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A stochastic analysis of highway capacity: Empirical evidence and implications

Shangjia Dong[a], Alireza Mostafizi[a], Haizhong Wang[a], and Jia Li[b]

[a]School of Civil and Construction Engineering, Oregon State University, Corvallis, OR, USA; [b]Center for Transportation Research, University of Texas at Austin, Austin, TX, USA

ABSTRACT
This paper presents a stochastic characterization of highway capacity and explores its implications on ramp metering control at the corridor level. The stochastic variation of highway capacity is captured through a Space–Time Autoregressive Integrated Moving Average (STARIMA) model. It is identified following a Seasonal STARIMA model $(0, 0, 2_3) \times (0, 1, 0)_2$, which indicates that the capacities of adjacent locations are spatially–temporally correlated. Hourly capacity patterns further verify the stochastic nature of highway capacity. The goal of this paper is to study (1) how to take advantage of the extra information, such as capacity variation, and (2) what benefits can be gained from stochastic capacity modeling. The implication of stochastic capacity is investigated through a ramp metering case study. A mean–standard deviation formulation of capacity is proposed to achieve the trade-off between traffic operation efficiency and robustness. Following that, a modified stochastic capacity-constraint ZONE ramp metering scheme embedded cell transmission model algorithm is introduced. The numerical experiment suggests that considering capacity variation information would alleviate the spillback effect and improve throughput. Monte Carlo simulation further supports this argument. This study helps verify and characterize the stochastic nature of capacity, validates the benefits of using capacity variation information, and thus enhances the necessity of implementing stochastic capacity in traffic operation.

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Introduction

Capacity, in general, represents the maximum amount or number that can be contained or accommodated by a certain facility or infrastructure. To transportation engineers, highway capacity is a central concept to the planning of either existing or construction of new infrastructure to achieve a proper demand-supply equilibration (Khanal, 2014), transportation facility design, operation, and management. The Highway Capacity Manual (HCM) defines the capacity of a road as "the maximum number of vehicles that can pass a given point during a specified period under prevailing roadway, traffic, and control conditions." The HCM states further that prevailing roadway, traffic, and control conditions define capacity and any change in the prevailing conditions change a facility's capacity (Khanal, 2014). From this definition, it is obvious that highway capacity is not a constant even for a fixed location due to the variation of prevailing roadway conditions (i.e. geometric and pavement conditions), traffic conditions (i.e. vehicle compositions and heterogeneous driver groups), and control conditions. Therefore, the capacity of a freeway segment changes constantly; the variations in capacity can be even more pronounced for other types of roadway facilities due to uncontrolled access to the roadway facility (Khanal, 2014).

An empirical analysis was conducted using Georgia State Route 400 (GA400) data over a year's observation in 2003. The day-to-day highway capacity was estimated based on a product limit method (PLM) (Minderhoud, Botma, & Bovy, 1997). Three different capacity variation patterns: concentrated (capacity fluctuates around the mean) as in Figure 1(a), half scattered and half concentrated (capacity fluctuations variate along the time) as in Figure 1(b), and fully scattered (larger variation exists in capacity) as in Figure 1(c) are identified and presented. The three different capacity patterns are discovered from three different detectors with same year's data. Pan, Sumalee, Zhong, and Indra-Payoong (2013) state that "…traffic flow, by nature, is correlated in both spatial and temporal domains due to its dynamics, similar environmental conditions, and human behaviors." The noticeable capacity variations over the temporal and spatial scale motivates this research to pursue a stochastic characterization of highway capacity and explore the implications of this treatment. The cause of variations in capacity can be attributed to heterogeneous driver

CONTACT Haizhong Wang haizhong.wang@oregonstate.edu School of Civil and Construction Engineering, Oregon Sate University, Kearney Hall 101.
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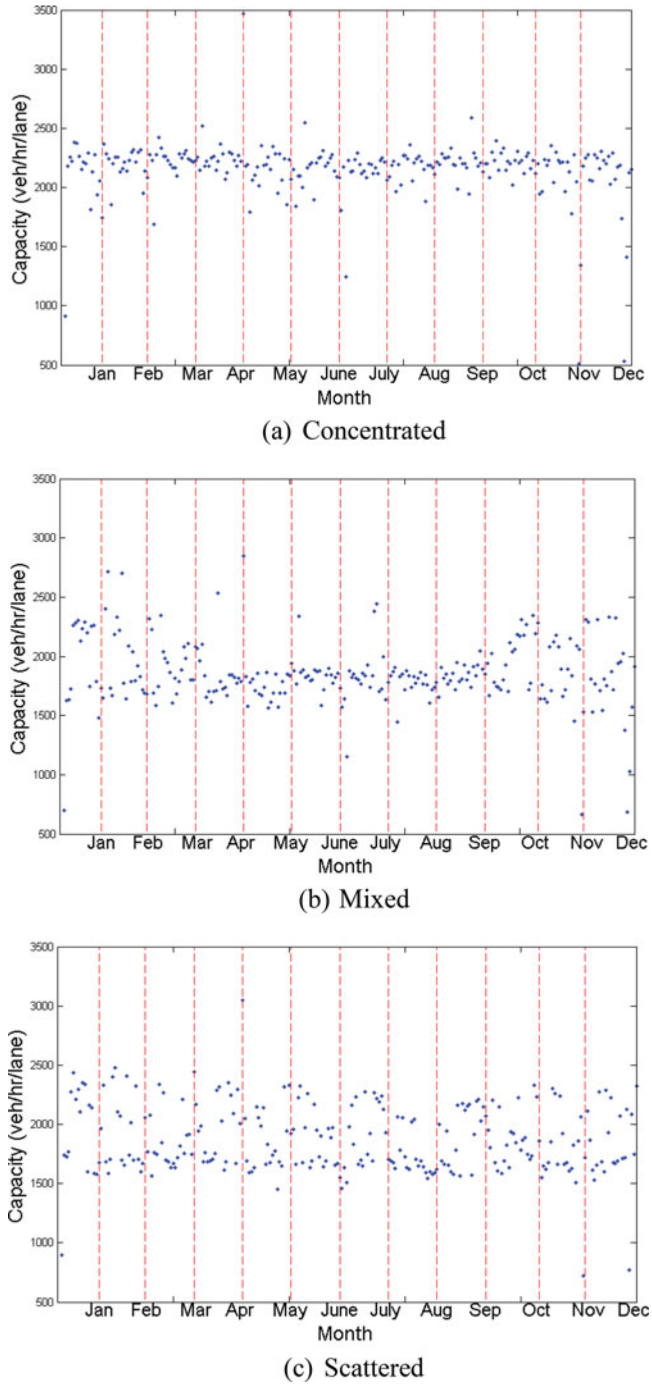


Figure 1. Three different highway capacity variation patterns from Georgia 400 over a year.

behavior and vehicle types, weather, incident/accident, and lane closure/work zone.

However, how the stochastic characterization of highway capacity would impact traffic control and management strategies (i.e. ramp metering) is not sufficiently addressed in existing literature. Traditional highway capacity can be interpreted as the mean of the capacity observations over a certain time period. Alternatively, deterministic highway capacity is generally treated as a threshold, above which traffic breakdown occurs while traffic is smooth if it is below it (Elefteriadou & Lertworawanich, 2003). For example, if the capacity of a location is 2400 veh/hr/ln, traffic flow is uninterrupted when below capacity and breakdown occurs when it exceeds capacity. The deterministic definition is simple to understand and easy to be implemented in practice but ignores the inherent capacity variations which are shown in Figure 1.

The impetus to model highway capacity as a stochastic process is largely driven by prevalent variations in empirical capacity observations. Therefore, when freeway capacity is considered to be a constant value, breakdowns become a deterministic phenomenon (Kittelson Associates, 2010). But researchers have found that breakdowns occur even under controlled conditions. In other words, breakdowns are a stochastic phenomenon. In addition, highway capacity is indirectly affected by various factors such as headway, speed, and density, etc., the stochasticity inherited in these elements (Wang, Li, Yu, & Dong, 2014; Dong, Wang, Hurwitz, Zhang, & Shi, 2015; Wang, Liu, Dong, Qian, & Wei, 2016) will also contribute to the stochastic nature of highway capacity. Therefore, the research question becomes what could engineers or decision-makers gain by knowing how capacity varies over a temporal and spatial domain in terms of designing more robust control and management strategies (i.e. ramp metering control scheme). To better contextualize the motivation, an example is used to illustrate what additional benefits can be gained when the hidden information (i.e. the variance of capacity) is incorporated in the design of ramp metering control scheme. For example, there are two parking charge strategies. One is a flat fee of 10 dollars per day, the other is to charge on average of 10 dollars but varies based on the availability in the parking lot. In the first scenario, drivers only need to pay 10 dollars regardless the availability of parking spaces. However, in the second scenario, drivers may pay more or less than 10 dollars depending on the availability of the number of parking spaces. A 10 dollar flat fee might lead to "parking failure." This is applicable to traffic control as well. Empirical observations indicate there are variations in capacity. A robust traffic control strategy requires a stochastic characterization of highway capacity (i.e. mean and variance). A stochastic analysis of highway capacity is also essential to understand freeway bottleneck breakdowns, congestion dynamics, and prediction of travel time reliability (Jia, 2013). In this paper, a stochastic characterization of highway capacity is conducted on two different time scales: day-to-day capacity and hour-to-hour capacity. First, a stochastic modeling of day-to-day highway capacity combining spatial and temporal correlations is presented. Second, hour-to-hour capacity is inspected. In order to prove the benefit of taking capacity as a stochastic notion, a modified ZONE ramp metering embedded cell transmission model (CTM) algorithm is proposed to demonstrate the performance discrepancies between considering both capacity mean and variance information and mean capacity only. Major contributions of this paper are two-fold: (1) a stochastic characterization of highway capacity through a spatial–temporal ARIMA and the sources of stochasticities; (2) a capacity-constrained ramp-metering control embedded CTM algorithm from the stochastic formulation and the performance of the algorithm is numerically evaluated through Monte Carlo simulation.

This paper begins by presenting a comprehensive literature review on related topics in Section 2. Section 3 provides a spatial–temporal analysis on daily capacity. In recognition of the stochastic nature of capacity, Section 4 introduces a mean–standard deviation capacity formulation and proposes a stochastic capacity-constraint ramp metering scheme. Section 5 presents a modified ZONE ramp metering embedded CTM algorithm, and a case study is followed. Finally, Section 6 summarizes the research and discusses major findings from the empirical study.

Literature review

Stochastic capacity

The conventional definition of capacity according to Highway Capacity Manual (2010) has practical limitations when representing the traffic operational impact of freeway system bottlenecks. In order to accurately quantify the capacity benefits of design, operation, and technology, it is essential to investigate the stochastic nature of capacity. Geistefeldt and Brilon (2009) suggested that randomness exists in freeway capacity and is better represented as a random variable. Minderhoud et al. (1997) stated that capacity is more a stochastic variate following a distribution function instead of a single capacity value.

Brilon, Geistefeldt, and Regler (2005) suggested that if freeway load is at 90% of conventional capacity, the highway will operate at the highest efficiency; this emphasizes that performance measure can be better described by stochastic characterization. "90% of conventional capacity" not only provides high efficiency, but also increases the travel time reliability. There is also potential that using conventional capacity in traffic control would overestimate the system performance, and thus lead to a gap between traffic control design and implementation. Li et al. (2017) investigated the travel time variability from stochastic capacity and demand variations perspectives. The model is effective for understanding the causes of travel time unreliability and evaluate the system-wide benefit of reducing demand and capacity variability. Kerner (2016) showed the connection between the understanding of empirical stochastic highway capacity and a reliable analysis of automatic driving vehicles in traffic flow.

Polus and Pollatschek (2002) also argued that momentary capacity values and the traffic volume observed before breakdown are stochastic in nature and follows shifted gamma distribution. Lorenz and Elefteriadou (2000) suggested that if freeway capacity is defined when the breakdown happens, the definition of capacity should be modified in regard to the probabilistic view of breakdown. Polus and Pollatschek (2002) developed an algorithm to identify the speeds and flow rates which were adopted as a threshold for data analysis to determine capacity. Brilon et al. (2005) used traffic flow counts at a 5-min interval to demonstrate that capacity follows a Weibull distribution with almost a constant shape parameter. Lorenz and Elefteriadou (2000) conducted extensive analysis of traffic speeds and flow rates which suggested a revised definition of capacity incorporating the stochastic breakdown component: " …the rate of flow (expressed in passenger car per hour per lane and specified for a particular time interval) along a uniform freeway segment corresponding to the expected probability of breakdown deemed acceptable under prevailing traffic and roadway conditions in a specified direction." Lo and Tung (2003) modeled link capacity as uniformly distributed random variables. Wu, Michalopoulos, and Liu (2010) studied the stochasticity of freeway operational capacity and found that values of freeway operational capacity under different traffic flow conditions generally fit normal distributions. Kerner (2004) presented a probabilistic theory of highway capacity based on the three-phase traffic theory. Dixit and Wolshon (2014) concluded that "there exists a consistent and fundamental difference between traffic dynamics under evacuation and those routines under non-emergency periods." This suggests that traditional capacity estimation is not suitable for extreme conditions. Tu, van Rij, Henkens, and Heikoop (2010) also showed that capacity is stochastic in nature.

Capacity estimation approaches

The following definitions are proposed to distinguish the different meanings of the various roadway capacities (Minderhoud et al., 1997).

- Design capacity: A single value represents the maximum traffic volume that passes a cross-section of a road with a probability under predefined road and weather condition. It is used for planning and designing roads.

Table 1. Summary of roadway capacity estimation methods.

Method	Assumption/requirement	Advantage/disadvantage
Headway model	Distribution of constrained drivers (followers) at capacity level can compared with the distribution at an intensity below capacity.	Only headway at one cross-section of an arterial observed at an intensity below capacity are needed. It substantially overestimates observed road capacity.
Bimodal distribution method	Two separate distributions represent the compound distribution of the observed flow rates. Capacity estimated with a normal, Gaussian type distribution can be accepted without much resistance.	That traffic demand can also be represented with a Gaussian-type distribution is doubtful and depends on the chosen observation period.
Expected extreme value method	Traffic volumes conform to a theoretical model such as the Poisson process.	Observations for all sampling intervals are independently (flow rates between sampling intervals are not related) and identically (all counts are elements of the same distribution function) distributed. It implies the mean flow rate during the observation period must be constant. Predicted capacity value strongly depends on the duration of the averaging interval.
Asymptotic method	Traffic volume observations for all averaging intervals are independently and identically distributed.	Estimated capacity strongly depends on the duration of the averaging interval.
Product limit method (PLM)	Requires more than a single day's volume and speed measurement. A bottleneck location should be chosen to be sure of the capacity state of the road whenever congestion is detected upstream.	There is no information about the quality of the estimated capacity value.
Fundamental diagram method	A mathematical mode that fits the observed data.	The parameters of the chosen model need to be obtained for each location anew. Sufficient data over a broad range of intensities are needed to make a reliable curve fitting possible.
Selected maxima method	The road capacity is equal to the selected traffic flow maxima observed during the total observation period.	The number of capacity observations strongly affects the reliability of the calculated capacity value. Choosing the average value is rather arbitrary.
Online procedure	Knowledge is required of the actual prevailing capacities of road sections. The relationship between intensity and occupancy maybe adapted with a scaling factor only to fit the intensity-occupancy curve under various prevailing road, weather, and traffic conditions.	Determination of the critical occupancy in the capacity-estimation procedure is in question.

- Strategic capacity: A value represents the maximum traffic volume a road section can handle. This value or distribution is derived from observed traffic flow by static capacity models. It is useful for analyzing conditions in road networks.
- Operational capacity: A value represents the actual maximum flow rate of the roadway. This capacity value is based on direct empirical capacity methods with dynamic capacity models. It is valuable for short-term forecasting with which traffic control procedures may be performed.

There are various approaches to describe the capacity of a road. Also, depending on the time scale, capacity may differ. In this paper, both day-to-day and hourly capacities are explored using empirical data. They represent roadway capacity under a selected probability that capacity value is lower than a given value. A rich body of methods has been proposed to estimate capacity. Table 1 presents a summary with the assumptions and shortfalls of the methods; only methods for uninterrupted roadway capacity estimation are discussed.

According to Minderhoud et al. (1997), the recommended superiority rank of aforementioned methods is (a) PLM, (b) the empirical distribution method, and (c) the fundamental diagram method. Geistefeldt and Brilon (2009) found that capacity estimation based on statistical models for censored data outperforms the direct estimation of breakdown probability for groups of traffic volumes. In addition, the PLM has superior performance because the theory is well-documented and the calculation generates a capacity distribution instead of a single value. Therefore, the PLM is adopted as the approach to estimate capacity. Capacity is represented as a distribution instead of treating capacity as a fixed value. When a probability is determined, a capacity value is selected accordingly.

Ramp metering

Ramp metering is widely implemented in freeway access control. It helps to reduce delays by managing on ramp influx. It also improves safety, increases the travel time reliability, and reduces emission (Zhang and Levinson, 2010). Ramp metering strategies are summarized below (Papageorgiou & Kotsialos, 2000):

(1) Fixed-time strategy: It is off-line for particular times of- day. Constant historical demands are used instead of real-time measurements, which can be a drawback. Due to the absence of real-time measurements, fixed-time ramp metering strategies can lead to an overload of the mainline flow or an underutilization of the freeway.

(2) Reactive ramp metering strategies: These are employed at a tactical level based on real-time measurements.
   - Local ramp metering: This makes use of traffic measurements in the vicinity of the ramp to calculate suitable ramp metering values and includes demand-capacity strategy, occupancy strategy, ALINEA (Papageorgiou, Hadj-Salem, & Blosseville, 1991), neural networks, and the ZONE algorithm, etc. (Demiral & Celikoglu, 2011). The trials show that ALINEA is superior to other local strategies and the no-control case with regards to total time spent, total travelled distance, mean speed, and mean daily congestion duration.
   - Multi-variable regulator strategy: This strategy tries to hold freeway traffic conditions near desired values. Instead of performing independently for each ramp as local ramp metering, multivariable regulators make use of all available mainline measurements to simultaneously calculate the ramp volume values for all controlled ramps. The representative method is METALINE, a generalization, and extension of ALINEA. It requires a rather complicated design procedure, but show no advantages over ALINEA under recurrent congestion. Due to comprehensive information, METALINEA performs better than ALINEA in the case of non-recurrent congestion.

(3) Non-linear optimal ramp metering strategy: This strategy calculates optimal and fair set values from a proactive, strategic point of view in real time. It considers current traffic states both on freeway and on-ramps, demand predictions over a sufficiently long time horizon, limited storage capacity of the on-ramps, non-linear traffic flow dynamics, etc.

(4) Integrated freeway network traffic control: Designed and implemented independently, most of the control strategies fail to exploit synergistic effects. Suitable extension of the optimal control approaches presented above can lead to integrated freeway network control.

Replacing the deterministic capacity by a probabilistic one that changes dynamically based on real-time traffic conditions and varying probabilities of risk, Wu et al. (2010) improved the Minnesota ZONE metering algorithm by converting the capacity-constraint into a chance-constraint algorithm. Cassidy and Rudjanakanoknad (2005) showed that "metering an on-ramp can recover the higher discharge flow at a merge and thereby increase the merge capacity." Zhang and Levinson (2010) found that meters increase the bottleneck capacity by "postponing and sometimes eliminating bottleneck activations." Papamichail, Kotsialos, Margonis, and Papageorgiou (2010) presented a non-linear model-predictive hierarchical control approach for coordinated ramp metering of freeway networks. Gomes and Horowitz (2006) proposed an asymmetric CTM to address on-ramp metering control problems. It resembles the CTM but two allocation parameters are used instead of one in the case of merging flows. Simulation results suggest a 17.3% delay will be reduced when queue constraints are enforced. Smaragdis, Papageorgiou, and Kosmatopoulos (2004) developed an extension of ALINEA that enables automatic tracking of the critical occupancy in the aim of mainline flow maximization. The proposed AD-ALINEA strategy is valuable in the case that the critical occupancy cannot be estimated beforehand or is subject to real-time change. An upstream-measurement-based strategy AU-ALINEA was also proposed. Both strategies exhibited good performance in a stochastic macroscopic simulation environment. For easy implementation and desirable results of local ramp metering strategy, a mean–standard deviation capacity-constraint ZONE algorithm is proposed to study the stochastic capacity impact on ramp metering in this research.

Conventional two traffic states: free-flow and congested are inadequate for traffic control. Therefore, Chow, Lu, Qiu, Shladover, and Yeo (2010) introduced the novel traffic analysis by investigating speed drop and develop an empirical approach to investigate the stochastic nature of freeway traffic speed drop. The probability of inducing a speed drop is formulated into a bivariate cumulative distribution function of speed and density of approaching traffic. Dervisoglu, Gomes, Kwon, Horowitz, and Varaiya (2009) developed a procedure to automatically calibrate the freeway flow characteristics in terms of the fundamental diagram. CTM is implemented for the calibrated model simulation with a case study in a segment of Interstate 880 of San Francisco Bay Area. The capacity variation and its relation to breakdown and capacity drop are investigated from the fundamental diagram perspective and achieved overall accurate performance. Similarly, based on CTM, Kurzhanskiy and Varaiya (2012) proposed an algorithm to predict and estimated the state of a road network that contains freeway and arterial. Considering the demand and supply uncertainties, Chow and Li (2014) presented a robust optimization model for devising motorway ramp metering strategies which are formulated as a minimax problem. The results show the effective control during transition periods. Motivated by the significant variation of capacity when traffic breakdowns occur, Geroliminis, Srivastava, and Michalopoulos (2011) design a coordinated traffic-responsive ramp metering algorithm for Minnesota's freeways based on density measurements instead of flow rates. The results show the improved freeway and ramp performance.

Empirical analysis

Capacity estimation

Minderhoud et al. (1997) introduced a methodology for the derivation of freeway capacity distribution function. It is based on a statistical method which is commonly used for lifetime or failure data analysis. The formulations are as follows:

$$F\left(q\right) = \text{Prob}\left(q_c \le q\right) \tag{1}$$

More specifically, it could be written as

$$F\left(q\right) = N_c/\,N \tag{2}$$

where $C =$ set of observed congested flow measurement;
$F(q) =$ cumulative distribution function of capacity;
$q_c =$ capacity value;
$N_c =$ number of observation elements i from C with q_i less than or equal to q;
$N =$ total number of observations i in set C.

When choosing a value for $F(q)$, for example, $F(q) = 0.5$, a single capacity value q_c is estimated. A non-parametric approach, the PLM, is used to estimate the capacity distribution function. Function $G(q)$ is defined as the probability that the capacity value q_c is higher than a given value q. The function $F(q)$ is defined by $1 - G(q)$. The general expression of the PLM is presented below (Brilon et al., 2005; Minderhoud et al., 1997):

$$G\left(q\right) = \text{Prob}(q_c > q) \tag{3}$$

$$G\left(q\right) = 1 - \prod_{qi} \frac{k_{qi} - 1}{k_{qi}};\, i \in C \tag{4}$$

where $K_{qi} =$ number of observation elements l in set S with volume q_i larger than or equal to q;

$C=$ set of observed congested flow volume. For later use, $Q =$ denotes the set of observed free-flow volume, and $S = Q \cup^C$ and S is used to represent the set of all observations l.

A simple example is presented to understand the calculation of PLM. As shown in Table 2, a 15-min interval is used to calculate the capacity. Derived density data are used to classify the observations into set C or set Q. Critical density is k_c. In the last column, $F(q) = 1 - G(q)$ was derived. In this example, defining capacity at $F(q) = 0.5$ (the median) would result in a road capacity of 4200 veh/hr per two lanes. If only observations were used, an average of 4025 veh/hr per two lanes would be resulted.

However, this method requires data collected from a bottleneck, the empirical dataset does not meet these criteria in reality. Therefore, the PLM combined with a worst 15-min interval calculation according to FHWA (2010) are adopted to estimate the highway capacity (Flow rate = Auto flow + Van flow + Truck flow × PCE_e). When congestion is detected, the PLM is used to estimate highway capacity. When there are no obvious congestion, the worst 15-min interval is used to estimate a capacity.

Table 2. Product limit method calculation.

Interval i	q_i [veh/h]	Set	Order j	$K_q,\ q_i \in \{C\}$	$G(q)$	$F(q)$
16:00–16:15	3200	C	3	6	5/6 = 0.85	0.17
16:15–16:30	2600	Q	1	—	—	0
16:30–16:45	3000	Q	2	—	—	
16:45–17:00	4000	C	4	5	5/6 ∗ 4/5 = 0.67	0.33
17:00–17:15	4200	Q	6	—	—	
17:15–17:30	4400	C	7	2	5/6 ∗ 4/5 ∗ 1/2 = 0.33	0.67
17:30–17:45	4500	C	8	1	0	1
17:45–18:00	4100	Q	5	—	—	

Capacity = (4000 + 4400) / 2 = 4200.

Spatial–temporal capacity correlation

Day-to-day capacity is vital to traffic controls such as lane closure and work zone. On a daily basis, the temporal effect like weather or spatial effect such as geometrical features would impact capacity. However, how temporal and spatial effects interact is not explicitly explored. A spatial–temporal analysis is thus conducted to characterize the stochasticity in capacity.

Study area and data description

This paper uses data that were collected by Georgia Department of Transportation ITS program on state route GA400 through the whole year of 2003. The data was initially collected through video cameras and extracted through the virtual loop detectors. The data interval is 20 seconds. This route is the North/South freeway entering/exiting city of Atlanta. The data were collected over a 20 mile long corridor by 100 detectors, in which 78 detectors were on the basic freeway and 22 were installed at on/off ramps, as shown in Figure 2.

The time interval for capacity estimation is important and impacts the resulting capacity values. Different time intervals are adopted in other researches, e.g. Brilon et al. (2005) adopt a 5-min interval. The time interval suggested by Transportation Research Board (2000) for

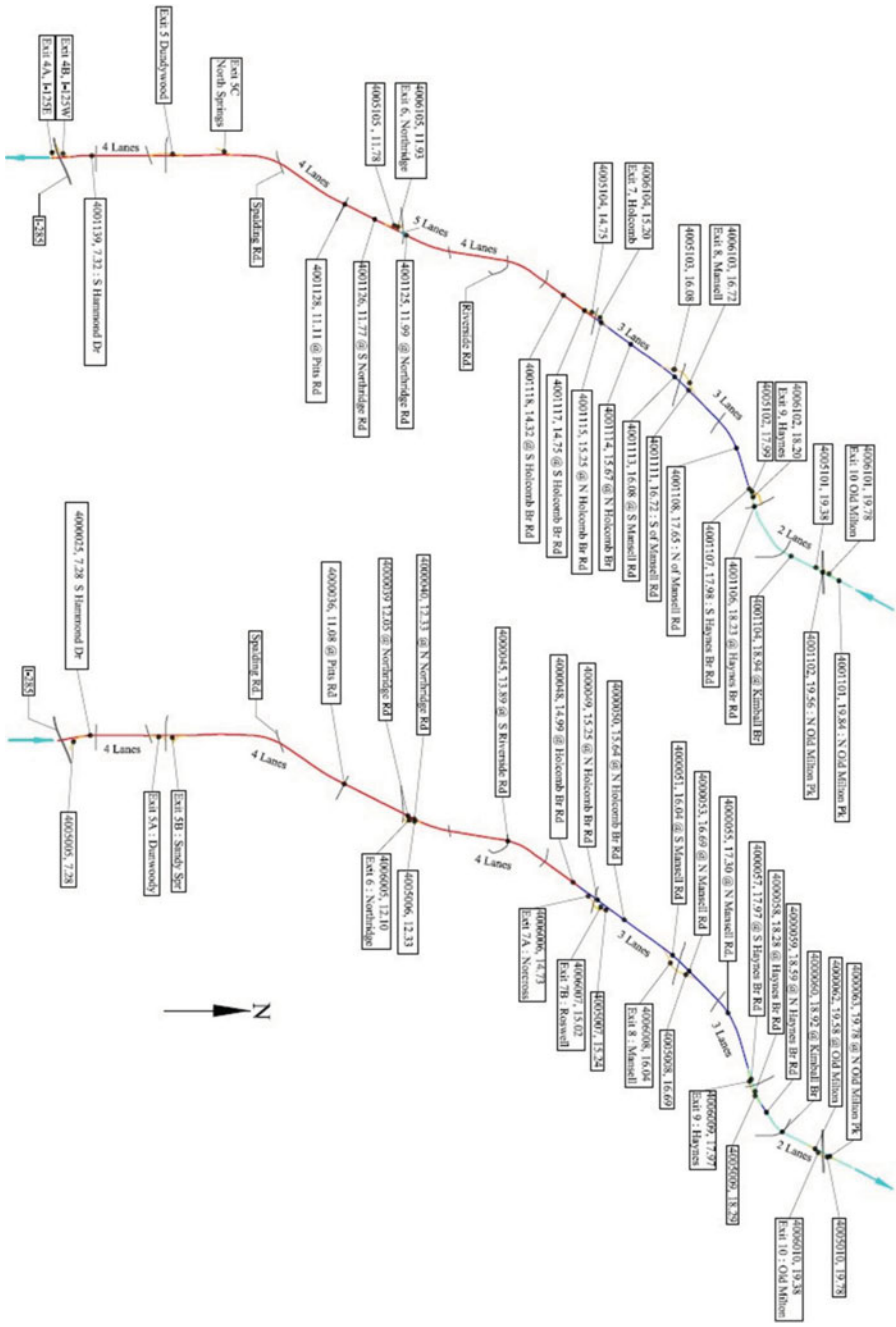


Figure 2. Study site: GA400 100 stations.

capacity observation is 15 min (Polus & Pollatschek, 2002). Minderhoud et al. (1997) suggested that a "15-min interval appears to be a good compromise because the independence of the observations between the averaging intervals can be defended, local fluctuation are smoothed out, and the maximum traffic volume holds for longer than the duration of the interval." In this paper, a 15-min interval is used to measure the day-to-day capacity and a 5-min interval is deployed to estimate the hour-to-hour capacity. The data investigated in this paper were obtained from the basic freeway segments.

Space–time ARIMA analysis

As Pfeifer and Deutrch (1980) characterized, "… STARIMA models reflect (through the specification of the weighting matrices) the idea that near sites exert more influence in each other than distant ones}". Therefore, Space–Time Autoregressive Integrated Moving Average (STARIMA) model expresses each observation at time *t* and location *i* as a weighted linear combination of observations and innovations both in space and time. The mechanism for this expression is the hierarchical

Table 3. Seasonal STARIMA autocorrelations and partial autocorrelations.

Spatial lag (l)	Space–time autocorrelations				Space–time partial autocorrelations			
Time lag (k)	0	1	2	3	0	1	2	3
1	0.126	0.120	0.118	0.119	0.342	– 0.061	– 0.057	– 0.025
2	– 0.455	– 0.360	– 0.341	– 0.328	– 0.748	– 0.009	0.009	0.009
3	– 0.130	– 0.127	– 0.124	– 0.123	0.190	– 0.002	– 0.013	0.004
4	– 0.019	– 0.009	– 0.006	– 0.006	– 0.439	– 0.083	– 0.052	– 0.026
5	0.072	0.064	0.064	0.064	0.101	0.055	0.037	0.031
6	0.020	0.018	0.016	0.016	– 0.245	– 0.108	– 0.078	– 0.034
7	– 0.085	– 0.070	– 0.076	– 0.076	– 0.047	0.086	0.058	0.027
8	– 0.012	– 0.012	– 0.10	– 0.010	– 0.124	– 0.110	– 0.077	– 0.028
9	0.015	0.011	0.010	0.010	– 0.021	0.063	0.037	0.013
10	0.005	0.009	0.005	0.005	– 0.179	– 0.046	– 0.011	– 0.006
11	0.045	0.044	0.052	0.052	0.123	– 0.014	– 0.037	– 0.016
12	– 0.052	– 0.057	– 0.056	– 0.056	– 0.279	0.036	0.051	0.033
13	– 0.056	– 0.062	– 0.072	– 0.072	0.083	– 0.019	– 0.044	– 0.025
14	0.031	0.029	0.026	0.026	– 0.127	0.014	0.027	0.014
15	0.032	0.036	0.042	0.042	0.030	– 0.002	0.018	– 0.001

ordering of the neighbors of each site and the corresponding sequence of weighting matrices (Kamarianakis & Prastacos, 2005).

Table 3 shows the pattern of autocorrelations and partial autocorrelations. Observed from Figure 3, the space–time autocorrelation is significant in time lag 2 and cuts off at spatial lag 3; the partial autocorrelations decays both in time and space. This is characterized by the space–time MA factor. Therefore, the candidate space–time ARIMA model would be Seasonal STARIMA $(0,\ 0,\ 2_3) \times (0,\ 1,\ 0)_2$. It implies that an observed station's performance could be severely influenced by the stations that locate within three degrees.

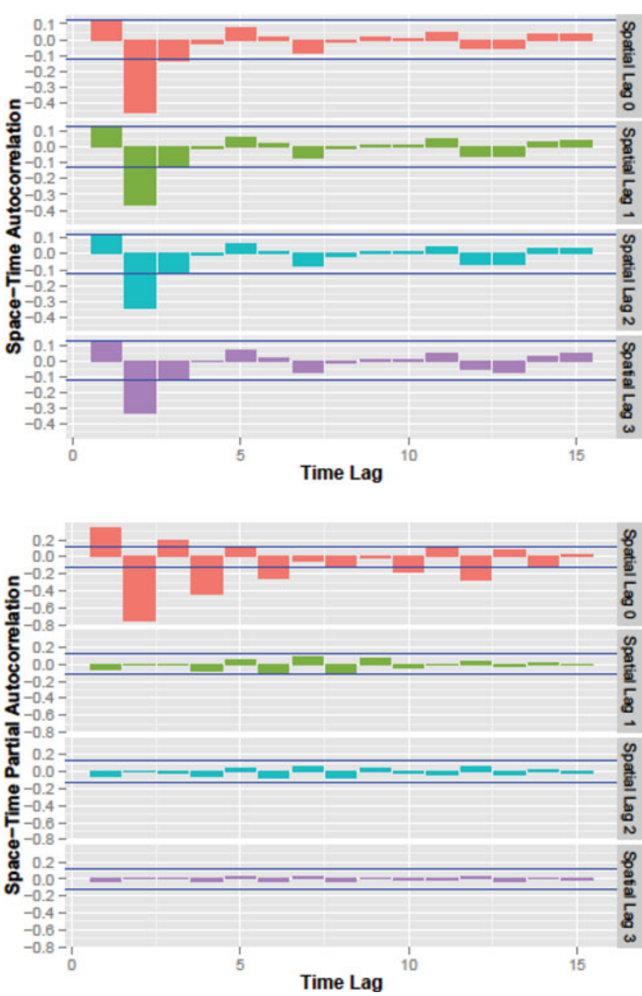


Figure 3. Seasonal STARIMA ACF and PACF.

The result suggests that a short-term seasonality lies in highway capacity. This can be explained from a psychological perspective. A large capacity indicates a higher possibility of traffic congestion. Drivers would change travel schedules or routes based on previous days' experiences which lead to the capacity drop and vice versa. The accident should be taken into account in modeling the stochastic highway capacity. However, due to the limitation of the data, no statistical evidence can be presented at this stage. This empirical study is conducted with weekday data. Traffic flow is thus mainly consisted of work commutes. Also, the traffic that leaves the city would be more likely to travel back on the following day. Therefore, weather conditions have a minor influence on capacity except for the case of inclement weather. Also, as leisure travel is mostly concentrated on weekends, weekday data can eliminate the exogenous factors of uncertainty.

Metering strategy considering stochastic capacity

How to incorporate the stochastic capacity in real-time traffic control and evaluate what additional benefits can be gained are the central arguments which motivated this case study. Ramp metering is chosen as an application in this paper because ramps are the joints within the transportation network. More importantly, the ramps are where the merging and diverging traffic occurs.

Travelers often observe long queues at on-ramps and the queue spill-back phenomenon particularly in peak hours. Therefore, ramps could be vulnerable depending on the performance of the ramp-metering control scheme. To fulfill this end, a mean–st.d capacity-constraint ZONE algorithm embedded CTM is proposed.

Proposed stochastic capacity-constraint ramp metering

Generally, ramp metering is a throughput maximization problem given a deterministic capacity constraint (Wu et al., 2010). Zone algorithms aim to maximize freeway throughput while balancing traffic entering and leaving the zone (Lau, 1996). In Minnesota's ZONE metering algorithm, capacity constraint is applied to regulate the input flow (Lau, 1996).

$$(A + E - X) \leq (S + B) \tag{5}$$

where A is the upstream mainline volume; E is the summation of entrance ramp flow; X is the summation of exit ramp flows; S is the vehicle storage on freeway; and B is the downstream bottleneck capacity.

In Eq. (5), B is a fixed number. However, capacity is a stochastic concept, without considering the inherent randomness, the traffic control scheme designs are far from optimal. For example, if capacity is overestimated, the roadway would be underutilized. If the capacities were actually lower than expected, traffic congestion would occur. Given the traffic data, mean and variance can be obtained. While variance is always neglected, mean capacity is normally used to measure a system's performance, but it is inadequate to use in designing a traffic control scheme. In order to avoid being overaggressive or conservative with traffic control, a trade-off needs to be pursued between efficiency and robustness, i.e. mean and variance.

Yin (2008) presents three models to determine the robust optimal signal timings. The scenario-based mean–variance optimization is relatively easier to implement due to the simple formulation which presents a reasonable approach to achieve a trade-off between robustness and efficiency. Nagengast, Braun, and Wolpert (2011) later introduce another mean–variance model to balance the benefits and returns. Enlightened by Nagengast et al. (2011) and Yin (2008), a modified mean-standard deviation scheme is proposed based on the empirical characteristics of highway capacity.

$$B = \mu + \gamma_t \sigma \tag{6}$$

where B is the equivalent downstream bottleneck capacity, μ denotes the mean of the empirical capacity observation, σ represents the variance of the capacity. To achieve a robust control strategy, designers' attitude toward the risk may vary along the time. γ_t is a weighting parameter that can reflect the amount of capacity variation engineer wants to include, essentially represents this risk changing at time step t. $\gamma_t < 0$ represents a risk-averse strategy; $\gamma_t = 0$ indicates it is risk neutral; while $\gamma_t > 0$ is risk seeking. According to chebyshev's inequity (Kvanli, Pavur, & Keeling, 2005), 75% of the values lie within two standard deviations, that is $\mu \pm 2\sigma$. It is reasonable to assume that the probability of extreme traffic conditions happening as fairly low. Thus, γ_t falls in the range of $[-2, 2]$.

Assuming the distribution of the hour-to-hour capacity in the specific location is known, the deterministic capacity is q_c. If the probability that real capacity q less than q_c is larger than 0.5, then the chances that the empirical capacity exceeds the predetermined capacity is less likely to happen. Then, weighting parameter γ_t should represent a risk-averse attitude. Similarly, if the probability that real capacity q less than q_c and is less than 0.5, the chance that the empirical capacity exceeds the predetermined capacity is more likely to happen. The weighting parameter γ_t would then represent a risk-taking attitude at time t. The reason it was called "attitude towards risk" is that even though the probability is less than 0.5, there is still a chance of occurring. Hence, selecting γ_t is also taking the risk into account.

Similar to the scenario-based mean–standard deviation optimization in Yin (2008), a set of capacities $\Omega = \{1, 2, 3, \ldots, K\}$ is introduced to represent the stochasticity of highway capacity. We assume that within one day, the capacities in a specific location are independent. For each capacity $C_k \in \Omega$, the probability of occurrence is p_k. Although criticized by the additional efforts to specify the scenarios, computational experiments in Yin (2008) demonstrate that "relatively small number of scenarios will be able to produce near-optimal policies."

$$\mu = \sum_{k \in \Omega} p_k C_k \tag{7a}$$

$$\sigma = \sqrt{\sum_{k \in \Omega} p_k (C_k - \sum_{k \in \Omega} p_k C_k)^2} \tag{7b}$$

In this paper, a simplified scenario is designed to prove the concept. Only the upstream mainline volume (A) and the volume from local access metered ramps (E) are considered (only one on-ramp for this experiment). Combined with the mean–standard deviation trade-off scheme, the modified stochastic capacity-constraint ZONE algorithm is presented as follows:

$$\begin{aligned}
&\text{Max } A_t + E_t \\
&A_t + E_t \le B_t \\
B_t = \sum_{k\in\Omega} p_k C_k + \gamma_t &\sqrt{\sum_{k\in\Omega} p_k \Big(C_k - \sum_{k\in\Omega} p_k C_k\Big)^2} \\
&E_t \ge E_{\min} \\
&E_t \le E_{\max}
\end{aligned} \tag{5}$$

Here, the objective is to maximize the throughput, and the throughput is less or equal to capacity. The ramp entrance flow is bounded by the minimum and maximum discharging rate. Due to the varying nature of the risk attitude, time information is contained in γ_t. This variation will lead to the stochasticity of the calculated equivalent capacity.

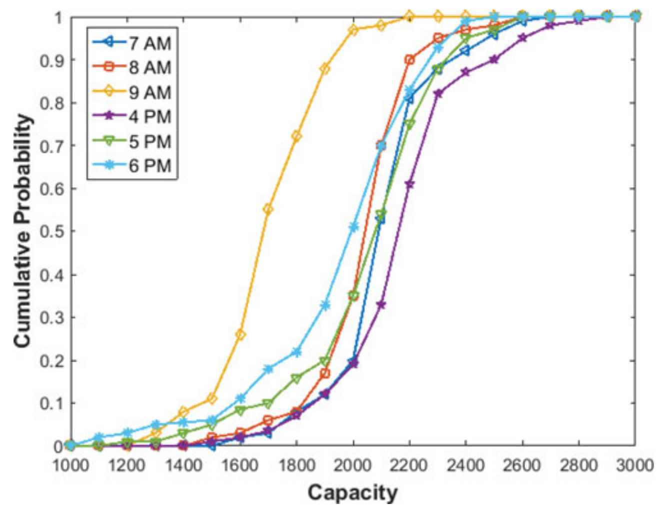


Figure 5. Cumulative distribution function of capacity at rush hours (station 4000025).

Weighting parameter estimation

Using the capacity estimation methodology proposed in Section 3.1, an hour-to-hour capacity can be estimated. After excluding invalid data points, hour-to-hour capacities in June's Mondays are plotted in Figure 4. Horizontally, hour-to-hour capacity within one day changes dramatically. Vertically, capacity varies from day to day in the same hour. Utilizing the mean capacity will lead to missing important variation details, resulting in a decrease of network reliability. In such a case, using deterministic capacity in traffic control design will significantly deteriorate the system's efficiency. Therefore, variations in different hours' capacity should be characterized to increase system robustness. Further, how to capacity variation information we gained from history data in the traffic operation is worth pursuing.

In this paper, rush hours 7 am, 8 am, 9 am, 4 pm, 5 pm, and 6 pm are selected to demonstrate the idea. For instance, the whole year's capacity at 8 am can be estimated and collected; the capacity series then can be empirically formulated into a cumulative distribution function ($P(q_k \le q)$). If the capacity is defined as 2000 veh/hr/lane, conventionally traffic engineer would use this value to design traffic control strategies. However, according to the calculated accumulative function, capacity can be expressed as a probabilistic value. For example, the probability that capacity at 7 am is less than the 2000 veh/hr/lane is 0.2, which means the capacity at 7 am will more likely to exceed 2000 veh/hr/lane. Thus, designer's attitude toward risk will be positive. In terms of the value, it can be decided depends on the probability. For example, at station 4000025, the mean of capacity at 5 pm is 1999 veh/hr/lane, and the standard deviation is 305 veh/hr/lane. Figure 5 implies that the probability that capacity less than 1999 veh/hr/lane is 0.35, which suggests that the capacity would be more likely larger than 1999 veh/hr/lane. γ_t should therefore represent a risk seeking strategy by taking a positive value or limiting the range of γ_t toward a risk-seeking attitude. Similarly, the weighting parameter γ_t at 8 am, 4 pm, and 5 pm can be determined. It is worth noting that capacity can vary from hour to hour. For example, the probability that capacity larger than 2000 veh/hr/lane is 0.8 at 4 pm, while the probability that capacity exceeds 2000 veh/hr/lane is 0.65 at 5 pm Therefore, different hours need different capacities to be adopted in the corresponding traffic control designs.

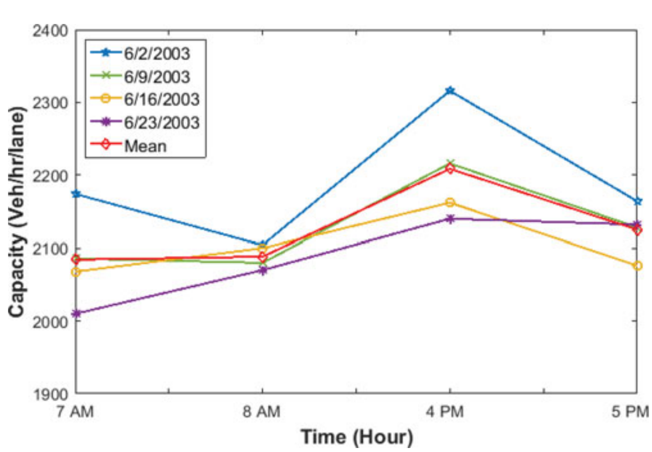


Figure 4. Hour-to-hour capacity at peak hours.

Simulation study

In order to discover how stochastic capacity would affect traffic operation, a ramp metering study was designed and evaluated numerically. A combined CTM and modified stochastic capacity-constraint ZONE algorithm was proposed to capture the performance discrepancies between the strategies that consider both mean and standard deviation information and mean information only.

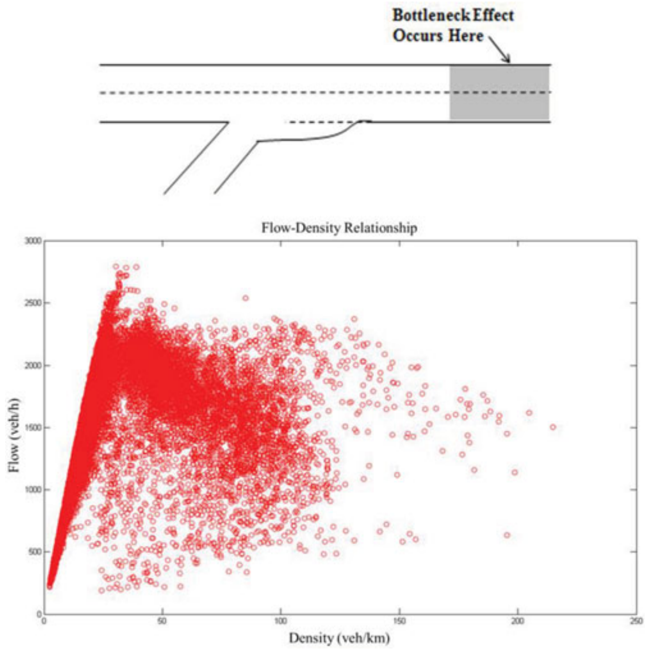


Figure 6. On-ramp metering and the fundamental diagram at 4000025.

Simulation setting

Figure 6 illustrates an on-ramp metering scheme. The simulation is conducted with the following settings. The simulation environment is a 1-km long mainline with a 300-m long on-ramp. The on-ramp is in the middle of the mainline. The scenario contains three components as formulated in Eq. (8). As observed from empirical speed-density and flow-density plot at station 4000025 in Figure 6, critical density at this location ranges from 25 veh/km to 35 veh/km and speed under capacity ranges from 60 km/h to 80 km/h. This also indicates the capacity varies in an interval instead of a fixed value. In this case study, collected empirical peak hour traffic is used to conduct the simulation.

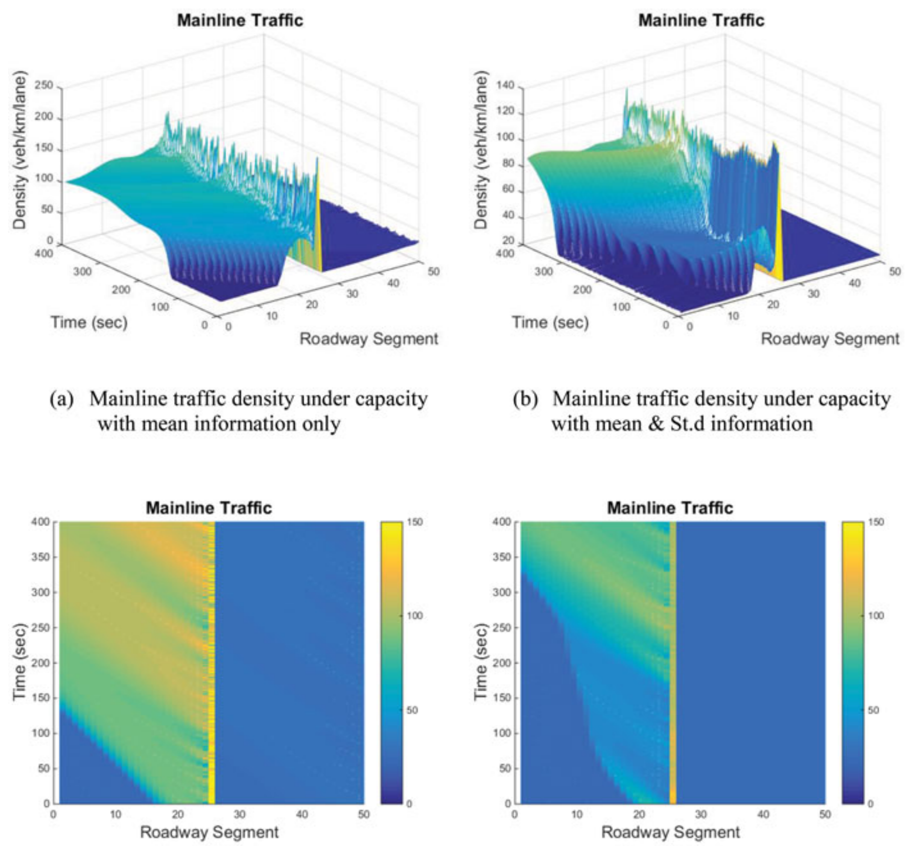
A combined CTM and modified stochastic capacity-constraint ZONE algorithm is designed to numerically evaluate the impacts of stochastic capacity on downstream bottleneck throughput. The algorithm is presented in Algorithm 1.

Highway segment density examination

Figure 7 captures the impact of utilizing stochastic capacity on-ramp metering control. To demonstrate the ramp metering performance, density of each road segment is collected and plotted. Looking at 3-D Figure 7(a) which presents the density when only mean capacity information is considered, as the simulation starts running, the density in the beginning segments increase. At the 25th segment, a sudden increase on density occurs. That is caused by the merge at the ramp. The density at the merge location ranges from 150 to 200 veh/km/lane. This is relatively high for a highway travel. Further, the spillback is observed. Start from 15th highway segment, as the simulation time increase, the density in earlier segments begin to accumulates, reaches to 100 veh/km/lane. The wave can be captured from segment 0 to 20 as the time moves from 0 to 200 seconds. Compare to the scenario in Figure 7(a) that only mean capacity information is considered, Figure 7(b) presents the case when both mean and St.d information of capacity are utilized in ramp metering and shows an improved performance.

Algorithm 1. Combined cell transmission model and capacity-constraint ZONE algorithm.

1. ***Initialization***: Given the initial conditions
2. ***Cell Capacity***:
   - Determine γ_t: Based on the empirical data, determine the risk parameter at the time step t
   - Equivalent cell capacity = mean capacity + γ_t × St.d capacity
3. ***Defining Functions***:
   - Supply: represents number of vehicles that could be accommodated by next cell, min(cell capacity, available space in the cell.
   - Demand: represents the number of vehicles that desire to enter into next cell, min(cell capacity, current traffic volume).
4. ***Cell Transmission***: For both ramp and mainline, flux = min(supply, demand).
5. ***Ramp Metering***: At merge location.
   - Mainline flux = min(supply, demand).
   - Ramp flux = min(minimum metering rate, supply-mainline flux).
6. ***Simulation Results***: For both ramp and mainline, vehicles in cell = initial flow + (in flux – out flux) × simulation time step.



(a) Mainline traffic density under capacity with mean information only

(b) Mainline traffic density under capacity with mean & St.d information

(c) Mainline traffic density under capacity with mean information only (heat map)

(d) Mainline traffic density under capacity with mean & St.d information (heat map)

Figure 7. Comparison of roadway segment density under different capacities.

Similarly, a density peak presents at the 25th segment, but the density value, range from 100 to 120 veh/km/lane, is much lower compare to the scenario that only mean capacity is used in ramp metering control. In addition, the density in the beginning segment did not increase dramatically until the 300 seconds.

To better capture the spillback, a 2-D view of the Figures 7(a) and 7(b) are plotted. In Figure 7(c), the density in highway segment is clearly higher than in the Figure 7(d). This indicates that ramp metering control with consideration of both mean and St.d capacity information reduce the upstream congestion compared to the case when only mean capacity information is involved. Furthermore, the density in the first segment starts to increase at 150 seconds in Figure 7(c), while it starts accumulates at 340 seconds in Figure 7(d), and its value is relatively low. This suggests that ramp metering control that considers variation in the capacity can effectively alleviate the congestion and spillback phenomenon on highway corridor. However, traffic density can only show the congestion information, the system efficiency needs to be further validated. Therefore, the throughput of the corridor is recorded to demonstrate the system performance under different ramp metering control strategies, i.e. stochastic capacity vs. traditional capacity.

Corridor level throughput comparison

As ramp metering is designed to maximize the throughput of the highway, throughput is investigated to further show the system performance. In Figure 8, mean throughput is recorded along the 400 time steps. At each step, throughputs are recorded for both stochastic and deterministic capacity constrained ramp metering strategies. Clearly, stochastic capacity constrained ramp metering delivers larger throughput than deterministic strategy. That is to say, when both mean and St.d capacity information are considered, highway, in general, has better performance than when only mean capacity is considered in metering control. Although there are cases in which stochastic capacity would lead to lower throughput, this is acceptable because pursuing high benefits would definitely require taking additional risks.

In Figure 8, only one simulation with 400 simulation steps is conducted. To further validate the argument, a Monte Carlo simulation with 100 runs is designed. At

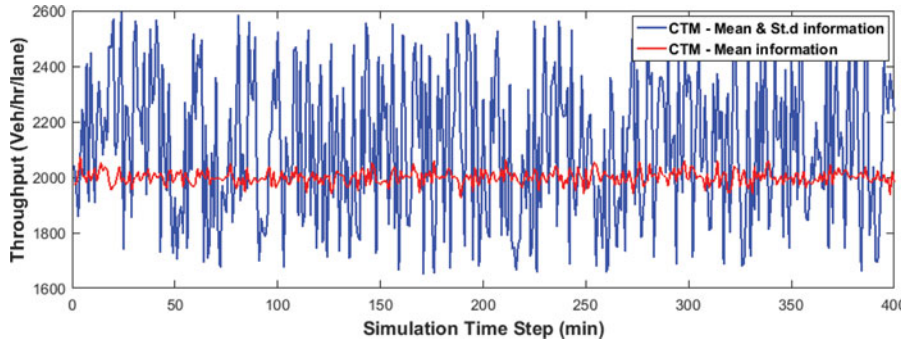


Figure 8. Throughput comparison between with first-order only and first- and second-order information.

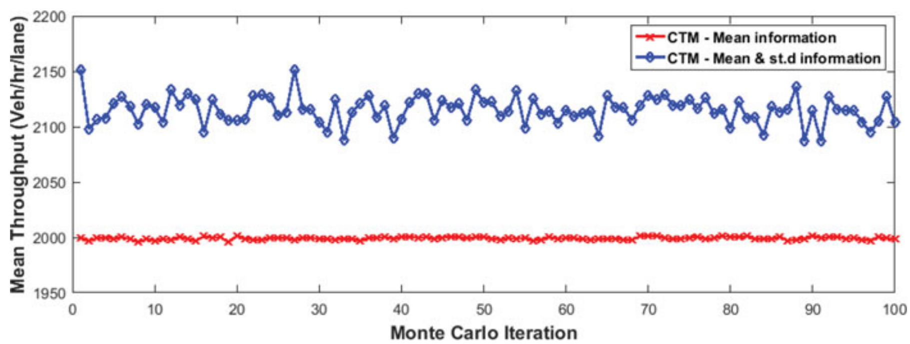


Figure 9. Monte Carlo throughput comparison.

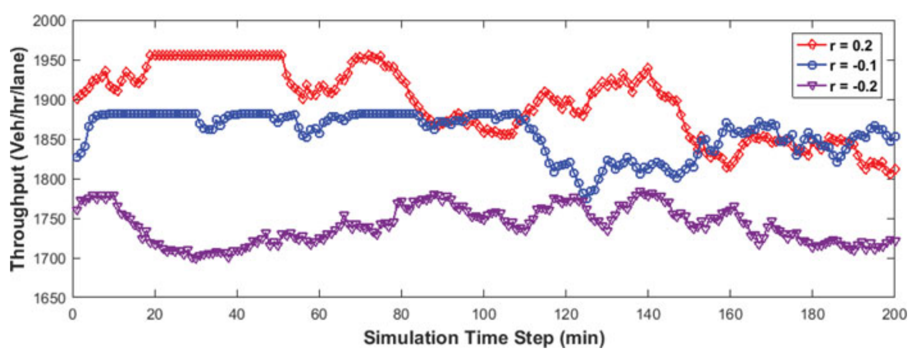


Figure 10. γ sensitivity analysis.

each iteration, the mean throughput is calculated under the investigated two ramp metering strategies. The results in Figure 9 show that stochastic capacity constrained ramp metering has overall performance.

Weighting parameter sensitivity analysis

It worth noting that the weighting parameter γ_t can be estimated based on the cumulative probability function presented in Figure 5. However, it still needs to be determined based on the engineering judgment. Here we present a sensitivity to demonstrate the impact of γ_t's change on the throughput of the highway corridor. As presented in Figure 10, at range of [0, 85], system delivers largest throughput when $\gamma_t = 0.2$; within [95, 110], highway reaches largest throughput when $\gamma_t = -0.1$; in the interval [110, 155], $\gamma_t = 0.2$ lead to the highest throughput; between [155, 185], $\gamma_t = 0.2$, and $\gamma_t = -0.1$ has similar performance; and at [190, 200], $\gamma_t = -0.1$ results in higher throughput. At different traffic condition, γ_t needs to vary to meet the optimal ramp metering performance. Thus, throughput is sensitive to the γ_t. However, the estimation of γ_t can be determined based on the empirical probability function and judgment of designers. The weighting parameter estimation will be further improved by employing learning algorithm in the future study.

Discussion

System efficiency and robustness have always been the focus of designers. For traffic operations, robustness means a system's capability to operate under different conditions. Traffic flow patterns change over time so it is critical that the traffic control scheme accommodate various situations. Advanced techniques allow us to acquire the transportation history data, while how to benefit from gained additional information is the focus of this paper. The proposed mean–standard deviation formulation allows the system to run at its efficient condition, but also adds the robustness based on the weighting parameter γ_t. A trade-off between efficiency and robustness is thus achieved.

Stochastic capacity-constraint ramp metering highly relies on the selected capacity value. If a predetermined capacity is higher than the real capacity, the freeway would be congested by discharging more vehicles from the ramp; the freeway would be underutilized if a lower capacity is used. Knowing the probability that capacity will exceed the predetermined value will help engineers decide if a risk adverse or risk seeking strategy should be taken. The capability that γ_t is able to adapt to both engineers' judgment and empirical experience allows the proposed stochastic-capacity constraint ramp metering algorithm to provide superior performance over deterministic capacity. This is validated by using system's second-order information which better informs the decision-maker.

In this paper, only one on-ramp was considered in the simulation for a proof of concept, but the model can be generalized to multiple ramps metering case. In addition, Wang et al. (2014) suggested that there is dependency exists in different entrance-ramp flows and different mainline flows. Thus, in order to consider multiple on-ramps scenario, the correlation between ramp flows and mainline flows should be considered, it will be another topic for the future research.

Summary, conclusion, and future work

The concept of stochastic capacity has been raised for decades but the causes of stochasticity and the formulation of stochasticity have not been sufficiently explored. This paper presents a stochastic characterization of highway capacity through studying the spatial–temporal correlation inherent in daily capacities and variations presented in the estimated hourly capacities. The numerical results show that the spatial–temporal variations in capacity can be captured through a seasonal STARIMA model $(0,\ 0,\ 2_3) \times (0,\ 1,\ 0)_2$. This presents a strong spatial correlation between detectors within three distance degrees and temporal correlation in two steps of time. The hourly capacity sequence further demonstrates the capacity's stochastic nature.

In addition, this paper proposed a stochastic capacity-constraint ZONE ramp metering embedded CTM algorithm. The capacity is formulated into a mean–standard deviation form to include both mean and variation information of capacity, and achieves a balance between system efficiency and robustness. The weighting parameter is based on the cumulative capacity probability and decision makers' attitude toward the risk. A ramp metering case study is conducted, and the numerical results show that when the capacity variation is considered, the throughput is increased overall and the congestion is also alleviated. The Monte Carlo simulation further validates the benefits of considering the capacity variation information in a stochastic system. However, the proposed stochastic capacity control scheme is designed to achieve improved performance compared to the deterministic ramp metering strategy. It does not give the optimal metering performance. In addition, the risk parameter γ_t is determined based on the engineering judgment. To achieve the optimal ramp metering performance, accurate parameter estimation should be devised, for example, optimize the γ_t to achieve maximal throughput with machine learning technique. Further, only one entrance ramp is considered in this study. To demonstrate the real-life performance of the proposed metering strategy, the study scale need include more ramps and different road designs.

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