(t) - \mu_1 Z_1(t) - \theta_1 \cdot Q_1(t)$$

$$Q_2(t+1) = Q_2(t) + p_{12}\mu_1 Z_1(t) - \mu_2 Z_2(t) - \theta_2 \cdot Q_2(t)$$

$$N_1(t) + N_2(t) \le N$$

$$Z_1(t) \le Q_1(t), \quad Z_1(t) \le N_1(t)$$

$$Z_2(t) \le Q_2(t), \quad Z_2(t) \le N_2(t)$$

$$N_1(i) = N_1(i+1) = \ldots = N_1(i+S-1) \qquad i = 1, S+1, 2S+1 \ldots \left\lfloor \frac{T}{S} \right\rfloor S + 1$$

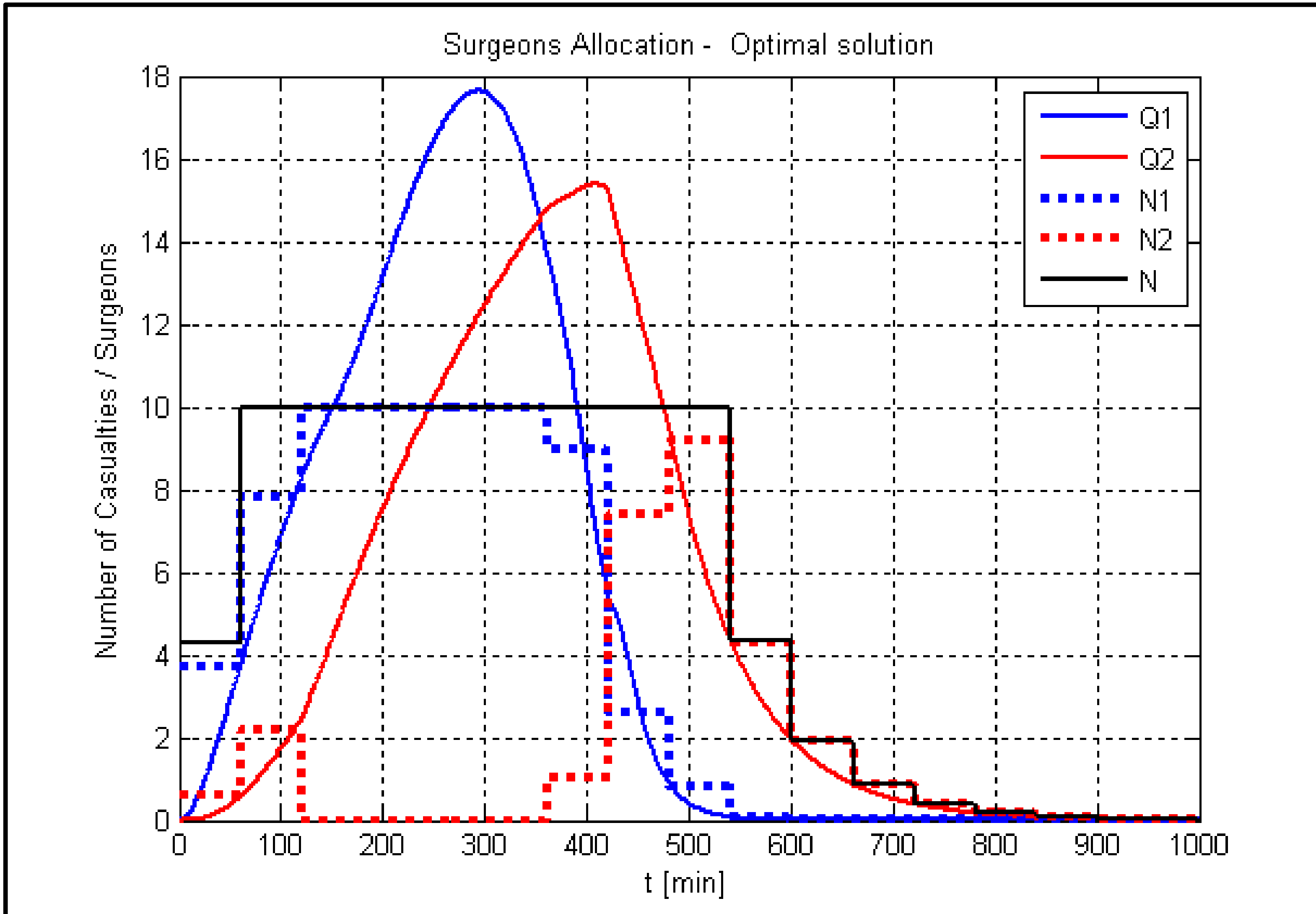
$$N_2(i) = N_2(i+1) = \ldots = N_2(i+S-1) \qquad i = 1, S+1, 2S+1 \ldots \left\lfloor \frac{T}{S} \right\rfloor S + 1$$

$$N_1(t) \ge 0, \quad N_2(t) \ge 0, \quad Q_1(t) \ge 0, \quad Q_2(t) \ge 0$$

$$Q_1(0) = 0, \quad Q_2(0) = 0$$

Minimal Time Window for Resource Allocation

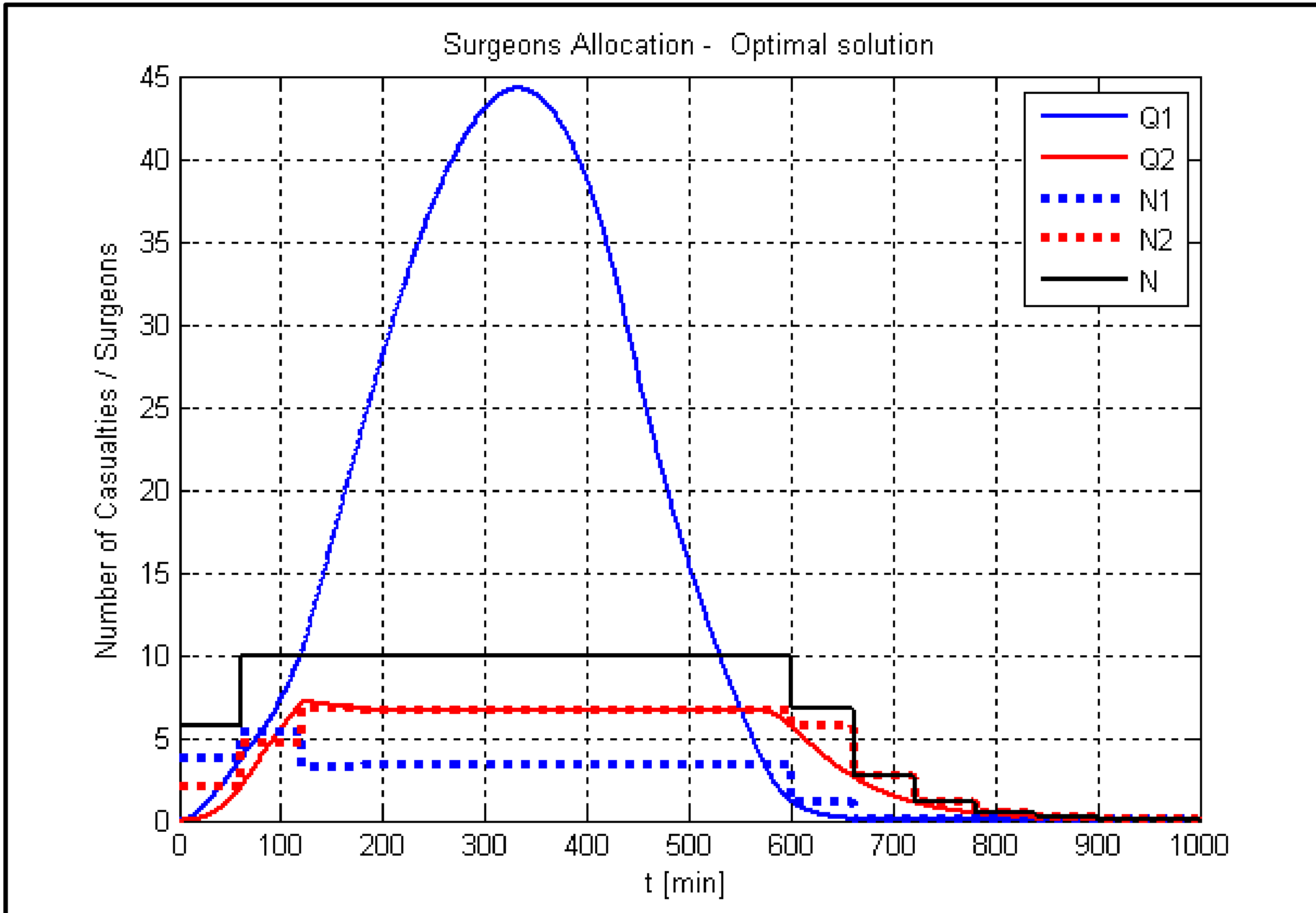
First Example: Priority is given to Station 1



μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/300, p12 = 0.25, N=10, S=60

Minimal Time Window for Resource Allocation

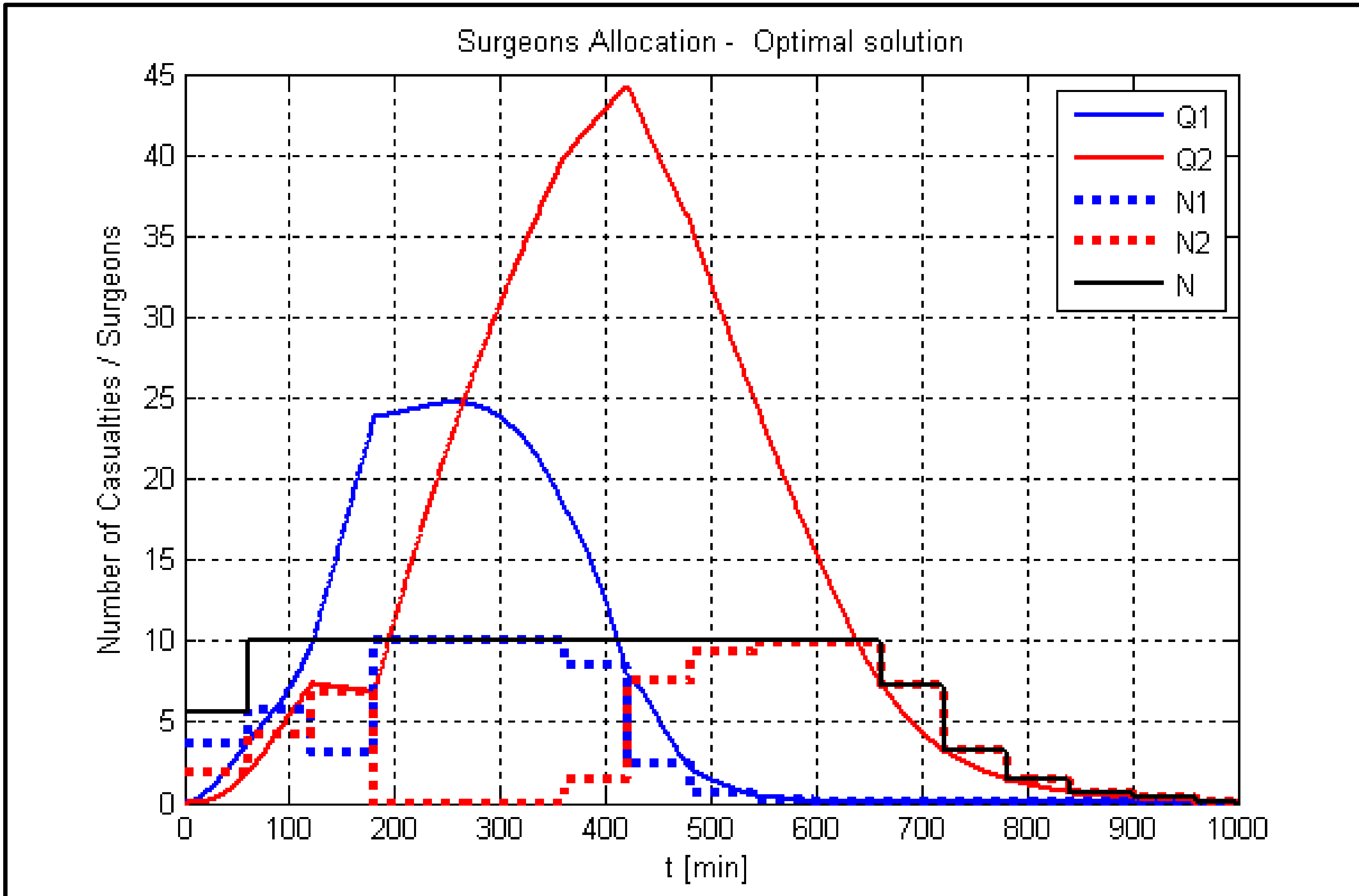
Second Example: Priority is given to Station 2



μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/180, p12 = 0.9, N=10, S=60

Minimal Time Window for Resource Allocation

Third Example: Priority is switching



μ_1=1/30, μ_2=1/100, θ_1=1/180, θ_2=1/300, p12 = 0.8, N=10, S=60

Summary & Conclusions

- The suggested model predicts the number of casualties in a hospital's ED during an MCE.

- Our solution approach finds the dynamic allocation of surgeons that minimizes mortality during an MCE.

- We formulated a greedy counterpart for the original problem and found the conditions under which its solution solves also the original problem.

Summary & Conclusions

- We defined a general approach to predict the structure of the optimal solution of the original problem.

- The model is simple enough yet able to describe a broad range of different MCE scenarios. As such, it can be used to help in preparing for, and managing an MCE.

- The model can be expanded also to non-conventional MCEs (biological, chemical, nuclear and radiation), each requires different emergency plan and different resources.

With Gratitude to:

- **My Advisors:** Prof. Avishai Mandelbaum, Dr. Cohen Izik
- **Dr. Michalson Moshe**, Medical Director of Trauma teaching center, Rambam hospital
- **Dr. Israelit Shlomi**, Chief of ED, Rambam hospital
- **Prof. Kaspi Haya**, Technion
- **Peer Roni**, Mathworks