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# TRIPS-IN-MOTION TIME MATRIX TO IDENTIFY TIME WINDOWS AS AN INPUT FOR TIME-OF-DAY MODELLING

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***ABSTRACT***

*Time-of-day modelling is an additional step to the conventional four-step Travel Demand Models (TDMs). Here, the target is to obtain more detailed outputs over the temporal dimension. With this additional step, daily (24-hour) travel demand is distributed into a discrete number of time-windows.*

*This paper aims to identify the most precise time windows that maximise the trips that fall within a given time-window and minimise the trip-tailing associated with it. The trips-in-motion method follows a more logical approach to capturing the entire trip duration. The Colombo Metropolitan Region Transport Masterplan database, developed in 2013, is analysed using Bentley Cube Voyager transport demand modelling software. The most precise starting timestamps of two-hour time windows were selected for the morning, mid-day, and evening peaks at 6:30 AM, 01:30 PM and 05:00 PM.*

*This study has developed a systematic approach to identify time-windows as input for time-of-day based modelling. This attempt is an initial step to simulate the third-dimension of a trip, which is called the temporal dimension of TDMs.*

*Finally, it is recommended to study the shift in peak periods with the change in time of demand, which would be the behavioural change most expected to occur post-COVID-19.*

**Keywords:** *Time of Day, Travel Demand Model, Time Window, Peak-Time*

## 1. INTRODUCTION

A trip is a movement between two geographic points of the spatial dimension and also a movement between two timestamps of the temporal dimension. Transport systems connect many such spatial points and facilitate trips to move forward along the temporal dimension. Traffic observed in the road transport network is an aggregation of many such trips that are moving within a particular time-window. Time-specific demand estimation is a significant concern in metropolitan Travel Demand Models (TDMs) [1]. The temporal resolution of static TDMs is usually into a few discrete time-periods [2]. The dynamic TDMs simulate shorter time intervals, typically 15 minutes each [3].

The microscopic and mesoscopic simulation models focus more on the temporal distribution of trips or tours than macroscopic simulation models [3]. However, due to various limitations, including computational capability, the study is limited to several square kilometres. Due to that limitation and many other reasons, the state (national) and metropolitan level TDMs are macroscopic models that generally adopt static assignment where the finer time resolution was not focusing as microsimulation models. Getting time-specific outcomes was difficult under such limitations of the static assignment.

Time-of-Day modelling is an addition to the conventional four-step travel demand models to enhance the forecasting capability over the temporal dimension. Time-of-day modelling disaggregates the nature of temporal aggregation in four-step TDMs and estimates temporally varying model outputs related to some discrete number of time periods. Temporal variation in traffic congestion, transit demand, and carbon emission are some of the output measures varying according to time-of-day.

There are two methods used for the time-of-day application, namely the ‘pre-defined fixed factors’ (fraction of the total trip) method or ‘the discrete choice models’. For both these methods, it requires to split the day (24 hours) into a few discrete numbers of time-windows. However, one of the most critical aspects of the time-of-day application is distinguishing the peak vs off-peak model outputs. Hence, the peak characteristics should be represented in the peak time-windows. Therefore, the logic behind deriving such time windows is significant and got focused in this study.

Usually, there is an error associated with the trips assigning process into time windows. Even though a trip is allocating to a time window, either one or both trip-ends may fall into the adjacent time windows (preceding window or following window). Therefore, the time-window must be defined in a manner in which the above error will be minimum.

There was no satisfactory evidence of an experimental approach to derive time-of-day time-window. Even though the ‘Trips-in-Motion’ concept shows greater precision, we could not find proper evidence for its application. When using the trips-in-motion, it is crucial to measure the errors associated with the trip-timing tails that have fallen into the adjacent time-windows. Minimising the percentage of error related to trip tails were not studied in past applications. The paper aims to identify the most precise peak period time-window which (1) maximise the trips fall within the window and (2) minimise the error due to trip tails fall into adjacent time-window.

## 2. LITERATURE REVIEW

Importance of studying the temporal resolution of urban TDMs emerged when analytics started to seek temporally varying outcomes [2] than the primary concerns of evaluating highway and transit capacity expansions [1]. It was required to measure the degrees of the variations in congestion speed and the transit availability between the peak and off-peaks of a day in order to evaluate the various strategic solutions proposed for the urban areas. Also, congestion speeds of TDMs were required for emission modelling as inputs for their model development [2]. Such demands were not able to cater by the traditional daily (24 hours) based macroscopic TDMs. Therefore, the conventional four-step in TDM needs an improvement that reflects the variations over the temporal dimension. Table 1 below summarises some of the significant advantages found in several past studies.

**Table 1: Advantages of Time-of-day Applications**

| No | Advantage | Sources |
|---|---|---|
| 01 | Measuring the impacts of peak tolling strategy | [4], [5] |
| 02 | Distinguish the peak vs off-peak travel demand for emission modelling and air quality analysis | [6], [7] |
| 03 | Identifying peak bottlenecks for traffic management | [8] |
| 04 | Accurate representation of timely varying transit availability | [9], [10] |
| 05 | Reflection of the proper directional distribution of traffic network capacity analysis | [10] |

In order to overcome the limitations of daily basis TDMs, a concept called time-of-day came into practice. Pendyala [10] and Smith [11] have mentioned the time-of-day application as an additional model step into four-step TDM processes TRB [1] reveals that 75% of the large (over 1 million population) Metropolitan Organisations (MPOs) in the USA have applied time-of-day for their TDMs. Moving from metropolitans to the larger state level, Donnelly and Moeckel [12] reveals that the time-of-day has enhanced the conventional four-step into a five-step modelling process of passenger TDMs. Further, they indicate that, out of the 34 state-wide TDMs in the USA, 35% applied time-of-day as a separate model step. However, there was no evidence found for applying time-of-day into four-step TDMs in the other parts of the world. Even though did not use in a four-step TDM, time-of-day choice modelling has been incorporated for various model developments in countries like the United Kingdom and Netherland [13], [9].

In the Sri Lankan Context, models developed for traffic demand estimations attempted to follow at least a few steps of the four-step modelling process. Intercity Passenger Travel in Sri Lanka; Demand Estimation and Forecasting for Bus and Rail [14] focused on public transport demand estimation and modal split. Another attempt was made in the study called Inter-City Demand Estimation for Auto Travel developed from road link traffic counts in 1986, which targeted inter-city movements of private vehicles. TransPlan had its three versions as V1 (1995), V2 (1997) and V3 (2001) which were developed for Colombo Municipal Council Area (CMC), Western Province (Kumarage, Bandara, & Wijerathne, TRANSPLAN V2: A Regional Traffic Estimation Model, 1999) and entire island respectively. There was no time-of-day application found in any of the above models, and all of them have estimated the daily demand. Time-of-day would be an innovative attempt to model some of the Sri Lankan transport system characteristics, mostly the metropolitan.

CoMTrans was the next step, and the comprehensive model development of the above TDM efforts in Sri Lanka developed for the Colombo Metropolitan Region (CMR). This study was based on their Household Visit Survey (HVS) [16]. The HVS covered more than 3% of the households in the CMR. Here, the daily trip tables were used for entire four-step, and there was no time-of-day application. However, CoMTrans, in their report, presented the peak hours volumes and speeds. Apparently, those outputs were not incorporated into the final assignments. We observed CoMTrans approach is quite similar to TDM of San Francisco in the 1990s [3]. Later, San Francisco model was developed as an activity-based TDM, which included the time-of-day based trip assignment. However, CoMTrans [16] has reported the 52% of modal share (among motorised modes) for public transport. Application of time-of-day modelling is mostly essential in analysing transit trips [17] in such a transport system.

The time-of-day modelling is commonly applied either using ‘pre-defined fixed factors’ (fraction of the total trip) method or ‘the discrete choice models’. National Cooperative Highway Research Program [2] and Martin & McGuckin [18] reveal that historical fixed factors are the commonly accepted method. USDOT [17] mentions insensitivity of the fixed factors to the transportation level of service is one of the significant shortcomings. However, Smith et al. [19] published a set of tables for hours trip ratios of different trip purposes related to USA urban areas. Furthermore, TRB [1] has emphasised the need for a more advanced application for TDMs. Discrete choice modelling has been proposed as an advanced application that develops relationships to select time-periods for travelling based on socio-economic, traffic, toll and many other factors [13], [20].

NCHRP [2] mentioned three aspects that need attention in the definition of time-windows, which are (1) analysis needs of the region (2) characteristics of congestion (3) difference in transport services; the definition should also be based on the available data [3]. However, data availability is one of the factors that decides the positioning within four-step modelling. Here, the trip-based approach is applied in pre-assignment steps of the four-step, and the link-based approach is used in the post-assignment stage [10].

Apart from that, capturing most directional commuting trips [11] is another aspect that needs to be considered. One of the primary targets of time-of-day application is to separate the peak vs off-peak outputs of a transport system from the daily assignment [19]. The congestion on transport networks usually associates with the peak-periods of the day. The diurnal distribution of the traffic shows peaks and off-peaks. Therefore, the diurnal distribution pattern of trips provides the basic ideology for deriving time windows [19], [17].

There is no exact number for the time windows, but many metropolitan and state-level models apply –four to five time windows [2], [17]. There are two or three peak periods and subsequent off-peak periods are in use. Some of state-wide TDMs such as Colorado, Ohio & Oregon have finer increments in time windows of 19 - 24 [12]. However, all these time-of-day windows are not assigned to the network due to the runtime limitations. Smith [11] reveals that a temporal window is needed more than the longest trip length in the network. But there was no evidence found to prove meeting such a condition in above three TDMs.

On the other hand, the length of the time window and the number of discrete-time windows have an inverse relationship. To obtain the maximum number of time-windows, the time window length must be smaller as much as possible. There are several questions: (1) maximum length of a time window, (2) requirement of unique length for all windows, (3) way of treating the trips which have either one or both ends outside the respective time-window, remain unanswered.

In order to determine the fixed-factors for each time-window, all trips must be allocated into one of the pre-defined discrete time-windows. As the basis for assigning trips into a time-window, departure time, arrival time, temporal midpoint are the available options [2], [17]. Among them, the temporal midpoint has been introduced as the preferred option. However, all of these return single timestamps that cannot represent the trip movement's entire time duration within the transport system. Therefore, a trip cannot be limited only to a timestamp since it exists within the transport network for a particular time duration. A much more realistic concept called ‘trips-in-motion’ considers the entire trip time and measures the actual number of trips within a specific time-window. Therefore, that can be introduced as the best alternative to defining the peak-periods because of its greater precision [20].

Eash [7] reveals that the Chicago Area Transport Study (CATS) in 1990 used trips-in-motion diurnal distribution for deriving into eight time-windows; however, the trips are allocated by using departure and arrival times of trips. In addition to that, the four-step model developed in the South California region for their six countries has applied trips-in-motion diurnal factors to divide daily trip tables into five time-windows [21].

Various TDMs have divided the day into time-windows in order to archive their modelling requirements. The time-of-day model developed for Louisville-Southern Indiana Metropolitan Area [11] divided a day into four time-windows (AM peak, midday, PM peak and overnight) and split AM & PM peaks into one hour. Here, capturing commuting trips and capturing trip purposes were the primary concerns in defining time windows. Usually, model developers use HVS data and its diurnal distribution for time-of-day application. The Mid-Ohio region's TDM is an activity-based model which has a temporal resolution of one hour. The model produced the departure & arrival hour as output, and the tours were allocated for seven time-windows [22]. In Tampa Bay's time-of-day Choice model, trips were categorised into four time-windows based on each trip's temporal midpoint [10]. However, the distinction of the peak was found as a common objective of all the above cases.

## 3. METHODOLOGY

In order to derive precise time-windows for time-of-day application, the methodology followed five steps.

### 3.1 Building the Trip Timing Matrix

In the initial step, the trip's start (departure) and the end time (arrival) obtained from HVS data were assigned into pre-defined discrete timestamps. Timestamp was a day sliced by the gap. The time difference between Start Timestamp ($S_s$) and End Timestamp ($S_e$) was the travel time of the relevant trip. A gap (interval) between two successive timestamps was defined from HVS respondents' sensitivity to the timing. The possible values for the gap (G) could be 1 min, 5 min, 10 min, 15 min, 30 min etc. Once the G is defined from the HVS database, the number of timestamps (N) for a day (24 Hours) can be defined as follows:

$$\text{Number of timestamps for a day (N)} = \frac{(24*60)}{G} \quad \text{......................(1)}$$

In traditional TDMs, the OD-matrix defines the origin and destination with spatial labelling called TAZs, whereas, in time-of-day based TDMs, the trip-timing matrix defines the start time and end time with its timestamps. A time matrix dimension will be N x N. The temporal movement of trips is coded with starts timestamp ($S_s$) and end timestamp ($S_e$).

Accordingly, ($S_{ij}$) is the total number of trips moving from the respective $i^{th}$ timestamp to the $j^{th}$ timestamp (where i & j ≤ N). The shaded cell of figure 1a below represent, as an example, trips of $S_{ij}$= $S_{45}$ (Trips starting from $4^{th}$ timestamp and ends in $5^{th}$ timestamp). The intra-zonal cells represent the number of trips which are not passing at least one successive gap (G).

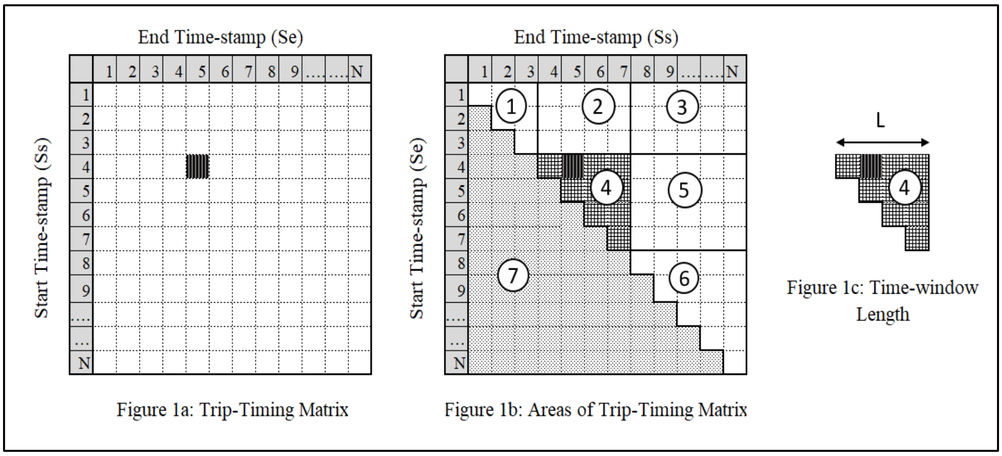


**Figure 1: Trip Timing Matrix**

### 3.2 Defining the Length of a Time-window

In most time-of-day applications, length (L) of a time-window was not defined with equal periods among all the time-windows. Focusing better simulation during peak period, the L was set into relatively shorter periods such as 1, 2 or 3 hours [10], [12], [21]. Usually, the off-peak was comparatively longer than peak time. However, this study follows equal periods for all 24 hours as the length (L) of a time-window for the analysis purpose.

### 3.3 Defining Matrix Areas

Once the L, $S_s$ and $S_e$ are defined, the time matrix cells were further categorised into seven areas relative to the respective time-window. Figure 1b above illustrates those areas relative to the time window from fourth to seventh timestamp. The areas were interpreted as,

- Area 1 - Trips start and end before the time-window
- Area 2 - Trips start before and end within the time-window
- Area 3 - Trips start before and ends after the time-window
- Area 4 - Trips start and end within the time-window
- Area 5 - Trips start within and end after the time-window
- Area 6 - Trips start and end after the time-window
- Area 7 - Trips move through the midnight

Then, the numbers of trips belonging to each of the above areas were determined. Under the defined L, all possible time windows ($W_L$) were interpreted as $(N - L)/G$ until midnight.

$$W_{L(\max)} = \frac{N-L}{G} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

### 3.4. Identifying the Best Time Windows

Here, the objective of this study was represented by three criteria. Maximising the number of trip's end was described under criteria 1 & 2 in Table 2 below. Minimising the error due to trip tails was represented under criteria 3-1 & 3-2.

**Table 2: Criteria for Selecting Best Time Windows**

| **No** | **Criteria** | **Matrix Area** | **Best $W_L$** |
|---|---|---|---|
| 1 | Maximum trips travel only within the $W_L$ | Area 4 | Maximum Trips |
| 2 | Maximum trips that touch the $W_L$ | Area 2, 3, 4 and 5 | Maximum Trips |
| 3-1 | Minimum trip ends (starts or ends) in adjacent windows | Area 2, 3 and 5 | Minimum Trips |
| 3-2 | Minimum trip-minutes of the trips that their end (starts or ends) in adjacent windows | Total trip-minutes laid before or after the time window | Minimum Trip-minutes |

Criteria 1 and 2 in the above Table 2 were set to find the time window, which has a maximum number of trips. The best time window under Criteria 1 had the highest number of trips travels only within the window. Criteria 2 gave the highest values related to trips-in-motion. Criteria 3-1 & 3-2 set to determine the error percentage of the time-windows occurred from the trip movements to adjacent time-windows. Criteria 3-2 determined the number of trip-minutes of the criteria 3-1 to check whether the longest part of the trip is in other time windows.

### 3.5. Selecting the Most Precise Time Window for Time-of-day Application

The possible number of time-windows *[N – (L/G)]* were considered against the criteria, as mentioned in Table 2 to select the precise time window by comparing the least absolute difference.

## 4. DATA ANALYSIS

The methodology of this study was tested with the database developed by the CoMTrans in 2013. Departure and arrival trip-timing of over 175,000 sample trips were used. As estimated by CoMTrans, more than ten million trips occurred within a day in the CMR. Among them, 78% of trips uses at least one motorised transport mode during their door-to-door journey. Therefore, a separate analysis was done for all door-to-door trips and motorised trips to identify the best time windows.

Observing the pattern of the HVS respondents' answers for trip arrival and departure times (how they rounded the answer), the gap (G) was defined as 15 minutes. Even though there were shorter alternatives for G (5 or 10 minutes), 15 minutes was chosen to reduce the number of time windows subjected to analysis. If G was increased further (e.g.: 30 min) impacted on the accuracy since the temporal movement of the considerable number of trips would have fallen into the same timestamp of the time-matrix. Smith [11] stated that the time span of time window must be similar to the longest trip in the study area. In the CMR, trip timing of the 96.9% of the door-to-door trips was less than two hours. Therefore, two hours was considered the length of all time-windows (L= 120 min). When G=15, the number of timestamps became 96 (N=96) for 24 hours.

Figure 2 below plotted the total number of door-to-door trips for two-hour (120 minute) time windows ($W_{120}$), where the time window starts at each timestamp of a 15-minute gap. The graph clearly shows that the trips-in-motion (triangular mark) always represent the higher value than the other two bases since it captures all trips at each timestamp. Based on above distribution, three time-periods (1) 5:00 AM – 8:00 AM, (2) 11:00 AM – 2:00 PM and (3) 3:00 PM to 7:00 PM were selected as the morning, mid-day and evening peak-periods respectively. The graph further shows that the rising slopes of the trips-in-motion points almost align with the departure time basis point in the respective time stamps. In the same manner, falling slope aligns with the arrival time points. These patterns prove almost all the trips at the timestamps in rising slopes are closer to their origin zones, and at the falling slopes trips are closer to the destination zones.

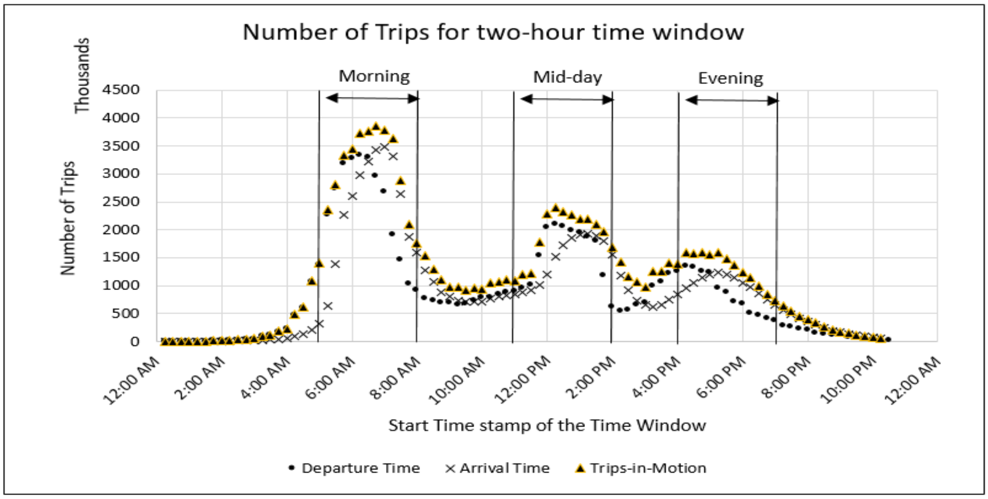


**Figure 2: Total Door-to-door Trips for Two-hour *($W_{120}$)* Time-Window**

The time matrix for 96 timestamps was developed using Citilabs Cube Voyager Traffic Demand Modelling Package. The number of trips belonging to Areas 1 through 6 of Figure 1b were determined for all 88 time-windows based on the developed matrix. Area 7 was not considered in the analysis since trips travel over the midnight was a neglectable value. To derive the precise time windows for the three peak periods, we analysed each peak period separately. Table 3 below shows the number of trips for $W_{120}$ at each timestamp of the morning peak period (5:00 AM – 8:00 AM).

**Table 3: Number of Trips for $W_{120}$**

| Start Timestamp ($S_S$) | Trips only within the window | | Trips under trips-in-motion | | Tail Trips | | Trip-Hours outside the window (x 1000) |
|---|---|---|---|---|---|---|---|
| | Trips (x 1000) | % from Daily Trips | Trips (x 1000) | % from Daily Trips | Trips (x 1000) | % from Daily Trips | |
| Criteria | Criteria 1 | | Criteria 2 | | Criteria 3 | | Criteria 4 |
| 5:00 | 296 | 3% | 1,405 | 14% | 1,109 | 11% | 782 |
| 5:15 | 570 | 6% | 2,354 | 23% | 1,784 | 18% | 1,042 |
| 5:30 | 1,337 | 13% | 2,811 | 28% | 1,474 | 15% | 812 |
| 5:45 | 2,153 | 21% | 3,325 | 33% | 1,172 | 12% | 752 |
| 6:00 | 2,467 | 24% | 3,445 | 34% | 978 | 10% | 583 |
| 6:15 | 2,611 | 26% | 3,733 | 37% | 1,122 | 11% | 644 |
| 6:30 | 2,767 | 27% | 3,772 | 37% | 1,005 | 10% | 596 |
| 6:45 | 2,577 | 26% | 3,854 | 38% | 1,276 | 13% | 730 |
| 7:00 | 2,424 | 24% | 3,774 | 37% | 1,349 | 13% | 860 |
| 7:15 | 1,607 | 16% | 3,637 | 36% | 2,030 | 20% | 1,156 |
| 7:30 | 1,249 | 12% | 2,885 | 29% | 1,636 | 16% | 1,079 |
| 7:45 | 824 | 8% | 2,092 | 21% | 1,268 | 13% | 871 |
| 8:00 | 767 | 8% | 1,756 | 17% | 988 | 10% | 822 |

The analysis reveals that the $W_{120}$ starts at 6:30 AM has the highest value (27% of daily door-to-door trips) for the trips only moving within the $W_{120}$. The 6:45 AM was the highest value for trips-in-motion under criteria-2 (38%). However, both selections showed only 1% - 3% difference to all others. $W_{120}$ starts within 6:00 AM and 7:00 AM. Both minimum tail trips and a minimum of trip-hours moving outside the $W_{120}$ were observed in the $W_{120}$ beginning at 6.00 AM.

We determined the absolute difference to other $W_{120}$ under each criterion to select the most precise $W_{120}$ compliance with all of the above criteria. As shown in Table 4 below, the first objective; maximising the trips for $W_{120}$ comply more with $S_S$= 6:30 AM. This $W_{120}$ showed only a 2% absolute difference to the best $S_S$ selected under criteria 2. If $S_S$= 6:45 AM had been chosen, it showed 7% difference to the 6:30 AM under criteria 1. Therefore, 6:30 AM became as the most precise $S_S$ in terms of maximising the trips. Following the same process, $S_S$= 6:00 AM was selected as the best $S_S$ that complied with both Criteria 3-1 & 3-2 under the objective of minimising errors. However, 6:30 AM was the next best $S_S$, which had only 2% absolute difference. From all different $S_S$ obtained for each criterion, we chose $S_S$ = 6.30 AM for $W_{120}$ in the morning peak-period.

**Table 4: Absolute difference from the selected $S_S$**

| Starting Timestamp ($S_s$) | Objective 1 (Max Number of Trips) | | | Objective 2 (Max Number of Trips/ Trip-hrs) | | |
|---|---|---|---|---|---|---|
| | Criteria 1 | Criteria 2 | Avg. | Criteria 3-1 | Criteria 3-2 | Avg. |
| 5:00 | 89% | 64% | 76.4% | 13% | 34% | 24% |
| 5:15 | 79% | 39% | 59.2% | 82% | 79% | 81% |
| 5:30 | 52% | 27% | 39.4% | 51% | 39% | 45% |
| 5:45 | 22% | 14% | 18.0% | 20% | 29% | 24% |
| 6:00 | 11% | 11% | 10.7% | 0% | 0% | 0% |
| 6:15 | 6% | 3% | 4.4% | 15% | 10% | 12% |
| **6:30** | 0% | 2% | 1.1% | 3% | 2% | 2% |
| 6:45 | 7% | 0% | 3.4% | 30% | 25% | 28% |
| 7:00 | 12% | 2% | 7.2% | 38% | 47% | 43% |
| 7:15 | 42% | 6% | 23.8% | 107% | 98% | 103% |
| 7:30 | 55% | 25% | 40.0% | 67% | 85% | 76% |
| 7:45 | 70% | 46% | 58.0% | 30% | 49% | 40% |
| 8:00 | 72% | 54% | 63.4% | 1% | 41% | 21% |

We applied the same calculation process for mid-day and evening peak periods to derive the best $S_S$ compliance with this study's objective. Table 5 shows the selected $S_S$ under each criterion for door-to-door trips.

**Table 5: Selected $S_S$ for Door-to-door Trips**

| Peak Period | Objective 1 (Max Number of Trips) | | | Objective 2 (Max No. of Trips/ Trip-hrs) | | | Final $S_S$ for $W_{120}$ |
|---|---|---|---|---|---|---|---|
| **Criteria** | **Criteria 1** | **Criteria 2** | **Best $S_S$** | **Criteria 3-1** | **Criteria 3-2** | **Best $S_S$** | |
| Morning Peak 5:00 - 8:00 | 6:30 (27%) | 6:45 (38%) | 6:30 | 6:00 | 6:00 | 6:00 | **6:30** |
| Mid-day Peak 11:00 - 14:00 | 13:00 (17%) | 12:15 (24%) | 13:00 | 11:00 | 11:00 | 11:00 | **13:30** |
| Evening Peak 15:00 - 18:00 | 17:00 (9%) | 16:45 (16%) | 17:00 | 15:00 | 17:00 | 17:00 | **17:00** |

To determine the peak $W_{120}$ for motorised trips, the same analysis process was conducted for the motorised trip transfers. Here, 22% of the door-to-door trips in CMR area were dropped since no motorised mode was used for transfers. Some of the trips contained with both motorised and non-motorised modes with transfers especially in transit trips. Therefore, the second phase of the analysis included only the motorised transfers of such trips. Also, waiting times captured in HVS data were filtered and dropped during the CUBE voyager scripting for the matrix manipulation. Table 6 below shows the resulted **$S_S$** at $W_{120}$ for all three peak periods of a day.

**Table 6: Selected $S_S$ for Motorised Trip Transfers**

| Peak Period | Objective 1 (Maximum Trips) | | | Objective 2 (Minimum Trips/ Trip-hours) | | | Final $S_S$ for $W_{120}$ |
|---|---|---|---|---|---|---|---|
| **Criteria** | **Criteria 1** | **Criteria 2** | **Best $S_S$** | **Criteria 3** | **Criteria 4** | **Best $S_S$** | |
| Morning Peak | 6:30 | 6:45 | 6:45 | 6:15 | 8:00 | 8:00 | 6:30 |
| Mid-day Peak | 13:15 | 12:30 | 13:15 | 11:00 | 11:00 | 11:00 | 13:30 |
| Evening Peak | 17:00 | 17:00 | 17:00 | 03:00 | 18:00 | 18:00 | 17:00 |

## 5. DISCUSSION

Analysis of the study reveals that around one-fourth (27%) of daily demand remains only within the $W_{120}$ from 6.30 AM to 8.30 AM. The same time window contains more than one-third (37%) of daily demand under trips-in-motion. By considering all together, the three $W_{120}$ derived in this study consist of 52% of trips. Also, 78% of door-to-door trips are trips in motion. Therefore, this suggests that improving the TDM with the time-of-day application will provide more accurate results in temporal variations.

In the second phase of the study conducted for motorised trips, 55% of the total motorised transfers were located only within the derived three $W_{120}$. Above value was distributed as 29%, 15% and 11% for the morning, mid-day and evening peak periods respectively. Further, 74% of the motorised trip-transfers touched or laid within the derived three $W_{120}$. An interesting finding was that door-to-door trips show almost similar distribution to motorised transfers in term of temporal distribution. Finally, that was proven by obtaining the same periods for $W_{120}$ under both door-to-door and motorised mode transfers. This study's derived result show many similar patterns to peak-periods reported by CoMTran, reported as 7 - 8 AM, 1 - 3 PM and 5 - 7 PM and containing 55% of the daily trips [16].

Compared to the morning peak, the mid-day and evening peaks $W_{120}$ did not comply with all criteria. This was shown in Figure 2, by flattening in the curve during mid-day and more flattening in the evening peak period. Instead of limiting to two-hour intervals ($W_{120}$), we recommend covering mid-day and evening peak periods with longer time windows. Table 7 compares this study's results against the time windows in departure time and arrival time basis determined for the same length. Similar to Figure 3, the derived peak time windows always lay between the departure time and arrival time basis.

**Table 7: $W_{120}$ for Three Approaches**

| Peak Period | Four criteria including trips-in-motion | Departure time | Arrival time |
|---|---|---|---|
| Morning | 06:30 AM | 06:15 AM | 07:00 AM |
| Mid-day | 01:30 PM | 12:15 PM | 04:15 PM |
| Evening | 05:00 PM | 05:00 PM | 05:15 PM |

However, industrial zones, administrative zones, educational zones might have trip scheduling that does not align with the time-windows derived in this study. A key effort in this study was to derive the time-windows precise to the entire study area. But passengers’ travel modes which influence trip-timing have not been considered.

## 6. CONCLUSION

The timestamp matrix is an aggregate representation of travellers' trip-timing in a macroscopic TDM. Deriving time windows using time matrix is suggested as an initial step to time-of-day model development. Since there are obvious three peak periods in CMR, the validity of daily trip tables is questionable in obtaining timely varying model outputs. Therefore, we recommend enhancing the four-step TDM in CMR with the time-of-day application. Advantage of the trips-in-motion concept is to determine the trips moving through a time window. This study's attempt is an initial step to simulate the third-dimension of a trip, which is called the temporal dimension of a TDM.

The method used in this study provides reasonable justification for derived time-windows with the portion on daily trips laying within the derived time-windows. In the research, the first phase was for the door-to-door trips and then repeated for filtered motorised trip transfers. Further, this study could be extended to many other aspects, such as mode, sub-regional, or purpose-specific analysis. The results of this study showing more rational values compared to the departure time and arrival time basis. Peak periods mentioned in the original TDM developed with the same database are almost similar to this study's results but not the same. CUBE Voyager Travel Demand Modelling Software was used for matrix manipulation is recommended as an excellent tool to formulate and develop the timestamp matrices.

Under the prevailing COVID-19 situation in the country, discussions on reducing crowding in public transport are underway. This paper reveals that 74% of the daily motorised trips move across peak periods totalling six hours. This study can be extended further to drive time windows longer than two hours. That congestion is moving towards the Central Business Districts (CBD) in the morning and outwards in the evening is another critical feature in CMR which could also be incorporated as a future study.

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## REFERENCES

[1] Transportation Research Board (TRB), "Metropolitan Travel Forecasting: Current Practice and Future Direction," National Academy of Sciences, Washington, D.C., 2007.

[2] National Cooperative Highway Research Program (NCHRP), “Travel Demand Forecasting: Parameters and Techniques,” Transportation Research Board, Washington, D.C., 2012.

[3] National Cooperative Highway Research Program (NCHRP), “Advanced Practices in Travel Forecasting,” Transportation Research Board, Washington, D.C., 2010.

[4] Q. Pan, P. Gordon, J. Moore and H. W. Richardson, “Modeling of Effects of Peak Load Pricing on Metropolitan Network and Activities,” *Transportation Research Record,* vol. 2255, no. 1, pp. 11-19, 2011.

[5] N. Holyoak and M. A. Taylor, “Modelling Trip Timing Behaviour and The Influence of Peak Spreading,” *Urban Transport XII: Urban Transport and the Environment in the 21st Century,* vol. 89, pp. 205-213, 2006.

[6] P. R. Stopher and H. Fu, “Travel Demand Analysis Impacts on Estimation of Mobile Emissions,” *Transportation Research Record,* vol. 1520, no. 1, pp. 104-113, 1996.

[7] R. Eash, “Time Period and Vehicle Class Highway Assignment for Air Quality Conformity Evaluation,” *TRANSPORTATION RESEARCH RECORD,* vol. 1641, no. 1, pp. 66-72, 1998.

[8] L. Zhang, C. Cirillo, C. Xiong and P. Hetrakul, “Feasibility and Benifits of Advanced Four-Step and Activity-Based Travel Demand Models for Maryland,” State Highway Administration, MaryLand, 2011.

[9] G. d. Jong, A. Daly, M. Pieters, C. Vellay, M. Bradley and F. Hofman, “A Model for Time of Day and Mode Choice Using Error Components Logit,” *Transportation Research Part E,* vol. 39, no. 3, pp. 245-268, 2003.

[10] R. M. Pendyala, “Time of day Modeling Procedures for Implementation in FSUTMS - Final Report,” Research Center - Department of Transportation, Florida, 2002.

[11] C. D. M. Smith, “Time-of-Day Travel Demand Model Phase 2,” Kentucky Transportation Cabinet, Kentucky, 2012.

[12] National Cooperative Highway Research Program (NCHRP), Statewide and Megaregional Travel Forecasting Models: Freight and Passenger, Washington, D.C.: Transportation Research Board, 2017.

[13] S. Hess, J. W. Polak, A. Daly and G. Hyman, "Flexible substitution patterns in models of mode and time of day choice: new evidence from the UK and the Netherlands," *Transportation,* vol. 34, pp. 213-238, 2007.

[14] A. S. Kumarage, S. C. Wirasinghe and L. L. Ratnayake, "Intercity Passenger Travel in Sri Lanka; Demand Estimation and Forecasting for Bus and Rail," International Development Research Centre, Ottawa, Canada, 1989.

[15] A. S. Kumarage, S. J. Bandara and I. k. Wijerathne, "TRANSPLAN V2: A Regional Traffic Estimation Model," in *Engineering Research Symposium, University of Moratuwa*, Colombo, 1999.

[16] Oriental Consultants Co Ltd., "Urban Transport System Development Project for Colombo Metropolitan Region and Suburbs," Japan International Cooperation Agency (JICA), Colombo, 2014.

[17] United States Department of Transportation (USDOT), Computer Programs for Urban Transportation Planning, Washington D.C.: Federal Highway Administration, 1977.

[18] W. A. Martin and N. A. Mcguckin, "Travel Estimation Techniques for Urban Planning," Transportation Research Board, Washington, D.C., 1998.

[19] National Cooperative Highway Research Program (NCHRP), "Analytical Travel Forecasting Approaches for Project-Level Planning and Design," Transportation Research Board, Washington D.C., 2014.

[20] Cambridge Systematics, Inc., Travel Model Validation and Reasonableness Checking Manual, 2nd ed., Cambridge: The Travel Model Improvement Program, 2010.

[21] Southern California Association of Governments, "SCAG Regional Travel Demand Model and 2012 Model Validation," 2016.

[22] R. S. Anderson, "Development of Mid-Ohio Regional Planning Commission Tour-Based Model," in *National Academies of Sciences, Engineering, and Medicine*, Washington, DC, 2008.