DEVELOPING AND VALIDATING JOINT DYNAMIC AMBULANCE RELOCATION AND FLEXIBLE DISPATCHING STRATEGIES: A SIMULATION-OPTIMIZATION APPROACH

by

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ABSTRACT

XUN LI Developing and validating joint dynamic ambulance location and flexible dispatching strategies: a simulation-optimization approach (Under the direction of DR. CEM SAYDAM)

Emergency Medical Services (EMS) system's mission is to provide timely and effective treatment to anyone in need of urgent medical care throughout their jurisdiction. The main goal of most EMS deployment is to reduce mortality, disability, pain and suffering. There are several metrics for level of EMS service, and among them, response time (RT) and call coverage rate are the most popular ones used by EMS providers and researchers. Ability to provide timely response is affected by fleet size and the locations of the ambulances. Hence, literature on ambulance location has been dominated by models which generally maximize or guarantee coverage, minimize mean response time, and alike. Essentially all models, including highly sophisticated queuing embedded optimization models, rely on several simplifying assumptions in order to make them tractable. These include the vehicle busy probabilities calculated a priori, dispatching the nearest ambulance to all incidents, a zone (call demand) being covered (can be reached) if it is within the distance/time threshold as a binary exogenous variable, static unit dispatch, and so on. The default dispatch policy is to send the nearest ambulance to all medical emergencies and it is widely accepted by many EMS providers. However, sending nearest ambulance is not always optimal, often imposes heavy workloads on ambulance crews posted in high demand zones while reducing available coverage or requiring ambulance relocations to ensure high demand zones are covered adequately.

In this study we propose a simulation embedded optimization approach for relocating ambulances and determining flexible dispatch policies that balance ambulance crew workloads while meeting fast response times for life-threatening calls. A realistic simulation model allows us to remove most of the simplifying assumptions which are required in analytical approaches such as integer programming models as well as queuing theory based models. We show that this approach provides a much richer output that can be used by EMS managers to estimate lives saved for multiple life threatening situations while providing a detailed statistics on important performance measures such as actual ambulance workloads and response times. We validate our approach with an advanced coverage optimization model using real-life data. We present computational statistics and demonstrate the efficacy of a tiered dispatch policy using real-world data.

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CHAPTER 1: INTRODUCTION

1.1. Problem Domain

Emergency Medical Services (EMS) system's mission is to provide timely and effective treatment to anyone in need of urgent medical care throughout their jurisdiction. The main goal of most EMS deployment is to reduce mortality, disability, pain and suffering. A typical process of providing emergency medical service begins when an emergency call is received by the emergency dispatch call center, the emergency medical dispatcher assesses the call by asking few questions and determines its urgency, and determines which EMS vehicle to dispatch according to the priority of the call. High priority calls are of great interest to the EMS provider, among which most are life threating. Usually the closest available vehicle is sent to the accident scene as quickly as possible [1, 2]. When the vehicle reaches the scene, some form of on-scene treatment is provided to the patient. Sometimes, a second vehicle with higher skilled officers may also be dispatched to ensure the correct level of care is provided at the scene for high priority calls. If the treatment on the scene is not satisfactory, then the patient is transported to a nearest hospital in order to receive further care. Otherwise, the vehicle becomes free at the scene and typically returns to its designated home base or a temporary post to await its next call [3-5].

Healthcare is an area of growing importance as well as cost in most countries and EMS is a crucial component of modern healthcare system. As a result EMS is an important research domain that has received a great deal of attention in the operations research (OR) community [4]. The design and operation of EMS has been a vibrant area for operation research professionals since mid-1960's [6]. Generally, most body of literature in EMS researches field concentrate on two objectives: reducing cost of operation and increasing the level of EMS service. EMS is often operated by city or local government with a limited budget [7, 8]. The maintenance cost of ambulances and the personnel costs make up majority the operating costs of EMS. Consequently, the number of ambulances is often used as a surrogate unit for cost.

1.2. EMS Performance Metrics

There are several metrics for level of EMS service, and among them, response time and call coverage rate are the most popular ones used by EMS providers and researchers [4, 6, 9]. Response time (RT) is often defined as the elapsed time between the call being received at the dispatch center and an ambulance arriving at the incident scene. Quickly arriving at the incident scene does reduce suffering while satisfying the public's perception that shorter RT always save lives. RTs are how EMS providers compete for contracts, and it's how EMS leadership proves to the community that they meet or exceed the contractually agreed performance goals [10]. Historically, RT has been perceived as a critically important factor and has been widely used as one of the most important criteria for evaluating and designing EMS. In 1979, Eisenberg and colleagues reported that survival from witnessed prehospital cardiac arrest of a medical origin in adults was maximized if the time from collapse to cardiopulmonary resuscitation and the time from collapse to definitive care were 4 and 8 minutes respectively [11]. Some follow up research also showed that sudden cardiac arrests require RT less than five minutes to be effective [12, 13] and that when RT is reduced from 14 minutes to 5 minutes the survival rate for cardiac arrests could almost be doubled [12]. One study indicates that for every 30 minutes of delay in receiving percutaneous coronary intervention (PCI), the myocardial infarction with ST elevation patient's one-year mortality increases by 7.5% [14].

Coverage is another critical aspect researchers must consider as well as EMS administrators or managers. A demand call is said to be covered if it can be reached within a certain pre-specified response time threshold (RTT) by at least one ambulance. Often researchers implement a given RTT as a distance threshold in their models. In most optimization models demand locations within the distance threshold of an ambulance are assumed to be covered and any demand location further away is not covered [4]. A call that cannot be reached by a vehicle within the RTT is said to be a lost call. The percentage of calls with response times less than RTT is referred as coverage [4]. The performance targets for response times vary by the location (metropolitan or rural area) of the call and the priority of the call. Metropolitan calls that are designated as life threatening (high priority) typically requires the shortest target response time, while low priority rural calls have longer RTT [5]. Although there is no universally accepted response time standard in the U.S. the most common EMS (ambulance) response time standard is based on National Fire Protection Association (NFPA) 1720 which is 8 minutes 59 seconds (inclusive of the 60 seconds of call handling time) for 90 percent of life threating calls [15].

1.3. Response Time and Patient Outcomes

Recently, the clinical effectiveness of using RT as a universal rule has been questioned. It makes intuitive sense that fast ambulance RTs should influence patient outcome, however, apart from cardiac arrest [13, 16], no evidence found in literature suggests a direct relationship between prehospital RTs and patient outcomes. In fact, there is growing evidence that, apart from out of hospital cardiac arrest, penetrating trauma (e.g., critical gunshot wound) kinds of medical emergencies, fast response times are not associated with improved patient outcomes [12]. In trauma cases the RT can be longer than five or eight minutes as long as the patient is transferred to a trauma center under one hour which is known as the “golden hour” or “golden time” [17].

Blackwell et al. [18] tested the hypothesis that patient outcomes do not differ substantially by a case-control retrospective study. The study patients which are cases defined as Priority 1 transports with RTs exceeding 10:59 minutes were compared with controls with RTs of 10:59 minutes or less. Their results indicated that the two groups do not have a statistically significant difference in neither the mortality nor the frequency of critical procedural interventions. Another retrospective study set in an EMS system that responds to calls for a population of approximately 1 million by Blanchard et al. [19] compared the risk of mortality in patients (all types) who received a response time greater or equal to 8 minutes with that of those who did not. This study suggested that RTs of $\geq$ 8 minutes were not associated with a decrease of survival to hospital discharge. Weiss et al. [20] conducted a study in specific traumatic and medical emergencies and found no evidence that increasing RT is associated with worse patients outcome. Though RTs represent an important performance indicator, but taken alone, it does not completely predict outcome of disease severity or mortality

The ultimate goal of an EMS is to maximize the number of patients that survive. Hence patient survival is regarded as the real performance measure of EMS systems [21].

As mentioned above in practice RTT is often used to evaluate EMS as opposed to patient survival for the following reasons [9]: First, estimating patient survival is difficult since it is assessed at the hospital and a patient may be discharged several days after delivery to the emergency department. Second, patient survival information is not readily available due to medical privacy regulations. On the other hand, RT statistics are easy to obtain and evaluate. However, without including survival rate, the coverage concept based on RTT has an important limitation due to its black-and-white nature [21]. Locating ambulances according to RTT may result in arbitrarily bad patient survival rates. As a result of increasing questions about the effectiveness of RTs, a few researchers began incorporating patient survivability in their objectives. Erkut et al. [21] illustrate the importance of explicitly linking ambulance location to patient survivability and modeled a survival function as a monotonically decreasing function of the response time that returns the probability of survival for the patient. They proposed a new model, Maximal Survival Location Problem (MSLP) by incorporating explicitly this survival function into existing covering models. Unlike previous covering models whose objective is to maximize total covered demand based on RTT, MSLP aims to maximize the expected number of survival patients. MSLP is able to examine consequences of different response time overcoming the weakness of hard RTT. Knight et al. [22] developed the Maximal Expected Survival Location Model for heterogeneous Patients (MESLMHP) extending Erkut et al.'s work. MESLMHP used a novel approach and made two significant advancements. Firstly, MESLMHP incorporates survival functions for capturing multiple-classes of heterogeneous patients rather than a single patient class in MSLP thus enabling more realistic analysis for various outcome measures. Secondly, the objective of

MESLMHP is to maximize the overall expected patient survival probability, where the survival probability of each patient type is summed up according to its weight.

1.4. Dispatch Policy

EMS vehicle dispatch policy is the protocol of sending vehicles to the incident scenes according to the priority of the calls. Emergency medical 9-1-1 calls are typically classified as Priority 1, 2, 3, where Priority 1 calls are life threatening emergencies, Priority 2 calls are emergencies that may be life-threatening, and Priority 3 calls do not appear to be life-threatening emergencies [9]. 2010 JEMS Survey [8] showed that 82.7% of the top 200 cities reported having a protocol-driven dispatch process and 68.1% indicated they objectively triage every call. The default dispatch policy is to send the nearest ambulance to all medical emergencies and it is widely accepted by many EMS providers. However, sending nearest ambulance is not always optimal and sometimes can be problematic. For instance fast response with lights and sirens can potentially place EMS providers, patients and in nearby public at risk [23, 24]. Carter et al. [25] showed the common rule of sending the closest ambulance is not always optimal by using a simple case where two units, A and B, have equally large areas of responsibility, but A's area has a significantly higher call frequency. In this case, allowing B to respond to some of the calls for which A is the closest unit will reduce the mean response time. Persse et al. [26] analyzed data from Houston and showed that prioritized dispatch policy where advanced life support (ALS) resources are dispatched to priority 1 calls significantly improves survival rates.

Since sending ambulances to all 9-1-1 calls reduces available coverage by taking valuable response resources out of place which jeopardizes another possible more critical request [8] a well-designed dispatch policy is necessary for an effective and efficient EMS system. Andersson and Varbrand [2] described the development of decision support tools for dynamic ambulance relocation and automatic ambulance dispatching. They calculated preparedness in a way as a trigger for their automatic relocation module. Once the level of preparedness has dropped below a certain threshold value, relocation of one or more ambulances is executed to raise the preparedness value. Bandara et al. [27] evaluated the performance of dispatching rules in terms of patients' survival probability to determine optimal dispatching strategies for EMS systems. A priority list based on the location and degree of urgency of the call is included in their model. They found that the optimal dispatching rules are different for different types of calls. Sending the closest ambulance is optimal for priority 1 calls while sending ambulance by following an ordered preference list is optimal for priority 2 calls. Toro-Díaz et al. [1] developed a joint model combining location and dispatching decisions simultaneously. Their results show that the commonly used closet dispatching rule leads to the best solutions when the objective is minimizing the mean response time and maximizing coverage simultaneously.

The underlying argument of sending the nearest ambulance to incidents is that shorter the response time and the better patient outcomes. As discussed earlier some high-acuity calls require a timely response such as cardiac arrest, shock and myocardial infarction but to treat every EMS call as though it's a cardiac arrest puts EMS providers and the public in danger because many other conditions are not time sensitive [10]. Emergency calls have different priorities and not every emergency call is life threatening. Even for life-threatening calls (priority 1) except for cardiac arrest which makes only small part of all events, there is no direct association between shorter RTs and increasing survival of patients at hospital discharge. Based on the weakness and potential problems of always sending the nearest ambulance discussed above we believe it is necessary to compare alternative dispatch policies with the default dispatch policy.

1.5 Study Motivation and Expected Contributions

This proposal has the following objectives. Our primary objective is to develop a realistic model to locate and dispatch ambulances by taking into account call priorities while meeting fast response times for life-threatening calls. Our second objective is to develop and test the efficacy of alternative dispatch policies with that of the closest ambulance dispatch policy. To achieve these objectives, we propose a simulation-optimization approach which removes the need for majority of the simplifying assumptions needed for mathematical modeling approaches. With the simulation model we implement alternate dispatch policies such as dispatching the nearest ambulance to priority 1 calls while for all other calls, we consider dispatch policies such as “dispatch the ambulance which has the least utilization”, and others. Further, a high fidelity simulation model allows us to track various performance measures and produce a continuous graph depicting the cumulative density function of the realized coverage. This graph will enable the decision makers to easily assess the predicted survival rates for multiple classes of high acuity medical emergencies.

As mentioned before MSLP is a relatively new research direction and is shown to be superior to more traditional approaches by Knight et al. [22]. This research will further contribute to this novel research direction. Our approach is based on the works of McLay and Mayorga [9], Knight et al. [22] and closely follows the principles outlined in

Mason’s simulation optimization approach [28]. We expect to show that using the maximal expected coverage location model to generate the initial vehicle locations followed by a high fidelity simulation model embedded optimization algorithm results in improved response and total service times for various critical emergencies. To the best of our knowledge, our high fidelity simulation model which includes real-life operational details such as dispatching ambulances when they become available regardless of their current locations (e.g., at the incident scene, at an hospital, etc.), patient transports to area hospitals and travel times based on real-data, has not been developed and used in a simulation-optimization framework. Another important contribution is the application of a weighted objective function which includes cardiac arrest survival function, tiered response times based on call priorities, and other metrics to be determined via experiments. Furthermore, with our approach we are able to test the efficacy of flexible dispatch policies on coverage statistics and ambulance crew workloads which has not been done previously.

In summary, with our simulation-optimization methodology reflects significantly more details of real EMS operations. Hence the results are expected to be more useful and practical for EMS administrators and managers.

1.6 Study Outline

In Chapter 2 we review relevant EMS ambulance location maximization and dispatch policy literature and in Chapter 3 we clean and conduct a thorough analysis of a historical EMS dataset to prepare the ground for development of our simulation model. In Chapter 4 we present the development of our simulation model based on our data analysis and previous literature. In Chapter 5 we describe the heuristic search algorithms implemented for our simulation-optimization approach and fine tune them via an experimental design. In Chapter 6 we apply our approach to Charlotte, and finally in Chapter 7 we summarize our results, discuss the limitations of this study and suggest directions for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 A Complex and Important Research Domain

Locating ambulances and vehicle dispatching policies are the key parts of EMS planning and management because they determine the performance of providing emergency medical service, which ultimately influences patient's life intimately. EMS vehicle locating, dispatching, and relocating are a very complex research topic due to the high variability of the call volume, location and severity of EMS, making it difficult to decide where to position ambulances and their crews while they wait for their next call [4]. The complexity and the importance of EMS has attracted a great amount of research interests which makes it one of the richest and most diverse areas in OR literature. Brotcorne et al. [29], Goldberg [6], Farahani et al. [30], and Li et al. [31] provide excellent reviews of the research developments in this domain. These location and relocation models span from early static, deterministic models to recent probabilistic and dynamic models. For the purpose of this study, we briefly review milestone models and those models relevant to our research and important optimization techniques used to solve those models.

2.2 Development of Classical Models and Extensions

The early models proposed were generally deterministic and static. Typically these pioneer models pursued the optimal solutions by using integer linear programming formulations. Set Covering Location Problem (SCLP) introduced by Toregas, Swain, ReVelle and Bergman [32] is widely known as the first EMS location covering model.

The SCLP minimizes the total number of ambulances needed to cover all demand points. The SCLP is a mandatory coverage model which assumes there are enough resources to acquire the servers needed to cover all demand points. The next important development was the Maximum Coverage Location Problem (MCLP) proposed by Church and ReVelle [33]. The MCLP use an alternative approach and overcomes some of the shortcomings of SCLP. Instead of minimizing the number of facilities needed to cover the entire population as in SCLP, MCLP maximizes demand coverage of the population constrained by the capability of EMS, represented by the ambulance fleet size. The SCLP and MCLP did not take into account that once an ambulance is called for service it might not be available to cover the next incoming call. This issue is quite common in congested systems. Hogan and ReVelle [34] introduced the concept of backup coverage which addressed the congestion problem in single coverage models by providing extra coverage. Gendreau et al. [35] proposed the Double Standard Model (DSM) and designed a tabu search heuristic for its solution. The DSM requires that all the population must be covered within a longer distance and a propotion of the demand must also be covered within a shorter distance standard. One of the first models explicitly addressing the unavailability probability of ambulances is the Maximum expected covering Location Problem (MEXCLP) suggested by Daskin [36] which maximizes the expected overage of demand while taking into account the possibility of ambulances being unavailable. In MEXCLP, the congestion is modeled by assuming that all servers (ambulances) operate independently and have the same busy probability p, computed a priori. Daskin showed that the coverage probability of a demand point can be modeled as $1 - p^m$ where m is the number of ambulances located with the RTT. Similarly ReVelle and Hogan [37] addressed the congestion effect in the Maximum Availability Location Problem (MALP) by explicitly considering ambulance busy probabilities and developing an expression for coverage reliability. The MALP I assumes all ambulances are equally busy while MALP II divides the region into sectors and computes busy fraction for each sector. These are some of the early probabilistic models for ambulance location problem and they are followed by many extensions. The adjusted MEXCLP model (AMEXCLP) proposed by Batta et al. [38] extended MEXCLP by relaxing three of MEXCLP's assumptions and utilizing the hypercube queuing model in its solution procedure. The AMEXCLP takes into account that ambulances do not operate independently and utilized the correction factor derived by Larson [39]. An extension of MEXCLP called TIMEXCLP, developed by Repede and Bernardo [40] explicitly considered variations in demand throughout the day. Another extension of MEXCLP proposed by Goldberg et al. [41] considered the stochastic travel times and the unequal vehicle utilizations. Marianov and ReVelle [42] proposed the queuing probabilistic location set covering problem (QPLSCP). In QPLSCP, busy fractions are site specific and where the minimum number of ambulances necessary to cover a demand point is computed under the condition that the probability of all of them being simultaneously busy does not exceed a given threshold.

2.3 Dynamic Redeployment Models

Dynamic redeployment models are more recent and more sophisticated in nature. Dynamic models deal with the real-time planning and management of EMS. It is well documented that demand for ambulances fluctuates spatially and temporally by day-of-the-week and time-of-the-day [43]. Dynamic redeployment models can aid managers make daily or even hourly plans to better respond to predictable demand fluctuations by time and space [44]. The basic idea of dynamic methods is to relocate emergency vehicles periodically in a strategic way to protect more areas with updated new information such as current status of ambulances and demand forecasts. The ideal way is that whenever there are idle EMS facilities located in low demand areas to move some of them to higher demand areas. Compared with static models, dynamic models are more flexible [31] and hence more challenging to solve requiring more powerful solution techniques [29]. Dynamic models are relatively rare in the ambulance location literature. The models currently found in the literature can be categorized into two categories: (1) Real-time, where ambulance redeployment decisions are computed with every call and (2) Planned Multi-period, where an ambulance redeployment plan considers an entire day or week based on demand forecasts [29, 43].

2.4 Real-time Redeployment Models

Real-time redeployment models typically relocate ambulances every time one is dispatched or becomes available for dispatch. The work by Gendreau et al. [45] is among the earliest real time redeployment models in ambulance literature. They developed the Dynamic Double Standard Model at time t ($DDSM^t$) based on their previous work on DSM. The $DDSM^t$ maximizes double coverage of demand while minimizing relocation costs. The $DDSM^t$ penalizes (1) repeated relocation of the same vehicle, (2) long round trips and (3) long trips between two sites. The model's input parameters are updated each time a call is received and $DDSM^t$ is solved each time. They developed a parallel tabu search heuristic to solve $DDSM^t$ quickly in real time. However, as pointed by the Gendreau et al. [46], the real-time redeployment algorithms heavily rely on the computing capability of EMS dispatch center. In fact not every center is able to do parallel computing. Furthermore when calls arrive in quick succession, there may not be enough time to generate a new solution or the solution could be infeasible. In addition, frequent ambulance relocations can cause a confusion of drivers because of the frequent changes of the route or destination [27] . As a result, Gendreau et al. [46] proposed an alternative approach i.e. preplanned repositioning in the Maximal Expected Coverage Relocation Problem (MECRP) [46]. In MECRP, a series of location scenarios for all vehicles are precomputed as a priori compliance table which can readily be applied wherever a call is made. This new approach comes along with the limitation of the number of ambulances to be planned. Similarly using compliance table policy Alanis et al. [47] developed a two-dimensional Markov chain which relaxed assumptions of deterministic response time and binomial probability distribution for the number of busy ambulances in EMCRP. The authors show that the model can be used to find the best or near optimal compliance table from a set of 100 random tables with the number of ambulances up to 18.

Maxwell et al. [48] formulated ambulance redeployment as a Markov decision process and explored a novel approximate dynamic programming (ADP) approach for solving real-time redeployment policy. Recently Schmid [49] proposed a stochastic dynamic model explicitly including time-dependent information for both traveling times and the request volume to maximize the number of calls reached within a time threshold. They also used an ADP approach to solve the optimization problem resulting in faster computation and improved performance.

2.5 Multi-period Redeployment Models

The TIMEXCLP can be viewed as the earliest multi-period redeployment model [43]. Schmid & Doerner [50] extended DSM from a single to a multi-period model. Time-dependent variations in travel times and coverage are also explicitly considered in this model. They formulated the problem as a mixed integer program which aims to optimize coverage at various points in time simultaneously and they developed a metaheuristic algorithm based on variable neighborhood search to solve it. Erdogan et al. [51] developed a two-stage approach to scheduling ambulance crews to maximize expected coverage for a typical planning horizon of one week. They utilize Budge et al.'s approximate hypercube model [52] to compute station-specific busy probabilities and solve the ambulance redeployment problem for every hour of the week. They use the output of the first stage as the input for the next stage of two crew-scheduling models and they show the tractable characteristic of the second approach. Rajagopalan et al. [44] proposed the Dynamic Available Coverage Location model (DACL) with the objective of minimizing the number of ambulances while meeting specified coverage availability requirements. Their approach extended QPLSCP by incorporating ambulance specific busy probabilities which are solved by using Jarvis' hypercube approximation algorithm [53]. They solved DACL using tabu search heuristic with a look-ahead procedure.

The number of relocations is not considered in the objective of DACL. Patients are not the only stake holder and the crew of EMS also should be considered. Frequent relocation often results in crew fatigue and lower morale and which in turn damages the quality of the service [7, 54]. More recently, Saydam et al. [43] proposed the Dynamic Redeployment Covering Location model (DRCL) which is an extension of the DACL to address crew fatigue phenomena. The DRCL has two objectives: minimize the number of ambulances and minimize the number of redeployments for a given fleet during a given shift, while meeting coverage requirements. They developed a fast meta-heuristic based on a steepest descent search and showed this new approach outperforms DACL across all key criteria.

2.6 Optimization Techniques

Ambulance location and relocation problems are typically NP-complete problems [55, 56] therefore to exactly solve them is prohibitive in computing time. Designing effective and efficient algorithms/solution procedures to solve the optimization problem is quite necessary in most situations. The heuristic algorithms are broadly used to solve large scale and NP-hard problems and the main heuristic algorithms utilized in this domain include Tabu Search (TS), Lagrangian Relaxation (LR), Simulated Annealing (SA) and Genetic Algorithm (GA) [31]. We refer the reader to Li et al. [31] for a comprehensive review of optimization techniques to solve ambulance location and relocation models. Brotcorne et al. [57] proposed heuristics for large-scale covering-location problems with continuous potential location sites and discrete sets of demand points. Beasley and Chu [58], Saydam and Aytug [59], Inanoni et al. [60] and Toro Diaz et al. [1] used GAs to solve their model. Gendreau et al. [35, 45] and Rajagopalan et al. [44] used TS to solve their EMS models. Arostegui et al. [61] conducted experimental studies to compare the performance of TS, SA and GA applied to EMS location model. They found that TS always yields satisfactory solutions faster and is easy to develop and implement. Similarly, Rajagopalan et al. [62] compared the performance of several meta-heuristics applied to a probabilistic location model via a statistical experimental design. They analyzed the results using ANOVA and showed that on average TS and SA find the best solutions in the least amount of time.

2.7 Simulation Approach in EMS Literature

While using simulation technique for EMS research traces back to about 1970s, it is much less frequently utilized and often it has been used as a descriptive tool to evaluate the quality of solutions obtained via an analytical approach. Savas [63] used simulation as a tool to analyze the possible improvements in ambulance service of New York. Haghani et al. [64] developed a simulation model to evaluate alternative emergency vehicle dispatching strategies aiming to minimize average response times. Andersson and Varbrand [2] developed a simulation model to test their decision support tools. Restrepo et al. [65] and Maxwell et al. [48] are recent researchers who developed simulation approaches for final evaluation of modeling. Yue et al. [66] used a simulation-based approach to maximize coverage over a distribution of requests.

St John Ambulance is said to be the first one that has implemented a comprehensive simulation technique in the ambulance location area [5]. St John Ambulance founded in 1877 in the United Kingdom is a well-known provider of medical first aid and ambulance service. It first used an ambulance simulation system named BartSim to address staff scheduling problems [28, 67]. Computer simulation based EMS models tend to have a higher degree of detail and try to precisely mimic the operations of the actual system. They also can have a high degree of face validity and can obtain extremely accurate replication and validation results [6].

CHAPTER 3: DATA ANALYSIS

In order to develop a realistic simulation model we analyzed historical emergency call dataset from Mecklenburg County, Charlotte, North Carolina. The dataset is collected from a region of approximately 540 square miles with a population of 801,137 in 2004. The original dataset provided by the emergency medical services agency (MEDIC) has 79,890 records. This dataset includes records of single- and multi-unit dispatches to 62,008 calls they received and scheduled, non-emergency patient transport records. The records include important fields for this study such as the call time stamp, call priority (1-4 for medical emergencies), latitude and longitude of the incident (patient) location, the responding unit(s) location coordinates, call-, chute-, travel-, service-times, and others. We first cleaned the data and compiled statistics for the following key variables:

- Call Time – the interval from a call being received to the dispatch of an ambulance.
- Chute Time – the time between the dispatch and the paramedic en route toward the incident scene.
- Travel Time – the time from the ambulance en route until its arrival at the incident scene.
- Service Time – the time elapse from the ambulance's arrival at the scene until it becomes available for the next dispatch.

- Distance to the scene – the distance between the responding ambulance current location and the incident scene.
- Single and multi-vehicle responses.

3.1 Data Cleaning Process

Prior to computing statistics and fitting distributions to key variables the data required some cleaning due to missing or incorrectly entered fields. First we only kept records which were identified as medical dispatches with call priorities 1-4, where 1 is a life threatening event as assessed at the time of the 911 call, also known as a delta-level event. This reduced the dataset to a total of 64,678 records, which comprise 81% of all dispatches. Second, we deleted records with blank fields for any of five variables. Third, we screened the data for apparent errors such as negative values in which case we eliminated that record and corrected errors such as latitude and longitude in reverse hence wrong columns. Fourth, we scrutinized the data by checking whether the values are reasonable. Each variable has practical meaning such that the values should fall in certain scope based on current operational practices, common sense and literature. For example, occasionally 9-1-1 call time exceeds several minutes whereas the dispatcher dispatches an ambulance early in the call time while staying on the phone assisting either the patient or the caller. We used a group of presumed scopes for the five variables: 0.25 minutes < Call Time < 5 minutes, 0.25 minutes< Chute Time < 5 minutes, 1 minute <Travel Time<30 minutes, and Distance < 15 miles. We excluded the records with values outside these ranges from the statistical analyses. The data cleaning process essentially eliminated about 8% of the records leaving 59,622 records to study single and multiple dispatch frequencies, compute descriptive statistics, and apply goodness-of-fit tests.

3.2 Summary of Findings

The data showed that number of units sent to a single call varied from 1 to 8. The percentage of single ambulance dispatches was 85%. The percentage of double dispatches was 14%. Clearly, the majority of calls have been serviced by one or two ambulances (99%). A very few of calls required more than 3 units, which can be explained by events such as floods, multi-vehicle traffic accidents, and alike. For calls serviced by multiple vehicles we kept only the records of the first arriving unit which gives us a total of 38,399 calls. We noted that there were relatively much fewer calls classified as priority three or four (both non-life threatening), therefore we combined them into priority three calls. This resulted in 8921, 24242, and 5236 priority one, two, and three calls respectively. From here on, we refer to priority 3 and 4 combined as priority 3. We first compiled summary statistics for all calls as shown in TABLE 1 below:

TABLE 1: Summary statistics

	Call Time (min)	**Chute Time (min)**	**Travel Time (min)**	**Service Time (min)**	**Euclidian Distance to Incident (miles)**
Minimum	0.25	0.25	1.00	5.02	0.00
Maximum	4.98	5.00	29.97	108.17	15.84
Mean	0.59	0.92	6.11	55.06	2.12

3.3 Travel Time

Average travel time of low priority calls is expected to be longer than that of higher priority calls considering that high priority calls ambulances are more likely to use lights and sirens and travel faster. To test this hypothesis we examined the travel time distributions by creating Box-and-Whisker Plots of travel time by priority. From FIGURE 1 we see travel time of priority 3 has higher median than those of priority 1 and priority 2 and also is more disperse. However, distributions of travel time of priority one and priority two are very similar. This is possible due to MEDIC applying the same travel guidelines for priority 1 and priority 2 calls in delivering ambulance to the accident scenes. A simple two-sample t-test showed that we fail to reject the null hypothesis that the means are equal ($p < 0.01$).

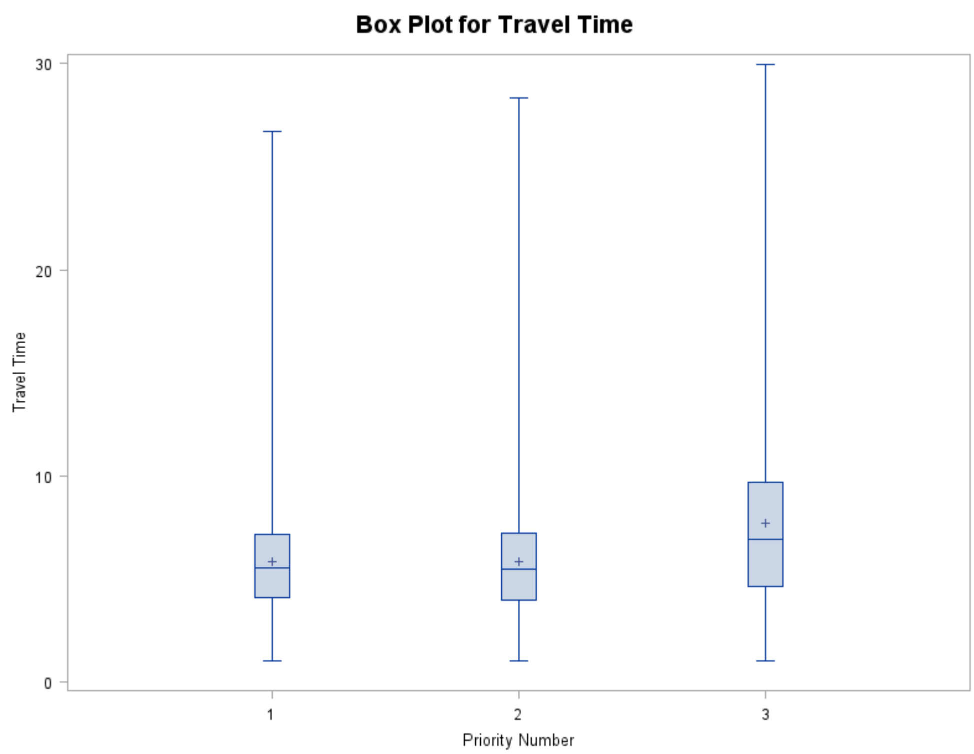

FIGURE 1: Travel time box plot

In order to generate travel times realistically in our simulation program, we developed regression models of travel time on distance for priority 1 and 2 combined, and priority 3 calls. The dependent variable is travel time in minutes and the independent variable is distance in miles which we initially computed using incident and responding ambulance coordinates with spherical law of cosines formula [68]. This resulted in a Euclidean distance which we then applied the Minkowski coefficient, 1.54, to estimate the actual road distances [69].

Subsequent to some exploratory analyses with various power transformations we found that the square root transformations applied to both dependent (travel time) and independent (distance) give the best results, resulting in R^2 values of 95.4% and 94.5% for priority 1 & 2 combined and priority 3 calls, respectively. In order to express the predictions in the original scale we back-transformed the resulting equations which are displayed in TABLE 2. From those relations we can also deduct that ambulances run to an incident scene at a speed of 35.40 miles/hour and 26.11 miles/hour for priority 1 & 2, and priority 3 calls, respectively.

TABLE 2: Travel time models for estimating real road network distances

Call Priorities	**Travel time models**
Priority 1, 2	$travel\ time = 1.6951\ *\ distance$
Priority 3	$travel\ time = 2.2976\ *\ distance$

3.4 Chute Time and Call Time

The data analysis of chute time showed that apart from some outliers, chute times are clustered around the mean of 0.9 minutes with a standard deviation of 0.54 minutes. In reality, chute time for different calls tend to have very small difference, because the crews are trained to quickly respond to all dispatches. In addition, chute time is a very small part of total service time, so, instead of sampling from a distribution we opted to use the mean chute time for every call in our simulation. For similar reasons, the mean (0.59 minutes) of call time is used as the simulated call time.

3.5 Service Time

Service time is a major part of the total time that an ambulance spends on an emergency call. For calls that don't need transportation to hospital service time is just the time spent on the incident scene. For calls, of which patients are transported to hospital, service time includes time spent on the scene, travel time to hospital and handover time in hospital. Although our dataset does not identify clearly which incidents needed transport to area hospitals a recent study with Charlotte data reported that about 75 percent of all calls require transport to a hospital [70].

We conducted a goodness-of-fit test with data of all priorities which showed that the service times follow a normal distribution with a mean of 55.06 (min) and a standard deviation of 15.36. As a rule of thumb, the service time of top priority calls is likely to be longer than low priority calls. To reflect this fact, we drilled down to fit normal distributions to different priority categories. Service time of priority 1 calls has a fitted normal distribution with a mean of 58.42 and a standard deviation of 14.56. The service time of priority 2 calls follows a fitted normal distribution with a mean of 54.63 and a standard deviation of 15.43. The service time of priority 3 calls follow a fitted normal distribution with a mean of 51.35 and a standard deviation of 15.27. These results are consistent with the reality that the on scene treatment provided for high acuity patients is more likely to be intensive and hence takes longer time. FIGURE 2 displays fitted normal distributions and the corresponding statistics of service times for all calls, priority 1 calls, priority 2 calls, and priority 3 calls.

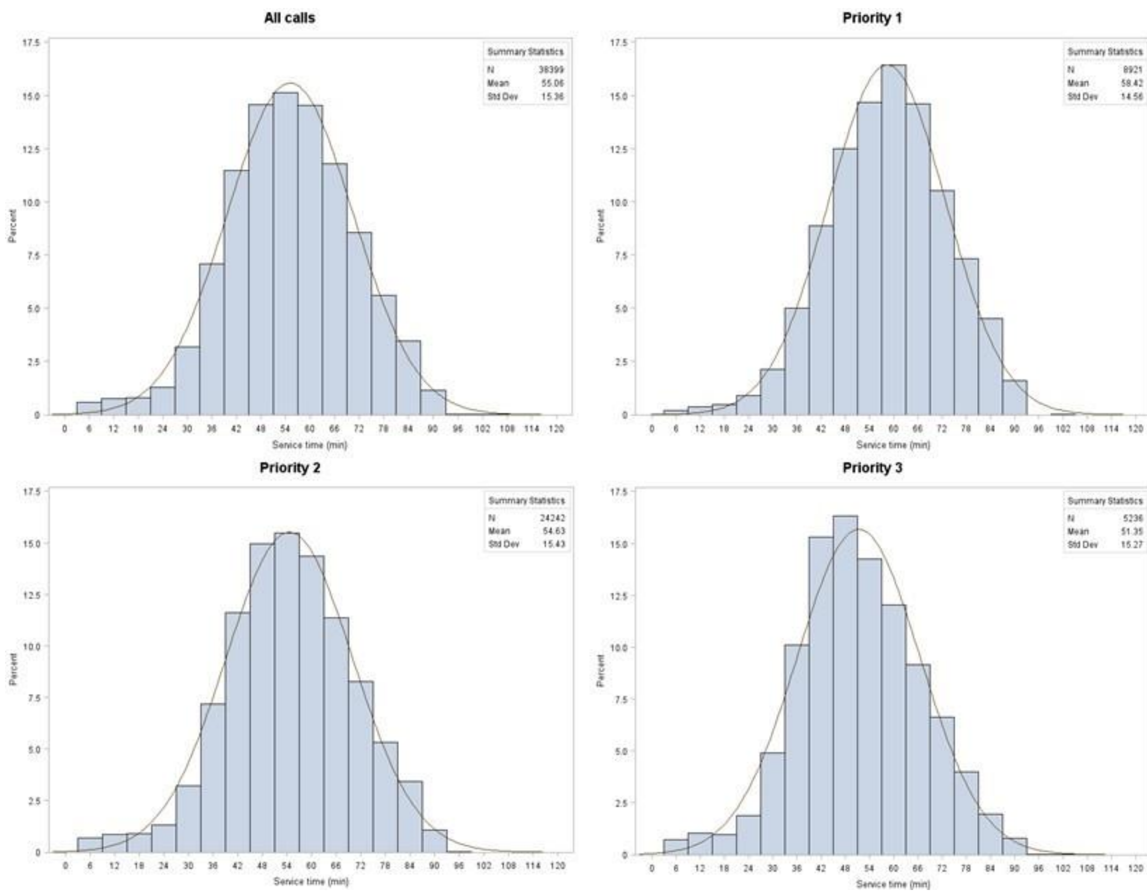

FIGURE 2: Service time distributions

In our simulation model, the corresponding normal distribution is used to generate the service time for an emergency call according to its specific priority category. This process happens when we create the file of emergency calls, which is before the running of the simulation model. In other words we pre-generate service time of each emergency call.

CHAPTER 4: THE SIMULATION MODEL

An important contribution of this study is the development of a high fidelity simulation model that mimics the operations of an EMS provider such as MEDIC. The basic assumption in our simulation model is that the real-time location and status of all vehicles are known which is true in practically all EMS systems in the U.S. The following is an overview of our simulation model.

The response process starts with the dispatch center receiving an emergency (9-1-1) call. The dispatch operator determines the call priority based on the dispatch protocol in use and dispatches one more ambulances to the incident scene. While the call center is waiting for the next urgent call, the ambulance(s) travels to incident scene. At the scene the crew treats the patient and determines if the patient needs to be transported to the nearest area hospital. If so, the ambulance departs for the hospital, arrives at the hospital and hands off the patient. At this moment the ambulance becomes available for the next dispatch, if any. Otherwise, the ambulance travels back to its post or to the next call location. If hospital transport is not needed then ambulance becomes available for the next call and departs to its post.

While developing the simulation model we attempted to include all important real-life aspects of an urban EMS operation and only made simplifying assumptions to ensure that the code is fast enough to be embedded in a search algorithm and when the impact of them on the statistics of interest is negligible. Next, we discuss the logic flow of the simulation model in more detail and present our rationale for the assumptions we made at various junctions.

4.1 Simulation Design

We developed the simulation module using Java (SE Version 7). The simulation module is designed to run a trace-driven simulation where the calls used in the simulation are read from a file. The calls are generated apriori for the first set of experiments and sampled from a real call database for the case study. Each call has a time stamp, location, priority, and service time information. This approach is beneficial for testing and model validation as well as for comparing various dispatch policies. The main logic flow the simulation model begins with a 9-1-1 call read from a file or retrieved from memory. The program updates all vehicles' information including current location and status (idle or busy). Then based on the status and location of vehicles as well as priority and location of this new incoming call the program decides which vehicle(s) to dispatch according to the dispatch policy applied. If there is no vehicle available, then the program counts this call as a missed call. Once an ambulance is assigned to a call its status is set to busy, after a short time of preparation (Chute time) it departs to the incident scene. As discussed previously we use 0.9 minutes as the chute time for all calls instead of sampling from a distribution. Next, we calculate the distance to incident followed by the travel time using the regression models developed earlier. When the vehicle reaches the scene, some form of on-scene treatment is provided to the patient. If the treatment on the scene is not satisfactory, then the patient is transported to a nearest hospital in order to receive further care. In our simulation if the generated service time is 15 minutes longer than the travel time to hospital we assume the patient is transported to hospital with a probability of

75%. The travel time to the nearest hospital is calculated by the corresponding regression models discussed earlier. If transportation to hospital is not needed then the call is completed at the scene and the ambulance becomes available for the next call. The ambulance could be assigned to the next call after service completion at the scene or at the hospital or en route. If it is not assigned to a new call, then it returns to its base station or post and waits for the next dispatch order.

In reality idle ambulances can be dispatched to a call while en route to their posts. To our best knowledge, no previous model included en-route dispatch. Our simulation model includes this important feature that an ambulance could be dispatched even en route to their posts as long as it is idle, which is another contribution of this research. An ambulance's completion time of previous call service denoted as t_1 is recorded in memory. When an emergency call is received, our simulation model reads its time stamp t_2 and calculates the time elapse $t_{2-}\ t_1$, which is used to calculate the distance this ambulance has traveled from its previous location (either an incident scene or a hospital) which is also recorded in memory. Based on the traveled distance and its last location the current location of this ambulance is identified. If the traveled distance is greater than the distance from its post to its last location then the ambulance is already back to the appointed base location. Otherwise a location on the path is identified as its current location. We don't have the data to know how fast ambulances travel back to their posts but until they are dispatched to a new priority 1, 2 calls we can assume that the ambulances return to their posts at an average speed of 26.11 miles/hour, same as running for priority 3 call as provided earlier and without lights and siren

A high-level flowchart of our simulation model is depicted in FIGURE 3. The detailed process of assigning available ambulances to a call is presented in FIGURE 4. If there is only one free ambulance then the system will just dispatch this ambulance to the new call. When the number of available ambulances is great than one, the system will first check the priority of the call. If it is a priority-one call, the nearest free ambulance will be dispatched to it. If the call is determined not priority one, then an ambulance will be dispatched according to one of the dispatch policies in our experiments. FIGURE 5 depicts the process of an ambulance from the dispatch to back at station.

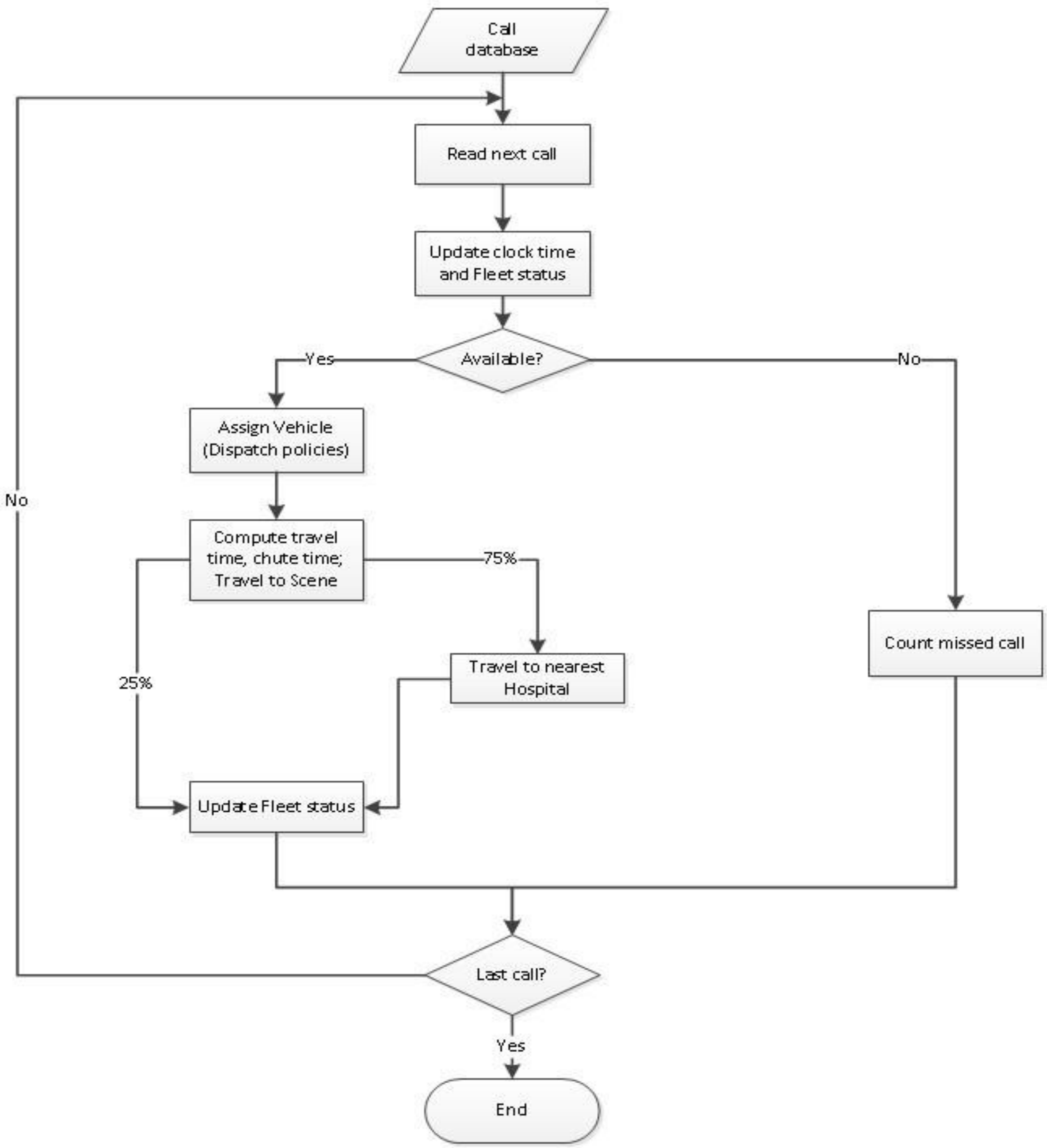

FIGURE 3: Simulation model overview flow chart

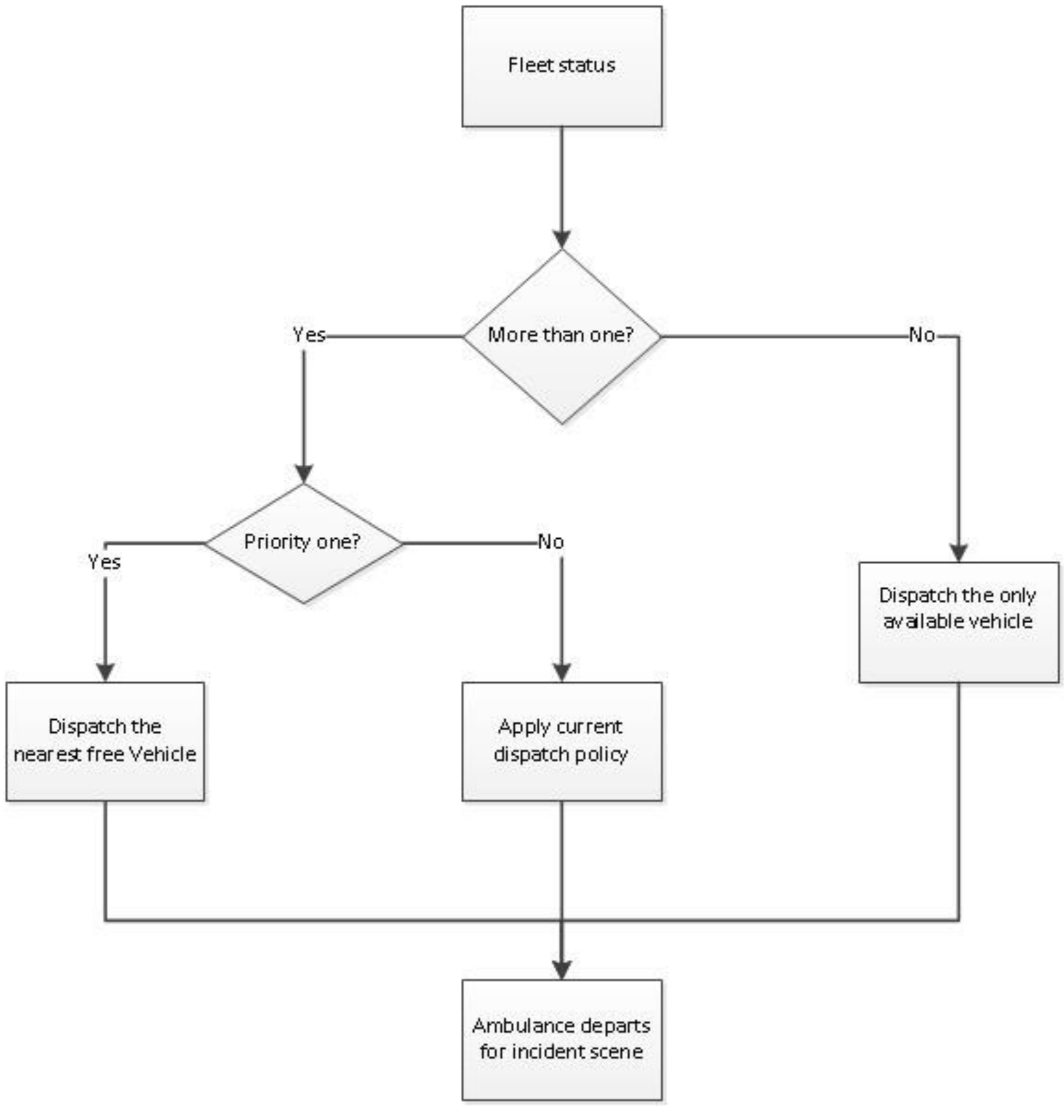

FIGURE 4: Dispatch process

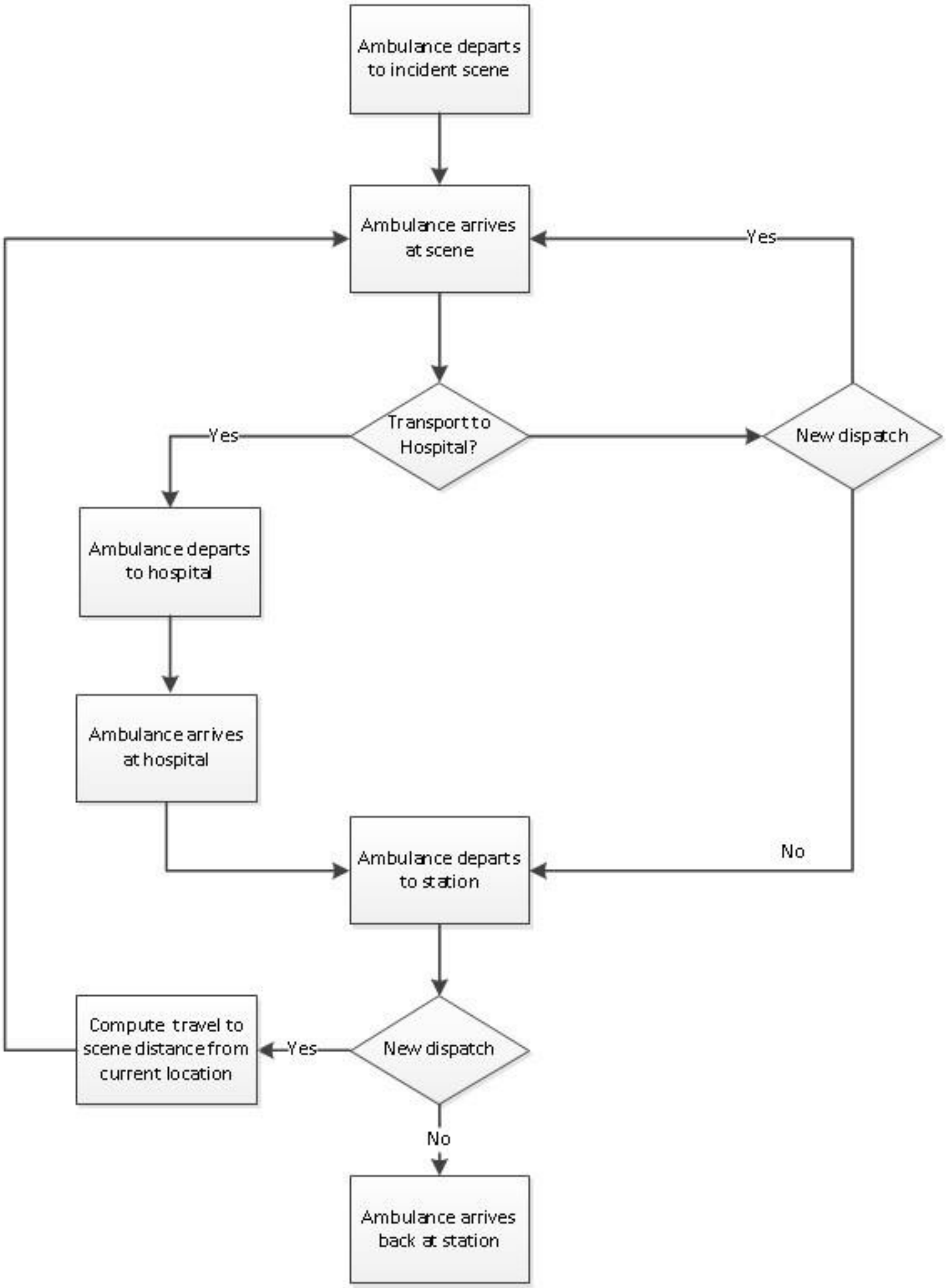

FIGURE 5: Proposed schema for ambulance dispatch to an [emergency] scene

CHAPTER 5: SEARCH ALGORITHMS FOR THE SIMULATION OPTIMIZATION FRAMEWOK

Assuming response units are homogeneous and in each zone at most one unit can reside, to locate M units in N zones the size of the solution space is the combination of N taken M at a time without repetition (N^M), which is a typical NP-complete problem. In our simulation model we don't limit the number of ambulances in a zone, so the solution space is even larger. When M and N are large numbers it is extremely expensive in computing to find the exact optimal solution by enumeration. However, we are encouraged by the fact that there have been various meta-heuristic search methods successfully applied in this domain that have found near-optimal solutions [44]. In this research, we implement three meta-heuristic algorithms: random-start hill-climbing algorithm, simulated annealing algorithm and tabu-search algorithm. Before we describe our meta-heuristic search algorithms implementations, it is necessary to illustrate the procedure of generating neighboring solution spaces and the data representation used in all meta-heuristics.

5.1 Generating Neighboring Solution Spaces

The process of generating neighboring solution spaces or successors of current solution space plays an important role in all three meta-heuristic search algorithms embedded in our simulation model. The three meta-heuristic search algorithms share a similar strategy of generating solution state successors.

To better illustrate the process of generating successors, we use a simplified example of 16 zones (4 by 4) and three ambulances. As depicted in FIGURE 6 the sixteen zones are numbered from 1 to 16 and three ambulances are labeled as A, B, and C. The location combination of zone 6, 7 and 8 is denoted as (6, 7, 8) which is the initial solution space. Since the ambulances are homogeneous (6, 8, 7), (7, 8, 6), (7, 6, 8), (8, 6, 7), and (8, 7, 6) are all same solution state as (6, 7, 8). We refer the initial solution state as the start state and we use current state to denote any intermediate solution state. Initially current state is start state. A successor or a neighbor solution of current state is generated by moving one of the ambulances from its current zone to another possible zone. If two solutions can be generated from each other by changing only one ambulance's location we say they are neighboring solutions. For instance, moving ambulance A from zone 6 to zone 2 gives a neighbor solution space (2, 7, 8). We say (6, 7, 8) and (2, 7, 8) are neighboring solutions. Similarly, (7, 7, 8) is another neighbor by moving ambulance A from zone 6 to zone 7, which means we have two ambulances allocated to the same location. On the other hand (1, 2, 3) is not a neighbor solution space of (6, 7, 8) because this implies that more than one ambulance is moved to another location. The total number of successor or neighbors of current state as depicted in this example is $3 \times 15 = 45$. These neighboring solutions are evaluated and one of them will be picked out to replace current solution state.

1	2	3	4
5	6 A	7 B	8 C
9	10	11	12
13	14	15	16

FIGURE 6: Initial solution space prior to generating successors

Each solution's objective function is evaluated by executing our simulation model presented in Section 4. The simulation model mimics the entire process how an EMS system handles all 9-1-1 calls within a period of time. So, each round of execution of the simulation model consumes significant portion of computing time. Hence, it is very important to eliminate duplicated solutions before evaluating the objective function. We notice that any two successive solution states have some common neighbors. For example: assume (2, 7, 8) is picked out from the 45 neighbors to replace current state (6, 7, 8), therefore (6, 7, 8) is followed by (2, 7, 8) as two successive solution states and they have common neighbors already evaluated in the previous iteration. To avoid generating and evaluating those solutions that are evaluated in previous state we simply tag the new location of the first ambulance which is "2" in this example.

5.2 Data Representation

We use a one-dimensional array of size m+2 to represent a solution where m is the number of ambulances in the system. The first m elements in each vector are the ordered zone numbers of ambulance posts. Index m in each vector stores the objective function value (ObjF) and index m+1 contains a tag used to track the location by changing which this solution is generated. TABLE 3 illustrates the vector used for all meta-heuristics.

TABLE 3: Data representation

Elements	3	7	9		ObjF	Tag
Index	0	1	2	…	m	m+1

5.3 Random-Start Hill-Climbing Search Algorithm (RSHC)

The hill-climbing search algorithm is a simple loop (iterative process) that continually moves in the direction of increasing objective value. It terminates when it reaches a “peak” where no neighbor has a higher objective value. Hill climbing is similar to a greedy local search algorithm because it grabs a good neighbor state without considering about where to go next. For that reason, hill-climbing often makes rapid progress toward a solution and also often encounters local maxima and gets stuck with nowhere else to go. The hill-climbing search algorithm [71] is shown in TABLE 4.

TABLE 4: Hill climbing algorithm

Hill-Climbing returns a state that is a local maximum current ←MAKE-NODE(problem.INITIAL-STATE) Loop do 1. Neighbors←Generate all successors of current state 2. Best_neighbor←Get the successor with the highest objective function value 3. if best_neighbor.VALUE ⩽ current.VALUE then return current.STATE and exit loop else current ← neighbor

Hill-climbing algorithm itself often cannot find a satisfactory solution because the possibility of being stuck at a local optimal solution. To avoid ending with a local optimal solution, random-restart hill climbing algorithm conducts a series of hill-climbing searches from randomly generated initial states. It records the state of each run of hill-climbing and at last return the state with highest value of objective function. The $state$ is a set of ambulances locations and the objective function in our model is not fixed which can be assigned according to different aims. When we do experiments and compare with existing models in literature we assign the objective function as the tally of covered calls under a threshold. We also designed a weighted objective function to overcome the weakness of solely objective. The random-start hill-climbing algorithm implemented in our simulation model is depicted in TABLE 5.

TABLE 5: Random start hill climbing algorithm

```
best ← Random-start
Loop i → 1 to K
    current ← Random-start
    Loop While
        neighbor ← a successor of current with highest value of ObjF
        If neighbor_ObjF ≤ current_ObjF then return current.STATE else
        current ← neighbor
        End IF
    End Loop
    If (best_ObjF < current_ObjF) then best ← Current
    End If
End Loop
```

5.4 Simulated Annealing Search Algorithm (SA)

As mentioned above the Hill-climbing algorithm never moves to a state with lower objective function value. Therefore, it is likely to get stuck at a locally optimum while simulated annealing allows such move with a probability that is negatively proportional to the gap between the objective value of current state and that of a neighbor state. The method simulated annealing employed to escape from a locally optimum is an analogy with a technique of cooling metal known as “annealing” [71]. The higher the “temperature” T, the higher probability is to accept a worse solution. The value of T is decreasing during the running time according to “cooling” ratio α. When the “temperature” drops below 30 the algorithm terminates and return the best found. The simulated annealing search algorithm implemented in our model is shown in TABLE 6. We follow Arostegui et al.’s procedure [72] to select the initial temperature T so that the resulting probability of accepting non-improving solution is 95% in the beginning of the run time.

TABLE 6: Simulated annealing search algorithm

```
current ← Initial-State (a set of locations assigned as ambulances base locations)
best ← Initial-State
T ← T0
Loop While (T > 30)
        L1 = current_ObjF
        candidate ← a successor of current with highest value of ObjF
        L2 = candidate_ObjF
        If L1 <  L2 then current ← candidate
            If(L2<best_ObjF) then best ← candidate
            End If
        Else ΔE = L2 − L1
              p = Exp( ΔE/T)
              best ← candidate only with probability p
           End Else
        End If
        T ←αT
  End Loop
```

5.5 Tabu Search Algorithm (TS)

The tabu search algorithm is originally proposed by Glover [73] in 1986. The overall approach is to avoid entrainment in a loop by forbidding or penalizing moves which point to solution spaces previously visited (known as “tabu list”). Unlike hill-climbing which won’t make a move where the objective is worse than that of current state, tabu search algorithm always makes a move to the accessible best neighboring solution.

A chief mechanism for exploiting memory in tabu search is to declare a subset of solutions similar to recently examined solutions are tabu. Each tabu has a tenure (duration) which determines how many iterations the tabu be in effect. The tabu list also referred to memory comprises of solutions (tabu) previously visited. The size of the tabu list equals the tenure of tabu because once a tabu passes tenure it will be automatically removed from the tabu list (memory). Tabu list size and tenure also define the maximum number of tabus allowed at any time. We described the process of generating neighboring solution spaces in Section 5.1. Our tabu search algorithm uses similar process of generating neighbors. However in tabu search algorithm we need to consider how to design tabu so that the algorithm won't move to a solution state previously visited. We use the locations of all response ambulances' posts i.e. the solution vector's previous m elements as tabu because the solutions are distinguished by the ambulance locations. In order not to repeat any previous accepted solution, we set tabu list size to the number of iterations. TABLE 7 describes the tabu search algorithm implemented in our simulation model.

TABLE 7: Tabu search algorithm

```
current ← start state
best ← current
Loop k → 1 to K
      Ordered_Neighbors_List ← generate_neighboring_solution (current) and
                                            sort in descending order by value of ObjF
       Loop While
              index ←  0
              neighbor ← get_index_th_element(Ordered_Neighbors_List)
              move_action←get_move_action(neighbor)
              If (tabu_Contains(move_action))
                   then index ← index + 1
              Else break While loop
              End IF
       End Loop
       current ← get_index_th_element(Ordered_Neighbors_List)
       Update_tabu ( )
       If (best_ObjF < current_ObjF) then best ← Current
       End If
End Loop
```

5.6 Experiments to fine tune the search algorithms

Prior to applying our simulation-optimization approach to a case study using real historical data, we generated a simulated dataset to train, test and refine our algorithms. Since we will utilize real data from Mecklenburg County (Greater Charlotte) in our case study which is divided into 168 zones by imposing a grid of 2 mile by 2 mile squares, we assume a hypothetical region (city) spanning 400 square miles (20 x 20). We divide this region into 100 zones with a 10 x 10 grid so each zone is also 2 mile by 2 mile square. In FIGURE 7, we show the call volumes originating from each zone where. The total number of calls is 1200. In Greater Charlotte there are three major hospitals, of which two are adjacent to each other. In our simulated we assume there is one hospital located in zone 45 (city center).

1	2	2	3	1	3	1	2	1	1
1	2	3	5	7	3	7	3	3	1
2	3	10	19	22	17	16	12	2	3
1	5	27	36	50	43	23	23	7	1
1	8	12	46	52	47	28	26	4	1
3	2	23	40	48	41	33	21	9	2
1	9	25	27	33	35	35	32	5	2
2	5	15	12	22	18	25	12	7	1
1	3	9	4	3	5	8	3	6	1
1	2	1	1	2	1	1	2	1	1

FIGURE 7: Hypothetical region (zones and calls distribution)

5.7 Preliminary Results

To fine tune our search algorithms we chose the MEXCLP model as the benchmark which is presented in Appendix A. Given a fleet of ambulances, the MEXCLP determines the optimal ambulance locations that maximize the expected coverage of calls. For the first set of runs, we set the average busy probability of ambulances to 30% (p = 0.3), assumed a fleet size of 24 ambulances, and set the distance threshold for coverage to 2.2 miles (S = 2.2). We developed a formulation generator which reads the call distribution data and grid information and develops the MEXCLP model in CPLEX format.

The CPLEX solution of the instance of the MEXCLP model covered 1,055 calls (an expected coverage of 87.92%) by placing the fleet in the following zones:

14, 22, 26, 27, 34, 35, 36, 38, 43, 44, 48, 55, 56, 57, 58, 63, 64, 65, 69, 72, 76, 77, 84, 88.

Next, to generate 1,200 calls which will simulate approximately the same parameter values used for the MEXCLP model, we assumed that the number of calls follow a Poisson distribution with a calculated mean of $\lambda = 6.9$ calls per hour. We applied the traffic intensity equation $\rho = {}^{\lambda}/_{m\mu}$ where $\rho = 0.3$ and $m = 24$. From TABLE 1 we know the averaged total service time is 62.68 minutes from which we calculated $\mu = 0.96$. Hence, we randomly generated 1,200 calls with time stamps, and randomly allocated the zone number of the calls based on the volume distribution in TABLE 7. For the purpose of this section, we only generated (assumed) priority 1 calls and used the default dispatch policy of sending the nearest vehicle. Next, the service time of calls is generated via the normal distribution of priority 1 calls presented in Section 3.5.

We first ran our simulation model with the MEXCLP solution (found by CPLEX). Interestingly, the simulation model resulted in covering 1019 calls (84.92% coverage) which is consistent with earlier published findings which indicate that MEXCLP tends to overestimate coverage [59]. Then we set the objective function as to maximize the number of covered calls. We ran our simulation model with random-start hill-climbing search algorithm of 10 random starts, after 507.5 seconds, it gives a result of 1073 (89.42%) with the following ambulance locations:

14, 26, 27, 29, 32, 35, 35, 38, 43, 45, 46, 47, 55, 57, 59, 63, 64, 65, 66, 73, 77, 78, 85, 88.

Simulated annealing solved this problem instance with a result of 1055 (89.42%) and the following ambulance locations:

23, 25, 27, 29, 34, 35, 36, 37, 42, 44, 46, 47, 48, 55, 55, 58, 62, 63, 67, 74, 76, 77, 84, 88.

We also ran tabu-search algorithm with a randomly generated initial solution (TS-RS), after 50 iterations (203.7 seconds) which resulted in a solution whose objective value is 1065 (88.75%) and the following ambulance locations:

14, 24, 26, 27, 29, 32, 34, 36, 44, 46, 47, 48, 53, 55, 55, 58, 63, 65, 67, 68, 73, 75, 79, 87.

Then we use the solution of MEXCLP as the initial solution of tabu search (TS-MEXCLP), after 50 iterations (194.4 seconds) it found its best solution with objective value of 1073 (89.42%), and the following ambulance locations:

14, 26, 27, 29, 32, 35, 35, 38, 43, 45, 46, 47, 55, 57, 59, 63, 64, 65, 66, 73, 77, 78, 85, 88.

Using MEXCLP as the initial solution tabu search algorithm founds a best solution exactly same as that of random-start hill climbing but with less time.

We conducted further experiments to compare MEXCLP and our simulation model embedded with each meta-heuristic algorithm. First, we tuned the parameters of all three meta-heuristics which resulted in following settings: number of random starts in RSHC is 5, number of iterations and tabu list size in TS is same as 60, initial temperature T = 2000 and cooling ratio is 0.92 in SA. Second, we generated 20 problem instances of 1200 calls using same process as the presented earlier to run the simulation model with each embedded meta-heuristics. Below TABLE 8 summarizes the results. The MEXCLP column represents the covered number of calls generated by our simulation model with the MEXCLP solution. For all search algorithms the first value is the best objective value (i.e. covered number of calls) found and the second value is the computing time in seconds. The average row shows the average of call number covered. The results show that all three meta-heuristics find better solutions than the MEXCLP model confirming that the three meta-heuristics are well-tuned and running effectively and efficiently. In addition we see that tabu search algorithm (TS-MEXCLP, TS-RS) outperform other two algorithms in computing time and in the quality of solutions (objective function value). These results confirm previous literature reports where GAs and other meta-heuristics have shown to produce very good results in this domain, but many researchers have also found that TS algorithms tend to produce even better solutions [1, 30, 35, 62, 74].

TABLE 8: Comparison of meta-heuristics and MEXCLP-Priority one

Instance	**MEXCLP OFV**	**RSHC OFV, CPU (sec)**	**TS-MEXCLP OFV, CPU (sec)**	**TS-RS OFV, CPU (sec)**	**SA OFV, CPU (sec)**
1	1007	1055, 244.2	1061, 232.0	1063, 239.6	1039, 233.9
2	992	1032, 258.0	1041, 241.0	1042, 236.6	1032, 237.7
3	982	1054, 304.0	1054, 232.5	1050, 224.0	1046, 236.9
4	990	1054, 282.8	1064, 230.5	1064, 229.8	1040, 227.0
5	1022	1069, 265.8	1078, 222.1	1073, 236.4	1072, 239.1
6	1021	1070, 313.6	1073, 229.8	1075, 226.7	1057, 229.9
7	1016	1060, 291.7	1062, 229.2	1062, 230.1	1052, 238.0
8	992	1039, 226.2	1042, 231.7	1047, 229.5	1048, 225.7
9	995	1049, 310.8	1054, 229.3	1051, 233.8	1044, 233.0
10	1005	1036, 246.7	1046, 226.4	1042, 226.4	1037, 225.0
11	995	1054, 312.5	1054, 245.0	1061, 231,1	1053, 236.2
12	993	1045, 322.6	1042, 227.7	1047, 218.9	1040, 235.8
13	999	1050, 291.4	1049, 235.0	1053, 237.5	1047, 229.8
14	1001	1041, 238.6	1041, 227.8	1052, 224.0	1049, 234.1
15	1021	1058 268.6	1060, 232.6	1064, 216.9	1060, 234.6
16	1000	1054, 259.3	1066, 227.9	1068, 230.9	1063, 232,9
17	989	1039, 313.6	1047, 220.9	1047, 223.1	1028, 232.4
18	998	1050, 297.2	1052, 237.3	1049, 232.0	1048, 242.6
19	999	1062, 294.0	1062, 237.1	1061, 240.7	1063, 232.0
20	1016	1061, 275.3	1060, 232,7	1063, 231.3	1053, 236.7
Average	**1001.7**	**1051.6, 280.8**	**1055.4, 231.4**	**1056.7, 229.96**	**1048.6, 233.6**

As can be seen in TABLE 8 both implementations of the TS algorithms produce nearly identical results. So, to further compare the performances of TS-RS and TS-MEXCLP we conducted experiments with same twenty problem instances but we reduced the number of iterations from 60 to 20 and 10. The results are presented in TABLE 9. From these results we see TS-MEXCLP has a better performance than TS-RS when the number of iterations is quite small (10 iterations). As we expected using the solution from MEXCLP as the initial solution of tabu search is a good strategy to find a near optimal solution considerably faster. We then repeated some experiments running both algorithms 120 iterations in which case they generated almost identical results. Clearly, if the number of iterations needs to be limited due to a need to solve the problems rapidly, TS-MEXCLP has a significant advantage over TS-RS due to starting with a very good initial solution (generated by MEXCLP). However, if the CPU time is not a major constraint in the study or application one can run the TS-RS algorithm longer (significantly more iterations) to find a high quality solution.

TABLE 9: Comparison of TS-MEXCLP and TS-RS

	10 iterations		**20 iterations**	
Instance	**TS-MEXCLP OFV, CPU (sec)**	**TS-RS OFV, CPU (sec)**	**TS-MEXCLP OFV, CPU (sec)**	**TS-RS OFV, CPU (sec)**
1	1057, 43.3	1035, 43.9	1058, 81.7	1053, 83.4
2	1039, 43.5	1035, 43.6	1041, 81.6	1036, 80.9
3	1043, 43.4	1042, 44.4	1047, 81.7	1050, 80.36
4	1053, 42.2	1051, 42.4	1054, 77.8	1049, 78.7
5	1073, 42.4	1058, 41.4	1078, 77.8	1068, 78.5
6	1053, 42.1	1034, 43.6	1073, 81.4	1070, 81.5
7	1055, 43.3	1038, 43.2	1055, 81.5	1057, 80.7
8	1038, 42.5	1017, 42.4	1038, 80.4	1043, 81.8
9	1044, 42.8	1035, 43.4	1051, 80.2	1040, 78.0
10	1046, 41.4	1025, 42.6	1046, 76.1	1038, 80.6
11	1053, 41.4	1043, 42.7	1053,81.3	1053, 81.7
12	1033, 42.7	1038, 44.2	1034, 76.0	1034, 80.3
13	1038, 44.2	1029, 43.8	1046, 81.8	1045, 77.6
14	1038, 43.3	1035, 42.5	1038, 79.1	1043, 91.4
15	1053, 43.3	1031, 41.5	1061, 121.2	1061, 105.0
16	1043, 41.9	1049, 44.5	1061, 79.5	1060, 81.3
17	1042, 43.1	1032, 40.9	1043, 78.2	1040, 76.6
18	1047, 43.0	1032, 46.1	1047, 81.1	1042, 80.7
19	1050, 44.6	1050, 41.8	1054, 80.6	1063, 80.5
20	1057, 42.5	1045, 43.1	1057, 82.0	1054, 77.7
Average	**1047.8, 42.8**	**1037.7, 43.1**	**1051.8, 82.1**	**1050.0, 81.9**

In our last set of experiments we tested the search algorithms with data which included call priorities. The 20 instances were generated by following same process as before but the priority number is not always one. As mentioned in Chapter 3, there are 8921, 24242, and 5236 priority one, two, and three calls, respectively. The priority number of a call (1, 2 and 3) is assigned based on the percentage of each type of calls:

priority one 23.23%, priority two 63.13% and priority three 13.64%. We also generated the travel and service times based on the priority of the calls by applying the distributions in Chapter 3. The results from these experiments are summarized in TABLE 10 which show that the TS consistently produces higher quality solutions in reasonably fast CPU times.

TABLE 10: Comparison of meta-heuristics and MEXCLP-Priorities

Instance	**MEXCLP OFV**	**RSHC OFV, CPU (sec)**	**TS-MEXCLP OFV, CPU (sec)**	**TS-RS OFV, CPU (sec)**	**SA OFV, CPU (sec)**
1	1013	1052, 290.4	1061, 302.7	1061, 302.0	1059, 365.6
2	1004	1051, 322.9	1060, 284.4	1061, 279.5	1042, 359.5
3	1001	1056, 279.7	1063, 283.1	1061, 279.1	1049, 370.9
4	1018	1054, 250.7	1055, 280.7	1055, 280.7	1061, 280.9
5	1007	1057, 295.6	1061, 288.1	1061, 282.7	1047, 368.0
6	1007	1059, 341.1	1057, 288.0	1061, 287.8	1054, 373.7
7	1030	1058, 306.6	1061, 285.1	1061, 280.1	1054, 361.8
8	1014	1058, 298.6	1063, 279.5	1061, 279.9	1045, 382.7
9	1011	1054, 321.4	1062, 281.5	1061, 283.4	1050, 362.6
10	1012	1051, 307.0	1060, 280.0	1061, 278.7	1052, 364.5
11	1037	1057, 347.9	1058, 280.6	1061, 276.5	1056, 365.4
12	1011	1058, 322.5	1064, 279.0	1061, 278.1	1052, 364.9
13	1011	1054, 324.8	1063, 283.2	1061, 283.1	1045, 371.0
14	976	1054, 280.6	1058, 234.2	1061, 236.7	1052, 316.1
15	1011	1051, 306.8	1063, 244.2	1061, 238.4	1047, 309.1
16	1010	1060, 251.6	1061, 232.7	1061, 224.8	1058, 291.5
17	1026	1058, 246.2	1058, 224.0	1061, 223.1	1055, 290.6
18	1033	1057, 260.6	1063, 225.1	1061, 223.9	1054, 292.2
19	1037	1053, 275.5	1060, 241.3	1061, 225.2	1052, 292.2
20	997	1051, 253.5	1058, 223.8	1061, 223.4	1052, 292.9
AVERAGE	**1013.3**	**1055, 294.2**	**1060.45, 266.1**	**1060.7, 263.4**	**1051, 388.8**

CHAPTER 6: APPLICATION OF THE SIMULATION-OPTIMIZATION MODEL TO CHARLOTTE

In this chapter we apply our simulation-optimization model to the historical 9-1-1 call dataset from Mecklenburg County (Greater Charlotte) EMS service agency. We first compare our simulation-optimization model with an advanced analytical model, the dynamic expected coverage location model (DECL) developed by Rajagopalan et al. [74]. Second, we develop a weighted objective function which draws upon on an out of hospital cardiac arrest survival rate function and further takes different priority calls into consideration. We apply our simulation-optimization model with the weighted objective function to Greater Charlotte and compare the efficacy of alternate dispatch policies. The application of our model is intended to demonstrate its usefulness in determining near optimal solutions to real-life ambulance dispatch policies while providing detailed coverage and ambulance workload statistics.

6.1 Description of the Model Settings for Greater Charlotte Area

As mentioned in Chapter 3 we have access to a complete 9-1-1 call dataset provided by the Mecklenburg County EMS agency, MEDIC. For the application of our approach the Greater Charlotte area is mapped into 168 2-by-2 mile nodes as depicted in FIGURE 8. All historical demand calls fall in a particular node according to its latitude and longitude. There are three major hospitals located in the center of each of the three yellow colored nodes (29, 60, and 91). The nodes that make the boundary (orange nodes) have the lowest call volumes. Therefore it is neither practical to place ambulances on those nodes nor possible for them being solution nodes by search algorithm, hence our search algorithm is programmed to exclude these nodes while searching for ambulance locations. The four red nodes are outside the official Mecklenburg County boundary however we created these dummy nodes so that the en-route dispatch algorithm can work properly, essentially travel across these nodes as needed. There are no demands from the dummy nodes and they cannot be the used as ambulance locations. In our en-route dispatch algorithm, when an ambulance completes its service for a call either at the scene or at a hospital and there are no pending dispatch requests, it will travel back to its base node via the nearest route via Manhattan distance principle. For example if an ambulance placed on node 40, when it completes service at node 58 it can travel back via route 58 → 38 → 40 or route 58 → 60 → 40. If both routes are fully within the area the algorithm will pick up an arbitrary route, and if one route is not fully covered by the area the algorithm choose the one fully covered by the area. For example, an ambulance whose base is node 130 completes a service at node 166 then the only route it will travel back is 166 → 133 → 130.

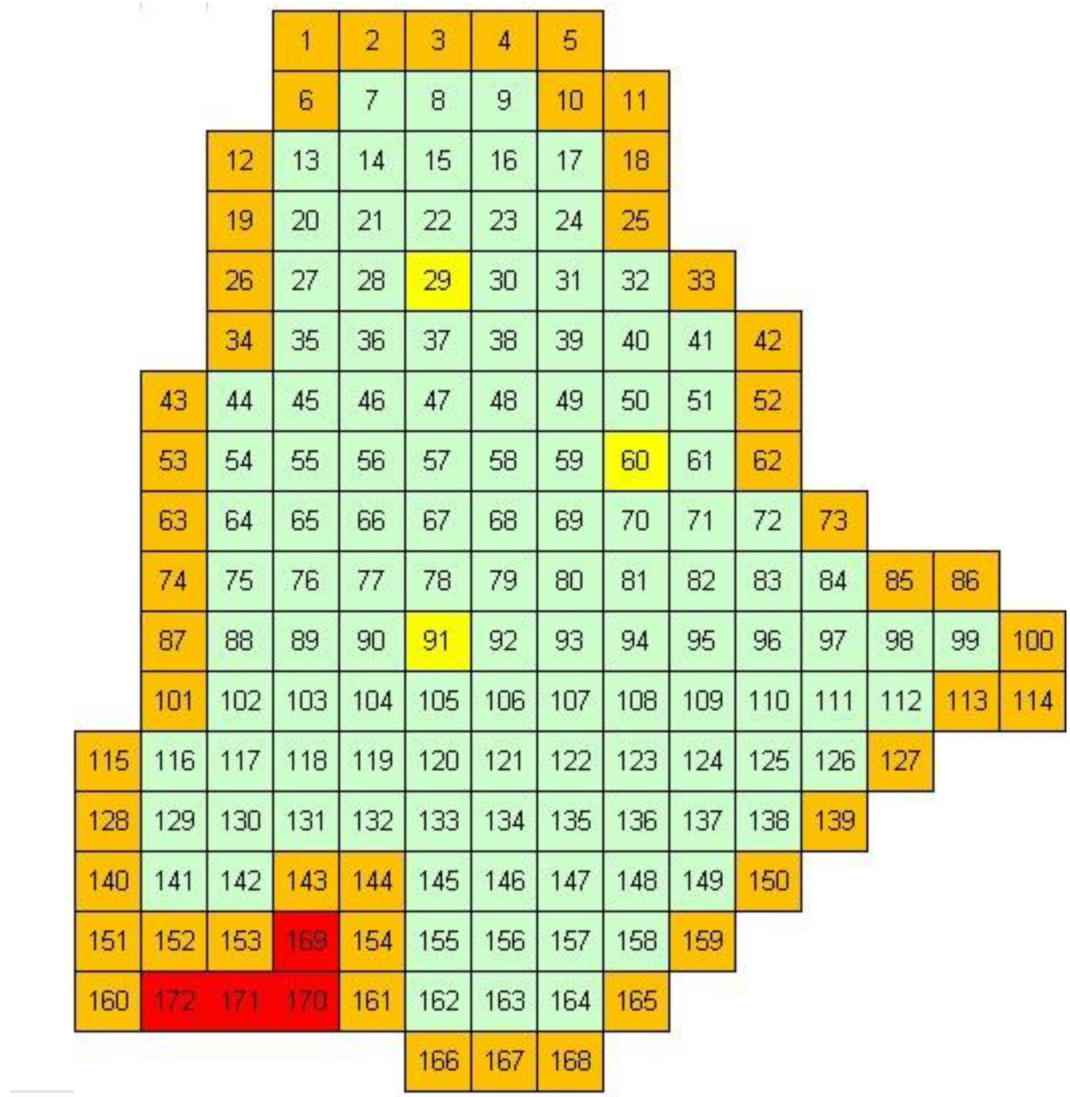

FIGURE 8: Mecklenburg county (Greater Charlotte) gridded to 168 demand zones

6.2 Comparisons with DECL

To demonstrate the benefits of using simulation-optimization approach to determine the near optimal ambulance posts instead of using an analytical approach we ran a series of comparisons with the dynamic expected coverage location (DECL) model developed by Rajagopalan et al. [74]. Briefly, DECL determines the minimum number of ambulances and their locations for a requirement of 95% coverage for each time interval.

Complete description of the DECL is in Appendix B. In applying the DECL, Rajagopalan et al. divided days of the week into twelve 2-hour time intervals which resulted in a total of 84 time intervals, hence 84 problem instances and utilized the same call dataset from Charlotte MEDIC. It is important to note the key assumptions and differences between the two approaches:

- DECL assumes all calls are of same priority while in our model calls are assigned priority 1, 2 and 3, based on the percentage of each type of calls: priority 1 23.23%, priority 2 63.13% and priority 3 13.64%.
- Service times of different priority calls are generated from the distribution shown in FIGURE 2.
- Travel times of different priority calls are computed based on travel time models in TABLE 2.
- In our model 75% of the patients are transported to the nearest hospital.
- In our model ambulances can be dispatched when they complete a service and while en-route to their posts.
- For these runs, we used the default dispatch policy of sending the nearest ambulance to all calls.

We ran our model with the same number of ambulances obtained by DECL for each of the 84 problem instances and obtained the following call coverage statistics displayed in TABLE 11.

TABLE 11: Simulation-optimization coverage (%)

Intervals	**Sunday**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**
12 am – 2 am	88.43	85.05	94.17	90.63	92.31	94.99	97.51
2 am – 4 am	86.82	92.35	96.14	96.06	92.21	96.58	91.13
4 am – 6 am	93.68	96.61	98.10	94.67	94.70	99.04	89.97
6 am – 8 am	91.67	90.41	90.98	87.46	90.73	89.46	91.61
8 am – 10 am	89.64	84.75	85.22	82.98	81.88	88.40	90.55
10 am – 12 pm	87.10	84.75	84.91	82.28	79.86	87.84	87.27
12 pm – 2 pm	83.08	82.09	84.39	77.17	82.13	81.78	86.64
2 pm – 4pm	84.13	80.47	86.40	83.57	81.23	79.89	83.15
4 pm – 6 pm	81.67	76.49	81.30	78.73	77.44	77.36	81.40
6 pm – 8 pm	82.85	80.78	84.56	76.80	72.84	81.57	80.33
8 pm – 10 pm	78.97	85.79	82.06	80.27	81.70	82.10	85.55
10 pm – 12 am	89.01	85.52	88.85	83.19	83.08	82.65	80.11

Next, we computed the difference between the DECL estimated coverage rates and coverage rates from the simulation optimization model which are shown in TABLE 12. The coverage statistics estimated by DECL are significantly higher than our simulation-optimization coverages in 78 of the 84 problem instances. On average DECL overestimates coverage by a 9.39 percent and the maximum net deviation is 24 percent.

In the six problem instances where DECL essentially under-estimates the true coverage, the average difference is -1.65 percent and the maximum difference is -3.33 percent. It is also interesting to note that these problem instances are among lowest demand time intervals. Further analysis reveal that during low demand instances throughout the week, typically 2-6 a.m. Monday-Friday, DECL tends to be relatively more accurate resulting in coverage estimation errors under four percent. We can conclude that DECL can predict coverage rates accurately under low demand intervals which are the early hours of workdays, Monday through Friday 2-4 and 4-6 a.m. One possible reason for this is that during these times the call demand volumes are the lowest resulting in low workloads which in turn implies fewer, if any, en-route and end-of-service dispatches. However, DECL estimated coverages rapidly degrade under high congestion and high demand intervals because of the nature of analytical models' inability to capture the dynamic nature of the ambulance dispatch practices, essentially due to the necessity of simplifying real-life details, a common phenomenon in this class of analytical models.

TABLE 12: Difference between DECL and Sim-Opt coverage rates (%)

Intervals	**Sun.**	**Mon.**	**Tues.**	**Wed.**	**Thur.**	**Fri.**	**Sat.**
12 am – 2 am	6.89	9.95	1.46	4.71	2.86	0.76	-2.20
2 am – 4 am	8.18	3.09	-0.63	0.28	3.14	-1.11	3.97
4 am – 6 am	2.29	-0.53	-2.64	0.55	0.84	-3.33	5.55
6 am – 8 am	4.00	4.94	4.70	8.41	4.80	5.69	3.74
8 am – 10 am	6.05	10.39	10.26	12.43	13.73	6.93	5.14
10 am – 12 pm	8.03	10.96	10.40	12.86	15.37	7.65	8.67
12 pm – 2 pm	11.93	13.66	11.30	17.87	13.61	13.26	9.17
2 pm – 4pm	11.34	14.65	8.70	12.34	14.32	15.15	12.16
4 pm – 6 pm	13.47	18.71	14.04	16.81	18.27	17.72	14.59
6 pm – 8 pm	12.18	14.94	11.36	18.98	22.63	13.76	14.78
8 pm – 10 pm	16.12	10.38	13.10	14.86	14.30	13.12	9.59
10 pm – 12 am	6.41	10.24	6.89	12.33	12.54	13.15	15.04
Average	8.91	10.11	7.41	11.04	11.37	8.56	8.35

In summary, the DECL generally overestimates the coverage. The tendency to overestimate coverage by expected coverage class of models has been repeatedly reported in the literature [38, 56, 59]. When we further check the average workload of ambulances based on the *optimal* fleet size found by the DECL, we noticed that the average workload is close to 60% which is nearly the twice the rate considered reasonable in the EMS community. In other words, DECL overestimates coverage which essentially means it underestimates the number of ambulances required to achieve the target 95% coverage. Though a simulated comparison has been done in their article leading to small differences but the simulation used in their comparison is quite limited compared with the one we developed in this study. Our simulation-optimization model as discussed in Chapter 4 captures almost every aspect of real life operations of a typical EMS.

6.3 Objective Function

The majority of the existing objective functions in the EMS literature are based on single aspect of EMS, e.g. coverage or cardiac arrest survivability function For example, deterministic or probabilistic coverage functions do not consider that different types of calls have different priorities. Survivability function as discussed before is specific to only OHCA and less than 0.5% of all calls are classified as OHCA [70]. Recently Knight et al. [22] extended Erkut et al.'s cardiac arrest survival function [21] by taking into account multiple-classes of patient outcomes. They developed a multi-objective function based on an OHCA function and the call categories similar to MEDIC's call priorities (1, 2, and 3). In order to capture different types of calls and their different level of interests to EMS administration we adapted Knight et al.'s objective function. The objective function we will maximize is a weighted sum of the four objectives shown below:

$$\mathrm{ObjF(state)} = \mathrm{SF(RT)w_0} + \mathrm{CV_1(RT\,)w_1} + \mathrm{CV_2(RT\,)w_2} + \mathrm{CV_3(RT)w_3} \qquad (1)$$

, where SF is a survival probability function for cardiac arrest patients shown in Eq. (2):

$$\mathrm{SF(RT)} = 1/(1 + \exp(-0.26 + 0.139 * \mathrm{RT})) \qquad (2)$$

CV denotes a function which tallies the number of calls reached for priority 1, 2 and 3 within the pre-determined RT thresholds (targets). We follow Knight et al.'s heterogeneous measures [22] and use 8-, 14-, and 21-minutes as hard RT targets for priority 1, 2, and 3 calls, respectively. Hence, the CV functions can be expressed as follows:

$$CV_1(RT) = \begin{cases} 1 & 0 \le RT \le 8 \\ 0 & RT > 8 \end{cases} \tag{3}$$

$$CV_2(RT) = \begin{cases} 1 & 0 \le RT \le 14 \\ 0 & RT > 14 \end{cases} \tag{4}$$

$$CV_3(RT) = \begin{cases} 1 & 0 \le RT \le 21 \\ 0 & RT > 21 \end{cases} \tag{5}$$

It is important to note that the probability of survival after an OHCA with a RT = 0 is about 57 percent and with a RT = 8 minutes the odds of survival drops to 30 percent. FIGURE 9 below displays the rapid decline of survival probability as the RT increases.

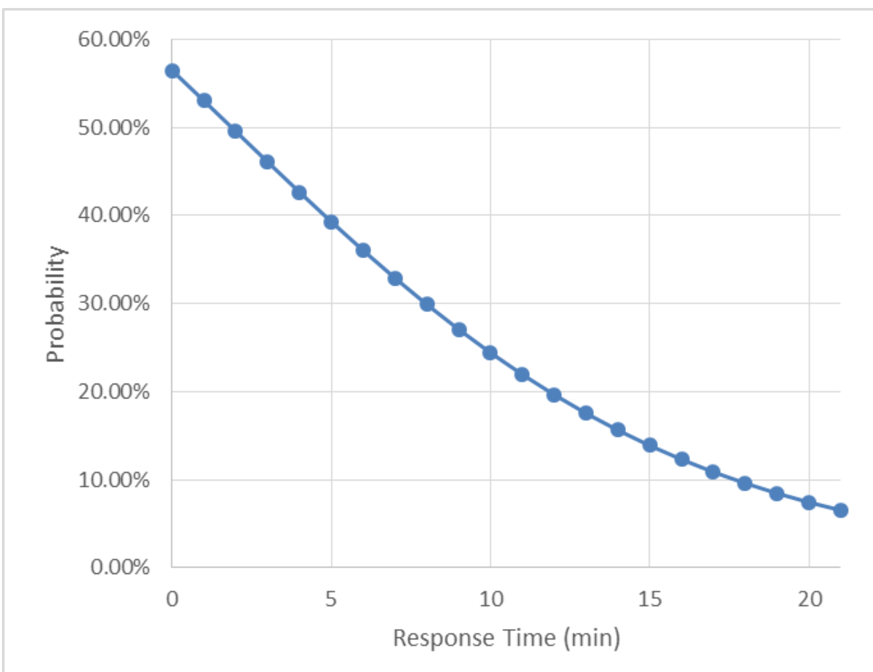

FIGURE 9: Survival probability function for OHCA

The objective function showed in Eq. (1) combines heterogeneous outcome measures into a single function which takes four types of calls into consideration. For each type of call the EMS administrator can choose different weights according to call statistics of the region. In this research we adopted the same weights use by Knight et al. $w_0 = 16, w_1 = 8,\ w_2 = 2,\ w_3 = 1$, for cardiac arrest calls, priority 1 calls, priority 2 calls and priority 3 calls, respectively. Clearly EMS administrators can choose different RT targets and different weights according to their contractual requirements.

6.4 Results from Using a Tiered Ambulance Dispatch Policy

6.4.1 Analysis of Results

In order to test the efficacy of tiered (alternate) dispatch policies on OHCA survival rates, response times per call priority (via the weighted objective function), and the resulting ambulance crew workloads we solved a series of problems using the same real call data set organized into 84 meaningful scenarios. Importantly, when testing alternate dispatch policies in these runs we utilized the *call priorities* to determine which vehicle to dispatch. Also noteworthy is the fact that, in our approach, fleet size is an input variable whereas DECL finds the minimum number of ambulances to meet the target coverage rate.

In this regard, we noticed that, with the DECL prescribed (recommended) fleet sizes for the 84 problem scenarios, an interesting phenomenon occurred: In running the simulation optimization model with the default dispatch policy, the resulting average ambulance workload was approx. 54-56%, which is considered high in the EMS community; normally, the ideal (practical) average workload is about 30%. Hence, we conducted experiments for each of the scenarios in order to determine those fleet sizes that would result in a 30-32% average workload. This would then allow us to test the efficacy of alternate dispatch policies under lower average workloads.

The numbers of ambulances for high- and low-average workloads are shown in TABLES 13 and 14. Note that two different dispatch policies, and two sets of fleet sizes, provide a total of four different settings for each of the 84 intervals, which imply 4 x 84 = 336 runs.

TABLE 13: Numbers of ambulances resulting in high average workload

Intervals	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
12 am – 2 am	11	14	13	14	15	19	17
2 am – 4 am	13	14	13	13	14	15	16
4 am – 6 am	12	13	12	13	14	13	13
6 am – 8 am	15	16	15	15	15	13	13
8 am – 10 am	17	18	17	17	18	16	15
10 am – 12 pm	19	19	17	18	19	18	17
12 pm – 2 pm	19	19	18	19	19	19	18
2 pm – 4 pm	19	19	19	18	19	18	18
4 pm – 6 pm	18	19	18	18	19	18	16
6 pm – 8 pm	17	19	16	16	17	18	16
8 pm – 10 pm	16	16	15	16	17	18	16
10 pm – 12 am	14	16	14	14	17	17	15

TABLE 14: Numbers of ambulances resulting in low average workload

Intervals	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
12 am – 2 am	15	21	19	19	20	24	27
2 am – 4 am	19	19	18	20	18	23	26
4 am – 6 am	15	14	15	15	16	18	19
6 am – 8 am	23	22	22	22	22	19	18
8 am – 10 am	29	30	31	30	29	25	24
10 am – 12 pm	34	33	33	33	33	29	28
12 pm – 2 pm	34	33	35	34	34	32	30
2 pm – 4 pm	36	33	33	34	36	32	31
4 pm – 6 pm	37	35	35	35	38	32	29
6 pm – 8 pm	35	33	31	32	32	33	30
8 pm – 10 pm	28	29	29	29	32	31	29
10 pm – 12 am	25	26	24	25	30	32	25

In the first set of runs, we used the DECL-provided fleet sizes (high average workloads) along with the default (current) dispatch policy of sending the nearest ambulance to all calls. TABLE 15 displays the outcomes of these runs for Monday only. The columns in TABLE 15, and the subsequent TABLES 16-18, below, represent the following:

- Column “OBJ-Fun” provides the objective function value of the best solution found.
- Under column “OHCA”, we report the expected number of survivors of OHCA based on the total number of simulated OHCA incidents within priority 1 calls, as well as the survival probability (SF%).
- Columns “P1-P3” display, respectively, the number of priority 1-3 calls reached under the corresponding target, RT; the total number of priority 1-3 calls; and the resulting (percent) coverages.

- Column "Workload" displays the workload statistics (average, standard deviation, minimum, maximum, and range). For example, in TABLE 15, row '12 a.m. – 2 a.m.' we display the results from applying the default dispatch policy with a DECL- prescribed fleet size of 11 ambulances (high average workload). Results show that the average workload is 0.401 with a range of [0.246-0.482]. There are three OHCA calls, where the expected number of survivors, based on realized RTs, is 1.506. The corresponding average survival probability is 50.19%.

How we track the OHCA calls is an important real-life feature of our proposed model. As mentioned earlier, approximately 0.5% of all calls tend to be confirmed as OHCA. As previously noted, an OHCA- triggered call must be categorized as 'priority 1.' With the percentage of priority 1 calls being 23.23%, in our trace-driven simulation, the percentage of OHCA incidents among priority 1 calls was 2.15%.

For example, in the specified time interval (see above), there were a total of 428 calls from which 100 calls were randomly sampled as priority 1, 274 as priority 2, and 54 as priority 3 (with corresponding percentages 23.23%, 63.13% and 13.64%, respectively). From the sampled 100 priority 1 calls, three were categorized as OHCA (with corresponding percentages 2.15% figure listed above).

The results from all 336 runs are listed in Appendix C. We analyzed the findings for each day, and conducted a series of paired t-tests to determine whether there are significant differences between the average values of each of the key performance metrics (viz., OHCA survival probability, coverage rates by call priority, and workload range). The test results are presented in Appendix D. We found that, overall the results are consistent across ‘days of the week.’ Thus, hereafter we will use *Monday’s* results to summarize the results of our experiments.

TABLE 15: Monday high average workload DEF results

Monday High Workload Default Dispatch Policy																			
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload					
		Exp. Saved	Total	SF(%)	Covered	Total	%	Covered	Total	%	Covered	Total	%	AVG	STD	MIN	MAX	Range
12 am – 2 am	967.09	1.506	3	50.19	58	97	59.79	216	274	78.83	47	54	87.04	0.401	0.060	0.246	0.482	0.237
2 am – 4 am	926.98	1.499	3	49.95	51	77	66.23	225	249	90.36	45	50	90.00	0.453	0.104	0.196	0.606	0.410
4 am – 6 am	718.88	0.993	2	49.63	39	58	67.24	178	200	89.00	35	35	100.00	0.386	0.097	0.229	0.544	0.315
6 am – 8 am	1431.86	1.491	3	49.70	92	141	65.25	303	365	83.01	66	75	88.00	0.482	0.051	0.377	0.569	0.192
8 am – 10 am	1791.10	2.006	4	50.16	103	199	51.76	416	525	79.24	103	118	87.29	0.588	0.065	0.466	0.697	0.230
10 am – 12 pm	2314.77	3.048	6	50.81	145	244	59.43	496	621	79.87	114	139	82.01	0.606	0.069	0.455	0.746	0.291
12 pm – 2 pm	2131.61	2.038	6	33.96	128	238	53.78	477	608	78.45	121	136	88.97	0.605	0.074	0.459	0.718	0.259
2 pm – 4pm	2217.16	3.010	6	50.17	137	247	55.47	479	627	76.40	115	139	82.73	0.641	0.062	0.507	0.742	0.235
4 pm – 6 pm	2101.70	2.544	6	42.40	129	247	52.23	461	629	73.29	107	139	76.98	0.659	0.067	0.538	0.777	0.239
6 pm – 8 pm	1831.67	2.042	4	51.04	108	209	51.67	416	541	76.89	103	120	85.83	0.621	0.074	0.472	0.717	0.245
8 pm – 10 pm	1541.44	1.528	3	50.92	91	169	53.85	353	448	78.79	83	98	84.69	0.554	0.073	0.403	0.714	0.311
10 pm – 12 am	1360.39	1.524	3	50.80	84	138	60.87	299	364	82.14	66	75	88.00	0.525	0.081	0.325	0.623	0.298
	Sum	23.228	49			Avg	58.13			80.52			86.80	0.543		0.389	0.661	0.272

TABLE 16: Monday high average workload LU results

Monday High Workload Least Utilization Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	SF(%)	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	STD	MIN	MAX	Range
12 am – 2 am	863.09	1.506	3	50.19	58	97	59.79	165	274	60.22	45	54	83.33	0.421	0.007	0.41	0.433	0.023
2 am – 4 am	802.98	1.499	3	49.95	52	77	67.53	159	249	63.86	45	50	90.00	0.473	0.007	0.464	0.484	0.021
4 am – 6 am	662.88	0.993	2	49.63	39	58	67.24	150	200	75.00	35	35	100.00	0.400	0.041	0.268	0.439	0.172
6 am – 8 am	1256.86	1.491	3	49.70	88	141	62.41	231	365	63.29	67	75	89.33	0.499	0.009	0.484	0.514	0.030
8 am – 10 am	1559.10	2.006	4	50.16	99	199	49.75	318	525	60.57	99	118	83.90	0.612	0.024	0.517	0.630	0.114
10 am – 12 pm	1944.03	2.565	6	42.74	125	244	51.23	394	621	63.45	115	139	82.73	0.625	0.026	0.518	0.645	0.127
12 pm – 2 pm	1903.42	3.026	6	50.44	129	238	54.20	351	608	57.73	121	136	88.97	0.623	0.016	0.556	0.640	0.084
2 pm – 4pm	1906.16	3.010	6	50.17	124	247	50.20	371	627	59.17	124	139	89.21	0.654	0.026	0.546	0.670	0.124
4 pm – 6 pm	1828.70	2.544	6	42.40	117	247	47.37	371	629	58.98	110	139	79.14	0.673	0.040	0.508	0.693	0.185
6 pm – 8 pm	1591.67	2.042	4	51.04	104	209	49.76	312	541	57.67	103	120	85.83	0.639	0.009	0.625	0.662	0.036
8 pm – 10 pm	1390.44	1.528	3	50.92	89	169	52.66	286	448	63.84	82	98	83.67	0.569	0.049	0.434	0.594	0.160
10 pm – 12 am	1179.39	1.524	3	50.80	82	138	59.42	216	364	59.34	67	75	89.33	0.545	0.042	0.425	0.572	0.147
	Sum	23.732	49			Avg=	55.96			61.93			87.12	0.561		0.480	0.581	0.102

TABLE 17: Monday low average workload DEF results

Monday Low Workload Default Dispatch Policy																			
Intervals	**OBJ-Fun**	**OHCA**			**P1**			**P2**			**P3**			**Workload**					
		Exp. Saved	**Total**	**SF(%)**	**covered**	**Total**	**%**	**covered**	**Total**	**%**	**Covered**	**Total**	**%**	**AVG**	**STD**	**MIN**	**MAX**	**Range**
12 am – 2 am	1198.09	1.506	3	50.19	78	97	80.41	250	274	91.24	50	54	92.59	0.297	0.089	0.156	0.463	0.307
2 am – 4 am	1081.98	1.499	3	49.95	65	77	84.42	244	249	97.99	50	50	100.00	0.300	0.092	0.099	0.455	0.356
4 am – 6 am	814.88	0.993	2	49.63	48	58	82.76	190	200	95.00	35	35	100.00	0.302	0.095	0.148	0.451	0.303
6 am – 8 am	1822.86	1.491	3	49.70	127	141	90.07	354	365	96.99	75	75	100.00	0.304	0.094	0.08	0.442	0.362
8 am – 10 am	2606.10	2.006	4	50.16	177	199	88.94	520	525	99.05	118	118	100.00	0.328	0.117	0.119	0.520	0.401
10 am – 12 pm	3208.77	3.048	6	50.81	224	244	91.80	615	621	99.03	138	139	99.28	0.332	0.124	0.101	0.629	0.528
12 pm – 2 pm	3154.42	3.026	6	50.44	223	238	93.70	594	608	97.70	134	136	98.53	0.324	0.109	0.11	0.560	0.451
2 pm – 4pm	3310.16	3.010	6	50.17	235	247	95.14	622	627	99.20	138	139	99.28	0.324	0.125	0.126	0.619	0.492
4 pm – 6 pm	3298.19	3.074	6	51.24	232	247	93.93	627	629	99.68	139	139	100.00	0.308	0.121	0.047	0.578	0.531
6 pm – 8 pm	2784.67	2.042	4	51.04	195	209	93.30	536	541	99.08	120	120	100.00	0.286	0.113	0.108	0.609	0.501
8 pm – 10 pm	2207.44	1.528	3	50.92	151	169	89.35	439	448	97.99	97	98	98.98	0.299	0.107	0.092	0.594	0.502
10 pm – 12 am	1808.39	1.524	3	50.80	123	138	89.13	363	364	99.73	74	75	98.67	0.286	0.102	0.112	0.466	0.355
	Sum	24.746	49			Avg=	89.41			97.72			98.94	0.307		0.108	0.532	0.424

TABLE 18: Monday low average workload LU results

Monday Low Workload Least Utilization Policy																		
Intervals	**OBJ-Fun**	**OHCA**			**P1**			**P2**			**P3**			**Workload**				
		Exp. Saved	**Total**	**SF(%)**	**covered**	**Total**	**%**	**covered**	**Total**	**%**	**Covered**	**Total**	**%**	**AVG**	**STD**	**MIN**	**MAX**	**Range**
12 am – 2 am	1055.09	1.506	3	50.19	75	97	77.32	191	274	69.71	49	54	90.74	0.311	0.006	0.298	0.319	0.021
2 am – 4 am	975.98	1.499	3	49.95	66	77	85.71	187	249	75.10	50	50	100.00	0.318	0.039	0.171	0.346	0.175
4 am – 6 am	724.88	0.993	2	49.63	47	58	81.03	149	200	74.50	35	35	100.00	0.316	0.057	0.163	0.352	0.189
6 am – 8 am	1550.86	1.491	3	49.70	118	141	83.69	254	365	69.59	75	75	100.00	0.324	0.031	0.200	0.345	0.145
8 am – 10 am	2162.10	2.006	4	50.16	162	199	81.41	359	525	68.38	116	118	98.31	0.352	0.007	0.329	0.362	0.032
10 am – 12 pm	2769.77	3.048	6	50.81	213	244	87.30	440	621	70.85	137	139	98.56	0.356	0.022	0.270	0.378	0.108
12 pm – 2 pm	2688.42	3.026	6	50.44	208	238	87.39	420	608	69.08	136	136	100.00	0.348	0.010	0.312	0.366	0.054
2 pm – 4pm	2783.16	3.010	6	50.17	215	247	87.04	438	627	69.86	139	139	100.00	0.347	0.035	0.218	0.375	0.157
4 pm – 6 pm	2847.19	3.074	6	51.24	218	247	88.26	458	629	72.81	138	139	99.28	0.331	0.029	0.219	0.353	0.134
6 pm – 8 pm	2378.67	2.042	4	51.04	185	209	88.52	373	541	68.95	120	120	100.00	0.307	0.008	0.289	0.331	0.042
8 pm – 10 pm	1931.44	1.528	3	50.92	144	169	85.21	329	448	73.44	97	98	98.98	0.319	0.022	0.249	0.343	0.094
10 pm – 12 am	1503.39	1.524	3	50.80	112	138	81.16	255	364	70.05	73	75	97.33	0.306	0.074	0.130	0.347	0.216
	Sum	24.746	49			Avg=	84.50			71.03			98.60	0.328		0.238	0.351	0.114

6.4.2. OHCA Survival Probability and Priority 1 Call Coverage Comparisons.

We are primarily interested in the magnitude of the difference between the mean OHCA survival probabilities resulting from the default dispatch policy (DEF), and the alternate dispatch policy of LU; and, further, whether or not this difference is statistically significant. Similarly, we are interested in differences in the mean coverage rates of the dispatch policies.

For brevity, we formally state the null and alternate hypotheses for the OHCA survival probability as follows:

- H0: The difference in the mean OHCA values under DEF and LU policies is zero.
- H1: The difference in the mean OHCA values under DEF and LU policies is greater than zero.

TABLE 19 below, summarizes the results of the 20 paired t-tests of Monday's runs.

TABLE 19: Summary of paired t-test results

Mean Difference	High Average Workload		Low Average Workload	
	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	-0.0070	0.33*	0.0000	NA
P1 Coverage	0.0217	<0.01	0.0491	<0.01
P2 Coverage	0.1860	<0.01	0.2670	<0.01
P3 Coverage	-0.0033	0.34*	0.0034	0.12*
WL range	0.1699	<0.01	0.3103	<0.01

Under high average workload conditions, we note that the mean difference in OHCA survival probability between DEF and LU is -0.0070. While this implies that, on Mondays, the LU policy *improves* OHCA survival probability by 0.7%, it is clearly statistically insignificant (p-value = 0.33). Importantly, across all days, we note nearly identical results where the mean differences range from -0.0102 (Sunday) to 0.0227 (Wednesday) with all statistically insignificant (1-tail, 5% significance level).

Under low average workload conditions, the mean difference in OHCA survival probability between DEF and LU policies is zero for all days. This is, in fact, an expected result. The system wide ambulance busy probability is in the neighborhood of 30% since both dispatch policies send the nearest ambulance to OHCA calls probability of finding an idle ambulance nearby is thus much greater than it would be in systems where the average busy probability is high.

The null and alternate hypotheses for priority 1 call coverage are as follows:

- H0: The difference in the mean priority 1 call coverage values under DEF and LU policies is zero.
- H1: The difference in the mean priority 1 call coverage values under DEF and LU policies is greater than zero.

Under high workload conditions, the mean difference in priority 1 call coverage between DEF and LU is seen to be (TABLE 19) 0.0217, and is statistically significant at the $\alpha = 0.01$ level. Across all days, we note similar results, i.e., that the difference is statistically significant at $\alpha = 0.01$ except for Thursdays at the $\alpha = 0.05$ level. We also note that the differences range from 0.0206 (Thursday) to 0.0414 (Sunday).

Under low average workload conditions, we see nearly identical results where the mean differences range from 0.0477 (Sunday) to 0.0620 (Wednesday), with all statistically significant (1-tail, 1% significance level).

These results suggest that the default and alternative dispatch policies have different priority 1 call coverage values. The former thus achieves 2.06% to 4.14% more coverage under high workload conditions, and 4.77% to 6.20% more coverage under low workload conditions than does the latter.

6.4.3. Priority 2 and 3 Call Coverage Comparisons

Utilizing similar forms from earlier comparisons, the null and alternate hypotheses for priority 2 call coverage are as follows:

- H0: The difference in the mean priority 2 call coverage values under DEF and LU policies is zero.
- H1: The difference in the mean priority 2 call coverage values under DEF and LU policies is greater than zero.

Referring again to TABLE 19, we find that, under high workload conditions, the mean difference in priority 2 call coverage between DEF and LU is 0.1860. This implies that, on Mondays, the DEF policy achieves 18.6% more coverage for priority 2 calls. The p-value is less than 0.01. We thus reject the null hypothesis that the two policies have same mean coverage at the $\alpha = 0.01$ significance level. Across all days, we note identical results, where the mean differences range from 0.1699 to 0.1992 and, again, all are statistically significant at the 1% single-tail significance level.

Under low workload conditions, the mean differences range from 0.2649 to 0.276, where, again, all are statistically significant at the 1% significance level.

The null and alternate hypotheses for priority 3 call coverage are as follows:

- H0: The difference in the mean priority 3 call coverage values under DEF and LU policies is zero.

- H1: The difference in the mean priority 3 call coverage values under DEF and LU policies is greater than zero.

Under high average workload conditions, TABLE 19 results show that the mean difference in priority 3 call coverage between the two policies is -0.0033 (-0.3%). This implies that, on Mondays, the LU policy results in a slightly higher priority 3 call coverage. However, the one tail t-test critical value is 0.34, which allows acceptance of the null hypothesis, H0.

Examining other days, we find the same results, except that on Saturdays, a small, statistically significant (P-value = 0.025) difference (1.45%) occurs in favor of the DEF policy. Again, though, on all other days, the mean difference is not statistically significant.

Under low average workload, the results are similar to those for high workload conditions. Thus, with the exception of Tuesday's results, where the mean difference is quite minimal (0.64%) but statistically significant (P-value =0.038), the mean difference on all other days was found to be not statistically significant. Hence, we can safely conclude that coverage of priority 3 calls under LU policy will not result in a significant reduction under either high- or low-workload conditions. This is a finding of some practical and theoretical importance.

6.4.4. Workload Imbalance Comparisons

Workload *range* reflects the degree to which the load is balanced/imbalanced across all ambulances. It is an important metric that adds to the information needed by administrators in order to create a more efficient and effective fleet of ambulances. We follow a similar procedure to test the mean difference of workload between the various dispatch policies. According to the design of *least utilization dispatch policy* described previously, we expect to see LU reduce the workload range considerably more relative to DEF.

We formally state the relevant null and alternative hypotheses below:

- H0: The difference in the mean workload ranges under DEF and LU policies is zero.
- H1: The difference in the mean workload ranges under DEF and LU policies is greater than zero.

As shown in TABLE 19, under high workload conditions the difference of mean ranges between DEF and LU is 0.1699 (16.99%) which is statistically significant at the 1% significance level. As anticipated, the latter reduced the workload imbalance from 27.18% to 10.19%, representing a sizeable 62.51% reduction in magnitude. Further, across all days, we note significant reductions in workload imbalance where the mean differences ranges from 0.1441 to 0.2109, with all statistically significant (1-tail 1% significance level).

Of note, we observe a larger reduction in imbalances under low workload conditions where Monday's results show a difference of 0.3103 (31.03%). Essentially, LU policy reduced the imbalance from 0.4242 to 0.1138, representing a 73.20% reduction. Not surprisingly, a t-test shows this reduction to be statistically significant at the 1% level. Similarly, across all days, the mean differences ranges from 0.2662 to 0.3389, where, again, all are statistically significant (1-tail 1% significance level).

6.4.5 Overall Comparisons

From previous sub-sections, we see that neither DEF nor LU is likely to make a statistically significant difference in terms of the OHCA survival rate or priority 3 call's coverage. We are thus not able to determine which of them is the better dispatch policy based on either OHCA or priority 3 call's coverage outcomes.

For the coverage of priority 1 calls, excluding OHCA, DEF is statistically better than LU; but, the magnitude of this difference is rather small. For instance, under high workload conditions on Mondays, DEF provides coverage of 58.13% of priority 1 calls, while LU offers coverage of 55.96%.

For coverage of priority 2 calls, the difference between DEF and LU is statistically significant and substantial in size. For instance, under high workload conditions on Mondays, DEF has coverage of 80.52% of priority 2 calls, while LU generates only 61.93% coverage. In terms of coverage of priority 1 (excluding OHCA) calls, DEF thus provides slightly better performance than does LU. In covering priority 2 calls, DEF is *considerably* better than LU. Interestingly, however, is the fact that, for the workload range, LU achieves significantly better outcomes than does DEF. For instance, under high workload conditions on Mondays, LU reduces the workload from DEF's 0.2718 to 0.1019, a notable reduction of 62.51%.

The key reasons for DEF and LU generating nearly identical outcomes in terms of both OHCA and coverage of priority 1 calls is, we believe, the following: Both DEF and LU send the nearest available ambulance to priority 1 calls, including OHCA. The objective function in the search algorithm heavily favors covering OHCA and priority 1 calls by placing the units in the areas where these calls tend to originate from. Also, there are very few (<0.5% of all; <2.15% of priority 1 calls) OHCA calls. Lastly, the OHCA survival probability is a continuous function based on RT. When an OHCA RT is, say 8 minutes 1 second vs. 8 minutes, the difference in the computed survival probability is the difference 0.2990 – 0.2985 = 0.0005, clearly negligible. Taken all together, mean difference in OHCA survival probability between DEF and LU is, as expected, negligible. However, none-OHCA priority 1 calls hold the second largest weight and they are also being covered with the nearest ambulances. The results show that LU policy tends to cover 2-4% less than DEF policy and the difference is statistically significant. We believe that this difference is in part due to the simple 0/1 tally function used in the objective function (as well as widely in the literature) where a RT of 8 minutes counts towards being the covered (1), conversely an RT of 8 minutes 1 second will not count at all (0). Further, as we detailed in Chapter 1, Section 1.3, outside the OHCA incidents there appears to be no clear connection between fast RTs and patient outcomes. Therefore, we can argue that 2-4% less coverage of non-OHCA P1 calls do not necessarily imply significant reduction in the patient survival.

Interestingly, DEF and LU lead to significantly different coverages of priority 2 calls since the former, unlike the latter, chooses to send its nearest ambulance to priority 2 calls. This generally results in less travel time and, hence, a shorter RT. Curiously, it is not entirely clear why there is little or no difference between the two policies in terms of priority 3 call coverage. One possible explanation is that these calls are much less insensitive to RT. For example, in our simulation, the target RT of priority 3 coverage is 24 minutes, which is not difficult to meet, even if the nearest ambulance is not dispatched. The alternative dispatch policy was designed to favor sending less busy vehicles from all those available so it reduces the workload range significantly relative to DEF.

6.4.6 Comparing and Evaluating Priority 1 Coverage via CDFs

Regardless of the dispatch policy implemented, the simulation optimization approach provides detailed coverage statistics by call type, individual workload of all ambulances (not shown for brevity), workload ranges and even call by call location and dispatch details. The below FIGURE 10 is a snapshot of a piece of detail dispatch output data.

Call Id	Call Zone	Call Arrivi	Priority	Response	Response	Survivabi	Miss	Hospital	TimeToH	totalTime
1	92	0.0675	2	14	4.894	0	false	true	3.394	50.03325
2	119	0.090278	1	27	4.8902	0	false	true	10.1706	58.78659
3	119	0.093333	3	18	10.6852	0	false	true	13.7778	63.52018
4	80	0.141389	2	16	1.5	0	false	true	10.182	70.57551
5	134	0.150833	2	28	4.894	0	false	true	13.576	77.1138
6	147	0.170833	2	32	4.894	0	false	true	20.364	42.30794
7	135	0.187222	2	23	8.288	0	false	true	16.97	62.61707
8	120	0.255278	1	22	4.8902	0	false	false	0	85.81733
9	39	0.268889	2	3	4.894	0	false	true	10.182	54.73281
10	92	0.29	2	15	4.894	0	false	false	0	79.53743
11	109	0.336389	2	25	1.5	0	false	true	16.97	48.33024
12	77	0.360556	2	12	4.894	0	false	true	6.788	69.61338
13	79	0.380556	2	13	4.894	0	false	true	6.788	60.75123
14	107	0.403611	1	19	4.8902	0	false	true	10.1706	92.60624
15	80	0.57	3	9	10.6852	0	false	true	13.7778	51.64397
16	39	0.621389	2	4	8.288	0	false	true	10.182	63.28212
17	15	0.697778	2	2	1.5	0	false	false	0	44.20692
18	107	0.761389	1	24	4.8902	0	false	true	10.1706	65.07184
19	48	0.801111	3	7	6.0926	0	false	false	0	58.62314

FIGURE 10: Detailed dispatch output

In order to illustrate one of these features we consider the interval of Monday which has the largest call volume in a 2-hour period. Period 4 pm – 6 pm had, in our research, a total of 1021 calls, the largest number amongst the 12 intervals. Of these calls, six were OHCA, 247 were none-OHCA priority 1, 629 were priority 2 calls while 139 were priority 3 calls.

FIGURE 11 shows the cumulative coverage function with respect to response time for high average workload mode for all priority 1 calls and FIGURE 12 shows the cumulative coverage function with respect to response time for low average workload mode for all priority 1 calls. On the graphs the green curve represents default dispatch policy, while the red curve is alternative LU dispatch policy.

These graphs developed from the actual call statistics, and the fitted theoretical CDFs, are designed to provide the EMS administrator with the information and flexibility to evaluate their deployment and dispatch policies to effectively respond high priority calls. For example, via Figure 11 the EMS manager can assess the expected coverage of priority 1 calls with, say 8 minutes of RT, which shows that under high average workload and DEF dispatch policy it is 69.37%, whereas for LU policy it drops to 64.92%. And from Figure 11 we also can tell that under high workload condition DEF achieve slightly better priority 1 call coverage when RT < 26 min and the two curves merges towards 100% coverage when RT>26 min.

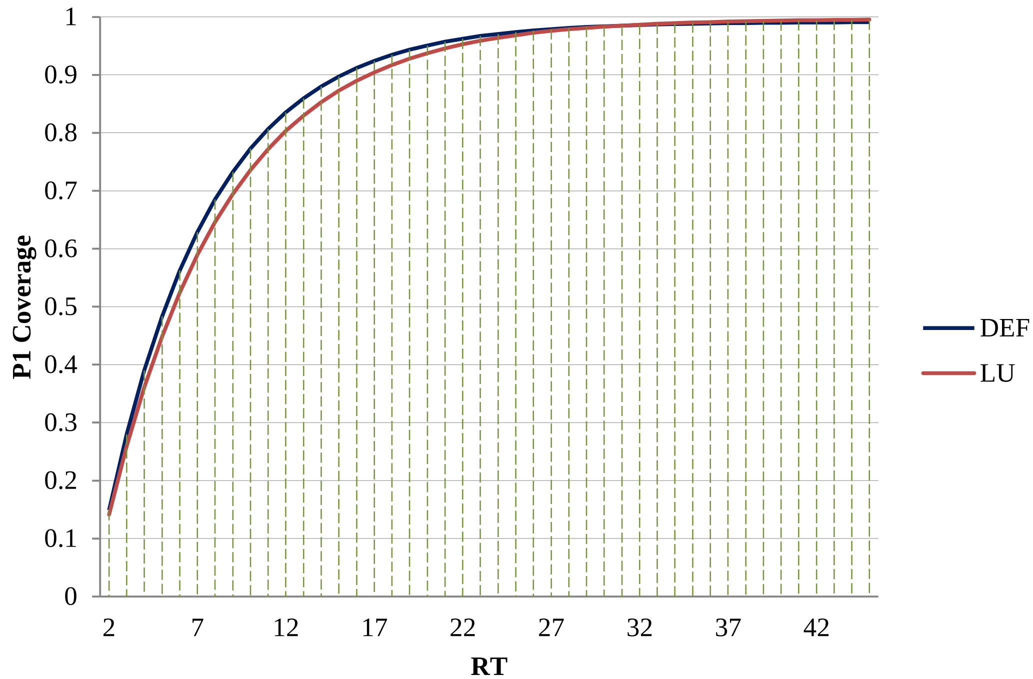

FIGURE 11: CDF (High workload) of priority 1 calls

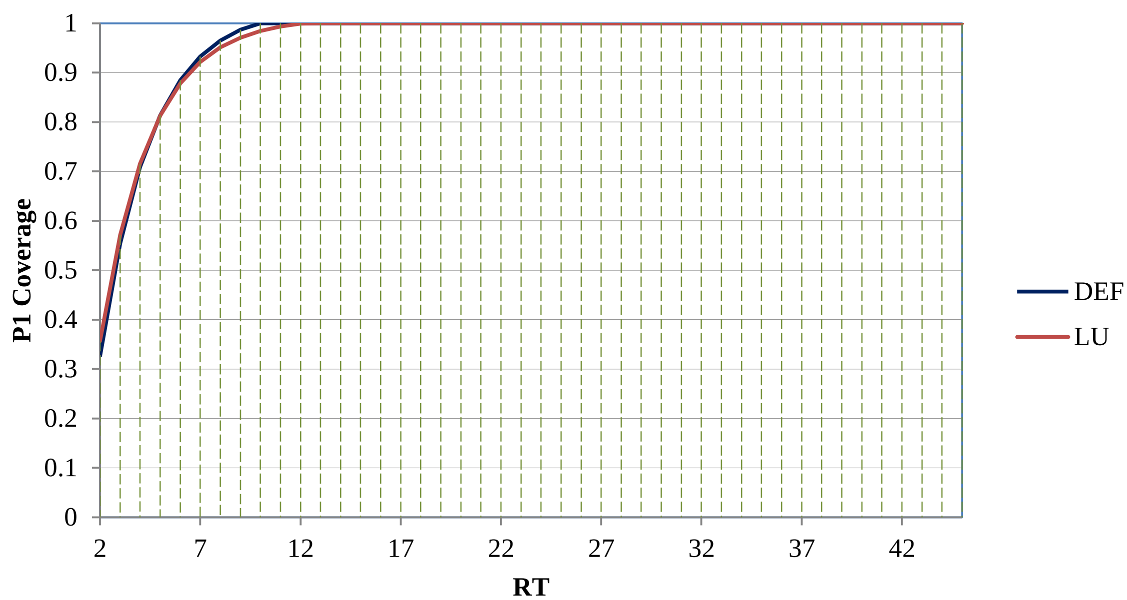

FIGURE 12: CDF (Low workload) of priority 1 calls

In Figure 12, DEF and LU cross at RT = 5 min (rounded). When RT < 5 min LU is actually performs slightly better than DEF with some small gains in OHCA survival probabilities. Whereas when RT > 5 min and RT < 12 min DEF tends to perform slightly better. Clearly When RT > 12 both DEF and LU provides 100% coverage.

In summary, the simulation-optimization approach appears to be superior to analytical approaches and can accommodate different dispatch policies and provide a holistic analysis of the EMS practices, current or planned.

CHAPTER 7: CONCLUSIONS AND FUTURE RESEARCH

In the current research effort, we developed a simulation embedded optimization approach to relocate ambulances and determine flexible dispatch policies for maximum performance. The proposed approach is based on a thorough analysis of a large historical dataset which makes the model and outcomes more realistic.

In particular, we considered various call priorities; modeled distribution and travel time based on historical data analysis; compared selected dispatch policies; and, then, developed weighted objective functions for multiple classes of concerned interests. In addition, in our trace-driven simulation model, we included en-route dispatching in which ambulances can be dispatched to the next call when one completes a previous call regardless of its current location. This, we believe, is the first simulation model to incorporate rich, real-life conditions of a functioning EMS. Doing so allows us to remove most of the simplifying assumptions that were required in earlier analytical approaches that utilize more classic OR/MS models such as integer programming and, queuing theory.

Three search algorithms (TS, SA and RSHC) were developed and embedded in our simulation model. We used both designed (constructed) and real data to tune, test, and compare these algorithms for efficiency and effectiveness. We subsequently found that TS was the most suitable in terms of solving the maximization problem of interest here.

We applied our simulation-optimization model to the historical 9-1-1 call dataset and compared results with DECL. We then showed that DECL was able to predict coverage more accurately under low demand conditions. However, this ability rapidly degrades under high congestion and high demand circumstances as it is unable to capture those real-life details of central importance in the current research effort.

In order to capture different types of calls and their different level of interests to EMS administration we adapted Knight et al.'s objective function which combines heterogeneous outcome measures into a single function that takes four types of calls into consideration. The objective function was able to capture a variety of phenomena of interest to EMS administrators, while providing sufficient flexibility for them to create their own 'best' objective function. In this regard, we applied two dispatch policies (DEF and LU) in an effort to examine how various policies might affect the performance of an EMS system.

We ran our simulation model for seven days, creating 12 time intervals within each day under both high and low workload conditions. This was done using both two dispatch policies. Results suggest that there is little or no difference between DEF and LU in terms of OHCA survival rate and priority 3 call coverage. DEF achieves higher coverage of priority 2 calls than does LU. Although DEF tends to have better performance in its coverage of priority 1 calls, the difference is rather small and in all likelihood does not impact patient outcomes. On the other hand LU significantly reduced the workload range which suggests that it can help balance the workload amongst ambulances and potentially have a positive impact on quality of medical care delivered by the crews.

In general, there appears to be some benefits to practicing DEF or LU dispatch policy. We are able offer some guidelines. For example, if an EMS administrator is concerned more about strict call coverage vs., say, workload balance of ambulance crews, he/she should probably favor the default dispatch policy that sends the nearest ambulance to all calls. On the other hand, if he/she seeks a more balanced workload amongst vehicles, LU policy is clearly more appropriate. However, should an EMS agency adopt a tiered dispatch policy similar to LU they should monitor RTs and patient outcomes as well as keeping track of coverage statistics which are the industry norm. We have thus demonstrated that our proposed approach can be used by EMS managers to evaluate their current practices and test the efficacy of alternate policies.

Although the findings are promising we are quite aware of the potential limitations of our approach. The simulation-optimization model can be applied in a true GIS environment utilizing the exact roads and highways, including one-way streets which will further increase its realism and usefulness. Ambulance travel models can also be improved by taking into account the traffic conditions which vary especially during the rush hours.

In terms of future research, there are a number of possible directions. The approach can be extended to consider optimal time of base (post) swaps for the busiest and least busy pairs of ambulances in order to balance their workloads, while dispatching the closest unit to priority 1 and 2 calls. Another extension of the base simulation-optimization model can be to include a two-tiered response where fire engines with EMTs are dispatched to P3 calls and ambulances are dispatched to P1 & P2 calls. After EMTs assess the patient's condition they can request an ambulance for transfer to a hospital. Finally, our simulation optimization model can be extended to study emergency room crowding and ambulance diversion policies.

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APPENDIX A: MEXCLP

The classic Maximum Expected Coverage Location Problem (MEXCLP) is developed by Daskin [36]. In this model, it is assumed that each ambulance has the same probability of being unavailable to answer a call and all ambulances operate independently. Let,

λ = Average arrival rate, and μ = Average service rate,

$p = \dfrac{\lambda}{m\mu}$ = system wide unit busy probability,

$$y_{jk} = \begin{cases} 1 \text{ if node } j \text{ is covered by } k \text{ ambulances} \\ 0 \text{ if not} \end{cases}$$

Maximize:

$$\sum_{j=1}^{n}\sum_{k=1}^{m} h_j y_{jk}(1-p)p^{k-1} \qquad (3)$$

Subject to:

$$\sum_{i=1}^{n} a_{ij}x_i \geq \sum_{k=1}^{m} y_{jk} \quad \forall j \qquad (4)$$

$$\sum_{i=1}^{n} x_i \leq m \qquad (5)$$

$$y_{jk} \in \{0,1\} \quad \forall j$$

(6)

$$x_i \in \{0,1\} \quad \forall i \qquad (7)$$

The objective function (3) maximizes the expected number of covered demands. The inner term $h_j \sum_{k=1}^{m} y_{jk} p^{k-1}$ when multiplied by $(1-p)$ represents the expected number of covered demand at demand node *j*. This when summed overall demand nodes *j* gives the expected number of covered demands. Constraint (4) tracks the number of times each zone is covered and constraint (5) places an upper bound on the fleet size. Constraints (6) and (7) are integrality constraints.

APPENDIX B: DECL

The dynamic available coverage location (DECL) model proposed by Rajagopalan et al. [74] determines the minimum number of ambulances and their locations to meet a system wide coverage requirement for each time interval. The authors utilize Jarvis' hypercube approximation algorithm [53]. An added advantage of Jarvis' methodology is that it allows for server specific general service time distributions which in this study we found that they are normally distributed. Let t be the index of time intervals, $h_{j,t}$ be the fraction of demand at node j at time interval t, n be the number of nodes in the system, and c_t be the minimum expected coverage requirement at time t. Let $p_{k,t}$ be the busy probability of the k^{th} preferred server for a given demand node at time interval t, ρ_t be the average system busy probability at time interval t, m be the total number of servers available for deployment, and set N_j is the set of all servers that can cover node j. The main decision variable is defined as follows:

$$x_{j,k,t} = \begin{cases} 1 \text{ if server } k \text{ is located at node } j \text{ at time } t \\ 0 \text{ if not} \end{cases}$$

$$y_{j,k,t} = \begin{cases} 1 \text{ if node } j \text{ is covered by server } k \text{ during time interval } t \\ 0 \text{ if not} \end{cases}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m}(Z,\rho_t,k-1)h_{j,t}y_{k,j,t}(1-\rho_{k,t})\prod_{l=1}^{k-1}\rho_{l,t} \tag{8}$$

Minimize:

$$Z = \sum_{t=1}^{T}\sum_{j=1}^{n}\sum_{k=1}^{m}x_{j,k,t} \tag{9}$$

Subject to:

$$\sum_{k=1}^{m}x_{j,k\in N_{j,t}} = \sum_{k=1}^{m}y_{j,k,t} \quad \forall_{j,t} \tag{10}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m}(Z,\rho_t,k-1)h_{j,t}y_{k,j,t}(1-\rho_{k,t})\prod_{l=1}^{k-1}\rho_{l,t} \geq c_t \tag{11}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m}x_{j,k,t} \leq m \quad \forall t \tag{12}$$

$$y_{k,j,t}, x_{j,k,t} = \{0,1\} \quad \forall i, j, k, t \tag{13}$$

Objective (9) minimizes the total number of ambulances deployed. Constraint (10) counts the number of ambulances that cover each node and tracks which server's cover each demand node. Constraint (11) ensures that total system wide coverage will be greater than c_t the pre-specified required coverage. A constraint (12) sets the maximum number of servers in the system. Constraints (13) enforce binary and non-negativity requirements.

APPENDIX C: RESULTS OF TUESDAY TO SUNDAY

TABLE 20: Tuesday high average workload DEF results

Tuesday High Workload Default Dispatch Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1151.09	1.506	3	50.19	72	101	71.29	249	286	87.06	53	56	94.64	0.451	0.088	0.293	0.643	0.350
2 am – 4 am	887.976	1.499	3	49.95	52	70	74.29	204	224	91.07	40	40	100.00	0.409	0.087	0.246	0.555	0.309
4 am – 6 am	692.881	0.993	2	49.63	42	53	79.25	156	177	88.14	29	31	93.55	0.324	0.085	0.149	0.459	0.310
6 am – 8 am	1294.86	1.491	3	49.70	83	121	68.60	273	327	83.49	61	70	87.14	0.444	0.110	0.256	0.61	0.354
8 am – 10 am	1890.13	1.508	3	50.26	121	191	63.35	400	505	79.21	98	113	86.73	0.546	0.077	0.392	0.713	0.321
10 am – 12 pm	2175.03	2.565	5	51.29	134	233	57.51	476	587	81.09	110	129	85.27	0.58	0.071	0.428	0.671	0.243
12 pm – 2 pm	2082.57	2.536	5	50.71	123	227	54.19	471	575	81.91	116	128	90.63	0.588	0.074	0.424	0.706	0.282
2 pm – 4pm	2202.12	2.508	6	41.79	133	237	56.12	489	606	80.69	120	136	88.24	0.604	0.077	0.463	0.738	0.275
4 pm – 6 pm	2224.19	3.074	6	51.24	129	260	49.62	511	649	78.74	121	144	84.03	0.651	0.057	0.496	0.75	0.254
6 pm – 8 pm	2042.57	2.536	5	50.72	120	219	54.79	466	561	83.07	110	122	90.16	0.58	0.080	0.403	0.694	0.291
8 pm – 10 pm	1631.44	1.528	3	50.92	98	175	56.00	365	464	78.66	93	105	88.57	0.594	0.065	0.474	0.712	0.238
10 pm – 12 am	1578.39	1.524	3	50.80	99	150	66.00	341	399	85.46	80	85	94.12	0.503	0.069	0.397	0.617	0.220
	Sum	23.265	47			Avg=	62.58			83.22			90.26	0.52		0.368	0.656	0.287

TABLE 21: Tuesday high average workload LU results

Tuesday High Workload Least Utilization Policy																		
Intervals	**OBJ-Fun**	**OHCA**			**P1**			**P2**			**P3**			**Workload**				
		Exp. Saved	**Total**	**%**	**covered**	**Total**	**%**	**covered**	**Total**	**%**	**Covered**	**Total**	**%**	**AVG**	**Std.Dev.**	**MIN**	**MAX**	**Range**
12 am – 2 am	1035.09	1.506	3	50.19	73	101	72.28	186	286	65.03	55	56	98.21	0.469	0.031	0.361	0.488	0.127
2 am – 4 am	767.976	1.499	3	49.95	48	70	68.57	162	224	72.32	36	40	90.00	0.428	0.038	0.304	0.469	0.165
4 am – 6 am	628.881	0.993	2	49.63	42	53	79.25	124	177	70.06	29	31	93.55	0.337	0.008	0.328	0.359	0.032
6 am – 8 am	1152	1.000	3	33.33	79	121	65.29	219	327	66.97	66	70	94.29	0.458	0.048	0.279	0.492	0.213
8 am – 10 am	1621.13	1.508	3	50.26	107	191	56.02	321	505	63.56	99	113	87.61	0.566	0.010	0.538	0.583	0.044
10 am – 12 pm	1843.03	2.565	5	51.29	121	233	51.93	361	587	61.50	112	129	86.82	0.598	0.024	0.497	0.611	0.114
12 pm – 2 pm	1819.57	2.536	5	50.71	121	227	53.30	351	575	61.04	109	128	85.16	0.608	0.017	0.542	0.622	0.080
2 pm – 4pm	1898.16	3.010	6	50.17	124	237	52.32	372	606	61.39	114	136	83.82	0.625	0.037	0.469	0.643	0.174
4 pm – 6 pm	1882.19	3.074	6	51.24	120	260	46.15	377	649	58.09	119	144	82.64	0.67	0.026	0.568	0.691	0.123
6 pm – 8 pm	1769.57	2.536	5	50.72	114	219	52.05	355	561	63.28	107	122	87.70	0.602	0.051	0.44	0.632	0.192
8 pm – 10 pm	1416.44	1.528	3	50.92	92	175	52.57	282	464	60.78	92	105	87.62	0.608	0.005	0.6	0.616	0.016
10 pm – 12 am	1409.39	1.524	3	50.80	93	150	62.00	282	399	70.68	77	85	90.59	0.519	0.020	0.454	0.535	0.081
	Sum	23.277	47			Avg=	59.31			64.56			89.00	0.54		0.448	0.562	0.113

TABLE 22: Tuesday low average workload DEF results

Tuesday Low Workload Default Dispatch Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1375.09	1.506	3	50.19	91	101	90.10	284	286	99.30	55	56	98.21	0.292	0.110	0.101	0.469	0.368
2 am – 4 am	997.976	1.499	3	49.95	63	70	90.00	215	224	95.98	40	40	100.00	0.294	0.107	0.139	0.489	0.351
4 am – 6 am	726.881	0.993	2	49.63	44	53	83.02	164	177	92.66	31	31	100.00	0.299	0.078	0.174	0.41	0.235
6 am – 8 am	1544.86	1.491	3	49.70	103	121	85.12	314	327	96.02	69	70	98.57	0.312	0.095	0.176	0.516	0.340
8 am – 10 am	2509.13	1.508	3	50.26	172	191	90.05	498	505	98.61	113	113	100.00	0.315	0.100	0.102	0.484	0.382
10 am – 12 pm	3020.03	2.565	5	51.29	211	233	90.56	581	587	98.98	129	129	100.00	0.324	0.103	0.097	0.548	0.451
12 pm – 2 pm	2997.57	2.536	5	50.71	211	227	92.95	571	575	99.30	127	128	99.22	0.321	0.116	0.118	0.612	0.494
2 pm – 4pm	3140.16	3.010	6	50.17	220	237	92.83	598	606	98.68	136	136	100.00	0.329	0.109	0.145	0.558	0.413
4 pm – 6 pm	3323.19	3.074	6	51.24	230	260	88.46	645	649	99.38	144	144	100.00	0.34	0.114	0.101	0.603	0.502
6 pm – 8 pm	2854.57	2.536	5	50.72	198	219	90.41	554	561	98.75	122	122	100.00	0.323	0.102	0.156	0.56	0.404
8 pm – 10 pm	2327.44	1.528	3	50.92	160	175	91.43	459	464	98.92	105	105	100.00	0.312	0.114	0.093	0.551	0.458
10 pm – 12 am	1962.39	1.524	3	50.80	133	150	88.67	395	399	99.00	84	85	98.82	0.3	0.119	0.125	0.55	0.425
	Sum	23.768	47			Avg=	89.47			97.97			99.57	0.31		0.127	0.529	0.402

TABLE 23: Tuesday low average workload DEF results

Tuesday Low Workload Least Utilization Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1220.09	1.506	3	50.19	89	101	88.12	215	286	75.17	54	56	96.43	0.31	0.029	0.201	0.339	0.138
2 am – 4 am	873.976	1.499	3	49.95	60	70	85.71	165	224	73.66	40	40	100.00	0.312	0.054	0.146	0.375	0.229
4 am – 6 am	655.881	0.993	2	49.63	45	53	84.91	125	177	70.62	30	31	96.77	0.313	0.010	0.285	0.324	0.039
6 am – 8 am	1370.86	1.491	3	49.70	100	121	82.64	239	327	73.09	69	70	98.57	0.33	0.011	0.305	0.357	0.052
8 am – 10 am	2121.13	1.508	3	50.26	162	191	84.82	344	505	68.12	113	113	100.00	0.337	0.014	0.296	0.365	0.069
10 am – 12 pm	2540.03	2.565	5	51.29	198	233	84.98	394	587	67.12	127	129	98.45	0.35	0.034	0.233	0.375	0.142
12 pm – 2 pm	2548.57	2.536	5	50.71	196	227	86.34	407	575	70.78	126	128	98.44	0.345	0.015	0.28	0.363	0.083
2 pm – 4pm	2707.16	3.010	6	50.17	210	237	88.61	422	606	69.64	135	136	99.26	0.354	0.025	0.261	0.377	0.116
4 pm – 6 pm	2829.19	3.074	6	51.24	221	260	85.00	434	649	66.87	144	144	100.00	0.365	0.039	0.23	0.389	0.159
6 pm – 8 pm	2439.57	2.536	5	50.72	183	219	83.56	407	561	72.55	121	122	99.18	0.348	0.022	0.272	0.369	0.098
8 pm – 10 pm	1981.44	1.528	3	50.92	152	175	86.86	318	464	68.53	105	105	100.00	0.335	0.020	0.234	0.353	0.119
10 pm – 12 am	1737.39	1.524	3	50.80	129	150	86.00	298	399	74.69	85	85	100.00	0.319	0.046	0.193	0.352	0.159
	Sum	23.768	47			Avg=	85.63			70.90			98.93	0.33		0.245	0.361	0.117

TABLE 24: Wednesday high average workload DEF results

Wednesday High Workload Default dispatch Policy																		
Intervals	**OBJ-Fun**	**OHCA**			**P1**			**P2**			**P3**			**Workload**				
		Exp. Saved	**Total**	**%**	**covered**	**Total**	**%**	**covered**	**Total**	**%**	**Covered**	**Total**	**%**	**AVG**	**Std.Dev.**	**MIN**	**MAX**	**Range**
12 am – 2 am	1010.09	1.506	3	50.19	58	97	59.79	235	273	86.08	52	54	96.30	0.455	0.088	0.297	0.555	0.258
2 am – 4 am	929.976	1.499	3	49.95	55	72	76.39	213	237	89.87	40	43	93.02	0.383	0.079	0.237	0.510	0.273
4 am – 6 am	801.881	0.993	2	49.63	51	61	83.61	172	202	85.15	34	35	97.14	0.377	0.133	0.132	0.560	0.429
6 am – 8 am	1371.86	1.491	3	49.70	86	136	63.24	296	360	82.22	68	75	90.67	0.475	0.073	0.343	0.660	0.317
8 am – 10 am	1837.1	2.006	4	50.16	112	199	56.28	406	525	77.33	97	118	82.20	0.592	0.061	0.463	0.669	0.206
10 am – 12 pm	2007.03	2.565	5	51.29	122	228	53.51	438	576	76.04	114	128	89.06	0.648	0.054	0.544	0.720	0.176
12 pm – 2 pm	2023.57	2.536	6	42.26	113	253	44.66	480	637	75.35	119	142	83.80	0.663	0.061	0.507	0.757	0.250
2 pm – 4pm	2271.16	3.010	6	50.17	144	238	60.50	479	606	79.04	113	136	83.09	0.604	0.070	0.391	0.685	0.294
4 pm – 6 pm	2082.19	3.074	6	51.24	121	248	48.79	475	632	75.16	115	139	82.73	0.662	0.063	0.529	0.767	0.238
6 pm – 8 pm	1839.57	2.536	5	50.72	117	209	55.98	383	541	70.79	97	120	80.83	0.637	0.073	0.524	0.735	0.210
8 pm – 10 pm	1581.44	1.528	3	50.92	93	175	53.14	363	467	77.73	87	105	82.86	0.596	0.071	0.429	0.677	0.248
10 pm – 12 am	1295.39	1.524	3	50.80	72	145	49.66	312	375	83.20	71	78	91.03	0.536	0.066	0.429	0.642	0.214
	Sum	24.267	49			Avg=	58.80			79.83			87.73	0.55		0.402	0.662	0.260

TABLE 25: Wednesday high average workload LU results

Wednesday High Workload Least Utilization Policy																		
Intervals	**OBJ-Fun**	**OHCA**			**P1**			**P2**			**P3**			**Workload**				
		Exp. Saved	**Total**	**%**	**covered**	**Total**	**%**	**covered**	**Total**	**%**	**Covered**	**Total**	**%**	**AVG**	**Std.Dev.**	**MIN**	**MAX**	**Range**
12 am – 2 am	923.09	1.506	3	50.19	59	97	60.82	188	273	68.86	51	54	94.44	0.469	0.015	0.451	0.498	0.047
2 am – 4 am	798.976	1.499	3	49.95	49	72	68.06	172	237	72.57	39	43	90.70	0.401	0.043	0.255	0.424	0.169
4 am – 6 am	720.881	0.993	2	49.63	47	61	77.05	147	202	72.77	35	35	100.00	0.388	0.038	0.269	0.436	0.167
6 am – 8 am	1158.86	1.491	3	49.70	81	136	59.56	210	360	58.33	67	75	89.33	0.49	0.008	0.479	0.510	0.031
8 am – 10 am	1580.1	2.006	4	50.16	99	199	49.75	329	525	62.67	98	118	83.05	0.612	0.027	0.507	0.625	0.118
10 am – 12 pm	1743.03	2.565	5	51.29	114	228	50.00	338	576	58.68	114	128	89.06	0.666	0.017	0.609	0.690	0.081
12 pm – 2 pm	1817.57	2.536	6	42.26	109	253	43.08	392	637	61.54	121	142	85.21	0.685	0.006	0.673	0.700	0.027
2 pm – 4pm	1922.16	3.010	6	50.17	125	238	52.52	382	606	63.04	110	136	80.88	0.627	0.038	0.48	0.653	0.172
4 pm – 6 pm	1805.55	2.034	6	33.91	115	248	46.37	370	632	58.54	113	139	81.29	0.674	0.018	0.603	0.689	0.086
6 pm – 8 pm	1583.67	2.042	5	40.83	101	209	48.33	321	541	59.33	101	120	84.17	0.647	0.026	0.549	0.660	0.111
8 pm – 10 pm	1366.44	1.528	3	50.92	91	175	52.00	265	467	56.75	84	105	80.00	0.617	0.004	0.611	0.625	0.015
10 pm – 12 am	1127.39	1.524	3	50.80	72	145	49.66	229	375	61.07	69	78	88.46	0.562	0.028	0.465	0.583	0.118
	Sum	22.732	49			Avg=	54.77			62.85			87.22	0.57		0.496	0.591	0.095

TABLE 26: Wednesday low average workload DEF results

Wednesday Low Workload Default Dispatch Policy																		
Intervals	**OBJ-Fun**	**OHCA**			**P1**			**P2**			**P3**			**Workload**				
		Exp. Saved	**Total**	**%**	**covered**	**Total**	**%**	**covered**	**Total**	**%**	**Covered**	**Total**	**%**	**AVG**	**Std.Dev.**	**MIN**	**MAX**	**Range**
12 am – 2 am	1236.09	1.506	3	50.19	78	97	80.41	267	273	97.80	54	54	100.00	0.304	0.095	0.12	0.502	0.382
2 am – 4 am	1049.98	1.499	3	49.95	66	72	91.67	228	237	96.20	42	43	97.67	0.272	0.096	0.05	0.474	0.424
4 am – 6 am	888.881	0.993	2	49.63	56	61	91.80	195	202	96.53	35	35	100.00	0.294	0.106	0.1	0.533	0.433
6 am – 8 am	1735.86	1.491	3	49.70	119	136	87.50	343	360	95.28	74	75	98.67	0.316	0.104	0.175	0.573	0.398
8 am – 10 am	2700.1	2.006	4	50.16	188	199	94.47	523	525	99.62	118	118	100.00	0.31	0.108	0.135	0.527	0.391
10 am – 12 pm	3046.03	2.565	5	51.29	217	228	95.18	571	576	99.13	127	128	99.22	0.315	0.099	0.101	0.544	0.443
12 pm – 2 pm	3342.42	3.026	6	50.44	236	253	93.28	633	637	99.37	140	142	98.59	0.327	0.102	0.129	0.587	0.458
2 pm – 4pm	3131.16	3.010	6	50.17	218	238	91.60	602	606	99.34	135	136	99.26	0.338	0.129	0.058	0.601	0.543
4 pm – 6 pm	3105.19	3.074	6	51.24	209	248	84.27	623	632	98.58	138	139	99.28	0.329	0.155	0.09	0.623	0.533
6 pm – 8 pm	2794.57	2.536	5	50.72	195	209	93.30	537	541	99.26	120	120	100.00	0.317	0.122	0.068	0.616	0.548
8 pm – 10 pm	2403.44	1.528	3	50.92	169	175	96.57	461	467	98.72	105	105	100.00	0.302	0.106	0.11	0.522	0.413
10 pm – 12 am	1872.39	1.524	3	50.80	130	145	89.66	365	375	97.33	78	78	100.00	0.306	0.099	0.117	0.504	0.387
	Sum	24.757	49			Avg=	90.81			98.10			99.39	0.31		0.104	0.550	0.446

TABLE 27: Wednesday low average workload LU results

Wednesday Low Workload Least Utilization																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Save	Total	%	covered	Total	%	covered	Total	%	Covere	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1049.09	1.506	3	50.19	71	97	73.20	202	273	73.99	53	54	98.15	0.322	0.027	0.222	0.373	0.151
2 am – 4 am	940.976	1.499	3	49.95	63	72	87.50	185	237	78.06	43	43	100.00	0.287	0.027	0.18	0.303	0.122
4 am – 6 am	780.881	0.993	2	49.63	52	61	85.25	157	202	77.72	35	35	100.00	0.308	0.013	0.269	0.324	0.055
6 am – 8 am	1440.86	1.491	3	49.70	107	136	78.68	243	360	67.50	75	75	100.00	0.335	0.019	0.255	0.351	0.096
8 am – 10 am	2286.1	2.006	4	50.16	175	199	87.94	370	525	70.48	114	118	96.61	0.334	0.006	0.322	0.357	0.036
10 am – 12 pn	2608.03	2.565	5	51.29	205	228	89.91	400	576	69.44	127	128	99.22	0.338	0.025	0.225	0.357	0.132
12 pm – 2 pm	2868.42	3.026	6	50.44	226	253	89.33	436	637	68.45	140	142	98.59	0.352	0.028	0.256	0.378	0.122
2 pm – 4pm	2636.16	3.010	6	50.17	203	238	85.29	414	606	68.32	136	136	100.00	0.362	0.045	0.211	0.393	0.182
4 pm – 6 pm	2750.19	3.074	6	51.24	211	248	85.08	437	632	69.15	139	139	100.00	0.352	0.044	0.195	0.382	0.187
6 pm – 8 pm	2364.57	2.536	5	50.72	182	209	87.08	374	541	69.13	120	120	100.00	0.341	0.020	0.268	0.363	0.096
8 pm – 10 pm	2036.44	1.528	3	50.92	155	175	88.57	334	467	71.52	104	105	99.05	0.323	0.022	0.244	0.337	0.094
10 pm – 12 an	1584.39	1.524	3	50.80	118	145	81.38	269	375	71.73	78	78	100.00	0.326	0.021	0.255	0.348	0.093
	Sum	24.757	49			Avg=	84.93			71.29			99.30	0.33		0.242	0.356	0.114

TABLE 28: Thursday high average workload DEF results

Thursday High Workload Default dispatch Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1084.09	1.506	3	50.19	65	100	65.00	244	284	85.92	52	55	94.55	0.431	0.116	0.148	0.608	0.459
2 am – 4 am	962.976	1.499	3	49.95	55	79	69.62	227	252	90.08	45	51	88.24	0.451	0.094	0.3	0.594	0.294
4 am – 6 am	814.881	0.993	2	49.63	49	61	80.33	186	204	91.18	35	35	100.00	0.346	0.109	0.151	0.521	0.370
6 am – 8 am	1349.86	1.491	3	49.70	80	130	61.54	308	345	89.28	70	72	97.22	0.45	0.101	0.286	0.657	0.371
8 am – 10 am	1807.1	2.006	4	50.16	106	201	52.74	411	527	77.99	105	118	88.98	0.579	0.078	0.432	0.713	0.281
10 am – 12 pm	2057.77	3.048	6	50.81	117	249	46.99	479	633	75.67	115	140	82.14	0.637	0.068	0.428	0.733	0.306
12 pm – 2 pm	2128.42	3.026	6	50.44	120	250	48.00	498	637	78.18	124	142	87.32	0.636	0.070	0.497	0.795	0.298
2 pm – 4pm	2117.16	3.010	6	50.17	123	243	50.62	484	619	78.19	117	139	84.17	0.643	0.044	0.564	0.741	0.178
4 pm – 6 pm	2159.19	3.074	6	51.24	128	258	49.61	480	647	74.19	126	144	87.50	0.661	0.044	0.56	0.720	0.160
6 pm – 8 pm	1710.67	2.042	5	40.83	99	219	45.21	393	556	70.68	100	122	81.97	0.665	0.054	0.546	0.761	0.215
8 pm – 10 pm	1579.44	1.528	3	50.92	89	175	50.86	376	471	79.83	91	105	86.67	0.585	0.072	0.443	0.705	0.262
10 pm – 12 am	1427.39	1.524	3	50.80	84	158	53.16	330	413	79.90	71	88	80.68	0.546	0.049	0.479	0.674	0.195
	Sum	24.746	50			Avg=	56.14			80.92			88.29	0.55		0.403	0.685	0.283

TABLE 29: Thursday high average workload LU results

Thursday High Workload Least Utilization Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	966.09	1.506	3	50.19	65	100	65.00	186	284	65.49	50	55	90.91	0.445	0.013	0.417	0.472	0.056
2 am – 4 am	853.976	1.499	3	49.95	56	79	70.89	169	252	67.06	44	51	86.27	0.47	0.066	0.292	0.520	0.228
4 am – 6 am	686.881	0.993	2	49.63	43	61	70.49	146	204	71.57	35	35	100.00	0.363	0.010	0.349	0.379	0.030
6 am – 8 am	1154.86	1.491	3	49.70	77	130	59.23	223	345	64.64	69	72	95.83	0.469	0.043	0.324	0.507	0.184
8 am – 10 am	1555.1	2.006	4	50.16	97	201	48.26	322	527	61.10	103	118	87.29	0.598	0.007	0.586	0.609	0.023
10 am – 12 pm	1792.77	3.048	6	50.81	106	249	42.57	389	633	61.45	118	140	84.29	0.654	0.006	0.64	0.662	0.022
12 pm – 2 pm	1872.42	3.026	6	50.44	118	250	47.20	381	637	59.81	118	142	83.10	0.66	0.038	0.501	0.678	0.178
2 pm – 4pm	1817.16	3.010	6	50.17	119	243	48.97	351	619	56.70	115	139	82.73	0.663	0.010	0.634	0.685	0.051
4 pm – 6 pm	1911.19	3.074	6	51.24	124	258	48.06	374	647	57.81	122	144	84.72	0.679	0.005	0.67	0.688	0.018
6 pm – 8 pm	1469.67	2.042	5	40.83	93	219	42.47	299	556	53.78	95	122	77.87	0.675	0.024	0.591	0.698	0.107
8 pm – 10 pm	1410.44	1.528	3	50.92	90	175	51.43	288	471	61.15	90	105	85.71	0.599	0.017	0.539	0.616	0.077
10 pm – 12 am	1290.39	1.524	3	50.80	86	158	54.43	251	413	60.77	76	88	86.36	0.563	0.009	0.533	0.573	0.040
	Sum	24.746	50			Avg=	54.08			61.78			87.09	0.57		0.506	0.591	0.084

TABLE 30: Thursday low average workload DEF results

Thursday Low Workload Default Dispatch Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1305.09	1.506	3	50.19	85	100	85.00	273	284	96.13	55	55	100.00	0.31	0.124	0.101	0.531	0.430
2 am – 4 am	1147.98	1.499	3	49.95	72	79	91.14	249	252	98.81	50	51	98.04	0.287	0.114	0.129	0.532	0.402
4 am – 6 am	861.881	0.993	2	49.63	54	61	88.52	190	204	93.14	34	35	97.14	0.297	0.125	0.118	0.476	0.358
6 am – 8 am	1663.86	1.491	3	49.70	112	130	86.15	336	345	97.39	72	72	100.00	0.298	0.101	0.15	0.536	0.386
8 am – 10 am	2637.1	2.006	4	50.16	182	201	90.55	517	527	98.10	115	118	97.46	0.317	0.095	0.183	0.551	0.368
10 am – 12 pm	3217.77	3.048	6	50.81	224	249	89.96	621	633	98.10	135	140	96.43	0.344	0.119	0.128	0.619	0.492
12 pm – 2 pm	3242.42	3.026	6	50.44	223	250	89.20	634	637	99.53	142	142	100.00	0.343	0.129	0.13	0.606	0.476
2 pm – 4pm	3197.16	3.010	6	50.17	222	243	91.36	617	619	99.68	139	139	100.00	0.327	0.122	0.127	0.601	0.474
4 pm – 6 pm	3313.19	3.074	6	51.24	230	258	89.15	640	647	98.92	144	144	100.00	0.325	0.119	0.109	0.559	0.450
6 pm – 8 pm	2851.57	2.536	5	50.72	199	219	90.87	549	556	98.74	121	122	99.18	0.323	0.102	0.147	0.569	0.422
8 pm – 10 pm	2317.44	1.528	3	50.92	157	175	89.71	466	471	98.94	105	105	100.00	0.301	0.095	0.095	0.514	0.419
10 pm – 12 am	2038.39	1.524	3	50.80	140	158	88.61	403	413	97.58	88	88	100.00	0.295	0.089	0.153	0.495	0.341
	Sum	25.241	50			Avg=	89.18			97.92			99.02	0.31		0.131	0.549	0.418

TABLE 31: Thursday low average workload LU results

Thursday Low Workload Least Utilization Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1150.09	1.506	3	50.19	82	100	82.00	208	284	73.24	54	55	98.18	0.327	0.009	0.304	0.343	0.040
2 am – 4 am	1003.98	1.499	3	49.95	70	79	88.61	185	252	73.41	50	51	98.04	0.303	0.047	0.159	0.340	0.181
4 am – 6 am	744.881	0.993	2	49.63	49	61	80.33	151	204	74.02	35	35	100.00	0.312	0.055	0.108	0.337	0.230
6 am – 8 am	1385.86	1.491	3	49.70	98	130	75.38	253	345	73.33	72	72	100.00	0.316	0.011	0.285	0.329	0.044
8 am – 10 am	2231.1	2.006	4	50.16	167	201	83.08	373	527	70.78	117	118	99.15	0.338	0.014	0.288	0.352	0.064
10 am – 12 pm	2669.77	3.048	6	50.81	204	249	81.93	427	633	67.46	135	140	96.43	0.367	0.024	0.274	0.386	0.112
12 pm – 2 pm	2696.42	3.026	6	50.44	210	250	84.00	413	637	64.84	142	142	100.00	0.369	0.036	0.238	0.398	0.159
2 pm – 4pm	2707.16	3.010	6	50.17	211	243	86.83	416	619	67.21	139	139	100.00	0.353	0.048	0.217	0.393	0.176
4 pm – 6 pm	2897.19	3.074	6	51.24	228	258	88.37	440	647	68.01	144	144	100.00	0.35	0.019	0.285	0.365	0.080
6 pm – 8 pm	2441.57	2.536	5	50.72	184	219	84.02	404	556	72.66	121	122	99.18	0.346	0.009	0.311	0.361	0.051
8 pm – 10 pm	1999.44	1.528	3	50.92	148	175	84.57	343	471	72.82	105	105	100.00	0.323	0.025	0.237	0.345	0.109
10 pm – 12 am	1772.39	1.524	3	50.80	134	158	84.81	295	413	71.43	86	88	97.73	0.316	0.010	0.292	0.342	0.050
	Sum	25.241	50			Avg=	83.66			70.77			99.06	0.34		0.250	0.358	0.108

TABLE 32: Friday high average workload DEF results

Friday High Workload Default Dispatch Policy																			
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload					
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1253.09	1.506	3	50.19	80	105	76.19	265	291	91.07	59	60	98.33	0.398	0.063	0.32	0.521	0.201
2 am – 4 am	887.976	1.499	3	49.95	49	72	68.06	216	234	92.31	40	42	95.24	0.385	0.115	0.242	0.625	0.382
4 am – 6 am	862.881	0.993	2	49.63	53	63	84.13	194	209	92.82	35	37	94.59	0.346	0.106	0.139	0.488	0.350
6 am – 8 am	1327.86	1.491	3	49.70	83	128	64.84	288	338	85.21	64	72	88.89	0.456	0.084	0.315	0.630	0.315
8 am – 10 am	1898.13	1.508	3	50.26	117	186	62.90	417	495	84.24	104	109	95.41	0.534	0.059	0.418	0.638	0.220
10 am – 12 pm	2172.03	2.565	5	51.29	129	230	56.09	495	582	85.05	109	129	84.50	0.602	0.071	0.48	0.699	0.219
12 pm – 2 pm	2133.42	3.026	6	50.44	120	255	47.06	501	640	78.28	123	142	86.62	0.622	0.059	0.528	0.761	0.232
2 pm – 4pm	2311.16	3.010	6	50.17	141	265	53.21	506	661	76.55	123	152	80.92	0.66	0.060	0.526	0.782	0.256
4 pm – 6 pm	2144.19	3.074	6	51.24	125	268	46.64	484	673	71.92	127	153	83.01	0.667	0.071	0.51	0.767	0.257
6 pm – 8 pm	1854.57	2.536	5	50.72	112	210	53.33	408	544	75.00	102	120	85.00	0.618	0.072	0.483	0.721	0.238
8 pm – 10 pm	1834.42	2.027	4	50.66	105	207	50.72	425	536	79.29	112	119	94.12	0.61	0.077	0.487	0.710	0.222
10 pm – 12 am	1769.99	0.999	3	33.31	107	188	56.91	401	499	80.36	96	111	86.49	0.564	0.075	0.387	0.660	0.273
	Sum	24.233	49			Avg=	60.01			82.67			89.43	0.54		0.403	0.667	0.264

TABLE 33: Friday high average workload LU results

Friday High Workload Least Utilization Policy																			
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload					
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1088.09	1.506	3	50.19	76	105	72.38	199	291	68.38	58	60	96.67	0.417	0.015	0.369	0.434	0.065
2 am – 4 am	764.976	1.499	3	49.95	48	72	66.67	158	234	67.52	41	42	97.62	0.404	0.075	0.173	0.448	0.275
4 am – 6 am	749.881	0.993	2	49.63	52	63	82.54	143	209	68.42	32	37	86.49	0.364	0.014	0.326	0.381	0.055
6 am – 8 am	1133.86	1.491	3	49.70	76	128	59.38	219	338	64.79	64	72	88.89	0.474	0.006	0.465	0.483	0.018
8 am – 10 am	1618.13	1.508	3	50.26	104	186	55.91	332	495	67.07	98	109	89.91	0.558	0.012	0.529	0.573	0.044
10 am – 12 pm	1854.03	2.565	5	51.29	124	230	53.91	354	582	60.82	113	129	87.60	0.625	0.019	0.555	0.654	0.098
12 pm – 2 pm	1911.42	3.026	6	50.44	120	255	47.06	391	640	61.09	121	142	85.21	0.642	0.006	0.629	0.651	0.022
2 pm – 4pm	2011.16	3.010	6	50.17	131	265	49.43	398	661	60.21	119	152	78.29	0.679	0.008	0.667	0.693	0.026
4 pm – 6 pm	1867.7	2.544	6	42.40	118	268	44.03	376	673	55.87	131	153	85.62	0.684	0.007	0.675	0.700	0.025
6 pm – 8 pm	1614.57	2.536	5	50.72	109	210	51.90	300	544	55.15	102	120	85.00	0.637	0.006	0.619	0.644	0.025
8 pm – 10 pm	1621.42	2.027	4	50.66	103	207	49.76	329	536	61.38	107	119	89.92	0.629	0.031	0.509	0.647	0.138
10 pm – 12 am	1453.99	0.999	3	33.31	90	188	47.87	311	499	62.32	96	111	86.49	0.583	0.012	0.545	0.603	0.059
	Sum	23.702	49			Avg=	56.74			62.75			88.14	0.56		0.505	0.576	0.071

TABLE 34: Friday high average workload DEF results

Friday Low Workload Default Dispatch Policy																			
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload					
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range	
12 am – 2 am	1415.09	1.506	3	50.19	96	105	91.43	282	291	96.91	59	60	98.33	0.291	0.084	0.125	0.453	0.327	
2 am – 4 am	1008.98	1.499	3	49.95	61	72	84.72	228	234	97.44	41	42	97.62	0.294	0.105	0.122	0.518	0.396	
4 am – 6 am	903.881	0.993	2	49.63	57	63	90.48	198	209	94.74	36	37	97.30	0.301	0.111	0.128	0.521	0.393	
6 am – 8 am	1631.86	1.491	3	49.70	109	128	85.16	332	338	98.22	72	72	100.00	0.301	0.107	0.121	0.530	0.410	
8 am – 10 am	2461.13	1.508	3	50.26	169	186	90.86	488	495	98.59	109	109	100.00	0.32	0.116	0.134	0.547	0.414	
10 am – 12 pm	2973.03	2.565	5	51.29	208	230	90.43	570	582	97.94	128	129	99.22	0.332	0.122	0.075	0.610	0.535	
12 pm – 2 pm	3224.42	3.026	6	50.44	222	255	87.06	629	640	98.28	142	142	100.00	0.332	0.103	0.14	0.572	0.431	
2 pm – 4pm	3407.16	3.010	6	50.17	238	265	89.81	652	661	98.64	151	152	99.34	0.33	0.114	0.147	0.618	0.471	
4 pm – 6 pm	3550.19	3.074	6	51.24	252	268	94.03	666	673	98.96	153	153	100.00	0.322	0.112	0.127	0.643	0.517	
6 pm – 8 pm	2805.57	2.536	5	50.72	198	210	94.29	531	544	97.61	119	120	99.17	0.312	0.091	0.104	0.462	0.358	
8 pm – 10 pm	2729.42	2.027	4	50.66	190	207	91.79	529	536	98.69	119	119	100.00	0.307	0.091	0.149	0.470	0.321	
10 pm – 12 am	2466.39	1.524	3	50.80	169	188	89.89	490	499	98.20	110	111	99.10	0.308	0.124	0.095	0.581	0.487	
	Sum	24.757	49			Avg=	90.00			97.85			99.17	0.31		0.122	0.544	0.422	

TABLE 35: Friday high average workload LU results

Friday Low Workload Least Utilization Policy																			
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload					
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range	
12 am – 2 am	1223.09	1.506	3	50.19	89	105	84.76	214	291	73.54	59	60	98.33	0.31	0.007	0.299	0.320	0.021	
2 am – 4 am	864.976	1.499	3	49.95	57	72	79.17	172	234	73.50	41	42	97.62	0.31	0.037	0.173	0.337	0.165	
4 am – 6 am	807.881	0.993	2	49.63	53	63	84.13	166	209	79.43	36	37	97.30	0.316	0.054	0.168	0.353	0.184	
6 am – 8 am	1367.86	1.491	3	49.70	99	128	77.34	243	338	71.89	66	72	91.67	0.32	0.023	0.243	0.338	0.095	
8 am – 10 am	2059.13	1.508	3	50.26	154	186	82.80	347	495	70.10	109	109	100.00	0.341	0.049	0.197	0.389	0.192	
10 am – 12 pm	2523.03	2.565	5	51.29	191	230	83.04	413	582	70.96	128	129	99.22	0.356	0.027	0.246	0.376	0.129	
12 pm – 2 pm	2758.42	3.026	6	50.44	210	255	82.35	445	640	69.53	140	142	98.59	0.355	0.032	0.246	0.380	0.134	
2 pm – 4pm	2943.16	3.010	6	50.17	227	265	85.66	464	661	70.20	151	152	99.34	0.354	0.011	0.306	0.380	0.074	
4 pm – 6 pm	3000.19	3.074	6	51.24	236	268	88.06	455	673	67.61	153	153	100.00	0.349	0.028	0.238	0.366	0.128	
6 pm – 8 pm	2352.57	2.536	5	50.72	181	210	86.19	372	544	68.38	120	120	100.00	0.335	0.012	0.293	0.352	0.059	
8 pm – 10 pm	2343.42	2.027	4	50.66	181	207	87.44	372	536	69.40	119	119	100.00	0.331	0.007	0.319	0.353	0.034	
10 pm – 12 am	2051.39	1.524	3	50.80	150	188	79.79	358	499	71.74	111	111	100.00	0.33	0.005	0.322	0.344	0.022	
	Sum	24.757	49			Avg=	83.39			71.36			98.51	0.33		0.254	0.357	0.103	

TABLE 36: Saturday high average workload DEF results

Saturday High Workload Default dispatch Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1839.09	1.506	3	50.19	122	152	80.26	377	401	94.01	85	87	97.70	0.41	0.103	0.247	0.633	0.386
2 am – 4 am	1399.98	1.499	3	49.95	84	132	63.64	316	354	89.27	72	75	96.00	0.476	0.096	0.234	0.581	0.347
4 am – 6 am	893.988	1.499	3	49.97	54	73	73.97	199	238	83.61	40	45	88.89	0.408	0.055	0.302	0.503	0.201
6 am – 8 am	1017.86	1.491	3	49.70	61	93	65.59	229	268	85.45	48	53	90.57	0.441	0.083	0.322	0.568	0.246
8 am – 10 am	1482.13	1.508	3	50.26	82	155	52.90	361	410	88.05	80	88	90.91	0.494	0.083	0.351	0.676	0.325
10 am – 12 pm	1911.26	1.516	3	50.54	116	191	60.73	427	510	83.73	105	113	92.92	0.541	0.078	0.4	0.668	0.267
12 pm – 2 pm	2137.57	2.536	5	50.71	133	225	59.11	459	571	80.39	115	127	90.55	0.592	0.057	0.473	0.690	0.216
2 pm – 4pm	1973.12	2.508	5	50.15	119	223	53.36	436	567	76.90	109	125	87.20	0.62	0.063	0.489	0.736	0.247
4 pm – 6 pm	2043.7	2.544	5	50.88	121	229	52.84	462	579	79.79	111	128	86.72	0.606	0.065	0.466	0.699	0.233
6 pm – 8 pm	1906.57	2.536	5	50.72	104	234	44.44	462	592	78.04	110	130	84.62	0.625	0.065	0.474	0.745	0.271
8 pm – 10 pm	1912.42	2.027	4	50.66	116	206	56.31	423	536	78.92	106	119	89.08	0.587	0.073	0.446	0.720	0.274
10 pm – 12 am	1916	2.563	5	51.26	114	217	52.53	430	552	77.90	103	121	85.12	0.634	0.063	0.494	0.722	0.228
	Sum	23.731	47			Avg=	59.64			83.00			90.02	0.54		0.392	0.662	0.270

TABLE 37: Saturday high average workload LU results

Saturday High Workload Least Utilization Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1615.09	1.506	3	50.19	118	152	77.63	281	401	70.07	85	87	97.70	0.431	0.023	0.338	0.448	0.111
2 am – 4 am	1253.98	1.499	3	49.95	84	132	63.64	244	354	68.93	70	75	93.33	0.495	0.077	0.21	0.527	0.318
4 am – 6 am	817.988	1.499	3	49.97	55	73	75.34	157	238	65.97	40	45	88.89	0.424	0.017	0.371	0.445	0.073
6 am – 8 am	887.858	1.491	3	49.70	57	93	61.29	181	268	67.54	46	53	86.79	0.452	0.036	0.362	0.484	0.122
8 am – 10 am	1319.13	1.508	3	50.26	80	155	51.61	288	410	70.24	79	88	89.77	0.512	0.024	0.419	0.524	0.105
10 am – 12 pm	1639.26	1.516	3	50.54	108	191	56.54	324	510	63.53	103	113	91.15	0.563	0.035	0.431	0.599	0.168
12 pm – 2 pm	1852.57	2.536	5	50.71	126	225	56.00	344	571	60.25	116	127	91.34	0.609	0.044	0.424	0.630	0.206
2 pm – 4pm	1770.12	2.508	5	50.15	118	223	52.91	338	567	59.61	110	125	88.00	0.634	0.040	0.476	0.653	0.176
4 pm – 6 pm	1760.7	2.544	5	50.88	115	229	50.22	348	579	60.10	104	128	81.25	0.626	0.018	0.554	0.641	0.087
6 pm – 8 pm	1666.67	2.042	5	40.83	103	234	44.02	350	592	59.12	110	130	84.62	0.641	0.006	0.63	0.654	0.024
8 pm – 10 pm	1667.42	2.027	4	50.66	111	206	53.88	320	536	59.70	107	119	89.92	0.603	0.022	0.517	0.625	0.108
10 pm – 12 am	1690	2.563	5	51.26	107	217	49.31	348	552	63.04	97	121	80.17	0.651	0.005	0.644	0.658	0.014
	Sum	23.236	47			Avg=	57.70			64.01			88.58	0.55		0.448	0.574	0.126

TABLE 38: Saturday low average workload DEF results

Saturday Low Workload Default Dispatch Policy																			
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload					
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range	
12 am – 2 am	2002.09	1.506	3	50.19	138	152	90.79	394	401	98.25	86	87	98.85	0.321	0.118	0.149	0.563	0.414	
2 am – 4 am	1694.98	1.499	3	49.95	113	132	85.61	346	354	97.74	75	75	100.00	0.302	0.124	0.123	0.561	0.437	
4 am – 6 am	1055.99	1.499	3	49.97	67	73	91.78	226	238	94.96	44	45	97.78	0.285	0.070	0.144	0.393	0.249	
6 am – 8 am	1241.86	1.491	3	49.70	83	93	89.25	251	268	93.66	52	53	98.11	0.295	0.096	0.152	0.459	0.307	
8 am – 10 am	2000.13	1.508	3	50.26	136	155	87.74	400	410	97.56	88	88	100.00	0.302	0.083	0.135	0.543	0.408	
10 am – 12 pm	2531.26	1.516	3	50.54	174	191	91.10	502	510	98.43	111	113	98.23	0.32	0.073	0.174	0.465	0.290	
12 pm – 2 pm	2945.57	2.536	5	50.71	206	225	91.56	565	571	98.95	127	127	100.00	0.334	0.101	0.168	0.546	0.377	
2 pm – 4pm	2881.12	2.508	5	50.15	200	223	89.69	558	567	98.41	125	125	100.00	0.331	0.120	0.131	0.549	0.418	
4 pm – 6 pm	2961.7	2.544	5	50.88	207	229	90.39	569	579	98.27	127	128	99.22	0.331	0.118	0.145	0.594	0.449	
6 pm – 8 pm	2980.57	2.536	5	50.72	204	234	87.18	589	592	99.49	130	130	100.00	0.328	0.127	0.136	0.577	0.442	
8 pm – 10 pm	2717.42	2.027	4	50.66	188	206	91.26	531	536	99.07	119	119	100.00	0.326	0.091	0.12	0.472	0.352	
10 pm – 12 am	2811	2.563	5	51.26	195	217	89.86	545	552	98.73	120	121	99.17	0.322	0.140	0.143	0.576	0.433	
	Sum	23.731	47			Avg=	89.68			97.79			99.28	0.32		0.143	0.525	0.381	

TABLE 39: Saturday low average workload LU results

Saturday Low Workload Least Utilization Policy																	
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload			
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1716.09	1.506	3	50.19	131	152	86.18	280	401	69.83	84	87	96.55	0.34	0.013	0.296	0.355	0.059
2 am – 4 am	1490.98	1.499	3	49.95	111	132	84.09	253	354	71.47	73	75	97.33	0.319	0.028	0.191	0.337	0.146
4 am – 6 am	918.988	1.499	3	49.97	60	73	82.19	185	238	77.73	45	45	100.00	0.303	0.039	0.166	0.326	0.161
6 am – 8 am	1039.86	1.491	3	49.70	74	93	79.57	186	268	69.40	52	53	98.11	0.312	0.025	0.241	0.350	0.109
8 am – 10 am	1700.13	1.508	3	50.26	125	155	80.65	294	410	71.71	88	88	100.00	0.322	0.019	0.262	0.340	0.078
10 am – 12 pm	2113.26	1.516	3	50.54	157	191	82.20	360	510	70.59	113	113	100.00	0.343	0.013	0.294	0.359	0.065
12 pm – 2 pm	2589.57	2.536	5	50.71	202	225	89.78	404	571	70.75	125	127	98.43	0.359	0.015	0.288	0.370	0.083
2 pm – 4pm	2485.12	2.508	5	50.15	195	223	87.44	380	567	67.02	125	125	100.00	0.355	0.023	0.251	0.391	0.140
4 pm – 6 pm	2509.7	2.544	5	50.88	195	229	85.15	391	579	67.53	127	128	99.22	0.354	0.025	0.228	0.375	0.146
6 pm – 8 pm	2540.57	2.536	5	50.72	197	234	84.19	398	592	67.23	128	130	98.46	0.351	0.038	0.221	0.380	0.159
8 pm – 10 pm	2345.42	2.027	4	50.66	179	206	86.89	381	536	71.08	119	119	100.00	0.35	0.010	0.316	0.368	0.052
10 pm – 12 am	2475	2.563	5	51.26	192	217	88.48	390	552	70.65	118	121	97.52	0.345	0.040	0.184	0.369	0.185
	Sum	23.731	47			Avg=	84.73			70.42			98.80	0.34		0.245	0.360	0.115

TABLE 40: Saturday high average workload DEF results

Sunday High Workload Default Dispatch Policy																			
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload					
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range	
12 am – 2 am	1818.09	1.506	3	50.19	111	174	63.79	405	463	87.47	96	103	93.20	0.519	0.101	0.278	0.673	0.395	
2 am – 4 am	1587.98	1.499	3	49.95	97	162	59.88	354	426	83.10	80	92	86.96	0.538	0.065	0.426	0.625	0.199	
4 am – 6 am	944.988	1.499	3	49.97	56	77	72.73	215	250	86.00	43	50	86.00	0.437	0.101	0.201	0.575	0.373	
6 am – 8 am	995.858	1.491	3	49.70	59	84	70.24	225	257	87.55	50	52	96.15	0.406	0.092	0.265	0.559	0.294	
8 am – 10 am	1470.13	1.508	3	50.26	91	147	61.90	322	387	83.20	74	81	91.36	0.512	0.069	0.332	0.601	0.269	
10 am – 12 pm	1760.26	1.516	3	50.54	108	180	60.00	387	484	79.96	98	108	90.74	0.518	0.076	0.379	0.627	0.248	
12 pm – 2 pm	1866.8	1.550	4	38.76	112	202	55.45	419	532	78.76	108	119	90.76	0.562	0.083	0.386	0.676	0.290	
2 pm – 4pm	1889.25	2.016	4	50.39	112	206	54.37	431	534	80.71	99	119	83.19	0.592	0.072	0.453	0.699	0.246	
4 pm – 6 pm	1664.34	1.521	3	50.70	96	191	50.26	386	506	76.28	100	113	88.50	0.605	0.058	0.431	0.683	0.252	
6 pm – 8 pm	1738.67	2.042	4	51.04	97	202	48.02	417	532	78.38	96	119	80.67	0.628	0.069	0.466	0.717	0.251	
8 pm – 10 pm	1747.42	2.027	4	50.66	105	198	53.03	387	518	74.71	101	117	86.32	0.595	0.050	0.475	0.661	0.186	
10 pm – 12 am	1519.39	1.524	3	50.80	96	150	64.00	326	399	81.70	75	85	88.24	0.519	0.081	0.333	0.638	0.305	
	Sum	19.698	40			Avg=	59.47			81.49			88.51	0.54		0.369	0.645	0.276	

TABLE 41: Saturday high average workload LU results

Sunday High Workload Least Utilization Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	1550.09	1.506	3	50.19	106	174	60.92	294	463	63.50	90	103	87.38	0.546	0.006	0.534	0.553	0.019
2 am – 4 am	1407.98	1.499	3	49.95	94	162	58.02	274	426	64.32	84	92	91.30	0.559	0.018	0.494	0.571	0.077
4 am – 6 am	836.988	1.499	3	49.97	50	77	64.94	184	250	73.60	45	50	90.00	0.45	0.042	0.31	0.480	0.170
6 am – 8 am	860.858	1.491	3	49.70	56	84	66.67	171	257	66.54	47	52	90.38	0.422	0.011	0.403	0.439	0.036
8 am – 10 am	1248.13	1.508	3	50.26	82	147	55.78	248	387	64.08	72	81	88.89	0.529	0.009	0.503	0.541	0.038
10 am – 12 pm	1490.26	1.516	3	50.54	97	180	53.89	294	484	60.74	102	108	94.44	0.539	0.027	0.462	0.566	0.104
12 pm – 2 pm	1574.61	2.038	4	50.95	104	202	51.49	304	532	57.14	102	119	85.71	0.583	0.011	0.548	0.601	0.053
2 pm – 4pm	1662.25	2.016	4	50.39	108	206	52.43	331	534	61.99	104	119	87.39	0.606	0.038	0.454	0.628	0.174
4 pm – 6 pm	1441.34	1.521	3	50.70	90	191	47.12	297	506	58.70	103	113	91.15	0.621	0.004	0.616	0.630	0.014
6 pm – 8 pm	1483.67	2.042	4	51.04	86	202	42.57	334	532	62.78	95	119	79.83	0.647	0.009	0.626	0.661	0.036
8 pm – 10 pm	1501.42	2.027	4	50.66	102	198	51.52	279	518	53.86	95	117	81.20	0.616	0.009	0.597	0.634	0.037
10 pm – 12 am	1314.39	1.524	3	50.80	88	150	58.67	253	399	63.41	80	85	94.12	0.539	0.004	0.53	0.549	0.018
	Sum	20.185	40			Avg=	55.33			62.55			88.48	0.55		0.506	0.571	0.065

TABLE 42: Saturday low average workload DEF results

Sunday Low Workload Default Dispatch Policy																		
Intervals	OBJ-Fun	OHCA			P1			P2			P3			Workload				
		Exp. Saved	Total	%	covered	Total	%	covered	Total	%	Covered	Total	%	AVG	Std.Dev.	MIN	MAX	Range
12 am – 2 am	2257.09	1.506	3	50.19	152	174	87.36	457	463	98.70	103	103	100.00	0.317	0.145	0.094	0.613	0.519
2 am – 4 am	2059.98	1.499	3	49.95	139	162	85.80	416	426	97.65	92	92	100.00	0.319	0.136	0.086	0.637	0.551
4 am – 6 am	1116.99	1.499	3	49.97	71	77	92.21	238	250	95.20	49	50	98.00	0.291	0.113	0.085	0.527	0.442
6 am – 8 am	1136.86	1.491	3	49.70	71	84	84.52	247	257	96.11	51	52	98.08	0.286	0.092	0.166	0.505	0.339
8 am – 10 am	1871.13	1.508	3	50.26	126	147	85.71	379	387	97.93	81	81	100.00	0.308	0.109	0.138	0.595	0.458
10 am – 12 pm	2288.26	1.516	3	50.54	151	180	83.89	475	484	98.14	106	108	98.15	0.305	0.101	0.116	0.559	0.442
12 pm – 2 pm	2678.61	2.038	4	50.95	185	202	91.58	524	532	98.50	118	119	99.16	0.329	0.094	0.122	0.545	0.422
2 pm – 4pm	2670.25	2.016	4	50.39	183	206	88.83	528	534	98.88	118	119	99.16	0.327	0.103	0.136	0.548	0.412
4 pm – 6 pm	2497.34	1.521	3	50.70	169	191	88.48	504	506	99.60	113	113	100.00	0.322	0.108	0.097	0.526	0.429
6 pm – 8 pm	2663.67	2.042	4	51.04	182	202	90.10	528	532	99.25	119	119	100.00	0.319	0.113	0.102	0.519	0.417
8 pm – 10 pm	2563.42	2.027	4	50.66	175	198	88.38	507	518	97.88	117	117	100.00	0.32	0.102	0.156	0.529	0.372
10 pm – 12 am	1994.39	1.524	3	50.80	137	150	91.33	395	399	99.00	84	85	98.82	0.298	0.111	0.114	0.555	0.441
	Sum	20.185	40			Avg=	88.18			98.07			99.28	0.31		0.118	0.555	0.437

TABLE 43: Saturday low average workload LU results

Sunday Low Workload Least Utilization Policy																		
Intervals	**OBJ-Fun**	**OHCA**			**P1**			**P2**			**P3**			**Workload**				
		Exp. Saved	**Total**	**%**	**covered**	**Total**	**%**	**covered**	**Total**	**%**	**Covered**	**Total**	**%**	**AVG**	**Std.Dev.**	**MIN**	**MAX**	**Range**
12 am – 2 am	1970.09	1.506	3	50.19	146	174	83.91	338	463	73.00	102	103	99.03	0.337	0.015	0.286	0.353	0.067
2 am – 4 am	1809.98	1.499	3	49.95	133	162	82.10	315	426	73.94	92	92	100.00	0.34	0.067	0.149	0.375	0.225
4 am – 6 am	968.988	1.499	3	49.97	66	77	85.71	184	250	73.60	49	50	98.00	0.305	0.046	0.156	0.337	0.181
6 am – 8 am	985.858	1.491	3	49.70	68	84	80.95	184	257	71.60	50	52	96.15	0.305	0.026	0.206	0.338	0.132
8 am – 10 am	1599.13	1.508	3	50.26	118	147	80.27	275	387	71.06	81	81	100.00	0.328	0.009	0.308	0.351	0.044
10 am – 12 pm	2006.26	1.516	3	50.54	154	180	85.56	322	484	66.53	106	108	98.15	0.327	0.015	0.27	0.356	0.086
12 pm – 2 pm	2255.61	2.038	4	50.95	175	202	86.63	353	532	66.35	117	119	98.32	0.353	0.026	0.259	0.379	0.119
2 pm – 4pm	2297.25	2.016	4	50.39	177	206	85.92	365	534	68.35	119	119	100.00	0.35	0.012	0.295	0.364	0.068
4 pm – 6 pm	2127.34	1.521	3	50.70	160	191	83.77	355	506	70.16	113	113	100.00	0.344	0.006	0.33	0.357	0.027
6 pm – 8 pm	2257.67	2.042	4	51.04	163	202	80.69	401	532	75.38	119	119	100.00	0.341	0.014	0.277	0.359	0.082
8 pm – 10 pm	2185.42	2.027	4	50.66	166	198	83.84	354	518	68.34	117	117	100.00	0.344	0.022	0.231	0.358	0.127
10 pm – 12 am	1677.39	1.524	3	50.80	129	150	86.00	268	399	67.17	85	85	100.00	0.319	0.005	0.31	0.327	0.018
	Sum	20.185	40			Avg=	83.78			70.46			99.14	0.33		0.256	0.355	0.098

APPENDIX D: T-TESTS OF TUESDAY TO SUNDAY

TABLE 44: Tuesday summary of paired t-test results

Tuesday				
Mean Difference	High Average Workload		Low Average Workload	
	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	0.0067	0.34*	0.0000	NA
P1 Coverage	0.0327	<0.01	0.0384	<0.01
P2 Coverage	0.1866	<0.01	0.2706	<0.01
P3 Coverage	0.0126	0.18*	0.0064	**<0.05**
WL range	0.1740	<0.01	0.2850	<0.01

TABLE 45: Wednesday summary of paired t-test results

Wednesday				
Mean Difference	High Average Workload		Low Average Workload	
	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	0.0227	<0.10	0.0000	NA
P1 Coverage	0.0403	<0.01	0.0588	<0.01
P2 Coverage	0.1699	<0.01	0.2681	<0.01
P3 Coverage	0.0051	0.21*	0.0009	0.42*
WL range	0.1644	<0.01	0.3324	<0.01

TABLE 46: Thursday summary of paired t-test results

Thursday				
Mean Difference	High Average Workload		Low Average Workload	
	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	0.0000	NA	0.0000	NA
P1 Coverage	0.0206	<0.05	0.0552	<0.01
P2 Coverage	0.1915	<0.01	0.2715	<0.01
P3 Coverage	0.0120	0.08*	-0.0004	0.46*
WL range	0.1982	<0.01	0.3104	<0.01

TABLE 47: Friday summary of paired t-test results

Friday				
Mean Difference	High Average Workload		Low Average Workload	
	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	0.0074	0.17*	0.0000	NA
P1 Coverage	0.0327	<0.01	0.0660	<0.01
P2 Coverage	0.1992	<0.01	0.2649	<0.01
P3 Coverage	0.0129	0.11*	0.0067	0.19*
WL range	0.1930	<0.01	0.3183	<0.01

TABLE 48: Saturday summary of paired t-test results

Saturday				
Mean Difference	High Average Workload		Low Average Workload	
	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	0.0082	0.17*	0.0000	NA
P1 Coverage	0.0194	<0.01	0.0495	<0.01
P2 Coverage	0.1900	<0.01	0.2738	<0.01
P3 Coverage	0.0145	**<0.05**	0.0048	0.15*
WL range	0.1441	<0.01	0.2662	<0.01

TABLE 49: Sunday summary of paired t-test results

Sunday				
Mean Difference	High Average Workload		Low Average Workload	
	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	-0.0102	0.17*	0.0000	NA
P1 Coverage	0.0414	<0.01	0.0440	<0.01
P2 Coverage	0.1893	<0.01	0.2761	<0.01
P3 Coverage	0.0002	0.49*	0.0014	0.28*
WL range	0.2109	<0.01	0.3389	<0.01

TABLE 50: All days' t-tests results

All 84				
	High Average Workload		Low Average Workload	
Mean Difference	DEF - LU		DEF - LU	
	Diff.	P - value	Diff.	P - value
OHCA	0.0040	0.19*	0.0000	NA
P1 Coverage	0.0298	<0.01	0.0516	<0.01
P2 Coverage	0.1875	<0.01	0.2703	<0.01
P3 Coverage	0.0077	**<0.05**	0.0033	<0.05
WL range	0.1792	<0.01	0.3088	<0.01