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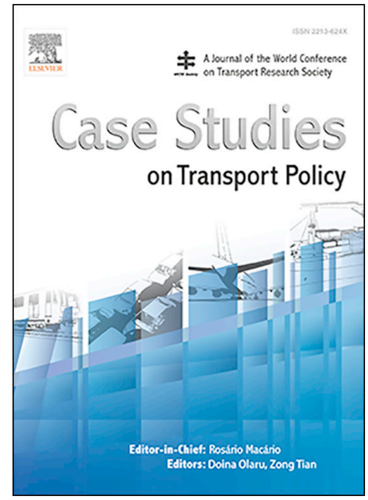

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PII: S2213-624X(20)30148-6
DOI: https://doi.org/10.1016/j.cstp.2020.11.013
Reference: CSTP 538

To appear in: *Case Studies on Transport Policy*

Received Date: 9 November 2019
Revised Date: 3 October 2020
Accepted Date: 20 November 2020

Please cite this article as: H. Mansoori, H. Haghshenas, M.A. Esfahani, J.A. Groeger, The fuzzy modelling of personal vehicle usage in Isfahan: Quantifying contributions from different Travel Demand Management strategies, *Case Studies on Transport Policy* (2020), doi: https://doi.org/10.1016/j.cstp.2020.11.013

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Acknowledgements

This work was supported by the Isfahan Municipality. Also, it’s necessary to thank the efforts of Mrs. Shirin Rafiaei and Milad Nouri who helped us in gathering the data.

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Abstract

Modifying travel behavior is a pressing issue in the face of increasing urbanization and the challenges that poses for existing infrastructure and deteriorating environmental conditions. Such challenges are particularly acute in cities which have a rich history and which have seen substantial population growth. One such is Isfahan, the third largest city in Iran, where the current study was conducted. Successful modification of travel behavior relies on an understanding of that behavior, but there are substantial methodological and theoretical barriers to doing so. This study reports a survey (N=400) of Isfahan residents and visitors, and the modeling of the resulting data using a fuzzy logic approach. Together they illustrate the relative desirability, and potential effectiveness, of different Travel Demand Management strategies that might be employed to address the traffic challenges of Isfahan and other heritage cities worldwide.

Keywords: Travel demand management, Fuzzy logic, Travel behavior, Transport policy, Decision making process.

1. INTRODUCTION

Widespread urbanization is a relatively recent phenomenon. In 1900 just 15% of the world's population lived in cities. A little more than a century later, over half of the world's people did so (Spence et al., 2009). This rapid change is one of the main reasons for the lack of adequate public transportation infrastructure, another is the remarkable degree of independent mobility afforded by the motor car. In Iran, a developing country and with almost 75% of its population urbanized (see, https://data.worldbank.org/indicator/sp.urb.totl.in.zs), the results of these challenges are seen in its traffic problems, particularly in its large industrial cities. Isfahan, a city with a population of nearly 2 million people, is the third largest city in Iran and is located in the center of the country. It is an important industrial city which, because of its historical monuments and tourist attractions, welcomes many domestic and foreign tourists every year. This combination of modern industry and heritage tourism poses huge challenges in traffic management. Besides the economic and social damage it poses, traffic is one of the main reasons of pollution in the city. Between 2007 and 2014, city-wide pollution resulted in unhealthy, or worse, atmospheric conditions for about one-third of each year. It is estimated that 78% of the pollution of Isfahan is caused by transportation and industrial activity (Momeni, 2012), and each year some 15% of all city deaths are attributed to air pollution. During colder months, pollution-related health challenges increase, causing temporary closure of schools and public offices. These health consequences, and short-term disruption of daily activities, may also have very long term consequences: research has shown that air pollution also causes the gradual destruction of historical monuments (Kucera and Fitz, 1995). Solving the travel and associated pollution problems of Isfahan city, which has three UNESCO-registered historical monuments, is a key issue for Isfahan, its residents and visitors.

1.1. Travel Demand Management

Travel Demand Management (TDM) refers to a collection of strategies which attempt to optimize the utilization of infrastructure and transport facilities, seeking improvement through changing the mode of transport adopted, journey time, distance travelled and routes used (see Victoria Transport Policy Institute for an excellent overview of approaches, http://www.vtpi.org/tdm/tdm42.htm). The principle aim of the research reported below is to demonstrate the utility of fuzzy logic, a methodological approach which allows the combination of objective and subjective sources of data (DušanTeodorović, 1999), as a means for selecting the optimal combination of such strategies for overcoming the traffic challenges of a particular set of traffic scenarios (i.e. those of Isfahan city). Before doing so we overview the various TDM strategies which might be applied.

Motivated in part by increases in the price of crude oil, and repeated energy crises (Meyer, 1999), Litman contrasted the anticipated efficacy of fuel efficiency standardization, alternative fuel types, increasing fuel taxation and various TDM policies. Litman's analysis suggested that TDM was expected to lead to the greatest reduction in travel time, air pollution, traffic density, and accidents (Litman, 1999).

Congestion pricing is a frequently advocated TDM strategy, and empirical evaluations of its effectiveness have demonstrated positive results. Application of congestion pricing in the Singapore, Milan, Stockholm, and London has resulted in the reduction of traffic load, an increase of vehicle speed in the targeted zone and an increase in the public transportation use (Li and Hensher, 2012). Similarly, the effects of applying the congestion taxes for entering the busiest traffic zone in Stockholm city resulted in the 24% decrease in traffic initially and a longer term steady state -22%. Still more specific application of this policy showed that the use of a personal vehicle for educational and work goals reduced from 25% to 22% and public transportation use increased from 66% to 74% (Sørensen et al., 2014). Mere application of TDM policies does not, in itself, guarantee success: social support for the policy is also essential. For example, the positive results in London and Stockholm compared with the failure traffic congestion pricing in New York have been attributed to such a lack of social support (Zheng et al., 2014). Other studies also demonstrate that how the policy is regarded mediates its acceptance and efficacy, including: the perceived fairness of the policy (Jakobsson et al., 2000, Schade and Schlag, 2003), the level of trust in the political figures advocating it (Fujii, 2005, Schmöcker et al., 2012), understanding of the problems faced in the wider community (Steg, 2003), the popular belief that the policy will be effective (Bartley, 1995, Taylor and Kalauskas, 2010), adequate advance notification of its introduction (Litman, 2006, Bhatt et al., 2008) and the socio-economic demographics of the users of the areas affected (Francke and Kaniok, 2013, Xenias and Whitmarsh, 2013).

TDM policies differ in the way they attempt to change behavior: by discouraging the undesirable behavior through deterrence, or encouraging more desirable behavior by incentivizing it. Deterrents and Incentives can be combined to positive effect. For example, interviews in Cambridge (UK) and Newcastle (UK) showed that improvements in public transport were more popular than the more punitive policies of reducing access to particular zones, or increasing parking or road use charges, with controlling zone access more popular than increased pricing (Thorpe et al., 2000). The results suggested that combining improved transport with road use charges was the most likely to reduce personal vehicle use (Thorpe et al., 2000). Other studies have modeled the possible effect of combining different TDM strategies, on the extent of a particular travel problem (e.g. delays) implemented in specific locations, showing that effectiveness was likely to increase as the number of simultaneously-implemented TDM strategies increased (May et al., 2012). Many TDM strategies encourage changing mode of transport. Subjective beliefs such as feelings of personal safety in and near home, trust in other people, can substantially influence the frequency of use of public transport. Thus, for example, in Melbourne (Australia), respondents who felt safe and trusting in their neighborhood were more likely to feel safe when using public transport, and more likely to use public transport (Delbosc and Currie, 2012). They were influenced almost as much by these feelings than whether they had access to a car, and feelings of safety were far more influential than the distance that would have to be travelled. Using a structural equation approach, this study also showed that the respondent's age affected intention to use public transport far more than whether the respondent was male or female.

Taken together, these studies show that TDM strategies can affect travelers' intentions, but these intentions are also influenced by more subjective or abstract beliefs, that may lie beyond the transport planner's intent or control, e.g. the beliefs which is outside our direct experience, conveyed through language, as well as the traveler's own direct and perhaps unrepresentative experience of travel time, traffic load, route choice, quality/safety/reliability of fleets, etc.. It follows that in order to adequately estimate the possible effectiveness of different interventions, the methodology used must be capable of incorporating more precise, quantitative information as well as more diffuse, subjective indications of what may be important to that traveler. The study reported below uses of the fuzzy logic approach to address this possible weakness in previous approaches. Fuzzy logic is a multi-valued logic which was introduced so that research might incorporate data arising from vague and less easily quantifiable ideas. It is an extension to the conventional Aristotelian and Boolean logic as it deals with "degrees of truth" rather than absolute assigned or measured values that are binary or integer. Instead, it is similar to human thinking and interpretation and gives meaning to expressions like "often", "smaller" and "higher". Fuzzy logic takes into account that real world is complex and there are uncertainties: everything cannot have absolute values and follow a linear function (Godil et al., 2011).

Before considering the methodology used in more detail, we first briefly overview previous research on traffic management in Isfahan.

1.2. Studies of Travel Demand Management in Isfahan city

Studies of TDM have investigated the possible efficacy of different TDM strategies from the perspective residents and visitors to Isfahan city. One such study (Slavati, 2010), used a survey and the stated preference technique in order to assess the possible effects on private vehicle use in Isfahan's Central Business District (CBD) of introducing a cost for parking and improving public transport travel times. Modeling of the effects of these new policies, using binary, multinomial and nested logit models, revealed that the parking pricing and public transportation travel time would reduce private vehicle use, and that many individual respondents' characteristics, such as education, sex, car ownership, etc. influenced mode choice in Isfahan

(Slavati, 2010). Mode choice by tourists coming to Isfahan city was also studied using the stated preference survey technique (Ranjbaran, 2013). Results showed that 94% of the tourists traveled to Isfahan using their own car, with the vast majority of these (80%) using that vehicle to visit the tourist areas of the city. Using binary, multinomial and nested logit models, it was revealed that the TDM policies such as congestion pricing and ticket prices for public transportation, influenced tourists' mode choice, as did the value of the respondent's vehicle, where they lived and the number of those travelling with them. Finally, the effects of congestion pricing on travel into the CBD was also studied using binary, multinomial and nested logit models (Noori, 2015). Lack of access to the public transportation system and personal wealth influenced the decision to use one's own vehicle, but congestion pricing was predicted to reduce this, especially when the journey purpose was discretionary (e.g. shopping trips).

1.3. Beyond binary decision making

Most of the TDM studies reviewed above make use of linear mathematical choice models based on binary logic. While few would contest the importance of such a mathematical approach, the highly influential development of fuzzy logic by the Iranian Lofti Zadeh has also greatly added to our understanding of travel behavior (Zadeh, 1965, Zadeh, 2015). In particular, as the traffic applications of fuzzy set theory reviewed below illustrate, the approach is especially appropriate where the variables of interest are not necessarily dichotomous, or measured on an interval scale.

There are a few basic principles of fuzzy logic which were laid down by Lotfi Zadeh:

- Exact reasoning is viewed as a limiting case of approximate reasoning
- Everything is a matter of degree
- Knowledge is interpreted as a collection of elastic, fuzzy constraints on collection of variables
- Inference is viewed as a process of propagation of elastic constraints
- Any logical system can be "fuzzified"

The theoretical basis of the fuzzy logic is the concept of a fuzzy set. A fuzzy set defines the extent to which members belong to the set using values ranging between zero to one. Such sets are provide, as Zadeh (1965, p 399) puts it "a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria of class membership rather than the presence of random variables". This radical view contrasted with classical set theory

in which a "classical" or "crisp set" (Halmos, 2017), where membership values are either zero or one.
One of the first studies to implement this approach compared efficacy of a vehicle-actuated intersection traffic control system and a "fuzzy logic controller", based on a qualitative description of the system and a protocol of control instructions as might be used by a human operator. The average delays of the vehicles which would result from the implementation of the fuzzy logic controller shorter than those obtained from the simulated vehicle-actuated controller (Pappis and Mamdani, 1977). This approach was extended to studying traffic flow along the Osaka-Sakai the route of the Hanshin highway in Japan, showing that a fuzzy logic traffic controller system could adequately take the place of human operators and with a lower error coefficient (Sasaki and Akiyama, 1988). Applications studying route or travel mode choice are more directly relevant to the present study. These have demonstrated that the route choice of a driver is not dependent on the actual physical travel time, but on a subjective "fuzzy" categorization (Teodorovic and Kikuchi, 1990), and that where the uncertainty of the "fuzzy" estimate of travel by a driver time is higher the wider range of routes are chosen (Teodorovic and Kikuchi, 1991). In the latter study, travel time, cost and distance were all treated as "fuzzy" variables. Teodorovic extended the "fuzzy logic" approach to travel mode choice (Teodorovic and Kalic, 1996). A fuzzy rule base, created using the differences between the travel time and travel cost of the competitive modes, with fuzzy rules based on existing numerical information, and using the Wang-Mendel method for classification, proved remarkably effective. The same authors have also applied fuzzy logic modeling to trip generation, using artificial neural networks and multiple regression (Kalic and Teodorovic, 1997), and also to trip distribution (Kalić and Teodorović, 2003), both with again with very positive results compared with more classical approaches to these topics.
More recently, the fuzzy approach has been extended to address still more challenging and uncertain challenges. Examples include applications which seek to (a) anticipate system conflicts that may result from increases vehicle automation and changes in future travel, using "fuzzy cognitive maps" (FCM) (Vogt et al., 2015); (b) incorporate sustainability assessments through optimizing mode selection among conventional, hybrid, and alternative fuel vehicles and buses), using multicriteria decision making (MCDM). Importantly, this approach was validated by traffic composition data by vehicle technology from a 33.2-km (20.6-mi) network in urban Honolulu (Mitropoulos and Prevedouros, 2016), who showed that a fuzzy logic method yielded more stable data than a weighted sum method. A final example among many that could be offered is the work on prioritizing emergency vehicle progress without

compromising vehicle flow (Kaur et al., 2020). In conventional traffic control systems, a fixed time is allowed for green, red, and yellow signals regardless of the traffic density, and without consideration of the presence of emergency vehicles. By using a new fuzzy-based approach which gives preference to high priority vehicles, (Kaur et al., 2020) showed that the waiting time of the priority vehicles were reduced and overall traffic flow rate.

Despite the range of transport studies which have used the fuzzy logic approach, we believe the study below is the first to use this methodology to estimate the effectiveness of combinations of TDM policies. We believe that the fuzzy logic approach, with its increased capacity to use both quantitative and qualitative data in combination makes this, in principle, a more appropriate methodology than those based on classic choice models.
We do in the context of a large ancient city, with many tourist attractions, as well as a thriving Central Business District.

2. METHOD

2.1. Data Collection

Four hundred interviews were completed with respondents in Isfahan city's Central Business District (CBD), during typical traffic days, over a period of three weeks in May 2015. This sample size was selected on the basis of exceeding the minimum recommended by Cochran (Cochran, 1963), for a population of Isfahan's size, with a possible 5% error rate. An intercept survey approach was adopted and three transportation experts, interviewed the respondents face to face at all zones of Isfahan CBD. Each interview lasted 10-15 minutes, and all participants responded to questions about themselves (sex, education, socio-economic status, etc.), reasons for travelling to the CBD that day, general travel patterns and typical mode of travel (see Table 1). The population of interest of the study was the users of all travel modes, who travelled inside the Isfahan CBD, however, the sample was balanced to reflect current mode-use as available from Municipality data. For example, the data showed that inside the Isfahan CBD, private car use share is 39%, then we allocate 39% of the questionnaires to them, sampling also reflected sex differences in local demographics. Data from private vehicle users and public transport users are important for us, therefore respondents identifying themselves as typically private vehicle users or public transport users were sampled to reflect patterns of use, and were then asked questions about TDM policies which might incentivize or disincentivize use of their typical mode of transport, as detailed in the next sections.

2.2. Socioeconomic and demographic status results

The characteristics of the study sample is presented below.

Table 1 Sample characteristics

Variables	Value	Share (%)
Gender	Male	65
	Female	35
Education	High school diploma or bellow	37
	Associate or Bachelor	53
	MSc or PhD	10
Driving license status	Licensed	79
	Unlicensed	21
Monthly income	No income	32
	Up to 5,000,000 IRR*	29
	5,000,000 – 10,000,000 IRR	22
	10,000,000 – 20,000,000 IRR	13
	Above 20,000,000 IRR	4
Age	18-24	36
	25-35	45
	36-45	8
	46-55	5
	More than 56	6
Usual mode of daily travel	Personal vehicle	39
	Motorcycle	8
	Bus	37
	Taxi	12
	Walk	3
	Bicycle	1
Purpose of travel	Work	42
	Education	13
	Medical	7
	Entertainment	8
	Shopping	24
	Administrative	6

* Rial is Iran's currency: For comparative purposes, at the time of the study, Iran's minimum wage was approximately 600k IRR per month, minimum hourly wage was around 25k IRR, a liter of Milk (25k IRR) and a 0.33l Coke/Pepsi 15k IRR).

2.3. Private vehicle users

Respondents who typically used private transport to travel were asked, using the stated preference method, their opinion of four deterrent policies (congestion pricing, parking fee increases, fuel price increases, parking restrictions) and six incentivizing policies (reduction in travel time difference between public and private transport, improved access to public transport, improved public transport comfort, quality, safety and reliability) which might change their tendency to use private transport. For policies which might reduce private vehicle use, respondents were asked to identify an amount of money within a specified range which would have a low, moderate or large deterrent effect, or, in the case of parking restriction, one of four levels of parking space availability. As it can be seen from Table 2, all the policy levels (options of the questionnaire) are descriptive and linguistic. This is because we can define them directly inside the fuzzy model as membership function and the answer of the respondents helps us to determine/specify the territory (range/span) of each membership function (see below for more detailed description) Table 2 summarizes both the range of the alternatives used, and the average preferences expressed.

Table 2 Private vehicle users' response to the policy questions

Policy group	Policy (and range)	Policy levels	Response	Current conditions
Deterrent	Cordon pricing (0 to 100,000 IRR)	Low	17,140 IRR	—
		Moderate	41,960 IRR	
		High	66,780 IRR	
	Parking fees increase (2,500 to 30,000 IRR)	Low	9,370 IRR	5,000 IRR per hour
		Moderate	17,210 IRR	
		High	25,050 IRR	
	Fuel price increase (10,000 to 30,000 IRR)	Low	12,930 IRR	10,000 IRR Per liter
		Moderate	18,290 IRR	
		High	25,650 IRR	
	Parking restriction	1-Parking space can be easily found	0%	—
		2-With a little search, space can be found	22%	
		3-Parking space can be hardly found	45%	
		4-No parking space can be found	33%	
Incentivizing	Decrease in delta travel	Low	12%	42.73%

Table 2 Private vehicle users' response to the policy questions

Policy group	Policy (and range)	Policy levels	Response	Current conditions
	time PT and PC	Moderate	24%	
		High	39%	
	PT accessibility improvement	Low	185 m	443 meters
		Moderate	433 m	
		High	681 m	
	PT comfort improvement	1-No possibility to sit	2%	Level 3.42
		2-Hardly find a place to sit	7%	
		3- Standing in difficulty	5%	
		4- Standing in comfort	39%	
		5-The possibility of sitting	24%	
		6- Always find a place to sit	23%	
	PT quality improvement	1-Severely worn-out	2%	Level 1.54
		2-Somewhat worn-out	14%	
		3-Brand-new fleet	61%	
		4-Fleet with more facilities	23%	
	PT safety improvement	1-Very low	0%	Level 3.14
		2-Low	1%	
		3-Moderate	12%	
		4-High	44%	
		5-Very high	43%	
	PT reliability improvement	1-Always late	1%	Level 2.56
		2-Usually late	2%	
		3-Sometimes late and sometimes on-time	8%	
		4-Usually on-time	43%	
		5-Always on-time	46%	

NB PT: Public Transport; PC: Private Car; Current conditions are based on the 50th centile of the cumulative distribution of all answers [i.e. for PT comfort improvement the median is between response levels 3 (Standing in difficulty) and 4 (Standing in comfort)]

The potential influence of the incentivizing policies is also summarized in Table 2. The first policy proposal sought to assess the effect reducing the travel time difference between public and private transport might have in increasing use of public transport. The possible travel time difference ranged from almost none, to 60% of the current difference. Participants were encouraged to think about the time it takes to make their most frequent journey during a week, they were then presented with response options, in minutes of the equivalent of reductions of 0, 10, 20, 30, 40, 50 and 60%. Improved accessibility to public transport was presented as shorter walking time/distance, ranging from 0 to 1000m/15 minutes. Table 2 specifies the response options for the remaining four incentives: improvements in comfort, quality, safety and reliability.

Finally, respondents were asked to compare the likely effectiveness of the deterrent and incentivizing policies by ranking each category of policies, with a rank of 1 allocated to the policy which would cause the greatest change, 2 to the next most influential, and so forth. Table

3 presents these data, together with a summary of which the alternative transport mode choice would be.

Table 3 Perceived influence of different TDM policies

Question	Options	Answers (%)
Which one is the most effective deterrent policy?	Fuel price increase	30
	Parking restriction	27
	Cordon pricing	26
	Parking fees increase	17
Which one is the most effective incentivizing policy?	Decrease in TT difference between PT and PC	21
	Public transportation comfort improvement	17.5
	Public transportation safety improvement	17
	Public transportation reliability improvement	15.5
	Public transportation quality improvement	15
	Public transportation accessibility improvement	14
Which policy group is more effective?	Deterrent	31
	Incentivizing	69
In case of not using the personal vehicle, which one is the alternative mode?	Bus	31
	Taxi	28
	Motorcycle	19
	Bicycle	12
	Walk	10

NB TT: Travel time; PT: Public Transport; PC: Private Car

2.4. Public Transport users

The questions asked those who described themselves as primarily users of public transport were almost identical, except that the emphasis, of course, with regard to primary mode of transport changed. This section was made use of the revealed preference method to quantify users' current experience of the six aspects of public transport we considered might incentivize their public transportation use. The data gathered from this section, help us to define the current condition of each input parameter inside the fuzzy model. The current condition which if not improved, the private vehicle use won't decrease. The answers can be seen at the last column of six incentivizing policies of Table 2.

3. MODELING AND ANALYSIS

Data from the survey described above were used as generation of the fuzzy models, using the Wang and Mendel method (Wang and Mendel, 1992).

3.1. Weight calculation

The judgments of private vehicle users (Table 3) were used to estimate the weighting of each policy. Calculating the Normalized Effectiveness (i.e. E Table 4), allows us to define the output range in of each fuzzy model. We do so by first ranking both deterrent and incentivizing policies in terms of effectiveness and then multiplying these "raw weights" (i.e. perceived effectiveness of a particular policy deterrent /incentivizing group, B, see Table 4) by the effectiveness of each individual policy within that group (A, see Table 4). For example, the raw weight for decrease in travel time difference between use of Private and Public transport (21%, see Table 3) is calculated by multiplying 21% by the overall popularity of Incentivizing policies (69%, see Table 3), i.e. 14.49%. The raw weight of all the policies is presented in Table 4. We then normalize each raw weight by finding the normalized coefficient (D) from Eq.1 for deterrent policies and Eq.2 for incentivizing policies.

(Eq. 1, Normalization for deterrent policies)

$$[(1-C_1).D]*[(1-C_2).D]*[(1-C_3).D]*[(1-C_4).D]=0.69$$

Key:

C: the raw weight of the policy

D: Normalizing coefficient (unknown)

[(1-0.093)×D] × [(1-0.0837)×D] × [(1-0.0806)×D] × [(1-0.0527)×D]=0.69

From solving the above equation, D_{det} is derived as 0.98851

(Eq. 2, Normalization for incentivizing policies)

$$[(1-C_5).D]*[(1-C_6).D]*...*[(1-C_{10}).D]=0.31$$

[(1-0.1449)×D] × [(1-0.1207)×D] × [(1-0.1173)×D] × [(1-0.1069)×D] × [(1-0.1035)×D] × [(1-0.0966)×D]=0.31

From solving the above equation, D_{inc} is derived as 0.92879

We then estimate the normalized effectiveness (E, see Table 4) of each policy using Equation 3. Thus, for example, the maximum policy efficiency of decreasing travel time difference between PT and PC policy, would reduce personal vehicle use from the current 100% to 79.41%.

(Eq. 3, Normalized effectiveness)

$$E_n=(1-C_n)*D_n$$

Table 4 The calculated weight and normalized effectiveness of the policies

Policy	The effectiveness of the policy (A)	The effectiveness of the policy group (B)	The raw weight of policy (A*B=C)	The normalized coefficient (D)	The normalized effectiveness (E)
1- Fuel price increase	0.30	0.31	0.093	0.98851	0.8966
2- Parking restriction	0.27		0.0837		0.9042
3- Congestion pricing	0.26		0.0806		0.9088
4- Parking fees increase	0.17		0.0527		0.9364
5- Decrease in TT difference	0.21	0.69	0.1449	0.92879	0.7941
6- PT comfort improvement	0.175		0.1207		0.8173
7- PT security improvement	0.17		0.1173		0.8201
8- PT reliability improvement	0.155		0.1069		0.8303
9- PT quality improvement	0.15		0.1035		0.8359
10- PT accessibility improvement	0.14		0.0966		0.8390

NB TT: Travel time; PT: Public Transport; PC: Private Car

3.2. Scenario definition

If the evidence from other cities worldwide were replicated, improvements in traffic conditions in the CBD of Isfahan would result from application of widely used TDM policies. The challenge is to identify which policies, or combinations of policies, would be likely to show the most improvement (i.e. in terms of reducing use of private transport), given the implications of each for the level of cost, disruption, time until the system is operative, and challenges of managing their implementation. Four possible implementation scenarios were modelled: (a) Introducing a Mass Rapid Transport System (subway, tramway, LRT …); (b) Improving the quality and quantity of public transport; (c) Restricting use of certain lanes to public transport; (d) Introducing TDM policies whose effects would strengthen each other. The criteria for choosing these scenarios were derived from studying other cities' experience and consulting with local transportation experts to make a judgement of the implementation feasibility of each policy in Isfahan city, taking account, where possible, of all a wide range of resource implications (i.e. budget and time). The first of these obviously involved very substantial costs and a long period of time and disruption before the policy can be implemented, the second scenario would require less of each. The third and fourth scenarios would be the least costly and most rapidly introduced. Ten models were generated for our scenarios, for the first three, the effect of each TDM alone was quantified, then with each of two deterrent policies (parking restriction, congestion charging). In each case, as shown in Table 5, the current state, worst and best predicted outcomes were quantified. Inputs of the models are the parameters which are expected to change after scenario implementation. The current state values reflect the stated views of public transport users as summarized in Table 2. It was assumed if these values were sustained that would be no reduction in private car use (i.e. reduction percentage would be 0). The "worst case" condition values are the lowest values that experts predicted would result from at best poor implementation of that scenario. The "best case" condition values are derived from expert predictions of what would result from optimal implementation of that scenario. By changing the worst and best case values used as input parameters, the fuzzy model will identify the outcome chance expected (i.e. reduction in private car use).

Table 5
Scenarios, inputs and outputs of the models

Scenario	Model	Condition	Input parameters							Predicted reduction in PC use (%)
			TTD(1) (%)	C(2) (level)	R(3) (level)	Q(4) (level)	PR(5) (level)	CP(6) (IRR)	PF(7) (IRR)	
Mass Rapid Transit System implementation	*1- Mass Rapid Transit System*	*Present*	*42.73*	-	*2.56*	*1.54*	-	-	-	*0*
		Worst	*30*	-	*3*	*2*	-	-	-	*21*
		Best	*0*	-	*5*	*4*	-	-	-	*45*
	2- Mass Rapid Transit System + restricted parking	*Present*	*42.73*	-	*2.56*	*1.54*	-	-	-	*0*
		Worst	*30*	-	*3*	*2*	*3*	-	-	*23*
		Best	*0*	-	*5*	*4*	*4*	-	-	*50*
	3- Mass Rapid Transit System + congestion	*Present*	*42.73*	-	*2.56*	*1.54*	-	-	-	*0*
		Worst	*30*	-	*3*	*2*	-	*50,000*	-	*22*

	pricing	*Best*	*0*	*-*	*5*	*4*	*-*	*100,000*	*-*	*50*
Quality and quantity improvement in public transportation system	*4- PT Quality and quantity improvement*	*Present*	*42.73*	*3.42*	*2.56*	*1.54*	*-*	*-*	*-*	*0*
		Worst	*35*	*4*	*3*	*2*	*-*	*-*	*-*	*21*
		Best	*25*	*6*	*4*	*3*	*-*	*-*	*-*	*33*
	5- PT Quality and quantity improvement+ restricted parking	*Present*	*42.73*	*3.42*	*2.56*	*1.54*	*-*	*-*	*-*	*0*
		Worst	*35*	*4*	*3*	*2*	*3*	*-*	*-*	*32*
		Best	*25*	*6*	*4*	*3*	*4*	*-*	*-*	*42*
	6- PT Quality and quantity improvement+ congestion pricing	*Present*	*42.73*	*3.42*	*2.56*	*1.54*	*-*	*-*	*-*	*0*
		Worst	*35*	*4*	*3*	*2*	*-*	*50,000*	*-*	*26*
		Best	*25*	*6*	*4*	*3*	*-*	*100,000*	*-*	*42*
Exclusive use of lanes by public transportation	*7- PT designated lanes*	*Present*	*42.73*	*-*	*2.56*	*-*	*-*	*-*	*-*	*0*
		Worst	*30*	*-*	*3*	*-*	*-*	*-*	*-*	*8*
		Best	*10*	*-*	*5*	*-*	*-*	*-*	*-*	*29*
	8- PT designated lanes+ restricted parking	*Present*	*42.73*	*-*	*2.56*	*-*	*-*	*-*	*-*	*0*
		Worst	*30*	*-*	*3*	*-*	*3*	*-*	*-*	*20*
		Best	*10*	*-*	*5*	*-*	*4*	*-*	*-*	*37*
	9- PT designated lanes+ congestion pricing	*Present*	*42.73*	*-*	*2.56*	*-*	*-*	*-*	*-*	*0*
		Worst	*30*	*-*	*3*	*-*	*-*	*50,000*	*-*	*17*
		Best	*10*	*-*	*5*	*-*	*-*	*100,000*	*-*	*40*
Parking restriction +Parking fee increase	*10- Parking restriction +Parking fee increase*	*Present*	*-*	*-*	*-*	*-*	*-*	*-*	*5,000*	*0*
		Worst	-	-	-	-	3	-	5,000	6
		Best	-	-	-	-	4	-	30,000	16

(1) Travel time difference between PC and PT; (2) Comfort; (3) Reliability; (4) Quality; (5) Parking restriction; (6) Congestion pricing; (7) Parking fee

3.3. Modeling

Implementing the fuzzy logic technique in a real application requires completing three steps (Bai and Wang, 2006):

1- Fuzzification - convert classical data or crisp data into fuzzy data or Membership Functions (MFs)
2- Fuzzy Inference Process – combine membership functions with the control rules to derive the fuzzy output
3- Defuzzification – use different methods to calculate each associated output.

3.3.1. Fuzzification and Membership Functions

Fuzzification is the first step to apply a fuzzy inference system, allowing one to convert crisp variables (both input and output) to fuzzy variables, and then applying fuzzy inference to process those data to obtain a useful output. In most cases, fuzzy outputs need to be converted back to crisp variables to so that a more precise indication of efficacy is provided. Generally, fuzzification requires deriving membership functions for input and output variables and representing these with linguistic variables. This process is equivalent to converting or mapping a classical set to a fuzzy set

In practice, membership functions can have multiple different types, such as triangular waveform, trapezoidal waveform, Gaussian waveform, etc. The exact type depends on the actual applications (Bai and Wang, 2006). Membership functions are usually scaled between zero to unity, and they overlap. This overlapping is one of the most useful properties of this approach since it allows an input to be distributed across a number of rules, giving rise to an interpolation effect. The choice of these membership functions as well as the optimization of their parameters is a matter of design (Morabito and Versaci, 2001).

We will use the difference in travel time between PC (private car) and PT (public transport) to illustrate the process of fuzzification Let us assume that the reduction in car use inside the CBD of a city only affects by the travel time difference percentage between PT and PC. If the travel time difference is High, the reduction in car use is Low. If the travel time difference is Medium, the reduction in car use is Medium, and if the travel time difference is Low, the reduction in car use is High. According to the PC users answers (see Table 2):

Low travel time difference:	Around 12%
Medium travel time difference:	Around 24%
High travel time difference:	Around 39%

These levels must now be converted to linguistic variables: LOW, Medium and High, and defining the range of each one according to PC users' responses in the survey.

The membership functions of Travel Time Difference input are shown in Figure 1.We have added two additional membership functions (Very Low (VL) and Very High (VH)) in order to enhance the utility of the results. By defining response options as a Membership Value, rather than a specific (i.e. 'crisp') number, the 'fuzzification' process can allow to individuals with quite different experience and beliefs to use terms ('fast' or 'safe') without their natural understanding of these terms to be over-ridden by some specific numerical value. As mentioned above, the range of each membership function is derived from the information provided by the participants themselves (see Table). Next we define fuzzy rules.

3.3.2. Fuzzy control rules

Fuzzy control rules can be thought of as the knowledge of an expert in any related field of application. The fuzzy rule is represented by conditional IF-THEN rules, leading to algorithms describing what action or output should be taken given a particular circumstance.

A fuzzy IF-THEN rule associates a condition, described using linguistic variables, and fuzzy sets to an output or a conclusion. The "IF" is mainly used to capture knowledge by using elastic conditions, and the "THEN" is used to give a conclusion or output in linguistic variable form. IF-THEN rule is widely used by the fuzzy inference system to compute the degree to which the input data matches the condition of a rule (Bai and Wang, 2006).
In this study, fuzzy rule base was generated using expert knowledge, as this applied to reducing private car use (i.e. the output). For example, from Tables 2 and 5, we see that the survey had five options for Travel Time Difference (three which asked from the interviewees and 2 added levels (VL and VH) for better rule generation), four for Public Transport Quality, and five for Public Transport Reliability, i.e. 100 (5×4×5) possible fuzzy rules. For model 1 (Mass Rapid Transit System), only 49 of these response combinations were used, and these when combined with the normalized effectiveness (see Table 4), generate rules of the following type:

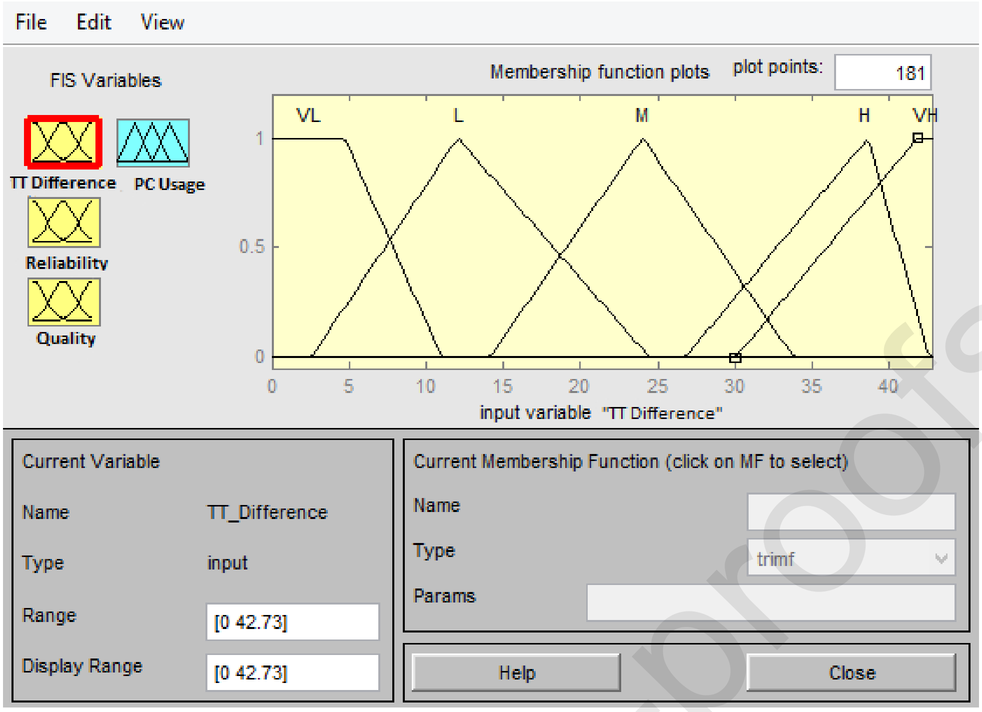
1- IF the travel time difference between PT and PC is low (about 12%), and the reliability in public transportation is high (always on-time), THEN the personal vehicle use will be low.
2- IF the travel time difference between PT and PC is high (about 39%), and the quality of public transportation is high (brand-new fleet), THEN the personal vehicle use will be high.
3- IF the reliability in public transportation is very low (always late), and the quality of public transportation is low (severely worn-out), THEN the personal vehicle use will be high.

3.3.3. Defuzzification

The conclusion or control output derived from the combination of input, output membership functions and fuzzy rules is still a vague or fuzzy element. To make that conclusion or fuzzy output available to real applications, a defuzzification process is needed which will convert the fuzzy output (which is a linguistic variable) back to a crisp or classical output (i.e. numerical). Three defuzzification techniques are commonly used, which are: Mean of Maximum method, Center of Gravity method and the Height method (Bai and Wang, 2006).

3.3.4. Model definition

The modeling reported here uses the fuzzy logic approach as implemented in the MATLAB toolbox. Models were generated using the Mamdani inference system (Mamdani and Assilian, 1975, Mamdani, 1977), triangular membership function and center of gravity defuzzification method.



N.B. Qualitative levels of Travel Time Difference: VL: Very Low, L: Low, M: Medium, H: High, VH: Very High

Figure 1- Defined membership functions for the travel time difference input parameter in the Mass Rapid Transit System implementation model.

After definition of inputs, generation of the rules and calibration of the membership functions, the output of each model can be visualized within MATLAB's fuzzy logic toolbox. This allows the researcher, by changing the levels and amounts (dragging the RED vertical line, see Figure 2) of each model's input (see Figure 2, where separate inputs for Travel Time Difference, PT Reliability and PT Quality are represented in YELLOW), to observe the impact of that change on the output (shown in BLUE). For example, Figure 2 shows the current situation, without improving the input parameters of Mass Rapid Transport System (i.e. model 1), and the best possible outcome given optimization of the differently valued benefits of implementing a Mass Rapid Transport System.

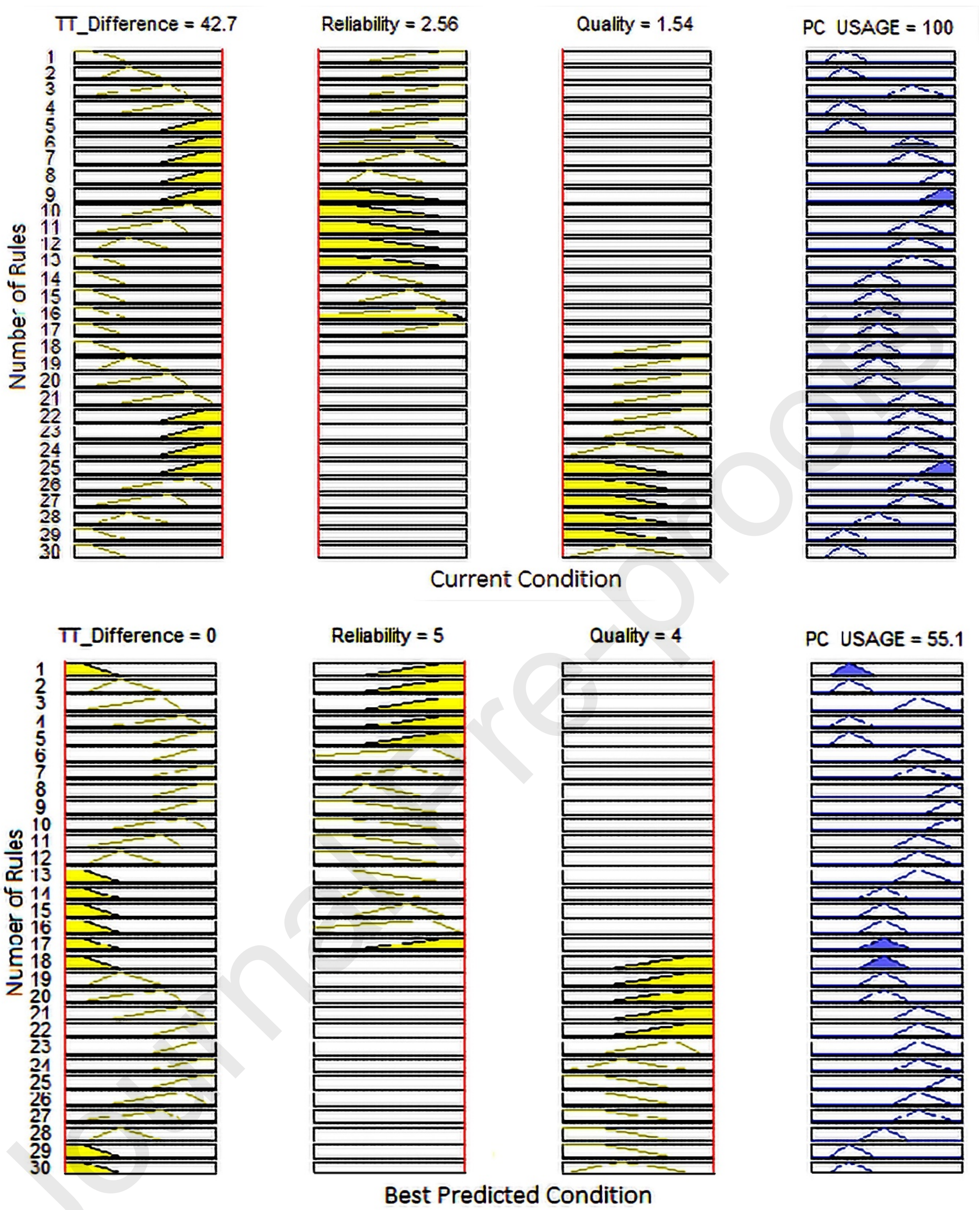


Figure 2- Rules viewer of the Mass Rapid Transit System implementation model

Thus, as Figure 2 shows, the current level of Private Car use, as well as current perceptions of the Isfahan public transport system in terms of Travel Time Difference, Reliability and Quality (as obtained from the opinions of the public transportation users). When Quality is perceived to be at the 1.54 level, Reliability at the 2.56 level and Travel Time Difference around 42.7% longer than private transport, 100% of the current users will still use their personal vehicle.

But, if these three inputs are optimized, personal vehicle use would be predicted to reduce to about 55%. This is calculated by multiplying normalized effectiveness values of inputs (see Table 4) together, and shows the maximum reduction percentage in car use for each model (specify the output range of the fuzzy model). For example, in this case, 55% is derived as follow:

0.7941 (TTD) × 0.8303 (Reliability) × 0.8359 (Quality) ≈ 0.55 = 55%

That is, there will be a 45% (100-55) reduction in car use. Is to be expected. All the values for best predicted condition are calculated as above and are presented in last column of Table 5. The output range of each model is the value from the best predicted condition percentage of car use to the current condition of it.

Surface View is another MATLAB tool for output presentation, and in Figure 3, the effect of inputs on the output are visualized differently. In each cube we can see how Private Vehicle use changes as travelers' opinions of the Public Transport system's Quality, Reliability or Travel Time difference improves.

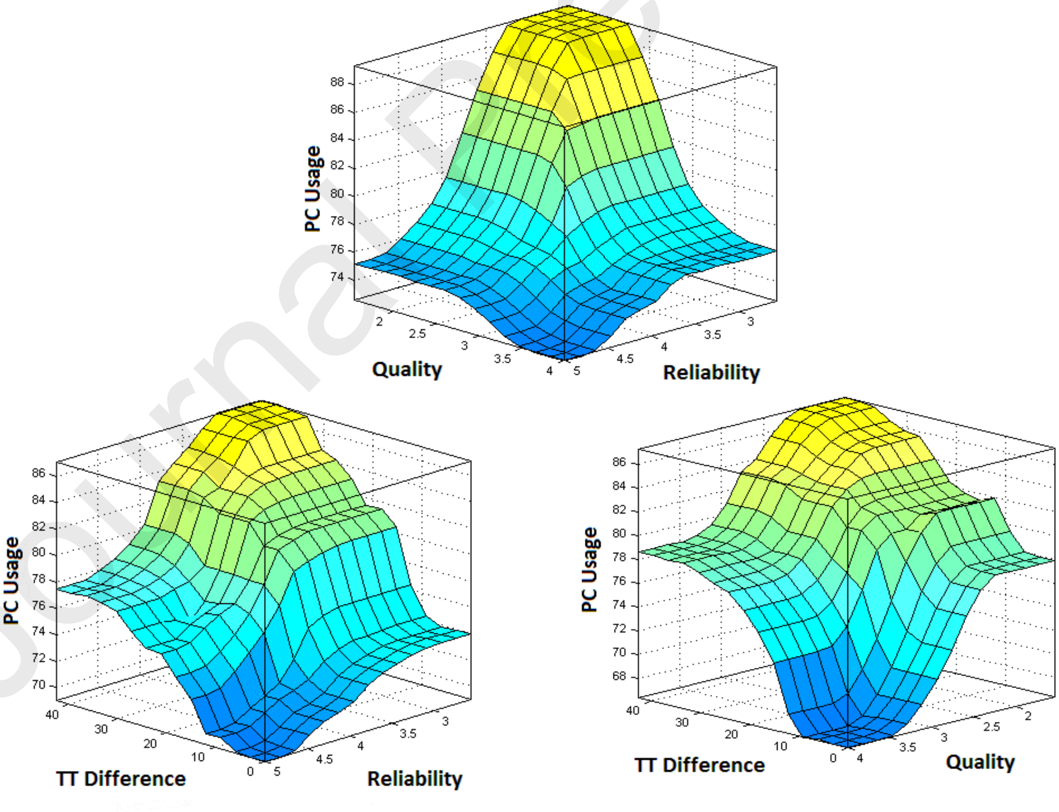


Figure 3- Surface view of the mass rapid transit system implementation model

In the Surface View, the effect of inputs on the output is visualized differently. As it's shown in Figure 3, the levels which from the personal vehicle users' opinion, have the highest impact on their mode change, has resulted in significant decrease in personal vehicle use. For example, as it can be seen from Table 2, for Travel Time Difference around 24%, for Quality around level 3, and for Reliability around level 4 are the important values for PC users which can switch the decision. As can be seen in Figure 3, reaching around to these levels is resulted in significant change in the slope of the graphs. This approves that the fuzzy rules and membership functions of the model are defined correctly.

Table 5 summaries the inputs and outcomes for all of the ten different models investigated here.

4. RESULTS & DISCUSSION

The results of the survey will be considered before the outcome of the modeling carried out using those data. Where monetary values are referred to we have attempted to render these in the local currency, and the purchasing power of the amounts concerned, as well as USD- inevitably these figures are affected by inflation and local circumstances.

Residents' perceptions of transport in Isfahan city

There is currently no congestion pricing in Isfahan city. The survey findings indicate that charging around 65k IRR (about 6 liters of fuel, $1.5) per entrance to the city would greatly reduce personal vehicle use for such trips. Parking fees are currently 5k IRR per hour (0.5l fuel; 12c), but the survey indicates that a charge of twice that would only have a small deterrent effect, and it would need to be equivalent to the cost of 2.5l of fuel to be have a reasonable deterrent effect. Interestingly, although the current price of fuel is 10k IRR per liter, respondents actually over estimated its actual cost, by about 30%. This raises an important question, which the current research cannot address- is it the current actual cost, or perceived current cost, or indeed the value of that money to the individual which determines reported mode choice intentions? Moreover, do changes in the likely effect, scale similarly as amounts are increased or decreased? We suspect that assumed rather than actual costs shape behavior (Groeger, 2000), and, following gambling research, small gains and large losses are not equally attractive outcomes (Wagenaar, 1988).

When the survey was carried out, there was no systematic parking restriction in the CBD of the city. Despite this, perhaps because of this, Table 2 shows that over 75% of those surveyed stated that they would not use their car to travel to the CBD if they could not find parking spaces. According to the public transportation users' opinions, the average travel time difference (TTD) between public transportation and when using a personal vehicle is about 43%. This is longer than the TTD that current car users would consider High (i.e. 39%), revealing that there is currently a very weak incentive to change. TTD is potentially the powerful incentive for changing mode, but the difference would need to narrow to a TTD of 24% or lower, to be effective. The distance respondents would have to travel to access public transport is about 450m, which is only slightly higher than the distance with is seen as acceptable (433m). Given small discrepancy, which, statistically would not apply to the majority of users, it is unsurprising that for Isfahan residents, changes in the travel distance to access public transport is the least influential TDM policy.

Various characteristics of public transport as it was perceived in the survey, makes it unattractive to use. The majority of respondents report having to stand on public transport (see Table 2), for the vast majority (86%) of private car users to change to public transport, the likelihood of getting a sat would have to change substantially. So too would the perceived quality of public transport, which currently perceived as 'worn out'; a brand new fleet would be required to motivate most private transport users to change. Punctuality improvements would influence mode choice, but as most users consider that services are typically late, again substantial improvement would be required. Finally, public transport is generally considered to be only moderately safe, it would have to be perceived as considerably safer for the majority of potential users to adopt that mode.

Fuzzy modelling of user perceptions and expert knowledge

Taken together these views of actual current public transport users identify a range of different perceptions of the transport system in Isfahan, and what might be needed to change patterns of use from private to public transport. As we presented in section 3.3.4, the fuzzy logic modelling of these responses allow us to predict how effective these might be when used in combination with each other.

Table 5 shows that the first model, which is mass rapid transit system implementation scenario would, at worst, yield a 21% reduction private vehicle use, and at best a reduction of 45%. To achieve the smaller of these travel time difference would need to reduce by 13%, the reliability of public transport would need to move being 'sometimes late and sometimes on-time', and a new fleet would be required. To achieve the greatest reduction, in addition to a brand new fleet, punctuality would have to be perfect and travel time would have to be perceived to be the same as private transport. Implementing these changes in conjunction with introducing parking restrictions would only achieve further reductions of 2-5%. Implementing a new mass rapid transit system, in conjunction with congestion charging (ranging from the equivalent of the cost of 5 to 10 liters of fuel), would only reduce private vehicle use by 1-5%.

Improving the quality and quantity of public transport (See Table 5, model 4), would achieve an estimated 21 to 33% reduction in personal vehicle use. The changes required to reduce private car use by 21% would need crowding to be reduced such that most users could at least stand in comfort, reduce the TTD from the current 43% to 35%, punctuality to the point where it was only occasionally late, and the state of vehicles to being 'somewhat worn out'. To achieve the greatest reduction possible (35%), TTD would have to be 25%, seats would always be available, transport would always need to be on time, and the vehicle condition would have to be equivalent to a brand new fleet. Improvements in the quality and quantity of public transport, together with parking restriction or congestion pricing, would result in a further estimate reduction in private car use of 9-11% and 5-9% respectively.

Introducing the TDM policy of excluding use of particular lanes for public transport (See Table 5, model 7) would result in reductions in personal vehicle use of between 8% (13% travel time difference reduction, occasionally late) and 29% (33% travel time difference reduction, always on time). Making these changes, in conjunction with introducing either parking restrictions or congestion charges, would leads to further estimates decreases of 8-12% or 9-11%.

Finally, introducing only parking restriction and congestion charging in combination with each other (See Table 5, model 10) would be expected lead to reductions of 6 to 16% in personal vehicle use depending on the severity of the measures adopted.

In summary, the perceived costs and benefits to private vehicle users can be quantified, and the potential of changes in these costs and benefits can be modeled in order to estimate the extent of changes in mode choice that might result. The financial cost, disruption and time scale of these changes is beyond the scope of this paper, but these and their state/public acceptability could be used to guide public policy. For Isfahan city, given its particular cultural and economic context, private car use is likely to be reduced using by improving public transport comfort and punctuality, ensuring that some lanes are only used by public transport, together with increasing the cost of using private transport to travel to the city, would seem to most effective and feasible alternatives.

5. CONCLUSIONS

This paper had three aims: to illustrate the usefulness of a fuzzy approach to modelling Travel Demand Management policies (TDM), to demonstrate and make available the methods for doing so, and to offer practical solutions to the problems poses by private car use in the Central Business District (CBD) of Isfahan city. We believe that we have demonstrated that fuzzy logic modelling offers substantial advantages over more simple ways of assessing public opinion, illustrated this in one specific environment, as well as providing a working implementation to guide those who might seek to follow this approach. The implementation developed here, using MATLAB, offers an accessible way of exploring this potential still further, and translating these benefits to other cities. For Isfahan, we believe we have identified a range of options for how various travel demand management policies might be introduced, and how effective they might be. The proposed method in this study, can help other similar cities with traffic problem to find the solutions based on the characteristics of their own city and those who live in and visit it. We believe that fuzzy logic, by reducing the scope for mis- or over interpretation of survey respondents' views by considering linguistic inputs, using membership functions instead of crisp values, and combining descriptive and numerical values together provides a powerful framework for amalgamating user experience and expert knowledge, in order to provide a basis for predicting future outcomes. Therefore, we believe that the presented method can offer more reliable outcome in case of human based studies (as it did in previous studies in other fields). We believe that four presented scenarios could be considered according to the available budget and time, however implementation of the "Mass Rapid Transit System" scenario, due to its effectiveness (21% – 50% reduction in car use) is suggested for solving the traffic problem in Isfahan CBD. Ultimately, empirical evaluation of these predictions should refine, and determine the utility of the case study reported above.

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Highlights:

- We illustrated the usefulness of a fuzzy approach to modelling Travel Demand Management (TDM) policies
- We demonstrated and made available the methods for predicting the effectiveness of TDM scenarios
- We offered practical solutions to the problems poses by private car use in the Central Business District (CBD) of Isfahan as a touristic city
- We proposed a mechanism for decision makers, to see the effectiveness rate of each TDM scenario before implementation
- We analyzed the reaction of private car users, facing with 10 deterrent and incentivizing policies.