

# Traffic-aware Time of Day Breakpoints for Traffic Light Optimization at Scale with Probe Data

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**Abstract**—Fixed-time strategy is a common approach in signal traffic control, characterized by simple and periodic signal plans that are easy to implement without detection mechanisms. A major step in the design of such plans refers to the grouping of the day hours such that the same plan applies for several consecutive hours. The efficacy of the plan, measured by vehicle delays, relies on the matching of traffic with the fixed plan. Accordingly, the time-of-day breakpoints between plans are selected based on the variability of the traffic within each group. The paper studies the selection of time-of-day breakpoints (TODs) based on real traffic characteristics from two cities. Motivated by the Google Green Light project, this study presents an approach to compute TODs based on aggregated traffic statistics computed from anonymized trajectories from navigation applications. We evaluate an optimal dynamic programming algorithm to compute time-of-day breakpoints at an intersection, based on traffic variability among hours. We analyze typical forms of efficient time-of-day breakpoints and examine the impact of the number of daily plans on the ability to predict traffic behavior. We refer to various metrics to measure the variability of the traffic within sets of hours concerning the amount of traffic and its distribution among various movements. We measure the dissimilarity of the time-of-day breakpoints when computed for the different metrics. We also address the joint computation of TODs in adjacent intersections to improve coordination potential.

## I. INTRODUCTION AND MOTIVATION

Efficient traffic signal control is key factor to reducing traffic congestion at intersections [1], [2]. Vehicle movements follow the indications of traffic signals. A sequence of phases repeats periodically where a phase allows traffic of a particular subset of movements. A fixed-time strategy is often applied, where each phase in the cycle takes a constant time, resulting in cycles of the same length. Alternatives to fixed plans can change the plan based on real-time data from infrastructure-based sensors (actuation) or adaptively, based on updated predictions for near-future traffic [3]. Such flexibility is often expensive and challenging to implement due to infrastructure and computation costs, implying the popularity of fixed plans and the necessity for their effectiveness. As traffic patterns vary throughout the day, fixed plans become potentially inefficient if applied uniformly across all hours.

Accordingly, in the design of fixed-plan signal control there are two main steps:

(i) Computing plan time periods - Dividing the day into windows of consecutive hours such that traffic has similar

characteristics within each hour window [4], [5]. Time-of-day breakpoints (TODs) define the boundaries between time windows.

(ii) Plan allocation for each time period - Computing traffic plans for each of the hour windows by optimizing the time allocated within a given cycle to each of its phases. In a plan, each phase only allows a particular subset of the movements to cross the intersection [1], [2].

This study focuses on the first task, namely on *finding efficient time-of-day breakpoints (TODs)*. Often, due to implementation costs, the number of daily plans supported at an intersection is small, typically ranging from 2 to 8 (e.g., plans for morning peak, afternoon peak, midday, and night) [6]. Optimizing time-of-day breakpoints is important for several key reasons: (i) As traffic patterns vary throughout the day, selection of TODs allows matching the plan to the traffic demand; It can be impossible to do so when the same plan has to be applied to various hours with different traffic patterns; (ii) Incorrect selection can lead to saturation at the intersection; (iii) Overall, efficient TODs allow finding plans that match the traffic well and can smooth traffic flow, reduce delay, fuel consumption and carbon emission.

In this study, we develop and evaluate *a methodology to compute time-of-day breakpoints for traffic light plans from vehicle probe data, considering various traffic characteristics*. Our study analyzes data from two cities over five weeks in mid 2024, focusing on weekdays (Monday - Friday).

For our analysis, we rely on a dataset reporting statistics on vehicle count every 15 minutes within the time period. Such a dataset does not refer to a single vehicle but jointly to values of all vehicles in the same hour. This aggregated and anonymized dataset is computed based on the processing of anonymized trajectories from navigation applications. Collecting such data does not require expensive measurement equipment such as cameras. The motivation for this study comes from the large-scale traffic light planning in our Google Green Light project [7], [8]. Green Light helps reduce emissions in cities by analyzing anonymized Google Maps driving trends to develop intelligent recommendations that optimize traffic light timing and coordination. The project has been deployed in over 18 cities including Rio de Janeiro, Seattle, Boston and Bangalore. Following their computation, recommendations for changes in plans of selected traffic lights are provided to the transportation departments of the city. Then, the city traffic engineers evaluate the recommendation and decide whether to adopt a change. Following its adoption, the impact of the

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change is measured as part of the project and a detailed report on the impact is provided to the city. Green Light also supports recommendations that improve coordination among intersections. It can also detect and provide indications for intentional and unintentional changes in traffic light plans [9]. To mitigate the impact of anomalies in traffic patterns, the project prioritizes selection of intersections with lower variability of its traffic patterns [10].

**Contributions.** This paper presents a comprehensive study of the design of time-of-day breakpoints, based on real traffic data. The paper makes the following main contributions:

- 1) The paper presents various variability metrics to examine traffic characteristics within windows of hours, using probe data.
- 2) The paper presents a dynamic programming algorithm for computing ideal time-of-day breakpoints (TODs), which can consider various variability metrics.
- 3) The paper describes an extensive evaluation of the methodology, based on real traffic data from two cities and examines typical ideal time-of-day breakpoints.
- 4) The paper evaluates the impact of the number of daily plans as well as the impact of the variability metric on the time-of-day breakpoints.
- 5) The paper describes a methodology for joint computation of time-of-day breakpoints for intersections along corridors, to improve coordination.

We focus on the computation of TODs in a single intersection. In Section VII we explain how to jointly compute a TOD solution for intersections along corridors. In recent related studies we presented an experimental study of time-of-day breakpoints [11]. We also studied the impact of day-of-the-week awareness in the selection of time-of-day breakpoints that can differ among weekdays [12].

## II. THE TIME-OF-DAY BREAKPOINT COMPUTATION PROBLEM

**Formal Problem Definition.** We now describe the time-of-day breakpoint computation problem, the focus of this paper.

The input to the problem consists of traffic characteristics, often represented as values for every 15 minutes of the day, for every day over a time period. The variable  $N$  denotes the number of daily plans. The aim is to divide the hours of the day into  $N$  windows of consecutive hours, such that traffic has similar statistical properties within each window. Consider a time period of  $D$  days and a particular movement. For every quarter hour  $t$  of the day, let  $X_t = (x_1, x_2, \dots, x_D)$  be the traffic values in that time in each of the  $D$  days. A variability metric  $S(H_i)$  examines the variability for an hour window  $H_i$ , based on the values in  $\{X_t | t \in H_i\}$ .

In the time-of-day breakpoint computation problem, the goal is to divide the 24 hours of the day  $\{0, 1, \dots, 23\}$  into  $N$  (disjoint) windows of consecutive hours  $H = (H_1, \dots, H_N)$ . A solution should have a minimal total traffic variability, computed as:

$$\min_{H=(H_1, \dots, H_N)} S(H) = \min_{H=(H_1, \dots, H_N)} \sum_{i \in [1, N]} S(H_i).$$

Namely, as the sum of variability values for the windows  $H_1, \dots, H_N$ .

For simplicity, we use the hour value  $t$  to denote the hour between  $t:00$  and  $t:59$ . An alternative common form to present a solution  $H = (H_1, \dots, H_N)$  is through the breaking time between each hour window which is the minimal hour in each group  $d_1, \dots, d_N = \min(H_1), \dots, \min(H_N)$ . For instance, for  $N = 5$  the windows  $H_1 = \{6, 7, 8\}$ ,  $H_2 = \{9, 10, 11, 12, 13, 14, 15\}$ ,  $H_3 = \{16, 17, 18, 19\}$ ,  $H_4 = \{20, 21, 22\}$ ,  $H_5 = \{23, 0, 1, 2, 3, 4, 5\}$  refer to five daily plans with time-of-day breakpoints of  $d_1, \dots, d_5$  of 6:00, 9:00, 16:00, 20:00 and 23:00.

Hours are considered in a cyclic manner such that for instance the hours 23 and 0 can be in the same hour window even when  $N \geq 2$ . In Section III we detail several potential variability metrics  $S(H)$  based on traffic demand  $S_V(H)$  or traffic distribution over movements  $S_P(H)$ .

**Types of Traffic Characteristics.** The input hourly traffic values  $X_t = (x_1, x_2, \dots, x_D)$  can be of various forms and detail levels. For instance, they can measure traffic or an estimation of it through sampling, for instance, based on the number of recorded sessions in some navigation application. Another important point is the level of data: it can refer jointly to all vehicles in an intersection or, for instance, be detailed to each of the intersection movements.

**Time Resolution.** Computing time-of-day breakpoints aims to indicate the daily time boundaries of periodic plans in an intersection. In many cities, such plans can change only at the beginning of an hour so focus on hourly resolution of the start time of plans. Similarly, traffic characteristics can also be described at various time levels and focus on detailed traffic characteristics measured every 15 minutes.

**Related Work and Existing Studies.** As finding time-of-day breakpoints (TODs) is a fundamental problem in traffic light optimization, it has been well studied and several approaches have been suggested.

(i) *Traditional traffic engineering* - By this method a day is divided into four windows of hours by identifying traffic pattern with a morning peak-hour window of hours and evening peak-hour window. Time of the windows are selected based on traffic data such that two additional hour windows refer to the time between the peak windows [13], [14].

(ii) *Clustering methods* - This method considers day hours and aims to iteratively merge several of the hours based on similarity of their traffic, representing each window of hours in the time-of-day as a cluster of hours. Two main types of clustering methods were used: K-means and Fuzzy C-means (FCM). In the K-means method, each data point (e.g., an hour of the day or shorter amount of time) is assigned to exactly one cluster. With  $K$  clusters, data points are iteratively assigned to the cluster that its centroid is of a minimal distance from the data point [15], [16], [17]. On the other hand, in Fuzzy C-means (FCM), a data point can belong to multiple clusters with a varying level of membership [18], [19].

(iii) *Genetic algorithms and AI-based methods* - Such methods consider a space of efficient solutions and compute additional solutions by modifying existing solutions and merging several of them. Genetic algorithms have the potential

to avoid locally optimal solutions towards finding globally optimal solutions [4], [20], [21]. They often result in finding efficient TOD solutions but there are cases they need to be modified manually due to convergence issues [21], [22].

### III. TIME-OF-DAY VARIABILITY METRICS BASED ON TRAFFIC CHARACTERISTICS

Towards computing ideal time-of-day breakpoints (TODs), we describe metrics measuring the inherent traffic variability within an hour window over the time period of the data.

#### Variability Metric (i): Variance of Traffic Demand.

The first simple metric examines the variance of the traffic values. For an evaluated hour window the variability measures changes in the amount of traffic over days as well as over the various hours in the window  $H$ .

The hourly score  $S$  for a movement  $i \in [1, m]$  simply examines the normalized standard deviation in the time period over the days. Let  $\mu_t = \frac{1}{D} \sum_j x_j$  be the mean value in hour  $t$  in the time period. Let  $\mu_H$  be the mean traffic value over the hours in  $H$  such that  $\mu_H = \frac{1}{|H|} \cdot \sum_{t \in H} \mu_t$  serves as a representing value for the window  $H$ . The score is

$$S_V(H) = \left( \frac{1}{D} \sum_{t \in H} \sum_{x_j \in X_t} (x_j - \mu_H)^2 \right)^{0.5}.$$

The score examines a total of  $|H| \cdot D$  values and is weighted by the number of window hours  $|H|$  and accordingly the denominator refers to  $D$  itself. The score itself refers to the sum of the scores over all the hour windows, one for each of the daily plans and measures the distance of the hourly value from the representative value of the window.

**Variability Metric (ii): Distribution of Traffic Over the Intersection Movements.** The second metric we consider is motivated by viewing a dominant property of a signal control plan: the partial time it allocates to each of the intersection movements. Accordingly, the metric aims to measure changes in the distribution of traffic over the movements in terms of their part among the total traffic in the intersection.

Let  $X^i = (x_1^i, x_2^i, \dots, x_D^i)$  be the traffic values in some time period  $t$  over the  $D$  days in a movement  $i \in [1, m]$ . The average distribution  $P_t$  at time  $t$  over all days is simply computed as the average ratio for each movement over the days  $P_t = (P_t^1, P_t^2, \dots, P_t^m)$  such that  $P_t^i = (\sum_{j \in [1, D]} x_j^i) / (\sum_{i' \in [1, m], j \in [1, D]} x_j^{i'})$ . Similarly, let  $P_H = (P_H^1, P_H^2, \dots, P_H^m)$  be the corresponding distribution while considering traffic from all time periods in  $H$ .

Consider an hour window  $H$ , representing a set of hours. The score is

$$S_P(H) = \sum_{t \in H} \sum_{i \in [1, m]} |P_t^i - P_H^i|.$$

The score for a solution itself refers to the sum of the scores over all its hour windows, one for each of the daily plans.

### IV. A METHODOLOGY FOR COMPUTING EFFICIENT TIME-OF-DAYS (TODs)

In this section we describe the approach we use in the paper for finding the time-of-day breakpoints.

**Methodology inputs.** The methodology we developed to detect transitions in traffic light plans makes use of traffic aggregated statistics. Such information does not refer to a single vehicle but jointly to the values of all vehicles in some part of the day, such as a particular hour. This aggregated and anonymized dataset is computed based on the processing of anonymized trajectories from navigation applications. It does not require expensive measurement equipment such as cameras. The statistics refer to traffic demand (number of vehicles) for every 15 minutes over the day.

**Overview.** As mentioned in Section II, a solution to the problem is given as a division of the day hours  $\{0, 1, \dots, 23\}$  into  $N$  disjoint windows  $H = (H_1, \dots, H_N)$  of consecutive hours or similarly as the hours  $d_1, \dots, d_N$  that describe the time-of-day breakpoints in which a new window starts. There are two natural approaches for finding efficient solutions.

**An optimal and time-efficient dynamic-programming approach.** As the number of all potential solutions increases as a function of the number of daily plans and the time resolution, we present an alternative approach that allows finding an optimal solution without enumerating all solutions. The approach is based on dynamic programming and relies on a simple observation: Whenever the score of a solution is given as the sum of the values of the variability metrics for the different hour windows, parts of an optimal solution are necessarily optimal for the subset of hours they refer to. This is possible due to the property that *in an optimal solution for hours 0-23 (a total of 24 hours) with  $N$  windows that apply for  $h_1, h_2, \dots, h_N$  hours (such that  $h_1 + h_2 + \dots + h_N = 24$ ), the last  $N-1$  windows necessarily also imply an optimal solution but for the last  $h_2 + h_3 + \dots + h_N = 24 - h_1$  hours.* The reason is intuitive as otherwise, these windows could be replaced by other  $N-1$  for the same hours with a lower sum of variability values. Together with the first window of  $h_1$  hours this can reduce the score of the optimal solution for hours 0-23.

Overall, the approach is intuitive and relies on a basic dynamic programming approach that applies for all types of partitions of an ordered sequence of values with some variability function (called often also a loss function) computed for each subset. As it is very natural, such an approach was described early in the seminal work of Bellman in 1954 [23] (for a general context) and many times later over the years for various fields such as signal processing and hydrology [24], [25]. In the context of time-of-day partitioning, such an approach was proposed by Ma et al. in [26] that considered traffic demand. Note that we refer to a generic variability metric, unlike the particular variability function in [26] that is based on traffic demand.

Consider a traffic variability metric  $S(H)$  and an optimal solution  $M^{opt} = (M_1, \dots, M_N)$  such that  $S(M^{opt}) = \min_{H=(H_1, \dots, H_N)} S(H)$  for some variability metric  $S(H)$  (such as  $S_V(H)$  or  $S_P(H)$  from Section III). Let  $\ell_i = |M_i|$ , namely the number of hours in the window  $M_i$ . The  $N-1$  windows  $M_2, \dots, M_N$  refer to hours  $\ell_1, \dots, 23$  for some value  $\ell_1$  such that together  $(M_2, \dots, M_N)$  indicate an optimal solution for such hours with  $N-1$  windows of hours. As the value of  $\ell_1 = |M_1|$  for an optimal solution is not known, to find an optimal solution, we iterate over its value and rely

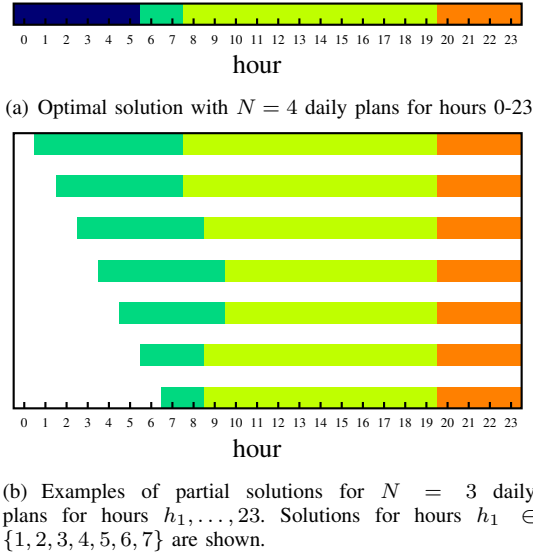


Fig. 1. Illustration of the dynamic programming approach. A solution with  $N$  plans is computed for hours  $[0, 23]$  based on adding a first solution  $[0, h_1 - 1]$  to an optimal solution with  $N - 1$  plans for the hours  $[h_1, 23]$ . Various values of  $h_1$  are considered.

on optimal solutions with  $N - 1$  windows computed for all  $24 - \ell_1$  hours the first window does not include.

We now define a function  $\Phi(n, h)$  for an integer  $n \geq 1$  and  $h \in [0, 23]$  as the minimal variability value that can be obtained for a solution with  $n$  hour windows that applies for hours  $h, \dots, 23$ . Similarly, let  $M^{opt}(n, h)$  be an optimal solution that achieves such a minimal value. By definition, the variability value of the optimal solution  $M^{opt} = M^{opt}(n = N, h = 0)$  satisfies  $S(M^{opt}) = \Phi(n = N, h = 0)$ .

The above structure of an the optimal solution implies that

- The variability value of an optimal solution satisfies

$$\Phi(n, h) = \min_{i \in [1, 23-h]} \left( S([h, h+i-1]) + \Phi(n-1, h+i) \right).$$

Let  $\ell_1$  be the (minimal) value of  $i$  that achieves this minimal value.

- An optimal solution can be computed as

$$M^{opt}(n, h) = \left( [h, h + \ell_1 - 1] + M^{opt}(n-1, h + \ell_1) \right).$$

Note that there can be more than a single optimal solution, but this method always computes an optimal solution. To compute an optimal solution  $M^{opt} = M^{opt}(n = N, h = 0)$ , in the dynamic programming we compute solutions  $M^{opt} = M^{opt}(n, h)$  for  $h \in [0, 23]$  by a decreasing order of  $h$ , starting from  $h = 23$  till  $h = 0$ . For each value of  $h$ , we compute the solution for all values  $n \in [1, N]$ .

The dynamic programming is illustrated in Fig. 1. First, Fig. 1(a) shows a solution for  $N = 4$  plans for all day hours 0-23. The solution is  $H_1 = \{0, 1, 2, 3, 4, 5\}$  (shown in blue),  $H_2 = \{6, 7\}$  (green),  $H_3 = \{8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19\}$  (lime),  $H_4 = \{20, 21, 22, 23\}$  (orange) with windows of lengths  $h_1 = 6, h_2 = 2, h_3 = 12$  and  $h_4 = 4$  hours. With dynamic programming the solution can be computed by considering multiple options for the length  $h_1$  of a first

plan that starts at hour 0 (till hour  $h_1 - 1$ ) along with an optimal solution with 3 plans for hours  $[h_1, 23]$ . Some of such solutions are shown in Fig. 1(b) and differ at the hour at which the second plan starts. The figure shows such solutions for  $h_1 \in \{1, 2, 3, 4, 5, 6, 7\}$  where  $h_1$  indicates the length of the first window of hours. As the optimal solution with  $N = 4$  plans (shown in Fig. 1(a)) has a first plan with  $h_1 = 6$  hours, the dynamic programming adopts the solution for  $N = 3$  plans for hours  $[h_1, 23] = [6, 23]$  which is shown as the sixth (from top) solution for the plans in Fig. 1(b).

**Time complexity:** Overall, we compute  $N \cdot 24$  values, each selected by considering at most 24 values based on the value of  $\Phi(n, h)$ . So the solution and its variability value are derived with a number of  $24^2 \cdot N = 576 \cdot N$  steps.

## V. DISTANCE AMONG VARIABILITY METRICS BASED ON TIME-OF-DAY BREAKPOINTS IN EACH INTERSECTION

This paper introduces two major variability metrics to measure the quality of TOD breakpoints for given traffic characteristics. For a better understanding of the variability metrics, we aim to examine their dissimilarity. Optimizing the TODs based on one metric does not take into account the other metrics. In this section, we aim to better understand that potential concern by examining levels of dissimilarity between solutions to the TOD breakpoint problem. We refer to such metrics as distance metrics and propose a simple method to measure distance among TODs:

**Distance test I.** *Examining the distance of any two solutions. An example for such solutions can be the two TODs an algorithm computes while considering (independently) each of the variability metrics.*

Formally, consider two solutions  $H = (H_1, \dots, H_N)$  and  $M = (M_1, \dots, M_N)$  with the same number of windows  $N$  such that each solution is described as a  $N$  windows of hours. Upon considering two variability metrics, the solutions can be the optimal solutions that correspond to the two variability metrics, as derived by the algorithm from Section IV. For simplicity, we also refer to  $H(\cdot), M(\cdot)$  as functions mapping the hours  $0, 1, \dots, 23$  to an index in  $[1, N]$  based on the index of the window the hour belongs to. *The intuition for the distance metric is as follows: We view a solution as grouping hours into windows. Two solutions would be considered similar if the pairs of hours that share a window in one solution often share the same window in the other solution.*

Formally, in computing the distance of the solutions, we refer to all pairs of hours and examine whether the hours belong to the same window in one solution and also share a window in the second solution or alternatively in both solutions the hours appear in different windows. The distance is simply the ratio of pairs of hours with such property among all pairs of hours. The distance between the two solutions  $H, M$  is defined as

$$R_I(H, M) = \frac{1}{276} \sum_{i=0}^{23} \sum_{j=i+1}^{23} \left( I(H(i) = H(j), M(i) \neq M(j)) + I(H(i) \neq H(j), M(i) = M(j)) \right).$$

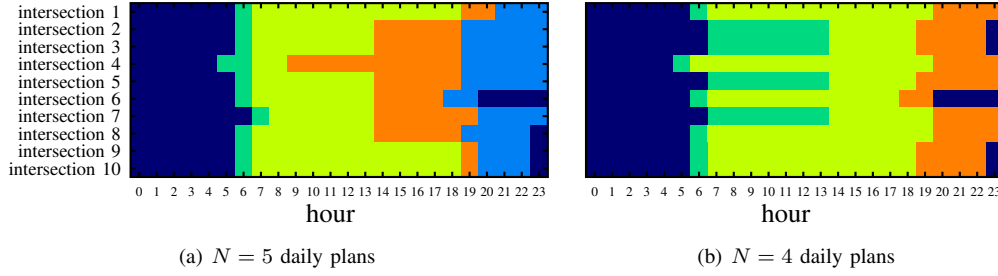


Fig. 2. Hamburg - Illustration of the hourly plan index for 10 major intersections. Variability metric is variance of traffic demand in the intersection.

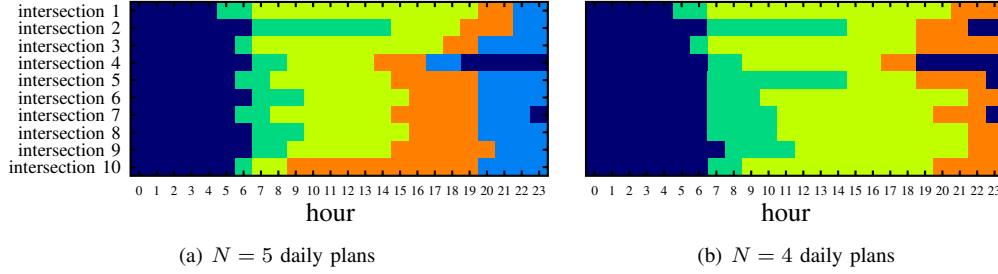


Fig. 3. Seattle - Illustration of the hourly plan index for 10 major intersections. Variability metric is variance of traffic demand in the intersection.

Here,  $276 = \binom{24}{2}$  is the total number of pairs of hours. The function  $I(\cdot)$  is the indicator function that takes the value of 1 if the condition it receives holds. This distance test is symmetric such that  $I_I(H, M) = I_I(M, H)$ .

## VI. ANALYSIS OF TIME-OF-DAY BREAKPOINTS BASED ON REAL TRAFFIC DATA OF TWO CITIES

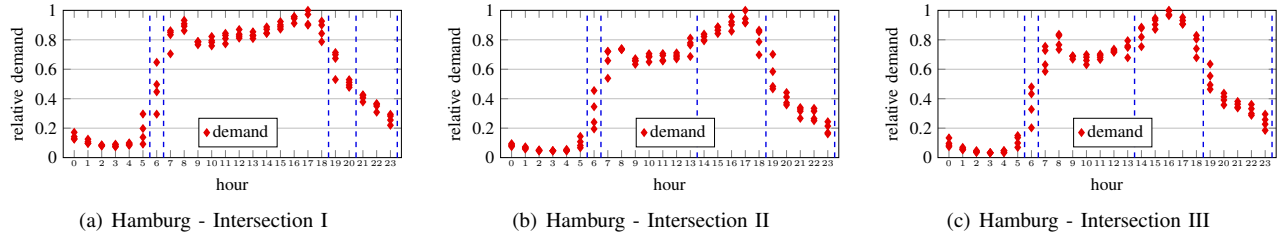
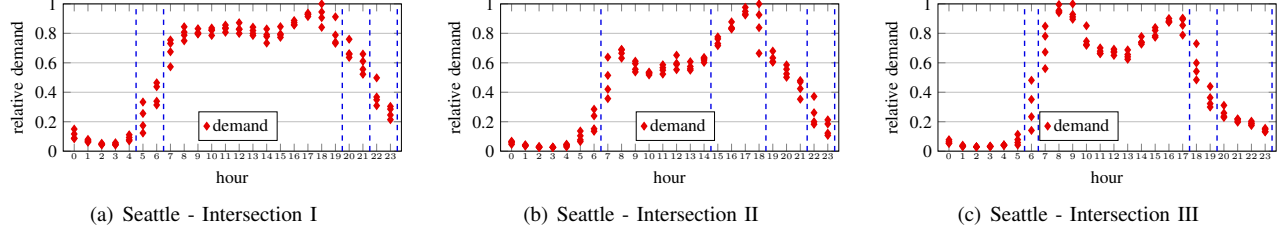
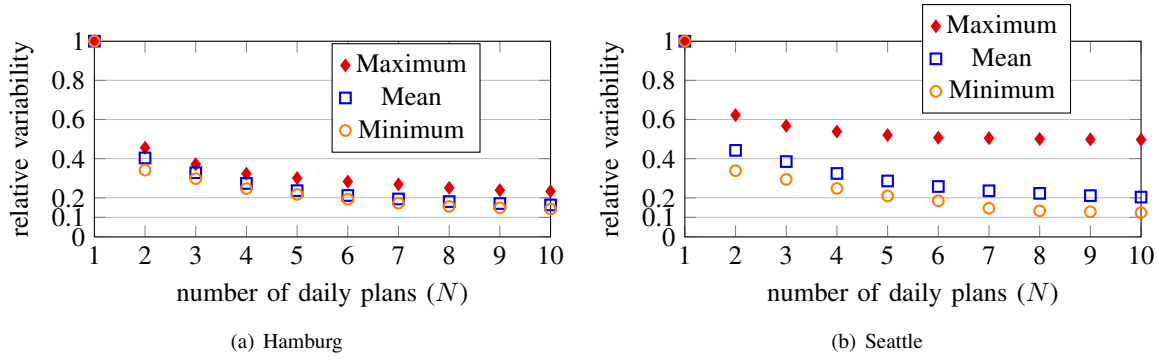
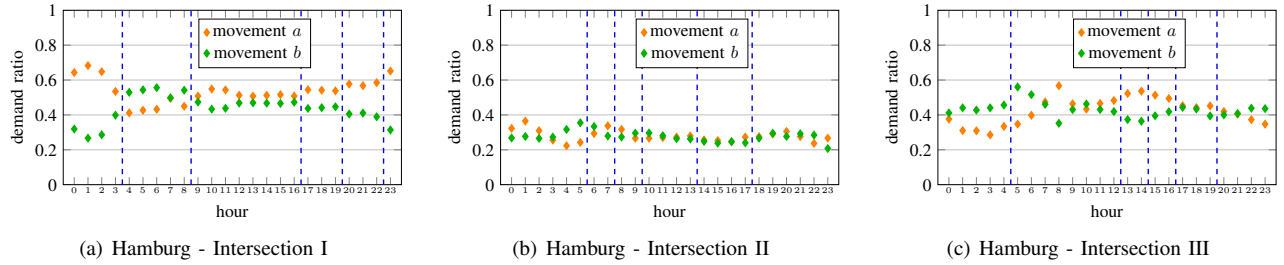
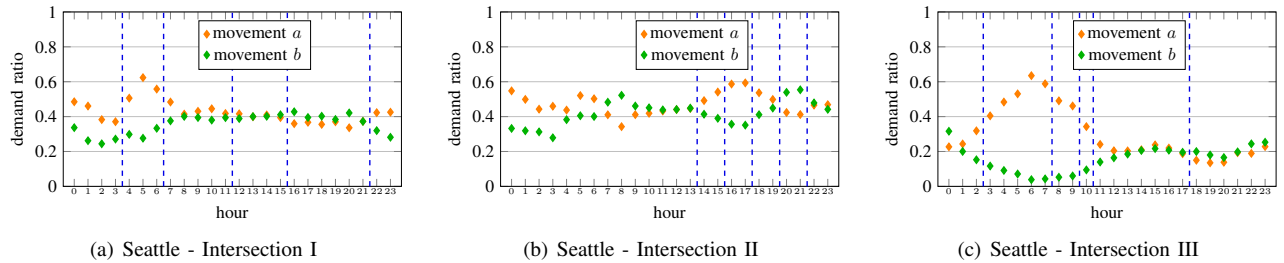
**Settings of the Real Data.** As mentioned, we refer to real traffic data of two cities: Hamburg in Germany and Seattle in the state of Washington. We collect traffic data between May 2 to June 5, 2024 among which we focus on 25 weekdays Monday through Friday. We refer to an aggregated and anonymized dataset summarizing the amount of traffic sampled based on the processing of anonymized trajectories from navigation applications. The traffic demand data refers to every 15 minutes in each of the days in the study with four values per hour. To compute time-of-day breakpoints (TODs), we rely on the optimal dynamic-programming approach from Section IV and consider variability metrics from Section III. In this analysis, we study questions such as:

- What is a typical form of ideal TODs in real intersections?
- What is the impact of the number of daily plans  $N$ ?
- Are the time-of-day breakpoints influenced by the considered variability metric?

**Results and Analysis.** To illustrate the time-of-day breakpoints (TODs), we refer to 10 major intersections in each of the two cities. Intersections were selected based on the number of observed trajectories at each intersection. As such trajectories are samples of the traffic, this number does not necessarily indicate the 10 intersections with the highest amount of traffic but provides some estimation of those. For each intersection, we compute the optimal time-of-day breakpoints based on the dynamic-programming approach from Section IV. As a

variability metric, we refer to the variance of traffic demand (for the whole intersection, summarized over its movements) as defined in Section III. The TODs are shown in Fig. 2 - Fig. 3 for Hamburg and Seattle. For each city, the left subfigure shows the TODs for the case of  $N = 5$  daily plans and the right subfigure refers to  $N = 4$  daily plans. A line refers to an intersection for which an ideal solution is shown with a different color for each of its plans.

In Hamburg, for instance, consider the case of  $N = 4$  daily plans. The computed TODs for the various intersections have a similar form: A night plan, a plan for early morning, a plan for most day hours, and an evening plan. For instance, the TODs for intersection 1 are of the form  $H = (H_1, \dots, H_4)$  with  $H_1 = \{0, 1, 2, 3, 4, 5\}$ ,  $H_2 = \{6\}$ ,  $H_3 = \{7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19\}$  and  $H_4 = \{20, 21, 22, 23\}$ . Often, the night plan starts at midnight and lasts for six hours. The morning plan is either short and lasts a single hour, or it is longer and lasts till early afternoon, so the plan for the day hours is shorter. Increasing the number of daily plans to  $N = 5$  often results in two different plans for the day hours between 7 and 18. For some intersections, the five windows for  $N = 5$  can be derived by partitioning into two one of the windows for  $N = 4$  and maintaining the three other windows. However, this is not necessarily the case as the algorithm selects the optimal TOD among all possible ones without enforcing such a constraint. For instance, for the same first intersection, for  $N = 5$  the solution has the form of  $M = (M_1, \dots, M_5)$  with  $M_1 = \{0, 1, 2, 3, 4, 5\}$ ,  $M_2 = \{6\}$ ,  $M_3 = \{7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18\}$ ,  $M_4 = \{19, 20\}$  and  $M_5 = \{21, 22, 23\}$  such that based on the solution for  $N = 4$  the first two windows are not changed while a new window covers the last hour in  $H_3$  and the first hour in  $H_4$  into a new window  $M_4 = \{19, 20\}$ . In Seattle, we observe higher diversity in the form of the solutions such that night plans last till 4, 5 or 6 for  $N = 5$  and till 4, 5, 6 or 7 for  $N = 4$ .


 Fig. 4. Hamburg - Illustration of intersections with their hourly demand values and the corresponding TOD breakpoints with  $N = 5$  daily plans.

 Fig. 5. Seattle - Illustration of intersections with their hourly demand values and the corresponding TOD breakpoints with  $N = 5$  daily plans.

 Fig. 6. Impact of the number of daily plans  $N$ . Scores for 10 major intersections compared to the score with a single daily plan. The variability metric is the variance of traffic demand in the intersection. The graphs demonstrate the diminishing reduction in the variability values upon allowing an additional window.

 Fig. 7. Hamburg - Illustration of intersections with hourly demand distribution over movements and corresponding TODs with  $N = 5$  daily plans.

 Fig. 8. Seattle - Illustration of intersections with hourly demand distribution over movements and corresponding TODs with  $N = 5$  daily plans.



Next, we illustrate in Fig. 4-Fig. 5 how the derived TODs relate to traffic demand. We dive into the first three intersections in each of the cities. For each of the day hours  $0, \dots, 23$ , we show the mean demand value over days with four values per hour, one for every 15 minutes. The values are normalized with respect to the hour with the largest demand. In addition, we illustrate in blue the corresponding TODs computed by the optimal algorithm with  $N = 5$ . These are the same TODs, shown previously in the top three lines of Fig. 2-Fig. 3.

Consider again Intersection I in Hamburg for which with  $N = 5$  the windows were  $M = (M_1, \dots, M_5)$  with  $M_1 = \{0, 1, 2, 3, 4, 5\}$ ,  $M_2 = \{6\}$ ,  $M_3 = \{7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18\}$ ,  $M_4 = \{19, 20\}$  and  $M_5 = \{21, 22, 23\}$ . We can see that these five windows indeed match different ranges of values of the traffic demand. The first window, for instance, for hours  $0, \dots, 5$  refers to values of  $0.074 - 0.296$  while the window of the single hour 6 refers to values of  $0.295 - 0.647$ . The next window for hours  $7, \dots, 18$  includes values of  $0.705 - 1.000$ . Lower demand values are observed for later hours  $19, \dots, 23$  with a clear distinction between the ranges of values in hours  $19, 20$  vs. those of  $21, 22, 23$ . TODs are not uniform over all intersections.

We also examine the potential impact of the number of daily plans as supporting a larger number of daily plans  $N$  has higher operation costs. Fig. 6 shows the variability score (for the variability metric considering traffic demand) in an optimal solution as a function of the number of daily plans  $N \in [1, 10]$ . For the two cities, the graph shows the maximal (in red), mean (in blue) and minimal (in orange) values over the 10 intersections. The mean values demonstrate the diminishing returns of increasing the number of daily plans  $N$  in reducing variability, particularly when  $N$  exceeds 6. Overall, values are similar among the two cities with Seattle observing slightly higher mean values due to a single intersection with relatively high variability values for various values of  $N$ .

So far we focused on the first variability metric, that considers the variance of the demand in the intersection as a sum for its movements. We now refer to the second variability metric that examines changes in the distribution of traffic over the intersection movements. Intuitively, a signal plan might need to be changed even when the total intersection demand is kept but the demand of some movements increases while of other decreases. The optimal dynamic programming algorithm can take into account that variability metric as well.

Fig. 7-Fig. 8 show (in blue) the computed TODs for the same three intersections in each of the cities. The figures also illustrate (in orange and green) for each intersection the ratio of the demand in two of its movements as part of the total hourly demand in the intersection. The two movements are selected among the intersection movements as those of high average demand. As the TODs are computed to reflect changes in the distribution ratios of all movements, they often closely align with changes in the demand ratio between the two specific movements. Note that the TODs for that variability metric are often different than TODs computed based on the first variability metric considering the total intersection demand that were previously shown in Fig. 4-Fig. 5.

Next, we aim to measure the distance of time-of-day break-

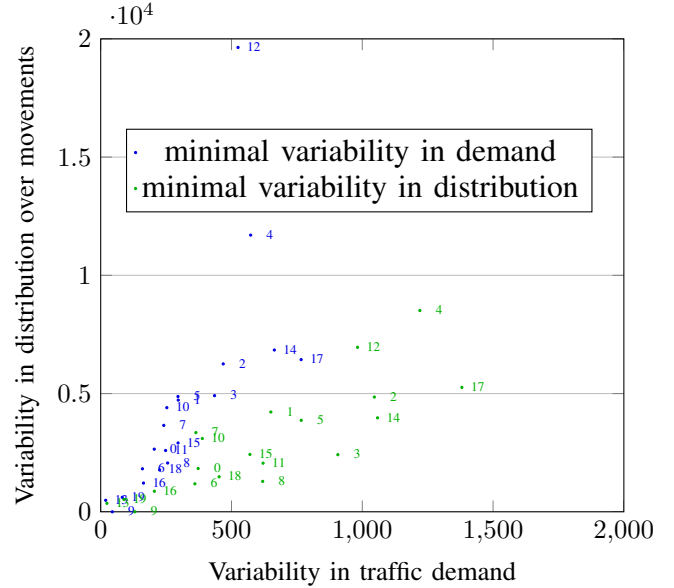


Fig. 9. Tradeoff of scores for two variability metric scores. Each intersection has two pairs of variability values: For a plan optimizing variability in traffic demand and for a plan optimizing variability in distribution over movements.

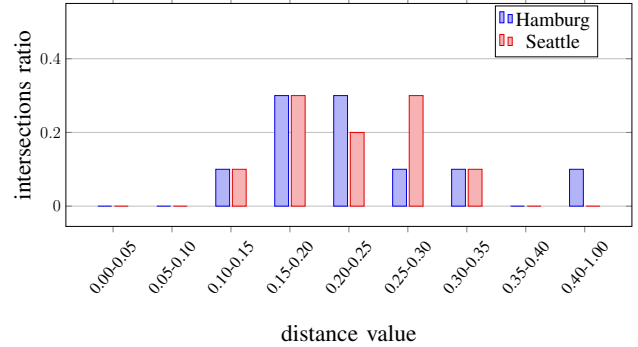


Fig. 10. Distance of optimal solutions in the same intersection for the two variability metrics - Distribution of distance values for distance test I over 10 intersections in each city. Mean values of  $R_I(V^{opt}, P^{opt}) = R_I(P^{opt}, V^{opt})$ .

points computed for two variability metrics from Section III: (i) Variance of traffic demand; and (ii) variance of distribution of traffic over the intersection movements. To do so, we use distance test I from Section V.

We consider the above 20 intersections, 10 intersections from each city. For each intersection, it computes two TODs: An optimal solution of minimal variance of traffic demand and optimal solution of minimal variance of the distribution of traffic over the intersection movements. For each solution, we then compute two values as the values of the two variability metrics. Fig. 9 measures the tradeoff between the values of the two variability metrics. It shows the two variability values of the two solutions for each of the 20 intersections, with a total of 40 solutions. In the figure, the x-axis refers to the variability in demand and the y-axis to the variability in the distribution over movements. Each intersection has an index in the range 0-19 and its two points appear in blue (minimal variability in demand) and green colors (minimal variability in distribution

over movements). Thus for each intersection index the green point appears more to the right and lower than the blue point.

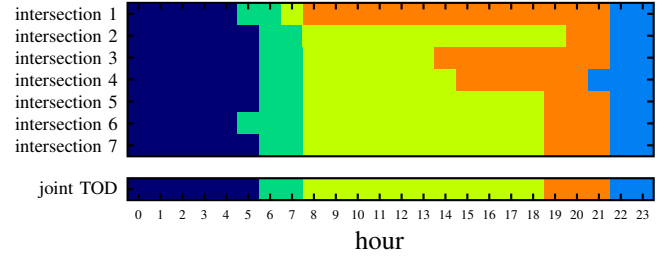
To further understand this tradeoff between the variability metrics, we refer to the distance test from Section V and check the distributions of its values over 20 intersections based on the two solutions for each intersection. Fig. VI shows the values of distance test I for each intersection. The distance test considers the two solutions and indicates the ratio of pairs of hours which are within the same window of hours in one solution while they belong to different hours in the other solution. We denote its value as  $R_I$ . Its values are in the range of  $[0,1]$  and lower values indicate higher similarity. Over the intersections, the distance value  $R_I$  ranges between 0.101 to 0.427 and the distribution in each city is shown. The mean values of the metric are 0.231 and 0.221 for Hamburg and Seattle, respectively.

#### VII. JOINT COMPUTATION OF TIME-OF-DAY BREAKPOINTS FOR INTERSECTIONS ALONG CORRIDORS.

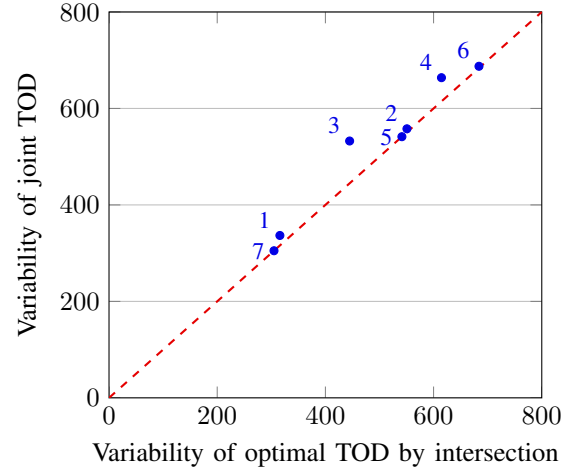
We focused on computation of the TODs based on traffic characteristics in each intersection. To further enhance the potential for synchronization of intersections along corridors, identical TODs can be enforced for multiple intersections. The proposed methodology can simply jointly consider traffic characteristics from multiple intersections and derive a single solution based on all of them. We explain *how the dynamic programming algorithm from Section IV can be tuned to do so*: The variability value for a window of hours  $S(H)$  in the dynamic programming algorithm should be set as the sum of the variability values of that window in all intersections. Note that the joint TOD solution is not necessarily one among the solutions for the intersections along the corridor.

We illustrate the approach of joint computation of TODs of several intersections for a real corridor in Seattle. The corridor has 7 intersections. The ideal TOD solutions computed independently for each of the intersections are illustrated in Fig. 11(a). Upon computing the solutions for the various intersections, we see high similarity among solutions but they are not identical. In particular, for this corridor we observe 6 distinct solutions for the 7 intersections. The joint TOD solution computed while considering traffic from all 7 intersections is also shown in the bottom part of Fig. 11(a). In this example, the joint TOD is identical to the TOD of intersection 5 and intersection 7.

To examine the impact of enforcing a joint solution for all 7 intersections along the corridor, we measure the implied variability based on the variability in traffic demand. Fig. 11(b) shows for each intersection the variability of the joint solution vs. the variability of the ideal TOD of the intersection. The intersections are numbered 1, ..., 7 based on the location in the corridor. The joint TOD always implies higher or equal variability as the optimal TOD for an intersection. As intersections 5 and intersection 7 share the same solution with the joint solution their variability is not increased upon applying the joint TOD. On the other hand, for the five other intersections, we observe a small relative increase of 0.5%-19.7% in the variability when the joint TOD in the corridor is used rather than the optimal TOD for each intersection.



(a)  $N = 5$  daily plans



(b) Variability scores of TOD solutions

Fig. 11. Joint TOD solution along corridor. For a corridor in Seattle with 7 intersection, illustration of the TODs for intersections along a corridor and the TOD solution computed jointly for all intersections. The variability of the joint TOD is compared in each intersection (indicated by its number) to the variability of the TOD of that intersection.

#### VIII. CONCLUSION

This paper provides a comprehensive study of the problem of finding time-of-day (TOD) breakpoints in intersections for the design of traffic light plans. We suggested variability metrics based on which time-of-day breakpoints can be computed. We also define a distance metric to examine the dissimilarity among solutions for the TOD breakpoints that are computed for different variability metrics. We evaluated the approach by analyzing real traffic data from Hamburg and Seattle. We illustrated the computed TOD breakpoints in the cities and how they refer to the inputs to the variability metrics. We also examined the impact of the number of daily plans and the distribution of the lengths of windows of hours in efficient solutions. The study observes several key findings such as:

- It is important to consider several traffic characteristics as solutions for different variability metrics can differ.
- For a variability metric, an optimal solution with ideal time-of-day breakpoints can be computed based on dynamic programming.
- Increasing the number of daily plans beyond 5 or 6 often does not contribute much to reducing variability scores.
- Ideal time-of-day breakpoints often have similarity along corridors where identical solutions can be enforced.



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