The Impact of Intelligent Transportation Systems on Supply Chain Management

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In Partial Fulfillment of the Requirements for the Degree of

Master of Engineering in Logistics

at the

Massachusetts Institute of Technology

June 2004

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ABSTRACT:

Businesses are constantly searching for ways to reduce costs and increase revenue. This is a fact of life in a world where shareholder value drives corporate actions. In order to become more profitable, these businesses develop new processes and techniques to create efficiency. This paper is focused on one particular new technology that can be used to increase corporate profitability – intelligent transportation systems.

The primary research objective of this thesis is to determine the impact that differing levels of information can have on transportation practices, and therefore, in turn on corporate profitability. This information is collected, analyzed, and disseminated through the use of intelligent transportation systems. The end result of this work is a quantification of this impact and conclusions related to which informational practices should be implemented into the supply chain.

An experimental setup is designed that uses the Los Angeles Highway System as a test-bed. Traffic data is collected on this network over a two-week period. This data is used as the foundation to perform a series of simulations using differing levels of information. Each of these information levels is compared to a baseline to yield a % time savings. Next, a sensitivity analysis is performed by introducing a random error term which is normally distributed with mean zero and a specified standard deviation.

The author concludes that there appears to be a fairly consistent trend in the way differing levels of information provide value. Progressing up the information spectrum, it appears that more and more value can be extracted in the form of time savings over the baseline.

A monetary framework is examined which translates the time savings derived in the simulations into financial performance. It is shown that a regional carrier with a modest fleet size is able to add millions of dollars per year in operating profit by using the highest levels of information in its supply chain practices. After the implementation costs are incorporated into the analysis, the savings from ITS have the potential to unlock significant value for a company.

The author recommends that supply chain professionals incorporate intelligent transportation systems into their operations. All in all, the author believes that the pre-trip, predictive information level is likely to offer the most benefit to corporations at a reasonable cost for the near-term if an accurate forecast can be made.

Thesis Supervisor: Dr. Tomer Toledo
Title: Research Associate, MIT Intelligent Transportation Systems Program

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The best way to start any large work is to acknowledge those people that made the final product possible. While it is true that I spent a great deal of time thinking through the major issues alone, the paper that follows would be of much lower quality if it were not for the following “advisors” — both formal and informal — who contributed significantly to this work:

- Tomer Toledo – I owe a tremendous amount of thanks to Tomer for his clear suggestions and guidance throughout the development of this paper. The final structure was a direct result of his thoughtful insights on how to best position the ultimate message. In addition, Tomer and I had numerous conversations and brainstorming sessions on extensions and next steps to the analysis in this paper. I can not thank you enough for all your help, Tomer. You have been a fantastic advisor.

- Chris Caplice – Chris’s guidance on the principles of supply chain management inspired me to look for new areas of research that would prove valuable in the future. As the director of the MLOG program, Chris forced me to manage my scheduling on this paper. (As an aside, the very first day we met, he told me to start thinking about my thesis!). Thanks for letting me into the Program, Chris.

- MLOG Class of 2004 – The students of the MLOG class were always willing to discuss my “radical” ideas. They provided me with a platform to explore my thoughts in a developmental atmosphere. In addition, they provided me with needed relief from my academic rigors. Thank you all for being a part of my M.I.T. experience.

- George Kocur – George was an invaluable resource on shortest path algorithms and systems integration technologies. His availability and
experience was a re-assuring factor in my path towards finishing this work. George, you are a model of excellence for any academic faculty member. Thank you for your help.

- My family – The only people in my life who are unconditionally accepting of me. Your constant support inspires me to do great things with my life. I would not be where I am today if it were not for all your help. Moreover, I would not have enough room in this thesis to thank you properly for all that you have done for me.

To those who I have left out, I am grateful for all your help and support. You have provided me with intelligent guidance. Being unnamed does not lessen your contribution to this work.
This work is dedicated to anyone who has been stuck in traffic.
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Chapter 1: Introduction

Section 1.1: Research Objective

Businesses are constantly searching for ways to reduce costs and increase revenue. This is a fact of life in a world where shareholder value drives corporate actions. In order to become more profitable, these businesses develop new processes and techniques to create efficiency. This paper is focused on one particular new technology that can be used to increase corporate profitability – intelligent transportation systems.

And before we are off, a question quickly emerges. What is so special about intelligent transportation systems that such a claim could be made? For one thing, intelligent transportation systems offer the ability to provide a wide range of information to business managers. Whether this information is valuable in one form or another is the problem that this work seeks to address. What is claimed, however, is that supply chain managers make decisions based on information. Better information may make for better managers.

It is quite intuitive to think that information has the ability to unlock value in the supply chain. Several quick examples can make this point clear. Imagine a manager that is responsible for transporting a truck filled with gold from one bank to another. Intelligent transportation systems can help this manager in a number of different ways. First, the probability of the freight being hijacked can be reduced by minimizing the time that the truck is at rest. Second, the truck can be monitored in real-time to assess if a problem has occurred. So if a threat does happen, the manager is in much better position to respond. Finally, if there is work time remaining in the day, the manager can schedule the truck for additional drop-offs. In all of these cases, information can be used to better manage the truck.

A second example can illustrate a more classical use of intelligent transportation systems. Consider the case of a delivery company that makes scheduled drop-offs every day. The delivery driver picks up goods from a central distribution center and needs to transport these products to several end retailers. However, there are a number of different paths that this driver can take. In today’s world, drivers often rely on “learned
experience" of the transportation network. They have a mental image of the network and generate an immediate solution from their origin to their desired endpoints.

The problem with this type of solution is that it lacks a global perspective. The driver may have mentally generated a route that is inefficient. Moreover, this route might not even be a "correct" solution – with the result being that the driver ends up lost in frustration! The mental calculations that everyday drivers use to derive routes is a simplified framework of a much more complicated problem. This network problem can be quantified and solved using complex mathematical techniques (discussed in Chapter 3). For example, link costs can be assigned to a transportation network in order to derive shortest or least cost paths.

Sophisticated navigational systems are replacing the mental calculations that drivers have been using since the dawn of the automobile. These "intelligent" systems are able to guide the delivery driver from the distribution center to the desired endpoints in an efficient manner. Traffic patterns and distances can be incorporated into complex informational models to generate optimal routes. In the end, a system of millions of nodes can be methodically solved to provide an intelligent solution.

The primary research objective of this thesis is to determine the impact that differing levels of information can have on transportation practices, and therefore, in turn on corporate profitability. This information is collected, analyzed, and disseminated through the use of intelligent transportation systems. The end result of this work is a quantification of this impact and conclusions related to which informational practices should be implemented into the supply chain.

Section 1.2: Structure of Thesis

This thesis is structured in such a way as to guide the reader through the relevant knowledge needed to progress from the very beginning to the end. In this manner, the structure is really the progression that the author went through in developing this work. This progression can be broken into six main sections (excluding the preliminary comments contained in this chapter).

1) The background education needed to understand the fundamentals associated with intelligent transportation systems (often referred to as "ITS") and supply
chain management (often referred to as “SCM”) is described in Chapter 2. A brief introduction of transportation issues within SCM is discussed. This is quickly followed by a consideration of how ITS and SCM can be coupled as a cohesive unit. Finally, the chapter presents a review of prior research that has been conducted – specifically related to the value of information.

2) Chapter 3 begins by introducing some useful scientific notation. This scientific notation is used to quantitatively model the problem being investigated. Once the core problem has been defined, the analysis is subdivided along two major lines: pre-trip/en-route and deterministic/stochastic. Each of these subdivisions is analyzed mathematically. Chapter 3 ends by discussing how simulation can be used to investigate the problem that has been defined.

3) Chapter 4 introduces the experimental paradigm that will be used to evaluate ITS within a supply chain context. The Los Angeles Highway System is decomposed into a model using the mathematics described in Chapter 3. In addition, the data sources and model parameters are discussed in depth. The chapter concludes by carefully considering each of the information levels discussed above.

4) Chapter 5 presents the results of the simulations performed for each of the levels of the information spectrum. Specifically, traffic data from the Los Angeles Highway system is used to build a model which mimics a realistic set of delivery scenarios. A random number generator is used to produce these hypothetical delivery trips. With the help of ITS, the driver is guided from origin to destination and his/her trip time is recorded. The chapter concludes with a comparison of the results produced using different levels of information and a quantification of the financial benefits that these results should imply for a typical regional carrier.

5) The simulations run in Chapter 5 assume that the data collected from the Los Angeles traffic network is error-free. This implies that the sensors used to collect the traffic information are both accurate and precise. Most likely, this assumption will be difficult to achieve in practice. Chapter 6 introduces
random perturbations into the traffic data as a means to introduce error into the model. What this means in practice is that drivers will be routed on information that does not perfectly match up with the experience that will be encountered. As such, the simulations are re-run with error and the results are now re-analyzed.

6) The thesis concludes with a deep analysis of the results that were derived above. The final image is a big picture framework of where intelligent transportations systems are likely to emerge in future supply chain management practices.

Section 1.2.1: The Information Spectrum

The structure outlined above is the framework for ultimately testing the research hypothesis. In particular, Chapters 4, 5 and 6 address how differing levels of information can be incorporated into intelligent transportation systems. These varying levels of information might not have been clear in the discussion above. Fortunately, a more in-depth view of the information spectrum will now be considered.

Information can be divided along a number of different lines. Figure 1 highlights two major lines of divisions: by time-period and by time-update. The first spectrum relates to the time-period of the information that is being fed into the intelligent transportation system. In other words, several different forms of data can be used as a base for the mathematical computation that occurs within an ITS unit. For example, the theoretically most-restrictive type of system will be based on no information at all. A degree above this level is a system that is run using historical information. This means that a set of historical data that represents past traffic states could be used to guide drivers in the present. All that need to happen is that this information is logged over time. However, real-time sensors now offer the ability to incorporate instantaneous data into ITS methods. Real-time guidance has become possible through technological advancements. Finally, at the top of this information spectrum are ITS units that are run using predictive information.

The second division shown in Figure 1 is the level of informational updates that an ITS unit can incorporate. In theory, the lowest limit is to never update at all – and is
represented by the no information tag. Of course this type of system is nonsensical and for all practical purposes at least one input point needs to occur. This is the definition of a pre-trip system. Information is entered into the system once and is not updated as time progress. In practice this translates into a driver being guided at an initial time point with no successive informational updates along the way. A level above the pre-trip update is an ITS unit that updates a driver’s path en-route. For example, the system could be clocked to re-compute the guidance at twenty minutes intervals. If traffic conditions have changed, it is quite likely that the guidance will also be changed. These adaptive systems therefore can have great practical use in real world applications. Finally, one can think of an en-route system that is updated continuously as the highest level of information updates. In such a system, drivers would constantly have the best information that is available.

![Diagram showing information along the time-period and time-update spectrum](image)

**Figure 1. The two dimensions of information**

The interesting phenomenon related to these two dimensions of information is that they can be integrated to describe a specific landscape (shown in Figure 2). This landscape provides an insightful look into the possibilities of various ITS types. Clearly, if there is no information input into the system – represented by the none/none box – the ITS unit will be non-rational. This type of system would generate guidance in a random or haphazard fashion. What is more interesting to look at is the sub-matrix that
represents the feasible choices for an ITS unit. This 3x2 matrix can be understood by considering a diagonal movement along the x-y axis. The level of information incorporated into the ITS unit becomes more complex and powerful as we move from the upper left to the lower right corner of the matrix. This movement fosters more updates and greater "freshness" of the data being considered. In a theoretically ideal world, an en-route/predictive ITS unit would be the gold standard.

Before moving on, let's discuss the division made for historical information. Historical information is based on a set of traffic data that has already occurred. In this manner, it does not make sense to speak of pre-trip or en-route updates of historical information because all information is available pre-trip. We will discuss this matter further in Chapter 4. For now, it is sufficient to note that historical information can be analyzed in a static or time-dependent fashion. Static/historical information refers to a snapshot of the data set at a specific time. This level of information is analogous to a driver being routed using only a specific time period's traffic data (e.g. the conditions at 9:10 a.m.). One can view this level of information as being very similar to a pre-trip calculation.

Time-dependent information takes into consideration the entire information set. Drivers are now routed along in a dynamic sense using the historical information. The best path is determined by analyzing the changing conditions of the transportation network. This type of information system is similar to an en-route calculation. The distinction made in the historical information box is subtle, but it is important to realize that different flavors of ITS units can be modeled even within a component of the information spectrum. More will be said about these information levels when the experimental design is investigated.
### Section 1.2.2: Los Angeles Highway System

The information spectrum described above classifies the feasible landscape of ITS units. One of the major areas of difference between this work and other ITS papers is that this spectrum is applied to an *actual* network. In other words, many analyses that will be addressed in the literature review section have been run off of theoretically generated data on simplified network structures. In contrast, this paper uses data taken from the Los Angeles Highway System as the basis to analyze the various ITS units described above. In this manner, the results that are derived should be a consistent reflection that adopters of this technology would achieve.
There are a number of benefits from using the Los Angeles Highway System as a testing ground for this work. Foremost among them is that this network has an advanced set of sensors dispersed along the highways. What this means in practice is that information can be collected and disseminated in real-time to drivers. The highway system is shown in Figure 3 above. A quick glance at this map indicates just how extensive the sensor network in this area is. Each of the circles (green, yellow, or red in color) represents a sensor point where information can be collected and used within intelligent transportation systems. This information is the basis of the spectrum discussed in the preceding section: namely that information can be 1) historical, instantaneous, or predictive; and can be updated 2) pre-trip or en-route.

A second benefit of this highway system is that it is reasonably complex, but not overly sophisticated. Many of the prior ITS analyses, such as [Levinson 2002], focused
on a network of only 2 links. In real-world applications, ITS systems will be run off of thousands of nodes. For purposes of this work, the author wanted to keep a measure of realism while simultaneously managing the data intensity. Therefore, the Los Angeles Highway System met these requirements perfectly. This system can be translated into a set of 51 nodes.

Los Angeles is a traffic hotbed. According to the 2003 Mobility Report [Schrank and Lomax 2003], Los Angeles has the worst traffic out of any city in the United States. Los Angeles scored a 1.56 on the study's roadway congestion index. To put this index into perspective, consider that Boulder, Colorado had a score of only 0.84 (almost half the congestion level of Los Angeles)! It was with this in mind that the author chose Los Angeles as the base city to test the research hypothesis. An ITS unit operating within Los Angeles could provide maximum benefits to corporations and drivers because of the level of traffic congestion it experiences. In short, if there is no traffic congestion along the highways, a primitive shortest-distance approach would almost always be the best type of guidance system to use.

Section 1.2.3: Preliminary Considerations

Before proceeding into the main body of this work, it is useful to consider a few important issues at the outset. The first aspect to consider is what will not be covered in this work. Referring back to the information spectrum matrix of Figure 2, the author has reworked the blocks to those indicated in Figure 4. The goal of this work is to provide broad recommendations for ITS implementation within the supply chain. As such, the boundaries of the analysis need to be investigated first. Once these bounds have been identified, it is hoped that the intermediate steps will fall out naturally.

Having said this, the en-route information levels have not been modeled as continuous in this work. This should not present any major issues because in practice, information will most likely be delivered in periodic intervals (at least during the initial roll-out phase). In addition, the author has chosen to model the pre-trip/en-route blocks for predictive scenario together. The reason for this aggregation will be presented in greater detail in Chapter 4. For now it is sufficient to note that these two blocks will
represent an upper boundary for the cross matrix spectrum that we have developed. Before moving on, we should also note that traffic prediction and estimation is a difficult task and is outside the scope of this thesis. However, we will still be able to analyze the predictive information level using perfect information assumptions.

In the opening remarks it was suggested that drivers traditionally use mental models to make their routing decisions. Because people are limited in the information they receive and the extent to which they optimize complex networks, they can be viewed as operating with extremely simple ITS units. While it is not true that they have no information, people have very little information about the current state of transportation networks. Most likely, it could be said that they operate at or below the historical environment.

A logical question emerges as to how we can model this traditional behavior of people. For the purposes of this work, this type of analysis is beyond the scope of investigation. The complexity that belongs to this question can be the topic of an entire discipline of traffic theory that tries to model the rational and irrational nature of people’s
behavior. In short, a model that incorporates human theory accurately and precisely is a thesis in-and-of itself.

So where are we left if we are not going to model people’s current behavior as a baseline to measure ITS systems? A logical alternative comes in the form of distance-based routing systems. Vendors, such as Mapquest.com™, provide directions to drivers based on purely geographical considerations. Systems that are based on geographical analysis do not consider current traffic conditions. Using a distance-based system as a baseline would capture a level of information below the submatrix shown in Exhibit 2. More to the point, we should not forget that this thesis deals with the corporate side of transportation and not personal drivers. In this manner, corporations value large, scalable protocols that can be rolled out to an entire fleet of drivers. At the time of this writing, both UPS and PepsiCo are planning to roll out geographical-based ITS units in their transportation operations.

Taking this a step further, a baseline that only considers distance can be thought of as an ITS system that uses no information about the traffic conditions on roads. It does not provide updates about traffic accidents, nor does it attempt to leverage past history, nor does it make any guess at prediction. For these reasons, the author has decided to use a geographical-based ITS system as the baseline representing the none/none information block shown in Figure 4. This baseline is actually a step above the random ITS system that was described earlier. But for modeling purposes it lends itself nicely to mathematical formulation and it also represents the current best practice in logistics.

A final consideration needs to be made regarding supply chain transportation operations. It was just mentioned that this work will not be considering private drivers. In contrast, this work will be focused on a private fleet of corporate drivers that are limited in number. This fleet is assumed to be the first adopters of the technology. Therefore, we shall be ignoring the system dynamics that result from providing information to drivers. If all drivers were given ITS systems, additional complications would need to be modeled to reflect the actions that other drivers would make in response to this information. This type of system can be thought of in game theory terms. Again, while this type of system is clearly capable of being modeled (as shown by [Ashok 1996]) it is beyond the scope of this work. In the end, it is assumed that a limited fleet
size equipped with ITS would not present major system effects in the context of the larger picture.

While it appears that the author has left out a great deal of analysis, it should be stated that none of these deletions are expected to have major influences on the conclusions drawn in this paper. The last assumption regarding system dynamics is an important point to consider, but theoretical studies [Adler 1999] have shown that information has proven to be valuable even in system dynamic contexts. Moreover, the areas that the author has chosen to avoid are ripe topics for another scholar to investigate. No one paper is a definitive statement on an organic discipline.
Chapter 2: Fundamentals

Section 2.1: Supply Chain Management Fundamentals

Supply chain management ("SCM") has become more and more important to corporations over the past fifty years. Innovative techniques and processes have enabled businesses to streamline their operations while simultaneously increasing customer satisfaction. As a result, SCM has the unique ability to be able to increase both the top and bottom lines of a company’s financial statement.

The role of supply chain managers has been increasing for several reasons. Sheffi and Klaus [Sheffi 1997] identify a few of these factors:

- Increased globalization of commerce has created a need for sourcing and selling goods and services across the world.
- Tightly coupled supply chains have led companies to decrease inventory levels. However, these tightly coupled supply chains are more vulnerable to breakdowns and interruptions.
- Customer expectations for ever better service, lower costs, and more choices have added pressure to business operations.
- Environmentalists are emphasizing the recycling and safe disposal of products.
- Mergers & Acquisitions have realigned corporate networks — both inbound and outbound.

These factors all imply that managers need to handle new tasks competently in order to prosper. And managers that are able to prosper under these conditions should be rewarded commensurately.

Section 2.1.1: Transportation

Within the changing environment that supply chain managers find themselves, they will need to continue to innovate in order to be successful. As supply chain complexity and customer expectations increase, these managers will need to develop new processes. One major area of exploration will be in the transportation sector. The
transportation segment accounts for a significant portion of business cost. For example, the annual revenue in 2001 of the different types of modes was over $700 billion dollars (shown in greater detail in Figure 5) [Caplice 2003]. The revenue that transportation companies receive is a direct reflection of that costs that firms pay to operate.

As seen in Figure 5, trucking dominates all the different modes on a total revenue basis. In fact, this trend has been increasing over the last 25 years as shown in Figure 6 [Caplice 2003]. What this means for supply chain managers is that they must be able to find more ways to use highway modes efficiently. Currently, transportation planners use sophisticated software packages called Transportation Management Systems ("TMS") to help optimize their trucking decisions. TMS works within a strategic plan and enables managers to procure carriers for shipments in real-time. Thus, TMS is one tool that has given supply chain managers greater control over highway-based decisions.

Supply chain managers will need to create new tools that will allow them to extract additional value from transportation. This need is becoming ever more pressing as globalization and customer expectations increase. A direct result of this pressure is that goods will need to be transported across longer distances in shorter times. So, a
prime method for supply chain managers to accomplish this goal is to innovate with new supply chain techniques.

![1975 Modal Shares](image1)
![1999 Modal Shares](image2)

Figure 6. 1975-1999 Modal Shares

Section 2.1.2: Commercial Vehicle Operators

The previous section highlighted the needs for increases in efficiency within the transportation sector. ITS offers a possible mechanism to achieve this efficiency. The trucking industry described above is a component of a larger class named Commercial Vehicle Operations ("CVO"). A major operational element associated with CVO is managing large fleets of trucks that are hauling business freight. In the past, ITS has only been used to help manage or regulate these fleets in particular ways. For example, state administrators of motor carrier programs would use ITS to receive trucker credentials, automate the taxing process, or enforce size/weight restrictions. This paper will avoid these traditional areas and will instead test the feasibility of ITS within commercial routing policies. Figure 7 highlights some possible routing options [Caplice 2003].

Fleet management techniques have been developed to route drivers in an efficient manner. In fact, the traveling salesman problem ("TSP") is one of the most widely known routing problems in existence. The TSP is a classic problem that determines which is the best possible route given a set of destinations. This scenario uses a bundling principle to lower transportation costs. For example, if a delivery driver needs to drop off a set of goods to several locations in a particular region, there is an optimal path that
could be followed to decrease cost and time. Fleet managers use heuristics and algorithms to optimize the path that drivers would take in making drop-offs to these destinations.

The TSP is one example of how mathematical algorithms can be used to guide transportation decisions within the supply chain for commercial operators. It should quickly be noted that the majority of work around ITS research, to date, has focused on the individual driver and not on the commercial vehicle side. Public agencies (e.g. LADOT) have been concerned with reducing traffic congestion. As stated previously, the majority of this traffic is composed of individual commuters and not commercial vehicle operators.

This paper focuses on the corporate side of the equation and looks to harness the power of ITS within businesses. A few papers have laid the framework for this work by studying ITS and CVO. For example, Kavalaris and Sinha [Kavalaris 1995] documented a survey of trucking companies that focused on the attitudes towards ITS technologies. Holguin-Veras and Walton [Holguin-Veras 1996] also investigated the use of information technology in port operations through interviews with port operators and a small survey.
of carriers. Most recently, Golub and Regan [Golub 2001] present a multivariate discrete model of the trucking industry’s adoption of communication and information technology based on a survey of carriers.

The author believes (to the best of his knowledge) that this paper is the first “corporate-focused” ITS work that uses advanced simulation techniques to model the information spectrum. The results produced from this work could set the foundation for a new area of research within supply chain management. Moreover, these results have the potential to be directly translated into best-practices.

Section 2.1.3: Review of Literature

There is a tremendous amount of literature that has been written about SCM. This section will focus specifically on the literature relating to fleet management within the larger discipline of the supply chain. Fleet management techniques have the most relevance to this thesis because of the coupling of mathematical analysis with routing policy. For a broader view of supply chain management as a whole, the reader is directed to an excellent text written by [Nahmias 2000].

The existing literature relating to fleet management revolves around vehicle routing problems (“VRPs”) which are usually concerned with how to best assign jobs to a set of locations. This assignment is generally subject to vehicle capacity and time constraints. When the problem involves static and deterministic parameters, there are a number of algorithms used to assign vehicles. [Bienstock 1993] and [Bramel 1996] provide a very insightful discussion of probabilistic analyses related to many of the heuristics for static VRPs. If the reader is interested in further exploring any of the literature discussed in the remainder of this section, s/he is directed to the list of references located at the end of the paper.

Stochastic VRPs have also been extensively classified. In the case where loads are random, it is common to assume Poisson-distributed loads. Several authors have also studied loads with other distributions. In fact, it has been shown that with one vehicle and independent identically distributed loads, the stochastic VRP can be reduced into the
time-dependent traveling salesman problem. The problem of stochasticity makes the VRP much more complicated to solve, but also provides for a more practical solution.

Another set of VRPs consider the problem when information is gradually revealed as the driver is en-route. In today’s environment, these real-time algorithms are becoming increasingly important. [Powell 1995] gives an extensive survey of dynamic network and routing models. Many other authors discuss dynamic vehicle routing problems and related issues. [Psaraftis 1995] and [Bertsimas 1996] describe the major issues associated with dynamic problems.

[Regan 1995] evaluates vehicle diversion as an operational strategy and considers local rules for dynamic vehicle assignment with real-time information. This approach is focused on easy-to-implement local rules that might not fully take advantage of existing information. In fact, an empirical analysis of these local rules was conducted using a limited exploratory framework. [Yang 1998] considers re-optimization of truckload problems under a more general objective function.

Finally, Yang and Jailet [Yang 2002] use simulation to experimentally identify and test heuristics under varying situations. A new optimization based policy for the truckload pick-up and delivery problem is presented which is analyzed under varying traffic intensities, varying degrees of advance information, and varying degrees of flexibility for job rejection decisions. The optimization-based policy turns out to be the best performing policy under all these different conditions, and clearly outperforms the simple local rules and other myopic strategies.

Section 2.2: Intelligent Transportation System Fundamentals

Now that it has been shown that a large portion of supply chain management costs are held in transportation, it is time to introduce the fundamentals of ITS. The primary objective of these intelligent systems is to create a more efficient distribution of travelers on transportation networks. And by increasing efficiency, travelers can reduce their travel time, lower their fuel consumption, and decrease fuel emissions. All of these benefits can be translated into significant monetary savings and increases in the quality of life for society as a whole.
The research on transportation technologies dates back to the 1950’s. This early research focused on creating urban traffic surveillance and control systems. Even though over fifty years have past, the primary goals of the first researchers still provides a guiding light for current academics. What has changed throughout the years is the level of technology that has been deployed as a backdrop for ITS. In the 1960’s and 1970’s, Los Angeles, Detroit and Chicago began deploying visual information displays to drivers. These variable messaging signs (“VMS”) were placed along the highways and alerted drivers of traffic conditions [Weinberg 1966]. In the late 1970’s efforts to develop in-vehicle navigation systems were undertaken. However, it wasn’t until the 1980’s and 1990’s when advances in computer and communication technologies occurred, that these navigation systems began to appear practical.

Section 2.2.1: Technology Overview

The basic technology of ITS pertinent to this work is directed along four major lines. The first major area involves sourcing the traffic data from the transportation network. Once this data is sourced, it is then aggregated with other data into a centrally controlled computer. Next, the aggregated data is manipulated — either to generate routes, forecasts, or visual displays. Finally, the data is disseminated back to the driver’s in-vehicle navigational unit. Each of these four major lines will be investigated below.

The input of intelligent transportation systems is data collected from sensors. In most large metropolitan systems, traffic is monitored by a hybrid of technologies. The most common of these systems are inductive loop detectors (both dual and single) which are installed on freeways. These loop detectors are constructed under the pavement and are triggered when a vehicle rolls over their field. A second common traffic monitoring technology is video surveillance cameras. Often these video cameras are located at key points along a transportation network, such as an intersection. Software technologies are used to translate traffic movements collected from the camera into parameters which are incorporated into ITS. There are a variety of other technologies in existence that provide for real-time monitoring of the transportation network.
Once the traffic has been sourced, it is routed via wireless, cable, or optical means to a central headquarters. Traffic centers are able to monitor this data in real-time. At the traffic centers, data is aggregated from the different sensors into a cohesive picture of the entire transportation network. Traffic centers are also able to manipulate the data using software packages. These packages can generate visual displays, forecasts, or routing policies for vehicles. In addition, these packages can scrub the data for errors or defects.

After the data is aggregated and manipulated, it is disseminated to drivers. The dissemination of traffic information can take several forms. Highway advisory radio ("HAR") is a popular method for alerting drivers of potential congestion areas. Special frequency bands are allocated to transportation authorities to broadcast to the public. In addition, the Internet is also a new medium for providing this information to the public. The Internet provides a quick, graphical picture of the state of traffic conditions.

Over the past few years, advances in wireless technology have enabled navigational units to be put inside vehicles. Global positioning systems ("GPS") operate via satellite and are hooked into spatial networks to indicate driver locations. These systems offer great promise is helping ITS to proliferate in the future. One likely area of proliferation will be the integration of the manipulated traffic information (from the traffic centers discussed above) into in-vehicle units. Traffic centers will be able to provide personalized information to drivers in the near future.

This section has focused on the basic process of collecting, aggregating, and disseminating traffic information to drivers. Figure 8 highlights this process. It should be noted that this framework only demonstrates the fundamentals of ITS. It is not inclusive of the entire range of services that intelligent transportation systems offer. For example, toll collection technologies are a popular example of ITS. Automated toll collection increases the throughput on the entrance and exits of toll roads. The author has focused on the basic framework shown in Figure 8 to provide the reader with a sufficient background for the rest of this work.
Section 2.2.2: Review of Literature

There has been a great deal of literature written about intelligent transportation systems. The literature is rife with papers describing the technology discussed in Section 2.2.1. From the traffic monitoring perspective, several papers have begun to document new technologies that can be used to cost-effectively capture data. As previously mentioned, video image processors and inductive loops are the primary types of sensors being employed today. However, novel methods of data collection [Angel 2002] such as remote aerial sensing have newly begun to be investigated. [Kogut 2002] presents a cogent survey on both the hardware and software needed to improve data sensing. Finally, [Knaian 2000] presents a new wireless sensor network for smart roadbeds and intelligent transportation systems.

Software and algorithms have been developed to improve data manipulation. Many of these processes have been coupled with virtual probe networks. For example, Dailey and Cathey [Dailey 2002] present algorithms that use transit vehicles as probes for determining traffic speeds along freeways and other primary arterials. They describe a method for using these "virtual" probe sensors with automatic vehicle location systems.
Li and McDonald [Li 2002] also describe a new approach to estimate travel time from single GPS equipped probes.

The MIT ITS lab has developed a proprietary computer system called dynaMIT\(^1\) which is designed to support the operation of Advanced Traveler Information Systems (“ATIS”). DynaMIT couples traveler behavior models with a detailed network representation to estimate and predict network conditions. MIT’s ITS lab has also built a simulation based laboratory named MITSIMLab\(^2\) which evaluates the impacts of alternative traffic management system designs. MITSIM models the response of drivers to real-time traffic information and controls.

**Section 2.2.2.1: The Value of Information**

A number of papers have focused directly on quantifying the time savings related to traffic information on transportation networks. This is particularly important to this paper because it provides a realistic baseline to measure our results against. In this and the two sections that follow, we will investigate these studies.

[Levinson 2002] presents the value of advanced traveler information systems for route choice. He suggests that driver behavior will become more informed as in-vehicle navigation systems increasingly are adopted. The paper further analyzes systems that provide the driver with a shortest-path route which is updated in real-time - considering both recurring and non-recurring congestion. He concludes that the traveler’s full cost per trip is a combination of both expected travel time and the reliability of the generated route. The paper explores these topics from a theoretical economic viewpoint and then simulates several case-scenarios.

[Wahle 2002] discusses the impact of real-time information in a two-route scenario using agent based simulation. These authors argue that the controversy surrounding the value of advanced traveler information systems will continue as long as drivers’ reactions upon current or even predictive information about the traffic situation are not known. This implies that traffic models must consider the feedback process of system dynamics. Wahle et al. presents a basic two-route scenario with different

\(^1\) [http://mit.edu/its/dynamit.html](http://mit.edu/its/dynamit.html)

\(^2\) [http://mit.edu/its/mitsimlab.html](http://mit.edu/its/mitsimlab.html)
information types and studies the impact of it using simulation. The road users are modeled as agents and different ways of generating information are tested. They conclude that the nature of the information influences the potential benefit of information systems.

Adler and Blue [Adler 2000] assess driver and network performance under bi-objective route guidance systems. They assume a viable market penetration of informed drivers have real-time in-vehicle route guidance systems. Drivers' route selection is based on a bi-objective route choice model - minimizing trip quality costs, a performance measure that represents both trip time and route complexity. Network simulation is performed to evaluate performance under low and high traffic volumes at a given range of market penetration. Their findings suggest that the perceived value of intelligent systems can be enhanced if they more accurately reflect the drivers’ multiple objectives.

[Wunderlich 1999] finds that advanced traveler information systems yield time management benefits. He suggests that there is no conflict between survey and empirical research results regarding time savings. When travel behavior focused on travel time, Wunderlich found advanced traveler information system users save time in terms of their total travel budget. However, in-vehicle time is not always minimized. In the end, Wunderlich suggests that annual time savings can be significant and highly valued with predictable travel helping to relieve traveler stress.

**Section 2.2.2.2: Major Conclusions**

The papers described above are some of the major studies that have taken place in the last several years to answer questions related to the value of information in an ITS context. Each of these papers has taken a unique view on the value that ITS can provide to travelers. We will present the major conclusions of these and other studies in this section.

Table 1 presents a snapshot of the results of studies that have tried to quantify the time savings from intelligent transportation systems. These studies have differed in terms of congestion level, congestion type, and the market share of drivers who have been provided with information.
<table>
<thead>
<tr>
<th>Author</th>
<th>Congestion level/type</th>
<th>Time Saved (%)</th>
<th>Market Share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levinson (2002)</td>
<td>95% of peak congestion</td>
<td>40%</td>
<td>50%</td>
</tr>
<tr>
<td>Al-Deek et al. (1989)</td>
<td>Incident conditions</td>
<td>30-40</td>
<td>N/A</td>
</tr>
<tr>
<td>Peckman (1996)</td>
<td>Field operational test</td>
<td>20</td>
<td>N/A</td>
</tr>
<tr>
<td>Levinson (2002)</td>
<td>50% of peak congestion</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>Wunderlich (1995)</td>
<td>Congestion (no saturation)</td>
<td>8-20</td>
<td>5</td>
</tr>
<tr>
<td>Wunderlich (1996)</td>
<td>Construction (50% drop in capacity)</td>
<td>18</td>
<td>10</td>
</tr>
<tr>
<td>Wunderlich (1995)</td>
<td>Capacity reducing incident</td>
<td>15</td>
<td>N/A</td>
</tr>
<tr>
<td>Wunderlich (1999)</td>
<td>Savings for “masco” commuters: PM travel</td>
<td>13</td>
<td>N/A</td>
</tr>
<tr>
<td>Wunderlich (1996)</td>
<td>Rain (25% drop in capacity)</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Inman et al. (1996)</td>
<td>Field operational test</td>
<td>11</td>
<td>50</td>
</tr>
<tr>
<td>Wunderlich (1995)</td>
<td>Saturation</td>
<td>7-12</td>
<td>5</td>
</tr>
<tr>
<td>Inman et al. (1996)</td>
<td>Field operational test</td>
<td>8</td>
<td>30</td>
</tr>
<tr>
<td>Emmerink et al. (1995)</td>
<td>Recurrent congestion</td>
<td>7</td>
<td>N/A</td>
</tr>
<tr>
<td>Wunderlich (1996)</td>
<td>Incident (50% drop in capacity)</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>Inman et al. (1996)</td>
<td>Field operational test</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Al-Deek et al. (1989)</td>
<td>Difference in system optimal and user equil.</td>
<td>3-4</td>
<td>N/A</td>
</tr>
<tr>
<td>Adler (1999)</td>
<td>Congestion</td>
<td>3.1</td>
<td>80</td>
</tr>
<tr>
<td>Adler (1999)</td>
<td>Free Flow</td>
<td>2.7</td>
<td>100</td>
</tr>
<tr>
<td>Wunderlich (1999)</td>
<td>Total travel savings</td>
<td>2-3</td>
<td>N/A</td>
</tr>
<tr>
<td>Emmerink et al. (1996)</td>
<td>Recurrent congestion</td>
<td>1-4</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 1. Summary of time saved by ATIS study

As can be seen in Table 1, there is a clear precedence to suggest that advanced traveler information systems may provide significant time savings to drivers. The median of the results presented above is approximately a 10% reduction (excluding the influence of market share). Market share seems to increase the time savings up to certain level. Once a share threshold has been reached, increases in the provision of information appear to hinder the time savings. [Wahle 2002] imply that this is the result of a
feedback process which involves over-reaction, over-saturation and concentration. In fact, [Levinson 2002] presents experimental evidence that this threshold is approximately 50% of the total market.

Congestion level also appears to influence the travel time savings. A higher congestion level appears to correlate to a greater degree of time savings – up to a point. Much like the market share scenario, if the entire network is congested, there is simply nowhere that a driver can go. Levinson finds that typical information benefits are at a maximum on the precipice of congestion, when vehicles are arriving at a rate of 95% of their capacity. He further finds that non-recurring congestion benefits are even greater.

Time savings may not be the only criteria to judge the value of information to drivers. Adler and Blue [Adler 2000] describe a bi-objective route choice model. They show that when travel time is traded off for lower path complexity the overall network experiences slightly higher travel times. However, the total quality cost per driver (measured by a linear bi-objective combination of trip time and route complexity) decreases by over 20%, even at 100% market share. This suggests that time savings are not the only criteria to evaluate the success of intelligent transportation systems.

Section 2.2.2.3: Strengths and Weaknesses

Each of the papers highlighted above has its own strengths and weaknesses. In this section we will examine these factors in order to gain some insight into how the current work offers value to the landscape as whole. It has previously been mentioned that this work will not include system dynamic effects. The reason for this is that we are investigating a specific CVO carrier which represents only a tiny fraction of the total vehicle base. That is not to say that there will be no feedback dynamics. To the contrary there will most certainly be a feedback mechanism as information is spread to a larger base of end users. But we will ignore this impact because it is most likely a small component.

One of the strengths of several of the papers described above is that they do take into account these system effects. For example, [Wahle 2002] mentions that many classical microscopic traffic models exclude to properly take into account this
phenomenon. He presents an environment where agents adapt their behavior to the
dynamics they perceive and interact with other agents in order to achieve a goal. In a
two-route simulation, agents presented with dynamic data will seek to optimize their trip.
The key in this type of simulation is to understand that feedback will occur because other
drivers will be provided with similar information. A model that fails to heed this point
will be less robust.

Another strength of several of the papers presented above is that they are field
tests. For example, [Inman 1996] and [Emmerink 1995] both present the results of trials
that have been conducted outside of a laboratory. [Wunderlich 1999] also presents the
results of a field test of drivers in the Washington D.C. area. These types of studies are
most likely better proxies for actual conditions because they can capture human affects
that typical computer simulations might miss. In this sense, they are closer to reality and
are less theoretical.

These papers do have weaknesses. The first one (that the current paper suffers
from as well) is that the data is limited. For example, the field operational test that
Wunderlich ran was conducted over the month of September. This dataset might not be
representative of the current or future traffic conditions that will result. Moreover, even
the simulation experiments are run off a limited dataset. Adler and Blue [Adler 2002]
assumes two scenarios: 1) free flow conditions where 800 vehicles arrive per hour; and 2)
more congested conditions where 1500 vehicles arrive per hour. Again, these two sets of
conditions might not match up with reality and are limited in nature. If this is the case, it
is misleading to extrapolate these results.

This leads to a major deficiency of several of the models presented above. They
are theoretical and are not absolutely reflective of actual conditions. For example,
[Levinson 2002] presents a modeling approach where driver headway is modeled by:

\[ H(v) = -\frac{\ln(RAND())}{\lambda} \]  \hspace{1cm} (1)

where RAND () indicates a random real number between 0 and 1 and \( \lambda \) is
the average arrival rate

By using a simplistic theoretical model, Levinson may miss many of the subtleties that
may occur on a real network. Levinson is not alone in providing a theoretical framework
to operate under. [Wahle 2002] uses a simulation technique where dynamic drivers choose their route at random.

Not only are many of these models theoretical in nature, but many of them are also simplistic. Wahle et al. uses only two routes to simulate the decision process that travelers will face. [Levinson 2002] does no better by analyzing the case of unexpectedly reducing capacity on one link in a network of only two parallel links. Adler and Blue [Adler 2000] do only slightly better by examining a network that is composed of 8 nodes and 15 bi-directional arcs.

The paper that follows is different from the ones presented in this section in a number of ways:

1. To the best of the author's knowledge, this is the first paper that charts time savings related to an information spectrum for commercial vehicles. While many of the papers above could be extended to a commercial framework, the author's intent was not focused on corporate profitability.

2. This paper uses actual traffic data from the Los Angeles Highway System. The results that are obtained are not absolutely theoretical in nature. In addition, the network is not overly simplistic. The final results should be a consistent reflection of the time savings that a commercial vehicle operator would experience.

3. This paper will present recommendations to supply chain managers as to possible best practices based on the results of the simulations. These recommendations will take into consideration a financial framework.
Chapter 3: Mathematical Considerations

Section 3.1: Problem Definition and Notation

The literature discussed in the previous chapter has set the stage for the shortest path problem ("SPP"). A shortest path problem is defined as the need to find the least cost (minimum weight) route from an origin to a destination on a specific network. Before proceeding further, we should present notation for a few of the basic parameters needed for this problem.

Let $G = (N, A, L, C)$ be the network under investigation. A network consists of a finite set of nodes and arcs. $N$ is the set of nodes and $A$ is the set of arcs. The number of nodes and arcs in the network are denoted $|N| = n$ and $|A| = m$ respectively. The network has an origin node $o$ and destination node $d$. We assume that decisions are made at nodes (i.e. once a driver is on a link, s/he must continue along to the end). The decision is what node $k$ to take next based on the current node, current time, and information. This decision vector can be represented as $x = \{j,t,I\}$.

Our network is directed in nature because the arcs determine which direction the flow propagates towards. In addition, our network has a time-dependent facet because the speeds on each arc change over time. To model this behavior, we separate the network into a set of $L$ discrete time updates $\{t(0)+n*\Delta\}$, where $n=0,1,2...D$. $D$ is the total number of time divisions that we consider. $\Delta$ is the smallest increment of time over which a perceptible change in the travel time distribution will occur for $t$ in $L$.

For each arc $(i,j)$ in $A$, the set $C(t)$ of non-negative real valued average speeds for traversing the arc at time $t$ is given, $k=1,2,...,K_{ij}(t)$ where $K_{ij}(t)$ is the number of distinct average speeds on arc $(i,j)$ possible at time $t$. Each of these average speeds will determine the travel time for traversing a specific arc $(i,j)$. In the geographical information level scenario, the set $C(t)$ will be represented by distances. These set will no longer be dependent on time so we can modify $C(t)$ to $C'$. In all other information levels we will be considering the average speed set $C(t)$.

The shortest path problem is to find the route that minimizes the total travel time from an origin node to a destination node. This shortest route is composed of a set of
nodes $M$ where $M \in N$. Each node in the network can be processed using a shortest path algorithm. For the algorithms that are typical (both label-setting and label-correcting), labels are associated with all nodes. The label vector that is maintained for a node $j$ contains information about the path from that node $j$ to the destination node. A temporary label is constructed from a predecessor node (i.e. $\forall \ i$ from $(i,j) \in A$) using both the travel times on arc $(i,j)$ and the label vector at node $j$ which maintains the least possible travel times known thus far. The final label vector yields the solution to the shortest path problem.

It is further assumed that the network under consideration is FIFO. We define a arc $(i,j)$ as FIFO iff $t(1) + c_i(t(1)) > t(2) + c_j(t(2))$ for $t(2) \in T$ and $t(1) > t(2)$. A network is FIFO iff all arcs are FIFO. We also assume that no waiting is allowed at each node. Even if these two assumptions are relaxed, mathematical extensions are available to handle creating an appropriate model structure. For the purposes of this work, these two assumptions are made to achieve both realism and simplicity.

Section 3.2: Pre-trip vs. En-route Information

In the opening chapter we made a distinction between pre-trip and en-route information levels. This distinction was based on when and how information was provided to the decision maker. In the pre-trip scenario, information was provided only once to the decision maker. One typical example of a pre-trip routing policy is a central dispatching office that finds the shortest path for a driver before the driver leaves. The driver follows along this path and is unaffected by future changes in the transportation network.

In a pre-trip shortest path problem we have two networks to consider. The solution to the SPP is found using a modified network (network #1). In mathematical terms we can say that this network, $G' = (N, A, L', C')$, is being investigated. $G'$ is a function of the same nodes and arcs as the in the general formulation presented in the preceding section. However, there is a modification now to both the set of time intervals and average speeds. In particular, the time vector $L'$ is now ignored for all but the first period, $t=0$. The vector of average speeds, $C'$, is now set to a constant equal to the set at
C(0). With this modification, we can translate our focus to a network \( G' = (N, A, C(0)) \). \( G' \) can be solved using standard shortest path algorithms.

It is important to understand that even though we have modified the generalized network to determine the pre-trip shortest path, the actual results of our routing policy will be determined by the original network \( G \) (network #2). In essence, we have extrapolated a “snapshot” of the network \( G \) and termed it \( G' \). The solution to \( G' \) is used as a proxy for the solution to \( G \). Most of the cases that will be considering in this thesis are modifications of the original network.

En-route networks extend the sets of \( L \) and \( C \). Returning to our definition of an en-route information level (presented in the opening chapter), we see that the routing policy is updated as the driver propagates through the network. As an example, a central dispatcher might have a wireless communication system with drivers in the field. S/he could provided modified routing instructions in real-time as new information is sourced and processed. This information would allow the decision maker to extend the principles derived in the pre-trip case.

In mathematical terms, the network we are considering is now \( G = (N, A, L, C) \). This is the original, generalized network developed in the opening section. The time vector \( L \) is discretized into one minute intervals for the simulations run in this work. So we can define \( L \) as discrete time updates \( \{t(0)+n\Delta\} \), where \( n=0,1,2,\ldots \)D. In our runs, \( \Delta \) is equal to 1 minute. D is equal to 180 minutes since we will be investigating the 3 hour rush-period block of time. The average speed vector \( C(t) \) is now a function of these time periods. Every \( \Delta \) time units, we have another speed vector to analyze.

Using the network \( G \), it is possible to derive a solution to the shortest path problem. However, we should note that the solution to this SPP is not necessarily the optimal shortest path tree for the system. This is true because the average speed set, \( C(t) \), is a stochastic, random variable. We will consider stochasticity in the next section. For now it is vital to realize that the network \( G \) we use to solve the SPP changes over time. By nature traffic flows are random – incidents and weather cause varying levels of unpredictability. If we are considering historical or real-time information levels, the future set of average speeds (i.e. \( C(t') \) where \( t' > t(i) \), \( i = \) current period) will be uncertain. This implies that the network we are solving may not be the network that results. Even if
we provide predicted information, there is still a high chance that the future average speeds will not reflect the predicted ones. Only in the case of perfect information will the two networks (both the actual and the one used to solve the SPP) be equal.

The research objective of this thesis postulates that the closer a decision maker is in matching the network used to solve the SPP with the actual network that results, the better will be the routing policy. This means that as we are able to provide better and more information to the decision maker, we are also able to extract better decisions. This work will investigate whether this claim is valid by analyzing differing levels of information used to make routing decisions. The decisions will then be extrapolated to the actual network to reveal true travel times.

**Section 3.3: Deterministic vs. Stochastic Information**

In the preceding section we broached the subject of stochasticity. In particular, we mentioned that the set of average speeds, \( C(t) \), is a stochastic, random variable. This section will investigate what is meant by the term “stochasticity”. The key feature of stochasticity is that the average speeds, \( C(t) \), are associated with probability distributions. They are not known \textit{a priori}. A routing policy that includes stochastic, random variables is often based on expected minimized travel time. Note that in the deterministic case, we are not dealing with expectations at all. A deterministic network excludes the probabilities of average speeds occurring on a particular arc. We will delve further into deterministic networks below.

In a stochastic network, the traveler learns what the average speeds on a given arc are by traversing it in real-time. We can extend the mathematical framework above to a network \( G'' = (N, A, L, C, P) \). This network is time-dependent and stochastic in nature. The average speed on each arc \((i, j, t)\) at each time period \( t \) is a random variable \( c_{ij}(t) \) with discrete, non-negative, real-valued numbers. \( P \) is the probabilistic representation of the average speed vector, \( C(t) \).

There are different descriptions for the set \( P \) which are based on different assumptions about network statistics [Gao 2002]. The most general one is in the form of a joint probability distribution for all the average speed random variables. Using the framework developed by Gao, we let \( P = \{v(1), v(2), \ldots, v(r)\} \) be the set of possible joint
realizations of average speeds on all the links in the network. The rth realization would then have a probability \( p(r) \), and \( \sum_{r=1}^{k} p(r) = 1 \). \( C_{ij}^r(t) \) is the average speed of arc \((i,j)\) at time \( t \) in the rth realization.

In contrast, a deterministic network can be represented without probabilities. We can return to our original formulation and let \( G = (N, A, L, C) \). In a deterministic network we assume \textit{a priori} that we know what the future average speeds will be. When we consider predictive information levels, these speeds are a result of traffic modeling algorithms. If we consider real-time or historic information levels, we assume the future speeds are approximated by a constant real-time or historical value. Therefore, deterministic networks can be solved without the use of complex statistical analysis.

As seen in the stochastic case, we need to derive a probability distribution for the vector of average speeds on an arc in order to solve the shortest path problem. The first question that naturally occurs when positing stochastic networks is where to get a good estimation of the probability vector, \( P \). Complex statistical analysis can be performed on historical datasets to obtain an unbiased an efficient representation of this vector. However, a significant amount of data must be available to perform this analysis. Because the author lacks such a robust dataset, in the work that follows, we will only consider deterministic networks. The extension of stochasticity is one that can be made by following the principles outlined by Gao.

The final aspect we need to note in this section is that both the stochastic and deterministic networks have a high probability of not matching the actual network that results. Again, we have stated that stochastic solutions rely on expectations of actual results. By definition, these expectations are only a proxy for actual results. In addition, deterministic networks will only be a true representation of actual speeds if these speeds are available \textit{a priori}. When we consider traffic speeds, these results are most certainly not available beforehand. The deterministic assumption is made to simplify the modeling framework. This implies that ITS units will most likely provide sub-optimal routing policies. Only in the case of perfect information will ITS units consistently provide optimal results. Our final simulation runs will assume that the decision maker has perfect information. We will return to this assumption in Chapter 4.
Section 3.4: Simulation of Information and Routing

Before proceeding to the simulations of Chapter 4, it is worthwhile to highlight some of the key principles related to simulation and routing. This chapter has presented a basic mathematical formulation for viewing traffic network problems. We have seen that the most complex type of problem representation can be described by a stochastic network \( G' = (N, A, L, C, P) \). If we limit ourselves to only deterministic networks then we can remove the probability set \( P \).

In order to model, simulate, and solve the SPP for an actual transportation network we need to understand the parameters that must first be collected. For a deterministic network \( G' = (N, A, L, C) \), the original modeling parameters that must be collected relate to the topological considerations of the network. We must know how many nodes and arcs are in the network. After this has been determined, we can then turn to the time set \( L \). \( L \) represents the feasible set of time updates that an ITS unit can capture. For preciseness, we have modeled a \( \Delta \) of 1 minute in this thesis. This delta allows a change in the average speed vector \( C(t) \) to be collected adequately. Larger intervals might miss important variances in traffic speeds.

The final parameter we must estimate is the average travel speeds on each link for a given time interval. The vector \( C(t) \) of travel speeds is the heart of the simulations. These will determine the routing policy that will result in the shortest travel time path. Since travel speed can be translated into travel time through a distance matrix, this is the final piece of the puzzle we need to begin the simulations.

The simulations of Chapter 5 follow the two-fold approach outlined above. The first step is to estimate and solve the network described in the preceding two paragraphs. We can find a routing policy that minimizes the travel time of a driver from an origin node \( o \) to a destination node \( d \). Using this routing policy, we can then take the second step and *simulate* how a driver (following this routing policy) would fare on the actual network. These simulations will allow us to capture the travel time of routing policies which are based on differing information levels. The goal of this thesis is to determine if information can be used to extract value for supply chain managers and corporations.
Section 4.1: Data, Network, and Simulation Description

Is information valuable to supply chain managers? Do the attributes of this information matter? If it does matter, is there a given attribute that matters most? These are the primary questions that this experiment seeks to answer.

In the opening chapter, Figure 3 depicted a snapshot of the traffic conditions on the Los Angeles Highway System. This is a real-world picture of the network that supply chain drivers encounter on a daily basis. We can log this information over a given time period to form an accurate representation of the Los Angeles Highway System. Returning to a key differentiating factor between this work and others that have preceded it, we should note the absence of the word “theoretical”. This work simulates the behavior that actual drivers would experience – there is no theoretical assumption involved.

One could argue that this information is actually one layer removed from true conditions because the sensors might be relaying an inaccurate picture of the network. This may indeed be the case. And we will investigate this further in Chapter 6. For now, let’s focus on the fact that we are going to run simulations that should be a direct reflection of the experience of corporate drivers. To this end, if we are able to demonstrate performance savings, we can abstract them to time savings for a specific corporation.

Section 4.1.1: The Network

Returning to the network shown in Figure 3, we can model this specific highway system using node and arc forms. Nodes can be represented by highway intersections. An intersection is a convenient point to place a node because it offers a choice point for a driver. At each node-intersection, a driver can make a decision which route to travel down. The streets can be represented by arcs on the system and can be associated with specific attributes. These attributes can range from distance to an average speed of travel.

An example of a node-arc overlay on the Los Angeles Highway System is shown in Figure 9. For this particular network, we can locate 51 unique nodes and 162 arcs.
(note that for modeling purposes we can also depict a total of 2601 arcs – which include all the “dead” arcs whose distance is set to infinity). In Figure 9, the nodes are indicated by the large black dots. Using this quantitative representation of the network, we have a specific platform to be able to route the drivers along simulated paths.

Figure 9. Node representation of the Los Angeles Highway System (http://traffic.tann.net)

Section 4.1.2: Data Sources

The previous section described the mathematical representation of the Los Angeles Highway System that the simulations will be run on. We can distill some specific parameters from this network. This information will be useful in both the modeling of the network as well as being able to calculate shortest path routes for differing information levels.
The first piece of data that we can abstract from the network shown in Figure 9 is the distance along each arc. This information is available from several different sources. One of them is the Los Angeles Department of Transportation. A second source for this information is a book of road maps and distances published by Rand McNally [McNally 2001]. The author chose to source the distance for the arcs from the latter reference. This choice was based on simplicity and convenience. A list of the arc distances can be found in the Appendix to this work.

The second piece of information that we need to obtain from this network is the average travel speeds along each link. It is important that we clarify why the average-travel speed is being used to calculate shortest-time paths. Traditional traffic modeling is based on a fundamental equation. This equation is of the form:

\[ q = u * k \]  \hspace{1cm} (2)

where the average density on a road is given by \( k \) (units of cars/km)

where the average flow on a road is given by \( q \) (units of cars/hour)

where the average speed on a road is given by \( u \) (units of km/hour)

As can be seen in these equations, it is important to know the flow and/or density in order to model the speed of the network. As an example, we can consider Greenshield’s simple microscopic model where average speed is a function of density parameters:

Greenshield model:  \[ u = u(max) * (1 - \frac{k}{k_{jam}}) \]  \hspace{1cm} (3)

where \( k_{jam} \) is the jam density of the road

In this model, the speed of the network is dependent upon the jam density of the road. So that if we route many drivers down a given road, this should make the average speed fall to zero. One could argue that it is inaccurate for us to simply use the average speed along an arc to determine the travel time for a single driver because this would change as drivers are routed.

The rebuttal to this argument lies in the word “single”. As mentioned in the preliminary considerations to this thesis, we are not considering system dynamic effects because of the small number of drivers that we are routing. So it is feasible to use the average travel speed along a network to determine the travel time that a simulated driver
would experience. These drivers would not cause the state of the system to change much from the current baseline.

We do need to consider changes in the travel speeds, however. In order to capture these changes, we must be able to log the information shown in Figure 9 frequently. For modeling purposes, the travel speed information was sourced from the publicly available Travel Advisory News Network website (http://traffic.tann.net). The data was collected in electronic form as a means to be input into the computer model for the simulation runs.

The information was captured by a custom script that the author wrote. It is based upon an internet macro that automated the data capture process. The author captured data over a two-week period during January-February 2004 timeframe. The traffic data has not been appended to this work because of space limitations. In total, this data contains millions of points and would take up hundreds of pages if included in the work. However, it is available upon request.

Section 4.1.3: Models

With a defined network and data parameters in hand, it is possible to mathematically model a simulated traffic run. The traffic runs were produced by a random number generator to simulate a corporate route. For example, if a food company needed to transport fresh bread from its distribution center in Encino to its retail outlet in Costa Mesa, the driver could be routed along several different paths. In particular, we can select the origin/destination pair of Encino and Costa Mesa randomly. This way we can simulate an unbiased pool of traffic runs for a collection of companies (equivalent to the food company above). The only constraint that we have imposed upon these runs is that they require at least 1 choice. This means that the traffic run must be longer than 1 arc. We provide this constraint in order to allow for the potential of differentiation in routing. Obviously, this constraint does not invalidate the research objective.

It is should be mentioned that the routes are single point origin/destination pairs. They do not represent a bucket of destinations that a traveling salesman type problem would encounter. The extension of the above analysis is quite straightforward to these types of problems, though. In particular, we provided a great deal of literature review on
VRPs because these techniques can be translated quite nicely from the single point framework that is developed in this work. In all, the author expects the results should hold for the larger subset of routing problems.

The simulations that are being run in this work are relegated to a specific number during a specific time of day. The time-of-day consideration is based on the premise that "traffic" is a requirement for information systems to have an effect. If the transportation networks are empty, then the shortest-time path will always be the one that is the shortest distance (assuming the driver can travel at any speed s/he wants). In this manner, the question of traffic management becomes trivial. To focus in on the impact of traffic, the author has run the simulations over the morning and evening rush-hour periods. This consists of 7 a.m. to 10 a.m. window in the morning and 4 p.m. to 7 p.m. window in the evening. For simplicity, all runs are assumed to start at the beginning of the time window. It is a straightforward extension if we want to be able to model a consecutive set of trips.

The second aspect of the simulations to highlight is the specific number of trips under investigation. The author had the ability to run hundreds or even thousands of different origin/destination pairs, but chose to limit the runs of randomly generated trips to 20 in number. Over a five-day time period, this implies that each information level would result in 200 unique trips. The author deemed this amount sufficient based on statistical sampling and data management considerations.

Let's now set the stage for the traffic runs that we will be considering in the next chapter. These runs were produced by a random number generator. Each node shown in Figure 9 is associated with a specific label and is given a number from 0 up to 50. For example, we might want to simulate a run from an origin node labeled 5 to a destination node labeled 41. In order to compare the results of all the different information levels, we need to have a common ground. This common ground is a consistent set of traffic runs. The runs that will be applied across all the simulations (with the specified node labels) are given in Table 2 below:
Table 2: Traffic runs: origin and destination nodes

<table>
<thead>
<tr>
<th>Traffic Run</th>
<th>Origin</th>
<th>Destination</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>39</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>49</td>
<td>16</td>
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<tr>
<td>3</td>
<td>33</td>
<td>22</td>
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<tr>
<td>4</td>
<td>19</td>
<td>8</td>
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<tr>
<td>5</td>
<td>23</td>
<td>38</td>
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<tr>
<td>6</td>
<td>42</td>
<td>28</td>
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<tr>
<td>7</td>
<td>42</td>
<td>3</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>28</td>
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<tr>
<td>9</td>
<td>46</td>
<td>4</td>
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<tr>
<td>10</td>
<td>49</td>
<td>27</td>
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<td>11</td>
<td>3</td>
<td>21</td>
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<td>12</td>
<td>47</td>
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<td>19</td>
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<td>39</td>
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<td>20</td>
<td>24</td>
<td>30</td>
</tr>
</tbody>
</table>

All of the above assumptions lead to a focused problem that can be mathematically simulated. The information spectrum levels discussed in the opening chapter each have different properties. As such, each is capable of being modeled differently. For example, the geographical information level (represented by the none/none information block in Figure 4) can be modeled as a shortest path problem based upon distance. This is a Mapquest.com™ methodology that routes the driver from one point to another based on geographical topology. The time that this routing policy would exhibit can be ascertained based upon the actual travel conditions that result on the highway system.

It is also possible to simulate drivers traveling under different routing policies. Each of these routing policies was shown in Figure 4. Again, we can use the actual parameters of the Los Angeles Traffic System to derive the time that these policies would result in. The final bridge to obtaining these results is to build a computer model to simulate the policies. Using the mathematical notation discussed in Chapter 3, it is possible to create a simulated environment to achieve time results. The primary shortest path algorithm that is used is a modified Dijkstra algorithm. The size of the problem lent
itself nicely to this type of algorithm (with a run time of under 1 second). If the network
was significantly larger, a different algorithm could have been used.

The computer models for each of the different simulations are included in the
Appendix of this thesis. The author chose to write these programs in C++. The distance
and average speed parameters were imported into the models using input/output stream
libraries. It should also briefly be noted that the geographic routing policy is built into
each of the other informational models as a baseline comparison.

Section 4.2: Level Zero Geographical Information

The research objective of this thesis is to determine if traffic information can
prove valuable to supply chain managers. In the opening chapter of this work, we spoke
about different baselines that could be used as a yardstick. It was suggested that today
most drivers use mental models to determine their routing policies. It was also suggested
that this type of model is extremely complex to mathematically simulate. A second
alternative was to consider a popular routing alternative – namely using geographical
principles as a basis of computation. Companies, such as PepsiCo and UPS, are looking
to benefit from this type of system. They feel confident that the consistency and
reproducibility of a geographic baseline will be useful to supply chain managers.

Section 4.2.1: Distance Matrix

It is logical, therefore, to model this type of approach as a baseline for our
analysis. As mentioned in the previous section, the distances of the arcs shown in Figure
9 have been captured from publicly available sources. This information is included in the
Appendix.

The routing policy that is simulated under the Level Zero information spectrum is
based on shortest distance. This means that the driver will follow a shortest path tree on a
network whose arcs are represented by distance. Using a classic Dijkstra approach, we
can easily determine this path. The time that this route takes is a function of the travel
speed along the arcs of the optimal path. If there is a major traffic jam along one of these
arcs, this type of routing policy will not be affected. The only consideration for the policy is distance. The output of the policy does depend on traffic conditions, however.

It should also be noted that a routing policy based on distance does not need to be modified over time. In other words, the shortest path tree will be the same if derived on different days of the week. As long as the network representation has not changed (i.e. the distance parameters are constant), then the route will be the same. We will see that this assumption does not hold at higher levels of the information spectrum.

Section 4.3: Level One Static & Time-Dependent Historical Information

Having set the baseline, it is now time to embark on the investigation of higher levels of information. As mentioned previously, the geographic baseline does not consider traffic conditions. It is based solely on topological design. This means that if there is a terrible traffic incident on a road that is part of the shortest distance path, the algorithm will be unaffected. Drivers will be routed right into the traffic incident. Is it possible to somehow incorporate traffic information into a corporate routing policy? This section presents the first set of simulations that accomplishes this task.

Historical information (in the context that we are using it) can actually mean a few different things. The basic premise is that real-time or instantaneous information is not available. In addition, we are not yet concerned with the predictive information level. This implies that decision makers only have access to past information. It might be possible to collect information for the previous day. For example, imagine there is a large time delay between the time the data is sourced and the time the data is received to be aggregated. This could result from technological considerations – where the network takes some time to do a certain task. Or imagine that technology is not involved at all. Instead people are deployed to monitor the traffic conditions at key junction points. In this scenario, it is feasible to believe that there would be some delay between when the data would be available for use.

Historical information, therefore, means information that is one-step prior to “real-time”. From a time perspective, this one-step can be 1 hour or 1 year. The only distinction that we are making is not allowing the information to be real-time (this will be considered in the next two major sections). So with this definition in mind, we can
question whether there is a difference between static and time-dependent historical
information.

The difference between static and time-dependent information for the historical
spectrum is slight. We briefly mentioned this difference in the opening chapter when we
examined the information spectrum matrix. Now we are ready to delve deeper into this
distinction.

The distinction lies in the traffic information set that is used to compute the
shortest path. Imagine that a full data set is available – with information provided every
minute during the entire time window. Using this full data set it is possible to derive a
route that would be optimal for the entire time window. This optimal route is the solution
to the time-dependent/historical information level. This solution is termed time-
dependent because the changes in the transportation network that evolve over time are
incorporated into the analysis.

In contrast, we can derive a solution using only a single time interval’s data. For
example, if we only have information for the conditions at 9 a.m., it is still possible to
derive a shortest path assuming these conditions remain constant. This solution is termed
static/historical. And this solution can be compared to a pre-trip calculation because it
does not take into consideration changes over time on the network. Therefore, from a
definitional perspective, we can’t make a pre-trip/en-route distinction for the historical
information level because all information is available at the time of calculation. We can
use similar analytical techniques by investigating a static/time-dependent bifurcation to
approximate the pre-trip/en-route distinction, however.

Finally, we should note that we from a notational perspective, we have subdivided
information Level One into two parts. In the remaining parts of the analysis, results will
be presented for each of these two components.

Section 4.3.1: Historical Information Considerations

As indicated above, there are many different ways to use historical information.
We have decided to use two approaches for the analysis. The first approach is to use the
prior day’s traffic information to guide drivers. The guidance is based on history, but the
conditions that the driver experiences are based on the present. So the first approach will
result in four separate days worth of runs (the first day must be skipped because it has no predecessor). The second approach will be a one day run that uses the prior week's analogous day's data as a guide. It is logical to think that certain days have corresponding patterns. For example, traffic on Mondays might be correlated as many people adjust from their weekends and return to work. We will test this correlation using the one-week prior day as a historical information base. For statistical purposes, it is inadequate to derive any meaningful results from this one data point/set. The author includes it only for the reader's interest.

Section 4.4: Level Two Pre-trip, Instantaneous Information

Up to this point, we have not considered real-time traffic information. Over the past several years government agencies and private companies have built out a vast sensor network over the highway infrastructure. This network is composed of video image processors, inductive loops, fiber-optical cable, and wireless technologies. We covered these technologies in Chapter 2. Now we are ready to see their impact.

It is important to understand that real-time traffic information has a great deal of power. Transmitting the current state of the network can be used for a variety of purposes. For example, if an accident occurs on a major highway, it might be possible to route police and ambulances to the scene in quicker timeframe. This routing might be quicker for all of the reasons we presented in the opening chapters. But, it might also be true because the incident was sensed quicker. Real-time information has the ability to give regulators greater visibility into the current transportation infrastructure.

Section 4.4.1: Pre-trip, Instantaneous Considerations

This information level is pre-trip. It is also instantaneous. What do we mean by a pre-trip, instantaneous information level? Taking the pre-trip part first, we can return to our previous definition of only 1 update. In other words, the driver is given a set of directions to get from a warehouse to retailer. These directions do not change as the driver propagates along the network. Even if the current traffic changes (which it invariably will), the driver is routed along unaffected.
A pre-trip system appears to be very practical. It requires less infrastructure than an equivalent en-route one (discussed in the next major section). Drivers can be presented with a clear route and should be less apt to ignore the instructions. In addition, the dispatcher/software need not constantly monitor the conditions of the network after the driver has departed.

The fact that this information is not only pre-trip, but is instantaneous means that it is real-time. The current state of the network is sensed immediately and transmitted back to the dispatcher/software for the routing to be determined. It uses the current state as the naïve prediction of the future. Note that we have not entered into the predictive dimension here. We have simply forced the algorithm to use the current state to calculate future traffic times. When we examine higher information levels, we will take into account the ability to predict what the state of the network will be when we expect the driver to encounter it.

Section 4.5: Level Three En-route, Instantaneous Information

Continuing along the information spectrum, we are now ready to investigate Level 3. This information level simulates an en-route, instantaneous environment. As indicated in the opening chapters, en-route/instantaneous ITS units are certainly attainable using today’s technology. The question that needs to be resolved is whether they hold any value. This information level seeks to investigate whether this question is indeed true.

Section 4.5.1: En-route, Instantaneous Considerations

What exactly is meant by en-route, instantaneous information? An example is probably most useful to clarify this definition. Returning to our fictitious food company, imagine that it wanted to transport its bread from a distribution center in Encino to a retailer in Costa Mesa. When the driver departs from the distribution center it can be given routing instructions that incorporates traffic information. This routing information can be pre-trip in nature (as discussed in section 4.4). If the information is pre-trip, the driver’s route would not be modified as s/he propagated along the network. In contrast,
en-route ITS units can be used to alter the pre-trip routing. Instantaneous traffic information can used to update the route.

If the food company wants to use these en-route, instantaneous systems, they will need to outfit their driver's vehicles with ITS units. These units must be able to receive real-time communication from a central dispatcher (or have significant computing power to determine the updated routes). Much like an in-vehicle GPS system, an en-route system will require additional hardware and wireless specifications. However, today's technology is at a level to accomplish these feats.

Section 4.6: Level Four Pre-trip & En-route Predictive Information

We have reached the final level of the information spectrum. Having traversed through geographical, historical, and instantaneous information, we are now ready to explore predictive traffic information. With prediction, a driver can forecast what the conditions in the future will be. By definition, all our trips propagate in three dimensions (x, y, and t). Given the time-dependent nature of the transportation network, it might be valuable to predict at a prior time, t', what the conditions will be at a time t*, where t' < t*. If an accurate forecast can be made, the driver can be routed at t' over the entire trip (which unfolds over time – including t*). In the end, predictive information can be viewed as incorporating future states into present decisions.

It is worthwhile to note that traffic congestion can be classified into two distinct types: 1) recurring; and 2) non-recurring. Recurring traffic congestion can be described by a historical time-series pattern. For example, most people go to work during rush-hour periods (which we have been analyzing). The major highways that these people use are consistently jammed. In contrast, non-recurring traffic congestion represents a "one-time" event. These can be traffic accidents, weather disruptions, or construction.

From a modeling perspective it is easier to forecast recurring traffic congestion. Much more difficult is being able to predict the non-recurring traffic patterns. This implies that almost all traffic forecasts will be an inaccurate picture of actual conditions. Nevertheless, providing a baseline forecast may have value for routing policy. Forecasts can be updated with real-time information to give a more precise estimate of future events. In addition, with technological improvements it might be possible to identify
non-recurring traffic incidents in real-time to be able to model them appropriately for the future.

This thesis will not examine traffic estimation and forecasting. As discussed in Chapter 2, the reader is directed to a number of papers that concentrate solely on traffic prediction (see dynaMIT). It is taken as a given that it is possible to come up with an unbiased and efficient traffic forecasting model.

Section 4.6.1: Predictive Information Considerations

This thesis is focused on analyzing whether ITS units can be used to extrapolate value for supply chain managers. If we have just said that we will not be examining traffic estimation and forecasting, how can we investigate the predictive information level?

The answer to this question lies in the fact that we are trying to determine appropriate bounds for the information spectrum – from no information to predictive information. Since we have collected a data set of average travel speeds over a certain time period, we have the ability to route vehicles using future information. In other words, we don’t have to come up with a model to estimate the future traffic conditions because we have the future traffic conditions a priori! This situation is termed “perfect information” because from the outset the future is known.

A few remarks are in order. Not modeling a traffic forecast does not mean that it is not a valuable task for another researcher to handle. In fact, it is quite worthwhile to determine whether a model such as dynaMIT will add value over and above the other information levels we have been considering. What we are saying is that building this model is outside the scope of this thesis. However, we still have the ability to determine an upper bound on what a perfect forecasting model would be able to accomplish.

Because we have collected the future average speeds, we can view our network as deterministic. There are several algorithms that can solve the shortest path problem for a deterministic network. We have developed a model (shown in the Appendix) that is based on an extension of a forward labeling algorithm. It has been shown [Chabini 1997] that a static forward labeling algorithm can be extended to solve the one-to-all shortest path problem in a discrete, time-dependent network for a single departure time.
Before moving into the simulations, we need to mention why we have aggregated both the pre-trip and en-route information blocks for the predictive information level. The reasoning is quite straightforward. Since we have perfect information before the driver departs, the pre-trip and en-route policies will be equivalent in nature. In other words, updating the driver with future information will not add any value over the pre-trip case. If we were modeling less than perfect information, this would certainly not be the case. In fact, it is the author's supposition that providing en-route updates to the pre-trip forecast should provide additional value to supply chain managers. As an aside, dynaMIT uses dynamic updates for its traffic prediction algorithm.
Section 5.1: Level Zero Geographical Information

We are now ready to present the results of the simulations. The first step will be to run the simulations for the baseline. Therefore, the starting will be to test a baseline that is composed of only geographical information. As stated in the preceding chapter, this baseline is an operating yardstick that a few companies are planning to implement in the near future. In each of the major sections that follow, we will be deriving the % time savings that result over the baseline. The final section of this chapter will discuss the results achieved in light of the baseline statistics.

Section 5.1.1: Origin/Destination Travel Times

This section presents the results of the simulations that were run for the two daily rush hour periods on five separate days. For completeness, each of these runs is shown on the five graphs below (depicted in Figures 10-14). As mentioned previously, there were 20 traffic runs simulated for each rush-hour window. This implies that a total of 200 unique runs were simulated for this information level. A total composite of this information level is found in Figure 15.

The origin/destination travel times (in minutes) for each of these days are presented in the following figures. It is important to realize that these simulations are supposed to set the baseline for the higher level information simulations. Therefore, these exhibits do not provide any clear insight into supply chain recommendations in-and-of themselves. They will become most useful when we begin a comparison of each of the information levels.
Figure 10: Origin/Destination travel times for Day 1

Figure 11: Origin/Destination travel times for Day 2
Figure 12: Origin/Destination travel times for Day 3

Figure 13: Origin/Destination travel times for Day 4
As can be seen in the graphs above, it is clear from this sample that the traffic is generally worse in the afternoon than in the morning. A summary of the average times for a particular run is presented in Figure 15. In addition, several statistics are presented in Table 3 to highlight some of the pertinent attributes from this sample set. These statistics include average and median trip times, differences between morning and afternoon travel, and ranges in travel time.
A closer look at Table 3 confirms the insight drawn from the graphs above. Morning traffic, on average, requires a shorter commuting time than the afternoon traffic runs for the sample under consideration. In addition, the standard deviation of the simulated trips is lower in the morning than the afternoon. The other interesting point to note about Table 3 is the smaller variance that results from averages. Intuitively this makes sense, because random traffic accidents occur which should average out over time. In particular, the standard deviation of the averages is 41.4 minutes for the morning and 45.7 minutes for the afternoon (compared with 43.0 and 48.3 for all origin/destination pairs above).

**Section 5.2: Level One Static & Time-Dependent Historical Information**

The first comparison level will be the use of historical information. As mentioned in the experimental set-up, we will be making a distinction between static and time-dependent information. First, we will derive the origin/destination travel times for both the static and time-dependent cases. Next, we will compare these results with baseline estimates that were displayed in Section 5.1. This will yield a % time savings over the baseline. Note that a negative % time savings indicates that the baseline has actually performed better than the corresponding comparator.

**Section 5.2.1: Origin/Destination Travel Times**

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**Summary Statistics (minutes)**

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<td>Mean</td>
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<td>81.0</td>
<td>179.0</td>
<td>9.0</td>
<td>48.3</td>
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Table 3: Summary statistics for the geographical origin/destination travel times
There will be a set of five days worth of runs (4 using the previous day and 1 using the previous week’s analogous day as the historical information set). In total, there will be 400 unique traffic runs – for both the static and time-dependent cases. We will first analyze the static, historical information level. For completeness, Figures 16 through 20 list the travel times for each of the 200 unique traffic runs. As a reminder these are the identical origin/destination pairs that have been investigated in the previous section.

Section 5.2.1.1: Static Information

![O/D Travel Times: Day 2 using Day 1 Data](image)

Figure 16: Origin/Destination travel times for day 2 using day 1 data
Figure 17: Origin/Destination times for day 3 using day 2 data

Figure 18: Origin/Destination travel times for day 4 using day 3 data
With this run times, we can perform some preliminary statistical tests. The average of the travel time data is presented in Figure 21. In addition, Table 4 depicts several statistics from this data set. These two exhibits again highlight the fact that traffic appears to be worse during the afternoon rush-hour period. The standard deviation of the run times is again larger during the afternoon period.
Figure 21: Average origin/destination travel times using previous day’s data

**Summary Statistics (minutes)**

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<tr>
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<td>74.9</td>
<td>73.0</td>
<td>174.0</td>
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<tr>
<td>Afternoon</td>
<td>87.0</td>
<td>78.0</td>
<td>179.0</td>
</tr>
</tbody>
</table>

Table 4: Summary statistics for static, historical information

Section 5.2.1.2: Time-dependent Information

The equivalent figures to those presented in Section 5.2.1.1 are presented below.
Figure 22: Origin/Destination travel times for day 2 using previous day 1 data

Figure 23: Origin/Destination travel times for day 3 using previous day 2 data
**Figure 24:** Origin/Destination travel times for day 4 using previous day 3 data

**Figure 25:** Origin/Destination travel times for day 5 using previous day 4 data
Figure 26: Origin/destination travel times for day 5 using previous weekday’s data

### Summary Statistics (minutes)

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<td>82.3</td>
<td>79.5</td>
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<td>Std Dev</td>
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<td>75.8</td>
<td>73.0</td>
<td>174.0</td>
<td>9.0</td>
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<td>Min</td>
<td>Std Dev</td>
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<tr>
<td></td>
<td>88.8</td>
<td>86.0</td>
<td>174.0</td>
<td>9.0</td>
<td>47.4</td>
</tr>
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</table>

Table 5: Summary statistics for time-dependent, historical information

**Section 5.2.2: % Time Savings Over Baseline**

Based on these travel runs, we can now make some comparisons against the geographical information level baseline. For completeness, the % time savings for each of the origin/destination pairs is shown in the sections that follow. We will start with the static information case.

**Section 5.2.2.1: Static Information**
Figure 27: % time savings for day 2 using day 1 data

Figure 28: % time savings for day 3 using day 2 data
Figure 29: % time savings for day 4 using day 3 data

Figure 30: % time savings for day 5 using day 4 data
The charts above demonstrate a wide range of % time savings. It is interesting to note that several of these values are negative. Negative values result because of our routing policy and the stochastic nature of traffic patterns. Because we are routing on historical information, it is possible that a driver will be routed through a traffic-laden path. As we will see at the predictive information level, if we have perfect information, these % time savings will never be negative because we could always route along the "shortest distance" path. Table 6 presents a brief summary of the % time savings attained for each of the five days.

**Summary Statistics (% time savings)**

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<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td>Day 1</td>
<td>Day 2</td>
<td>Day 3</td>
<td>Day 4</td>
<td>Day 5</td>
</tr>
<tr>
<td>Morning</td>
<td>-0.29%</td>
<td>-0.63%</td>
<td>2.23%</td>
<td>0.71%</td>
<td>0.32%</td>
</tr>
<tr>
<td>Afternoon</td>
<td>7.08%</td>
<td>-1.18%</td>
<td>-1.41%</td>
<td>-2.57%</td>
<td>1.95%</td>
</tr>
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</table>

Table 6: Summary statistics for the % time savings over baseline in the static, historical case

Section 5.2.2.1: Time-Dependent Information
We can now replicate the above analysis with time-dependent, historical information. Note the considerations that we mentioned previously. The main difference between these runs and the static runs is that the static simulations were a proxy for non-congested traffic congestions. In other words, early morning/afternoon traffic data was used as the information set. In the time-dependent case, we will be introducing a greater degree of congestion.

![Graph showing time savings for day 2 using day 1 data](image)

Figure 32: % time savings for day 2 using day 1 data

![Graph showing time savings for day 3 using day 2 data](image)

Figure 33: % time savings for day 3 using day 2 data
Figure 34: % time savings for day 4 using day 3 data

Figure 35: % time savings for day 5 using day 4 data
To complete this section, we can present the average % time savings for each day (shown above) given this information level. As shown in Table 7, only two of the days result in positive time savings. The other three days perform worse than the geographic baseline. The next sections will investigate if higher levels of information can prove more valuable to supply chain managers.

**Section 5.3: Level Two Pre-trip, Instantaneous Information**

A brief review of the previous information level did not reveal a statistically significant % time savings over the baseline level. We will return to a discussion of these
results later in the chapter. Now we turn our attention to instantaneous information which adds a real-time affect into the analysis.

Section 5.3.1: Origin/Destination Travel Time

This section presents the results of the pre-trip, instantaneous simulations. For completeness Figures 37 through 41 list the travel times for each of the 200 unique origin/destination/time pairs. As a reminder these are the identical origin/destination pairs that have been investigated in the previous sections.

Figure 37: Origin/Destination travel times for day 1
Figure 38: Origin/Destination travel times for day 2

Figure 39: Origin/Destination travel times for day 3
As done in the previous sections, we can perform some averaging and statistical analysis to inspect the pre-trip, instantaneous results. The averages for all five days are depicted in Figure 42. In Table 8, several statistical properties are presented. The trend of afternoon traffic being worse than the morning also seems to be confirmed by this information level.
Figure 42: Origin/Destination times for the averages of all days

Summary Statistics (minutes)

<table>
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<th>Origin / Destination Pair</th>
<th>Aggregate</th>
<th>Morning</th>
<th>Afternoon</th>
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</tr>
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<td></td>
<td>77.4</td>
<td>72.0</td>
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</tr>
<tr>
<td></td>
<td>83.6</td>
<td>76.5</td>
<td>174.0</td>
</tr>
</tbody>
</table>

Table 8: Summary statistics for pre-trip, instantaneous information

Section 5.3.2: % Time Savings Over Baseline

The next step in the analysis is to consider the differences between the baseline of geographic information and Level 2 information. For completeness, the percentage difference between the baseline and Level 2 information (each of the 200 traffic runs) is presented in Figure 43 through Figure 47 below.
Figure 43: % time savings on day 1

Figure 44: % time savings for day 2
Figure 45: % time savings for day 3

Figure 46: % time savings for day 4
The percentage time savings derived from each of the runs can be averaged across rush-hour periods and across total days. The results of these averages are presented in Table 9. As shown in the exhibit, the pre-trip, instantaneous information level has provided savings over the geographic baseline. This is the beginning of analytical substantiation of the research hypothesis. We will analyze these time savings in the final section of this chapter (as well as in Chapter 7).

### Summary Statistics (% time savings)

#### Aggregate

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<tr>
<th></th>
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<th>Day 3</th>
<th>Day 4</th>
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</thead>
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<tr>
<td>Morning</td>
<td>1.20%</td>
<td>4.71%</td>
<td>1.85%</td>
<td>4.12%</td>
<td>7.23%</td>
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<tr>
<td>Afternoon</td>
<td>0.27%</td>
<td>2.42%</td>
<td>1.34%</td>
<td>6.83%</td>
<td>4.88%</td>
</tr>
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</table>

Table 9: % average time savings for each day for pre-trip, instantaneous information

Section 5.4: Level Three En-route, Instantaneous Information
Pre-trip, instantaneous information appears to offer significant value over and above geographic information. The question is now whether higher levels of information can provide even more value. In this section we will investigate Level 3: En-route, Instantaneous Information. As a reminder, this information level is analogous to providing continual updates to drivers as they are on their path.

Section 5.4.1: Origin/Destination Travel Time

This section presents the results of the en-route, instantaneous simulations. For completeness Figures 48 through Figure 52 list the travel times for each of the 200 unique origin/destination/time pairs. As a reminder these are the identical origin/destination pairs that have been investigated in the previous sections.

Figure 48: Origin/Destination travel times for day 1
Figure 49: Origin/Destination travel times for day 2

Figure 50: Origin/Destination travel times for day 3
As done in the previous sections, we can perform some averaging and statistical analysis to inspect the en-route, instantaneous results. The averages for all five days are depicted in Figure 53. In Table 10, several statistical properties are presented. The trend of afternoon traffic being worse than the morning also seems to be confirmed by this information level.
The next step in the analysis is to consider the differences between the baseline of geographic information and Level 3. For completeness, the percentage difference between the baseline and Level 3 information (each of the 200 traffic runs) is presented in Figure 54 through Figure 58 below.
Figure 54: % time savings for day 1

Figure 55: % time savings for day 2
Figure 56: % time savings for day 3

Figure 57: % time savings for day 4
With these percentage time savings, it is possible to derive a summary table for each day. The averages are presented in Table 11. Based upon these observations we can conclude that greater time savings were obtained during the afternoon period. This suggests that we can confirm our previous assumption that traffic is needed for ITS systems to be effective. In fact, we might now conclude that the more congested traffic is, the more effective ITS systems might be (up to a certain point). This was a similar result drawn by prior literature.

**Summary Statistics (% time savings)**

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<td>Day 2</td>
<td>Day 3</td>
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<tr>
<td><strong>% Time Savings</strong></td>
<td>2.56%</td>
<td>6.87%</td>
<td>3.97%</td>
</tr>
</tbody>
</table>

Table 11: % average time savings for each day in the en-route, instantaneous case

**Section 5.5: Level Four Pre-trip & En-route Predictive Information**
We have reached the top of the information spectrum. In this section we are trying to determine the upper bound in time savings. Therefore, we will be assuming that the dispatcher has perfect information. As a reminder in the case of perfect information, there is no distinction between pre-trip and en-route updates. For in either case, the optimal route will be known in advance and will produce the same result. This section is intended to highlight the additional value that might be obtained if reliable prediction could be mastered.

Section 5.5.1: Origin/Destination Travel Time

This section presents the results for both the pre-trip and en-route predictive information level. As mentioned above, because we are considering perfect information, there is no difference between the pre-trip and en-route cases. For completeness Figure 59 through Figure 63 list the travel times for each of the 200 unique runs. As a reminder these are the identical origin/destination pairs that have been investigated in the previous sections.

![Origin/Destination Travel Times: Day 1](image)

Figure 59: Origin/Destination travel times for day 1
Figure 60: Origin/Destination travel times for day 2

Figure 61: Origin/Destination travel times for day 3
The next section of this chapter will focus on drawing conclusions from all the graphs and tables that have been presented. Before proceeding on to this section, let's present some final figures including a brief summary table and the graphs that demonstrate the time savings over the baseline. Note that since we are considering perfect information, the time savings will never be negative.
O/D Travel Times: Averages of All Day

Figure 64: Origin/Destination travel times for the averages of all days

Summary Statistics (minutes)

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<th>Section</th>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
<th>Min</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate</td>
<td>72.3</td>
<td>71.0</td>
<td>180.0</td>
<td>9.0</td>
<td>36.6</td>
</tr>
<tr>
<td>Morning</td>
<td>68.4</td>
<td>69.5</td>
<td>125.0</td>
<td>9.0</td>
<td>34.3</td>
</tr>
<tr>
<td>Afternoon</td>
<td>76.2</td>
<td>72.0</td>
<td>174.0</td>
<td>9.0</td>
<td>38.6</td>
</tr>
</tbody>
</table>

Table 12: Summary statistics for predictive information

Section 5.5.2: % Time Savings Over Baseline
Figure 65: % Time savings for day 1

Figure 66: % Time savings for day 2
Figure 67: % Time savings for day 3

Figure 68: % Time savings for day 4
Section 5.6: Initial Conclusions

Having presented each of the information levels in the preceding sections, we are now in a position to compare the results and begin to draw conclusions. Table 14 depicts the average % time savings over baseline for each day in aggregate (both morning and afternoon). The average of the five days time savings is then given in the composite column. The first conclusion to note is that there appears to be a fairly consistent trend in the way we have laid out the information spectrum. As we progress up the information spectrum, it appears that more and more value can be extracted in the form of time savings.
The notable exception is Level 1. Historical information seems to not offer any significant time savings over the baseline. In fact, the time-dependent, historical case appears to be worse than the baseline (only slightly, however). Why is this so? The first reason that can be suggested is the lack of a robust data set. In order to draw meaningful conclusions from a historical analysis, a great deal of data must be collected. This study has been limited by the number of data points that have been logged. Looking at a two-week time period might not be a representative sample of the results that a larger timeframe would yield.

A second conclusion to draw from Table 14 is that Level 2 and 3 seem to offer decent time savings over the baseline. It is important to realize that all days have a positive % time savings in each of these information levels. This implies that a high degree of reliability can be maintained with these systems. If there were large swings of positive and negative numbers, reliability might impede the roll-out of these types of systems in a large-scale manner. Finally, Day 5 appears to offer the most savings for both Level 2 and 3. Level 2 has a 7.23% time savings. Level 3 has a 9.18% time savings. This suggests that these types of systems have the ability to yield large savings on specific days.

**Summary Comparison: Aggregate % Time Savings Over Baseline**

<table>
<thead>
<tr>
<th>Level 1 Static, Historical</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.40%</td>
<td>-0.91%</td>
<td>0.41%</td>
<td>-0.93%</td>
<td>1.13%</td>
<td></td>
<td>0.62%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level 1 Time-dependent, Historical</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.09%</td>
<td>-3.26%</td>
<td>-3.84%</td>
<td>-1.42%</td>
<td>1.93%</td>
<td></td>
<td>-0.90%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level 2 Pre-trip, Instantaneous</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.20%</td>
<td>4.71%</td>
<td>1.85%</td>
<td>4.12%</td>
<td>7.23%</td>
<td></td>
<td>3.82%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level 3 En-route, Instantaneous</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.56%</td>
<td>6.87%</td>
<td>3.97%</td>
<td>7.56%</td>
<td>9.18%</td>
<td></td>
<td>6.03%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level 4 Predictive</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.60%</td>
<td>9.29%</td>
<td>5.25%</td>
<td>9.61%</td>
<td>11.75%</td>
<td></td>
<td>8.10%</td>
</tr>
</tbody>
</table>

Table 14: Summary comparison in aggregate over baseline

Table 15 shows the % time savings for only the morning period. Again, a consistent picture of increasing time savings at higher levels of information is depicted.
It is interesting to note that all the composite averages are positive in the morning scenario. However, in general, all the composite averages are lower than in the aggregate case presented in Table 15 (except for the Time-dependent, Historical case which is only slightly higher).

One of the obvious conclusions that we can draw is that traffic is a key requirement for ITS to be effective. We mentioned in the previous sections that it appeared that traffic congestion was worse in the afternoon than in the morning. This fact might help to explain why the % time savings are lower in the morning scenarios. In the morning case, even perfect information only yields an approximately 5% time savings. One might conclude that the baseline is a fairly good routing policy in the case of light traffic congestion.

### Summary Comparison: Morning % Time Savings Over Baseline

<table>
<thead>
<tr>
<th>Level</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static, Historical</td>
<td>-0.29%</td>
<td>-0.63%</td>
<td>2.23%</td>
<td>0.71%</td>
<td>0.32%</td>
<td>0.47%</td>
</tr>
<tr>
<td>Time-dependent, Historical</td>
<td>1.86%</td>
<td>-4.20%</td>
<td>0.41%</td>
<td>1.31%</td>
<td>1.18%</td>
<td>0.31%</td>
</tr>
<tr>
<td>Pre-trip, Instantaneous</td>
<td>0.27%</td>
<td>2.42%</td>
<td>1.34%</td>
<td>6.83%</td>
<td>4.88%</td>
<td>3.15%</td>
</tr>
<tr>
<td>En-route, Instantaneous</td>
<td>0.08%</td>
<td>2.48%</td>
<td>3.41%</td>
<td>7.14%</td>
<td>7.25%</td>
<td>4.07%</td>
</tr>
<tr>
<td>Predictive</td>
<td>2.18%</td>
<td>3.27%</td>
<td>4.31%</td>
<td>10.65%</td>
<td>7.74%</td>
<td>5.63%</td>
</tr>
</tbody>
</table>

Table 15: Summary comparison in the morning over baseline

The story is different in the afternoon. Table 16 presents the % time savings of each of the information levels in the afternoon rush-hour period. Again, the composite results appear to indicate a consistent trend along the information spectrum. In this table, the Time-dependent, Historical information level is worse than the baseline by approximately 2%. This is most likely due to the data set limitation referred to above.

The time savings are higher in the afternoon than in the morning. Most likely this relates to the increase in traffic congestion in the afternoon. The Day 5 time savings for both Level 2 and Level 3 are also significantly higher at 9.57% and 11.11%. This leads
to another interesting point. Even though the averages are all within the -10% to +15% range, the specific origin/destination travel time savings are much more volatile. If we look back to Figure 58, we will see that many of the individual runs have saved in excess of 60% of the baseline value. This is an important point because it could mean the prevention of extremely long delivery times which could translate into greater service levels for supply chain managers.

A second point to note is that the en-route, instantaneous level is only a few % points more effective than the pre-trip, instantaneous level. This is an important policy point because clearly there is a lot more capital investment if a company wants to implement an en-route policy. Logistically speaking, giving a pre-trip update to a driver has many advantages. The driver does not have to be as aware of the routing process and does not need to make sudden changes. In addition, the driver does not need to learn how to use the dynamic communication devices that such a policy would entail. This could translate into a safer ride for the driver (since s/he will not be distracted with the updates).

**Summary Comparison: Afternoon % Time Savings Over Baseline**

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static, Historical</td>
<td>7.08%</td>
<td>-1.18%</td>
<td>-1.41%</td>
<td>2.57%</td>
<td>1.95%</td>
<td>0.77%</td>
</tr>
<tr>
<td>Time-dependent, Historical</td>
<td>2.32%</td>
<td>-2.29%</td>
<td>-8.09%</td>
<td>-4.14%</td>
<td>2.72%</td>
<td>-1.90%</td>
</tr>
<tr>
<td>Pre-trip, Instantaneous</td>
<td>2.13%</td>
<td>6.99%</td>
<td>2.35%</td>
<td>1.42%</td>
<td>9.57%</td>
<td>4.49%</td>
</tr>
<tr>
<td>En-route, Instantaneous</td>
<td>5.03%</td>
<td>11.27%</td>
<td>4.53%</td>
<td>7.97%</td>
<td>11.11%</td>
<td>7.98%</td>
</tr>
<tr>
<td>Predictive</td>
<td>7.02%</td>
<td>15.30%</td>
<td>6.19%</td>
<td>8.57%</td>
<td>15.76%</td>
<td>10.57%</td>
</tr>
</tbody>
</table>

Table16: Summary comparison in the afternoon over baseline

A third point to consider is why the perfect information case does not offer significantly more value than is shown in the tables. In the perfect information case, we have assumed that the drivers/dispatchers are able to predict traffic accidents. In the aggregate case, this knowledge only saves 8.10% over the baseline. What reasons can explain this? I would suggest that the network we are considering (51 nodes) does not...
give a plethora of choices to the driver. This is a realistic representation of the trucking industry, however. Large trucks simply cannot travel down side roads and alleys are limited in the paths they travel along. Primarily, they keep to highways where they know they will be able to meet size restrictions. If commercial vehicles primarily use the highway system then their choices will be limited. Even with perfect information, this small choice set will not be expanded.

In order to see how the other information levels fair against the perfect information case, Table 17 highlights the value that is left on the table. In other words, these numbers suggest how far away from the best case each of the information levels is. As can be seen in the table, the En-route, Instantaneous case is only 2.48% above the best case scenario. This means that an additional forecasting mechanism would not be able to add more than 2.5% to the overall time savings that would result. The pre-trip, instantaneous situation is only 5.11% off of the best case. This suggests that both Level 2 and Level 3 do a reasonably good job of extracting the value of information from transportation networks.

The overall time savings numbers we have presented – in the 0 to 10% range – are consistent with the prior research shown in Table 1. However, it is important to note that the numbers we have presented are times savings above a baseline of geographical information. This suggests that the results derived in this chapter should actually be higher if compared to a pure no information case. We have already mentioned the strengths and weaknesses of these prior studies. In Chapter 7, we will draw additional conclusions from the simulations run in this chapter.
Section 5.7: A Monetary Framework

Having derived the time savings that various information levels were able to obtain through simulation, we can begin to financially quantify these results. This will provide an expected measure of profit improvement for a company that adopts ITS into its supply chain practices.

Section 5.7 will begin by identifying the areas of improvement that ITS can provide. A deep examination of the costs associated with each of these areas will next be explored. This should lead to a financial quantification of the time savings derived in each of the information levels above. The final part of this section will then apply this financial quantification to a typical company that operates a regional fleet (within the Los Angeles Highway System). The end result will be an expectation of profit improvement for this typical company.

Section 5.7.1: ITS Benefits to Supply Chain Operations

In the introductory chapters, we spoke about the ability of ITS to improve corporate profitability. The most obvious improvement would be the time savings that result from better routing. A decrease in the routing time can translate into a number of different benefits. Total labor expense can be reduced if drivers do not use this time to do

---

### Summary Comparison: Aggregate % Above Perfect Information

<table>
<thead>
<tr>
<th>Level</th>
<th>Static, Historical</th>
<th>Time-dependent, Historical</th>
<th>Pre-trip, Instantaneous</th>
<th>En-route, Instantaneous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 0</td>
<td>Day 1: 5.68%</td>
<td>Day 2: 13.24%</td>
<td>Day 3: 6.60%</td>
<td>Day 4: 14.30%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1</td>
<td>Day 1: 10.11%</td>
<td>Day 2: 12.24%</td>
<td>Day 3: 5.30%</td>
<td>Day 4: 13.36%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 2</td>
<td>Day 1: 11.76%</td>
<td>Day 2: 14.23%</td>
<td>Day 3: 9.83%</td>
<td>Day 4: 13.88%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 3</td>
<td>Day 1: 3.75%</td>
<td>Day 2: 5.65%</td>
<td>Day 3: 4.17%</td>
<td>Day 4: 6.51%</td>
</tr>
</tbody>
</table>

Table 17: Summary comparison in aggregate over perfect information
other things. It is a real concern to make sure that drivers do not waste the additional
time savings. However, most drivers do not like to be stuck in traffic and so this
temptation should be minimal.

A decrease in the routing time can also be translated into fuel savings. While it is
beyond the scope of this paper to get into the physical dynamics of fuel combustion, it is
logical to deduce that lower travel times can be associated with a decrease in fuel. From
a physics perspective, fuel is consumed most during the acceleration phase. When a
driver is stuck in traffic, the constant stopping and starting maximizes the number of
accelerations, thereby wasting fuel. A driver that is able to take advantage of Newton’s
laws will be able to maximize fuel efficiency. Schrank and Lomax [Schrank 2003]
confirm that traffic congestion wastes fuel. They conclude that the amount of wasted
fuel per person due to traffic congestion ranges from 52 gallons per year in very large
urban areas to 10 gallons per year in small urban areas.

The Schrank and Lomax study calculates the financial cost of traffic congestion in
75 urban areas using a using two-fold methodology. They only consider the value of
wasted time and fuel. However, there are other areas of cost savings to consider. Table
18 gives a list of potential areas of savings for a company that incorporates ITS into their
supply chain. We have already discussed the first two items on this list.

Capital expenditures can be decreased by using ITS units because vehicles will be
out on the roads for a shorter period of time. This should translate into lower
maintenance expenses and higher corporate profitability. In addition, general &
administrative expenses could be lowered by automating data intensive processes. As an
example of this, billing could be tied into the electronic ITS unit. When a delivery is
made, an electronic bill can be sent to the customer. This could decrease account
receivable days and eliminate employees dedicated to inefficient administrative
procedures.

While we have mentioned that time savings can be obtained by using ITS, a
company can use this additional time to make more deliveries. This should increase the
overall revenue of a company. In addition, because the deliveries are made in a shorter
period of time, customers might be happier with their service. And an increase in
customer satisfaction might lead to more orders and higher revenue. This type of revenue
increase does not eliminate the time savings gap identified in the chapter above. The power of increasing revenue and decreasing costs simultaneously is one of the prime attractions of implementing ITS in the supply chain.

There are a number of external or intangible benefits that result from the increased efficiency in routing vehicles. Driver safety can be improved. If a driver is no longer in danger of being lost, s/he can concentrate on the road and not other factors. This should improve the accident rate. In addition, insurance expenses might be lowered as a result of this safety improvement.

Society as a whole should also benefit from an increase in vehicle efficiency. Increases in pollution are creating a potential global problem. As the population grows, this problem will become larger and larger. By reducing the amount of fuel consumed, ITS will also decrease the amount of pollution emitted by vehicles. This is an external benefit to all of society.

The cost of implementing an ITS unit will vary depending on the information level employed. Clearly, en-route systems will be more costly than pre-trip ones due to the wireless transmissions that are needed to inform drivers of route changes. We will discuss these costs later on this chapter. For now, we should note that as technology improves these costs are likely to drop considerably.

<table>
<thead>
<tr>
<th>Area of Potential Savings</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor</td>
<td>A decrease in the time of a trip could decrease the total labor expense</td>
</tr>
<tr>
<td>Fuel</td>
<td>A decrease in the time of a trip could decrease the total fuel consumed</td>
</tr>
<tr>
<td>Capital Expenditures</td>
<td>A decrease in the time that vehicles are on the road could decrease maintenance expenses</td>
</tr>
<tr>
<td>General &amp; Administrative</td>
<td>The implementation of an ITS unit could streamline administrative procedures</td>
</tr>
<tr>
<td>Additional Revenue</td>
<td>If additional trips are able to be made with the decrease in time, additional revenue could be obtained</td>
</tr>
<tr>
<td>Safety</td>
<td>Driver safety improvement through routing features, lower the accident rate and decreasing insurance</td>
</tr>
<tr>
<td>Pollution</td>
<td>A decrease in the amount of fuel consumed will lower the external pollution</td>
</tr>
</tbody>
</table>

Table 18: Areas of potential savings by using ITS

Section 5.7.2: The Value of Time

We will now begin our conservative estimate of the financial value of implementing ITS into the supply chain. We will be limiting the savings to the value of time effects (labor and fuel). This means that the estimate we derive will not include any
of the other effects listed in Table 18 (e.g. additional revenue, lower capital expenditures, etc.).

The first step in the monetary framework will be deriving a value of time for commercial operators. Levinson and Smalkoski [Levinson 2003] present a nice quantification of the value of time for commercial operators in Minnesota. This value was derived using an adaptive stated preference survey. Because they had truncated data, they decided to use a tobit model – which is hybrid of probit and regression techniques. The tobit model yielded an estimate of $49.42/hour for the value of time for commercial vehicle operators in Minnesota.

Levinson and Smalkoski present a summary of the previous studies of the value of time for commercial operators. This data is replicated in Table 19 and also includes Levinson’s and Smalkoski’s value. The mean and standard deviation of these values is presented as well. We will use both the Levinson/Smalkoski statistic and the average of $29.04 for the value of time per one hour for a commercial operator. This implies that if 1 truck is able to save 1 hour on 1 delivery run then corporate profitability would be increased by either $49.42 or $29.04. Note that this excludes the tax effects that would result from higher earnings.

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Focus</th>
<th>Location</th>
<th>Value of Time</th>
<th>Adjusted to 2003</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levinson and Smalkoski</td>
<td>2003</td>
<td>Truck Operators</td>
<td>Minn.</td>
<td>$49.42</td>
<td>$49.42</td>
</tr>
<tr>
<td>Kawamura</td>
<td>1998</td>
<td>Truck Operators</td>
<td>N/A</td>
<td>$26.80</td>
<td>$30.14</td>
</tr>
<tr>
<td>Waters et al.</td>
<td>1995</td>
<td>Truck Operators</td>
<td>N/A</td>
<td>$6.10 to $34.60</td>
<td>$6.86 to $38.92</td>
</tr>
<tr>
<td>Haning and McFarland</td>
<td>1963</td>
<td>Truck Operators</td>
<td>N/A</td>
<td>$17.40 to $22.60</td>
<td>$19.57 to $25.42</td>
</tr>
<tr>
<td>Brownstone et al.</td>
<td>2002</td>
<td>Automobiles</td>
<td>San Diego</td>
<td>$30.00</td>
<td>$30.58</td>
</tr>
<tr>
<td>Small and Yan</td>
<td>2001</td>
<td>Automobiles</td>
<td>California</td>
<td>$20.63</td>
<td>$21.36</td>
</tr>
<tr>
<td>Adkins et al.</td>
<td>1967</td>
<td>Cargo Vehicles</td>
<td>N/A</td>
<td>$4.08 to $5.52</td>
<td>$22.41 to $30.32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Standard Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$29.04</td>
<td>$9.71</td>
</tr>
</tbody>
</table>

Table 19: Value of Time for Commercial Operators

Section 5.7.3: Application to a Regional Carrier

Now that we have obtained the value of time we can calculate the savings for a regional carrier that uses ITS units. The first aspect we need to mention is that we are taking conservative estimates of this value because of two factors. First, we have
excluded a number of different components such as additional revenue, a decrease in capital expenditures, less general & administrative costs, and a decrease in intangibles. This suggests that the value calculated in this section should significantly underestimate the value of ITS units in the supply chain.

The second factor that is probably more important to consider is that the time savings we are evaluating is related to the baseline (geographical information). Since most companies do not even incorporate the baseline into their supply chain operations, the benefits we calculate should be much larger than what we calculate in this section.

We can apply the value of time to a fictional company called ABC Inc. The first stage in the analysis is to calculate how much time is saved per day for 1 commercial vehicle. Based on a 6 hour driving window, we can apply the % time savings over the baseline for each of the information levels (1 through 4). We are using the six hour period because this is the sum of the two rush-hour periods. We can make the assumption that the vehicle is out making deliveries during this entire period.

Using the time saved per day, we can apply the value of time from Section 5.7.2 to determine the total savings per day for one vehicle. The next stage in the analysis is to assume a fleet size for ABC Inc. As a benchmark, UPS has more than 1,000 vehicles in its private fleet [Chandler 2003]. Wal-Mart maintains a fleet of 7,000 tractors and 35,000 trailers [Shein 2003]. Continuing our trend of being conservative, we will use a fleet of 250 vehicles. Using this fleet size, we can calculate the total savings per year (after assuming a 300 day work year).

Looking at Table 20, we can see that ITS can give additional benefits over the baseline of hundreds of thousands of dollars. With perfect information, the savings can get up to a million days per year. The historical information level does not add value over the baseline. We should also note that there is an implementation cost for ITS units. This cost can be significant if we are considering above the pre-trip instantaneous level. The cost of implementation for an en-route system might wipe out a year’s worth of savings. However, the pre-trip implementation costs are most likely substantially lower than the en-route scenarios.
Total Savings for ABC Inc. using Average Value of Time

<table>
<thead>
<tr>
<th>Units</th>
<th>Level 1</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
<th>Level 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of time</td>
<td>$/hour</td>
<td>$29.04</td>
<td>$29.04</td>
<td>$29.04</td>
<td>$29.04</td>
</tr>
<tr>
<td>Hours per day</td>
<td>hour</td>
<td>6.0</td>
<td>6.0</td>
<td>6.0</td>
<td>6.0</td>
</tr>
<tr>
<td>% savings</td>
<td></td>
<td>0.6%</td>
<td>-0.9%</td>
<td>3.8%</td>
<td>6.0%</td>
</tr>
</tbody>
</table>

| Time savings per day | hour | 0.0 | (0.1) | 0.2 | 0.4 | 0.5 |
| Total savings per day | $/day | $1.08 | -$1.57 | $6.66 | $10.51 | $14.11 |
| Number of trucks | trucks | 250 | 250 | 250 | 250 |
| Total savings | $/day | $270 | -$392 | $1,664 | $2,627 | $3,528 |
| Days per year | day | 300 | 300 | 300 | 300 |

Table 20: Total Savings using Average Value of Time

Looking at Table 21, the ITS benefits using the Levinson/Smalkoski value of time is considerable higher (almost double). Above level 2, the yearly savings are most likely in the millions of dollars over the baseline. After the implementation costs are incorporated into the analysis, the savings from ITS have the potential to unlock significant value for a company like ABC Inc.

Total Savings for ABC Inc. using Levinson/Smalkoski Value of Time

<table>
<thead>
<tr>
<th>Units</th>
<th>Level 1</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
<th>Level 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of time</td>
<td>$/hour</td>
<td>$49.42</td>
<td>$49.42</td>
<td>$49.42</td>
<td>$49.42</td>
</tr>
<tr>
<td>Hours per day</td>
<td>hour</td>
<td>6.0</td>
<td>6.0</td>
<td>6.0</td>
<td>6.0</td>
</tr>
<tr>
<td>% savings</td>
<td></td>
<td>0.8%</td>
<td>-0.9%</td>
<td>3.8%</td>
<td>6.0%</td>
</tr>
</tbody>
</table>

| Time savings per day | hour | 0.0 | (0.1) | 0.2 | 0.4 | 0.5 |
| Total savings per day | $/day | $1.84 | -$2.67 | $11.33 | $17.88 | $24.02 |
| Number of trucks | trucks | 250 | 250 | 250 | 250 |
| Total savings | $/day | $460 | -$667 | $2,832 | $4,470 | $6,005 |
| Days per year | day | 300 | 300 | 300 | 300 |

Table 21: Total Savings using Levinson/Smalkoski Value of Time
Chapter 6: Sensitivity Analysis

Section 6.1: Stochastic Error

All technologies are flawed. In other words, there are weak points in any new large-scale system that is being rolled out for the first time. ITS is no exception to this rule. It has its advantages and disadvantages. One of these disadvantages is the likely error that will result from deficiencies in sensing technology. Up until this point, we have taken it as a given that the data which the sensor relayed to the aggregator was accurate. What were to happen to the results produced by these ITS units if this data was erroneous?

This chapter introduces stochastic error into the data that we use to route corporate drivers. As an example of this situation, imagine that due to a malfunction (caused by mechanical failure, inclement weather, etc.) a random error component is appended to the true average speed parameter. We can label the true speed parameter \( c(t) \) and say that the estimate of \( c(t) \) is \( c'(t) = c(t) + \varepsilon \), where \( \varepsilon \) is a random error term. One could logically deduce that if this random component were large enough, it will affect the ultimate route that an ITS unit would produce. On the other hand, it might be the case that small random fluctuations will have no influence on the end route. We will investigate these questions further in the remainder of the chapter.

To be clear, we are still taking the initial speeds investigated in the previous chapter as the ground truth of the analysis. When a random error term is introduced into the vector of true speeds, we now can study two different vectors: the original and the random. The ITS units will be routed using the random speed vector. However, the conditions that the driver experiences will be based on the true speed vector.

What might the results of this type of sensitivity analysis imply? If it is the case that the data is robust (meaning that large introductions of random error do not influence the route), then one could conclude that investment at the margin should be made in the ITS algorithms at the expense of sensor technology. Such a result could have large financial implications in how governments and private agencies invest in highway infrastructures. However, if the opposite result holds – and the introduction of small
error invalidates the previous chapter’s results – then one might come to the opposite conclusion and invest in sensor technology at the margin.

While sensors are a major potential contributor of error in an ITS platform, it is by no means the only source. It might be the case that the ITS units themselves are flawed. For example, what would happen if the algorithms were mathematically unsound? This is analogous to the situation where a driver, using a mental model, becomes lost. In this scenario, the mental ITS unit produced an erroneous route. A similar phenomenon could occur with mathematical ITS units. However, for the purposes of this work, we will assume that the algorithms have been coded correctly. It is outside the scope of the work to investigate the robustness of ITS manipulators themselves.

Another source of stochastic error could come from origin/destination pairs. If a driver enters/requests the wrong origin or destination, the resulting route will definitely be inaccurate. In any functional ITS unit, the destination must be decided upon by a human. Either the dispatcher determines the destination by information relayed by a retailer or the driver decides him/her self on a specific point. Whatever the situation, this destination must trace its root back to a decision made by humans. And as such it has the potential to be flawed.

Similar, the origin could be entered into the ITS unit inaccurately. If GPS technology is used to derive an origin, we are back to our original problem. All technology is flawed. GPS has the ability to provide an inaccurate origin point through technological failure. If a driver happens to be on a narrow road between two tall skyscrapers, the satellite transmission might be impeded. This impedance could introduce error into a fully-integrated ITS unit. Whatever the case, error will be a part of a functional intelligent transportation system. We will investigate in the remainder of this chapter how the results derived in the previous chapter would change if a random error component was introduced into the system.

Before proceeding on to the error-filled simulations for the various information levels, one comment is needed. We are introducing a random error term only to traffic information. Since the baseline we modeled does not contain traffic information (it only uses geographic information), this type of error will not affect the results derived in section 5.1. Therefore, we can derive time savings against this baseline even when we
introduce stochastic error to the higher information levels. In addition, we will exclude a sensitivity analysis on Level Zero Information for the reasons just mentioned.

Section 6.1.1: Methodological Considerations

The first aspect that we shall consider in this sensitivity analysis relates to the appropriate ranges of the random fluctuations. In the opening remarks to this chapter, it was mentioned that a large deviation from true average speed might affect the ultimate route. What do we mean by “large” deviations? Conversely, what do we mean by “small” deviations?

The random error terms that we are introducing in this section will be modeled using a Normal distribution with a mean of zero and a certain variance level. Mathematically, the random error terms can be represented as:

$$\varepsilon \sim N(0, std_{dev})$$

(4)

This means that the error terms will follow a distribution that is centered on zero. As such, given a large enough sample, the average perturbed speeds should approximate the true speeds.

The methodology that is being used in the sensitivity analysis is based on running an error-filled model with a specified standard deviation. Larger standard deviations will create bigger swings in the random speed vector, which in turn, might create larger changes in routing behavior. In contrast, smaller standard deviations will create a tighter range in the random speed vector. The level we will investigate is represented by a 5% standard deviation. This percentage will be applied to the true speed term. So, for example, if the true speed is 100 mph and +5% random error term was introduced, then the random speed will be 105 mph. If the speed is 1 mph, then a +5% random error term will result in a 1.05 mph random speed. The choice of standard deviation was made by the author as a likely representation of ITS error. Clearly, additional levels could be investigated and would certainly add to the analysis in this chapter.

Within this level, the number of different samplings was made based on statistics and time management. Each arc within the Los Angeles Highway system will have a random error term appended to it. A statistical test can be performed to determine the
number of simulations to be run at a given confidence level. As suggested by Fisherman this test is of the form:

\[ R \geq R_\alpha = \max \left( 2, \left( \frac{s_n(Y_i) t_{\alpha/2}}{d_i} \right)^2 \right) \]  

(5)

where \( Y_i \) are the outputs, \( R \) is the number of replications performed. \( R_\alpha \) is the minimum number of replications required to estimate the mean of \( Y_i \) with tolerance \( d_i \). \( s_n(Y_i) \) is the sample standard deviation of \( Y_i \) based on \( R \) replications. \( t_{\alpha/2} \) is the critical value of the \( t \)-distribution at significance level \( \alpha \) [Fisherman 1978].

Based on the above considerations, three separate replications were performed for each information level. This implies that over 3000 origin/destination pair simulations will be performed in total. These origin/destination pairs are equivalent to those presented in Chapter 5.

Section 6.2: Level One Static & Time-Dependent Historical Information

The first sensitivity analysis to be performed will be run on the historical information level. The introduction of error will be on the historical data. This means that the data the ITS aggregator receives will contain error and will also not be real-time. Once again, it is important to understand that the actual conditions that the driver will experience will be a separate vector of speeds.

In comparing the sensitivity analysis to the runs performed in Section 5.2, we can note a few differences. The most obvious difference is that the speed vector that is being used to determine the routing is different in the two cases. In Section 5.2, the speed vector that was used to route the vehicles was based on the true speeds on prior days. In this section we will determine routing using the perturbed speed of prior days. The result of this is a second difference between the two runs: namely the routes traveled could potential be different. In addition, this section uses the average of three replications to obtain the perturbed speed vector. The prior section had only one replication.

Section 6.2.1: Sensitivity Analysis
In this section we will investigate how sensitive the results of Chapter 5 are to the introduction of a small error term. As mentioned previously, this error term is normally distributed with a mean of zero and standard deviation of 5%. Three separate replications of error terms have been made using a random number generator coupled within a normal distribution model. The results of these replications were imported into the C++ models (shown in the Appendix) that were used to derive the results in Chapter 5. However, now the routing decisions were made based on the new speeds. The travel times are still based on the old/actual speeds.

This section will also investigate both the static and time-dependent historical information levels. The arguments made for a distinction between static and time-dependent levels in the previous chapters still holds. We will be continuing along the lines shown in Chapter 5 by using the previous day’s information to route drivers. In Section 6.2.1.1 we will first examine the static information case. This will be followed by an examination of the time-dependent information case. Both of these analyses are part of the Level One Information classification.

Section 6.2.1.1: Static Information

Because there were multiple replications of the simulations, an average time savings % percentage over the baseline (geographic information) can be obtained for each rush hour period on each day. In this chapter we will not be presenting the travel times for each of the different information levels. Since the baseline numbers were shown in Chapter 5, the average travel times using the perturbed travel speeds can be derived using the % time savings given in the figures below. Figures 70 through 74 present average % savings for the static information case. In Table 22, we present the summary statistics for this information level.
Figure 70: % Time savings for day 2 using day 1 data

Figure 71: % Time savings for day 3 using day 2 data
Figure 72: % Time savings for day 4 using day 3 data

Figure 73: % Time savings for day 5 using day 4 data
Summary Statistics (% time savings)

<table>
<thead>
<tr>
<th>Aggregate</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.21%</td>
<td>-2.00%</td>
<td>-0.60%</td>
<td>-2.23%</td>
<td>1.11%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Morning</th>
<th>Day 1</th>
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<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.57%</td>
<td>-2.54%</td>
<td>1.28%</td>
<td>-0.63%</td>
<td>0.23%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Afternoon</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.86%</td>
<td>-1.47%</td>
<td>-2.47%</td>
<td>-3.83%</td>
<td>2.00%</td>
</tr>
</tbody>
</table>

Table 22: Summary statistics for the static historical informational level

As can be seen in the table above, two of the days have positive savings in aggregate and three have negative savings. All of these numbers are within 2.5% of zero which suggests a nominal difference between the baseline and this information level. However, as seen in Table 6, these numbers are not significantly different than that shown in the Section 5.2.1.1. We will do a full comparison of these sections at the end of this chapter.

Section 6.2.1.2: Time-dependent Information
In this section we will investigate time-dependent information. Time-dependent information differs from the static case in that routing will be based on traffic information throughout the day and not just in the beginning of the time period. In Figures 75 through 79, the average percent times savings over the baseline is shown. Table 23 presents the summary statistics for this information level.

Figure 75: % Time savings for day 2 using day 1 data

Figure 76: % Time savings for day 3 using day 2 data
Time Savings: Day 4 using Day 3

Figure 77: % Time savings for day 4 using day 3 data

Time Savings: Day 5 using Day 4

Figure 78: % Time savings for day 5 using day 4 data
Table 23 displays the average % time savings that the time-dependent historical information level has produced. Similar to the static historical simulations, two days yield positive time savings and three days have negative time savings. The afternoon statistics appear to have a greater range of time savings than the morning rush-hour period.

Section 6.3: Level Two Pre-trip Instantaneous Information
This section will duplicate the analysis performed in the prior section using information level 2. We will now be examining instantaneous information and not historical information. The first subsection will investigate the sensitivity analysis.

Section 6.3.1: Sensitivity Analysis

Figures 80 through 84 present the average % time savings for each day using information level 2 adjusted using the low sensitivity analysis. Table 24 shows the summary statistics for this analysis.

![Graph: % Time Savings: Day 1](image)

*Figure 80: % Time savings for day 1*
Figure 81: % Time savings for day 2

Figure 82: % Time savings for day 3
Figure 83: % Time savings for day 4

Figure 84: % Time savings for day 5
Summary Statistics (% time savings)

<table>
<thead>
<tr>
<th></th>
<th>Aggregate</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
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<td>Day 2</td>
<td>Day 3</td>
<td>Day 4</td>
<td>Day 5</td>
</tr>
<tr>
<td></td>
<td>1.43%</td>
<td>4.57%</td>
<td>1.19%</td>
<td>4.41%</td>
<td>6.76%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Morning</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Day 1</td>
<td>Day 2</td>
<td>Day 3</td>
<td>Day 4</td>
<td>Day 5</td>
</tr>
<tr>
<td></td>
<td>0.22%</td>
<td>1.87%</td>
<td>-0.11%</td>
<td>5.79%</td>
<td>4.02%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Afternoon</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Day 1</td>
<td>Day 2</td>
<td>Day 3</td>
<td>Day 4</td>
<td>Day 5</td>
</tr>
<tr>
<td></td>
<td>2.64%</td>
<td>7.27%</td>
<td>2.49%</td>
<td>3.03%</td>
<td>9.50%</td>
</tr>
</tbody>
</table>

Table 24: Summary statistics for the pre-trip instantaneous informational level

All days, in aggregate, have positive times savings over the baseline. Day 5 has a 9.5% increase in performance over the baseline during the rush-hour period. We will examine these results further at the end of this chapter.

Section 6.4: Level Three En-route Instantaneous Information

This section will duplicate the analysis performed in the prior section using information level 3. We will now be examining en-route instantaneous information and not pre-trip instantaneous information. The first subsection will investigate the sensitivity analysis.

Section 6.4.1: Sensitivity Analysis

Figures 85 through 89 present the average % time savings for each day using information level 3 adjusted using the low sensitivity analysis. Table 25 shows the summary statistics for this analysis.
Figure 85: % Time savings for day 1

Figure 86: % Time savings for day 2
Figure 87: % Time savings for day 3

Figure 88: % Time savings for day 4
Summary Statistics (% time savings)

<table>
<thead>
<tr>
<th></th>
<th>Aggregate</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Day 1</td>
<td>Day 2</td>
<td>Day 3</td>
<td>Day 4</td>
<td>Day 5</td>
</tr>
<tr>
<td>Morning</td>
<td>2.28%</td>
<td>6.85%</td>
<td>3.61%</td>
<td>6.11%</td>
<td>9.19%</td>
</tr>
<tr>
<td>Afternoon</td>
<td>4.85%</td>
<td>11.13%</td>
<td>4.33%</td>
<td>6.19%</td>
<td>11.52%</td>
</tr>
</tbody>
</table>

Table 25: Summary statistics for the en-route instantaneous informational level

As Table 25 shows, even with the introduction of a small bit of error, the en-route instantaneous information level proves quite robust. In fact, Day 5 has a 9.19% time improvement over the baseline in aggregate. These results appear to signify that ITS units are able to handle a small degree of error. We will return to this hypothesis at the end of this chapter.

Section 6.5: Level Four Predictive Information

In this section we will be analyzing the predictive information scenario. Note that we now only have perfect information into the perturbed random speed vector (not the
true speed vector). This implies that it is theoretically possible to have a negative time savings compared to the baseline.

Section 6.5.1: Sensitivity Analysis

Figures 90 through 94 present the average % time savings for each day using information level 4 adjusted using the low sensitivity analysis. Table 26 shows the summary statistics for this analysis.
Figure 92: % Time savings for day 3

Figure 93: % Time savings for day 4
As can be seen in Table 26, the predictive information level is still able to offer significant savings over the baseline - even with a low degree of error introduced. Day 5 has double-digits savings over the baseline in aggregate. In fact, both the Day 2 and Day afternoon rush-hour period have a greater than 15.0% improvement over the baseline information level.

Section 6.6: Initial Conclusions

We are now ready to draw some conclusions from the results in this chapter. The first aspect to investigate is how the results of this chapter compare with the analogous
results derived in Chapter 5. By viewing this comparison, we will be able to see the level of robustness of intelligent transportation systems that incorporate error. The second aspect we will investigate is the trend in the time savings along the information spectrum. As shown in Chapter 5, each successive level of the information spectrum offered additional time savings. We will find out whether this is true when error has been introduced into the information spectrum.

Section 6.6.1: Level One Static & Time-Dependent Historical Information

The first information level to be examined is Level 1: historical information. Following the same methodology outlined in the earlier part of this work, we will subdivide this section into static/historical and time-dependent/historical parts. First, we will analyze the static case. Next, we will analyze the time-dependent case.

Section 6.6.1.1: Static Information

Table 27 gives an aggregate compilation of the three different scenarios for the static, historical information level. The first row highlights the results derived in Chapter 5. This row has been computed based on the true speed vector. In contrast, the other row in the table gives the results when error has been introduced into the model.

As seen in this table, there is only a slight reduction in the % time savings in the low error case compared with the no error case. We can draw an initial hypothesis that if there is only a small degree of error present in the system, the results may still prove sound. This has important policy implications because it means that sensors do not have to be absolutely accurate for ITS units to operate effectively. As previously mentioned, most likely the sensors will include a small bit of error. If this error can be held to a low level (i.e. under a 5% standard deviation), it is likely that ITS will still offer benefits to corporations.
Table 28 presents similar information for the morning rush-hour period. We should note that the introduction of error has not improved the performance compared to the baseline. However, the low error case is fairly representative of the no error scenario. This confirms the hypothesis proposed in the preceding paragraph.

Table 29 displays the same information for the afternoon rush-hour periods. The hypothesis developed in the previous paragraphs appears to hold in the afternoon period as well.

Section 6.6.1.2: Time-dependent Information

Turning to the time-dependent, historical information level, Table 30 displays the aggregate % time savings for the three different scenarios run in this work. Once again,
there is only a slight differential between the no and low error scenarios. The hypothesis developed in the prior section can therefore be applied to the time-dependent case as well. Namely, small introductions of error may pose no major problem for intelligent transportation systems.

It should also be noted that the low error case performs slightly worse than the no error case. The composite average is 0.41% worse in the low error case than in the no error case. This differential is extremely small when translated in actual minutes.

Summary Comparison: Aggregate % Time Savings Over Baseline for Time-dependent Historical

<table>
<thead>
<tr>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>2.09%</td>
<td>-3.25%</td>
<td>-3.84%</td>
<td>-1.42%</td>
<td>1.98%</td>
</tr>
<tr>
<td>Error</td>
<td>1.43%</td>
<td>-2.94%</td>
<td>-3.13%</td>
<td>-3.11%</td>
<td>1.25%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>-0.66%</td>
<td>0.31%</td>
<td>0.71%</td>
<td>1.73%</td>
<td>-0.68%</td>
</tr>
</tbody>
</table>

Table 30: Summary comparison – aggregate time-dependent historical

Table 31 presents the morning % time savings for the two different scenarios. The hypothesis still holds in this situation as well. It is interesting to note, though, that the low error case performs slightly better in the morning than in the afternoon.

Summary Comparison: Morning % Time Savings Over Baseline for Time-dependent Historical

<table>
<thead>
<tr>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>1.86%</td>
<td>-4.20%</td>
<td>0.41%</td>
<td>1.31%</td>
<td>1.15%</td>
</tr>
<tr>
<td>Error</td>
<td>1.88%</td>
<td>-3.49%</td>
<td>0.47%</td>
<td>-1.21%</td>
<td>-0.11%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>0.02%</td>
<td>0.71%</td>
<td>0.06%</td>
<td>-2.52%</td>
<td>-1.26%</td>
</tr>
</tbody>
</table>

Table 31: Summary comparison – morning time-dependent historical

Table 32 gives the same information for the afternoon period. The message is consistent in this table as well. Note that both the scenarios perform slightly worse (in composite) than the baseline for this information level.
Summary Comparison: Afternoon % Time Savings Over Baseline for Time-dependent Historical

<table>
<thead>
<tr>
<th></th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>2.32%</td>
<td>-2.29%</td>
<td>-8.09%</td>
<td>-4.14%</td>
<td>2.72%</td>
<td>-1.90%</td>
</tr>
<tr>
<td>Error</td>
<td>0.99%</td>
<td>-2.40%</td>
<td>-6.73%</td>
<td>-5.12%</td>
<td>2.62%</td>
<td>-2.13%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>-1.33%</td>
<td>-0.11%</td>
<td>1.36%</td>
<td>-0.98%</td>
<td>-0.10%</td>
<td></td>
</tr>
</tbody>
</table>

Table 32: Summary comparison – afternoon time-dependent historical

Section 6.6.2: Level Two Pre-trip Instantaneous Information

In this section, we will investigate information level two: pre-trip instantaneous information. Table 33 presents the aggregate % time savings for the two different scenarios. The first aspect to note is that both the no and low error cases are approximately 4% better than the baseline. There is very little difference between the low and no error scenarios.

On Day 5, the aggregate % time savings over the baseline is approximately 7% for both the no and low error cases. In addition, all five days have positive % time savings over the baseline.

Summary Comparison: Aggregate % Time Savings Over Baseline for Pre-trip Instantaneous

<table>
<thead>
<tr>
<th></th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>1.20%</td>
<td>4.71%</td>
<td>1.85%</td>
<td>4.12%</td>
<td>7.23%</td>
<td>3.82%</td>
</tr>
<tr>
<td>Error</td>
<td>1.43%</td>
<td>4.57%</td>
<td>1.19%</td>
<td>4.41%</td>
<td>6.76%</td>
<td>3.67%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>0.23%</td>
<td>-0.14%</td>
<td>-0.66%</td>
<td>0.29%</td>
<td>-0.47%</td>
<td></td>
</tr>
</tbody>
</table>

Table 33: Summary comparison – aggregate pre-trip instantaneous

Table 34 presents the results for the morning rush-hour period. In the error-filled scenario, there is a little less than a 1% reduction in the % time savings composite compared with the no-error case.
Summary Comparison: Morning % Time Savings Over Baseline for Pre-trip Instantaneous

<table>
<thead>
<tr>
<th></th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>0.27%</td>
<td>2.42%</td>
<td>1.34%</td>
<td>6.83%</td>
<td>4.88%</td>
<td>3.15%</td>
</tr>
<tr>
<td>Error</td>
<td>0.22%</td>
<td>1.87%</td>
<td>-0.11%</td>
<td>5.79%</td>
<td>4.02%</td>
<td>2.36%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>-0.05%</td>
<td>-0.56%</td>
<td>-1.45%</td>
<td>-1.04%</td>
<td>-0.86%</td>
<td></td>
</tr>
</tbody>
</table>

Table 34: Summary comparison – morning pre-trip instantaneous

The results of the afternoon origin/destination pair simulations are presented in Table 35. In the afternoon period, the composite in the low error case is actually better than the no error case. This is most likely explained by error routing the driver in the “right” direction – given that stochastic accidents occur in the future. Once again, on Day 5, the no and low error scenarios produces a significant result at almost 10% better than the baseline.

Summary Comparison: Afternoon % Time Savings Over Baseline for Pre-trip Instantaneous

<table>
<thead>
<tr>
<th></th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>2.13%</td>
<td>6.99%</td>
<td>2.35%</td>
<td>1.42%</td>
<td>9.57%</td>
<td>4.49%</td>
</tr>
<tr>
<td>Error</td>
<td>2.64%</td>
<td>7.27%</td>
<td>2.49%</td>
<td>3.03%</td>
<td>9.50%</td>
<td>4.99%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>0.51%</td>
<td>0.28%</td>
<td>0.14%</td>
<td>1.61%</td>
<td>-0.07%</td>
<td></td>
</tr>
</tbody>
</table>

Table 35 Summary comparison – afternoon pre-trip instantaneous

Section 6.6.3: Level Three En-route Instantaneous Information

In this section we will investigate the en-route instantaneous information level. Table 36 presents the aggregate % time savings for the two different scenarios. The no and low error cases are fairly close with both producing almost 6% time savings over the baseline. All five days produce positive time savings. This reinforces the hypothesis that intelligent transportation systems might be able handle a small degree of error.
Table 36: Summary comparison – aggregate en-route instantaneous

Table 37: Summary comparison – morning en-route instantaneous

In table 38, the afternoon % time savings is exhibited. Now the composite of the no and low error scenarios is almost 8% better than the baseline. On Days 2 and 5, there is a double-digit percent time savings compared with the baseline. In the afternoon period, en-route instantaneous information appears to offer significant value compared to the baseline – even when a small degree of error is introduced.

Table 38: Summary comparison – afternoon en-route instantaneous

Section 6.6.4: Level Four Predictive Information

- 140 -
The final information level to investigate is the predictive information level. As mentioned previously, because there is perfect information only into the random speed vector and not the true speed vector, it is possible to perform worse than the baseline for a given trip. The no and low error cases produce about 8% time savings over the baseline. Once again, all five days produce positive time savings.

Summary Comparison: Aggregate % Time Savings Over Baseline for Predictive Information

<table>
<thead>
<tr>
<th>Day</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>4.60%</td>
<td>9.25%</td>
<td>5.25%</td>
<td>9.61%</td>
<td>11.75%</td>
</tr>
<tr>
<td>Error</td>
<td>4.43%</td>
<td>9.21%</td>
<td>4.80%</td>
<td>9.15%</td>
<td>11.31%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>-0.17%</td>
<td>-0.08%</td>
<td>-0.45%</td>
<td>-0.46%</td>
<td>-0.44%</td>
</tr>
</tbody>
</table>

Table 39: Summary comparison - aggregate predictive

Table 40 presents the same information for the morning rush-hour period. A similar trend holds from above where the morning period performs worse than the afternoon period. There is still very little difference between the no and low error cases with both of the composites performing about 6% better than the baseline.

Summary Comparison: Morning % Time Savings Over Baseline for Predictive Information

<table>
<thead>
<tr>
<th>Day</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td>2.18%</td>
<td>3.27%</td>
<td>4.31%</td>
<td>10.65%</td>
<td>7.74%</td>
</tr>
<tr>
<td>Error</td>
<td>2.09%</td>
<td>3.27%</td>
<td>3.87%</td>
<td>10.57%</td>
<td>7.48%</td>
</tr>
<tr>
<td>Change from No Error</td>
<td>-0.09%</td>
<td>0.00%</td>
<td>-0.44%</td>
<td>-0.08%</td>
<td>-0.26%</td>
</tr>
</tbody>
</table>

Table 40: Summary comparison – morning predictive

In table 41, the afternoon time savings are presented. The composite time savings for both the no and low error scenarios are both double-digit numbers. With perfect information, significant savings can be obtained using ITS in the supply chain.
Summary Comparison: Afternoon % Time Savings Over Baseline for Predictive Information

<table>
<thead>
<tr>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Error</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>7.02%</td>
<td>15.30%</td>
<td>6.19%</td>
<td>8.57%</td>
<td>10.57%</td>
</tr>
<tr>
<td>Error</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6.78%</td>
<td>15.15%</td>
<td>5.73%</td>
<td>7.73%</td>
<td>15.14%</td>
</tr>
<tr>
<td></td>
<td>-0.24%</td>
<td>-0.15%</td>
<td>-0.46%</td>
<td>-0.84%</td>
<td>-0.62%</td>
</tr>
</tbody>
</table>

Table 41: Summary comparison – afternoon predictive

Section 6.6.5: The Entire Information Spectrum

The last aspect to consider in this section is how the time savings along the information spectrum trend. In Chapter 5, it was shown that as we proceeded to a higher information level, additional time savings were added. With the introduction of error we can now see if the same trend holds.

Section 6.6.5.1: Error

Table 42 shows the aggregate results presented in the previous four sections on one table. This is a representation of the information spectrum: from level 1 through 4. As can be seen in the table, there is clearly a positive trend along the information spectrum. Information level 1 (static & time-dependent historical) performs a little worse than the baseline. The reasons for this are equivalent to those given in Chapter 5. Primarily, the limited dataset is a key driver in the soundness of these results.

The instantaneous information levels (level 2 and 3) both produce positive time savings compared to the baseline – even with the introduction of a small bit of error. Because it is highly likely that a real-world ITS unit would contain such error, it is encouraging to see that the results still hold at small error levels. If the sensors can keep there errors below a 5% standard deviation level, it is likely that intelligent transportation systems will be able to add value to the supply chain.

The highest level of information (level 4) only offers about an 8% increase in time savings over the baseline. It is worthwhile to note that most companies don’t even employ the baseline methodology. So if a company implements any level above level 1
in their supply chain operations, they might be able to achieve significant operating savings to their current operating costs.

Summary Comparison: Aggregate % Time Savings Over Baseline - Error

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static, Historical</td>
<td>2.21%</td>
<td>-2.00%</td>
<td>-0.66%</td>
<td>-2.23%</td>
<td>1.11%</td>
<td>-0.30%</td>
</tr>
<tr>
<td>Time-dependent, Historical</td>
<td>1.43%</td>
<td>-2.94%</td>
<td>-3.13%</td>
<td>-3.17%</td>
<td>1.25%</td>
<td>-1.31%</td>
</tr>
<tr>
<td>Pre-trip, Instantaneous</td>
<td>1.43%</td>
<td>4.57%</td>
<td>1.19%</td>
<td>4.41%</td>
<td>6.76%</td>
<td>3.67%</td>
</tr>
<tr>
<td>En-route, Instantaneous</td>
<td>2.28%</td>
<td>8.85%</td>
<td>3.61%</td>
<td>6.11%</td>
<td>9.19%</td>
<td>5.61%</td>
</tr>
<tr>
<td>Predictive</td>
<td>4.43%</td>
<td>9.21%</td>
<td>4.80%</td>
<td>9.15%</td>
<td>11.31%</td>
<td>7.78%</td>
</tr>
</tbody>
</table>

Table 42: Summary comparison - error aggregate

Table 43 shows the same information as table 42, except that it is for the morning rush-hour period. The trend clearly holds in this table as well. It should be noted, however, that performance is generally worse in the morning than in the afternoon (except for level 1). This suggests that a small bit of error doesn’t change the trends observed in Chapter 5.

Summary Comparison: Morning % Time Savings Over Baseline - Error

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static, Historical</td>
<td>0.57%</td>
<td>-2.54%</td>
<td>1.28%</td>
<td>-0.63%</td>
<td>0.23%</td>
<td>-0.22%</td>
</tr>
<tr>
<td>Time-dependent, Historical</td>
<td>1.88%</td>
<td>-3.49%</td>
<td>0.47%</td>
<td>-1.21%</td>
<td>-0.11%</td>
<td>-0.49%</td>
</tr>
<tr>
<td>Pre-trip, Instantaneous</td>
<td>0.22%</td>
<td>1.87%</td>
<td>-0.11%</td>
<td>5.79%</td>
<td>4.02%</td>
<td>2.36%</td>
</tr>
<tr>
<td>En-route, Instantaneous</td>
<td>-0.28%</td>
<td>2.57%</td>
<td>2.90%</td>
<td>6.03%</td>
<td>6.86%</td>
<td>3.62%</td>
</tr>
<tr>
<td>Predictive</td>
<td>2.09%</td>
<td>3.27%</td>
<td>3.87%</td>
<td>10.57%</td>
<td>7.48%</td>
<td>5.46%</td>
</tr>
</tbody>
</table>

Table 43: Summary comparison - error morning
The afternoon time savings are presented in Table 44. Once again the trend holds along the information spectrum. The time savings for level 2 are now about 5% better than the baseline. For level 3, the time savings are almost 8% better than the baseline. Finally, with perfect information, the time savings reach the 10% level in composite. For the highway system under investigation, one might conclude that there is real value to be unlocked during the afternoon rush-hour period. It is probably worthwhile for governments/private corporations to ensure that the sensors used to monitor traffic be fairly accurate. This should maximize the value derived from intelligent transportation systems.

**Summary Comparison: Afternoon % Time Savings Over Baseline - Error**

<table>
<thead>
<tr>
<th>Level</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Static, Historical</td>
<td>3.86%</td>
<td>-1.47%</td>
<td>-2.47%</td>
<td>-3.83%</td>
<td>2.00%</td>
<td>-0.83%</td>
</tr>
<tr>
<td><strong>Level 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time-dependent, Historical</td>
<td>0.99%</td>
<td>-2.40%</td>
<td>-6.73%</td>
<td>-5.12%</td>
<td>2.62%</td>
<td>-2.13%</td>
</tr>
<tr>
<td><strong>Level 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-trip, Instantaneous</td>
<td>2.64%</td>
<td>7.27%</td>
<td>2.49%</td>
<td>3.03%</td>
<td>9.50%</td>
<td>4.93%</td>
</tr>
<tr>
<td><strong>Level 3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>En-route, Instantaneous</td>
<td>4.85%</td>
<td>11.13%</td>
<td>4.33%</td>
<td>6.19%</td>
<td>11.52%</td>
<td>7.60%</td>
</tr>
<tr>
<td><strong>Level 4</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predictive</td>
<td>6.78%</td>
<td>15.15%</td>
<td>5.73%</td>
<td>7.73%</td>
<td>15.14%</td>
<td>10.11%</td>
</tr>
</tbody>
</table>

Table 44: Summary comparison – error afternoon
Chapter 7: Conclusions and Results

Section 7.1: Comparison of Information Levels

Having reached the last chapter of this thesis, it is time to wrap up the analysis and apply the results of the previous chapters to supply chain management as a whole. Chapters 4, 5, and 6 spent a great deal of time examining the time savings that various information levels were able to obtain through simulation. In this section, we will give a final discussion of how the different information levels compare to one another. Specifically, the two dimensions of the time spectrum will be analyzed.

The first dimension to be examined is the pre-trip/en-route split. Since the historical information level didn't really add significant savings over the baseline, we will limit our discussion to the instantaneous division. First, the en-route information level did add additional savings over the pre-trip information level. This confirmed the initial hypothesis that by providing the ability to modify the trip en-route, a driver would be able to achieve better performance. In this manner, the en-route/pre-trip classification can be compared to a pre-trip vs. en-route distinction. Providing en-route information adds to overall performance. The second aspect to consider is the level of increase between en-route and pre-trip instantaneous information. This level is quite small. We will discuss the meaning of this gap in the supply chain recommendations section.

The second dimension to be examined is the historical/instantaneous/predictive split. As previously mentioned the historical analysis did not provide savings over the baseline. The reasons for this are most likely related to the limited dataset that was used to run the simulations. It should not be assumed that this analysis means that historical information is not important to ITS units. On the contrary, an effective ITS unit will most likely incorporate some level of historical analysis, but will need to be modified with real-time and predictive information. In this manner, there will be a hybrid information level driving the routing decisions.

Instantaneous information was able to add time savings over the baseline. Again our initial hypothesis appears to be confirmed by the simulation results. Better information may make for better supply chain operations. As sensors are rolled out across the transportation networks, these information levels will be more easily attainable.
by corporations. More importantly, instantaneous information offers the ability to detect traffic incidents in real-time. This information could be extremely valuable to a system that only uses level zero information.

Predictive information was able to add a positive amount of time savings over the baseline. It was surprising, however, how little perfect information was able to add. One would think that the ability to perfectly predict traffic accidents could be an extremely valuable asset in traffic engineering. The most likely reason that this is not the case is the particular network under consideration. Because we have dealt with a highway system, the combinatorial nature of the realistic route choice is limited. In other words, even if a traffic accident occurs on the shortest-distance route, the additional distance needed to get on an alternative route eliminates the time savings gained from avoiding the traffic accident. In fact, in many cases the shortest-distance approach was the best approach to take.

In all respects, the baseline is not a poor algorithm to put in place. It is a cheap alternative that will prove valuable to corporations that employ it. This paper is about exposing the benefits of all the information levels – including information level zero. The author has argued that additional value can be obtained by using real-time or predictive information in routing decisions. As businesses constantly search for ways to increase profitability, they may turn beyond a baseline-type approach and seek to gain additional value from higher levels. The value that large players should be able to realize is in the millions of dollars per year.

The sensitivity analysis that was performed in Chapter 6 also confirmed an earlier hypothesis. It was shown that intelligent transportation systems should still be effective under low error scenarios. Specifically, a 5% standard deviation on a normally distributed error term with mean zero maintained the results from Chapter 5. This has practical importance in policy issues when a decision is being made where to invest resources within ATIS units.

Section 7.2: Final Considerations
We have reached the final section of this work. The last two aspects to be considered are supply chain recommendations and improvements/extensions to this paper. The former is particularly important because it will bridge the gap from an academic simulation to real-world best practices. At the end of the day, this paper is about exposing a potentially unique new technology to supply chain professionals. The primary goal is to be able to increase corporate profitability through the use of intelligent transportation systems.

Section 7.2.1: Supply Chain Recommendations

The first recommendation is the most important. The author recommends that supply chain professionals incorporate intelligent transportation systems into their operations. We should quickly note that this paper has not used current practices as the baseline. We discussed the reasons for this in the introductory chapters. Returning to these arguments, we concluded that many businesses simply do not employ any systematic process in their intra-routing decisions. Modeling such a baseline would be extremely challenging because of the psychological factors involved.

Currently, several companies employ fleet management techniques that determine the order of customer/supplier pickup and deliveries. Very few of these companies have even employed a shortest-distance based routing policy between these origin and destinations. Drivers are left to their own mental maps to be able to find the best way to get from start to finish.

The best practice in supply chain operations for these leading companies is to employ a distance-based approach to supply chain operations. This policy provides clear turn-by-turn instructions to drivers. Such a policy can help unskilled or unfamiliar laborers work more efficiently. This paper suggests that at a minimum all companies should look to employ a level zero type routing policy into supply chain operations.

There is additional value to be obtained from using higher levels of information. In fact, pre-trip instantaneous information can be a cheap alternative to improve the baseline performance. One of the biggest differences between implementing a pre-trip vs. en-route system is cost. In order to get an en-route system to operate, all of the driver
vehicles must have a communication device to receive modified routing instructions. Drivers must also deal with changing their routes. This could be a taxing challenge for a driver (leading to non-compliance). In addition, the vehicle must be equipped with a GPS device to indicate to the ITS unit the current location of the driver. This will add to the cost as well. All of these factors make the implementation of an en-route system more costly than a pre-trip system. For this reason, the en-route levels must offer a large degree of time savings compared to a pre-trip system. As seen in the simulations, this was not the case. There was only a 2 percentage point increase in the en-route and pre-trip instantaneous levels.

En-route information should not be eliminated from future consideration, however. As technology proliferates and the cost of providing the dynamic features described above falls, en-route information might be the best option. In fact, the author believes that in the future, en-route systems will prevail. The fact of the matter is that en-route systems may perform better than pre-trip systems (as evidenced by Chapter 5’s results). But the cost from moving between pre-trip and en-route systems is currently too great to justify the benefit. In the long-run, this cost will likely fall and the en-route systems will hold sway.

The cost of prediction is extremely low. Modeling techniques can be used to forecast the system. In today’s corporate world, forecasts are made from everything to employee headcount to product demand. It does not make sense to not employ the same tactics to transportation planning. Moreover, it was demonstrated in the simulation results that prediction is likely to offer additional benefits to corporations.

One of the specific levels of information that we did not test was pre-trip predictive (not using perfect information). The author believes that a pre-trip, predictive model would have additional value over the pre-trip instantaneous information level. Essentially, the pre-trip instantaneous model based all of its routing decisions on an uncongested highway system. Since the routing decisions were made pre-trip and at pre-rush hour levels, a pre-trip instantaneous model was extremely naïve. All in all, the author believes that pre-trip, predictive information level is likely to offer the most benefit to corporations at a reasonable cost for the near-term if an accurate forecast can be made.
Section 7.2.2: Improvements and Extensions

There are a number of different ways to improve and extend this paper. The first improvement relates to the information set. As was previously mentioned, the author believes the primary reason for the non-performance of the historical information level was the lack of data. In order to do a more robust analysis on the value of historical information, daily averages over a long period – several months – need to be examined using time series techniques. In the end, the author still holds the hypothesis that historical information will prove valuable to supply chain managers.

A second improvement would be to add a medium error sensitivity analysis. This would show whether the sensors could be less reliable and still offer value to supply chain managers. While a low error case was examined – we did not find the threshold that eliminated the time savings in the error-free scenario. If this threshold level was found, a minimum quality of level of the sensors could be employed in the infrastructure roll-out.

A third improvement to this paper would be applying the time savings to an actual company. In other words, translate all the benefits in potential profit for an actual company. In Chapter 5, we only performed a high-level, conservative estimate of value savings. A more in-depth analysis of the financial rewards of adopting ITS into the supply chain would prove helpful. In addition, the cost of implementing ITS needs to be examined much more rigorously. This is especially true based on the supply chain recommendations that distinguished between pre-trip and en-route costs. If these recommendations are to hold sway, these costs need to be flushed out carefully.

A major extension of this work revolves around prediction. We assumed that drivers had perfect information. This is not a real-world assumption. Predictive traffic models, like dynaMIT, need to be used to model the highest information levels. A pre-trip, predictive vs. en-route, predictive test should be performed to ascertain the difference in performance levels. If an accurate prediction can be made for a reasonable cost, the author believes that these two information levels will be the gold standard of ITS units in the future.
The paper can be further extended by considering fleet management techniques. One of the limitations of the work was considering only single origin/destination pair routings. This is fine for a "mom and pop" store that has only a single truck. But when we start considering complicated fleets, we need to employ more systematic procedures. Modeling a traveling-salesman type problem is a logical extension to this paper.

The final extension to this paper is to consider system dynamics. Naturally, as more and more people have information, system dynamic effects will occur. There is most likely a threshold level of information dispersion that gives a plateau of time savings effectiveness. While we made the assumption that only a few of the drivers on the transportation network will have information, in the long run it is possible that the majority of drivers will have information. Performing an analysis that includes these system dynamics is a logical extension to this work.

Section 7.3.2: Concluding Remarks

This paper has hopefully given the reader a look into the future of the supply chain. In particular, it is hoped that the reader now has an appreciation of how powerful intelligent transportation systems can be. These systems are cutting-edge technology and are rapidly expanding in presence and scope.

In the future, corporations that want to achieve higher profitability will need to turn to new technologies like intelligent transportation systems. Those companies that fail to be adopters will face a significant competitive disadvantage. ITS offers corporations visibility into transportation networks in much the same way that radio frequency identification offers visibility into inventory. It is a powerful new tool that companies should begin to adopt.

As a concluding remark, it is insightful to quote how [McQueen 2002] view the future of transportation networks.

"The year is 2020 and our future traveler information system makes use of multiple information delivery mechanisms to deliver traveler information to the traveler when required, in the appropriate format and with the necessary content and timing to effectively support travel decisions, such as choice of mode, choice of route, and timing of journey. The system will also deliver sufficient
information to enable hybrid or multimode trip options to be assessed in terms of time, distance, and cost parameters, alongside the more typical single-mode options. The information is available at each stage of the trip: prior to departure (short and long-term advance trip planning), at departure, during the course of the journey, afterwards for analysis and cost-management purposes. The information is available in a wide variety of customizable formats, including voice synthesized information bulletins, short messages, and sophisticated map-type displays.”

The future is coming…
Appendix
```cpp
#include <iostream>
#include <fstream>
#include <cstdlib>

#define DESTINATION 51
#define ORIGIN 51
#define INTERVAL 180

int DistDijkstra (int r, int s);
int TimeDijkstra (int y, int z, int timer1);
int TravelTime (int d, int n, int timer2);
int ShortestDistPath (int a, int b, int timer3);
int ShortestTimePath (int e, int j, int timer4);

float distance [ORIGIN][DESTINATION];
float speed [ORIGIN][DESTINATION][INTERVAL];
float speedMirror [ORIGIN][DESTINATION][INTERVAL];

int t = 1; // time interval used between speed updates
int totaltime1 = 0;
int totaltime2 = 0;

int startnode = 0; // initialize the starting node
int endnode = 0; // initialize the goal
int currentnode = 0; // initialize the current node
int minutes = 1; // set the time equivalent of interval step
int starttime = 0; // set the start time

int m=0; // counter used to initialize the starting matrices
int n=0; // counter used to initialize the starting matrices
int xx=0; // counter used to initialize the time intervals

int main ()
{
    // initialize distances
    int size = 2601;
    float data[size];
    std::ifstream data_file("Distance.prn");

    if (data_file.bad())
    {
        std::cerr << "Error opening file"
        exit(8);
    }
```

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for (m=0; m<size; m++)
{
    assert(m>=0);
    assert(m<sizeof(data)/sizeof(data[0]));
    data_file >> data[m];
}

for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
{
    distance [n][m] = data[xx];
    xx++;
}

// initialize the actual speeds
int size2 = 468180;
float data2[size2];
std::ifstream data_file2("DataThur2Aft.txt");

if (data_file2.bad())
{
    std::cerr << "Error opening file";
    exit(8);
}

for (m=0; m<size2; m++)
{
    assert(m>=0);
    assert(m<sizeof(data2)/sizeof(data2[0]));
    data_file2 >> data2[m];
}

int ii=0;
for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
for (xx=0; xx<INTERVAL; xx++)
{
    speed [n][m][xx] = data2[ii];
    ii++;
}

// initialize the mirror speeds
int size3 = 468180;
float data3[size3];
std::ifstream data_file3("DataThurlAft.txt");

if (data_file3.bad())
{
    std::cerr << "Error opening file";
    exit(8);
}

for (m=0; m<size3; m++)
{
    assert(m>=0);
    assert(m<sizeof(data3)/sizeof(data3[0]));
    data_file3 >> data3[m];
}

int iii=0;
for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
for (xx=0; xx<INTERVAL; xx++)
{
    speedMirror [n][m][xx] = data3[iii];
    iii++;
}

std::cout << "Please enter the desired starting node " << "\n";
std::cin >> startnode; // read in the starting node
std::cout << "Please enter the desired ending node " << "\n";
std::cin >> endnode; // read in the goal

currentnode = startnode; // set the start node equal to the current node

totaltime1 = ShortestDistPath (currentnode, endnode, starttime) * minutes;
totaltime2 = ShortestTimePath (currentnode, endnode, starttime) * minutes;
std::cout << "The total time for ShortestDistance was " << totaltime1 << "\n";
std::cout << "The total time for ShortestTime was " << totaltime2 << "\n";
std::cout << "The total time difference is " << totaltime1 - totaltime2 << "\n";
return 0;

int ShortestDistPath (int a, int b, int timerSDP)
{
    int time1 = 0;
    int timeholder1 = 0;
    int nextnode1;
nextnode1 = DistDijkstra (a, b); // initialize the nextnode using Dijkstra
std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
while (a != b)
{
    timeholder1 = TravelTime (a, nextnode1, timerSDP);
    time1 = time1 + timeholder1;
    timerSDP = time1;
    a = nextnode1;
    if (a == b) break;
    nextnode1 = DistDijkstra (a, b);
    std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
}
return (time1);
}

int ShortestTimePath (int e, int j, int timerSTP)
{
    int time2 = 0;
    int timeholder2 = 0;
    int nextnode2;
    std::cout << "The STP algorithm is now being run " << "\n";
    nextnode2 = TimeDijkstra (e, j, timerSTP);
    std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
    while (e != j)
    {
        timeholder2 = TravelTime (e, nextnode2, timerSTP);
        time2 = time2 + timeholder2;
        timerSTP = time2;
        e = nextnode2;
        if (e == j) break;
        nextnode2 = TimeDijkstra (e, j, timerSTP);
        std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
    }
    return (time2);
}

int TravelTime (int d, int n, int timerTT)
{
    float c = 0;
    float f = 0;
    int l = 0;
    while (f < distance [d][n])
    {
        c = minutes * t * speed [d][n][timerTT];
        f = f + c;
        l = l + t;
    }
int DistDijkstra (int r, int s)
{
    float shortdist [ORIGIN]; // length of shortest path from r to node j
    int predecessor1 [ORIGIN]; // immediate predecessor of node j in short path
    int state1 [ORIGIN]; // state of node - either open (0) or closed (1)
    int selectnode1;

    for (int ul = 0; ul < ORIGIN; ul++) // initialize the labels
    {
        shortdist [ul] = 10000;
        predecessor1 [ul] = ORIGIN + 1;
        state1 [ul] = 0;
    }

    shortdist [r] = 0; // initialize the current node label
    predecessor1 [r] = r;
    state1 [r] = 1;
    selectnode1 = r;

    loop1:
    for (int h1 = 0; h1 < ORIGIN; h1++)
    {
        if (state1 [h1] == 0)
        {
            if (shortdist [h1] > shortdist [selectnode1] + distance [selectnode1][h1])
            {
                shortdist [h1] = shortdist [selectnode1] + distance [selectnode1][h1];
                predecessor1 [h1] = selectnode1;
            }
        }
    }

    float currentmin1 = 10000;

    for (int q1 = 0; q1 < ORIGIN; q1++) // find the shortest open node distance
    {
        if (state1 [q1] == 0)
        {
            if (shortdist [q1] < currentmin1)
            {
                currentmin1 = shortdist [q1];
                selectnode1 = q1;
            }
        }
    }

    return (1);
}
for (int g1=0; g1 < ORIGIN; g1++) // find the predecessor of selectnode
{
    if (state1 [g1] == 1)
    {
        if (shortdist [selectnode1] == shortdist [g1] + distance [g1][selectnode1])
        {
            predecessor1 [selectnode1] = g1;
            state1 [selectnode1] = 1;
        }
    }
}

int TimeDijkstra (int y, int z, int timerTD)
{
    float shorttime [ORIGIN]; // time of shortest path from y to j
    int predecessor2 [ORIGIN]; // immediate predecessor of node j is shortpath
    int state2 [ORIGIN]; // state of node - either open (0) or closed (1)
    int selectnode2;

    timerTD = 1;

    for (int u2 = 0; u2 < ORIGIN; u2++) // initialize the labels
    {
        shorttime [u2] = 500;
        predecessor2 [u2] = ORIGIN + 1;
    }
state2[u2] = 0;
}

shorttime[y] = 0;
predecessor2[y] = y;
state2[y] = 1;
selectnode2 = y;

loop2:
for (int h2 = 0; h2 < ORIGIN; h2++)
{
    if (state2[h2] == 0)
    {
        if (shorttime[h2] > shorttime[selectnode2] + (distance[selectnode2][h2] / speedMirror[selectnode2][h2][timerTD]))
        {
            shorttime[h2] = shorttime[selectnode2] + (distance[selectnode2][h2] / speedMirror[selectnode2][h2][timerTD]);
predecessor2[h2] = selectnode2;
        }
    }
}

float currentmin2 = 500;
for (int q2 = 0; q2 < ORIGIN; q2++) // find the shortest open node time
{
    if (state2[q2] == 0)
    {
        if (shorttime[q2] < currentmin2)
        {
            currentmin2 = shorttime[q2];
selectnode2 = q2;
        }
    }
}

for (int g2=0; g2 < ORIGIN; g2++) // find the predecessor node
{
    if (state2[g2] == 1)
    {
        if (shorttime[selectnode2] == shorttime[g2] + (distance[g2][selectnode2] / speedMirror[g2][selectnode2][timerTD]))
        {
            predecessor2[selectnode2] = g2;
state2[selectnode2] = 1;
        }
    }
}
if (selectnode2 == z)
{
    for (int k2 = z;;)
    {
        if (predecessor2 [k2] == y)
            {  
                if (k2 != y) return (k2);
            }
        k2 = predecessor2 [k2];
    }
    else
    {
        goto loop2;
    }

}
#include <iostream>
#include <fstream>
#include <cstdlib>

#define DESTINATION 51
#define ORIGIN 51
#define INTERVAL 180

int DistDijkstra (int r, int s);
int TimeDijkstra (int y, int z, int timer1);
int TravelTime (int d, int n, int timer2);
int ShortestDistPath (int a, int b, int timer3);
int ShortestTimePath (int e, int j, int timer4);

float distance [ORIGIN][DESTINATION];
float speed [ORIGIN][DESTINATION][INTERVAL];
float speedMirror [ORIGIN][DESTINATION][INTERVAL];

int t = 1;  // time interval used between speed updates
int totaltime1 = 0;
int totaltime2 = 0;

int startnode = 0;  // initialize the starting node
int endnode = 0;    // initialize the goal
int currentnode = 0; // initialize the current node
int minutes = 1;   // set the time equivalent of interval step
int starttime = 0; // set the start time

int m=0;    // counter used to initialize the starting matrices
int n=0;    // counter used to initialize the starting matrices
int xx=0;   // counter used to initialize the time intervals

int main ()
{
    // initialize distances
    int size = 2601;
    float data[size];
    std::ifstream data_file("Distance.prn");

    if (data_file.bad())
    {
        std::cerr << "Error opening file"
                   exit(8);
    }
}
for (m=0; m<size; m++)
{
    assert(m>=0);
    assert(m<sizeof(data)/sizeof(data[0]));
data_file >> data[m];
}

for (n=0; n<ORIGIN; n++)
    for (m=0; m<DESTINATION; m++)
    {
        distance[n][m] = data[xx];
        xx++;
    }

// initialize the actual speeds

int size2 = 468180;
float data2[size2];
std::ifstream data_file2("DataThur2Aft.txt");

if (data_file2.bad())
{
    std::cerr << "Error opening file";
    exit(8);
}

for (m=0; m<size2; m++)
{
    assert(m>=0);
    assert(m<sizeof(data2)/sizeof(data2[0]));
data_file2 >> data2[m];
}

int ii=0;
for (n=0; n<ORIGIN; n++)
    for (m=0; m<DESTINATION; m++)
        for (xx=0; xx<INTERVAL; xx++)
        {
            speed[n][m][xx] = data2[ii];
            ii++;
        }

// initialize the mirror speeds

int size3 = 468180;
float data3[size3];
std::ifstream data_file3("DataThurl1Aft.txt");

if (data_file3.bad())
{
    std::cerr << "Error opening file";
    exit(8);
}

for (m=0; m<size3; m++)
{
    assert(m>=0);
    assert(m<sizeof(data3)/sizeof(data3[0]));
    data_file3 >> data3[m];
}

int iii=0;
for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
for (xx=0; xx<INTERVAL; xx++)
{
    speedMirror [n][m][xx] = data3[iii];
    iii++;
}

std::cout << "Please enter the desired starting node " << "\n";
std::cin >> startnode; // read in the starting node
std::cout << "Please enter the desired ending node " << "\n";
std::cin >> endnode; // read in the goal

currentnode = startnode; // set the start node equal to the current node

totaltime1 = ShortestDistPath (currentnode, endnode, starttime) * minutes;
totaltime2 = ShortestTimePath (currentnode, endnode, starttime) * minutes;
std::cout << "The total time for ShortestDistance was " << totaltime1 << "\n";
std::cout << "The total time for ShortestTime was " << totaltime2 << "\n";
std::cout << "The total time difference is " << totaltime1 - totaltime2 << "\n";
return 0;
}

int ShortestDistPath (int a, int b, int timerSDP)
{
    int time1 = 0;
    int timeholder1 = 0;
    int nextnode1;
nextnode1 = DistDijkstra (a, b); // initialize the nextnode using Dijkstra
std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
while (a != b)
{
    timeholder1 = TravelTime (a, nextnode1, timerSDP);
    time1 = time1 + timeholder1;
    timerSDP = time1;
    a = nextnode1;
    if (a == b) break;
    nextnode1 = DistDijkstra (a, b);
    std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
}
return (time1);
}

int ShortestTimePath (int e, int j, int timerSTP)
{
    int time2 = 0;
    int timeholder2 = 0;
    int nextnode2;
    std::cout << "The STP algorithm is now being run " << "\n";
    nextnode2 = TimeDijkstra (e, j, timerSTP);
    std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
    while (e != j)
    {
        timeholder2 = TravelTime (e, nextnode2, timerSTP);
        time2 = time2 + timeholder2;
        timerSTP = time2;
        e = nextnode2;
        if (e == j) break;
        nextnode2 = TimeDijkstra (e, j, timerSTP);
        std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
    }
    return (time2);
}

int TravelTime (int d, int n, int timerTT)
{
    float c = 0;
    float f = 0;
    int l = 0;
    while (f < distance [d][n])
    {
        c = minutes * t * speed [d][n][timerTT];
        f = f + c;
        l = l + t;
    }
    return (time2);
int DistDijkstra (int r, int s)
{
    float shortdist [ORIGIN]; // length of shortest path from r to node j
    int predecessor1 [ORIGIN]; // immediate predecessor of node j in short path
    int state1 [ORIGIN]; // state of node - either open (0) or closed (1)
    int selectnode1;

    for (int u1 = 0; u1 < ORIGIN; u1++) // initialize the labels
    {
        shortdist [u1] = 10000;
        predecessor1 [u1] = ORIGIN + 1;
        state1 [u1] = 0;
    }

    shortdist [r] = 0; // initialize the current node label
    predecessor1 [r] = r;
    state1 [r] = 1;
    selectnode1 = r;

    loop1:
    for (int h1 = 0; h1 < ORIGIN; h1++)
    {
        if (state1 [h1] == 0)
        {
            if (shortdist [h1] > shortdist [selectnode1] + distance [selectnode1][h1])
            {
                shortdist [h1] = shortdist [selectnode1] + distance [selectnode1][h1];
                predecessor1 [h1] = selectnode1;
            }
        }
    }

    float currentmin1 = 10000;

    for (int q1 = 0; q1 < ORIGIN; q1++) // find the shortest open node distance
    {
        if (state1 [q1] == 0)
        {
            if (shortdist [q1] < currentmin1)
            {
                currentmin1 = shortdist [q1];
                selectnode1 = q1;
            }
        }
    }
for (int gl = 0; gl < ORIGIN; gl++) // find the predecessor of selectnode
{
    if (state1[gl] == 1)
    {
        if (shortdist[selectnode1] == shortdist[gl] + distance[gl][selectnode1])
            {
                predecessor1[selectnode1] = gl;
                state1[selectnode1] = 1;
            }
        if (selectnode1 == s)
            {
                for (int kl = s;;)
                    {
                        if (predecessor1[kl] == r)
                        {
                            if (kl != r) return (kl);
                        }
                        kl = predecessor1[kl];
                    }
            }
        else
        {
            goto loop1;
        }
    }
}

int TimeDijkstra (int y, int z, int timerTD)
{
    float shorttime[ORIGIN]; // time of shortest path from y to j
    int predecessor2[ORIGIN]; // immediate predecessor of node j is shortpath
    int state2[ORIGIN]; // state of node - either open (0) or closed (1)
    int selectnode2;

    for (int u2 = 0; u2 < ORIGIN; u2++) // initialize the labels
    {
        shorttime[u2] = 500;
        predecessor2[u2] = ORIGIN + 1;
        state2[u2] = 0;
    }
}
shorttime[y] = 0;
predecessor2[y] = y;
state2[y] = 1;
selectnode2 = y;

loop2:
for (int h2 = 0; h2 < ORIGIN; h2++)
{
    if (state2[h2] == 0)
    {
        if (shorttime[h2] > shorttime[selectnode2] + (distance[selectnode2][h2] / speedMirror[selectnode2][h2][timerTD]))
        {
            shorttime[h2] = shorttime[selectnode2] + (distance[selectnode2][h2] / speedMirror[selectnode2][h2][timerTD]);
            predecessor2[h2] = selectnode2;
        }
    }
}

float currentmin2 = 500;
for (int q2 = 0; q2 < ORIGIN; q2++) // find the shortest open node time
{
    if (state2[q2] == 0)
    {
        if (shorttime[q2] < currentmin2)
        {
            currentmin2 = shorttime[q2];
            selectnode2 = q2;
        }
    }
}

for (int g2 = 0; g2 < ORIGIN; g2++) // find the predecessor node
{
    if (state2[g2] == 1)
    {
        if (shorttime[selectnode2] == shorttime[g2] + (distance[g2][selectnode2] / speedMirror[g2][selectnode2][timerTD]))
        {
            predecessor2[selectnode2] = g2;
            state2[selectnode2] = 1;
        }
    }
    if (selectnode2 == z)
    {
        // Code here
    }
}
for (int k2 = z;;)
{
    if (predecessor2[k2] == y)
    {
        if (k2 != y) return (k2);
    }
    k2 = predecessor2[k2];
}

else
{
    goto loop2;
}
#include <iostream>
#include <fstream>
#include <cstdlib>

#define DESTINATION 51
#define ORIGIN 51
#define INTERVAL 180

int DistDijkstra (int r, int s);
int TimeDijkstra (int y, int z, int timer1);
int TravelTime (int d, int n, int timer2);
int ShortestDistPath (int a, int b, int timer3);
int ShortestTimePath (int e, int j, int timer4);

float distance [ORIGIN][DESTINATION];
float speed [ORIGIN][DESTINATION][INTERVAL];

int t = 1; // time interval used between speed updates
int totaltime1 = 0;
int totaltime2 = 0;

int startnode = 0; // initialize the starting node
int endnode = 0; // initialize the goal
int currentnode = 0; // initialize the current node
int minutes = 1; // set the time equivalent of interval step
int starttime = 0; // set the start time

int m=0; // counter used to initialize the starting matrices
int n=0; // counter used to initialize the starting matrices
int xx=0; // counter used to initialize the time intervals

int main ()
{
    // initialize distances
    int size = 2601;
    float data[size];
    std::ifstream data_file("Distance.prn");

    if (data_file.bad())
    {
        cerr << "Error opening file";
        exit(8);
    }
}
for (m=0; m<size; m++)
{
    assert(m>=0);
    assert(m<sizeof(data)/sizeof(data[0]));
    data_file >> data[m];
}

for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
{
    distance [n][m] = data[xx];
    xx++;
}

// initialize speeds

int size2 = 468180;
float data2[size2];
std::ifstream data_file2("DataThur2Aft.txt");

if (data_file2.bad())
{
    std::cerr << "Error opening file";
    exit(8);
}

for (m=0; m<size2; m++)
{
    assert(m>=0);
    assert(m<sizeof(data2)/sizeof(data2[0]));
    data_file2 >> data2[m];
}

int ii=0;
for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
for (xx=0; xx<INTERVAL; xx++)
{
    speed [n][m][xx] = data2[ii];
    ii++;
}

std::cout << "Please enter the desired starting node " << "\n";
std::cin >> startnode; // read in the starting node
std::cout << "Please enter the desired ending node " << "\n";

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std::cin >> endnode; // read in the goal

currentnode = startnode; // set the start node equal to the current node

totaltime1 = ShortestDistPath (currentnode, endnode, starttime) * minutes;
totaltime2 = ShortestTimePath (currentnode, endnode, starttime) * minutes;
std::cout "The total time for ShortestDistance was " << totaltime1 "\n"
std::cout "The total time for ShortestTime was " << totaltime2 "\n"
std::cout "The total time difference is " << totaltime1 - totaltime2 "\n"
return 0;
}

int ShortestDistPath (int a, int b, int timerSDP)
{
int time1 = 0;
int timeholder1 = 0;
int nextnode1;

nextnode1 = DistDijkstra (a, b); // initialize the nextnode using Dijkstra
std::cout "The nextnode in the SDP path is " nextnode1 "\n"
while (a != b)
{
    timeholder1 = TravelTime (a, nextnode1, timerSDP);
    time1 = time1 + timeholder1;
    timerSDP = time1;
    a = nextnode1;
    if (a == b) break;
    nextnode1 = DistDijkstra (a, b);
    std::cout "The nextnode in the SDP path is " nextnode1 "\n"
}
return (time1);
}

int ShortestTimePath (int e, int j, int timerSTP)
{
int time2 = 0;
int timeholder2 = 0;
int nextnode2;
std::cout "The STP algorithm is now being run " "\n"
nextnode2 = TimeDijkstra (e, j, timerSTP);
std::cout "The nextnode in the STP path is " nextnode2 "\n"
while (e != j)
{
    timeholder2 = TravelTime (e, nextnode2, timerSTP);
    time2 = time2 + timeholder2;
    timerSTP = time2;
}
e = nextnode2;
if (e == j) break;
nextnode2 = TimeDijkstra (e, j, timerSTP);
std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
}
return (time2);

int TravelTime (int d, int n, int timerTT)
{
    float c = 0;
    float f = 0;
    int l = 0;
    while (f < distance [d][n])
    {
        c = minutes * t * speed [d][n][timerTT];
        f = f + c;
        l = l + t;
    }
    return (l);
}

int DistDijkstra (int r, int s)
{
    float shortdist [ORIGIN]; // length of shortest path from r to node j
    int predecessor1 [ORIGIN]; // immediate predecessor of node j in short path
    int state1 [ORIGIN]; // state of node - either open (0) or closed (1)
    int selectnode1;

    for (int u1 = 0; u1 < ORIGIN; u1++) // initialize the labels
    {
        shortdist [u1] = 10000;
        predecessor1 [u1] = ORIGIN + 1;
        state1 [u1] = 0;
    }

    shortdist [r] = 0; // initialize the current node label
    predecessor1 [r] = r;
    state1 [r] = 1;
    selectnode1 = r;

    loop1:
    for (int h1 = 0; h1 < ORIGIN; h1++)
    {
        if (state1 [h1] == 0)
        {

if (shortdist[h1] > shortdist[selectnode1] + distance[selectnode1][h1])
{
    shortdist[h1] = shortdist[selectnode1] + distance[selectnode1][h1];
    predecessor1[h1] = selectnode1;
}
}
}

float currentmin1 = 10000;

for (int q1 = 0; q1 < ORIGIN; q1++) // find the shortest open node distance
{
    if (state1[q1] == 0)
    {
        if (shortdist[q1] < currentmin1)
        {
            currentmin1 = shortdist[q1];
            selectnode1 = q1;
        }
    }
}

for (int g1=0; g1 < ORIGIN; g1++) // find the predecessor of selectnode
{
    if (state1[g1] == 1)
    {
        if (shortdist[selectnode1] == shortdist[g1] + distance[g1][selectnode1])
        {
            predecessor1[selectnode1] = g1;
            state1[selectnode1] = 1;
            if (selectnode1 == s)
            {
                for (int k1 = s;;)
                {
                    if (predecessor1[k1] == r)
                    {
                        if (k1 != r) return (k1);
                    }
                    k1 = predecessor1[k1];
                }
            }
        }
    }
    else
    {
        goto loop1;
    }
}
int TimeDijkstra (int y, int z, int timerTD)
{
    float shorttime [ORIGIN]; // time of shortest path from y to j
    int predecessor2 [ORIGIN]; // immediate predecessor of node j is shortpath
    int state2 [ORIGIN]; // state of node - either open (0) or closed (1)
    int selectnode2;

    timerTD = 1;

    for (int u2 = 0; u2 < ORIGIN; u2++) // initialize the labels
    {
        shorttime [u2] = 500;
        predecessor2 [u2] = ORIGIN + 1;
        state2 [u2] = 0;
    }

    shorttime [y] = 0;
    predecessor2 [y] = y;
    state2 [y] = 1;
    selectnode2 = y;

    loop2:
    for (int h2 = 0; h2 < ORIGIN; h2++)
    {
        if (state2 [h2] == 0)
        {
            if (shorttime [h2] > shorttime [selectnode2] + (distance [selectnode2][h2] / speed [selectnode2][h2][timerTD]))
            {
                shorttime [h2] = shorttime [selectnode2] + (distance [selectnode2][h2] / speed [selectnode2][h2][timerTD]);
                predecessor2 [h2] = selectnode2;
            }
        }
    }

    float currentmin2 = 500;
    for (int q2 = 0; q2 < ORIGIN; q2++) // find the shortest open node time
    {
        if (state2 [q2] == 0)
        {
            // Rest of the code...
        }
    }
}
if (shorttime[q2] < currentmin2)
{
    currentmin2 = shorttime[q2];
    selectnode2 = q2;
}
}

for (int g2=0; g2 < ORIGIN; g2++) // find the predecessor node
{
    if (state2[g2] == 1)
    {
        if (shorttime[selectnode2] == shorttime[g2] + (distance[g2][selectnode2] / speed[g2][selectnode2][timerTD]))
        {
            predecessor2[selectnode2] = g2;
            state2[selectnode2] = 1;
            if (selectnode2 == z)
            {
                for (int k2 = z;;)
                {
                    if (predecessor2[k2] == y)
                    {
                        if (k2 != y) return (k2);
                    }
                    k2 = predecessor2[k2];
                }
            }
            else
            {
                goto loop2;
            }
        }
    }
}
En-route Instantaneous Model

#include <iostream>
#include <fstream>
#include <cstdlib>

#define DESTINATION 51
#define ORIGIN 51
#define INTERVAL 180

int DistDijkstra (int r, int s);
int TimeDijkstra (int y, int z, int timer1);
int TravelTime (int d, int n, int timer2);
int ShortestDistPath (int a, int b, int timer3);
int ShortestTimePath (int e, int j, int timer4);

float distance [ORIGIN][DESTINATION];
float speed [ORIGIN][DESTINATION][INTERVAL];

int t = 1; // time interval used between speed updates
int totaltime1 = 0;
int totaltime2 = 0;

int startnode = 0; // initialize the starting node
int endnode = 0; // initialize the goal
int currentnode = 0; // initialize the current node
int minutes = 1; // set the time equivalent of interval step
int starttime = 0; // set the start time

int m=0; // counter used to initialize the starting matrices
int n=0; // counter used to initialize the starting matrices
int xx=0; // counter used to initialize the time intervals

int main ()
{
    // initialize distances
    int size = 2601;
    float data[size];
    std::ifstream data_file("Distance.prn");

    if (data_file.bad())
    {
        std::cerr << "Error opening file";
        exit(8);
    }
}
for (m=0; m<size; m++)
{
    assert(m>=0);
    assert(m<sizeof(data)/sizeof(data[0]));
    datafile >> data[m];
}

for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
{
    distance [n][m] = data[xx];
    xx++;
}

// initialize speeds

int size2 = 468180;
float data2[size2];
std::ifstream data_file2("Speed5.txt");

if (data_file2.bad())
{
    std::cerr << "Error opening file";
    exit(8);
}

for (m=0; m<size2; m++)
{
    assert(m>=0);
    assert(m<sizeof(data2)/sizeof(data2[0]));
    data_file2 >> data2[m];
}

int ii=0;
for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
for (xx=0; xx<INTERVAL; xx++)
{
    speed [n][m][xx] = data2[ii];
    ii++;
}

std::cout << "Please enter the desired starting node " << "\n";
std::cin >> startnode; // read in the starting node
std::cout << "Please enter the desired ending node " << "\n";
std::cin >> endnode; // read in the goal
currentnode = startnode; // set the start node equal to the current node

totaltime1 = ShortestDistPath (currentnode, endnode, starttime) * minutes;
totaltime2 = ShortestTimePath (currentnode, endnode, starttime) * minutes;
std::cout << "The total time for ShortestDistance was " << totaltime1 << "\n";
std::cout << "The total time for ShortestTime was " << totaltime2 << "\n";
std::cout << "The total time difference is " << totaltime1 - totaltime2 << "\n";
return 0;
}

int ShortestDistPath (int a, int b, int timerSDP)
{
    int timel = 0;
    int timeholderl = 0;
    int nextnode1;

    nextnode1 = DistDijkstra (a, b); // initialize the nextnode using Dijkstra
    std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
    while (a != b)
    {
        timeholderl = TravelTime (a, nextnode1, timerSDP);
        timel = timel + timeholderl;
        timerSDP = timel;
        a = nextnode1;
        if (a == b) break;
        nextnode1 = DistDijkstra (a, b);
        std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
    }
    return (timel);
}

int ShortestTimePath (int e, int j, int timerSTP)
{
    int time2 = 0;
    int timeholder2 = 0;
    int nextnode2;
    std::cout << "The STP algorithm is now being run " << "\n";
    nextnode2 = TimeDijkstra (e, j, timerSTP);
    std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
    while (e != j)
    {
        timeholder2 = TravelTime (e, nextnode2, timerSTP);
        time2 = time2 + timeholder2;
        timerSTP = time2;
        e = nextnode2;
    }
if (e == j) break;
nextnode2 = TimeDijkstra (e, j, timerSTP);
std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
}
return (time2);
}

int TravelTime (int d, int n, int timerTT)
{
float c = 0;
float f = 0;
int l = 0;
while (f < distance [d][n])
{
    c = minutes * t * speed [d][n][timerTT];
    f = f + c;
    l = 1 + t;
}
return (l);
}

int DistDijkstra (int r, int s)
{
float shortdist [ORIGIN]; // length of shortest path from r to node j
int predecessor1 [ORIGIN]; // immediate predecessor of node j in short path
int state1 [ORIGIN]; // state of node - either open (0) or closed (1)
int selectnode1;

for (int ul = 0; ul < ORIGIN; ul++) // initialize the labels
{
    shortdist [ul] = 10000;
    predecessor1 [ul] = ORIGIN + 1;
    state1 [ul] = 0;
}
shortdist [r] = 0; // initialize the current node label
predecessor1 [r] = r;
state1 [r] = 1;
selectnode1 = r;

loop1:
for (int h1 = 0; h1 < ORIGIN; h1++)
{
    if (state1 [h1] == 0)
    {
       if (shortdist [h1] > shortdist [selectnode1] + distance [selectnode1][h1])

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\[
\{ \\
\text{shortdist}[h1] = \text{shortdist}[\text{selectnode1}] + \text{distance}[	ext{selectnode1}][h1]; \\
\text{predecessor1}[h1] = \text{selectnode1}; \\
\}
\]

float currentmin1 = 10000;

for (int q1 = 0; q1 < ORIGIN; q1++) // find the shortest open node distance
{
    if (state1[q1] == 0)
    {
        if (shortdist[q1] < currentmin1)
        {
            currentmin1 = shortdist[q1];
            selectnode1 = q1;
        }
    }
}

for (int g1 = 0; g1 < ORIGIN; g1++) // find the predecessor of selectnode
{
    if (state1[g1] == 1)
    {
        if (shortdist[selectnode1] == shortdist[g1] + distance[g1][selectnode1])
        {
            predecessor1[selectnode1] = g1;
            state1[selectnode1] = 1;

            if (selectnode1 == s)
            {
                for (int k1 = s;;)
                {
                    if (predecessor1[k1] == r)
                    {
                        if (k1 != r) return (k1);
                    }
                    k1 = predecessor1[k1];
                }
            }
        }
    }
}
else
{
    goto loop1;
}
int TimeDijkstra (int y, int z, int timerTD)
{
    float shorttime [ORIGIN]; // time of shortest path from y to j
    int predecessor2 [ORIGIN]; // immediate predecessor of node j is shortpath
    int state2 [ORIGIN]; // state of node - either open (0) or closed (1)
    int selectnode2;

    for (int u2 = 0; u2 < ORIGIN; u2++) // initialize the labels
    {
        shorttime [u2] = 500;
        predecessor2 [u2] = ORIGIN + 1;
        state2 [u2] = 0;
    }

    shorttime [y] = 0;
    predecessor2 [y] = y;
    state2 [y] = 1;
    selectnode2 = y;

    loop2:
    for (int h2 = 0; h2 < ORIGIN; h2++)
    {
        if (state2 [h2] == 0)
        {
            if (shorttime [h2] > shorttime [selectnode2] + (distance [selectnode2][h2] / speed [selectnode2][h2][timerTD]))
            {
                shorttime [h2] = shorttime [selectnode2] + (distance [selectnode2][h2] / speed [selectnode2][h2][timerTD]);
                predecessor2 [h2] = selectnode2;
            }
        }
    }

    float currentmin2 = 500;
    for (int q2 = 0; q2 < ORIGIN; q2++) // find the shortest open node time
    {
        if (state2 [q2] == 0)
        {
            if (shorttime [q2] < currentmin2)
            {
                currentmin2 = shorttime [q2];
            }
        }
    }
}
selectnode2 = q2;
}
}

for (int g2=0; g2 < ORIGIN; g2++) // find the predecessor node
{
    if (state2 [g2] == 1)
    {
        if (shorttime [selectnode2] == shorttime [g2] + (distance [g2][selectnode2] / speed [g2][selectnode2][timerTD]))
        {
            predecessor2 [selectnode2] = g2;
            state2 [selectnode2] = 1;

            if (selectnode2 == z)
            {
                for (int k2 = z;;)
                {
                    if (predecessor2 [k2] == y)
                    {
                        if (k2 != y) return (k2);
                    }
                    k2 = predecessor2 [k2];
                }
            }
        }
        else
        {
            goto loop2;
        }
    }
}
#include <iostream>
#include <fstream>
#include <cstdlib>
#define DESTINATION 51
#define ORIGIN 51
#define INTERVAL 180

int DistDijkstra (int r, int s);
int TimeDijkstra (int y, int z, int timer1);
int TravelTime (int d, int n, int timer2);
int ShortestDistPath (int a, int b, int timer3);
int ShortestTimePath (int e, int j, int timer4);

float distance [ORIGIN][DESTINATION];
float speed [ORIGIN][DESTINATION][INTERVAL];

int t = 1; // time interval used between speed updates
int totaltime1 = 0;
int totaltime2 = 0;

int startnode = 0; // initialize the starting node
int endnode = 0; // initialize the goal
int currentnode = 0; // initialize the current node
int minutes = 1; // set the time equivalent of interval step
int starttime = 0; // set the start time

int m=0; // counter used to initialize the starting matrices
int n=0; // counter used to initialize the starting matrices
int xx=0; // counter used to initialize the time intervals

int main ()
{
    // initialize distances
    int size = 2601;
    float data[size];
    std::ifstream data_file("Distance.pm");

    if (data_file.bad())
    {
        std::cerr << "Error opening file";
        exit(8);
    }
}
for (m=0; m<size; m++)
{
    assert(m>=0);
    assert(m<sizeof(data)/sizeof(data[0]));
    data_file >> data[m];
}

for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
{
    distance [n][m] = data[xx];
    xx++;
}

// initialize speeds

int size2 = 468180;
float data2[size2];
std::ifstream data_file2("DataThur2Aft.txt");

if (data_file2.bad())
{
    std::cerr << "Error opening file"
    exit(8);
}

for (m=0; m<size2; m++)
{
    assert(m>=0);
    assert(m<sizeof(data2)/sizeof(data2[0]));
    data_file2 >> data2[m];
}

int ii=0;
for (n=0; n<ORIGIN; n++)
for (m=0; m<DESTINATION; m++)
for (xx=0; xx<INTERVAL; xx++)
{
    speed [n][m][xx] = data2[ii];
    ii++;
}

std::cout << "Please enter the desired starting node " << "\n";
std::cin >> startnode; // read in the starting node
std::cout << "Please enter the desired ending node " << "\n";
std::cin >> endnode; // read in the goal
currentnode = startnode; // set the start node equal to the current node

int ShortestDistPath (int a, int b, int timerSDP)
{
    int time1 = 0;
    int timeholder1 = 0;
    int nextnode1;

    nextnode1 = DistDijkstra (a, b); // initialize the nextnode using Dijkstra
    std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
    while (a != b)
    {
        timeholder1 = TravelTime (a, nextnode1, timerSDP);
        time1 = time1 + timeholder1;
        timerSDP = time1;
        a = nextnode1;
        if (a == b) break;
        nextnode1 = DistDijkstra (a, b);
        std::cout << "The nextnode in the SDP path is " << nextnode1 << "\n";
    }
    return (time1);
}

int ShortestTimePath (int e, int j, int timerSTP)
{
    int time2 = 0;
    int timeholder2 = 0;
    int nextnode2;
    std::cout << "The STP algorithm is now being run " << "\n";
    nextnode2 = TimeDijkstra (e, j, timerSTP);
    std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
    while (e != j)
    {
        timeholder2 = TravelTime (e, nextnode2, timerSTP);
        time2 = time2 + timeholder2;
        timerSTP = time2;
        e = nextnode2;
    }
if (e == j) break;
nextnode2 = TimeDijkstra (e, j, timerSTP);
std::cout << "The nextnode in the STP path is " << nextnode2 << "\n";
}
return (time2);

int TravelTime (int d, int n, int timerTT)
{
float c = 0;
float f = 0;
int l = 0;
while (f < distance [d][n])
{
    if (speed [d][n][timerTT] < .01) { return (1000);}
    c = minutes * t * speed [d][n][timerTT];
    f = f + c;
    l = l + t;
}
return (l);
}

int DistDijkstra (int r, int s)
{
float shortdist [ORIGIN]; // length of shortest path from r to node j
int predecessor1 [ORIGIN]; // immediate predecessor of node j in short path
int state1 [ORIGIN]; // state of node - either open (0) or closed (1)
int selectnode1;

for (int u1 = 0; u1 < ORIGIN; u1++) // initialize the labels
{
    shortdist [u1] = 10000;
    predecessor1 [u1] = ORIGIN + 1;
    state1 [u1] = 0;
}
shortdist [r] = 0; // initialize the current node label
predecessor1 [r] = r;
state1 [r] = 1;
selectnode1 = r;

loop1:
for (int h1 = 0; h1 < ORIGIN; h1++)
{
    if (state1 [h1] == 0)
    {


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if (shortdist[h1] > shortdist[selectnode1] + distance[selectnode1][h1])
{
    shortdist[h1] = shortdist[selectnode1] + distance[selectnode1][h1];
    predecessor1[h1] = selectnode1;
}
}

float currentmin1 = 10000;

for (int q1 = 0; q1 < ORIGIN; q1++) // find the shortest open node distance
{
    if (state1[q1] == 0)
    {
        if (shortdist[q1] < currentmin1)
        {
            currentmin1 = shortdist[q1];
            selectnode1 = q1;
        }
    }
}

for (int g1=0; g1 < ORIGIN; g1++) // find the predecessor of selectnode
{
    if (state1[g1] == 1)
    {
        if (shortdist[selectnode1] == shortdist[g1] + distance[g1][selectnode1])
        {
            predecessor1[selectnode1] = g1;
            state1[selectnode1] = 1;
        }
    }
    else
    {
        goto loop1;
    }
}

if (selectnode1 == s)
{
    for (int k1 = s;;)
    {
        if (predecessor1[k1] == r)
        {
            if (k1 != r) return (k1);
        }
        k1 = predecessor1[k1];
    }
}
int TimeDijkstra (int y, int z, int timerTD)
{
    int shorttime [ORIGIN];    // time of shortest path from y to j
    int predecessor2 [ORIGIN]; // immediate predecessor of node j is shortestpath
    int state2 [ORIGIN];       // state of node - either open (0) or closed (1)
    int selectnode2;
    int bbb = 0;

    for (int u2 = 0; u2 < ORIGIN; u2++) // initialize the labels
    {
        shorttime [u2] = 500;
        predecessor2 [u2] = ORIGIN + 1;
        state2 [u2] = 0;
    }

    shorttime [y] = 0;
    predecessor2 [y] = y;
    state2 [y] = 1;
    selectnode2 = y;

    loop2:
    for (int h2 = 0; h2 < ORIGIN; h2++)
    {
        if (state2 [h2] == 0)
        {
            bbb = TravelTime (selectnode2, h2, shorttime [selectnode2] + timerTD);
            if (shorttime [h2] > shorttime [selectnode2] + bbb)
            {
                shorttime [h2] = shorttime [selectnode2] + bbb;
                predecessor2 [h2] = selectnode2;
            }
        }
    }

    int currentmin2 = 500;
    for (int q2 = 0; q2 < ORIGIN; q2++) // find the shortest open node time
    {
        if (state2 [q2] == 0)
        {
            if (shorttime [q2] < currentmin2)
        }
currentmin2 = shorttime [q2];
    selectnode2 = q2;
}
}
}

for (int g2 = 0; g2 < ORIGIN; g2++) // find the predecessor node
{
    if (state2 [g2] == 1)
    {
        if (shorttime [selectnode2] == shorttime [g2] + TravelTime (g2, selectnode2, shorttime [g2] + timerTD))
        {
            predecessor2 [selectnode2] = g2;
            state2 [selectnode2] = 1;

            if (selectnode2 == z)
            {
                for (int k2 = z;;)
                {
                    if (predecessor2 [k2] == y)
                    {
                        if (k2 != y) return (k2);
                    }
                    k2 = predecessor2 [k2];
                }
            }
            else
            {
                goto loop2;
            }
        }
    }
}
### Distance Matrix

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<th>Distance</th>
</tr>
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</tr>
<tr>
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<td>3</td>
<td>20.00</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>21.43</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>9.14</td>
</tr>
<tr>
<td>2</td>
<td>7</td>
<td>5.71</td>
</tr>
<tr>
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<td>1</td>
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<td>4</td>
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<td>8</td>
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[38] Wunderlich, K.E. “An Assessment of Pre-Trip and En-Route ATIS Benefits in a Simulated Regional Urban Network.” Intelligent Transportation: Realizing the Future. 1996
