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Criteria for Temporal Aggregation of the Traffic Data from a Heterogeneous Traffic Stream

Suvin P. V.[a*], Ankita R. Karmakar[b], Sabina Y. Islam[b], Mallikarjuna C.[c]

[a]*Research Scholar, Civil Engineering Department, Indian Institute of Technology Guwahti, Guwahati, Assam, India-781039*
[b]*Undergraduate Student, Civil Engineering Department, Assam College of Engineering, Guwahati, Assam, India-781039*
[c]*Associate Professor, Civil Engineering Department, Indian Institute of Technology Guwahti, Guwahati, Assam, India-781039*

Abstract

Temporal aggregation of the traffic stream characteristics has a significant influence on the performance of any mathematical model derived thereafter. For a heterogeneous traffic stream, selection of the data aggregation interval is further complicated due to the possibility of different vehicle mixes within the aggregation period. Present study critically investigates and models the variation of the vehicle composition with the aggregation period. Traffic composition for a particular aggregation interval was represented using the coefficient of variation of the traffic composition corresponding to that aggregation interval. Findings from this study reveal that the traffic composition variation with the data aggregation interval could be modelled as a rational function. From the modelled variation, the minimum aggregation interval corresponding to the consistent traffic composition could be estimated. The present study suggests that the minimum aggregation interval could be approximated corresponding to the aggregation interval at which the rate of change of the coefficient of variation approaches zero from the direction of the lower aggregation period. The variation of the traffic composition within this aggregation interval would be minimal, hence safeguard the data from a wide scattering caused by the vehicle mix.

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Keywords: Traffic Composition, Heterogeneous Traffic, Data Aggregation Interval, Traffic Stream Characteristics, Macroscopic Modelling

1. Introduction

Aggregation of time series traffic information is one of the primary steps in the empirical macroscopic traffic flow modelling. It is evident from the literature that the performance of traffic flow models is highly sensitive to the aggregation period (Vlahogianni and Karlaftis, 2011). For a heterogeneous traffic stream, impact of the aggregation interval may get further aggravated with varying proportion of the vehicle mixes within the aggregation period. Detailed study in this direction is widely ignored in the transportation literature that representing the heterogeneous traffic stream. Generally in the macroscopic traffic studies, the aggregation of the time series data was performed

* Corresponding author. Tel.: +91-8547621084;
E-mail address: pv.suvin@iitg.ac.in

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across a larger regular time intervals such as 15 minutes, hours, days, months and so on (Vlahogianni and Karlaftis, 2011). In fact, the Highway Capacity Manual (1998) recommends to practice a minimum of 15-min measurement intervals for a ‘‘stable’’ traffic flow rates. Nonetheless, most of the time-series traffic data aggregation attempts reveal that with the increase in the aggregation period the traffic flow tends to become more stable (Guo et al., 2008; Smith and Ulmer, 2003; Vlahogianni et al., 2004). On the other hand, researchers pointed out that the longer aggregation period may lead to oversimplification of the traffic dynamics by averaging between different traffic states. It is evident from Figure 1 that the higher aggregation intervals produce a smooth variation of the traffic state and creating a time series structure that has reduced sensitivity to the short term changes in the traffic stream. Whereas a shorter aggregation period may cause intense fluctuations and noise that may lead to modelling difficulties (Banks, 1999; Qiao et al., 2004, 2003; Smith and Ulmer, 2003). The increased fluctuations and noise for the shorter aggregation period could be attributed to the huge variability in the vehicle mixes within the aggregation period, resulting incomparable average behavior. In order to trade-off between the ‘oversimplification of the traffic dynamics’ caused by the ‘longer aggregation period’ and the ‘intense fluctuation and noise’ from the ‘shorter aggregation period’, it is important to identify an optimum aggregation period for the time series traffic data. For a heterogeneous traffic stream, the mix of vehicle classes with varying physical and dynamical characteristics act as a major cause of traffic fluctuation. In such circumstances, it is important to implicitly consider the vehicle mix variation across the aggregation period as a criterion for the estimation of the minimum aggregation period.

Data aggregation is an interdisciplinary concept generally considered as the process of presenting the information from data in a summary form that encapsulates all the relevant information in the original data. In case of macroscopic traffic studies, the common practice for selecting the aggregation period for averaging the traffic stream characteristics was based on the stationary conditions of the traffic stream (Cassidy, 1998). Though the conditions for stationarity proposed by Cassidy (1998) considers the vehicles’ (dynamic) heterogeneity through the speed analysis, presence of homogeneous vehicle types as well as the lane disciplined driving is mandatory for such analyses due to the use of cumulative arrival curves. Unfortunately, for a heterogeneous and no lane-disciplined traffic stream attaining the conditions of the stationarity is a challenging task. Moreover, for a heterogeneous traffic stream, ensuring a consistent composition between the aggregation periods is important since the vehicles’ dimension is directly proportional to the crowdedness in the traffic stream. The condition of constant composition between the aggregated data will safeguard the data from a wide scattering caused by the vehicle mix. Main objective of the present study is to review the importance of traffic composition in the macroscopic analysis of heterogeneous traffic stream dynamics, henceforth propose a methodology to identify the optimum aggregation interval for the macroscopic studies based on the traffic composition. Present study critically analyses the traffic composition variation with the aggregation intervals and proposes a methodology to identify the optimal aggregation interval at which traffic composition begins to stabilize. In this study, authors distinguishably uses the terms ‘proportion’ and ‘composition’ with the following definitions. The term ‘proportion’ associated to a particular vehicle type and is the percentage of that particular class within the traffic composition. Whereas, the term ‘composition’ relates the entire traffic stream which includes the proportion of all the vehicle classes and the total will be hundred.

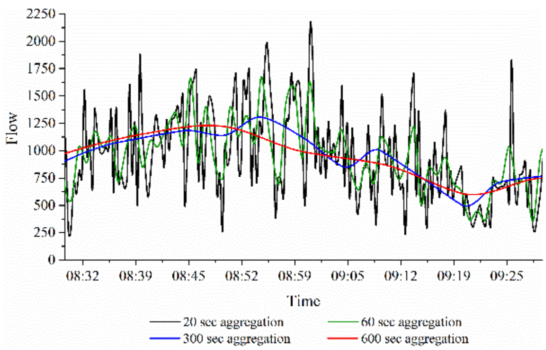


Figure 1: Temporal Variation Traffic Flow for Different Aggregation Periods

The rest of the paper is organized as follows. Section 2 briefly reviews the past researches on the traffic composition. In Section 3, the details of the data collection and the primary calculations are described. Section 3 briefs the methodology proposed to determine the minimum possible aggregation period for a heterogeneous traffic stream.

Section 4 presents a detailed analysis of the results. Section 5 summarizes the study and presents the major conclusions.

2. **Background**

Traffic composition is an important factor considered in the studies related to the multiclass traffic flow modelling (Fan and Work, 2015; Gupta and Katiyar, 2007; Hoogendoorn and Bovy, 2000; Logghe and Immers, 2003; Tuerprasert and Aswakul, 2010), traffic noise related studies (Filho et al., 2004; Gündoğdu et al., 2005; Hatzopoulou et al., 2013), development of Passenger Car Units (PCU) (Al-Kaisy et al., 2002; Ballari et al., 2018; Gautam et al., 2018; Kumar et al., 2018; Raj et al., 2018), capacity and the Level of Service (LoS) analysis (Chandra et al., 2016), and so on. However, most of the previous studies have not explicitly considered the impact of the data aggregation period on the research outputs (Guo et al., 2008). Generally, the traffic composition is determined as the proportion of the vehicles classes observed during a longer observation period. Although the composition obtained from the longer observation periods would be accurate, no studies have been investigated the minimum possible aggregation interval at which the composition remains similar to the longer one. Similarly, most of the previous investigations on the impact of traffic composition were limited to the analysis of the effect of the trucks traffic on the traffic stream (HCM, 2000; Wu, 2002). As the traffic composition is time dependent and heterogeneously distributed in an urban network, relating the fundamental relationship to traffic composition is quite complex (Kimber et al., 1985; Rao and Rengaraju, 1998). Very few studies have been performed to understand the effect of traffic composition on the macroscopic behavior of the urban traffic (Vlahogianni, 2007).

Literature suggests that, for most of the numerical studies of the multiclass traffic flow models, an equal distribution of the vehicle mix is a necessary criteria (Gupta and Katiyar, 2007). Attaining such an ambitious condition for the traffic flow is difficult in the real settings. However, the traffic stream could be approximated with an equal mix only once the aggregation interval is chosen appropriately. Several researchers have investigated the impact of the data aggregation period on the performance of various traffic flow modelling approaches (Smith and Ulmer, 2003). Guo et al., (2008) have found that, in the context of short-term traffic flow forecasting, the selection of appropriate forecasting approach would be contingent to the choice of the data aggregation time interval. Proper determination of aggregation level of traffic data will ensure the retention of necessary information and the elimination of as much unnecessary information as possible (Qiao et al., 2004). For a heterogeneous traffic stream, the change in the traffic composition has a direct impact on the flow that represented in PCU and hence the speed and V/C ratio (Nahdalina et al., 2017). Vlahogianni (2007) has found that the effect of traffic composition on the flow and speed decreases with the onset of congestion. However, in the stop-and-go traffic conditions, the characteristics of platoon dispersion process are significantly influenced by the traffic composition and the distribution of the desired speed of the vehicle classes (Gupta and Katiyar, 2007; Wong and Wong, 2002).

The literature survey clearly shows that the traffic composition as an important criterion to be considered while dealing with the heterogeneous traffic stream. Though several studies have been conducted to understand the impact of traffic composition on various aspects of the transportation engineering, there was no detailed study on the impact of composition variation across the data aggregation intervals. It is evident from the literature that the appropriate selection of the aggregation interval ensures the retention and elimination of information from the raw data. Evidently, there is a need of research on the data aggregation interval, considering the variation of traffic composition.

3. **Data Collection**

In order to understand the traffic composition variation within the aggregation levels, a classified count of the vehicles from different regions of the country has been collected. The study locations and the details of the data are given in Table 1. From each of these locations, the classified count of the vehicles for different aggregation periods was taken. Present study suppose that the traffic stream is mainly composed of four vehicle types, namely, Auto, Bike, Light Motorized Vehicles (LMV), and Heavy Motorized Vehicles (HMV). The aggregation interval considered for traffic data aggregation were 15, 30, 60, 120, 180, 240, 300, …., 900-sec. Figure 2 shows the distribution of the count of different vehicle classes for an aggregation interval of 60-Sec observed at VIP road, Kolkata. From the classified count data, the proportion of each vehicle class for different aggregation intervals were estimated. Corresponding to an aggregation interval, the mean proportion of the particular vehicle class and its standard deviation were also estimated. Table 2 shows the mean proportion and its standard deviation for each vehicle type obtained from VIP road, Kolkata.

Table 1: Information of Data collection Location and Observation Period

Study Area	Lane Width (Meter)	Observation Period (Hour)
Dispur, Assam	8.5	2
VIP Road, Kolkata	10.8	7
Dabri Road, Delhi	10.5	3
Maharani Bagh, Delhi	12.5	4
Kodhalli, Bangalore	8.5	2
Indira Nagar, Bangalore	12	2

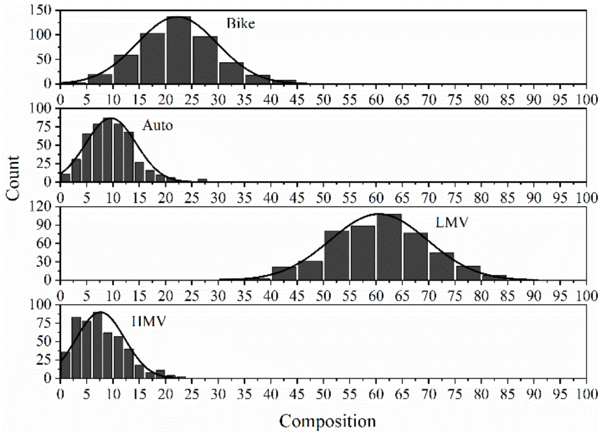


Figure 2: Distribution of the vehicle count for an aggregation period of 60-Sec, observed at VIP road, Kolkata

Table 2: Traffic composition details for different aggregation periods

Agg. Period	Composition												Mean CV
	Auto			Bike			LMV			HMV			
	Mean	*SD*	*CV*	*Mean*	*SD*	*CV*	*Mean*	*SD*	*CV*	*Mean*	*SD*	*CV*	
15	9.67	9.44	0.98	22.81	14.28	0.63	59.27	17.50	0.30	8.24	9.67	1.17	0.77
30	9.71	6.82	0.70	22.39	10.54	0.47	59.89	13.12	0.22	8.00	6.68	0.84	0.56
60	9.62	4.77	0.50	22.21	7.59	0.34	60.54	9.25	0.15	7.63	4.58	0.60	0.40
120	9.60	3.34	0.35	22.15	5.87	0.27	60.76	6.10	0.10	7.48	3.12	0.42	0.28
180	9.67	2.79	0.29	22.24	5.02	0.23	60.72	4.60	0.08	7.38	2.68	0.36	0.24
240	9.64	2.48	0.26	22.18	4.89	0.22	60.82	4.10	0.07	7.37	2.33	0.32	0.22
300	9.64	2.31	0.24	22.19	4.64	0.21	60.81	3.89	0.06	7.35	2.32	0.32	0.21
360	9.66	2.07	0.21	22.17	4.14	0.19	60.82	3.35	0.06	7.35	2.09	0.28	0.19
420	9.66	2.08	0.22	21.99	4.24	0.19	60.98	3.05	0.05	7.36	2.12	0.29	0.19
480	9.65	2.07	0.21	22.00	4.44	0.20	61.00	3.22	0.05	7.35	2.06	0.28	0.19
540	9.68	1.89	0.20	22.05	4.17	0.19	60.93	2.88	0.05	7.33	2.06	0.28	0.18
600	9.64	1.89	0.20	22.19	4.20	0.19	60.81	2.79	0.05	7.35	1.97	0.27	0.17
660	9.66	1.90	0.20	22.06	4.20	0.19	60.88	2.88	0.05	7.39	2.02	0.27	0.18
720	9.67	1.89	0.20	22.18	4.12	0.19	60.80	2.18	0.04	7.34	1.96	0.27	0.17
780	9.55	1.68	0.18	22.05	4.00	0.18	61.04	2.68	0.04	7.34	1.90	0.26	0.17

840	9.65	1.90	0.20	21.97	4.10	0.19	61.02	2.58	0.04	7.34	1.97	0.27	0.17
900	9.67	1.81	0.19	22.18	4.19	0.19	60.82	2.71	0.04	7.34	1.89	0.26	0.17

1. Methodology

According to Edie's generalized definitions (Edie, 1963), the traffic stream characteristics, such as the flow, density, and speed are defined in a spatiotemporal region. It is evident from Equation 1 & 2 that the size of spatiotemporal region is a deciding factor of the nature of these characteristics. As discussed earlier, achieving a reproducible bivariate relationship between the traffic flow characteristics in a heterogeneous traffic stream demands a consistent traffic composition between each time-space region. Developing such a criterion requires a comprehensive understanding of the traffic composition variation across the time-space regions.

$$Flow,\ \mathrm{q} = \frac{\text{Total Distance Travelled by all the vehicles}}{\text{Area of 'Time-Space' Region}}$$

$$q = \frac{\sum_{i=1}^{n} x_i}{|L.T|} \tag{1}$$

$$Density,\ \mathrm{k} = \frac{\text{Total Time Spent by All the Vehicles}}{\text{Area of 'Time-Space' Region}}$$

$$k = \frac{\sum_{i=1}^{n} t_i}{|L.T|} \tag{2}$$

Where,

x_i = Distance travelled by i^{th} vehicle in the spatiotemporal region of dimensions L and T

t_i = Time spent by i^{th} vehicle in the spatiotemporal region of dimensions L and T

As mentioned earlier, one of the important properties of the data aggregation period that should be fulfilled, particularly in case of a heterogeneous traffic stream, is the minimal variation of the traffic composition within the aggregation period. The methodology proposed in this study could handle the stated problem through a simple statistical analyses. Figure 3 Figure 4 show the variation of the mean proportion of each vehicle type and its standard deviation with the aggregation period, respectively. It is evident from the figures that, the mean proportion and its variations (standard deviation from the mean proportion) stabilizes as the aggregation period increases.

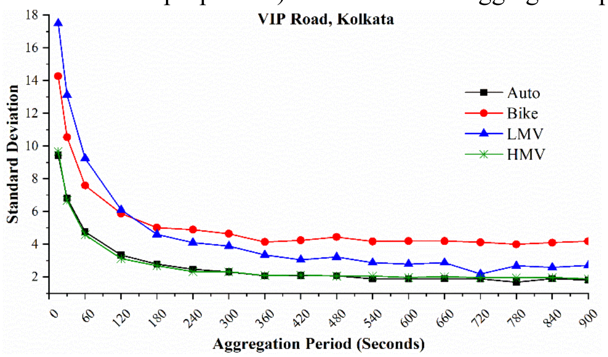


Figure 3: Variation of the Standard Deviation from the Mean proportion with the Aggregation Period

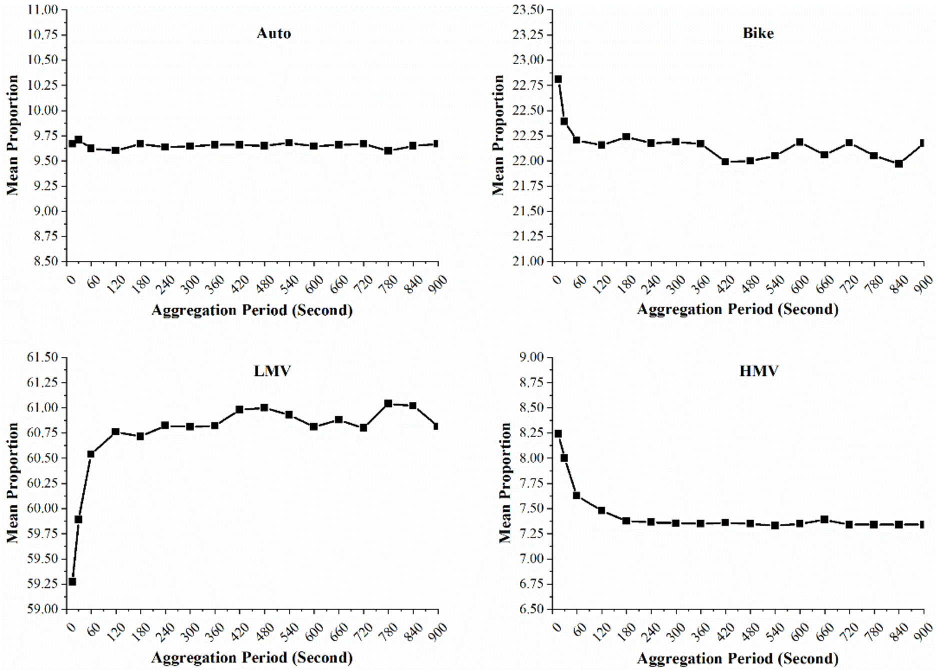


Figure 4: Mean proportion Variation with Aggregation Period

While the mean composition as well as the standard deviation from the mean composition are consistently varying with the aggregation interval, a single relative factor need to be considered for describing this variability. To capture the relative variability of the composition of each vehicle type, the coefficient of variation (CV) is considered and shown in Figure 5. It is evident from the figure that the coefficient of variation systematically varies for all vehicle types and stabilizes as the aggregation period increases.

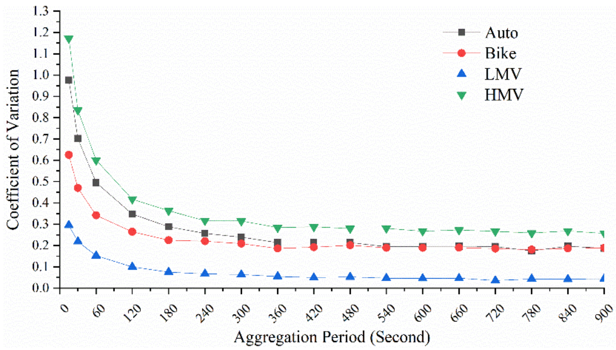


Figure 5: Variation of the Coefficient of Variation with the Aggregation Period

The optimal aggregation interval could possibly be defined as the time interval at which the traffic composition begins to stabilize. Since the traffic composition is a relative measure, which is independent of the actual numbers of each vehicle classes, the composition-stabilization process could be ascertained as a collective process between all the entering vehicle types into the measurement section. Hence, the coefficient of variation of all the vehicle types corresponding to an aggregation interval could be averaged to a single variable which is nothing but the coefficient of variation of the composition of the traffic stream. Figure 6(a) shows the variation of the coefficient of variation of traffic composition (CV_{mean}) with the aggregation interval. It is evident from the figure that the consideration of a longer aggregation interval inherently ensures the consistent traffic composition between the aggregation intervals. However, as evident from the literature, a longer aggregation period may oversimplify the traffic dynamics and results in the loss of valuable information corresponding to the short-term traffic dynamics. Present study suggests to consider the minimum possible aggregation interval at which the traffic composition starts to stabilize. Obtaining such a measure requires a single model that captures composition variation with the aggregation period. It was found that the mean coefficient of variation follows a trend that corresponds to the Rational Function (RF) as shown in Equation 3. Figure 6(a) shows the fitted model to the data.

$$CV_{mean} = \frac{\alpha + \beta.\mathrm{T}_{agg}}{1 + \gamma.\mathrm{T}_{agg} + \eta.\mathrm{T}_{agg}^{2}} \tag{3}$$

Where,

CV_{mean} = Coefficient of variation of the mean traffic composition (which is the mean of coefficient of variation of composition of each vehicle type)

T_{agg} = Aggregation period

$\alpha, \beta, \gamma, \eta$ = Model parameters

The Rational Function Models (RFM) has been widely used as an alternative to the rigorous mathematical models due to its better interpolation properties and very high fitting accuracy, and so on (Tao and Hu, 2001). Such models are widely considered to model the time dependency of real-life problems that have the asymptotic behavior. These models are generic, i.e., the model parameters do not carry any physical meaning (Hu et al., 2004). As we are also investigating the time dependency of traffic composition and is expected to show an asymptotic behavior after certain aggregation interval, the RFM could be a better choice.

Apparently, the optimal aggregation interval happens at the point at which the rate of change of the coefficient of variation approaches to zero from the direction of the minimum aggregation interval. For simplicity, the optimal aggregation period was assumed corresponding to the aggregation period where the rate of change of coefficient of variation is 0.0005. For obtaining the optimal aggregation period, the first derivative of Equation (1) has been taken which is nothing but the rate of change of coefficient of variation (Figure 6(b)). The variation of the rate of change CV_{Mean} with the aggregation interval for other locations are shown in Appendix A.

$$\frac{d}{dx}\left(CV_{mean}\right) = \frac{\beta}{1 + \gamma.\mathrm{T}_{agg} + \eta.\mathrm{T}_{agg}^{2}} - \frac{\left(\alpha + \beta.\mathrm{T}_{agg}\right).\left(\gamma + 2\eta.\mathrm{T}_{agg}\right)}{\left(1 + \gamma.\mathrm{T}_{agg} + \eta.\mathrm{T}_{agg}^{2}\right)^{2}} \tag{4}$$

$$\dot{CV}_{Mean} = -\frac{\beta\eta x^{2} + 2\alpha\eta x + \alpha\gamma - \beta}{\left(x\left(\eta x + \gamma\right) + 1\right)^{2}} \tag{5}$$

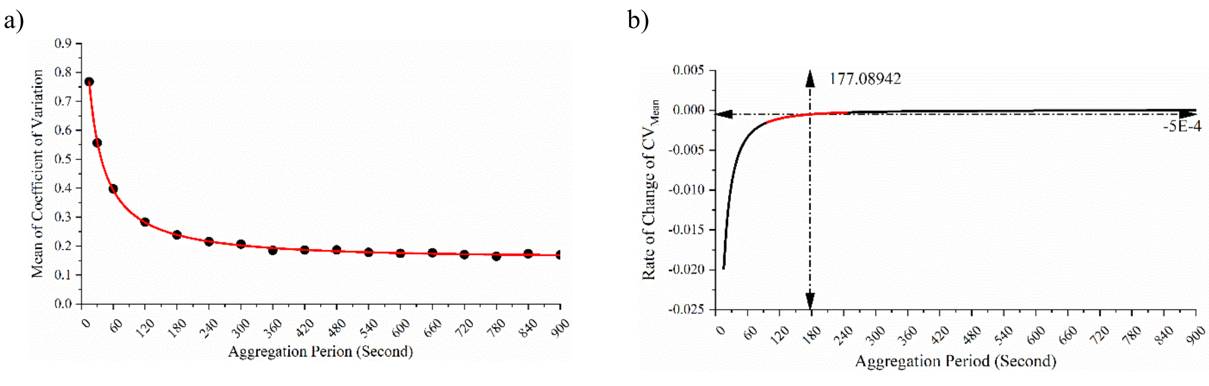


Figure 6: a) Variation of the Mean Coefficient of Variation with Aggregation Period b) Rate of Change of Mean Coefficient of Variation with Aggregation Period

4. Results and Discussion

The appropriateness of the proposed model is validated with the time series traffic data collected from various locations. Table 3 shows the model calibration results considering the data from different locations. It is clear from table that the proposed model is well representing the empirical data.

Table 3: Model Calibration Result Corresponding to Different Study Sites

Location	Statistics	Parameters				adj. R^2	Reduced Chi-Square
		α	β	γ	η		
Dispur	*Value*	0.813	0.005	0.019	-4.29E-06	0.9531	5.21E-04
	Std. Error	0.081	0.003	0.009	1.82E-06		
	t-Value	10.080	1.536	2.101	-2.361		
	Prob>|t|	1.64E-07	0.148	0.056	0.035		
VIP Road, Kolkata	*Value*	1.365	8.72E-03	0.063	-4.41E-06	0.9994	1.61E-05
	Std. Error	0.040	8.71E-04	0.004	2.54E-06		
	t-Value	34.524	10.009	15.477	-1.737		
	Prob>|t|	3.57E-14	1.78E-07	9.38E-10	0.106		
Dabri Road, Delhi	*Value*	2.039	0.078	0.192	3.51E-05	0.9806	3.05E-04
	Std. Error	1.022	0.071	0.165	4.42E-05		
	t-Value	1.996	1.111	1.169	0.795		
	Prob>|t|	0.069	0.289	0.265	0.442		
Maharani Bagh, Delhi	*Value*	0.765	0.011	0.083	3.70E-05	0.9975	2.63E-05
	Std. Error	0.084	0.004	0.021	2.01E-05		
	t-Value	9.071	3.108	3.951	1.841		
	Prob>|t|	2.72E-04	0.027	0.011	0.125		
Kodhalli, Bangalore	*Value*	9.010	0.204	0.024	-2.13E-07	0.9733	5.46E-04
	Std. Error	0.086	0.096	0.011	1.28E-07		
	t-Value	105.221	2.129	2.155	-1.67E+00		
	Prob>|t|	1.47E-09	0.086	0.084	1.57E-01		
Indira Nagar, Bangalore	*Value*	10.057	0.297	0.033	-2.39E-07	0.9970	1.79E-04
	Std. Error	0.066	0.050	5.50E-03	9.90E-08		
	t-Value	151.687	5.980	6.074	-2.42E+00		
	Prob>|t|	2.36E-10	1.87E-03	1.75E-03	6.03E-02		

From the calibrated models, the optimal aggregation intervals were estimated by solving the Equation 5 corresponding to a $\dot{CV}_{Mean}$ value of 0.0005. At optimal aggregation interval, the proportion of a particular vehicle class would be corresponding to the mean proportion of that particular vehicle class (Figure *4*) and the maximum deviation from the mean would be within the minimum possible standard deviation (Figure *3*) for that vehicle class. The optimal aggregation intervals for the study sites are shown in Table 4. It is evident from the table that the optimum aggregation interval at which the traffic composition stabilizes is different for different cities. Hence, consideration of a constant aggregation interval may not be appropriate for all the cases. The temporal measure of traffic flow from Dispur, Assam, was aggregated considering the optimum aggregation interval of 180-Sec and shown in Figure 7. The figure clearly shows that the optimum aggregation interval could capture the short term fluctuations in the traffic stream.

Table 4: Optimum Aggregation Interval for Different Study Sites

Study Location	Optimum Aggregation Interval (Sec)	Nearest multiple of 5 on the Higher Side (Sec)
Dispur, Assam	177.68	180
VIP Road, Kolkata	177.25	180
Dabri Road, Delhi	134.75	135
Maharani Bagh, Delhi	119.53	120
Kodhalli, Bangalore	174.46	175
Indira Nagar, Bangalore	219.64	220

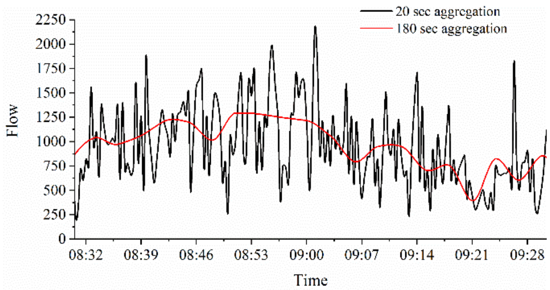
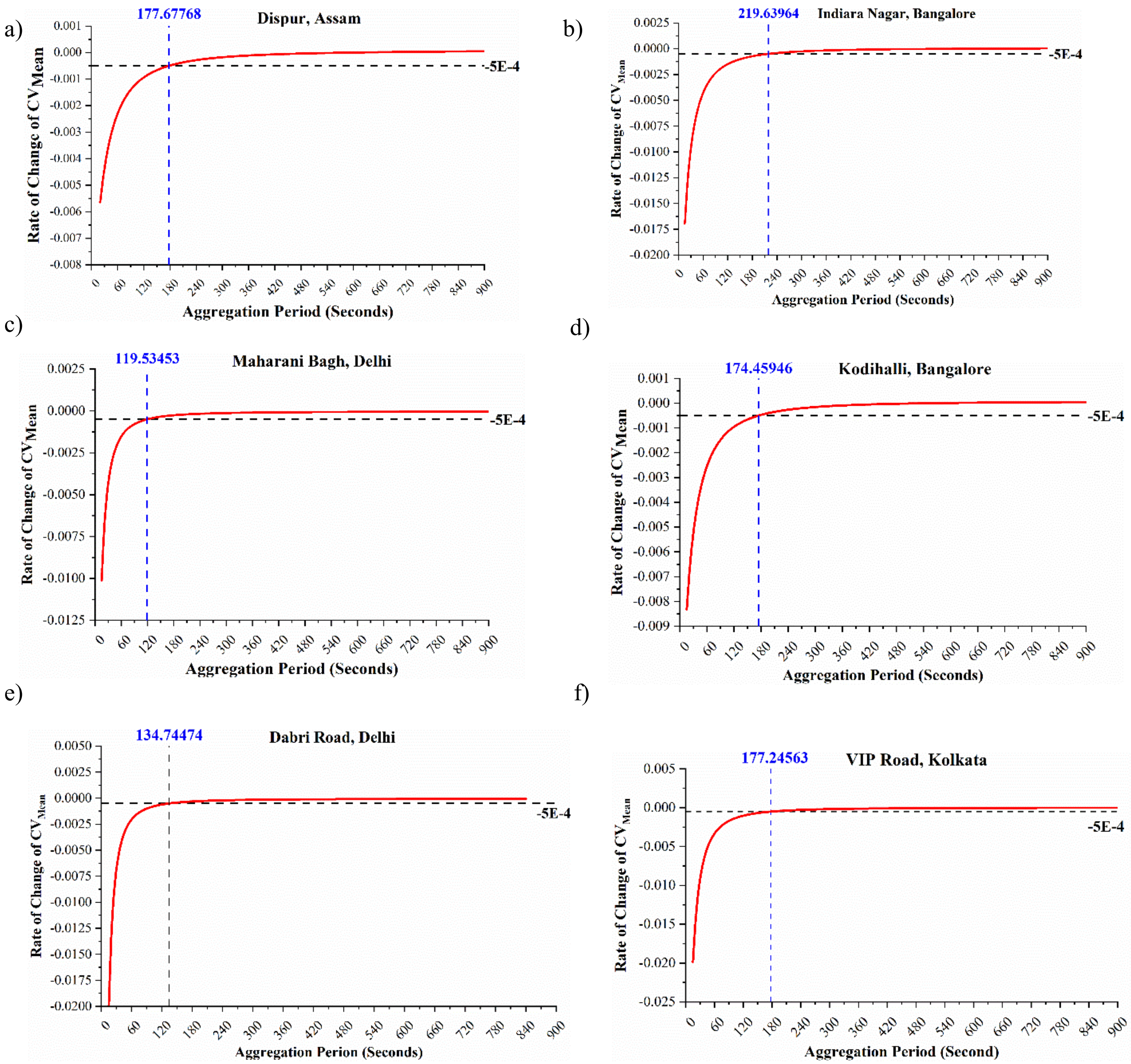


Figure 7: Variation of the Traffic Flow Aggregated by Considering the Optimum Aggregation Interval

5. **Summary and Conclusions**

Present study empirically investigates the relationship between the aggregation interval and the traffic composition. For a heterogeneous traffic stream, variation of the traffic composition between the aggregated data may cause intense fluctuation and noise in the data and thereby difficulties in modelling. An appropriate choice of the aggregation interval could solve this issue by ensuring minimum variation of the traffic composition within that aggregation interval. Hence, the optimal aggregation interval was defined as the time interval at which the traffic composition begins to stabilize. In this study, the traffic composition was represented with the mean coefficient of variation (CV_{Mean}) and the variation of the traffic composition with the aggregation period was modelled with a Rational Function (RF). The present study suggests that the minimum aggregation interval could be approximated corresponding to the aggregation interval at which the rate of change of the coefficient of variation approaches zero from the direction of the lower aggregation period. Hence the optimal aggregation interval was estimated corresponding to a $\dot{CV}_{Mean}$ value of 0.0005. At optimal aggregation interval, the proportion of a particular vehicle class would be corresponding to the mean proportion of that particular vehicle class and the maximum deviation from the mean would be within the minimum possible standard deviation for that vehicle class.

Appendix A: Optimal Aggregation Interval Estimation



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