In this study we propose to use Fuzzy Preference Analytic Hierarchy Process (AHP) for normalization of characterized data. Proposed method alleviates the problem of non-sensitivity (external normalization) of normalized results to weightages. The characterized data is normalized based on the decision maker choices. Even, the uncharacterized data can also be normalized. This method permits decision makers to use multiple reference system in external normalization. The normalization is performed through the intervention of DMs rather than pseudo criteria.

Proposed Method for Normalization

The study proposed an internal normalization method, but the authors recommend to perform external normalization initially and to use that results as a guidance for internal normalization. Sometimes DMs needs to use multiple reference systems to understand the significance between two designs for an impact category. For example, external normalized EUT values for Design 1 (0.36 N-Eq tons) and Design 2 (0.25 N-Eq tons) as per Figure 2 are 155 and 108 people equivalent. The difference between Design 1 and Design 2 is 47 people equivalent, which appears as not a significant difference. If the same impacts are normalized with respect to emissions of an average passenger car in US, then the normalized values are 9272 and 6452 (difference is 2820 car equivalents) passenger cars equivalent for Design 1 & 2 respectively("Greenhouse Gas Emissions from a Typical Passenger Vehicle" 2015). The proposed method allows to use multiple reference systems for normalizing the data. The theories of proposed method are explained briefly in the following sections.

Fuzzy Preference Analytic Hierarchy Process (AHP):

AHP is a widely used multi criteria decision model for its simple analytical efforts and ease of understanding. In AHP, the relative significance between alternatives is evaluated (called as pairwise comparison in AHP terminology) based on a predefined significance scale. AHP also has capacity to check the consistency in decision maker pairwise comparisons. Once the required pairwise comparisons were given by DM, AHP uses multiplicative transitivity property to back calculate the remaining pairwise comparisons. Once, pairwise comparisons were complete, simple analytic methods are used to calculate final weightages among alternatives compared.

In spite of its merits, the AHP method has drawbacks. It requires rigorous consistency requirement in pairwise judgments which shifts the focus of DMs towards satisfying consistency rather than his/her actual judgments (Li et al. 2013), and also needs more number of pairwise comparisons (n(n-1)/2 pairwise comparisons for analyzing n criteria) (Lee et al. 2014). In order to alleviate the drawbacks associated with AHP, Herrera-Viedma et al. (2004) proposed to use the additive transitivity property on fuzzy preference relations. This method needs $(n-1)$ pairwise comparisons unlike $n(n-1)/2$ inputs required for evaluating n criteria by the conventional AHP. The remaining pairwise comparisons are constructed based on $(n-1)$ inputs by using the additive transitivity property on fuzzy preference relations.

Herrera Viedma Approach

Consider a set of alternatives, $X = \{x_1, x_2, \ldots. x_n\}$ each alternative is related with a reciprocal multiplicative preference relation $A = (a_{ij})$ for $a_{ij} \epsilon [1/q, q]$ (e.g.,(1/9,9)) where q is the range of comparison scale .The value of 9 (q) indicates as most preferred option and 0.11(1/q) as least preferred. For example, the pairwise comparison of x_1 to x_2 was given as $a_{12} = 9$ (i.e., x_1 is more preferred than x_2) using the multiplicative transitive property ($a_{12} \times a_{21} = 1$) the pairwise comparison x_2 to x_1 can be calculated as $1/a_{12} = a_{21} = 1/9$ (x_2 is least preferred than x_1). Instead of using multiplicative transitive property in AHP, fuzzy additive transitive property can be used. According to additive transitive property($a_{12} + a_{21} = 1$), but a_{12} has a value of 9 which yields a_{21} to '-8', which is beyond the comparison scale (1/9, 9). To apply the transitive property, the pairwise comparison needs to be normalized to a scale of 0 to 1 and fuzzy preference relation can be used for converting the pairwise comparisons. The following equation 2 shows the fuzzy preference relation $P = (p_{ij})$ with $p_{ij} \epsilon [0,1]$ associated with A is given as

$$p_{ij} = g(a_{ij}) = \frac{1}{2}\left(1 + \log_q a_{ij}\right) \quad (2)$$

This proposition is very important because it can be used to construct a consistent fuzzy preference relation from the set of $n-1$ values $\{p_{12}, p_{23}, \ldots, p_{(n-1)n}\}$. In simple terms, using normal AHP needs n (n-1)/2 pairwise comparisons from DMs and remaining were calculated by using multiplicative transitive property, whereas using transitive additive property needs (n-1) pairwise comparisons from DMs. The pairwise comparisons are converted to fuzzy preference relation, remaining pairwise comparisons are constructed using additive transitive property as shown in Equation 3. Once, all the pairwise comparisons are back calculated, both methods use same analytic process for estimating weightages. If $p_{i,j} = 1$, means alternative i is the most preferred than alternative j, if $p_{i,j} = 0$, i is least preferred than j, $p_{i,j} = 0.5$ both i and j are equivalent.

$$\begin{cases} p_{ij} + p_{jk} + p_{ki} = \frac{3}{2}, \forall\, i, j, k \\ p_{ij} + p_{jk} + p_{ki} = \frac{3}{2}, \forall\, i < j < k \\ p_{i(i+1)} + p_{(i+1)(i+2)} + \cdots + p_{(j-1)(j)} + p_{(j)(i)} = \frac{j-i+1}{2}, \forall\, i < j \end{cases} \quad (3)$$

$$f: [-k, 1+k] \rightarrow [0,1], f(x) = \frac{x+k}{1+2k} \quad (4)$$

Sometimes the constructed preference relation falls in the interval $[-k, 1+k]$, $k > 0$ rather than$[0, 1]$. Then, the obtained values can be transformed within the desired range $[0, 1]$ using a transformation function that preserves reciprocity and additive consistency. The transforming function shown in Equation 4 can be used to preserve consistency. To demonstrate the method, Ryberg et al. (2013) normalization method was selected for impact categories GWP, EUT, SMOG, ACID, HHCR, and energy consumption were normalized by comparing it with US Transportation Sector Energy Consumption for 2014 ("Annual Energy Review " 2015).

The normalized values are shown in the Table 2 that can be used as a guide for DM's for pairwise comparisons. An example of proposed method is demonstrated (Figure 5) for energy consumption of various designs. The designs were compared based on the external normalized data and the pairwise comparisons required by proposed AHP were assigned (by a DM) as shown in Step 1 of Figure 5. In this study, the scale used for pairwise comparisons (1/9 to 9) is similar to scale proposed by Saaty (1980). For example the Design 3 vs Design 4 has a pairwise comparison of 9, which indicates that the Design 3 has very low energy consumption than Design 4 i.e., Design 3 is preferred than Design 4. Once the pairwise comparisons matrix is filled as shown in step 4, the final normalized values for energy consumption are calculated using computations of AHP method. The normalized weights obtained in this example were {0.22,0.34,0.34,0.09} respectively. Similarly, the normalization factors are calculated for other impact categories and are displayed in Figure 3c. There is an association between weighting and normalization methods as explained below.

Table 2. Normalized Data.

Designs	Normalization					
	No of equivalent people in US impacted in 2008					% Transportation sector energy consumption for 2014
	GWP	EUT	SMOG	ACID	HHCR	Energy Consumption
Design 1	1982	155	1378	698	160	0.34
Design 2	1918	108	962	471	132	0.21
Design 3	1873	107	952	470	121	0.20
Design 4	824	50	451	417	106	0.55

Step 1: Pairwise comparisons from DMs

	Design 1	Design 2	Design 3	Design 4
Design 1	1	1/3		
Design 2		1	1	
Design 3			1	9
Design 4				1

Step 2: Conversion of Pairwise comparisons into Preference Relations

	Design 1	Design 2	Design 3	Design 4
Design 1	0.5	0.25		
Design 2		0.5	0.5	
Design 3			0.5	1
Design 4				0.5

Step 3: Decision Matrix Conversion (Equation 2)

	Design 1	Design 2	Design 3	Design 4
Design 1	0.5	0.25	0.25	0.75
Design 2	0.75	0.5	0.5	1
Design 3	0.75	0.5	0.5	1
Design 4	0.25	0	0	0.5

Step 4: Perform Check and Transform using Equation 4, if needed

	Design 1	Design 2	Design 3	Design 4
Design 1	0.5	0.25	0.25	0.75
Design 2	0.75	0.5	0.5	1
Design 3	0.75	0.5	0.5	1
Design 4	0.25	0	0	0.5

Figure 5. Normalized Values for Energy Consumption Estimation.

Weighting

Weighting in LCIA aspires at rating different impact categories against each other to determine their significance with respect to the context of conducting LCA (Stranddorf et al., 2003). One such attempt was reported in 2007 by Gloria et al. They calculated the weighting of various impact categories by obtaining input from users, producers, and LCA experts over the weightage of various impact categories. The weightages created were specifically in the context of assisting environmentally preferable purchasing of building products in the U.S. In this study the authors assumed similar weightages only to demonstrate the relationship between normalization and weighting. The weightages for GWP, EUT, SMOG, ACID, HHCR, and Energy consumption are 47.5%, 9.8%, 6.6%, 4.9%, 14.8%, and 16.4% respectively. Since the normalized data (external) has similar units, the linear weightage of the four designs (Σ normalized data X weightages) yielded the following results as shown in Table 3 .

In external normalization scenario, the normalized impacts of GWP is in the range of 800-2,000 per capita equivalent and HHCR is 100-160, irrespective of the weightages assigned. The results are biased towards GWP and is less sensitive to change in weightages. If another reference system is selected where normalized HHCR is dominating than other impacts, then the results will be biased towards HHCR. Hence, linear weighted sum of normalized impacts with the predefined weights may not be practical for external normalization. In addition, design 4 in terms of energy consumption (related with fossil fuel depletion) is not considered for normalization due to inventory data limitations that may affect the final design selection. Internal normalization (compared with best solution) alleviates this problem. In this study the final weightages are in favor of Design 4 irrespective of normalization method, because the Design 4 outperforms other designs in five out of six impact categories. The advantage of proposed method will be more evident if the alternatives more competitive with each other.

Table 3.Weightages of Designs from Various Methods.

Design	External Normalization		Internal Normalization (compared with best)		Outranking Normalization (PROMETHEE Method)		Proposed Normalization (PAHP)	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
1	1309.44	4	-222.67	4	-1.35	4	0.15	4
2	1216.02	3	-187.04	3	-0.25	3	0.23	3
3	1187.86	2	-148.78	2	-0.12	2	0.26	2
4	547.62	1	38.35	1	1.72	1	0.35	1

Conclusions

The decisions made without normalization may led to improper selection as DM's incline towards their first impressions or depend on their own intuition. Systematic approach is required for selection of any alternative (design), hence, this study proposed a new normalization method using Proposed AHP (PAHP) method. The PAHP alleviates the drawbacks involved in conventional AHP and aids decision makers to normalize the characterized data considering the context of the study. The proposed method can also be applied to weighting phase of LCIA as well.

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Estimation of Dynamic PCU Using the Area Occupancy Concept at Signalised Intersections

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Abstract

Variability in vehicle mix necessitates the use of Passenger Car Units (PCU), the widely accepted common measure in the estimation of saturation flow. Previous research works show that PCU for a vehicle is not static, but it varies with the level of interaction among vehicles. This study proposes a methodology based on area occupancy for the estimation of PCU. Number of standard car spaces (N_{cs}) corresponding to a vehicle category is determined based on area occupancy of subject vehicle category and occupancy time of equivalent homogeneous traffic stream. The variations in dynamic PCU values of vehicles with respect to traffic characteristics, control conditions and approach width are studied and it is found that all the cars in the traffic stream do not have PCU value one. It is also observed that PCU values of all categories of vehicles except small cars exhibit a decreasing trend with increase in its own proportion. In order to facilitate easy and quick estimation of dynamic PCU values, mathematical models are developed incorporating the effect of traffic composition and saturation flow.

1. INTRODUCTION

In order to improve safety and efficiency of vehicular as well as pedestrian movements signalised intersections are provided in traffic networks. Accurate quantification of saturation flow is highly essential for the capacity analysis and performance evaluation of signalised intersections. Heterogeneous or mixed traffic systems operate differently, compared to homogeneous traffic system due to wide variations in the operating and performance characteristics of the vehicles. Hence the representation of saturation flow in number of vehicles passing stop line per unit time will be inappropriate for heterogeneous traffic conditions unless it is accompanied by vehicle composition. The variability in vehicle mix can be accounted for in the estimation of saturation flow by using the widely accepted measure, Passenger Car Unit (PCU). Studies have established that PCU is not static but varies with traffic and geometric conditions Many researchers have put forward various methods for the estimation of dynamic PCU values based on changes in various performance measures such as headway, density, delay, queue discharge, speed, vehicle-hours, travel time etc. These performance measures are suitable for traffic streams with less degree of heterogeneity and traffic following strict lane discipline. The wide variations in physical and dynamic characteristics of vehicles present in the heterogeneous traffic conditions similar to the one existing in India demand an alternative measure which explains the extent of usage of road space by vehicles in a better way. This paper is concerned with the development of a new methodology based on area occupancy concept for the realistic estimation of dynamic PCU values of various categories of vehicles at signalised intersections under heterogeneous traffic conditions.

2. LITERATURE REVIEW

Since 1965, after the inception of the concept PCE by Highway Capacity Manual (HCM), considerable research has been done for the estimation of PCU/PCE of various categories of vehicles under heterogeneous traffic conditions. To account for the effect of heavy vehicles on saturation flow, HCM 2010 has considered each heavy vehicle as equivalent to two numbers of through cars. In India, IRC 106-1990 provided a set of static PCU values for 10 categories of vehicles normally found on Indian roads depending on vehicle composition in the traffic stream. IRC SP 41 gives PCU values for vehicles at signalised intersections.

Chandra et al. (1996) proposed a methodology for the estimation of dynamic PCU based on vehicle area and speed. According to the proposed method, PCU values for different vehicles under mixed traffic situation is directly proportional to the speed ratio and inversely proportional to the space occupancy ratio with respect to the standard design vehicle (passenger car). Benekohal and Shao (2000) derived delay based passenger car equivalents (D_PCE) for single unit trucks and combination trucks at signalised intersections. The results of the study indicated that D_PCE were highly correlated with traffic volume, but to a lesser degree with percentage of heavy vehicles. Rahman et al. (2003) investigated the effect of heavy vehicle's position in the queue on total delay estimation and developed PCE values for heavy vehicle at signalised intersections. Researchers opined that PCE value for heavy vehicle decreases as position in the queue increases. Radhakrishnan and Mathew (2011) derived PCU values for different categories of vehicles at signalised intersections by minimising the observed and ideal saturation flow profile. Optimum PCU values were determined by an iterative procedure using Theil's coefficient as the objective function.

Review of literature showed that PCU is a complex parameter and its value changes with traffic and geometric conditions. Its value also depends on the selected measure of performance. The objective of the present study is to deduce PCU value of various categories of vehicles during saturation flow based on a measure which explains the extent of road usage by various categories of vehicles under heterogeneous traffic conditions in a better way. For prediction of PCU values under prevailing road way and traffic conditions mathematical models are also developed. Variation in PCU values of vehicles in through traffic with saturation flow, vehicle composition is discussed. The effect of right turn traffic in the PCU values of vehicles in through traffic, when both movements are allowed in the same phase is also discussed.

3. METHODOLOGY

Area occupancy concept proposed by Arasan and Dhivya (2010), an alternative measure of density for heterogeneous traffic conditions is adopted here as the basis for the estimation of dynamic PCU. In this study PCU of a vehicle category is considered as the number of standard car spaces that can replace that vehicle category keeping area occupancy of the entire traffic stream constant during saturated green time. In order to eliminate the impact of various factors on estimation of dynamic PCU the following base conditions, are set in the present study: intersections on level grade, no curb parking, no bus stoppages near intersection, only through traffic on carriage way, and no pedestrians and bicycles.

3.1 Area Occupancy

Area occupancy is defined as the proportion of time a set of observed vehicles occupy the chosen stretch of a roadway (Arasan and Dhivya, 2010). Eq. (1) shows the expression for area occupancy (AO),

$$AO = \frac{\sum_i a_i t_i}{TA} \tag{1}$$

where, t_i is the occupancy time of vehicle category i in seconds in the selected area, a_i is the horizontal projected area of the vehicle i in m^2, T is the total observation period in seconds and A is the area of study stretch in m^2.

In order to estimate area occupancy, vehicles in the traffic stream were divided into five categories such as small car (SC), big utility vehicle (BUV) which include big cars and light commercial vehicles, heavy vehicle (HV) which include bus and truck, motorized three wheeler (3W) and motorized two wheeler (2W). The horizontal projected areas of these categories of vehicles are 5.36, 8.11, 24.54, 4.48 and 1.20 m^2 respectively. In this study cars having average length and width 3.72 and 1.44 m is fixed as standard car (small car) (Dhamaniya and Chandra 2010) and dynamic PCU is estimated with respect to this standard passenger car.

Let a_{SC}, a_{BUV}, a_{3W}, a_{2W} and a_{HV} be the horizontal projected areas of small car, big utility vehicle, motorized three wheeler, motorized two wheeler and heavy vehicle respectively and t_{SC}, t_{BUV}, t_{3W}, t_{2W} and t_{HV} are the occupancy time of these vehicles during observation period T (saturated green time). L and W be the length and width of observation region. Then area occupancy can be estimated using Eq. (2)

$$AO = \frac{1}{WLT}\left(a_{sc}\sum t_{sc} + a_{BUV}\sum t_{BUV} + a_{3W}\sum t_{3W} + a_{2W}\sum t_{2w} + a_{HV}\sum t_{HV}\right) \tag{2}$$

Area occupancy is a non dimensional parameter and its value ranges from 0 to 1. Total area occupancy can be considered equivalent to the sum of area occupancy of individual categories of vehicles during the observation period. Thus the area occupancy can be expressed as shown in Eqs. (3) and (4).

$$AO = \sum_i (AO)_i \tag{3}$$

$$AO_i = \frac{a_i \sum_n t_i}{TA} \tag{4}$$

where, AO_i is the area occupancy of i^{th} category vehicle, a_i is the horizontal projected area of i^{th} category vehicle in m^2 and t_i is the occupancy time of i^{th} category vehicle in seconds and n is the number of vehicles in i^{th} category.

The total area occupancy of a vehicle category during saturated green time can be considered equivalent to standard car area occupancy provided only standard cars are in the traffic stream and its occupancy time is equivalent to weighted average occupancy time of vehicles present in the intersection area during saturated green time.

Let $(A_{eq})_i$ be total standard car horizontal projected area (equivalent homogeneous traffic stream area) equivalent to i^{th} category vehicle clearing the observation region during saturated green time and t_s be the average occupancy time of the traffic stream in the intersection area during observation period. $\frac{(A_{eq})_i t_s}{TA}$ will be the total standard car occupancy corresponding to the observed area occupancy. Total occupancy of a vehicle category i can be converted to standard car area occupancy as shown in Eqs. (5) and (6).

$$AO_i = \frac{a_i \sum_n t_i}{TA} = \frac{(A_{eq})_i t_s}{TA} \quad (5)$$

$$(A_{eq})_i = \frac{a_i \sum_n t_i}{t_s} \quad (6)$$

where, $(A_{eq})_i$ is the equivalent standard car area that is occupied corresponding i^{th} category of vehicle during saturated green time.

The equivalent number of standard car spaces corresponding to i^{th} category of vehicle, $(N_{cs})_i$, present in the intersection area during saturated green time can be determined using Eq.(7).

$$(N_{cs})_i = \frac{(A_{eq})_i}{a_{SC}} \quad (7)$$

where, a_{SC} is the horizontal projected area of standard car in m^2.

The number of standard car spaces obtained through Eq. (7) can be considered as the equivalent number of passenger cars replacing the total number of the vehicles in the category i. Let n_i be the number of vehicles in the i^{th} category then the dynamic PCU value of the vehicle can be found out using the equation shown below (Eq. 8)

$$PCU_i = \frac{N_{(cs)i}}{n_i} \quad (8)$$

4. DATA COLLECTION

Data required for this study was collected from fifteen approaches located at various signalised intersections in urban areas of Thiruvanathapuram and Kochi of the State of Kerala, India and Bengaluru in the State of Karnataka, India by videographic technique. Out of the fifteen approaches seven approaches satisfied base conditions set for the present study. The width of road space in the selected approaches were in the range 7m to 11m while the average vehicle composition were in the range; SC- 23 to 30%, BUV- 5 to 7%, 3W- 15 to 21%, 2W- 43 to 49% and bus - 4 to 10%. Data collected from these approaches were analysed to deduce PCU values of various categories of vehicles during saturation flow at intersection approaches that have only through movement. Rest of the eight approaches have right turn traffic along with through traffic. The width of these was also in the range 7 to 11m. The average vehicle composition were : SC- 17 to 35%, BUV- 2 to 9 %, 3W- 12 to 25%, 2W- 36 to 48%, bus- 7 to 11%.The data collected from these approaches were adopted for studying the variation in PCU values of straight moving vehicles in the presence of right turn traffic.

The data required for the study are: compositional share and horizontal projected area of each vehicle category crossing stop line during saturated green time, entry and exit time of each vehicle in the observation region, geometric details of the intersection area and saturated green time. Traffic flow data were collected during peak hours on typical week days for 1.5 to 2 hours for each approach leg. No non motorized vehicles and trucks were observed during the data collection period. Pedestrian traffic was also negligible in the selected study locations. Only buses were observed during data collection period in the heavy vehicle category. The geometric details such as width of approach, distance between stop lines were physically measured from field.

5. EXTRACTION AND ANALYSIS OF FIELD DATA

For the extraction of data from the video, video editing software was used. The video film recorded was played on a large screen monitor. A longitudinal trap of 15 m was marked in the intersection area ahead of stop line and this area was selected as the observation region. The observation was started after five seconds from the initiation of green time to the approach under consideration to account for the start up loss time. The video film was played to extract the occupancy time of each category of vehicle. The entry time and exit time of each vehicle in the observation region were noted and the occupancy time is taken as the difference between the entry time and exit time. The video film was replayed many times to extract the required details accurately.

Observed saturation flow in the data set ranged between 2000 to 10,000 veh/hr for intersection approaches that have only through movement while the saturation flow for approaches that have through and right turn movement in same phase ranged between 2000 and 7500 veh/hr. Observed area occupancy for these saturation flow values ranged between 0.18 to 0.58. Corresponding to same value of observed saturation flow many values of area occupancy is observed. This might be due to the variation in vehicle composition in the traffic stream from cycle to cycle.

6. DETERMINATION OF DYNAMIC PCU VALUE

The dynamic PCU values estimated for various categories of vehicles at the selected approaches are shown in Table 1. As may be seen from Table1 the dynamic PCU values for various categories of vehicles present in through traffic changes with variations in approach width, traffic composition and movement allowed in a phase.

It was also observed that all the cars in the traffic stream do not have PCU value one. Variation in PCU values were observed depending on traffic composition, approach width and control condition.