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Modelling commuters' travel time perception on an urban corridor using the fuzzy logic technique: A case study of Surat, India

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Abstract

On the one hand, travel time is important in planning and managing urban roads; on the other hand, it is important in commuters' route and departure time decisions. Often, mode and route choices and a sense of departure time are mainly based on one's perceived travel time (PTT). This study focuses on modelling travellers' PTT considering socio-economic and trip attributes for an urban corridor, taking Surat as a case study. An ANOVA test has been conducted to identify factors governing PTT. Analysis shows that trip attributes (e.g., traffic conditions, traffic environment, and travel distance) influence PTT more than travellers' socio-economic characteristics (e.g., income, occupation, age, and vehicle ownership). Commuters overestimate PTT (min/km) nearly two-fold, and the overestimation decreases with increasing trip distance. A PTT Estimation Model has been developed using Fuzzy Logic, considering the epistemic uncertainty associated with attributes. The developed model can help inform necessary improvement measures to bring travel times to a reasonable level.

Keywords: Perceived travel time; socio-economic attributes; trip attributes; ANOVA test; fuzzy logic.

1. Introduction

Recently, traffic congestion, owing to the significant growth in the vehicular population in metropolitan areas, has reached an alarming level. It has resulted in longer, unpredictable, and unreliable travel times in most of the urban corridors in India (Verma et al., 2021). Therefore, it is becoming increasingly important to study various aspects of corridor travel time. Travel time can be interpreted in two terms: measured travel time (MTT) and perceived travel time (PTT). The MTT reflects the realistic traffic and road situation, whereas the PTT is primarily concerned with the commuters' perception of the holistic assessment of the entire corridor. As such, PTT is the outcome of integrating a series of stimuli or enroute sequential journey episodes, and it has no straightforward relationship to MTT (Fraisse, 1984). Hence, the subjective duration experienced by commuters does differ from the actual one (Nicholson and Munakata, 2009; Malichova

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et al., 2022). Perhaps this is why commuters prefer to consider perceived times in their trip planning, such as route and departure time choices. It is also a fact that most commuters give weight to the cost based on perceived travel time rather than the actual cost of the trip. Hence, travel time perceived by commuters is more relevant than physical travel distance (MacEachren, 1980). This is a fact that planners and managers cannot overlook PTT when planning for a city's transport system. Moreover, the perception of travel time is a complex phenomenon with an associated degree of uncertainty in assessing traffic situations. Such uncertainty can be dealt with by a soft computing technique, namely, fuzzy logic (Klir and Yuan, 1996). The objectives of this paper are, therefore, to investigate the correlation of commuters' socio-economic and trip characteristics with their PTT and to model commuters' PTT using fuzzy logic for an urban corridor.

The study progresses in four stages. The first stage covers study objectives and study area selection, whereas database development for the defined objectives is dealt with in the second stage. The focus of the third stage is on the analysis of attributes for their influence on PTT, whereas the development of a fuzzy logic model for the estimation of perceived travel time is part of the fourth stage. Database development covers PTT and MTT characteristics for the selected 12 km-long corridor in Surat, India. The PTT is based on the home interviews of the commuters about their trips on the study corridor. In the present study, PTT is the travel time sensed by commuters based on their riding experience in prevailing traffic conditions, traffic environment, and trip length.

The home interview data is related to both socio-economic attributes and the travel time experienced by commuters. The MTT on the study corridor has been collected using V-Box probe vehicles. A statistical analysis has been carried out to understand the perceived travel time variation and weightage of the attributes. The identified input variables are considered in developing the Perceived Travel Time Estimation Model (PTTEM) by employing fuzzy logic to address the uncertainty in travellers' perceptions of attributes.

2. Literature Support

Travel time perception has recently received more attention than ever in transportation planning. For example, Zhang et al. (2005) found that PTT is a better parameter to measure a traffic control system's performance improvement in terms of driver acceptance than minimising overall absolute trip time. As per Poon and Stopher (2011), PTT varies from driver to driver or commuter to commuter depending on how they perceive traffic in different scenarios, and commuters and drivers plan their routes accordingly. Gkavra (2021) and Anna et al. (2022) underline the need to account for the PTT of active travel modes such as walking and cycling to guide transport planning decisions. Van Exel et al. (2010) evaluated the accuracy of travellers' perceptions of public transport trip time as well as the potential impact of these perceptions on their mode of travel choices. Tang et al. (2013) created a departure time decision model based on perceived travel time, whereas Kim and Lim (2012) demonstrated route choice modelling.

It is vital to note that PTT has been defined in a variety of ways by different studies. According to the Victoria Transport Policy Institute (2013) and Meng et al. (2018), perceived (also known as cognitive) travel time is the amount of time a passenger perceives he or she spent between departure and arrival. PTT was defined by Lee et al. (2007) as the driver's expected travel time on each link before departing the origin. However, Ramazani et al. (2011) defined PTT as the anticipated duration of travel on a whole route (including multiple links). Szeto and Wong (2012) define the PTT as the sum of the expected travel time and the perception error, with the perception error characterised by a probability distribution to capture variation for analysis. However, in the present study, PTT is defined as commuters' perceived travel time based on their riding experience under prevailing traffic conditions, traffic environment, and trip duration.

Because the PTT differs from the actual travel time, travel experience frequently influences travel time perception (Tawfik et al., 2010; Meng et al., 2018). Factors such as commute characteristics, journey episodes, travel surroundings, and expectations all have an impact on PTT (Li, 2003). Hatoyama et al. (2019) observed that secondary tasks such as listening to music, taking a quiz, or conversing with a fellow passenger reduce tourists' PTT. According to Parthasarathi et al. (2013), network characteristics such as relative discontinuity, street density, and access control also influence journey time perception. Trip duration perception changes with traffic circumstances (Ushiwaka et al., 2004; Carrion and Levinson, 2019).

PTT is also affected by the number of intersections and the degree of traffic congestion (Zhang and Levinson, 2008). In a case study conducted by Varotto et al. (2014), the mode choice aspect was revealed to have a substantial impact on individual travellers' perceptions of trip time. Saw et al. (2016) observed that not only trip parameters but also passengers' socioeconomic variables, such as income, have a substantial influence on PTT. Pourhashem et al. (2022) found that male and female public transport riders have considerably different perceptions of travel time. However, in research conducted by Burnett (1978) and Peer et al. (2014), numerous socioeconomic variables (e.g., age, gender, education, and income) were not found to have a significant effect on PTT.

Another key factor is the overestimation or underestimation of PTT on urban corridors, as Vreeswijk et al. (2014) and Peer et al. (2014) found that overestimation ranged from 40% to 50%. PTT overestimation was also found to be higher for shorter journeys by Parathasarathi et al. (2013) and Vreeswijk et al. (2014). Brands et al. (2022) observed that users of multi-modal public transport networks overestimate their PTT just modestly (11%). Ivehammar and Holmgren (2015) discovered that vehicle commuters overestimate their reported trip time while using the bus to work.

Based on the above literature, it becomes apparent that PTT is subject to a degree of ambiguity because it is based on commuter understanding and experience. This ambiguity stems from travellers' appraisals of a variety of aspects during the cognitive process (Khademi et al., 2014). Fuzzy logic, a soft computing method, can be used to overcome such ambiguity (Kalinic and Krisp, 2019). Zadeh introduced fuzzy logic in 1965, and it is effective in dealing with problems characterised by uncertainty. Fuzzy logic is an acceptable method for dealing with ambiguous and imprecise information as well as uncertainty encoded in qualities (Palacharla and Nelson, 1999; Kedia et al., 2015). This technique tolerates suboptimal and imprecise results and provides a quick, simple, and adequate solution. Previously, this approach has been applied to modelling mode choice, route choice, destination choice, and measured travel time. For example, Dhulipala et al. (2020) demonstrated the use of fuzzy logic in route selection while accounting for traffic congestion and the traffic environment. Errampalli et al. (2013) used a traffic microsimulation approach to model the behaviour of drivers. Das et al. (2016) adopted fuzzy logic to relate traffic and roadside friction for congestion modelling in heterogeneous traffic conditions. Hassan et al. (2019) used the fuzzy logic technique in modelling travellers' recreational destination choices. Given this, an attempt has been made to estimate travellers' PTT for urban corridors using the fuzzy logic technique.

The majority of PTT studies were conducted for homogeneous traffic in developed countries and were limited to analysis. It should be emphasised that there are just a few studies on PTT modelling. The current work covers PTT analysis for heterogeneous traffic in a developing nation and looks at PTT modelling using fuzzy logic to deal with ambiguity and uncertainty.

3. Study Corridor and Data Collection

3.1 Study Corridor

A stretch of nearly 12 km of the Udhana-Sachin corridor in the south-west zone of Surat city in south Gujarat has been selected for the study. The corridor connects Udhana Junction on the Ring Road to Unn Junction on the other end, passing through business, residential, and industrial areas (Refer to Figure 1). It is a vital corridor since it allows regional traffic from Maharashtra, a neighbouring state, to enter the city. The corridor has six lanes, two dedicated to Bus Rapid Transit Systems (BRTS), while the other four are used for mixed traffic, with two lanes on either side of the BRTS lanes.

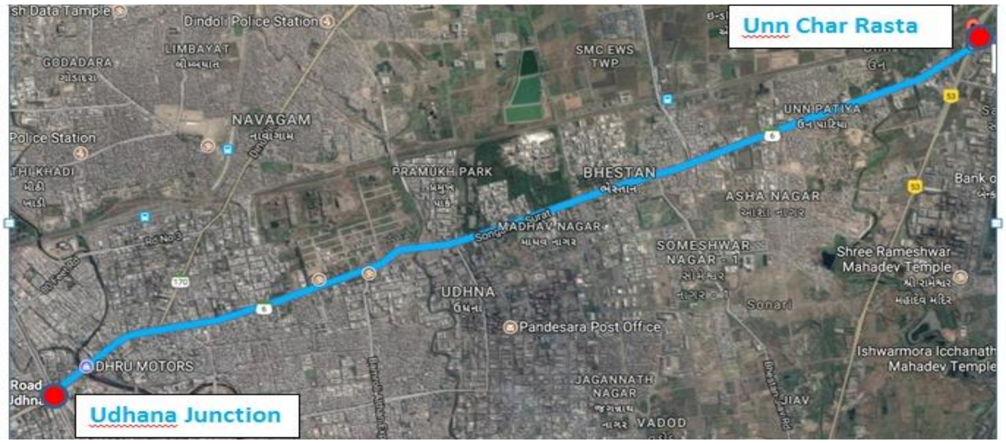


Figure 1. Location Map of the Study Corridor (Source: Authors)

3.2 Data Collection

PTT Survey

PTT surveys were conducted via home interviews with commuters residing in areas adjacent to the study corridor. PTT surveys included responses from people undertaking work trips only. A questionnaire was designed and updated in the second stage based on the pilot survey. For commuters' convenience, a map showing the location of intersections and distances on the research corridor was included in the questionnaire. The questionnaire was divided into two sections. The first section included various socio-economic attributes such as occupation, income level, age, education, and vehicular ownership, whereas the second section included trip attributes such as traffic conditions (TC), traffic environment (TE), trip distance, and PTT. 'TC' is visualised in terms of traffic intensity, congestion, and vehicle kinematics of acceleration, deceleration, stop-and-move situations, and queue or platoon movement. On the other hand, 'TE' refers to pedestrian interruptions caused by encroachment on carriageways or road crossings and haphazard kerb parking. The term 'travel distance' refers to the distance travelled on the study corridor solely, i.e., the distance travelled by commuters between the corridor's entry and exit points. It should be noted that the distance travelled to access the corridor and the distance travelled after exiting the corridor were not taken into account. Respondents were asked about their origin and destination, the reporting time at the office or workplace, as well as the distance travelled on and off the corridor. The reporting time indicates the time of day at which participants travelled on the study corridor. PTT is the perceived length of time travelled on the corridor. The questionnaire used in the survey is provided in Appendix I.

A sample of about 300 responses was randomly collected in May 2018. The questionnaires were distributed in the morning by trained enumerators to help obtain realistic and accurate data for the study. The filled-out questionnaires were collected in the evening or at a time that respondents specified. The enumerators had the opportunity to interact with commuters and explain the survey in detail, which process is believed to have increased the reliability of the data. Commuters were asked to score TC and TE on a four-point scale ranging from 1 to 4. The linguistic expressions used are shown in Table 1.

Table 1: Attribute Ratings

Rating on Scale	*TC*	*TE*
1	Low	Good
2	Medium	Fair
3	High	Poor
4	Very High	Very Poor

(Source: Authors)

A rating of '1' for TC indicates a free-flow condition where commuters can attain the minimum possible travel time for the corridor, whereas a rating of '4' indicates a near-jam condition with 'Stop and Go' traffic. A rating of '1' for TE indicates no road-side disturbances or interruptions, whereas '4' indicates the corridor is highly concentrated with road-side interruptions. The evaluations are based on commuters' experiences and visual perceptions.

MTT Survey

An MTT, or actual travel time survey, is carried out on the study corridors with V-Box-laden probe vehicles. A probe vehicle equipped with V-Boxes provides real-time or spot-to-spot speed information. For example, a speed profile collected by the probe vehicle is shown in Figure 2. The surveys were undertaken in the morning peak (8:30 a.m. to 10:30 a.m.), off-peak (3:30 p.m. to 4:30 p.m.), and evening peak (5:30 p.m. to 6:30 p.m.). Note that the above times were identified based on previous traffic data for the corridor.

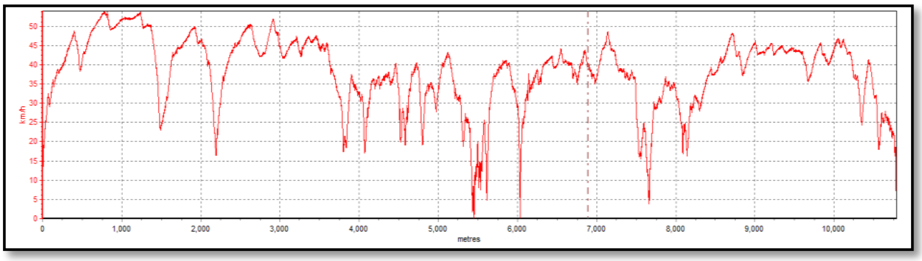


Figure 2: Speed Profile of Probe Vehicle (Source: Authors)

4. Survey Observations

4.1 Statistical Measures of PTT Values

PTT refers to the time commuters estimate for their trips along the corridor based on their daily travel experience. It differs from one individual to the next, depending on visual assessment and vehicle movement. Table 2 shows the statistical measurements of PTT values for the study in five slots of trip length on the corridor. In column II, average PTT values are provided based on commuter distance travelled, and in column III, average PTT values are provided per km. The former offers a range of PTT values ranging from 9 to 40 minutes for distances (trip length) varying from 1 to 12 km in progressive order. However, it is important to note that the average PTT per km decreased from 6.2 to 3.5 minutes, indicating a reduction in perception error (Figure 3, PTT/km). In this regard, Parathasarathi et al. (2013) made similar observations. The average PTT per km was found to be 5.47 minutes. With increasing trip length, the standard deviation appears to decrease.

Table 2. Statistical Measures of PTT (min)

Trip Length (km)	*Average (PTT)*	*Average (PTT/KM)*	*Min. (PTT/KM)*	*Max. (PTT/KM)*	*Std. Dev. (PTT/KM)*
0-2.5	9	6.20	2.5	10.0	2.0
2.5-5	21	5.60	2.0	8.8	1.5
5-7.5	31	4.82	2.9	8.0	1.0
7.5-10	36	4.13	2.5	5.6	0.9
10-12	40	3.47	2.5	5.0	0.8

(Source: Authors)

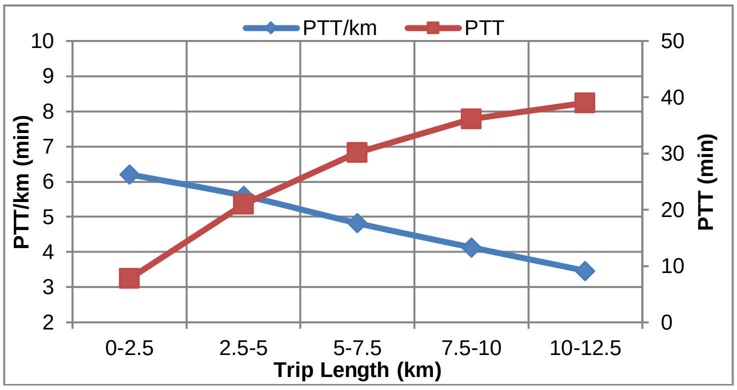


Figure 3: PTT for Trip Length (Source: Authors)

4.2 PTT Profile on Time Basis

The peak and off-peak PTT time profiles can be observed for both the morning and evening periods (Refer to Figure 4). The PTT values were found to be the lowest during the 14:00 to 16:00 hours, while the highest values were observed during the 18:00 to 20:00 hours.

The profile indirectly shows the PTT values in relation to the current traffic scenario on the route. The MTT values on the study corridor during peak and off-peak periods were found to be 2.8 min/km and 2.5 min/km, respectively, compared to the average PTT values of 6.1 min/km and 4.5 min/km for peak and off-peak periods, respectively (Refer to Table 3). As a result, the study reflects a two-fold overestimation of PTT compared to MTT. Vreeswijk et al. (2014) and Peer et al. (2015) found similar overestimations of PTT.

Table 3. Ratio of PTT to MTT

Period	*MTT (min/km)*	*PTT (min/km)*	*PTT/MTT*	*Remark*
Peak Period	2.8	6.1	2.17	Overestimated
Off Peak Period	2.5	4.5	1.80	Overestimated

(Source: Authors)

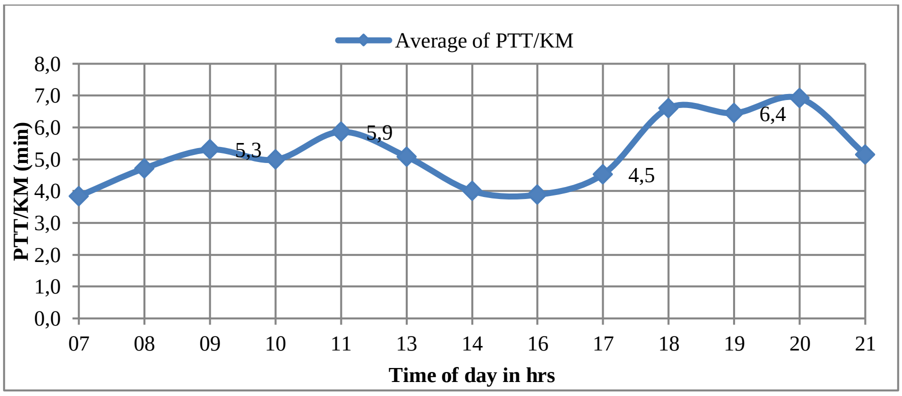


Figure 4: PTT to Time of Day (Source: Authors)

5. Analysis of PTT Factors

5.1 Socio-economic Attributes

Income, vehicle ownership, occupation, age, and education are the socio-economic attributes considered in this study. These attributes are categorised as shown in Table 4, to understand their likely impact on the perception of travel time.

Table 4. Socio-economic Attributes

Attributes	*Subgroups*
Income (₹, 000)	<10, 10-25, 25-50, >50
Vehicle Ownership	1,2,3, >4
Occupation	Upper-Level Officer, Mid-Level Officer, Lower-Level Officer, Business (Upper), Business (Lower)
Age (Years)	<26, 26-35, 36-45, 46 and above
Education	Non-Metric, Metric, Graduate

(Source: Authors)

The PTT per km for each category of socio-economic attributes with reference to four levels of traffic conditions, namely, low, medium, high, and very high, is provided in Table 5. The table also provides the sample size of each category. It shows that the maximum respondents belong to the income range of ₹10,000 to ₹25,000, the car ownership category of one vehicle, the lower-level officer category of occupation, the age range of 36 to 45 years, and the graduate category of education.

The analysis reveals that, given a specific traffic condition, the PTT values don't seem to differ much across different socio-economic attribute categories. However, as expected, there is an increasing trend in PTT values from low traffic to very high traffic levels.

Table 5. PTT/km w.r.t Socio-economic Attributes and Traffic Conditions (min)

Socio-economic Attributes	***PTT/km***				
Income (₹)	***Low (n)***	***Medium (n)***	***High (n)***	***Very High (n)***	***Average (n)***
<10,000	5.00 (2)	5.10 (4)	7.29 (4)	5.83 (2)	5.94 (12)
10,000-25,000	3.35 (9)	4.54 (45)	5.82 (49)	6.93 (23)	5.39 (126)
25,001-50,000	3.79 (6)	4.56 (26)	5.82 (46)	7.11 (20)	5.63 (98)
>50,000	2.83 (2)	4.62 (25)	5.26 (21)	6.78 (16)	5.32 (64)
Vehicle Ownership	***Low (n)***	***Medium (n)***	***High (n)***	***Very High (n)***	***Average (n)***
1	3.5 (12)	4.5 (37)	5.7 (54)	6.5 (15)	5.15 (118)
2	3.5 (4)	4.5 (26)	5.7 (30)	7.4 (20)	5.62 (80)
3	-	4.9 (15)	5.8 (12)	7.0 (15)	5.92 (42)
≥4	4.2 (3)	4.62 (22)	5.4 (24)	6.4 (11)	5.44 (60)
Occupation	***Low (n)***	***Medium (n)***	***High (n)***	***Very High (n)***	***Average (n)***
Mid-level officer	3.38 (4)	4.28 (9)	5.47 (16)	6.58 (13)	5.35 (42)
Lower-level officer	3.22 (6)	4.28 (35)	5.77 (35)	6.71 (16)	5.20 (92)
Business Upper	4.83 (2)	4.80 (30)	5.49 (32)	6.72 (18)	5.49 (82)
Business Lower	3.73 (7)	4.88 (26)	6.29 (37)	7.71 (14)	5.87 (84)
Age (years)	***Low (n)***	***Medium (n)***	***High (n)***	***Very High (n)***	***Average (n)***
<26	3.33 (2)	4.66 (12)	6.72 (15)	5.56 (7)	5.62 (36)
26-35	4.30 (7)	4.67 (26)	6.01 (26)	7.10 (24)	5.68 (90)
36-45	2.64 (6)	4.39 (51)	5.37 (51)	7.25 (25)	5.15 (108)
≥46	4.00 (4)	4.79 (28)	5.78 (28)	6.92 (15)	5.64 (66)
Education	***Low (n)***	***Medium (n)***	***High (n)***	***Very High (n)***	***Average (n)***
Non-Metric	3.40 (5)	4.96 (19)	6.42 (19)	7.39 (9)	5.76 (52)
Metric	4.33 (6)	4.70 (45)	5.87 (44)	7.34 (25)	5.66 (120)
Graduate	3.20 (8)	4.26 (36)	5.48 (57)	6.37 (27)	5.18 (128)
Average	3.61 (19)	4.59 (100)	5.77 (120)	6.92 (61)	5.47 (300)

(n) Sample size (Source: Authors)

To understand the impact of socio-economic attributes on PTT values statistically, ANOVA tests were carried out at a 95% confidence level. The test results show that, apart from the education attribute, no other attributes have a significant influence on the PTT (Refer to Table 6).

Table 6. ANOVA Test- Socio-economic Attributes

Variable	*Group*	*F Value*	*P Value*	*F-*	*Influence*
Income (0000)	<10, 10-25, 26-50, >50	0.846	0.470	2.635	No
Vehicle Ownership	1, 2, 3, ≥4	2.006	0.113	2.635	No
Occupation	Upper-level officer, Mid-level officer, Lower-level officer, Business (Upper), Business (Lower)	2.428	0.066	2.636	No
Age	<26, 26-35, 36-45, ≥46	2.056	0.106	2.635	No
Education	Non-Metric, Metric, Graduate	3.403	0.035*	3.026	Yes

*Significant at a 95% confidence level (Source: Authors)

5.2 Trip Attributes

This study considers three trip attributes: TC, TE, and travel distance, as discussed above. The commuters perceived TC and TE for their trips via their visual and situational cognisance regarding their travel distance. ANOVA tests of trip attributes were conducted at a 95% confidence level, and the results are summarised in Table 7. The statistical analysis rejects the null hypothesis that each level does not influence specific attributes with 'F' values higher than the critical one, indicating that trip attributes have a significant influence on PTT values. Similarly, extremely low 'p' values support the proposition.

Table 7. ANOVA Test -Trip Attributes

Variable	*Group*	*F Value*	*P Value*	*F-Critical*	*Influence*
TC	Low, Medium, High, Very High	47.461	<0.001	2.635	Yes
TE	Good, Medium, Poor, Very Poor	39.490	<0.001	2.635	Yes
Trip Distance (km)	<2.5, 2.5-5, 5-7.5, 7.5-10, >10	14.601	<0.001	2.402	Yes

(Source: Authors)

Further, the effects of four levels of TC, as well as TE, on PTT/km are shown in Figures 5(a) and 5(b). It can be observed that as the congestion level increases, PTT also increases. The variation is from an average of 3.61 min/km to 6.92 min/km during low to very high traffic conditions. With an increase in traffic congestion, the traffic environment degrades, and PTT values increase.

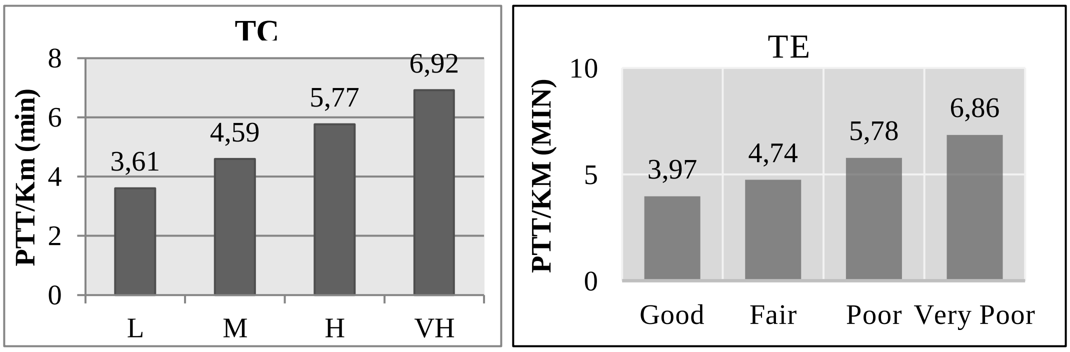


Figure 5. PTT/km for (a) Sub-groups of TC and (b) Sub-groups of TE (Source: Authors)

6. Development of PTTEM

As previously stated, a fuzzy rule-based approach is used to address the uncertainty that exists in human perception when rating attributes. The technique is commonly used in understanding the human decision process, where ambiguity and impreciseness are common.

6.1 Model Structure

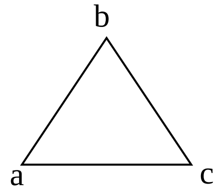
Fuzzy rule bases work in three stages, namely fuzzification, fuzzy inference systems, and defuzzification. Fuzzification is an important step in fuzzy logic theory that converts crisp inputs into fuzzy sets. The membership function (MF) is the mathematical expression that deals with the fuzziness of attributes. Fuzzy inference is the process of mapping given inputs to outputs to help arrive at decisions. Here, the Mamdani fuzzy inference system is used to develop the model for its simplicity offered by the intuitive and interpretable nature of the rule base compared to other complex inference systems, such as the Sugeno fuzzy inference system (Kedia, 2014). A fuzzy rule-based system is generated based on the association between the input and output variables. Defuzzification is a closing phase where fuzzy output values are converted into crisp values to realise the impacts in realistic terms. To obtain crisp outputs, the Centroid method of defuzzification is adopted.

6.2 Fuzzification of Attributes

‘TC’, 'TE', and travel distance are considered the inputs for the present model-based PTT attribute analysis, as discussed earlier. Although the 'education' attribute has indicated its influence on PTT, it is ignored due to its negligible 'F' value when compared to trip attributes. Table 8 shows the variable categorisation in linguistic terms, the membership shape used, and the input ranges for each input level. Clustering is a powerful tool for naturally grouping data from large datasets, and it allows for concise data representation (Salini et al., 2016; Othayoth and Katti, 2017; Huo et al., 2022). Fuzzy C-mean clustering, an efficient technique, was applied to MFs for 'Travel Distance' and 'PTT,' yielding five clusters, as shown in Figures 6(a) and 6(b). As shown in Figures 7(a) and 7(b), triangular MFs are preferred in the cases of 'TC' and 'TE' due to their simplicity (Ishizaka, 2014). The following expressions (1) and (2) provide μ(x) values for triangular and trapezoidal MFs, respectively.

MFs of Triangular Shape

$$\mu_A(x; a, b, c) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & x \ge c \end{cases} \quad \ldots\ldots\ldots\ldots (1)$$



MFs of Trapezoidal Shape

$$\mu_A(x; a, b, c, d) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1 & b \le x \le c \\ \frac{d-x}{d-c}, & c \le x \le d \\ 0, & x \ge d \end{cases} \quad \ldots\ldots\ldots..(2)$$

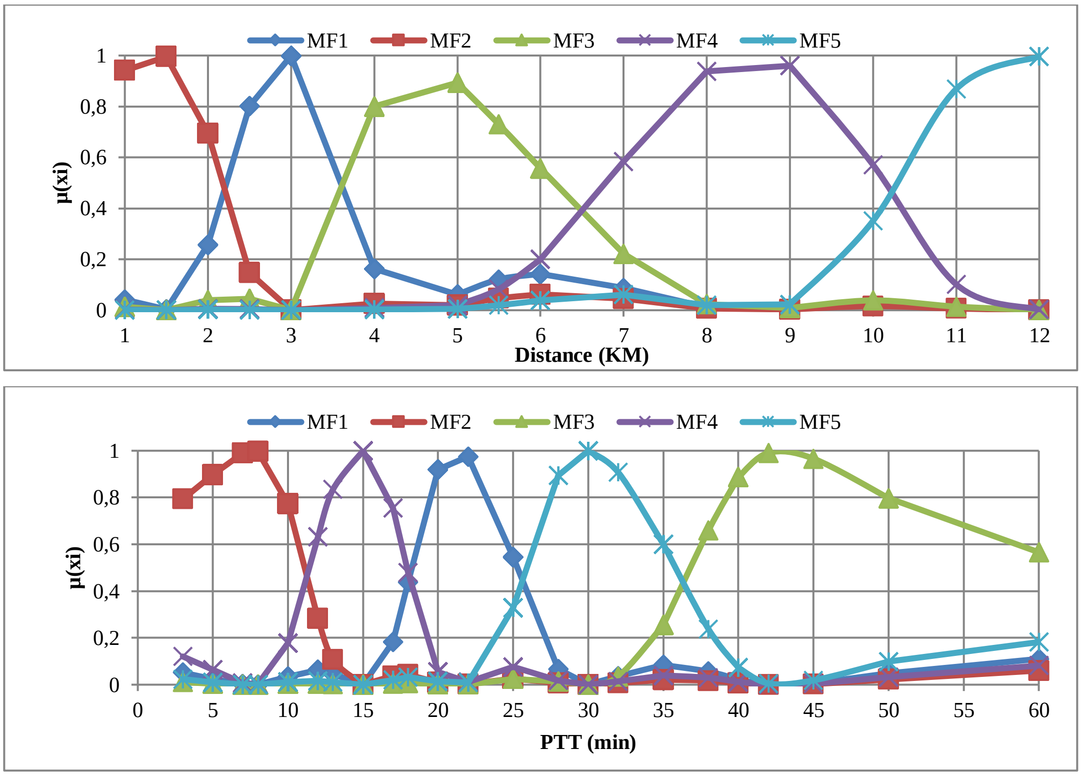


Figure 6 (a) Clustering – Distance; (b) Clustering – PTT

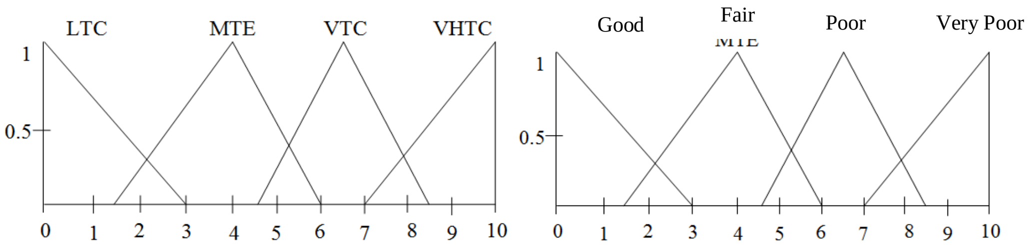


Figure 7 (a) MFs – 'TC'; (b) MFs – 'TE' (Source: Authors)

Table 8. Details of MFs

Variable	*No. of MFs*	*Linguistic Variable*	*Type of MFs*	*Fuzzy No.*
TC	4	Low	Triangular	[0 0 3]
		Medium	Triangular	[1 4 6]
		High	Triangular	[4.5 6.5 8.5]
		Very High	Triangular	[6.75, 10, 10]
TE	4	Good	Triangular	[0 0 3]
		Fair	Triangular	[1 4 6]
		Poor	Triangular	[4.5 6.5 8.5]
		Very Poor	Triangular	[7, 10, 10]
Travel Distance (km)	5	Very Short	Trapezoidal	[0 0 1.25 2.5]
		Short	Triangular	[1.8 3 4.5]
		Medium	Triangular	[3.5 5.3 7.5]
		High	Triangular	[6 5.25 10.5]
		Very High	Trapezoidal	[9 11.5 12 12]
PTT	5	Very Low	Trapezoidal	[0 0 5 15]

Variable	*No. of MFs*	*Linguistic Variable*	*Type of MFs*	*Fuzzy No.*
(min)		Low	Triangular	[7.5 15 21]
		Medium	Triangular	[17 22.5 29.5]
		High	Triangular	[25 33 43]
		Very High	Trapezoidal	[38 49 60 60]

(Source: Authors)

6.3 Fuzzy Rules Framing

Fuzzy inference is the process of mapping given inputs to an output that can be used to make decisions. In association with the output variable, a fuzzy rule-based system is generated. 80 "IF-Then" rules (4*4*5) were produced using four levels for ‘TC’ and ‘TE’ and five levels of travel distance. For example, a few fuzzy-based rules are listed below.

IF<TC is Low> and <TE is Good> and <Distance is Very Short>THEN<PTT is Very Low>

IF <TC is Medium>and <TE is Poor> and <Distance is Medium>THEN<PTT is Medium>

IF<TC is High>and <TE is Poor > and <Distance is High>THEN <PTT is High>

IF<TC is Very High>and <TE is Very Poor> and <Distance is Very High>THEN<PTT is Very High>

6.4 Defuzzification

The fuzzy inference system generates fuzzy outputs that must be converted to crisp values via the defuzzification process. The Centroid method was used in the defuzzification process to obtain an algebraic summation of the model's fuzzy output. This method is commonly used for defuzzification as it provides comparatively good results (Kumar et al. 2013, Kedia et al. 2015). A fuzzy-based PTTEM model has been developed using the MATLAB platform. Figure 8 depicts how the fuzzy model's results can be interpreted. For example, the input variables TC (5), TE (5), and travel distance (6 km) generate a PTT of 23.1 minutes from PTTEM. The figure also shows that the PTT increases as the TC and TE increase (i.e., as the traffic condition and traffic environment deteriorate).

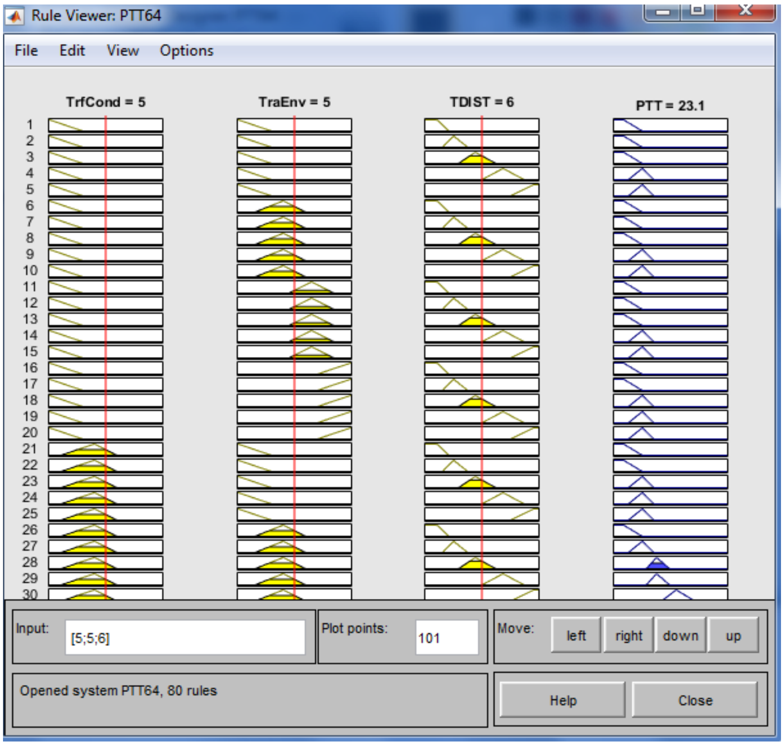


Figure 8. Typical MatLab Snapshot of Rule Viewer Window (Source: Authors)

6.5 Model Validation and Performance Evaluation

The field-reported PTT and model output values are validated with an R^2 value of 0.86, as shown in Figure 9, indicating satisfactory agreement. Further, the performance accuracy of the model is checked by three different measures, namely: Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE). RMSE and MAPE provide information about error variance, whereas MPE indicates estimation bias (Krishnamoorthy 2008). The RMSE, MPE, and MAPE performance measures were 3.91 minutes, -6.20 percent, and 19.52 percent, respectively. According to Kenneth and Roland (1982), any forecast with a MAPE value of less than 10% is considered highly accurate, 10 to 20% is considered good, 21 to 50% is considered reasonable, and more than 50% is considered inaccurate.

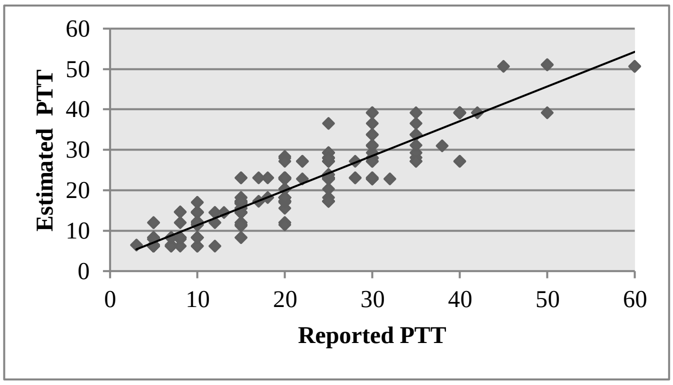


Figure 9. Reported Vs Estimated PTT (Source: Authors)

7. Discussion and Conclusion

The performance of an urban traffic corridor is typically measured in terms of travel time and travel time variations, whether for a specific segment or the entire route. Travel time measurement on a perception basis plays a vital role in realising human response to various traffic attributes, as trip makers are the ultimate corridor users. Identifying factors affecting PTT is a rather complex process involving human decision-making behaviour. The factors governing PTT can be classified into two groups: socioeconomic and trip characteristics. Income level, occupation, vehicle ownership, age, and education are examples of the former, while traffic conditions, traffic environment, and travel distance are examples of the latter. The ANOVA test performed on these attributes demonstrated that socioeconomic factors have little influence on the perception of travel time, except for education. The study reveals that 'traffic conditions', 'traffic environment', and 'travel distance' are statistically significant factors in commuters' perception of travel time.

The study also reveals that the difference between PTT and MTT decreases with trip distance, implying that perceived error is higher for shorter trips than longer trips. The PTT in the study decreased from 6.2 min/km to 3.47 min/km (44%) when comparing a short trip of 1.5 km to a long trip of 12 km. Moreover, the ratios of PTT and MTT were found to be 2.7 and 1.8 during peak and off-peak periods, respectively.

As epistemic uncertainty prevails in ratings of traffic conditions, traffic environment, and judgements of perceived travel time, a fuzzy logic approach has been advocated in developing the PTTEM. As some of the attributes are qualitative, linguistic expression and relevant ratings are adopted. The PTTEM model demonstrates that as traffic conditions and the traffic environment deteriorate, the perceived travel time for the same distance increases dramatically. The proposed PTTEM can be used to collect commuter feedback on current traffic circumstances, allowing traffic and transportation managers to reinforce their traffic-improvement efforts. Second, a variable message sign (VMS) indicating current trip duration or stream travel speed can be displayed, allowing passengers to determine the realistic travel time and so raise their level of satisfaction. It provides the possibility of appreciating the mechanisms underlying travel features that are typically difficult to assess in the field.

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Appendix I

Interview Based Travel Time Perception Survey

Ref. No________ Date: ____________________

Residential Location: - Sub-Zone__________________ Ward No. ________________

1. FAMILY STRUCTURE

Household Size ☐ a. Working Member ☐ b. Non-Working (Other Family Member) ☐

Family Income ☐

Vehicle Ownership – Car ☐ Two Wheeler ☐

2. WORKING MEMBER - **A** ☐ **B** ☐ **C** ☐ **D** ☐ **E** ☐

A- Upper Level Officer, B - Mid Level Officer, C- Lower Level (Class III), D – Business (Upper), E – Business (Lower)

PART-(A): Socioeconomic Characteristics

i. Gender – Male ☐ Female ☐

ii. Age – ☐

iii. Income – <10000 ☐ 10000-25000 ☐ 25000-50000 ☐ > 50000 ☐

iv. Education –Non Metric ☐ Metric ☐ Graduate ☐

Part - (B): Trip Particulars

i. Trip Purpose – Work

ii. Mode of travel - Car ☐ 2W ☐ 3W ☐

iii. Office Reporting Time -________________

iv. Origin (Place) -_____________________ Destination (Place)__________________

v. Appx. Distance (km)- From Residence to Work Place________________

vi. Name of Main Road -

vii. Entry Point (Main Road) - ___________Exit Point (Main Road)___________App. Distance

viii. Perceived Travel Time (PTT) on Main Road

	Going From Home to Work				**Returning From Work to Home**			
Day	Journey Starting	Perceived Travel Time	Traffic Congestion*	Traffic Environ' #	Journey Starting	Perceived Travel Time	Traffic Congestion*	Traffic Environ' #
Mon								
Tues								
Wed								
Thurs								
Fri								

Traffic Congestion - *(**L** – Low, **M** – Medium, **H** – High, **VH** – Very high)

Environmental Condition

Overall feeling towards Pedestrian disturbance, Roadside disturbance etc.

(**A** – Very good, **B** – Good, **C** – Fair, **D** – Poor, **E** – Very poor)

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