

Evaluation of Network Performance under Provision of Short Predictive Traffic Information

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Abstract

Traffic information systems have been considered to play an important role in reducing traffic congestion. Understanding the effects of information provision to the network performance is crucial before real implementation of the systems. In this paper, we investigated the effect of provision of predictive information with short prediction horizon. A traffic simulation model was developed to evaluate the efficiency of the information. The simulations were conducted on a test grid network. The network performances in term of average trip travel times were compared with other traffic information types. In addition, sensitivity analyses of level of market penetration and update intervals are also presented. The results obtained indicate that the predictive information can improve the overall network performance even though the prediction horizon is short.

Keywords: Advanced traveler information systems, predictive traffic information, traffic simulation, routing strategies

Introduction

Advanced traveler information systems (ATIS) regarding the provision of real-time traffic information have been considered to play an important role in reducing traffic congestion and enhancing traffic flow and improving safety. Providing travelers with information of actual network conditions or recommended alternative routes will help them make better travel decisions. With good-quality traffic information, travelers can find a better route with less traffic and avoid congested roads, and consequently the overall network performance is improved.

Traffic information provided to drivers may be classified into these 3 categories based on their nature of the data and estimations: *historical*, *current*, and *predictive* [1]. Historical information is based on travel times derived from a historical database that describes traffic conditions prevailing in the past. The historical information is just an average of past travel time data and cannot capture day-to-day variability that may be caused by fluctuations in demand and by events. Current (or Instantaneous) information is travel times generated from real-time estimation of current traffic conditions, and normally provides a snapshot of current traffic conditions of the network. The data are collected from the field and disseminated to travelers instantly. Predictive information is based on predictions of future network conditions, which are made in real-time. The travel times are estimated for the forward time horizon based on the historical or current traffic conditions. The generation of predictive information may use statistical or data-based algorithms or be model-based. The important aspect of predictive information is that it allows travelers to know ahead of time about traffic conditions that they will experience.

It has been known in the transportation science community [2-4] that traffic information supplied to travelers should be predictive information rather than historical and/or current information. This is because networks are dynamic and change over time. Traffic conditions prevailing at the time reaching a particular location may change significantly from traffic conditions at the current time. Therefore, only information based on the currently prevailing traffic conditions is not sufficient to accurately use for travel planning. Information of future conditions that are likely to occur at a later time down the road is also important and needed.

Many studies have evaluated and compared the impact of providing current and predictive information [1,3,5-7]. It has been demonstrated that predictive information has a benefit over current prevailing information. However, in those studies they evaluated for the case that predictive information has a long range future forecast and expected experienced travel times between origins and destinations can be estimated. Since prediction of future traffic conditions is very elaborate and requires very high computational power to estimate [8], it is difficult to provide a long prediction horizon information in practice. With a limited amount of time and resources, only a short horizon of the future travel times could be generated and provided. Moreover, the predictive information is typically reliable and valid only over short future periods. Prediction is usually less accurate for times further into the future than for the near future due to error propagation and unexpected disruptions. The less precise the information for far ahead might result in poor travel planning and adverse effects to the network. Therefore, it is not always suggested to use a long prediction horizon for real-world implementation.

In this work, the effect of provision of short predictive information was investigated. Since the information has a short prediction horizon, it might not be sufficient for estimation of expected travel times from origins to destinations for long commutes, and such information could poorly guide travelers. The results reported in this paper demonstrate the potential reduction in efficiency due to the not-long-enough prediction for future traffic conditions. A traffic simulation model was developed to evaluate the network performance under such information and compare the efficiency of other information provision strategies, i.e., no information, current information, and predictive information with long range forecast. In addition, this work also performed a sensitivity analysis to examine the effect of factors such as the update interval and the level of market penetration upon the efficiency of the information.

Literature review

Over the decades, there has been an enormous published literature on short-term traffic flow forecasting. Many efforts have been done to predict traffic conditions ranging from a few seconds to possibly few hours into the future. Most research has concentrated on developing methodologies that can be used to accurately generate anticipated traffic conditions. A comprehensive review of the state-of-the-art research work in the area of short-term traffic forecasting can be found in the recent special issue published in *Transportation Research Part C* [9]. Research relating to investigation of network performance under various travel information provision strategies has also been a subject of interest and has been studied extensively. In this section, we summarize previous evaluation of the impact on network performances due to the traffic information provision.

Ben-Akiva *et al.* [3] used an analytical approach to investigate the effectiveness of predictive information for a small prototypical network. They found that total travel time is slightly lower when providing predictive information rather than instantaneous information, where the latter type of information results in large discrepancies in travel times between alternate routes. Some previous research has shown that provision of real-time traffic information based on historical or instantaneous conditions may result in negative effects [2,10,11].

Mahmassani [12] presented an application of the simulation-based DTA system DYNASMART to evaluate and compare the impacts of various information supply strategies under incident conditions. Comparison of different levels of travel information provision based on current or predictive information has been explored in [5-7]. They conducted a computational experiment to demonstrate that predictive time-dependent travel time information is preferred over prevailing travel time. Similar investigations have been done using DynaMIT in [13,14], showing the benefits of providing consistent predictive

information. In those studies, the predictive information was generated to account for the entire duration of any trip.

In prior studies, impacts of several traffic information system design parameters have been examined, for example, frequency of information updating [15], the effect of market penetration [16], the effect of error in prediction [17], and others. Antoniou *et al.* [14] have evaluated the effectiveness of predictive diversion strategies in incident scenarios. Some even attempted to develop a system to estimate and provide predicted information for real-time traffic operations [18]. However, there has been little concern of the impact of the short prediction horizon lengths on the traffic information system effectiveness. Bottom *et al.* [15], evaluated the performance of an anticipatory route guidance system under a rolling horizon framework and found that prediction horizons shorter than 30 min led to a reduction of the overall savings of the guidance. Surprisingly, they also found that by increasing the prediction length to over 30 min, the overall performance somehow reduced.

Impact of short predictive information on route selection

Traffic information has a significant impact on travelers' route choice decision. When travelers receive the information, they will gain more knowledge about the network and could use this knowledge in their trip-decision making especially in terms of route selection. The information is usually presented in the form of travel times or delays on segments of the road. For most travelers, the travel time is perceived as an indirect measure of the travel cost, with longer travel times implying higher travel costs. Based on the received travel time information, travelers are willing to seek for the shortest-time paths that minimize their total travel time from origins to destinations.

Different types of supplied information could result in different selected routes. Shortest routes obtained by current travel-time and predictive travel-time approaches may not be the same because the travel times in these 2 types of information are different. The current information provides just travel times for each link of the road network prevailing at departure times. Thus, the trip times are computed based on the "snapshot" of the current link travel times. Unlike the current information, the predictive information considers the dynamic of travel times, and the travel times as a function of time for each link are provided. So, "time-varying" link travel times can be used in calculating trip times along the path "time-dependently". If the predicted future travel times are accurate, one would obtain the path travel times that reflect more closely to the actual experienced travel times. Based on different estimated travel times, the perceived best travel paths could be significantly different.

In practice, the prediction can generate link travel time data several minutes into the future. However, the problem is that this time span of the prediction may not be sufficient to cover the entire path of travel. As an example illustrated in **Figure 1**, a trip is supposed to take 30 min to travel from the start to the destination. The driver would like to know the traffic conditions for this 30 min period to completely plan his route. However, at the departure only information in the interval of first 10 min is available, and the travel times beyond the minute 10 cannot be estimated correctly due to the absence of the information.

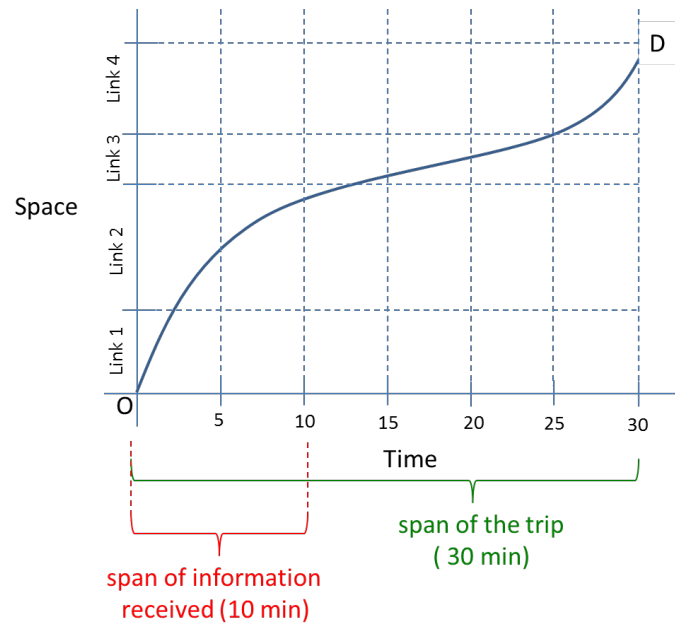


Figure 1 Illustration of the problem in lacking information for the later part of the trip due to the short-span of prediction.

Insufficient length of the predictive data makes it impossible to calculate the time-dependent path travel time of the whole path as it would in the predictive information because the required link-travel times are beyond the scope of available data. Therefore, the path travel times estimated based on the travel time information that can cover partial parts of the path are not the actual travel time and cannot be reliable. This might cause a problem in a pre-trip information system, where travelers use information to make a path decision before departure because the paths that seem to be very fast in the beginning may be severely congested later on.

Simulation model

To estimate and analyze network performance under provision of traffic information, a traffic simulation model has been developed based on dynamic traffic assignment concepts and micro-simulation. This simulation model represents the situation where pre-trip information is available to the drivers.

Model framework

The overall structure of the simulation is presented in **Figure 2**. A list of vehicle trips is generated according to a time-dependent origin-destination (OD) demand, which is assumed to be known beforehand. The drivers are divided into 2 classes: uninformed and informed drivers. The uninformed drivers travel on their predetermined habitual paths, assuming that they select the routes in a way that corresponds to the stochastic shortest path. On the other hand, the informed drivers, who receive traffic information, select the paths to travel based on the provided information. We assume that drivers use the latest information to seek for the fastest route before their departure. The travel paths from both classes of drivers are then loaded simultaneously into the microsimulation model, which explicitly simulate dynamic movements of vehicles through the network and generate the network performance statistics.

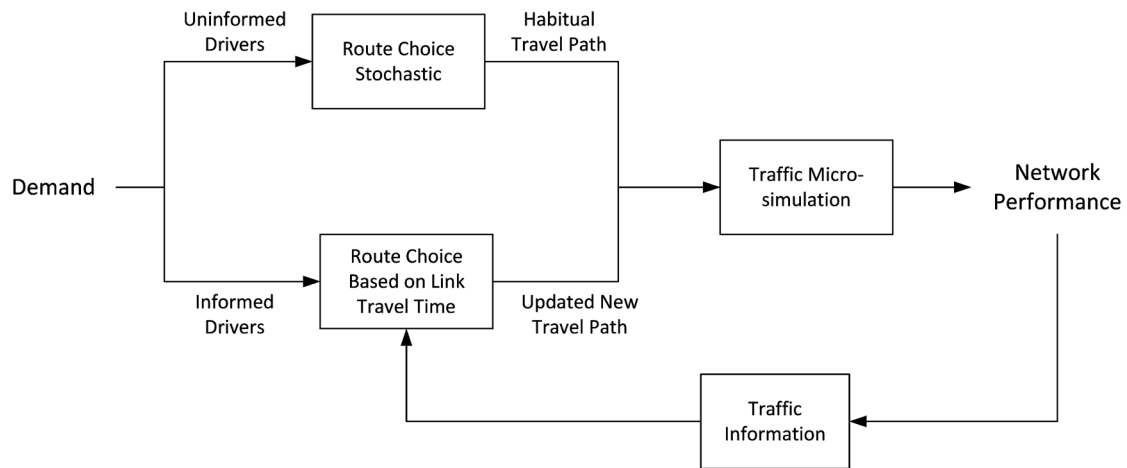


Figure 2 Framework of the simulation model.

The model has been implemented using TRANSIMS [19] suite tools that can be combined in a variety of ways to model a wide range of transportation scenarios. Two major modules of TRANSIMS that are employed in the simulation model are: Route Planner and Microsimulator modules. The Route Planner module attempts to assign the time-dependent fastest route to individual travelers. It implements Dijkstra's time-dependent algorithm to solve for the minimal travel time path based on the time-dependent, link travel time information. The Microsimulator module is used to execute individual travel plans and evaluate the performance of the network. The travel movements according to the plans generated from the Route Planner module of all travelers are executed simultaneously in the Microsimulator, resulting in overall dynamics along the network. The movement and interaction of vehicles in the system are explicitly simulated based on the Cellular Automata (CA) technique [20].

The basic assumptions behind the simulation model are summarized as follows:

- Each driver decides from his point of view on the appropriate action. Based on minimal disutility principle, drivers will choose the fastest route to travel.
- There is no change in the route after departure. This study focuses on the case that drivers can have the information available before their travel but cannot access information after that.
- Each vehicle accelerates up to maximum speed limited by the links if no other cars are ahead. If a car is ahead, then it adjusts velocity so that it is proportional to the distance between the cars. However, it can sometimes randomly decelerate to account for inherent variability in vehicle speed and vehicle over-reaction when slowing down.
- Drivers decide for lane changing in the case of a slow vehicle in front and the other lane is faster.

Information strategies

Since we are interested in the performance of an information strategy, it would be better to evaluate the performance compared with other information strategies. Four information strategies of interest in this study, namely, no information, current information, long predictive information, and short predictive information are illustrated in **Figure 3**. The simulation period is subdivided into pre-specified sub-periods $p = 1, 2, \dots, P$. In each time period, the traffic condition of a link is represented by the average link travel time over that period. The information is updated and released at the end of every interval. Over the duration of the update interval, the content of the information from the last update is maintained, and informed travelers who start the trip in the same interval have the same information.

(1) *No information*. The no information scenario was included in the analysis as a based case. The drivers' route choice behavior of the uninformed drivers was modeled according to the shortest path in which the travel times are stochastic [21]. Drivers who cannot acquire perfect travel time information are

assumed to have some perception error in the route choice process. The imperfect perception of network conditions is represented by a random disturbance on the actual travel time on each link. At each traveler's route choice decision, the link travel times (based on free flow speeds) are adjusted with a zero-mean random number, and the route choice criterion is to minimize the perceived value of the route travel time. Due to variations in travelers' perceptions of travel times, travelers do not travel on the correct minimum travel time routes. In addition, travelers with the same origin-destination and departure times may not select the same routes since the randomness is applied at each traveler.

(2) *Current information.* Link travel times of currently prevailing traffic conditions are provided. The travel times of vehicles passing through the links are observed for a period of time before they are averaged and provided to newly departing informed vehicles. Travelers who start the trip in the current update period will receive the average link travel times prevailing within the past update period (See **Figure 3a**). Then, the time-independent shortest paths are calculated on the basis of these received link travel times.

(3) *Long predictive information.* The predictive information provided to travelers is predicted path travel times or origin-to-destination travel times, which is derived from a future traffic flow pattern. It consists of time-dependent link travel times ranging from the current time interval to many time intervals into the future (See **Figure 3b**).

(4) *Short predictive information.* The provided information is the future link travel times similar to the predictive information. However, the information contains link travel times only for one period ahead into the future (see **Figure 3c**). With this type of information, path travel times from origins to destinations can be computed by using information available in the latest period for the rest periods. In fact, this case is equivalent to the time-independent calculation, estimated based on upcoming link travel times.

Information generation model

The provided information in the strategies given in the previous section is either based on prevailing travel times or predictive travel times. The method to generate both prevailing and predictive travel times and also to use it to evaluate the network performance is illustrated below.

For the current information, it is quite straightforward to generate the travel time information. The simulation horizon is subdivided into several intervals corresponding to the update interval. The simulation is performed for each time interval in succession. At each interval, a fraction of travelers who start the trip in the current interval is selected to perform route selection and traffic micro-simulation. The travelers are assigned with the shortest paths based on the resulting travel times from the micro-simulation in the previous interval. In the next interval, travelers that have not arrived at their destination yet are loaded into the microsimulation to continue their journey along with newly selected travelers.

For the predictive information, a prediction is made to obtain the future traffic flow pattern. One essential aspect of providing predictive information is to ensure internal consistency, that is, the network forecasts on which the predictive information is based are the same as or sufficiently close to the expected traffic conditions when travelers react to the predictive information. The method of generating consistent predictive information has been formulated as a fixed-point problem in [15]. The information in this study is given in the form of link travel times, and optimal route choice model is used to assign the paths. In such a case, the consistency condition is equivalent to the user equilibrium condition of the dynamic traffic assignment (DTA) problem [22].

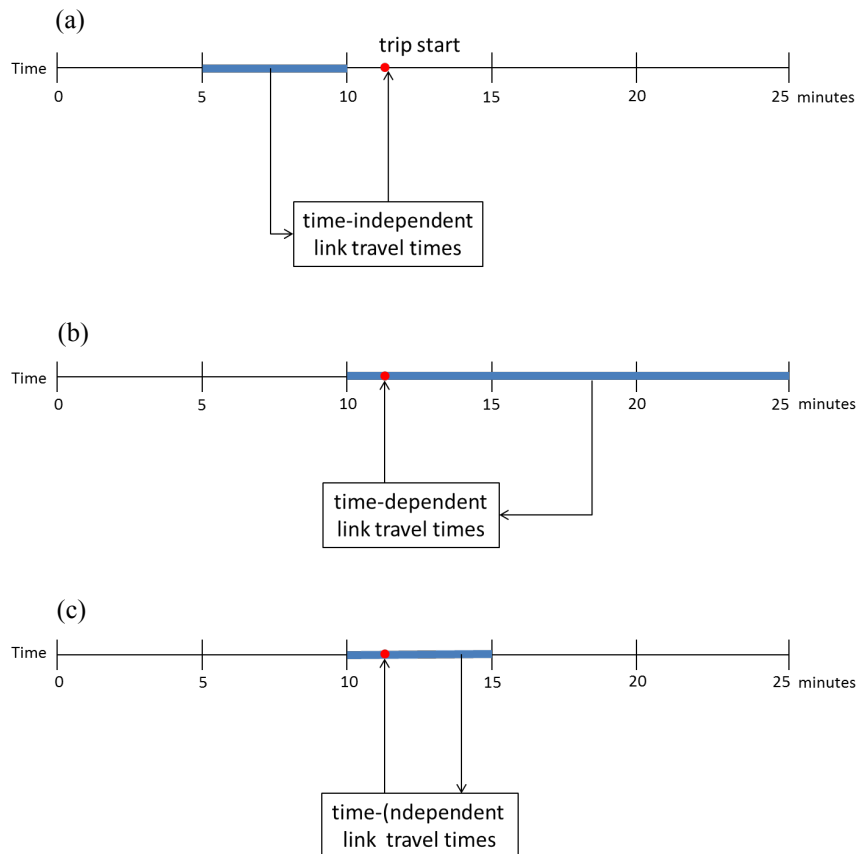


Figure 3 Illustration of information characteristics of each information strategy (a) current information, (b) long predictive information and (c) short predictive information.

In our model, a simulation-based DTA model, as in DYNASMART [23] and DynaMIT [24], is developed to determine the dynamic user equilibrium (DUE) condition in the network. The OD demand for the entire simulation is assumed to be known and served as the input in the DTA prediction. The iterative procedure for solving the time-dependent user-equilibrium conditions as in [25] is used. The algorithm proceeds by iteratively revising travel paths selected by travelers. In a particular iteration, drivers react to a given set of time-dependent link travel times and generate a new set of time-dependent link travel times. The latest link travel times are combined with the ones from the previous iteration, and then feedback to the drivers to reselect their routes again. This process continues until no drivers are willing to change their paths. Once the equilibrium is achieved, traffic flows and consistent travel times for the whole simulation horizon can be extracted from the DUE solution.

Simulation experiment

Simulation-based experiments were conducted to evaluate the impacts of the information provision strategies discussed above. The four information provision strategies/scenarios were evaluated and compared in the experiment. The network performance in terms of travel times and delays is measured from the simulation.

Network and demand

The simulations were implemented on a fictitious network illustrated on **Figure 4**. The network, which is similar to the network employed in [26], consists of a grid with 36 nodes and 60 links. All of the links are uni-directional, and one kilometer long. There are 2 types of links in the network. One with 4 lanes and the other with 2 lanes. The 4-lane links (indicated by a bold line in **Figure 4**) represent main streets, which possess a greater capacity and faster driving speed than those of the smaller streets. The free flow speed is set to be 54 km/h and 36 km/h for the bigger links and the smaller links, respectively.

The time-dependent OD demand on this network is assumed to be known and fixed. The total trips generated in the simulation are 15,000 trips. The origin, destination and departure time of each trip is assigned as follows. The origin and the destination are randomly selected from the locations distributed over the network. At the middle of each link is the location where serves as an origin and a destination of the trips, with the total locations in the network of 60 locations. However, to make the scenario more realistic, the probability of selecting an origin and destination is not homogeneous. The location on link 21 is the main business area with 20 % chances of being a destination, and the locations on link 12, 40 and 60 are three main residential areas with each 5 % probability of being an origin. The locations on the other links have equal probabilities of being selected. The time of day when the trip starts is randomly specified with equal probability within the first hour period of the simulation. The simulation lasts until all vehicles arrive at their destinations.

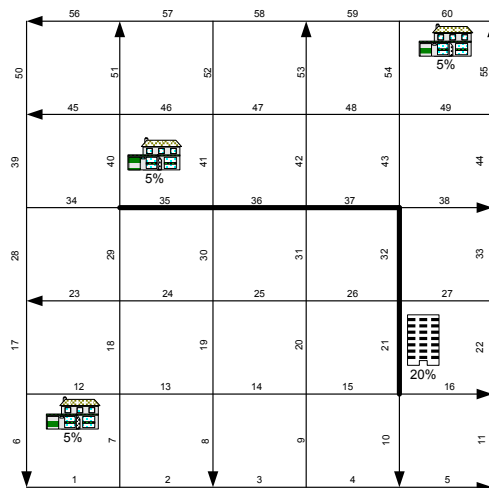


Figure 4 6×6 grid test network.

Experiment setup

A set of experiments was setup to conduct comprehensive evaluations. As described earlier, 4 information scenarios were tested in the experiment: (1) no information, (2) current information, (3) long predictive information, and (4) short predictive information. Each experiment reported here involved a comparison of aggregate simulation results i.e., average system travel time. Two factors that can have a significant effect on the information performance were considered in the experiment;

- the number of informed drivers (baseline value: 100 % informed),
- the length of update interval (baseline value: 1 min).

The experiment was conducted as follows. First, with the generated demand the no information scenario was run first to use the results as a base case in determining the benefit of the information. Then,

the other information strategy scenarios were run using the assigned travel paths from the no information case for the uninformed drivers.

Multiple runs were conducted to consider stochastic variability of the simulation. In each scenario, ten replications of different OD demands were carried out, and the simulation results were averaged. At each replication, OD demand was randomly created as described above. As the results vary due to differences of OD setting, the purpose of the replication is to eliminate a dependency on demand configurations, and allow us to make a more accurate estimate of the results.

Results and discussion

Comparison of network performance

The comparison of the average trip travel times due to each information provision strategies is presented in **Figure 5**. The results are for the case that all of vehicles in the network receive the information. The 95 % confidence intervals associated with each average value are presented as the error bars. The results clearly demonstrate that the informed drivers, regardless of information strategies, reduced their travel times over the no information case. The most travel time saving is the case of long-span predictive information, as expected. The predictive information strategy gives 16 % travel time saving relative to the no information scenario, while the current information and short-span predictive information result in 9 and 13 % reduction in travel times, respectively.

In order to compare the performance of the information strategies, paired t-test analyses were conducted to see if the differences are significant. **Table 1** lists the result of the differences between the means and computing t-test statistics for all pairs of information strategy. The results clearly show that the differences in the average travel times between each pair of information scenario are statistically significant.

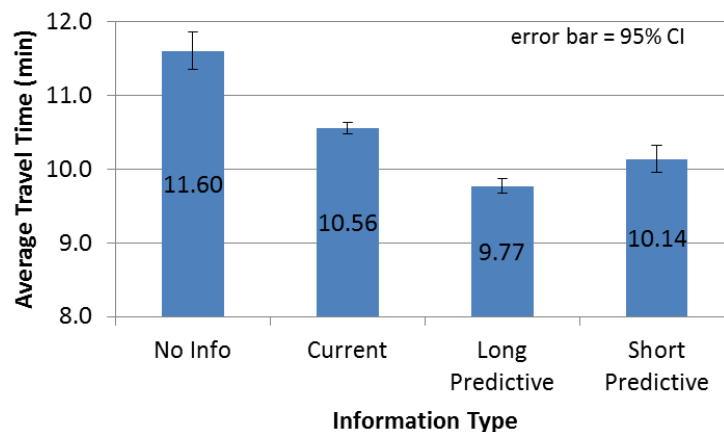


Figure 5 Average travel time of each information scenario.

Table 1 Paired t-statistics.

Pair	Mean difference	t-Test	Sig. (2-tailed)
No info - Current	1.05	8.019	0.000
No info - Long Predictive	1.83	13.299	0.000
No info - Short predictive	1.47	13.154	0.000
Current - Long Predictive	0.78	15.958	0.000
Current - Short predictive	0.42	4.194	0.002
Long Predictive - Short predictive	-0.36	-4.331	0.002

Table 2 displays the results of three common quantities used as measures of effectiveness (MOE) in transportation analysis, which are vehicle hours of travel (VHT), vehicle miles of travel (VMT), and mean system speed (VMT/VHT). The percent differences with respect to the base case (no information) are also given in the parentheses below. Also, we analyze in more detail the evolution of these MOEs for the four information scenarios as shown in **Figure 6**. The graph represents the measurements at each minute over the simulation horizon from a replication.

Table 2 Measures of effectiveness by information strategies.

Information Strategy	VHT (vehicle-hours)	VMT (vehicle-miles)	Speed (mph)
No information	2931.7 (-)	60642.5 (-)	20.7 (-)
Current	2717.2 (-7 %)	61262.0 (1 %)	22.5 (9 %)
Long Predictive	2561.0 (-13 %)	62030.6 (2 %)	24.2 (17 %)
Short Predictive	2664.8 (-9 %)	61568.3 (2 %)	23.1 (12 %)

It appears that the VMT or traveling distance of these 3 information types are about the same, indicating that the distributed traffic flow over the wider area on this network are not much different. This might be because the network is quite small, and there are not many alternative routes to travel. Focusing on the speed results, the average speed of the no information scenario is 20.7 mph or 33 km/h. If we compare to the free flow speed, it suggests that overall traffic in the network is slightly congested. Nevertheless, providing information can significantly improve the system speed, with the long predictive information strategy giving the best improvement, followed by the short predictive and the current information strategy.

The performances of the three information scenarios have similar dynamic patterns. In fact, they are about the same in the first 20 min, but the differences can be seen from 25 min onwards. The VHTs keep increasing since the start to the first hour of the simulation time as the accumulative number of vehicles in the system is growing. Consequently, the average speed of the system exhibits a decreasing trend. From the minute 30 to 60, the graphs of the short predictive information are moving between that of the current and the long predictive information. This is consistent with the total average results in **Figure 5**. As can be seen in the graphs, the impact of the information to the system reaches a maximum at minute 60, where the number of vehicles in the system is highest.

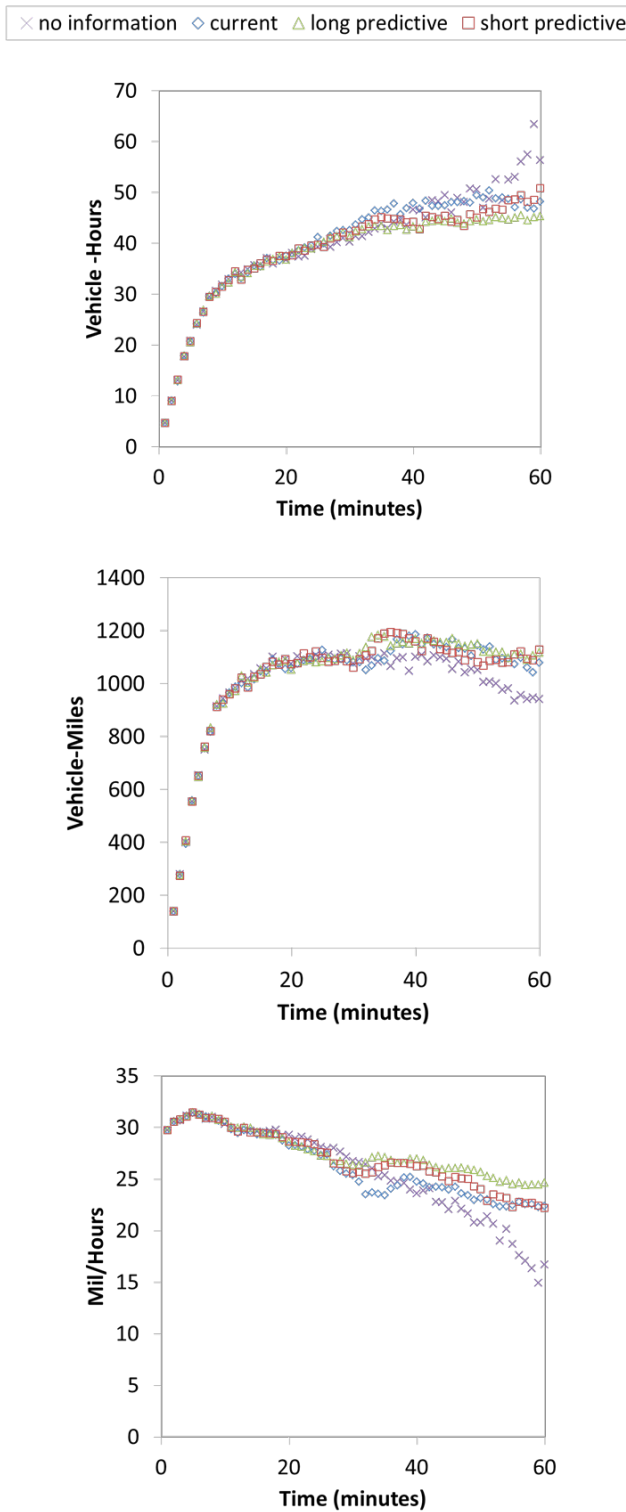


Figure 6 The measures of effectiveness at every minute for each information strategy.

In **Figure 7**, we show the path travel times prevailing at each minute of 3 major routes from origin 12 (main residence area) to destination 21 (main business area). Path 1 is the main road between the origin and destination, comprised of link 12-18-29-35-36-37-32-21. Path 2 and 3 are other alternative roads comprised of link 12-13-14-15-16-22-27-21 and 12-13-14-20-31-37-32-21, respectively. The path travel times are calculated by summing up the link travel times comprising that path at that time.

At the first 20 min, when there are not so many vehicles in the system, the travel times among the three paths are not much different, and the 3 information strategies exhibit the same results. The path 1 has the lowest travel times because it uses the main streets so that the vehicles can travel at higher speeds in this path. In the provision of current information, there is oscillation of traffic flow among the alternatives. This is because of the overreaction problem that the faster routes attract too many drivers and become slower, whereas the previously slower ones turn faster. The overreaction problem is a consequence of the fact that it lacks of anticipation of drivers behavior react to the information [11,15]. In contrast, the predictive information produces little variation of travel time across different path in an O-D pair. For the long predictive information scenario, all of the alternative paths have about the same travel times. This is because the long predictive information takes account of other drivers' reaction and lead to the equilibrium that no one can improve their travel time by moving to another path. For the short predictive scenario, there is no oscillation pattern among the alternatives. However, the travel times of these paths are not equal as appeared in the long predictive case. Even though, the solving for the equilibrium in the feedback iteration is converged, there are still significant discrepancies across the different paths in the short predictive case. This is because in the solution the travelers have equal perceived travel times (the path travel times based on the information) but not the real experienced travel times.

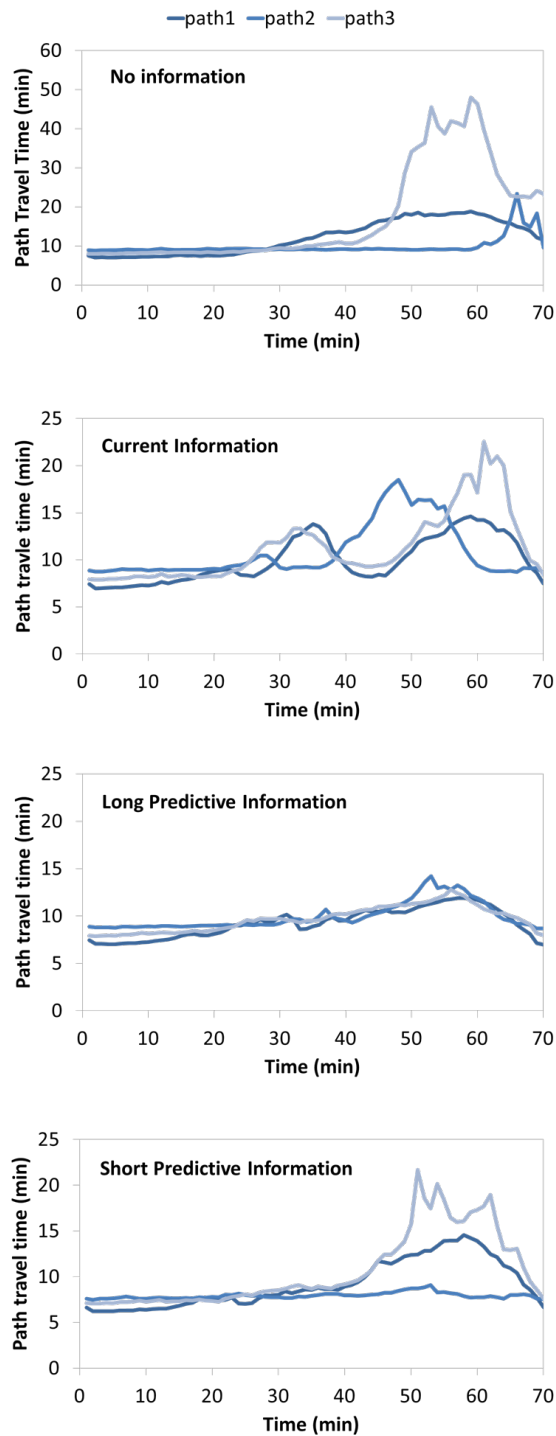


Figure 7 Path travel time over the simulation time of 3 major routes between origin 12 and destination 21.

Effect of number of informed drivers

Since the performance of the information depends on the number of informed vehicles in the system, the effect of market penetration level is investigated. Market penetration defined here as the percentage of vehicles receiving and complying with the provided information. With specifying the number of informed drivers, x % of vehicles in the network are assumed to receive and follow the shortest route according to the information, and the other $(100-x)$ % of vehicles do not receive the information and stay on their predetermined usual paths.

Plot of the average travel times as a function of the level of market penetration are presented in **Figure 8**. The simulation results show that there is strong effect of market penetration levels and the network performance of the information. The average travel times decrease quickly when the level of market penetration increases and saturate beyond 40 %. Therefore, increasing market penetration beyond this limit may not be beneficial. The decreasing curves for the current and long predictive information scenarios were also found in similar study by Dong *et al.* [6].

For the current information case, the optimal network performance is not reached at full market penetration, but there is a slightly increase in travel time at the higher market penetration level. A similar trend was also found in Al-Deek *et al.* [27]. They suggested that a high level of market penetration could possibly lead to overreaction and a deterioration of the network-wide performance [2]. However, this is not present in the predictive information cases as the impact of information itself is taken into consideration.

An interesting point is that the short predictive information that seems to outperform the current information turns out to have a worse performance at the lower market penetration levels, i.e. below 60 %. This might be because the slightly increasing trend of the current information due to the overreaction phenomena that makes it has higher travel times, while the travel time of the short predictive case continues to drop at high market penetration levels.

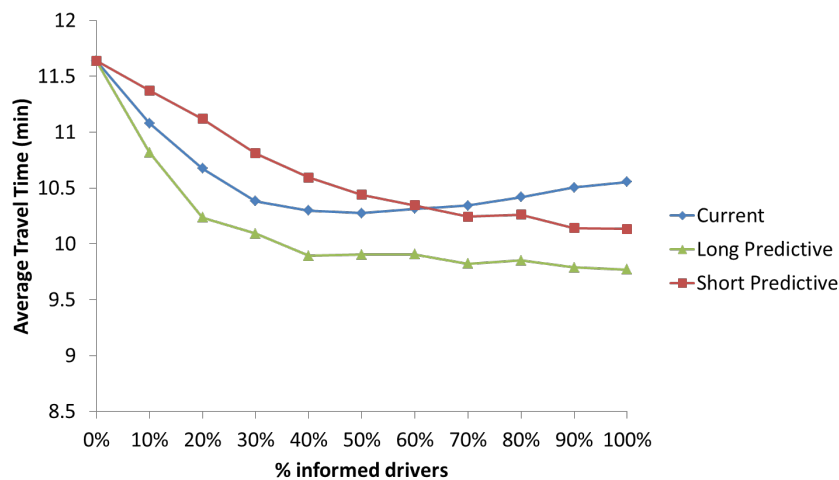


Figure 8 Average trip time as a function of market penetration rate.

Next, we investigated the discrepancy between the supplied information and the real-experienced travel time. The travel times information given to travelers in the current and short predictive information cases are not exactly equal to the actual travel times that travelers experience. This is not for the case of the long predictive information scenario, where the predictive information is developed from the traffic conditions that would be experienced by travelers.

The root mean square of the difference between the real-experienced travel time and the supplied travel time under different market penetration scenarios are shown in **Figure 9**. It shows that at 100 % of market penetration level the current information produces greater discrepancy than the short predictive information. Conversely, the result is the other way around when market penetration level is lower than 60 %, where the short-predictive information gives a higher of discrepancy. We expected that this might be the cause of why the average travel times of the system in the short predictive information scenario are higher than those of the current information when the number of informed travelers is below 60 %.

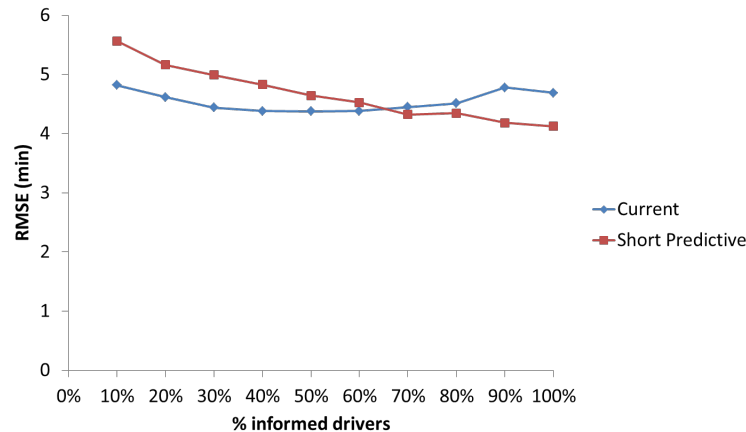


Figure 9 Root mean square of the difference between the real-experienced travel time and the supplied travel time.

Impact on uninformed drivers

The impact on each class of drivers was investigated. In **Figure 10**, the average travel time saving between informed and uninformed driver (for the case of 50 % market penetration) are compared. The result shows that in any information scenario, the uninformed drivers also have benefit in reducing the average travel times from the information. This is because the informed drivers distribute to the other roads, making the congested roads more free for others on those roads. Although it can be seen that the informed vehicles are better off than the uninformed vehicles, the benefit of the former is just marginally higher than that of the latter.

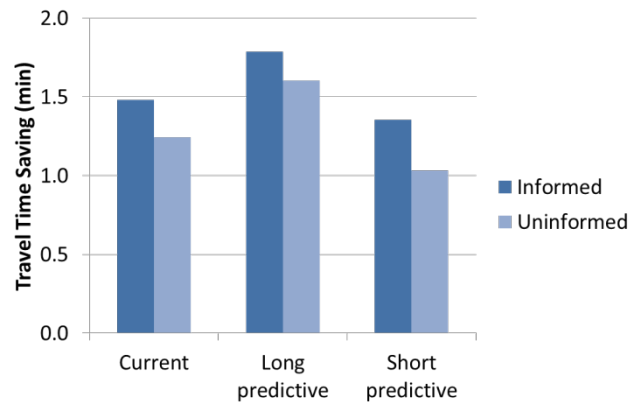


Figure 10 Comparison of travel time saving for 50 % informed and 50 % uninformed drivers scenario.

Effect of update interval

We have investigated the sensitivity of the length of subinterval. In our simulation model, this interval is the interval that the link travel times are averaged over and also the interval between two successive updating. Moreover, since the length of information provided in the short predictive information strategy equals one step interval, the length of the interval also defines the period of time over which predictions are made. In **Figure 11**, the results of the variation of the update interval range from 1 to 5 min are illustrated.

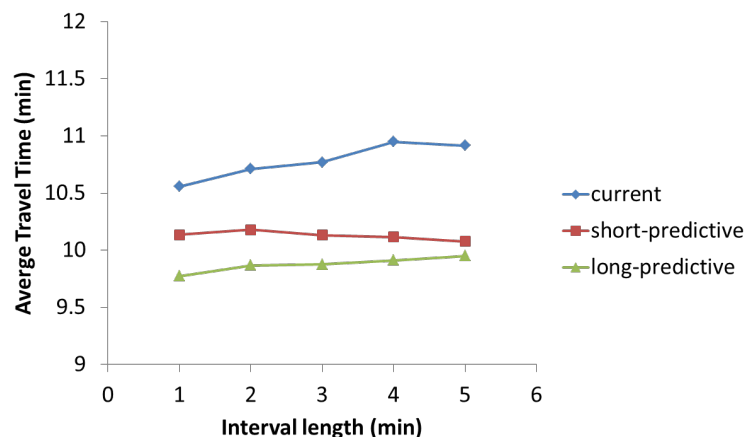


Figure 11 Plot between the results of average travel time and the update interval.

In the case of the current information, the results indicate that there exists a strong relationship between the update interval and the travel time. The average travel time of the system significantly increases as the length of the update interval increases. Thus, using short-interval length and frequent updating information is better when providing the current traffic information. On the other hand, the travel times in the long predictive information case seem to slightly increase, while the travel times in the short predictive information case are quite steady and do not change with the size of the update interval. It was expected that shorter update intervals would allow travelers to more frequently and rapidly react to

the current traffic conditions. However, a shorter update interval also leads to a short time horizon of future conditions to account for in the state estimation, which would affect its accuracy and compensate its performance.

Conclusions

In this paper, the network performance under short predictive information provision were evaluated and compared to the other information strategies including current and long predictive strategy. A microscopic simulation-based model was developed and used for evaluation on a test network. Some factors were investigated to identify the effect on the information performance.

Based on our simulation results, the short predictive information can improve the network performance and benefit travelers although the predicted data is available just a few minutes ahead. Its average trip times are not as good as those of the long predictive information as expected but are better compared to the current information cases. Preliminary results based on this simple application network provide a promising indication that it is not necessary to have a very long forecasting horizon in predictive information system. Nevertheless, the benefit of the system gains with the range of prediction, which should be weighed against the cost of forecasting.

In future research, the various beneficial and adverse impacts of the short predictive information needs to be investigated in greater detail through a more systematic and ranging variation in problem parameters. For example, the future study could be targeted on the impact on various traffic demand/congestion scenarios. Moreover, as this study is done on a small-sized network, the trips are quite short, and so the effect between short and long term prediction may not be seen clearly. The work could be improved by extending for larger networks. Further research could also be conducted to test with a more realistic network and in more interesting situations such as highly congestion or with an incident in the network. These efforts are expected to lead to a better understanding and to be guidance for practical implementation and operation of the information.

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