MISSION CRITICAL LOGISTICS – ESSAYS IN GAME TRANSPORTATION AND NAVAL LOGISTICS

by

ANDREW E. JOHNSON, JR.

A Dissertation submitted to the

Graduate School-Newark

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Graduate Program in Management

written under the direction of

Professor Yao Zhao

and approved by

Newark, New Jersey

October, 2015

ABSTRACT OF THE DISSERTATION

Mission Critical Logistics – Essays in Game Transportation and Naval Logistics

By ANDREW E. JOHNSON, JR.

Dissertation Director:

Dr. Yao Zhao

Mission critical logistics focuses on the application of cutting edge project and supply chain management techniques to solve problems involving truncated timelines, where failure to meet such a timeline results in a substantial loss to business or mission effectiveness. This dissertation studies two exemplary topics in mission critical logistics – Game Transportation and Naval Logistics.

First, we explore transportation planning and scheduling for a real world, one-time mega sporting event, the Special Olympics 2014 USA Games. The Games were hosted in New Jersey where over 4,000 athletes and coaches competed in 16 sports spread out across 10 locations within a 40-mile radius. We designed timely, convenient, and reliable bus routes and schedules for thousands of people with intellectual disabilities to attend games and special events over eight days under a budget of $600K. We solved this transportation problem using a three-phase approach. Phase 1 optimizes the number and routes of shuttle-loops and buses required to efficiently transport athletes and coaches to competition venues using the enumeration method. Phase 2 sees the integration of the athletes proposed travel habits and a more focused volume estimation model detailed in

hourly variations instead of a daily volume total. Finally, Phase 3 solves the shuttle-bus problem by developing a set of direct easy-to-follow routes.

Secondly, we diagnose a complex logistics network by analyzing historical data of a destroyer fleet for the US Navy. Naval logistics represents an important facet of mission critical logistics, as timing and inventory play a key role in the fulfillment of onboard parts while the ship is on deployment. A general problem that the US Navy has encountered is that critical parts, which make up part of the Aegis Ballistic Missile Defense System, have the potential to either malfunction or breakdown during an operation. We will extend the mission critical logistics domain by analyzing the fulfillment process for 17 US Navy destroyer's. We will also evaluate the current logistics fulfillment performance of the Defense Logistics Agency, who in this scenario is the distributor to the US Navy, and identify potential drivers behind the performance.

Acknowledgements

I would first and foremost like to thank my advisor and friend Dr. Yao Zhao for his continuous support and leadership throughout this four-year process. His encouragement and advice helped me to not only complete this thesis, but to also guide me in the right direction. I will always remember our talks together about life and our families. I couldn't have done this without him.

I would like to thank Dr. Weiwei Chen, Dr. Tan Miller, Dr. Xiaowei Xu, and Dr. David Dobrzykowski for their invaluable support and intuitive comments on the draft of this dissertation. There were other professors at Rutgers and other universities that could have been a part of this, but I know with a doubt that I wouldn't be where I am now without their expertise.

I would also like to thank the PhD Program Department, specifically Goncalo Flippie and Monnique DeSilva for their outstanding assistance. Whenever I had a question or needed advice, they were always prompt, patient, and professional when responding.

Finally, I would like to thank the Defense Logistics Agency and the US Navy for their continued and patient support. This dissertation would not have been possible if it were not for Mr. John Corbett, CAPT Bernard Knox, LT Joseph Landon, Mr. Bruce Nelson, Mr. Thomas Meyer, and Ms. Marian Unterman's advice and guidance throughout this process.

Dedication

I would like to dedicate this dissertation to my wife Cindy Johnson. The past four years have been very challenging not just with the typical graduate work, but with the difficulties everyday life brings. She was the foundation on which I stood enabling me to complete this work. When I was down, she was always to there to pick me up and keep me going always telling me there was light at the end of the tunnel. I truly appreciate and will never forget the countless hours she spent with the children, home duties, and her own course work, continuously ensuring I was where I needed to be. I am eternally grateful for everything she has and continues to do for our family.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

This dissertation studies two paramount topics in mission critical logistics: transportation and fulfillment management. First, we develop bus routes and crew schedules for a real world, one-time mega-type sporting event, the Special Olympics 2014 USA Games. For bus routing, we investigate multiple research streams: taxicab, more commonly referred to in this dissertation as dedicated service, and vehicle and shuttle bus routing problems in an effort to build an efficient transportation network. For scheduling, the focus is to develop a volume estimation model based on competition and special event schedules to estimate the volume we anticipate to be at each venue for pickup either after competition or sightseeing at different venues. The last topic analyzes the supply chain network for the Defense Logistics Agency (DLA), a government entity who provides parts to the United States Armed Forces. We analyzed the fulfillment time by evaluating the demand and fulfillment data for 17 US Navy Destroyers. In this chapter, we provide motivation for the study and review the structure of the thesis.

1.1. Motivation

1.1.1. Special Olympics 2014 USA Games

Planning and designing an efficient transportation network for an Olympic sporting event is challenging (Beis, Loucopoulos, Pyrgiotis, & Zografos, 2006). The Games Organizing Committee (GOC) is responsible for constructing multiple venues spanning numerous miles between locations within a constrained budget. An additional challenge of hosting an event of this nature is the finite element, as the event will end at a specific time. This places a great deal of pressure on the GOC to get it right the first time, as there is not an opportunity to do it again.

The Special Olympics is a non-profit organization, which grew out of Eunice Kennedy Shriver's observations on how unjustly, and unfairly people with intellectual disabilities were treated in the 1960s ("Special Olympics, Inc.," 2015). The mission of Special Olympics is thus to provide access to children and adults with intellectual disabilities in sports training and athletic competition so they can achieve, succeed, develop physical fitness, experience joy, and be an active part of their local communities. The global inspiration of all Special Olympic athletes is characterized by their powerful oath: "Let me win. But if I cannot win, let me be brave in the attempt" ("Special Olympics: Our Athletes," 2014).

In June 2014, the Special Olympics USA Games was hosted by the state of New Jersey. 3,300 athletes and 1,000 coaches competed in 16 sports across 10 locations and over 70,000 spectators were in attendance. More than 10,000 volunteers were needed as the workforce behind the Games. For the first time in Special Olympics USA history, opening ceremonies and select competition events were televised, signifying a positive shift in acceptance of special Olympians. Numerous media outlets across the United States shared in telling the story of "Welcome and Acceptance", the 2014 USA Games slogan.

The Special Olympics 2014 USA Games marked the third national games held in the United States. The first was at Iowa State University in Ames, Iowa. The university hosted over 3,000 athletes competing in 13 sports and accompanied by 1,000 coaches. The second was held at the University of Nebraska in Lincoln, Nebraska. Close to 3,000 athletes and over 1,000 coaches were in attendance competing in 14 sports. Because both locations held events within the universities, an elaborate transportation system was not required.

The 2014 USA Games was an eight-day event culminating four years of detailed planning by the GOC. The committee was comprised of eight departments including: sports and competition, logistics, information technology, sponsorship, delegation services, special events, communications, and volunteer services. The overall budget for this event was $15 million with a recognized economic impact of $100 million for the state of New Jersey.

As with any mega-event of this magnitude, transportation was among the top dominant factors in realizing the success of the Games (Beis et al., 2006). The GOC needed to develop efficient bus routes and schedules to ensure timeliness and convenience between 10 venues, four airports, and five special event locations while remaining under the recognized transportation budget of $600K. Also, keeping the following objectives in mind:

1. Cost efficiency, as it related to this event, was defined as the level of service provided compared to the cost of resources required to operate the transportation system. With a budget of $600,000, it was quite difficult to

provide sufficient transportation to and from each competition venue, accommodation, special event, and airport delivery and pickup. To design bus routes and schedules that could be implemented with the minimum number of active buses had to be carefully considered,

2. To provide a reasonable cost estimate, schedule, and number of buses, as well as "what if" analysis to determine a reasonable budget for the desired service level,
3. When serving individuals with developmental disabilities, consideration must be made in regards to long wait times and multiple bus transfers, so convenience played a significant role in transportation planning,
4. To create a legacy component for future national Special Olympics Games and other large-scale events with multiple locations and a tight schedule, and
5. The transportation system (e.g., bus routes) must be simple and easy to follow by the participants besides being cost efficient and convenient. The system should also allow an outside constituent, such as a bus company, to easily execute and modify if needed.

The frequency of shuttles also played an important role, as the waiting time needed to be as minimal as possible. The GOC established a goal of 20-minute intervals between shuttles at each of the competition venues and a 30-minute interval between shuttles for the airport pickup/drop-offs. In order to meet these stringent objectives, this dissertation established an efficient transportation model based on crew scheduling and shortest path algorithms.

1.1.2. Naval Logistics

Naval Logistics represents an important facet of mission critical logistics. Timing and inventory control play a key role in the fulfillment of onboard critical parts while the naval ship is deployed on a compulsory mission.

The US Navy comprises a diversified naval fleet responsible with protecting North America and its allies' global interests. Two classes of vessels charged with this duty are the DDG and CG Class Destroyers, accounting for 12% of the US Naval inventory (NVR Ships, 2015). These ships are combat ready and utilize the Aegis Ballistic Missile Defense (BMD) System, designed to counter-balance missiles of all ranges. These ships are integrated with technologies that have the ability to destroy enemy launched missiles before they can reach specific targets. They currently operate in Europe, Western Pacific, and the Persian Gulf in defense of potential attacks (O'Rourke, 2015).

A general problem that the US Navy has encountered is that critical parts, which make up part of the Aegis BMD System, have the potential to either malfunction or breakdown during an operation. Because of their low demand nature, the part(s) may not be readily available and in essence render the vessel non-operational. Also, an additional issue that leadership is experiencing is quantifying the cost of not having an asset at a designated location or region of responsibility because of the missing or damaged part(s). The absence of this Presidentially directed resource has potentially long reaching strategic effects in the political landscape of an adversarial country.

We will extend the scope of mission critical logistics by analyzing the fulfillment process for the US Navy destroyer fleet's BMD System. Given 6-year data on fulfillment for every BMD related parts, we first analyze the demand using the Pareto Principle or more commonly referred to as the 80-20 rule, to determine if there are a certain number of ships and parts that account for a majority of the annual requisitions. We then evaluate the current logistics fulfillment performance of DLA, who in this scenario is the distributor to the US Navy. We lastly conduct a Root Cause Analysis (RCA) by correlating the fulfillment performance with various system parameters, such as, demand volume, lead times, order characteristics, traffic or the number of orders being processed in the system, system failure, and logistics processing capacity. An extension to this research will be to develop models and algorithms and suggest an actionable optimization plan to DLA and the US Navy regarding inventory levels at distribution centers and the onboard store, as well as to quantity cost and time in the event a Presidentially directed navy ship is not in the area of responsibility during a possible hostile missile launch.

1.2. Thesis Structure

This thesis is organized into four chapters and an appendix section. The first chapter provides an introduction about the mission critical logistics domain. In chapter 2, we propose methodologies for volume estimation models and genetic algorithms by constructing a robust transportation system and crew schedules for a one-time mega event, the Special Olympics 2014 USA Games. Chapter 3 diagnoses a complex logistics supply chain network and the fulfillment process for the DLA and the United States Navy. Finally, chapter 4 concludes the dissertation and mentions future research directions.

Chapter 2

Transportation Planning for Olympic Games

The 2014 Special Olympics USA Games were hosted in New Jersey where over 4,000 athletes and coaches competed in 16 sports distributed across 10 locations within a 40-mile radius. We designed timely, convenient and reliable bus routes and schedules for thousands of people with intellectual disabilities to attend games and special events over eight days under a budget of $600K.

We solved this transportation problem using a three-phase approach. Phase 1 optimizes the number and routes of shuttle-loops and buses required to efficiently transport athletes and coaches to competition venues using the enumeration method. We then developed a time matrix and volume estimation models to ensure the transportation network was equal to or under the budget. During this phase, we also designed a genetic algorithm enabling us to find the sub-optimal solution faster than by enumeration alone. Phase 2 sees the integration of the athletes proposed travel habits and a more focused volume estimation model detailed in hourly variations instead of a daily volume total. Finally, Phase 3 solves the shuttle-bus problem by a set of more direct and easy to follow routes. Due to the constrained competition and special event schedules, we needed a direct route to and from each hub and non-hub venue to ensure all timelines were met. We evaluated this three-phase methodology by applying to a real-world mega-event (the 2014 Special Olympics USA Games) where transportation was key to success.

2.1. Literature Review

There are a number of studies relating to the development of transportation systems within a supply chain network. A key element of many transportation systems is the routing and scheduling component. In this dissertation we target the taxicab problem, the vehicle routing problem, and crew scheduling literature as this most represents our requirements.

2.1.1. Taxicab Problem

The taxicab problem is well known and studied extensively. This service identifies the demand request, timing, route, and number of passengers per trip (Atkins, 2012; Giveen, 1963; Hai, Min, Wilson Hon-Chung, & Sze Chun, 2005; Orr, 1969). We used this as the foundation for the early morning shuttles or more formally, the dedicated shuttle system in our transportation network. This system ensured the participants arrived to their first competition on time. The criterion established by the Special Olympics 2014 USA Games GOC is that athletes and coaches will need to be at the venue at minimum an hour earlier than competition and if part of a team, must arrive in one group.

2.1.2. Vehicle Routing Problem

Supply Chain Management and Operations Research (OR) literature is primarily saturated with solving the distribution of goods between depots and consumers or better known as Vehicle Routing Problems (VRP) (Toth & Vigo, 2002). There are many variants of the VRP; Generalized VRP (GVRP), the Traveling Salesman Problem (TSP), VRP with time windows (VRPTW), Capacitated VRP (CVRP), General Pickup and Delivery Problem (GPDP), VRP with Backhauls (VRPB), and School Bus Routing Problem (SBRP) to name just a few. These variations are detailed in the following paragraphs.

The GVRP is concerned with combining loads with the objective of minimizing the cost of deliveries or collection of routes (Ulrich Derigs et al., 2011; U. Derigs & Kaiser, 2007; Garaix, Artigues, Feillet, & Josselin, 2010; Goel & Gruhn, 2008; Pop, Matei, Sitar, & Chira, 2010).

The TSP is one of the most widely studied problems in mathematics (Applegate, Bixby, Chvátal, & Cook, 2006). The use of OR and optimization packages has helped solve this issue in recent years. The problem is one of finding the shortest path among *n*-nodes to ensure all locations are visited with the objective of minimizing travel cost (Bandyopadhyay & Sajadi, 2014; Behdani & Cole Smith, 2014; Blaser & Wilber, 2013; Boyd, Sitters, Ster, & Stougie, 2014; Feng & Liao, 2014; Karabulut & Fatih Tasgetiren, 2014; Mladenović, Todosijević, & Urošević, 2014; Toriello, Haskell, & Poremba, 2014; Wang, Guo, Zheng, & Wang, 2015).

The VRPTW seeks to solve deliveries of products to customers geographically separated within a specific time window to avoid stock outs and meet user demands (Cattaruzza, Absi, Feillet, & Vigo, 2014; Desrochers, Desrosiers, & Solomon, 1992; Lau, Sim, & Teo, 2003; Potvin, Garcia, & Rousseau, 1996; Taillard, Badeau, Gendreau, Guertin, & Potvin, 1997; Tavakkoli-Moghaddam, Gazanfari, Alinaghian, Salamatbakhsh, & Norouzi, 2011; Taş, Jabali, & Van Woensel, 2014).

The CVRP involves a fixed fleet of vehicles with a homogenous capacity to meet the demands of customers from a single depot (Achuthan & Caccetta, 1998; Baldacci, Mingozzi, Roberti, & Calvo, 2013; Gounaris, Wiesemann, & Floudas, 2013; Jin, Crainic, & Løkketangen, 2012, 2014; Lysgaard & Wøhlk, 2014; Mu & Eglese, 2013; Rodríguez & Ruiz, 2012; Sungur, Ordóñez, & Dessouky, 2008; Sörensen & Schittekat, 2013).

GPDP normally has an established set of routes with known customer demands, starting and ending locations, and identical vehicle capacities are also known (Savelsbergh & Sol, 1995). The goal of the GPDP, as like the other VRP variants, is to minimize transportation cost and meet consumer demand (Alfredo Tang Montané & Galvão, 2006; Bianchessi & Righini, 2007; Dethloff, 2002; Minis & Tatarakis, 2011; Mosheiov, 1994; Rieck & Zimmermann, 2013; Savelsbergh & Sol, 1995; Sheridan et al., 2013; Swihart & Papastavrou, 1999; Urban, 2006).

The VRPB is similar to the GPDP, but with a product return feature not offered in the latter variation. The challenge with this alternative is the vehicle is required to have the capacity or space to haul the item back to the depot (Cheung & Hang, 2003; Crispim & Brandão, 2005; Duhamel, Potvin, & Rousseau, 1997; Palhazi Cuervo, Goos, SÃrensen, & ArrÃ!iz, 2014; Salhi, Wassan, & Hajarat, 2013; Toth & Vigo, 1997; Wassan, 2007; Yazgı Tütüncü, Carreto, & Baker, 2009; Zhong & Cole, 2005). The customer now has the option to return a product using the same routing sequence as in the GPDP.

While the previously mentioned VRP variants have been studied thoroughly and solved using well-known models, we needed a variation specifically appropriate for transporting people. So, we reviewed literature detailing shuttle bus routing or more precisely, school bus routing models and optimization techniques.

The Shuttle Bus Routing Problem (SBRP) is a modified version of the VRP and solely focuses on the transportation of individuals as opposed to the delivery of products (Park & Kim, 2010). The difference between the typical VRP and the SBRP are the additional constraints required to safely meet customer timelines. We used the SBRP literature stream as the groundwork for the 2014 USA Games transportation shuttle service network.

2.1.3. Scheduling

We drew our scheduling methodology from the Bus Driver Scheduling Problem (BDSP) literature. The BDSP have previously been studied and mathematically solved using computer based techniques for all sorts of crew or bus scheduling issues (Lourenço, Paixão, & Portugal, 2001). The goal of the BDSP is to find an optimal bus driver schedule to cover all demands during a standard duty day (Beaumont, 1997; De Leone, Festa, & Marchitto, 2011; Dias, de Sousa, & Cunha, 2002; Kecskeméti & Bilics, 2013; Liping, 2006; Lourenço et al., 2001; Martello & Toth, 1986; Paias & Paixão, 1993; Song, Hao, Huo, & Li, 2012).

Crew scheduling closely resembles the BDSP in that the goal is to not only develop an optimal work schedule, but to also improve quality and customer service (K. R. Baker & Magazine, 1977; Lourenço et al., 2001; Song et al., 2012).

We developed metaheuristics to solve this problem by designing a new genetic algorithm to quickly find the sub-optimal solution. This allowed us to implement the transportation plan with relative ease and more importantly enabled us to make quick contingency decisions during the games.

2.2. Problem Description

The 2014 Special Olympics USA Games was hosted by New Jersey in June 2014. More than 4,000 athletes and coaches from all 50 states participated in 16 sports for 8 days. Unlike the previous two National games, which were hosted in one location, the 2014 USA Games were spread across 10 locations within a 40-mile radius in not only one of the most populous and busy areas in New Jersey, but across the county. One key challenge was to design an on-time, convenient and reliable transportation system for thousands of people with intellectual disabilities under a meager budget of $600,000. The total budget for the entire event was just $15 million.

The event budget did not allow for the construction of new housing and multi-purpose sporting facilities that could have accommodated all participates and hosted all games at one location. Thus, the athletes and their coaches were disseminated to multiple locations for accommodation and competition. The College of New Jersey (TCNJ) and Rider University (RU) were the primary locations for housing. The games were also hosted at TCNJ and RU (hubs 0 and 1 respectively) in addition to eight other locations throughout the state of New Jersey (Figure 2.1).

ID	Venues	Sports
TCNJ	The College of New Jersey (Hub 0)	Basketball, Bocce and Powerlifting
RU	Rider University (Hub 1)	Basketball and Volleyball
PU	Princeton University	Aquatics and Athletics
TLS	The Lawrenceville School	Flag Football
MCP	Mercer County Park	Baseball, Soccer, Softball, Tennis, Triathlon
MOG	Mercer Oaks Golf Course	Golf
HUN	Hun School of Princeton	Basketball
PED	Peddie School	Gymnastics
CBZ	Carolier Brunswick Zone	Bowling
SKM	Skillman Park	Cycling

Figure 2.1 The description of each location by competitive sport

Due to the multiple facilities used for accommodations and competitions, the GOC needed to provide on time, convenient and reliable transportation services for the athletes and coaches. Transportation was divided into three categories: airport operations, special events, and competition.

- Airport Operations: provided pickup/drop-off services arriving/departing through Newark Liberty International, Philadelphia International, Trenton-Mercer, and John F. Kennedy airports.
- Special Events: divided into two categories: Type-1 and Type-2.

Type-1:

- Opening and Closing Ceremonies
- Dinner Cruise
- Trenton Baseball Game
- Events had discrete start/end times allowing pre-arranged set times for transportation to and from events.

Type-2:

- Olympic Town
- Continuous daily shuttle services provided the flexibility of

transportation between each hub to and from Olympic Town.

- Competitions: divided into two categories: dedicated and shuttle.

2.2.1. Type of Services – Dedicated and Shuttle

We took on this challenge, and after 2 and 1/2 years' of intensive interactions with the GOC and bus companies, we crafted an effective and simple system for transportation planning and scheduling that met all requirements and was successfully implemented, contributing to the success of the 2014 USA Games. The system provided both **dedicated** services for passenger flows with known timing and destinations (such as opening/closing ceremonies, dinner cruise, and morning first moving-in to game venues), and **shuttle** services to pick up random intermittent flows (such as returning and sight-seeing flows from venues, special events, and airport arrivals/departures) as shown in Figure 2.2. While the purpose of the dedicated services was to be on time and reliable, the objective of the shuttle services was convenience (short waiting and traveling time, minimal bus switches) and reliability.

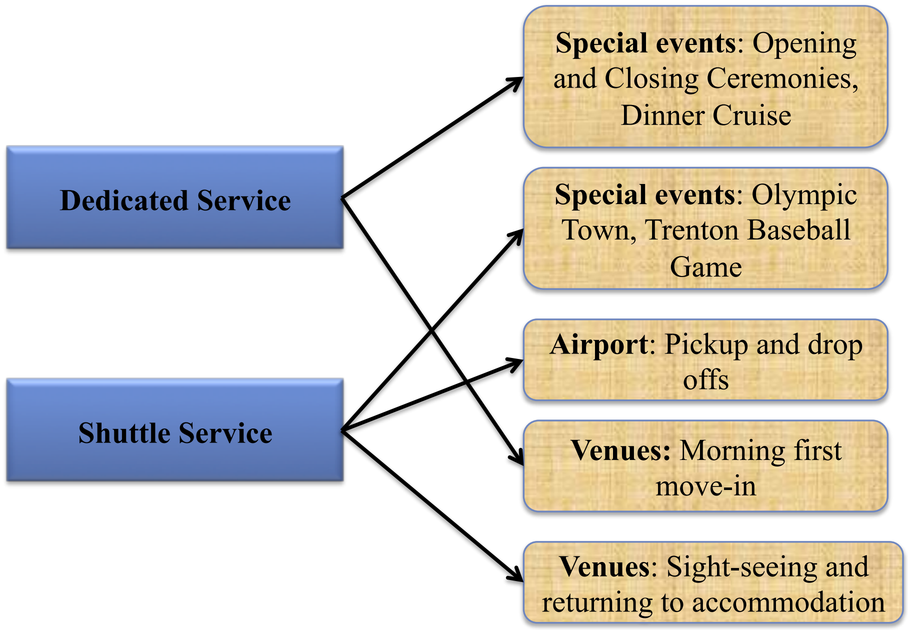

Figure 2.2 The two types of services offered for each special event

Dedicated

Dedicated service is defined as the guarantee pick-up and delivery of athletes and coaches to their first competition and to those venues that are beyond the 30-mile threshold. This service was based on the familiar taxicab problem, where we know the timing, route, and headcount for every event and location (Giveen, 1963). The difference between dedicated services and the taxicab problem, is the customer demand follows a static time period from 6:30 am to 10:00 am, mandating attendance to ensure on-time delivery for competitions instead of a "call in" type of service.

Departure time was critical as some locations were 30 miles from the hubs and could take upwards of 40 minutes to arrive due to the highly congested region. An additional timing component for dedicated services was 38% of competitors were part of team competition. To ensure capacity was met for this type of demand, a sufficient number of buses needed to be available to transport entire teams.

Shuttle

The most challenging and costly part of the system was the shuttle-bus planning problem. We first built a traffic volume model to estimate the uncertain returning flows from venues by days and by hours. Then we optimized the shuttle-bus loops and routes to determine the sequence of venues to visit in each loop. Finally, we designed the bus driver hourly schedule to determine the number of drivers needed per shift to meet changing demands over a day.

This shuttle system minimized the total number of buses required and travel time spent at bus stops and routes. When dedicated services ended at 10:00 am, the shuttles would begin servicing participants.

Numerous options were developed enabling an efficient system; one loop including every location, direct routes from hub(s) to non-hub locations, and multiple routes with multiple stops to name a few. Regardless of the choice of system, all loops needed to run at regular intervals ensuring customer demands were met. One of the goals for our system was to ensure buses were available at each location every 20 minutes while providing a continuing provision for intermittent and random passenger flow.

This also served as a continuous daily shuttle service, which provided the flexibility of transportation between hubs and competition venues allowing for the ease and convenience of athletes and coaches to become spectators for other events and participate in ongoing special activities.

2.3. Transportation Planning and Scheduling

2.3.1. Transportation

Transport for the Games was delivered through a partnership between the GOC and the Academy and First Student bus companies. The selection was based on inventory levels and multiple capacities the companies were able to provide. Figure 2.3 shows the type of vehicles and capabilities provided for the games, as well as the hourly cost. The motor coach style bus was used for competition, airport services and special events. The low step style transit bus was used for the shuttle services from TCNJ and Rider venues due to the advantage of fast loading and unloading. The school bus type was used for evening dedicated show case sports and special events. According to the contracts with the two companies, the minimum time required to engage a bus was 4 hours for all services.

Type	Capacity	Cost/Hour	Total
Motor Coach	50	$90	300
Low Step	50	$75	10
School Bus	45	$54	25

Figure 2.3 Bus capacity, cost per hour, and total number of buses

2.3.2. Schedules

Overall, the competition and special event schedules were very tight throughout the week. There was little room for error regarding arrival and departures times for each event, as one was dependent on the other. If for example, the sport of cycling did not start on time due to the late arrival of participants, their attendance for the dinner cruise that evening could have been jeopardized. As such, the GOC was reliant on developing an efficient transportation system. See appendices 1 and 2 for detailed competition and special event schedules for TCNJ and RU respectively.

2.3.3. Travel Volume

Travel volume, as seen in Figure 2.4, was the most difficult aspect of the transportation system to estimate. There was little historical data to research or to know, with confidence, the travel habits of athletes and coaches. We conducted a survey which will be described in a later section, to estimate the number of participants who, potentially, would sightsee after competition (Bixby, Downs, & Self, 2006). Travel volume is defined as the number of people needed to transport per unit of time (hour). For example, during the Olympic Town special event, a shuttle ran between TCNJ and RU every 20 minutes (time interval) from 3:00 pm to 9:00 pm nightly starting on Monday and ending Friday (9:00 am to 1:00 pm). The GOC estimated the number of shuttles and the number of buses per shuttle needed to support this service. The number of shuttles depended on the round trip time, described as the two-way driving time plus all stopping times (the stopping time is estimated to be 5 minutes, or 0.08 hour, at each venue) and the required time interval, as follows:

Location	Volume
TCNJ	643
RU	427
PU	945
TLS	226
MCP	952
MOG	292
SKM	74
HUN	174
PED	47
CBZ	361

Figure 2.4 Location and volume

$$\# \; of \; shuttles = \frac{Round \; trip \; time}{time \; interval}$$

For each shuttle, we needed to have enough buses to transport all people arriving during the time interval (so the average waiting time is not more than the time interval), thus

$$\#\ of\ buses\ per\ shuttle\ \geq \frac{time\ interval \times volume}{bus\ capacity}$$

The results indicated the GOC needed 2 shuttles with 4 buses on each shuttle to ensure the demand of 500 passengers per hour was met.

2.4. Mathematical Models and Solutions

We developed four technical tools for transportation planning and scheduling for the Games. The first tool was a volume estimation model based on the number of participants at each venue and their traveling habits (chances of sight-seeing, etc.). The second tool was an integer programming model with flow variables to optimize the shuttle loops and routes (Meng & Zhou, 2014). To handle the challenging issue of bus switching among loops we developed a third tool, a genetic algorithm, to determine the number and routes of loops so as to cover all venues while optimizing the volume-weighted average traveling time, the cost and number of bus switches. The fourth tool, metaheuristics, scheduled the buses/drivers on each loop on an hourly basis to meet changing demands over a day. We implemented the tools using Microsoft Excel, the Python programming language, and ran the model using the Gurobi Optimization program.

The methodology for this endeavor was outlined in three phases as shown in Figure 2.5. Phase 1 developed the minimal amount of shuttles easing confusion making decisions simpler for the athletes and coaches. In Phase 2, we saw a significant change in our approach of modeling the transportation system by adding the travel habits of participants and confining the loop structure to two hubs and one venue. In Phase 3, a simpler, more robust approach was developed as we chose the direct pair method, but from a singular hub to non-hub only.

Phase	Timeframe	Structure
1	1 year out	Direct pairs, 1 loop, 2 loops, & 3 loops
2	6 months out	Travel Habits & 1 loop with two hubs and 1 venue
3	1 month out	Direct pair between 1 hub and 1 venue

Figure 2.5 Timeframe for each of the three phases developed for the model

2.4.1. Phase 1.1

Phase 1 was divided into two steps, 1.1 and 1.2 respectively. Phase 1.1 was the foundational step for the transportation network. The time matrix was developed, volume estimation established, and shuttle-loop models were optimized. We altered the volume estimation matrix and shuttle loop choices in future phases, but the time matrix would be preserved.

- Travel Times

  Travel times were collected using Google Maps® to initially construct the models and was the basis of the price analysis for bidding purposes only. Six months prior to the event, the GOC and Academy Bus Company developed an accurate representation of travel times as shown in Figure 2.6, by driving to and from each hub and non-hub locations using a motor coach bus.

	TCNJ	RU	PU	TLS	MCP	MOG	HUN	PED	CBZ	SKM
TCNJ	0	6	16	7	19	14	16	30	31	27
RU	6	0	15	6	19	13	14	29	26	24
PU	16	15	0	13	21	11	6	25	20	17
TLS	7	6	13	0	17	13	11	27	26	20
MCP	19	19	21	17	0	8	20	16	31	26
MOG	14	13	11	13	8	0	14	18	27	22
HUN	16	14	6	11	20	14	0	30	27	15
PED	30	29	25	27	16	18	30	0	26	32
CBZ	31	26	20	26	31	27	27	26	0	27
SKM	27	24	17	20	26	22	15	32	27	0

Figure 2.6 Travel time for each location reflected in minutes

- Volume Estimation

Estimating the number of participants at each location at any given 20-minute period proved difficult, especially without travel data from previous events. We separated this task into three models: volume 1, volume 2, and volume 3.

Volume 1

Assumptions:

- Everyone visits one other venue for sight-seeing before returning to hubs
- Between venues A and B, the volume (of sight-seeing) from A to B is proportional to attendance in A and attendance in B, and
- The fraction of athletes and coaches who would travel between venues for sightseeing is α= 25%. The fraction of participants living at hub 0 was λ= 65%. After conducting a survey with the Chief Operating Officer of the 2014 USA Games and leadership from the Special Olympics North America, the results indicated a confident 25% of participants would sightsee after competition.

Volume 2

Formulation: parameter and indices

A_i Attendance at each venue, $i = 0,1,\ldots,9$

S_{ij} Number of participants sightseeing from *i* to *j*

A_k Attendance on each cycle *k*

H_i Represents either hub 0 or hub 1

The goal for volume 2 was to estimate the number of athletes and coaches that would return to their residency, hubs 0 or 1, or would prefer to visit another non-hub venue for sightseeing purposes.

The total number of participants sightseeing out of venue *i* and the fraction of athletes and coaches going to venue *j*: thus,

$$S_{ij} = \alpha A_i \times \frac{A_j}{\sum_{k \neq i} A_k} \tag{1}$$

The total volume returning from venue *i*: part one represents the non-sightseeing volume at venue *i* and part two is the sightseeing volume into *i*: thus,

$$H_i = (1-\alpha)A_i + \sum_{j \neq i} S_{ji} \tag{2}$$

Volume 3

The goal was to estimate the volume between hubs 0 and 1 along with sightseeing participants at non-hub venues. There were four choices for the participants.

1) Competing at 0 and sightseeing at 1.
2) Sightseeing at 0 and living at 1.
3) Competing at 0, living at 1 and not sightseeing anywhere.

Formulation:

$$
\begin{aligned}
V_{01} = S_{01} + \lambda \sum_{j} S_{j0} \\
+ \lambda(1-\alpha)A_0 \\
= S_{01} + \lambda H_0
\end{aligned}
\tag{3}
$$

(4) Competing at non-hub venues and sightseeing at another non-hub venues. For example, competing at 2 and sightseeing at 3.

Formulation:

$$V_{23} = S_{23} \tag{4}$$

- Shuttle-Loop Optimization

The initial planning stages resulted in a limited number of loops and a reasonable amount of venues on each loop. The options were direct pairs, one loop for all venues, and optimal loops (# of loops, # of venues per loop).

The assumptions for this model were each stop will take a maximum of 5 minutes and each switch between loops will take 20 minutes. Based on the small amount of proposed number of loops and venues, we initially modeled the transportation network by using the enumeration method to evaluate the sets of loops where each loops equaled the hubs, non-hub venues sequence as illustrated in Figure 2.7 (Yih-Long & Sullivan, 1990). We needed to ensure that

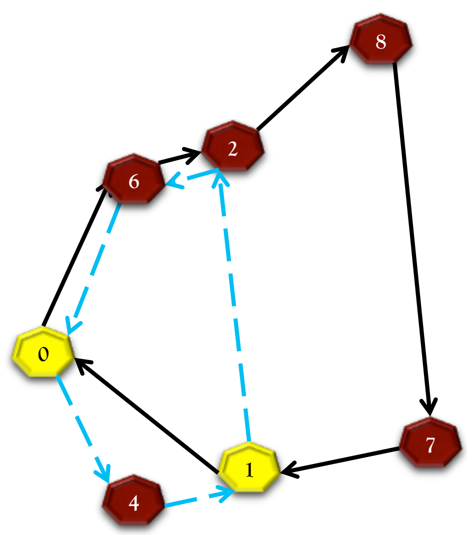

Figure 2.7 Multiple venues solution

each loop was complete, meaning each venue was included in at least one loop and the loops were non-repetitive where one loop can visit a venue at most once.

The objective function for this model was to minimize the weighted average traveling time.

Formulation of objective function:

$$\frac{\sum_{(mn)} \left(V_{mn} \times \sum_{ij} t_{ij} y_{ij}^{mn} \right)}{\sum_{mn} V_{mn}} \tag{5}$$

- The scenarios we initially evaluated were direct pairs, one loop, two loops with seven venues, and three loops with five venues.
    - Direct Pairs

      The direct pairs option (Figure 2.8) refers to venues having at least one loop to every hub and non-hub location. This is the most expensive option of the four scenarios due to the amount of buses required to operate the system.

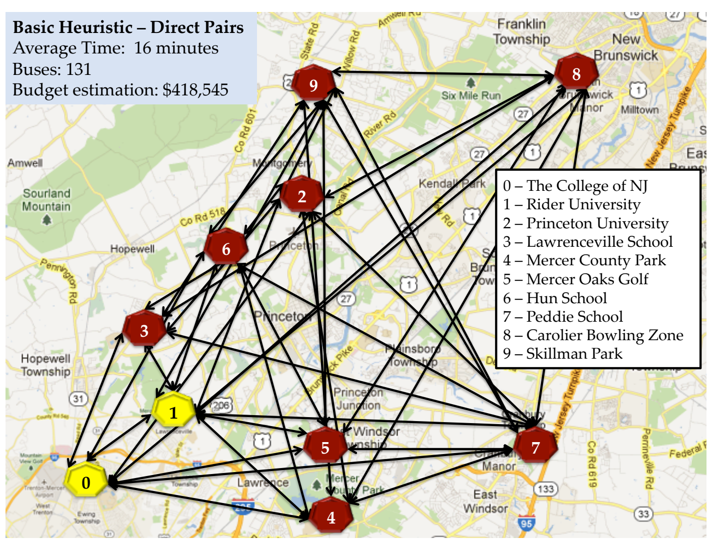

Figure 2.8 Direct pair solution

- One loop

This method saved money and resulted in an average travel time of 14 minutes, six minutes under the established 20-minute goal. When considering the customer's special needs, this option (Figure 2.9) proved to be too long of a wait.

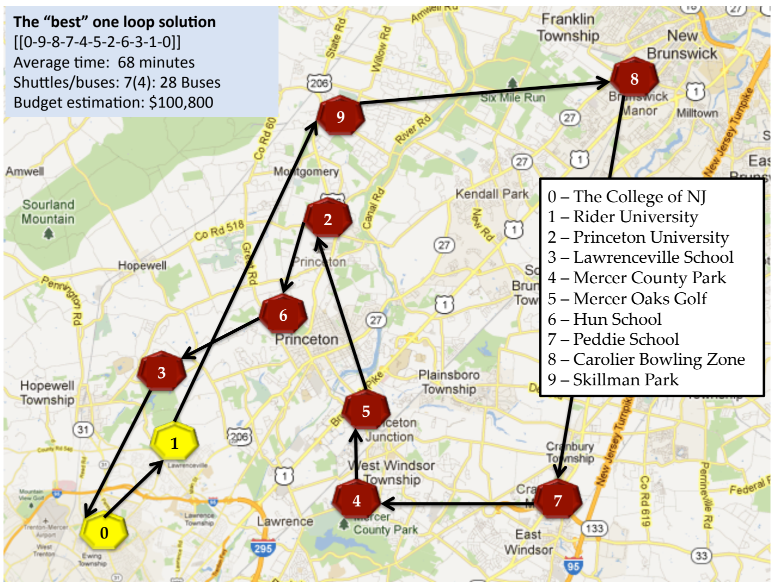

Figure 2.9 One loop with 10 venues solution

- Two loops with seven venues

Each loop serviced seven venues including the two hubs. Even though the budget increased, this option decreased the average travel time for each shuttle to 32 minutes, nevertheless 12 minutes above our goal as seen in (Figure 2.10).

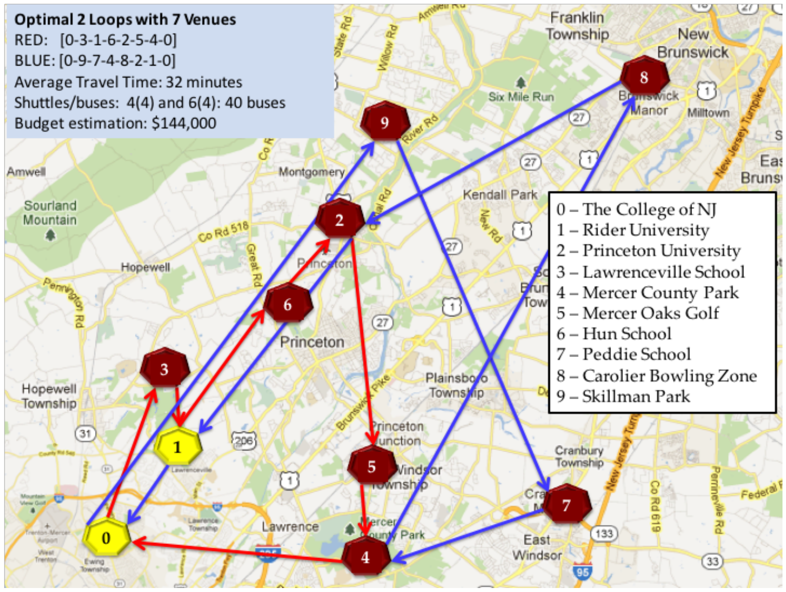

Figure 2.10 Two loops with seven venues solution

- Three loops with five venues

Each loop serviced six venues and the two hubs as illustrated in Figure 2.11. Just as the two loops with seven venues decreased the time spent on the routes, the average time of 28 minutes was still above our goal of 20 minutes.

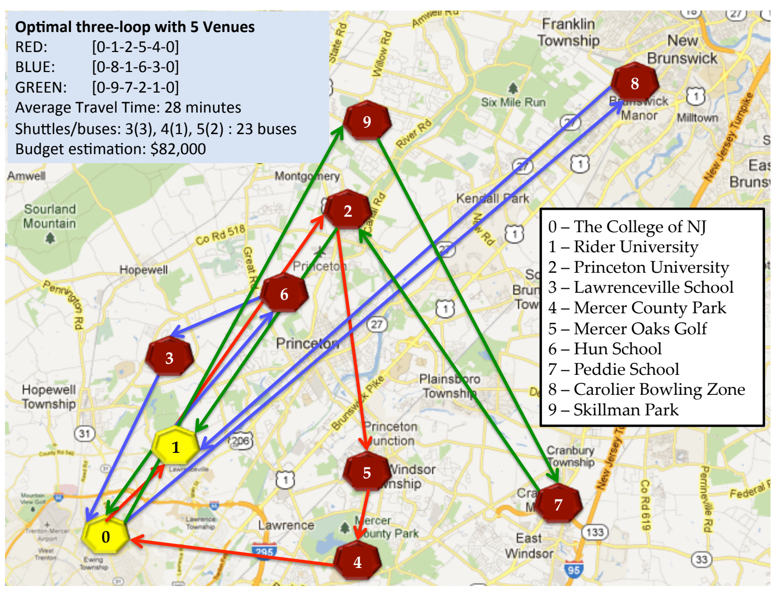

Figure 2.11 Three loops with five venues solution

2.4.2. Phase 1.2

The objective for this phase was to develop more efficient algorithms, as the enumeration method for three or more loops was not feasible. There were too many combinations and the computational times needed to optimally solve proved unrealistic and would not be transferable to future events.

In this phase, the model needed to handle the sightseeing volume, visit multiple venues in a loop, minimize average traveling times, and apply a time penalty by converting the inconvenience of switching buses. Since the inconvenience of switching buses was considered, the model is not linear nor does it limit the number of venues per loop.

A genetic algorithm (GA) is a stochastic optimization technique which finds the sub-optimal solution quickly and is simple and flexible to implement (Liu, Jiang, & Geng, 2008). GAs have been used to solve Vehicle Routing, Traveling Salesman, and Shuttle Bus Routing Problems to name a few (Antony Arokia Durai Raj & Rajendran, 2012; B. M. Baker & Ayechew, 2003; Chu & Beasley, 1997; Heung-Suk, 2002; Jeon, Leep, & Shim, 2007; Nia, Sharif, Habibzadeh, & Rezvani, 2011; Xie & Jia, 2012). By nature of a GA, the program we designed automatically searched the entire solution space, but did not have a significant impact on the final outcome. However, it did reduce the complexity of coding.

The SO2014 GA included four iterations: assumption, modeling, solution, and client review and feedback. The sequence was defined in six steps with the sixth step returning to step 2 as seen in Figure 2.12. The CONDITION defined in the program was the number of iterations. Once the number of iterations was reached, the CONDITION was met.

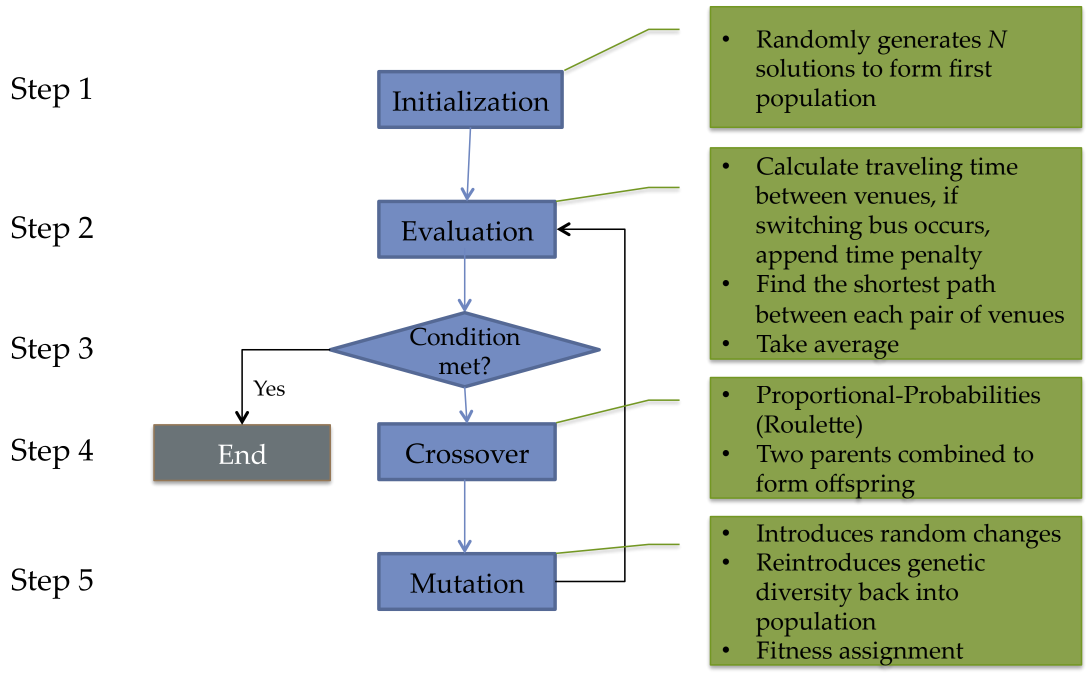

Figure 2.12 SO2014 genetic algorithm design

Parameters:

1. Number of iterations.
2. P_c : Probability that crossover will occur. Recommend 0.6~0.8 3 spaces
3. P_m : Probability that mutation will occur. Recommend 0.15 you have 2 spaces
4. Population size: Recommend 30

We evaluated two scenarios using the SO2014 GA, (1) one chromosome with 16 genes (Figure 2.13) and (2) one chromosome with 24 genes (Figure 2.14). See appendix 3 for the SO2014 GA technical design.

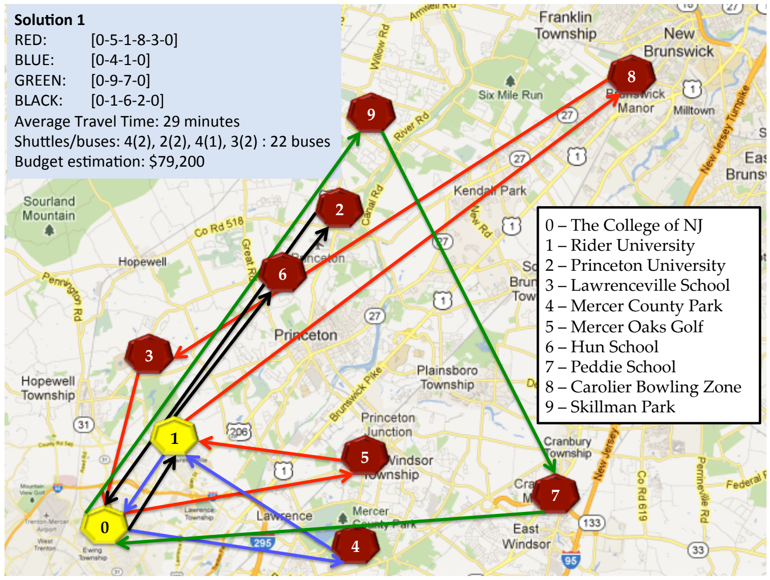

Figure 2.13 SO2014 GA solution 1

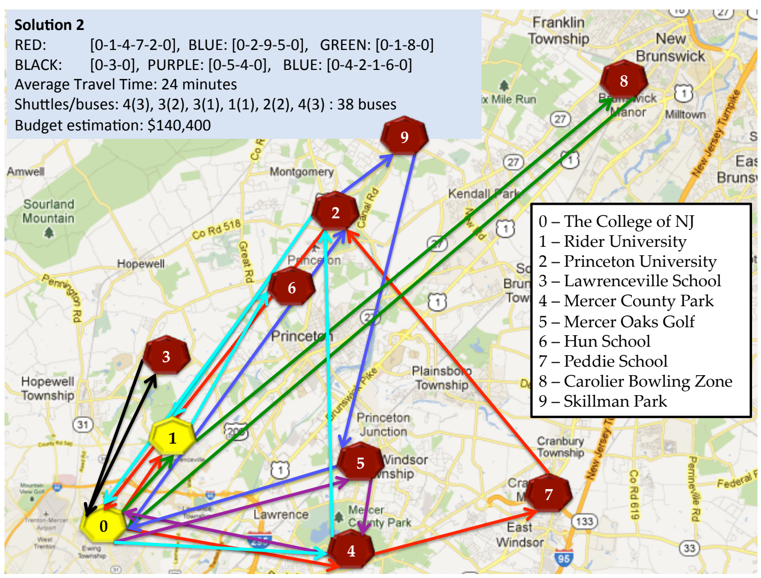

Figure 2.14 SO2014 GA solution 2

2.4.3. Model Development for Phases 2 and 3

This model considered time windows for buses. We expect that a venue will have bus arrivals every 15 minutes. From 10:00 am to 6:00 pm, the time frame is divided into 32 pieces. 10:00-10:15, 10:15-10:30, … etc. For example, suppose the time horizon begins at 10:00 am (so that the first bus will be able to drive 30 minutes to arrive at the farthest venue). 10:00 is then converted to A_0 =60; 10:15 is A_1 =75, and so on. In general, $A_k = 60 + 15 * k$, k=0,1,…,32

We hoped a bus would serve only one venue during a day in order to reduce the risk. By this assumption, the problem could be decomposed to a set of sub-problems. Each sub-problem considered the bus-scheduling problem for one venue only.

Parameters:

C: Capacity of a bus

V_k: Volume at cycle *k*

A_k: Arrival time of cycle *k*

T: One-way traveling time from hub to venue

Cycle duration: 15 minutes

Variables:

x_k^b: Binary, when =1, bus b will satisfy the demand of the kth cycle

y^b: Binary, when =1, bus b is used

u^b: Integer, the last cycle to satisfy

l^b: Integer, the first cycle to satisfy

h^b: Integer, reservation length for bus b (hours)

Objective Function:

$$\min \sum_b h^b \tag{6}$$

Constraints:

1. The volume at each cycle must be satisfied (capacity constraint)

$$C \sum_b x_k^b \geq V_k \qquad \text{for all } k \tag{7}$$

2. If Bus b visits venue at A_k (cycle k), the timeframe should satisfy (non-overlapping task constraint):

$$x_k^b (A_k - 2T) + M*(1 - x_k^b) \geq x_i^b A_i \qquad \text{for all } i \leq k\text{-}1 \tag{8}$$

3. Relationship between x_k^b and y^b (big-M for bus):

$$\sum_k x_k^b \leq M * y^b \qquad \text{for all } b \tag{9}$$

4. A bus, if reserved, must be reserved for at least 4 hours (minimum time requirement)

$$u^b - l^b + M(1 - y^b) + 2T \geq 4*60 \qquad \text{for all } b \tag{10}$$

5. Relationship among u^b, l^b and h^b (starting and ending time constraints):

$$u^b \geq x_k^b A_k, \qquad \text{for all } k \text{ and } b \tag{11}$$

$$l^b \leq x_k^b A_k + (1 - x_k^b) M, \qquad \text{for all } k \text{ and } b \tag{12}$$

$$u^b \geq l^b, \qquad \text{for all } b \tag{13}$$

$$u^b - l^b + 2T \leq 60 \times h^b + M(1 - y^b), \qquad \text{for all } b \tag{14}$$

2.4.4. Phase 2

Even though the results from Phase 1 were positive with outcomes under budget, minimal required buses, and favorable average travel times, senior management viewed the optimal transportation system as too complex, not intuitive, thus demanding a simpler solution. With the games less than six months out, the competition schedule was 95% complete, enabling us to fine tune the model. We administered a second survey with the games Chief Operating Officer and leadership from the Special Olympics North America office, requesting the travel habit of the athletes and coaches from previous games related to traveling either to a hub or non-hub once their individual competition was completed. Based on the combined 90+ years of experience organizing International and National games, appendix 4 represents the results from the survey.

We first built a traffic volume model to estimate the uncertain returning flows from venues by days and by hours. Then we optimized the shuttle-bus loops and routes to determine the sequence of venues to visit in each loop. Finally, we designed the bus driver hourly schedule to determine the number of drivers needed per shift (Yoshitomi, 2002). We adjusted the model by breaking down daily total volume into 15-minute variations producing an output, which included the number of buses/drivers needed per shift (Figure 2.15).

Bus Driver	Start Shift	End Shift
1	10:45 AM	3:30 PM
2	11:00 AM	4:00 PM
3	11:15 AM	5:15 PM

Figure 2.15 Bus driver schedule

Each bus would depart from hub 1 to venue *i* and return to hubs 0 and 1. Each bus would only serve one venue and the number of buses used in each would vary over time.

2.4.5. Phase 3

In this final phase, we saw a slight shift in the design of the model from Phase 2. Leadership made the decision to have direct pairs from each hub to each venue for convenience and due to the rigid time lines as seen in Figure 2.16. It was also a much simpler system to absorb for individuals with intellectual disabilities. Instead of including both hubs with a single non-hub, the new model connected one hub to one non-hub directly. The model formulation is the same as in Phase 2, with the only difference being the adjustments to the volume for each cycle.

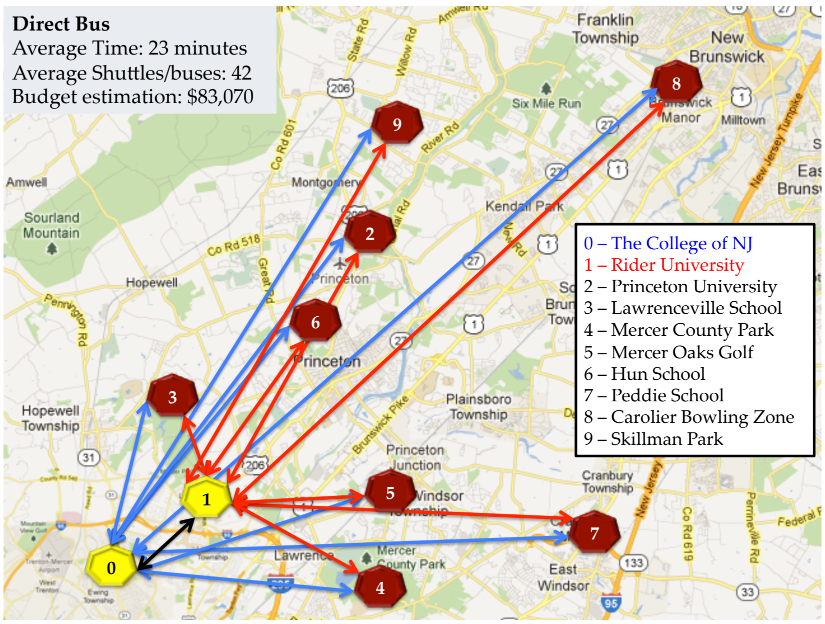

Figure 2.16 Direct pair final solution

2.5. Implementation

The implementation process was very challenging due to the many layers of risks and the overall number of tasks requiring modifications and adjustments throughout each phase (Bixby et al., 2006). An additional challenge was the games budgetary structure which fluctuated consistently, resulting in various perspectives of the required number of buses and transportation construct from senior leadership (Varelas et al., 2013).

2.5.1. Risk Management

Before implementation, we comprised a list of what we believed were common risks for a transportation network and developed risk management and contingency plans as illustrated in Table 2.1.

Risk	Definition
Traffic	The event locations were scattered throughout central New Jersey. This region is busy with typical everyday volume, coupled with the influx of new observers for the event, there may be traffic concerns to plan for. In particular, during morning rush hours, the driving time may increase by 20-50% as compared to non-rush hours.
Volume	The passenger volumes for all transportation services are best estimates, subject to real time changes. While over-estimation results in waste, under-estimation leads to long wait times and poor customer service.
Technology	There will be various communication devices used in the transportation system. The use of radios, Global Positioning Systems (GPS), cellular phones, and hand-held tablets are a just a few of the devices. With any mechanic device, there will be the potential of either malfunctioning or breaking down.
Weather	As this event will transpire in the summer, the probability of excessive heat and thunderstorms is high.
Driver error	The vehicle operators will be professional drivers from well-established bus companies. Even with their experience, we were cognizant of the fact that some individuals would not arrive at the locations on time, due to human error.
Route Closures	There will always be a chance of scheduled outages or unplanned accidents. Alternate routes will need to be scheduled during the planning stage.
Mechanical	Vehicle performance, even with proper maintenance, can be affected by unplanned mechanical problems.

Table 2.1 Transportation risk and definitions

The GOC selected Academy and First Student bus companies as the transportation providers based on two primary facts, their large inventory of buses and their superb customer service. Their operation manager's worked closely with the GOC for two years prior to the games to ensure the end result would be an efficient transportation network.

Once the competition and special event schedules were solidified and provided to the delegations across the United States: Academy, First Student, and the GOC conducted a “table-top” exercise to decide the number of buses needed. This proved to be very fruitful as we identified troubled areas and assigned the number of drivers needed throughout each day. Appendix 5 details a print out of day 1 competitions given to the operation managers, which included the number of required buses needed, originating hubs, assignment locations, driver schedules, and hours of service.

Both transportation companies used the plan to schedule routes and the quantity of buses needed to transport the athletes and coaches to their respective competition venues and return to originating hubs. This information was critical to determine the number of buses required to increase their New Jersey fleet as they provide services for the entire northeast region.

The transportation risk management plan was carried out by the GOC with assistance from Academy and First Student. To ensure communication was cohesive throughout the multiple locations, a Main Operations Center (MOC) was established at one of the campuses. There were several departments represented on a 24-hour schedule: Games Transportation, New Jersey Department of Transportation (NJDOT), Law Enforcement, and Public Safety to list a few. To combat transportation issues, the MOC contained multiple display screens connected to real-time GPS monitoring and the NJDOT regional ITV systems. The benefits of having real-time and ITV monitoring provided the ability to have “eyes on” every bus in our network and use alternate routes if needed.

2.5.2. Contingency Plan

The contingency plan was developed upon completion of the risk management plan. Once the plan was in hand, the GOC and the bus companies conducted scenario base training with the following objectives.

1. To develop an interagency team with a common understanding of the transportation aspects of a planned special event,
2. To test the transportation plan to ensure that it addresses a range of concerns including contingencies,
3. To prepare for the event including unexpected changes to the risk management plan, and
4. To improve individual and agency performance.

Based on the transportation risks listed in Table 2.1, we evaluated the managers by asking the following questions.

1. Traffic: How do you communicate traffic issues with the drivers?
2. Volume: What is the process in place to help control volume issues? What is the process to help alleviate long wait times?
3. Technology: What is the process to help mitigate technical issues?
4. Weather: If required, what are the procedures to evacuate a venue?
5. Driver error: What are the steps to help the drivers with poor decision-making?
6. Route closures: Are there alternate routes selected in the event of an unscheduled closure?

7. Mechanical: What are the procedures for a vehicle breakdown on a route? Is there a daily maintenance plan developed?

2.6. Results and Impact

2.6.1. Results

The design and implementation processes are iterative much like peeling an onion – addressing one layer of concerns only reveals another. We were committed to provide a solution to completely satisfy the GOC. The project experienced three phases:

1. We designed shuttle-bus loops and routes based on daily traffic volume → not satisfactory because athletes traveling habits (human behaviors) were not considered.
2. We revised the shuttle system to take traveling habits into account → not satisfactory because the system was too complex (too many stops in each loop) for people who have special needs.
3. We simplified the shuttle systems by limiting the number of stops in each loop while managing to keep it within budget → still not satisfactory because we ignored peak demands in a day → we responded by designing hourly schedules for bus drivers.

Thanks to this iterative process, in the end, we came up with an elegant system striking the balance between **effectiveness** and **simplicity**. Specifically, the system was very simple to follow. First, it provided a convenient 20-minute interval between consecutive buses and an average traveling time over all pairs of locations of about 23 minutes. Secondly, the system provided one-stop services without the need to switch buses. Finally, it was cost efficient, as it not only met the budget but also left a sizable surplus of $45,000. We used the budget surplus to enhance the reliability of the transportation system by pooling a fleet of extra buses at a central location near the venues to provide emergency services – which was proven very valuable in the Games, as our hourly traffic prediction didn't match the peak demand exactly.

Computational

The main objective for this event was to ensure efficient, on time, and reliable transportation for athletes and coaches to every competition, special event, and airport service. To arrive late to anyone one these was deemed a mission failure.

All numerical tests were carried out on an Intel Core-i7 CPU, 3.5 GHz (8 core) desktop workstation with 16MB of memory. The algorithms were coded in Python and run using the Gurobi Optimization program.

The results for all phases including budget, average travel times, and computational times are shown in Table 2.2. The table is categorized by the three phases, with Phase 1 divided into two steps; Phase 1.1 and Phase 1.2, Phase 2, and Phase 3 respectively.

Phases	Budget	Average Travel Time	Computational Time
Phase 1.1			
- Direct pairs	$418,545	14 Minutes	9.7 Seconds
- 1 Loop	$100,800	68 Minutes	402 Seconds
- 2 Loops & 6 venues	$72,000	39 Minutes	21.8 Hours
- 2 Loops & 7 venues	$144,000	32 Minutes	8.2 Days
- 3 Loops & 5 venues	$82,800	27 Minutes	50.9 Hours
Phase 1.2			
- 4 Loops & multiple venues	$82,800	29 Minutes	53.2 Seconds
- 6 Loops & multiple venues	$136,800	24 Minutes	405.4 Seconds
Phase 2			
- 2 Hubs & 1 non-hub	$142,335	25 Minutes	56 Seconds
Phase 3			
- Direct pairs	$153,945	23 Minutes	85 Seconds

Table 2.2 Optimization results for each phase

Phase 1 was created approximately two years before the games and was the foundational work for the bid and remaining phases. The main adjustments were in how we estimated the volume for all loop structures. In Phase 2, we included a proposed athlete travel habit matrix, which proved to be of significant value in our estimation. As in Phase 2, Phase 3 incorporated athlete travel habits, but also the final wishes of the GOC leadership, which resulted in the final adoption. The remaining sub-sections to this topic details the results for the budget, the number of buses used, travel time, and total volume of participants by day.

Observations

Overall Budget

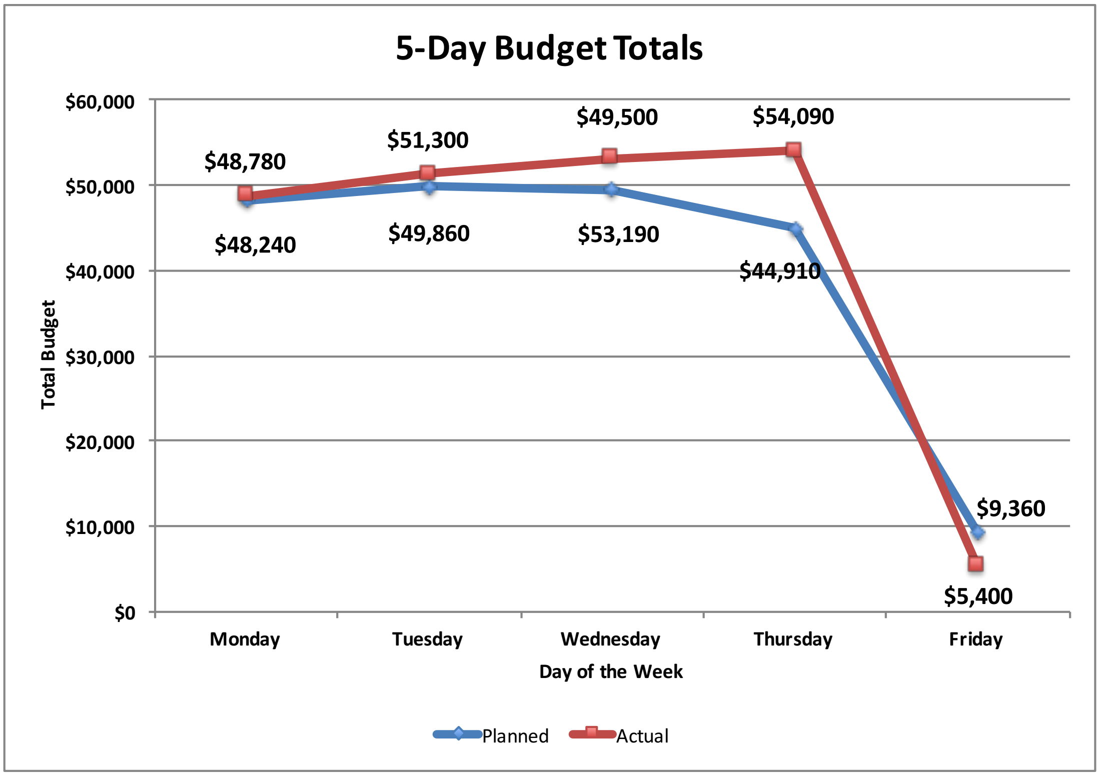

Figure 2.17 5-day budget totals

As previously mentioned, the budget fluctuated frequently, mostly due to donors and corporate sponsors levels of interest, as this was a non-profit event it relied solely on their generosity. As we approached the event, funds began to materialize enabling the GOC to solidify the budget. Regarding the transportation allocation, the GOC established a firm $600K allotment. As depicted in Figure 2.17, we were able to optimize below the budget line five of the eight runs, with a final decision choosing the Phase 3 model.

Travel Time

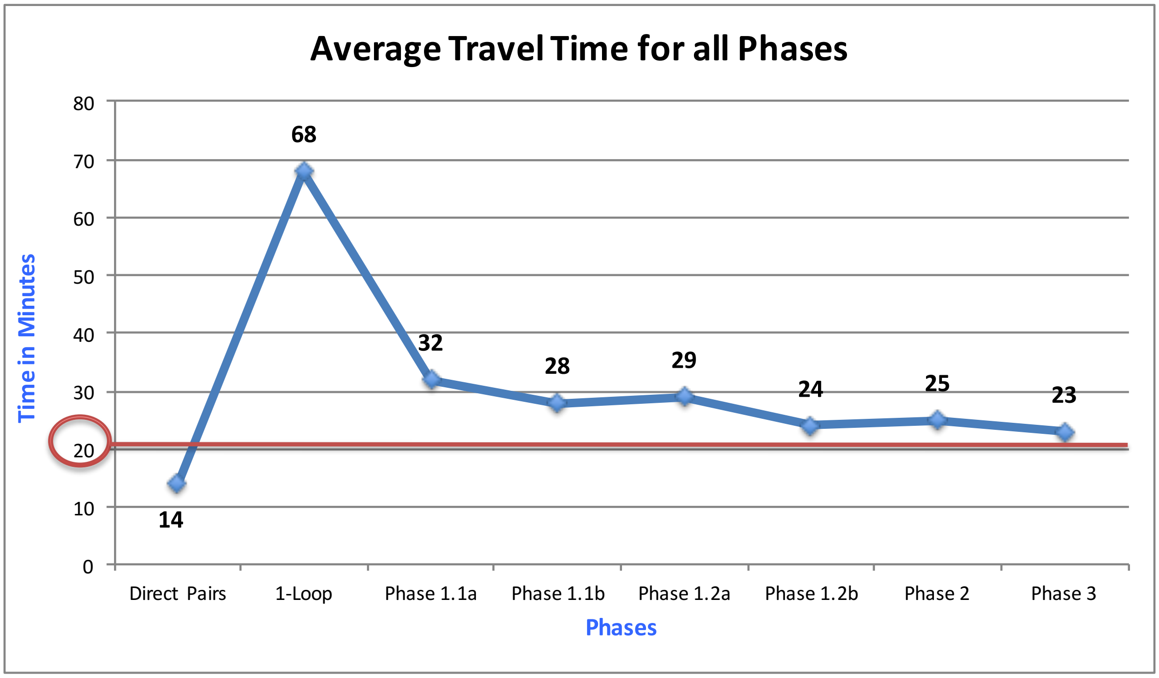

Figure 2.18 Average travel time for all phases

Figure 2.18 explains the average travel time intervals between every venue established during the planning stages. However, during the event, we were able to mark an average travel time of 20 minutes, approximately three minutes better than the planned Phase 3 result.

Our system was implemented by Academy and First Student bus companies and achieved a 100% on time success rate. Specifically, we had:

1. A reliable system resulting in zero competition delays,
2. Zero delays for special events and airport arrivals and departures,
3. Maintained an average of 20-minute intervals to all venues as planned,
4. 100% customer satisfaction (random interviews of 20 athletes and coaches, and observations by several hundred managers at bus stops).

Buses

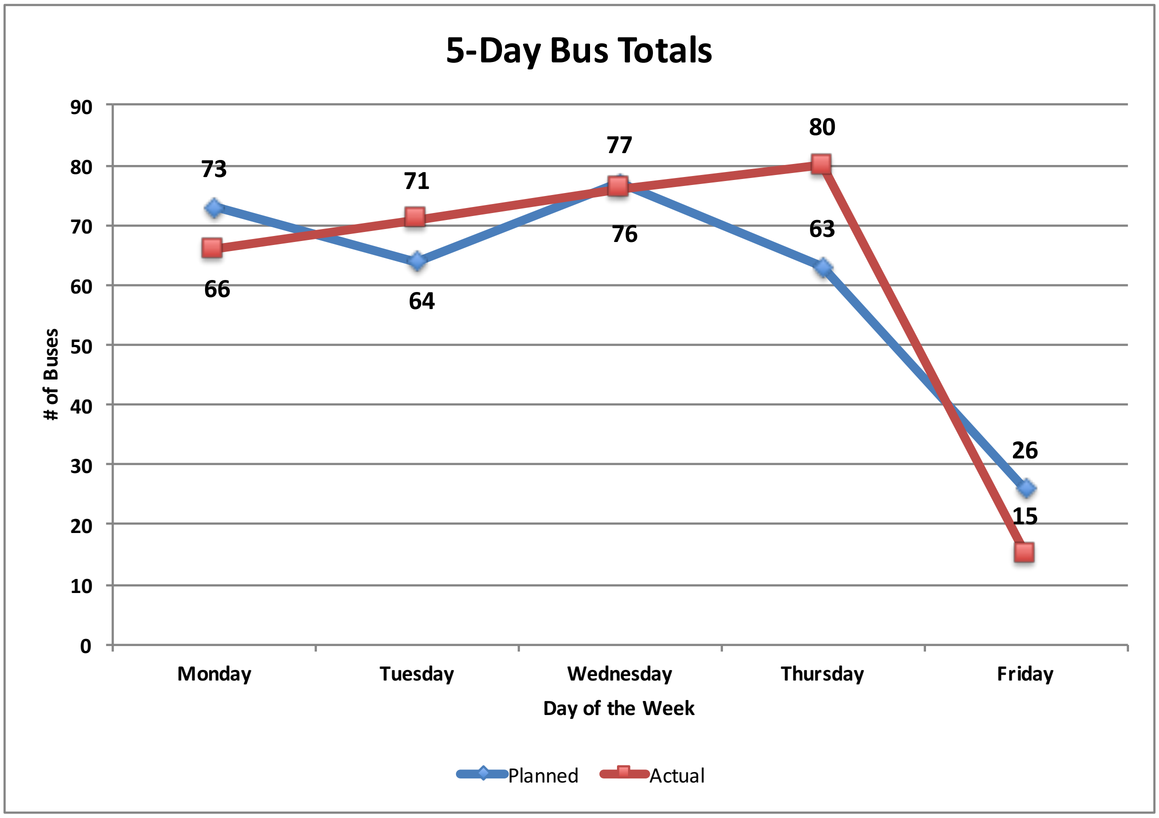

Figure 2.19 5-day bus totals

During the planning stages, we optimized several models to come up with an initial number of buses required to transport athletes and coaches to competition locations, special events, and airport service. We knew this number would more than likely change as additional information was presented, but still need this number to construct a bid to submit to bus companies. We estimated a total need of 64 buses, with an additional 16 buses to manage changes in travel habits and emergency maintenance situations, to handle the demand for the entire week as indicated in Figure 2.19.

Volume

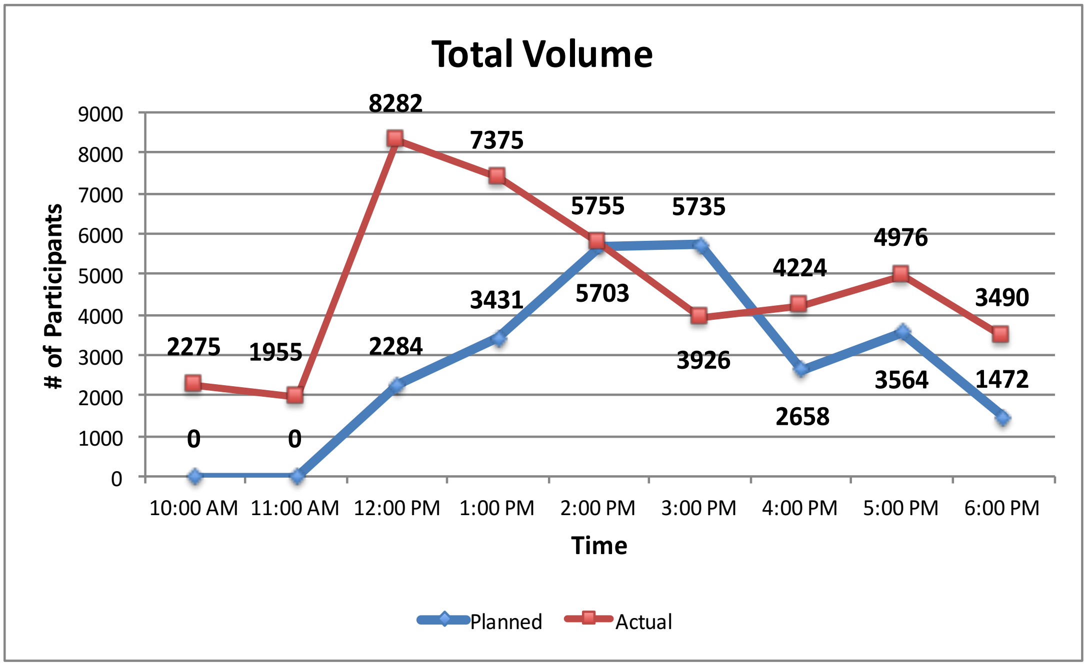

Figure 2.20 Total volume

Figure 2.20 details the stark contrast in the planned volume versus the actual volume of athletes and coaches traveling in the network. We anticipated minimal movement during the hours from 10:00 am to 1:00 pm due to competition and lunch being served at the locations. What we seen was a significant demand increase of 248% from non-hub locations to the two hubs. The reason for this huge increase was delegates who completed morning competition decided to return to their dorms for clean up and to eat lunch at the hub cafeterias. The extra buses pooled at the hub locations proved to be a sound decision as this demand surge was managed efficiently with no change in competition schedules.

2.6.2. Impact

First, the key challenge was not the mathematics and algorithms development, but implementation, and more specifically, how to strike the balance between effectiveness and simplicity. Second, one-time mega events allow no errors and learning during the event, thus one must plan ahead for any unexpected issues. Lastly, information necessary for design wasn't always available in the beginning, and an iterative process of frequent interactions with customers should be expected.

The following lists the key implications for the event;

1. At budget,
2. Minimized wait time at all venues,
3. Can be replicated for us by other mega-type events with a constrained budget,
4. Provided initial financial analysis, and
5. Excellent service level

Interviews

Coaches and Athletes

Timothy Dole (Coach) - Special Olympics Virginia

"I feel that the transportation system in place is adequate, but there has been some glitches. But it's more just because there are so many different moving pieces of that puzzle of these teams trying to get to different places; sometimes it is a struggle between the teams to get on the bus first. It is an adequate system in place; it is more internal that the teams think they have priority over other teams."

Rodney Leath (Coach) - Special Olympics Florida

“The transportation system was adequate and had more than enough buses. They were on time with a gap of like every 15-20 minutes on arrivals, and very helpful.”

Bruce Kelly (Coach) - Special Olympics Arkansas

“Couldn’t have asked for better bus transportation system. Buses were on time and didn’t have to wait.”

Amy Clark (Coach) - Special Olympics North Carolina

“I felt overall the transportation went fairly well. There were some issues I had with my team riding between Rider and Princeton for aquatics. There were plenty of buses, I think where some of the issues came they were trying to fill up the buses before they pulled out and it was hard to determine when to board a bus to get to your destination. I was on time by cushioning myself. You did a good job. Overall, this is an unbelievably huge undertaking.”

Dante White (Olympian) - Special Olympics Florida

“I liked the transportation system. The buses were fast and comfortable. I made all of my competitions on time”.

<u>Leadership</u>

Governor Chris Christie – Governor of New Jersey

“What this event will do, is to place an absolute spotlight on that which makes New Jersey the greatest and that is the human spirit”.

Timothy Shriver – Chairman of Special Olympics Inc.

“New Jersey will use the 10 days to signal to the country that everyone counts”.

Chapter 3

Diagnosis of a Complex Logistics Network

Naval Logistics represents an important facet of mission critical logistics. The US Navy comprises a diversified naval fleet responsible for protecting North America and its allies' global interests. A general problem that the US Navy has encountered is that critical parts, which make up part of the Aegis Ballistic Missile Defense (BMD) System, may malfunction or breakdown during an operation. Because of their low demand nature, the part(s) may not be readily available and can in essence render the vessel non-operational. Thus timely fulfillment of these critical parts is essential while the ship is on deployment. Using data received from the Defense Logistics Agency (DLA) and US Navy, we analyze the demand and fulfillment processes for the US Navy destroyer fleet's BMD platform. We statistically evaluate the current logistics fulfillment performance and identify correlations between the performance and various factors such as demand volume, lead times, order characteristics and traffic, with the objective of detecting the drivers for the performance.

3.1. Literature Review

The Navy uses thousands of different parts to maintain its naval force to ensure mission readiness. In our study, we focus solely on the Aegis BMD System items that make up the Aegis platform (O'Rourke, 2015). We categorized these parts as fast, medium, and slow movers anticipating problem areas regarding on board inventory levels.

3.1.1. Low Demand Parts

Stocking low demand parts can be very expensive and can take up space that otherwise another part could be carried. However, a random failure of one of these parts can cause a system to break down, jeopardizing the mission. Our goal is to develop a balance of parts that a ship would need to satisfy the BMD System while on deployment.

The literature is extant regarding the low demand nature of some parts. (Ghobbar & Friend, 2003) introduce techniques to predict inventory levels for low demand parts in the aviation industry. They devised a new approach to forecasting evaluation, comparing methods based on factor levels when faced with low demand. They also suggest that their findings may be transferrable to other industries with similar demand patterns, in our case naval ships.

The basic forecasting tool in industry for low demand parts is the Croston method (Croston, 1972). This standard tool is incorporated in many statistical packages and separates low demand into two elements; demand size and inter-demand intervals (Teunter, Syntetos, & Zied Babai, 2011). Teunter et al. (2011) propose a new forecasting model that builds upon the Croston method. This new approach for intermittent or low demand is always up-to-date and deals efficiently with obsolescence. Their method also achieves increased flexibility by using different smoothing constants for demand size. Snyder (2002) also builds upon the Croston approach by improving the method and its use in inventory management. The author stresses the need to identify the statistical models for the generation of approximations to the probability of lead time demand, also in the automotive industry.

The categorization of demand patterns is a common method in locating the low demand nature of certain items (Syntetos, Boylan, & Croston, 2005). By separating the demand into distinct sections, we can find potential issues with a set of parts, particularly low demand parts. In this paper, of nearly 5,400 items the Navy requisitioned between 2008 and 2013, 97% were slow moving parts.

The cost of maintaining low demand parts in a warehouse or depot can reach into the millions of dollars. A company who has a strong inventory strategy can potentially advert holding too many of these expensive slow moving items, resulting in reduced inventory holding cost. One approach is to allocate a selection of these parts by pooling them in a handful of locations. Karsten, Slikker, & van Houtum (2012) develop models to address the pooling of low demand parts based on cost. The higher the cost, the more likely the part(s) should be pooled. Our example follows along the same trajectory, in that the items we analyzed, the slow moving parts totaled $3.8M and were distributed among several national and international depots.

3.1.2. Spare Parts Logistics

Spare parts logistics is another important aspect of inventory management. An efficient spare parts program can solidify a company's standing among its competitors and can provide value to its customer base (Wagner, Jönke, & Eisingerich, 2012). A thorough review of spare parts inventory models can be found in (Kennedy, Patterson, & Fredendall, 2002).

As previously discussed, pooling can be an effective process of stocking low demand items in certain a location(s). Another way of stocking spare parts with a low demand nature is by partial pooling these items. Kranenburg & van Houtum (2009) consider networks consisting of several depots stocking expensive parts. They develop several models that match network structures observed in practice and an approximation evaluation method for real-life size instances.

An alternate inventory control approach is the use of transshipments as an intermediate way for maintaining spare parts with low usage. Kukreja, Schmidt, & Miller (2001) and Tagaras & Cohen (1992) develop strategies for dealing with low demand spare parts in multilocation inventory systems. The authors develop heuristics for slow-moving and expensive consumable parts common to multiple locations where pooling can occur. Lead times are also included in their analysis as a significant effect on optimal transshipment policies (Tagaras & Cohen, 1992).

This chapter is organized into two sections. The first section describes the background of the study including the origin of the data, the logistics network structure, and the material flow process. The second section provides the empirical results broken down by phases and implications explained.

3.2. Background

3.2.1. Data

We received from DLA six years of consumption from ships with the Aegis BMD system installed from 2008 to 2013. The dataset included 106,324 individual orders, of which only 54,177 were analyzed due to missing cells. The data consisted of the requisition numbers, ships, dates and quantities for demanded and shipped parts.

We also received a detailed part list including the part number, description of the item, price, administrative lead times (ALT), and production lead times (PLT) which added together provided the total lead time for each stock-keeping unit (SKU). We merged the two datasets using a local database, with the merged data representing the analysis for the study.

3.2.2. Logistics Network Structure

The logistics network structure for DLA and the Navy is diversified and complex with several phases of checks and balances. The complexity of this supply chain network encompasses multiple global vendors, manufacturers, suppliers, warehouses, distribution centers, naval ports, depots, and cargo vessels as seen in Figure 3.1. Each element is comprised of several levels of importance that consist of a specific sequential pull system. The following is an example of the steps taken when a part is demanded on board a ship during a mission. Note all orders regardless of location are backfilled.

1. Part requisitioned and pulled from ship inventory.
2. Part requisitioned in Navy Enterprise Resource Planning system and will begin to search Navy wide for part. Navy will look to the nearest Distribution Center (DC) first. If part is available, the Navy will either fly or transport (via smaller vessel) the part to the demand ship.
3. If part is unavailable, then the Navy will conduct a global DC search. If part is found at another DC, the part is transported via FedEx, UPS, USPS, or a

Government asset to the nearest DC or Port. The Navy will either fly or transport (via smaller vessel) the part to the demand ship.

4. If part is unavailable at another DC, the request is sent to Susquehanna Depot (East Coast Hub) or San Joaquin Depot (West Coast Hub). If part is available, the part is transported via FedEx, UPS, USPS, or a Government asset to the nearest DC or Port. The Navy will either fly or transport (via smaller vessel) the part to the demand ship.
5. If part is unavailable at the Susquehanna or San Joaquin depots, the request is sent to DLA. If part is available at the closest DC to the ship, DLA/Navy will either fly or transport (via smaller vessel) the part to the demand ship.
6. If part is unavailable at closest DC, DLA will check availability at the Germany DC[1]. If part is found at Germany DC, the part is transported via FedEx, UPS, USPS, or a Government asset to the nearest DC or Port. DLA/Navy will either fly or transport (via smaller vessel) the part to the demand ship.
7. If part is unavailable at Germany DC, DLA will conduct a global search. If part is located, it is transported via FedEx, UPS, USPS, or a Government asset to the nearest DC or Port. DLA/Navy will either fly or transport (via smaller vessel) the part to the demand ship.
8. If a replacement cannot be located, then the part will go on backorder.

An added issue with this network structure is the multiple organizations responsible for their own material flow, who seldom cross paths.

---

[1] The Germany DC houses mostly parts for the US Army. However, DLA can pull parts, if available, that could fulfill the US Navy's requirements.

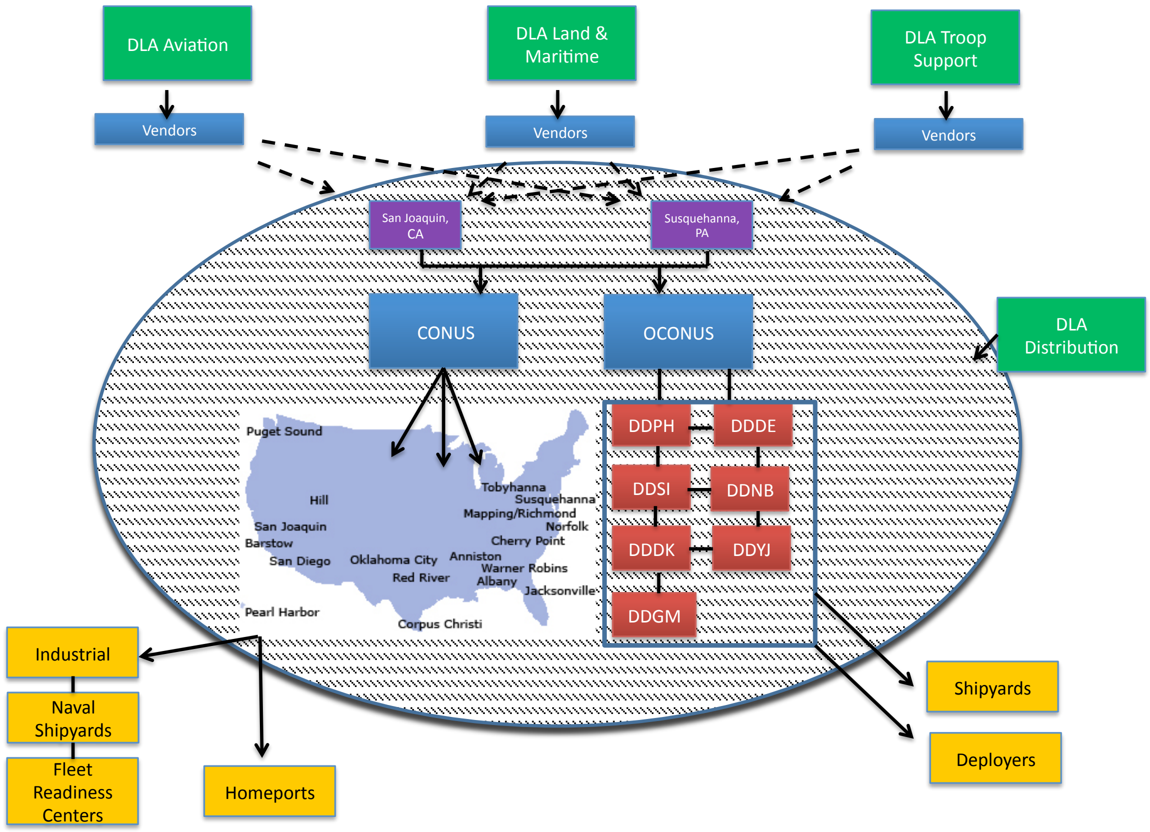

Figure 3.1 Defense Logistics Agency distribution network structure

3.2.3. Material Flow Process

Once a part has been requisitioned and the location of the part identified, the following describes the fulfillment processing time at each phase across the network ("Defense Logistics Agency," 2015). Note that actual days are not represented, as each part will be based on a different transportation priority and criticality level.

1. **Requisition Submission Time:** Elapsed time from the date on the requisition to the date the requisition was received at Transaction Services[2] ("Transaction

[2] Transaction Services designs, develops, and implements logistics solutions that improve customers' requisition processing and logistics management processes worldwide. https://www.transactionservices.dla.mil/daashome/homepage.asp

Services," 2015). Transaction Services compares the requisition date to Transaction Services Receipt Date to determine the lapsed days.

2. **Service Processing Time:** Elapsed time from the transmission of the requisition to the Service by Transaction Services to the re-transmission of the requisition by service back to Transaction Services for routing to the Inventory Control Point (ICP) for fill.
3. **Initial Source Processing Time (ISPT):** Elapsed time from transmission of requisition by Transaction Services to receipt by Transaction Services of supply action (i.e., a material release or issue instruction or a supply status transaction indicating a direct vendor delivery) from the ICP.
4. **Storage Activity Processing Time (Distribution Depot Storage Processing &Transportation Time) (DSST & DTHT):** Elapsed time from receipt at Transaction Services of material release order or DVD to the shipment date shown in a shipment status transaction received by Transaction Services.
5. **Depot to Containerization Point Transportation Time:** Elapsed time from shipment of material from depot to arrival of material at containerization point.
6. **Containerization Point Processing Time (CPT):** Elapsed time from receipt of material by container consolidation point until release of the material by container consolidation point.
7. **CONUS In Transit Time (CIT):** For CONUS (United States territory) customers it is the elapsed time from release of the shipment to the carrier until receipt by the CONUS consignee. For OCONUS (Overseas) Customers it is the elapsed time from release of the shipment to the carrier to receipt at the port of embarkation for

shipments not going through the CCP and the elapsed time from release of the shipment to the carrier to receipt at the container consolidation point for shipments going through the CCP.

8. **Port of Embarkation Processing Time (POET):** Elapsed time from receipt at port of embarkation until lift from the port of embarkation.
9. **In Transit to Theater Time:** Elapsed time from lift at the port of embarkation (ITTT) to receipt at the port of debarkation.
10. **Port of Debarkation Processing Time (PODT):** Elapsed time from the date the material is received at the port of debarkation until lift from the port of debarkation.
11. **In Transit In Theater Time (ITIT):** Elapsed time from release by the port of debarkation until the date the material is received by the consignee.
12. **Receipt Take-Up Time (RTT):** Elapsed time from receipt by the consignee to posting in the consignee's stock records or issue to the ultimate customer indicated by the customer receipt date in the MRA transaction.
13. **Total Pipeline Time (TPT):** Elapsed time from requisition serial date to customer receipt date in the MRA transaction.

3.3. Empirical Results

3.3.1. Phase 1 – Demand Pattern Analysis

Demand pattern analysis investigates customer demand trends across a specific time horizon in order to predict future requirements (De Sensi, Longo, & Mirabelli, 2008). In our study, demand is defined as the time the maintainer submits the requisition in the Navy Enterprise Resource Planning system as detailed in the previous material flow process section. We first analyze the demand pattern for the Naval ships and the BMD parts. We assessed a total of 54,177 requisitions between 2008 and 2013, identifying 5,391 unique part numbers. We post the following research questions for this phase:

1. Which ships are the most troublesome?
2. What are the most demanded parts?
3. Which parts are the fastest and slowest movers?
4. Are there any trends or patterns in demand over time?

Ships

We initially reviewed the data using the Pareto Principle (Pencavel, 2014) to discover if there were a list of ships that would make up most of the demand for the years researched for this project. As shown in Figure 3.2, this principle does not work as the demand is quite evenly distributed among ships. Based on this result, we included the demand and shipped requisitions for all 17 ships, as there wasn't a troublesome list of ships that we could focus on. Figure 3.3 details the class, age and years in service for the ships in this study. The top five ships have an average year in service of 23 years, which possibly could attribute to the high demand based on continued care for older classes. The remaining ships averaged 19 years in operational service. However, note that our demand data is solely based on BMD parts, which only make up a certain portion of total parts for the ships.

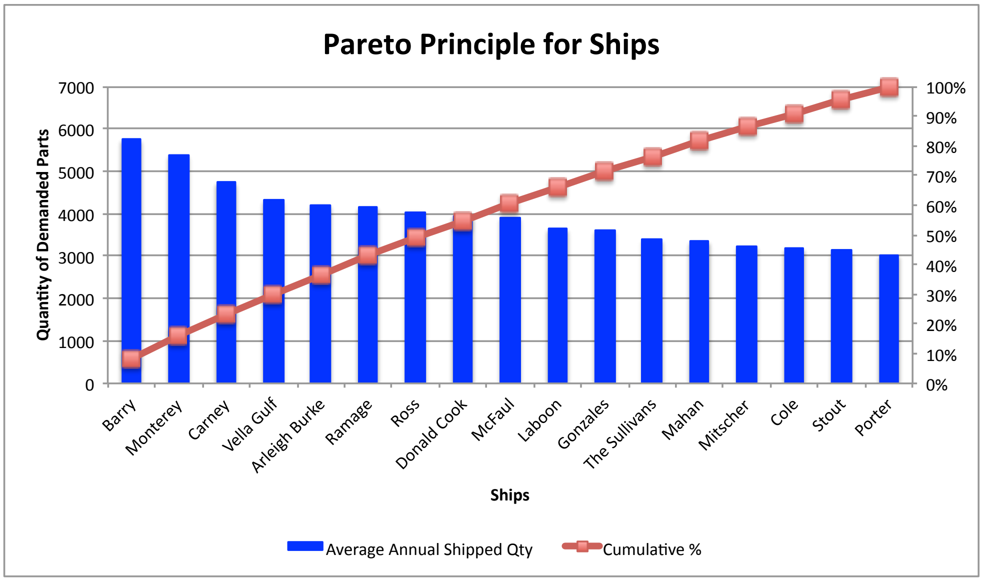

Figure 3.2 Pareto principle for ships

Ship Name	Class	Year Launched	Years in Service
Arleigh Burke	DDG-51	1989	26
Barry	DDG-52	1991	24
Carney	DDG-64	1994	21
Cole	DDG-67	1995	20
Donald Cook	DDG-75	1997	18
Gonzalez	DDG-51	1995	20
Laboon	DDG-58	1993	22
Mahan	DDG-72	1996	19
McFaul	DDG-74	1997	18
Mitscher	DDG-57	1993	22
Monterey	CG-61	1988	27
Porter	DDG-78	1997	18
Ramage	DDG-61	1994	21
Ross	DDG-71	1996	19
Stout	DDG-55	1992	23
The Sullivans	DDG-68	1995	19
Vella Gulf	CG-72	1992	23

Figure 3.3 Ship characteristics

Parts

The next step was to determine if there was a large concentration of demand on a small portion of parts. Again, applying the Pareto Principle we ascertained that this rule does apply in this circumstance as detailed in Figure 3.4. The results indicated that there were

296 out of the total 5,391 parts, approximately 5%, accounted for 80% of the amount demanded. So failures and repairs are heavily focused on a small portion of parts.

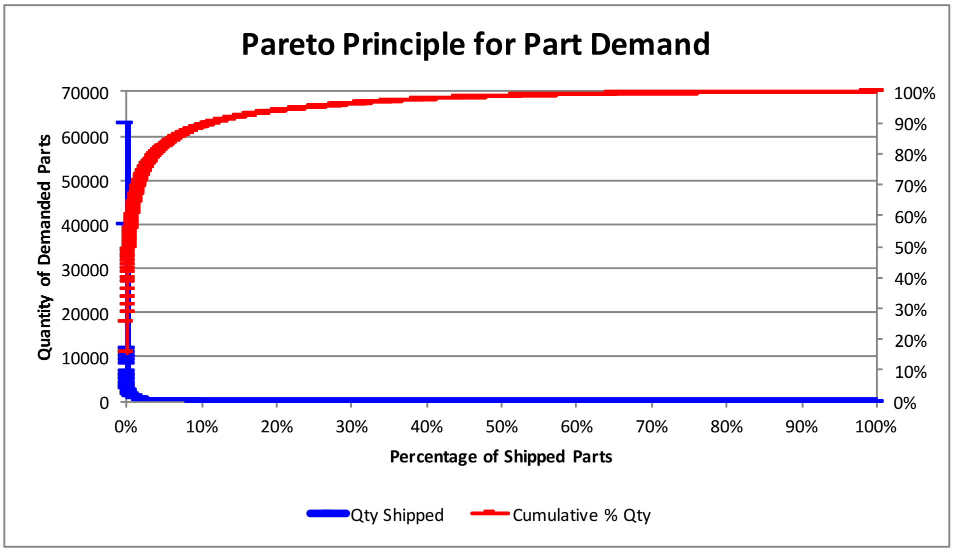

Figure 3.4 Pareto principle for demanded parts

Figures 3.5 and 3.6 detail the highest demanded parts by shipped quantity and number of orders by percentage. This result could possibly assist in knowing which parts and how many would need to be carried while on deployment.

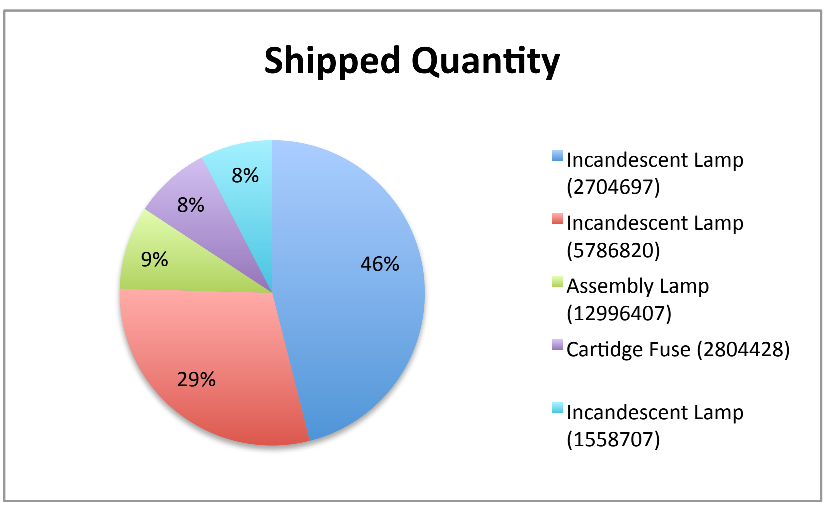

Figure 3.5 Top five demanded parts by shipped quantity

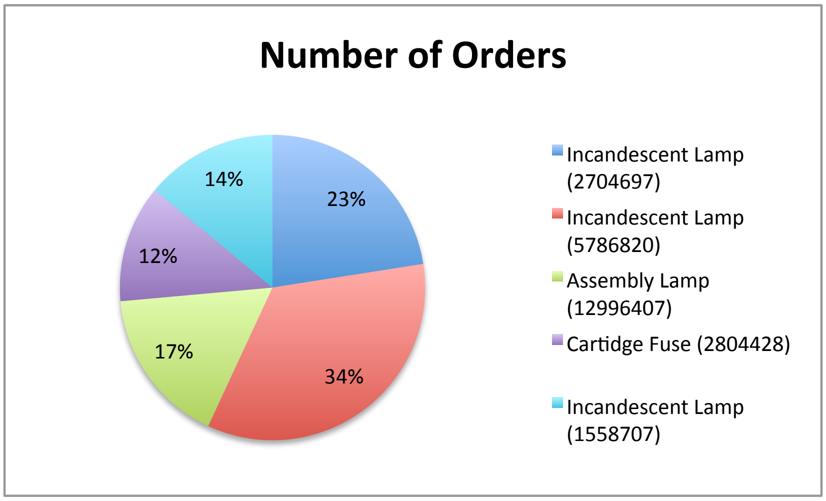

Figure 3.6 Top five demanded parts by number of orders

We were also interested to reveal how quickly parts moved during the fulfillment process. So, we applied the ABC categorization method (Bhattacharya, Sarkar, & Mukherjee, 2007) and apportioned the part numbers into three classes as seen in Figure 3.7. These classes are defined as fast (>120 units a year), medium (<120 and >36 units a year) and slow (<36 units a year). The results show that most, in fact 97% of demanded parts, are slow movers in the supply chain.

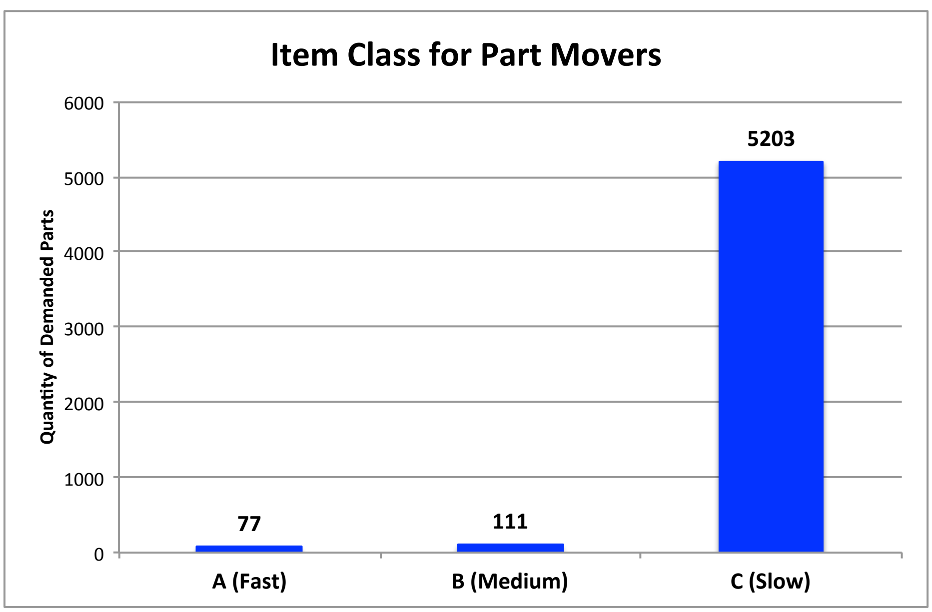

Figure 3.7 ABC categorization methods for demanded parts

Demand trends

The main objectives for this step in the analysis are two-fold: first, to locate high demand time periods by year and month/week which can help in detecting possible causes for long fulfillment times; second, to determine if the annual demand projects a seasonal pattern and or has a specific trend based on fiscal year spending.

Figure 3.8 illustrates by year total demanded and shipped quantities. Based on the results, it is evident the supply system met all requirements even with the huge demand surge in 2012. We speculate the reason for this 67% increase in 2012 from the previous year, was an escalation in mission objectives based on global threats. DLA did confirm our logic but did not provide specific information due to the classification nature of the related events.

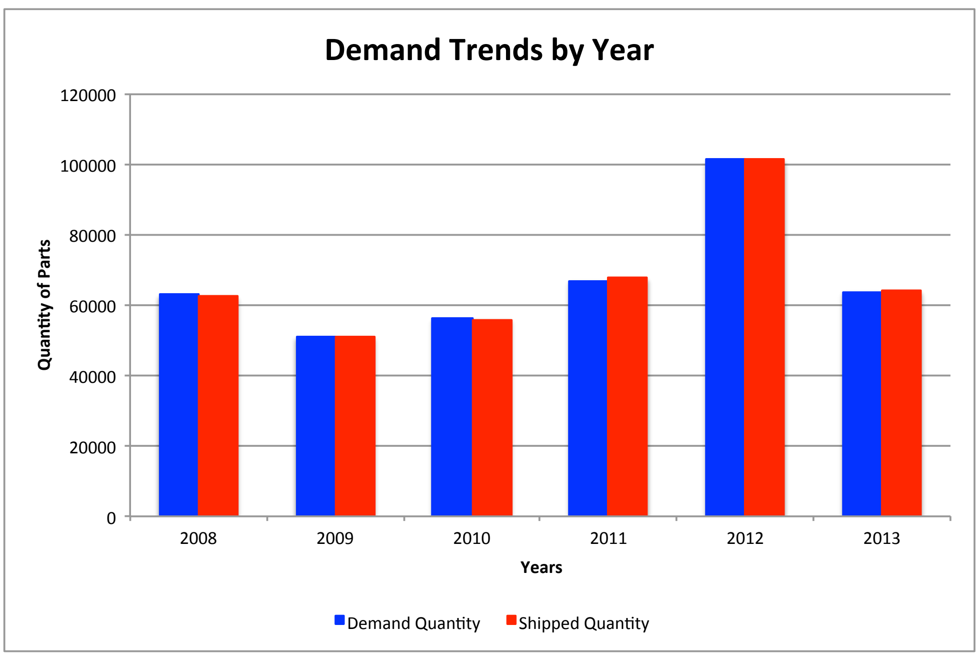

Figure 3.8 Demand trend by years

We then analyzed the demand patterns by month and week to see if there were any indications of seasonality and an end of fiscal year spending trend. The results affirmed that the monthly and weekly demand is erratic and can peak in a certain month, which can change from year to year. Figures 3.9 and 3.10 illustrate that the demand has no clear seasonality and can fluctuate significantly making in very unpredictable.

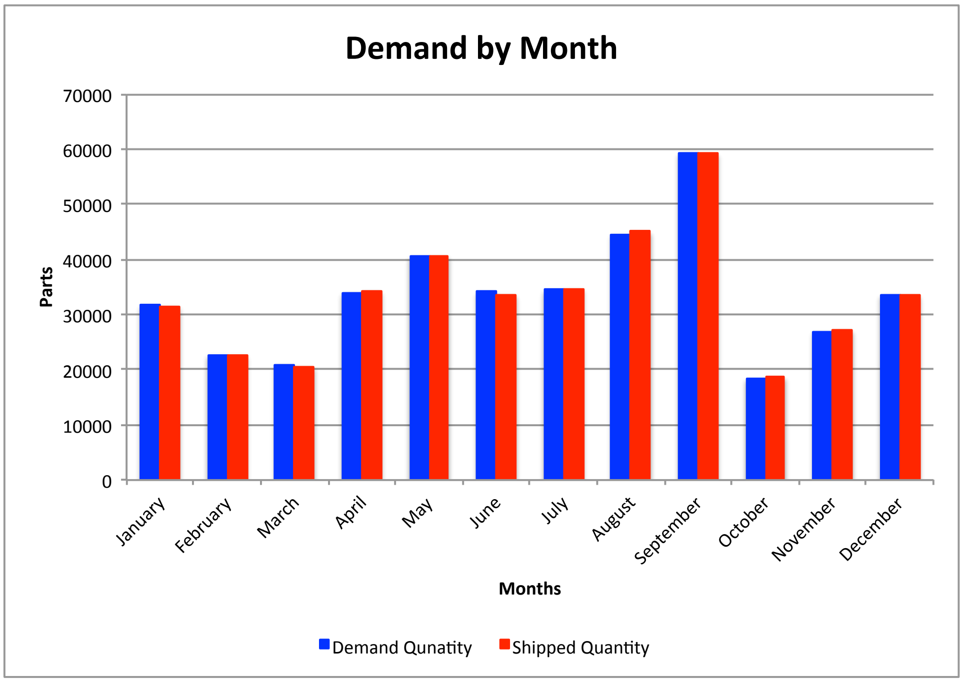

Figure 3.9 Demand trend by month - aggregated by years

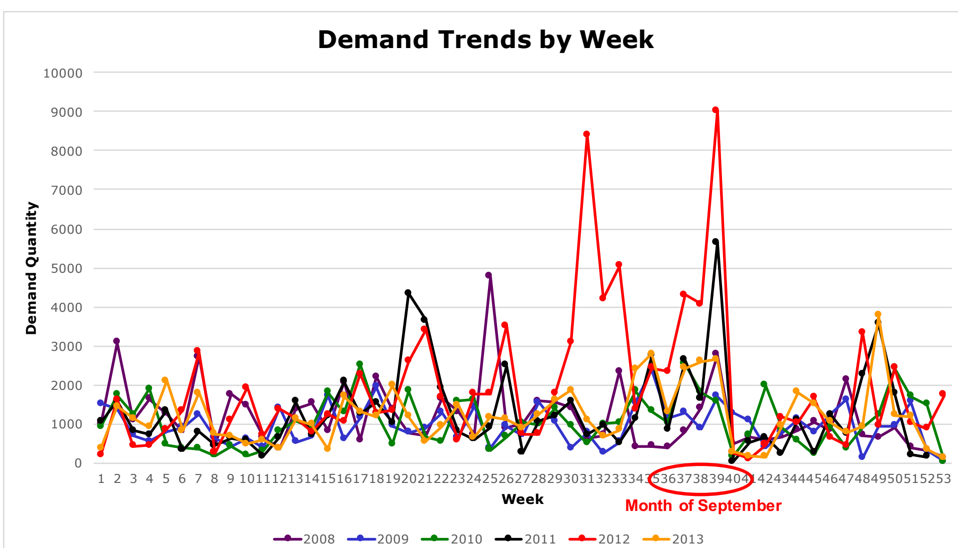

Figure 3.10 Demand trend by week for each individual year

3.3.2. Phase 2 – Supply (Fulfillment) Performance Analysis

The supply fulfillment process goals for DLA are outlined in Figure 3.11. We concentrated our analysis on the fulfillment of routine requisitions within 3 days. This goal includes all parts owned by DLA, which also contains the BMD parts that we are analyzing.

Description	Goal
High Priority Requisitions	85% on time/1 Day
Routine Requisitions	85% on time/3 Days
New Procurement Receipts	
- Tailgate to Induction	90% on time/24 Hours
- Tailgate to Stow	90% on time/7 Days
Customer Return Receipts	
- Tailgate to Induction	90% on time/24 Hours
- Tailgate to Stow	90% on time/10 Days
Denial Rate	0.5%
Location Accuracy	99.5%

Figure 3.11 DLA fulfillment goals

To study the actually fulfillment performance, we first performed a histogram analysis on the fulfillment time of all orders in the 6-year period with bins of 1 (day), 2, …, 180 (days). The overall supply fulfillment performance is shown in Figure 3.12. Based on our findings, the overall fulfillment performance of BMD parts did not meet DLAs service target. The chance of the customer receiving their demanded part the same day was a mere 16.9%. The fulfillment process for the next day and day 3 was 29.9% and 40.8% respectively. To reach the 85% mark, the fulfillment time was 10 weeks, clearly not within the established timeframe.

We then analyzed the fulfillment performance by year to better understand the yearly variation. Figure 3.13 illustrates that fulfillment in years 2011 and 2012 under performed in comparison to the other years of the study. Because of the unusually high demand in these two years, the result may indicate that demand fulfillment performance may be influenced by the overall level of demand.

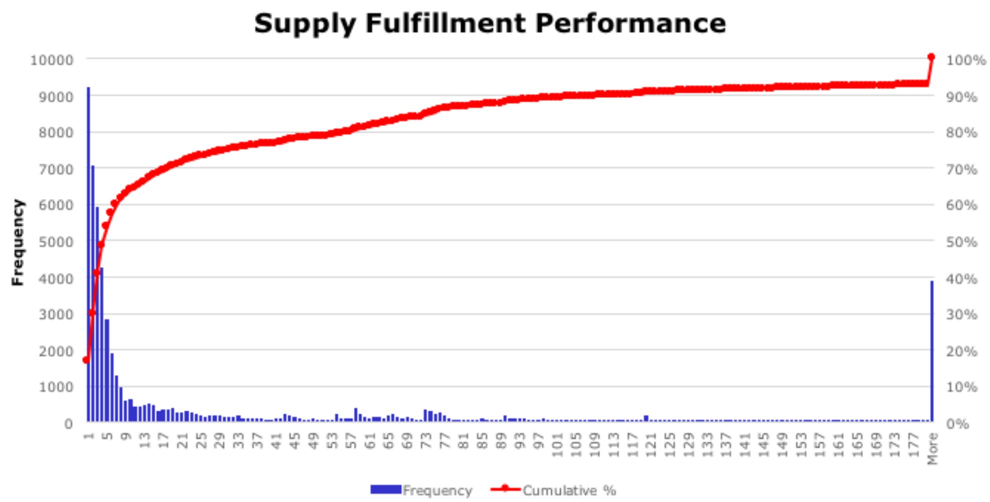

Figure 3.12 Overall supply fulfillment performance

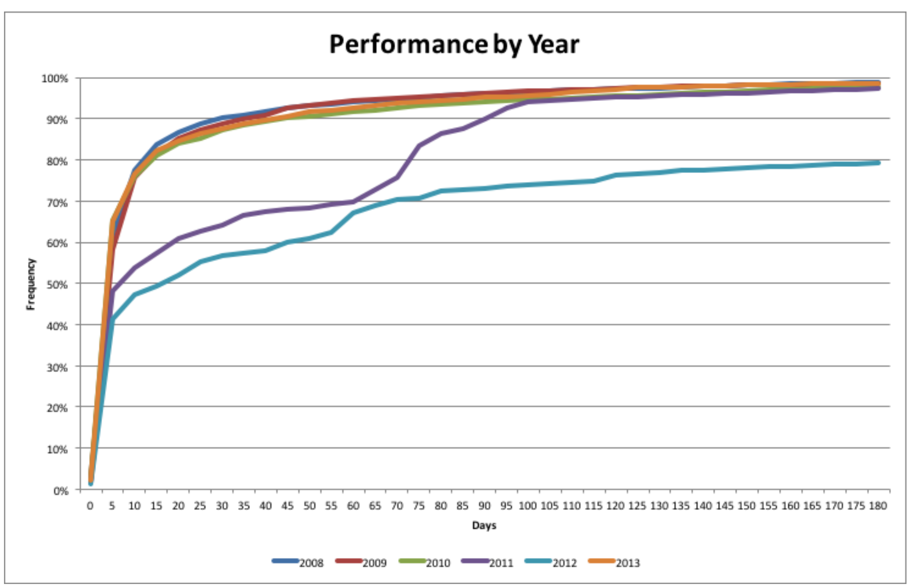

Figure 3.13 Supply fulfillment performance by year

The next step in our fulfillment performance analysis is to detect abnormality by comparing the average and actual fulfillment times with total lead times. As stated previously, the total lead time is the combination of administrative and production lead times for each part, which is supposed to be the longest fulfillment time. We first compared the actual fulfillment time against the total lead time to see if there were any parts that were fulfilled beyond the lead time. We observed that this did occur 8% of the time, which can indicate that inventory status cannot be the only factor influencing fulfillment time and something else must also be driving the fulfillment performance. We also note the fulfillment time can be as long as 1,105 days (Figure 3.14).

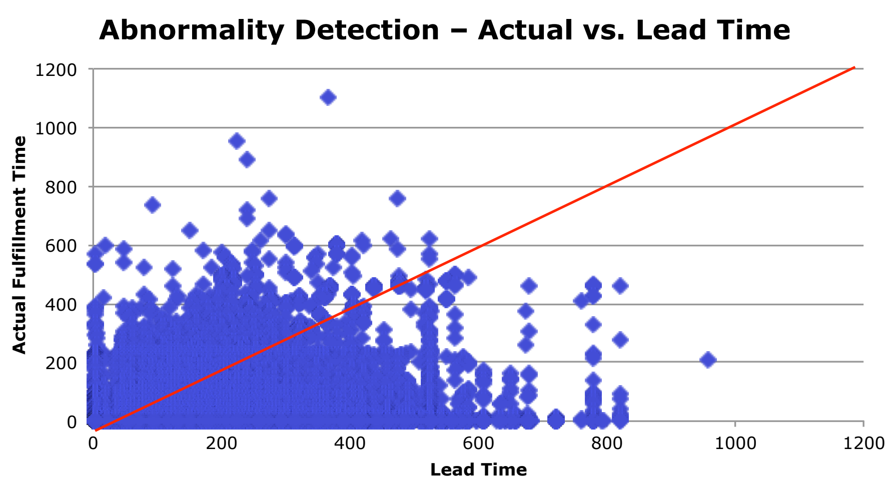

Figure 3.14 Abnormality detection: actual fulfillment time versus total lead time

Figure 3.15 demonstrates that even the average fulfillment time can be greater the than the total lead time. The chance of this occurrence happening is also not rare, occurring 6% of the time.

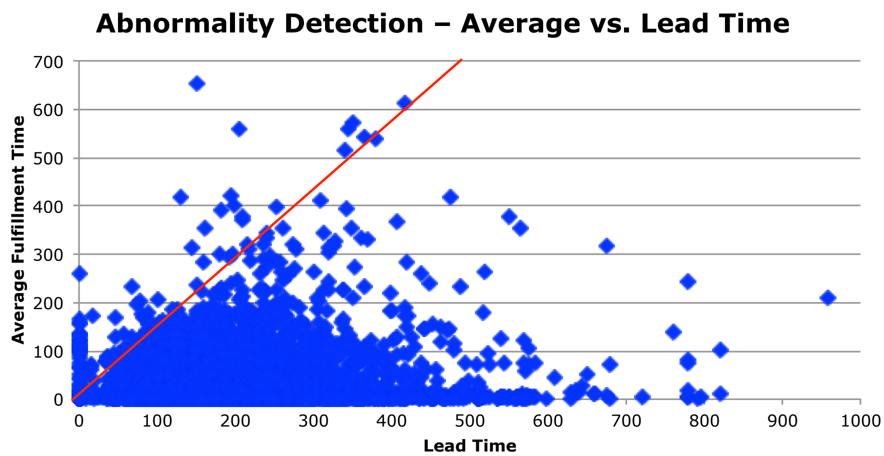

Figure 3.15 Abnormality detection: average fulfillment versus total lead time

3.3.3. Phase 3 – Root Cause Analysis

This research phase seeks to answer the following questions: What drives supply (fulfillment) performance and what fulfillment may depend on? To answer these questions, Root Cause Analysis (RCA) is performed. RCA is a method of problem solving that strives to identify the root causes of faults or problems (Blickstein, Nemfakos, & Sollinger, 2013; Kumar & Schmitz, 2011; Vidyasagar, 2015).

To conduct the analyses, we frame several specific questions:

1. Fulfillment versus demand volume → do fast movers have quicker fulfillment?
2. Fulfillment versus order size → does larger order size result in slower fulfillment (i.e., longer time to fulfill)?
3. Fulfillment versus lead time & price → does the longer lead time or higher price bring longer fulfillment time?
4. Fulfillment versus traffic → does higher traffic (i.e., greater number of orders being processed) induce slower fulfillment time?

Using fulfillment data of all orders placed in the 6-year period, we attempt to answer each question by testing the relationships between fulfillment time and various variables on demand volume, order characteristics, lead time and traffic, for validity and reliability to perceive if the variables had an impact on fulfillment time:

1. **Fulfillment versus demand volume: slow versus fast movers**

   Figure 3.16 plots the sum of demanded quantity over the 6-year period versus the average fulfillment. It shows that there is a reverse relationship between fulfillment time and mean demand, implying that fast movers have quicker fulfillment and slow movers can have a much longer and more unpredictable fulfillment time. As a result, we found that inventory may play an important role here.

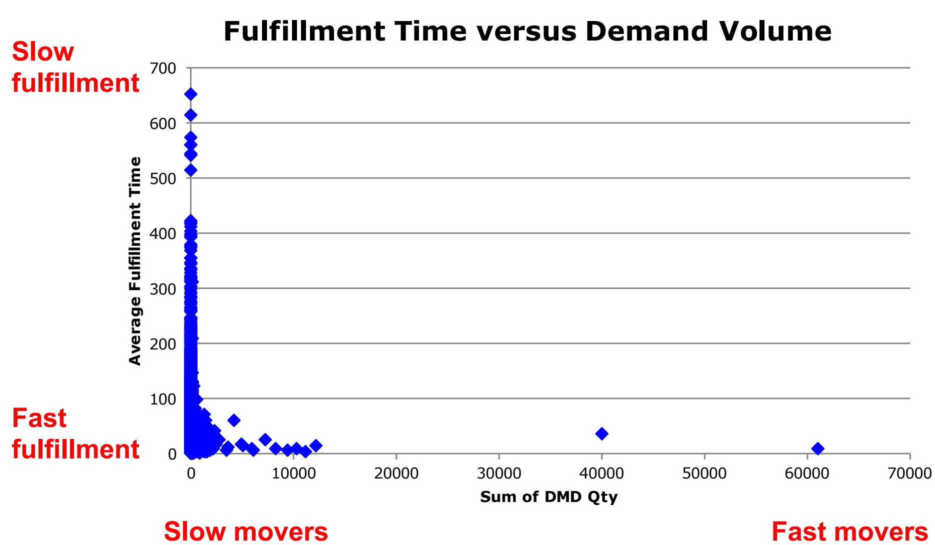

Figure 3.16 Fulfillment time versus demand volume

2. **Fulfillment versus order size: larger order size**

   To find out the relationship between fulfillment time (days) and order size (quantity) of individual orders, we performed a regression analysis between them.

The results indicate a nearly zero correlation and the corresponding R^2 is 0.00345. So, the inference is that the fulfillment time is independent of the order size.

3. **Fulfillment versus lead time & price: longer lead time, higher price:**

   The regression between average fulfillment time (by part) and lead time and price of the part was conducted and revealed that there exists little correlation between them and R^2 in the regression test is 0.0167. Thus the deduction is drawn that the lead time and price have little impact on fulfillment.

4. **Fulfillment versus traffic: higher traffic (greater number of orders being processed with a certain period of time)**

   Lastly, the regression between average fulfillment time and the number of orders placed per week (note that 53 observations were used, which is aggregated data over 6 years) was conducted, and the results show that there is a high correlation between the variables, R^2 = 56.6%, slope = 0.0288, and p-value = 5E-11. Hence, the implication is that supply processing capacity can be a significant factor driving fulfillment time. The slope indicates that on average, 100 more orders/week increases fulfillment time by 2.8 days.

Figure 3.17 compares the number of orders in a certain week and their average fulfillment time. It shows a clear correlation between fulfillment time and the traffic variable. Also, the line fit plot (Figure 3.18) shows that the model that predicts fulfillment time based on traffic matches the actual fulfillment time quite well.

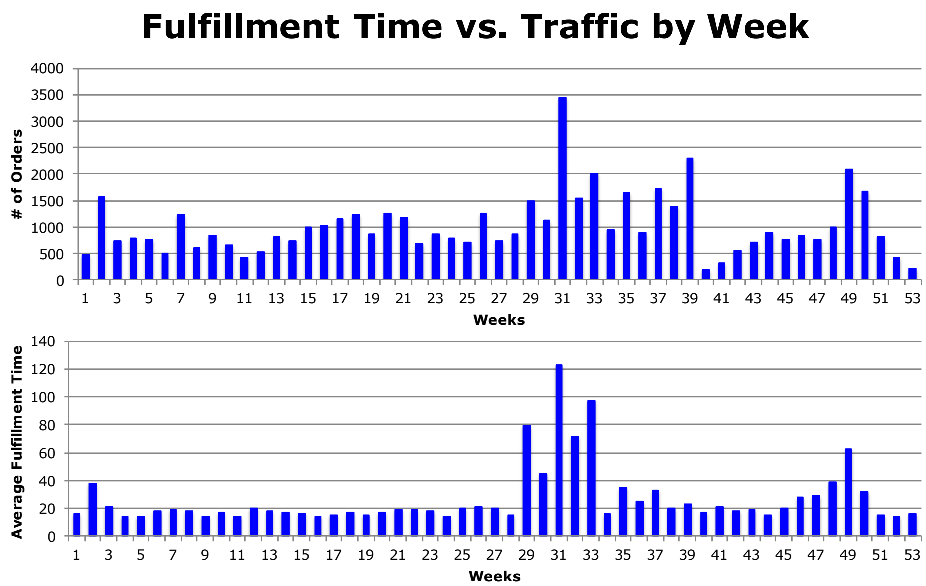

Figure 3.17 Fulfillment time versus traffic by week

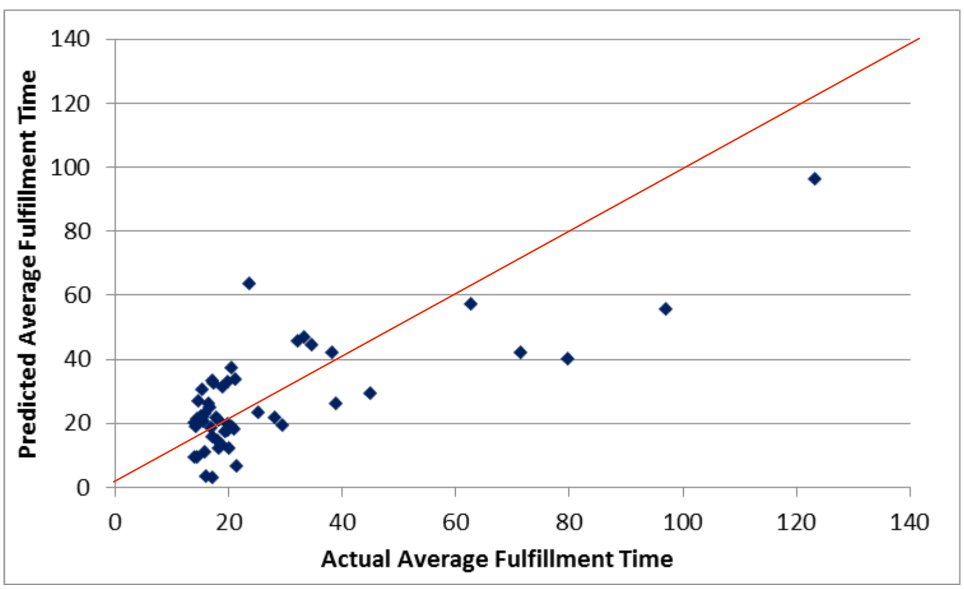

Figure 3.18 Actual fulfillment time line fit plot

Figure 3.19 plots the average and standard deviation of fulfillment times against the number of orders in a week (the traffic variable). We make two findings: first, both the average and standard deviation of fulfillment time tend to increase as traffic increases. Second, the fact that the standard deviation of fulfillment time is larger than the average means highly random fulfillment times were observed. In summary, our statistical analysis strongly indicates that the root causes for the underperforming fulfillment are related to inventory issues and traffic (supply processing capacity limits).

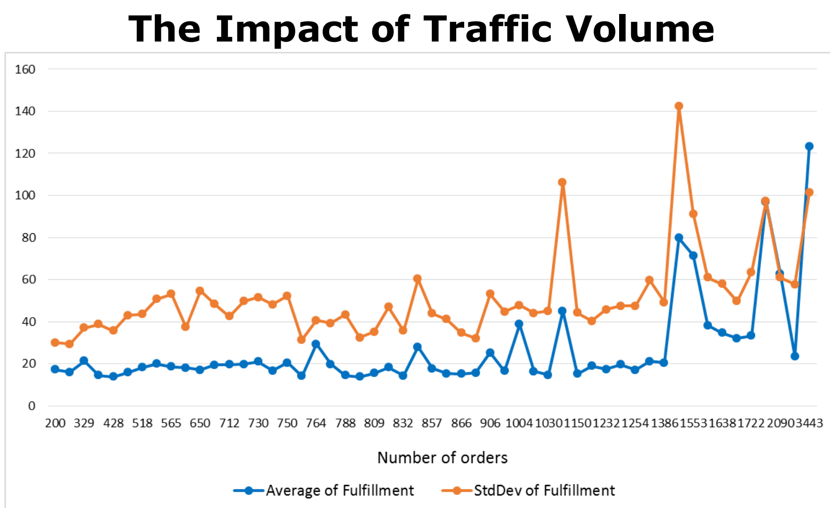

Figure 3.19 The impact of traffic volume

Chapter 4

Conclusion and Future Research

The overall goal of this dissertation is to link games transportation and naval logistics under the umbrella of the mission critical logistics using supply chain optimization techniques. To review, mission critical logistics focuses on the timing of product and service availability in the supply network. Unlike an organization that places emphasis on the bottom line, the lack of an item or service could possibly only affect their revenue stream. In our example, the absence of either a ship part or a bus service could possibly result in mission failure.

The first essay reviewed the research stream relating to games transportation. We first provided background information of Special Olympics and highlighted the non-existent historical data from previous Special Olympics games. We then defined the problem, emphasized the multiple challenges associated with a mega-event like the 2014 USA Games, estimated the costs required to operate the transportation network, and listed the schedules for the week’s event. Next, we proposed and assessed the efficiency of the three-phase solution methodology for solving volume estimation, choices of loops, number of buses, and the daily bus driver schedule. We then implemented the transportation plan by establishing risk management and contingency plans, as well as working with the bus company operation managers in the Main Operation Center during the games. Finally, we provided the results of the transportation network by explaining the differences between our initial plan and the actual scheme carried out for the week.

The objective of the second essay was to diagnose the complex DLA and Navy supply chain network and identify potential root causes for the underperforming fulfillment process.

In Phase 1, our demand pattern analysis of the 17 ships and 50,000 plus orders shows that the demand for spare parts come quite evenly from all ships, but only a small portion of parts accounted for 80% of the demand. We found erratic surges in certain years and months, which are hardly predictable in advance. We found no evidence of seasonality but hypothesize that end of fiscal and calendar year spending does transpire in all years studied.

Phase 2 examined the overall supply fulfillment performance for DLA and found it fell short by far the established service goals, especially during the years with higher demand than others. We also found that the average and actual fulfillment times can be much greater than the average expected total lead time, indicating that issues other than inventory status may have an impact on fulfillment.

In Phase 3, we evaluated possible root causes to the under performing fulfillment performance we found in Phase 2. Our data analysis shows that fulfillment time strongly depends on demand volume by parts and weekly total traffic volume, implying the driving force of inventory management and processing capacity behind the fulfillment processes. However, the fulfillment time does not depend on order size, part price, and total lead times.

This dissertation is the first attempt at analyzing the BMD data and attempting to define the underlying issues associated with fulfillment for the Aegis platform. The next logical step will be to develop inventory control strategies for not only the low demand parts that the Navy uses for their BMD ships, but defining the criticality of some of these low usage parts as not all items need to be immediately available in the ship warehouse.

DLA and the Navy want to include, in the next step, every BMD ship to better understand the demand on the parts used for this system. They also would like the focus to be on one region instead of the multiple locations they are deployed and operate in. One important region that is receiving a great deal of exposure is in the Mediterranean Sea (Figure 3.20). The distribution center located in this region is NAS Sigonella and will be included in this study. We will compare the inventory levels for this DC and those ships who are operating in this region to attempt to strike a balance between the critical parts on board and those that can be stocked at the DC.

We will extend our current research with two additional phases. In Phase 4, we will compare our inventory suggestions with the Navy's standard policies by developing algorithms and models not only for the ships, but also for the distribution centers. In Phase 5 we will outline a cost structure for the Navy's deployment time, attempting to quantify the strategic value of this asset, and define the risk of not being located in the designated region due to a non-stocked item upon failure.

Figure 4.1 Mediterranean operations

Appendices

Appendix 1 – TCNJ Competition and Special Event Schedules

SHUTTLE SCHEDULE: FROM THE COLLEGE OF NEW JERSEY

SPECIAL OLYMPICS 2014 USA GAMES

		SUNDAY	MONDAY	TUESDAY	WEDNESDAY	THURSDAY	FRIDAY
SPORT	LOCATION	HOURS	HOURS	HOURS	HOURS	HOURS	HOURS
Aquatics	Princeton University	6:30am – 9:00am	6:30am – 5:00pm	6:30am – 6:00pm	6:30am – 4:00pm	6:30am – 10:00pm	7:30am – 2:00pm
Athletics	Princeton University	6:30am – 9:00am	6:00am – 1:30pm	6:30am – 6:00pm	6:30am – 4:00pm	6:30am – 10:00pm	
Baseball	Mercer County Park		6:30am – 3:30pm	6:30am – 3:00pm	6:30am – 3:00pm	3:00pm – 10:00pm	
Basketball	Rider University		6:45am – 5:00pm**	6:45am – 2:30pm**	6:45am – 10:00pm**	6:45am – 4:00pm**	6:45am – 1:30pm**
Basketball	The Hun School		6:30am – 6:00 PM	6:30am – 3:00pm	6:30am – 3:00pm	6:30am – 4:30pm	6:30am – 1:30pm
Bocce	The College of New Jersey						
Bowling	Brunswick Zone – Carolier		6:30am – 12:30pm*	6:30am – 12:30pm*	6:30am – 12:30pm*	6:30am – 12:30pm*	
Cycling	Skillman Park		7:00am – 1:00pm*	7:00am – 2:00pm*	7:00am – 1:00pm*	7:00am – 1:00pm*	
Flag Football	The Lawrenceville School		6:30am – 4:30pm	6:30am – 3:00pm	6:30am – 10:00pm	6:30am – 6:00pm	
Golf	Mercer Oaks Golf Club		6:30am – 3:30pm	6:30am – 3:30pm	6:30am – 3:00pm		
Gymnastics	Peddie School		10:15am – 3:30pm*	7:45am – 4:00pm*	7:45am – 1:00pm*	10:15am – 9:00pm*	
Powerlifting	The College of New Jersey						
Soccer	Mercer County Park		6:30am –10:00pm	6:30am – 6:00pm	6:30am – 5:00pm	6:30am – 2:00pm	6:30am – 1:00pm
Softball	Mercer County Park		6:30am – 4:00pm	6:30am – 10:00pm	6:30am – 3:30pm	6:30am – 6:00pm	
Tennis	Mercer County Park	6:30am – 9:00am	6:30am – 2:30pm	6:30am – 3:00pm	6:30am – 5:00pm	6:30am – 5:00pm	
Triathlon	Mercer County Park			9:00am – 1:00pm	4:30pm – 9:00pm		
Volleyball	Rider University		6:45am – 2:30pm**	6:45am – 10:00pm**	6:45am – 5:30pm**	6:45am – 4:30pm**	6:45am – 12:00pm**
SPECIAL EVENT							
Opening Ceremony	Prudential Center	12:00pm – 9:00pm*					
Closing Ceremony	Sun National Bank Center						5:00p.m. – 10:00pm*
Olympic Town	The College of New Jersey						
Dinner Cruise			3:30pm – 11:00pm*	3:30pm – 11:00pm*	3:30pm – 11:00pm*	3:30pm – 11:00pm*	
Trenton Thunder	Arm & Hammer Park		5:30pm – 10:00pm***	5:30pm – 10:00pm***	5:30pm – 10:00pm***	5:30pm – 10:00pm***	

SHUTTLES RUN EVERY 20 MINUTES UNLESS NOTED.

* Remains at location until competition is over.
** TCNJ to Rider Shuttle: runs continuously from 6:45am – 10:00pm Sunday – Thursday and 6:30am – 4:00pm on Friday.
*** Shuttle will begin at the top of the 4th inning.

Appendix 2 – Rider Competition and Special Event Schedules

SHUTTLE SCHEDULE: FROM RIDER UNIVERSITY

SPECIAL OLYMPICS 2014 USA GAMES

		SUNDAY	MONDAY	TUESDAY	WEDNESDAY	THURSDAY	FRIDAY
SPORT	LOCATION	HOURS	HOURS	HOURS	HOURS	HOURS	HOURS
Aquatics	Princeton University	6:30am – 9:00am	6:30am – 5:00pm	6:30am – 6:00pm	6:30am – 4:00pm	6:30am – 10:00pm	7:30am – 2:00pm
Athletics	Princeton University	6:30am – 9:00am	6:00am – 1:30pm	6:30am – 6:00pm	6:30am – 4:00pm	6:30am – 10:00pm	
Baseball	Mercer County Park		6:30am – 3:30pm	6:30am – 3:00pm	6:30am – 3:00pm	3:00pm – 10:00pm	
Basketball	The College of New Jersey		6:45am – 4:00pm**	6:45am – 2:30pm**	6:45am – 8:30pm**	6:45am – 4:00pm**	6:45am – 1:00pm**
Basketball	The Hun School		6:30am – 6:00pm	6:30am – 3:00pm	6:30am – 3:00pm	6:30am – 4:30pm	6:30am – 1:30pm
Bocce	The College of New Jersey		6:45am – 2:30pm**	6:45am – 10:00pm**	6:45am – 4:30pm**	6:45am – 4:30pm**	
Bowling	Brunswick Zone – Carolier		6:30am – 12:30pm*	6:30am – 12:30pm*	6:30am – 12:30pm*	6:30am – 12:30pm*	
Cycling	Skillman Park		7:00am – 1:00pm*	7:00am – 2:00pm*	7:00am – 1:00pm*	7:00am – 1:00pm*	
Flag Football	The Lawrenceville School		6:30am – 4:30pm	6:30am – 3:00pm	6:30am – 10:00pm	6:30am – 6:00pm	
Golf	Mercer Oaks Golf Club		6:30am – 3:30pm	6:30am – 3:30pm	6:30am – 3:00pm		
Gymnastics	Peddie School		10:15am – 3:30pm*	7:45am – 4:00pm*	7:45am – 1:00pm*	10:15am – 9:00pm*	
Powerlifting	The College of New Jersey	6:45am– 11:00am**	6:45am – 6:30pm**	6:45am – 6:30pm**		6:45am – 10:00pm**	6:45am – 2:00pm**
Soccer	Mercer County Park		6:30am – 10:00pm	6:30am – 6:00pm	6:30am – 5:00pm	6:30am – 2:00pm	6:30am – 1:00pm
Softball	Mercer County Park		6:30am – 4:00pm	6:30am – 10:00pm	6:30am – 3:30pm	6:30am – 6:00pm	
Tennis	Mercer County Park	6:30am – 9:00am	6:30am – 2:30pm	6:30am – 3:00pm	6:30am – 5:00pm	6:30am – 5:00pm	
Triathlon	Mercer County Park			9:00am – 1:00pm	4:30pm – 9:00pm		
Volleyball	Rider University						
SPECIAL EVENT							
Opening Ceremony	Prudential Center	12:00pm – 9:00pm*					
Closing Ceremony	Sun National Bank Center						5:00pm – 10:00pm*
Olympic Town	The College of New Jersey		3:00pm – 10:00pm**	3:00pm – 10:00pm**	3:00pm –10:00pm**	3:00pm – 10:00pm**	9:00am – 1:00pm**
Dinner Cruise	Hoboken, NJ		3:30pm – 11:00pm*	3:30pm – 11:00pm*	3:30pm – 11:00pm*	3:30pm – 11:00pm*	
Trenton Thunder	Arm & Hammer Park		5:30pm – 10:00pm***	5:30pm – 10:00pm***	5:30pm – 10:00pm***	5:30pm – 10:00pm***	

SHUTTLES RUN EVERY 20 MINUTES UNLESS NOTED.

* Remains at location until competition is over.

** TCNJ to Rider Shuttle: runs continuously from 6:45am – 10:00pm Sunday – Thursday and 6:30am – 4:00pm on Friday.

*** Shuttle will begin at the top of the 4th inning.

Appendix 3 – SO2014 Genetic Algorithm Technical Design

1. Gene coding

   In the one hub case, it was natural to design the gene as 0132457890. The transportation plan required multiple loops as well as, a gene should contain multiple loops. We used 0 as the separator between loops in a gene. This gene contains two loops: 12012340567189045, the loops are 012340 and 05671890. Each loop in a gene must start with 0 and end with 0. A gene is was valid only if it visited all the venues in its loops and each loop visited a venue at most once.

Examples:

- 12**0**1234**0**5671**0**45 effective part: **0**1234**0**5671**0**, two loops, not valid because 8 and 9 are missing,
- **0**1**0**234**0**5678971**0**45 effective part: **0**1**0**234**0**5678971**0**, three loops, not valid because loop **0**5678971**0** visits 7 twice,
- **0**568971**0**1256**0**34**0** effective part: **0**568971**0**1256**0**34**0**, three loops, valid

2. Initialization

   a. Generate a permutation of 1~9. Sample: 134567289
   b. Randomly select two permutations and combine with **0** as the separator between them.
   c. Repeat until the population reaches the pre-selected population size.

Example:

- 134567289 and 154367289 -> 01345672890154367289O

3. Fitness function

When open, a point-to-point transportation system between each pair of venues, we have had the minimal average transit time $T_{\min}$. For each gene, we extracted the transportation plan and computed the average transit time T_{avg} . The fitness function was then calculated by F= 1/($T_{avg} - T_{\min}$).

4. Crossover

Crossover is a three-step procedure.

<u>Step 1</u>: Randomly select two genes (parents). This random selection process is followed by proportional-probabilities system (roulette system) using the fitness of each gene.

<u>Step 2</u>: We now have two parents on hand from Step 1. There is a probability of Pc that the crossover will happen. Generate a random number p, if p<Pc, then go to Step 3, else directly return the two parents as children.

<u>Step 3</u>: Crossover between the two parents: randomly an index number, switch the genes of parents at this index, save as children. REFINE the two children, check whether they are valid. If valid, return the two children else redo Step 3

REFINE a gene: after the crossover or mutation, the gene may become invalid because of redundant visits within a loop and thus needs to be refined. Given a gene, first find its effective part, then for each loop, check the redundancy. If a venue is visited multiple times, keep the first visit and remove all other visits and append them to the end of the gene. For example:

- 12**0**1234546789**0** -> 12**0**123456789**0**4
- **0**12123456789**0**1234**0** -> **0**123456789**0**1234**0**12

5. Mutation

   After the crossover, we have the group of children. For each child, perform mutation procedures. The mutation is a two-step procedure.

   - Generate a random number p, if p<Pm, then go to Step 2, else return.
   - Generate two random indices, and switch the genes at these two indices. REFINE and check whether the new gene is valid. If valid, return the new gene, else redo Step 2.

Divide the day into cycles, from 6:30 am to 6:00 pm, each cycle is 15 minutes. Assume each loop visit 0, venue i, 1 and finally return to 0. The number of dedicated buses in the morning is B_{max}.

Appendix 4 – Athlete Travel Habits

	Monday	Tuesday	Wednesday	Thursday	Friday
Aquatics	N	N	N	N	N
Athletics	N	N	N	N	N
Baseball	N	N	N	N	N
Basketball	N	N	M	M	N
Bocce	N	N	N	M	N
Bowling	N	N	Y	N	N
Cycling	N	N	N	M	N
Flag Football	N	N	N	M	N
Golf	N	N	N	M	N
Gymnastics	N	N	M	N	N
Power Lifting	N	N	Y	M	N
Soccer	N	N	N	M	N
Softball	N	N	N	M	N
Tennis	N	N	N	M	N
Triathlon	N	N	N	Y	N
Volleyball	N	N	N	M	N

Yes =	Y
No =	N
Maybe =	M

Appendix 5 - Driver schedule

Driver	Hub	Venue	Start	End	Hours
1	Rider	Princeton	10:30 AM	1:30 PM	4
2	Rider	Princeton	12:40 AM	5:00 PM	5
3	Rider	Princeton	1:10 PM	4:30 PM	4
4	Rider	Princeton	1:10 PM	4:30 PM	4
5	Rider	Princeton	12:40 PM	5:00 PM	5
6	Rider	Lawrenceville School	11:52 AM	3:30 PM	4
7	Rider	Mercer Park	2:00 PM	5:12 PM	4
8	Rider	Mercer Park	2:30 PM	5:42 PM	4
9	Rider	Mercer Park	2:00 PM	5:12 PM	4
10	Rider	Mercer Golf	3:00 PM	6:24 PM	4
11	Rider	Mercer Golf	3:00 PM	6:24 PM	4
12	Rider	Mercer Golf	3:30 PM	6:54 PM	4
13	Rider	Mercer Golf	3:30 PM	6:54 PM	4
14	Rider	HUN	4:30 PM	7:52 PM	4
15	Rider	HUN	5:00 PM	8:22 PM	4
16	Rider	HUN	5:00 PM	8:22 PM	4

Driver	Hub	Venue	Start	End	Hours
1	TCNJ	Princeton	1:30 PM	4:48 PM	4
2	TCNJ	Princeton	1:00 PM	4:18 PM	4
3	TCNJ	Princeton	1:00 PM	4:18 PM	4
4	TCNJ	Princeton	1:30 PM	4:48 PM	4
5	TCNJ	Princeton	1:30 PM	4:48 PM	4
6	TCNJ	Princeton	1:00 PM	4:18 PM	4
7	TCNJ	Lawrenceville School	12:50 PM	4:26 PM	4
8	TCNJ	Lawrenceville School	3:00 PM	6:36 PM	4
9	TCNJ	Mercer Park	12:18 PM	3:30 PM	4
10	TCNJ	Mercer Park	11:48 PM	3:00 PM	4
11	TCNJ	Mercer Park	11:48 PM	3:00 PM	4
12	TCNJ	Mercer Park	12:48 PM	4:00 PM	4
13	TCNJ	Mercer Park	12:18 PM	3:30 PM	4
14	TCNJ	Mercer Park	12:48 PM	4:00 PM	4
15	TCNJ	Mercer Golf	3:30 PM	6:52 PM	4
16	TCNJ	Mercer Golf	13:38 pm	5:00 PM	4

Bibliography

Achuthan, N. R., & Caccetta, L. (1998). Capacitated vehicle routing problem: Some new cutting planes. *Asia-Pacific Journal of Operational Research, 15*(1), 109.

Alfredo Tang Montané, F., & Galvão, R. D. (2006). A tabu search algorithm for the vehicle routing problem with simultaneous pick-up and delivery service. *Computers & Operations Research, 33*(3), 595-619.

Antony Arokia Durai Raj, K., & Rajendran, C. (2012). A genetic algorithm for solving the fixed-charge transportation model: Two-stage problem. *Computers & Operations Research, 39*(9), 2016-2032.

Applegate, D. L., Bixby, R. E., Chvátal, V., & Cook, W. J. (2006). *The Traveling Salesman Problem*: Princeton Univeristy Press.

Atkins, F. (2012). The Taxicab Problem. *Business in Calgary, 22*(8), 12-12.

Baker, B. M., & Ayechew, M. A. (2003). A genetic algorithm for the vehicle routing problem. *Computers & Operations Research, 30*(5), 787-800.

Baker, K. R., & Magazine, M. J. (1977). Workforce Scheduling with Cyclic Demands and Day-off Constraints. *Management Science, 24*(2), 161-167.

Baldacci, R., Mingozzi, A., Roberti, R., & Calvo, R. W. (2013). An Exact Algorithm for the Two-Echelon Capacitated Vehicle Routing Problem. *Operations Research, 61*(2), 298-314.

Bandyopadhyay, A., & Sajadi, F. (2014). On the Nearest-neighbor Algorithm for the Mean-field Traveling Salesman Problem. *Journal of Applied Probability, 51*(1), 106-117.

Beaumont, N. (1997). Scheduling staff using mixed integer programming. *European Journal of Operational Research, 98*(3), 473-484.

Behdani, B., & Cole Smith, J. (2014). An Integer-Programming-Based Approach to the Close-Enough Traveling Salesman Problem. *INFORMS Journal on Computing, 26*(3), 415-432.

Beis, D. A., Loucopoulos, P., Pyrgiotis, Y., & Zografos, K. G. (2006). PLATO Helps Athens Win Gold: Olympic Games Knowledge Modeling for Organizational Change and Resource Management. *Interfaces, 36*(1), 26-42.

Bhattacharya, A., Sarkar, B., & Mukherjee, S. K. (2007). Distance-based consensus method for ABC analysis. *International Journal of Production Research, 45*(15), 3405-3420.

Bianchessi, N., & Righini, G. (2007). Heuristic algorithms for the vehicle routing problem with simultaneous pick-up and delivery. *Computers & Operations Research, 34*(2), 578-594.

Bixby, A., Downs, B., & Self, M. (2006). A Scheduling and Capable-to-Promise Application for Swift & Company. *Interfaces, 36*(1), 69-86.

Blaser, R., & Wilber, J. (2013). A comparison of human performance in figural and navigational versions of the traveling salesman problem. *Psychological Research, 77*(6), 761-772.

Blickstein, I., Nemfakos, C., & Sollinger, J. M. (2013). Digging Out the Root Cause: Nunn-McCurdy Breaches in Major Defense Acquisition Programs. *Defense Acquisition Research Journal: A Publication of the Defense Acquisition University, 20*(2), 128-153.

Boyd, S., Sitters, R., Ster, S., & Stougie, L. (2014). The traveling salesman problem on cubic and subcubic graphs. *Mathematical Programming, 144*(1/2), 227-245.

Cattaruzza, D., Absi, N., Feillet, D., & Vigo, D. (2014). An iterated local search for the multi-commodity multi-trip vehicle routing problem with time windows. *Computers & Operations Research, 51*, 257-267.

Cheung, R. K., & Hang, D. D. (2003). Multi-attribute label matching algorithms for vehicle routing problems with time windows and backhauls. *IIE Transactions, 35*(3), 191.

Chu, P. C., & Beasley, J. E. (1997). A genetic algorithm for the generalised assignment problem. *Computers & Operations Research, 24*(1), 17.

Crispim, J., & Brandão, J. (2005). Metaheuristics applied to mixed and simultaneous extensions of vehicle routing problems with backhauls. *Journal of the Operational Research Society, 56*(11), 1296-1302.

Croston, J. (1972). Forecasting and stock control for intermittent demand. *Operational Research Quarterly, 23*, 289-304.

De Leone, R., Festa, P., & Marchitto, E. (2011). Solving a bus driver scheduling problem with randomized multistart heuristics. *International Transactions in Operational Research, 18*(6), 707-727.

De Sensi, G., Longo, F., & Mirabelli, G. (2008). Inventory policies analysis under demand patterns and lead times constraints in a real supply chain. *International Journal of Production Research, 46*(24), 6997-7016.

Defense Logistics Agency. (2015). Retrieved from http://www.dla.mil/Pages/ataglance.aspx

Derigs, U., Gottlieb, J., Kalkoff, J., Piesche, M., Rothlauf, F., & Vogel, U. (2011). Vehicle routing with compartments: applications, modelling and heuristics. *OR Spectrum, 33*(4), 885-914.

Derigs, U., & Kaiser, R. (2007). Applying the attribute based hill climber heuristic to the vehicle routing problem. *European Journal of Operational Research, 177*(2), 719-732.

Desrochers, M., Desrosiers, J., & Solomon, M. (1992). A New Optimization Algorithm for the Vehicle Routing Problem with Time Windows. *Operations Research, 40*(2), 342.

Dethloff, J. (2002). Relation between vehicle routing problems: an insertion heuristic for the vehicle routing problem with simultaneous delivery and pick-up applied to the vehicle routing problem with backhauls. *Journal of the Operational Research Society, 53*(1), 115.

Dias, T. G., de Sousa, J. P., & Cunha, J. F. (2002). Genetic algorithms for the bus driver scheduling problem: a case study. *Journal of the Operational Research Society, 53*(3), 324.

Duhamel, C., Potvin, J.-Y., & Rousseau, J.-M. (1997). A Tabu Search Heuristic for the Vehicle Routing Problem with Backhauls and Time Windows. *Transportation Science, 31*(1), 49-59.

Feng, H.-M., & Liao, K.-L. (2014). Hybrid evolutionary fuzzy learning scheme in the applications of traveling salesman problems. *Information Sciences, 270*, 204-225.

Garaix, T., Artigues, C., Feillet, D., & Josselin, D. (2010). Vehicle routing problems with alternative paths: An application to on-demand transportation. *European Journal of Operational Research, 204*(1), 62-75.

Ghobbar, A. A., & Friend, C. H. (2003). Evaluation of forecasting methods for intermittent parts demand in the field of aviation: a predictive model. *Computers & Operations Research, 30*(14), 2097.

Giveen, S. M. (1963). A Taxicab Problem With Time-Dependent Arrival Rates. *SIAM Journal on Computing, Vol. 5*(No.2), 119-127.

Goel, A., & Gruhn, V. (2008). A General Vehicle Routing Problem. *European Journal of Operational Research, 191*(3), 650-660.

Gounaris, C. E., Wiesemann, W., & Floudas, C. A. (2013). The Robust Capacitated Vehicle Routing Problem Under Demand Uncertainty. *Operations Research, 61*(3), 677-693.

Hai, Y., Min, Y., Wilson Hon-Chung, T., & Sze Chun, W. (2005). A Multiperiod Dynamic Model of Taxi Services with Endogenous Service Intensity. *Operations Research, 53*(3), 501-515.

Heung-Suk, H. (2002). An improved model for vehicle routing problem with time constraint based on genetic algorithm. *Computers & Industrial Engineering, 42*(2-4), 361.

Jeon, G., Leep, H. R., & Shim, J. Y. (2007). A vehicle routing problem solved by using a hybrid genetic algorithm. *Computers & Industrial Engineering, 53*(4), 680-692.

Jin, J., Crainic, T. G., & Løkketangen, A. (2012). A parallel multi-neighborhood cooperative tabu search for capacitated vehicle routing problems. *European Journal of Operational Research, 222*(3), 441-451.

Jin, J., Crainic, T. G., & Løkketangen, A. (2014). A cooperative parallel metaheuristic for the capacitated vehicle routing problem. *Computers & Operations Research, 44*, 33-41.

Karabulut, K., & Fatih Tasgetiren, M. (2014). A variable iterated greedy algorithm for the traveling salesman problem with time windows. *Information Sciences, 279*, 383-395.

Karsten, F., Slikker, M., & van Houtum, G.-J. (2012). Inventory pooling games for expensive, low-demand spare parts. *Naval Research Logistics, 59*(5), 311-324.

Kecskeméti, B., & Bilics, A. (2013). Bus driver duty optimization using an integer programming and evolutionary hybrid algorithm. *Central European Journal of Operations Research, 21*(4), 745-755.

Kennedy, W. J., Patterson, J. W., & Fredendall, L. D. (2002). An overview of recent literature on spare parts inventories. *International Journal of Production Economics, 76*(2), 201-215.

Kranenburg, A. A., & van Houtum, G. J. (2009). A new partial pooling structure for spare parts networks. *European Journal of Operational Research, 199*(3), 908-921.

Kukreja, A., Schmidt, C. P., & Miller, D. M. (2001). Stocking Decisions for Low-Usage Items in a Multilocation Inventory System. *Management Science, 47*(10), 1371-1383.

Kumar, S., & Schmitz, S. (2011). Managing recalls in a consumer product supply chain - root cause analysis and measures to mitigate risks. *International Journal of Production Research, 49*(1), 235-253.

Lau, H. C., Sim, M., & Teo, K. M. (2003). Vehicle routing problem with time windows and a limited number of vehicles. *European Journal of Operational Research, 148*(3), 559.

Liping, Z. (2006). A Heuristic Method for Analyzing Driver Scheduling Problem. *IEEE Transactions on Systems, Man & Cybernetics: Part A, 36*(3), 521-531.

Liu, R., Jiang, Z., & Geng, N. (2008). A hybrid genetic algorithm for the multi-depot open vehicle routing problem. *OR Spectrum, 36*(2), 401-421.

Lourenço, H. R., Paixão, J. P., & Portugal, R. (2001). Multiobjective Metaheuristics for the Bus Driver Scheduling Problem. *Transportation Science, 35*(3), 331.

Lysgaard, J., & Wøhlk, S. (2014). A branch-and-cut-and-price algorithm for the cumulative capacitated vehicle routing problem. *European Journal of Operational Research, 236*(3), 800-810.

Martello, S., & Toth, P. (1986). A heuristic approach to the bus driver scheduling problem. *European Journal of Operational Research, 24*(1), 106-117.

Meng, L., & Zhou, X. (2014). Simultaneous train rerouting and rescheduling on an N-track network: A model reformulation with network-based cumulative flow variables. *Transportation Research: Part B, 67*, 208-234.

Minis, I., & Tatarakis, A. (2011). Stochastic single vehicle routing problem with delivery and pick up and a predefined customer sequence. *European Journal of Operational Research, 213*(1), 37-51.

Mladenović, N., Todosijević, R., & Urošević, D. (2014). Two level General variable neighborhood search for Attractive traveling salesman problem. *Computers & Operations Research, 52*, 341-348.

Mosheiov, G. (1994). The Travelling Salesman Problem with pick-up and delivery. *European Journal of Operational Research, 79*(2), 299-310.

Mu, Q., & Eglese, R. (2013). Disrupted capacitated vehicle routing problem with order release delay. *Annals of Operations Research, 207*(1), 201-216.

Nia, S. G., Sharif, B., Habibzadeh, N., & Rezvani, M. (2011). Using the Genetic Algorithm for Optimization of the Integrated Urban Transportation Systems. *Journal of Technology Management for Growing Economies, 2*(1), 103-113.

NVR Ships (2015). Retreived from http://www.nvr.navy.mil

O'Rourke, R. (2015). Navy Aegis Ballistic Missile Defense (BMD) Program: Background and Issues for Congress. Retrieved from http://www.crs.gov

Orr, D. (1969). The 'Taxicab Problem': A Proposed Solution. *Journal of Political Economy, 77*(1), 141.

Paias, A., & Paixão, J. (1993). State space relaxation for set covering problems related to bus driver scheduling. *European Journal of Operational Research, 71*(2), 303-316.

Palhazi Cuervo, D., Goos, P., SÃrensen, K., & ArrÃ!iz, E. (2014). An iterated local search algorithm for the vehicle routing problem with backhauls. *European Journal of Operational Research, 237*(2), 454-464.

Park, J., & Kim, B.-I. (2010). The school bus routing problem: A review. *European Journal of Operational Research, 202*(2), 311-319.

Pencavel, J. (2014). The changing size distribution of U.S. trade unions and its decsriptioin by pareto's distribution. *Industrial & Labor Relations Review, 67*(1), 138-170.

Pop, P. C., Matei, O., Sitar, C. P., & Chira, C. (2010). *A Genetic Algorithm for Solving the Generalized Vehicle Routing Problem* (Vol. 6077): Springer Berlin Heidelberg.

Potvin, J.-Y., Garcia, B.-L., & Rousseau, J.-M. (1996). The Vehicle Routing Problem with Time Windows -- Part I: Tabu Search. *INFORMS Journal on Computing, 8*(2), 158.

Rieck, J., & Zimmermann, J. (2013). Exact Solutions to the Symmetric and Asymmetric Vehicle Routing Problem with Simultaneous Delivery and Pick-Up. *Business Research, 6*(1), 77-92.

Rodríguez, A., & Ruiz, R. (2012). A study on the effect of the asymmetry on real capacitated vehicle routing problems. *Computers & Operations Research, 39*(9), 2142-2151.

Salhi, S., Wassan, N., & Hajarat, M. (2013). The Fleet Size and Mix Vehicle Routing Problem with Backhauls: Formulation and Set Partitioning-based Heuristics. *Transportation Research: Part E, 56*, 22-35.

Savelsbergh, M. W. P., & Sol, M. (1995). The General Pickup and Delivery Problem. *Transportation Science, 29*(1), 17.

Sheridan, P. K., Gluck, E., Guan, Q., Pickles, T., Balcıog˜lu, B., & Benhabib, B. (2013). The dynamic nearest neighbor policy for the multi-vehicle pick-up and delivery problem. *Transportation Research Part A: Policy & Practice, 49*, 178-194.

Snyder, R. (2002). Forecasting sales of slow and fast moving inventories. *European Journal of Operational Research, 140*(3), 684-699.

Song, X., Hao, J., Huo, L. I., & Li, B. (2012). Study on Crew Scheduling Model for the Passenger Dedicated Line. *International Journal of Pattern Recognition & Artificial Intelligence, 26*(3), -1.

Special Olympics, Inc. (2015). Retrieved from http://www.specialolympics.org/mission.aspx

Special Olympics: Our Athletes. (2014). Retrieved from http://www.specialolympics.org/athletes.apsx

Sungur, I., Ordóñez, F., & Dessouky, M. (2008). A robust optimization approach for the capacitated vehicle routing problem with demand uncertainty. *IIE Transactions, 40*(5), 509-523.

Swihart, M. R., & Papastavrou, J. D. (1999). A stochastic and dynamic model for the single-vehicle pick-up and delivery problem. *European Journal of Operational Research, 114*(3), 447-464.

Syntetos, A., Boylan, J., & Croston, J. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society, 56*(5), 495-503.

Sörensen, K., & Schittekat, P. (2013). Statistical analysis of distance-based path relinking for the capacitated vehicle routing problem. *Computers & Operations Research, 40*(12), 3197-3205.

Tagaras, G., & Cohen, M. A. (1992). Pooling in two-location inventory systems with non-negligible replenishment lead times. *Management Science, 38*(8), 1067-1083.

Taillard, É., Badeau, P., Gendreau, M., Guertin, F., & Potvin, J.-Y. (1997). A Tabu Search Heuristic for the Vehicle Routing Problem with Soft time Windows. *Transportation Science, 31*(2), 170.

Tavakkoli-Moghaddam, R., Gazanfari, M., Alinaghian, M., Salamatbakhsh, A., & Norouzi, N. (2011). A new mathematical model for a competitive vehicle routing problem with time windows solved by simulated annealing. *Journal of Manufacturing Systems, 30*(2), 83-92.

Taş, D., Jabali, O., & Van Woensel, T. (2014). A Vehicle Routing Problem with Flexible Time Windows. *Computers & Operations Research, 52*, 39-54.

Teunter, R. H., Syntetos, A. A., & Zied Babai, M. (2011). Intermittent demand: Linking forecasting to inventory obsolescence. *European Journal of Operational Research, 214*(3), 606-615.

Toriello, A., Haskell, W. B., & Poremba, M. (2014). A Dynamic Traveling Salesman Problem with Stochastic Arc Costs. *Operations Research, 62*(5), 1107-1125.

Toth, P., & Vigo, D. (1997). An Exact Algorithm for the Vehicle Routing Problem with Backhauls. *Transportation Science, 31*(4), 372.

Toth, P., & Vigo, D. (2002). *The Vehicle Routing Problem* (Vol. 1): Society for Industrial and Applied Mathematics.

Transaction Services. (2015). Retrieved from https://www.transactionservices.dla.mil/daashome/homepage.asp

Urban, K.-P. (2006). A guided simulated annealing search for solving the pick-up and delivery problem with time windows and capacity constraints. *International Journal of Logistics: Research & Applications, 9*(4), 369-381.

Varelas, T., Archontaki, S., Dimotikalis, J., Turan, O., Lazakis, I., & Varelas, O. (2013). Optimizing Ship Routing to Maximize Fleet Revenue at Danaos. *Interfaces, 43*(1), 37-47.

Vidyasagar, A. (2015). The Art of Root Cause Analysis. *Quality Progress, 48*(2), 64-64.

Wagner, S. M., Jönke, R., & Eisingerich, A. B. (2012). A Strategic Framework for Spare Parts Logistics. *California Management Review, 54*(4), 69-92.

Wang, Z., Guo, J., Zheng, M., & Wang, Y. (2015). Uncertain multiobjective traveling salesman problem. *European Journal of Operational Research, 241*(2), 478-489.

Wassan, N. (2007). Reactive tabu adaptive memory programming search for the vehicle routing problem with backhauls. *Journal of the Operational Research Society, 58*(12), 1630-1641.

Xie, F., & Jia, R. (2012). Nonlinear fixed charge transportation problem by minimum cost flow-based genetic algorithm. *Computers & Industrial Engineering, 63*(4), 763-778.

Yazgı Tütüncü, G., Carreto, C. A. C., & Baker, B. M. (2009). A visual interactive approach to classical and mixed vehicle routing problems with backhauls. *Omega, 37*(1), 138-154.

Yih-Long, C., & Sullivan, R. S. (1990). Schedule generation in a dynamic job shop. *International Journal of Production Research, 28*(1), 65.

Yoshitomi, Y. (2002). A Genetic Algorithm Approach to Solving Stochastic Job-shop Scheduling Problems. *International Transactions in Operational Research, 9*(4), 479-495.

Zhong, Y., & Cole, M. H. (2005). A vehicle routing problem with backhauls and time windows: a guided local search solution. *Transportation Research: Part E, 41*(2), 131-144.