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FAULT TOLERANT AIRBORNE SENSOR NETWORKS FOR AIR OPERATIONS

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14. ABSTRACT
This report summarizes the main results of research conducted during the summer of 2007 on tasking a finite number of cooperative agents to randomly emerging targets for their removal. Faults occur when some agents engaged in a mission are expired. Agents are subject to threat at a level determined by the number of targets present. On the other hand, the rate at which a target is removed depends on the number of cooperative agents assigned to it. Faults effectively change the network architecture and, therefore, degrade the network performance. Designs of control policies that determine the number of agents assigned are based on the network life when expired agents cannot be replenished, and on the network availability when expired agents are replenished at a certain rate. Tasking process is described by a discrete event system in the form of a queuing network, where agents are servers and targets are customers. Optimal policies are determined by solving a Markov decision problem.

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Abstract

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This work has resulted in a Master's thesis by Yan Guo whose graduate study was partially supported by this grant, a paper submitted to 2008 IFAC World Congress, and another paper submitted to *International Journal of Control, Automation, and Systems.*

Some simulation results are also included. These results are not fully satisfactory and are incomplete. Continued work is desired.

1 Introduction

This work considers tasking a finite number of cooperative agents to randomly emerging targets for their removal. It focuses on enhancing the network performance in the face of expiration of its agents. The resulting network is said to be fault-tolerant. When the agents considered are networked airborne sensors, the mobility and a multiplicity of the sensing nodes make fault-tolerance possible. Fault-tolerant tasking in this work is achieved by implementing operation policies optimized for network availability.

Control of networked multiple agents has been an intensively discussed topic recently in the controls literature [1]. [12], for example, describes a pursuit evasion game, where mobile agents are to chase and capture multiple moving targets in a minimum amount of time, and a network of stationary sensors serves to help enhance the target observability in the game.

With unmanned aerial vehicles (UAVs) replacing stationary networks and manned vehicles, significant improvements in network performance can be expected. Networking in a hostile environment, however, poses new challenges. Data exchange inherent to a networked operation and prolonged mission time due to poor execution expose the otherwise passive location sensors, thus increase the likelihood of the vehicles being destroyed.

Examine a situation where the motion of two unmanned aerial vehicles (UAV) and a hostile radar lie within a plane, as illustrated in Fig. 1.1. Let us assume that the two vehicles are equipped to acquire both the time difference of arrival and the frequency difference of arrival of the radar signal [6]. The sensors are mounted on the vehicles, and thus are subject to the same speed and curvature constraints as that of the vehicles. The sensors are passive nodes when acquiring data from the transmitter, but become active when exchanging data between them in order to provide a location estimate.

It can be seen from Figure 1 that at least two sensor carrying vehicles, which make both a TDOA measurement and an FDOA measurement, are needed in a 2-dimensional setting to locate the target. A noiseless measurement of time difference of arrival by a pair of sensors on the two vehicles is given by

$$\begin{aligned} s_T &= \frac{1}{c}[\sqrt{(x_2-x_e)^2+(y_2-y_e)^2} \\ &- \sqrt{(x_1-x_e)^2+(y_1-y_e)^2}], \end{aligned} \tag{1.1}$$

and a noiseless measurement of frequency difference of arrival by the same pair of sensors is given

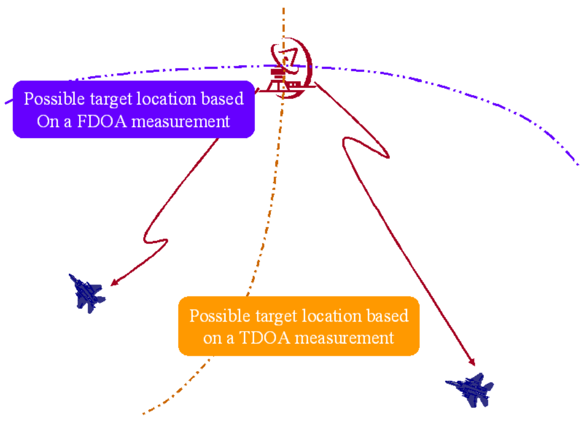

Possible target location based
On a FDOA measurement
Possible target location based
on a TDOA measurement

Figure 1.1: Transmitter location using a TDOA measurement and an FDOA measurement by two airborne sensors.

by

$$
\begin{aligned}
s_F &= \frac{f_e}{c}\Big[\frac{(x_2-x_e)u_2+(y_2-y_e)v_2}{\sqrt{(x_2-x_e)^2+(y_2-y_e)^2}} \\
&- \frac{(x_1-x_e)u_1+(y_1-y_e)v_1}{\sqrt{(x_1-x_e)^2+(y_1-y_e)^2}}\Big],
\end{aligned}
\tag{1.2}
$$

where (x_e, y_e) is the transmitter location to be estimated, (x_1, y_1) and (x_2, y_2) are the positions of the two vehicles, respectively, (u_1, v_1) and (u_2, v_2) are the velocities of the vehicles, f_e is the carrier frequency of the transmitted signal, and c is the speed of light.

Since the measurements are always noisy, multiple measurements are needed for an accurate location estimation of the emitter. Such measurements can be distributed temporally along the trajectories of motion of a pair of sensors, or spatially over multiple pairs of sensors, or both. Measurements made by multiple pairs of sensors, which form a network, offer greater degree of fault-tolerance, and greater potential for improved speed and accuracy in target location. The reader is referred to [6] and [14] for more detailed discussion on methods for location estimation and accuracy analysis.

A tasking problem that is specific to this application refers to that of allocating a finite number of sensor pairs to randomly emerging microwave transmitters to maximize the network availability. A tasking policy that is too greedy tends to exhaust resources before the arrival of unanticipated radars, whereas a tasking policy that is too conservative tends to lengthen the exposure of the sensor carrying vehicles. Tasking is treated as a server allocation problem of a queuing network. Optimal policies are sought as the solutions of Markov decision problems.

The report is organized as follows. Chapter 2 modeling the tasking process for a small scale sensor network. Chapter 3 designs supervisory control policies for optimal tasking for the cases where lost sensors can and cannot be replenished by solving appropriate Markov decision problems. Chapter 4 evaluates the network performance in terms of expected network life and steady-state availability. Chapter 5 concludes the report.

2 Modeling of tasking process

An optimized tasking is one that maximizes the expected life of the network where the lost air-borne sensors cannot be replenished, or one that maximizes the expected steady-state availability of the network where the lost sensors can be replenished. In this study fault-tolerance refers to the network's tolerance to vehicle loss.

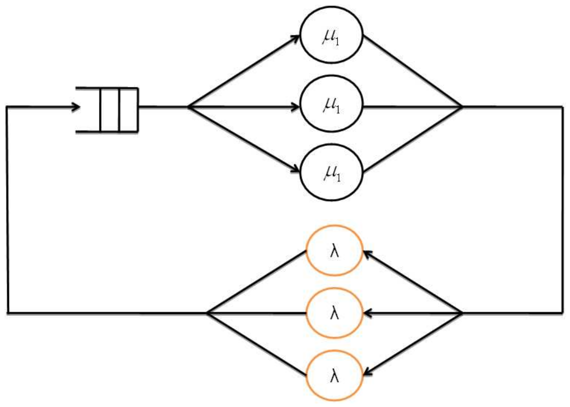
Figure 2.1 is a queuing network model of a six-sensor, finite target population tasking process, where each server represents a pair of sensors capable of independently locating a target to a certain accuracy in the absence other pairs, and a customer is a randomly emerging target.

Each customer resides in the queue or a server is regarded as a detected target which is being or to be served by one or more servers or sensor-pairs. Service is complete as soon as the target location is determined to a required accuracy. A target is then considered removed. A sensor-pair allocated to a target is tied to the target until its service is complete, or the life of the sensor-pair is terminated, whichever comes first. The three delay elements of average delay $1/\lambda$ imply that target population is limited by three at any given time. A new target is generated or replenished at a delay element with rate λ upon the service completion of a target at one or multiple servers.

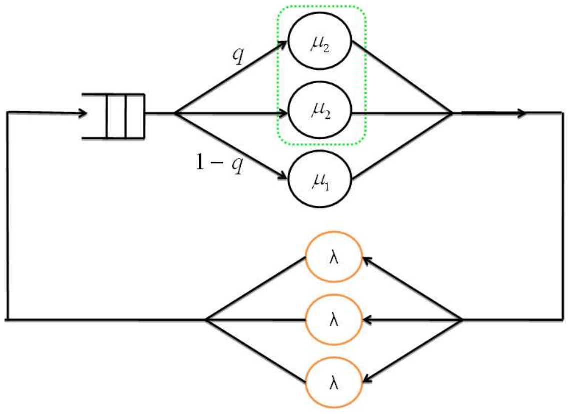
An supervisory control policy determines whether to allocate one, or two, or three pairs of sensors to each reported target, with a corresponding mean service time of $1/\mu_1, (\geq)1/\mu_2, (\geq)1/\mu_3$, respectively, where μ_i denotes the service rate of committing i pairs of sensors to a target. Given the sensing mechanism, the mean service time by a single pair of sensors is in the range of seconds to tens of seconds, dominated by the time required to adjust sensor positions and velocities for continued data collection, exchange, and processing needed for target location to a required accuracy. Each sensor-pair has a mean lifetime $1/\nu_0 \geq 1/\nu_1 \geq 1/\nu_2 \geq 1/\nu_3$, depending on the threat level quantified by the number of targets present as indexed by the subscript. $1/\nu_0$ is the server life representing the expected natural endurance of a vehicle, which is "often an hour or so at best" [13]. It also reflects sensor lives affected by undetected targets. The network is said to have expired when there is no longer a single surviving sensor-pair.

Tasking process model is built in this study with the premise that event life distributions have been established for the process of target arrival (exp$(\lambda) \equiv 1 - e^{-\lambda t}$), the process of target location (exp(μ_i)), the process of loss of a sensor-pair (exp(ν_i)), and the process of sensor replenishment (exp(ω)) when new sensor carrying vehicles are supplied for an expired network. Since all event lives are assumed to be exponentially distributed, the database unit can be conveniently modeled as a Markov chain specified by a state space $\mathcal{X}$, an initial state probability mass function (pmf) $\pi_x(0)$, and a set of state transition rates λ, μ_i, ν_i, and ω.

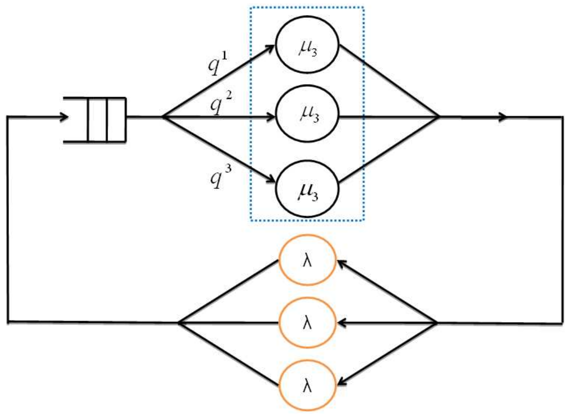
A state name is coded with a 4-digit number indicative of the number of targets present and



(a) One sensor-pair/target allocation



(b) Two sensor-pair/target allocation



(c) Three sensor-pair/target allocation

Figure 2.1: A queuing network model of a three sensor-pair, finite target population airborne sensor network.

the network configuration. A valid state representation is given by QS, where queue length $Q \in \{0, 1, 2, 3\}$, and server state $S = (i, j, k)$, with $i \in \{0, 1, 2, 3, 4\}$, and $j \in \{0, 1, 2, 3, 4, 5\}$, and $k \in \{0, 1, 3, 4, 5\}$. A server state "0", represented by the value of i, or j, or k, indicates an idle sensor-pair, a "1" indicates a target's being located by one server (or one sensor-pair), a "2" and a "3" indicate that a target's being located by two and three cooperating servers, respectively, a "4" indicates a lost server, and a "5" indicates that the lost server has been tied to another server in serving a target. The expired network requires 4 distinct states to memorize the possible queue length distributions. Note that this state specification has assumed homogeneous sensor-pairs and homogeneous targets, and has made use of the symmetry which results in 37 states. A set of alternative state names are assigned from $\mathcal{X} = \{1, 2, ..., 37\}$ with 0000 mapped to $x = 1$ and the network expiration states mapped to $x = 34, 35, 36$, and 37.

Events that trigger the transitions and the corresponding transition rates are given as follows. An emerging target enters with rate $(3 - Q) \times \lambda$. A target is located by one sensor-pair with rate μ_1, and $i(> 1)$ cooperative sensor-pairs with rate μ_i. In the latter case, the i servers are configured as a single hyper-exponential server with i parallel stages [4]. An arriving target enters any one of the servers with probability $1/i$, which has a service time distribution $\exp(\mu_i)$. When service is completed, the target is removed, while no new target can enter service when the hyper-exponential server is busy. The service time distribution of a hyper-exponential server is

$$F_i(t) = \sum_{j=1}^{i} \frac{1}{i}(1 - e^{-\mu_i t}) = 1 - e^{-\mu_i t}, \tag{2.1}$$

which assumes homogeneity of the servers. Loss of a sensor-pair occurs at rate $m\nu_0$ when the network is idle with m remaining sensor-pairs, $m\nu_1$ when one target emerges, and $m\nu_i$ when $i(> 1)$ targets emerge. Replenishment process begins at the network expiration with rate ω. If one of the sensor-pairs is lost while locating a target with other sensor-pairs, the surviving sensor-pairs continue to locate the target at the same rate. This is a simple way to memorize the service already being provided without resorting to a more complex model.

Let $X \in \mathcal{X}$ denote the random state variable at time t. The set of state transition functions is given by

$$p_{i,j}(t) \equiv P[X(t) = j | X(0) = i], \quad i, j = 1, 2, ..., 37. \tag{2.2}$$

The continuous-time Markov chain can be solved from the forward Chapman-Kolmogorov equation [4],[9]

$$\dot{P}(t) = P(t)Q(u(x)), \quad P(0) = I, \quad P(t) = [p_{i,j}(t)] \tag{2.3}$$

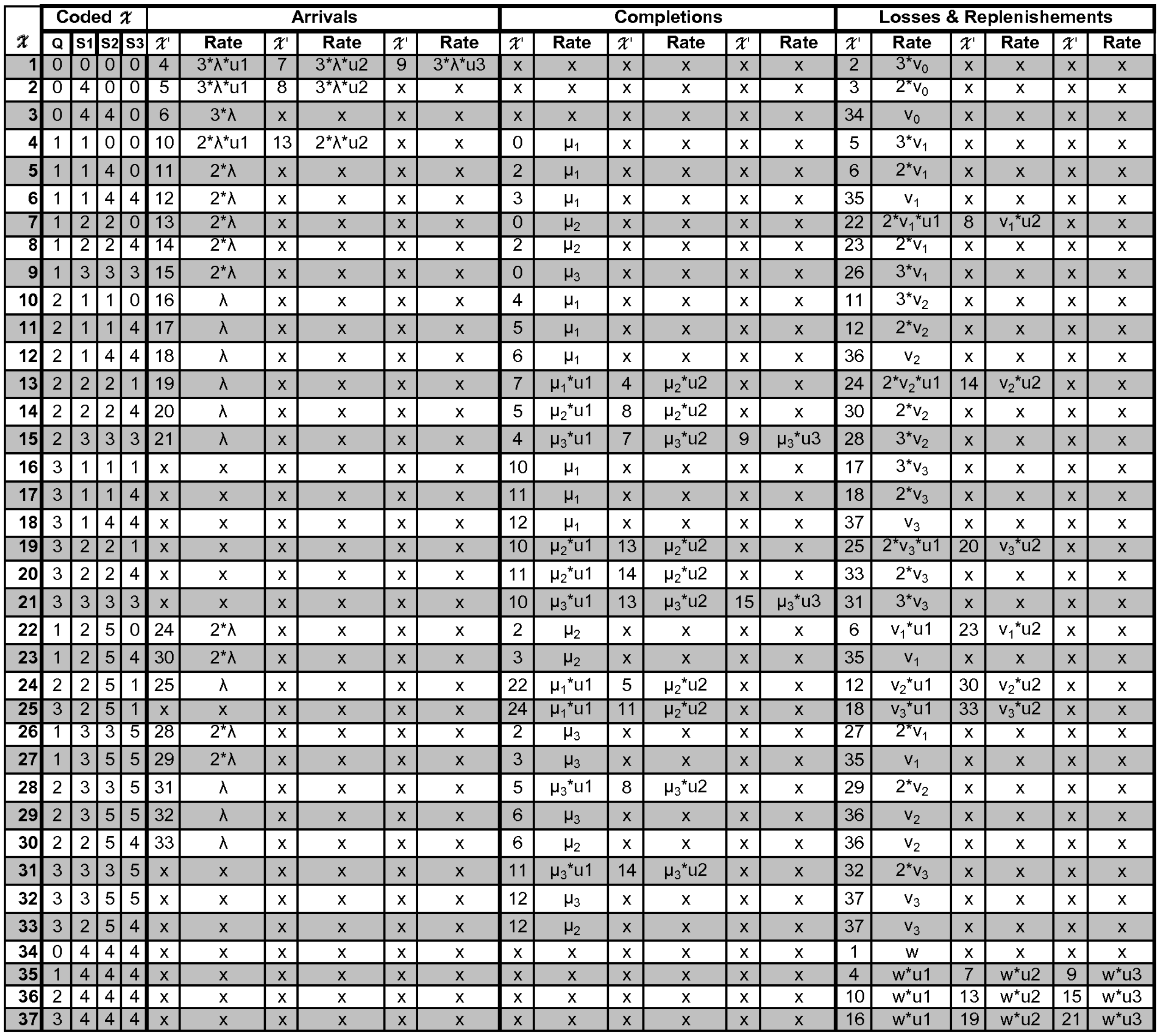
and $Q(u(x))$ is called an infinitesimal generator or a rate transition matrix whose $(i, j)^{th}$ entry is given by the rate associated with the transition from current state i to next state j. Table 1 summarizes information contained in transition rate matrix $Q(u(x))$. Control variable $u(x)$ will be discussed shortly. State probability mass function at time t

$$\pi(t) = [\pi_1(t)\ \pi_2(t)\ \cdots\ \pi_{37}(t)], \quad t \geq 0 \tag{2.4}$$

can be solved from

$$\dot{\pi}(t) = \pi(t)Q(u(x)), \quad \text{given } \pi(t = 0). \tag{2.5}$$

A Markov chain for the tasking process of Figure 2 has been established so far. Since transition rate matrix Q is dependent on control actions, the state transition functions $p_{i,j}(t)$ are being controlled, and so are the state probabilities. Rate transition matrix Q is given in the form of a table in Table 1.



$\mathcal{X}$	Coded $\mathcal{X}$				Arrivals						Completions						Losses & Replenishements					
	Q	S1	S2	S3	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate	$\mathcal{X}'$	Rate
1	0	0	0	0	4	$3*\lambda*u1$	7	$3*\lambda*u2$	9	$3*\lambda*u3$	x	x	x	x	x	x	2	$3*v_0$	x	x	x	x
2	0	4	0	0	5	$3*\lambda*u1$	8	$3*\lambda*u2$	x	x	x	x	x	x	x	x	3	$2*v_0$	x	x	x	x
3	0	4	4	0	6	$3*\lambda$	x	x	x	x	x	x	x	x	x	x	34	v_0	x	x	x	x
4	1	1	0	0	10	$2*\lambda*u1$	13	$2*\lambda*u2$	x	x	0	μ_1	x	x	x	x	5	$3*v_1$	x	x	x	x
5	1	1	4	0	11	$2*\lambda$	x	x	x	x	2	μ_1	x	x	x	x	6	$2*v_1$	x	x	x	x
6	1	1	4	4	12	$2*\lambda$	x	x	x	x	3	μ_1	x	x	x	x	35	v_1	x	x	x	x
7	1	2	2	0	13	$2*\lambda$	x	x	x	x	0	μ_2	x	x	x	x	22	$2*v_1*u1$	8	v_1*u2	x	x
8	1	2	2	4	14	$2*\lambda$	x	x	x	x	2	μ_2	x	x	x	x	23	$2*v_1$	x	x	x	x
9	1	3	3	3	15	$2*\lambda$	x	x	x	x	0	μ_3	x	x	x	x	26	$3*v_1$	x	x	x	x
10	2	1	1	0	16	λ	x	x	x	x	4	μ_1	x	x	x	x	11	$3*v_2$	x	x	x	x
11	2	1	1	4	17	λ	x	x	x	x	5	μ_1	x	x	x	x	12	$2*v_2$	x	x	x	x
12	2	1	4	4	18	λ	x	x	x	x	6	μ_1	x	x	x	x	36	v_2	x	x	x	x
13	2	2	2	1	19	λ	x	x	x	x	7	μ_1*u1	4	μ_2*u2	x	x	24	$2*v_2*u1$	14	v_2*u2	x	x
14	2	2	2	4	20	λ	x	x	x	x	5	μ_2*u1	8	μ_2*u2	x	x	30	$2*v_2$	x	x	x	x
15	2	3	3	3	21	λ	x	x	x	x	4	μ_3*u1	7	μ_3*u2	9	μ_3*u3	28	$3*v_2$	x	x	x	x
16	3	1	1	1	x	x	x	x	x	x	10	μ_1	x	x	x	x	17	$3*v_3$	x	x	x	x
17	3	1	1	4	x	x	x	x	x	x	11	μ_1	x	x	x	x	18	$2*v_3$	x	x	x	x
18	3	1	4	4	x	x	x	x	x	x	12	μ_1	x	x	x	x	37	v_3	x	x	x	x
19	3	2	2	1	x	x	x	x	x	x	10	μ_2*u1	13	μ_2*u2	x	x	25	$2*v_3*u1$	20	v_3*u2	x	x
20	3	2	2	4	x	x	x	x	x	x	11	μ_2*u1	14	μ_2*u2	x	x	33	$2*v_3$	x	x	x	x
21	3	3	3	3	x	x	x	x	x	x	10	μ_3*u1	13	μ_3*u2	15	μ_3*u3	31	$3*v_3$	x	x	x	x
22	1	2	5	0	24	$2*\lambda$	x	x	x	x	2	μ_2	x	x	x	x	6	v_1*u1	23	v_1*u2	x	x
23	1	2	5	4	30	$2*\lambda$	x	x	x	x	3	μ_2	x	x	x	x	35	v_1	x	x	x	x
24	2	2	5	1	25	λ	x	x	x	x	22	μ_1*u1	5	μ_2*u2	x	x	12	v_2*u1	30	v_2*u2	x	x
25	3	2	5	1	x	x	x	x	x	x	24	μ_1*u1	11	μ_2*u2	x	x	18	v_3*u1	33	v_3*u2	x	x
26	1	3	3	5	28	$2*\lambda$	x	x	x	x	2	μ_3	x	x	x	x	27	$2*v_1$	x	x	x	x
27	1	3	5	5	29	$2*\lambda$	x	x	x	x	3	μ_3	x	x	x	x	35	v_1	x	x	x	x
28	2	3	3	5	31	λ	x	x	x	x	5	μ_3*u1	8	μ_3*u2	x	x	29	$2*v_2$	x	x	x	x
29	2	3	5	5	32	λ	x	x	x	x	6	μ_3	x	x	x	x	36	v_2	x	x	x	x
30	2	2	5	4	33	λ	x	x	x	x	6	μ_2	x	x	x	x	36	v_2	x	x	x	x
31	3	3	3	5	x	x	x	x	x	x	11	μ_3*u1	14	μ_3*u2	x	x	32	$2*v_3$	x	x	x	x
32	3	3	5	5	x	x	x	x	x	x	12	μ_3	x	x	x	x	37	v_3	x	x	x	x
33	3	2	5	4	x	x	x	x	x	x	12	μ_2	x	x	x	x	37	v_3	x	x	x	x
34	0	4	4	4	x	x	x	x	x	x	x	x	x	x	x	x	1	w	x	x	x	x
35	1	4	4	4	x	x	x	x	x	x	x	x	x	x	x	x	4	w*u1	7	w*u2	9	w*u3
36	2	4	4	4	x	x	x	x	x	x	x	x	x	x	x	x	10	w*u1	13	w*u2	15	w*u3
37	3	4	4	4	x	x	x	x	x	x	x	x	x	x	x	x	16	w*u1	19	w*u2	21	w*u3

$u1=I_1$, $u2=I_2$, $u3=I_3$, $\mathcal{X}$: current state, $\mathcal{X}'$: next state

Figure 2.2: Transitions and transition rates of the tasking process

3 Design of supervisory control policy

Several possible supervisory control policies associated with tasking are examined. An aggressive policy allocates as many available sensor-pairs to as many targets present; A greedy policy allocates all available sensor-pairs to one target at a time; A conservative policy always allocates only one sensor-pair to every target present to reserve assets in anticipation of new targets. In addition, four optimal policies have been attempted to minimize the cost of sensor loss, threat level, unattended targets, and time needed to replenish upon network expiration, respectively.

The optimal policies are obtained by solving Markov decision problems of appropriate penalty functions. A discrete-time Markov chain model suitable for this purpose can be derived under each cost criterion by the application of a uniformization procedure [9]

$$\pi(t_{k+1}) = \pi(t_k)[I + \frac{1}{\rho}Q(u(x_k))], \tag{3.1}$$

where the uniform rate ρ is greater than any total outgoing transition rates at any states of the original continuous-time Markov chain (2.5).

Each Markov decision problem considered in this report assumes that a cost, denoted by $C(i, u)$, is incurred at every state transition, where i is the state entered and u is a control action selected from a set of admissible actions [4], [2]. A solution amounts to determining a stationary policy $\pi = \{u(x_k),\ k = 0, 1, \cdots\}$ that minimizes the following expected total discounted cost

$$V_\pi(x_0) = E_\pi \sum_{k=0}^{\infty} \alpha^k C(X_k, u_k) \tag{3.2}$$

where $0 < \alpha < 1$ is a discount factor. $C(X_k, u_k)$ in each of the four Markov decision problems takes the form of total number of lost sensor-pairs, ω^{-1} at the state of network expiration, ν_i at the state where it is the server loss, and Q at the state where it is the queue length, respectively.

Let $X_k \in \{1, 2, \cdots, 37\}$ denote the random state variable at $t_k = k/\rho$ in the discrete time Markov chain. Control action

$$u(x_k) = \begin{cases} 1, & \text{allocate one sensor-pair to a target} \\ 2, & \text{allocate two sensor-pairs to a target} \\ 3, & \text{allocate three sensor-pairs to a target} \end{cases} \tag{3.3}$$

Note that the indicator functions in Table 1 are defined follows

$$I_i = \begin{cases} 1, & u = i \\ 0, & \text{otherwise} \end{cases}, i = 1, 2, 3. \tag{3.4}$$

It is known [4, 2] that under the condition $0 \leq C(j,u) < \infty$ for all j and all u that belongs to some finite admissible sets U_j, the minimum cost $V^*(i)$ satisfies the following optimality equation:

$$V(i) = \min_{u \in U_i} \left\{ C(i,u) + \alpha \sum_{j=1}^{37} p_{i,j} V(j) \right\}, \ u \in U_i, \tag{3.5}$$

$i = 1, \cdots, 37$, where $p_{i,j}$ is the $(i,j)^{th}$ entry of $I + \frac{1}{\rho} Q(u(x_k))$.

The solution to (3.5) can be obtained via linear programming [3, 2]. In this case, the set of optimality equations is turned into a set of affine constraints on the set of optimization variables $\{V(i)\}$, and the problem can be formally stated as follows.

$$\begin{aligned} &\text{Maximize} && V(1) + V(2) + \cdots + V(36) + V(37) && (3.6) \\ &\text{Subject to} && V(i) \geq 0, \ \ i \in \mathcal{X} = \{1, \cdots, 37\} && (3.7) \\ & && V(i) \leq [C(i,u) + \alpha \sum_j p_{i,j} V(j)] \mid_u, && (3.8) \end{aligned}$$

$\forall u \in U_i, \ \ i \in \mathcal{X}.$

In the tasking process considered, U_j is nonempty only at state $j = 1$, 2, 4, 7, 13, 14, 15, 19, 20, 21, 22, 24, 25, 28, 31, 35, 36, 37. Therefore, (3.8) leads to 99 affine inequality constraints. This problem is readily solvable by `linprog` in MATLAB's Optimization Toolbox [11]. The active constraints are checked with a MATLAB script to determine the optimal control policy.

Figure 3.1 shows an example of 4 stationary control policies depicted in terms of indicator functions, as defined in (3.4), of the state $x \in \mathcal{X}$. It can be seen that the optimal policy takes into consideration of anticipated targets more than the aggressive policy, but is much more aggressive in terms of use of resources than the conservative policy. Among the four optimal policies solved, only the policy derived under the least sensor loss is plotted (bottom), which will be shown shortly to outperform other three optimal policies in terms of both MTTNE and availability. The minimum queue length policy coincides with the greedy policy, as expected. The other two optimal policies make less aggressive use of resources than the optimal policy shown. The least sensor loss policy will be called the optimal policy from this point on.

The control policies are robust with respect to the range of parameter variations that have been examined: $\nu_1 \in [0.001, 0.01]$ $1/sec.$, and $\lambda \in [0.001, 0.1]$ $1/sec.$ The optimal policy is calculated at $\alpha = 0.0792$. All optimal policies drift slightly toward more conservative actions (using fewer resources) as the discount factor α increases, which is consistent with the outcome of the longer term policy making. Because of the finite target population setup, the effect of increasing the target arrival rate is not fully reflective of the target traffic intensity. Simulations with *MATLAB SimEvets* [10] are being performed without limiting the target population.

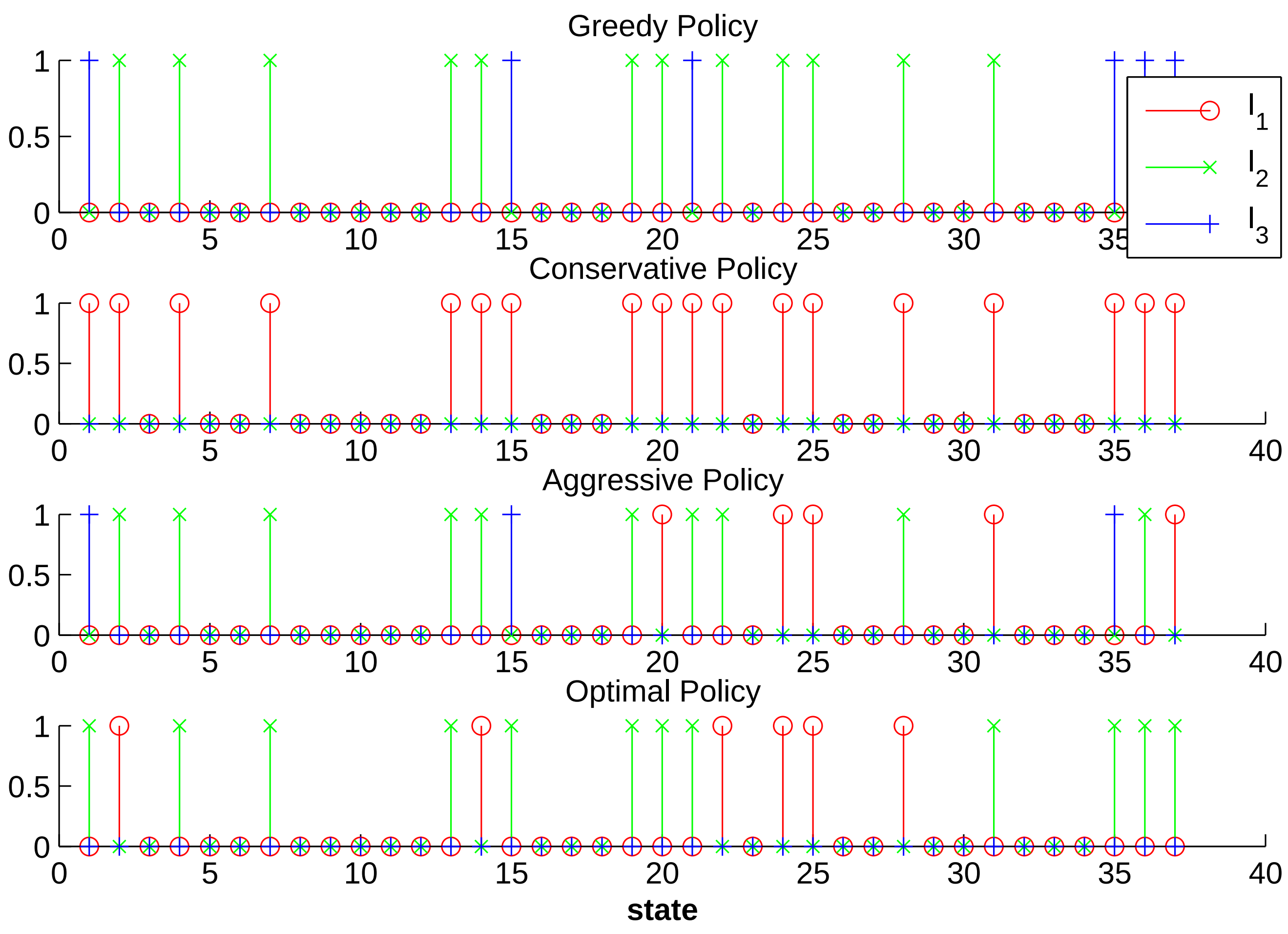


Figure 3.1: Control policy indicators. red: one sever/target; green: two servers/target; blue: three servers/target

4 Performance analysis

The seven policies developed in Section 3 are compared against one another with respect to two common measures of fault-tolerance: mean time to network expiration (MMTNE) and availability. These have been used in [15] in a similar fashion as performance measures of a database unit.

When no replenishment is provided, the network life eventually expires when all sensor-pairs are lost. This occurs when the network enters one of its absorbing states at 34, 35, 36, or 37. Decompose the state probability vector

$$\pi(t) = [\underbrace{\pi_\tau(t)}_{1\times 33} \;\; \underbrace{\pi_\alpha(t)}_{1\times 4}] \tag{4.1}$$

where vector $\pi_\tau(t)$ contains transient state probabilities, and $\pi_\alpha(t)$ contains absorbing state probabilities. Decomposing the rate transition matrix Q accordingly yields

$$Q = \begin{bmatrix} Q_{11} & Q_{12} \\ 0 & 0 \end{bmatrix} \tag{4.2}$$

From (4.2), it can be determined that mean time to network expiration is given by

$$\text{MTTNE} = -\pi_\tau(0)Q_{11}^{-1}1_\tau, \;\; 1_\tau = [\underbrace{1 \;\cdots\; 1}_{1\times 33}]^T \tag{4.3}$$

Suppose as soon as the network expires, a replenishment process starts. Suppose with a rate ω the airborne sensors are replenished, and at the completion of the replenishment, the tasking process immediately resumes. In this case, the Markov chain (2.5) becomes irreducible, and a unique steady-state distribution exists [9]. The steady-state availability, which can be roughly thought of as the fraction of time the network has at least one surviving pair of sensors, is computed by

$$A_{net} = 1 - \pi_F(\infty), \tag{4.4}$$

where $\pi_F(\infty) = \pi_{34}(\infty) + \pi_{35}(\infty) + \pi_{36}(\infty) + \pi_{37}(\infty)$, the sum of state probabilities associated with network expiration, which can be determined by solving

$$\pi(\infty)Q = 0, \text{ and } \sum_{x=1}^{37} \pi_x(\infty) = 1. \tag{4.5}$$

A slightly different notion of availability is also examined, where the network is considered unavailable as long as unattended targets are present. In this case, the network availability is given by

$$\begin{aligned} A_{tgt} &= \\ & \sum_{i=1}^{11} \pi_i(\infty) + \pi_{13}(\infty) + \pi_{16}(\infty) + \pi_2(\infty) \\ & + \pi_{23}(\infty) + \pi_{24}(\infty) + \pi_{26}(\infty) + \pi_{27}(\infty). \end{aligned} \tag{4.6}$$

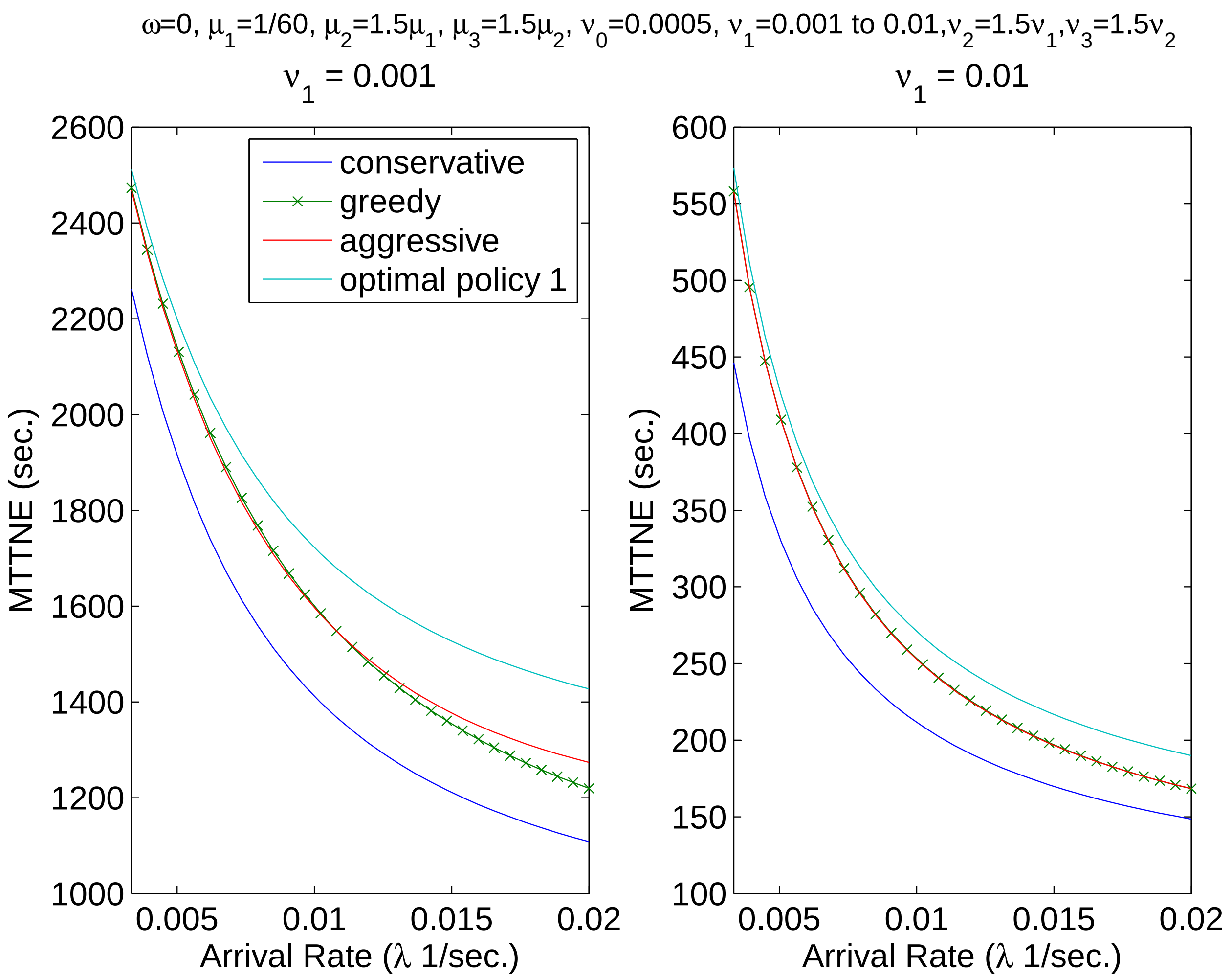


Figure 4.1: Mean time to network expiration as a function of target arrival rate with two sets of sensor loss rates as parameters.

Mean time to network expiration is plotted in Figure 4.1 against target arrival rate with two sets of sensor loss rates as parameters at $\alpha = 0.0792$. It shows that compromise that optimal policy makes between being too greedy and too conservative enhances the network life consistently for all parameters values considered.

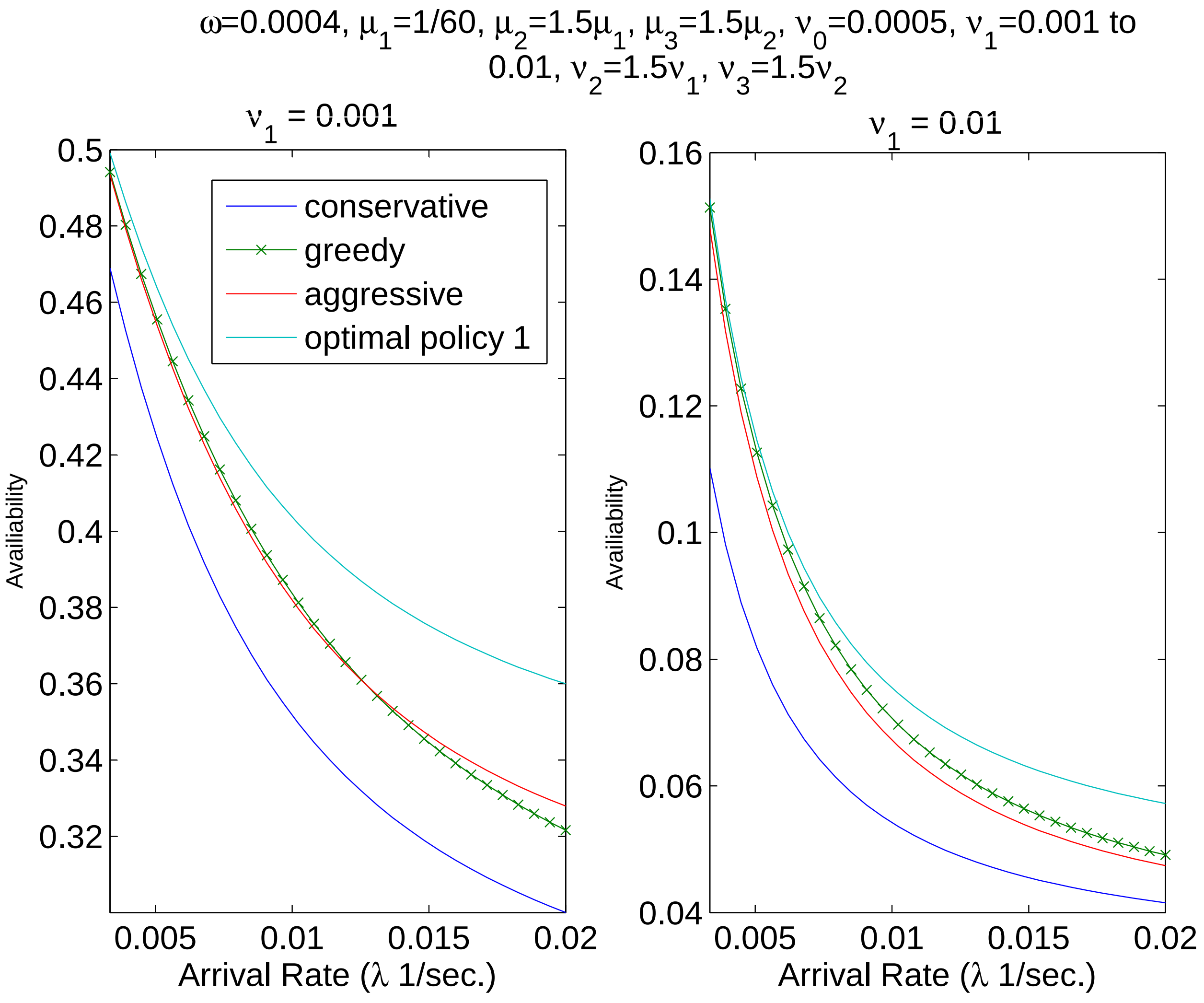


Figure 4.2: Network availability with at least one surviving server.

In Figure 4.2, availability is also plotted against target arrival rate with two sets of sensor loss rates as parameters at discount factor $\alpha = 0.0792$. The observations from the MTTNE apply in terms of the gain the optimal policy offers. It is noted that the availability is low. This is because of the low replenishment rate used in the computation, which corresponds to an expected time of more than 40 minutes to reestablish the lost network.

It is expected that the network availability defined as the probability that all targets is lower than the availability defined as the probability that there is at least one surviving server. On the other hand, the dependence of both notions of availability on the sensor loss rate and on the target arrival rate stays the same. Figure 4.3 shows the plot of the two availabilities against target arrival rate with two sets of sensor loss rates ν_i as parameters under the optimal policy.

Extensive simulations using [10] is being conducted to generate a more complete picture of the network performance in response to control policies for a larger size of networks. The results will be reported elsewhere.

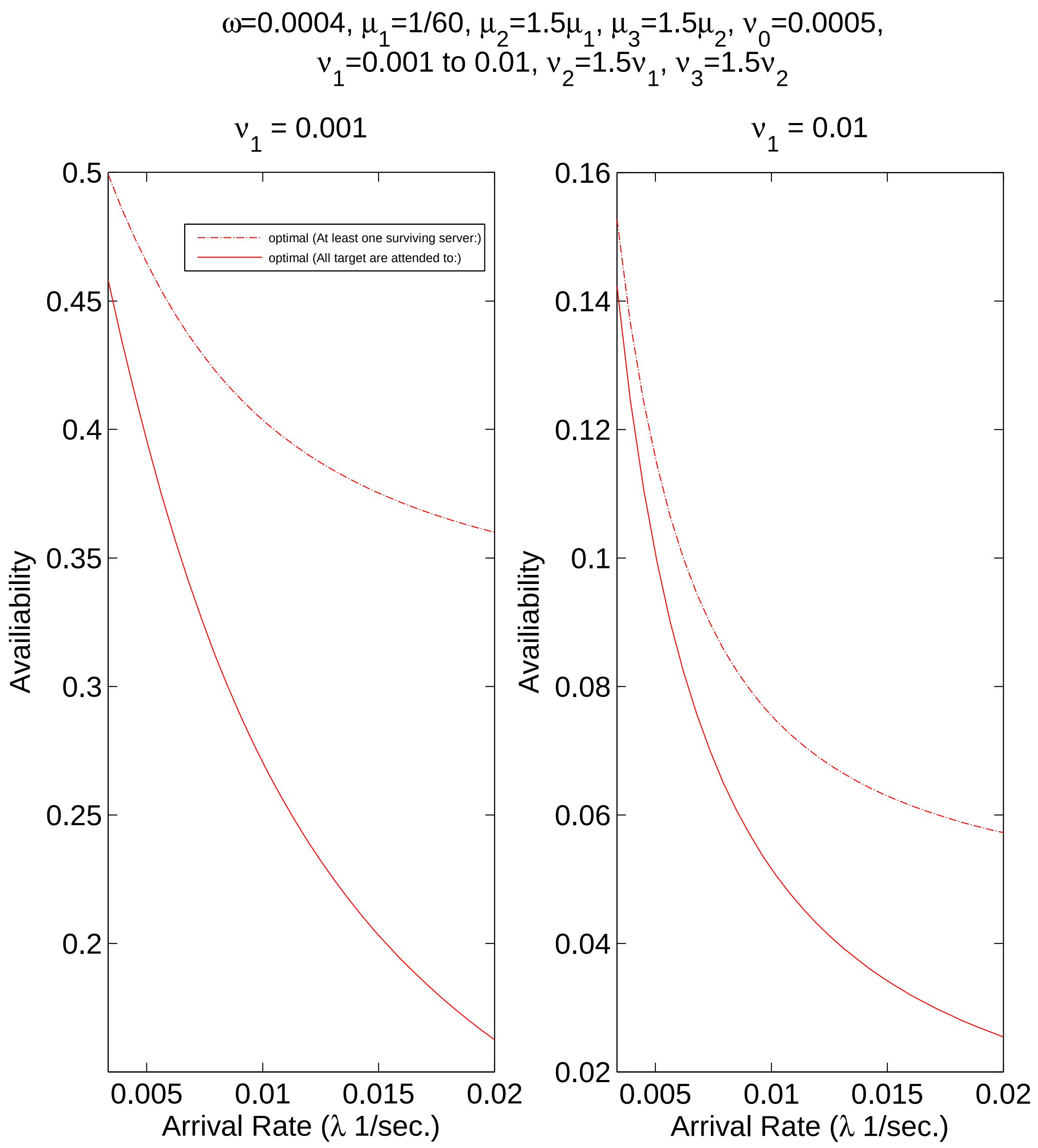


Figure 4.3: Comparison between availability with at least one surviving server (dash) and availability with all targets being attended (solid).

5 Conclusions

This work sought to determine supervisory control policies that best configure an airborne location sensor network to provide a high degree of guarantee of prompt completion of coordinated data acquisition and processing missions in the face of loss of vehicles. Use of redundancy and dynamic allocation of participating sensors was the key enablers.

The report presented a queuing network approach to optimal sensor-pair assignment to locate detected targets for a small scale airborne sensor network, where use of redundancy is balanced with avoiding more vehicle exposure.

A number of related issues are being investigated. In addition to loss of sensors, degradation of network performance can also be the result of broken communication links. Such incidents are modeled as intermittent faults of the servers in queuing networks. The effects of such faults will be studied using discrete event simulations, which will also examine possible emergent phenomenon of larger networks, and non-homogeneous sensors and targets.

A highly relevant task is to solve a guidance and then a control problem of the vehicles. Guidance problem [7] refers to that of establishing a criterion and deriving a set of desired vehicle trajectories under the criterion that the airborne sensors are expected to follow to expedite the target location estimation to a required accuracy. It is known that the quality of acquired data by the airborne sensors depends highly on both the network architecture which is determined by the number of sensor-pairs, and the *states* of all participating sensors relative to the target and to one another. A guidance principle based on the entropy [5] of the noise distribution of the sensed signal has been established, based on which one seeks to adjust the states of the sensors to the most suitable positions and velocities for further data acquisition and processing.

Once the guidance principle is determined, feasible vehicle trajectories can be generated. Path following control can be performed with time coordination [8] to achieve synchronous data acquisition by the sensors. Both the guidance and the control problems are being investigated, and will be reported separately in the near future.

6 Designs and simulation modeling

In general, the sensors of the sensor networks are subject to random breakdowns. This has a heavy influence on the performance measures. Thus, if we model a system containing unreliable sensor-pairs, it is important to take it into account in the model construction. Of course, the breakdown of the sensor-pairs has the most significant negative impact on the performance of the system. The complexity of the system, such as its stochastic, unpredictable behavior, independencies between individual events and the informal nature of many events, makes the analysis profoundly problematic. Such a modeling problem is very significant in large complex systems. The advantage of using simulation is listed below:

1. Simulation provides a controlled environment for performance measurements.
2. Changes can be made easily to the model.
3. Simulation and modeling provides an easy way to control influence of parameters and conduct sensitivity analysis.
4. It does not rely on mathematical concepts heavily and is a very robust technique.

Simulation of the airborne system is conducted in Simulink of MATLAB using the event-based package Simevents [10], [11]. We began with three simulation models. These three models are closed queue with finite homogenous sensor-pairs and finite arrival targets. The first model is reducible, without both system replenishment and channel fading. We used this model to measure the mean time to network expiration (MTTNE). The second model is irreducible with the feature of system replenishment. The third model is also irreducible with both replenishment and channel fading. Both the second and third model is used to measure steady state availability and mean response time of the system. Several control policies associated with tasking are examined in the simulation and compared with the analytic results.

6.1 Basic algorithm of the simulation models

Events do not have equal probability; some events are more likely to occur than others; the execution order of simultaneous events is set to be randomized instead of arbitrary through all simulations. Upon the occurrence of permanent failures, targets are ejected out from the sensor-pairs before service completion and re-attending the queue with priority, and they require the same service time that was assigned. These targets preempt the waiting targets in the queue but don't preempt the targets that are already in service. Upon occurrence of intermittent failures, targets are ejected out from the sensor-pairs, and they memorize their residual event lives. They immediately return to the assigned sensor-pairs upon recovery of the sensor-pairs. The system is said to be down when all sensor-pairs end their life. No actions can be taken during the repairing process. The event of failure is activated again once the system is operational. The system contains a finite population of targets; the delay elements in the feedback loop generate new targets upon service completion of the targets from one or more sensor-pairs from the upper part of the closed loop system. Appendix C convolutes the simulation and implements the following algorithm:

1. Initialize the system to state 0000.
2. Activate all feasible events
3. Create an initial entity and set a service time for it.
4. Service time is updated according to the number of entities in the system.
5. Failure time of the servers is updated with respect to the number of entities in the system as well. A new failure entity will be generated by the random number generator and preempts the previous failure entity when the queue length changes. The old failure entity is discarded under this condition.
6. Compare the transition times of the feasible events; choose the shortest time and resolve the trigger event. Update to new state upon service completion, entity arrival and server failure.
7. Simulation stops for non-repairable systems once the absorbing states are reached. For repairable systems, simulation stops only if there is a stopping rule.

For most communication systems, redundancy is desired. Assume the stopping rule of this airborne system is defined as the system is down when the backups of severs are also gone or when the system is only allowed to replenish once. Another issue has to do with the failure time. If the current simulation time is greater than the failure time of a sensor-pair, the sensor-pair fails right away. If the current simulation time is less than the failure time, then the service time of the target is equal to the failure time minus the old simulation time.

6.2 Techniques for steady state analysis

Unlike in queuing theory where steady state results in analytic models are easily obtainable, the steady state simulation is not an easy task. Gathering steady state simulation output requires a statistical assertion that the simulation model reached the steady state. The main difficulty is to obtain independent simulation runs with exclusion of the transient period. There are two techniques commonly used for steady state simulation, the Method of Batch means, and the Independent

Replication [18], [19]. None of these two methods is superior to the other in all cases. Intuitively one may say the method of independent replication is superior in producing statistically good estimates for the system's performance measurements. In fact, not one method is superior in all cases, and it all depends on the traffic intensity.

We are using independent replication in this experiment. This technique gets n independent runs of the simulation experiment by running the simulation n times with different initial random seeds for the simulator's random number generator. The main question is determination of the number of runs. The confidence level of simulation output drawn from a set of simulation runs depends on the size of the data set. The larger the number of runs, the higher is the associated confidence. However, more simulation runs require more effort for large systems. Hence, the main goal is to find the smallest number of simulation runs that will also provide the desired confidence. One main limitation of these designs is that the outputs are random from the simulations. Thus, estimates of parameter effects are subject to possibly considerable variance. Unlike physical experiments, we have the luxury in simulation of replicating the runs many times to reduce this variance or perhaps replicating the whole design many times to get many independent and identically distributed estimates of main parameter effects, which could then combine to form a confidence interval. Due to the lengthy simulation time, all results are averaged over 30 simulation runs.

6.3 Performance analysis from simulation

To run a simulation multiple times and gather statistics, the initial seed value would have to be reassigned for each run in all blocks containing it. The MATLAB code initial seed value generator from [10] shown in appendix 9.4 generates random initial seeds for the system. This is one of the methods that may be used to obtain results from multiple runs. To see the performance over the range of arrival rate, we can also use the code 'Running a simulation and varying a parameter' from appendix 9.4. The following subsections are the performance analysis with data collected from simulations. They are plotted in Excel.

6.3.1 Closed - queue reducible model

Fig 6.1 shows the Mean time to network expiration vs. arrival rate. It has the same arrangement as fig. 3.3 with the closeness of the curves at slow arrival rate and the spread of the curves at faster arrival rate. The result is not exactly the same as the analytic result, but very close.

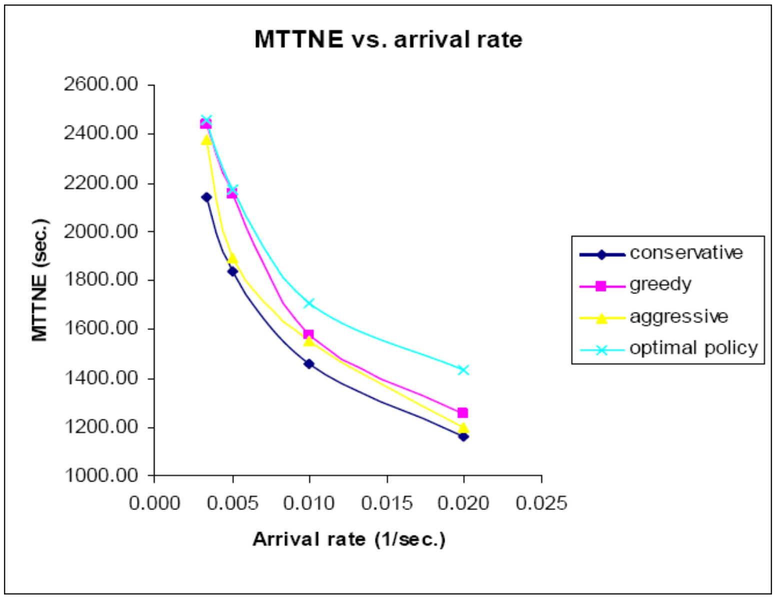


Figure 6.1: Mean time to network expiration vs. arrival rate (simulation model 1)

6.3.2 Closed - queue irreducible model

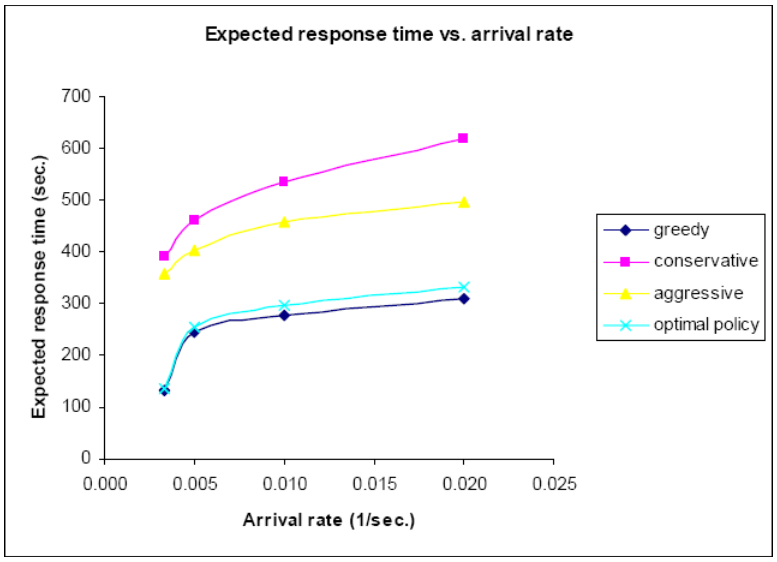


Figure 6.2: Expected response time vs. arrival rate (simulation model 2)

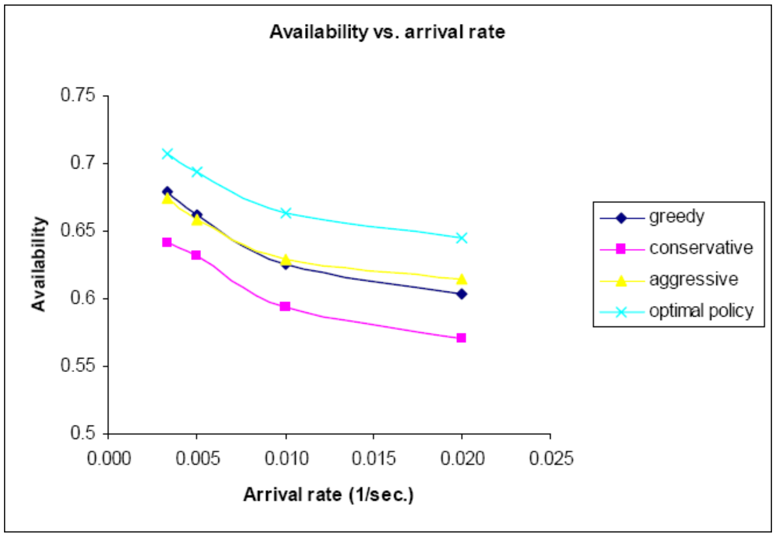


Figure 6.3: Availability vs. arrival rate (simulation model 2)

Compare fig. 6.3 to fig 3.4, the system availability obtain from the simulation is much higher than the analytic model, that is because the simulation only allows to replenish the system once.

6.3.3 Closed - queue irreducible model with intermittent channel fading

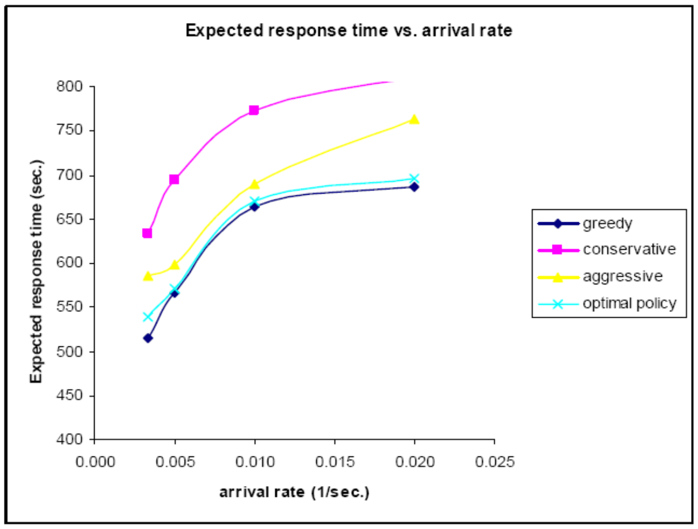


Figure 6.4: Expected response time vs. arrival rate (simulation model 3)

From fig. 6.4, the response time for the system with intermittent channel fading is longer than the response time without intermittent channel fading. It is expected that the time to locate a target would be extended.

6.4 Simulation conclusion

The set up of the simulation models is somewhat different from the analytic model. First of all, in the analytic model, the performance measurements are obtained under all possible states of the system. In the simulation models, the simulation is running under the selection of the control policies, not all system states would be presented. For example, if the conservative policy is applied, a state in which all three sensor-pairs tie together to serve a target would never occur.

Secondly, change of simulation results may be due to the run time of a model and randomness of the event lives. Compare fig. 6.1 to 3.3, the MTTNE is slightly different from the Markov model. The expected response times obtained from simulation model 3 are longer than those for model 2. This is predictable where the intermittent channel fading extends the time to locate targets (additional time is needed for data recovery). The response times from the simulation models 2 and 3 are not the same as fig. 3.6b because fig 3.6b is plotted under the assumption that the number of served targets for all policies is constant. The number of served targets in simulation models is correct and changes by the arrival and service rate. Also, another fact is that the run time for simulations was too short; the systems are not under steady state condition. A more ideal set of data can be obtained by having longer run time with a larger number of departed targets over time.

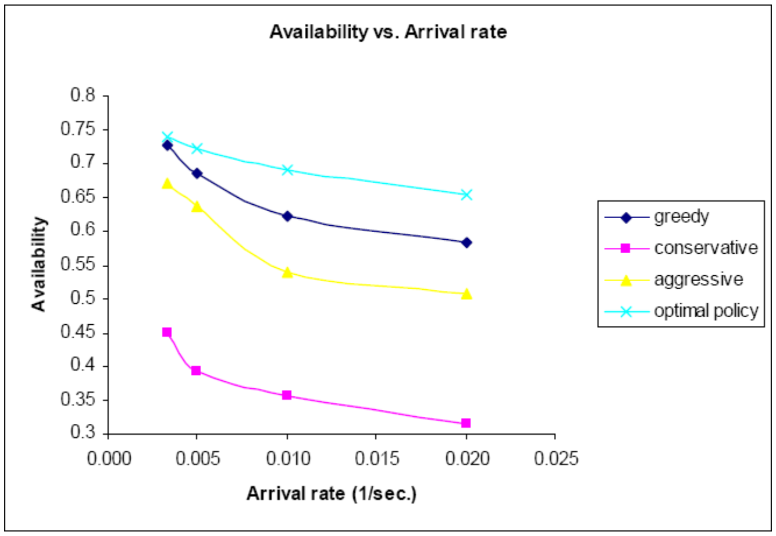


Figure 6.5: Availability vs. arrival rate (simulation model 3)

Similarly, the availabilities from the simulation models are higher than the analytic model. This is also due to the short simulation run time and the effect of non-steady state operation.

7 References

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8 MATLAB code for the analytic model of the airborne network

8.1 Transition rate matrix

The transition rate matrix is computed from the transition rate diagram from the previous page or from Table 4.

8.2 Mean time to network expiration

```
clc, clear

% parameters
la=linspace(1/300, 1/50, 30);
nu1=linspace(1/1000, 1/100, 2);
nu0=0.0005; nu2=1.5*nu1; nu3=1.5*nu2;
mu1=1/60; mu2=1.5*mu1; mu3=1.5*mu2;

%% compute mean time to network expiration (reducible case)
for i=1:length(la)
    for j=1:length(nu1)
        setpara(mu1, mu2, mu3, nu0, nu1(j), nu2(j), nu3(j), la(i), 0);

        Q =Qnew1;

        pi_T = [1 zeros(1,(length(Q)-5))];
        ones_T = ones((length(Q)-4),1);
        Q_T = Q(1:(length(Q)-4),1:(length(Q)-4));
        MTTNE1(i,j) = -pi_T * inv(Q_T) * ones_T;                  % greedy

        Q2=Qnew2;

        pi_T2 = [1 zeros(1,(length(Q2)-5))];
        ones_T2 = ones((length(Q2)-4),1);
        Q2_T = Q2(1:(length(Q2)-4),1:(length(Q2)-4));
        MTTNE2(i,j) = -pi_T2 * inv(Q2_T) * ones_T2;             % conservative
        Qag=Qnewag;

        pi_Tag = [1 zeros(1,(length(Qag)-5))];
        ones_Tag = ones((length(Qag)-4),1);
        Qag_T = Qag(1:(length(Qag)-4),1:(length(Qag)-4));
        MTTNEag(i,j) = -pi_Tag * inv(Qag_T) * ones_Tag;         % aggressive

        Qopt1=Qnewopt1;
        pi_Topt1 = [1 zeros(1,(length(Qopt1)-5))];
        ones_Topt1 = ones((length(Qopt1)-4),1);
        Qopt1_T = Qopt1(1:(length(Qopt1)-4),1:(length(Qopt1)-4));
        MTTNEopt1(i,j) = -pi_Topt1 * inv(Qopt1_T)
                * ones_Topt1;  % optimal policy 1

        Qopt2=Qnewopt2;
        pi_Topt2 = [1 zeros(1,(length(Qopt2)-5))];
        ones_Topt2 = ones((length(Qopt2)-4),1);
        Qopt2_T = Qopt2(1:(length(Qopt2)-4),1:(length(Qopt2)-4));
        MTTNEopt2(i,j) = -pi_Topt2 * inv(Qopt2_T)...
                * ones_Topt2;  % optimal policy 2

        Qopt3=Qnewopt3;
        pi_Topt3 = [1 zeros(1,(length(Qopt3)-5))];
        ones_Topt3 = ones((length(Qopt3)-4),1);
        Qopt3_T = Qopt1(1:(length(Qopt3)-4),1:(length(Qopt3)-4));
        MTTNEopt3(i,j) = -pi_Topt3 * inv(Qopt3_T)...
                * ones_Topt3;  % optimal policy 3

end,end

diff1 = MTTNEag-MTTNE1;         % diff between aggressive & greedy
diff2 = MTTNE1-MTTNE2;          % diff between greedy & conservative
diff3 = MTTNEag - MTTNE2;       % diff between aggressive & conservative

%% plot MTTNE vs. arrival rate

figure(1)
subplot(1,2,1)
plot(la,MTTNE2(:,1), la,MTTNE1(:,1), '-x', la,MTTNEag(:,1), la,MTTNEopt1(:,1))
title({'\omega=0, \mu_1=1/60, \mu_2=1.5\mu_1, \mu_3=1.5\mu_2, \nu_0=0.0005,...
        \nu_1=0.001 to 0.01, \nu_2=1.5\nu_1, \nu_3=1.5\nu_2';...
        'MEAN TIME TO NETWORK EXPIRATION VS. ARRIVAL RATE';'\nu_1 = 0.001'})

legend('conservative','greedy','aggressive','optimal policy 1')
xlabel('Arrival Rate (\lambda 1/sec.)')
ylabel('MTTNE (sec.)'),  xlim([1/300, 1/50])
subplot(1,2,2)
plot(la,MTTNE2(:,2), la,MTTNE1(:,2), '-x', la,MTTNEag(:,2), la,MTTNEopt1(:,2))
title('\nu_1 = 0.01'), xlabel('Arrival Rate (\lambda 1/sec.)')
ylabel('MTTNE (sec.)'), xlim([1/300, 1/50])
```

```

figure(2)
subplot(1,2,1), plot(la,MTTNEopt1(:,1), '-+', la, MTTNEopt2(:,1), '-o',....
        la,MTTNEopt3(:,1))
title({'\omega=0, \mu_1=1/60, \mu_2=1.5\mu_1, \mu_3=1.5\mu_2,...
        \nu_0=0.0005, \nu_1=0.001 to 0.01, \nu_2=1.5\nu_1, \nu_3=1.5\nu_2';...
        'MEAN TIME TO NETWORK EXPIRATION VS. ARRIVAL RATE';'\nu_1 = 0.001'})

legend('optimal policy 1', 'optimal policy 2','optimal policy 3')
xlabel('Arrival Rate (\lambda 1/sec.)'), ylabel('MTTNE (sec.)')
xlim([1/300, 1/50])
subplot(1,2,2)
plot(la,MTTNEopt1(:,2), '-+', la, MTTNEopt2(:,2), '-o', la,MTTNEopt3(:,2))
title('\nu_1 = 0.01')
xlabel('Arrival Rate (\lambda 1/sec.)')
ylabel('MTTNE (sec.)')
xlim([1/300, 1/50])
```

8.3 Steady-state availability

```
clc,clear

% parameters
la=linspace(1/300, .02, 30);
nu1=linspace(1/1000, 1/100, 2);
nu0=0.0005; nu2=1.5*nu1; nu3=1.5*nu2;
mu1=1/60; mu2=1.5*mu1; mu3=1.5*mu2;
w=0.0004;

%% computing steady state availability
for i=1:length(la)
    for j=1:length(nu1)
        setpara(mu1, mu2, mu3, nu0, nu1(j), nu2(j), nu3(j), la(i), w);

        Q =Qnew1;       %greedy
        Q2=Qnew2;       %conservative
        Qag=Qnewag;       %aggressive
        Qopt1=Qnewopt1;   %optimal 1
        Qopt2=Qnewopt2;   %optimal 2
        Qopt3=Qnewopt3;   %optimal 3

        Q(:,length(Q)) = [ones(1,length(Q))];
        p_ss = [zeros(1,(length(Q)-1)), 1]*inv(Q);

%avail 1 when the system is up
        A_sys1(i,j) = p_ss(1:(length(Q)-4))*ones((length(Q)-4),1);

        %avail 2: all targets are in service
A_sys1_2(i,j) = 1-p_ss(12)-p_ss(14)-p_ss(15)-p_ss(17)-p_ss(18)-p_ss(19)...
```

```
        -p_ss(20)-p_ss(21)-p_ss(25)-p_ss(28)-p_ss(29)-p_ss(30)-p_ss(31)...
        -p_ss(32)-p_ss(33)-p_ss(34)-p_ss(35)-p_ss(36)-p_ss(37);

        Q2(:,length(Q2)) = [ones(1,length(Q2))];
        p_ss2 = [zeros(1,(length(Q2)-1)), 1]*inv(Q2);
        A_sys2(i,j) = p_ss2(1:(length(Q2)-4))*ones((length(Q2)-4),1);
A_sys2_2(i,j) = 1-p_ss2(12)-p_ss2(14)-p_ss2(15)-p_ss2(17)-p_ss2(18)...
        -p_ss2(19)-p_ss2(20)-p_ss2(21)-p_ss2(25)-p_ss2(28)-p_ss2(29)...
        -p_ss2(30)-p_ss2(31)-p_ss2(32)-p_ss2(33)-p_ss2(34)-p_ss2(35)...
        -p_ss2(36)-p_ss2(37);

        Qag(:,length(Qag)) = [ones(1,length(Qag))];
        p_ssag = [zeros(1,(length(Qag)-1)), 1]*inv(Qag);
        A_sysag(i,j) = p_ssag(1:(length(Qag)-4))*ones((length(Qag)-4),1);
A_sysag_2(i,j) = 1-p_ssag(12)-p_ssag(14)-p_ssag(15)-p_ssag(17)-p_ssag(18)...
        -p_ssag(19)-p_ssag(20)-p_ssag(21)-p_ssag(25)-p_ssag(28)-p_ssag(29)...
        -p_ssag(30)-p_ssag(31)-p_ssag(32)-p_ssag(33)-p_ssag(34)-p_ssag(35)...
        -p_ssag(36)-p_ssag(37);

        Qopt1(:,length(Qopt1)) = [ones(1,length(Qopt1))];
        p_ssopt1 = [zeros(1,(length(Qopt1)-1)), 1]*inv(Qopt1);
        A_sysopt1(i,j) = p_ssopt1(1:(length(Qopt1)-4))...
                *ones((length(Qopt1)-4),1);
A_sysopt1_2(i,j) = 1-p_ssopt1(12)-p_ssopt1(14)-p_ssopt1(15)-p_ssopt1(17)...
        -p_ssopt1(18)-p_ssopt1(19)-p_ssopt1(20)-p_ssopt1(21)-p_ssopt1(25)...
        -p_ssopt1(28)-p_ssopt1(29)-p_ssopt1(30)-p_ssopt1(31)-p_ssopt1(32)...
        -p_ssopt1(33)-p_ssopt1(34)-p_ssopt1(35)-p_ssopt1(36)-p_ssopt1(37);

        Qopt2(:,length(Qopt2)) = [ones(1,length(Qopt2))];
        p_ssopt2 = [zeros(1,(length(Qopt2)-1)), 1]*inv(Qopt2);
        A_sysopt2(i,j) = p_ssopt2(1:(length(Qopt2)-4))...
                *ones((length(Qopt2)-4),1);
A_sysopt2_2(i,j) = 1-p_ssopt2(12)-p_ssopt2(14)-p_ssopt2(15)-p_ssopt2(17)...
        -p_ssopt2(18)-p_ssopt2(19)-p_ssopt2(20)-p_ssopt2(21)-p_ssopt2(25)...
        -p_ssopt2(28)-p_ssopt2(29)-p_ssopt2(30)-p_ssopt2(31)-p_ssopt2(32)...
        -p_ssopt2(33)-p_ssopt2(34)-p_ssopt2(35)-p_ssopt2(36)-p_ssopt2(37);


        Qopt3(:,length(Qopt3)) = [ones(1,length(Qopt3))];
        p_ssopt3 = [zeros(1,(length(Qopt3)-1)), 1]*inv(Qopt3);
        A_sysopt3(i,j) = p_ssopt3(1:(length(Qopt3)-4))...
            *ones((length(Qopt3)-4),1);
A_sysopt3_2(i,j) = 1-p_ssopt3(12)-p_ssopt3(14)-p_ssopt3(15)-p_ssopt3(17)...
        -p_ssopt3(18)-p_ssopt3(19)-p_ssopt3(20)-p_ssopt3(21)-p_ssopt3(25)...
        -p_ssopt3(28)-p_ssopt3(29)-p_ssopt3(30)-p_ssopt3(31)-p_ssopt3(32)...
        -p_ssopt3(33)-p_ssopt3(34)-p_ssopt3(35)-p_ssopt3(36)-p_ssopt3(37);

    end,end

diff1=A_sysag - A_sys1;       % diff between aggressive and greedy
diff2=A_sys1 - A_sys2;        % diff between greedy and conservative
```

```
diff3=A_sysag-A_sys2;        % diff between aggressive and conservative

%% plots: avail 1 vs. arrival rate

figure(1)
subplot(1,2,1)
plot(la,A_sys2(:,1), la,A_sys1(:,1), '-x', la,A_sysag(:,1), la, A_sysopt1(:,1))
title({'\omega=0.0004, \mu_1=1/60, \mu_2=1.5\mu_1, \mu_3=1.5\mu_2,...
        \nu_0=0.0005, \nu_1=0.001 to 0.01, \nu_2=1.5\nu_1, \nu_3=1.5\nu_2';...
        'AVAILABILITY VS. ARRIVAL RATE';'\nu_1 = 0.001'})
legend('conservative','greedy','aggressive','optimal policy 1')
xlabel('Arrival Rate (\lambda 1/sec.)'),ylabel('Availiability')
xlim([1/300, 1/50])
subplot(1,2,2)
plot(la,A_sys2(:,2), la,A_sys1(:,2), '-x', la,A_sysag(:,2), la, A_sysopt1(:,2))
title('\nu_1 = 0.01'), xlabel('Arrival Rate (\lambda 1/sec.)')
ylabel('Availiability'), xlim([1/300, 1/50])

figure(2)
subplot(1,2,1), plot(la,A_sysopt1(:,1), la,A_sysopt2(:,1), '-+', la,A_sysopt3(:,1))
title({'\omega=0.0004, \mu_1=1/60, \mu_2=1.5\mu_1, \mu_3=1.5\mu_2,...
        \nu_0=0.0005, \nu_1=0.001 to 0.01, \nu_2=1.5\nu_1, \nu_3=1.5\nu_2';...
        'AVAILABILITY VS. ARRIVAL RATE';'\nu_1 = 0.001'})
legend('optimal policy 1', 'optimal policy 2','optimal policy 3')
xlabel('Arrival Rate (\lambda 1/sec.)'), ylabel('Availiability')
xlim([1/300, 1/50])
subplot(1,2,2), plot(la,A_sysopt1(:,2), la,A_sysopt2(:,2), '-+', la,A_sysopt3(:,2))
title('\nu_1 = 0.01'), xlabel('Arrival Rate (\lambda 1/sec.)')
ylabel('Availiability'), xlim([1/300, 1/50])

%% plot of avail 1 vs. avail 2
figure(3)
subplot(1,2,1)
plot(la,A_sysopt1(:,1),'-.r', la,A_sysopt2(:,1), '-xg',...
        la,A_sysopt3(:,1),'-ob', la,A_sysopt1_2(:,1),'r', la,...
        A_sysopt2_2(:,1), 'g', la,A_sysopt3_2(:,1),'b')
title({'\omega=0.0004, \mu_1=1/60, \mu_2=1.5\mu_1, \mu_3=1.5\mu_2,...
        \nu_0=0.0005, \nu_1=0.001 to 0.01, \nu_2=1.5\nu_1, \nu_3=1.5\nu_2';...
        'AVAILABILITY VS. ARRIVAL RATE';'\nu_1 = 0.001'})
legend('optimal 1 (avail 1)', 'optimal 2 (avail 1)','optimal 3 (avail 1)',...
        'optimal 1 (avail 2)', 'optimal 2 (avail 2)', 'optimal 3 (avail 2)')
xlabel('Arrival Rate (\lambda 1/sec.)'), ylabel('Availiability')
xlim([1/300, 1/50])
subplot(1,2,2)
plot(la,A_sysopt1(:,2),'-.r', la,A_sysopt2(:,2), '-xg', la,A_sysopt3(:,2),...
        '-ob', la,A_sysopt1_2(:,2), 'r',la,A_sysopt2_2(:,2), 'g', la,...
        A_sysopt3_2(:,2),'b')
```

8.4 Expected response time

```
    state = [ 0      0      0      0
              0      4      0      0
              0      4      4      0
              1      1      0      0
              1      1      4      0
              1      1      4      4
              1      2      2      0
              1      2      2      4
              1      3      3      3
              2      1      1      0
              2      1      1      4
              2      1      4      4
              2      2      2      1
              2      2      2      4
              2      3      3      3
              3      1      1      1
              3      1      1      4
              3      1      4      4
              3      2      2      1
              3      2      2      4
              3      3      3      3
              1      2      5      0
              1      2      5      4
              2      2      5      1
              3      2      5      1
              1      3      3      5
              1      3      5      5
              2      3      3      5
              2      3      5      5
              2      2      5      4
              3      3      3      5
              3      3      5      5
              3      2      5      4
              0      4      4      4
              1      4      4      4
              2      4      4      4
              3      4      4      4];

%% parameters

la=linspace(1/300, 0.02, 30);
nu1=linspace(1/1000, 1/100, 2);
nu0=0.0005; nu2=1.5*nu1; nu3=1.5*nu2;
mu1=1/60; mu2=1.5*mu1; mu3=1.5*mu2;
w=0.0004;

for i=1:length(la)
    for j=1:length(nu1)
        setpara(mu1, mu2, mu3, nu0, nu1(j), nu2(j), nu3(j), la(i), w);
        failure = [nu0 nu0 nu0 nu1 nu1 nu1 nu1 nu1 nu1 nu2 nu2 nu2 nu2 nu2...
            nu2 nu3 nu3 nu3 nu3 nu3 nu3 nu1 nu1 nu2 nu3 nu1 nu1 nu2 nu2 nu2...
```

```
              nu3 nu3 nu3  0  0  0  0];

          Q =Qnew1;                               % greedy case
          Q(:,length(Q)) = [ones(1,length(Q))];
          p_ss = [zeros(1,(length(Q)-1)), 1]*inv(Q);
          T=p_ss*state(:,1);                      % expected number of targets
          R(i,j)=T/((3-T)*la(i));                 % expected response time

          Q2=Qnew2;                               % conservative case
          Q2(:,length(Q2)) = [ones(1,length(Q2))];
          p_ss2 = [zeros(1,(length(Q2)-1)), 1]*inv(Q2);
          T2=p_ss2*state(:,1);                    % expected number of targets
          R2(i,j)=T2/((3-T2)*la(i));              % expected response time

          Qag=Qnewag;                             % aggressive case
          Qag(:,length(Qag)) = [ones(1,length(Qag))];
          p_ssag = [zeros(1,(length(Qag)-1)), 1]*inv(Qag);
          Tag=p_ssag*state(:,1);                  % expected number of targets
          Rag(i,j)=Tag/((3-Tag)*la(i));           % expected response time

          Qopt1=Qnewopt1;                         % optimal 1
          Qopt1(:,length(Qopt1)) = [ones(1,length(Qopt1))];
          p_ss_opt1 = [zeros(1,(length(Qopt1)-1)), 1]*inv(Qopt1);
          Topt1=p_ss_opt1*state(:,1);             % expected number of targets
          Ropt1(i,j)=Topt1/((3-Topt1)*la(i)); % expected response time

          Qopt2=Qnewopt2;                         % optimal 2
          Qopt2(:,length(Qopt2)) = [ones(1,length(Qopt2))];
          p_ss_opt2 = [zeros(1,(length(Qopt2)-1)), 1]*inv(Qopt2);
          Topt2=p_ss_opt2*state(:,1);             % expected number of targets
          Ropt2(i,j)=Topt2/((3-Topt2)*la(i)); % expected response time

          Qopt3=Qnewopt3;                         % optimal 3
          Qopt3(:,length(Qopt3)) = [ones(1,length(Qopt3))];
          p_ss_opt3 = [zeros(1,(length(Qopt3)-1)), 1]*inv(Qopt3);
          Topt3=p_ss_opt3*state(:,1);             % expected number of targets
          Ropt3(i,j)=Topt3/((3-Topt3)*la(i)); % expected response time

      end,end

  % response time under the breakdown condition of servers
  % p=10; % assume 10 customers have completed the service.
  %         R=(R*p+1/w*ones(30,2))/p;
  %         R2=(R2*p+1/w*ones(30,2))/p;
  %         Rag=(Rag*p+1/w*ones(30,2))/p;
  %         Ropt1=(Ropt1*p+1/w*ones(30,2))/p;
  %         Ropt2=(Ropt2*p+1/w*ones(30,2))/p;
  %         Ropt3=(Ropt3*p+1/w*ones(30,2))/p;

  %% response time vs. arrival rate

```

```
figure(1)
subplot(1,2,1)
plot(la,R2(:,1), '-o', la,R(:,1), '-x', la,Rag(:,1), '--', la,Ropt1(:,1),...
     '-.', la,Ropt2(:,1), '-+', la, Ropt3(:,1))
title({'\omega=0.0004, \mu_1=1/60, \mu_2=1.5\mu_1, \mu_3=1.5\mu_2,...
        \nu_0=0.0005, \nu_1=0.001 to 0.01, \nu_2=1.5\nu_1, \nu_3=1.5\nu_2';...
        'RESPONSE TIME VS. FAILURE RATE';'\nu_1 = 0.001'})
ylabel('Response Time (sec.)'), xlim([1/300, 1/50])

subplot(1,2,2)
plot(la,R2(:,2), '-o', la,R(:,2), '-x', la,Rag(:,2), '--', la,Ropt1(:,2),...
    '-.', la,Ropt2(:,2), '-+',la, Ropt3(:,2))
legend('conservative','greedy=optimal 4','aggressive','optimal 1',...
        'optimal 2','optimal 3')
title('\nu_1 = 0.02'), xlabel('Arrival Rate (\lambda 1/sec.)')
ylabel('Response Time (sec.)'), xlim([1/300, 1/50])
```

8.5 Linear Programming

```
for k = 1:length(state)
     l(k) = state(k,1);        %queue length at each state
  end
%% parameters
la=1/100;          % arrival rate
w=0.0004;          % overhaul rate
nu1=1/1000; nu0=0.0005; nu2=1.5*nu1; nu3=1.5*nu2;        %failure rate
mu1=1/60; mu2=1.5*mu1; mu3=1.5*mu2;                      %service rate
rho = 3*(mu1+mu2+mu3+la+nu1+nu2+nu3)+w;                  %uniform rate
beta = 3;                         % discount factor
alpha = rho/(beta+rho);           % discount factor for equivalent Discrete Markov

% number of failed servers in each state
m = [0 1 2 0 1 2 0 1 0 0 1 2 0 1 0 0 1 2 0 1 0 1 2 1 1 1 2 1 2 2 1 2 2 3 3 3 3];
%states would lead to system failure
n = [0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 1 1 0 1 1 0 0 0 0];
p = [3*nu0 2*nu0 nu0 3*nu1 2*nu1 nu1 2*nu1 2*nu1 3*nu1 3*nu2...
    2*nu2 nu2 2*nu2 2*nu2 3*nu2 3*nu3 2*nu3 nu3 2*nu3 2*nu3...
    3*nu3 nu1 nu1 nu2 nu3 2*nu1 nu1 2*nu2 nu2 nu2 2*nu3 nu3 nu3 0 0 0 0];

 step_cost = m;     %cost of failed servers
% step_cost = n/w ;  %cost of replenish
% step_cost = p;      %cost of failure rate
% step_cost = l;     %cost of queue length

setpara(mu1, mu2, mu3, nu0, nu1, nu2, nu3, la, w);
Q1 = Qmatrix(1,0,0);
Q2 = Qmatrix(0,1,0);
Q3 = Qmatrix(0,0,1);
P1=eye(37)+Q1/rho; P2=eye(37)+Q2/rho; P3=eye(37)+Q3/rho;  %P matrices
```

```

%% linear programming
f = -ones(37,1);  %length of f must be same as number of columns of A.

A = -alpha*[P1-eye(37)/alpha; P2-eye(37)/alpha;
    P3(1,1)-1/alpha P3(1,2:37);
    P3(3,1:2) P3(3,3)-1/alpha P3(3,4:37);
    P3(5,1:4) P3(5,5)-1/alpha P3(5,6:37);
    P3(6,1:5) P3(6,6)-1/alpha P3(6,7:37);
    P3(8,1:7) P3(8,8)-1/alpha P3(8,9:37);
    P3(9,1:8) P3(9,9)-1/alpha P3(9,10:37);
    P3(10,1:9) P3(10,10)-1/alpha P3(10,11:37);
    P3(11,1:10) P3(11,11)-1/alpha P3(11,12:37);
    P3(12,1:11) P3(12,12)-1/alpha P3(12,13:37);
    P3(15,1:14) P3(15,15)-1/alpha P3(15,16:37);
    P3(16,1:15) P3(16,16)-1/alpha P3(16,17:37);
    P3(17,1:16) P3(17,17)-1/alpha P3(17,18:37);
    P3(18,1:17) P3(18,18)-1/alpha P3(18,19:37);
    P3(21,1:20) P3(21,21)-1/alpha P3(21,22:37);
    P3(23,1:22) P3(23,23)-1/alpha P3(23,24:37);
    P3(26,1:25) P3(26,26)-1/alpha P3(26,27:37);
    P3(27,1:26) P3(27,27)-1/alpha P3(27,28:37);
    P3(29,1:28) P3(29,29)-1/alpha P3(29,30:37);
    P3(30,1:29) P3(30,30)-1/alpha P3(30,31:37);
    P3(32,1:31) P3(32,32)-1/alpha P3(32,33:37);
    P3(33,1:32) P3(33,33)-1/alpha P3(33,34:37);
    P3(34,1:33) P3(34,34)-1/alpha P3(34,35:37);
    P3(35,1:34) P3(35,35)-1/alpha P3(35,36:37);
    P3(36,1:35) P3(36,36)-1/alpha P3(36,37);
    P3(37,1:36) P3(37,37)-1/alpha];

b =[step_cost step_cost step_cost(1) step_cost(3) step_cost(5)...
    step_cost(6) step_cost(8) step_cost(9) step_cost(10) step_cost(11)...
    step_cost(12) step_cost(15) step_cost(16) step_cost(17) step_cost(18)...
    step_cost(21) step_cost(23) step_cost(26) step_cost(27) step_cost(29)...
    step_cost(30) step_cost(32) step_cost(33) step_cost(34) step_cost(35)...
    step_cost(36) step_cost(37)]';  %length b must be = number of rows of A.

lb = zeros(37,1);
[x,fval,exitflag,output,lambda] = linprog(f,A,b,[],[],lb);
%% comparison
for i=1:37
    v1(i)=step_cost(i)+alpha*(P1(i,:)*x);
    v2(i)=step_cost(i)+alpha*(P2(i,:)*x);
    v3(i)=step_cost(i)+alpha*(P3(i,:)*x);
    a1(i)=v1(i)-x(i);
    a2(i)=v2(i)-x(i);
    a3(i)=v3(i)-x(i);
end

%display optimal cost and cost from the three control sets
```

```
disp('  opt_value      v1        v2         v3')
disp([x  v1' v2' v3'])

% determine the control policy for each state by
% checking out the smallest value among a1 a2 a3
disp('control policy: ')
disp('u1   u2   u3')
for i=1:37
    if (abs(a1(i)') > abs(a3(i)')) & (abs(a2(i)') > abs(a3(i)'))
        disp(' 0    0    1')
    elseif (abs(a1(i)') > abs(a2(i)')) & (abs(a3(i)') > abs(a2(i)'))
        disp(' 0    1    0')
    elseif (abs(a2(i)') > abs(a1(i)')) & (abs(a3(i)') > abs(a1(i)'))
        disp(' 1    0    0')
    else disp(' 0    0    0')
    end
end
```

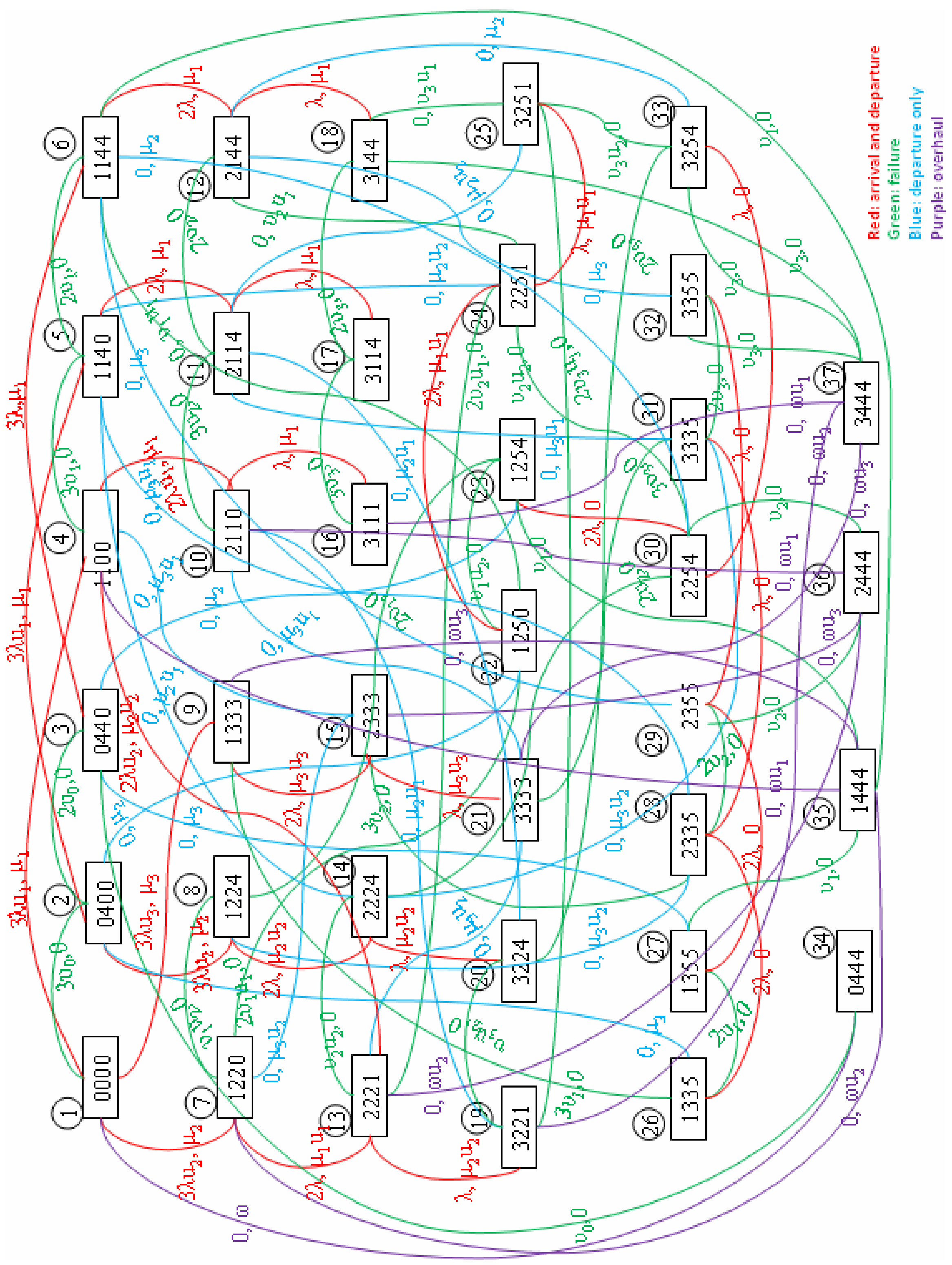

Figure 8.1: Transition rate diagram

9 MATLAB codes and simulations of the airborne Network

9.1 Closed queuing network (reducible)

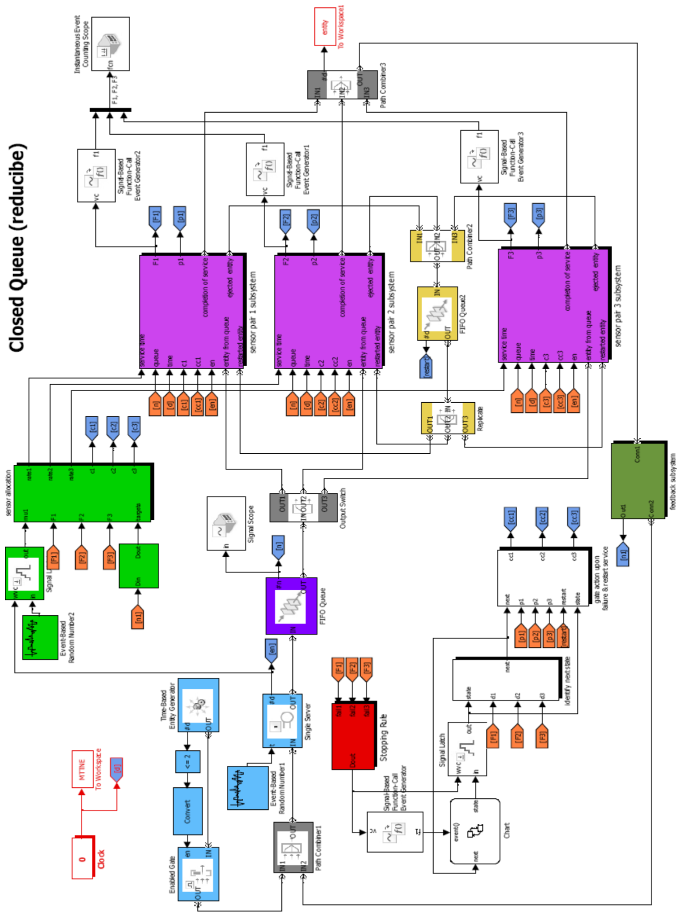

Figure 9.1: Top level Simulink block diagram of simulation model 1

9.1.1 Stateflow diagram of the system state (reducible)

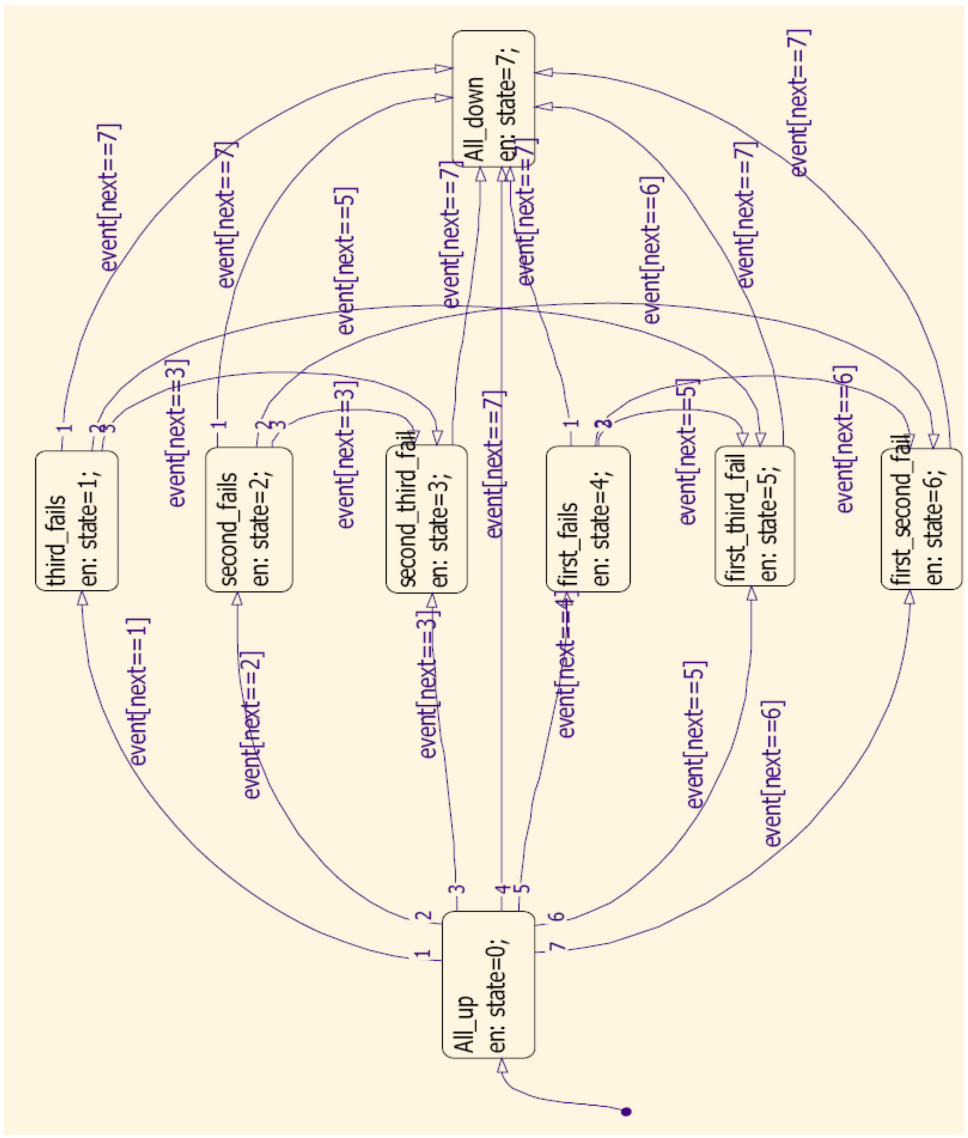

Figure 9.2: System Stateflow diagram of simulation model 1

9.1.2 Stopping rule

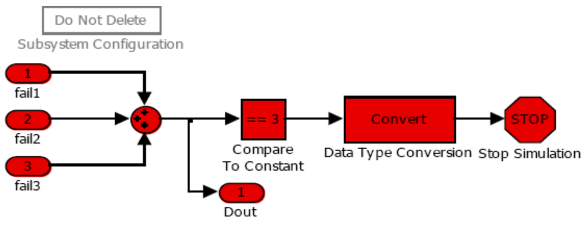

Figure 9.3: Stopping rule of simulation model 1

9.1.3 Computing total number of targets in the system

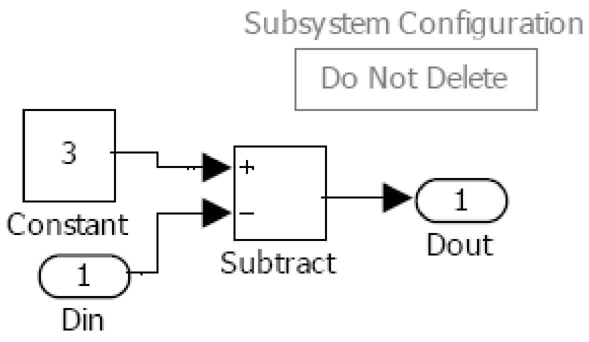

Figure 9.4: Computing total number of targets

9.1.4 Feedback subsystem

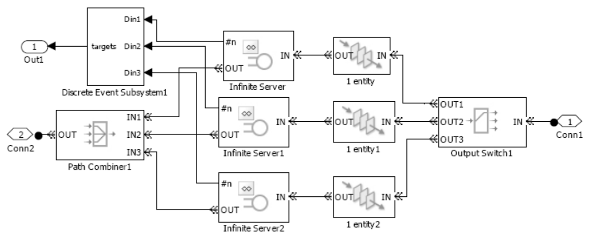

Figure 9.5: Lower portion subsystem

9.1.5 Identify system's next state

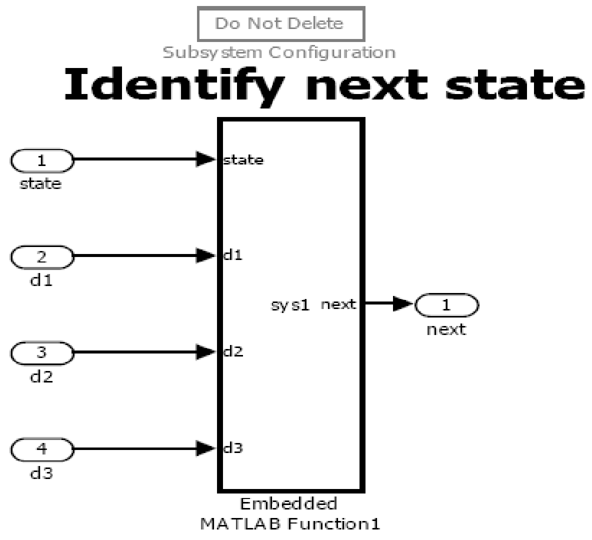

Figure 9.6: Identify next state

The following is the embedded MATLAB code for the next state subsystem:

```
function next = sys1(state,d1,d2,d3)
persistent last_state;

%  states:(d1,d2,d3), 0 represents sensor up, 1 represents sensor down.
%      0  --  000
%      1  --  001
%      2  --  010
%      3  --  011
%      4  --  100
%      5  --  101
%      6  --  110
%      7  --  111

% initialize output
next=0;
switch state
    case 0
        xs=[d1;d2;d3];
        states=[4 2 1];
      if xs(1)==1 && xs(2)==1 && xs(3)==1
          next=7;
      elseif xs(1)==1 && xs(2)==1 && xs(3)==0
          next=6;
      elseif xs(1)==1 && xs(2)==0 && xs(3)==1
          next=5;
      elseif xs(1)==0 && xs(2)==1 && xs(3)==1
          next=3;
      elseif xs(1)==0 && xs(2)==0 && xs(3)==0
          next=0;
      else [x ind]=max(xs);
        next=states(ind);
      end

    case 1
        xs=[d2; d1; -inf];
        states=[3 5 0];
        if xs(1)==0 && xs(2)==0
            next=1;
        elseif xs(1)==1 && xs(2)==1
            next=7;
        else [x ind]=max(xs);
            next=states(ind);
        end

    case 2
        xs=[d3; d1; -inf];
        states=[3 6 0];
        if xs(1)==0 && xs(2)==0
            next=2;
        elseif xs(1)==1 && xs(2)==1
            next=7;
        else [x ind]=max(xs);
        next=states(ind);
        end

    case 4
        xs=[d3; d2; -inf];
        states=[5 6 0];
        if xs(1)==0 && xs(2)==0
            next=4;
        elseif xs(1)==1 && xs(2)==1
            next=7;
        else [x ind]=max(xs);
          next=states(ind);
        end

    case 3
        if d1==1
            next=7; end
    case 5
        if d2==1
            next=7; end
    case 6
        if d3==1
            next=7; end
    case 7
```

```
        next=7;
end
```

9.1.6 Service rate generator

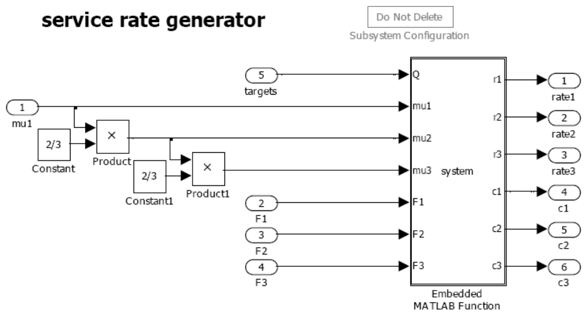

Figure 9.7: Service rate generator

```
function [r1,r2,r3,c1,c2,c3] = system(Q,mu1,mu2,mu3,F1,F2,F3)
%   Q = queue length
%   F1, F2, F3: state of sensors. 0-->UP, 1-->DOWN
%   c1,c2,c3: enable gate signal
%   This script contains four control policies. Run the simulation
%   at each control policy and plot the results together.
%-----------------------------------------------------------

%%GREEDY
%     if F1==0 && F2==0 && F3==0
%         r1 = mu3; r2=mu3; r3=mu3;
%         c1=1; c2=0; c3=0;
%     elseif F1==0 && F2==0 && F3==1
%         r1 = mu2; r2=mu2; r3=0;
%         c1=1; c2=0; c3=0;
%     elseif F1==0 && F2==1 && F3==0
%         r1 = mu2; r2=0; r3=mu2;
%         c1=1; c3=0; c2=0;
%     elseif F1==1 && F2==0 && F3==0
%         r2 =mu2; r1=0; r3=mu2;
%         c2=1; c3=0; c1=0;
%     elseif F1==0 && F2==1 && F3==1
%         r1 = mu1; r2=0; r3=0;
%         c1=1; c2=0; c3=0;
%     elseif F1==1 && F2==0 && F3==1
%         r2 = mu1; r1=0; r3=0;
%         c2=1; c1=0; c3=0;
%     elseif F1==1 && F2==1 && F3==0
%         r3 = mu1; r1=0; r2=0;
%          c3=1; c1=0; c2=0;
%      else r1=0; r2=0; r3=0;
%          c1=0; c2=0; c3=0;
%      end
%%--------------------------------------------------------

% %% CONSERVATIVE
%  if F1==0 && F2==0 && F3==0
%          r1 = mu1; r2 = mu1; r3 =mu1;
%          c1=1; c2=1; c3=1;
%      elseif F1==0 && F2==0 && F3==1
%          r1 = mu1; r2= mu1; r3 = mu1;
%          c1=1; c2=1; c3=0;
%      elseif F1==0 && F2==1 && F3==0
%          r1 = mu1; r3 = mu1; r2 =mu1;
%          c1=1; c3=1; c2=0;
%      elseif F1==1 && F2==0 && F3==0
%          r2 =mu1; r3 = mu1; r1 = mu1;
%          c2=1; c3=1; c1=0;
%      elseif F1==0 && F2==1 && F3==1
%          r1 = mu1; r2 = mu1; r3 = mu1;
%          c1=1; c2=0; c3=0;
%      elseif F1==1 && F2==0 && F3==1
%          r2 = mu1; r1 = mu1; r3 = mu1;
%          c2=1; c1=0; c3=0;
%      elseif F1==1 && F2==1 && F3==0
%          r3 = mu1; r1 = mu1; r2 = mu1;
%          c3=1; c1=0; c2=0;
%      else r1=0; r2=0; r3=0;
%          c1=0; c2=0; c3=0;
%  end
%%--------------------------------------------------------

% AGGRESSIVE
% if F1==0 && F2==0 && F3==0 && Q==0
%      r1 = mu3; r2=mu3; r3=mu3;
%          c1=1; c2=1; c3=1;
% elseif F1==0 && F2==0 && F3==0 && Q==1
%      r1 = mu3; r2=mu3; r3=mu3;
%          c1=1; c2=0; c3=0;
% elseif F1==0 && F2==0 && F3==0 && Q==2
%      r1 = mu2; r2=mu2; r3=mu1;
%          c1=1; c2=0; c3=1;
% elseif F1==0 && F2==0 && F3==0 && Q≥3
%      r1 = mu1; r2=mu1; r3=mu1;
%          c1=1; c2=1; c3=1;
%
% elseif F1==0 && F2==0 && F3==1 && Q==0
%      r1 = mu2; r2=mu2; r3=0;
%          c1=1; c2=1; c3=0;
% elseif F1==0 && F2==0 && F3==1 && Q==1
%     r1 = mu2; r2=mu2; r3=0;
%         c1=1; c2=0; c3=0;
% elseif F1==0 && F2==0 && F3==1 && Q==2
%     r1 = mu1; r2=mu1; r3=mu1;
%         c1=1; c2=1; c3=0;
% elseif F1==0 && F2==0 && F3==1 && Q≥3
%     r1 = mu1; r2=mu1; r3=mu1;
%         c1=1; c2=1; c3=0;
%
% elseif F1==0 && F2==1 && F3==0 && Q==0
%     r1 = mu2; r2=0; r3=mu2;
%         c1=1; c3=0; c2=1;
% elseif F1==0 && F2==1 && F3==0 && Q==1
%     r1 = mu2; r2=0; r3=mu2;
%         c1=1; c3=0; c2=0;
% elseif F1==0 && F2==1 && F3==0 && Q==2
%     r1 = mu1; r2=0; r3=mu1;
%         c1=1; c3=1; c2=0;
% elseif F1==0 && F2==1 && F3==0 && Q≥3
%     r1 = mu1; r2=0; r3=mu1;
%         c1=1; c3=1; c2=0;
%
% elseif F1==1 && F2==0 && F3==0 && Q==0
%         r2 =mu2; r1=0; r3=mu2;
%         c2=1; c3=1; c1=0;
% elseif F1==1 && F2==0 && F3==0 && Q==1
%         r2 =mu2; r1=0; r3=mu2;
%         c2=1; c3=0; c1=0;
% elseif F1==1 && F2==0 && F3==0 && Q==2
%         r2 =mu1; r1=0; r3=mu1;
%         c2=1; c3=1; c1=0;
% elseif F1==1 && F2==0 && F3==0 && Q≥3
%         r2 =mu1; r1=0; r3=mu1;
%         c2=1; c3=1; c1=0;
%
% elseif F1==0 && F2==1 && F3==1
%         r1 = mu1; r2=0; r3=0;
%         c1=1; c2=0; c3=0;
%
% elseif F1==1 && F2==0 && F3==1
%         r2 = mu1; r1=0; r3=0;
%         c2=1; c1=0; c3=0;
%
% elseif F1==1 && F2==1 && F3==0
%         r3 = mu1; r1=0; r2=0;
%         c3=1; c1=0; c2=0;
% else r1=0; r2=0; r3=0;
%         c1=0; c2=0; c3=0;
% end
%------------------------------------------------------------------
%%Optimal 1
```

```
    if F1==0 && F2==0 && F3==0 && Q==0
        r1 = mu2; r2=mu2; r3=mu2;
        c1=1; c2=1; c3=1;
    elseif F1==0 && F2==0 && F3==0 && Q==1
        r1 = mu2; r2=mu2; r3=mu1;
        c1=1; c2=0; c3=1;
    elseif F1==0 && F2==0 && F3==0 && Q==2
         r1 = mu2; r2=mu2; r3=mu1;
         c1=1; c2=0; c3=1;
    elseif F1==0 && F2==0 && F3==0 && Q≥3
         r1 = mu2; r2=mu2; r3=mu1;
         c1=1; c2=0; c3=1;

    elseif F1==0 && F2==0 && F3==1 && Q==0
        r1 = mu2; r2 =mu2; r3 = mu1;
        c1=1; c2=0; c3=0;
    elseif F1==0 && F2==0 && F3==1 && Q==1
        r1 = mu2; r2 =mu2; r3 = mu1;
        c1=1; c2=0; c3=0;
    elseif F1==0 && F2==0 && F3==1 && Q≥2
        r1 = mu1; r2 =mu1; r3 = mu1;
        c1=1; c2=1; c3=0;

    elseif F1==0 && F2==1 && F3==0 && Q==0
        r1 = mu2; r2=0; r3=mu2;
        c1=1; c3=0; c2=0;
    elseif F1==0 && F2==1 && F3==0 && Q==1
        r1 = mu2; r2=0; r3=mu2;
        c1=1; c3=0; c2=0;
    elseif F1==0 && F2==1 && F3==0 && Q≥2
        r1 = mu1; r2=0; r3=mu1;
        c1=1; c3=1; c2=0;

    elseif F1==1 && F2==0 && F3==0 && Q==0
        r2 =mu2; r1=0; r3=mu2;
        c2=1; c3=0; c1=0;
    elseif F1==1 && F2==0 && F3==0 && Q==1
        r2 =mu2; r1=0; r3=mu2;
        c2=1; c3=0; c1=0;
    elseif F1==1 && F2==0 && F3==0 && Q≥2
        r2 =mu1; r1=0; r3=mu1;
        c2=1; c3=1; c1=0;
    elseif F1==0 && F2==1 && F3==1
        r1 = mu1; r2=0; r3=0;
        c1=1; c2=0; c3=0;
    elseif F1==1 && F2==0 && F3==1
        r2 = mu1; r1=0; r3=0;
        c2=1; c1=0; c3=0;
    elseif F1==1 && F2==1 && F3==0
        r3 = mu1; r1=0; r2=0;
        c3=1; c1=0; c2=0;
    else r1=0; r2=0; r3=0;
         c1=0; c2=0; c3=0;
   end
```

9.1.7 New allocation for return targets

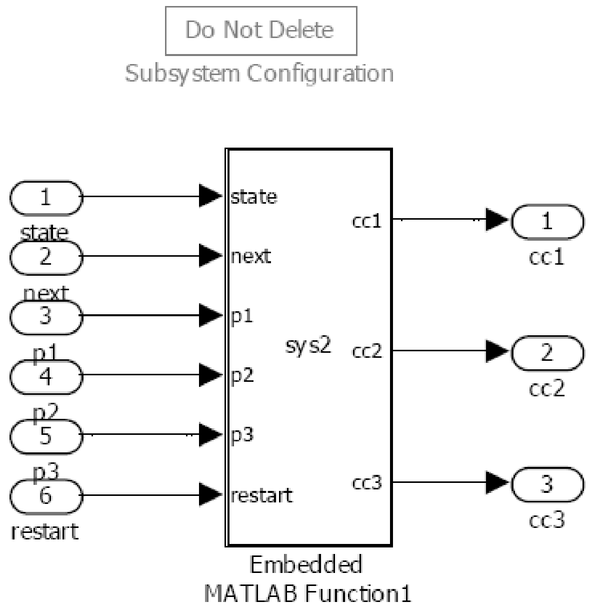

Figure 9.8: New allocation for return targets

```
function [cc1,cc2,cc3] = sys2(state,next,p1,p2,p3,restart)

% p1,p2,p3 are the ejected entities from servers
% Q: upper system queue length, include the ones in service
% state: current state of the system
% next: next state of the system
% cc1,cc2,cc3: signals determine which server serves a restarted entity
% ---------------------------------------------------------------------

if restart ≥1
    if state ==0 && next==1 && p3==1
            cc1=1; cc2=0; cc3=0;
    elseif state==0 && next==2 && p2==1
            cc1=1; cc2=0; cc3=0;
    elseif state==0 && next==4 && p1==1
            cc1=0; cc2=1; cc3=0;

    elseif state ==1 && next==3 && p2==1
            cc1=1; cc2=0; cc3=0;
    elseif state ==1 && next==5 && p1==1
            cc1=0; cc2=1; cc3=0;

   elseif state==2 && next==3 && p3==1
            cc1=1; cc2=0; cc3=0;
    elseif state==2 && next==6 && p1==1
            cc1=0; cc2=0; cc3=1;

    elseif state==4 && next==5 && p3==1
            cc1=0; cc2=1; cc3=0;
    elseif state==4 && next==6 && p2==1
            cc1=0; cc2=0; cc3=1;

    elseif state==3 && next==7
             cc1=0; cc2=0; cc3=0;

    elseif state==5 && next==7
             cc1=0; cc2=0; cc3=0;

    elseif state==6 && next==7
             cc1=0; cc2=0; cc3=0;

    else cc1=0; cc2=0; cc3=0;
    end
else cc1=0; cc2=0; cc3=0;
end
```

9.1.8 Sensor-pair subsystem

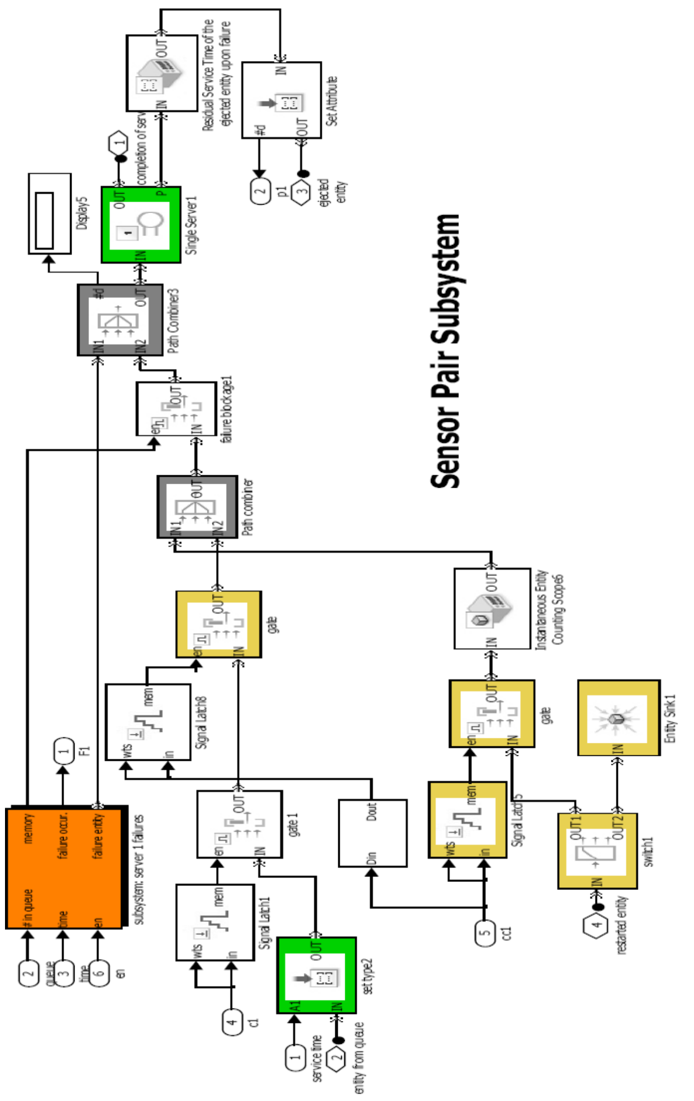

Figure 9.9: Sensor-pair subsystem for simulation model 1

The system has three identity sensor-pairs subsystem.

9.1.9 Failure generation subsystem

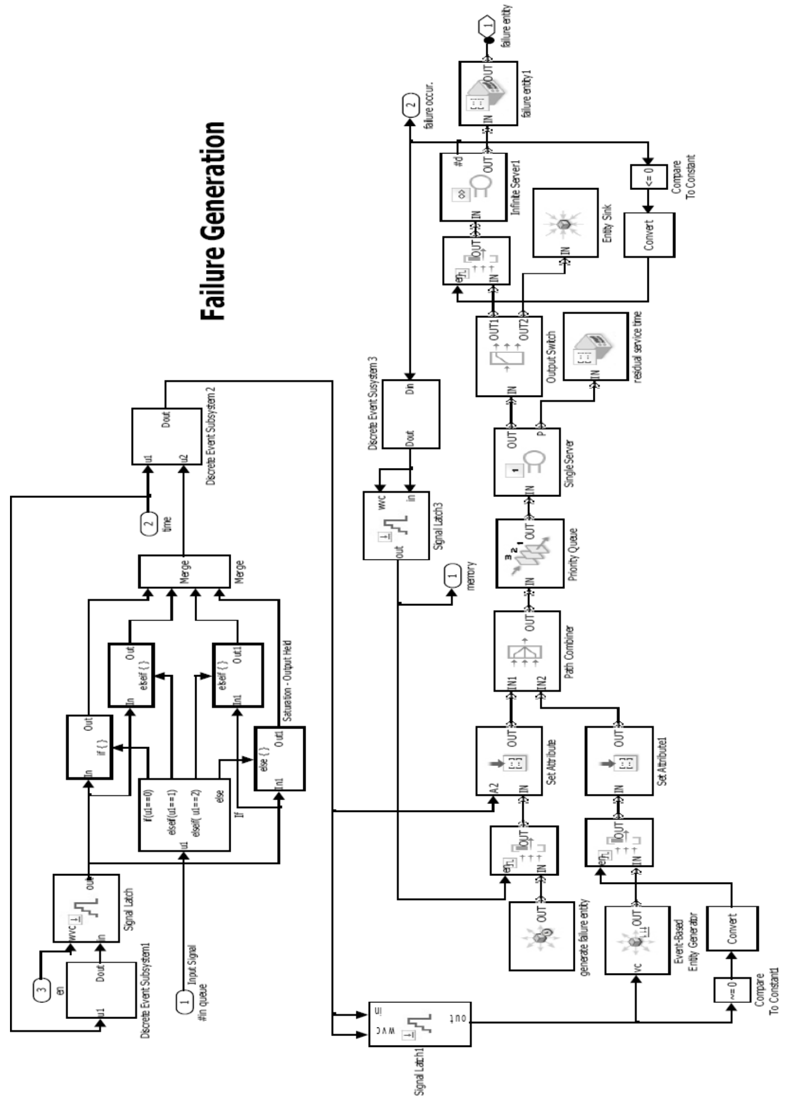

Figure 9.10: Failure generation subsystem

All sensor-pairs have same random failure time; therefore all sensor-pairs subsystems contain the following subsystem.

9.1.9.1 Discrete event subsystem1

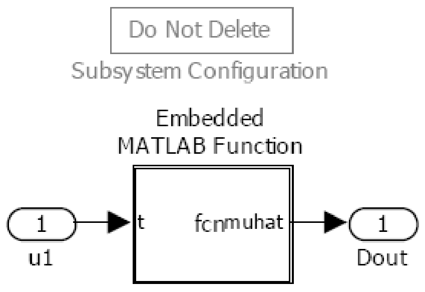

Figure 9.11: Discrete event subsystem1

This block is within the failure generation subsystem, follow code is embedded in the block. The code generates exponential failure time of the sensor-pairs.

```matlab
function muhat = fcn(t)
persistent oldtime;
%initialize output
muhat=2000;
%initialize persistent variable
if isempty(oldtime)
    oldtime=0;
end
%update
if (t>oldtime)
oldtime=t;
muhat= expfit(exprnd(2000,10,1));
end
```

9.1.9.2 Discrete event subsystem 2

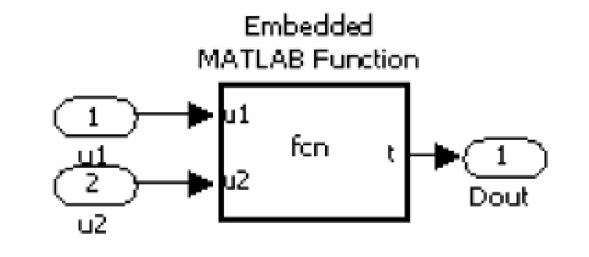

Figure 9.12: Discrete event subsystem 2

The above block is also within failure generation subsystem, following code is embedded in the block which assigns failure time to failure entity.

```
function t = fcn(u1,u2)
persistent oldtime;
%initialize output
t=0;
%initialize persistent variable
if isempty(oldtime)
    oldtime=0;
end
%update
if (u1>oldtime)
oldtime=u1;
end
if u1≥u2
    t=0;
else t=u2-oldtime;
end
```

9.1.9.3 Discrete event subsystem 3

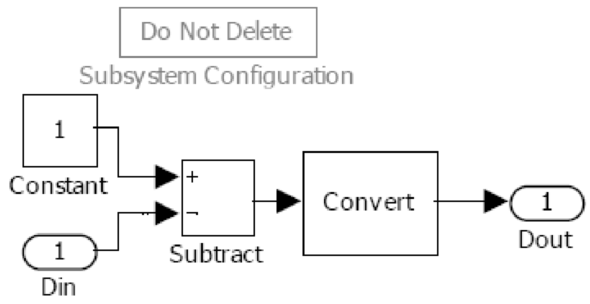

Figure 9.13: Discrete event subsystem 3

If there is an entity exits the server in the failure generation subsystem of a sensor-pair, then that sensor-pair fails. Otherwise, the sensor-pair is still up.

9.2 Irreducible case with system replenishment and with or without channel fading

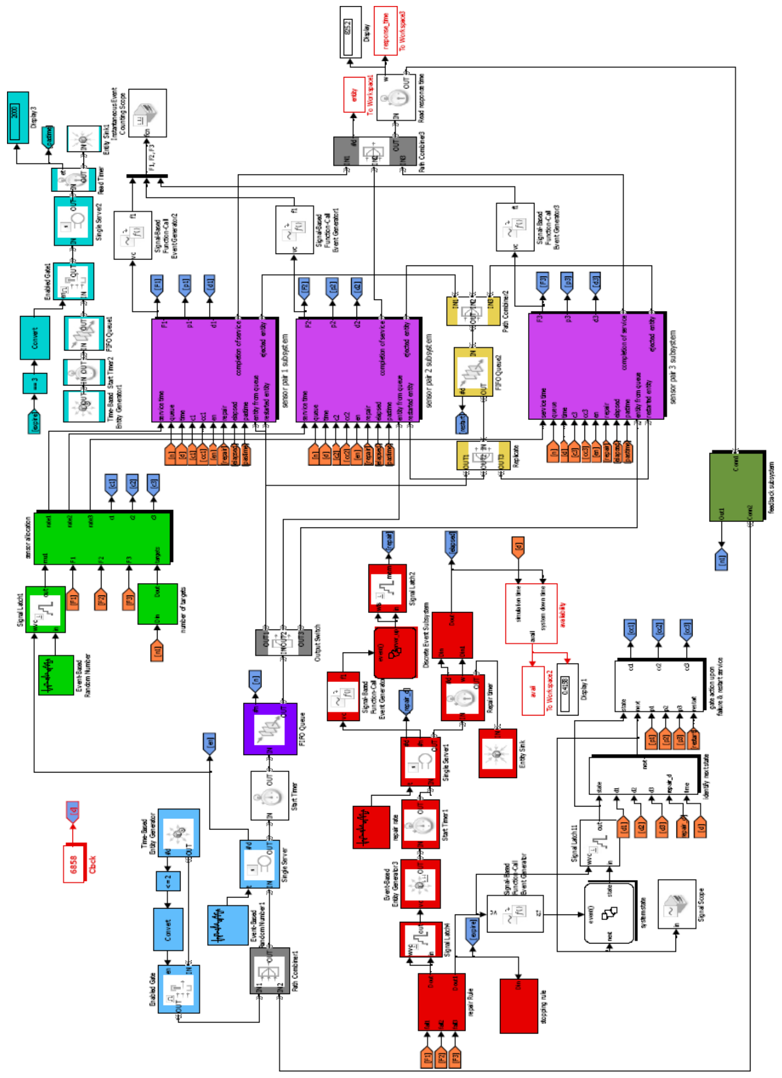

Figure 9.14: Top level Simulink block diagram for simulation model 2 and 3.

9.2.1 Stateflow diagram of the system (irreducible)

The stateflow diagram is similar to fig C.2, except it has a transition from final failure state to initial state.

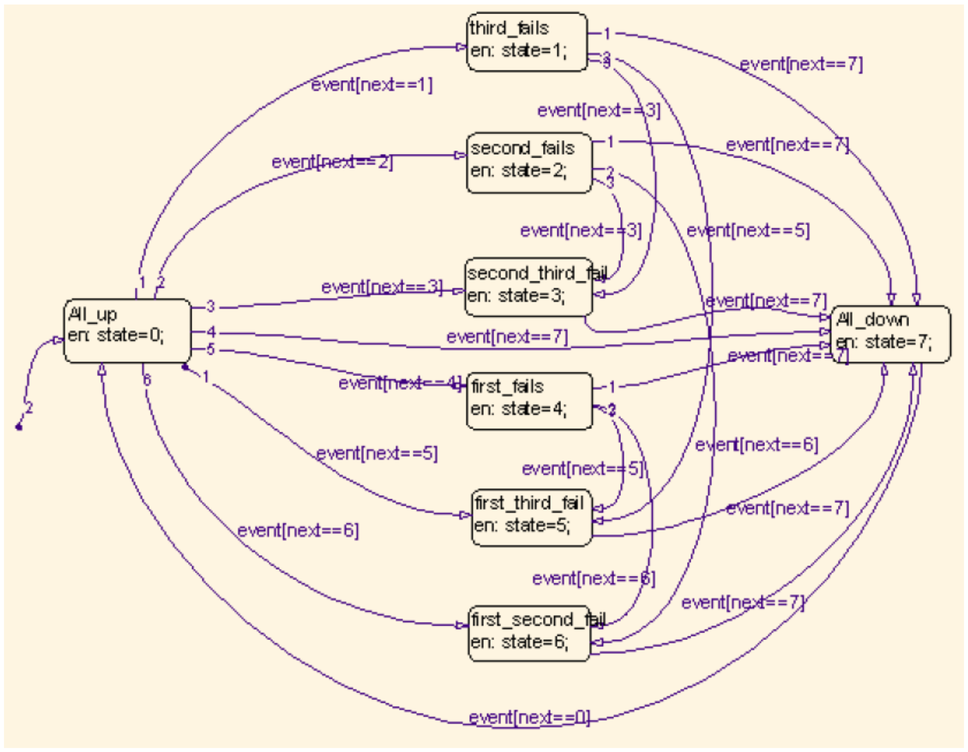

Figure 9.15: System state-flow diagram for simulation model 2 and 3.

9.2.2 System up/down stateflow diagram

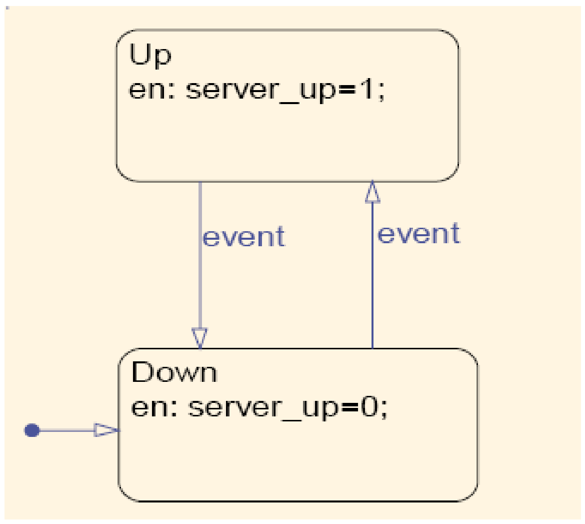

Figure 9.16: State-flow diagram of network status.

9.2.3 Stopping rule (irreducible)

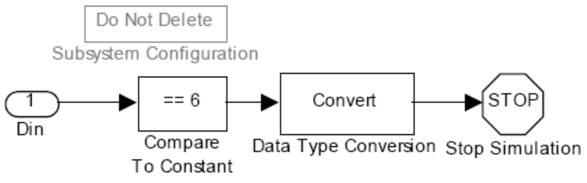

Figure 9.17: Stopping rule for simulation model 2 and 3.

9.2.4 Repairing rule

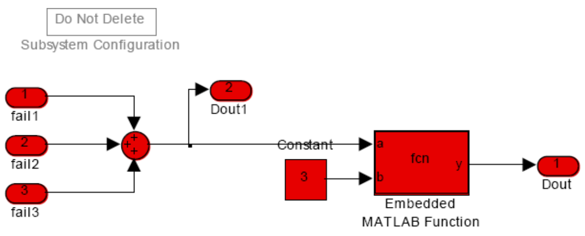

Figure 9.18: Repairing rule of simulation model 2 and 3.

9.2.5 Sensor-pair subsystem (irreducible) without channel fading

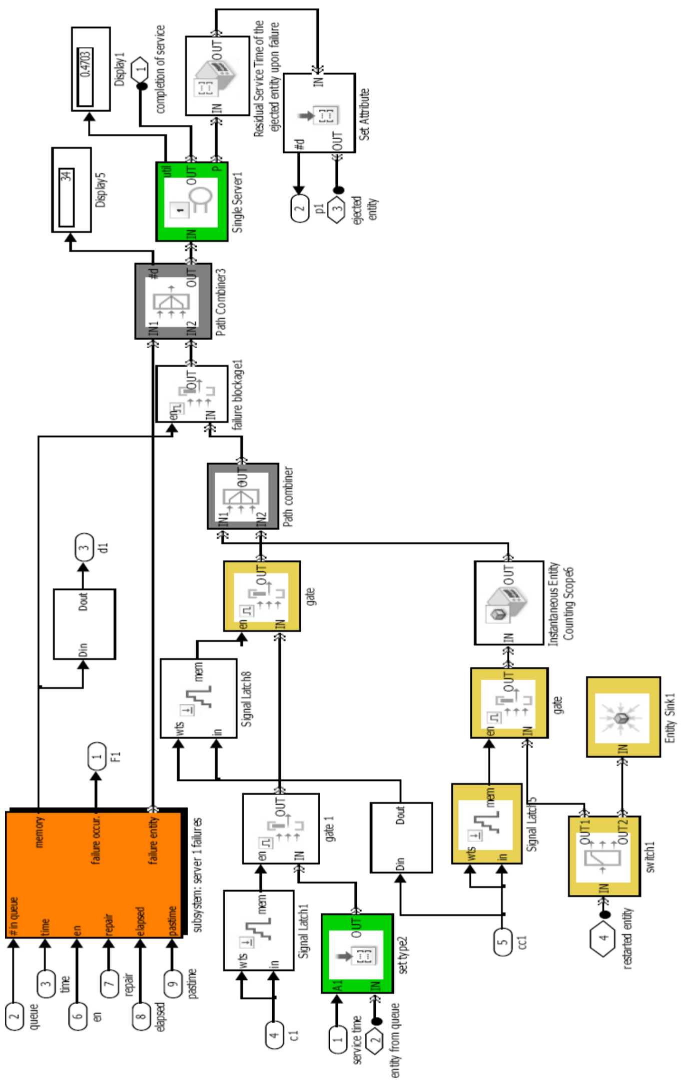

Figure 9.19: Sensor-pair subsystem without channel fading

9.2.6 Failure generation subsystem (irreducible)

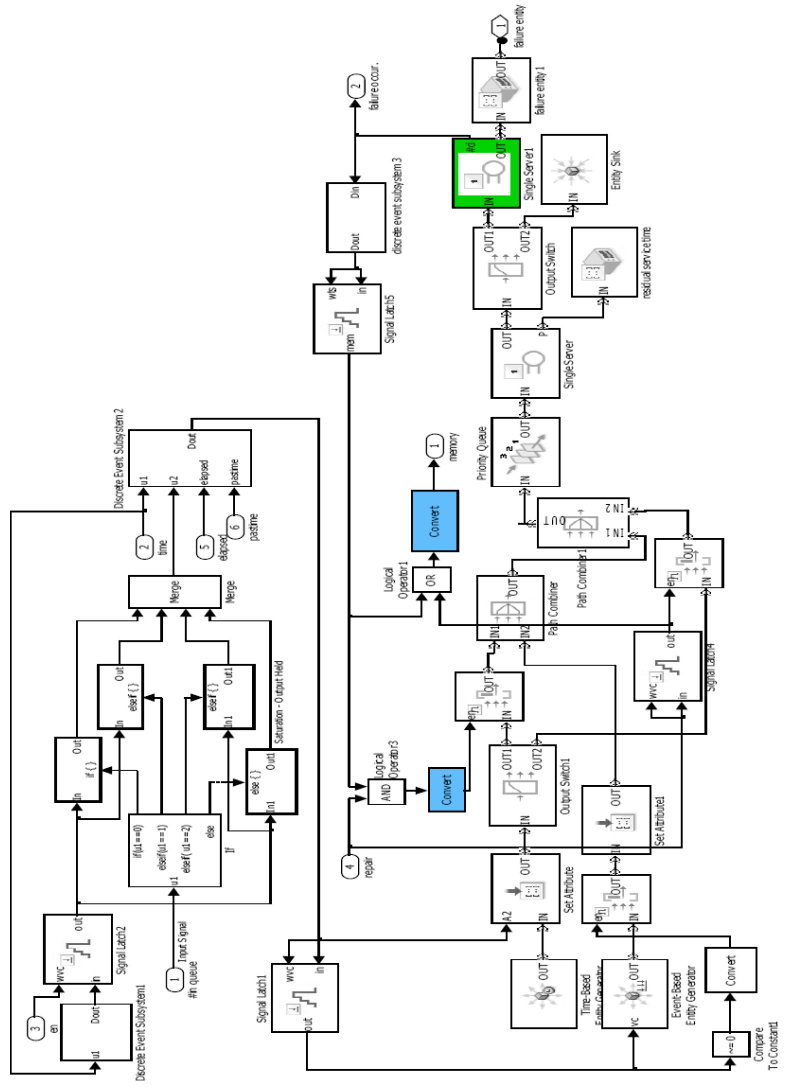

Figure 9.20: Failure generation subsystem for simulation model 2 and 3.

9.2.6.1 Discrete event subsystem 2

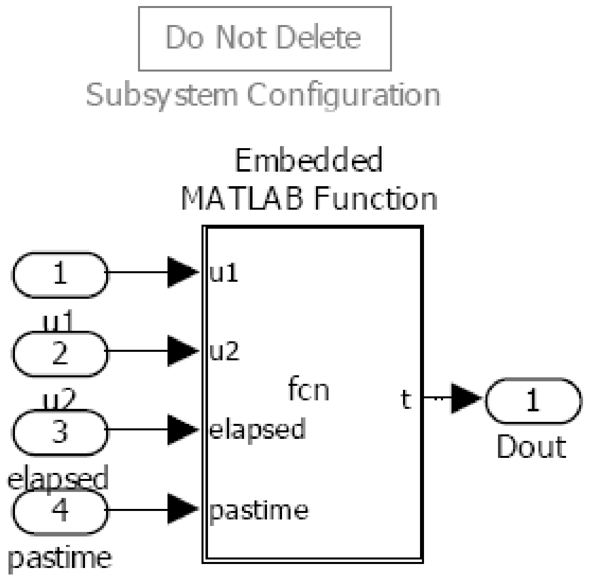

Figure 9.21: This block is within Fig. C.16, the function of this block generates failure time.

```
function t = fcn(u1,u2,elapsed,pastime)
persistent oldtime;
%initialize output
t=0;
%initialize persistent variable
if isempty(oldtime)
    oldtime=0;
end
%update
if (u1>oldtime)
oldtime=u1;
end
T = elapsed+pastime;
if u2 ≤ u1-T
    t=0;
else t=u2-u1+T;
end
```

9.2.6.2 Discrete event subsystem 3

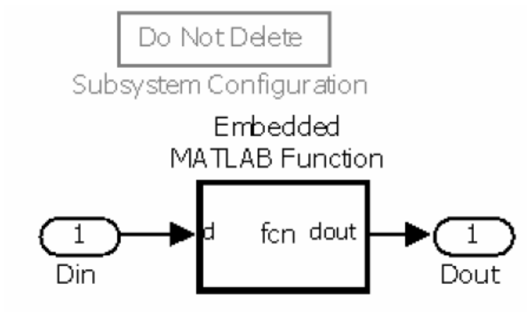

Figure 9.22: Discrete event subsystem 3

```
function dout=fcn(d)

if d==0
    dout=1;
else dout=0;
end
```

9.3 Irreducible case with system replenishment and intermittent channel fading

This model is similar to model 2 except intermittent channel fading exists; the top level block diagram is the same as model 2's. This section illustrates the additional blocks to the sensor-pair subsystem shown in the following figure.

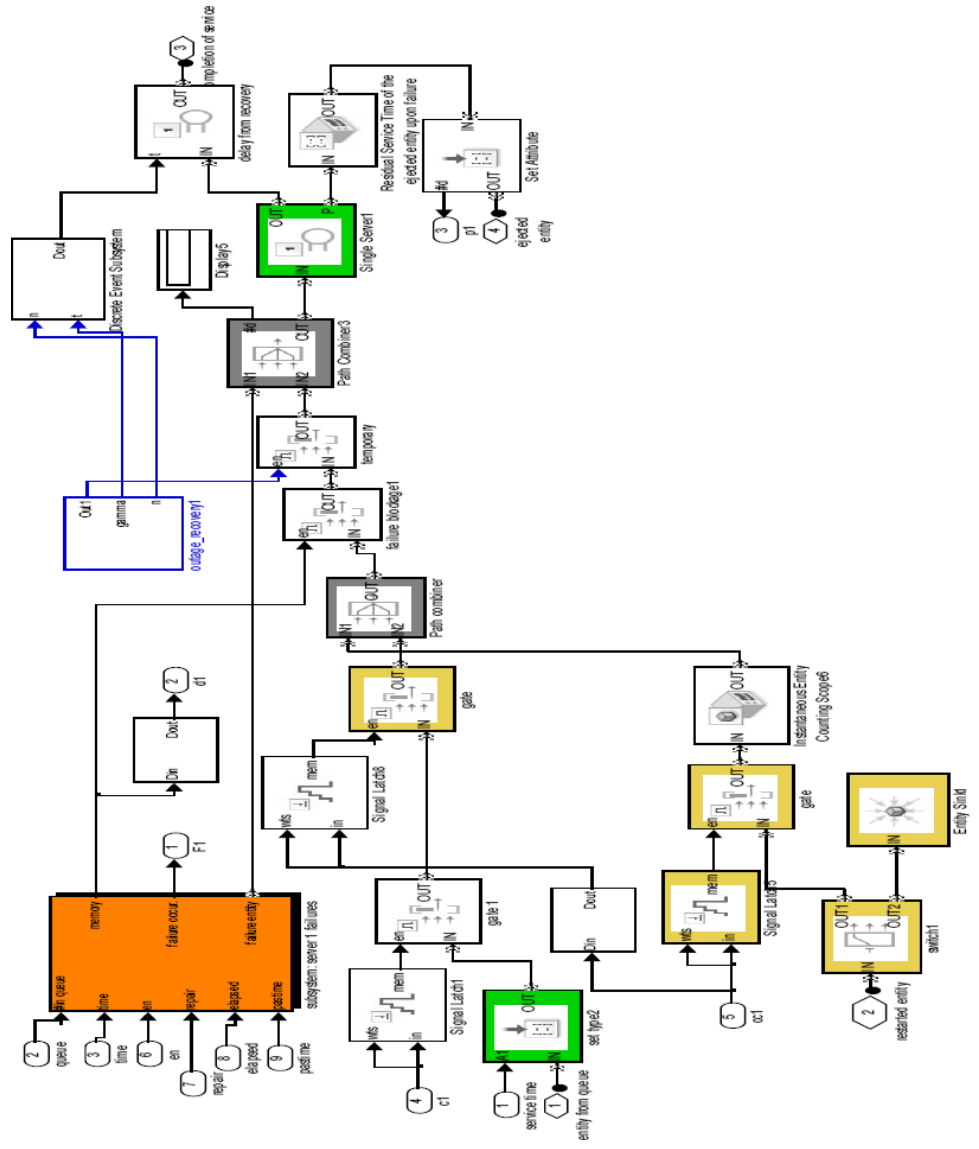

Figure 9.23: Sensor-pair subsystem of simulation model 3

Figure C.18 shows how to setup the temporary outage and how to recovery the loss data for the sensor pairs and figure C.19 determines the recovery rate.

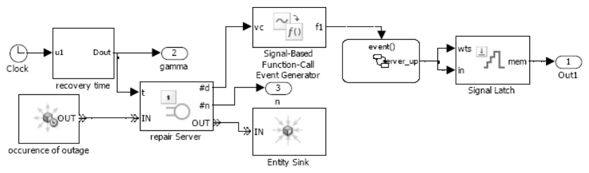

Figure 9.24: Outage and recovery subsystem

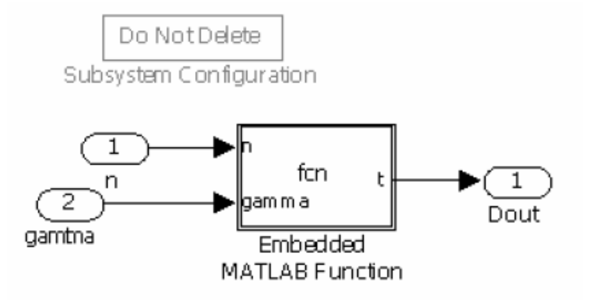

Figure 9.25: Discrete-event subsystem for recovery rate

```
function t = fcn(n,gamma)
if n==0
    t=0;
else t=gamma;
end
```

9.4 Code for running the simulations repeatedly

9.4.1 Initial seed value generator:

```
% Generate a vector of large odd numbers.
newseed = (30000 : 2 : 79999);

% Randomly permute the numbers to avoid always using the same set of seeds.
perm = randperm(length(newseed));
paramname = {'initialseed', 'seed'}; % Parameter names to consider
np = length(paramname);
idx = 1;

for jj=1:np

    % Find blocks that have the parameter with a numerical value
    blocks = find_system(bdroot,'RegExp','on','LookUnderMasks','all',...
    paramname{jj},'\d+');

    % Replace initial seed parameter values with numbers from the vector.
    for kk = 1:length(blocks)
        newseedparamvalue = num2str(newseed(perm(idx)));
        idx = idx + 1;
        set_param(blocks{kk},paramname{jj},newseedparamvalue);
        disp(['Setting parameter to ' newseedparamvalue ' in ' ...
        strrep(blocks{kk},char(10),' ') '.']);
    end
end
```

9.4.2 Run simulation repeated to gather results and varying a parameter

9.4.2.1 1. Mean time to network expiration

```
% execute the following two comments in MATLAB, resave the model, then
% start the simulation.
% set_param('closetest1','PostLoadFcn','')
% set_param('closetest1','CloseFcn','')

clear global all;

load_system('closetest1'); % Load system
nruns = 30; % Number of simulation runs

%initialization
w = zeros(nruns,1);  %MTTNE
d = zeros(nruns,1);  %# of entity departed
opts = simset('SrcWorkspace','Current','DstWorkspace','Current');
h = waitbar(0,'Running simulations. Please wait...Be patient');
 seedarray1 = ceil(rand(nruns,1)*99999)*2+1;
 seedarray2 = ceil(rand(nruns,1)*99999)*2+1;

% Vary the mean arrival rate.
la = linspace(1/300,0.02,4); % Values of mean arrival rate
wavg = zeros(length(la),1);
davg = zeros(length(la),1);
for i = 1:length(la)
% m is a parameter in the random number block, so changing m changes the
% mean arrival rate in the simulation.
    m = la(i);
    disp(['Simulating with mean arrival rate=' num2str(m)]);

% Replicate for each value of m
    for k = 1:nruns
        waitbar(k/nruns,h);
        seedvalue1 = seedarray1(k);
        seedvalue2 = seedarray2(k);
        sim('closetest1',[],opts); % Run simulation.
        w(k) = MTTNE;
        d(k) = entity;
    end
    wavg(i) = mean(w);      % Average for fixed value of m
    davg(i) = mean(d);
end
close(h);
disp('average # of entity departed: ')
disp(davg)
disp(wavg)
%% plot avg. MTTNE
figure;
plot(la,wavg,'-o');
title('Mean Time to Network Failure vs. Arrival Rate')
xlabel('Arrival Rate'), ylabel('MTTNE (sec)')
```

9.4.2.2 Response time and availability

The following code is for design 2, may change the model name for design 3.

```
% execute the following two comments in MATLAB, resave the model, then
% start the simulation.
%set_param('closed_replenishment3','PostLoadFcn','')
%set_param('closed_replenishment3','CloseFcn','')

clear global all;

load_system('closed_replenishment3'); % Load system
nruns = 30; % Number of simulation run

%initialization
R = zeros(nruns,1);  %response time
A = zeros(nruns,1);  %availability
opts = simset('SrcWorkspace','Current','DstWorkspace','Current');
h = waitbar(0,'Running simulations. Please wait...');
 seedarray1 = ceil(rand(nruns,1)*99999)*2+1;
 seedarray2 = ceil(rand(nruns,1)*99999)*2+1;
 seedarray3 = ceil(rand(nruns,1)*99999)*2+1;

la = linspace(1/300,1/50,4); % Values of mean arrival rate
Ravg = zeros(length(la),1);
Aavg = zeros(length(la),1);

% Vary the mean arrival rate.
for i = 1:length(la)
% m is a parameter in the random number block, so changing m
% changes the mean arrival rate in the simulation.
    m = la(i);
    disp(['Simulating with mean arrival rate=' num2str(m)]);

    % Replicate for each value of m
    for k = 1:nruns
        waitbar(k/nruns,h);
        seedvalue1 = seedarray1(k);
        seedvalue2 = seedarray2(k);
        seedvalue3 = seedarray3(k);
        sim('closed_replenishment3',[],opts);  % Run simulation.
        R(k) = response_time;
        A(k) = avail;
    end
    Ravg(i) = mean(R);   % Average for fixed value of R and A
    Aavg(i) = mean(A);
end
close(h)

% plot response time and availability
figure(1), plot(la,Ravg,'-o');
title('Response Time vs. Arrival Rate')
xlabel('Arrival Rate'), ylabel('Response Time (sec)')
figure(2), plot(la,Aavg,'-x');
title('Availability vs. Arrival Rate')
xlabel('Arrival Rate'), ylabel('Availability')
```

10 Symbols, Abbreviations and Acronyms

FDOA	Frequency Difference of Arrival
MTTNE	Mean Time to Network Expiration
TDOA	Time Difference of Arrival
UAV	Unmanned Aerial Vehicle