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THESIS

A KERNEL APPROACH TO THE ESTIMATION OF PERFORMANCE MEASURES IN A HELICOPTER AMBULANCE SERVICE WITH MISSING DATA

by

Ersan GUNES

June 2005

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A KERNEL APPROACH TO THE ESTIMATION OF PERFORMANCE MEASURES IN A HELICOPTER AMBULANCE SERVICE WITH MISSING DATA

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ABSTRACT

We study two different operational scenarios for a regional air ambulance service-company which has bases in Northern California. Two of these bases serve the land areas encompassed roughly in a circular area of radius 100 miles centered in Gilroy and Salinas, respectively; with a large part of their coverage areas reachable from either base. The base in Salinas currently operates one helicopter only from Thursday to Monday, whereas the base in Gilroy operates one helicopter 24/7. The company is considering extending the operation of one helicopter to 24/7 for its Salinas base. In this study we analyze the operational impacts of that extension, and develop a framework that can be applied towards the study of the ambulance assignment problem faced by small operators.

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To my Grandfather Naim and Uncle Husamettin…May they rest in peace.

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EXECUTIVE SUMMARY

This study addresses the helicopter assignment problem faced by CALSTAR, a regional air ambulance service provider that wishes to assess the operational impact of extending its Salinas-based single helicopter operation from a Thursday-through-Monday schedule to 24/7. More specifically, CALSTAR is interested in gaining knowledge about expected changes in helicopter utilization; the number of missions completed, and helicopter response times that would result from expanding its Salinas-based operation.

To solve the problem we gathered flight-log sheets from CALSTAR's Gilroy and Salinas based helicopters for the years 2002, and 2003, and for eleven months of 2004. Although these log sheets include detailed information about complete missions, data for incomplete missions is mostly missing. Furthermore, EMS (Emergency Medical Service) calls that are rejected by a CALSTAR base due to helicopter unavailability are generally not recorded. Another relevant source of data was EMS itself; they provided monthly aggregate demands for air transport for Monterey and Santa Cruz counties and yearly totals for Santa Clara county. A first-order approximation of our problem would discard missed and rejected missions. However, the log-sheets indicate that EMS calls that result in incomplete missions fall in the range 17% to 43%, and, using EMS's data as a measure of overall demand, it can be found that about 3% to 7% of EMS's calls are rejected by CALSTAR. This suggests that incomplete and rejected missions need to be accounted for in our model.

For the purpose of our analysis, missions, rather than patients (there may be multiple patients per mission), are divided into three types. First, "complete flights" are unplanned missions triggered by EMS that occur at a random location where the helicopter picks up the patient and transports her to a regional hospital. If no helicopter is available on base upon receiving the EMS call, the request is rejected and the call is not recorded (i.e., there is no waiting buffer in the queue). Second, we consider "inter-facility" missions, in which a patient is picked up from a local hospital and transported to a more sophisticated hospital. Because there is a contractual relationship between local hospitals and the helicopter-ambulance companies (e.g., CALSTAR), EMS is not involved in these missions. Patients can generally wait up to one hour for helicopter pick-up; in practice, this means that the buffer size is infinite and that transport occurs once a helicopter becomes available. Last, we have the “incomplete” missions. These are unplanned, randomly located missions dispatched by EMS for which the helicopter returns to base without picking up any patient because the air transport is cancelled. Incomplete missions can be triggered by a mechanical failure, adverse weather conditions, EMS cancellation, etc. If no helicopter is available, the call is lost (there is no waiting buffer in the queue).

The steps followed and recorded in the flight log sheet for complete missions are the following. First, a helicopter is dispatched by the base operator upon receipt of an EMS order. After a random amount of time, called the Reaction time, the helicopter departs from base. Next, the helicopter arrives at the scene of the accident and, soon after, there occurs nurse-patient contact. The time elapsed between the departure from base and nurse-patient contact is called the Waiting time. The final steps are departure from the scene, arrival at the hospital, and return to base. We call the cumulative time spent in the latter steps the Service time. All of these steps are illustrated in Figure 5.

Due to the nature of inter-facility missions, the only relevant time measurement recorded in the log-sheet is the total amount of time spent between helicopter take-off and its return to base. These steps are illustrated in Figure 6.

The steps recorded in the flight log-sheet for incomplete missions include only the dispatch times. Therefore, there are two steps: dispatch time (time known), and the time helicopter becomes available (time unknown). The latter is modeled under some reasonable assumptions. These steps are illustrated in Figure 7.

We now briefly discuss the operational measures considered in our study. The window of time that starts at the time of an emergency and finishes when the helicopter reaches the hospital is crucial. Of this time, only the part from Dispatch → Nurse Patient Contact depends on the helicopter allocation policy; we call that time the Response time. From the operator’s perspective the number of complete and inter-facility missions per base per year and the yearly average of helicopter utilization are two other measures of interest, because of their impact on revenues. For any given year, the average helicopter utilization is the ratio of busy times over busy-plus-idle times: this is found separately for the Gilroy-based and the Salinas-based helicopters. Assigning a helicopter 24/7 to the Salinas base will tend to decrease utilizations in both Gilroy and Salinas, although this might be compensated by accepting additional inter-facility missions from local hospitals (which we don't include into our model).

Regarding the data, we needed to analyze the mission arrival process and the variables associated to each mission. For the mission arrival process, we used a denominator-free chi-square goodness-of-fit test. We used full-year 2002 and 2003 data to fit the model, and eleven months of year 2004 data for cross-validation. For mission-dependent variables, we tested their independence through correlation tests, and non-parametrically estimated their density using kernel techniques.

We built a simulation model to study the performance measures of interest. The model was validated against the *real* year 2004 eleven month data (which is the most complete data set) for complete, incomplete and inter-facility missions under the *current configuration*. From that run, we observed that 575 of 609 actual flights (complete and inter-facility) were served by Gilroy, whereas 215 of 202 actual flights were served by Salinas. About 21 flights were 'missed' in that simulation run; we conjecture that these were caused by data-entry errors. A simulation run under the proposed Salinas 24/7 configuration, the same data trace, would have increased the Salinas total number of flights by 61 (assuming no additional inter-facility transport), and Gilroy would have decreased its total by 53. These figures are illustrated in Table 5.

The validity of the estimated randomness associated with mission time variables was checked by using real mission-arrival epochs for eleven months of 2004 and random samples drawn from the *estimated* variables. In that simulation run, 572 (versus 575 with our model and real data) missions are served by Gilroy, whereas 215 (versus 215 with our model and real data) missions are served from Salinas. We conclude that our simulation model and estimated time variables adequately represent CALSTAR's operations at its Gilroy and Salinas bases. These figures are illustrated in Table 6.

To capture expected changes in response time, the number of complete and inter-facility missions per base per year, and the yearly average helicopter utilization under both helicopter configurations, we ran the simulation model in the current and the new (Salinas 24/7) configurations. (We randomized mission arrival times and mission variable times.) Under the current helicopter configuration, for a complete year, we found:

- For Gilroy, the expected number of complete and inter-facility missions is 522 with the expected utilization 13.57%.
- For Salinas, the expected total is 211 with utilization of 13.53% for the weekdays during which it is operative.

The simulation for the 24/7 Salinas configuration model yields:

- For Gilroy, the expected number of complete and inter-facility missions decreases to 485, and the expected utilization is 12.5%.
- For 24/7 Salinas, the expected number of complete and inter-facility missions is 280 (about 5.4 flights per week), the expected utilization is 7.58% (assuming no increase in inter-facility missions), and the expected average response time for missions located in Monterey county decreases by 2 minutes (response times for the other counties will stay the same). See Table 7 and 8 for complete output.

I. INTRODUCTION

A. BACKGROUND

The right to life is universally accepted and should be ensured in all conditions, especially during emergencies when a person’s life is in danger. Ambulance services are established in communities to save lives by transporting critically ill or injured patients to the appropriate facilities for treatment. Air ambulance/rescue services are the part of that service that utilizes air transport assets for time-critical pre-hospital patient care and transportation. The idea of using helicopters for patient transport is based on successful military experience in the Korean and, especially the Vietnam Wars. The first commercial EMS (Emergency Medical Service) program to use helicopters was started in Denver, Colorado, in 1972 (Slack, 2001).

In California, CALSTAR-California Shock/Trauma Air Rescue was founded in June 1983, “to save lives, reduce disability and speed recovery for victims of trauma and illness through rapid transport, quality medical care and education” (CALSTAR website). CALSTAR is the first regional, public, non hospital-based, non profit helicopter ambulance program in northern California. CALSTAR started its operations in June of 1984 with a single helicopter, and then added a second one in 1986. As a result of its rapid expansion, done without doing proper market development, the company suffered financially and was forced to return to operating a single helicopter.

Today CALSTAR has eight bases. Seven of them are helicopter ambulance bases; and one is a fixed-wing ambulance base that is used for long-range patient transportation. The locations of CALSTAR bases are illustrated in Figure 1.

Figure 1. CALSTAR Bases and Service Areas (From CALSTAR website)

B. PROBLEM DEFINITION

CALSTAR is on the verge of making another expansion decision, concerning primarily Monterey, San Benito, south Santa Cruz and Santa Clara counties. Currently, CALSTAR serves those regions with CS-2 “Gilroy” and CS-5 “Salinas.” CS-2 is the busiest base overall; its coverage area starts at the southern San Francisco Bay Area and goes as far as San Luis Obispo. CS-2 operates 24/7 and primarily serves trauma patients (about 80%); the rest is dedicated to inter-facility transports. CS-5 serves all of Monterey, San Benito, and south Santa Cruz counties; CS-5 was established in April 2002 as a part-time operation base. This base presently runs from Thursday at 10:00 am to Monday at 10:00 am in a given week. During the times when CS-5 is not operative, CS-2 primarily responds to air ambulance demands from Monterey and San Benito counties, depending on helicopter availability. CALSTAR is not the only air ambulance service in the region, but according to the county EMS’s call list, CS-5 is the primary responder when it is operative for Monterey County and for a large portion of San Benito County. For south Santa Cruz, Santa Clara, and the northern part of San Benito, CS-2 is the primary responder. CS-5 is the secondary responder for the regions where CS-2 is the primary responder.

The current system and the problem to be studied in the thesis might be summarized as follows.

CALSTAR is considering an extension of its CS-5 “Salinas” operation to 24/7 (like CS-2 “Gilroy”). The key drivers in deciding whether to go along with the 24/7 extension, are the expected changes in three key measures:

1. Number of successful transportations.
2. Helicopter average utilization in each base.
3. Window of time that starts at dispatch and ends when there is nurse-patient contact.

The first two measures have a direct impact on revenues. The third measure is important from a quality-of-service standpoint. By making CS-5 Salinas a 24/7 operation we expect the number of the successful transportations to increase, the average helicopter utilization to decrease, and the dispatch to nurse-patient contact time to decrease. In brief, our goal in this thesis is, using all available data, to provide a statistically valid measure of the expected changes.

For the study, CALSTAR provided all available flight data, for calendar years 2002 and 2003 and for eleven months of 2004, pertaining to CS-2 and CS-5. It turns out that CALSTAR does not keep detailed records of missed, cancelled, or rejected-due-to-helicopter-unavailability calls. For a complementary data source we made contact with four county EMS agencies and requested data and EMS air regulations that we use in building an assignment policy in our simulation. From those contacts we learned that the Monterey county EMS only keeps records of aggregate monthly statistics, beginning with February 2004, the San Benito County EMS keeps rough monthly statistics, and the Santa Cruz EMS kept a count of flights out of the county each month for the calendar years 2003/2004 and of attempted or completed flights for the year 2004. Those three counties provided that available data as well as their regulations. The Santa Clara EMS provided yearly aggregate statistics for 2002/03/04.

The overall data provided has some problematic issues (Leemis, 2001). First of all, CALSTAR only provided data for accepted missions, and to build a valid model of the present system, true air ambulance *demand* should be known. Moreover, CALSTAR is not the only service provider. So CALSTAR's data is considered as *censored*. Data from the county EMS agencies have the *wrong amount of aggregation,* because the exact times of the incidents are very critical for base operations. Data from CALSTAR have a wrong *distribution in time,* as the company is interested in the future, but could only provide data belonging to the past three years.

To end up with credible results for both CALSTAR and the county EMS agencies, we first parameterized all the relevant random variables and stochastic processes, and then built a discrete-event simulation model that enables us to evaluate the performance measures of interest. As there is great structural and operational commonality between the existing and the proposed systems, we have confidence in the model of the proposed system (Law and Kelton, 2000, p.279).

C. BENEFITS

According to the American Trauma Society, each year about 150,000 Americans die from injuries. By having a well-established viable trauma system, the risk of death can be reduced by more than 50 percent for seriously injured trauma patients (American Trauma Society website). In addition to the need for advanced health facilities, the financial crisis faced by many hospitals means that many rural and suburban communities are too distant from high level trauma centers. Air ambulances are therefore their only option for emergency transportation. The case in northern California is shown in Figure 2 (SV/SJ Business Journal, October 22, 2004 and Santa Cruz Sentinel, September 23, 2004).

This thesis explores the operational impact of a 24/7-operating CS-5 "Salinas" base, on both CALSTAR operations and the four counties' emergency air ambulance response quality, by analyzing the data provided. The estimated air-ambulance demand characteristics of south Santa Clara, Santa Cruz, Monterey, and San Benito counties, where CALSTAR is the primary responder, will be useful for county EMS agencies' system evaluation and planning. Our approach to the problem can be used by other air ambulance companies, and the created simulation model can be extended and used for to evaluate all CALSTAR base operations in northern California.

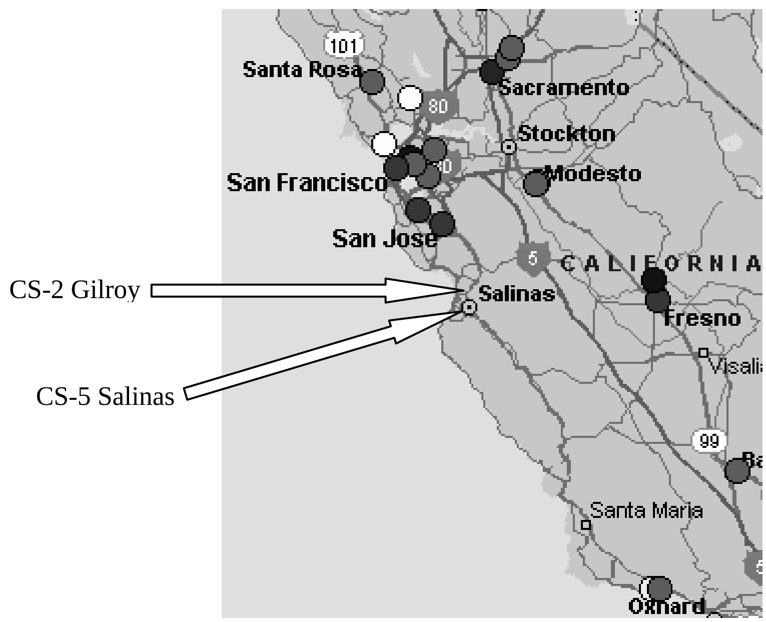

Figure 2. Northern California Trauma Centers and CALSTAR Base Locations. Dark grey dots stand for Level-I trauma centers, grey dots for Level-II trauma centers (From EMSA website)

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II. AN OVERVIEW OF THE EMS AIR AMBULANCE DISPATCH POLICIES AND CALSTAR BASE OPERATION

“Trauma centers and trauma specialists are critical components of our public health infrastructure and must be well-equipped and staffed to meet trauma emergencies.”

Richard Carmona, M.D., M.P.H., F.A.C.S. Vice Admiral, U.S. Surgeon General

A. EMS AIR-AMBULANCE DISPATCH POLICIES

Our goal in this section is to present policies that define conditions under which county EMS services dispatch an air ambulance for a trauma patient. A typical schema, followed from start to end, in a case of trauma injury is depicted in Figure 3. County EMS agencies initially categorize injury incidents as either life-threatening or less serious. That categorization determines whether to dispatch a ground or an air ambulance. Life-threatening injuries should be treated in appropriate trauma centers, whereas less serious injuries can be treated in emergency rooms/departments.

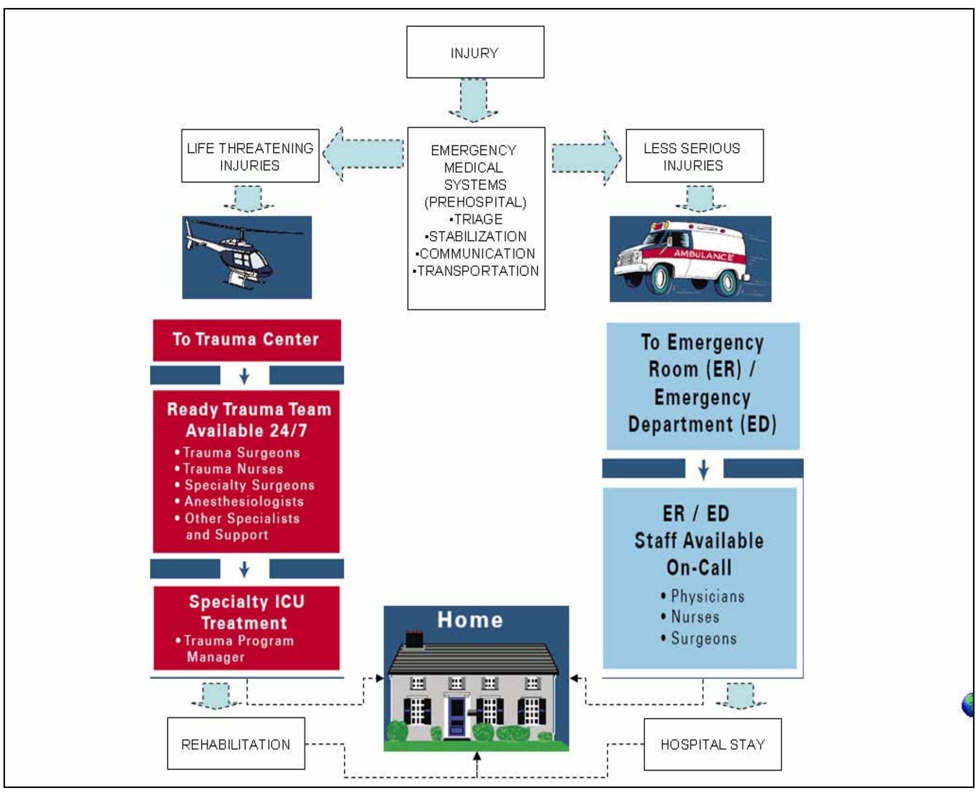

Figure 3. Trauma systems as explained by American Trauma Society (From American Trauma Society website)

Patients with life-threatening injuries that require special treatment not provided by regular hospitals should be immediately transferred to the nearest trauma center, preferably within the so-called “Golden Hour” (Tallon et al., 2002). The importance of air assets in such transfers appear to be substantial: as helicopters offer a faster and more reliable means of transportation over more flexible routes as compared to ground ambulances, especially for counties like Monterey, and San Benito, where there is no trauma center, and patients needs to be transported, in some cases, more than 100 miles (as depicted in Figure 2).

In California, counties that integrate aircraft into their pre-hospital patient system should meet California Code title 22 regulations in which local EMS agencies are urged to develop policies and procedures for the use of air ambulances.

According to the County of Monterey’s EMS Policy 500-59, “an EMS aircraft may be activated after the first agency on scene determines that the patient meets a M.A.P. score of 2 or greater” (MAP is the acronym for Mechanism, Anatomy and physiology). Santa Cruz County Policy 7050 is the same. An EMS aircraft also will be dispatched automatically outside an urban response zone in which the response time is nine minutes or greater under the following criteria:

- High-impact mechanisms
- High speed rollover
- Head on collision combined speed approximately 50 mph
- Difficult patient extrication and/or access
- Pedestrian vs. MVA (greater 20 mph)
- Multiple patients involved
- Ejection of passenger(s)
- Death of occupant(s)
- Falls greater than 20 feet.
- Burns
- Significant penetrating wounds
- Critical medical condition in remote location

During the transportation decision process, the patient's condition, and the availability of local-hospital resources and capabilities are also taken into consideration. The processes as summarized in Santa Cruz county EMS Policy 7050 in a schematic algorithm are depicted in Figure 4. The process starts with a M.A.P score determination at the event scene and ends with the patient destination, either a local hospital or a trauma center via an air or a ground ambulance.

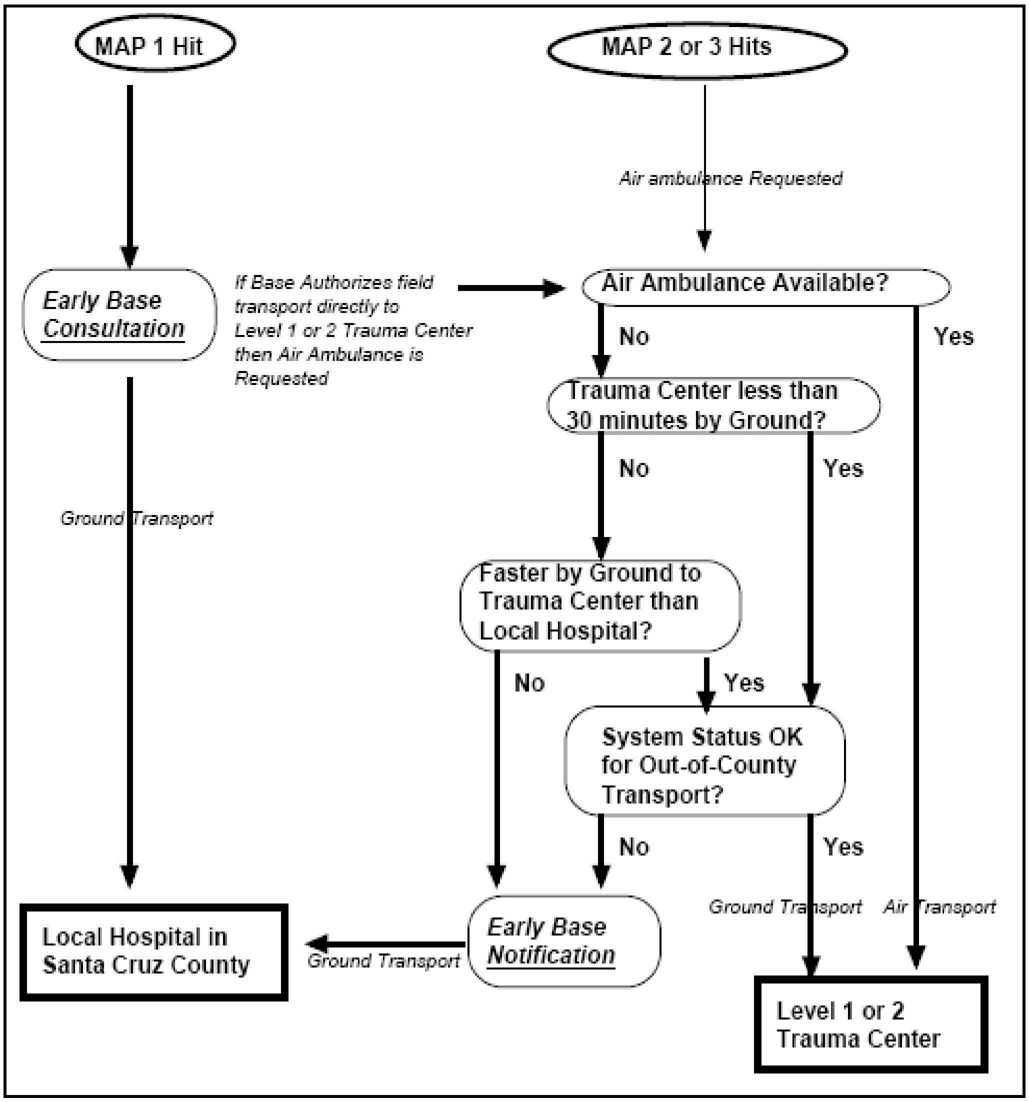

Figure 4. Major-Trauma Victim Transport and Destination Schematic Algorithm for Santa Cruz County (From Santa Cruz Policy 7050)

B. CALSTAR BASE OPERATION

CALSTAR bases are set up in a fashion similar to fire stations. A typical base has fourteen employees; four pilots, a mechanic, seven nurses, and a director. Nurses work 24 hours on and 24 hours off, whereas pilots work 12-hour shifts. Nurses are experienced critical-care nurses. All flights include two nurses and one pilot. CALSTAR's goal is to be in flight within five minutes after dispatch, and, in the study, it is recognized that they usually meet that goal. They don't have hoisting capability. In case of a need for hoisting, they coordinate their work with a CHP helicopter that has a hoisting capability. If a patient is in a remote area, nurses hike in; if patient is stuck in his vehicle, thenurses wait for his rescue, and it may take some time to load a patient at those times. But they try to get the patient loaded within ten minutes (Black Lake Buzz 2004).

III. LITERATURE REVIEW

A. AIR AMBULANCE

Emergency response systems have greatly benefited from management science studies; see, for example, the survey paper by Green and Kolesar (2004) and references therein. Regarding ground ambulance transport, the standard setting is that of a unique emergency transport provider, and the problem is to find optimal base locations and the minimum number of ambulances per base to meet certain performance targets; see, for example, Iskander (1989), and Henderson and Mason (2004). The air-ambulance assignment problem has traditionally been studied in the context of a regional public-emergency medical service (EMS). Parker and Johnson (1970) is an early reference on the subject, and, more recently, Wears and Winton (1993) and Stundzia and Lumsden (1994).

B. DENSITY FUNCTION ESTIMATION

Leemis (2001) explains introductory techniques for simulation input modeling. Law and Kelton (2000) dedicate a whole chapter to the selection of input probability distributions. There are basically two approaches to density function estimation of discrete and continuous distributions. A parametric approach that uses a family of continuous and discrete distributions is studied broadly. Parameter estimates of desired distributions can be found by using the least squares method, the method of moments and maximum likelihood methods. Among those the maximum likelihood method is preferred, due to its desirable statistical properties. In a nonparametric approach, the observed data themselves might be used to specify a distribution, called *empirical distribution*, in cases where a theoretical distribution that fits the data adequately cannot be found. That approach can be extended to kernel-smoothing techniques, which are well studied by Wand and Jones (1995).

C. NONHOMOGENEOUS POISSON PROCESS INTENSITY FUNCTION ESTIMATION

In our problem the service requests from each county EMS and contracted facilities are found to follow the nonhomogeneous Poisson process. Regarding the estimation of a Poisson process intensity function, nonparametric approaches include Law and Kelton (2000, p. 390-393), Arkin and Leemis (2000), Henderson (2003), and Leemis (2004). The papers Kuhl et al. (1997), (2001), and (2004), deal with the estimation of an intensity function subject to periodic effects and trends. The intensity function estimation problem also can be tackled using kernel techniques: see Lewis and Shedler (1976), Diggle and Marron (1988), Brooks and Marron (1991), Hall et al. (1991), and Jones et al. (1996), for more details. Zhu and McKnew (1997) use a piece-wise linear approximation of the Poisson intensity function to model arrivals in an emergency ambulance service. Lastly, Wu et al. (2005) provide the queueing perspective of our problem.

IV. DENSITY AND INTENSITY FUNCTION ESTIMATION

In this chapter we define mission types and associated variables. Next, we explain the data utilized for the study, propose the kernel method that we selected for the variable density estimation, and explain the Matlab implementation. Last, we show the goodness-of-fit test used for the estimation of the weekly rate functions, followed by the arrivals' intra-week density estimation for the missions generated out of four counties.

A. VARIABLE SELECTION AND DESCRIPTION

For the purpose of analysis, missions are divided into three types. First, *complete flights* are unplanned missions triggered by EMS that occur at random locations, where the helicopter picks up the patient and transports her to a regional hospital. If no helicopter is available on base upon receiving the EMS call, the call is lost (i.e., there is no waiting buffer in the queue). Motorcycle accidents are a frequent instance of this type of mission. Second, *inter-facility missions* are considered, in which a patient is picked up from a local hospital and transported to a more sophisticated hospital. Because there are contractual relationships between such local hospitals and helicopter-ambulance companies, EMS is not involved in these missions. Patients can generally wait up to one hour for helicopter pick-up; in practice, this means that the buffer size is infinite and the transport occurs only when a helicopter becomes accessible. An example of this kind of mission is that of a new-born baby transported from a local clinic to a high-complexity hospital. Last, *incomplete missions* are looked at. These are unplanned, randomly located missions dispatched by EMS, in which the helicopter returns to base without picking up any patients because the air transport is cancelled either by the incident commander, or because of adverse weather conditions or a mechanical failure. If no helicopter is available, the call is lost (there is no waiting buffer in the queue).

The steps followed in the flight log sheet for complete missions are as follows. First, a helicopter is dispatched by the base operator upon receipt of an EMS order. After a random amount of time, called the *reaction time*, the helicopter departs from base. Next, the helicopter arrives at the scene of the accident, and, soon after, nurse-patient contact occurs. The time elapsed between the helicopter's departure from base and nurse-patient contact is called the *waiting time*. The sum of the reaction time and the waiting time is called *response time*. The final steps are: departure from the scene, arrival at the hospital, and return to base; the cumulative time spent in those latter steps is called the *service time*. The steps and time intervals involved in complete missions are illustrated in Figure 5.

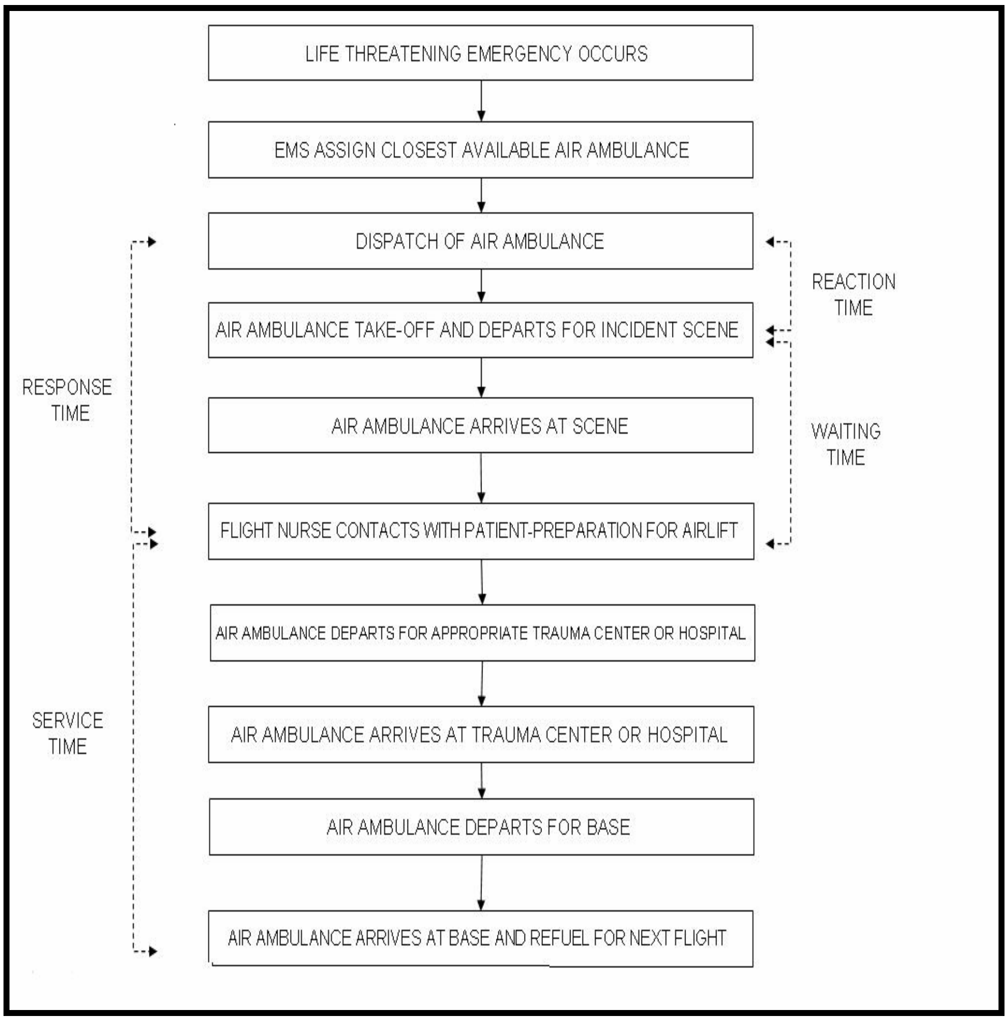

Figure 5. Complete mission process steps

Due to the nature of inter-facility missions, the only relevant time measurement recorded in the log-sheet is the total amount of time spent between helicopter take-off and helicopter return to base, called *total service time.* The steps followed in a typical inter-facility mission are illustrated in Figure 6.

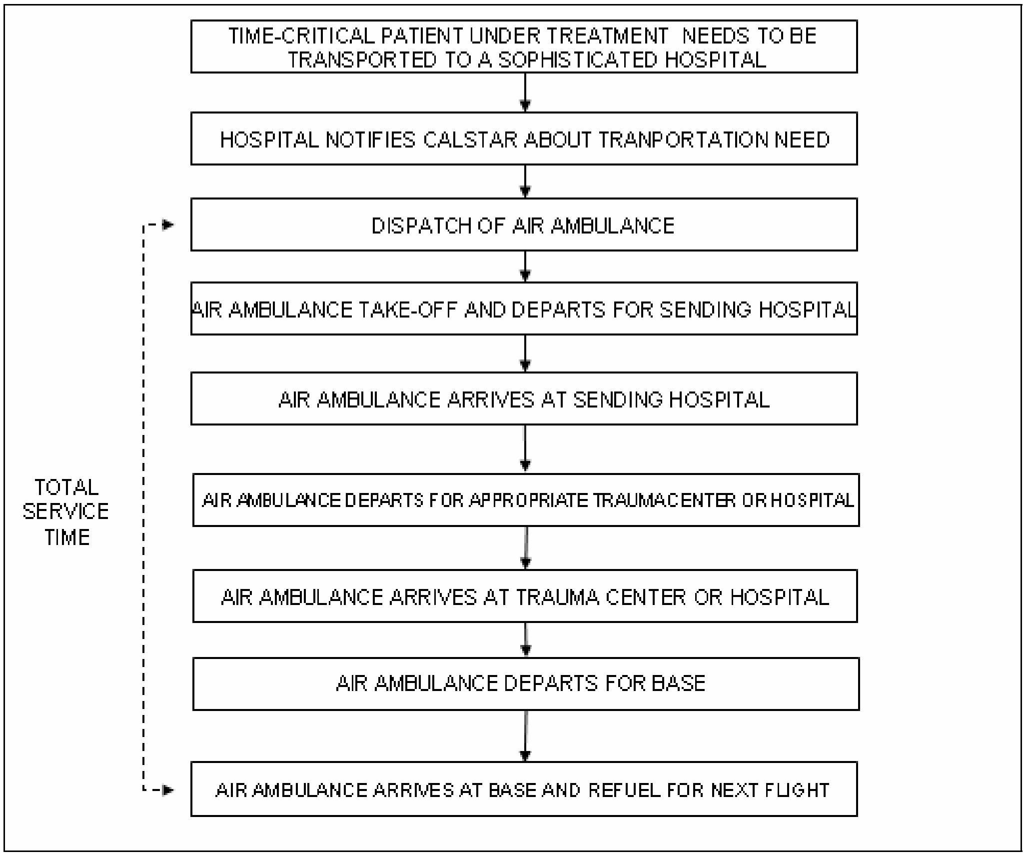

Figure 6. Inter-facility mission process steps

The steps recorded in the flight log sheet for incomplete missions only include dispatch times. Therefore, there are only two steps: dispatch time (time known) and helicopter-becomes-available time (time unknown). This time interval is called *delay*, the amount of time a helicopter is busy with a mission not to be completed. Basic steps are illustrated in Figure 7.

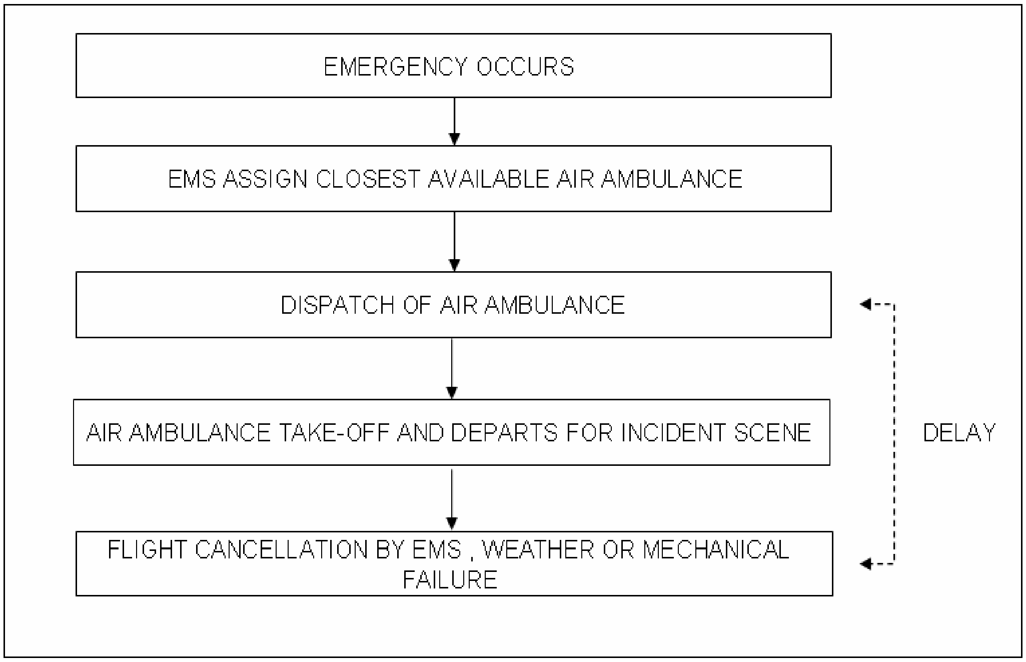

Figure 7. Incomplete mission process steps

B. DATA

Most of the data used in this study was provided by CALSTAR. It includes all completed-flights information flown by CS-2 “Gilroy” and CS-5 “Salinas”, out-of-service log sheets for the calendar years 2002, 2003, and 2004 (except the month of December 2004) and other flights’ dispatch-time information that were cancelled/aborted/incomplete for calendar years 2003 and 2004 (except the month of December 2004) in MS Access format.

Another data source was the county EMS’s databases. Monterey County EMS provided monthly data that shows counting information of air ambulance requests and completed flights, beginning February 2004, in MS Excel format. Destination information, which shows which company transported how many patients to the appropriate facilities in year 2004, was also acquired. Santa Cruz County EMS provided monthly count data for airlifted trauma cases for calendar year 2003 and daily incident data for year 2004 in MS Excel format. Santa Clara County provided yearly aggregated data with air-ambulance-company information in MS Excel format. San Benito County EMS just provided average monthly estimates via phone.

CALSTAR's completed and inter-facility-flight data files basically include the following information:

Flight number

Base dispatched: 'S' for the Salinas base , 'G' for Gilroy base

Date of the incident

Type of incident: on-the-scene/inter-facility

Agency-requested service

Rough incident location info

County, if on-the-scene; hospital, if inter-facility

Facility that the patient was transported to

General explanation of the incident

Time of dispatch

Time helicopter took off and left the base

Arrival time at the landing zone

Time flight nurse contacted with the patient

Departure time from landing zone

Arrival time at emergency room

Departure time from the facility

Time helicopter returned to base

Aircraft number

Distance traveled with patient on board

Distance traveled without patient

Unlike completed and inter-facility flight data files, incomplete-flight data files only include:

Flight number

Reason why the flight not completed

Base dispatched: ‘S’ for Salinas base, ‘G’ for Gilroy base

Date of the incident

Time of dispatch

Rough incident location info

Agency-requested service

For usability purposes, the data files were converted from MS Access to MS Excel files by using the program called “Stat Transfer.” Related time-data column cells were formatted to the Excel date-time format. Apparent typos were corrected by hand, compared with other data columns if applicable, and otherwise treated as missed data. Following that, formatted data were sorted by type-of-incident, requester county, and time of dispatch. Six separate data files were created: four for county on-the-scene demands for Monterey, San Benito, Santa Cruz, and Santa Clara; one for all inter-facility calls and one for incomplete flights. Duplicate entries in the acquired data files, where more than one patient was transported in the same flight mission, and entries that belong to fixed-wing flights were not taken into consideration in the analysis and estimation processes.

Incidentally, the chronological order in which this part of the thesis was pursued started with the data-gathering phase. The data analysis gave us a deeper understanding of CALSTAR’s operations and allowed us to refine our objectives and course of action.

C. NONPARAMETRIC DENSITY ESTIMATION

Before estimating the densities we tested the sample independence and dependence between variables. For each variable, sample independence is assessed by using auto-correlation, as proposed by Leemis (2001), with the testing hypothesis:

Ho: Observations are an independent sample from some underlying distribution.

Ha: Not Ho

As S-Plus cannot handle ACF with missing data but can compute correlation with missing data, a function called "ACFwNA" is written into S-Plus and used in the study (thanks to helps from Prof. Buttrey), as illustrated in Figure 8. In addition to the approximate 95% confidence limits in ACF, an approximate 99% confidence limit was added to the function.

```
      > ACFwNA
      function(x, max.lag = 5)
      {
            lags <- numeric(max.lag)
            n <- length(x)
            bound95 <- 2/sqrt(n)
            bound99 <- 2.57/sqrt(n)
            for(i in 1:max.lag)
                  lags[i]  <-  round(cor(x[  -  ((n  -  i  +
1):n)], x[
      - (1:i)],
                        na.method = "omit"), 6)
            return(lags, bound95, bound99)
      }
```

Figure 8. ACFwNA Function with 5 lags

After testing the hypothesis for each variable, the null hypothesis, "observations are an independent sample from some underlying distribution," cannot be rejected for all of the selected variables.

Following that, the dependence between variables is tested by using the "Pearson correlation test." By definition, the reaction times of the bases are not correlated with the waiting-time or service-time distributions. The only issue might be between waiting time and service time distributions. As depicted in Figure 5, service time starts with the flight-nurse/patient contact and ends when helicopter returns to base. It consists of time spent between flight-nurse/patient contact and helicopter take-off, time spent on the way to the hospital, time spent at the hospital, and time spent on the way to back to base. On the other hand, waiting time starts with the helicopter ambulance take-off from the base and ends when the flight nurse contacts with the patient. It consists of time spent on the way to the scene and time spent till the flight nurse contacts with the patient. Times spent on the way to the event scene and on the way to the hospital are deterministic as they depend on the distance and the average helicopter speed. Unlike those, other elements are of a random nature. Deterministic elements may cause dependence between service time and waiting time. One may suspect that the more time spent on the way to the scene may cause more time to be also spent on the way to an appropriate trauma center, so that service time is increased. Considering that we explored the degree of dependence between the two variables for each county testing the hypothesis:

Ho: The two variables are not correlated.

Ha: They are correlated.

As a result of the hypothesis testing, it turns out that there is some correlation between two variables as one may expect. That is an issue for all counties except Santa Cruz, which may be explained by its relative proximity to appropriate trauma centers. To correct that dependence, we split the waiting-time/service-time pairs into two groups: for one, the waiting time is less than or equal to 20 minutes, which represents a quick response time and associated service time. For the other group, the waiting time is greater than 20 minutes, which represents a longer response time. With that division, we repeated the correlation test, and this time we cannot reject that the two variables are not correlated. So we concluded for Santa Clara, Monterey, and San Benito Counties that the waiting times and service times are conditionally uncorrelated, so are independent.

After testing these hypotheses, we set out to input probability distributions for *reaction times*, *waiting times*, and *service times* for completed missions, and *total service times* for inter-facility missions. As we work with collected data, we can use one of three approaches to specify a distribution in an increasing order of desirability (Law and Kelton, 2000).

1. The data values themselves are used directly in the simulation, or *trace-driven simulation*, which we used for model validation and verification.

2. The data values themselves are used to define an empirical distribution function in some way, for which we used nonparametric kernel density estimators.

3. Standard techniques of statistical inference are used to “fit” a theoretical distribution that we used to model delays in incomplete missions.

We now discuss the method of kernel density estimation (Wand and Jones, 1995) used to fit the data associated with each variable to a density. The reason for using kernel techniques is that its theory is well developed, and an implementation is available in the Matlab distribution fitting tool. The main idea is relatively straightforward: Given n independent and identically distributed Salinas-based reaction times $R_1, R_2, \ldots, R_n$, the kernel density estimator is

$$f\left(r,h\right)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{r-R_i}{h}\right)$$

Here K is a function satisfying $\int K(x)dx=1$ and called *kernel,* and h is a positive number, usually called the *bandwidth* or *window width.* The bandwidth is selected to minimize the mean integrated squared error of $f\left(r,h\right)$. In particular, we used a Gaussian kernel and the optimal bandwidth selection method proposed by Hall et al. (1991). The estimated reaction-time density for CS-5 “Salinas” is illustrated in Figure 9. The short reaction times in Figure 9 were observed when a completed-mission dispatch is done; the air ambulance is already in the air on its way back to base, from an incomplete flight or training, and has enough fuel to complete the mission. Other estimated densities of the associated variables are annexed in Appendix A.

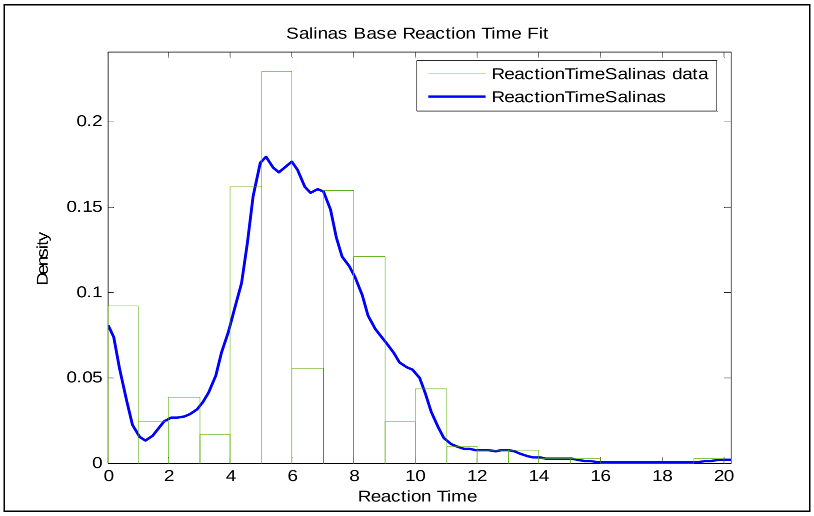

Figure 9. Matlab output for Salinas base reaction time by kernel density estimator.

D. NONPARAMETRIC INTENSITY FUNCTION ESTIMATION

Our goal in this section is to estimate the intensity function of a nonhomogeneous Poisson process for each mission type. A nonhomogeneous Poisson process is defined by the following properties:

1. Missions arrive one at a time.

2. N(t+s)-N(t) (the number of arrivals in the time interval (t,t+s]) is independent of $\{N(u), 0 \le u \le t\}$.

We believe these properties are satisfied by the mission arrival process. The papers Kuhl et al. (1997), (2001), and (2004) deal with the estimation of a parametric intensity function subject to periodic effects and trends, but from an application point of view, it is not practical. So we decided to leverage nonparametric methods for each of the four counties that feed the Gilroy and Salinas bases; and for each type of mission, we apply the denominator-free χ^2 goodness-of-fit test of a nonhomogeneous Poisson process, described in Jacobs (2005). Given K independent Poisson random variables with means $m_1, \ldots, m_K$, and observed arrivals $n_1, \ldots, n_K$, the statistic

$$T = \sum_{i=1}^{K} \left(\sqrt{n_i} + \sqrt{n_i + 1} - \sqrt{4m_i + 1} \right)^2 \sim \chi_K^2$$

We used this test to fit an appropriate piecewise constant rate function from weekly counts, by using year-2002 and year-2003 weekly count data and cross-validating with year 2004-data. As an example, the estimated and cross-validated piecewise constant rate function for Santa Clara completed missions is illustrated in Figure 10. Summary of the χ^2 fits are given in Table 1, along with other counties' fit summaries. Rate function estimates of the other counties and mission types are annexed in Appendix B.

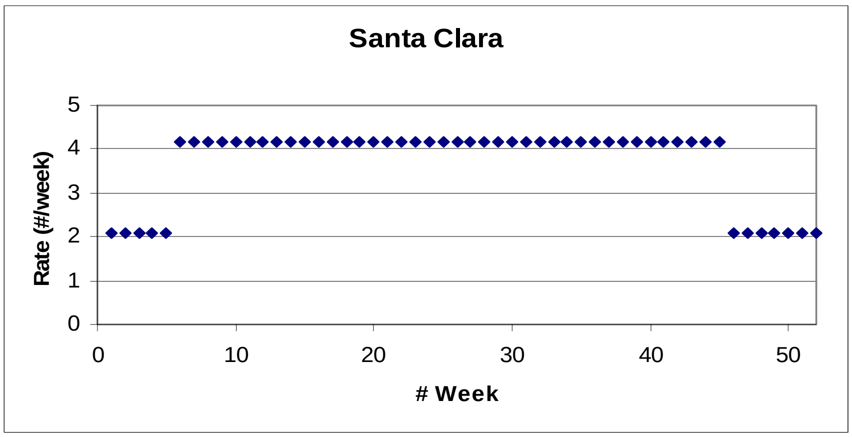

Figure 10. Intensity function for Santa Clara completed flights

Despite the statistical validity of weekly rate functions, after taking a closer look at the data, it is clear that the rates are not constant on a daily and intra-day basis. One important reason for this is that most of the arrivals are trauma incidents, of which traffic accidents are a large proportion; and these tend to occur on certain days of the week and in certain hours of the day. For the homogeneous Poisson process, it is uniformly distributed; but in our case, it is not uniform, so that distribution should be estimated. For this reason, for each of the four counties, and for all kinds of missions, we estimated intra-week densities to dispatch times, using kernel density estimation procedures with bandwidths that are able to capture multi-modalities like morning-affect, evening rush-hour effect, and Saturday night effect, as illustrated in Figure 11, for Santa Clara complete missions intra-week density.

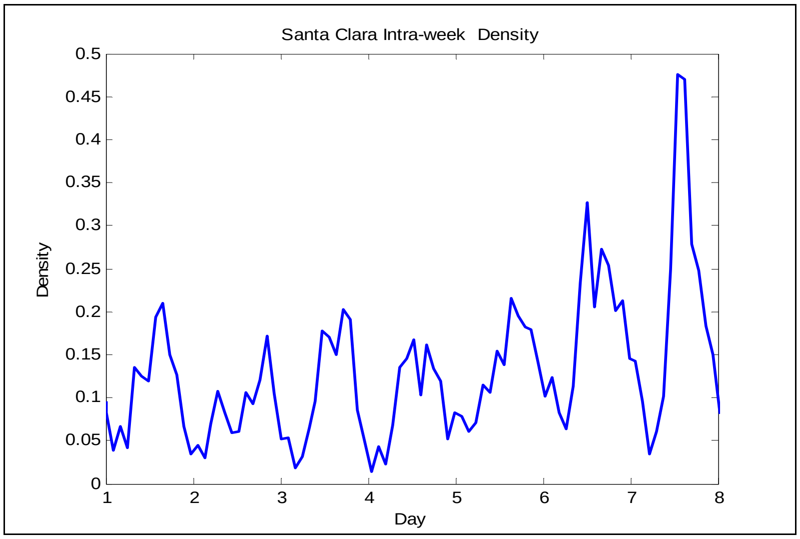

Figure 11. Santa Clara intra-week density

On the horizontal axis of Figure 11, 1 and 8 are Monday at 00:00.\; 2 is Tuesday, 3 is Wednesday, 4 is Thursday, 5 is Friday, 6 is Saturday, and 7 is Sunday at 00:00. From Figure 11 we can infer that, for a given complete mission, it is more likely to occur on Sunday evening, rather than Wednesday midnight. Other intra-week densities are annexed in Appendix B.

	GOF 2002/2003	GOF 2004 (11 months)
SCL	$P\{\chi^2_{50} \le T_{SantaClara}\} = 0.83$	$P\{\chi^2_{48} \le T_{SantaClara}\} = 0.8$
SCR	$P\{\chi^2_{50} \le T_{SantaCruz}\} = 0.593$	$P\{\chi^2_{48} \le T_{SantaCruz}\} = 0.135$
MON	$P\{\chi^2_{50} \le T_{monterey}\} = 0.499$	$P\{\chi^2_{48} \le T_{monterey}\} = 0.305$
SBE	$P\{\chi^2_{50} \le T_{SanBenito}\} = 0.42$	$P\{\chi^2_{48} \le T_{SanBenito}\} = 0.692$

Table 1. χ^2 Goodness-of-fit for complete-flights estimated rates

	GOF 2002/2003
SCL	$P\{\chi^2_{46} \le T_{SantaClara}\} = 0.08$
SCR	$P\{\chi^2_{46} \le T_{SantaCruz}\} = 0.114$
MON	$P\{\chi^2_{46} \le T_{monterey}\} = 0.119$
SBE	$P\{\chi^2_{47} \le T_{SanBenito}\} = 0.098$

Table 2. χ^2 Goodness-of-fit for incomplete-flights estimated rates

	GOF 2002/2003	GOF 2004 (11 months)
CS-2	$P\{\chi^2_{50} \leq T_{Gilroy}\} = 0.175$	$P\{\chi^2_{48} \leq T_{Gilroy}\} = 0.622$
CS-5	$P\{\chi^2_{50} \leq T_{Salinas}\} = 0.844$	$P\{\chi^2_{48} \leq T_{Salinas}\} = 0.662$

Table 3. χ^2 Goodness-of-fit for inter-facility-flights estimated rates

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V. MODEL BUILDING AND SIMULATION

The goal in this chapter is to explain how we built a discrete-event simulation model that allows us to find expected changes in measures of interest. The model is represented as an event graph (Buss, 2001). Implementation details are discussed in Section B.

A. MODEL BUILDING

1. Model Description

After performing input analysis, we model CALSTAR operations with the queueing perspective proposed by Wu et al. (2005). From CALSTAR's point of view, company's operations around the Bay area can be considered as a queueing system in which the number of identical servers changes periodically over time. Servers basically serve three types of missions: complete on-the-scene emergency, incomplete on-the-scene emergency and inter-facility patient transportation missions. When an emergency incident that requires an air ambulance happens in Monterey, San Benito, Santa Clara, or Santa Cruz County, the county EMS demands service from the closest CALSTAR base, following their procedures. If that base is busy or unavailable at that time, a service request is made to the second closest CALSTAR base. If either base, CS-2 or CS-5 is unavailable, CALSTAR would miss that service opportunity, because no queue is allowed in emergency calls. This sequence is the same for both complete and incomplete mission types. For the third mission type, inter-facility transportations, hospitals demand service from the closest CALSTAR base. The assigned base accomplishes that service, if it is available or patients can wait about one hour, which, considering the system, can be considered an "infinite" queue. When the helicopter starts either a complete on-the-scene emergency mission or an inter-facility transportation mission, it will be busy until it returns to base and refuels. Then, it immediately returns to service if an inter-facility mission is waiting in a first-in, fist-out queue. For incomplete missions, a helicopter will be busy with that mission for a time interval uniformly distributed between 0 and 15 minute. Then it will return to base or, if there awaits another type of mission, it begins service. These steps are illustrated in the event-graph of Figure 12.

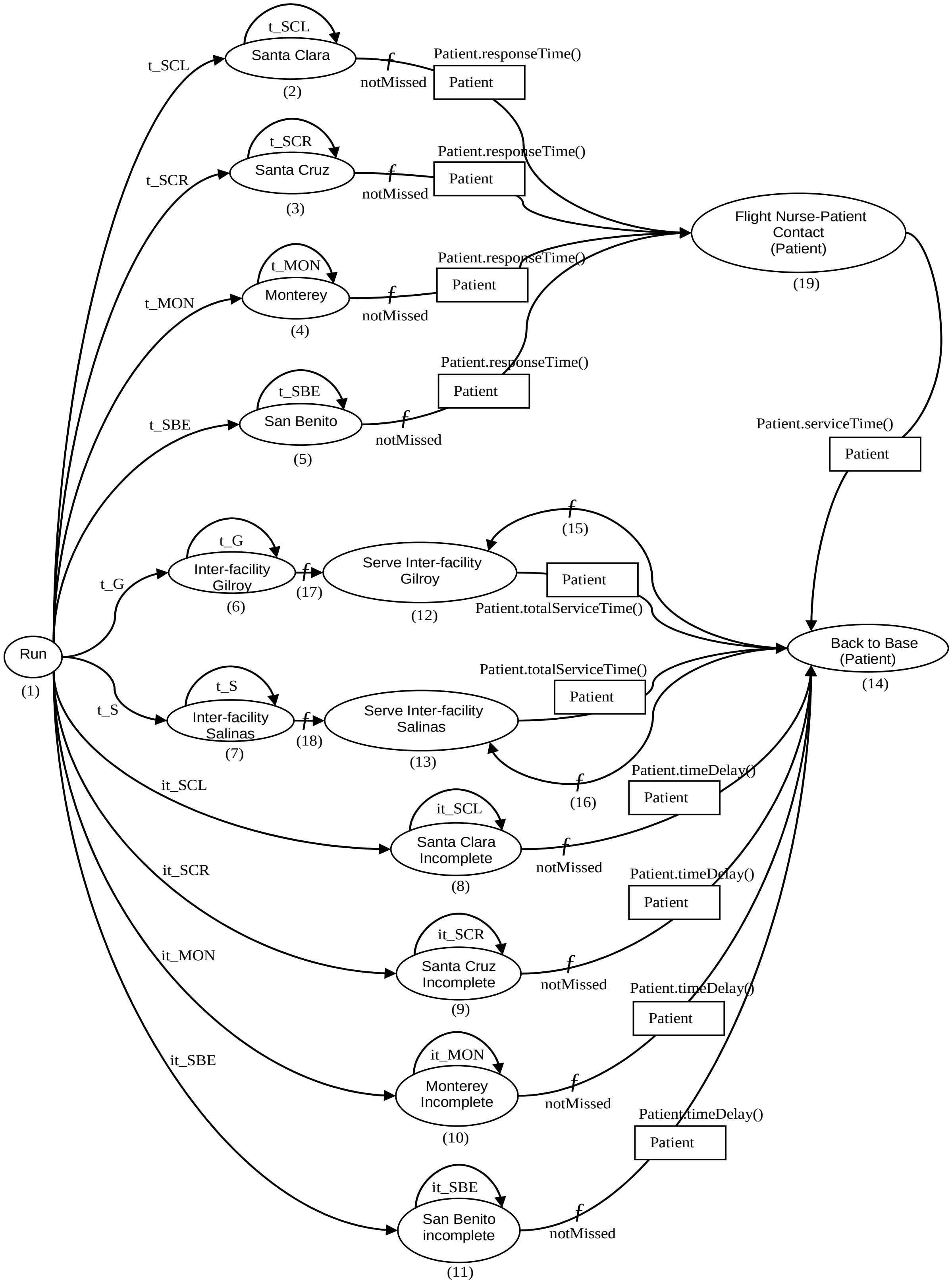

Figure 12. Event-graph diagram

(1)
numberAvailableServersGilroy= numberAvailableServersSalinas =1
numberServedGilroy= numberServedSalinas=0
numberArrivalSCL=numberArrivalSCR=numberArrivalMON=numberArrivalSBE=0
numberInterfacilityArrivalGilroy=numberInterfacilityArrivalSalinas=0
missedSCL=missedSCR=missedMON=missedSBE=0
interFacilityGilroyQueue.clear()
interFacilitySalinasQueue.clear()
Initialize all types of arrivals

(2)
numberArrivalSCL++
Schedule the next arrival event
if (numberAvailableServersGilroy > 0) {
    notMissed=true, numberAvailableServersGilroy--, numberServedGilroy++, new Patient(Gilroy,responseTime,serviceTime)
    Schedule Flight nurse – Patient Contact}
else if (numberAvailableServersSalinas > 0) {
    notMissed=true, numberAvailableServersSalinas--, numberServedSalinas++, new Patient(Salinas,responseTime,serviceTime)
    Schedule Flight nurse – Patient Contact}
else{
    notMissed=false, missedSCL++}

(3)
numberArrivalSCR++
Schedule the next arrival event
if (numberAvailableServersGilroy > 0) {
    notMissed=true, numberAvailableServersGilroy--, numberServedGilroy++, new Patient(Gilroy,responseTime,serviceTime)
    Schedule Flight nurse – Patient Contact}
else if (numberAvailableServersSalinas > 0) {
    notMissed=true, numberAvailableServersSalinas--, numberServedSalinas++, new Patient(Salinas,responseTime,serviceTime)
    Schedule Flight nurse – Patient Contact}
else{
    notMissed=false, missedSCR++}

(4)
numberArrivalMON++
Schedule the next arrival event
if (numberAvailableServersSalinas > 0) {
    notMissed=true, numberAvailableServersSalinas--, numberServedSalinas++, new Patient(Salinas,responseTime,serviceTime)
    Schedule Flight nurse – Patient Contact}
else if (numberAvailableServersGilroy > 0) {
    notMissed=true, numberAvailableServersGilroy--, numberServedGilroy++, new Patient(Gilroy,responseTime,serviceTime)
    Schedule Flight nurse – Patient Contact }
else{
    notMissed=false, missedMON++}

```
(5)
numberArrivalSBE++
Schedule the next arrival event
if(randomNumber>proportion_d ){
        if (numberAvailableServersSalinas > 0 ) {
                notMissed=true,  numberAvailableServersSalinas--,  numberServedSalinas++,
                new Patient(Salinas,responseTime,serviceTime)
                Schedule Flight nurse – Patient Contact}
        else if (numberAvailableServersGilroy > 0 ) {
                notMissed=true, numberAvailableServersGilroy--, numberServedGilroy++, new
                Patient(Gilroy,responseTime,serviceTime)
                Schedule Flight nurse – Patient Contact}
        else{
                notMissed=false, missedSBE++}

}

else{
        if (numberAvailableServersGilroy > 0 ) {
                notMissed=true, numberAvailableServersGilroy--, numberServedGilroy++, new
                Patient(Gilroy,responseTime,serviceTime)
                Schedule Flight nurse – Patient Contact }
        else if (numberAvailableServersSalinas > 0 ) {
                notMissed=true,  numberAvailableServersSalinas--,  numberServedSalinas++,
                new Patient(Salinas,responseTime,serviceTime)
                Schedule Flight nurse – Patient Contact }
        else{
                notMissed=false, missedSBE++}
}

(6)
numberInterfacilityArrivalGilroy++
Schedule the next arrival event
interFacilityGilroyQueue.add(new Patient(Gilroy,totalServiceTime))
if (numberAvailableServersGilroy>0){
        Schedule Serve inter-facility Gilroy}

(7)
numberInterfacilityArrivalSalinas++
Schedule the next arrival event
interFacilitySalinasQueue.add(new Patient(Salinas, totalServiceTime))
if (numberAvailableServersGilroy>0){
        Schedule Serve inter-facility Gilroy}


(8)
Schedule the next arrival event
if (numberAvailableServersGilroy > 0 ) {
        notMissed=true, numberAvailableServersGilroy--, new Patient(Gilroy,delay)
        Schedule Back to base }
else if (numberAvailableServersSalinas > 0 ) {
        notMissed=true, numberAvailableServersSalinas--, new Patient(Salinas,delay)
        Schedule Back to base}
else{
        notMissed=false}
```

```
(9)
Schedule the next arrival event
if (numberAvailableServersGilroy > 0 ) {
        notMissed=true, numberAvailableServersGilroy--, new Patient(Gilroy,delay)
        Schedule Back to base }
else if (numberAvailableServersSalinas > 0 ) {
        notMissed=true, numberAvailableServersSalinas--, new Patient(Salinas,delay)
        Schedule Back to base}
else{
        notMissed=false}

(10)
Schedule the next arrival event
if (numberAvailableServersSalinas > 0 ) {
        notMissed=true, numberAvailableServersSalinas--, new Patient(Salinas,delay)
        Schedule Back to base }
else if (numberAvailableServersGilroy > 0 ) {
        notMissed=true, numberAvailableServersGilroy--, new Patient(Gilroy,delay)
        Schedule Back to base }
else{
        notMissed=false}



(11)
Schedule the next arrival event
if(randomNumber>proportion_d ){
        if (numberAvailableServersSalinas > 0 ) {
        notMissed=true, numberAvailableServersSalinas--, new Patient(Salinas,delay)
        Schedule Back to base }
else if (numberAvailableServersGilroy > 0 ) {
        notMissed=true, numberAvailableServersGilroy--, new Patient(Gilroy,delay)
        Schedule Back to base}
else{
        notMissed=false}
}
else{
        if (numberAvailableServersGilroy > 0 ) {
        notMissed=true, numberAvailableServersGilroy--, new Patient(Gilroy,delay)
        Schedule Back to base }
else if (numberAvailableServersSalinas > 0 ) {
        notMissed=true, numberAvailableServersSalinas--, new Patient(Salinas,delay)
        Schedule Back to base }
else{
        notMissed=false}
}

(12)
interFacilityGilroyQueue.removeFirst()
numberAvailableServersGilroy--
numberServedGilroy++
Schedule Back to base
```

```
(13)
interFacilitySalinasQueue.removeFirst()
numberAvailableServersSalinas--
numberServedSalinas++
Schedule Back to base

(14)
if (Patient.base()==Gilroy) {
        ++numberAvailableServersGilroy
        If (interFacilityGilroyQueue.size()>0){
                Schedule Serve inter-facility Gilroy}
if (Patient.base()==Salinas) {
        ++numberAvailableServersSalinas
        If (interFacilitySalinasQueue.size()>0){
                Schedule Serve inter-facility Gilroy}

(15)
if(numberAvailableServersGilroy>0 and interFacilityGilroyQueue.isNotEmpty())

(16)
if(numberAvailableServersSalinas>0 and interFacilitySalinasQueue.isNotEmpty())

(17)
if(numberAvailableServersGilroy>0)

(18)
if(numberAvailableServersSalinas>0)


(19)
Record Response times
Schedule Back to base
```

2. Measures of Interest

The window of time that starts at the time of an emergency and finishes when the helicopter reaches the hospital is crucial. If this time window, known as the “golden hour,” is less than one hour, then the chances of patient survival increase significantly if trained professionals start to treat the patient (Tallon et al., 2002). Of this time, only the part, Dispatch → Nurse-Patient Contact, depends on the helicopter allocation policy; that time is called *the response time* (see Figure 5). By configuring Salinas as a 24/7 operation, one expects response times to decrease.

From operator’s perspective, the number of complete missions per base per year and the yearly average helicopter utilization are two other measures of interest, because of their impact on revenues. For any given year, the average helicopter utilization is the ratio of the busy times over the busy-plus-idle times, which is found separately for the

Gilroy-based and Salinas-based helicopters. Assigning a helicopter 24/7 to the Salinas base will tend to decrease utilizations in Gilroy and Salinas, although this might be compensated for by taking additional inter-facility missions from local hospitals (not included in our model).

B. SIMULATION

Our model uses discrete-event simulation techniques (Law and Kelton, 2000), and is implemented in Java, using the Simkit software package (Buss, 2001).

1. Variate Generation

One of the main components of the simulation model is the generation of the random variates for mission dispatches and associated time variables. The Matlab distribution fitting tool allows users to evaluate the quantile (inverse CDF) function of fitted univariate distributions. In order to obtain random variables from the fitted kernel densities, inverse CDF vectors of these densities that represent these functions with at least 2000 points are evaluated in Matlab. Following that, a Java class named "KernelITVariate" is written to obtain random variables by using the method below.

Let inverse CDF vector, which composed of $X_{(i)}$, where i = 0….(vectorLength-1), is stored in an array.

1. Generate U~U (0, 1).
2. Upper = ceiling (U*vectorLength).
3. Lower = max (1, floor (U*vectorLength)).
4. X = interpolated value between $X_{(Lower-1)}$ and $X_{(Upper-1)}$.

   If X >0, Return X.

   Else, go back to step 1.

Following that, a Java class named "ArrivalGenerator," which has two parameters and returns an ArrayList that includes inter-arrival times of the mission, is written to obtain random arrival epochs for three mission types by using the following algorithm:

Let $R_{(w)}$ is the estimated Poisson rate for week w, where w = 1…numberOfWeeks, and kernel (intraweek) is a kernel random variate that represents distribution within a given week.

For each w do {

1. Draw a Poisson distributed random sample from Poisson($R_{(w)}$) and assign it to numberArrivals

2. Draw numberArrivals samples from kernel (intraweek)

3. Sort them in ascending order and add as arrivals within week w

}

Compute inter-arrival times

Return ArrayList which is composed of inter-arrival times.

2. Java - Simkit Implementation

The simulation model is implemented in Simkit with seven classes that model the current system, in which CS-5 “Salinas” is available from Thursday at 10:00 a.m. to Monday at 10:00 a.m. We then modified the main and server classes to model the proposed system, where CS-5 “Salinas” operates 24/7. Basic class definitions are presented in Table 4.

CLASS	DESCRIPTION
CurrentConfigSimulationRunMain	The main class for current configuration simulation
Salinas247ConfigSimulationRunMain	The main class for proposed configuration simulation
ServerCalstar	Model simulation class. Salinas base operates in current part-time configuration.
ServerCalstarSalinas247	Model simulation class. Salinas base operates 24/7
Patient	This class keeps information of each patient
Simkit.random.RandomVariate	Abstract superclass of KernelITVariateBase class
KernelITVariate	Inverse transform class for estimated kernel densities.
KernelITVariateBase	Abstract class for kernel variates
KernelVariateWithFile	This class does input operations for KernelITVariate class. Class takes large vector of kernel inverse quantile generated by Matlab and returns KernelITVariate RandomVariate from that vector.
ArrivalGenerator	This class generates arrival epochs. It is constructed by weekly arrival rate and intra-week density files. It returns an ordered inter-arrival vector.

Table 4. Class descriptions

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VI. VALIDATION AND ANALYSIS

A. MODEL VERIFICATION AND VALIDATION

The simulation model constructed in Chapter V was verified and validated several times, until we were satisfied with our implementation and input data handling, before analyzing the output. To verify the model, in the development phase we wrote and debugged the computer program in three modules, which are input, run, and simulation model. We also split the input module into a variable generation and an arrival generation module. We verified both the variable generation and the arrival generation statistically and graphically by using Matlab and Splus. In order to verify and validate the helicopter assignment policy in the simulation model, we did a trace-driven simulation for the Gilroy and Salinas bases, comparing the number of complete missions with the recorded data, for eleven months of 2004, as this data set is the most complete data set in terms of the complete, incomplete and inter-facility flight information.

Base	Actual	Simulated	% coverage
Gilroy	609	575.1	94.4 %
Salinas	202	214.9	105.9 %

Table 5. Assignment Model Validation

As seen from the results in Table 5, by using real data for arrival epochs for three types of missions and their associated time information, two sets of data compare “closely,” and it is concluded that the simulation model adequately represents the actual system being studied. There are about 21 lost flights in the simulation, which are considered to happen due to errors in data entry.

In the second phase of validation, the validity of the input module variable generation is tested against real data. For that phase, we re-utilized real arrival-epochs, but randomized reaction-times, waiting times and service times, using their estimated density.

Base	Actual Data	Estimated Data	% coverage
Gilroy	575.1	571.7	99.4 %
Salinas	214.9	215.5	100.2 %

Table 6. Estimated Parameter Validation

Table 6 summarizes the results. We concluded that random variables with estimated kernel density fit the simulation model well.

Throughout the course of the simulation study, we interacted with Tom Goff, the program manager at CS-2 “Gilroy” base. As a manager, he also accepted the model as “correct.” After the existing system model validation, we modified the simulation model so that it represents the proposed operation schedule, in which CS-5 “Salinas” base is operative 24/7 and everything other than that extension is unchanged. Considering commonality between the two systems, we concluded that the model is capable of predicting the proposed system behavior

B. OUTPUT ANALYSIS

The goal of this section is to analyze the output generated by the discrete-event simulation. Law and Kelton (2000) describe two types of simulations, *terminating simulations* and *nonterminating simulations*. As analyzing simulation experiments depends on the type of simulation, one should decide whether the built model is terminating or nonterminating. In a terminating simulation there is a “natural” event E that specifies the length of each replication; in our model it is one full year composed of 52 weeks that starts with a Tuesday in every run. Therefore, we are dealing with a terminating simulation.

Given a random variable X that describes some performance measure of interest, we wish to find an estimator of μ = E(X). The sample average $\bar{X}(n)$ is an unbiased point estimator for μ (Law and Kelton, 2000), and an approximate 100(1-α) percent confidence interval for μ is:

$$\bar{X}(n) \pm t_{n-1,1-\alpha/2}\sqrt{\frac{S^2(n)}{n}} \qquad (1)$$

So by using Formula (1) we find 95% confidence intervals for both the present system and the proposed system, running simulations with randomized mission arrival times and mission variable times. The results are presented in Tables 7 and 8.

	Sample Mean	Sample Std.	95% Conf. Interval
SCL #Arrival	193.115	13.1837	(191, 195)
SCR #Arrival	114.185	10.4054	(113, 116)
MON #Arrival	168.975	13.6457	(167, 171)
SBE #Arrival	98.4	10.1516	(96.8, 100)
#Gilroy Serve	521.55	18.7321	(519, 525)
#Salinas Serve	210.47	11.6494	(209, 212)
SCL Response	24.7804	0.1395	(24.76, 24.80)
SCR Response	27.4889	0.1721	(27.46, 27.52)
MON Response	29.294	0.1766	(29.27, 29.32)
SBE Response	25.4762	0.1557	(25.45, 25.50)
Gilroy Utilization	0.1357	0.005	(0.1349, 0.1365)
Salinas Utilization	0.1353	0.0076	(0.1341, 0.1365)

Table 7. Output for current system simulation

	Sample Mean	Sample Std.	95% Conf. Interval
SCL #Arrival	193.115	13.184	(191, 195)
SCR #Arrival	114.185	10.405	(113, 116)
MON #Arrival	168.975	13.646	(167, 171)
SBE #Arrival	98.4	10.152	(96.8, 100)
#Gilroy Serve	484.63	18.593	(482, 488)
#Salinas Serve	279.495	14.411	(277, 282)
SCL Response	24.872	0.1277	(24.9, 24.9)
SCR Response	27.5226	0.1414	(27.5, 27.6)
MON Response	27.6486	0.1731	(27.62, 27.68)
SBE Response	25.1288	0.1729	(25.10, 25.16)
Gilroy Utilization	0.125	0.0051	(0.124, 0.126)
Salinas Utilization	0.0758	0.0038	(0.0751, 0.0764)

Table 8. Output for proposed system simulation

Comparing two systems with the simulation model, it is seen that for Gilroy, the total completed and inter-facility missions drop by 37. On the other hand Salinas increases its total by about 69, which means an expected number of 32 additional complete and inter-facility missions that cannot be completed in the present system with its changing number of servers.

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VII. CONCLUSIONS

Following an analysis of the simulation results of both the current and the new (CS-5 “Salinas” 24/7) configurations, it is estimated that:

- For CS-2 “Gilroy” in the current configuration, the expected number of complete and inter-facility missions is 522 with the expected utilization 13.57%.
- For CS-5 “Salinas” in the current configuration, the expected number of complete and inter-facility missions is 211 with the expected utilization 13.53% for the weekdays that is operative.
- For CS-2 “Gilroy” in the proposed configuration, the expected number of complete and inter-facility missions decreases to 485, and the expected utilization decreases to 12.5%.
- A 24/7-operative CS-5 “Salinas” is expected to perform 280 complete and inter-facility missions (about 5.4 flights per week), with the utilization 7.58% (assuming there is no increase in the inter-facility mission rate).
- The expected average response time for complete emergency missions located in Monterey County decreases about two minutes, while other counties’ response times stay the same.

After getting these results, we contacted CALSTAR and presented our findings for their evaluation. CALSTAR agreed on the credibility of the model and the results and decided to operate the CS-5 “Salinas” base 24/7, based on the results presented.

This thesis demonstrates that emergency events that require immediate transportation by air-ambulance and inter-facility transportation in northern California can be adequately modeled by a nonhomogeneous Poisson process and kernel methods prove very useful to estimate variable densities. This thesis also supports the idea that modeling air-ambulance operations as stochastic events in discrete-event simulations offers a great opportunity as decision support. Considering that an estimated 700 medical helicopters operate in the United States (The New York Times May 3, 2005), this approach might also be used for other small operators.

The same modeling approach can also be used for military purposes. For regions like southeastern Anatolia, where the Turkish Army fights terrorists who mainly infiltrate from northern Iraq, soldiers who are wounded by land-mines or roadside bombs need to be transported immediately to sophisticated trauma centers which in some cases, are more than a hundred miles away. In those cases, the Turkish military depends on its utility helicopter fleet, which is distributed over a number of bases in the region. Therefore, the same type of modeling approach might be used for military planning purposes.

APPENDIX A. DISTRIBUTION FITS AND DATA SUMMARIES

A. REACTION TIME DENSITY ESTIMATION

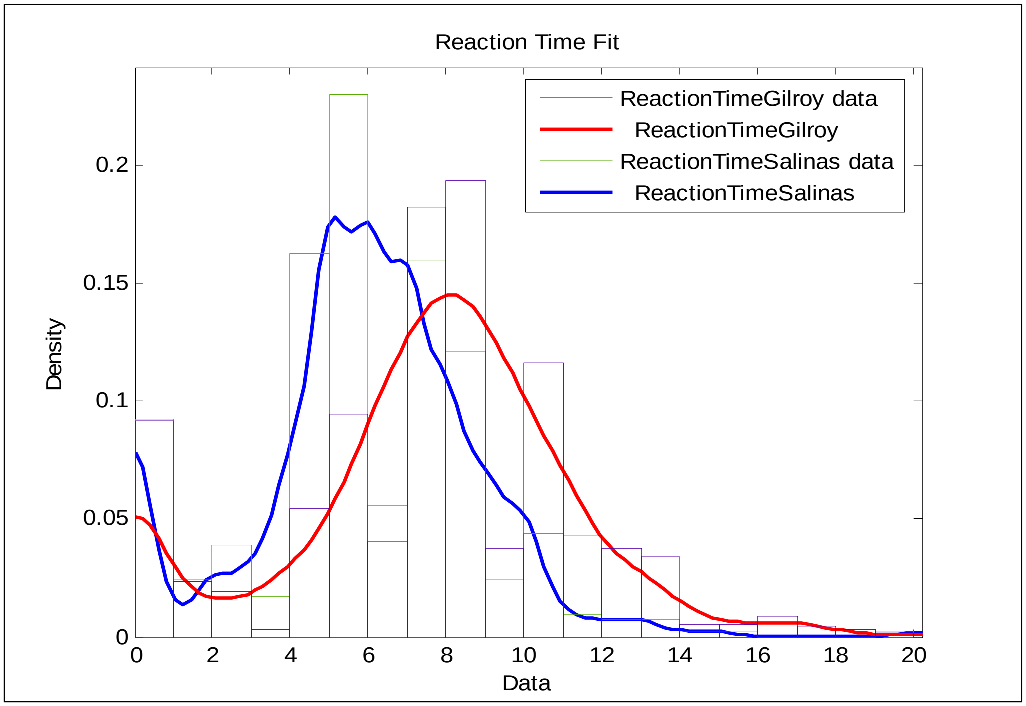

Figure 13. Reaction Time Fit

	CS-2 “Gilroy”	CS-5 “Salinas”
Mean RT	7.540	5.925
Standard Deviation	3.656	2.977
Median	8	6

Table 9. Reaction Times Data Summary

Reaction time fits for CS-2 and CS-5 are illustrated in Figure 13. A summary of the observed data is presented in Table 9. There are many short reaction times, as is shown in Figure 13. That is a result of instant responses to new emergency calls when a helicopter is already in the air with a sufficient amount of fuel.

B. WAITING TIME DENSITY ESTIMATION

1. Monterey County

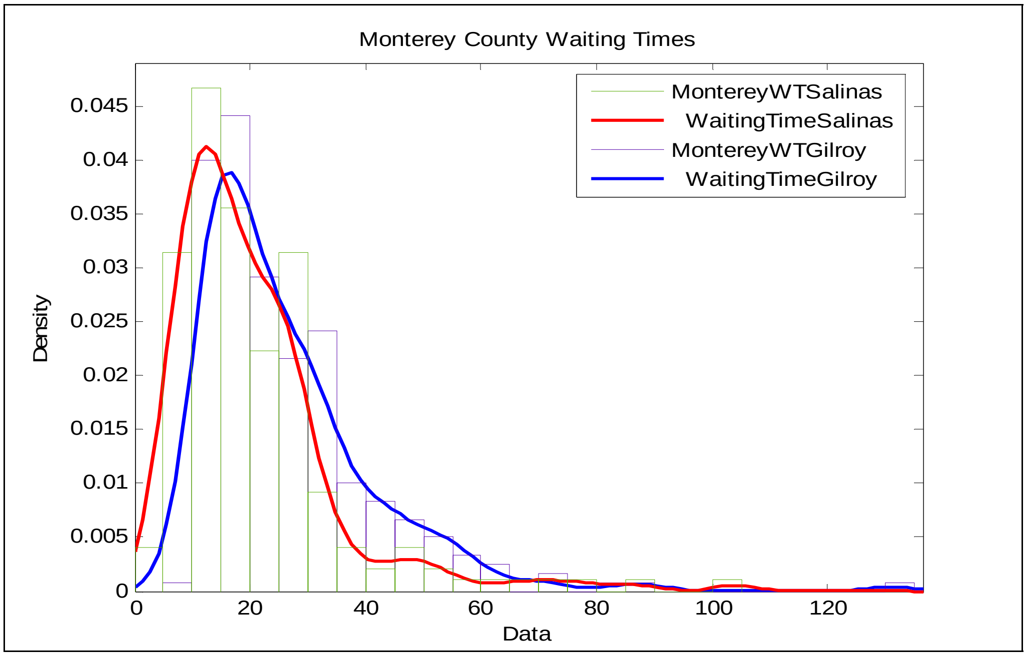

Figure 14. Monterey County Waiting Time Fits

	CS-2 "Gilroy"	CS-5 "Salinas"
Mean WT	26.254	20.523
Standard Deviation	15.464	14.597
Median	22	17

Table 10. Monterey Waiting Times Data Summary

Waiting time shapes resemble Gamma and Lognormal distributions for all counties (Figure 14). As Wand and Jones (1995) state these types of shapes are quite difficult to achieve by a kernel estimator unless n is extremely large. So we log-transformed the data and applied the fit afterward. A summary of the observed waiting times data for CS-2 and CS-5 is presented in Table 10. When we look at the median and the mean waiting times for Gilroy and Salinas, we see that the waiting time for Salinas base is approximately five minutes less than the waiting times for the Gilroy base because Salinas is closer than Gilroy to Monterey.

2. San Benito County

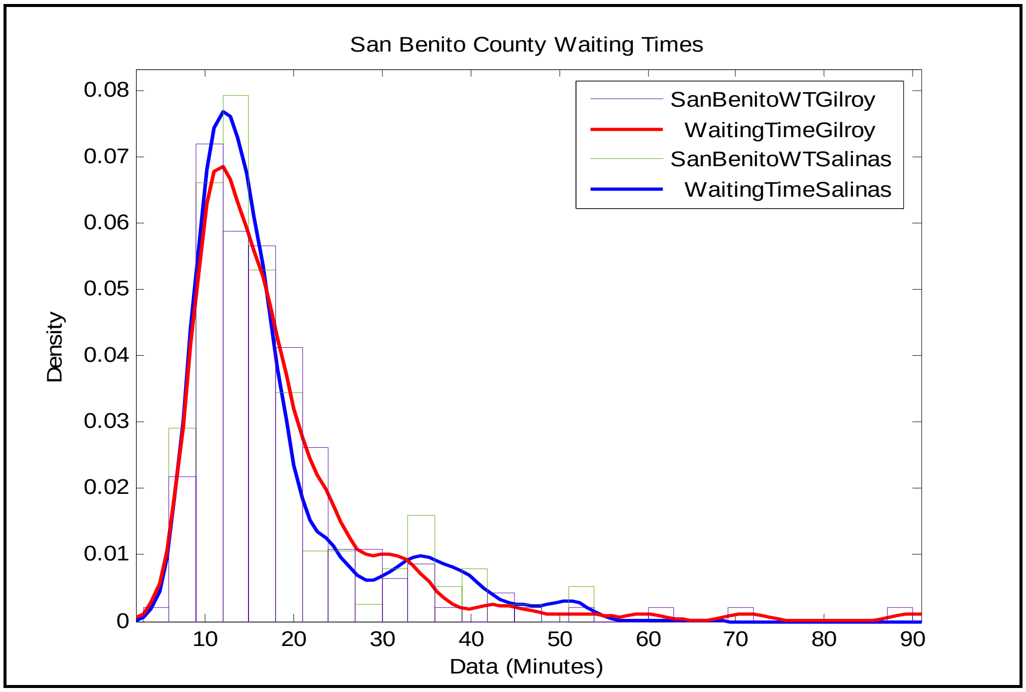

Figure 15. San Benito County Waiting Time Fits

	CS-2 “Gilroy”	CS-5 “Salinas”
Mean WT	18.209	17.571
Standard Deviation	11.445	9.654
Median	15	14

Table 11. San Benito Waiting Times Data Summary

Waiting time fits for CS-2 and CS-5 for San Benito County are illustrated in Figure 15. A summary of observed waiting times data from CS-2 and CS-5 is presented in Table 11. One remarkable issue to point out in Figure 15 is that the mean and median waiting times for Gilroy are close to waiting times for Salinas base, because the distances of the two bases to the same San Benito location do not differ very much.

3. Santa Clara County

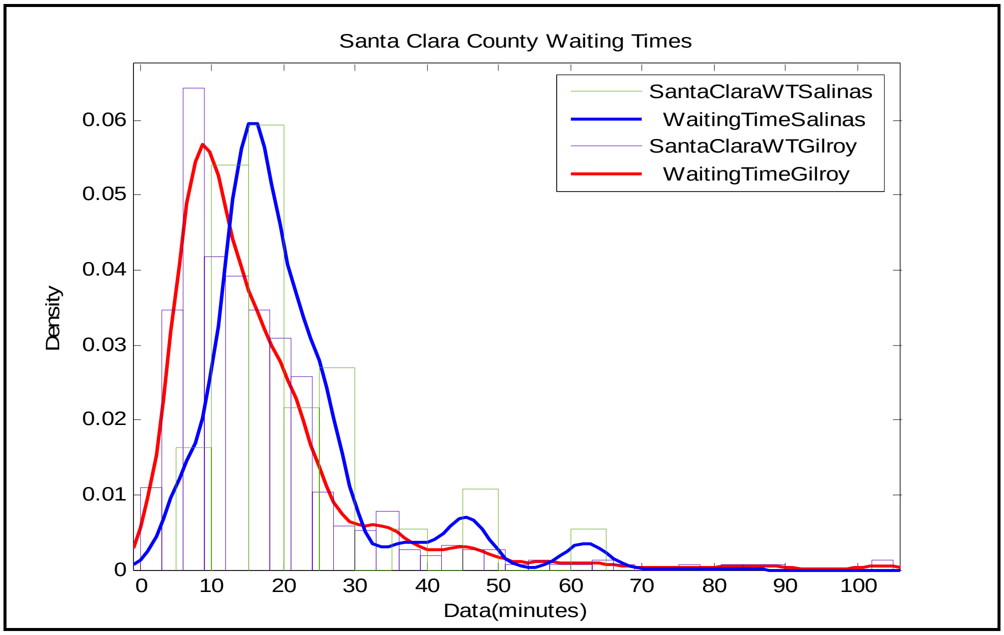

Figure 16. Santa Clara County Waiting Time Fits

	CS-2 “Gilroy”	CS-5 “Salinas”
Mean WT	16.277	20.324
Standard Deviation	13.413	11.387
Median	12.5	18

Table 12. Santa Clara Waiting Times Data Summary

Waiting time fits for CS-2 and CS-5 for Santa Clara County are illustrated in Figure 16. A summary of the observed waiting times data from CS-2 and CS-5 is presented in Table 12. When we look at the median and the mean waiting times for Gilroy and Salinas, we see that the waiting times for the Gilroy base are approximately four minutes less than the waiting times for the Salinas base, because Gilroy is closer than Salinas to Santa Clara.

4. Santa Cruz County

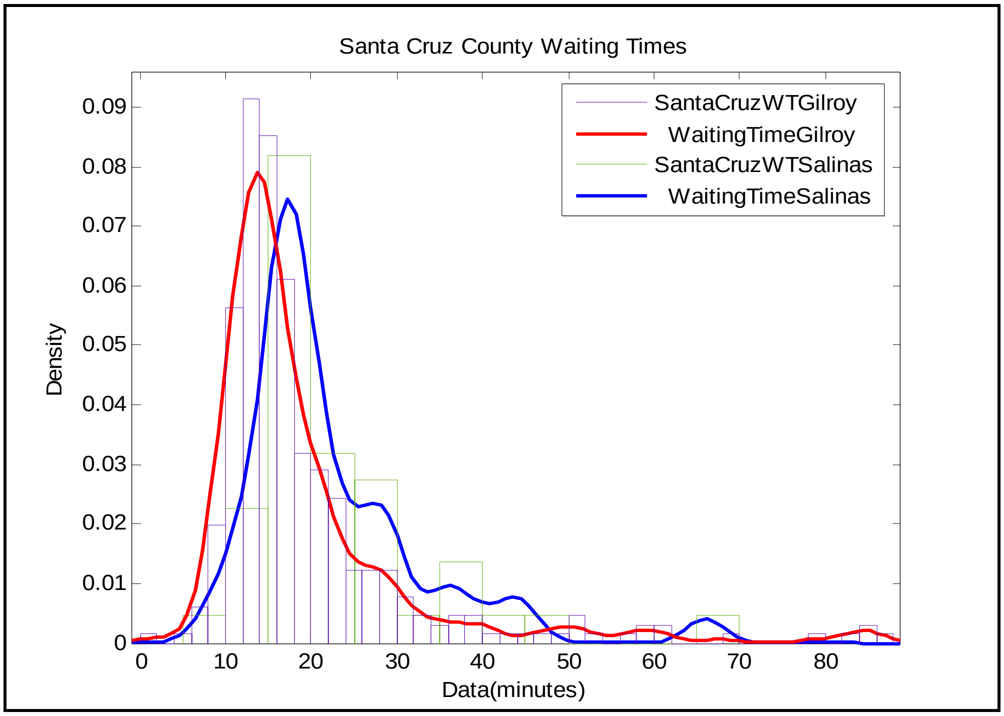

Figure 17. Santa Cruz County Waiting Time Fits

	CS-2 “Gilroy”	CS-5 “Salinas”
Mean WT	19.330	22.455
Standard Deviation	12.707	10.713
Median	15	18.5

Table 13. Santa Cruz Waiting Times Data Summary

Waiting time fits for CS-2 and CS-5 for Santa Cruz County are illustrated in Figure 17. A summary of the observed waiting times data from CS-2 and CS-5 is presented in Table 13. When we look at the median and the mean waiting times for Gilroy and Salinas, we see that the waiting times for the Gilroy base are approximately three minutes less than the waiting times for the Salinas base because Gilroy is closer than Salinas to Santa Cruz.

C. SERVICE TIME DENSITY ESTIMATION

1. Monterey County

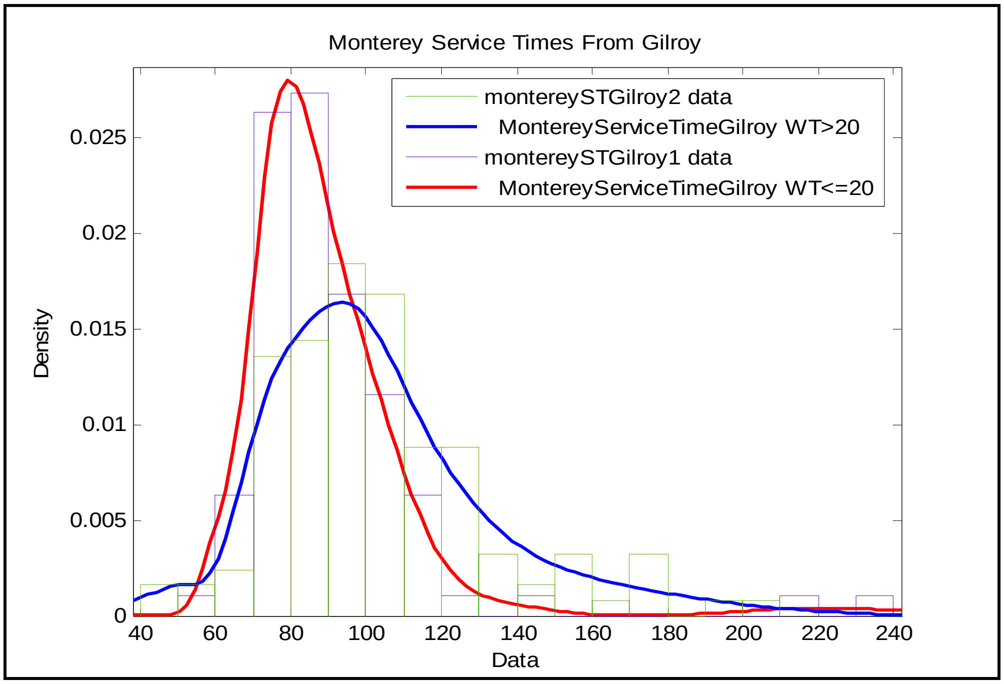

Figure 18. Monterey service time fits from Gilroy base

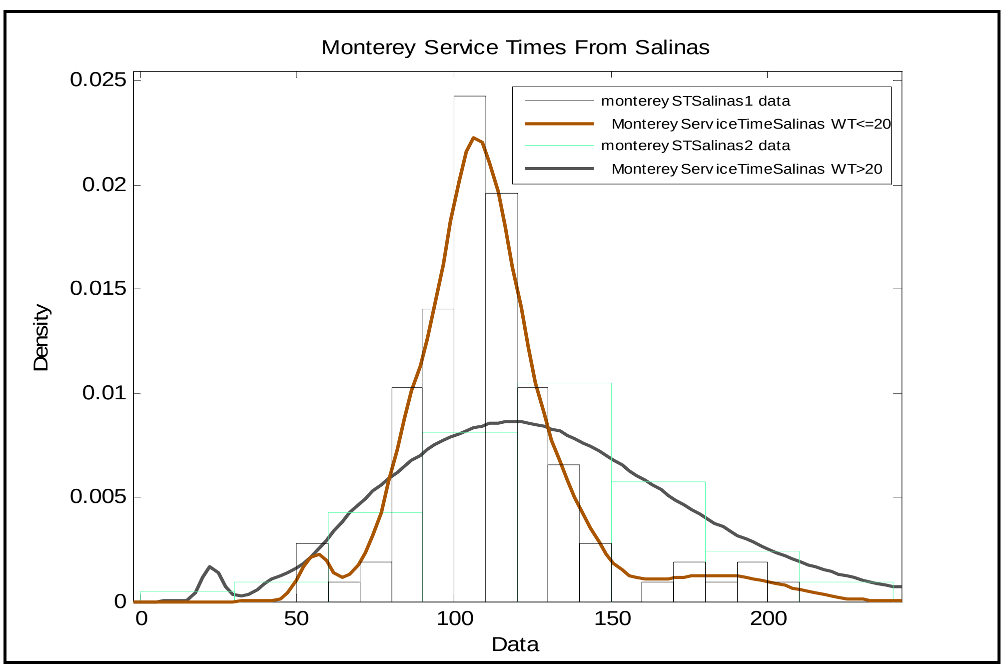

Figure 19. Monterey service time fits from Salinas base

WT<=20	CS-2 “Gilroy”	CS-5 “Salinas”
Mean ST	89.715	111.514
Standard Deviation	24.639	26.201
Median	84	107

Table 14. Monterey Service Times Data Summary where WT<=20

WT>20	CS-2 “Gilroy”	CS-5 “Salinas”
Mean ST	102.720	127.4
Standard Deviation	29.028	42.617
Median	99	123

Table 15. Monterey Service Times Data Summary where WT>20

Service time fits for CS-2 and CS-5 for Monterey are illustrated in Figures 18 and 19. A summary of the observed service time data from CS-2 and CS-5 is presented in Tables 14 and 15. One remarkable issue to point out in Figures 18 and 19 is that, for the waiting times that are greater than 20 minutes, the service time tends to increase about 15 minutes, on average, for both the Gilroy and Salinas bases.

2. San Benito County

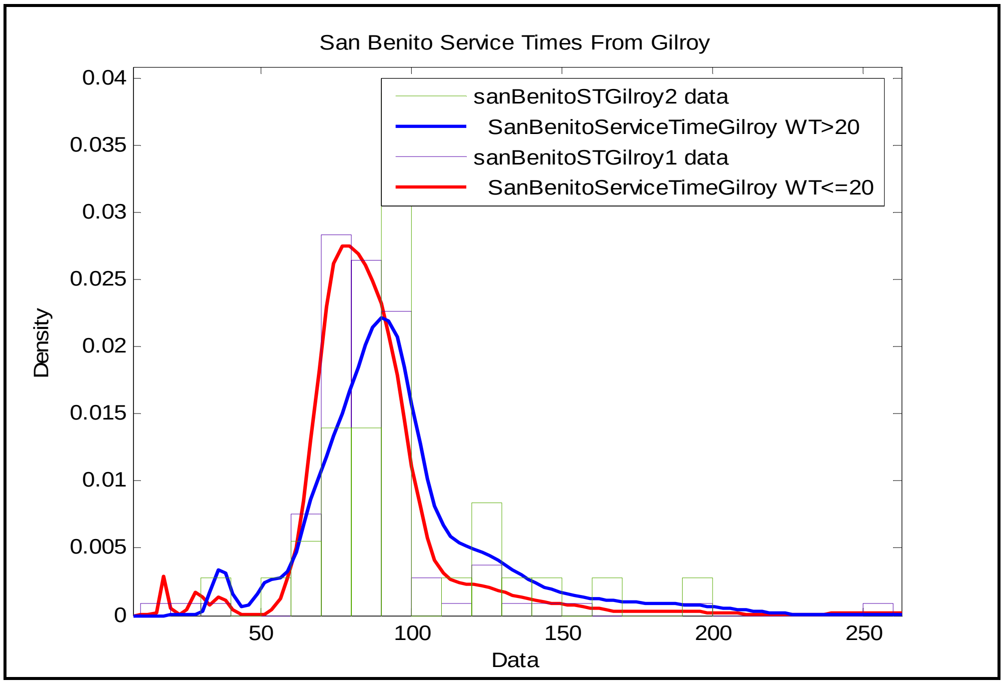

Figure 20. San Benito service time fits from Gilroy base

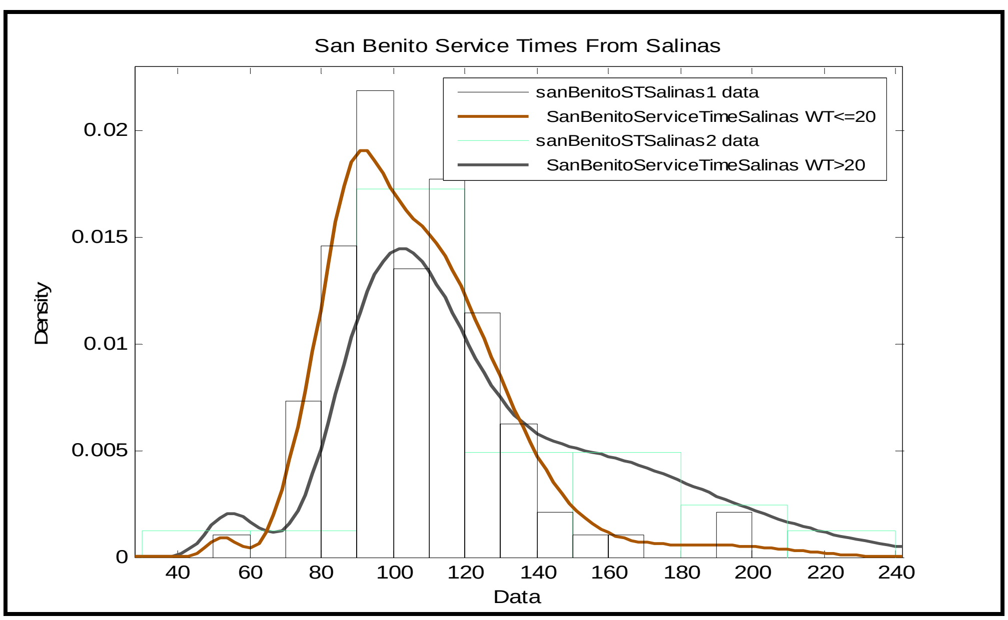

Figure 21. San Benito service time fits from Salinas base

WT<=20	CS-2 “Gilroy”	CS-5 “Salinas”
Mean ST	87.745	106.635
Standard Deviation	27.449	23.728
Median	84.5	104

Table 16. San Benito Service Times Data Summary where WT<=20

WT>20	CS-2 “Gilroy”	CS-5 “Salinas”
Mean ST	95.750	125.037
Standard Deviation	29.450	37.001
Median	92	114

Table 17. San Benito Service Times Data Summary where WT>20

Service time fits for CS-2 and CS-5 for San Benito are illustrated in Figures 20 and 21. A summary of the observed service time data from CS-2 and CS-5 is presented in Tables 16 and 17. One remarkable issue to point out in Figures 20 and 21 is that, for the waiting times that are greater than 20 minutes, the service time tends to increase about eight minutes for Gilroy base and 18 minutes for the Salinas base, on average.

3. Santa Clara County

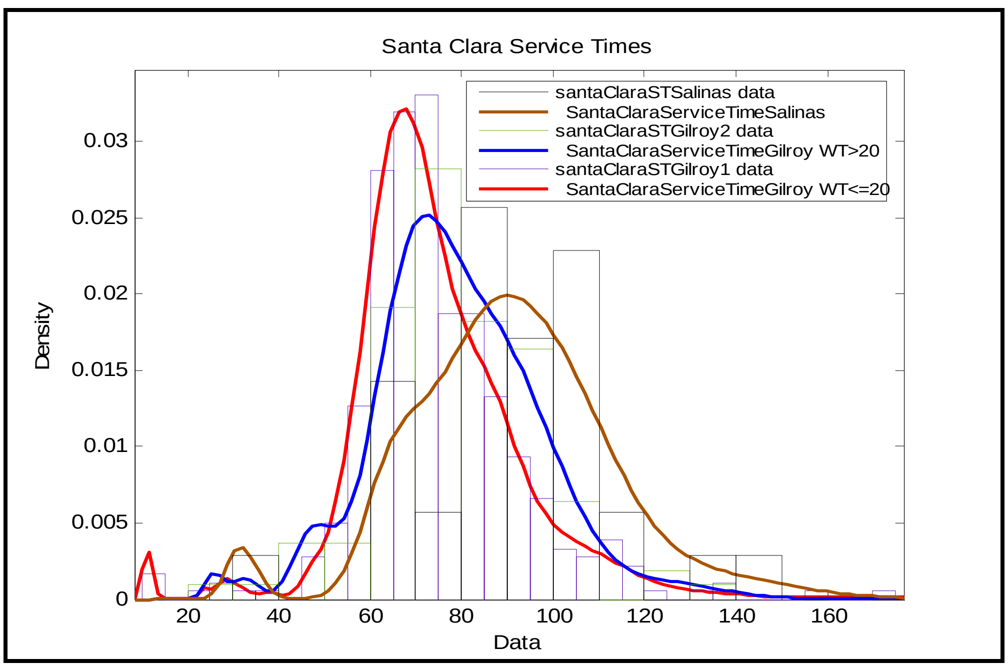

Figure 22. Santa Clara service time fits

	CS-2 "Gilroy"		CS-5 "Salinas"
	WT<=20	WT>20	
Mean ST	74.598	78.573	90.400
Standard Deviation	18.300	17.256	20.555
Median	71	77	90

Table 18. Santa Clara Service Times Data Summary

Service time fits for CS-2 and CS-5 for Santa Clara are illustrated in Figure 22. Data summaries are in Table 18. One remarkable issue to point out in Figure 22 is that, for the waiting times that are greater than 20 minutes, the service time tends to increase about four minutes for the Gilroy base. There is an insufficient amount of data to see that kind of change for the Salinas base.

4. Santa Cruz County

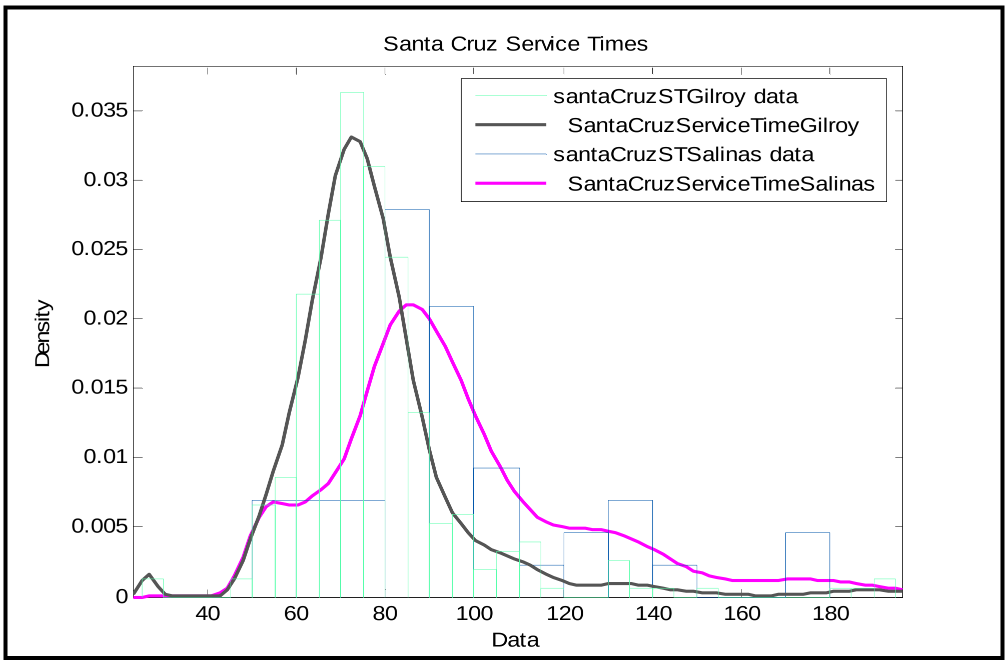

Figure 23. Santa Cruz service time fits

	CS-2 "Gilroy"	CS-5 "Salinas"
Mean ST	77.775	95.279
Standard Deviation	20.708	28.159
Median	74	90

Table 19. Santa Cruz Service Times Data Summary

Service time fits for CS-2 and CS-5 for Santa Cruz are illustrated in Figure 23. Data summaries are in Table 19. As a result of the correlation test, for Santa Cruz County, the waiting times and service times are found to be independent.

D. INTER-FACILITY TRANSPORTATION TOTAL SERVICE TIME DENSITY ESTIMATION

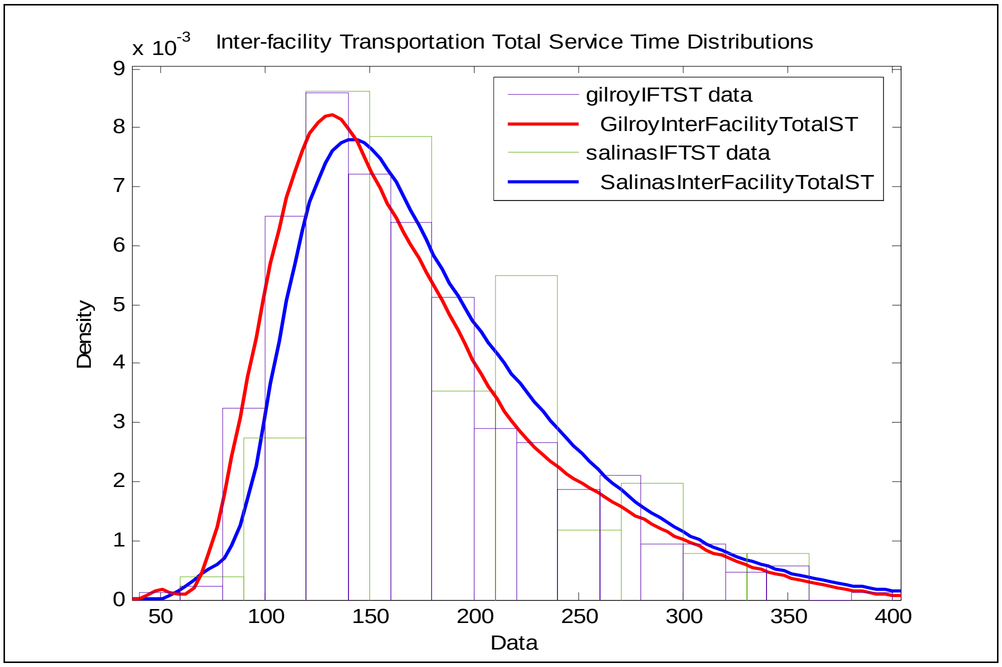

Figure 24. Inter-facility transportations total service time distributions

	CS-2 “Gilroy”	CS-5 “Salinas”
Mean TST	169.665	180.559
Standard Deviation	59.710	57.109
Median	155.5	169

Table 20. Inter-facility Total Service Times Data Summary

Total service time fits for CS-2 and CS-5 for inter-facility transportations are illustrated in Figure 24. Data summaries are in Table 20. Observe that the average total service time for Gilroy is about eleven minutes less than the average total service time for Salinas. Most of the sophisticated hospitals and trauma centers are located in the north of Salinas, so for the Salinas base, it takes more time to complete an inter-facility transportation.

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APPENDIX B. NONHOMOGENEOUS POISSON PROCESS RATE FUNCTION ESTIMATION

On the horizontal axis of intra-week density figures, 1 and 8 are Monday at 00:00; 2 is Tuesday, 3 is Wednesday, 4 is Thursday, 5 is Friday, 6 is Saturday, and 7 is Sunday at 00:00.

A. COMPLETE MISSION RATE FUNCTION ESTIMATION

We used 2002 and 2003 data to find the rates, and the 2004 data (which consists of only eleven months) to cross-validate the parameters.

1. Monterey County

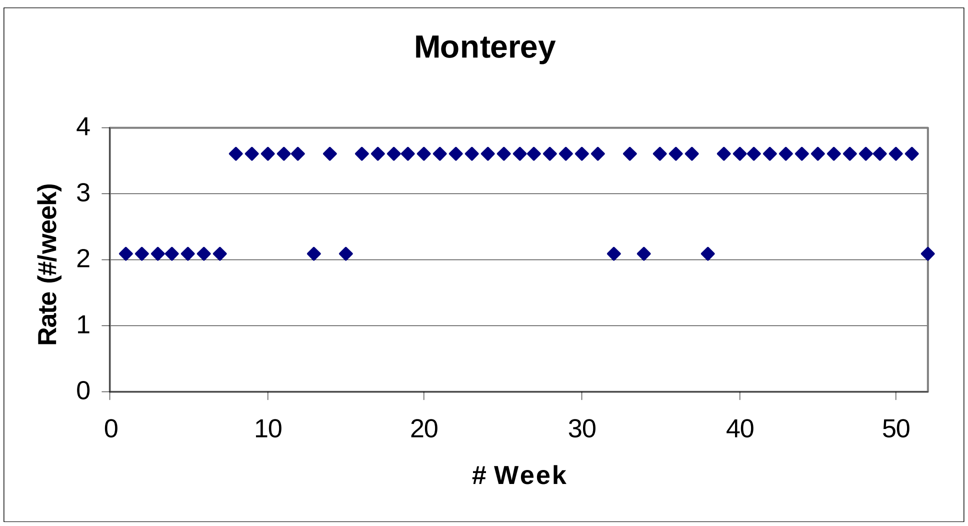

Figure 25. Intensity function for Monterey completed flights

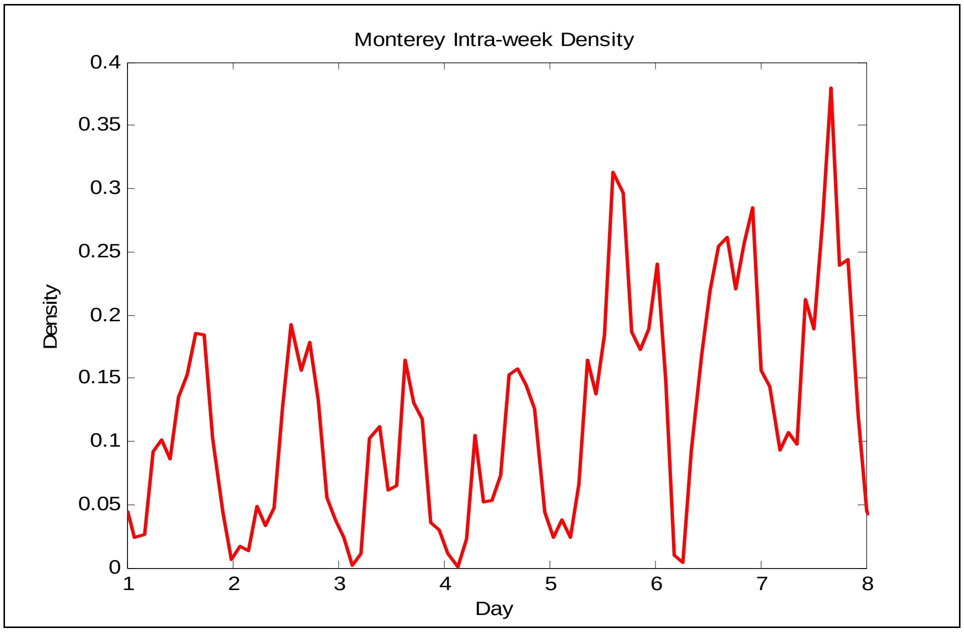

Figure 26. Monterey intra-week density

The estimated weekly piece-wise rate function for Monterey County is illustrated in Figure 25. Given that rate, the intra-week density is illustrated in Figure 26. Observe that the density is higher in the morning as compared to noon for Monday, Wednesday, and Thursday and Friday evening hours and midnight are critical in terms of trauma incidents, such as traffic accidents.

2. San Benito County

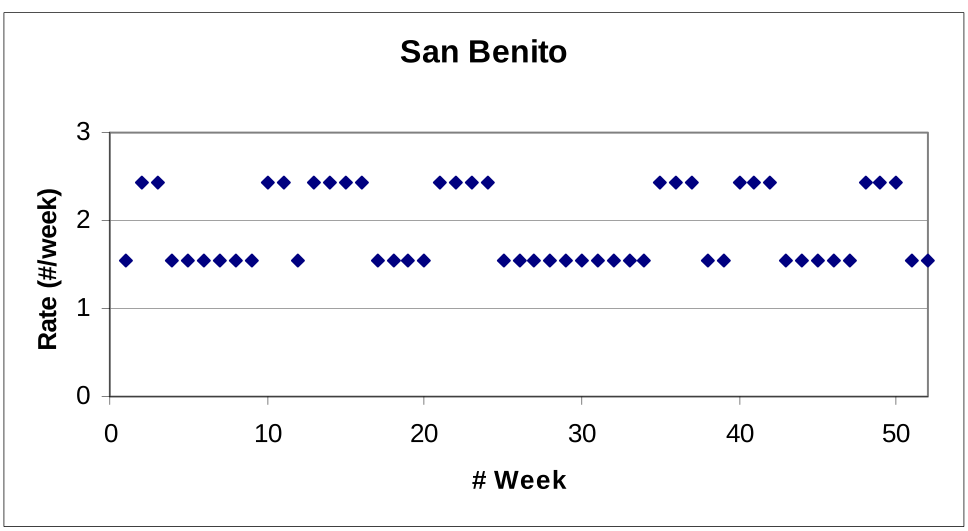

Figure 27. Intensity function for San Benito completed flights

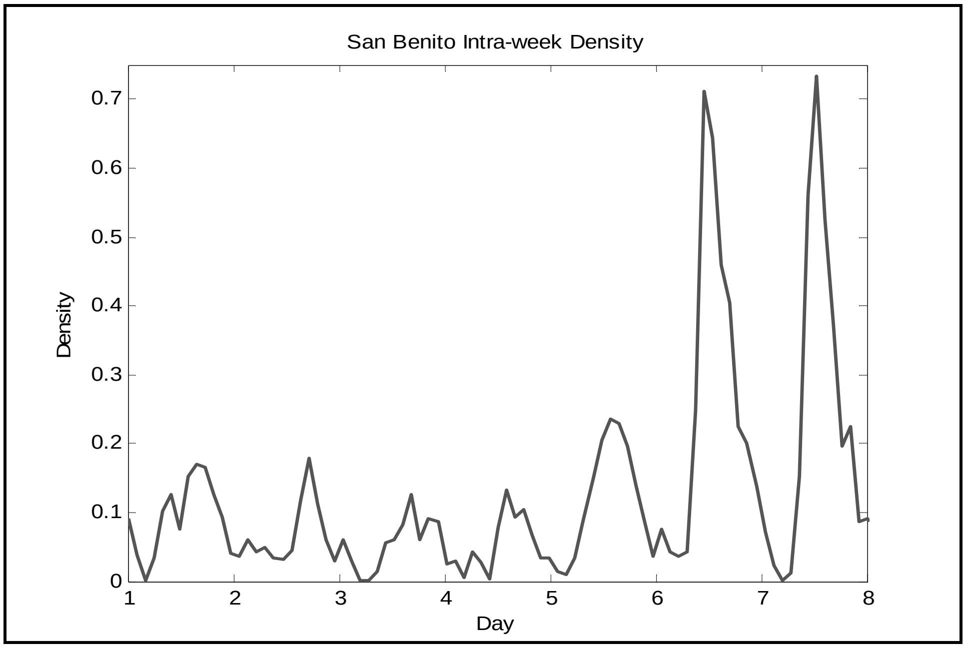

Figure 28. San Benito intra-week density

The estimated weekly piece-wise rate function for San Benito County is illustrated in Figure 27. Given that rate, the intra-week density is illustrated in Figure 28. Observe that the density is high on weekends in San Benito County, because of the motorcycle accidents that happen in Hollister.

3. Santa Clara County

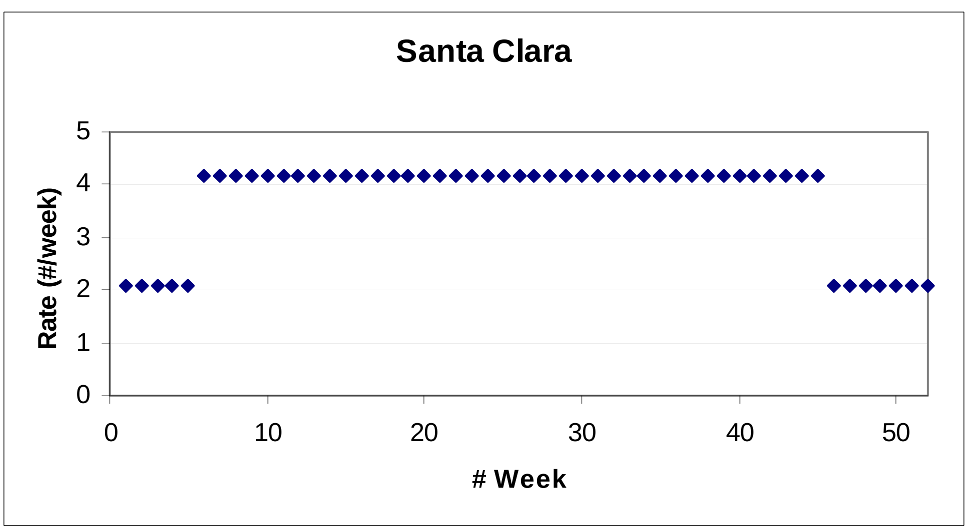

Figure 29. Intensity function for Santa Clara completed flight

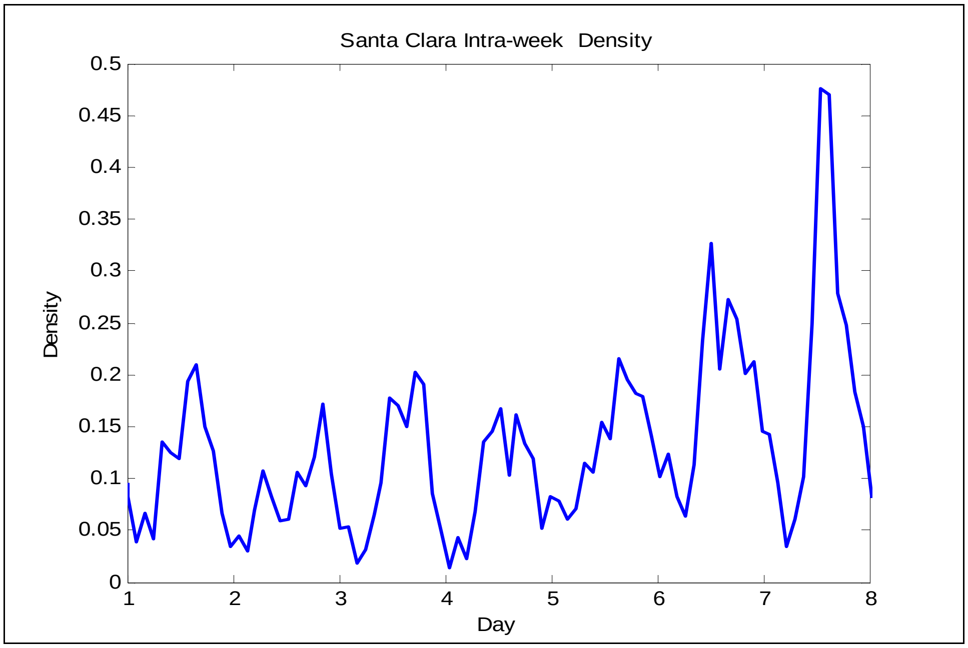

Figure 30. Santa Clara intra-week density

The estimated weekly piece-wise rate function for Santa Clara County is illustrated in Figure 29. Given that rate, the intra-week density is illustrated in Figure 30. Observe that the density during the Sunday afternoon to evening period is high as compared to the rest of the week, because people coming back from weekend activities tend to have more accidents on the roads.

4. Santa Cruz County

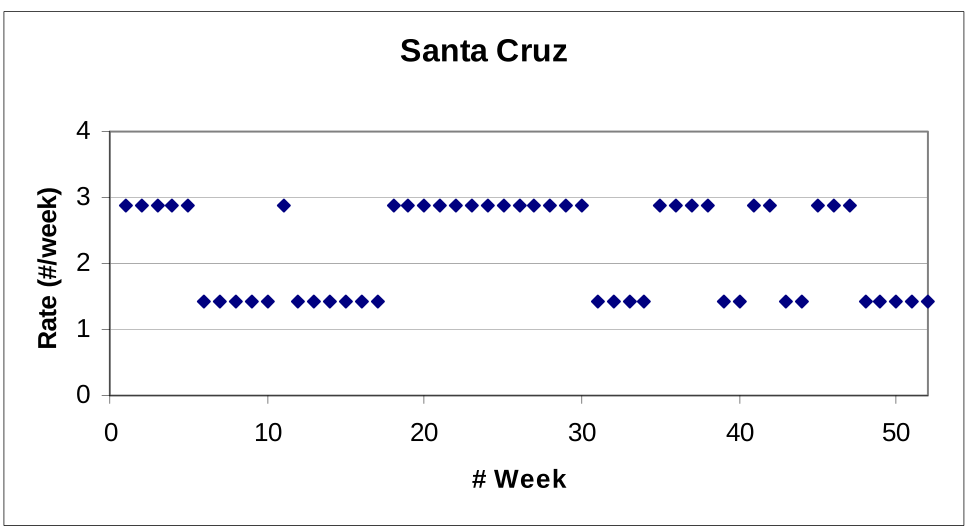

Figure 31. Intensity function for Santa Cruz completed flights

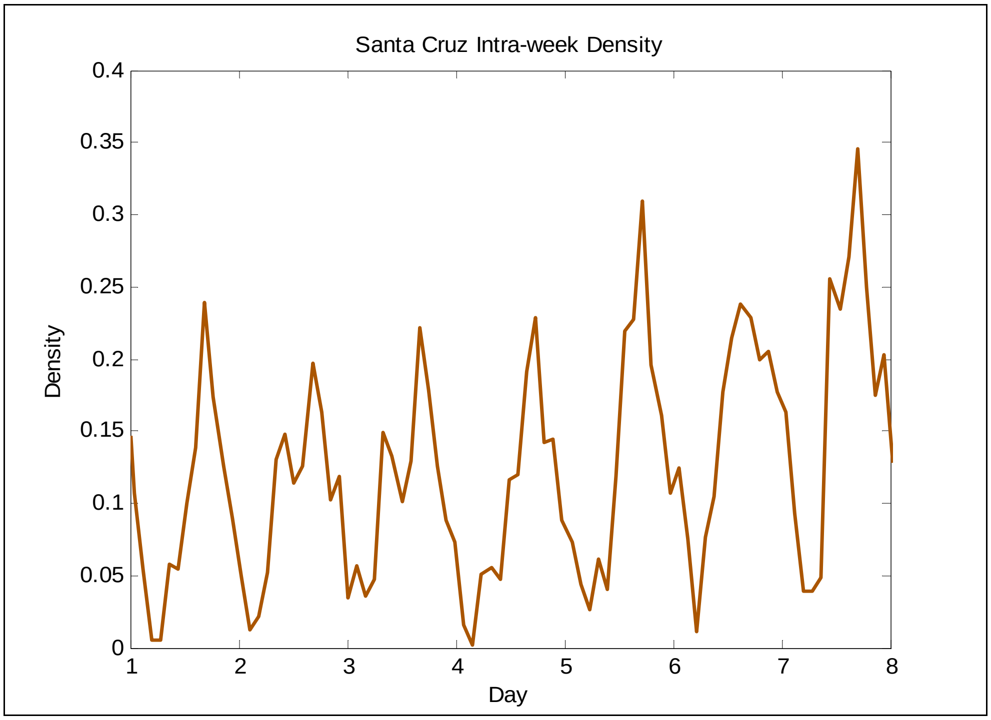

Figure 32. Santa Cruz intra-week density

The estimated weekly piece-wise rate function for Santa Cruz County is illustrated in Figure 31. Given that rate, the intra-week density is illustrated in Figure 32. Observe that the density does not differ so much on most days of the week. Only Friday and Sunday seem to have a slightly higher density than the rest of the week.

B. INCOMPLETE MISSION RATE FUNCTION ESTIMATION

CALSTAR only provided year-2004 incomplete-flight information for the counties, so it is impossible to cross-validate the estimated rate function. But by observing the completed-flight rate function fits, it is plausible to use estimated rates from the year 2004 data. Table 2 presents a summary of results for incomplete flights. Observe from the intra-week density figures that they resemble the complete-mission intra-week densities. These figures also represent the densities of the emergency incidents observed in the counties, but these incidents are not so critical and can be treated by local hospital resources.

1. Monterey County

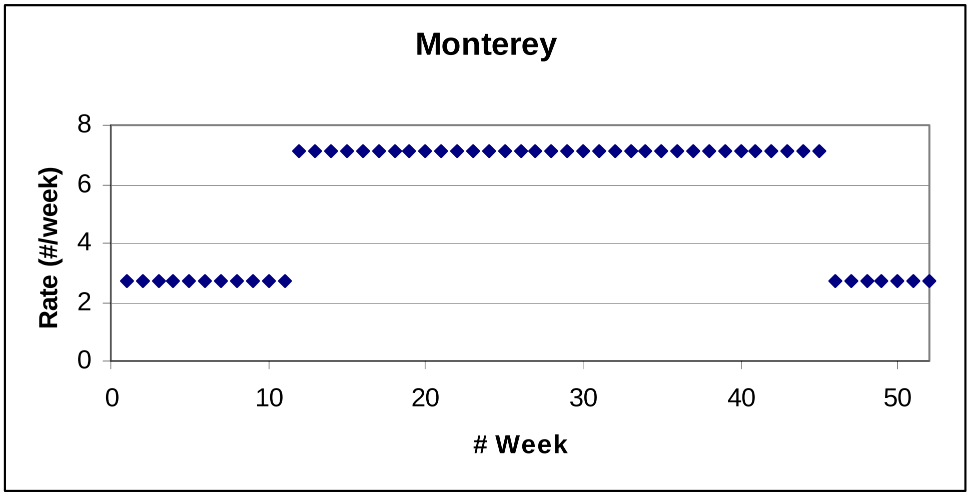

Figure 33. Intensity function for Monterey incomplete flights

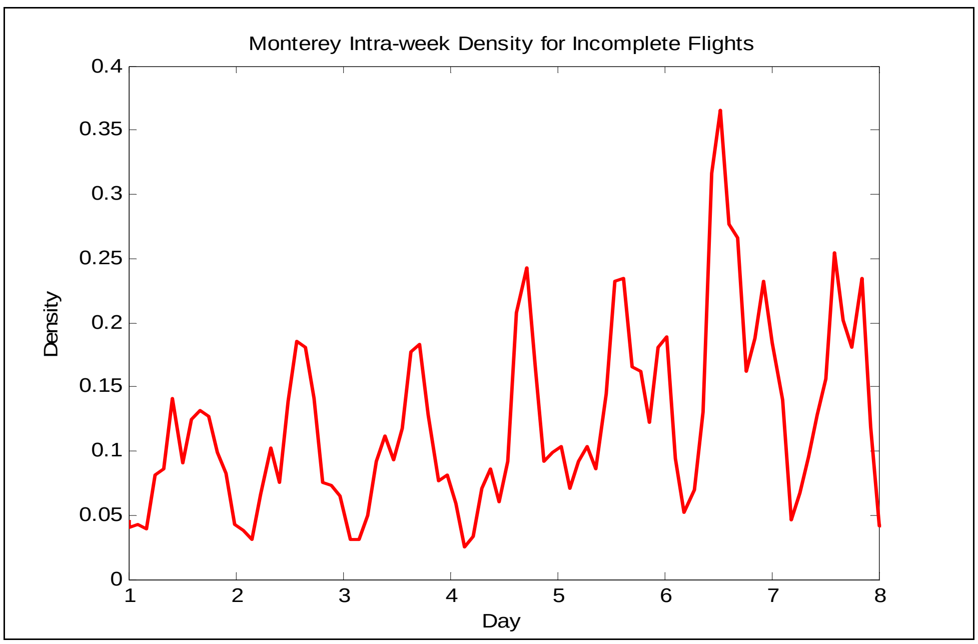

Figure 34. Monterey intra-week density for incomplete flights

The estimated weekly piece-wise rate function for Monterey County is illustrated in Figure 33. Given that rate, the intra-week density is illustrated in Figure 34.

2. San Benito County

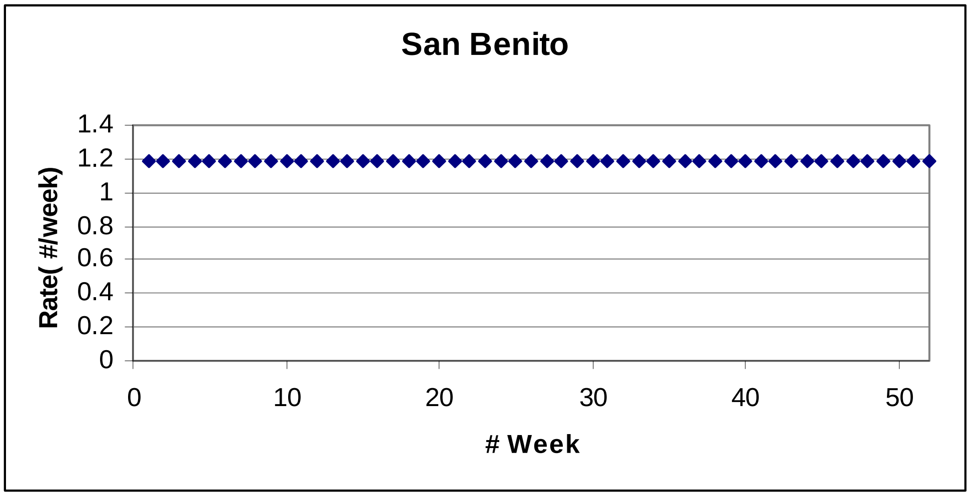

Figure 35. Intensity function for San Benito incomplete flights

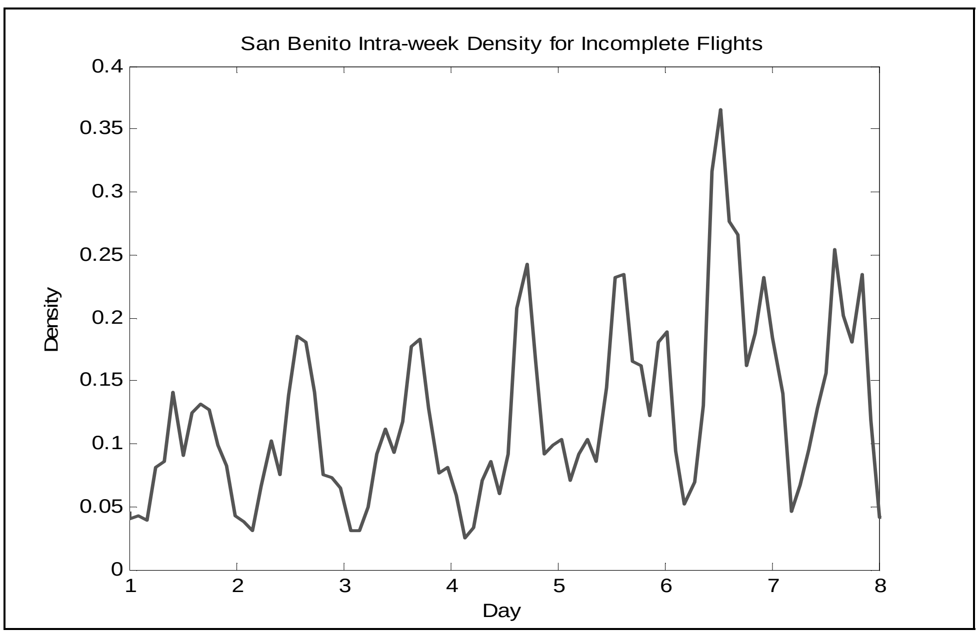

Figure 36. San Benito intra-week density for incomplete flights

The estimated weekly piece-wise rate function for San Benito County is illustrated in Figure 35. Given that rate, the intra-week density is illustrated in Figure 36.

3. Santa Clara County

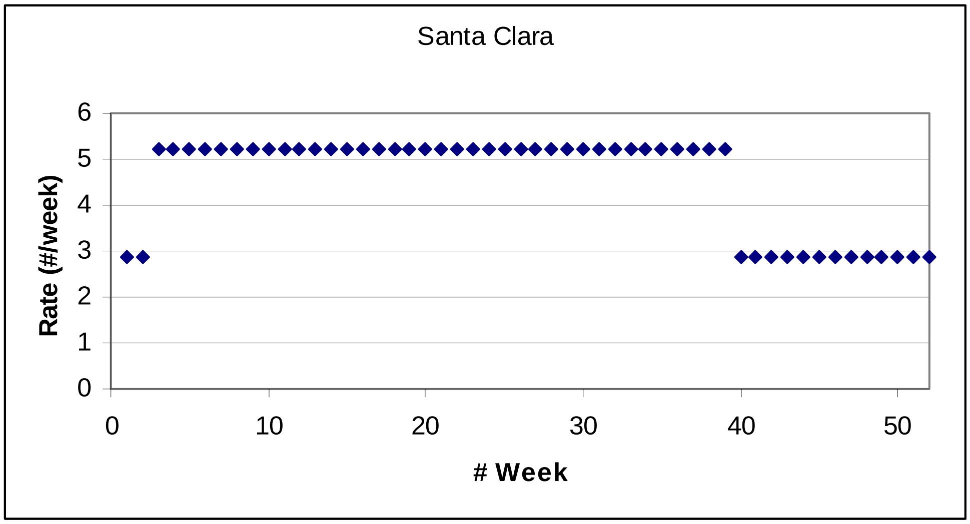

Figure 37. Intensity function for Santa Clara incomplete flights

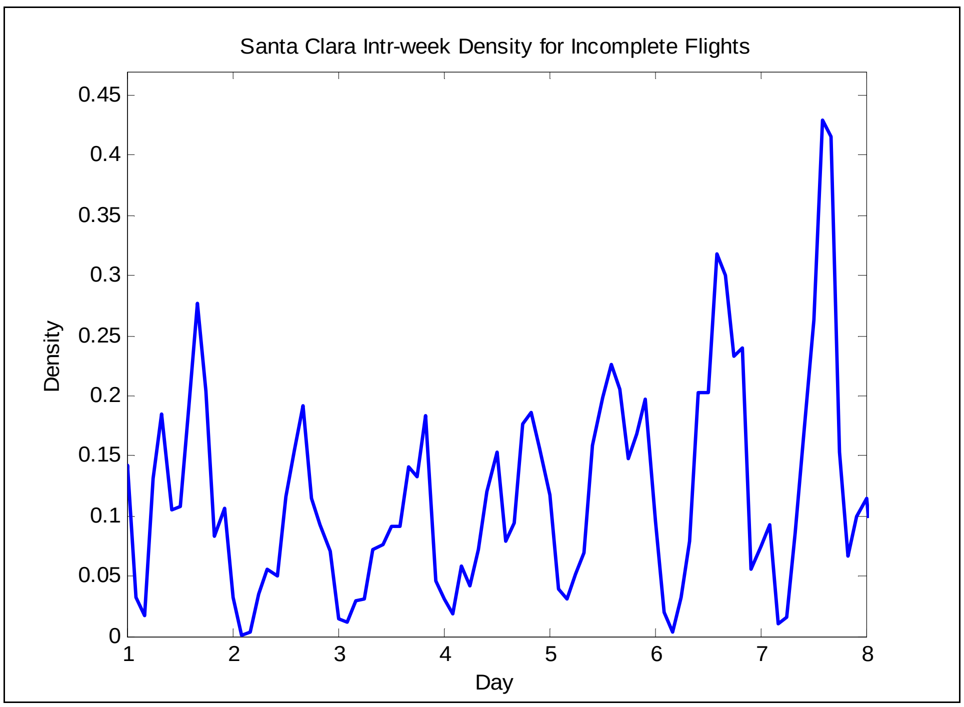

Figure 38. Santa Clara intra-week density for incomplete flights

The estimated weekly piece-wise rate function for Santa Clara County is illustrated in Figure 37. Given that rate, the intra-week density is illustrated in Figure 38.

4. Santa Cruz County

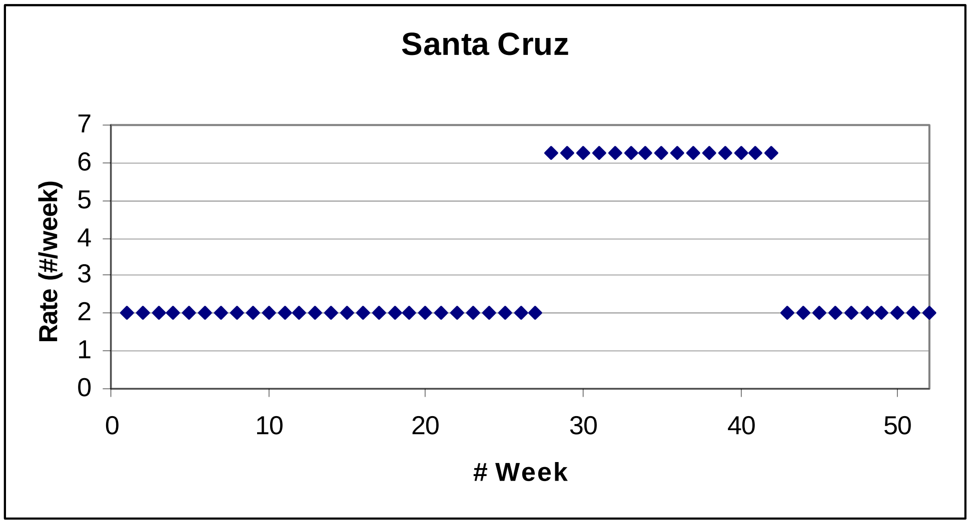

Figure 39. Intensity function for Santa Cruz incomplete flights

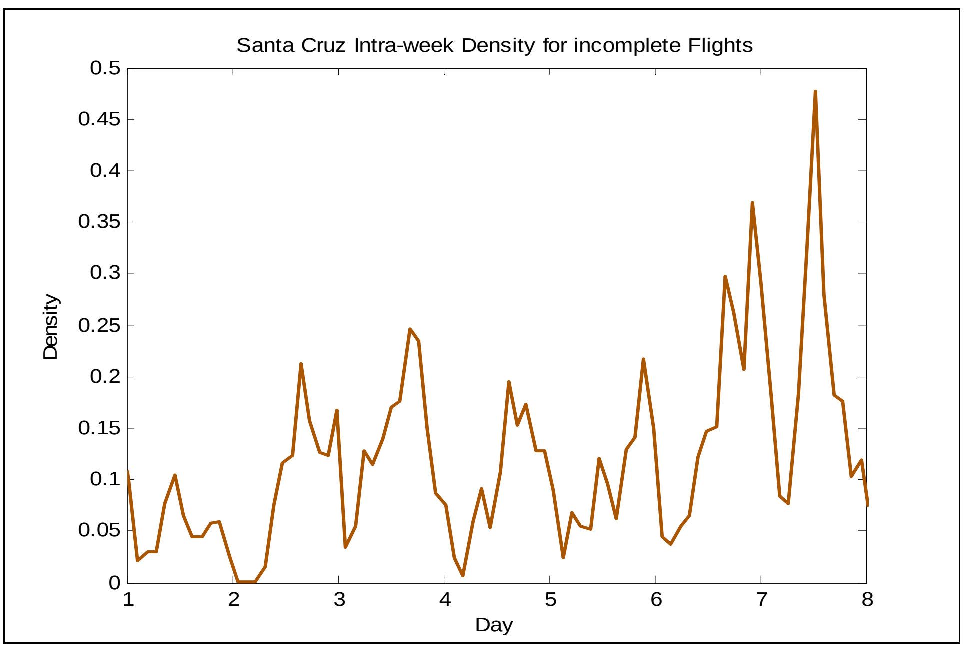

Figure 40. Santa Cruz intra-week density for incomplete flights

The estimated weekly piece-wise rate function for Santa Cruz County is illustrated in Figure 39. Given that rate, the intra-week density is illustrated in Figure 40.

C. INTER-FACILITY MISSION RATE FUNCTION ESTIMATION

We used 2002 and 2003 data to find the rates, and the 2004 data (which consists of only eleven months) to cross-validate the parameters.

1. CS-2 "Gilroy" Base

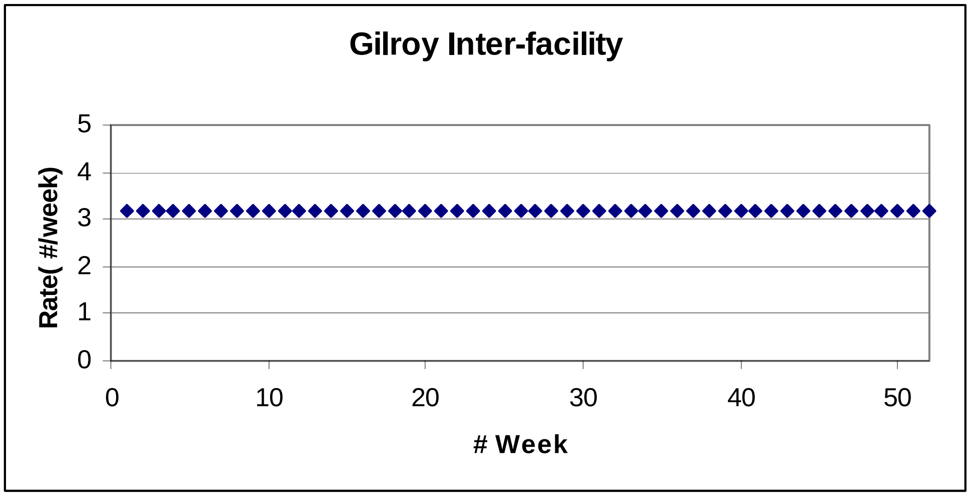

Figure 41. Intensity function for Gilroy inter-facility flights

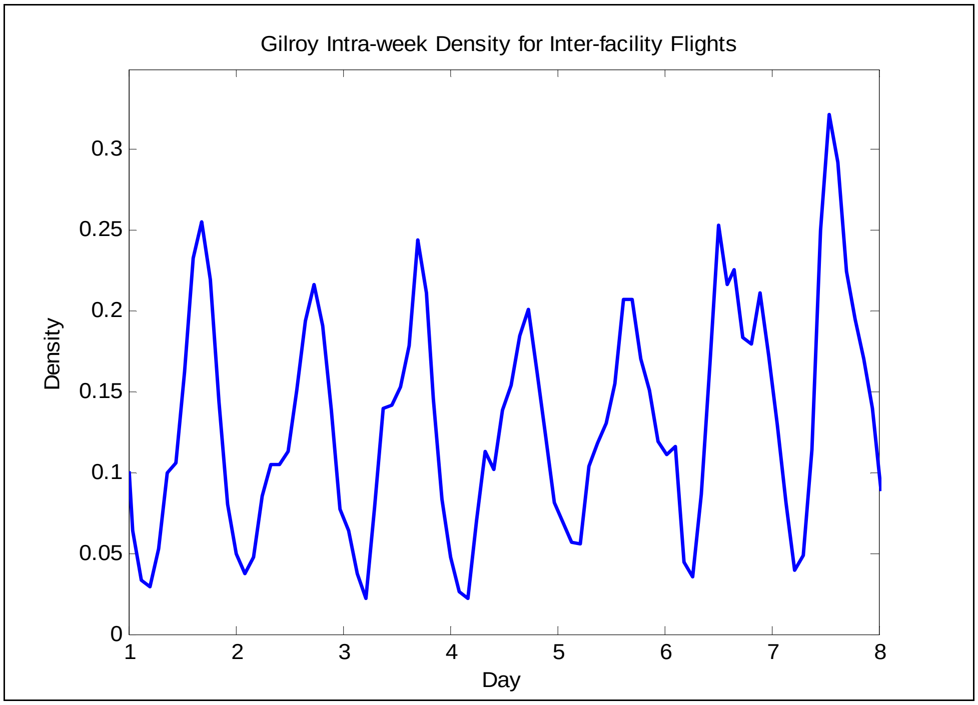

Figure 42. Gilroy intra-week density for inter-facility flights

The estimated weekly piece-wise rate function for the CS-2 "Gilroy" base is illustrated in Figure 41. Given that rate, the intra-week density is illustrated in Figure 42.

Observe that the inter-facility mission demand rate for the Gilroy base is constant over the year, but the density over a week tends to be higher during the afternoon to evening period and on Sunday evening the inter-facility mission arrival density reaches its top.

2. CS-5 "Salinas" Base

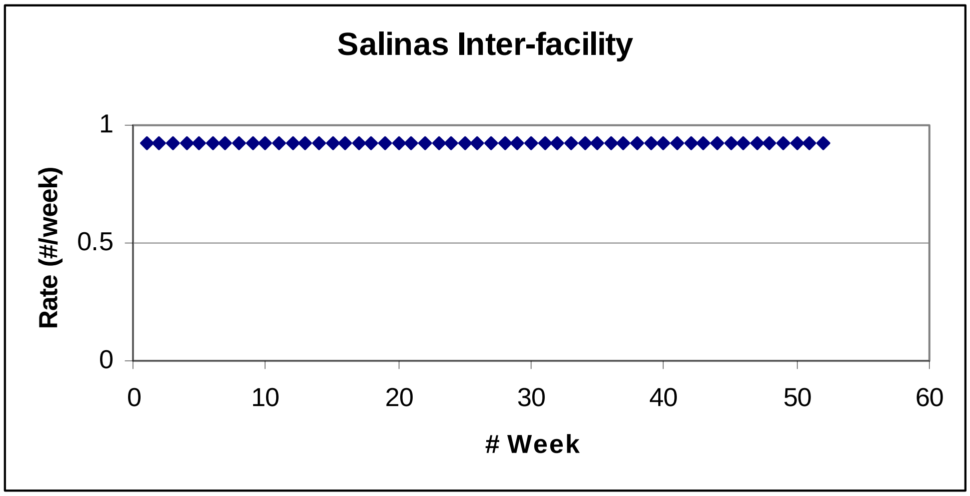

Figure 43. Intensity function for Salinas inter-facility flights

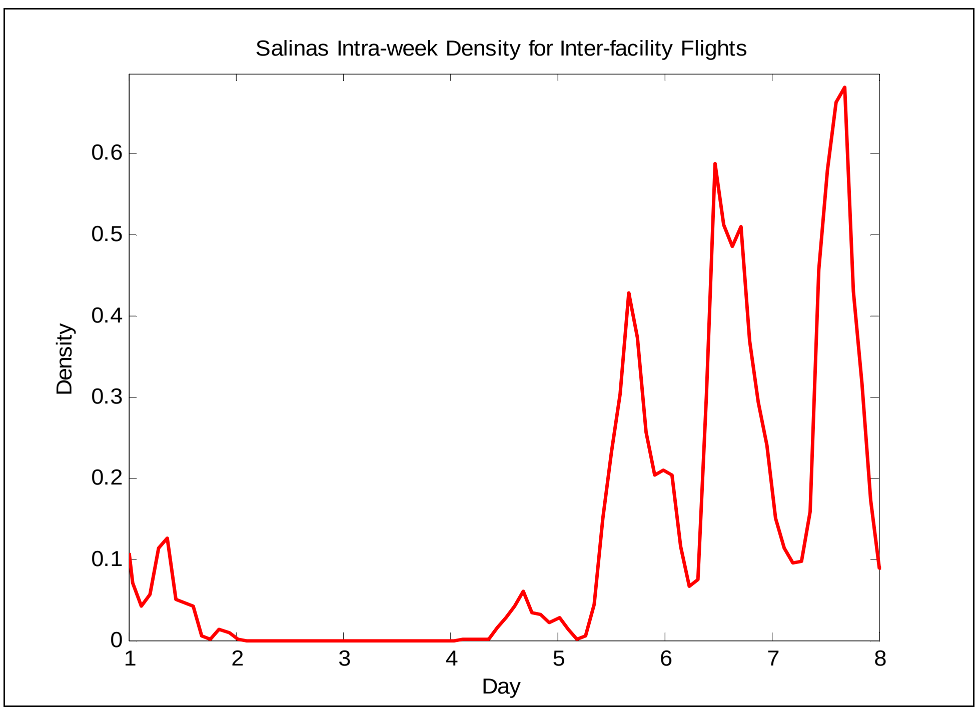

Figure 44. Salinas intra-week density for inter-facility flights

The estimated weekly piece-wise rate function for the CS-5 “Salinas” base is illustrated in Figure 43. Given that rate, the intra-week density is illustrated in Figure 44. Observe that the inter-facility mission demand rate for the Salinas base is constant over the year and is close to one mission per week. The density reflects the current operational schedule as the Salinas base is operative from Thursday to Monday. Observe that the density on Thursday and Monday is quite low as compared to Friday, Saturday and Sunday, because, most of the time, hospitals consider the Salinas base not operative and do not request service.

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