



Temporal and weather related variation patterns of urban travel time: Considerations and caveats for value of travel time, value of variability, and mode choice studies



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ABSTRACT

By merging a large data set containing GPS records of taxi trips and historical weather records for New York City (NYC), the descriptive statistics of travel time (e.g. average travel time (ATT), standard deviation (SDTT), and coefficient of variation (CoV)) are calculated for each hourly period throughout the week and various weather conditions. Then, a Classification and Regression Trees methodology is used to determine the temporal patterns of ADTT, SDTT, and CoV, again for all time periods and weather conditions. Finally, the identified temporal patterns are discussed with respect to the findings and assumptions of value of time (VOT), value of reliability (VOR), and mode choice studies in the literature. The analysis shows that traditional peak hours are not necessarily the most congested periods and that the peak periods also exhibit inter-period heterogeneity in terms of ATT and SDTT. As opposed to ATT and SDTT, the coefficient of variation was shown to exhibit more consistent patterns among the days. In this respect, caution is advised for VOT–VOR studies regarding the temporal discrepancies in ATT and SDTT patterns; and CoV is suggested to be considered in VOT studies as a more robust measure. In terms of weather impacts, inclement weather is shown to have the potential to decrease SDTT and CoV at certain time periods, resulting in higher travel time reliability. This counter-intuitive finding is discussed with regards to traveler perceptions and possible implications on route and mode choice.

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1. Introduction

The travel time variation on road networks is mainly the result of recurrent congestion. In addition, non-recurrent events (incidents, weather, etc.) also create travel time variations. Researchers have investigated travel time variability for freeways and arterials using loop detector data, probe vehicles, Bluetooth devices, GPS records, electronic toll collection devices and similar technologies that can track vehicles in the road network. The findings are used to model route choice on road networks and analyze the mode choice with additional input from transit travel time variability. Travel time variability is also suggested as a measure for level of service (Chen et al., 2003), cost-benefit analysis (Taylor, 2009), regional transportation planning improvements (Lyman and Bertini, 2008), and policy and investment decisions (Van der Waard, 2009). Following

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the increasing interest in travel time variability and reliability, researchers started studying *value of travel time variability/reliability* (VOR) alongside *value of time* (VOT). As an additional measure, the reliability ratio ($RR = \frac{VOR}{VOT}$) is also introduced. The studies on VOT and VOR mainly employ expected/random utility theory and stated/revealed preference surveys to assign a monetary value to travel time and its variability.

Intuitively, VOT and VOR should be different for peak periods with scheduling constraints (i.e. making it on time for work) compared to off-peak periods with fewer or no scheduling constraints. VOT and VOR are basically the marginal rates of substitution between the travel cost and travel time and variability. In this respect, the *varying* magnitude and standard deviation of travel times at particular time periods are expected to affect the monetary values attributed to the travel time saving. VOT/VOR studies are generally conducted for AM-peak periods (Carrion and Levinson, 2012). As discussed in Wardman and Inabaz (2012), the traffic conditions affect travelers' VOT and studies need to consider more than simple congested–uncongested traffic dichotomy. They suggest congestion multipliers that reflect the impact of congestion levels on value of travel time savings. Hence, identifying periods with consistent travel time characteristics can help re-assess the estimated VOT and VOR values for different time periods.

Moreover, the travel choices in the surveys are stated within “laboratory conditions”, so to speak, by giving several hypothetical route choices with accompanying travel time, variability, and cost. Hence, the travelers' real life perceptions of a particular route at a particular time are generally ignored. Carrion and Levinson refer to the actual travel time for a route as objective travel time and the travelers' perception as subjective travel time. On one hand, referring to the psychology studies, they discuss that accumulated previous experience would provide a basis for one's expectation for the duration of a certain task (Carrion and Levinson, 2013). A well-informed, frequent traveler can be assumed to have a good estimation of the travel time and value their travel time savings. On the other hand, Carrion and Levinson report that this is not necessarily the case (Carrion and Levinson, 2013). Perception errors in self-reported travel times are prone to invalidate the calculated VOT and VOR values. The travelers can be wrong about the *level* of average travel time and variation, e.g. higher actual travel time than self-reported times, or they can have completely incorrect perceptions, e.g. expecting higher travel time variation whereas actual conditions indicate lower variation. Such errors can be fully studied *only* with data covering *both* the actual and perceived travel times. However, such data are very scarce and may not exist for many locations. Actual travel time records are relatively easier to obtain, and the literature also includes studies on travelers' perceptions. In this sense, comparison of anticipated and actual travel time patterns may help identify the discrepancies.

Meanwhile, as a future research direction, Carrion and Levinson (2013) suggest focusing on the influence of external sources of information on the magnitude of VOT and VOR. Although referred to as non-recurrent events in the literature, weather conditions are different from other non-recurrent events (i.e. incidents) by the fact that they are relatively predictable and travelers can have advance-notice of them through weather forecasts. It may be overreaching to say that weather impacts on travel time variability would have long term implications. Nonetheless, travel time variability is used for studying short-term route choice in transportation networks (Liu et al., 2004; Tilahun and Levinson, 2006; Abdel-Aty and Abdalla, 2006; Hainen et al., 2011) as well. Weather conditions can also affect the travel time perceptions of travelers and may play an important role in day-to-day mode choice decisions (Khattak and De Palma, 1997; Sumalee et al., 2011; Eluru et al., 2012). Overall, quantifying the actual weather impacts on travel time variability can help uncover the influence of weather information on VOT and VOR, and can be further used in route-mode choice models.

Considering the issues discussed above, the current study objectives are to:

1. Report the average travel time and travel time variation characteristics in New York City for all time periods and all days of the week (24/7).
2. Quantify the weather impacts on travel time and variability.
3. Identify temporal periods that exhibit similar travel time characteristics.
4. Identify the discrepancies between the *generally anticipated* and actual travel time patterns, and discuss potential caveats for VOT, VOR, and mode choice studies.

The study of actual travel time distributions is not new, however the existing studies mainly focus on certain days of the week and time of day periods and the sample sizes are relatively small. The recent higher market penetration of GPS devices makes it possible for a vehicle to function as a probe vehicle and to provide accurate documentation of travel times. There are almost 13,000 taxis with a GPS device in New York City (NYC) working 24/7. The current study uses GPS records of taxi trips with more than 370 million records covering a period of 18 months to calculate the travel time distributions in the urban network of NYC. Such a large data set offers very large sample sizes for all time periods and allows a detailed analysis of weather conditions.

The outline of the current paper is as follows. First, a literature review on VOT/VOR and existing studies on actual travel time distributions is presented. Second, the data employed for the current study is described in detail, followed by the descriptive statistics of travel time for all day-of-week (DOW) and time-of-day (TOD) periods along with the weather impacts. Third, a Classification and Regression Trees (C&RT) methodology is used to determine the periods that exhibit similar average travel time and travel time variance characteristics. Finally, the possible implications of findings on VOT/VOR and mode choice are discussed and summarized.

2. Literature review

Researchers employ vehicles equipped with Bluetooth, GPS, and similar technologies as probes to analyze the *actual* travel time variation (Tu et al., 2007; Fosgerau et al., 2008; Martchouk et al., 2010; Chien and Kolluri, 2010; Peer et al., 2010a,b; Yazici et al., 2012; Chien and Liu, 2012; Zheng and Van Zuylen, 2013). Studies agree that the mean and standard deviation of travel times vary recurrently for different time-of-day/day-of-week periods and non-recurrently for events such as weather and incidents. Travel time variability is most commonly measured by the standard deviation, variance, and coefficient of variation. Table 1 summarizes the type of analyzed facility, employed variability measures, and important findings of some selected studies on travel time variability. The travel time variability/reliability measures in the literature cover a wide range from simple standard deviation or variance to more complex measures based on distribution percentiles (e.g. Skew Index). Nonetheless, standard deviation, variance and coefficient of variation (which is the mean over the standard deviation) are the most commonly used measures. For details of other measures, the interested reader can refer to the cited works in Table 1 or read Lomax (2003) for a comprehensive review. Overall, the literature presents conflicting findings about the effects of time-of-day and weather on variability. The nature of the roadway facility (freeway/highway vs. urban roads) also needs to be taken into account.

Although the actual travel times provide insights for the travel time reliability on transportation networks, the calculation of VOT requires identification of travelers' preferences. Research on value of travel time and value of travel time reliability/variability is mainly based on stated preference (SP) surveys. In SP surveys, the respondents are given hypothetical route or mode choices with variations of travel times and corresponding costs. Revealed preference (RP) surveys are also used but such studies are relatively rare as the availability of RP data is limited. For the calculation of VOT and VOR, expected/random utility theory is employed mainly along with the mean–variance and scheduling models as the functional forms for the utility modeling. Carrion and Levinson (2012) discuss two other utility forms derived from existing functional forms such as “scheduling delay + dispersion” and “mean-lateness”. Mean–variance utility models follow the functional form:

$$U = \alpha\mu + \beta\sigma$$

where α , β are model coefficients; μ is the mean travel time; and σ is the standard deviation (or variance) of travel time. Mean–variance models do not consider the departure or arrival time whereas scheduling delay utility functions focus on the timing details of the trip and include variables for early departure and late arrival:

$$U(T_d; T_a) = \alpha T + \beta SDE + \gamma SDL + \theta DL$$

where α , β , γ , θ are the model coefficients; T_d and T_a are the departure and arrival times, respectively; T is the travel time; SDE is the schedule-early delay; SDL is the schedule-late delay; and DL is the late arrival penalty. Since scheduling delay models employ variability as early and late schedule delay, the monetary value for variability is represented by Value of Schedule Delay-Early (VSDE) and Value of Schedule Delay-Late (VSDEL). After adding a travel cost term ($+\delta C$) in both mean–variance and scheduling models, the VOT, VOR, VSDE, and VSDEL can be formulated as:

Mean-variance model Scheduling Delay Model

$$\begin{array}{l} \text{VOT} = \frac{\partial U}{\partial \mu} \\ \frac{\partial U}{\partial C} \\ \text{VOR} = \frac{\partial U}{\partial \sigma} \\ \frac{\partial U}{\partial C} \end{array} \quad \begin{array}{l} \text{VOT} = \frac{\partial U}{\partial T} \\ \frac{\partial U}{\partial C} \\ \text{VSDE} = \frac{\partial SDE}{\partial U} \\ \frac{\partial U}{\partial C} \\ \text{VSDEL} = \frac{\partial SDL}{\partial U} \\ \frac{\partial U}{\partial C} \end{array}$$

Considering that VOT and VOR are the marginal rates of substitution between the travel cost and travel time and variability, researchers also introduced Reliability Ratio (RR) formulated as:

$$RR = \frac{\text{VOR}}{\text{VOT}}$$

RR is practically the value attributed to saving 1 min of standard deviation, divided by the value attributed to saving 1 min of average travel time. If only VOT is known, a previously estimated RR for a network permits estimation of the VOR (Cambridge Systematics, 2012). For a comprehensive review of VOT and VOR studies and the theoretical background, the readers are referred to Noland and Polak (2002) for an early review, Carrion and Levinson (2012) and Li et al. (2010) for a more recent review of the research area.

As compiled in Carrion and Levinson (2012), Wardman and Inabaz (2012), and Li et al. (2010), the literature reports varying VOT, VOR and RR values. Possible reasons for the discrepancy among these values include the time of day for which the

Table 1
Summary of selected descriptive travel time studies and findings.

Study	Roadway type	Variation measure(s)	Findings
Tu et al. (2007)	Freeway (Netherlands)	STD	<ul style="list-style-type: none"> Adverse weather increases the variation Adverse weather has higher impact during <u>low demand</u> hours
Van Lint et al. (2008)	Freeway (Netherlands)	STD, CoV, BI, MI, PR, SI, WI	<ul style="list-style-type: none"> Travel time patterns vary from day-to-day Travel time distributions are: symmetric with low variance during free-flow; symmetric with high variance during congested flow; right skewed during congestion on- and off-set
Franklin and Karlstrom (2009)	Urban roads (Sweden)	STD/Mean lateness	<ul style="list-style-type: none"> Variation in travel time can be mainly explained by segment and TOD High mean-lateness values for up and down shoulder of peak periods
Peer et al. (2010a,b)	Freeway (Netherlands)	STD	<ul style="list-style-type: none"> Unit increase in mean travel time is associated with a larger increase in variability during free-flow conditions Variability on freeways and urban roads has different characteristics.
Chien and Kolluri (2010)	Freeway (USA)	STD, BI	<ul style="list-style-type: none"> Tuesday and Friday have higher average travel times Inclement weather increases the variation Higher impacts during <u>peak</u> hours
Martchouk et al. (2010)	Freeway (USA)	STD	<ul style="list-style-type: none"> Travel time can vary up to 100% of average time during any given day Higher standard deviation during peak periods Same days do not necessarily exhibit a consistent travel times Snow conditions significantly affect the average travel time and standard deviation
Kwon et al. (2011)	Freeway (USA)	BI	<ul style="list-style-type: none"> PM peak has higher demand compare to AM peak but PM variability is lower (possible reason is stated to be the downstream bottlenecks) Weather has relatively little impact on variability No weather effect observed around <u>midday</u>
Yazici et al. (2013)	Urban Roads (USA)	STD, CoV	<ul style="list-style-type: none"> Higher travel times but higher reliability (lower CoV) during peak hours Inclement weather increases the travel time reliability (decreases CoV)

STD: standard deviation, WI: width index, BI: buffer index, PR: probability, CoV: coefficient of variation, SI: Skew Index, MI: misery index.

values are calculated, the trip type, the study region, and the congestion levels. Tseng (2004) and Small et al. (2005) also discuss the fact that SP studies underestimate the savings compared to RP studies. Hensher (2010) discusses theoretical and practical aspects of SP and RP differences in detail, as well as the impacts of perception. In another study of Hensher (2006) citing Severin, 2001, he suggests, with respect of stated choice studies, “statistical considerations have to be balanced against behaviorally sensible strategies”. Carrion and Levinson (2013) also argue that travelers’ travel time perceptions are a likely reason for the discrepancy of SP and RP studies. Peer et al. (2010a,b) reports a discrepancy in self-reported and actual travel times of travelers. Carrion and Levinson (2013) state that their work “scratches the surface of the influence of perception on the valuation of travel time” and emphasizes the importance of traveler perception of travel times. They report that survey subjects value travel time reliability more than the travel time savings calculated based on self-reported travel times. Carrion and Levinson (2013) suggest additional analysis of the discrepancy between actual and perceived travel time as a future research direction in VOT studies. Given the scarcity of actual and perceived travel time data for the same sample/region, the current study focuses on the actual travel time and variability patterns in an urban context. Then, with reference to the relevant literature, the calculated temporal travel time patterns are used to discuss the discrepancy between the actual and assumed/perceived travel time characteristics.

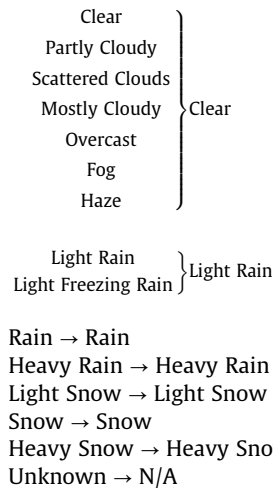
3. Data

This paper uses the taxi travel times available through the GPS records of taxi trips obtained from the Taxi and Limousine Commission (TLC) of New York City. The dataset has more than 370 million taxi trips covering the period from January 1, 2009 to November 28, 2010. The vast majority of trips originate and end in NYC (the main origin and destination points being in Manhattan). The dataset includes other destinations such as Long Island and New Jersey. Overall, the data include trips for all possible time periods and traffic conditions, as well as almost all regions in and around the city. For each taxi trip, the travel time is calculated using pick-up and drop-off date and time. As indicated in the literature (Bhat and Pinjari, 2000; Anastasopoulos et al., 2012), trip purpose or activity and corresponding trip distance are a few of the factors that affect the duration of the trip. Lomax et al. (2003) suggests using “travel rate” (in minutes per mile) as a length-neutral surrogate for trip duration variation, and in the current paper, each trip travel time is divided by the trip length and used as a length-neutral travel time measure. This conversion makes it possible to analyze the system-wide travel times and to avoid using particular origin–destination pairs or a representative trip length. Similarly, travelers’ demographics and their mode choice can also affect the trip duration. Since the taxi passenger’s mode choice is already revealed and the taxi driver operates the taxi rather than the traveler, travel rate is free from the impact of travelers’ mode choice and demographics. However, the single source of travel time data (taxi trip data) might introduce a selectivity bias which is discussed below.

Data on weather conditions are gathered from the weather underground website and includes various weather-related information such as temperature, wind speed and direction and precipitation. The weather conditions are classified based on precipitation, cloud structure, visibility, and so on. Varying severity levels of rain and snow conditions are also categorized

based on precipitation levels. In this study, the clear and rain categories are investigated where the rain conditions include three sub-categories (e.g., light rain, and heavy rain). Snow conditions are not included mainly due to their low rate of occurrence, resulting in relatively lower trip record sample sizes. Conditions such as “overcast” or “partly cloudy” with no precipitation are assumed to be no different from “clear” conditions as far as traffic conditions are concerned. Although “fog” conditions may have an impact on traffic flow for freeways, it was assumed that effect of fog would be negligible for travel within New York City. Hence, the following categorization scheme is followed for the analysis:

Existing Categories → Assigned Categories



Wunderground updates weather conditions at least every hour unless there is any change in weather condition. While combining taxi trip and weather information, the weather conditions at the beginning time of each trip was assumed to be valid for the whole trip. Considering that around 75% of taxi trips are completed within 15 min, the probability of weather condition changing over the course of a single trip is very low.

3.1. Data cleaning

The dataset includes erroneous records such as those with zero trip distance or zero trip duration (e.g. same pick-up and drop-off time stamp). These records are excluded from the analysis. Besides such possible machine errors, some trips have unreasonable travel time and distance records. A trip record is initiated manually by the driver via starting the meter when a customer gets in the cab. The record is completed, again by the driver, when the passenger gets out of the cab. Hence, the aforementioned unreasonable records are likely to be the result of human error, e.g. taxi driver starting the meter without a passenger and then stopping the meter immediately, which produces a trip record with a trip duration of a few seconds or a trip distance of a few yards. Similarly, if the passenger makes a temporary stop at an intermediate location, the taxi meter keeps running. Such a trip record might have a very high trip duration regardless of the trip distance. The unit of analysis in the paper is the travel rate (minutes per mile), which is mathematically the inverse of speed. Travel rate is calculated by dividing the trip duration by the traveled distance. In this respect, the aforementioned taxi records may yield travel rates which correspond to very large or very low travel rates. In order to exclude these possible human errors, the records with a travel rate higher than 1 min per mile (corresponding to an average speed of 60 mph for the complete trip) and those with a travel rate lower than 40 min per mile (1.5 mph; half of the average human walking speed) are deleted. It is practically impossible for the average speed of a complete trip to be over 60 mph in NYC’s urban network. Meanwhile, extreme congestion in NYC may cause speeds lower than 1.5 mph under particular conditions (e.g. due to road work during peak hours in midtown). However, it is very unlikely for a complete trip to have such a low average speed or high travel rate. Overall, 1.4% of all records are excluded by data cleaning. Less than 1% of the records are deleted due to very high travel rates (very low trip speeds), which are more likely due to a human error involved with initiating the trip record. Hence, the bias – if any – introduced by data cleaning is not substantial. After merging the taxi data with weather data, a very small number of records with “unknown” or “N/A” weather conditions were also excluded.

3.2. Selectivity bias

The data consist of travel time records of taxis (and taxi drivers) and may not fully reflect the trip times for ordinary drivers in the city. Ordinary drivers may spend more time determining the right path or drive slower to avoid missing turns; thus their travel times may vary based on their unfamiliarity with the network. Similarly, taxi drivers’ driving habits are known to

be different from those of ordinary drivers. On one hand, these facts introduce a selectivity bias to the analysis. On the other hand, taxi drivers are very experienced about the congestion patterns in New York City. They can easily figure out the shortest paths (in terms of both distance and travel time) between two points. The analysis treats taxis as probes and aims to extract the variation in travel times. In this respect, the introduced bias is – arguably – a preferred one as the travel time records exclude the uncertainty introduced by drivers' unfamiliarity with the network. A similar bias can also be discussed in terms of the areas typically served by NYC taxis. Taxi trips in NYC are mainly concentrated in Manhattan. Nevertheless, the high number of taxi trips in NYC (daily average of over 400,000 trips) provides a sufficient sample to make inferences about the overall traffic conditions in NYC. The richness of the data is recognized by the New York City Department of Transportation which uses the data set as one of the data sources for investigating transportation issues in NYC, including congestion (NYCDOT, 2013). The current study also assumes that the taxi trip records accurately reflect the travel time conditions in NYC.

4. Descriptive analysis

As a first step in identifying the temporal variation in travel time, the travel time distributions for each hourly period for all days of the week are extracted for clear weather conditions. Then, the average, the standard deviation, and the coefficient of variation (CoV) of the travel time distributions for each hourly period are used to investigate the travel time and variability patterns. Fig. 1 shows the average travel times ($ATT = \mu$), standard deviation ($SDTT = \sigma$) and coefficient of variation ($CoV = \frac{\sigma}{\mu}$) for all hourly intervals and all days of the week.

As expected, the travel times during the work day and commuting periods (7 AM to 8 PM) are higher. Periods around midnight on Saturday and Sunday (referring to Friday and Saturday nights) have relatively higher ATT compared to weekday nights. This is an expected result considering the higher traffic on weekend nights mainly due to night-out activities in NYC. The lowest ATTs are recorded during early morning hours (5–7 AM). As an unexpected result, the highest travel times are not observed during weekday peak hours, but around midday on weekdays. ATT among the weekdays also differs. Monday has relatively lower travel times whereas Wednesday and Thursday have higher day-time average travel time values. The midday and mid-week peaks are also recognized by NYC officials (New York Times, March 23rd 2010). Among weekend days, Saturday has higher travel times compared to Sunday.

SDTT follows more or less the same trend as ATT. The higher variations are generally observed in the same days and periods that have higher travel times. An important exception is the 7–8 AM period. ATT shows a sharp increase after 7 AM. For SDTT, a similar sharp increase is observed after 8 AM. During PM peaks, the reverse situation is observed. SDTT values generally start decreasing after 6 PM whereas ATT values sustain high values until 7 PM. These periods can generally be viewed as the congestion build-up and dissipation periods. Hence, SDTT reaches its highest value after congestion is fully built up and does not start decreasing until the maximum congestion dissipates.

The values for the coefficient of variance exhibit an opposite pattern as ATT and SDTT; CoV is lower during working and commuting hours and higher during uncongested evening, late night, and early morning hours. Between 6 AM and 10 PM (high daily activity period), CoV values are lower compared to relatively less busy hours. Wenjing (2011) investigates the analytical relationship between several travel time reliability measures and suggests CoV as a good proxy for several other reliability measures. Considering that lower CoV implies higher reliability, the time periods with relatively higher travel times and higher standard deviations have, counter-intuitively, higher levels of travel time reliability.

4.1. Impact of weather on travel time and variability

On one hand, adverse weather conditions are generally expected to increase the travel time, which agrees with the past literature and the current study findings. Fig. 2 shows the percentage increase in ATT during light rain conditions. ATT increases up to 21% except for a few time periods. Late night periods exhibit lower ATT, but the change is only –1%. On the other hand, the literature has contradictory findings regarding weather's impact on variability and current study findings agree with this contradictory result as well. As shown in Fig. 3, percentage changes in SDTT under light rain vary between –12% to 51%. CoV varies between –14% and 25% under light rain, where the changes are mainly in the negative direction (Fig. 4). Hence, considering that lower CoV values suggest higher reliability, it can be argued that inclement weather may result in higher travel times but also in higher travel time reliability.

The severity of rain conditions (light rain → rain → heavy rain) affects the magnitude of change in ATT, SDTT and CoV. As shown in Figs. 2 and 3, ATT and SDTT mostly increase as the weather severity increases (Figs. 2 and 3). It should be noted that the empty boxes in Figs. 2 and 3 refer to the time periods for which there was no observation of that particular condition, e.g. no heavy rain occurred during the 5–6 AM period on any Wednesday in the data. This limitation implies that the findings are more reliable for more common weather conditions, i.e. clear and light rain.

5. Identification of travel time patterns

The previous sections report the descriptive statistics for travel time in NYC for different time periods and weather conditions. In this section a Classification and Regression Trees (C&RT) methodology is used to estimate the ATT, SDTT, and CoV for all hourly periods, all days and clear weather conditions. The purpose of this analysis is not to obtain estimated travel

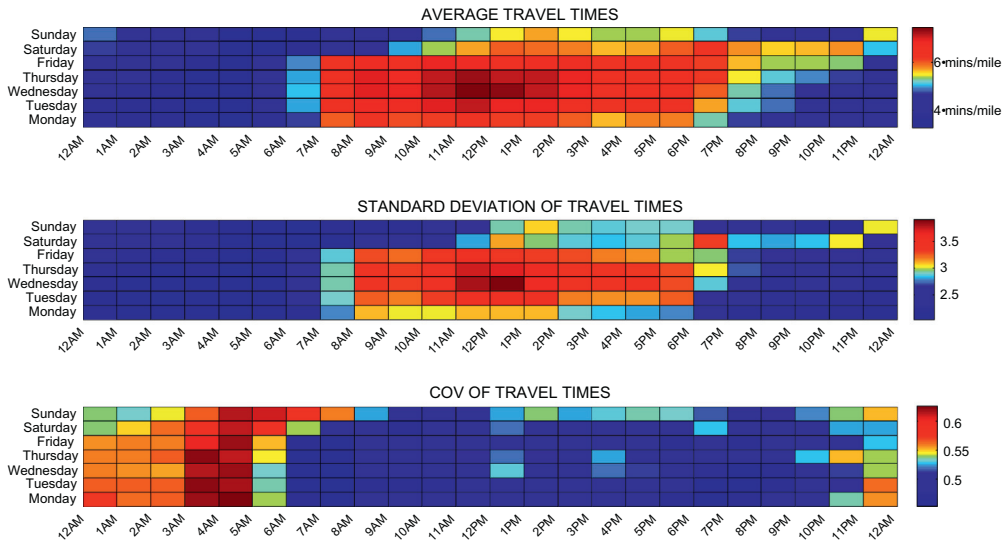


Fig. 1. The 24/7 visualization of ATT, SDTT and CoV.

time values which have significant importance in terms of prediction, since the large taxi GPS dataset provides actual travel time information with a very high reliability. The focus of this section is rather to identify the DOW–TOD partitions that exhibit similar travel time characteristics. Once the periods with similar travel time characteristics are identified, the implications for VOT, VOR, and mode choice studies can be elaborated.

5.1. Classification and Regression Trees

Classification and Regression Trees (C&RT) is a non-parametric model proposed by Breiman et al. (1984) and used in a variety of fields such as statistics, data mining, artificial intelligence, and machine learning. C&RT uses categorical or continuous input to predict the target variable which can also be either continuous or categorical. The calculated tree is a classification or a regression tree, when the target variable is categorical or continuous, respectively. In the current paper, the C&RT method was chosen particularly for its:

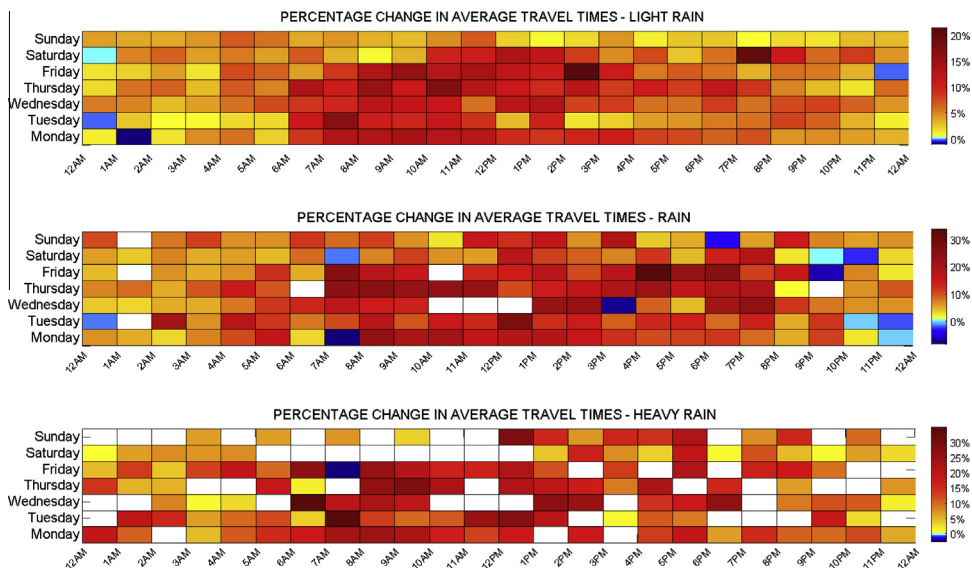


Fig. 2. Percentage change in light rain ATT with respect to clear weather.

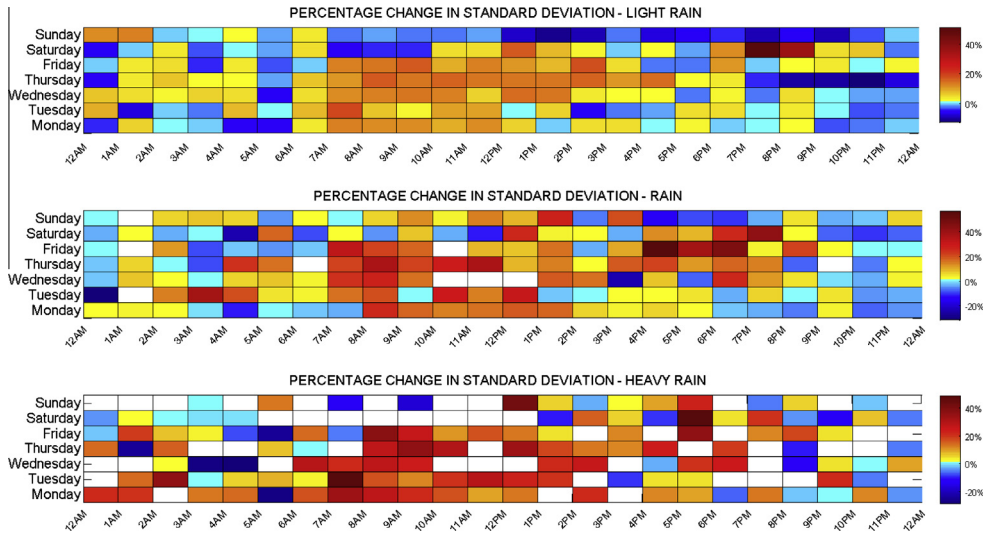


Fig. 3. Percentage change in light rain SDTT with respect to clear weather.

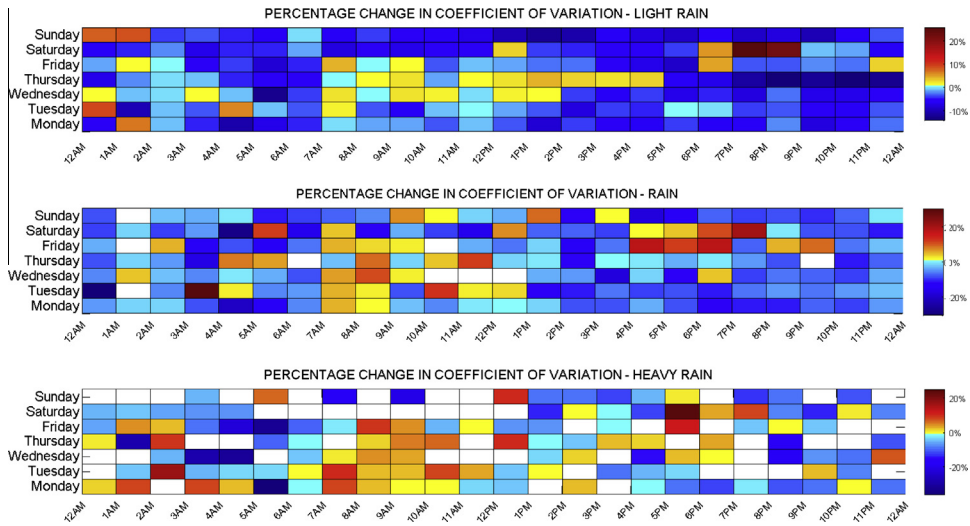


Fig. 4. Percentage change in light rain CoV with respect to clear weather.

- non-parametric nature which does not require any functional relationship or any distributional properties of the independent and independent variables;
- robustness and ability to handle outliers effectively;
- ability to handle categorical variables with many levels (such as all the input data in the current paper, e.g. 24 TOD and 7 DOW categories) efficiently;
- binary tree structure which is easy to interpret.

As shown in Fig. 5, the C&RT algorithm partitions the target variable into more homogenous clusters by constructing a binary tree that narrows the decision space at each node, based on a split criteria. The Gini Index is a commonly used criterion for node split in C&RT and is employed in the current paper. The Gini Index suggests an impurity criterion, $i(t) = 1 - \sum_{j=1}^J p^2(j/t)$ where $p(j/t)$ is the estimated probability that an observation in node t belongs to class j for a particular classification tree. Let p_{LEFT} and p_{RIGHT} be the proportions of data in t_{LEFT} and t_{RIGHT} , respectively. At each node, the split is performed so that change in impurity $i(t) = 1 - p_{LEFT} i(t_{LEFT}) - p_{RIGHT} i(t_{RIGHT})$ is maximized. For regression trees, the computation of the impurity function is based on sum of squared residuals, but the tree is still constructed similar to classification trees by maximizing the change in impurity.

The C&RT algorithm expands the tree to the level where it fully represents the target variable. Therefore, the tree may have a large number of nodes which is referred as high tree complexity. A fully developed complex tree does not necessarily

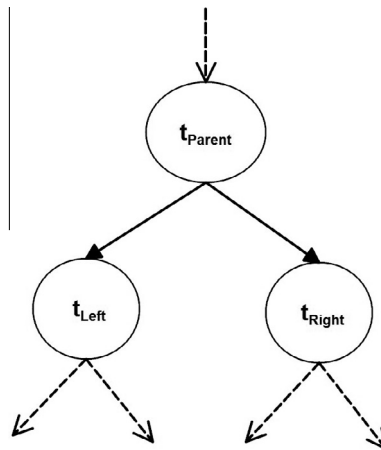


Fig. 5. Node split structure of C&RT.

have good prediction power due to over-fitting. To obtain a tree with less complexity, yet the best prediction power, model validation is performed via cross validations for different levels of tree complexities. The “optimal” tree size is determined based on the trade-off between the tree costs after *cross validation* and *re-substitution*. Re-substitution cost refers to the tree “pruning”. Pruning starts from the terminal nodes in the full C&RT tree and child nodes are pruned one by one. Pruning results in a simpler tree, however, the pruning results in a cost of misclassifying the target variable. On the other hand, as the tree complexity increases, the cross validation error starts increasing after a certain level of tree complexity. The optimal tree can be selected as the minimum cost tree or the tree with the smallest number of nodes which is around one standard deviation away from the minimum cost tree. In this study, MATLAB statistics toolbox (Release, 2012) C&RT functions are used and ten-fold cross validation is performed to validate the tree estimations. The minimum cost tree is assigned as the optimal final tree.

5.2. Classification and Regression Trees (C&RT) model findings

As the input for the C&RT, the travel time distributions of the trips that fall into certain DOW–TOD–weather categories are extracted, then the mean, mode and coefficient of variation (CoV) for each distribution are calculated. C&RT can be formed using each DOW–TOD–weather category as the categorical input X with the target variable Y representing mean, standard deviation and CoV of the corresponding travel-time distribution. Fig. 6 shows the estimated optimal regression tree for ATT under clear weather conditions. Fig. 7, on the other hand, maps the estimated values of clear weather ATT, SDTT and CoV values onto all DOW–TOD periods. Overall, these identified periods are consistent with the actual patterns shown in Fig. 1.

Overall, Fig. 6 indicates that the traditional peak/off-peak and weekend/weekday convention may fall short of representing the actual variation patterns of ATT and SDTT. For instance, the highest ATT level is observed between 8 AM and 3 PM covering the AM-peak in part (excluding 7–8 AM) and the whole off-peak period, but excluding the PM-peak. For Mondays, no TOD pattern is found. The C&RT methodologically confirms that there are variations among the days of the week and the differences are not confined only to a weekday–weekend difference. Mid-week days can be distinguished from the rest of the weekdays. Sunday and Saturday travel times are different as well. Similar day-to-day variances exist in SDTT as well. SDTT patterns for weekdays are closer to traditional peak-off peak patterns, but with a shortened AM-peak (8–10 AM) and an extended PM-peak (2–6 PM). Similar to ATT, the highest SDTT is observed during midday hours rather than in the peak hours. On the other hand, calculated CoV patterns are relatively more consistent for all days with the – reasonable – exception of Sunday. Overall, CoV stands out as a more robust and consistent indicator for the variation of travel time characteristics.

6. Considerations for VOT, VOR, and mode choice studies

The results shown so far consist of the descriptive statistics for actual travel times and the temporal and weather related patterns. It should be kept in mind that the findings are based on travel time data on an urban network. Researchers previously pointed out the difference in travel time patterns between urban networks and freeways (Franklin and Karlstrom, 2009; Yazıcı et al., 2012). Hence, the descriptive findings and suggested implications do not apply to all types of study, but rather are illustrative of an urban network case study among various road network structures. This being said, the current study focuses on the impacts of time periods and weather conditions. However, travel times in an urban network can be affected by other variables, which are not included in the GPS records of the taxi trips. The complex urban activity patterns and external conditions such as road work and incidents, have impacts on the traffic conditions, which in turn affect travel time in the city. Moreover, as discussed previously, the taxi drivers' driving behavior and travel time records may not be fully

travel time can serve as a measure of congestion and can be used to make inferences on VOT. On the other hand, the literature indicates that there is a strong interaction between VOT and VOR, which are related to ATT and SDTT respectively. In this respect, identified temporal patterns for ATT and SDTT (Fig. 7) can be used to discuss the transferability of period specific VOT and VOR values for other time periods.

The current study confirms findings from the literature that ATT and SDTT vary throughout the periods of each day and from week day to week day. However, this study has identified to key findings: (1) the high-ATT periods do not coincide with traditional AM–PM peak periods but rather occur throughout the day; and (2) the standard peak and off-peak periods are not homogeneous and may exhibit inter-period heterogeneity. As shown in Fig. 7, ATT initially increases around 7 AM and SDTT starts increasing with around an hour lag, around 8 AM. The reverse trend is observed during the PM-peak. In other words, lower travel time variation is observed during congestion build up and dissipation and higher variation is observed during high congestion. Hence, re-calculating VOT solely on congestion levels (represented by ATT) may not be justifiable.

In brief, the current study findings imply that the constant ATT and SDTT assumption in VOT–VOR studies is violated as ATT (μ) and SDTT (σ) are indeed time dependent. Moreover, ATT and SDTT follow different temporal patterns even during any traditional peak or off-peak periods of interest. Fosgerau and Karlstrom (2010) show that, under certain assumptions on travel time distribution, the value of variability can be successfully approximated assuming constant ATT and SDTT. Hence, the violation of the constant ATT and SDTT assumption may be theoretically tractable with some restrictions. However, this theoretical suggestion cannot address several issues in the survey data, i.e. perception errors, and/or discrepancies between SP and RP estimates of VOT and VOR. In scheduling delay models, the departure time (T_d) is a decision variable that is calculated based on preferred arrival time (T_a) and travel time characteristics (T, SDE, SDL). Based on the current study findings, the actual choice of early departure during AM-peak (or late departure choice during PM-peak) could be a result of a traveler's correct perception of lower travel time variance. In other words, travel time might be consistent for a certain period, but SDE and SDL can be functions of the decision variable (departure time) in scheduling delay models. Hypothetically stated choices may better capture the actual behavior if the actual travel time variance characteristics are reflected in the choice alternatives. In this respect, the current study suggests a more detailed investigation of SDTT and ATT patterns and trends so that behaviorally sensible surveys can be devised.

6.2. Midday and mid-week peak

It has been shown that the peak hours are not necessarily the most congested periods. The midday ATTs are found to be the highest compared to peak hours. Mid-week days (Wednesday and Thursday) are also found to be more congested than the rest of the week days. Hence, a traveler who avoids road transportation (car or bus) during peak hours mainly due to perceived high congestion should behave similarly during midday hours as well. Whether such travelers are aware of the midday peak, and if they are, whether their mode choice behavior is consistent can shed light on the impact of congestion on mode choice.

6.3. Lower travel time variance during inclement weather

Inclement weather is found to increase travel time (as expected) but it also shown to have the potential to reduce variability (not expected) depending on the severity and time period. At the same time, CoV values under inclement weather decrease for most time periods, implying more reliable travel times. Hence, travelers face (or fail to realize that they face) the contradiction of higher travel times, yet higher reliability with inclement weather. Several studies (Guo et al., 2008; Stover and MacCormack, 2012; Nesse, 2012) investigate transit ridership based on TOD, DOW and weather related factors (e.g. precipitation, temperature, etc.). The general consensus is that inclement weather has a negative impact on ridership, but Guo et al. (2008) shows that the impact is higher for buses compared to rail. A wide range of factors can play a role in this difference, e.g. travel time reliability for rail transport is less affected by weather conditions. Considering average travel time and all other factors to be equal, a traveler is expected to choose the mode with higher travel time reliability. In this respect, an incorrect perception of low road transportation reliability during inclement weather can also contribute to the relatively higher decrease in bus ridership. Research on the existence of such incorrect perceptions and the resulting contribution to mode choice may help uncover one of the reasons for the poor perceptions of bus transit systems' reliability.

Quantifying weather's impact on VOT and VOR also merits further research. Noland et al. (1998) find that incidents (as one of the causes of non-recurrent congestion) can affect the scheduling delay costs considerably and argue that "policies aimed at reducing incident probabilities may be more effective at reducing social costs than policies increasing capacity". Jenelius et al. (2011) study the impact of traveler information (among several other factors) on the value of time and note the importance of information on reducing the scheduling costs. Weather conditions are non-recurrent events like incidents but can also be predicted by weather forecasts, which function as public information systems. Hence, weather forecast can help reduce the scheduling costs, provided that travelers perceive the actual impacts of weather correctly.

6.4. Coefficient of variation as a more consistent measure

CoV shows more consistent patterns throughout the week and the day. In that respect, use of CoV, as a more robust measure of variability in VOT and VOR calculations can be promising. Noland et al. (1998) employed CoV to model planning cost

in their simulation analysis and found that while it is insignificant, it has the proper sign. There is one other aspect of the [Noland et al. \(1998\)](#) study that is relevant to our findings. For the simulation analysis, they assume that “*the maximum standard deviation and coefficient of variation occur at the most congested time*”. Their assumptions are supported with reasonable explanations and later studies confirmed their assumption for highways. The current research findings agree that SDTT is higher during the peak (though not maximum) but contradict the assumption that maximum CoV is observed during congested periods. In this sense, the present findings point out a caveat while establishing similar assumptions for urban network travel time studies and help avoid possible wrong assumptions.

7. Conclusions

In this paper, the travel time characteristics (average travel time, standard deviation, and coefficient of variation) in New York City are calculated using a large set of GPS records of taxi trips obtained from the New York City Taxi and Limousine Commission. In addition, GPS records of taxi trips are merged with historical weather data gathered from the Wunderground website. Since the taxis operate 24/7, very reliable travel time statistics have been obtained for all day-of-week, time-of-day, and weather condition categories in New York City. In addition to the descriptive analysis of travel time characteristics, Classification and Regression Trees (C&RT) were used to methodologically determine the temporal patterns of average travel time, standard deviation, and coefficient of variation. Based on the calculated travel time patterns, the discrepancies between the *generally anticipated* travel times are identified and potential caveats for VOT, VOR, and mode choice studies were discussed.

It was also shown that, contrary to common belief, the traditional peak hours are not necessarily the most congested periods and mid-week days are also found to be more congested. Additionally, the peak periods also exhibit inter-period variation which implies that the assumption of constant average travel time and standard deviation in VOT/VOR studies is prone to violation. Coefficient of variation, on the other hand, was shown to exhibit more consistent patterns among the days and was suggested for consideration in VOT–VOR studies as a more robust measure. C&RT results suggest that different time period conventions than a traditional peak/off-peak scheme may be more appropriate while investigating VOT–VOR. The travelers’ perception of presumably high travel time during peak hour vs. even higher travel times during off-peak hours were discussed in terms of the impacts on mode choice. Travel time variation patterns were also discussed in terms of congestion multipliers that can help in the calculation of VOT.

Regarding the weather impacts, it was found that inclement weather indeed increases average travel times yet decreases variability, resulting in higher travel reliability indicated by lower coefficients of variation. The literature confirms the impact of non-recurrent events on the value of travel time and the benefits of traveler information to reduce the scheduling costs. Weather conditions are non-recurrent events, but unlike incidents, they have a predictable nature in which weather forecasts can function as a priori traveler information. In that respect, it is concluded that traveler perceptions on weather impacts should be investigated, so that both the impact of weather on the value of travel time and the possible benefits of providing accurate weather forecast information can be quantified.

It is worth mentioning again that the presented results and discussion are based on travel time data in an urban network. Although similar results are obtained in other urban travel time studies, these results may not be fully applicable to all types of roadway facilities (e.g. highways) without loss of generality. In addition, due to the available data fields, the analysis does not include all of the variables that have the potential to affect travel time. Nevertheless, the presented findings are based on an extensive reliable dataset, which is also used by public agencies to develop transportation policies in New York City. In this respect, the findings suggest important caveats and considerations to be taken into account in value of time and mode choice studies.

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