UNIVERSITY OF CALIFORNIA,
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Integration of Information of Transportation Flows in Disaster Relief Logistics Modeling

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil Engineering

by

Sarah Aly

Dissertation Committee:
Professor R. Jayakrishnan, Chair
Professor Will Recker
Associate Professor Wenlong Jin

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DEDICATION

To

My Daughters Hana and Sophia

To inspire them to reach for their dreams regardless of the obstacles ahead

My Husband Amr

For his continued support and encouragement

My Parents and Siblings

Who inspire me daily through their own personal accomplishments

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ABSTRACT OF THE DISSERTATION

Integration of Information and Transportation Flows in Disaster Relief Logistics Modeling

By

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Professor R. Jayakrishnan, Chair

Disasters, specifically earthquakes, result in worldwide catastrophic losses annually. The first seventy-two hours are the most critical and so any reduction in response time is a much-needed contribution. This is especially true in cases where parts of the communication infrastructure are severely damaged. Traditional disaster relief logistics models tend to rely on the assumption that information flow is continuous throughout the system following the onset of a natural disaster. A new integrated framework for disaster relief logistics that optimizes the movement of critical information along with physical movements is proposed in order to alleviate post-disaster conditions in a more accurate and timely manner. The framework consists of an information network and a transportation network with interrelationships. The framework was applied to the Irvine Golden Triangle Network and the Knoxville Network for up to three different cases. The DYNASMART-P simulation program performance was compared against the Time Dependent Network Simplex paths approach combined with the information updating feedback loop. The average total travel times of vehicles travelling to the trauma center in the study areas were compared in order to quantify the improvements of the integrated

solution framework. The results show a significant reduction of average total travel times for vehicles transporting injured patients to the trauma center.

CHAPTER 1: Introduction

1.1 Introduction

The 2010 Mw 7.0 earthquake and its aftershocks in the Port-au-Prince, Haiti region required a massive disaster relief effort on an international scale. The Haitian government reported that an estimated 222,570 people had died, 300,572 had been injured, and 2.3 million people were displaced [1]. Described as a 'logistical nightmare' by many, damage to the communications infrastructure was one of the major setbacks in post-disaster relief efforts.

The 2011 Mw 9.0 earthquake tsunami off the coast of Japan was recorded as the world's fourth most powerful earthquake. Based on a police agency report, 15,894 people were confirmed dead, 6,152 injured, and 2,561 people missing [2]. Damage to infrastructure included 121,805 fully collapsed buildings, 278,521 half collapsed buildings, and another 726,146 partially damaged buildings. The tsunami also caused a major nuclear accident putting the country in a state of emergency.

In 2013 an Mw 7.7 earthquake took place in Pakistan killing 393 people and injuring hundreds more [3]. About 21,000 homes were completely destroyed by the quake. At forty-eight hours after the earthquake, some areas were still out of reach for relief agents.

Most recently in Japan in 2016, a Mw 7.3 earthquake hit Kumamoto province. At least forty-one people were killed and a thousand more were injured. There was also significant damage to homes, roads, and bridges in the area. The earthquake resulted in "fires, power outages, collapsed bridges, a severed road hanging over a ravine and gaping holes in the earth" [4].

While the corpus of emergency and disaster logistics modeling research has understandably become more relevant given these events, the aftermath has revealed shortcomings in the latent assumptions of current prevalent disaster logistics models. One of the major assumptions is that information flow is continuous in post-disaster situations and that supply/demand of aid or network conditions are known or can be easily determined. The purpose of my dissertation is to account for the inaccuracy of underlying assumptions regarding information availability in order to improve current disaster relief logistics. With this work I hope to stimulate much needed advances in this topic in order to provide rapid and efficient resource allocation under conditions as extreme as the destruction experienced in these tragic and sudden events.

1.1 Motivation

Traditional disaster relief logistics models tend to rely on the assumption that information flow is continuous throughout the system following the onset of a natural disaster. This assumption is unrealistic and can be dangerous considering that significant damage to the communications infrastructure can lead to a complete immobilization of disaster relief efforts. As the first seventy-two hours are considered to be the most critical, a delayed response can lead to the loss of countless lives.

Despite the possibility of a break in communication through traditional channels such as telephones or radio broadcast, transfer of information is still expected to occur using other methods. These include approaches such as word of mouth and megaphones and may instigate movement solely for the purpose of transferring critical information within the system. In fact, "following the earthquake that struck [Indonesia] on 28 March 2005, just 3 months after the terrible tsunami, residents including police, soldiers, monks and fishermen used all modes of communication from megaphones to temple bells to warn people of the possibility of another tsunami" [5]. As this information flows through the information network, it is imperative to get it to the right place at the right time. Otherwise, it is completely useless to relief agents. To date, there has not been a comprehensive method that models the movement of information as a part of disaster relief logistics operations.

1.3 Objective

A new integrated framework for disaster relief logistics that optimizes the movement of critical information along with physical movements is proposed in order to alleviate post-disaster conditions in a more accurate and timely manner. The framework consists of an information network and a transportation network with interrelationships. The information network encompasses all movement of information using communicational links while the transportation network contains all movement of people, vehicles, and commodities using transportation links. Interrelationships include the movement of information, as different types of commodities in the system, through the use of a combination of information and transportation links depending on relative link conditions. In this work, a novel adaptive solution algorithm is proposed to model the two networks using an intermediary mesoscopic traffic simulation module.

1.4 Information Modeling

In disaster relief logistics, information is perhaps the most vital resource in the supply chain. Information visibility can lead to a more accurate and efficient response to post-disaster demand for aid and assistance. Ultimately, speed, accuracy, and comprehensiveness of information can save lives.

Borkulo et al identify the following underlying problems as complications in proper risk prevention or emergency response: "lack of good communication within the hierarchy, lack of information about the 'information', lack of data standardization, lack of up-to-date information about the effects of the disaster (victims, rescue teams technique, damages, etc.), and slow access to existing data and action plans" [6].

Knowledge Management is a tool responsible for identifying a need for certain information and for managing its collection and dispersion. Knowledge Management efficiency can not only improve the accuracy and reduce the response time of relief agents, but can also enable sharing and reuse of different resources among them. Knowledge Management is an important part of disaster relief operations specifically when coordinating between different agencies following a disaster situation. Wassenhove identified Knowledge Management as part of the disaster preparedness phase in the disaster relief management framework displayed in figure 1.

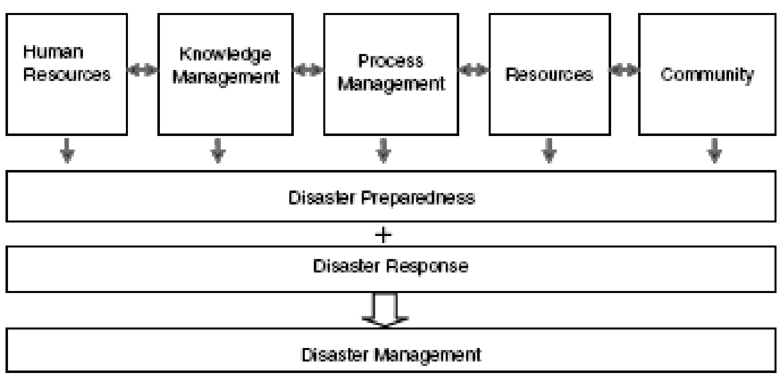

Figure 1: Creating Effective Disaster Management [5]

A good Knowledge Management framework is built on a good Knowledge Base. Zhang et al identifies the following components of a Knowledge Base: "disaster case base, relief organization catalog, satellite image and geography map catalog, humanitarian assistance/disaster relief knowledge repository" [7]. A disaster case base serves as a foundation for future decision making by matching past disaster experiences with currently similar disaster scenarios. The relief organization catalog provides contact and location information for different organizations as well as their roles and duties in disaster response. Lastly, the humanitarian assistance/disaster relief knowledge repository should contain proven and efficient knowledge such as prevention and management strategies.

While many researchers have stressed the importance of the creation of an online Knowledge Base for disaster relief operations, one has yet to be created. Potential frameworks and methodologies for information collection, however, have been described in great detail. Sapir and Lechat identified four system phases for information collection purposes. These are "the baseline information phase, the post-impact information phase (consisting of an immediate relief information phase and a secondary relief information phase), a rehabilitation information phase, and an evaluation information phase" [8]. In order to collect such information, Lee and Bui propose using templates to create a disaster management information system [9]. The templates are filled out before, during, and after a crisis in order to create a case base of crises. Case-based reasoning was described as the best tool to prepare for and respond to a crisis due to a similarity among crises as well as the urgency of the situation.

Bui et al propose a framework for a Global Information Network that goes beyond information gathering and dissemination. Functionalities of the desired Global Information Network include: prediction of disaster, timely and specific warning, collection of accurate and timely reporting, total asset visibility and logistics, remote medical expert support, and prediction and detection of the security needs. Although such a network would be extremely useful in post-disaster relief operations, its creation seems unlikely considering the uncertainty of disaster occurrences along with the unique characteristics of each disaster impact scenario.

Much of the work done on disaster relief and information flow has been in the development of information systems that support decision making and information sharing in post-disaster situations. Although it is useful to use past disaster information to create an early stage response to a disaster before information about the actual situation becomes known, it is impractical to use such information systems as a basis for disaster relief decision making throughout the response period. It may be more suitable to solve the information flow and disaster relief problem as an Operations Research problem that optimizes movement of critical information along with physical movements in the system.

1.5 Thesis Summary

This dissertation presents a framework that integrates information flow along with transportation flows in order to enhance the accuracy of disaster relief efforts. The framework treats critical information in the system as a commodity with a supply and demand and optimizes its movement in the network in order to provide feedback to aid with response planning.

Chapter 2 provides a summary of past work in disaster relief logistics as well as the linear program used for the framework. It also presents the idea of using network flow models to decompose and solve the linear program and a prioritization scheme for assigning commodity flows in the network.

Chapter 3 discusses the computation properties and complexity of the network flow algorithms proposed to solve the LP.

Chapter 4 describes the solution framework in greater detail and describes the role of DYNASMART-P in the implementation. A seismic risk analysis procedure is also described to simulate bridge damage states in a post-disaster scenario. Lastly, the reliability of the communications network and congestion modeling are discussed along with the use of Data MULEs to collect information in the system.

In Chapter 5 the solution procedure is first implemented using the Irvine Golden Triangle network as a study area. Three different cases are run in order to quantify the improvements of the integrated solution framework. The results show a significant improvement in the reduction of average total travel times for vehicles transporting injured patients to the trauma center located in the study area. In order to test the applicability of the solution procedure to a larger network, it is implemented on the Knoxville network. Lastly, the commodity prioritization scheme is tested on the Irvine Golden Triangle network.

CHAPTER 2: Formulation and Solution Framework

2.1 Disaster Relief Models

Disaster relief logistics is a branch of logistics that involves responding to disaster situations in a timely and efficient manner. The main objective is to minimize the loss of life and maximize the effectiveness of aid distribution. Much of the work done in disaster relief logistics has resulted in the formulation of the problem as a multi-commodity network flow model.

Haghani and Oh formulated the large-scale disaster relief problem as a multi-commodity, multi-modal network flow model on a time-space network [10]. This model is based mainly on the assumptions that cost functions are linear, commodity quantities are known at all supply and demand nodes, and that mode shift is allowed. A linear program was developed with a single objective function that minimizes the sum of all vehicle flow costs, commodity flow costs, supply/demand carryover costs, and mode transfer costs over time. Two solution algorithms were used to solve the linear program. The first solution algorithm decomposed the model into two sub problems that were solved using Langrangian relaxation while the second solution algorithm used an *ad hoc* fix and run method that fixes integer variables at each iteration until all integer variables in the LP are known. LINDO was used for both solution algorithms. Of the two algorithms, the second one performed better especially in terms of run-time. However, the run-time was affected by the network size making it difficult to apply in real-life scenarios where the networks are large and time is of the essence. Also, the assumption that cost functions are linear is unrealistic in real-life transportation problems. Furthermore, given the uncertainty following a disaster event, it's difficult to assume that supply and demand is known.

Yi and Ozdamar formulated a "mixed integer multi-commodity network flow model that treats vehicles as integer commodity flows rather than binary variables" [11]. They employ a two-stage modeling approach in which the first stage involves solving a compact model treating vehicles as integer flows. Next, in the second stage, a simple vehicle splitting algorithm is used to obtain vehicle instructions to converts integer vehicle flows into binary vehicle itineraries. Lastly a set of linear equations is solved to a assign a commodity loading/unloading schedule to each vehicle itinerary. By treating vehicles as integer flows, considerable computational burden is eliminated in comparison to traditional Vehicle Routing Problems. As a result, the model can solve relatively large size problems with a reasonable CPU time. However, the model is based on the assumption that only one transportation mode exists in the network. This could be one underlying reason for the aforementioned CPU time and is quite unrealistic when translating it to a real-life disaster scenario.

Another modeling attempt was carried out which utilized a hybrid method based on "fuzzy clustering and multi-objective dynamic programming models" [12]. A three-layer supply chain composed of "relief suppliers, urgent relief distribution centers (URDC), and relief demanding areas,"[12] makes up the logistics network of the study. Assumptions of the model include the availability of knowledge regarding the number of affected areas and the severity of the resulting damage as well as the number of casualties in each of these areas. A correlation between the number of survivors in the affected area and the demand for aid is also assumed. This correlation is the basis for the primary step of the approach, which involves forecasting relief demand at each affected area. Next, a fuzzy clustering technique is employed in order to group affected areas based on their respective degrees of demand severity. Lastly, a two-stage dynamic model is formulated to transport the optimal relief supply from relief suppliers to distribution centers then distribute it from distribution centers to the affected-area groups. Although the model was found to perform well when applied to known data from a past disaster occurrence, its underlying assumptions regarding detailed information availability may limit its capabilities in a real-life circumstance.

In an attempt to improve on the solution procedure proposed by Yi and Ozdamar [11], Yi and Kumar presented “a meta-heuristic of ant colony optimization for solving the logistics problem in disaster relief activities” [13]. The proposed method decomposes the original emergency logistics problem into a vehicle route construction phase along with a multi-commodity dispatch phase and is solved using an iterative approach. The first phase builds stochastic vehicle paths with the guidance of pheromone trails while a network flow based solver is used to assign vehicle flows to commodities. Although the quality of the solution found after a minute of computational time is found to be acceptable for a real-time decision making situation, the model is still based on the assumption that only one mode exists which deems it unsuitable for the objective of creating an accurate disaster relief response plan.

Barbarosoglu and Arda formulated the transportation problem as a two-stage, scenario based stochastic programming “linear model to represent the randomness arising from earthquake magnitude and impact” [14]. The resource allocation response is modeled as a multi-commodity, multi-modal network flow problem. The arc capacities as well as supply/demand requirements are assumed to be random. As a part of pre-earthquake preparation, a set of earthquake scenarios and their relative impact scenarios are estimated and used as a basis for the post-event response. A planner will need to solve a two-stage stochastic program for each of the earthquake scenarios integrating all possible impact scenarios. Upon the event, a plan for the relative earthquake scenario is implemented until more information is received regarding the actual impact. The model’s responsiveness to post-disaster relief demand to a large number of random expectations is dependent on accuracy in the estimation of the earthquake’s impact scenarios. Since all disasters are different and the reason uncertainties arise in the first place is due to inability to predict these impact scenarios, the model lacks in fixing the shortcomings of past disaster relief logistics models.

Although all the reviewed models are described to be responsive to new information regarding supply/demand and network conditions in the system, no model has attempted to actually incorporate and optimize the flow of critical information in the network along with physical movements.

2.2 Scope of the Problem

Figure 2 provides a visual of the integrated framework for disaster relief logistics that optimizes the movement of critical information along with physical movements.

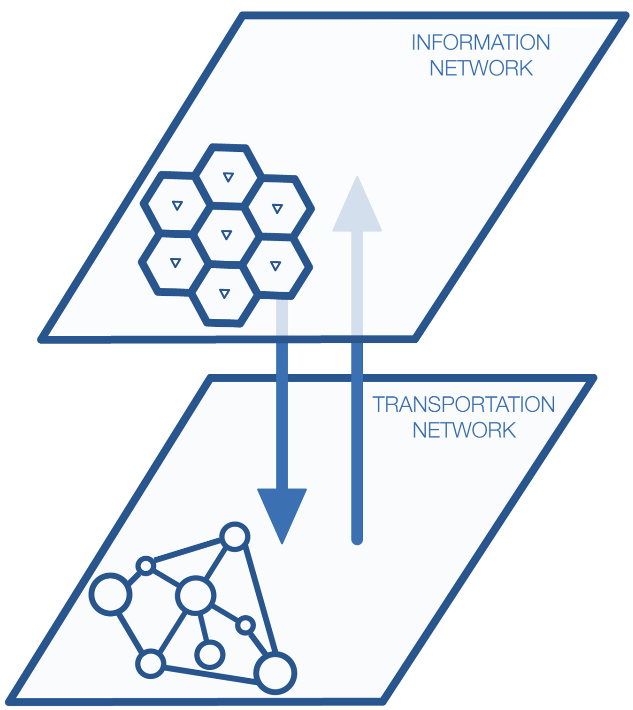

Figure 2: A Multi-Layered Disaster Relief Model with Interrelationships

The framework consists of an information network and a transportation network with interrelationships. The information network encompasses all movement of information using communicational links while the transportation network contains all movement of people, vehicles, and commodities using transportation links. Interrelationships include the movement of information, as a type of commodity in the system, through the use of a combination of information and transportation links depending on relative link conditions. Other interrelationships may include the transport of portable base stations on the transportation network in order to restore missing or inefficient links in the communication network. Figure 3 provides a few of the possible interrelationships between the two networks.

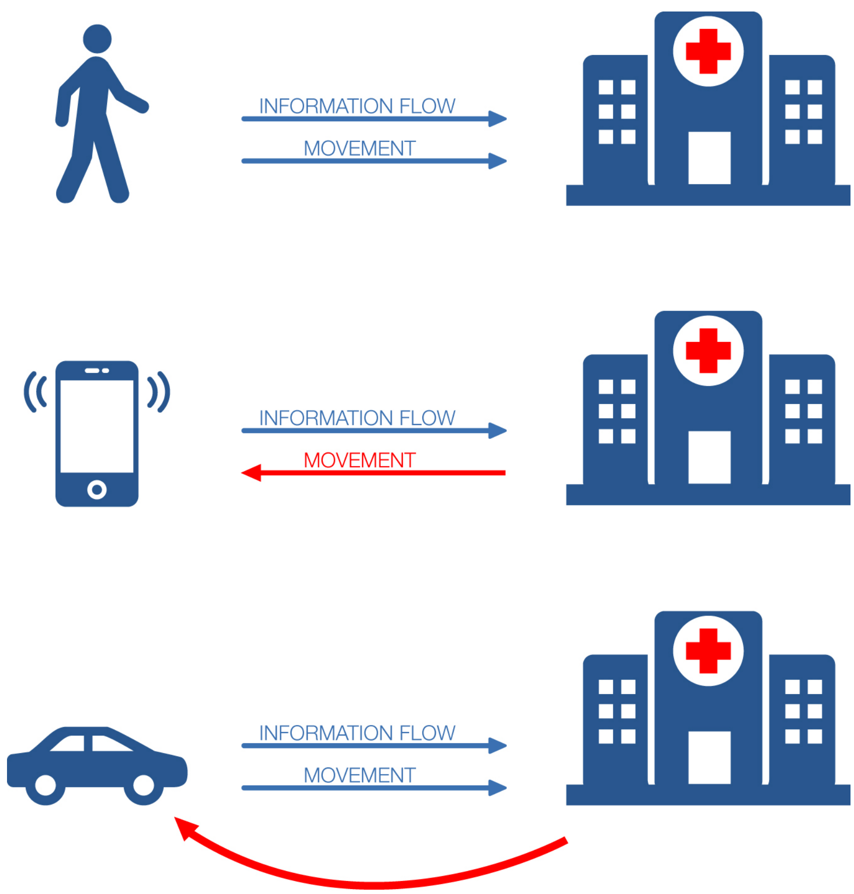

Figure 3: Interrelationships Between the Information and Transportation Networks

The integrated framework aims at minimizing the time it takes for critical information to move through the network along with the movement of people, private vehicles, disaster response vehicles/personnel, and physical goods. In an ideal scenario, the movement of information would take place solely on communication lines such as cell phones, landlines, and radio while the physical movements would travel on the transportation network. However, following the onset of a disaster, it is highly likely that breaks will occur in the communication links resulting in a need to use the transportation network in order to transfer critical information. This information is represented as a set of commodities with their own supply/demand at various points. Like any commodity, the goal is to minimize travel time to the destination point. Since information, unlike physical movements, has the option to either travel on communication links or transportation links, it may be transferred through the use of a combination of information and transportation links depending on relative link conditions. Thus, a single formulation is used incorporating both the information and transportation networks. This formulation aims to optimize all movements on both networks, which essentially results in a dynamic plan of response in a post-disaster situation.

2.3 Formulation

The multi-commodity, multi-modal network flow model on a time-space network formulated by Haghani and Oh [10] was chosen as a basis for my formulation. This is because, despite its simplicity, it encompasses many of the complexities of the disaster relief logistics problem. A few changes were made to the original formulation in order to account for some of its shortcomings.

New Assumptions:

- All relevant information is collected at Emergency Centers (ECs).

- Information is treated as a commodity on the transportation network.

Notation and definitions:

- N= set of nodes
- S= set of supply nodes
- SU= set of supply nodes that are also transshipment nodes
- D= set of demand nodes
- DU= set of demand nodes that are also transshipment nodes
- U= set of transshipment nodes
- A= set of links in the network
- M= set of modes
- G= set of commodities
- EPT_{gi}= earliest pickup time period of commodity g at node i
- SE_{git}= amount of exogenous supply of commodity g at node i at time t
- EDT_{gi}= earliest delivery time period of commodity g at node i
- DE_{git}= amount of exogenous demand of commodity g at node i at time t
- YE^{m}_{it}= number of vehicles of mode m which are available at node i at time period t
- YCA^{m}= vehicle capacity of mode m
- $ACA^{m}_{itjt'}$= arc capacity between node i at time period t to node j at time period t'
- $CVR^{m}_{itjt'}$= unit cost of moving vehicle of mode m from mode i at time period t to node j at time period t'
- $CGR^{gm}_{itjt'}$= unit cost of shipping commodity g by mode m from mode i at time period t to node j at time period t'

- CSC_{git}= unit cost for carrying over the supply for commodity g at node i from time period t to time period t+1
- CDC_{git}= unit cost for carrying over the demand for commodity g at node i from time period t to time period t+1
- $CGT^{gmm'}_{it(t+Kmm')}$= unit cost of transfer of commodity g from mode m to m' at node i at time period t. Kmm' represents the number of time periods required for this transfer
- Z_{ijt}= state of transportation link between i and j at time period t
- t_{ijEC}= time it takes for information regarding state of link between i and j to reach Emergency Center

Decision variables:

- $Y^{m}_{itjt'}$ = flow of vehicles of mode m from node I at time period t to node j at time period t'
- YC^{m}_{it} = no. of vehicles of mode m which is carried over from time period t to time period t+1 at node i
- $X^{gm}_{itjt'}$ = flow of commodity g by mode m from node i at time period t to node j at time period t'
- SC_{git}= amount of supply of commodity g which is carried over from time period t to time period t+1 at node i
- DC_{git}= amount of demand of commodity g which is carried over from time period t to time period t+1 at node i
- $XT^{gmm'}_{it(t+Kmm')}$ =amount of commodity g which is transferred from mode m to mode m' at node i at time period t

Internal decision variables:

- SE^{m}_{git}= amount of exogenous supply of commodity g assigned to mode m at node i at time period t.
- SC^{m}_{gt}= amount of supply of commodity g which is carried over by mode m from time period t to time period t+1 at node i.
- DE^{m}_{git}= amount of exogenous demand of commodity g assigned to mode m at node i at time period t.
- DC^{m}_{git}= amount of demand of commodity g which is carried over by mode m from time period t to time period t+1 at node i.

Among the decision variables, the vehicle related Y^{m}_{itjt} and YC^{m}_{it} are integer variables while the rest are continuous resulting in a mixed integer problem. Below is the mathematical formulation of the proposed model.

Minimize

$$\sum_i \sum_j \sum_t \sum_{t'} \sum_m \frac{CVR^m_{itjt'}}{z_{ijt}} \times Y^m_{itjt'} + \sum_i \sum_j \sum_t \sum_{t'} \sum_g \sum_m \frac{CGR^{gm}_{itjt'}}{z_{ijt}} \times X^{gm}_{itjt'} + \sum_{i\ \varepsilon\ S,SU,U} \sum_t \sum_g CSC_{git} \times \left(\sum_m SC^m_{git}\right) + \sum_{i\ \varepsilon\ D,DU} \sum_t \sum_g CDC_{git} \times \left(\sum_m DC^m_{git}\right) + \sum_{i\ \varepsilon\ SU,U} \sum_t \sum_g \sum_m \sum_{m'} CGT^{gmm'}_{it(t+Kmm')} \times XT^{gmm'}_{it(t+Kmm')} \qquad [1]$$

Subject to:

$$\sum_j \sum_{t'} X^{gm}_{jt'it} + \sum_{m'} XT^{gmm'}_{i(t-Km'm)t} + SC^m_{gi(t-1)} + SE^m_{git} = \sum_j \sum_{t'} X^{gm}_{itjt'} + \sum_{m'} XT^{gmm'}_{it(t+Kmm')} + SC^{\ m}_{git}$$

$$\sum_j \sum_{t'} X'_{jt} it^{gm} + \sum_{m'} XT^{gmm'}_{i(t-Km'm)t} - DC^m_{gi(t-1)} = \sum_j \sum_{t'} X^{gm}_{itjt'} + \sum_{m'} XT^{gmm'}_{it(t+Kmm')} - DC^m_{git} + DE^m_{git}$$

[2]

$$SE_{git} = \sum_m SE^m_{git}$$

$$DE_{git} = \sum_m DE^m_{git}$$

[3]

$DC^m_{git} = 0$ for all $t < EDT_{gi}$ [4]

$$X^{gm}_{itjt'} \geq 0,\ XT^{gmm'}_{it(t+Kmm')} \geq 0,\ SE^m_{git} \geq 0,\ SC^m_{git} \geq 0,\ DE^m_{git} \geq 0,\ DC^m_{git} \geq 0$$ [5]

$$YE^m_{it} + \sum_j \sum_{t'} Y^m_{jt'it} + YC^m_{i(t-1)} = \sum_j \sum_{t'} Y^m_{itjt'} + YC^m_{it}$$ [6]

$$Y^m_{itjt'} \leq ACA^m_{itjt'}$$ [7]

$$Y^m_{itjt'} \geq 0 \textit{ and integer}, YC^m_{it} \geq 0 \textit{ and integer}$$

[8]

$$YCA^m \times Y^m_{itjt'} - \sum_g X^{gm}_{itjt'} \geq 0$$ [9]

$$Z_{ijt} = 1 \textit{ for all } t < t_{ijEC}$$

$$Z_{ijt} = \begin{cases} 1 & \textit{if link ij is operational post} - \textit{disaster} \\ 0 & \textit{if link ij is not operational post} - \textit{disaster} \end{cases} \textit{ for all } t > t_{ijEC}$$ [10]

The objective function [1] aims to minimize the sum of vehicle flow costs, commodity flow costs, supply carryover costs, demand carryover costs, and mode transfer costs over all time periods. The carryover costs are the costs of any additional delay in the commodity moving in the network at the origin point and and delay in the commodity to exit the network at the destination point. As an example, an injured person waiting to be transported results in a supply carryover cost, and any wait for receiving treatment at the destination due to, say bed availability at a hospital, will result in a demand carryover cost. Note that the demand carryover costs are used to penalize unfulfilled demand. A higher penalty for demand carryover is given to those commodities that have a higher priority in a post-disaster situation. This is especially important when an unfulfilled demand for vital information can lead to the loss of lives.

The first set of constraints [2] represent the conservation of flow for any commodity g at any node i over all time periods. The inclusion of variables representing supply and demand carryover as well as exogenous supply and demand are vital in order to ensure that the commodity flow which enters a node is equal to that which leaves this node. In regards to exogenous supply and demand, they are constrained at each node i at each time period t over all modes m [3]. Time window constraints [4] are also included to make sure that, for each commodity g, delivery to node i cannot take place before the earliest delivery time period (EDT_g). In regards to information this indicates the time that new information reaches the ECs (t_{ijEC}). It is also used as re-planning period in order to make the model more dynamic. Lastly, non-negativity constraints [5] restrict all the commodity related variables to be greater than or equal to zero.

Vehicular flow conservation constraints [6] represent the vehicle flow conservation for each mode at each node at each time period. Arc capacity constraints [7] state that that the vehicular flow of mode m on an arc that starts at node i at time period t and ends at node j at time period t' should be less than or equal to the capacity of that arc at that time period. Non-negativity constraints [8] restrict the vehicular flow variables to integer values greater than or equal to zero.

The linkage constraints [9] represent the relationship between the vehicular flow and commodity flow variables by determining the minimum number of vehicles needed to move the commodity assigned to arc (ij) for each mode type.

Link condition information is represented by the final constraint [10]. This is a binary variable reflecting the state of link (ij) following the disaster onset. The value of this variable is constrained by the availability of information regarding the link. This is done using the earliest time it takes information regarding link (ij) to reach the emergency center t_{ijEC} as limitation. Note that Z_{ijt} was used in the objective function to ensure that flow on a link is zero when that link is broken. With this change, the cost coefficients of both vehicle and commodity transfer go to infinity when Z_{ijt}=0.

2.4 Solution Framework

Figure 4 provides an overview of the solution framework proposed to solve the multi-commodity, multi-modal network flow model on a time-space network that optimizes the flow of critical information along with physical movements in a post-disaster situation.

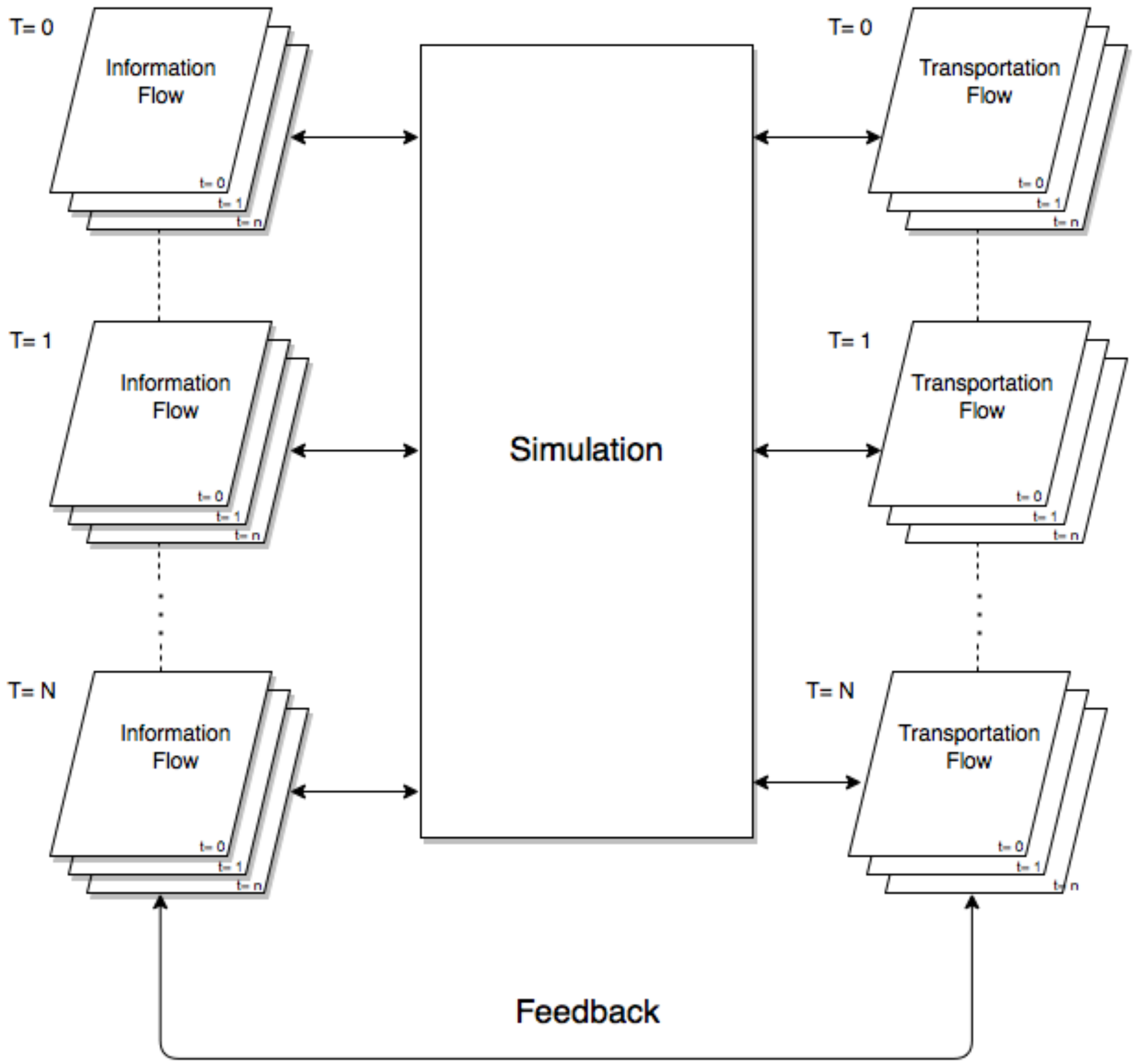

Figure 4: Solution Framework

Although the formulation encompasses all movements on both the information and transportation networks, the proposed solution algorithm decomposes them into two sub problems that can be solved more quickly. This is done since interdependencies exist between the two networks that may require updating certain variables in the formulation at different time periods. An intermediary simulation procedure is proposed as a means of accounting for the use of linear cost functions as a basis for the formulation.

2.4.1 Network Flow Models

The disaster relief logistics problem falls under a special class of linear programs called minimum cost flow problems. The objective of a minimum cost flow problem is to determine the most economic way to transfer a certain amount of goods from one or more production nodes to one or more consumption nodes through a given transportation network. Although linear programs can solve a wide range of models, one of their major drawbacks is the computational time needed especially in the case of larger networks. For example, LINDO was used by Haghani and Oh [10] for both solution algorithms and the computational time for the ten node and twenty two-way arc network used was over eight hours for the first solution algorithm and over three hours for the second. Network models, on the other hand, can be solved very quickly. For example, a problem whose linear program would have thousands of rows and columns can be solved in seconds using a network model. This makes them an excellent candidate when solving a problem that requires real-time decision-making such as in a post-disaster relief situation [15].

2.4.1.1 Network Simplex

One example of a particular type of network model is the Network Simplex algorithm [16]. The Network Simplex algorithm is a path based solution algorithm used to solve minimum cost flow problems in an efficient manner. The output of Network Simplex in an uncapacitated problem is an optimal spanning tree of **n-1** arcs connecting all nodes **n** in the network. The solution scheme begins with a feasible spanning tree solution and builds on it by the addition and removal of certain arcs until a minimum cost solution is achieved. Generally, the presence of cycles in the solution is not allowable except in the case of the capacitated Network Simplex

Algorithm. Practically, when using Network Simplex for transportation applications the capacitated approach is more realistic as there is typically a max possible flow on the network.

In the capacitated Network Simplex algorithm approach, the allowable flow is constrained by a vector of link capacities k. The formulation for a capacitated minimum cost flow problem is therefore as follows:

$$\text{Min } c^T x$$

$$Ax = b$$

$$x \leq k$$

$$x \geq 0$$

where **A** is the node incidence matrix, **c** is the link cost vector, and **b** is the demand vector for the network [16].

In the uncapacitated case, basic solutions correspond to spanning trees and can be used to split the set of arcs into basic arcs **B** and non-basic arcs **F**. In the capacitated case, however, the solution consists of three sets of arcs that are defined as empty **V**, saturated **S**, or neither empty nor saturated **B**. Of these arcs, those in set **B** cannot form a cycle in the basic solution [16].

2.4.1.2 Maximum Flow

Another type of network model is the Maximum Flow Problem. The objective of the Maximum Flow Problem is to send as much material as possible from a specified source node **s** in a network to another specified sink node **t**. No costs are considered with finding this flow [16]. "Associated with the maximum flow problem is a bottleneck, a set of arcs whose maximum capacity is equal to the maximum flow, the removal of which leaves no connected path from source to sink in the network" [15]. The significance of finding this bottleneck in regards to disaster relief logistics is that it can help with making some very important decisions. These decisions include how to prioritize certain commodities over others given the resulting network conditions and the associated carryover penalties in a post-disaster situation. Another possible decision is where to focus on restoring or rebuilding infrastructure such as damaged roads based on their impact on the critical path network.

If **v** denotes the amount of material sent from node **s** to node **t** and $\mathbf{x_{ij}}$ denotes the flow from node **i** to node **j** over arc **ij** the formulation is [16]:

Maximize v,

Subject to:

$$\sum_j x_{ij} - \sum_k x_{ki} = \begin{cases} v & if\ i = s\ (source) \\ -v & if\ i = t\ (sink) \\ 0 & otherwise \end{cases}$$

$$0 \leq x_{ij} \leq u_{ij}\ (i = 1,2,\dots,n;\ j = 1,2,\dots,n)$$

The summations are taken only over the arcs in the network. Also, $\mathbf{u_{ij}}$ represents the capacity of the arcs **ij** and is taken to be +∞ if arc **ij** has unlimited capacity. The interpretation for the maximum flow problem is that **v** units are supplied at **s** and consumed at **t** [16]. However, in this specific case, the maximum flow for each commodity based on the post-disaster network conditions will be used to calculate the total potential resulting supply and demand carryover costs (see equation). These costs will then be used to rank the commodities in order of importance in order to make the post-disaster relief response as effective as possible.

For every commodity g,

$$TCSC_{git} = CSC_{git} \times (S_{git} - V_{gijt})$$

$$TCDC_{gjt} = CDC_{gjt} \times (D_{gjt} - V_{gijt})$$

where $TCSC_{git}$ represents total supply carryover costs for commodity type **g** at node **i** at time **t**, $TCDC_{gijt}$ represents total demand carryover costs for commodity type **g** at node **j** at time **t**, and V_{gijt} represents the maximum flow of commodity type **g** from node **i** to node **j** at time **t**.

2.4.1.3 Shortest Path

The Shortest Path Problem is a network model with an objective of finding a path from a specified start node to a specified end node whose total weight is minimized. The Shortest Path Problem usually occurs as a sub problem in more complex situations such as the decomposition of traffic assignment problems [16].

Let $\mathbf{c_{ij}}$ represent arc weights and $\mathbf{x_{ij}}$ represent the amount of flow on arc ij, the general formulation for the Shortest Path Problem is as follows:

Minimize $z = \sum_i \sum_j c_{ij} x_{ij}$

Subject to:

$$\sum_j x_{ij} - \sum_k x_{ki} = \begin{cases} 1 & if\ i = s\ (source) \\ -1 & if\ i = t\ (sink) \\ 0 & otherwise \end{cases}$$

$$x_{ij} \geq 0\ for\ all\ arcs\ i - j\ in\ the\ network$$

To understand the shortest path problem as a network flow model, the objective is to send one unit of flow on the network from the source to the sink at minimum cost. There is a total supply of one unit at the source **s** and a total demand of one unit at the sink **t**, all other nodes are merely transshipment nodes.

In disaster relief logistics, the physical commodities such as vehicles, medical supplies etc. have a total supply and demand most probably greater than one unit. However, in the case of information, a group of information collected at a specified node can be viewed as a single information packet to be transferred to a specified emergency center sink node in the network. When is comes to critical information, the goal is to minimize the time it takes for it to reach the Emergency Center in order to update network conditions yielding a more accurate and timely response. Therefore, the Shortest Path Problem is an excellent candidate for the optimization of critical information in the network portion of the disaster relief response formulation.

2.5 Network Flow Decomposition Solution Scheme

Although the proposed formulation minimizes vehicle flow, commodity flow, mode transfer, and carryover costs using a single objective function, a decomposition scheme is proposed to solve it in a more efficient manner. The solution approach splits the problem by first determining the optimal vehicle flows on the network and then assigning the commodities to the resulting vehicle flows. This is done to reduce computational time, which is critical in a disaster relief scenario. The steps for the solution scheme are:

Step 1- Using the Network Simplex Algorithm code in MATLAB, find the optimal vehicle flows based on the transportation demands and link capacities at time period t_i.

Step 2- Multiply the resulting vehicle paths by the maximum number of units of each commodity type per vehicle to determine the link capacities for the commodity flow network.

Step 3- Using the Maximum Flow code in MATLAB, calculate the maximum flow for the given vehicle path network.

Step 4- Using the maximum flow for the network, determine the total Supply Carryover (SC) and Demand Carryover (DC) costs for each commodity type. Select the first commodity C_1 based on the highest penalty cost.

Step 5- Begin assigning C_1 onto the vehicle path network using the Network Simplex Algorithm code for MATLAB and the link capacities found in Step 2.

Step 6- Determine the remaining available link capacities by removing saturated links S, adding empty links V, and subtracting the flow on unsaturated links B from their respective link capacities.

Step 7- Run the Maximum Flow code for each remaining commodity type on the resulting network and calculate the SC and DC costs. Select C_2 based on the highest resulting penalty cost.

Step 7- Repeat Step 6 to readjust the link capacities for the commodity flow network.

Step 8- Repeat Step 4 to determine C_3.

Step 9- Continue to assign commodities in the hierarchy until all links are saturated.

Step 10- Carryover the remaining commodities to the next time step (t_{i+1}) and repeat the solution scheme based on the transportation demands and link capacities at time period t_{i+1}.

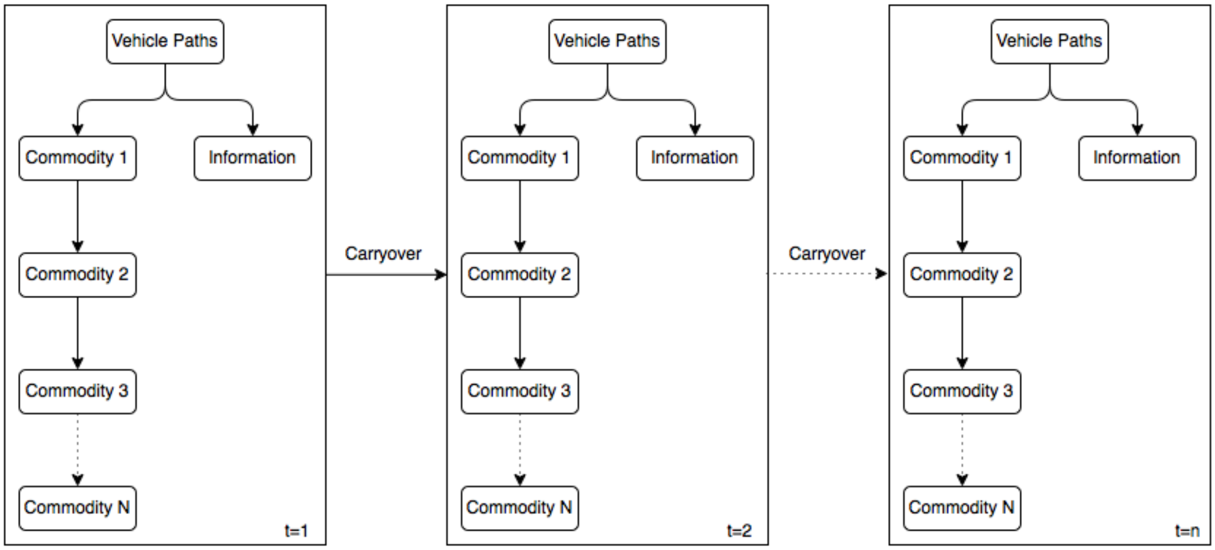

Figure 5: Order of Operations for Decomposition Scheme

The figure above represents the order of operations for the Network Flow Decomposition Scheme. The solution is carried out from time step to time step. The carryover represents the commodities that could not be loaded onto the network due to the prioritization of these commodities based on the severity of the demand as well as the capacity restrictions of the vehicle path network.

It is important to address the significance and possible outcomes of running the information module simultaneously with the commodity flow modules. Information on the severity of demand can affect the order of operations when it comes to commodity transfer. For example, for the first few time steps water can be considered a lower priority over injured people but as the supply of water begins to diminish, this can lead to a higher demand carryover cost associated with water making it a top priority to be transferred first at the next time step. Information on network conditions, such as blocked or damaged roadways, can also affect routing considerations forcing us to re-run vehicle paths accordingly. Lastly, it is important to consider how information regarding a commodity can affect the solution structure based on interrelationships between one or more commodities. In the case of fuel availability, information on shortages or availability can have an effect on vehicle paths and, in turn, reduce the capacities for the commodity flow network.

It is also essential to note that despite the optimal solution based on this decomposition scheme, logic may override certain precedence relationships despite their efficiency. For example, it may be faster or cheaper to transport a thousand pounds of rice than forty injured people in a given time step but in that case logic can sacrifice optimality in order to save lives.

2.6 Sample Problem

In order to demonstrate the solution scheme steps for further understanding, a small transportation network shown in figure 6 is used. The network consists of five nodes and eight links. The link capacities are indicated in squares and represent the maximum vehicle flow per link. The nodes are split into two supply nodes (1 and 2) a transshipment node (3) and two demand nodes (4 and 5). The problem data is

$$b = \begin{bmatrix} b1 \\ b2 \\ b3 \\ b4 \\ b5 \end{bmatrix} = \begin{bmatrix} 10 \\ 4 \\ 0 \\ -6 \\ -8 \end{bmatrix} \qquad c = \begin{bmatrix} c12 \\ c13 \\ c14 \\ c23 \\ c25 \\ c35 \\ c43 \\ c54 \end{bmatrix} = \begin{bmatrix} 10 \\ 8 \\ 1 \\ 2 \\ 7 \\ 4 \\ 1 \\ 12 \end{bmatrix} \qquad k = \begin{bmatrix} k12 \\ k13 \\ k14 \\ k23 \\ k25 \\ k35 \\ k43 \\ k54 \end{bmatrix} = \begin{bmatrix} 10 \\ 7 \\ 2 \\ 4 \\ 3 \\ 12 \\ 7 \\ 5 \end{bmatrix}$$

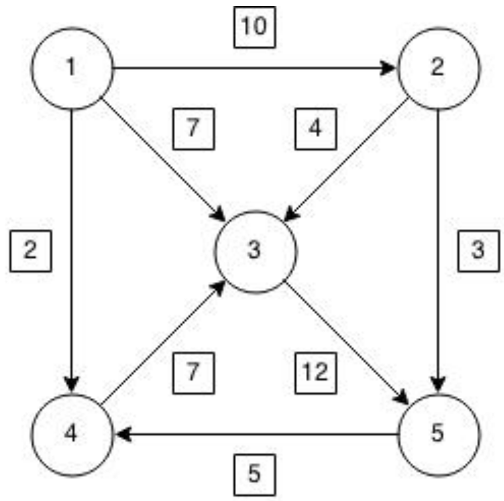

Figure 6: Sample Transportation Network

After inputting the network, with the given data, into the Network Simplex Algorithm code for MATLAB, the resulting minimum cost vehicle flow network is shown in figure 7.

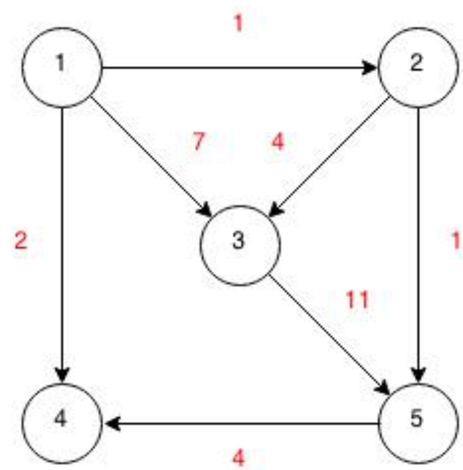

Figure 7: Minimum Cost Vehicle Flow Network

Assuming that the commodities have already been ranked in order of importance, the next step is to adjust the resulting vehicle paths to a minimum cost commodity flow network by multiplying the vehicle flow by the maximum number of units that each vehicle can carry. The maximum number of units regardless of the commodity type is four units and therefore the resulting network capacities are shown in figure 8.

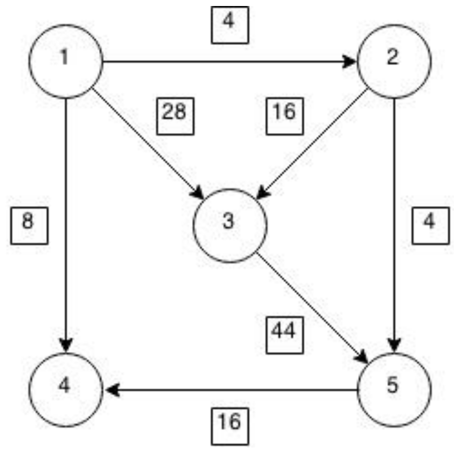

Figure 8: Vehicle Path Based Commodity Flow Network

Based on the ranking from Step 2, the first commodity to be assigned to vehicle path network is Commodity A. The problem data is

$$b = \begin{bmatrix} b1 \\ b2 \\ b3 \\ b4 \\ b5 \end{bmatrix} = \begin{bmatrix} 28 \\ 12 \\ 0 \\ -20 \\ -20 \end{bmatrix} \quad c= \begin{bmatrix} c12 \\ c13 \\ c14 \\ c23 \\ c25 \\ c35 \\ c54 \end{bmatrix} = \begin{bmatrix} 10 \\ 8 \\ 1 \\ 2 \\ 7 \\ 4 \\ 12 \end{bmatrix} \quad k= \begin{bmatrix} k12 \\ k13 \\ k14 \\ k23 \\ k25 \\ k35 \\ k54 \end{bmatrix} = \begin{bmatrix} 4 \\ 28 \\ 8 \\ 16 \\ 4 \\ 44 \\ 16 \end{bmatrix}$$

After inputting the network, with the given data, into the Network Simplex Algorithm code for MATLAB, the resulting minimum cost flow network for Commodity A is shown in figure 9.

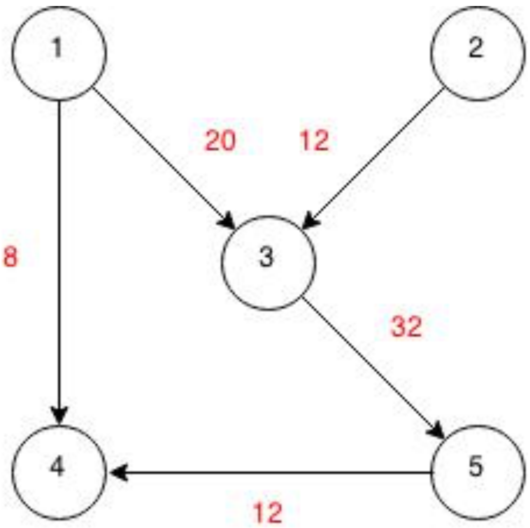

Figure 9: Minimum Cost Flow Network for Commodity A

Based on the optimal flow for commodity A on the vehicle path network, link 1-4 is saturated and therefore cannot be used to assign any other commodities. Links 1-2 and 2-5 are empty and therefore can be used to their full capacities for any other commodities. Links 1-3, 2-3. 3-5, and 5-4 are neither full nor empty and can be assigned other commodity types as long as the capacities are adjusted to reflect the optimal flow of Commodity A. This is done by subtracting the flow for Commodity A on each link from its relative capacity and using the results as the new network capacities. Figure 10 displays the adjusted network to be used for the assignment of Commodity B.

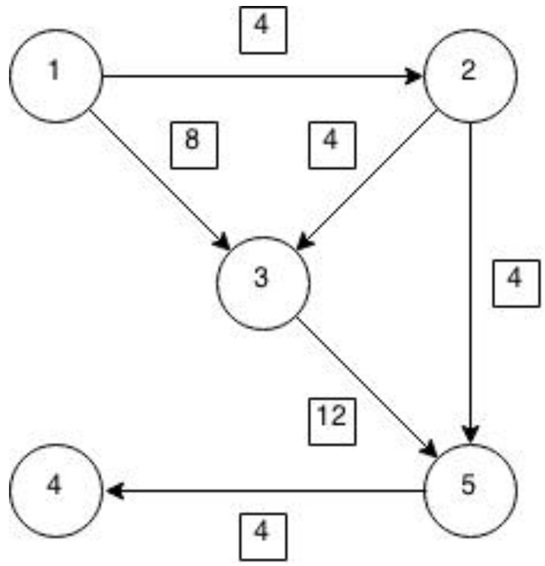

Figure 10: Adjusted Commodity Flow Network for Commodity B

The next step is to input the data for Commodity B into the Network Simplex Algorithm code for MATLAB based on the adjusted capacity for the vehicle path flows. The respective problem data is

$$b = \begin{bmatrix} b1 \\ b2 \\ b3 \\ b4 \\ b5 \end{bmatrix} = \begin{bmatrix} 8 \\ 2 \\ 0 \\ 0 \\ -10 \end{bmatrix} \quad \text{c=}\begin{bmatrix} c12 \\ c13 \\ c23 \\ c25 \\ c35 \\ c54 \end{bmatrix} = \begin{bmatrix} 10 \\ 8 \\ 2 \\ 7 \\ 4 \\ 12 \end{bmatrix} \quad \text{k=}\begin{bmatrix} k12 \\ k13 \\ k23 \\ k25 \\ k35 \\ k54 \end{bmatrix} = \begin{bmatrix} 4 \\ 8 \\ 4 \\ 4 \\ 12 \\ 4 \end{bmatrix}$$

After inputting the network, with the given data, into the Network Simplex Algorithm code for MATLAB, the resulting minimum cost flow network for Commodity **B** is shown in figure 11.

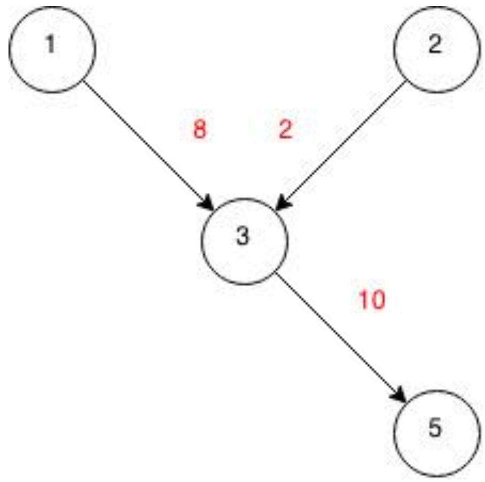

Figure 11: Minimum Cost Flow Network for Commodity B

Following the assignment of Commodity onto the vehicle path network, link 1-3 is now saturated. Links 1-2 and 2-5 remained empty and thus can still be used to their full capacities while links 2-3, 3-5, and 5-4 are only partially utilized. The adjusted network to be used for Commodity C is displayed in figure 12.

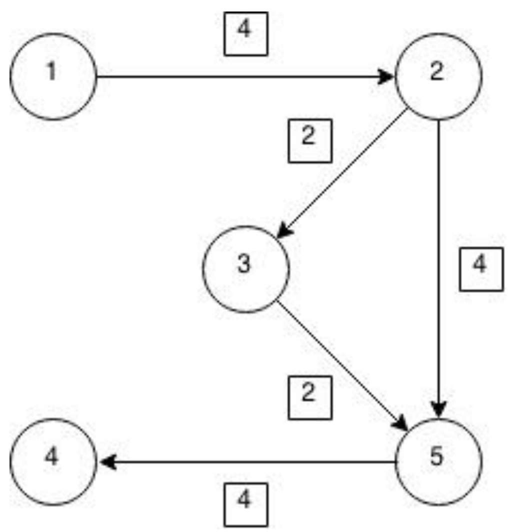

Figure 12: Adjusted Commodity Flow Network for Commodity C

Next, the Commodity C is assigned to the adjusted vehicle paths using the Network Simplex code for MATLAB. The problem data for commodity C is

$$b = \begin{bmatrix} b1 \\ b2 \\ b3 \\ b4 \\ b5 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \\ 0 \\ -2 \\ -4 \end{bmatrix} \qquad \text{c=}\begin{bmatrix} c12 \\ c23 \\ c25 \\ c35 \\ c54 \end{bmatrix} = \begin{bmatrix} 10 \\ 2 \\ 7 \\ 4 \\ 12 \end{bmatrix} \qquad \text{k=}\begin{bmatrix} k12 \\ k23 \\ k25 \\ k35 \\ k54 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \\ 4 \\ 2 \\ 4 \end{bmatrix}$$

The resulting minimum cost flow network for Commodity C is presented in figure 13.

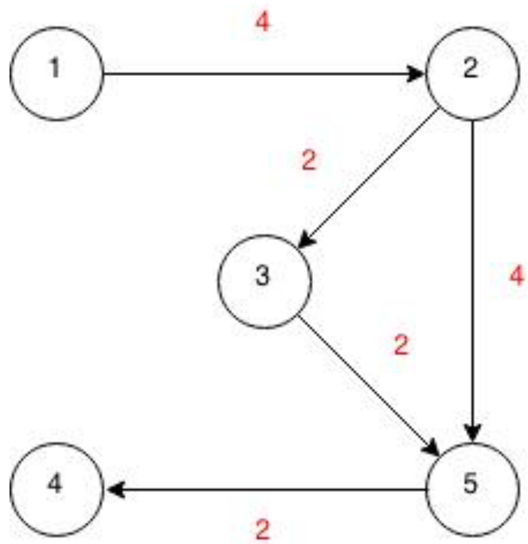

Figure 13: Minimum Cost Flow Network for Commodity C

After assigning Commodity C to the vehicle path network, links 1-2, 2-3, 2-5, 3-5 are all now saturated. The only link with available capacity is link 5-4. Because nodes 5 and 4 are demand nodes, no other commodities can be assigned to this specific vehicle fleet. The remaining commodities will have to be carried over to the next fleet of vehicles departing the supply nodes at time t+1.

The total cost for the objective function in time period t would be the sum of the units of flow on each link multiplied by the unit transfer costs per link. Based on the figures the cost is calculated as follows.

Vehicle Flow-

$$\sum[(\mathbf{10}*\mathbf{1})+(\mathbf{8}*\mathbf{7})+(\mathbf{1}*\mathbf{2})+(\mathbf{2}*\mathbf{4})+(\mathbf{7}*\mathbf{1})+(\mathbf{4}*\mathbf{11})+(\mathbf{12}*\mathbf{4})]=\mathbf{175}$$

Commodity A Flow-

$$\sum[(\mathbf{8}*\mathbf{20})+(\mathbf{1}*\mathbf{8})+(\mathbf{2}*\mathbf{12})+(\mathbf{4}*\mathbf{32})+(\mathbf{12}*\mathbf{12})]=\mathbf{464}$$

Commodity B Flow-

$$\sum(\mathbf{8}*\mathbf{8})+(\mathbf{2}*\mathbf{2})+(\mathbf{4}*\mathbf{10})]=\mathbf{108}$$

Commodity C Flow-

$$\sum[(\mathbf{10}*\mathbf{2})+(\mathbf{2}*\mathbf{2})+(\mathbf{7}*\mathbf{4})+(\mathbf{4}*\mathbf{2})+(\mathbf{12}*\mathbf{2})]=\mathbf{84}$$

Total Cost-

$$\sum[\mathbf{175}+\mathbf{464}+\mathbf{108}+\mathbf{84}]=\mathbf{831}$$

An important consideration when applying this method to the disaster relief scenario is that unlike physical commodities information has no capacity associated with it when travelling on the transportation network. Therefore, the information transfer portion of the problem can be optimized using the same Network Simplex method by combining the optimal vehicle path network with the conventional information transfer links (such as cellphones, landlines etc.) to determine the most efficient routes. In some cases, such as a broken link in the transportation network, new information can affect the vehicle paths and in turn the resulting commodity flow paths.

It is also important to note that the decomposition scheme may result in a loss in efficiency. However, the decomposition scheme allows updating of information and speeds up computational time, which is better suited for a real-time disaster relief response scenario. Two more detailed examples will be solved in Chapter 5 based on the Irvine Golden Triangle transportation network as well as the Knoxville network.

CHAPTER 3: Computational Properties

In order to properly assess the practicality of the solution approach at hand, the computational properties must be explored. In theory, computational complexity is usually measured by the worst-case running time. Basically, the best case and worst case running time of an algorithm help to identify what would be the best approach to solve a problem at hand given certain constraints.

In disaster relief logistics, time is a critical resource. The longer the response time in a post-disaster scenario, the higher the probabilities of deaths, unnecessary delay, and ineffective allocation of resources. Although the standard linear program solvers such as LINDO can solve an LP effectively, the running time can be very high depending on the size of the network. It is therefore more practical to use network models in a disaster situation in order to minimize the computational time and provide flexibility in post disaster conditions. This chapter will explore the computational properties of each of the Maximum Flow, Shortest Path, and Network Simplex algorithms used for implementation in the solution framework.

3.1 The Maximum Flow Problem

The *maxflow.m* algorithm in MATLAB returns the maximum flow between a source node **s** and destination node **t.** It uses the Boykov-Kolmogorov algorithm, which uses a minimum cut to compute the maximum flow by constructing two search trees associated with nodes **s** and **t**. The BoyKov-Kolmogorov algorithm runs in time $O(mn|C^2|)$ where **n** is the number of nodes and **m** is the number of edges in the graph. **C** is defined as the cost of the minimum cut [17].

3.2 Dijkstra's Shortest Path Algorithm

The *dijkstra.m* algorithm in MATLAB, returns the shortest path between a specified origin-destination pair. It is based on the original Dijkstra's algorithm and runs in time $O(|n^2|)$ where **n** is the number of nodes in the network [18].

3.3 Network Simplex Algorithm

The *networksimplex.m* algorithm in MATLAB returns the minimum cost flows in a capacitated network. The algorithm runs in time O(nmlog(n)log(nc)) where **n** is the number of nodes, **m** is the number or arcs, and **c** is the maximum cost of any arcs [19].

3.4 Summary

All three algorithms used in the solution procedure can be solved in polynomial or logarithmic time. The running time will increase depending on the size of the network, which is expected for any solution algorithm. The Network Simplex Algorithm's worst case running time can be quite high depending on the size of the network, however the benefits outweigh the costs in this case. Chapter 4 will describe a Time Dependent Network Simplex Algorithm while Chapter 5 will discuss why a modified approach was used when applying the solution framework to the chosen networks.

CHAPTER 4: Network Implementation

Figure 14 provides an overview of the solution framework proposed to solve the multi-commodity, multi-modal network flow model on a time-space network that optimizes the flow of critical information along with physical movements in a post-disaster situation.

Although the formulation encompasses all movements on both the information and transportation networks, the proposed solution algorithm decomposes them into two sub problems that can be solved more easily. This is done since interdependencies exist between the two networks that may require updating certain variables in the formulation at different time periods. An intermediary simulation procedure is proposed as a means of accounting for the use of linear cost functions as a basis for the formulation as well as to assess seismic risk and the communication infrastructure performance.

The time step **t** represents the fixed time step used in the LP formulation. Shortest Paths and Network Simplex flows are calculated based on the O-D demand for five-minute intervals. The time step T is a variable time step and represents the re-planning time period. In this specific case, the re-planning time period is the time at which new critical information arrives at the decision nodes in the system. This availability of new information will result in an update of either network conditions or commodity demand information, and may help to improve the current plan of action.

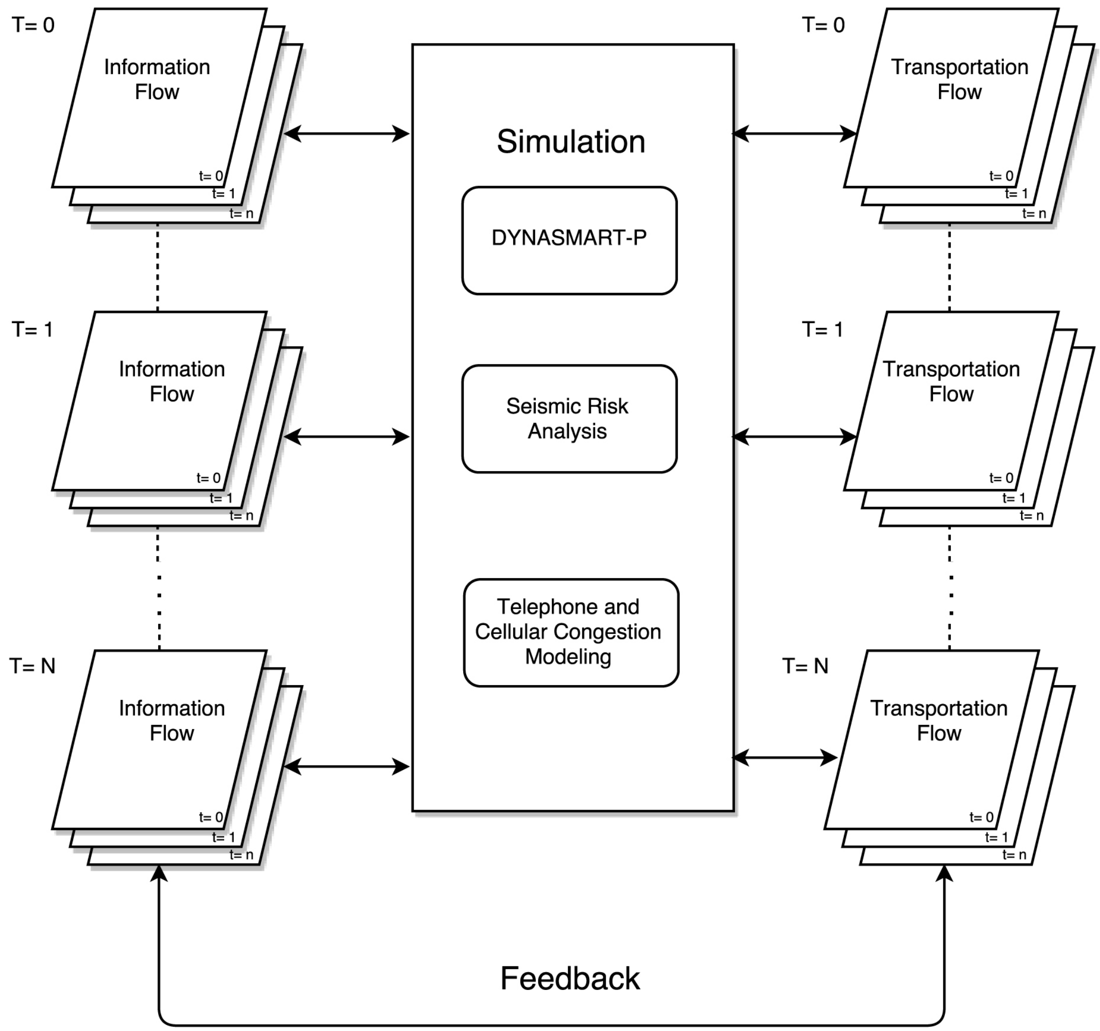

Figure 14: Solution Framework (Detailed)

4.1 The Transportation Network

4.1.1 DYNASMART-P

DYNASMART-P is a Dynamic Network Assignment Simulation Model for Advanced Roadway Telematics (Planning). The tool falls under the class of discrete time mesoscopic models as it combines microscopic dynamic network assignment models with macroscopic traffic simulation models. DYNASMART-P models the changes in the overall traffic flows in a traffic network based on the travel behavior of each individual driver in the network. The model can also represent the movements of a driver who seeks to fulfill a number of activities in the system such as certain stops on the way to a desired destination otherwise known as *Trip Chains*.

"Some of the modeling features of DYNASMART-P include [20]:

- Efficient hybrid traffic simulation-assignment approach, which moves individual vehicles according to robust macroscopic traffic flow relations.
- Ability to load trips and simulate trip chains with several intervening stops having associated durations.
- Representation of multiple vehicle types in terms of operational performance (e.g. trucks, buses, passenger cars).
- Detailed output statistics at both the aggregate and the disaggregate levels. For example, DYNASMART-P generates various performance measures over time for each link in the network. These measures of effectiveness (MOE) include vehicle trips, speeds, densities, and queues. It also produces the trajectory of each vehicle in the network, from origin to destination, including intermediate activity stops. Statistics such as average travel times, average stopped times, and the overall number of vehicles in the network is also provided at varying levels of aggregation."

One of the major advantages of DYNASMART-P is that it is not substantially limited by the size of the network structure. It can be used for various sized networks with multiple scales without overly significant effects on its performance. Although a sacrifice in the level of detail is usually expected when modeling any large network, DYNSMART-P is fully capable of modeling the fine details such as zones, intersections, links etc. One of the only major flaws of DYNASMART-P that is readily apparent would be its inability to model lane changing since two lane links are represented by two links rather than one link with multiple lanes similar to PARAMICS.

Many researchers choose mesoscopic simulation as a tool for transportation network management in emergency situations [21]. This is because it is a good compromise between the extreme computational requirements of microscopic simulation and yet provides more insightful analysis and better detail than macroscopic simulation. The DYNASMART-P simulator is used in this study in order account for the linearity assumption for the link travel times in the LP. The simulator is an extension of the macroparticle simulation model (MPSM) logic [22], which moves vehicles in bunches according to prevailing link speeds. Two types of a modified Greenshields model are used for traffic distribution. Type one represented in figure 15 "is a dual-regime model in which constant free-flow speed is specified for free flow conditions (1st regime) and a modified Greenshields model is specified for congested-flow conditions (2nd regime)" [20]. Generally, dual-regime models are better suited to freeways while single-regime models are applicable to arterials.

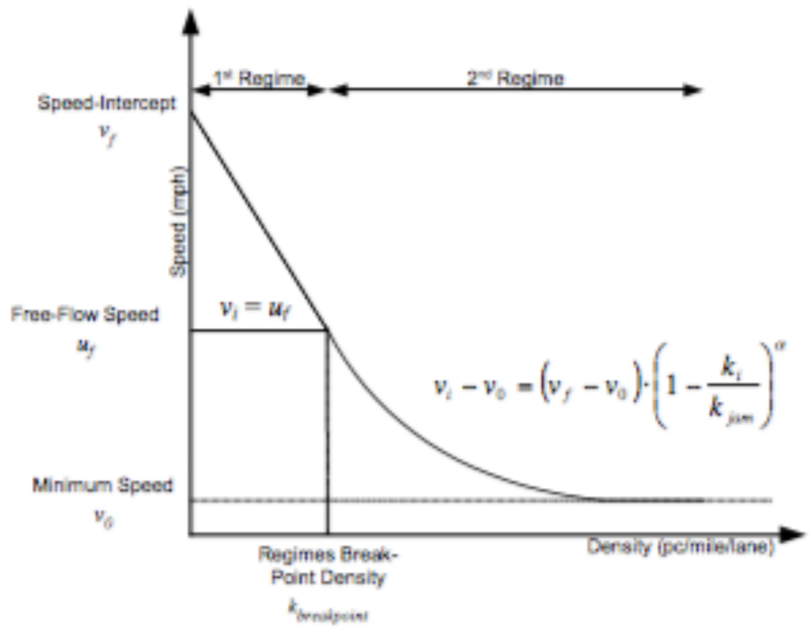

Figure 15: Type 1 Modified Greenshields Model [20]

In mathematical terms, the type 1 modified Greenshields from reference [20] is expressed as follows:

$$v_i = u_f \qquad 0 \le k_i \le k_{breakpoint}$$

$$v_i - v_0 = (v_f - v_0).\left(1 - \frac{k_i}{k_{jam}}\right)^{\alpha} \qquad k_{breakpoint} \le k_i \le k_{jam}$$

where,

v_i = speed on link i
v_f = speed-intercept
u_f = free-flow speed on link i
v_0 = minimum speed on link i
k_i = density on link i
k_{jam} = jam density on link i
α = power term
$k_{breakpoint}$ = breakpoint density

Type 2 uses a single-regime to model traffic relations for both free and congested-flow conditions (figure 16).

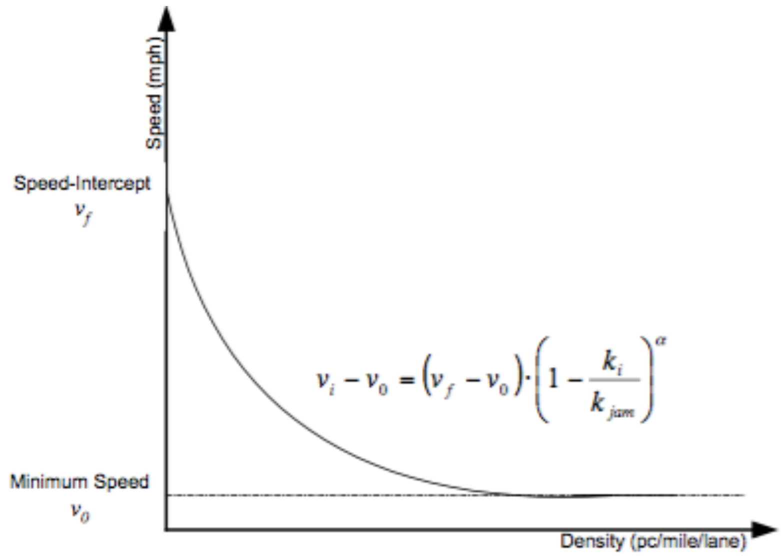

Figure 16: Type 2 Modified Greenshields Model [20]

In mathematical terms, the type 2 modified Greenshields from reference [20] is expressed as follows:

$$v_i - v_0 = (v_f - v_0).\left(1 - \frac{k_i}{k_{jam}}\right)^{\alpha}$$

DYNASMART-P simulates traffic based on a fixed time step method that uses a simulation interval of six seconds. The vehicles are moved in the system at every time step based on the link speeds at that time. Link densities are updated in the system and the k-shortest paths are recalculated accordingly. Although the simulation interval is fixed, the user can define the time steps for re-calculating the k-shortest paths and link density updating algorithms respectively. These time steps are defined with the number of simulation intervals as a basis. For example, if the k-shortest paths are calculated every 30 simulation intervals the time step for re-calculation is 3 minutes. This is significant given that the simulation time interval of 6 seconds is too small for an update of paths for a given origin destination pair as no significant change takes place in the system in a such a short period of time [22]. Thus, an assignment interval of a few minutes would be better suited for updating the k-shortest paths.

The role of DYNASMART-P in the solution framework is to serve as a representation of the 'real world' in a post-disaster situation. The idea is that the LP optimizes the movement of information, vehicles, and physical commodities based on the information available in the system at each time step. The resulting optimal vehicle paths from the LP are then input into DYNASMART-P to assess what the actual travel times on each link will be. The actual travel times are then input back into the LP in order to re-optimize the vehicle paths and vice-versa. This re-iteration process will continue until all critical information becomes known in the system. The aim is to minimize travel time for certain vehicles (such as ambulances carrying injured patients) in order to provide an effective plan of action in a post-disaster situation.

In order to maintain a real-time relationship between the LP and the 'real world' simulation it is important to re-create the vehicle paths up to the point that new information becomes available. While DYNASMART-P allows users to input specified vehicle paths, the path file overrides the simulation paths making it impossible to allow the simulation to take over at a certain point in time. One way to get around this issue is to use trip chaining where vehicles are permitted to exit the transportation network at intermediate nodes along their travel path to perform a specific activity for a time that is equal to the activity duration [20]. While these vehicles are out of the network at their intermediate destinations, they have no effect on traffic density in the network. Once the activity is completed, the trip maker resumes their trip again from this stopping point to complete the trip to its specified final destination. This feature can be used to fix vehicles to a specified path in order to re-create traffic up to a certain point in time. Since the k-shortest paths are updated and calculated based on a user specified number of simulation intervals, as long as the activity duration times are less than the time the k-shortest paths are updated, the resulting paths in the simulation and respective traffic conditions should remain unaffected despite the stopping time specified for each chain.

In order to integrate the simulation with an LP, an intermediate MATLAB program is needed, that converts the DYNASMART-P simulation output into input for the Network Simplex Algorithm. The resulting vehicle paths from the Network Simplex Algorithm are then input back into the DYNASMART-P simulation so as to assess resulting link travel times. Figure 17 below represents the DYNASMART-P feedback loop portion of the solution scheme.

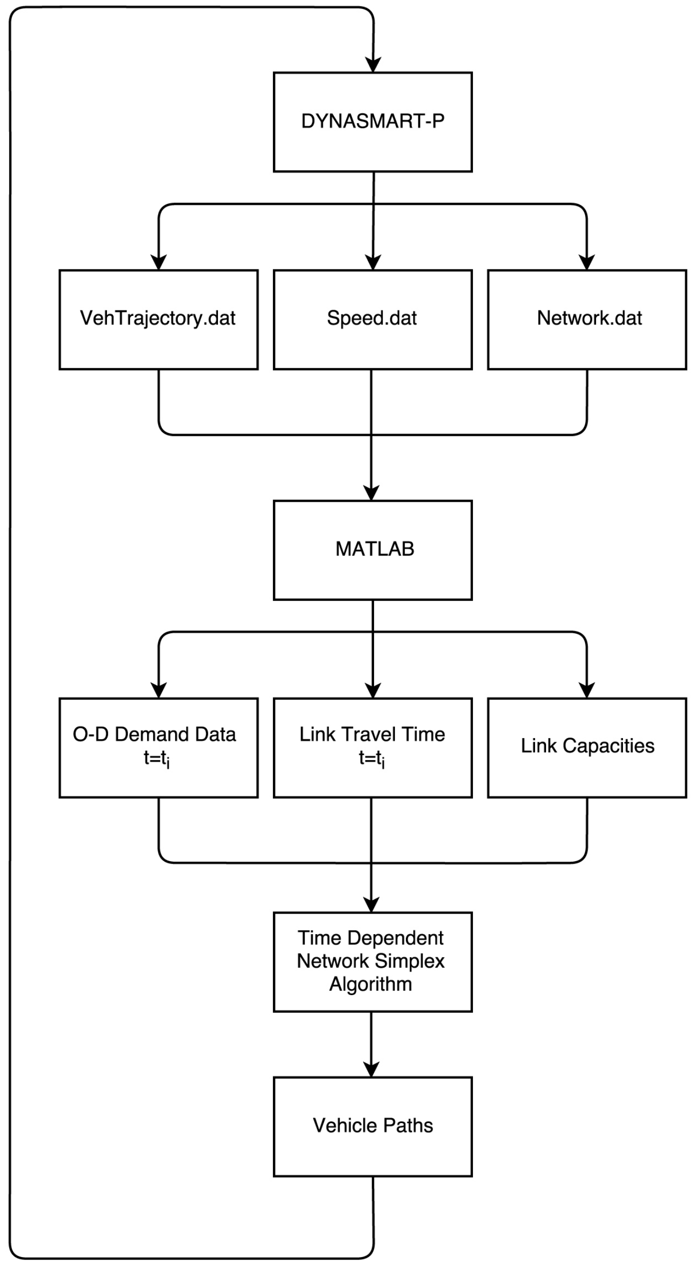

Figure 17: DYNASMART-P Feedback Loop

The MATLAB program serves as an intermediary between the DYNASMART-P simulation and the Time Dependent Network Simplex Algorithm by converting certain data files into the required input for the algorithm. The "VehTrajectory.dat" file provides us with the vehicle trajectory for each vehicle in the simulation including its start time, vehicle ID, total travel time, and vehicle type. For this specific file, the MATLAB program returns the following for all vehicles that leave a desired Orig Z for a desired Dest Z in a specific time window **t** [tStart,tEnd]: a list of the vehicles IDs, the total number of vehicles (O-D demand), the total travel time per vehicle, and the vehicle type. The "Speed.dat" file provides the speeds on each link for each minute in miles per hour. Combined with the link lengths that are extracted from the "Network.dat" file and converted from feet into miles, the MATLAB program returns the travel times on each link for each minute, which are then averaged over **t**. Lastly, also using the "Network.dat" file, the link capacities are calculated by multiplying the lane capacities by the number of lanes for the specified time window **t**.

4.1.2 Time Dependent Network Simplex Algorithm

The Network Simplex algorithm is a path based solution algorithm used to solve minimum cost flow problems in an efficient manner. The output of Network Simplex is an optimal spanning tree of **n-1** arcs connecting all nodes **n** in the network. The solution scheme begins with a feasible spanning tree solution and builds on it by the addition and removal of certain arcs until a minimum cost solution is achieved.

In the capacitated Network Simplex algorithm approach, the allowable flow is constrained a vector of link capacities **k**. The formulation for a capacitated minimum cost flow problem is therefore as follows:

$$\text{Min } c^T x$$

$$Ax = b$$

$$x \leq k$$

$$x \geq 0$$

where **A** is the node incidence matrix, **c** is the link cost vector, and **b** is the demand vector for the network.

When modeling real time traffic and circumstances following a post-disaster situation, a dynamic flow network is better suited for a decision-making process over time. “Time is an essential component because flows take time to pass from one location to another or because the structure of the network changes over time” [16]. In the case of the Time Dependent Network Simplex Algorithm, the inputs are time variant. For example, while using link travel time as a measure of link costs, the cost vector will vary according to the departure time of each vehicle. The demand vector **b** will also change based on each time step and the respective travel demand. In terms of link capacities, they will also vary based on travel time of the previously departed group of vehicles. Therefore, both travel time and network structure are important factors to consider in the Time Dependent Network Simplex Algorithm.

To visualize the Time Dependent Network Simplex Algorithm, it can be simplified as an iterative application of the Network Simplex Algorithm to a network that is changing at each time step according to previously assigned flows. If a First In First Out (FIFO) movement is assumed, the flow from the previous time step is prioritized over that of the following time steps and is thus unaffected by future demand. For future demand, however, the network structure will vary depending on whether the departure time is less than the total travel time of the vehicles from the previous time step.

In mathematical terms,

$$k_{ij}(t) = \begin{cases} k_{ij} - x_{ij}(t), & if\ t < \sum_{t=t-1}^{t} c_{ij}\,(t) \\ k_{ij}, & otherwise \end{cases}$$

where $k_{ij}(t)$ is equal to the link capacity at departure time t, x_{ij} is the residual flow on link ij at time t from the previous departure time interval, and the total travel time for the previous vehicles is calculated from the previous departure time up to the current departure time in order to determine the location of previously assigned vehicles in the network.

Another factor to consider in a dynamic flow network is that the travel time on each link varies according to the departure time of each group of vehicles at the origin node. As the flow moves through the system, travel times on each link will be dependent on the total travel time of the flow when entering that link and the respective travel time at that point.

In order to run the Network Simplex Algorithm, the travel time or the link cost vectors are input along with the supply/demand vector and the link capacity vector. To determine the travel time or link cost vector for a certain departure time in a time-dependent case, another algorithm can be used that determines all possible path combinations and their subsequent link travel times on each link. The outcome of this algorithm is a group of link cost vectors based on each of the possible path scenarios. The Network Simplex Algorithm is then applied for each of these scenarios and the Total Cost is compared to determine which yields the optimal solution for each departure time step.

4.1.3 Seismic Risk Analysis

One of the important processes following a disaster situation is to assess the resulting damage to the infrastructure in order to effectively mitigate proper relief. With the movement of people, vehicles, aid, and information, it is imperative to be able to estimate the post-earthquake link conditions as a basis for an initial response plan until information regarding link states becomes known.

Based on past earthquake scenarios and the resulting damages, bridges in a transportation highway network have been identified as a significant source of vulnerability. Thus assessing the seismic risk of a transportation network mainly involves the identification of the vulnerability of bridges in the network when subjected to various earthquake magnitudes and the resulting damage states. One approach is to represent these damage states in the form of fragility curves to account for uncertainties in an earthquake occurrence [23]. Based on Auza et al's past work, the procedure to simulate post-earthquake bridge states is displayed in figure 18 below [24].

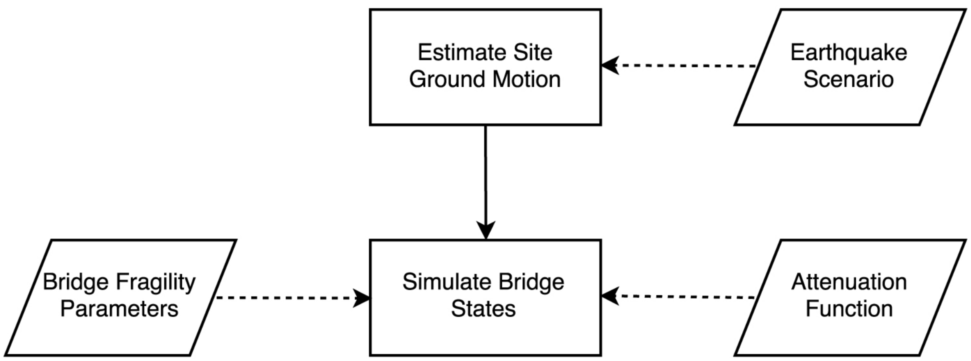

Figure 18: Seismic Risk Analysis Module [24]

The earthquake scenario input can either be the actual earthquake scenario including the magnitude and the location of the epicenter (if known) or it can be an estimate of the magnitude and epicenter based on previous approximation studies on the seismicity of the study area.

The following attenuation function [25] is used,

$$\ln(a_H) = -3.512 + 0.904M - 1.328ln\left(\sqrt{D^2 + (0.149e^{0.647M})^2}\right)$$

$$+ [0.405 - 0.222\ln(D)]S_{HR} + [0.440 - 0.171\ln(D)]S_{SR}$$

$$+ [1.125 - 0.112\ln(D) - 0.0957M]F$$

where:

a_H = Peak ground acceleration

M = Earthquake magnitude
D = Distance between epicenter and bridge site
F = Fault time: 1 for reverse thrust, 0 for strike slip
S_{HR} = 1 for hard rock, 0 otherwise
S_{SR} = 1 for soft rock, 0 otherwise

Following the onset of an earthquake and the resulting seismic ground motion a bridge is assumed to be in one of five damage states. These damage states are No Damage, Minor Damage, Moderate Damage, Severe Damage, and Collapse. In this study a bridge is considered temporarily incapable of transporting flow when found to be moderately damaged until further assessments are made and is completely incapable of transporting flow if it is found to be at least majorly damaged.

The cumulative probability of a bridge entering a specific damage state *j* can be expressed in the form of a two-parameter lognormal distribution function given below [23]:

$$F_j(a_i; c_j, \varsigma_j) = \phi\left[\frac{ln\left({a_i}/{c_j}\right)}{\varsigma_j}\right]$$

where:
a_i = PGA at bridge site i
c_j = median of fragility curve j
ς_j = standard deviation of fragility curve j

Figure 19 below shows the cumulative probability distribution for each of the four previously mentioned damage states known as fragility curves.

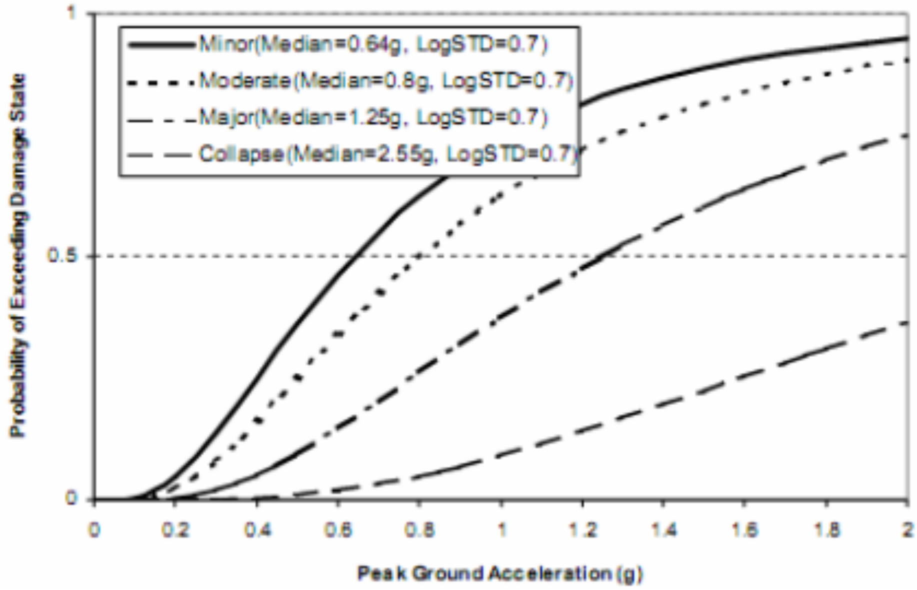

Figure 19: Fragility Curves and Parameters for all Bridges [23]

In order to simulate the bridge states the fragility curves are then used as an input for a Monte Carlo simulation yielding a probability distribution of damage for each link. This probability is then compared to the cumulative probability of entering each damage state in the fragility curves to determine an estimated damage state based on the PGA for each bridge in the network.

This procedure helps give a rough estimate of the damage state of bridges following an earthquake. However the actual link condition will not be fully known until the first vehicle in the system attempts travelling on the actual link and finds it to be broken. For modeling purposes it is helpful to be able to know at what time exactly this new information becomes available in the system. This time can be derived from DYNASMART-P using the VehicleTrajectory.dat file as a basis. The AccumulatedVolume.dat file tells us how many times we need to perform the "Find" operations described in the algorithm below as well as the number of vehicles that need to be rerouted based on the link conditions.

Algorithm to find the exact time that the first vehicle crosses a broken link and thus confirms the link damage condition:

- Step 1 - Identify the broken link.
- Step 2 - Look at the AccumulatedVolume.dat file to find the number of vehicles that eventually end up traversing that broken link. This provides a worst-case upper limit **(n_upper)** of "Find" operations that must be performed to find the moment the first vehicle crosses the broken link of interest.
- In the VehicleTrajectory.dat file,Step 3 - use the Find feature to identify an arbitrary vehicle A that crosses over the broken link.
- Step 4 - Note the time (under the "Node Exit Time Point") that vehicle A begins to traverse the link. Mark as **t_A**.
- Step 5 -Use the Find feature to identify another vehicle B that crosses over the broken link. Note the Node Exit Time Point **t_B** that vehicle B begins to traverse the link.

If t_A < t_B, **retain t_A** as the time that the first vehicle crosses the broken link of interest.

If t_B < t_A (i.e. if t_B is *before* t_A), then **retain t_B** as the time that the first vehicle crosses the broken link of interest.

Perform steps 3-5 a worst-case **n_upper** number of times. The algorithm may also terminate if changes are no longer seen after, say, 100 vehicles.

Note: This algorithm goes through all of the vehicles that traverse the broken link of interest, and finds the vehicle that arrived at that broken link.

By knowing when and at what point accurate information on post-disaster link conditions becomes available, one can direct this information to the decision-making nodes in the system in order to properly route vehicles to avoid broken and severely damaged links. The earliest delivery time at which this information reaches the decision-making nodes can also be a re-planning time period for which the chosen plan of response is modified based on the availability of new information on the transportation network status.

4.2 The Communication Infrastructure

One of the unique aspects of the proposed formulation is that it takes into account both the transportation and the communicational networks in a post-disaster situation as well as their interrelationships. In common disaster relief practices, the optimization of the transportation of goods, people, and relief agents is the main objective in a post-disaster situation. However, it is highly likely that disruptions may occur in wireless networks, landlines, and other conventional communication vessels designed to transfer critical information following the onset of a disaster. For example, a cellphone base station tower could get knocked out or damaged which would redirect its users to a further base station that may eventually get extremely congested bringing the entire network to a halt. Also, in another case, a temporary call center designed to collect information for relief agencies may be overloaded with calls resulting in very long and inefficient wait times. These are the type of scenarios that need to be taken into consideration when facilitating a response plan following the onset of a major disaster.

In the case of these conventional communication network links failing, it is possible that transfer of information could end up on transportation links, which is one of the main interrelationships between the two networks. This redirection of information that may occur at certain nodes can be represented as a mode transfer type of scenario in the formulation. For example, a packet of information may travel over a phone link in the communication network between two nodes and then continue on a moving vehicle at some point in its path due to network disruptions.

4.2.1 Cellular Traffic

In data networks, network congestion results from overloading links or nodes with data to the point that the quality of service deteriorates. Teletraffic engineering in telecommunications network planning aims to minimize network costs while maintaining the quality of service delivered to network users [26]. Generally, as the traffic generated on the network increases the amount of base stations needed in the network also increases. In the case of mobile telephones, a base station acts as an intermediary connection between a mobile phone and the wider telephone network. Therefore, the general assumption is that network efficiency can be improved by splitting up call demand over several base stations by reducing the area (or cell size) serviced by each station (see figure 20 below).

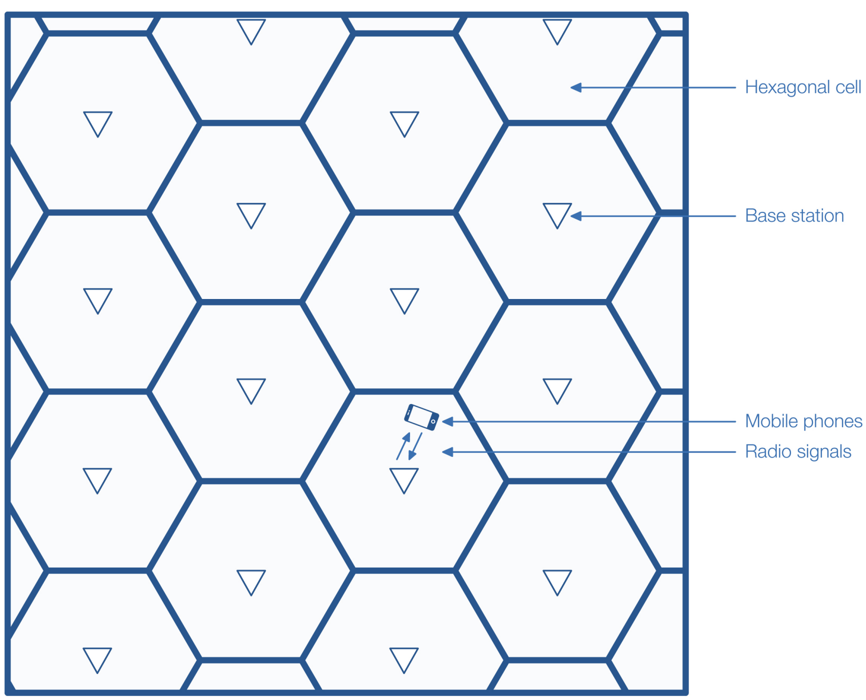

Figure 20: The Cell Structure of a Mobile Network

In disaster cases, the probability of network damage or failure is extremely high. In 2000 a fireworks factory exploded in the Netherlands resulting in twenty three deaths, 950 injuries, and the destruction of 4000 homes [27]. One of the main bottlenecks in response by the different relief agencies was network congestion. Although the network was split between emergency services and commercial cellular services, the congestion on both networks lead to a collapse of all communication systems. For hours after the explosion communication remained difficult and much time was wasted because experts couldn't get reliable information about the overall situation and the associated risks to the affected area. Other problems that can occur in a post disaster situation include loss of base stations due to either physical damage or loss of power in the affected area as a whole. The damage to a base station is assumed to be a measure of severity of the damage to the overall area, resulting in an even greater urgency for communication between relief workers to and from that specific location.

One way to restore coverage in a congested area is through the use of portable base stations. A portable base station is usually a vehicle that can be used to provide temporary wireless network connectivity. These stations can be used to enhance service during special events where a large number of users are gathered in a condensed area, or in disaster affected areas where damage to base stations is highly likely. The use of portable base stations in a post-disaster situation is another example of the interrelationships that exist between the communication and transportation networks. It demonstrates a case where movement on the transportation network can aid in restoring a missing or broken node, and possibly link, in the communication network.

4.2.2 A Portable Base Station Optimization Model

Optimizing the movement of portable base stations from storage facilities to intermediate staging areas and finally to disaster affected areas is generalized as a transshipment problem by Bartolacci et al [28]. “The "shipping" cost coefficients in the objective function represent a combination of factors including transport cost in monetary terms, transport time, and severity of need at a location.” An excerpt is taken from [28] and the variables and formulation are as follows:

X = Total number of portable base stations available

S = Number of storage facilities for portable base stations

F_{xs} = 1 if storage facility s houses portable base station x, 0 otherwise, where $s = 1...S$ and $x = 1...X$

A = Number of predefined staging points for portable base stations prior to

C_{xsa} = "Cost" to transport portable base station x from storage facility s to staging point a

P_{xa} = 1 if portable base station x is brought to staging area a, 0 otherwise, where $x =$

$1...X$ and $a = 1...A$

U = Total number of candidate sites of possible deployment for portable base stations

R_{xu} = 1 if portable base station x is deployed at candidate site u

M_{xau} = "Cost" to transport base station x from staging point a to candidate site u

Minimize $\sum_1^X \sum_1^S \sum_1^A C_{xsa} F_{xs} P_{xa} + \sum_1^X \sum_1^A \sum_1^U M_{xau} P_{xa} R_{xu}$

Subject to: (worded for ease of understanding)

1. Total number of portable base stations moved from storage facilities to staging areas has to be less than or equal to X.
2. Any capacity constraints for each staging area. (Maximum and/or minimum amounts of base stations)

3 Any capacity constraints for each storage facility. (Maximum and/or minimum amounts of base stations)

4 Conservation of base stations at storage facilities: for each storage facility, the total number of base stations moved from that storage facility area to staging sites added to the number remaining in the storage facility has to be equal to the number that originally was stored there.

5 Conservation of base stations at staging areas: for each staging area, the total number of base stations moved from that staging area to deployment sites added to the number remaining in that staging area has to equal the total number brought from storage facilities to that staging area.

6 Total number of portable base stations deployed at a candidate site from a given staging area has to be equal to 0 or 1.

7 If a deployment site has been allocated a base station from a staging area, another staging area cannot allocate another base station to that site.

8 Demand constraints for candidate sites - certain points or regions may require, and be suitable for, mobile base stations while others may be deemed unavailable due to current conditions"

The Base Station Optimization Problem is split into two stages that involve (1) minimizing the transport costs from storage to the staging locations and (2) minimizing the transport costs from the staging locations to the deployment locations. With some adjustments this process can be encompassed into the main formulation by representing the portable base stations as a commodity travelling on the transportation network to restore nodes and links in the communicational network.

4.2.3 Telephone and Cellular Congestion Modeling

Every communication link between two points can be regarded as a circuit regardless of the technology used to deliver it. Circuit switching is a process that involves assigning a circuit link between two points to transfer information between two nodes. This link stays in place until this transfer is complete and when referring to conventional phones and cell phones this transfer is completed when the users end the call.

The Erlang symbol is of traffic intensity on a network [29]. The carried load is measured as the average number of simultaneous calls (in erlangs) that are carried by the telephone circuit. This number is usually averaged over an hour but when there appears to be a very high demand at certain time intervals within the hour, they can also be calculated over smaller time periods. The offered traffic is the average number of simultaneous calls that can be carried by a system with unlimited capacity

Offered traffic is calculated based on the call arrival rate λ and the average holding time h using the following equation from [29]:

$$E = \lambda h$$

In a conventional call setting, the main goal of Erlang's Traffic Theory is to assess the number of telephone circuits or operator agents needed in order to meet user call demands. To do so, usually minimizing the number of blocked calls is used as a measure to ensure a specified quality of service target. In the case of post-disaster modeling however, the goal is to quantify call queue time based on the resulting resources available. Telephone traffic capacity is limited by several factors including the availability of functioning non-damaged servers as well as the number of call service providers following the onset of a natural disaster. The Engset formula is therefore a better fit for analysis since it deals with a finite number of M sources rather than an infinite number of sources as assumed by Erlang's theory.

The Engset equation is a measure of the probability of call blocking and is given by [29]:

$$P_b = \frac{\binom{M-1}{k}(\lambda h)^k}{\sum_{i=0}^{k}\binom{M-1}{i}(\lambda h)^i}$$

where:

λ = the idle source call arrival rate
h = the average call holding time
α = the offered traffic per source
M = the number of sources of traffic
k = the number of circuits
i = the number of busy circuits

The relationship between λh and the offered traffic per source α is

$$\lambda h = \frac{\alpha}{\left(1 - \alpha(1 - P_b)\right)}$$

When it comes to cellular phone traffic, however, since it's difficult to quantify the number of sources available, Erlang's theory is generally used for calculating the number of channels needed to carry an approximated amount of traffic in a cellular network. The Erlang B equation is founded on the assumption that blocked calls disappear from the system and are not retried. In the case of an emergency situation the likelihood of retrying a call is extremely high and so the Erlang C equation is better suited for this study.

The Erlang C equation calculates the probability of a call being delayed under the assumption that a call request will be retried rather than abandoned. Call arrival is assumed to be modeled by a Poisson distribution and the call holding times are modeled by a negative exponential distribution.

The equation is given as follows [29]:

$$P_W = \frac{\frac{A^k}{k!}\frac{k}{k-A}}{\left(\sum_{n=0}^{k-1}\frac{A^n}{n!}\right)+\frac{A^k}{k!}\frac{k}{k-A}}$$

where:

A	= the total traffic offered in units of erlangs
K	= the number of servers
N	= the number of busy servers
P_W	= the probability that a customer has to wait for service

4.2.4 Information Collection Using Data MULEs

In a post-disaster scenario the availability of information is a vital element in creating a successful response strategy. Wireless Sensor Networks (WSN) are widely used to collect information for a variety of applications including traffic monitoring as well as seismic structural analysis [30]. Traditionally, the information from sensors are relayed to an access point using a multi-hop approach in which sensors forward information in a chain directed towards the closest nodes to the access point or base station. Because sensors are battery operated, one of the major disadvantages with this multi-hop technique is that forwarding the information over long distances can result in a significant loss of power especially in the case of sparse sensor networks. Another possible issue is that because the closest nodes to the base station serve as information collection and transfer points for the entire network, they tend to run out of power very quickly resulting in complete network failure [31]. For efficiently gathering information from a sensor network while also conserving battery power, an approach that exploits mobility using Data MULEs (Data Mobile Ubiquitous LAN Extensions) is becoming very popular.

Data MULEs can be people, animals, vehicles, or even robots equipped with wireless transceivers whose purpose is to move through a network collecting data from static sensors and dropping it off at the access points or base stations. This results in significant power savings for sensors since information is transferred over a much shorter range and only at specific time intervals when the data MULEs are within range. Another benefit is enhanced network robustness, since data MULEs are interchangeable and thus the failure of one or more data MULEs does not result in total network failure [30]. Data MULEs also provide flexibility to the wireless sensor network through their movement which eliminates the need for sensor network connectivity altogether. However, one of the major disadvantages of using data MULEs is the increased latency in data delivery to the base station.

The movement of Data MULEs can be either controlled or random depending on whether a specific Data MULE is assigned to the system with the sole purpose of collecting and transferring information or if random movements within the system are exploited in order to access information from the static sensors and forward it to the base station. References [30] and [32] both regard data MULEs as serendipitous agents whose movements cannot be predicted or controlled. Paper [30] presents a three-tier architecture for sparse sensor networks and considers all mobile entities (including animals) in the environment as an intermediary between the sensors and access points (see figure 21). In order to address the high latency of information delivery to the access points, MULEs are allowed to communicate with each other in a multi-hop fashion to improve overall system performance and connectivity. Also, by equipping a MULE with a cellphone or satellite phone it can serve both as a second tier data collector as well as a top tier access point.

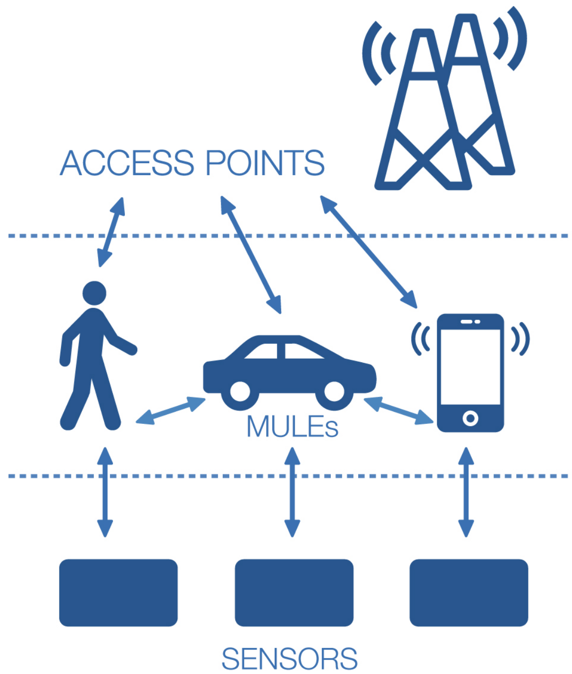

Figure 21: Three-Tier Architecture for Sparse Sensor Networks

By assigning costs to information trading in a Mobile Urban Sensing System (MUSS), [32] creates a self-optimizing model that relies on existing smart phone users in a network to act as data MULEs to transfer sensor data in the system. Motivation for using mobile phones as the data collection and transfer agents includes the large volume of present day mobile users, which provides flexibility to the overall network, as well as the powerful computing and communication capabilities of present day smartphones making them a cost effective alternative over specialized vehicles or robots. Some unique characteristics of MUSS include a wider coverage area, a huge volume of data, as well as the ability to adapt and reorganize accordingly with constantly evolving network conditions. The scheme treats the exchange of information between users as a sales trade where each user aims to maximize profits by selling data to its nearest neighbors within the link capacity constraints. This allows flexibility since devices can switch between short-range and long-range communication depending on which alternative is more profitable and accessible at any given time.

When a data MULE is treated as a random entity the goal is to optimize the movement of information packets in system between the sensor nodes and access points depending on the location of intermediary collection and transfer nodes in the network. However, when a data MULE is controlled, this means that a specific data MULE or group of data MULEs are assigned the task of moving through a network with the sole purpose of collecting and transferring information. The goal in a controlled data MULE scenario is to optimize the movement of the MULEs, and in turn to optimize the movement of information in an attempt to decrease data transfer latency. Papers [33] and [31] split the motion problem of data MULEs into three parts: path selection, speed control and job scheduling. While usually solved as three independent problems, interdependencies exist between these parts that make it difficult to separate them completely. For example, although path selection involves solving for the paths with the shortest travel times, a simple shortest path algorithm does not always yield the minimum travel times. This is because, although the travel distance may be minimized, the travel time may be long when the intersection between the data MULE and the sensor's communication range is short thus forcing the MULE to lower its speed in order to collect all the data from the sensor. How the data MULE changes speeds while travelling through the network is optimized through speed control. Data MULE scheduling involves managing the collection of data from all the sensor nodes in the minimum amount of times. Unlike real-time scheduling, the data MULE scheduling problem is constrained by both time and space making it much more complex.

In a post-disaster scenario, the likelihood of disruptions and breaks in a WSN is very high. The idea of applying a controlled Data MULE movement approach is infeasible since network conditions are unknown and movement within the network can be very random. The main objective in a post-disaster situation is to collect as much data as possible in the minimum amount of time. The MUSS framework from paper [32] is the best fit in this case due to its flexibility, wide coverage area, and the ability to adapt quickly to changes in network conditions. Although user willingness to participate in fulfilling MUSS related tasks is unpredictable and vital for the overall success of the approach, it is safe to assume that in a situation where this information can save lives by optimizing relief efforts user cooperation is absolutely expected. Lastly, one of the major setbacks in the Haiti earthquake was that a disruption in power lines made it impossible for people who had cell phone power to recharge their phones and so communication points that were available at some point completely disappeared. The advantage of power conservation through the use of data MULES is thus very relevant and important in disaster relief planning.

CHAPTER 5: Implementation and Results

5.1 Irvine Triangle Network

The Irvine Golden Triangle was chosen as the initial study area and is displayed in figure 22 below. Also known as El Toro Y, it is where the 405 and 5 freeways are merged. The relative network consists of 31 nodes, 16 of which are Traffic Analysis Zone (TAZs) centroids, 80 links, and 29 critical Caltrans bridges. The motivation for choosing this specific study area is that it is a "high accuracy network with detailed signal and ramp control schemes as well as real time traffic data from freeway and arterial loop detectors" [34]. The availability of real time traffic data in addition to highly detailed network coding makes it an excellent candidate for this study.

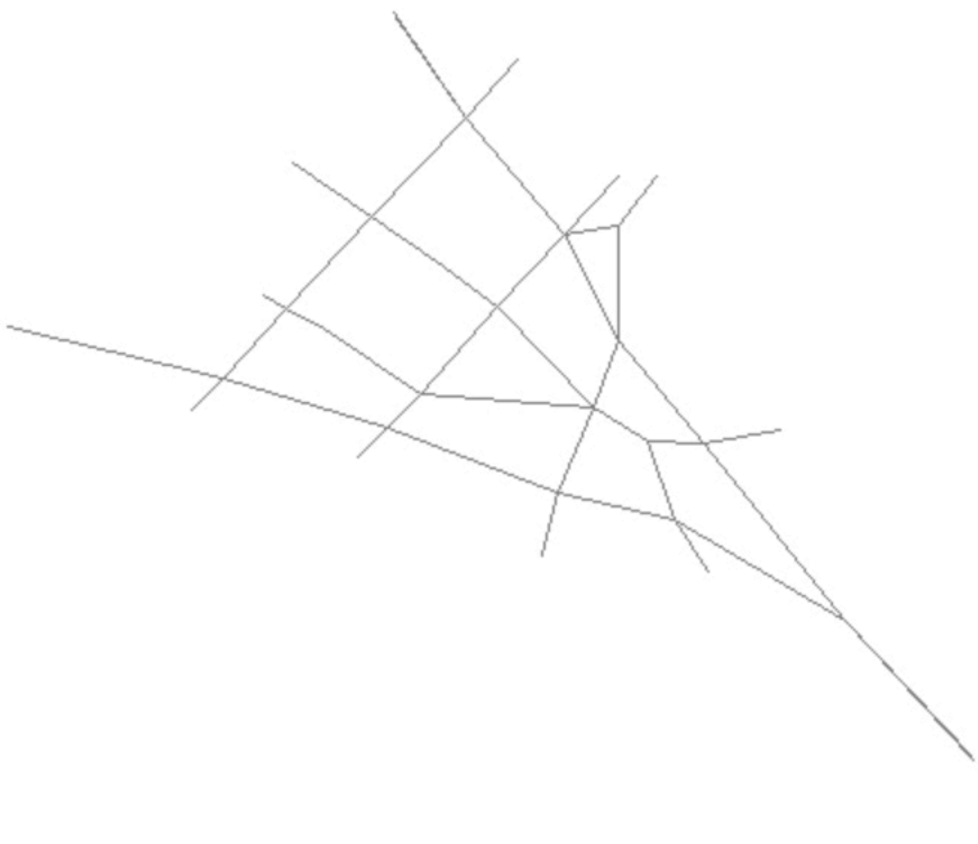

Figure 22: The Irvine Golden Triangle Network

In an initial assessment of the study area, it is important to identify the locations of any hospitals in order to identify the destination nodes for transferring injured people and ambulance vehicles in a disaster response scenario. There were four hospitals found within the study area one of which is a verified Level Two trauma center. Four more Level Two trauma centers were found outside of the study area. According to [36], a Level Two trauma center can initiate definitive care for injured patients including twenty-four hour immediate coverage by general as well as specialized surgeons. The number of beds in a verified trauma center range from less than two hundred for a small hospital to five hundred for a large hospital.

5.1.1 Network Analysis

5.1.1.1 Network Conditions

After identifying the location of the hospitals in the study area, an analysis of the demand data was performed under the assumption that hospital demand has a direct correlation with the severity of damage within a TAZ. Mission Hospital, located in TAZ 16, is the only Level Two trauma center in the study area. The total demand for trips to TAZ 16 is displayed in figure 22 below and is used as a measure of severity. The zone with the most travel demand to TAZ 16 is identified as TAZ 4. Therefore, TAZ 4 is assumed to experience the most damage post-earthquake. There is also a high level of activity between TAZs 12, 13, and 16. All three of these TAZs have been identified as hospital locations. Travel demand between hospitals is expected in a disaster situation and can result from the need to relocate stabilized patients from the trauma center to make room for more severe cases. Alternatively, the smaller hospitals may not be equipped to handle severe cases and thus need to transfer these patients to the nearest trauma center.

By using hospital trips as a measure of earthquake damage severity, one can also assume a correlation between these trips and the damage to the infrastructure in a TAZ. This is because injuries are likely to result from scenarios such as building damage or total collapse, bridge damage or total collapse, as well as disaster related traffic accidents among other possibilities. It is also highly likely that damage to the infrastructure would include damage to cellphone towers resulting in network congestion as well as breaks in the communication infrastructure. A correlation between these trips and the damage to the communication infrastructure such as cell phone base stations, mainly those located in TAZ 4 is thus assumed.

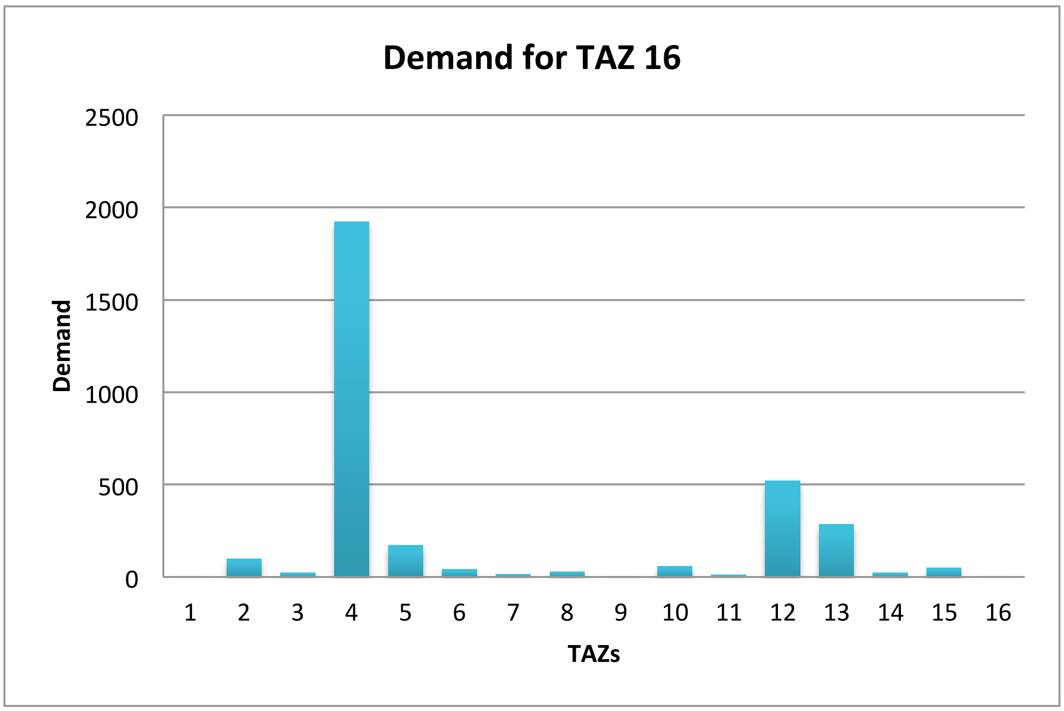

Figure 22: Demand for TAZ 16

5.1.1.2 Network Characteristics

In order to translate the DYNASMART-P output into input for the Time Dependent Network Simplex Algorithm, a MATLAB program is created to group the travel demand data. For any given origin destination pair at any given time step **t**, the program returns the total number of vehicles (O-D demand), a list of their respective vehicles IDs, the total travel time per vehicle, and the vehicle type. The total O-D demand is calculated for each TAZ per time step **t** using this program. The TAZs and their respective centroid nodes are then identified either as Sources, Sinks, or Transshipment nodes based on the following equation:

$$\text{If}\begin{cases} \boldsymbol{Flow_{IN} - Flow_{OUT} < 0} & \boldsymbol{Source} \\ \boldsymbol{Flow_{IN} - Flow_{OUT} > 0} & \boldsymbol{Sink} \\ \boldsymbol{Flow_{IN} - Flow_{OUT} = 0} & \boldsymbol{Transshipment} \end{cases}$$

Of the sixteen TAZs, seven were found to be sinks and nine were identified as sources. Of the nine sources, the difference between inflow and outflow for two was almost negligible. These two TAZs have an almost equal number vehicles entering and leaving which can be characteristic of a call center or emergency center that is set-up temporarily to mitigate a disaster response plan. Therefore, these two TAZs were classified as decision nodes in the system. It is when new information reaches these decision or control nodes, that the re-planning period T begins

5.1.2 Solution Procedure

5.1.2.1 Initialization

Step 1: Determine the Order of Operations

The solution procedure decomposes the LP into three types of flows. These are vehicle flows, information flows, and physical commodity flows. Although the formulation encompasses all these flows in one objective function the existence of interrelationships between them requires an iterative fix and run solution process that fixes certain variables to real values depending on the order of operations. Figure 23 below represents the query module used to determine the order of operations for each time step.

The process begins with an assessment of the communication infrastructure and the expected call wait times in comparison to the expected initial travel times. If the communication infrastructure can handle the information flow on its own and is faster than the transportation network, the optimal paths for information flows are first calculated using the Shortest Path algorithm.

Next, the information flows for the time step are fixed, and time dependent vehicle flows are found based on the information available at that time. The resulting vehicle flows are fixed and used as a basis for the physical commodity flow network. Since physical commodities require vehicles for transfer, the vehicle capacities are adjusted to reflect the link capacities for the commodity flow network.

In the case that the communication links are either broken or have very long expected wait times in comparison to the transportation network travel times, the order of the iterative fix and run process will vary. It is highly likely that the optimal information flows will travel on a combination of links in both the information and transportation networks depending on the respective link travel times.

First, the vehicle path flows are optimized using the Time Dependent Network Simplex algorithm. Based on the resulting vehicle flows per link, the transportation and information links are combined and a Shortest Path algorithm is run to determine the optimal paths for information flows. The vehicle flow capacities are then adjusted to represent the commodity flow network links. Next, the information available at the current time step is input and fixed and used as a basis to determine the optimal flows for the physical commodities in the network.

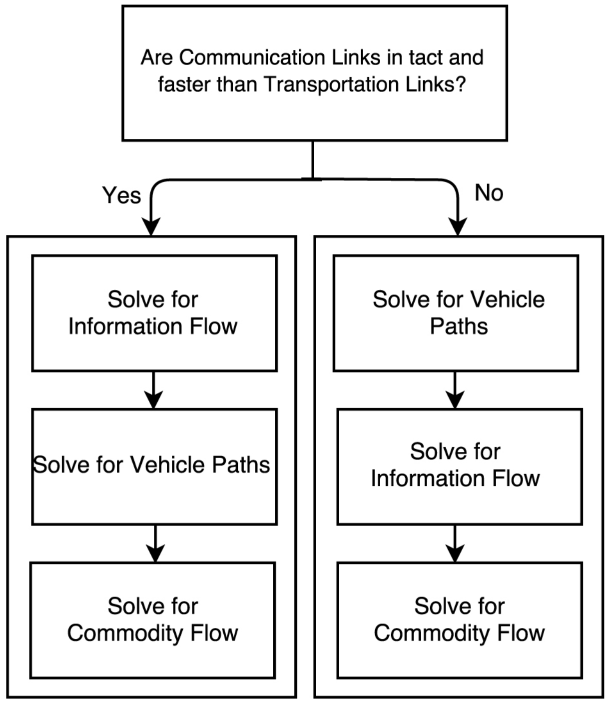

Figure 23: Order of Operations Module

Step 2: Establish Performance Measures

In order to properly assess the efficacy of disaster management techniques, a specific performance measure for the overall system must be chosen. Generally, in traffic simulation, the average travel time of the network is used to compare the performance of different approaches. However, in a disaster type situation, the average travel time may not be specific or relevant enough when determining how quickly higher priority vehicles arrive at their destinations.

An alternative approach is to extract and calculate the average travel time of a specific group of vehicles at each time step. The average travel times of vehicles travelling to TAZ 16 are chosen as a measure of the effectiveness of disaster management in this model. This is because TAZ 16 is the location of the only trauma center in the study area. Reducing the travel time of these specific vehicles will, in turn, reduce the travel time of severely injured people requiring medical care. This can greatly enhance relief efforts as the main objective of any disaster response is to minimize the loss of life.

Step 3: Establish Base Case Scenario

The first case, or base case, compares the average travel times between each TAZ and TAZ 16 for each time step when using the DYNASMART-P paths and the Time Dependent Network Simplex optimal paths under normal network conditions. This means that no disaster is present in the network and the two methods are implemented for a general idea on how they perform relative to one another.

5.1.2.2 Implementation

The Implementation Framework displayed in figure 24 integrates DYNASMART-P simulation, Seismic Risk, and Telephone and Cellular Congestion data with a Time Dependent Network Simplex Algorithm in order to determine the optimal vehicle paths based on the information available in a post-disaster scenario. The role of DYNASMART-P in the solution framework is to serve as a representation of the 'real world' in a post-disaster situation as described in Chapter 4.

The implementation process involves running two types of DYNASMART-P simulations and comparing the average travel times of all vehicles travelling to TAZ 16 at each time step. The first simulation allows DYNASMART-P to determine its own optimal paths based on the information available in the system at the beginning of the simulation. The resulting vehicle trajectories are input into a MATLAB program that sorts the vehicles based on their Origin and Destination, their start time, as well as their individual total travel time. The vehicles traveling to TAZ 16 are extracted and the resulting average total travel times are calculated from each TAZ to TAZ 16 at each time interval.

The second simulation combines the Time Dependent Network Simplex Algorithm with DYNASMART-P. The optimal vehicle paths are determined based on the information available in the system at each time step. These paths are then input into DYNASMART-P to assess what the actual travel times on each link will be. The actual travel times are then input back into the Time Dependent Network Simplex Algorithm in order to re-optimize the vehicle paths and vice-versa. This re-iteration process continues until all critical information becomes known in the system. Once the final optimal paths are determined, they are input into DYNASMART-P and the average total travel times are calculated for all vehicles travelling to TAZ 16 at each time step.

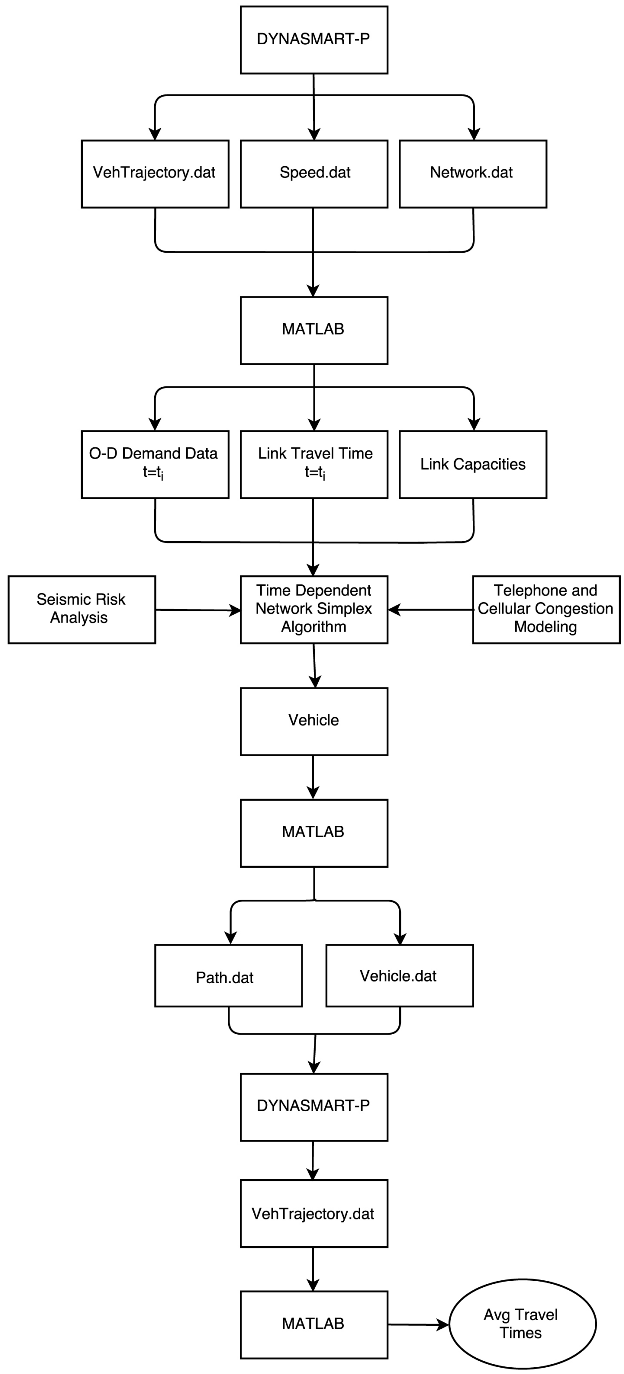

Figure 24: Implementation Framework

Step 1: Simulate Network Bridge Damage States

A seismic risk analysis is performed in order to predict the resulting damage states for the bridges in the network based on the magnitude of the earthquake and the location of the epicenter. To do so, the bridges in the network are first identified and located in the Irvine Golden Triangle Network. Next, using the peak ground acceleration, the damage states are simulated and compared to fragility curves to assess link conditions.

Of the twenty-nine bridges, one was expected to experience Major Damage, two were expected to experience Moderate Damage, and three were expected to experience Minor Damage. These predictions are used as a baseline for the initial DYNASMART-P simulation as well as the proposed plan of action from the LP until the actual information on damage states becomes available. At these times where new information becomes available and is delivered to the decision nodes, a re-run is required to update network conditions and the resulting travel times.

Step 2: Simulate Telephone and Cellular Congestion

In order to assess link travel times for the communication infrastructure it is imperative to determine the holding times for calls in a queue either in attempt to contact a call center with a telephone circuit or a even an emergency contact's cellular phone. In a post-disaster situation there will likely be breaks in the communication infrastructure as well as network congestion. In some cases, the network congestion can result in call wait times longer than the actual physical travel time from one node to another on the transportation network.

In order to solve for the call wait times, which can represent link travel times for the communication network, the probability of calls being delayed was simulated a number of times for both the links in the landline and cellphone networks. This is done using the Engset and Erlang C equations from reference [29]. The higher probabilities of a call being delayed from these simulations were used a basis for the links in the communication network closest to the

TAZs with the highest expected amount of infrastructure damage. The lower simulated probabilities for delay were used as a basis for links in the TAZs with minimal or no expected infrastructure damage. Using the equations, the holding time for both cell phones and telephone lines was found for each link in the communication network. These expected holding times are reflective of the expected travel time for information using the links in the communication network and are compared to the travel time on links in the transportation network in order to optimize the movement of critical information in the overall system.

Step 3: Time Dependent Network Simplex Algorithm

In disaster relief management, time is one of the most important resources. Minimizing travel time of information as well as high priority physical commodities can essentially save lives. The Time Dependent Network Simplex Algorithm is an effective tool to determine the optimal network flows as explained in both Chapters 2 and 4. However, when combined with a high amount of data, the run time becomes longer and the reiteration process is slowed down. The objective of the re-iteration process for implementation is to increase the accuracy of disaster response by updating network conditions in a real-time approach.

Because the number of vehicles simulated in DYNASMART-P may be too heavy a load on the Time Dependent Network Simplex Algorithm, after classifying the TAZs as either Sources, Sinks, or Transshipment nodes, each group of vehicles moving between a specific O-D pair per time step is represented as a single vehicle. The capacities were adjusted accordingly based on the actual total number of vehicles. Also, since the MATLAB lookup table keeps track of the vehicle IDs of each group of vehicles, the paths are changed for all vehicles travelling from each TAZ to TAZ 16 using a line replacement algorithm also created in MATLAB. The running time using this method is much shorter and although it slightly sacrifices accuracy, the results are still very promising and show an overall improvement in the average travel times to TAZ 16.

Step 4: Simulate Transportation Network

In order to quantify the improvements of the implementation framework, six full simulations were performed representing three different cases. For each case, two simulations were carried out and their average travel times were compared. The initial simulation represents DYNASMART-P or the 'real word' average travel times based on information available at the beginning of the simulation while the second simulation assesses the average travel times found using the Time Dependent Network Simplex Algorithm paths. Note that in Case (1), an additional simulation was needed and will be described in greater detail below.

Base Case (0):

Initially, the Time Dependent Network Simplex optimal paths are compared to those of DYNASMART-P under normal network conditions. No disaster is assumed for this case and the average travel times of all vehicles are calculated from all TAZs to TAZ 16. The purpose of these two simulations is to assess the performance of both DYNASMART-P and the Time Dependent Network Simplex Algorithm when all information is available to both and serves as a baseline assessment of both methods.

Case (1):

In order to determine the exact impact of an incident on a network, a base run simulation is performed in DYNASMART-P in order to get the path.dat and vehicle.dat files. These files are then used as input for the subsequent simulation scenario combined with the incident.dat file for the network. This is because if these files were not included, DYNASMART-P would simply reassign the vehicles to better paths, which would not capture the impact of the incidents on the transportation network. A key assumption in this case is that drivers will stick to their predetermined paths regardless of the network conditions and stop time experienced on their journey. Also, the incident information is based only on the seismic risk analysis simulations and is assumed to block of fourteen links in the network from beginning to end.

In addition to the aforementioned two simulations, another simulation is performed to calculate the average travel times using the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop. This simulation has a more accurate idea of post-disaster network conditions due to the inclusion of information on the severity and length of the incident. Also when using the DYNASMART-P feedback loop for reiteration, the travel times are continuously updated and so the resulting paths are expected to avoid the incidents in the shortest travel time possible.

Case (2):

While Case (1) assumes that drivers will stick to their original paths regardless of the network conditions and stopping times experienced along their journey, in a disaster scenario and especially when considering the purpose of transferring injured people to the trauma center in the network, it is more accurate to assume that drivers will detour and change their paths accordingly in order to minimize their total travel time. In this case, the path and vehicle files are not input into DYNASMART-P and the simulation program is given the freedom to assign the vehicles to better paths in order to avoid the incidents in the network. The average total travel times are calculated from all TAZs to TAZ 16 in order to determine how effectively DYNASMART-P can evolve to post-disaster network conditions. This simulation is then compared to the results of a second simulation, similarly to Case (1), based on the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop.

5.1.3 Results and Analysis

5.1.3.1 Results

To evaluate the performance of the two simulation approaches described previously, the model was implemented for each of the three cases and the resulting average total travel times are compared for each case. The average total travel times of the Time Dependent Network Simplex Algorithm were generally found to be lower than those of the DYNASMART-P simulations.

Of the sixteen TAZs, fourteen were found with a demand for travel to TAZ 16. The average total travel times were plotted based on the departure time intervals of the vehicles from the origin to TAZ 16. The departing times ranged from zero to thirty minutes and were split up into six five minute intervals (0 to 5, 5 to 10, 10 to 15, 15 to 20, 20 to 25, and 25 to 30). To illustrate the improvements only the three TAZs with the highest demand for travel to TAZ 16 were selected. These were TAZs 4, 12, 13. Of these three TAZs, TAZ 4 had the highest demand for hospital trips and was assumed to have more severe injury cases as explained previously. The results for all fourteen TAZs in all three cases are included in Appendix A.

Base Case (0)

The average total travel times of vehicles travelling from TAZs 4, 12, and 13 to TAZ 16 under normal network conditions are displayed in figures 25, 26, and 27 respectively. The Time Dependent Network Simplex Algorithm paths performed slightly better or almost equally depending on the origin zone. In the case of TAZ 4, however, the Time Dependent Network Simplex Algorithm paths yielded very high average total travel times in comparison to DYNASMART-P. Since TAZ 4 generates the highest number of trips to TAZ 16, the resulting average total travel times using the Time Dependent Network Simplex Algorithm paths were indicative of the performance of the method overall in the Base Case. It was concluded that, under normal network conditions with no disaster occurrence, DYNASMART-P is better suited when calculating the optimal paths for vehicles in the network.

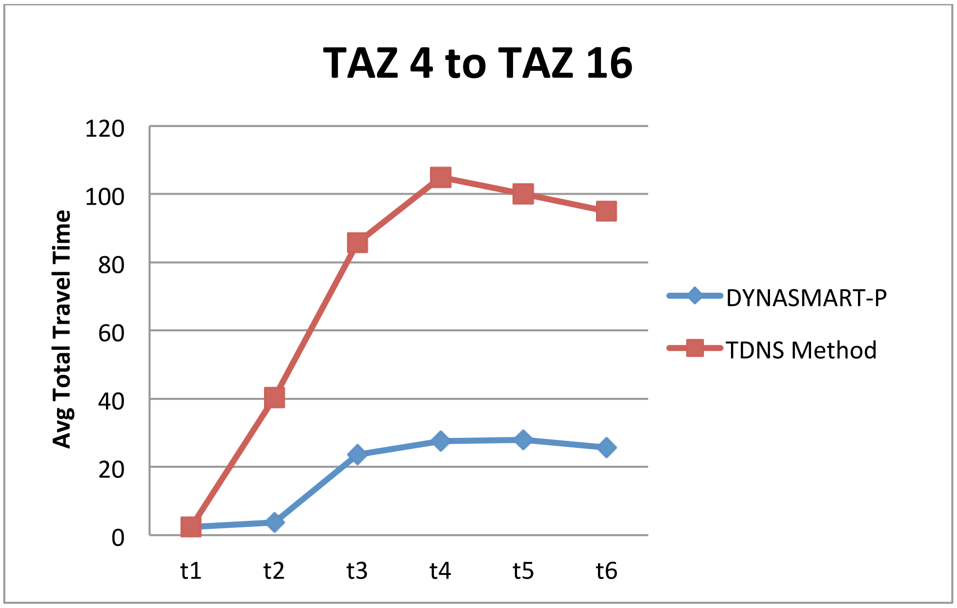

Figure 25: Average Total Travel Times for Base Case from TAZ 4 to TAZ 16

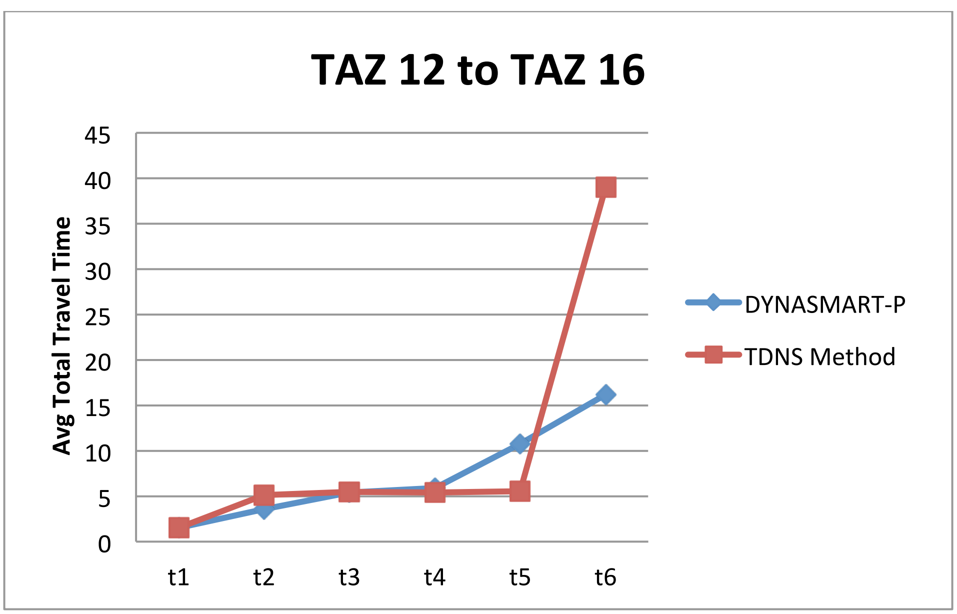

Figure 26: Average Total Travel Times for Base Case from TAZ 12 to TAZ 16

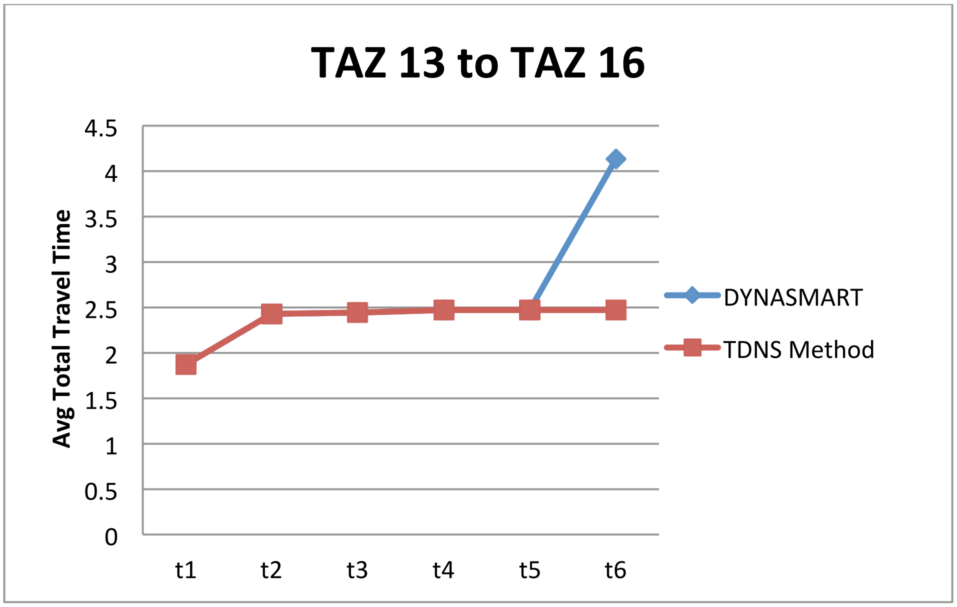

Figure 27: Average Total Travel Times for Base Case from TAZ 13 to TAZ 16

Case (1):

The average total travel times of vehicles travelling from TAZs 4, 12, and 13 to TAZ 16 under post-disaster conditions for Case (1) are displayed in figures 28, 29, and 30 respectively. In this case, when comparing DYNASMART-P with the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop, The Time Dependent Network Simplex Algorithm paths performed significantly better for all origin zones. This is because drivers are assumed to stick to their predetermined paths regardless of the network conditions or stopping time on their journey. As a result, the average total travel time becomes very high especially in the case of complete road closures resulting from earthquake damage. The planning period for the simulation was extended to 280 minutes in order to ensure that all vehicles enter the system. The vehicle trajectory file for the DYNASMART-P simulation indicated that a lot of vehicles were still in the system after the 280 min period was over. For the vehicles whose vehicle trajectories were not found, it was concluded that the total travel time was either equal or greater than the difference between the total running time of the simulation and their respective starting time interval.

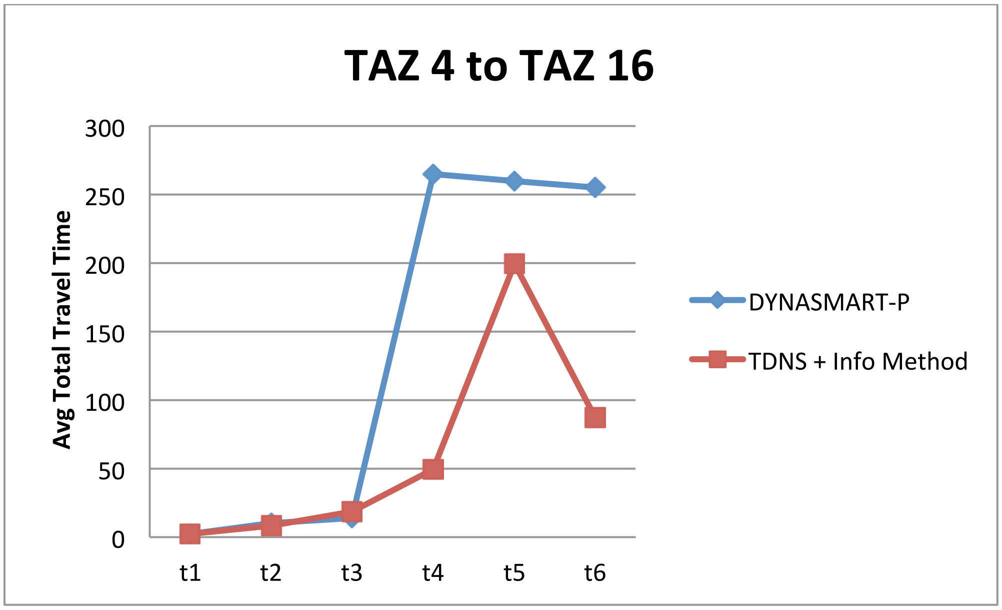

Figure 28: Average Total Travel Times for Case (1) from TAZ 4 to TAZ 16

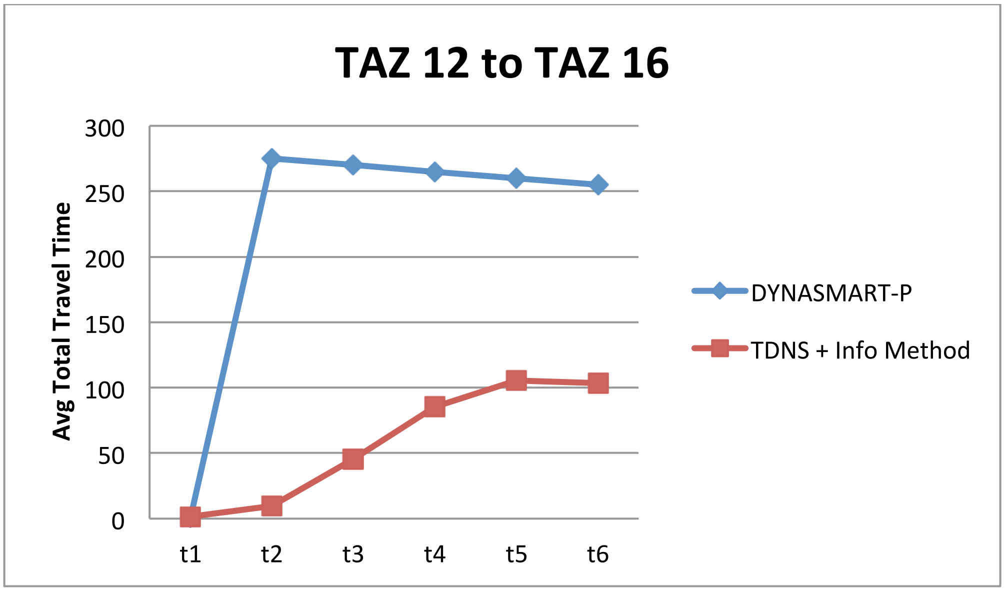

Figure 29: Average Total Travel Times for Case (1) from TAZ 12 to TAZ 16

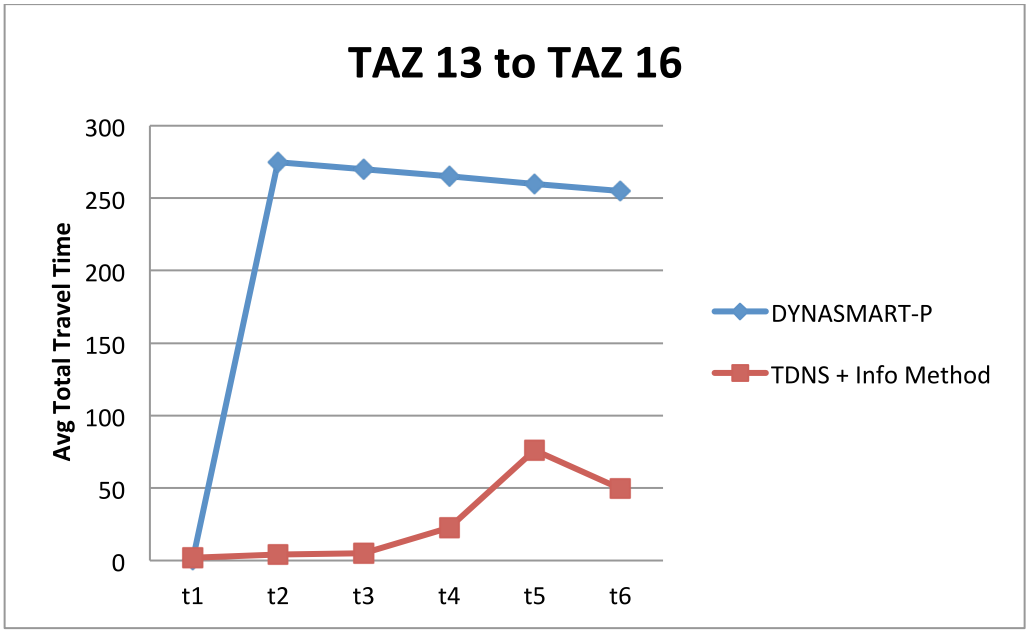

Figure 30: Average Total Travel Times for Case (1) from TAZ 13 to TAZ 16

Case (2):

The average total travel times of vehicles travelling from TAZs 4, 12, and 13 to TAZ 16 under post-disaster conditions for Case (2) are displayed in figures 31, 32, and 33 respectively. While Case (1) assumes that drivers will stick to their original paths regardless of the network conditions and stopping times experienced along their journey, it is more accurate to assume that drivers will detour and change their paths accordingly, in order to minimize their total travel time. In this case, DYNASMART-P was allowed to assign the vehicles to better paths in order to avoid the incidents in the network. For TAZ 4 the results of the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop yielded much better results. Considering the volume of vehicles travelling from TAZ 4 to TAZ 16, the reduction is very significant especially for the group of vehicles departing during the last time interval (25 to 30 min).

However, in regards to TAZs 12 and 13, the DYNASMART-P paths performed slightly better. The significance of this difference will be explored in the Analysis section. Overall, since TAZ 4 accounted for the greatest demand to TAZ 16 as well as a higher severity of damage, the success in reducing its travel times is found to be indicative of the success of the Time Dependent Network Simplex Algorithm with information feedback loop approach in Case 2.

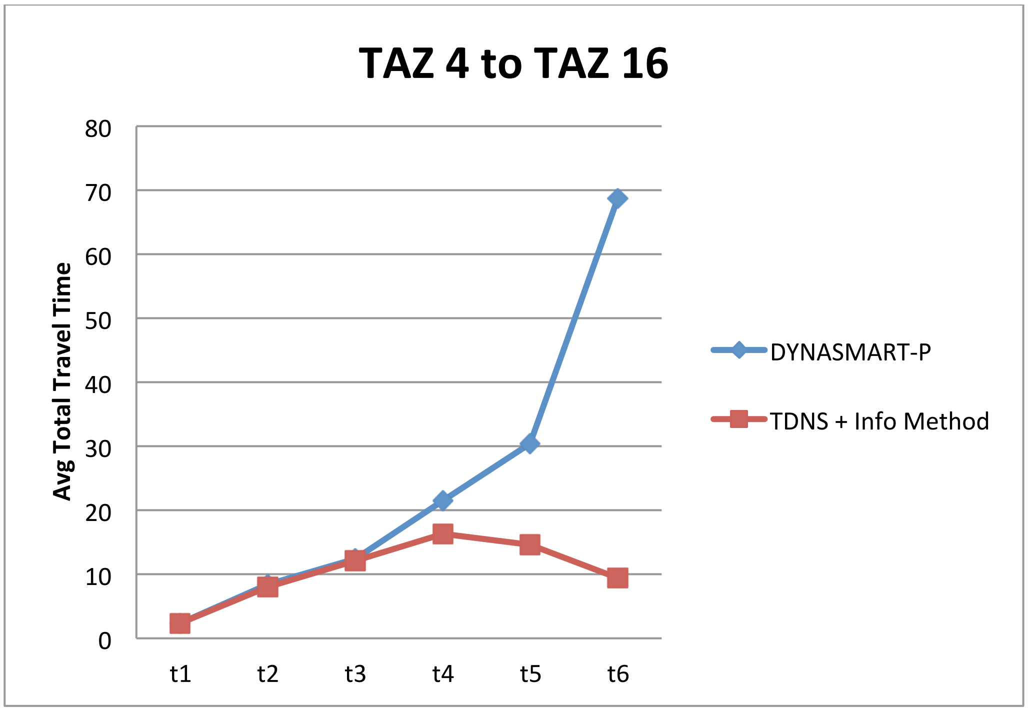

Figure 31: Average Total Travel Times for Case (2) TAZ from 4 to TAZ 16

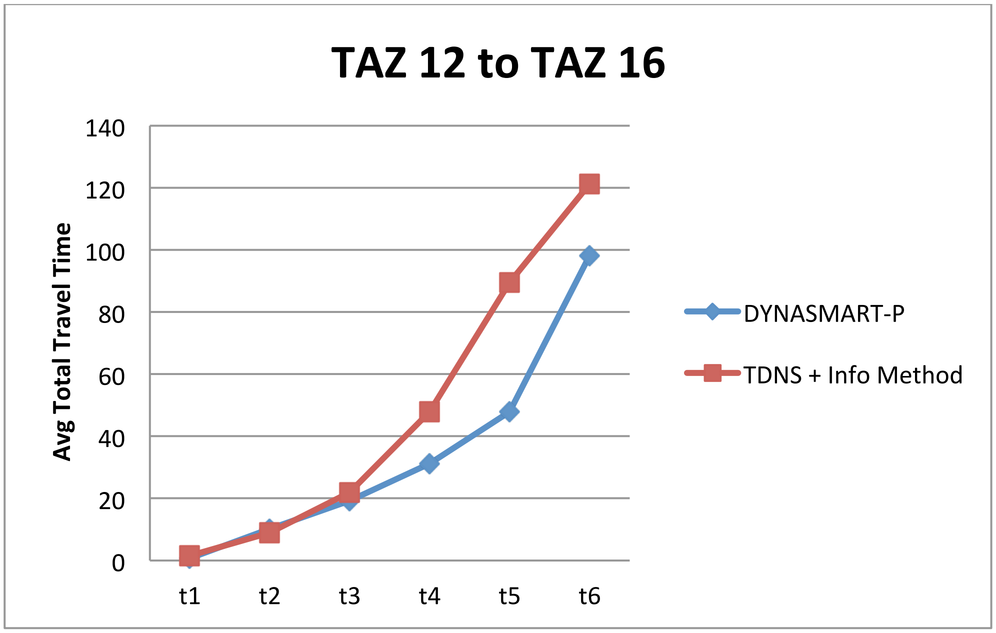

Figure 32: Average Total Travel Times for Case (2) from TAZ 4 to TAZ 16

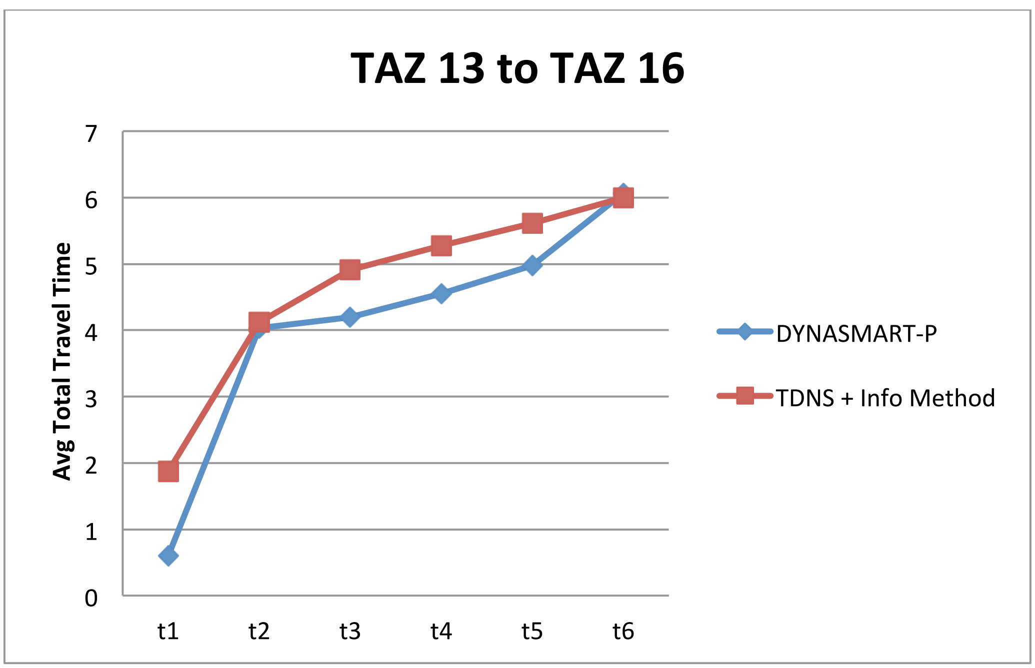

Figure 33: Average Total Travel Times for Case (2) from TAZ 13 to TAZ 16

5.1.3.2 Analysis

The Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop yielded significantly better results specifically for vehicles travelling between TAZs 4 and 16 for both Cases (1) and (2). For Case (2), however, the DYNASMART-P paths appeared to yield slightly better results. In order to quantify the significance of this difference, a two-sample t-test, with a 95% confidence level, was performed for the six average total travel times pertaining to each time step. This was done for both TAZs 12 and 13. For TAZ 12, the difference was found to be significant ($p<0.05$) while for TAZ 13 it was insignificant.

Although the difference between the average total travel times for vehicles travelling between TAZs 12 to 16 was found to be significant, the difference in minutes ranged between twenty to forty minutes depending on the time step. This increase in travel time for the three hundred vehicles travelling between TAZ 12 to TAZ 16 at time intervals 20 to 25 and 25 to 30 results in a fifteen minute and sixty minute average total travel time decrease for the one thousand vehicles travelling from TAZ 4 to TAZ 16 departing at the same time intervals.

Similarly to System Optimal Routing theory, in a disaster scenario an increase in travel time for a small portion of vehicles in order to decrease the travel times of a much larger portion of vehicles is a fair tradeoff for the overall objective of disaster management. This is especially true in this specific network where TAZ 12 already has a hospital on site. If the travel times are found to be too long for the more severe cases, the hospital can always opt to work its way around capacity limitations in order to provide on site care. However, the distance between TAZ 4 to all the hospitals in the network is far. The demand for trips is also very high which is indicative of the severity of the damage to the area and the need for critical care. Therefore, reducing the average total travel time from TAZ 4 to the trauma center from approximately seventy minutes to nine minutes is a substantial achievement in post-disaster management efforts.

5.2 Knoxville Network

The Knoxville network was chosen as the second study area and is displayed in figure 34 below. The network represents Knox County, Tennessee and includes the I-40 and I-75 interstates. There are 356 TAZs, 1347 nodes, and 3004 links within the network.

Figure 34: The Knoxville Network

5.2.1 Network Analysis

Similarly to the Irvine network, it is important to determine the locations of any hospitals in the network in order to identify the destination nodes for transferring injured people and ambulance vehicles in a disaster response scenario. One Level One trauma center was identified in the study area. A Level One trauma center provides the topmost level of care for trauma patients. According to [36], the likelihood of survival increases by twenty to twenty five percent when treatment occurs at a Level One trauma center.

Next, an analysis of the travel demand data was performed in order to determine which of the TAZs are sources of hospital trips. The University of Tennessee Medical Center, located in TAZ 107, is the only Level One trauma center in the study area. Based on a thirty minute loading period, sixty-four TAZs have a demand for trips to TAZ 107.

5.2.2 Solution Procedure

The previously described initialization procedure in section 5.1.2.1 is used to determine the order of operations as well as the performance measures. To evaluate the effectiveness of disaster management, the average total travel times of vehicles travelling to the Level One trauma center is chosen as a performance measure.

Using the same implementation framework presented in section 5.1.2.2, the transportation network link damage states and telephone and cellular network congestion are simulated. Nineteen links in the transportation network are found to experience major damage and are thus disabled.

In order to quantify the improvements of the implementation framework, two full simulations are performed representing Case 2 of the three cases in section 5.1.2.2. The initial simulation represents DYNASMART-P or the 'real word' average travel times based on information available at the beginning of the simulation while the second simulation assesses the average travel times found using the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop.

Case 2 was chosen since in a disaster scenario especially when considering the purpose of transferring injured people to the trauma center in the network, it is more accurate to assume that drivers will detour and change their paths accordingly in order to minimize their total travel time. In this case, DYNASMART-P is given knowledge of the incidents and the freedom to assign the vehicles to better paths in order to avoid them. The average total travel times are calculated from all TAZs to TAZ 107 in order to determine how effectively DYNASMART-P can evolve to post-disaster network conditions. This simulation is then compared to the results of a second simulation based on the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop.

5.2.3 Results and Analysis

5.2.3.1 Results

To evaluate the performance of the two simulation approaches described previously, the model was implemented for Case 2 and the resulting average total travel times are compared for each case. The average total travel times of the Time Dependent Network Simplex Algorithm were generally found to be lower than those of the DYNASMART-P simulations.

Of the 356 TAZs, sixty-four were found with a demand for travel to TAZ 107. The average total travel times were plotted based on the departure time intervals of the vehicles from the origin to TAZ 107. The departing times ranged from zero to thirty minutes and were split up into six five minute intervals (0 to 5, 5 to 10, 10 to 15, 15 to 20, 20 to 25, and 25 to 30). To illustrate the improvements only two of the departure time intervals were selected based on a higher demand for travel to TAZ 107. These were time intervals 15 to 20 and 20 to 25.

The average total travel times of vehicles travelling from all TAZs travelling to TAZ 107 at departure time intervals 15 to 20 and 20 to 25 under post-disaster conditions for displayed in figures 35, and 36 respectively. In this case, DYNASMART-P was allowed to assign the vehicles to better paths in order to avoid the incidents in the network. With a few exceptions, the results of the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop yielded much better results for both time intervals.

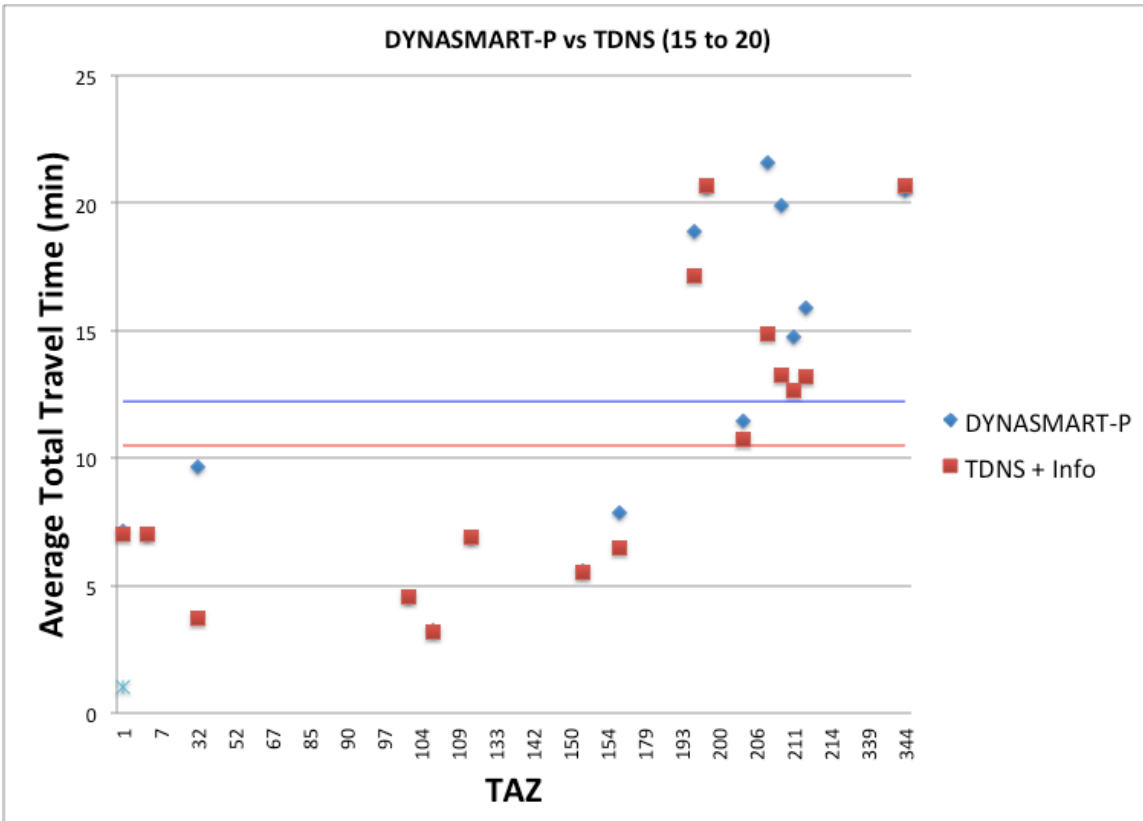

Figure 35: Average Total Travel Times to TAZ 107 at Time Interval 15 to 20

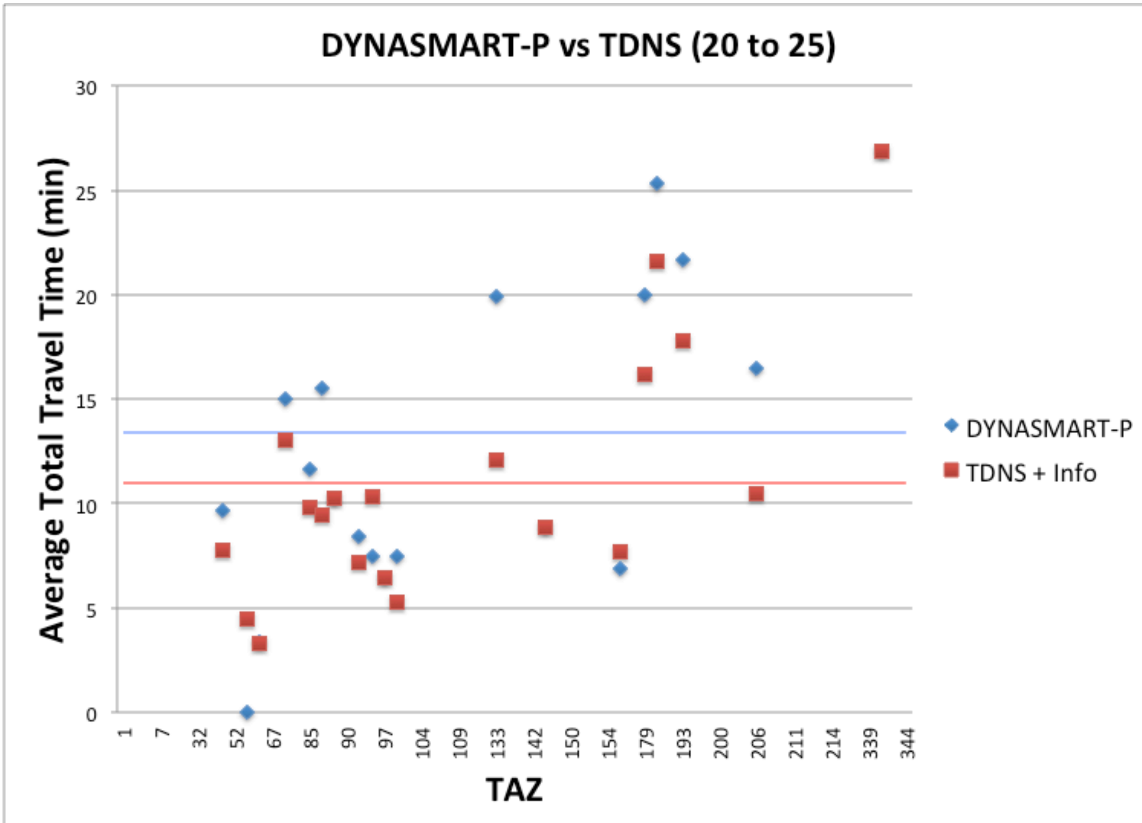

Figure 36: Average Total Travel Times to TAZ 107 at Time Interval 20 to 25

5.2.3.2 Analysis

The Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop yielded better results for the Knoxville Network with a few exceptions. Although the reduction of average total travel times was not as significant as the Irvine Triangle network, the incidents experienced in the case of the Knoxville network are very minor considering only nineteen out of 3004 links were damaged and disabled. Therefore, the disabling of these links should have minimal effects on travel time of the system as well as minor increases in travel times of vehicles seeking alternate routes. Despite the minor effects, however, it is significant that the Time Dependent Network Simplex Algorithm paths combined with the information updating feedback loop still results in lower average total travel times. The results demonstrate the robustness of the solution framework and its applicability to larger networks.

5.3 Further Work: Commodity Prioritization Scheme

One of the major decisions in disaster relief logistics is determining which commodities to prioritize over others in order to effectively meet demand based on the severity of need. By doing so, the most critical demands will be met over others thus minimizing the loss of life. A prioritization scheme described in section 2.4.1.2 was created in order to effectively distribute the higher priority commodities, such as injured patients, over others using the Maximum Flow Problem to calculate the potential supply and demand carryover costs. These costs are then used as a basis to rank the distribution of the commodities in order of importance. To assess the practicality of the prioritization scheme, it is applied to the Irvine Golden Triangle network displayed in section 5.1.

5.3.1 Implementation

Based on the network analysis performed in section 5.1.1, it was found that TAZ 4 experienced the highest severity of damage and thus required the greatest share of relief efforts. The majority of trauma center trips are generated from TAZ 4 thus making it a good candidate to test the commodity prioritization scheme.

Two commodities travelling from TAZ 4 to TAZs 15 and 16 respectively are chosen. Commodity A is a lower priority commodity in terms of time sensitivity such as rice or water while Commodity B is a higher priority commodity in terms of time sensitivity. In this specific example, Commodity B represents injured patients travelling from TAZ 4 to the Level Two trauma center located at TAZ 16. Based on two possible orders of operation, their resulting average total travel times as well as the total travel time of the system are used as performance measures.

5.3.1.1 Solution Procedure

The implementation process involves running two DYNASMART-P simulations and comparing the average total travel times of all vehicles travelling from TAZ 4 to TAZs 15 and 16 respectively at each time step. Based on the vehicle trajectories file from an initial DYNASMART-P simulation combined with the MATLAB sorting program described in section 5.1.2.2, the vehicles with demand for travel from TAZ 4 to TAZs 15 and 16 are extracted and identified.

In order to quantify the effects of the commodity prioritization scheme, two full simulations are then performed representing two difference cases. The first case gives higher priority to Commodity A over Commodity B while the second case gives Commodity B higher priority over Commodity A. When running the simulations, capacity on common links on the commodities' shortest paths is allocated to the higher priority commodity while the latter is redirected on an alternative path. The paths are then input into DYNASMART-P and the resulting average total travel times as well as the total travel time of the system are determined and compared.

5.3.2 Results and Analysis

5.3.2.1 Results

To evaluate the performance of the commodity prioritization scheme described previously, it was implemented for two different cases. The first case gives higher priority to Commodity A over Commodity B while the second case gives Commodity B higher priority over Commodity A. The average total travel times for each commodity are plotted based on the departure time intervals of the vehicles from TAZ 4. The departing times ranged from zero to thirty minutes and were split up into six five minute intervals (0 to 5, 5 to 10, 10 to 15, 15 to 20, 20 to 25, and 25 to 30).

The average total travel times of vehicles travelling from TAZ 4 to TAZ 15 fulfilling demand for Commodity A are displayed in figure 37 below. Two cases are plotted to illustrate the effect of the loading order on the travel time. Similarly, for Commodity B, the resulting average travel times of vehicles travelling from TAZ 4 to TAZ 16 are displayed in figure 38 below. Table 1 displays the effect of the prioritization order on the total system travel time.

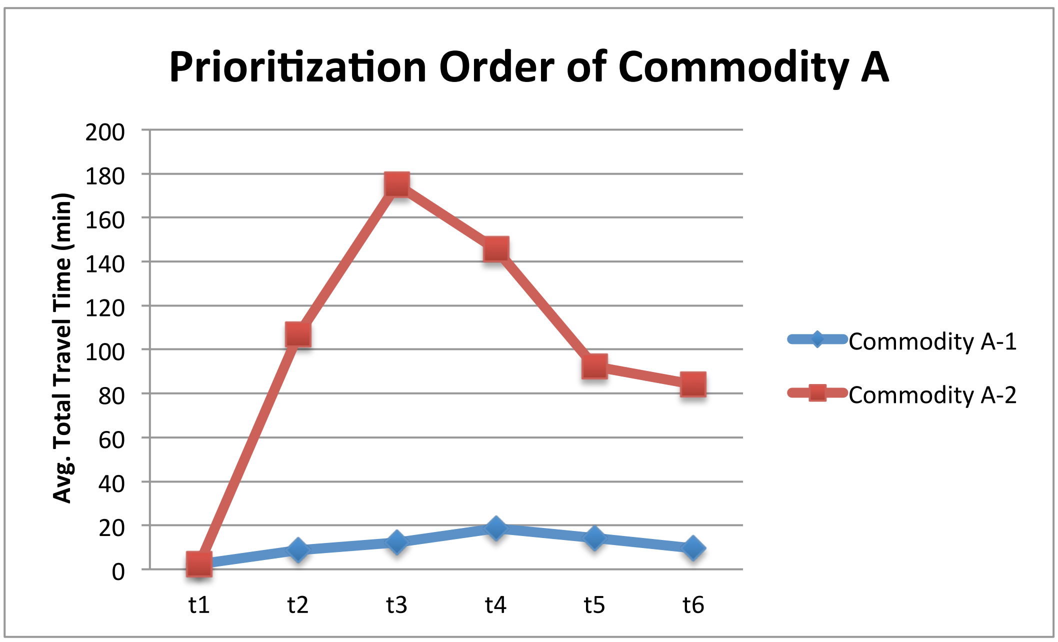

Figure 37: Average Total Travel Times of Commodity A Depending on Order

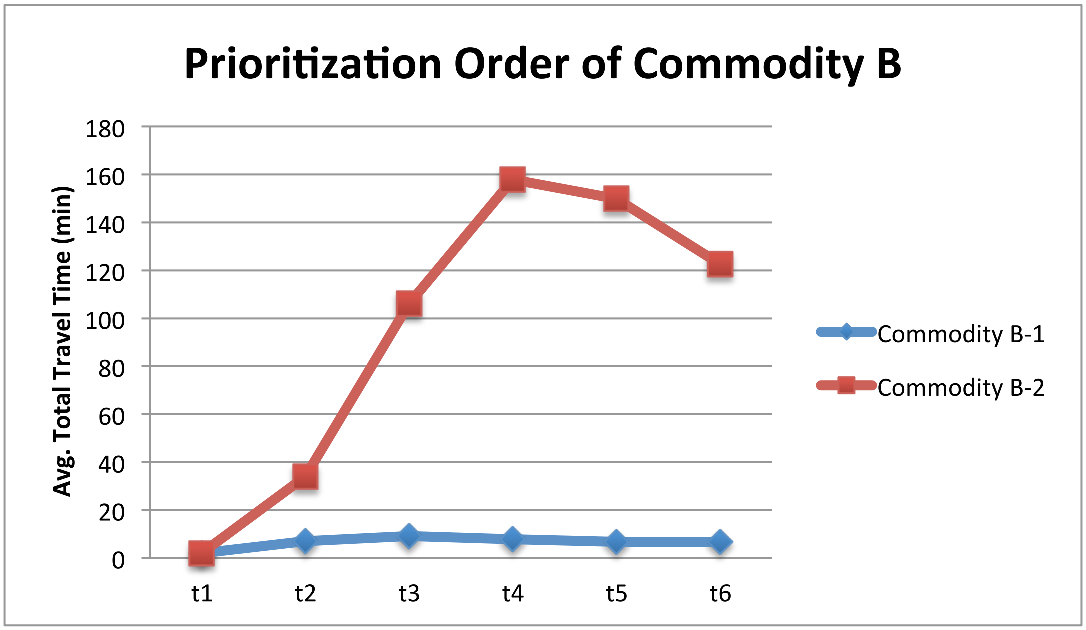

Figure 38: Average Total Travel Times of Commodity A Depending on Order

	System Total Travel Time (min)
Case 1: Commodity A over Commodity B	22214
Case 2: Commodity B over Commodity A	22404

Table 1: System Total Travel Time Depending on Order

5.3.2.1 Analysis

Based on the commodity prioritization scheme implementation, a lower prioritization order for both Commodities A and B results in an increase in average total travel times in both cases. The difference between the total travel times of the system depending on the loading order is 0.85% and is therefore considered negligible. However, when Commodity B is placed on a lower priority than Commodity A the difference in average total travel time for trauma patients is quite significant. An increase in travel time of about two hours for a severely injured patient can result in a much higher chance of mortality. However, in the case of the lower priority Commodity A, an increase of up to two hours in travel time is most likely not as critical.

While the results are certainly only representative, the results demonstrate the tradeoffs within the disaster relief logistics problem. While minimizing travel time for vehicles post-disaster is important, effectively managing the distribution of commodities is also vital for the success of a disaster response plan. Through the inclusion of supply and demand carryover penalties, a balance between the two objectives is achieved. Therefore, the commodity prioritization scheme is a vital component in minimizing the loss of life following a disaster occurrence.

CHAPTER 6: Conclusions

Disasters, specifically earthquakes, result in worldwide catastrophic losses annually. The first seventy-two hours are the most critical and so any reduction in response time is a much-needed contribution. This is especially true in cases where parts of the communication infrastructure are severely damaged thus isolating certain areas, most probably those with the greatest need for aid and medical attention, from the relief agents.

This dissertation presented a framework that integrates information flow along with transportation flow in order to enhance disaster relief management. It was projected that by doing so, relief agencies can create a more accurate plan of response.

The Linear Program (LP) optimizes the movement of information by treating it as a commodity traveling through the system along with physical commodities. Despite breaks in the communication network links, the information can travel on transportation links therefore ensuring that it gets to the right place at the right time.

By pairing the LP with a mesoscopic simulation program, a feedback loop was created providing real-time travel time projections used to re-iterate and fine-tune the routing paths for vehicles.

In order to speed up the computational time of the LP, a decomposition solution scheme was created splitting it up into three problems with interrelationships. A prioritization scheme was also created in order to effectively distribute the higher priority commodities, such as injured patients, over others.

A platform was created combining the mesoscopic simulation with seismic risk analysis projections as well as telephone and cellular congestion modeling in order to provide the information on resulting transportation and communication link states onset of a disaster. This created an information base that was used for the information updating feedback loop when implementing the solution framework.

The framework was applied to the Irvine Golden network as well as the Knoxville network for up to three different cases. The DYNASMART-P simulation program performance was compared against the Time Dependent Network Simplex paths combined with the information updating feedback loop specifically regarding average total travel times of vehicles travelling to the trauma center located in the study area.

6.1 Summary of Thesis

This dissertation presents a framework that integrates information flow along with transportation flows to enhance the accuracy of disaster relief efforts. The framework treats critical information in the system as a commodity with a supply and demand and optimizes its movement in the network in order to provide feedback to aid with response planning.

Chapter 1 explains the motivation behind the work as well as the objectives of disaster relief management. It also discussed the shortcomings in separating the information modeling problem from the disaster relief logistics problem and how a combination of both would be a better approach.

Chapter 2 provides a summary of past work in disaster relief logistics as well as the linear program used for the framework. It also presents the idea of using network flow models to decompose and solve the linear program into three problems with interrelationships. It also presents a prioritization scheme for assigning commodity flows in the network.

Chapter 3 discusses the computation properties and complexity of the network flow algorithms proposed to solve the LP.

Chapter 4 describes the solution framework in greater detail and describes the role of DYNASMART-P in the implementation. A seismic risk analysis procedure is also described to simulate bridge damage states in a post-disaster scenario. Lastly, the reliability of the communications network and congestion modeling are discussed along with the use of Data MULEs to collect information in the system.

In Chapter 5 the solution procedure is implemented using the Irvine Golden Triangle network as a study area. Three different cases are run in order to quantify the improvements of the integrated solution framework. The results show a significant improvement in the reduction of average total travel times for vehicles transporting injured patients to the trauma center located in the study area. The solution procedure is also applied to the Knoxville network in order to determine its applicability to larger networks. Finally, the commodity prioritization scheme is implemented using the Irvine Golden Triangle network.

6.2 Contributions

While researchers have attempted to make the disaster relief logistics and information modeling more dynamic, this is the first attempt to integrate both problems in order to create a dynamic adaptive response plan.

This integrated framework is the first of its kind to incorporate mesoscopic simulation with seismic risk analysis and telephone and cellular congestion modeling along with network flow solution algorithms. By approaching disaster relief management as a multi-faceted problem and incorporating the interrelationships between the individual focuses, the resulting response plan is greatly enhanced.

One major advantage of the framework is that the mesoscopic simulation can provide real-time updating of travel time projections used to re-iterate and fine-tune the routing paths for vehicles. Additionally, the seismic risk analysis portion helps to provide information on link vulnerability as well as expected damage states, a basis for initial routing paths until information on actual link states reaches the decision nodes.

By prioritizing certain commodities over others depending on the severity of demand, the framework ensures that the most severe demands will be met over others and in turn minimizes the loss of life. Ultimately, in any disaster management attempt, the main objective is to minimize the loss of life.

Reducing the computational time of the LP by splitting it into a three-part problem with interrelationships is another advantage of the approach. This ensures the practicality and applicability of a re-planning period as time progresses and more information about the disaster is known.

When implementing the framework to the Irvine Golden Triangle network, a significant reduction in travel time was experienced for a selected group of vehicles travelling to the trauma center in the study area. Three difference cases were created to compare the performance between the DYNASMART-P simulation on its own to the integrated framework incorporating Time Dependent Network Simplex Algorithm paths combined with an information updating feedback loop. It was found that the integrated framework performs better especially in cases of higher demand for trips to the trauma center resulting from a higher severity of damage. This reduction is indicative of the advantages of the framework as well as its projected contributions.

With this work I hope to stimulate much needed research in the subject of multi-faceted and integrative disaster relief modeling. By approaching the various problem elements in a post disaster scenario as interdependent rather than independent, the result is a more dynamic and adaptive approach for disaster relief response.

6.3 Future Work

The research in this dissertation shows promising results for integrative disaster relief management efforts. Some future research ideas include:

- Applying the framework to all the vehicles in the network rather than a subset of vehicles transporting injured patients.
- Exploring the idea of using Data MULEs to collect and deliver sensor information to create dynamic real-time mesoscopic simulations for any affected area.
- Creating a larger communication infrastructure model and simulating a real-time adaptive network for information transfer.
- Creating a module that automatically transforms Time Dependent Network Simplex paths into input for the DYNASMART-P mesoscopic simulation program and vice versa.

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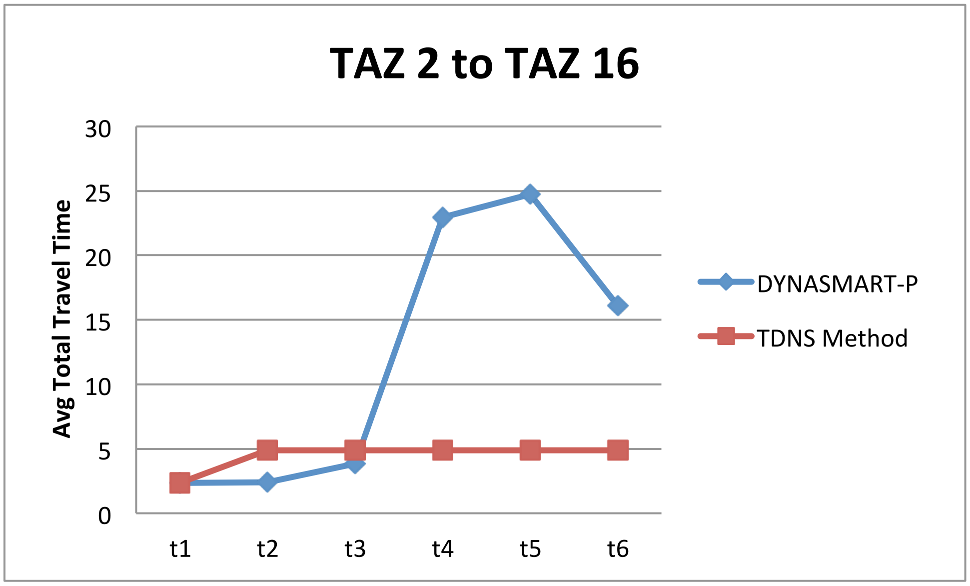
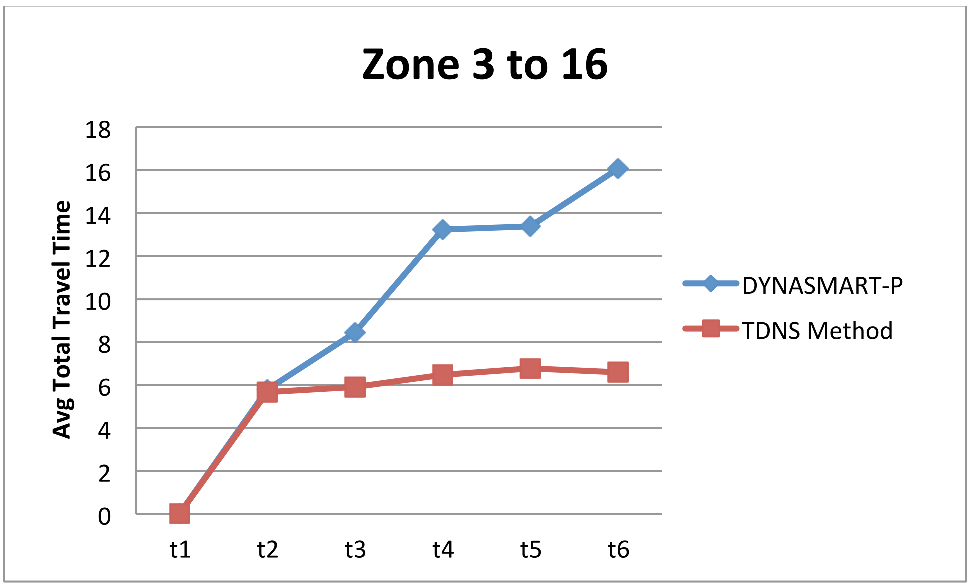
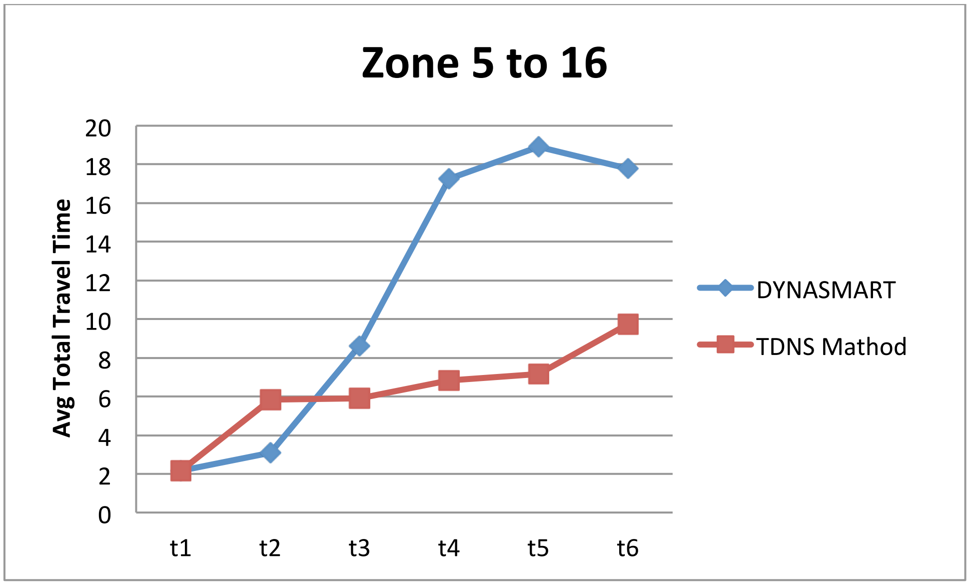
APPENDIX

1. Average Total Travel Times for Base Case from all remaining TAZs to TAZ 16






Zone 5 to 16
Avg Total Travel Time
20
18
16
14
12
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8
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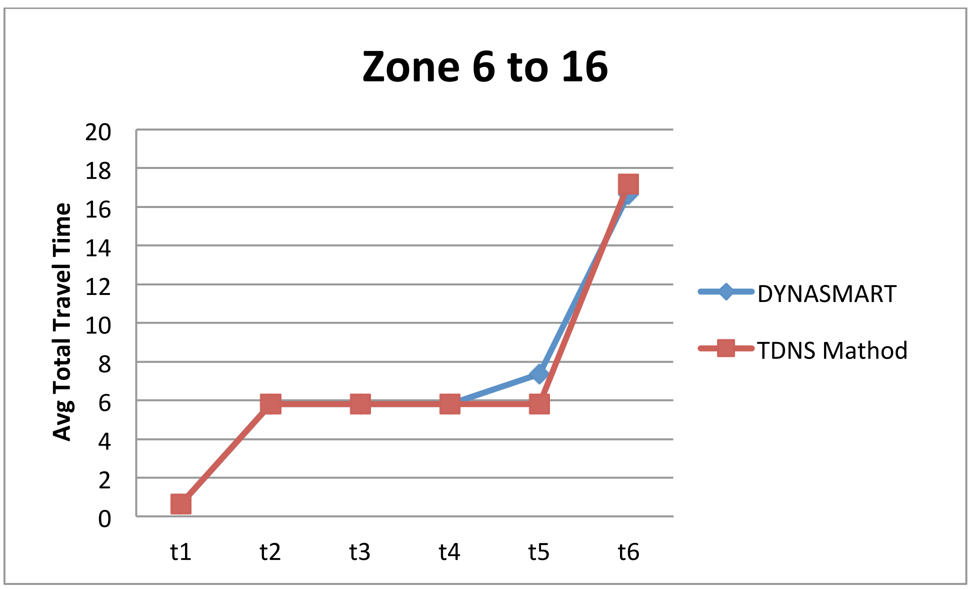
t6
DYNASMART
TDNS Mathod


Zone 6 to 16
Avg Total Travel Time
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18
16
14
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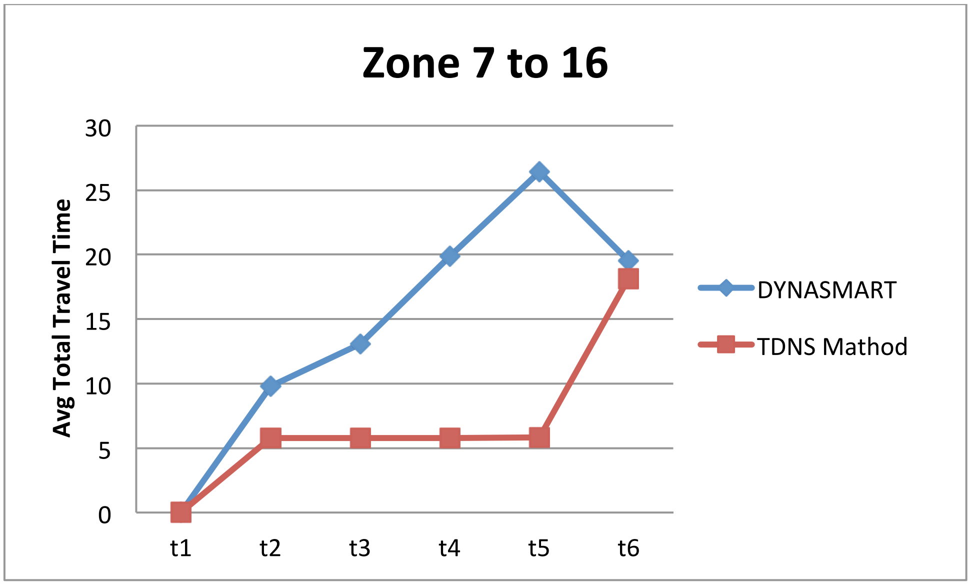
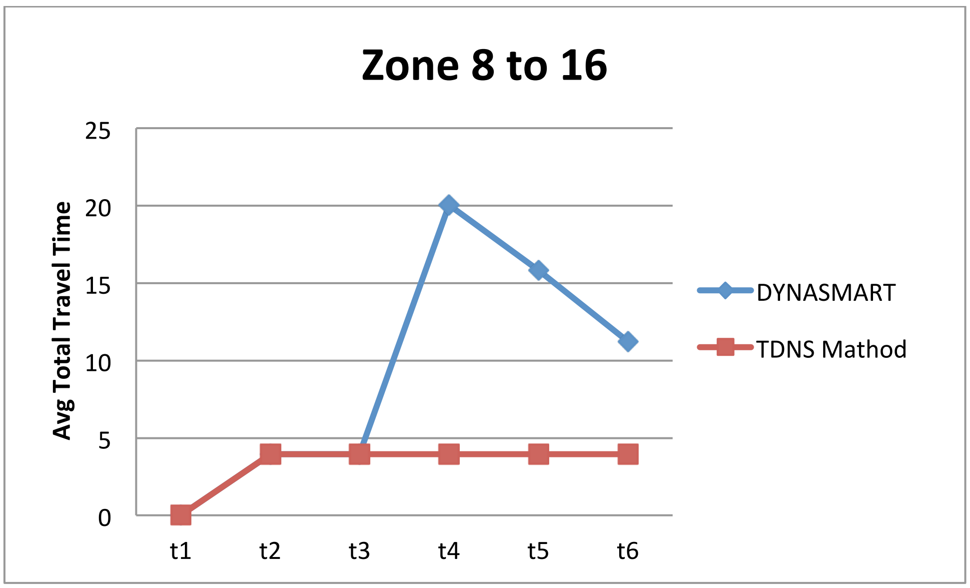
DYNASMART
TDNS Mathod


Zone 7 to 16
Avg Total Travel Time
30
25
20
15
10
5
0
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS Mathod


Zone 8 to 16
Avg Total Travel Time
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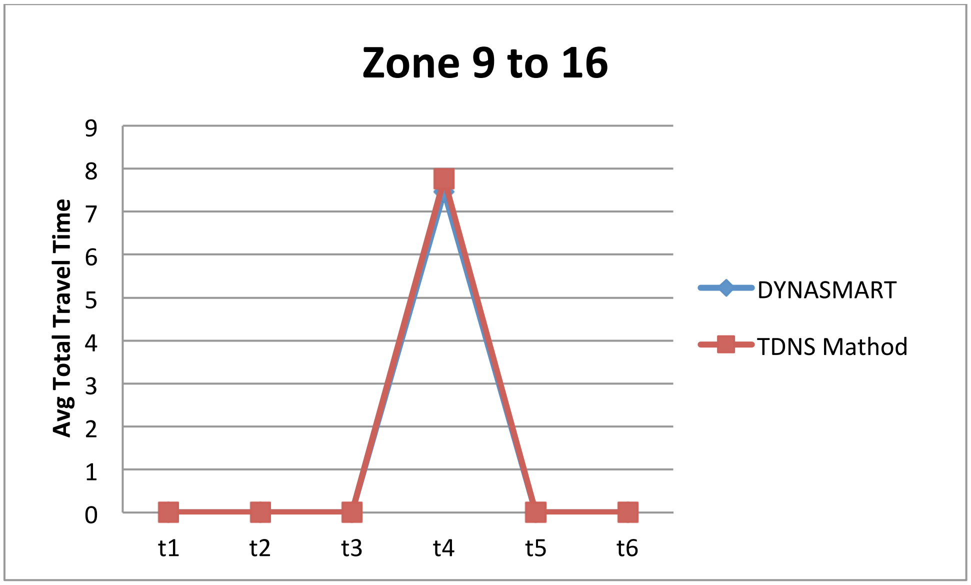
DYNASMART
TDNS Mathod


Zone 9 to 16
Avg Total Travel Time
9
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7
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5
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3
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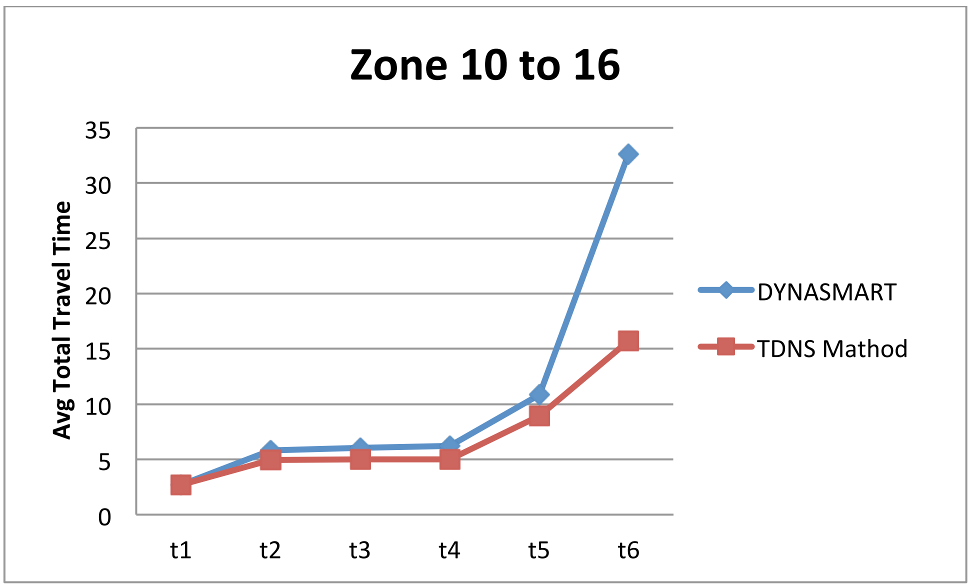
DYNASMART
TDNS Mathod


Zone 10 to 16
Avg Total Travel Time
35
30
25
20
15
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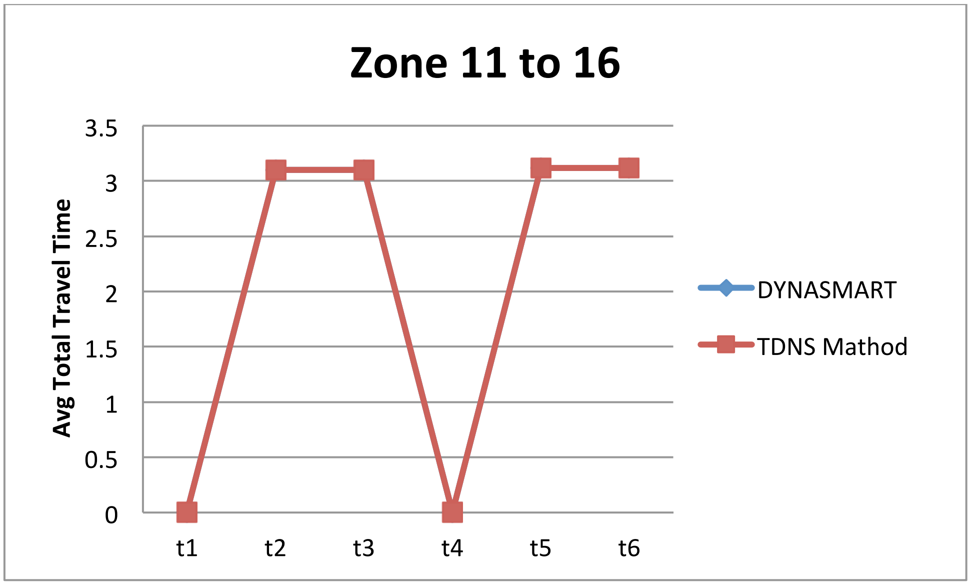
DYNASMART
TDNS Mathod


Zone 11 to 16
Avg Total Travel Time
3.5
3
2.5
2
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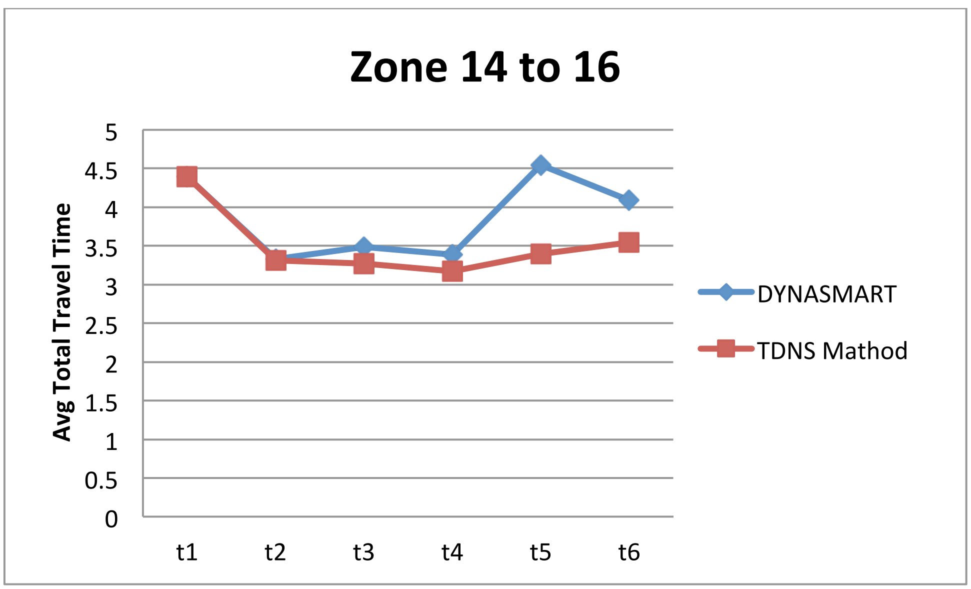
DYNASMART
TDNS Mathod


Zone 14 to 16
Avg Total Travel Time
5
4.5
4
3.5
3
2.5
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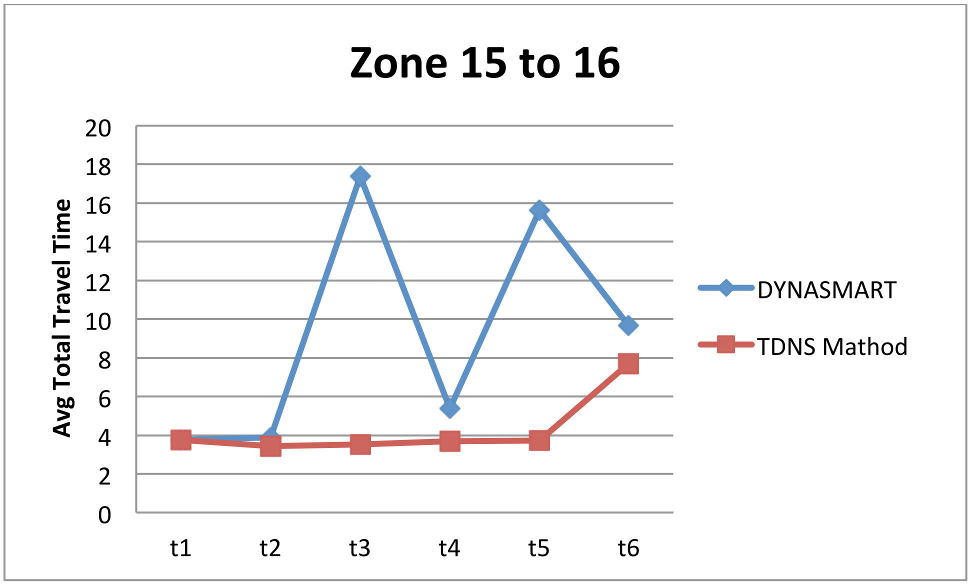
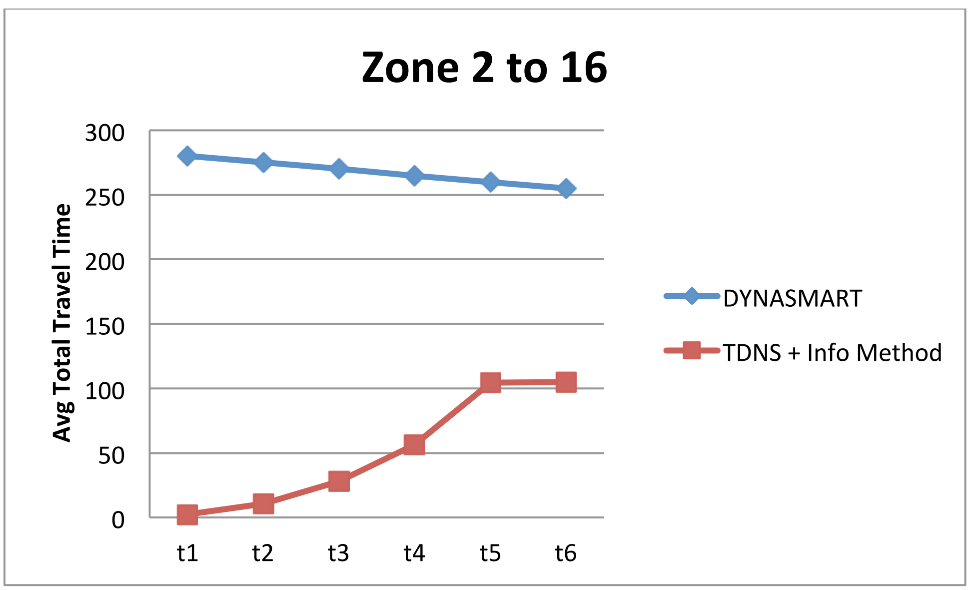
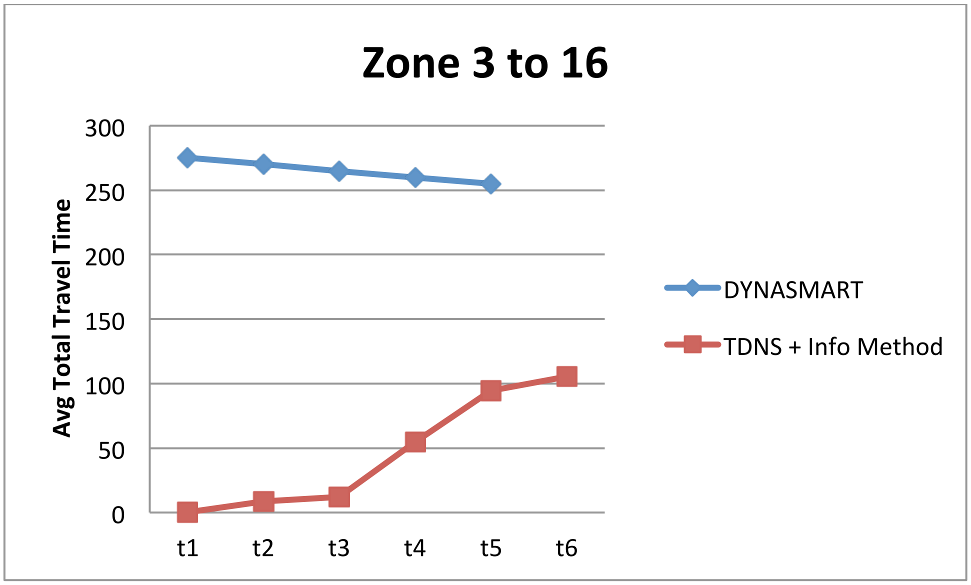
t6
DYNASMART
TDNS Mathod



2. **Average Total Travel Times for Case (1) from all remaining TAZs to TAZ 16**




Zone 3 to 16
Avg Total Travel Time
300
250
200
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50
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t1
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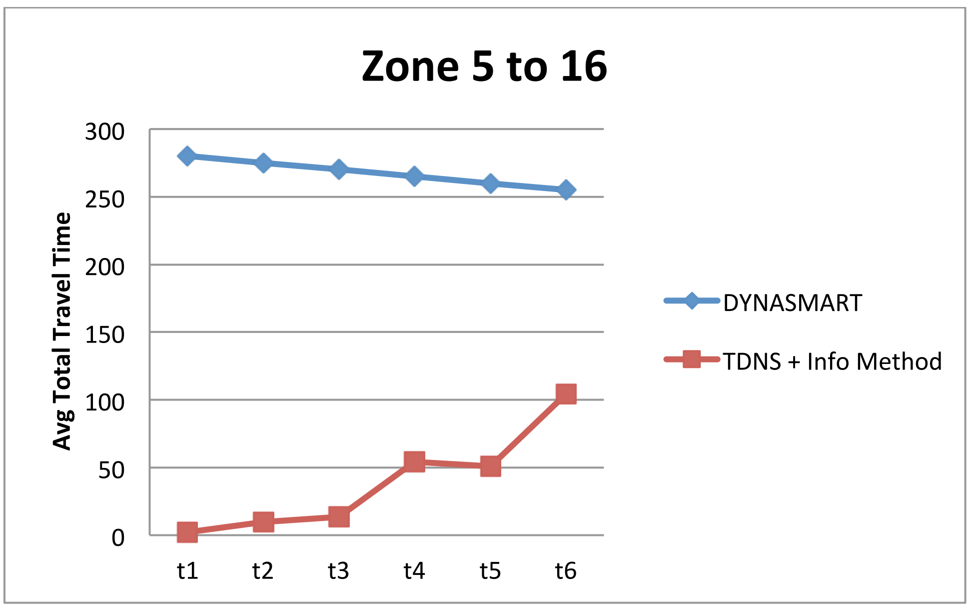
DYNASMART
TDNS + Info Method


Zone 5 to 16
Avg Total Travel Time
300
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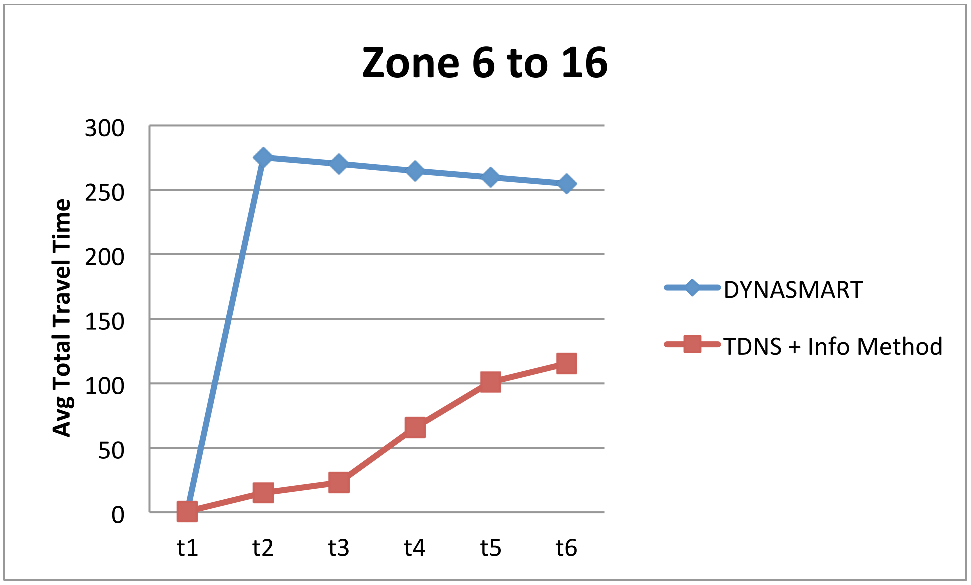
DYNASMART
TDNS + Info Method



Zone 6 to 16
Avg Total Travel Time
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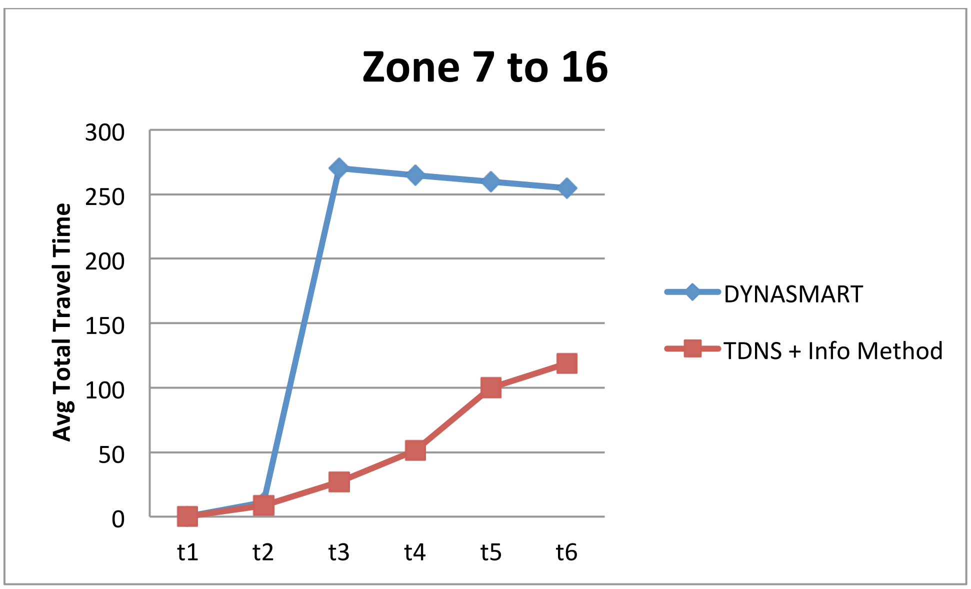
DYNASMART
TDNS + Info Method



Zone 7 to 16
Avg Total Travel Time
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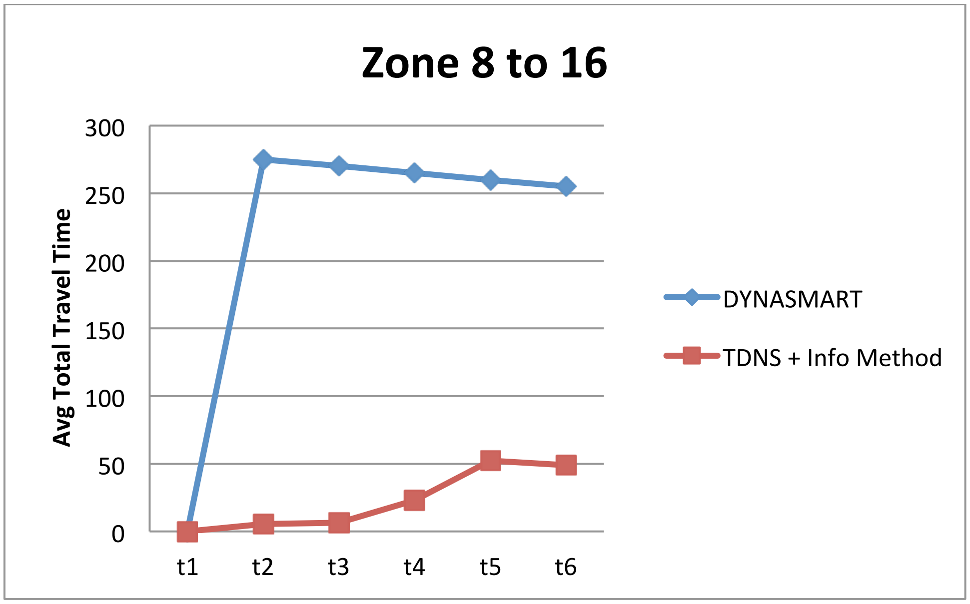
DYNASMART
TDNS + Info Method


Zone 8 to 16
Avg Total Travel Time
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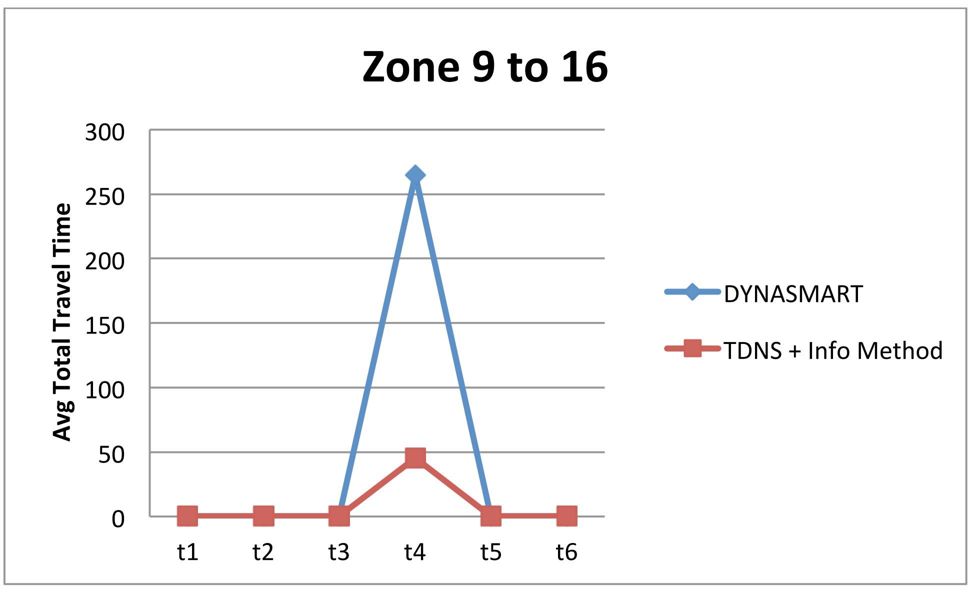
DYNASMART
TDNS + Info Method


Zone 9 to 16
Avg Total Travel Time
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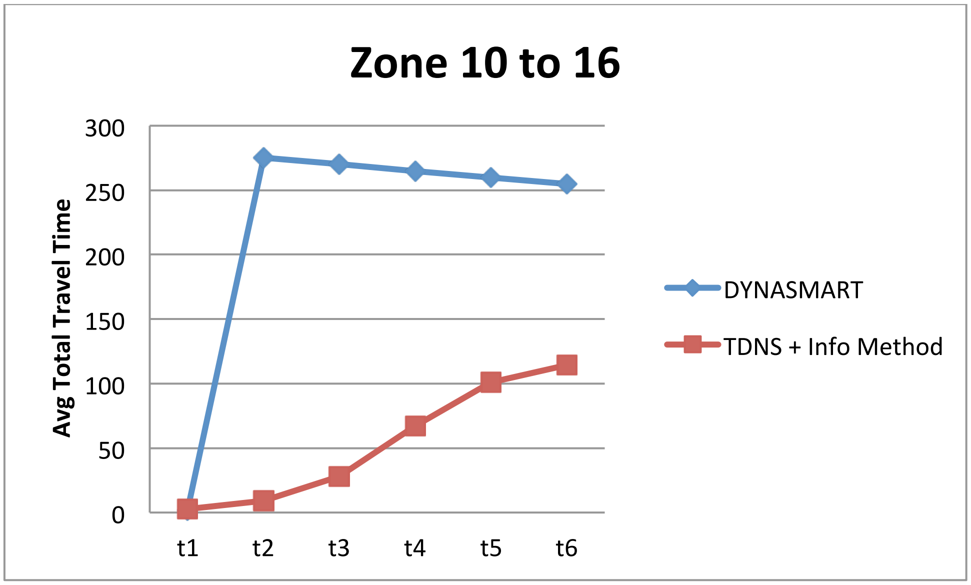
DYNASMART
TDNS + Info Method


Zone 10 to 16
Avg Total Travel Time
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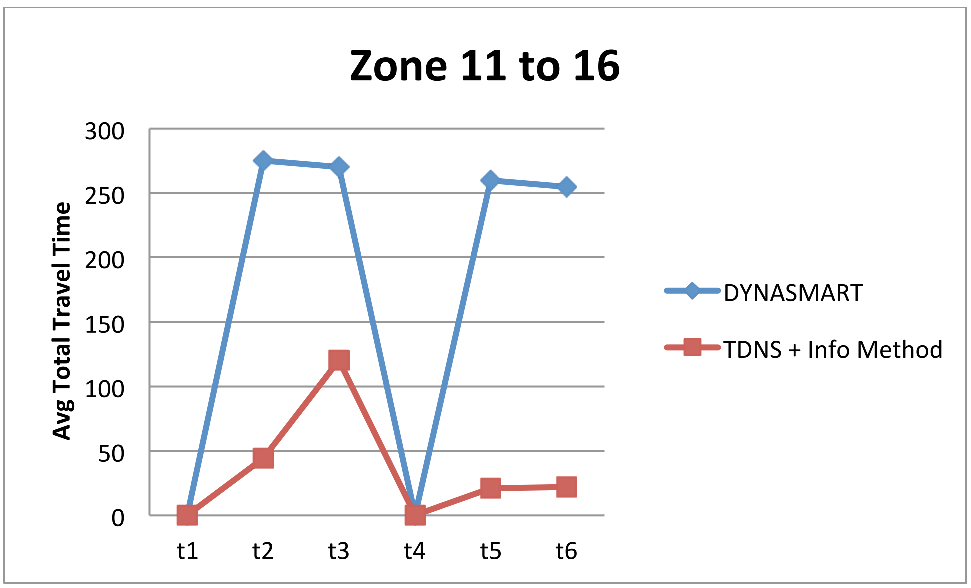
DYNASMART
TDNS + Info Method


Zone 11 to 16
Avg Total Travel Time
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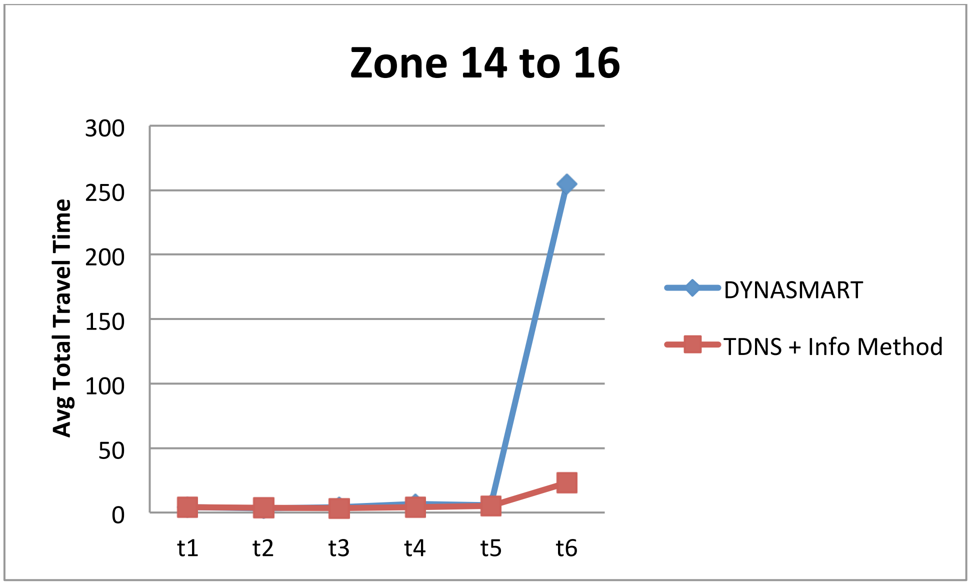
DYNASMART
TDNS + Info Method


Zone 14 to 16
Avg Total Travel Time
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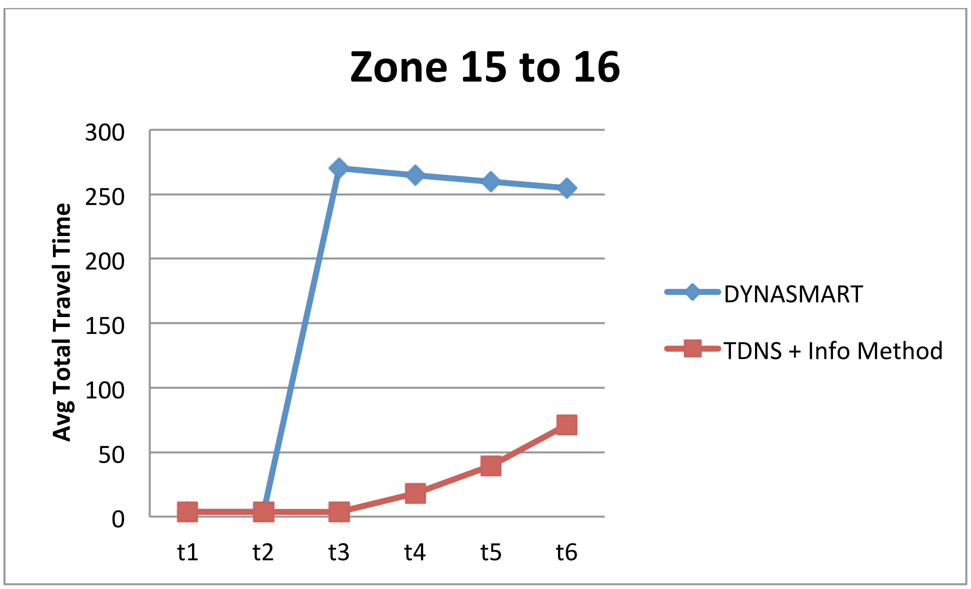
DYNASMART
TDNS + Info Method


Zone 15 to 16
Avg Total Travel Time
300
250
200
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100
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t1
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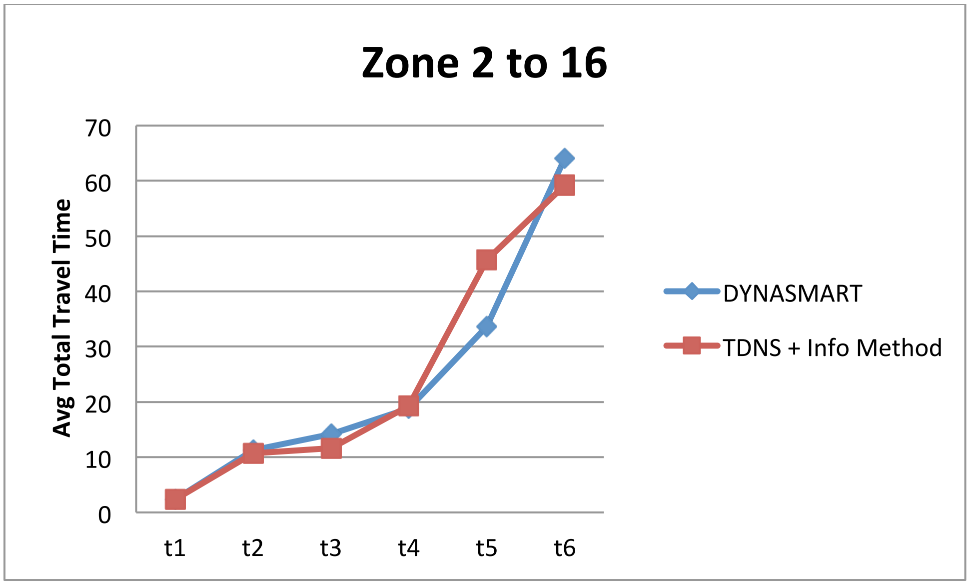
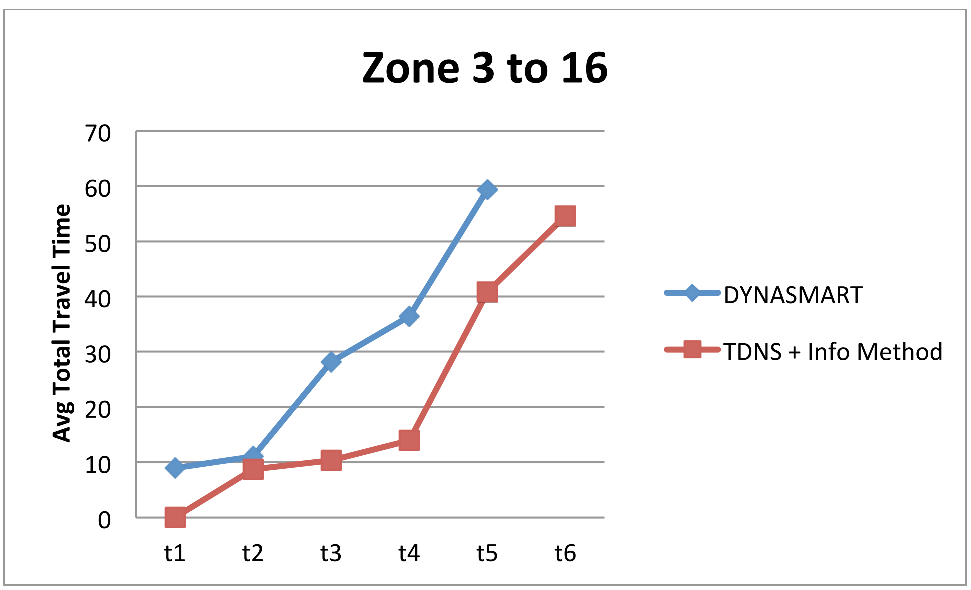
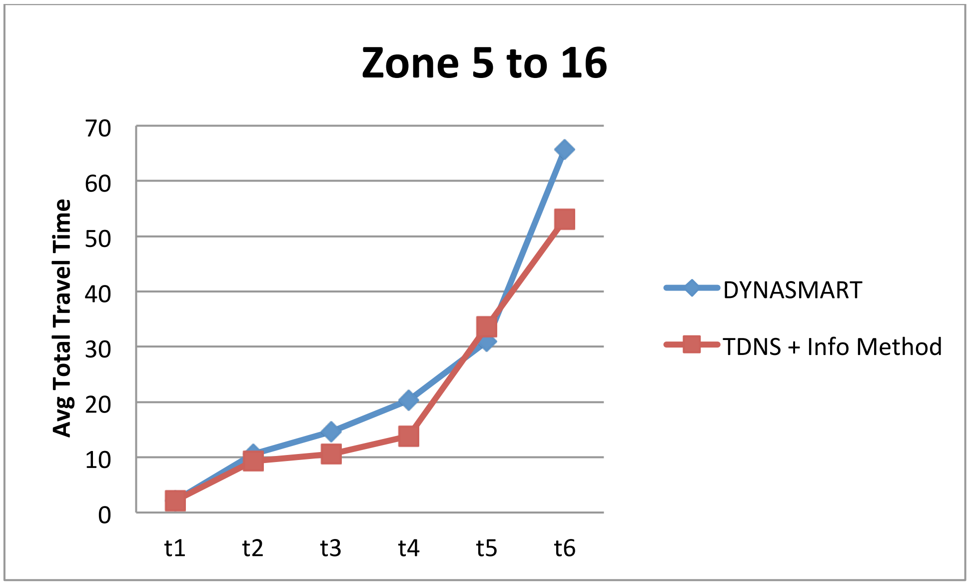
t6
DYNASMART
TDNS + Info Method

3. **Average Total Travel Times for Case (2) from all remaining TAZs to TAZ 16**






Zone 5 to 16
Avg Total Travel Time
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60
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30
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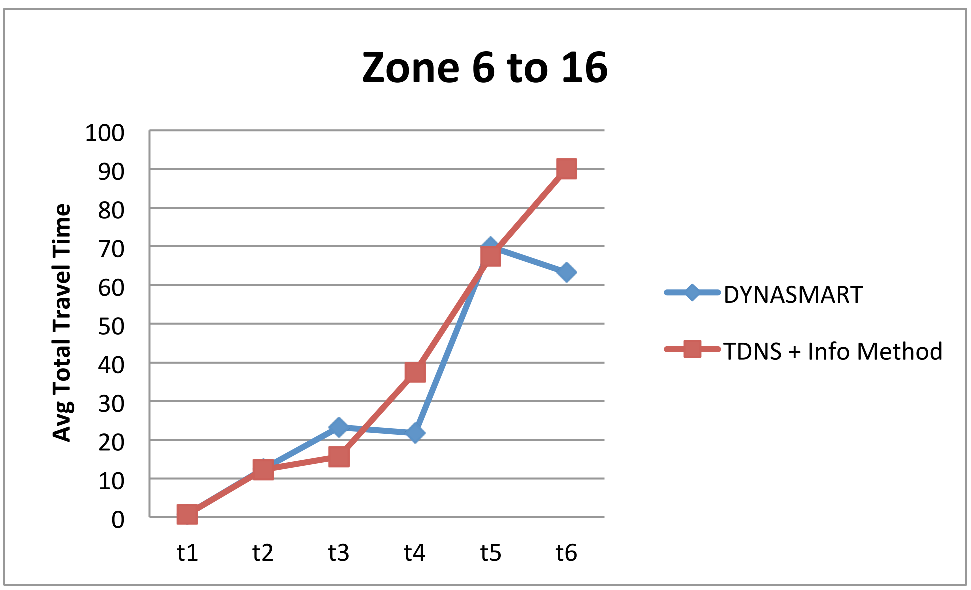
0
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS + Info Method


Zone 6 to 16
Avg Total Travel Time
100
90
80
70
60
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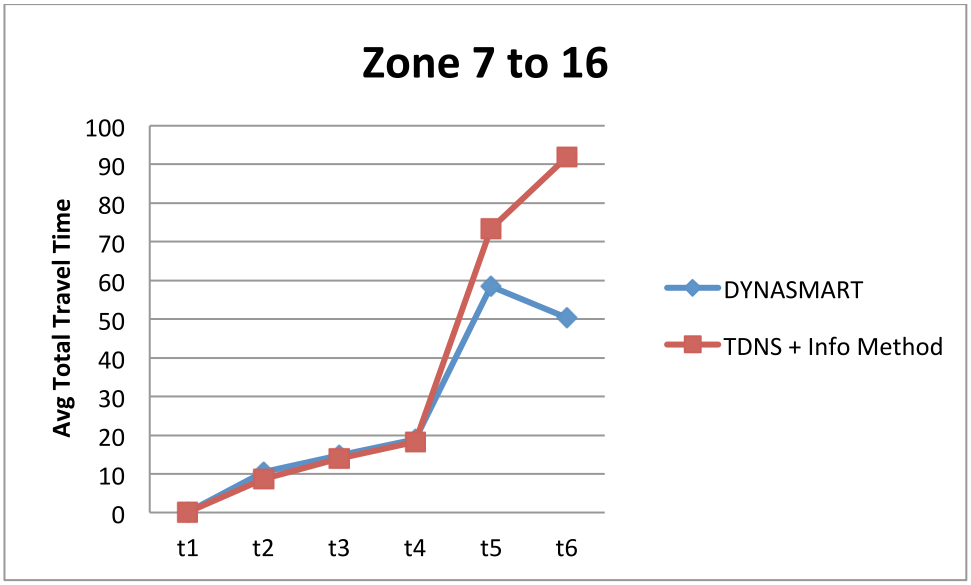
30
20
10
0
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS + Info Method


Zone 7 to 16
Avg Total Travel Time
100
90
80
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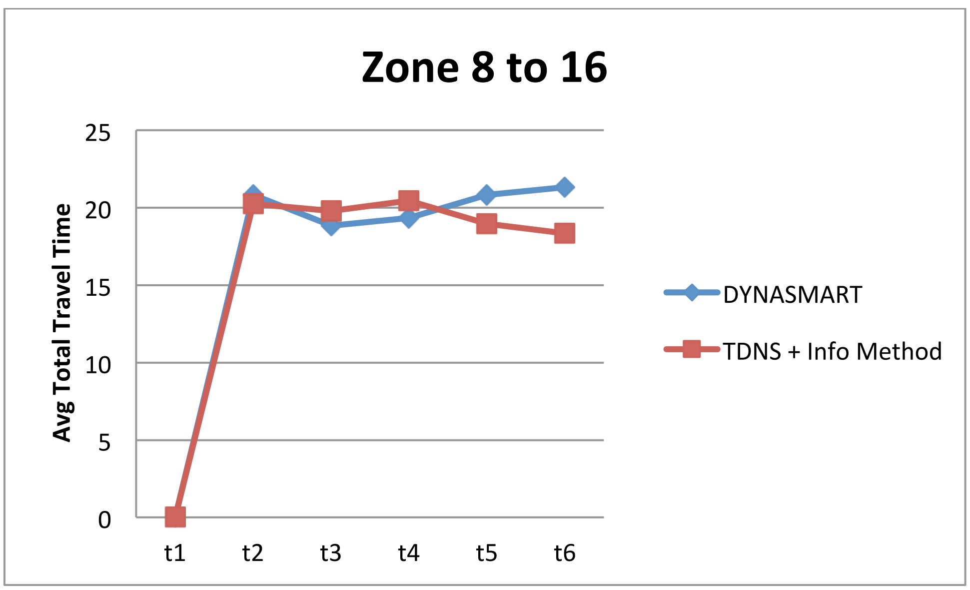
DYNASMART
TDNS + Info Method


Zone 8 to 16
Avg Total Travel Time
25
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15
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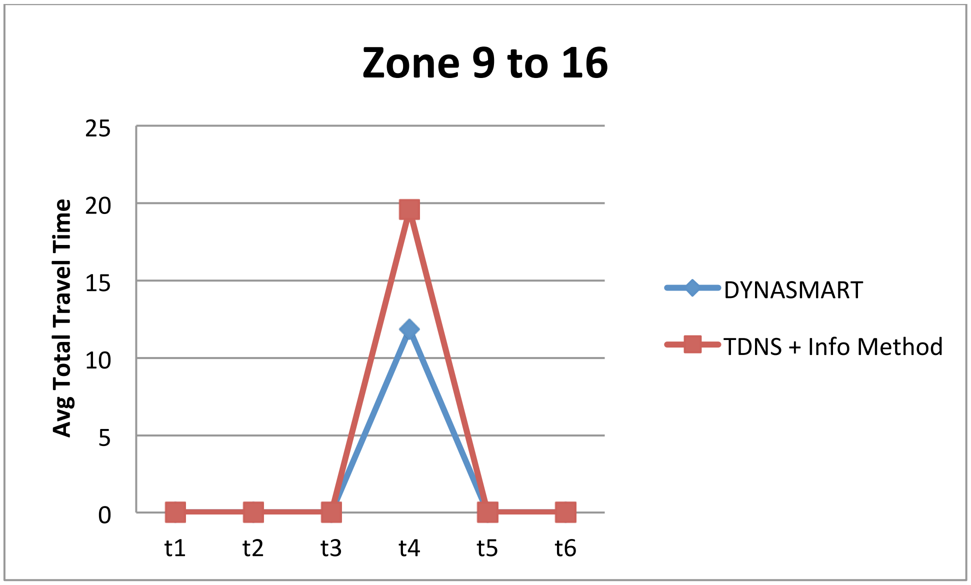
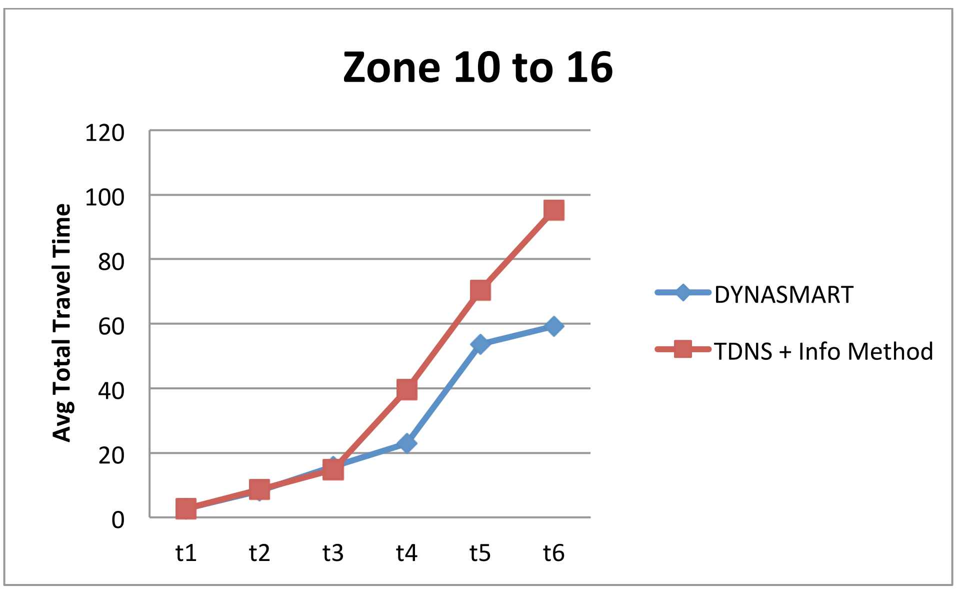
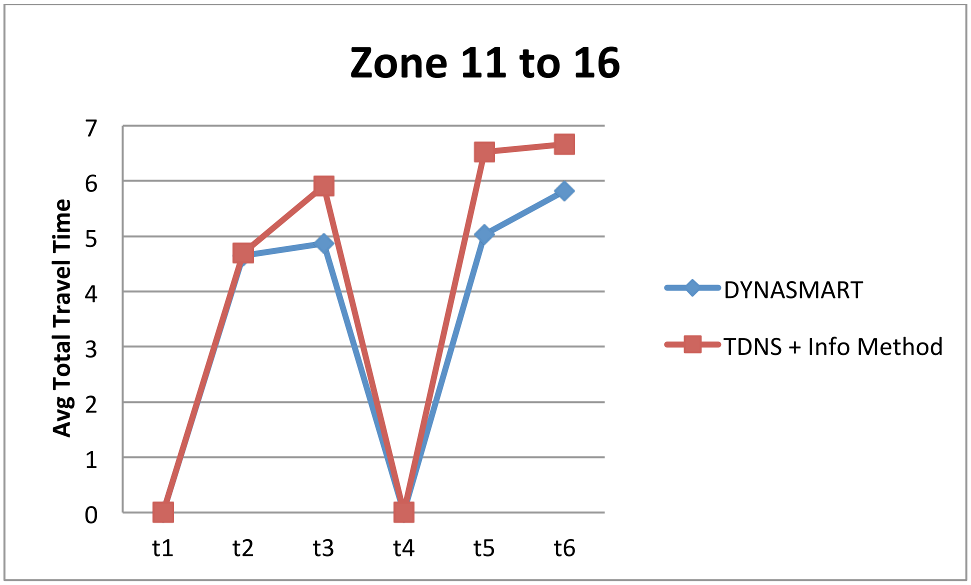
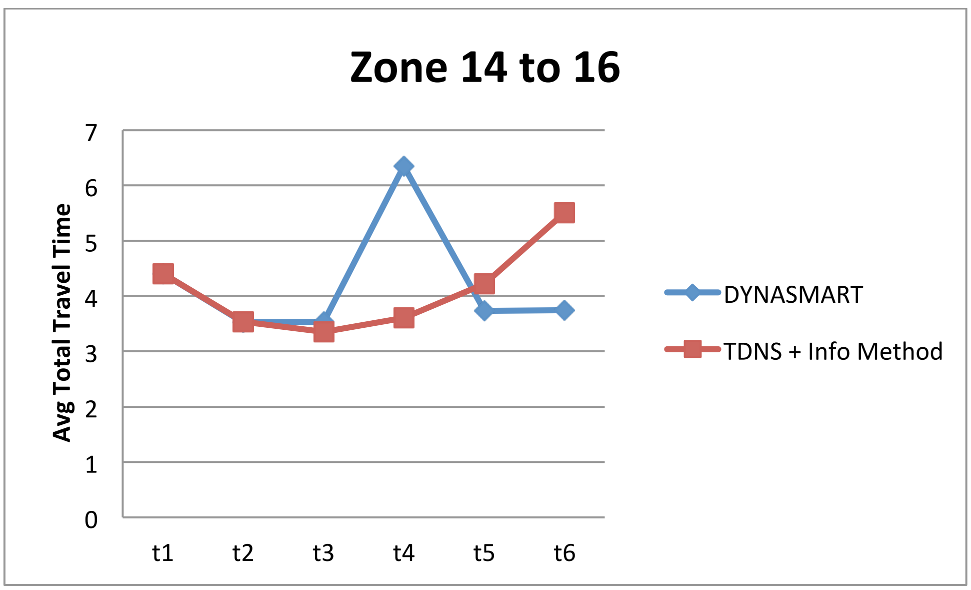
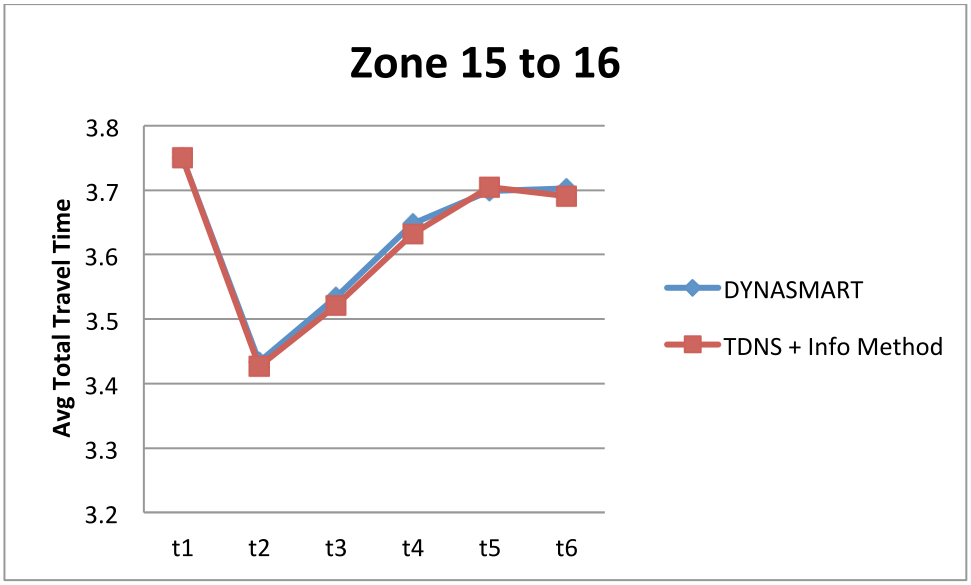
t4
t5
t6
DYNASMART
TDNS + Info Method


Zone 9 to 16
Avg Total Travel Time
25
20
15
10
5
0
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS + Info Method


Zone 10 to 16
Avg Total Travel Time
120
100
80
60
40
20
0
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS + Info Method


Zone 11 to 16
Avg Total Travel Time
7
6
5
4
3
2
1
0
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS + Info Method


Zone 14 to 16
Avg Total Travel Time
7
6
5
4
3
2
1
0
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS + Info Method


Zone 15 to 16
Avg Total Travel Time
3.8
3.7
3.6
3.5
3.4
3.3
3.2
t1
t2
t3
t4
t5
t6
DYNASMART
TDNS + Info Method