Time-of-day Traffic Signal Control

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Improperly scheduled signal timing plans are one of the main reasons for reduced efficiency of traffic signals at coordinated urban arterials. Time-of-day (TOD) traffic signal control is based on the principle where multiple TOD signal timing plans (STPs) are scheduled to operate during the day. TOD plans are characterized by a unique cycle length that is highly correlated with traffic volumes. The determination of characteristic periods during the day where certain signal timing plans should operate was primarily done using the 24 h volume plots from single intersection and engineering judgments. In cases where data availability is higher, the analytical methods that serve for the determination of robust TOD breakpoints were not in place.

signal timing plans scheduling traffic profiles

1. Introduction

Traffic conditions on urban arterial vary significantly over time, exhibiting variations in traffic volumes during various time intervals (e.g., within an hour, day, week, month, season, or a year) [1][2][3]. Developing an appropriate scheduling of multiple (time-of-day) signal timing plans is often seen as an efficient and cost-effective solution, in coping with such inevitable fluctuations in traffic demand [4][5][6][7]. To develop and schedule the multiple signal timing plans, most of the agencies continue to rely on the traffic data gathered for a few (or even single) representative days. Often, to reduce the signal retiming and data collection costs, agencies deploy the identical set of signal timing plans for each weekday while those plans developed for low/moderate traffic are in operations during the weekend [4]. Improperly scheduled signal timing plans (STPs) are one of the most important reasons for improper operations of traffic signals [4].

Since a few years ago, most of the urban arterial roads are equipped with intelligent transportation systems devices capable of reporting the collected data on high temporal and spatial resolutions. This valuable source of information can undoubtedly be widely used by agencies in solving practical traffic-related problems, such as signal re-timing applications and for evaluation of the existing time-of-day break points. Numerous studies were conducted in the past to address the issue of determination of time-of-day breakpoints [8][9][10][11][12][13]. Overall, previous studies either proposed methods based on small temporal and spatial resolution (thus preventing for appropriate inclusion of diurnal traffic fluctuations into signal timing plans), or they were based on various optimization approaches that serve to identify signal timing plan schedules in an automatic manner that prevent domain experts from interacting with the specifics of traffic data fluctuations, which is very valuable considering one’s in-house expertise. Consequently, determination of the TOD breakpoint is still being addressed without a comprehensive approach.

With the rapid development in sensor technology, a field of data science emerged as a consequence of the increased availability of data and the inability to appropriately analyze them [14]. This emerging field is called visual analytics (VA), which integrates domain principles with visual representations of the new information in order to gain insight and provide adequate solutions [15]. Numerous applications for analyzing large datasets in transportation domains are found so far [16][17][18]. However, very little attention is given to urban arterial management with respect to scheduling time-of-day (TOD) signal timing plans, also known as TOD breakpoints.

2. Research on Time-of-day Traffic Signal Control

Time-of-day (TOD) traffic signal control is based on the principle where multiple TOD signal timing plans (STPs) are scheduled to operate during the day. TOD plans are characterized by a unique cycle length that is highly correlated with traffic volumes. The determination of characteristic periods during the day where certain signal timing plans should operate was primarily done using the 24 h volume plots from single intersection and engineering judgments [19]. In cases where data availability is higher, the analytical methods that serve for the determination of robust TOD breakpoints were not in place.

Since early 2000, the problem of optimal determination of TOD plans was examined in greater detail. Smith et al. used a statistical, hierarchical clustering method on four months of data from a single intersection [19]. A follow-up study served to validate the proposed approach [20]. It was found that such statistical methods result in isolated clusters, whose assignment to dominant ones (e.g., AM peak) should be performed manually. Therefore, Park et al. proposed an heuristic approach to identify homogeneous TOD breakpoints, which will result in less frequent signal timing plans changes [21]. The follow-up study contained an automated approach which considered the effects of volume and signal timing plans while determining TOD breakpoints using the data from an arterial containing three intersections [8]. Later, Park and Lee also accounted plans transition costs while applying the heuristic-greedy algorithm on a 24 h dataset [9]. Wang et al. applied *k*-means clustering on several hours of volume data on two intersections [22]. A small aggregation interval (of 5 min) resulted in frequent transitions between plans [20]. In 2008, Wong and Woon proposed an iterative *k*-means clustering method on twelve hours of volume data obtained from microsimulation (i.e., MITSIMLab) [23]. Dong et al. utilized isomap and *k*-means clustering algorithms for one day of volume data collected at a single intersection [24].

In 2011, Ratrout proposed subtractive clustering-based *k*-means technique on three coordinated intersections for 24 h volume data [10]. Jun and Yang applied Kohonen neural network on five consecutive weekdays volume on a three-leg, signalized intersection [11]. Guo and Zhang clustered seven days traffic data from nine mid-block detectors per direction, separately [25]. A final TOD schedule was developed by arbitrarily combining different TOD patterns from both directions [25]. Hao and Dong performed a two-dimensional clustering analysis method based on 24 h volumes on the multiple spatially isolated intersections [12]. Therefore, the proposed method did not account for specifics of traffic operations at coordinated arterials. Wan et al., using the bisecting *k*-means, determined TOD breakpoints based on trajectory data collected for several days at one intersection [13].

Ma et al. solved the problem of TOD determination by time series partitioning using 24 h data from a single intersection [26]. Chen et al., in a comparative study, used different clustering methods (i.e., *k*-means, hierarchical, and Fisher ordinal clustering) to determine TOD breakpoints [27]. Data collected for three days at one intersection were used. Recently, Wang et al. proposed clustering of data collected for five consecutive days to account for data continuity rather than aggregating data for individual days [28]. Data were collected for one intersection and aggregated for all movements. Interestingly, the problem of characteristic time-of-day periods was examined recently for planning purposes [29]. Song and Yang used clustering on offline traffic data to examine similarity and characteristics of traffic flow patterns on the city-wide network area [30]. Researchers did not utilize examined data to estimate the quality of existing signal timing plan schedules [30].

Previous studies mainly relied on analytical reasoning of data, which hinders an analyst's understanding of specific temporal flow fluctuations in cases when a longer series of data are available. Furthermore, most of the studies examined small-scale networks where spatial characteristics of utilized datasets are not examined. One emerging scientific field that primarily serve to extract more information from data is visual analytics (VA). In the domain of transportation engineering, numerous applications of VA were found in the literature [16][17][18]. However, no related work to arterial management with respect to TOD breakpoints determination was found. Furthermore, big data were used for scheduling problems and intelligent transportation systems in many studies [31][32][33][34][35]. In their study, Shi and Adbel-Aty suggest constant monitoring of traffic operations and safety by using big data [31]. Antoniou et al. attempted to integrate a set of sensors and historical data using a data hub to generate signal traffic plans [32]. Fusco et al. utilized big data in public transportation for short prediction models [33]. Günther et al., developed driving cycle for busses using big data approach [34]. In 2015, Vij and Shankari discussed whether big data is big enough [35].

Schreck et al. developed a framework on visual interactive clustering analysis of vehicle trajectory data [36]. Andrienko et al. proposed an approach for extracting meaningful clusters from large databases by combining clustering and classification, driven by a human analyst through an interactive visual interface [16]. In a review study, Andrienko et al. presented the current state of practice in the field of visual analytics for movement and transportation systems [37]. Riveiro et al. developed a framework for the detection of anomaly events (e.g., near-accidents events) based on multidimensional road datasets [17]. Markovic et al. demonstrated the current application of trajectory data from the perspective of transportation agencies [18].

As shown, many research efforts were in development, with various modifications to clustering methods, in order to automatically develop TOD breakpoints. Mostly, small-sized networks and small datasets were considered. Even when relatively larger datasets were considered, due to the analytical reasoning approach, many prevailing traffic conditions were overlooked. For solutions created and validated, based on such limited datasets, it is questionable how they will accommodate yearly flow fluctuations.

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