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A COMBINED TRAVELER BEHAVIOR AND SYSTEM PERFORMANCE MODEL WITH ATIS

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Abstract

The goal of this study is to develop a framework for evaluating the effect of Advanced Traveler Information Systems (ATIS). The framework uses a traveler behavior model of route diversion imbedded in a queuing model to evaluate ATIS impacts in incident conditions. The unique feature of our methodology is the integration of realistic traveler behavior with a system performance model while accounting for the effect of real-time travel information.

To demonstrate the application of our methodology, we consider the evolution of queues on a two-link network with an incident bottleneck during unsaturated (off-peak) and over-saturated (peak) conditions. The assignment of traffic is based on a probabilistic reported behavior model of route diversion and a deterministic full compliance model which assumes behavior.

The results indicate that overall system performance, measured by delay and travel times, improves marginally with increased market penetration of ATIS with the reported behavior model. The reasons for limited benefits are that in real-life situations (1) people observe incident queues and receive incident information from radio reports, and (2) they place a relatively high value on avoiding queuing delay; consequently, they divert--congesting alternate routes and limiting the potential for additional benefits. The results also indicate that in certain situations, characterized by higher incident durations and flow rates, ATIS may provide significant system benefits.

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INTRODUCTION

Advanced Traveler Information Systems (ATIS) may offer significant benefits in terms of improving the travel experience of individuals and enhancing system performance. They may be particularly useful in the context of incident-induced congestion and recurring congestion. However, the true potential of these systems has yet to be evaluated. This study develops a framework for assessing the impacts of auto-related ATIS technologies in both incident and recurring congestion conditions. The framework can be used in addressing the key research issues: how will ATIS impact individual travel choices and system performance, and what are the benefits?

SYNTHESIS OF LITERATURE AND PROBLEM OVERVIEW

There have been worldwide efforts during the last decade to study various aspects of ATIS, including the evaluation of their impacts on travelers and on the transportation system (see conference proceedings of VNIS 1989 and 1991; TRB 1987-1993). But there remains a lack of "connectivity" between behavioral and system performance models, and no clearly defined mechanism exists for unifying them.

The impacts of ATIS technologies depend, to a large extent, on how travelers will respond to such systems. Therefore, it is important to understand what factors influence travel decisions. The existing behavioral choice models usually assume perfect information, that is, individuals have knowledge of all alternatives. Clearly, such an assumption cannot be supported when evaluating the effect of information. Similarly, a majority of network performance models do not explicitly account for the effect of information, and assume unrealistic behavioral rules.

The specific objective of this study is to assess traveler behavior impacts of **ATIS** technologies and the consequent system impacts at highway bottlenecks caused by incidents and recurring congestion. This research is based on our earlier work regarding impacts of congestion on traveler behavior and system performance in the presence of information (Al-Deek 1991; Khattak 1991). In this paper we enhance our previous work and develop a richer and more comprehensive approach for evaluating **ATIS** technologies. The unique features of this study are:

1) Integration of traveler behavior and system performance in the context of **ATIS**. It is based upon a dynamic network performance model (queuing) that incorporates a behavioral model responsive to traffic information.

2) Exploration of unsaturated and over-saturated conditions.

3) The possibility of congesting alternate routes as well as the issue of user equilibrium.

While **ATIS** is likely to influence travel decisions (e.g., mode, route, schedule, trip chaining, parking) and activity participation decisions (e.g., work, recreation, shopping), this study focuses on route diversions. Further, while **ATIS** may impact network performance in many ways, we choose a two-route corridor with single origin and destination. The intention is to describe our initial efforts and demonstrate the application of our methodology. Development of a network model complete with realistic behavioral rules which can evaluate impacts of information is an ambitious undertaking that would require extensive time. An ATIS-based network model may be validated by using real-life data gathered from field operational tests to be conducted in the future.

System Performance

Evaluation of system performance with **ATIS** requires the ability to model travel conditions at bottlenecks caused by incidents. With **ATIS,** drivers will be able obtain detailed information on travel conditions. Hence, traffic simulation models for **ATIS** purposes should include queuing conditions and dynamic path assignment capabilities.

Recently, an exhaustive study of existing traffic models was conducted by Gardes et al. (1990 and **1991),** followed by some applications to model traveler information systems (Gardes et al. 1993). They concluded that only three models had both assignment and queuing capabilities: SATURN, **CONTRAM,** and INTEGRATION. Based on our review of these models, it was found that none of them incorporate significant traveler behavior. INTEGRATION has dynamic path selection capabilities based on user-specified vehicle types; SATURN and **CONTRAM** do not have adequate dynamic path selection capabilities. A recent extension to **CONTRAM** is reported by Smith et al. **(1991),** in which the model is extended to accommodate a second route policy with minimum local marginal cost. However, the model assumes total compliance and travel time optimizing behavior of drivers. DYNASMART (Chang et al. 1985; Jayakrishnan and Mahmassani 1992; Chen and Mahmassani 1993) is a new macroscopic simulation model and has the ability to track individual vehicles. The model also has path selection capabilities, and appears to have route selection models based on bounded rational behavior.

The traveler decision process is an intrinsic element in modeling traffic conditions with traveler information systems. Consequently, several researchers have conducted simulation studies and/or proposed theoretical frameworks to incorporate behavioral characteristics into the traffic

modeling process (Arnott et al. 1990 and 1991; Ben Akiva et al. 1986, and 1991; Mahmassani et al. 1990; Mahmassani and Chen 1991; Mahmassani and Jayakrishnan 1991). The dynamic network modeling framework proposed by Ben-Al&a et al. (1991) presents a detailed description of the traveler decision process. Their research also explores deterministic user-equilibrium and system-optimal conditions. More specific simulation results are presented by Mahmassani et al. (1991) -- based on a three-route network. These studies address the impact of real-time information on travelers, supplied at the origin or en route, and exhibit both route switching and departure time decision capabilities. However, the studies by Mahmassani et al. do not explore the actual benefits of information under different incident and network characteristics. Studies by Arnott et al. (1990, 1991), and de Palma et al. (1991) have concentrated on the combined impact of tolls, pricing, and traveler information systems for recurrent congestion during the morning commute.

Several other researchers have also addressed the impact of information systems (Cascetta et al. 1991; Hamerslag et al. 1991; Van Vuren et al. 1991; Papageorgiou et al. 1991; Bonsall et al. 1991). However, these studies either assume total compliance of drivers, or do not incorporate realistic traveler behavior adequately. Research studies in stochastic equilibrium (Akamatsu et al. 1989; Horowitz 1984; Kawakama et al. 1989; Tsuji at al. 1985) also have not addressed the research issues presented in this paper.

Traveler Behavior

Understanding traveler behavior is complicated by a lack of strong theoretical basis and the fact that individuals change their responses over time. The important aspects of information

are its meaning and whether the information is (a) historical, real-time, or predictive, (b) qualitative or quantitative, and (c) accurate, timely, relevant, reliable (Schofer et al. 1993). On the issue of route diversion, researchers have found that travelers are more willing to divert in response to prescriptive and descriptive traffic information and increasing delays and/or congestion (Heathington 1969; Dudek et al. 1971; Dudek et al. 1983; Mannering 1989; Mahmassani et al. 1990; Allen et al. 1991; Bonsall 1991). In addition, longer trip length, lower number of traffic stops on alternate routes, and familiarity with the alternate route encourage diversion. Further, younger, male, and unmarried travelers are more likely to divert. Studies on diversion behavior provided useful insights, but indicated that the effect of information and other contextual factors on traveler behavior has not been adequately quantified.

Previous Models Considered as a Whole

Until recently the simulation/assignment models and behavioral models have been considered separately. A majority of the earlier traffic assignment models assume perfect information and rational behavior of travelers. Further, most traffic simulation models did not have route assignment capabilities. Under non-incident conditions, user equilibrium assumptions were considered acceptable, as it was believed that travelers used trial and error to find reasonable routes. However, this assumption is unrealistic when we wish to understand the effect of information. With ATIS, under non-recurrent congestion, individuals will be informed of the travel conditions on their routes, and sometimes may receive route guidance instructions. Compliance with such instructions by ATIS-equipped travelers, and diversion because of direct observation of the queue by travelers not equipped with ATIS, introduce additional complexities

to the problem. Moreover, the evaluation of benefits and their distribution is complicated because diversion of equipped travelers can benefit unequipped travelers.

It appears that no model sufficiently addresses the issue of combining system performance and traveler behavior in the presence of information. For instance, Mahmassani's bounded rational decision process and Ben-Akiva's between-day decision processes have not yet been confirmed by appropriate real-life empirical data. In addition, Van-Aerde's INTEGRATION program may not have the capabilities to represent accurate traveler behavior. These issues remain to be studied in greater detail.

CONCEPTUAL FRAMEWORK

Travel conditions are created by the interaction of network supply and travel demand. Congestion on urban area networks can be classified as incident-induced and recurring. Incidents reduce the network supply by reducing capacities of the network links. They can also reduce travel demand on certain routes, e.g., an automobile commuter may decide to change the usual route due to unexpected congestion.

Strategies for Information Dissemination

Managers of the transportation system will use variable message signs, in-vehicle information systems, and other **ATIS** technologies to optimize performance with either a user equilibrium (i.e. optimize travel time for each user) or system optimal strategy (i.e. optimize the total travel time for all users in the system). Each strategy will have a different effect on network supply, traveler decisions, travel demand, and may result in different travel conditions (see

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example presented by Ben-Akiva et al.(1991)). System performance can be evaluated for the strategy implemented.

This research investigates impacts of various information dissemination strategies on traveler behavior and system performance. Here we focus on strategies to produce user equilibrium:

Providing Descriptive Information. ATIS provides travelers with a description of traffic events such as incidents. This may support travelers' choice of route. No specific advice is given to travelers. Descriptive information may be qualitative or quantitative or both, An example of qualitative information is the message: "There is an accident at ___ [location];" an example of quantitative information is the message: "The accident will be cleared within one hour." Based on this strategy, travelers can be assigned according to how they would actually make diversion decisions, e.g., based on a reported behavior model.

Providing Prescriptive Information. ATIS gives instructions or advice on travel choices. Like descriptive information, prescriptive information can be qualitative or quantitative, or it can be a mixture of both. An example of a mixture of qualitative and quantitative information is to advise travelers to use a certain route and justify the advice by giving the expected time savings if the suggested route is followed. Based on this strategy, travelers can be assigned to the minimum time route if they are informed. In this strategy we assume full compliance by travelers.

Traveler Decisions

We hypothesized that traveler decisions can be influenced by real-time travel information

such as traffic reports and **ATIS** devices as well as by the following factors:

- Incident characteristics such as length of delay,

- Trip characteristics such as trip origin and destination and availability of alternate routes,

- Attributes of the preferred and alternate routes such as travel time and scenery,

- Environmental conditions such as weather,

- Traveler characteristics such as age, gender, and personality,

- Work rules such as flexibility in work arrival time and type of work, and

- Situational constraints such as remaining trip length.

During a trip travelers perceive information through direct and indirect contact with the environment; in response they make en route decisions. When there is a major delay, and a traveler perceives this, he or she may be motivated to change travel decisions, e.g., divert to an alternate route, add or cancel intermediate stops, or take public transit (after parking the vehicle). Travelers will change routes only if and when their delay thresholds are reached. While it is difficult to measure a person's thresholds, reported behavior can indicate whether the threshold was reached; e.g., if a person diverts in response to delay, then his or her time threshold was reached.

METHODOLOGY

Theoretical Models for System Performance

In the real world, traffic diversion during incidents can be complicated. Under normal

conditions, the hypothesis is that the transportation system is in equilibrium; i.e., no driver can improve his/her travel time by switching routes (**Wardrop** 1952). Traffic incidents cause system disequilibrium, and travelers may be able to reduce their travel time by diverting to alternate routes. Actual diversions will depend on many factors, including incident, network, and traveler behavior characteristics. The addition of **ATIS** increases the complexity of measurement, as the travelers' perception of the **ATIS** system and compliance to guidance instructions are also essential factors in estimating the total system benefits. In the following sections we will describe in detail the elements of our assumptions and models used in our research framework.

Idealized Corridor and Assumptions

The network analyzed in this paper is a simplified corridor which consists of two routes connecting a single origin (point A) and a single destination (point B), as shown in Figure 1. We have used a simplified corridor because we believe it is important to develop a comprehensive model which integrates traveler behavior and queuing at bottlenecks in a simple network before extending the model to simulate larger scale networks.

Route 1 is a freeway with capacity μ_1 and free-flow travel time T_1, and Route 2 is an alternate route with free flow travel time T_2 and capacity μ_2, where $\mu_2 \leq \mu_1$. The alternate route may represent a collection of city streets with lower speeds and very large capacity, or it could be a freeway with longer travel distance than Route 1. Furthermore, $T_1 < T_2$, and it is assumed that travel times on Routes 1 and 2 are independent of flow except under queuing conditions. This assumption has been empirically validated by Hurdle and Solomon (1986). The incident occurs at point C and reduces the capacity of Route 1 from μ_1 to μ_1^*. The incident occurs at time

t* and lasts for a duration **T.** As illustrated in Figure 1, point C is τ units of travel time away from point **A** along Route 1, and $0 < \tau < T_I$. If the arrival flow rate to point C, h,(t), exceeds the capacity of the bottleneck, a queue forms upstream of the incident bottleneck on Route 1.

In this paper, we simulate incidents which occur during the off-peak period (when demand is less than normal capacity and traffic conditions are unsaturated). Normal capacity is defined as flow under non-incident conditions. Moreover, incidents which occur during the peak period, or during over-saturated conditions, are also simulated. The cumulative queuing diagram for incidents is illustrated in Figure 2. During the unsaturated conditions arrival rate h,(t) is assumed to be constant, while during the over-saturated conditions h,(t) is a function of time.

ATIS information will be directed at traffic as it approaches point **A.** Once travelers pass point **A,** information from **ATIS** becomes irrelevant since they would already be committed to one of the two routes. In the absence of queues, Route 1 is usually preferred to Route 2. When the delay on Route 1 exceeds the difference in free-flow travel times between Routes 1 and 2, that is T_2-T_I, travelers may be able to reduce their travel time by switching to Route 2. However, if the travelers are unaware of the expected travel times and delays, they may continue to travel on Route 1, perpetuating disequilibrium between the two routes.

The amount of queuing delay experienced by a traveler depends on his/her arrival time at junction **A.** The expected delay at an arrival time **t** can be determined from the daily cumulative arrival pattern at the location of incident and the capacity of the section during the incident. Thus, based on their usual arrival times at the location of the incident, travelers could be advised of the expected delay and guided to alternate routes. A microscopic time slice approach for calculating expected delays is presented in the next section.

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Determination of Queuing Delays on Routes

In this section we derive the formulas for delays on Routes 1 and 2 with and without diversion as illustrated in Figures 3 and 4. Traffic arrives at the incident location according to curve $A_C(t)$ as shown in Figure 3. The departure curve $D_C(t)$ shows the departure from the incident bottleneck. The departure flow rate is initially μ^*_1, the reduced capacity of the bottleneck, and then after the incident is cleared at time T, is the restored capacity, μ_1.

The delay to the travelers arriving during the nth time interval on Route 1 in case of no traffic diversion to Route 2, is denoted as $d(t_n)$, and is given by:

$$d(t_n) = d(t_{n-1}) + (t_n - t_{n-1})((\lambda_n / \mu_1) - 1), \qquad \text{for } t_,, t_{n-1} > T' \qquad (1a)$$

$$d(t_n) = d(t_{n-1}) + (t_n - t_{n-1})((\lambda_n / \mu^*_1) - 1), \qquad \text{for } t_,, t_{n-1} < T' \qquad (1b)$$

where

$\quad d(t_n)$ = expected delay of travelers arriving during time interval t_n without diversion

$\quad d(t_{n-1})$ = expected delay of travelers arriving during time interval t_{n-1} without diversion

$\quad \lambda_n$ = arrival rate during time interval (t_{n-1}, t_n). Here, λ_n, equals the reciprocal of

$\qquad$ the inter arrival time or $1 / (t_n - t_{n-1})$

$\quad \mu_1$ = normal capacity of Route 1 without incidents

$\quad \mu^*_1$ = incident reduced capacity of Route 1

$\quad T'$ = $A_C^{-1}(\mu^*_1 T)$

$\qquad (= \mu^*_1 T / \lambda$, for the off-peak scenario with uniform arrival rate $\lambda)$

Note that $A_C^{-1}(\mu^*_1 T)$ does not account for the actual queue length and assumes that the queue does not occupy space (the physical growth of the queue is not calculated). When there is diversion to Route 2, the arrival curves to Routes 1 and 2 are affected and the above formulas

have to be modified. The modified delay formulas for Route 1 are:

$$d_1(t_n) = d(t_{n-1}) + (t_n - t_{n-1}) [(\lambda_n (1-r) / \mu_1) - 1], \quad \text{for } t_n, t_{n-1} > T' \qquad (2a)$$

$$d_1(t_n) = d(t_{n-1}) + (t_n - t_{n-1}) [(\lambda_n (1-r)/ \mu_1^*) - 1], \text{ for } t_n, t_{n-1} < T' \qquad (2b)$$

The formula for Route 2 is derived in a similar way as shown in Figure 4 and is given by:

$$d_2(t_n) = d_2(t_{n-1}) + (t_n - t_{n-1}) [(\lambda_n r / \mu_2) - 1] \qquad (3)$$

where $d_1(t_n)$ = expected delay of travelers arriving during time interval t_n on Route 1 with

diversion

$d_2(t_n)$ = expected delay of travelers arriving during time interval t_n on Route 2 with

diversion

μ_2 = normal capacity of Route 2

r = the proportion of travelers diverting to Route 2 between time t_{n-1}, and t_n.

Since the queue length at time when the incident occurs is zero, and the capacities and the flow rate can be measured by traffic sensors (such as loop detectors) and are known at all times, the delay at any time, t, can be determined using the above expression. The advantage of this approach is that it can represent individual behavior microscopically by choosing the time interval to be **sufficiently** small to reflect individual arrivals (we have used such an approach in our simulation). Furthermore, the above queuing equations are independent of the shape of the arrival and departure curves. Daily arrival patterns also can be simulated by approximating them linearly for small time intervals.

In the previous paragraphs we presented a time slice approach for determining bottleneck delays. Next, we discuss traffic assignment models used in conjunction with simulation of traffic delays at bottlenecks.

Microscopic Traffic Assignment and Simulation

Two traffic assignment models were used to estimate the reduction in delay due to **ATIS** in the simplified corridor. In the first model, travelers equipped with **ATIS** fully comply with information, that is they follow diversion instructions to the alternate route. In the second model, travelers are assigned randomly to routes with those informed through electronic media more likely to divert under incident conditions than those who observe congestion. The probabilities of diversion are based on travelers' responses of a survey conducted in the Chicago area (Khattak 1991). Results of the two models are compared to show the difference in the estimated benefits of **ATIS** between a model which assumes traveler behavior and another which explicitly considers traveler behavior.

Full Compliance Model

This model assumes traveler behavior such that **ATIS** equipped travelers always follow instructions by diverting to the shortest travel time route. Hence, whenever an equipped traveler arrives at junction A and is informed that travel time (including delay) on Route 1 is larger than travel time on Route 2, he or she uses Route 2 ($r=1$ because the time interval was set to reflect individual arrivals), The delay information is available only to equipped travelers. Unequipped travelers continue to choose Route 1 even when Route 2 travel time is smaller ($r=0$). Furthermore, the information regarding delay is updated for each time interval (every individual arrival).

Reported Behavior *Model*

The methodology used to capture realistic response of travelers to existing real-time traffic information uses a traveler behavior model based on a survey of travelers in Chicago. Automobile travelers who made repeated trips during which quantitative real-time traffic information broadcast by electronic media was available to them were asked via a mail-back survey if they knew about a delay, and if so what was the context and did they divert to an alternate route (see Khattak 1991).

A binary **logit** model of route choice was estimated using the responses of those who knew about the traffic delays **(N=382).** The dependent variable was the decision to divert to an alternate route or stay on the usual commute route. Table 1 shows a simple version of the model. A positive sign indicates increased likelihood of diverting. Longer travel times on the usual route and longer delay increase the probability of diversion. Travelers are more likely to take alternate routes if they receive delay information through traffic reports as opposed to observing congestion. This variable captures the effect of various attributes of information such as accuracy and relevance. Furthermore the information given in Chicago are point-to-point travel time and delay (quantitative and real-time).

The delay threshold in the model suggests that individuals are significantly more likely to divert if the expected delay exceeds 20 minutes. The use of a threshold is justified because travelers are expected to become sensitive to delay on their usual route only if it exceeds a certain level. For the sake of simplicity driver attributes are currently not included in the model--their inclusion is a logical extension of our framework. Also, the behavioral model does not consider those who reported that they never divert (30% of the sample) and those who did not

know of a delay within the past six months.

To assign individuals between the routes, the probability of diversion is calculated. Then a random number, n, is generated between 0 and 1. Suppose that P[diversion] = x, then

If (n ≤ x), then r = 1, otherwise r = 0.

The assignment model assumes individuals can observe the queue at point A. Such an assumption is restrictive, however in the simplified corridor this is the only decision point beyond which diversion is not possible. The impacts of additional delays caused on Route 2 by diversion due to incidents could not be quantified in the context of the survey due to limitations of survey research. With **ATIS,** equipped travelers may be able to obtain delay information on their alternate routes, and this additional information may also affect their diversion probability. Note that Route 1 travelers may have different thresholds for Route 2 delays, i.e., they may perceive stopped delays and free-flow travel times on Route 2 differently. However, in this behavioral model it was assumed that for both informed and uninformed drivers, the expected travel time on Route 2 was equal to the free-flow travel time.

In the following sections the reported behavior model (representing real-life situations) is compared with the full compliance model (future **ATIS** scenarios) to explore how much *additional* benefits would be achieved with **ATIS.**

SIMULATION OF SYSTEM PERFORMANCE

Description of the Simulation Experiment

The corridor performance was simulated using the full compliance and the reported behavior models. Incident cases were generated from a pool of random incident parameters (e.g.,

duration, capacity reduction, and location). Each parameter was generated randomly from a user specified range of values. For example, the range of the incident duration was determined on the basis of literature, as pointed out later. A base case was also simulated for each set of incident parameters. Under the base case it is assumed that no traveler has access to information, and hence all travelers stay on Route 1 (although Route 2 could be faster) throughout the simulation. Traffic conditions are simulated from the time the incident occurs until incident queue on Route 1 completely vanishes under the base case (no diversions).

The number of lanes on Route 1 was selected randomly from a range of 3 to 5 lanes with a capacity of 30 vehicles/lane/minute. This represents a typical freeway section in urban areas. The free-flow travel time on Route 1 can range from 15 to 60 minutes. The capacity of the alternate route was selected randomly from 10 vehicles/minute to the maximum capacity of the primary route (Route 1). The lower limit of 10 vehicles/minute was chosen to reflect a single lane local street. The travel time on the alternate route was determined by increasing the travel time on the primary route by an additional travel time between 0 and 30 minutes. These limits were also selected to ensure that the alternate route free-flow travel time was not less than the primary route free-flow travel time. Also, if the travel time difference between the two routes is large, then in most cases the Route 2 cannot be considered as a suitable alternate.

The location of the incident was randomly simulated on the primary route between points A and B (Figure 1). It should be noted that the location of the incident primarily determines the initial number of vehicles which are trapped on the primary route between points A and C. The capacity of the primary route during the incident was also randomly determined and ranged from almost total closure to almost no loss of capacity. The incident started at time 0 and the incident

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duration ranged from 15 to 60 minutes. These limits were based on our judgement and literature

on incident durations (DeRose 1964, Goolsby 1971, Juge et al. 1974, Golob et al. 1987, Giuliani

1989, and Jones et al. 1991). The arrival rate was also randomly determined and was assumed

to be constant during each simulation run. The unsaturated conditions were considered first,

where flows were always less than capacity before the incident started and after it was removed.

This reflects the occurrence and dissipation of incidents during off-peak. While most incidents

that were analyzed occurred during the unsaturated conditions, over-saturated conditions that last

for a specified duration were also considered in our analysis. In some of the incident cases, the

capacity of the primary route during incidents was greater than the flow rate, hence, the vehicles

experienced no delay.

Simulation results

In this section we present simulation results on the following issues:

- Changes in average delays (an indicator of system performance) with respect to market

  penetration of information;

- Travel times on routes and network equilibrium;

- Sensitivity of average delay to various incident parameters.

The results of two incident scenarios are presented to illustrate various concepts. The first

scenario represents incidents that occur during unsaturated conditions. The parameters for this

scenario are as follows. Route 1 free-flow travel time, T_1, is 15 minutes; Route 2 free-flow travel

time, T_2, is 25 minutes; Route 1 capacity, μ_1, is 90 vehicles/minute; Route 2 capacity, μ_2, is 40

vehicles/minute; corridor demand, h,(t), is 80 vehicles/minute; incident reduced capacity, μ^*_1, is

22.5 vehicles/minute; the incident location, τ, is 10 minutes from point $\boldsymbol{A;}$ and the incident duration, T, is 60 minutes. The second scenario represents incidents that occur during **over**-saturated conditions. The parameters for the second scenario are the same as those for the first scenario except that the corridor demand, h,(t), increases uniformly from 80 to 100 vehicles/minute during the **first** hour and decreases at the same rate thereafter. Next, we present the results of the full compliance and the reported behavior models under these two incident scenarios.

Results of the Full Compliance Model. The findings indicate that for both over-saturated and unsaturated scenarios the average delay for **all travelers** decreases with an increase in market penetration of equipped travelers (see Figures 5 and 6). This decrease continues up to a certain penetration level, after which no further significant reduction in delay can be achieved. The critical penetration level is around 50% (in this example), which is the level at which queues form on Route 2 as a result of diversion. The effect of increase in market penetration on average delay of equipped traffic depends on the particular incident scenario. For example, in case of the unsaturated incident scenario, an increase in market penetration has no effect on average delay as long as it is below **50%,** the critical level above which Route 2 becomes congested. When the penetration level exceeds **50%,** equipped traffic is diverted to the congested Route 2, and therefore, experiences increase in delay. In case of the over-saturated scenario, under the assumptions of the full compliance model, once an incident occurs equipped traffic is diverted to Route 2 (in this particular example). As a result Route 2 becomes more congested because the corridor demand is higher than capacity. Hence, the benefits of equipped traffic in the **over**-saturated conditions are reduced (average delay for equipped traffic increases sharply until the

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50% penetration level is reached but increases marginally after that where conditions become fully saturated). Another observation, in this particular example, is that the maximum reduction in average delay is much larger in the over-saturated incident than it is in the unsaturated scenario (e.g., around 30 minutes maximum reduction in average delay for the scenario of **over-**saturated conditions, compared with 18 minutes for the unsaturated conditions).

The travel times on Routes 1 and 2 for the two scenarios are depicted in Figures 7 through 10. These figures represent results for cases with 54% and 100% penetration of information analyzed for both incident scenarios.   As expected, the travel time on Route 1 increases initially due to the incident queuing delay while travel time on Route 2 starts to increase later as more vehicles divert to it. In all of these graphs, there is a period during which travel times on the two routes become equal (equilibrium duration). At the end of equilibrium, travel time on the freeway becomes less than that on Route 2 and no more diversion occurs. The increase in Route 2 travel time is due to the congestion caused by diversion.   In the **over-**saturated incident scenario, queues take longer to dissipate than with the unsaturated scenario. This results in longer diversion and equilibrium durations for the same percentage of equipped traffic. This is'obvious when comparing between Figures 7 and 8, and between Figures 9 and 10.

Results of the Reported Behavior Model. In this section we compare results of the same numerical example using the reported behavior model. As opposed to the full compliance model, the results do not show a clear trend of average delay with the increase in market penetration, see Figures 11 and 12. Hence, the relationship between average delay and market penetration of information will be investigated further using a regression model presented later. The average

delay in the reported behavior model is smaller than the full compliance model. Some informed travelers may not necessarily divert to the shorter travel time route, while some uninformed travelers observe the incident queue and divert to the shorter travel time route. The net effect of increasing market penetration on reduction of average delay depends on the diversion behavior of both informed and uninformed. Average delay may decrease with penetration in some cases (as demonstrated in this numerical example) but it may increase in others. In any case, note that the maximum reduction in average delay with increased market penetration of information for the behavioral model is much less than that of the full compliance model.

The results also illustrate the difference in travel times on both routes between the two models, see Figures 13 through 16. Equilibrium of travel times between the two routes has not been achieved in the behavior model because of insufficient diversion and/or because of over-diversion to Route 2. As expected, for the unsaturated conditions, travelers (whether or not they receive traffic information) are reluctant to divert for small savings in travel time to Route 2, see Figures 13 and 14. For incidents that occur in over-saturated conditions, both informed and uninformed travelers may over-divert to Route 2 (i.e., they may over-react), see Figures 15 and 16. In this example, it has been shown that in both over-saturated and unsaturated conditions, equilibrium between the two routes is not achieved. Also note that the queue on Route 2 lasts longer than that on Route 1.

Summary of System Performance. The difference in benefits were further analyzed by simulating a total of 1,167 random scenarios in the parameter ranges specified above. All scenarios were for unsaturated conditions, and the number of scenarios were arbitrarily chosen large enough to produce statistically significant results. For each run, the network was simulated

initially for the base case with no diversion, followed by the full compliance and reported

behavior models. The cases simulated included many where information about delay will not be

of benefit to travelers (from a system performance perspective). This occurs when the maximum

delay encountered on the primary route never exceeds the difference between the travel times on

both routes.

The averages of input parameters are presented in Table 2(a), and a comparison of

network performance measures is presented in Table 2(b). The measures were determined as

follows:

$$\text{Average duration of queue} \quad = \sum (T_q) / N$$

$$\text{Average delay per vehicle} \quad = \sum (d) / N$$

$$\text{Average percent of diversion} = \sum (p_{div}) / N$$

$$\text{Average travel time} \quad = \sum (t) / N$$

where

      N = Total number of scenarios

      T_q = Total duration of queue in the corridor for each scenario

      d = Average delay per vehicle for each scenario

      p_{div} = Percent of vehicles diverted for each scenario

      t = Average travel time in the corridor (i.e., free-flow travel time plus delay) for

               each scenario

The results show that the average queue duration on Route 1 and the average delay is shortest

for the reported behavior model. This is because in the behavioral model individuals can observe

congestion and they divert to avoid queuing delay, even though they may not save travel time. That is the probabilistic framework to make diversion more likely than the full compliance model in cases of delay on Route 1. Note that the queuing delay on Route 2 is higher in the reported behavior model, suggesting that in real-life individuals may be more likely to congest alternate routes partly due to lack of adequate information on alternate route performance. Further, the average travel time plus delay experienced on both routes is about the same for both models; however, it is smaller than the base case. The sample size for Route 2 travel time plus delay is smaller because it is calculated only if someone diverts. Note that for the full compliance model queuing delay was not large enough to warrant diversion in more scenarios than the behavioral model.

There are a total of 493 (42.2%) cases where the full compliance model results in lower average delay plus free-flow travel times compared with the reported behavior model, i.e., greater benefits. We found that such cases were characterized by higher values of incident duration, flow rate, Route 2 travel times, and capacity difference between Route 1 and Route 2 (at 5% level of significance). For example, in some cases additional reduction in delay of 18 minutes per vehicle were achieved with the full compliance model (over what reported behavior model can achieve). In the rest of the cases, the reported behavior demonstrates larger benefits than the ATIS full compliance model. This is a result of diversion of travelers based on traffic reports and/or queue observation. Therefore, active route guidance may not improve travel conditions, and it may be better (in the system performance sense) not to use ATIS in these situations.

A regression analysis including all the simulation runs for the reported behavior model (unsaturated conditions) was performed to summarize the association among network and incident

22

parameters and average delay. Note that the regression model is not causal, because the simulation assumes some of these relationships to start with (there was, however, a realistic chance of finding out that percent informed was not significant). The main value of regression is in analyzing the relative impacts of variables on delay while considering many scenarios, enhancing the generalizability of results.

The variables included in the regression analysis are shown in Table 3. The signs of the variables are as expected. Lower average delay per vehicle is weakly associated with increase in percent informed through radio traffic reports (as opposed to observation); lower delay is associated with higher capacity of the alternate route; and average delay increases with increasing incident duration and location (away from the decision point), higher capacity loss and higher travel time difference between the two routes.

CONCLUSIONS

In this paper, we have reported two models to evaluate the benefits of information (the benefit is measured in terms of travel times and delay due to information dissemination on traffic incidents). In the first model (the full compliance model), travelers equipped with **ATIS** fully comply with information; that is, they follow diversion instructions to the alternate route. In the second model (the reported behavior model), travelers are assigned probabilistically to routes with those receiving traffic information (e.g. radio reports) being more likely to divert under incident conditions than those who observe traffic congestion. The probabilities of diversion are based on travelers' responses to a behavioral survey conducted in the Chicago area. Results of the two models were compared to show the difference in estimated benefits of **ATIS** between a model

which assumes traveler behavior and another which explicitly considers traveler behavior. The reported behavior model presented diversion benefits of an existing traffic reporting system (and/or benefits because of diversion due to traveler's observation of incident queues). On the other hand, the full compliance model reflected the benefits that could be gained when **ATIS** is implemented.

It was clear from the full compliance model that for the same level of market penetration the maximum reduction in average delay was higher for incidents which occur during **over-**saturated conditions than those which occur during off-peak (or unsaturated conditions). The net effect of increasing market penetration on reduction of average delay depends on the diversion behavior of both equipped and unequipped travelers. Average delay may decrease with penetration in some cases (as was demonstrated in this paper) and it may not decrease in others.

Although the two models used entirely different set of assumptions and represented two different information scenarios (one with **ATIS** and another with reported diversion behavior), we found that the results of some system performance measures (e.g., average travel time in the corridor) are close. Following the results of the survey, the probabilistic behavior model placed high weight on the queuing delay and accounted for observation of congestion. This caused more traffic (informed and uninformed) to divert to the alternate route. When the two models were compared for the same market penetration level of information, smaller average delay per vehicle and smaller duration of queues were achieved under the assumptions of the reported behavior model. However, this benefit was offset by the longer free-flow travel time experienced by diverted traffic on the alternate route. On regular commute trips individuals acquire experience and update their knowledge of travel conditions by observation (and/or radio reports). They are

able to observe incident queues; some divert and consequently may benefit. Diverters may, however, congest alternate routes and reduce the chance of travelers equipped with **ATIS** to benefit by diversion. Although both models agreed in the sense that the benefits of an **ATIS** under incident conditions are expected to be marginal (at least in the analyzed two-route corridor), there are cases where active guidance can produce significant system benefits (e.g., incident cases with high demand rates, long incident durations). In such cases **ATIS** can be used to provide prescriptive information along with descriptive information. However, in other cases, it may be sufficient to listen to descriptive information (provided by traffic reports) and/or observe incident queues and possibly divert. Finally, there is a need to investigate benefits from diversion in larger-scale networks where several routes with surplus capacity are available for traffic diversion.

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TABLES AND FIGURES

TABLE 1: Traveler behavior Input for Reported Behavior Model

Variables	β	(t-Statistics)
Constant	-0.115	(-0.37)
Information source (= 1 if delay information received from radio traffic reports, = 0 if observation of delay)	0.384	(1.76)
Length of delay (= 1 if greater than 20 min, 0 otherwise)	0.443	(2.02)*
Average travel time on usual route (Minutes)	0.024	(2.96)*
Travel time on alternate route (Minutes)	-0.029	(-3.9 1)'

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Summary Statistics

Initial log-likelihood	-264.78
Log-likelihood at convergence	-250.75
Number of observations	382
Percent correctly predicted	**57.85**

* - acceptable at 0.05 level of significance

TABLE 2(a): Summary of Input Parameters for unsaturated conditions

DESCRIPTION OF INPUT	AVERAGE (RANGE)
Capacity of Route 1 (Vehicles/Minutes)	120 (90-150)
Capacity of Route 2 (Vehicles/Minutes)	58.5 (10-150)
Incident Capacity (Vehicles/Minutes)	32.0 (10-150)
Free-flow Travel Time on Route 1 (Minutes)	32.1 (5-60)
Free-flow Travel Time on Route 2 (Minutes)	46.5 (5-90)
Flow Rate (Vehicles/Minute)	62.3 (30-150)
Incident Location (Minutes)	15.9 (1-60)
Incident Duration (Minutes)	37.2 (15-60)
Percent Informed (%)	50.2 (0-100)

TABLE 2(b): Summary of System Performance Measures

DESCRIPTION OF OUTPUT	NO DIVERSION (Base Case) AVERAGE	FULL COMPLIANCE AVERAGE	REPORTED BEHAVIOR AVERAGE	
Average Duration of Queue on Route 1 (Minutes)	105.1	81.2	41.6	
Average Duration of Queue on Route 2 (Minutes)	0.0	3.3	7.1	
Average Delay per Vehicle (Minutes)	9.0	6.5	4.1	
Average Percent of Diversion (%)	0.0	3.7	13.8	
Average Free-flow Travel Time plus Delay *Experienced* on Route 1 (Minutes)	41.1	***38.8***	36.4	
Average Free-flow Travel Time plus Delay *Experienced* on Route 2 (Minutes)	0.0	41.7 (N=588)[*]	**49.3** (N=1097)[*]	
Average Free-flow Travel time plus Delay Experienced on Both Routes (Minutes)	41.10	38.8	38.1	

[*] Travel times were calculated based on the actual travel times plus delay *experienced* due to diversions, so the sample size is smaller; for all the rest N = 1167.

TABLE 3: Impact of Factors on Network Performance (Average Delay) Based on Reported Behavior Model

Variables	β	(t-Statistics)
Constant	-5.027	(-9.88)
Travelers who receive information (%)	-0.513	(-1.70)
Incident location (Minutes)	0.156	(22.53)*
Incident duration (Minutes)	0.064	(9.69)*
Arrival rate (Vehicles/Minute)	-0.004	(-1.29)
Free-flow travel time difference between primary and alternate routes (Minutes)	0.039	(3.89)*
Loss of capacity on primary route during incident (Vehicles/Minutes)	0.062	(20.50)*
Capacity of alternate route (Vehicles/Minutes)	-0.023	(-9.14)'

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Summary Statistics

R Square	0.48
Number of observations	1167
Sum of Squares	
Regression	9525.33
Residual	10204.43

* - acceptable at 0.05 level of significance
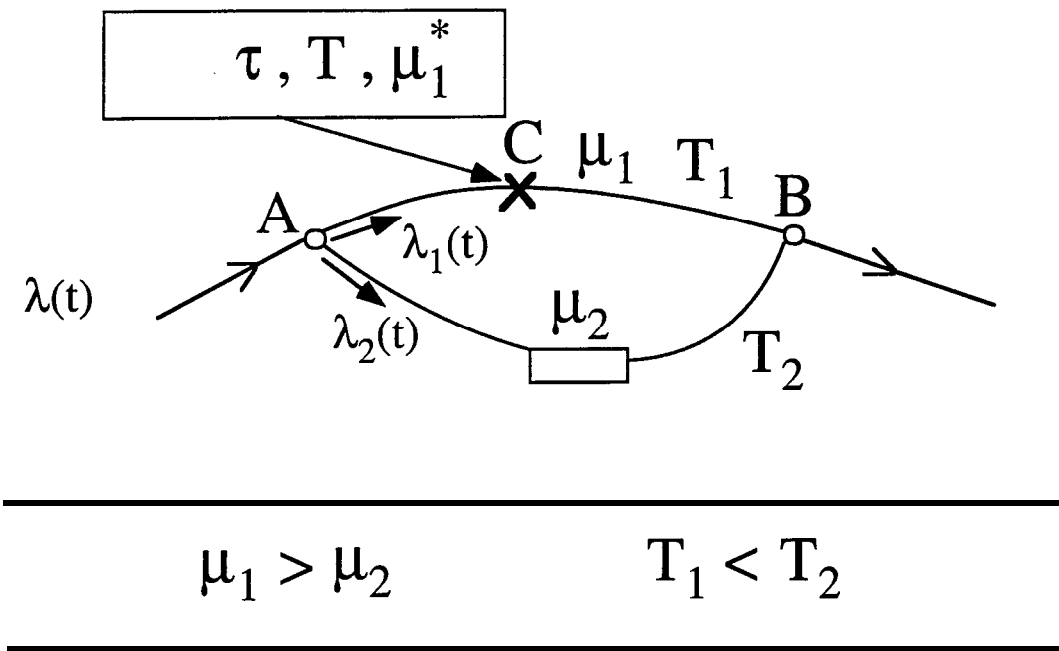
Figure 1: Corridor and incident parameters

Tl = Free flow travel time on Route 1
T2 = Free flow travel time on Route 2

μ_1 = Route 1 capacity

μ_2 = Route 2 capacity

λ_1 (t) = Flow rate on Route 1

λ_2 (t) = Flow rate on Route 2

λ (t) = Total flow rate

τ = Location of incident from point A
T = Incident duration

μ_1 * = Route 1 capacity during incident
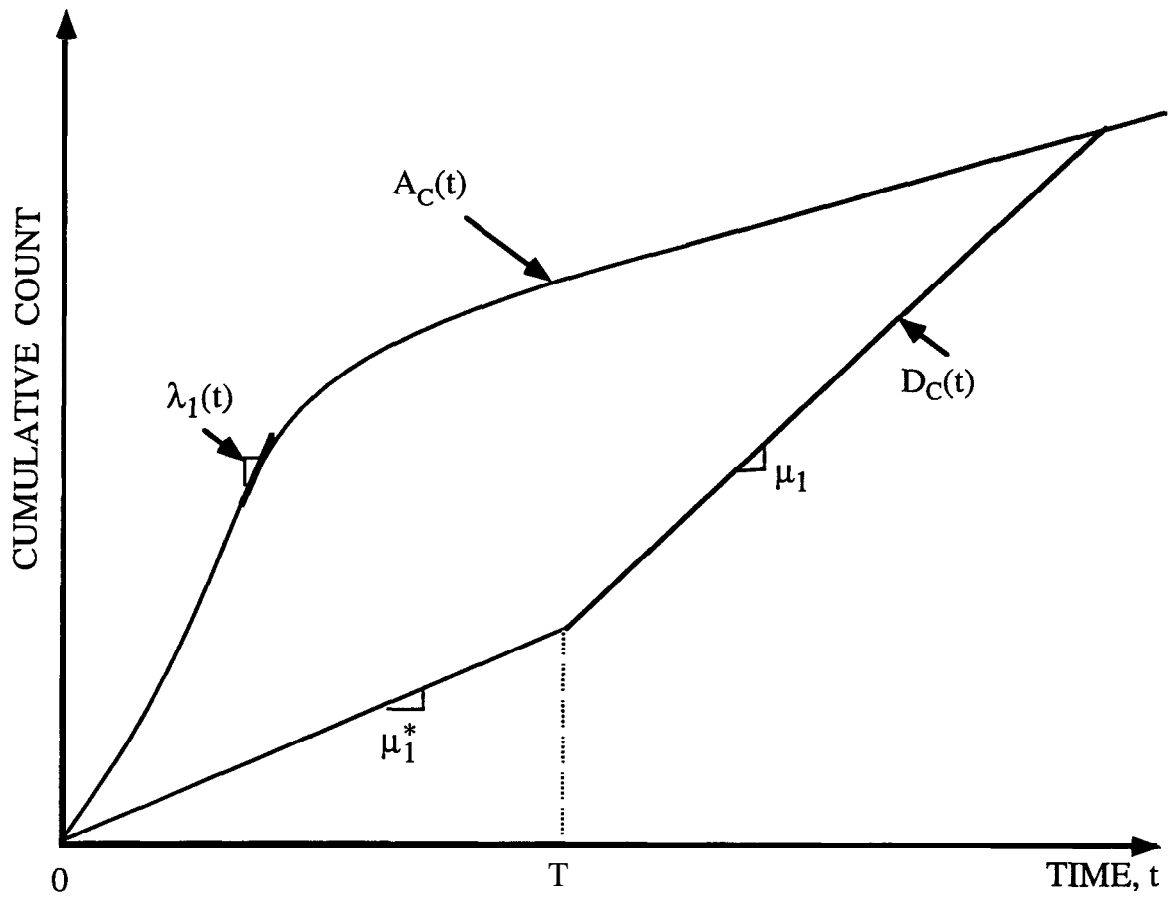
Figure 2: Queueing diagram for incident conditions

A, (t) = Cumulative arrivals

D_C (t) = Cumulative departures

μ_1 = Route 1 capacity

λ_1 (t) = Arrival rate on Route 1 at time t

μ_1^* = Route 1 capacity during incident

Figure 3: Derivation of delay formula for Route 1
(without diversion)

$A_c(t)$ = Cumulative arrivals

$D_c(t)$ = Cumulative departures

μ_1 = Route 1 capacity

$\lambda_1(t)$ = Arrival rate on Route 1 at time t

μ_1^* = Route 1 capacity during incident
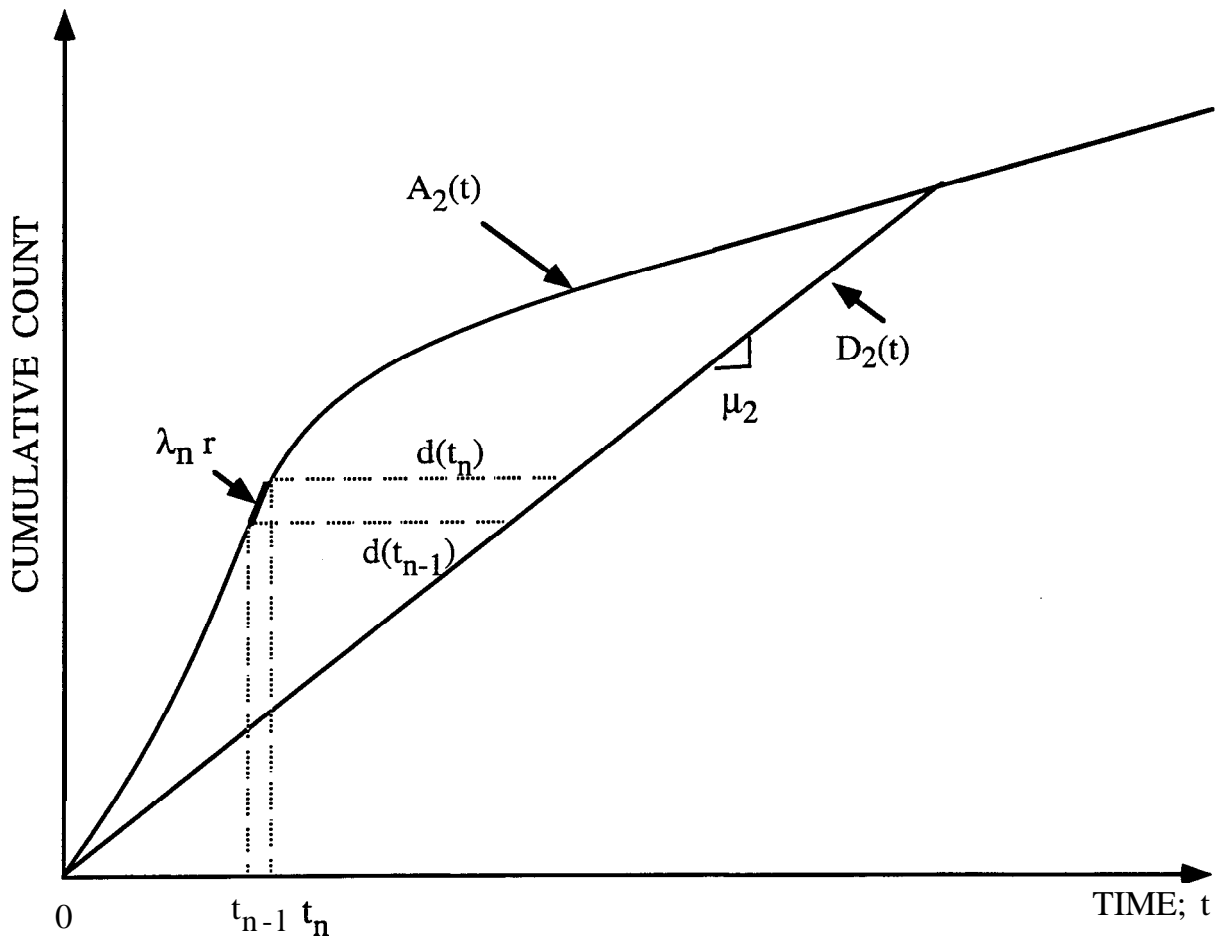
Figure 4: Derivation of delay formula for Route 2

A2 (t) = Cumulative arrivals

D2 (t) = Cumulative departures

μ_2 (t) = Route 2 capacity
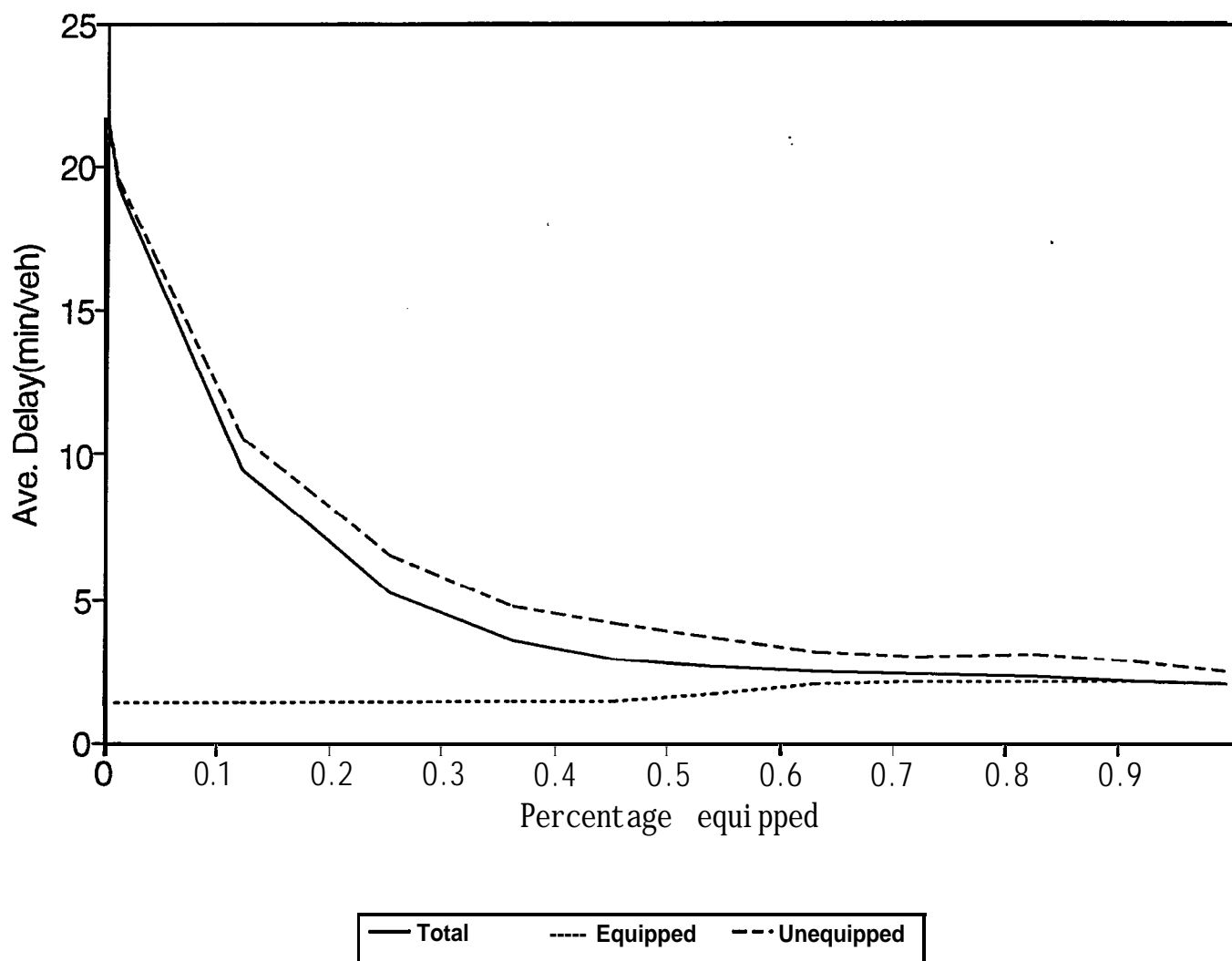
**FIGURE 5 - AVERAGE DELAY WITH FULL COMPLIANCE MODEL
UNSATURATED CONDITIONS**
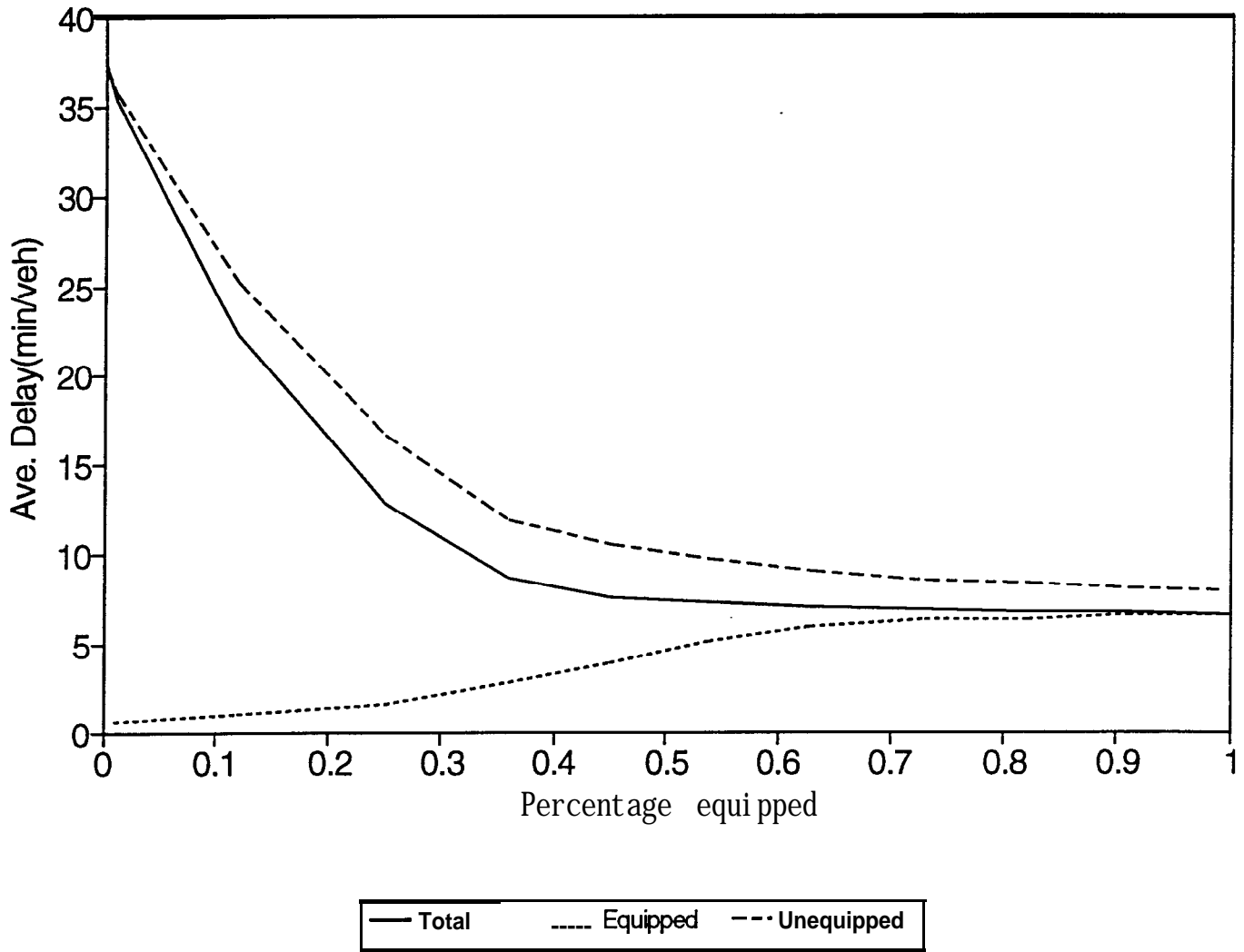
FIGURE 6 - AVERAGE DELAY WITH FULL COMPLIANCE MODEL OVER-SATURATED CONDITIONS
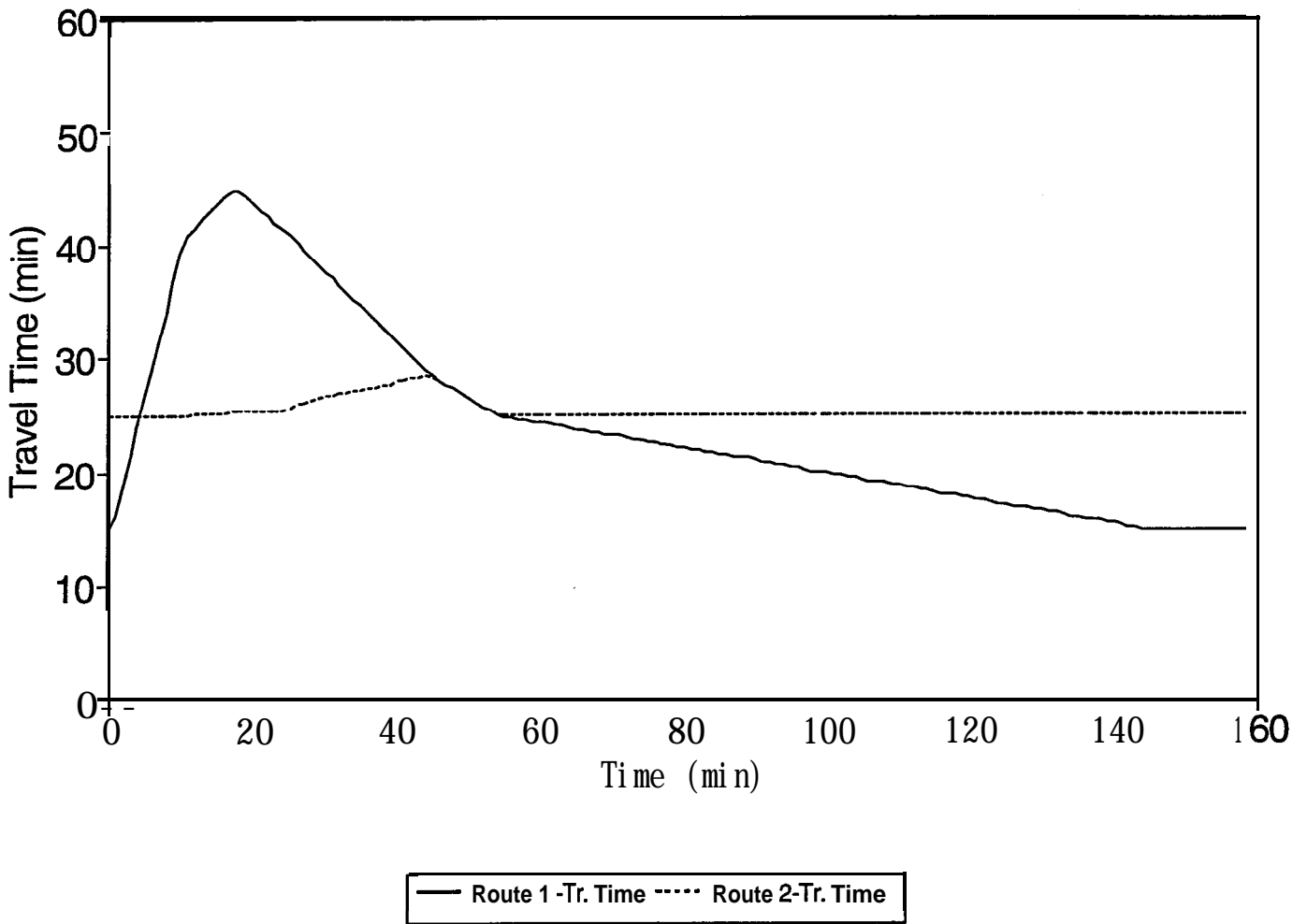
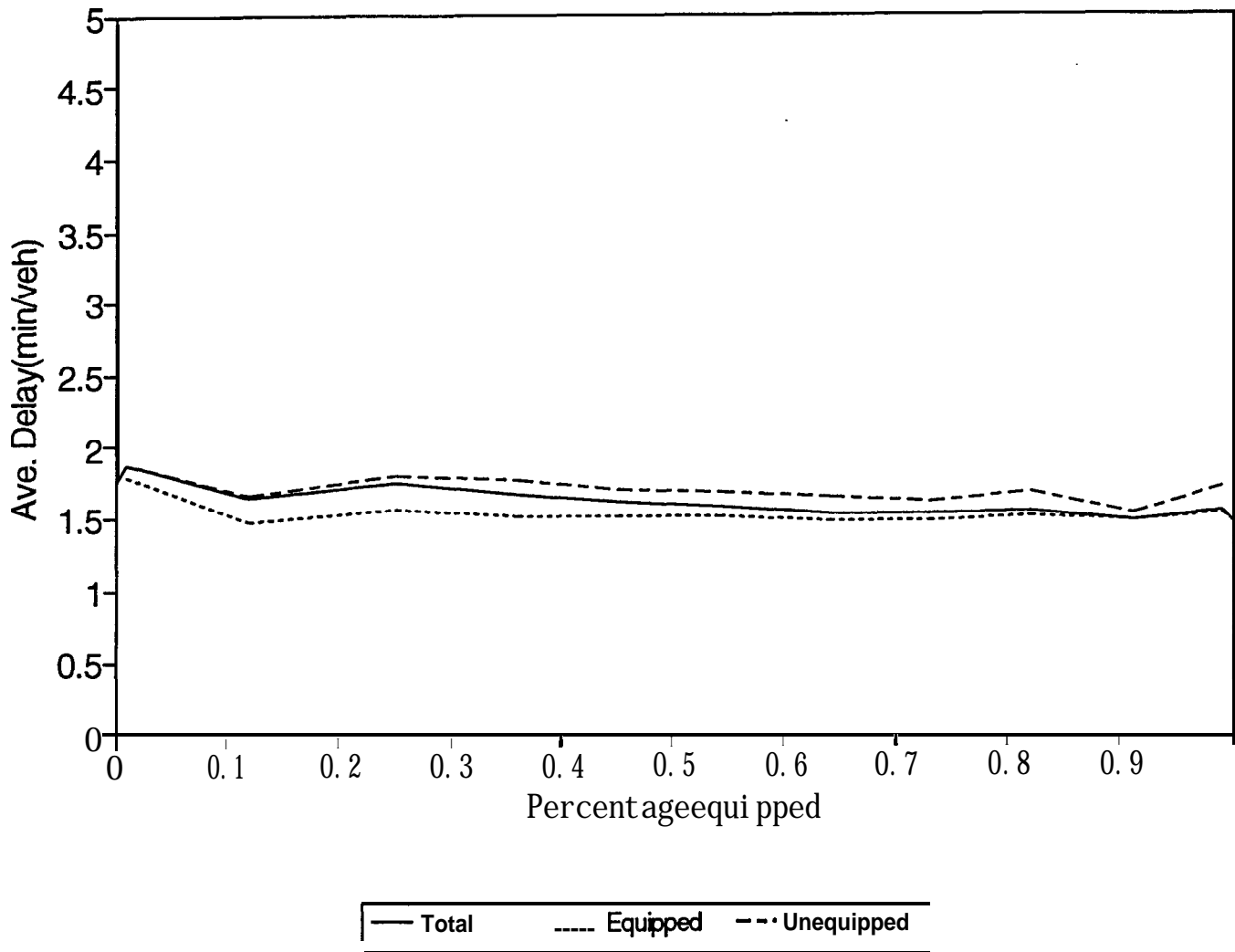**FIGURE 7 - TRAVEL TIMES WITH FULL COMPLIANCE-MODEL UNSATURATED CONDITIONS (EQUIPPED = 54 %)**
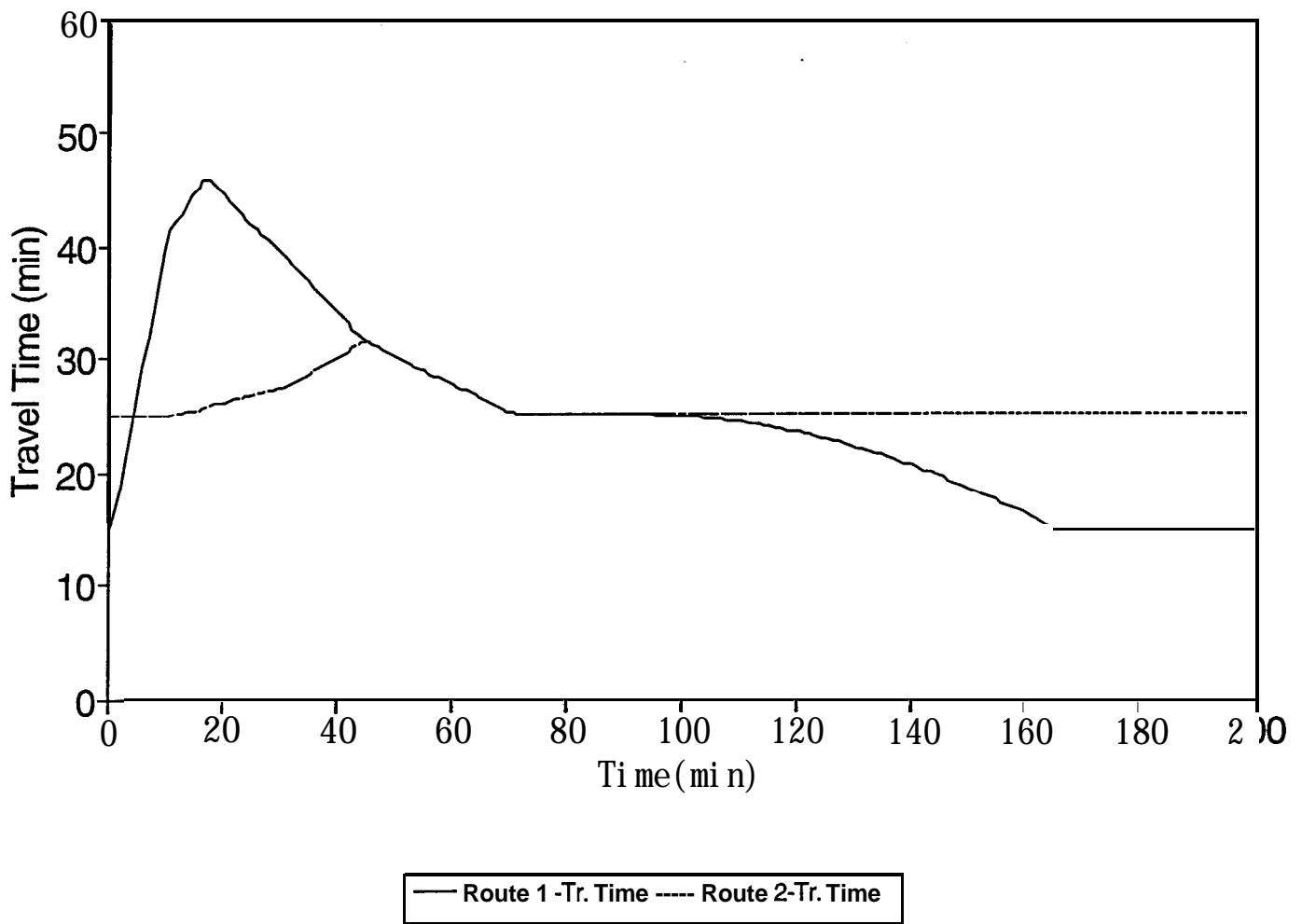
FIGURE 8 - TRAVEL TIMES WITH FULL COMPLIANCE MODEL OVER-SATURATED CONDITIONS (EQUIPPED = 54 %)
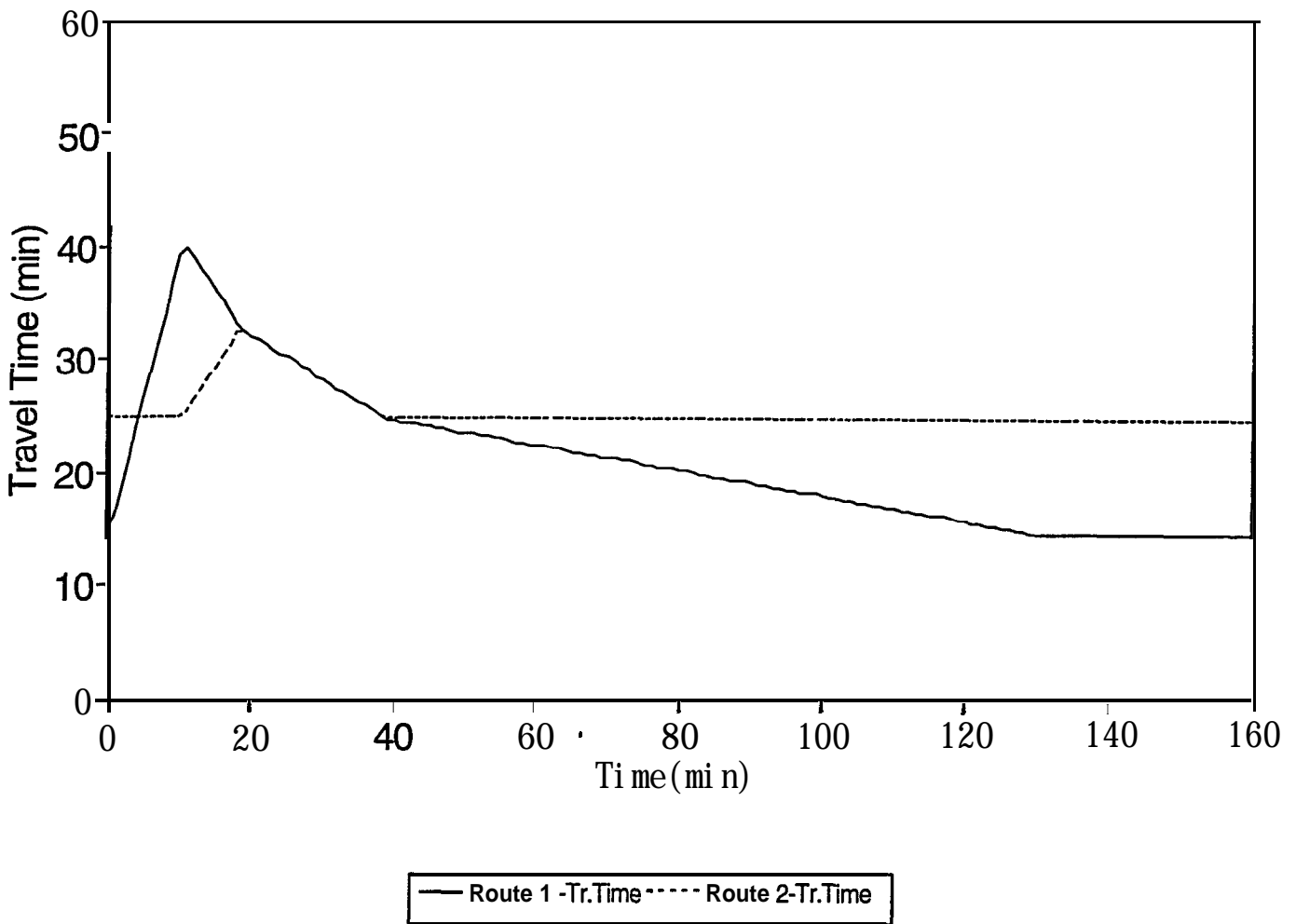
FIGURE 9 - TRAVEL TIMES WITH FULL COMPLIANCE MODEL UNSATURATED CONDITIONS (EQUIPPED = 100 %)
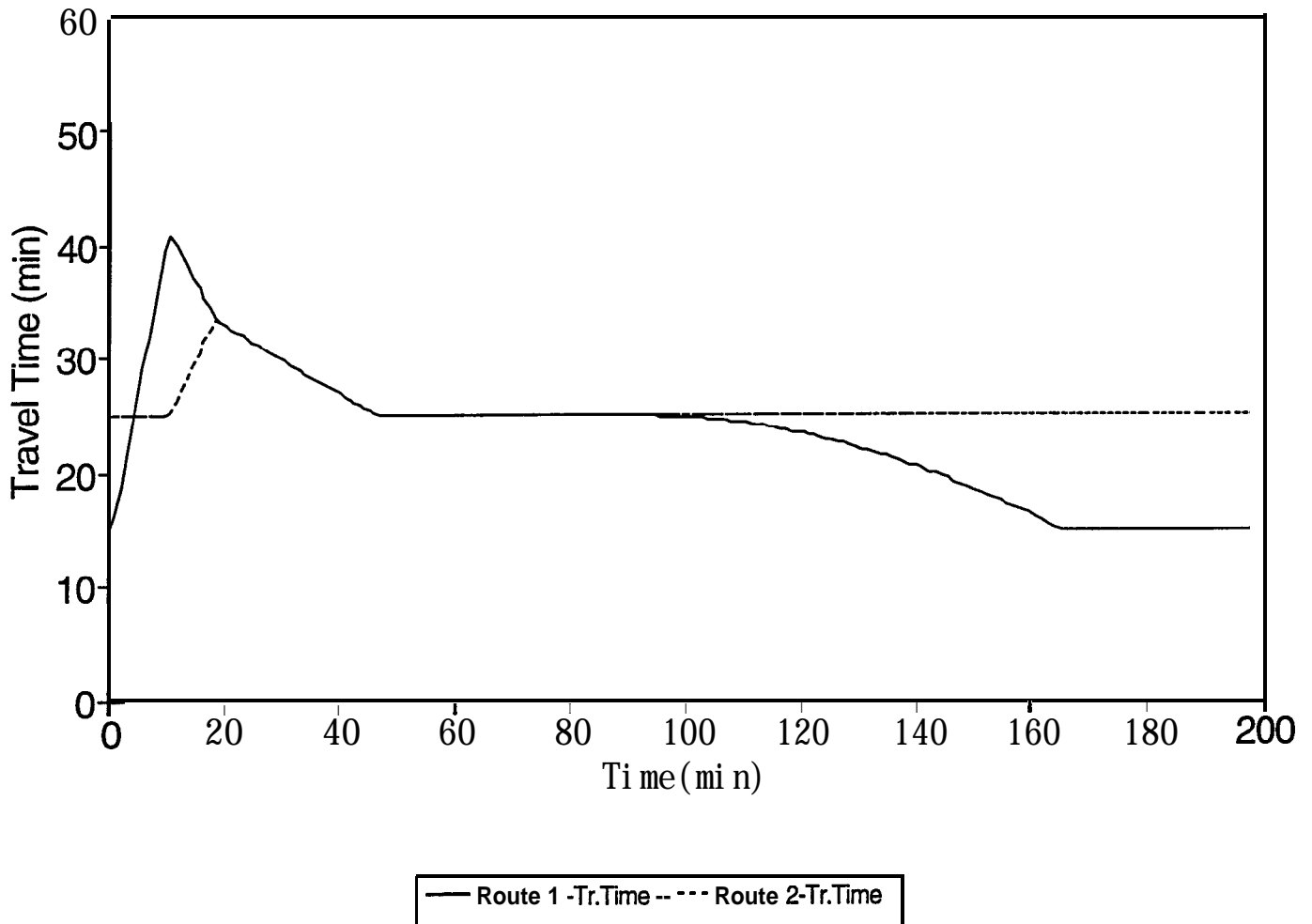
FIGURE 10 - TRAVEL TIMES WITH FULL COMPLIANCE MODEL OVER-SATURATED CONDITIONS (EQUIPPED = 100 %)

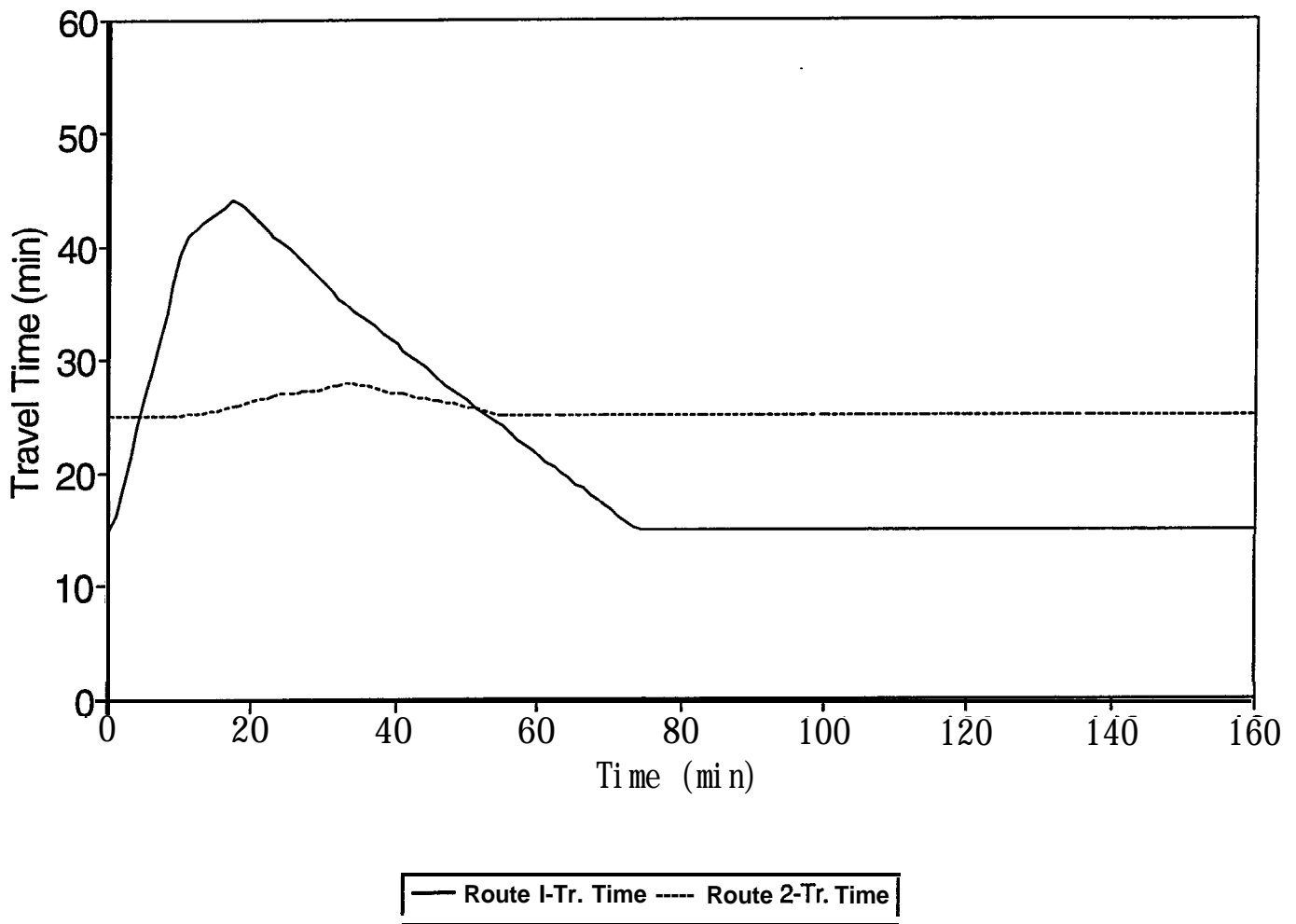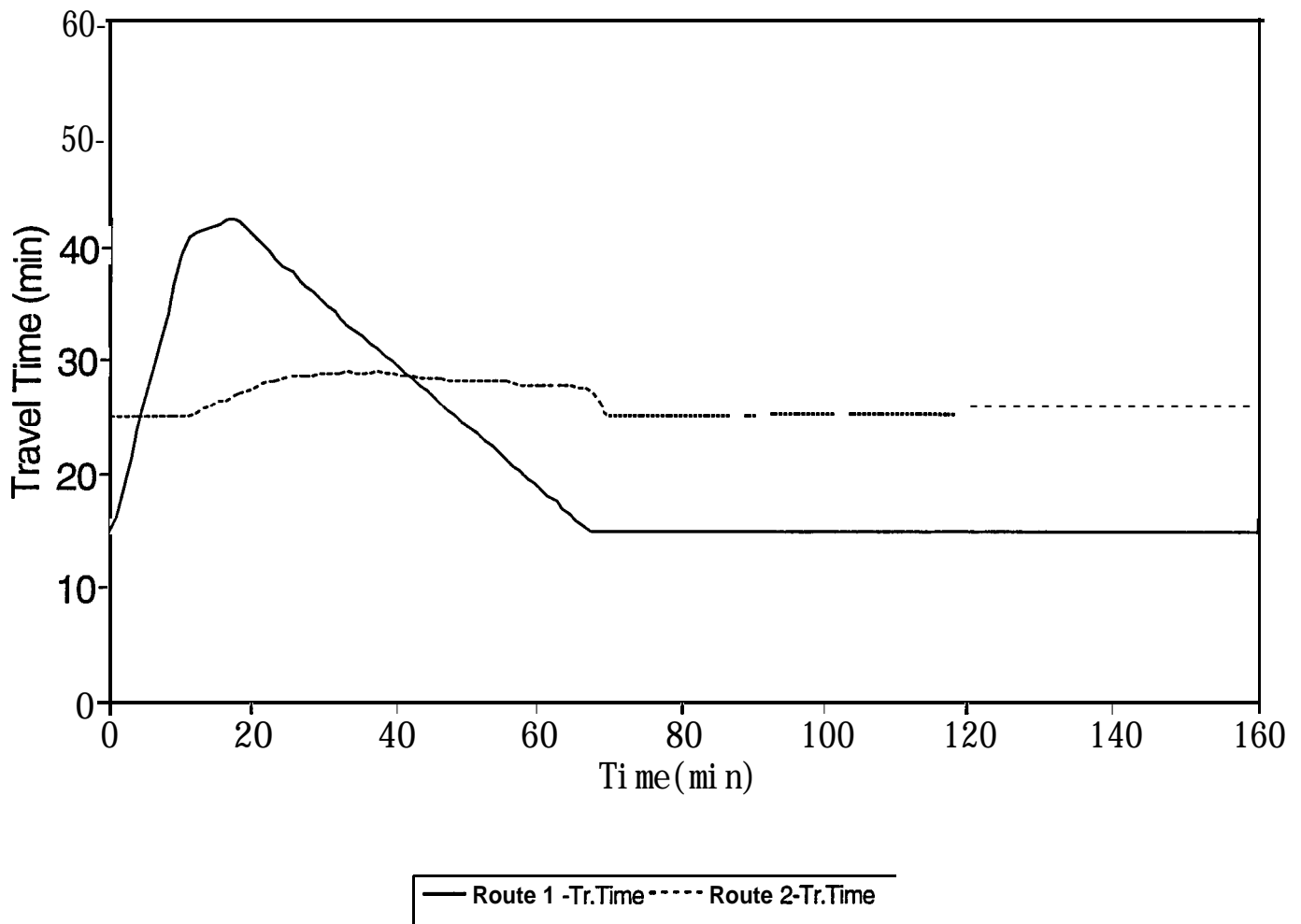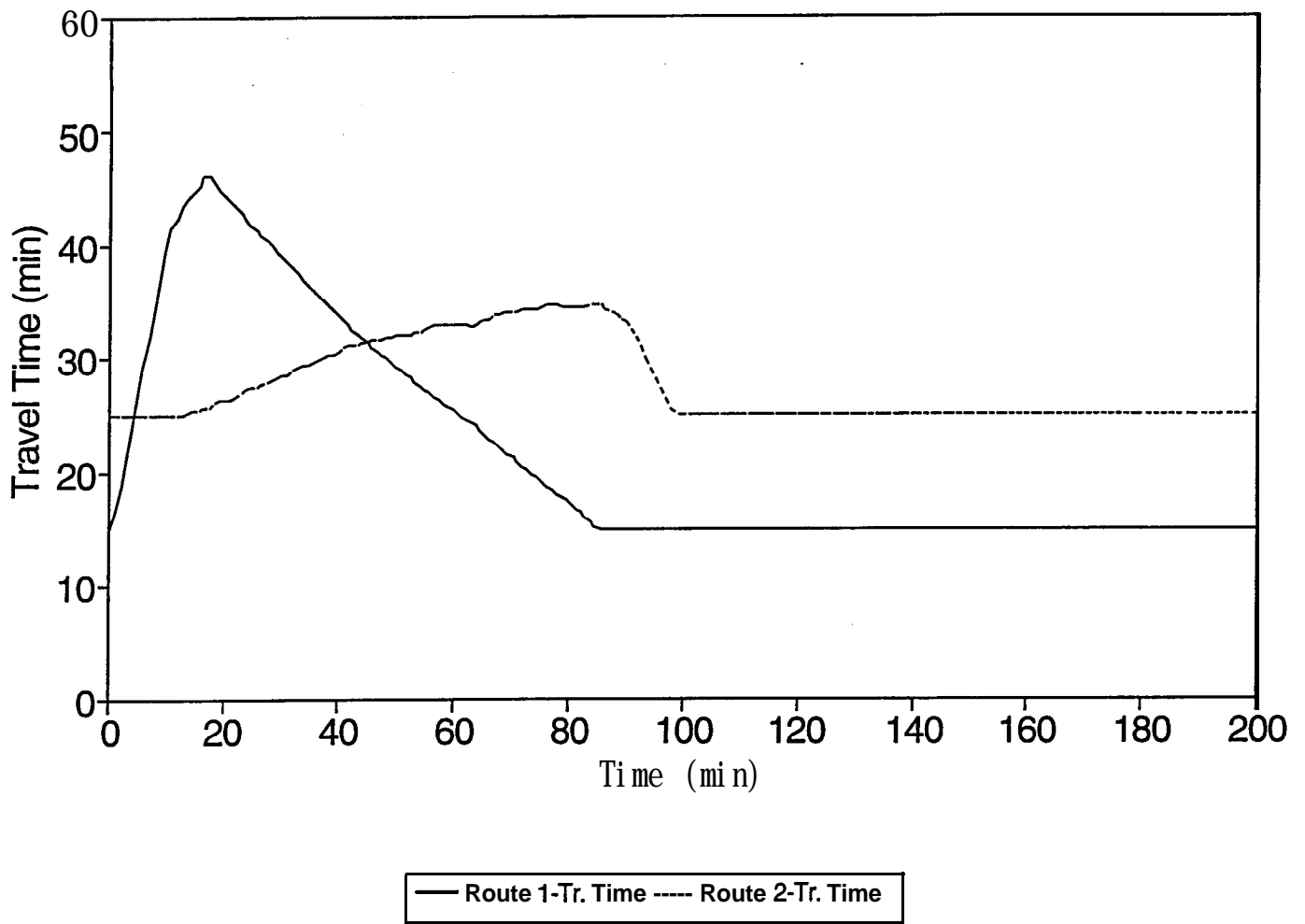**FIGURE 11 - AVERAGE DELAY WITH BEHAVIOR MODEL UNSATURATED CONDITIONS**
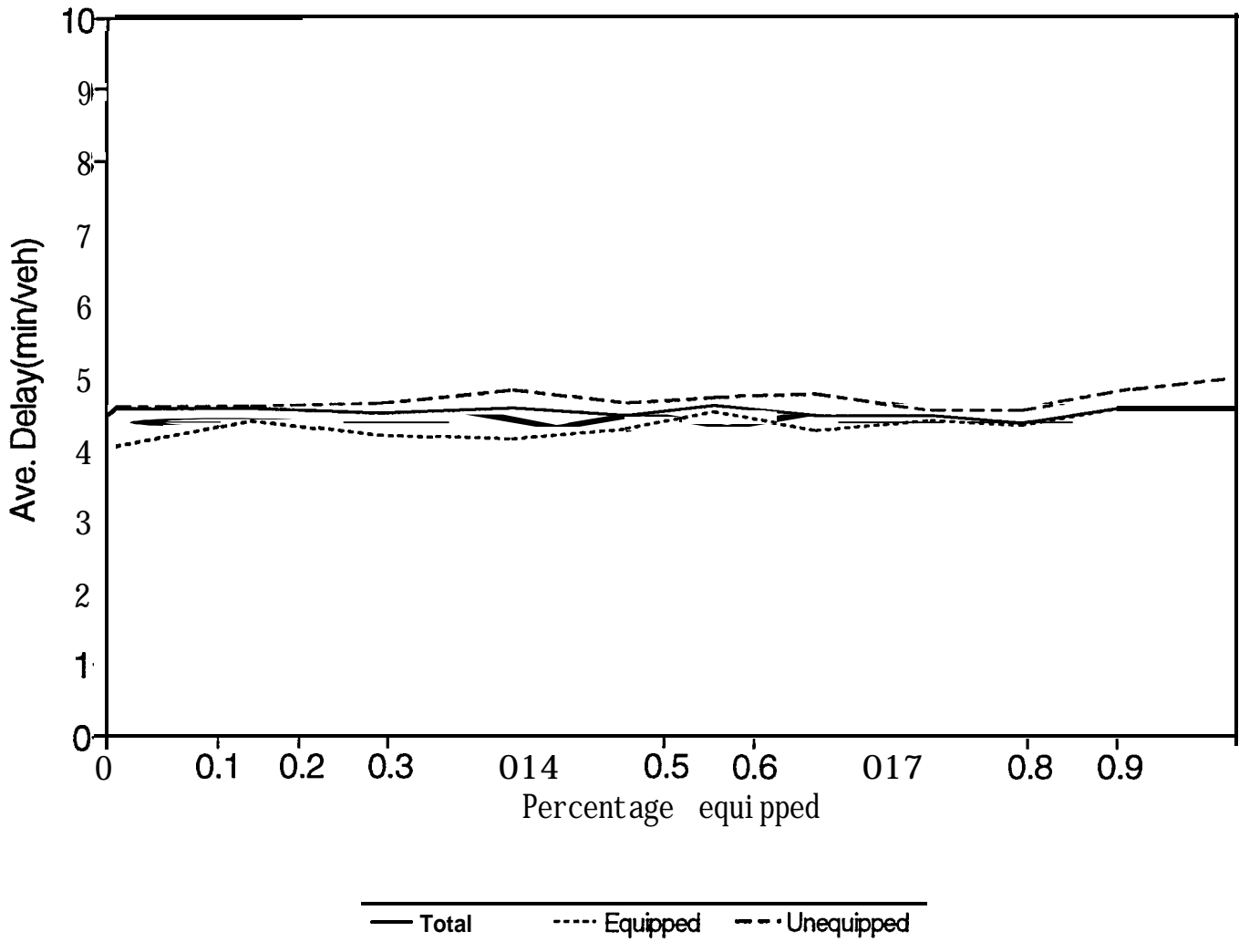
**FIGURE 12 - AVERAGE DELAY WITH BEHAVIOR MODEL
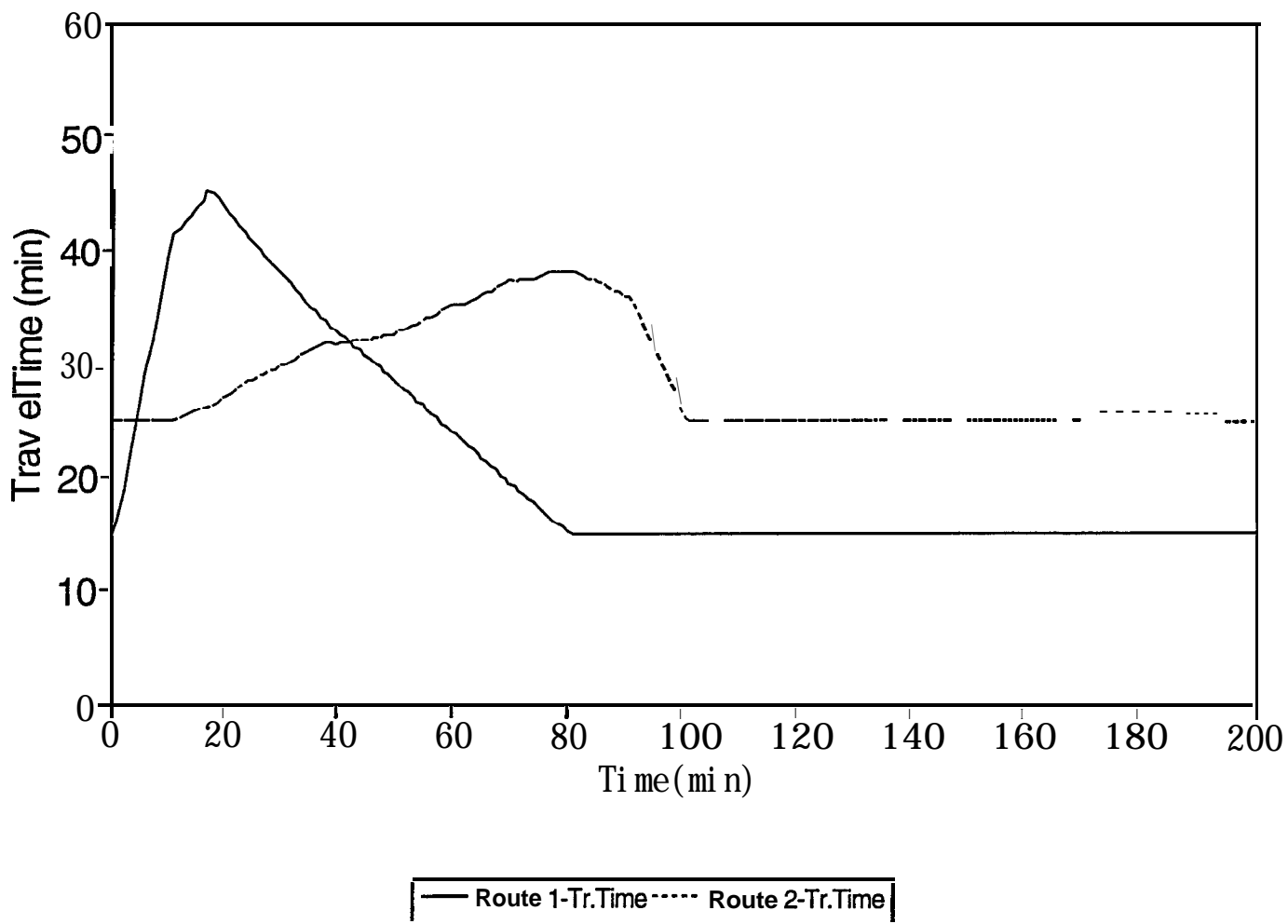OVER-SATURATED CONDITIONS**

FIGURE 13 - TRAVEL TIMES WITH BEHAVIOR MODEL UNSATURATED CONDITIONS. (INFORMED = 54%)

FIGURE 14 - TRAVEL TIMES WITH BEHAVIOR MODEL UNSATURATED CONDITIONS (INFORMED = 100%)

60

50

Travel Time (min)

40

30

20

10

0

0   20   40   60   80   100   120   140   160   180   200

Time (min)

——— Route 1-Tr. Time ----- Route 2-Tr. Time

**FIGURE 15 - TRAVEL TIMES WITH BEHAVIOR MODEL
OVER-SATURATED CONDITIONS (INFORMED = 54%)**

FIGURE 16 - TRAVEL TIMES WITH BEHAVIOR MODEL -- OVER-SATURATED CONDITIONS (INFORMED = 100%)