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Research paper



Effect of traffic congestion on infrastructure capacity: modeling commuters' behavior towards "stick & carrot" strategies to better manage infrastructure network: the case study of Cairo

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Abstract

In Cairo, alike many mega cities, suffers from the consequences of urban sprawl and traffic congestions. Recent studies report the cost of congestion in the Greater Cairo Area amounting to 4% of the nation's GDP. Traditionally governments have addressed congestion by boosting infrastructure capacity to meet increased demand. Although in some cases this expansion is inevitable, it has proven unsustainable on the long run. An alternative approach is to manage and control the demand given the existing infrastructure using different strategies. One such strategy aims to influence the behavior of transportation users to manage the demand. This study investigates two distinct - but related - approaches to influence traveler behavior. The "stick & carrot" technique applies both congestion pricing and peak-avoidance rewards to travelers. This paper models the change of commuters' behavior by measuring and comparing their willingness to pay (WTP) and attitude to earn (ATE) during peak hour travel. A mixed stated preference/revealed preference survey is developed and distributed online to investigate the effect of congestion on commuters' daily travel behavior. The collected responses are analyzed and modeled using a binary logit model for commuters' behavioral change for both their WTP and ATE potentials. Results indicate that there is a massive congestion problem in Cairo that people really suffer from, and it affects their daily life decisions, also, they seem not to prefer congestion pricing technique, while they prefer to be rewarded instead. Furthermore, a comprehensive development of Cairo's public transport network should be implemented. The obtained models from collected data emphasizes the previous hypothesis.

Keywords: *Cairo; Capacity Management; Congestion Pricing; Infrastructure Network; Modeling; Peak-Avoidance Rewards; Traffic Congestion.*

1. Introduction

The role of transportation systems in the prosperity and development of cities is undeniable. Equally undeniable are the losses to the global economy due to traffic congestion in major cities. In the US, the cost of congestion was estimated at $ 87 Billion or $1,348 per driver in 2018 [31]. Supply-side strategies that aim to increase the supply of road networks to meet increased demand for transportation have been proven to be problematic. Large investments required for road network expansion, excessive durations needed to complete large transportation capital projects, and the negative impacts these projects eventually have on the fabric of cities are among some of these concerns. Transportation Demand Management (TDM) strategies aim to reduce demand for travel to redistribute this demand both spatially and temporally across the city. TDM strategies involve a large "arsenal" of possible interventions aiming to change the way travelers use the transportation network. Among these interventions are the adoption of policies that aim to incentivize or disincentivize travelers to 1) use certain modes of travel, 2) use certain travel corridors and 3) travel during a particular time of the day.

Previous studies have mostly focused on investigating the feasibility of road pricing as a technique to mitigate congestion in several cities around the world depending on multiple techniques and approaches. A few studies concentrated on peak-avoidance rewards for such purpose. This study focuses on "stick & carrot" technique which applies both congestion pricing and peak-avoidance rewards to travelers, and models the change of commuters' behavior by measuring and comparing their WTP and ATE during peak hour travel using a mixed stated preference/revealed preference survey which developed to investigate the effect of congestion on Cairo commuters' daily travel behavior, and the collected responses were analyzed and modeled using a binary logit model for commuters' behavioral change. The previous lines guide to the main objective of this study, which is to better manage the infrastructure network, and incorporating road users on congestion alleviation process.

2. Review of literature

2.1. Traffic flow fundamentals and congestion

Traffic flow in mathematics and civil engineering is formally defined as "the study of interactions between travelers (including

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pedestrians, cyclists, drivers, and their vehicles) and infrastructure (including highways, signage, and traffic control devices), with the aim of understanding and developing an optimal transport network with efficient movement of traffic and minimal traffic congestion problems". It therefore helps transportation engineers understand the properties of traffic flow, and make informed decisions when assessing the capacity of existing highways, designing new roadways, or enhancing the performance of existing facilities.
More than two decades ago Lieu et al. (1999) claimed that traffic behaves in a complex and nonlinear way depending on a multitude of dynamic interactions between vehicles, infrastructure, and humans. These interactions result in conditions that are following the laws of mechanics largely due to the human behavior and heterogeneity of users and stochasticity of system conditions [1].
Knoop & Daamen (2017) indicated that in a free-flowing network, traffic flow theory refers to the traffic stream variables of speed, flow, and density; these relations are mainly concerned with characterizing. traffic flow conditions across a wide range of states: free-flow conditions (system is in steady state conditions with minimal queues and congestion), and congestion flow conditions (system reaches critical state beyond its maximum capacity resulting in breakdowns, queues, congestion). It is pivotal to understand the relation between the former three variables (speed, flow, and density) in modelling the behavior of congestion and its impacts, especially in dynamic and large urban areas.
Abdulhai (2013) indicated that Congestion is simple to explain, but extremely complex to solve; especially in large and more populous cities where congestion spreads more over space and over time. Causes of congestion are simply either more demand and/or less capacity (due to accidents or construction), resulting in more spread of congestion over wider space and longer time; and thereof lower overall service quality. Such spread of congestion negatively impacts our quality of life, economy, and the environment. [21]
The mitigation measures to congestions are logically either adding capacity (such like new lanes or roads), or managing / reducing the demand.
Capacity Expansion: Capacity expansion is infrastructure-intensive and costly, both in the financial and environmental senses. It is clear that cities can never build enough roads to completely eliminate congestion at all times and everywhere, therefore this options alone is often seen as an unsustainable alternative.
Demand Reduction (Management): Reducing demand is an alternative approach to manage congestion but it is harder to achieve because it is prohibitive —it involves telling people what not to do, especially that travelers hardly volunteer to reduce travel activities for the determinant of all (i.e. helping the system operate better). Additionally, disincentives such as congestion pricing or peak-avoidance rewards are often opposed and not well contextually studied in each environment as an alternative way to manage congestion. The rationale behind congestion pricing is that drivers should fully pay the cost of what they consume – similar to any other service: road travel. Although this seems controversial, it follows the basic principles of economics. For example, when drivers appear on the freeway, they contribute to slowing down everyone else a tiny tad, but this tiny tad affects thousands of others. This "marginal" delay is the social subsidy for our travel. Paying for this external cost of congestion rationalizes demand, reduces congestion, and maximizes social welfare [21].

2.2. Microeconomic within perspective of traffic engineering

Microeconomics is about studying the relation between demand and supply; the change in the quantity purchased to the price is denoted by "demand", which is represented by a downward slopping curve (Figure 1), indicating that demand increases as the price falls since more consumers can afford (more of) the good.

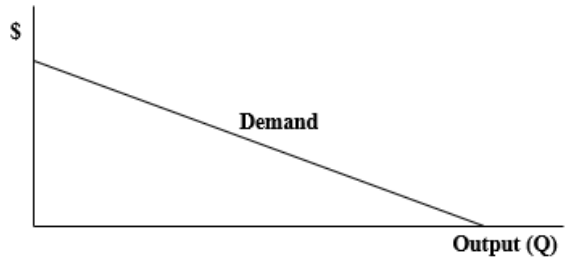


Fig. 1: Representation of Demand.

Another important terms should be denoted too, cost, benefit ad revenue. The average and marginal costs could be denoted by the following (Represented in figure 2):

Average Cost (AC) = Total Cost (TC)/Total Production (Q)

Marginal Cost (MC): the change in total cost required to increase output by one unit = ΔTC/ ΔQ → d (TC)/d (Q)

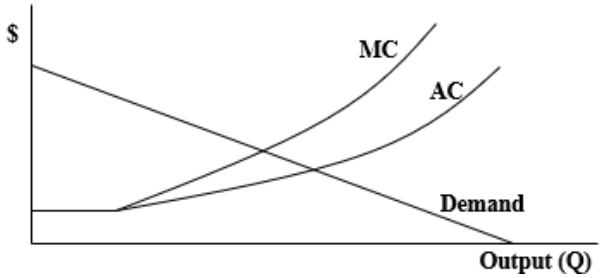


Fig. 2: Average and Marginal Costs Representation.

Also, revenue could be represented by (Figure 3):

Total Revenue (TR) = Price (p) * Total Production (Q)

Marginal Revenue (MR) = ΔTR/ ΔQ → d(TR)/d(Q)

Profit = TR – TC (maximized when MR = MC)

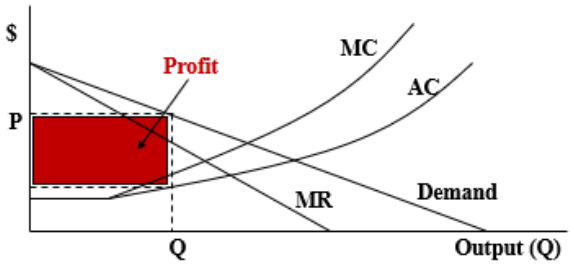


Fig. 3: Profit Representation.

In the field of transportation, the average cost (AC) = Monetary Expenses + VOT * Travel Time. The average cost increases with the level of road use. This implies that the MC exceeds the AC. This is because the MC includes both the cost incurred by the traveler himself (AC) and the additional cost (s)he imposes on all other travelers. This additional cost is known as the marginal external congestion cost (mecc) (Figure 4).

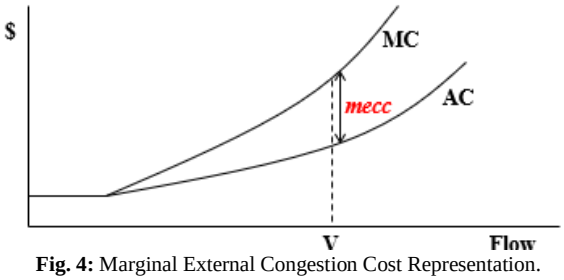


Fig. 4: Marginal External Congestion Cost Representation.

The relation obtained between MC and AC indicates that the extra cost added when a new vehicle enters the highway is composed of two parts: the variable private cost incurred by the new vehicle itself in addition to an extra cost (due to the increase in travel time caused by the new vehicle) incurred by the existing vehicles on the highway.

As flow increases, the gap between MC and AC (i.e., the externality cost) increases. Because:

1) The no. of existing vehicles (that are badly affected by entrance of new vehicle) is high.
2) The difference in travel time increases (since AC curve is highly deteriorating as flow increases).

It is worth noting that economists and traffic engineers have different technical perspectives on congestion, which can have policy implications and create confusion. From an economic perspective, a system (e.g. road or transit lines) is congested if the performance of the system (e.g. travel time) starts to deteriorate with the intensity of use (e.g. traffic volume). From a traffic engineering perspective, a road is considered congested when the traffic stream becomes unstable slipping into stop and go condition. More formally, when traffic density (vehicles per kilometer) exceeds the critical density (i.e. the density corresponding to capacity, Figure 5) resulting in traffic instability and breakdown.

What congestion means for traffic engineers is termed "hyper-congestion" for economists. Moreover, hyper-congestion causes a significant drop in capacity. This is notable at the critical density in Figure (5). Let's consider, for example, a single freeway lane. When traffic density is very low (a few cars per kilometer), flow is also low in terms of vehicles served per hour and speeds are very high, say, 110~120 km/hr. These are known as free flow conditions. As density increases, flow increases, and speed remains relatively high but gradually drops (travel time increases), until capacity (maximum flow) is reached. Further demand increases density beyond the tipping point, after which speeds rapidly drop and flow also drops. Capacity of a freeway lane is typically around 2,200-2,400 vehicles per hour. Corresponding speeds are roughly in the 80-90 km/hr range. Excessive demand can push the traffic stream to breakdown as drivers turbulently adjust their speed while surrounded by many other vehicles in closer proximity. If traffic is allowed to break down, the result can be significantly lower average speed (say ~40-60 km/hr) and reduced capacity (e.g. 1,800 vehicles per hour). In this example, the tolerable speed drop from 120 to 90 km/hr, is termed congestion by the economists' definition, but is of less significance for traffic engineers. The sudden breakdown that happens after is what is often perceived by drivers as congestion, and is termed by economists as hyper-congestion. The hyper part perhaps denotes that cost (travel time) increases, but service (flow) drops. As shown in the figure, there are two capacity values at critical density; one on the uncongested (left) side of the curve and one on the hyper congested (right) side of the curve, which is 15-25% lower. Preventing hyper-congestion therefore helps the traffic stream to avoid flow breakdown and the related sudden drop of capacity [25]. Since the lower capacity value is the norm during rush hours, preventing hyper-congestion increases capacity by the 15-25% [21].

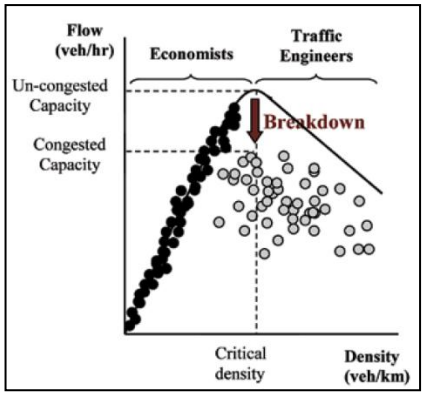


Fig. 5: Flow Density Relationship.

2.3. Congestion pricing

Small and Gomez (1997) defined congestion pricing as "a system of surcharging users of public goods that are subject to congestion through excess demand such as higher peak charges for use of bus services, electricity, metros, railways, telephones, and road pricing to reduce traffic congestion; airlines and shipping companies may be charged higher fees for slots at airports and through canals at busy times". This strategy of pricing could regulates demand, making it possible to better manage congestion without increasing supply [4].

It is known that there are two main approaches of modelling traffic flow for optimal congestion pricing; namely, static and dynamic models (Figure 6) [24]. Regarding static models, the static demand and the cost curves could be used for modelling, and the outcome is therefore static price/tolls (fixed over a period of time). The static pricing approach assumes a static demand curve for each congested route and time period, which implies that in response to congestion level and the congestion price charged, commuters who are tolled out either stay at home, take transit, carpool or move to uncongested routes or periods. Furthermore, this pricing model assumes that people who are tolled out do not dynamically shift to other congestible time periods (i.e. change their departure time) nor to other congestible parts of the transport network.

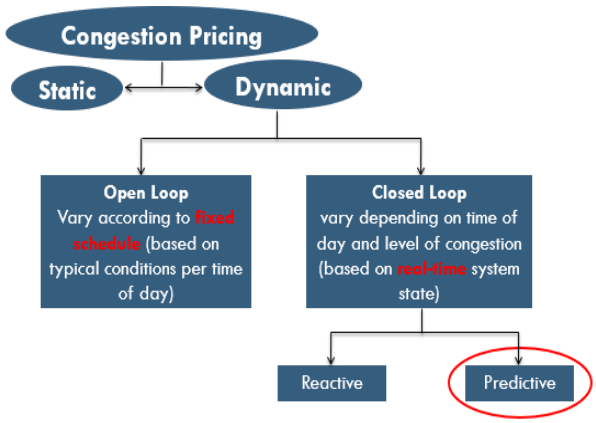


Fig. 6: Static vs. Dynamic Congestion Pricing Models.

Two approaches could be tracked to set road prices; regarding static models, which are: profit maximizing pricing and social-welfare maximizing pricing. They vary in the objective function to be maximized while expressing pricing. In social-Welfare maximizing pricing, each economic agent faces a price equal to its activity's social marginal cost, while in the profit-maximizing price, the price is determined by the demand curve (Figure 7).

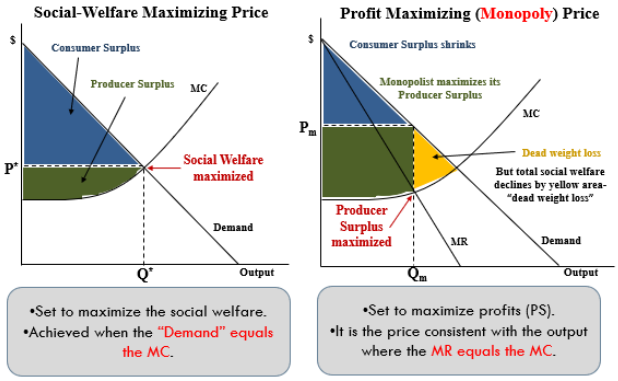


Fig. 7: Profit vs. Social Welfare Maximization.

On the other hand, in dynamic models, the differences of traffic demand with time are captured; consequently, these models produce dynamic prices/tolls that correspond to dynamics of traffic.

The first-best pricing from a dynamic perception is the "Bottleneck model" [24], which is the most widely used model of dynamic congestion pricing. It assumes the following:

- There is no delay if inflow is beneath capacity.
- The queue exit rate is equal to the capacity.
- Single anticipated queue exit time t.
- Total passages demand for Q is inelastic.

Two costs in un-priced equilibrium should be considered, which are travel delay cost $c_T(t)$ and schedule delay cost $c_s(t)$ (late and early arrival costs), as shown in figure (8). It is worth to mention that the main source of efficiency advances from optimal dynamic pricing is the rescheduling of departure times from the origin of trip.

Two alternatives for bottleneck model were indicated, which are Chu model and Verhoef model [24].

Congestion pricing gains some importance in cities worldwide for a few reasons; safety, money, and public desire. Many cities applied congestion such like, Singapore, London, San Diego and others.

The following table (1) summarizes application of the scheme around world cities [30]:

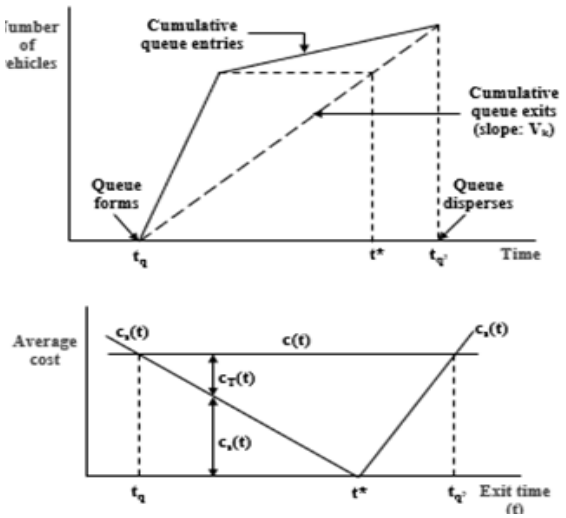


Fig. 8: Dynamic Pricing Representation.

Table 1: Congestion Pricing in Practice

City	Implementation Year	Due Pricing Fees	Type of Pricing	Time of Pricing	Applied Model
Singapore	1975	$ 1	Area licensing scheme	Morning Peak	Static
San Diego	1988	$ 0.5 - 4	Per lane	All Day	Dynamic
London	2003	£ 11.5	Cordon	All Day	Static
Stockholm	2006	$ 1.29 - 4.11	Area licensing scheme	All Day	Static
Milan	2008	N/A	Cordon	All Day	Static

2.4. Peak-avoidance rewards

People may respond differently when they are rewarded for good actions rather than punished for bad actions. Both rewards and punishments constitute types of incentives that influence human motivation. Maximizing pleasure and minimizing pain is a very basic instinct in human's behavior [5].

Considering traffic congestion as an example that is largely affected by travelers' choices and behavior; rather than pricing the infrastructure, an incentive/reward for avoiding peak hour travel could achieve a behavioral response similar to that of pricing [6]. The basic idea is to reward travelers who are willing to shift to earlier or later departure times or to alternative modes of travel or activities (i.e. teleworking). Thus, overall penalization of drivers through tolling is avoided and overall welfare could be potentially improved by reducing peak demand. Research in behavioral psychology shows the benefits of rewarding over punishments. As positive reinforcement, rewards have been applied extensively to strengthen motivation in various settings (such as work environments) and for various purposes (educational achievements, medical effectiveness, environmental protection, etc.). However, within the context of travel behavior, the concept of rewards has thus far played a minor role. Punishment and enforcement (such as policing, felony detectors, fines etc.) have been documented more widely than rewards. Given the fact that payment is more prevalent throughout society than rewards and given the fact that travel behavior has been for the most part subjected to and influenced by microeconomic theories, it is not surprising that the behavioral rationale of many demand-based strategies aimed at managing traffic congestion is based on negative incentives that associate the act of driving with punishment (in the form of tolls or increased parking costs) [7].

In other words, the challenge is to find innovative ways to engage citizens as a key stakeholder in addressing the challenges facing our cities today. A social experiment featured by MIT (10- Red Balloon Challenge) [19] revealed that the key to successfully mobilize and empower large number of people is incentives. In short, if we manage to engage citizens/travelers through technology and incentive/loyalty programs to eventually become more socially responsible and partner with governments and businesses; then this is a win-win strategy and can result in astonishing benefits across all government sectors.

According to a report titled "Towards Wise cities" [20], it shed some light on key success stories regarding using incentives, these stories were summarized on table [2]:

Table 2: Incentives in Practice

Sector	Implementation Year	Country	Description
Energy	2009	Korea	Online incentive program aims at reducing energy consumption and carbon emissions
Water	2010	USA	A platform combining analytics, cloud computing and community engagement to conserve water
Healthcare	2016	Canada	App use incentives to reward Canadians for making healthy lifestyle decisions
Smart Governance	2015	Indonesia	A platform to manage city operations to improve public safety
Intelligent Operation Center	2014	Brazil	An IoE-based central platform that improves safety, traffic flow, and emergency response capabilities
Traffic	2013	USA	Metropia ® created an advanced new mobile traffic app offers incentives for users avoiding congested routes

2.5. Traffic congestion in developing countries (Cairo as a case study)

Traffic congestion is a severe issue in Cairo with serious effects on both economy and life's quality. Besides the wasted time surviving in traffic, time that could be used productively, congestion results in needless consumption of fuel, which leads to harmful emissions decreasing air quality, rises costs of transport, and makes Cairo an unattractive location for businesses and industry. These contrary effects have very actual and huge monetary and non-monetary costs not only for the economy of Cairo, but for the economy of Egypt as well. Approximately 47 billion LE, are wasted every year in Cairo due to congestion, and this is expected to increase to 105 billion LE by 2030. It is estimated that 4% of GPD is lost yearly in Cairo due to congestion. As the population of Cairo continues to increase, traffic congestion is becoming worse and the need to trace this congestion is becoming more critical [3].

3. Methodology

With the objective of this study in mind – which is investigate possible approaches to better utilize the transport infrastructure network (supply) by altering road users' behavior (demand) - a mixed stated preference/revealed preference multinomial choice model survey is developed to measure road users' both (WTP) and their (ATE) in response to traffic congestion.
To develop the survey the approach depicted in Figure (9) is followed.

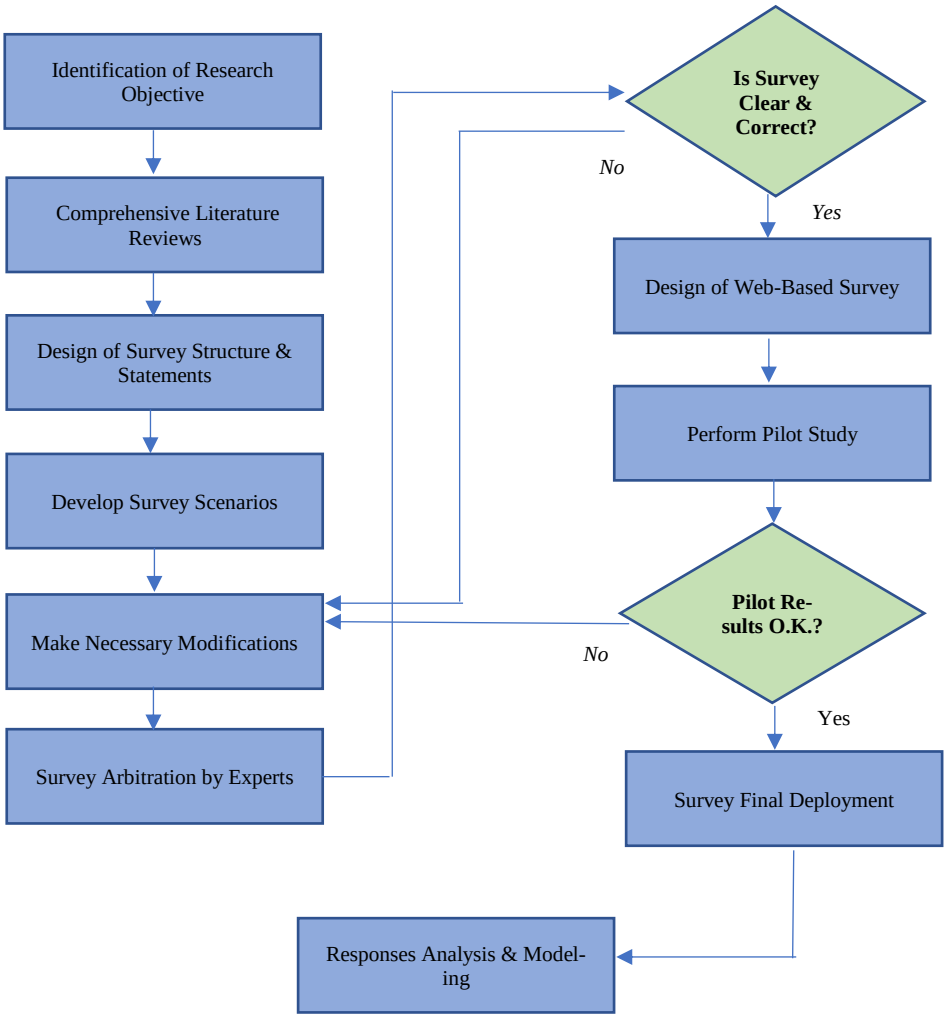


Fig. 9: Research Methodology.

With the above research objectives in mind, the survey is structured to address the following three main questions:

1) What are the common demographic variables of respondents who encounter traffic congestion?
2) How congestion affects the daily life of respondents, and how they deal and act with it?
3) What responses related to respondents' WTP or ATE when introduced to multiple scenarios, and to what degree are they willing to contribute to congestion mitigation?

As a first step a comprehensive comparative literature was performed to design the survey statements by deciding on the most significant variables found from previous studies, to be included and measured in this study.

Table (3) shows a comparative literature survey on efforts pertained to studying congestion pricing vs peak avoidance reward system. The summary in Table 3 indicates a sample of studies performed previously within the mentioned scheme. These studies were implemented in several countries to investigate applying pricing and/or rewards as techniques to manage traffic congestion within these countries up to each one circumstances depending on multiple perspectives. Referring to these studies, it was found that the most of it addressed congestion pricing while a few studies addressed peak-avoidance rewards, concluding that each scheme contributed positively in solving congestion problem.

Table 3: Congestion Pricing vs. Peak-Avoidance Rewards Comparative Studies

No.	Study	Year of Survey Implementation	Country	Data	Pricing or Reward	Study Findings & Conclusions
1	Tillema, T. (2007)	2005	Germany	SP/RP	Pricing	Author addressed road pricing from a transport geographical perspective, in the context of a larger multidisciplinary project called 'a Multi-Disciplinary study of Pricing policies, several types of geographical accessibility measures are distinguished such as: infrastructure based, location-based, person-based and utility-based measures.
2	Ubbels, B. (2006)	2004	Netherlands	SP/RP	Pricing	The study results from a project (MD-PIT) aims at providing a theoretical and empirical evaluation of the direct and indirect effects of practically feasible road pricing policies, include behavioral re-

						sponses and their consequences, acceptability of pricing and tax recycling schemes.
3	Mabrouk, A. & Abdenaddher, C (2016)	2014	Tunisia	SP	Pricing	Author aimed to estimate monetized value & trip time loss due to congestion, using contingent value method, implementing survey in Sfax, analyzing declared time preferences for drivers in rush hours.
4	Ettema, D. (2006)	2005	Netherlands	SP/RP	Pricing	The study proposes a conceptual model of departure time choice under travel time uncertainty and information, based on expected utility theory, and includes the variation in travel time, the quality of travel time information and travelers' perception of the travel time.
5	Hess, S. & Borjesson, M. (2017)	2011	Sweden /Finland/France	SP/RP	Pricing	The study makes use of data collected in four cities, measuring citizens' attitudes towards pricing, findings showed very strong similarities across the four cities, increase in the opinion towards pricing is not primarily an effect of changes in underlying attitudes, changes in how the underlying attitudes influence the support for congestion pricing, or differences in anticipated versus experienced or perceived self-interest.
6	Vrtic, M. & others (2010)	2008	Switzerland	SP	Pricing	The author studied the impact of road pricing on route and choice behavior in Switzerland, evaluation of costs of fuel, tolls & parking. Shifts in departure times were recorded.
7	Di Ciommo, F. & others (2013)	2009	Spain	SP/RP	Pricing	Author used hybrid models to improve analysis of road pricing acceptability, hybrid models were founded the better to improve that, Psycho-social variable is a strong indicator.
8	Bhat, C. & Castelar, S. (2002)	1996	USA	SP/RP	Pricing	The study formulates and applies a unified mixed-logit framework for joint analysis of RP and SP data, examine the travel behavior, responses, implied trade-offs among level-of-service attributes, heterogeneity and state-dependence effects, data fit, and substantive implications of congestion pricing policy simulations.
9	Borjesson, M. (2008)	2005	Sweden	SP/RP	Pricing	The author used a joint SP-RP data in a mixed logit analysis of trip timing decisions, the analysis implies systematic differences in the RP and SP data
10	Vrtic, M. & others (2007)	2006	Switzerland	SP	Pricing	Study showed an extensive SP survey for impact of possible pricing schemes on behavior, findings determined that charging level is the most important factor, the fuel tax and motorway vignette, was the least liked option, the most favored alternative is investment in public transport.
11	Golob, T. (2001)	1998	USA	SP/RP	Pricing	The author developed joint models of attitude & behavior to evaluate San Diego I-15 congestion pricing project, findings showed that some personal & situational explanations of opinions and perceptions are attributable to mode choices.
12	Jou, R. & others (2007)	2004	Taiwan	SP	Pricing	The study addressed three road pricing schemes: fixed, credit-based and differential pricing, proposed or implemented in different countries, are investigated, to obtain commuters' socioeconomic characteristics, travel characteristics, attitudes on different schemes, and attitudes on incentive alternatives on different road pricing Schemes, findings of study provided valuable insights into road pricing strategies to be regulated and implemented in the future.
13	Karlstrom, A. & Franklin, J. (2009)	2006	Sweden	SP/RP	Pricing	The study assessed the horizontal and vertical equity effects of the Stockholm trial with Congestion Pricing for morning commuters, in terms of both travel behavioral adjustments and welfare effects.
14	Kockelman, K. & Kalmanje, S. (2005)	2004	USA	SP	Pricing	Authors proposed a new credit-based congestion pricing policy to be investigated, findings showed that respondent estimates of congested travel times to work are almost double the uncongested times, those with fewer vehicles appear more willing to support such a policy and more likely to modify their travel behaviors.
15	Li, Z. & others (2010)	Comparison Study		SP	Pricing	The study reviewed the modelling frameworks and empirical measurement paradigms used to obtain willingness to pay for improved travel time reliability, estimate models to derive values of reliability, scheduling costs and reliability ratios.
16	Arentze, T. & Timmermans, H. (2007)	2006	Germany	SP	Pricing	Author reports the findings of a stated adaptation experiment conducted to assess possible long-term impacts of pricing scenarios, especially a change of job location and/or residential location, the findings indicate that individuals will first adjust their travel behavior, changes of job location and/or residential location are less often considered.
17	Saleh, W. & Farrell, S. (2005)	2002	Scotland	SP/RP	Pricing	The author investigated the potential impacts of implementing variable congestion charging on the peak spreading of departure time choices, calibrating departure time choice models, findings indicated that variables related to work and non-work scheduling, as well as socio-economic variables have improved the performance of the models.
18	Ben-Elia, E.; Ettema, D. (2009)	2006	Netherlands	RP	Reward	The study presented a model of departure time choice based on the notion of a latent preferred arrival time using the peak-avoidance data "Spitsmijden" experiment, estimating several models to identify car drivers" choice of departure time when rewards provided.
19	Peer, S. & others (2016)	2013	Netherlands	RP	Reward	Authors implemented an experiment in which participants could earn monetary rewards for traveling outside peak hours, as a result, the relative share of peak trips decreased by 22% during the reward period, and by 10% during the post-measurement.

20	Leblanc, R. & others (2013)	2011	USA	SP	Reward	The study investigated the impact of providing incentives on travelers' choices for their commute to work, results found that people are willing to change their commute, exhibiting a range of willingness to be paid $6.95-$18.98 per hour of travel time or $10.60-$28.93 per hour of schedule delay, travelers are much more sensitive to charges than to rewards.
21	Zhou, L. & others (2009)	2008	USA	SP/RP	Reward	Authores in this study focused on impact of incentives on toll road use by trucks, using interviews and survey data. More than 2,000 respondents indicated their preferred route and whether certain incentives would motivate them to use SH-130 route in Austin, resulted in that smaller companies preferring the non-toll route. The incentives that most interested the truckers were off-peak discounts.
22	Bie, J. & others (2010)	2009	Netherlands	SP	Reward	Authors introduced a route-based incentive program where drivers get rewarded for taking the safest routes within insurance company, where this company charges a discounted premium for vehicles which follow the safest routes, findings showed that drivers tend to ignore safety-related information in making their route choices; however, the incentives have some significant effects on these choices.
23	Ettema, D. & others (2010)	2010	Netherlands	SP/RP	Reward	The study reported "Spitsmijden" project, travelers received positive incentives if they avoided travelling in the peak by car, travelers' responses were measured using electronic detection equipment and travel diaries. Findings of study indicated that positive incentives are able to reduce the amount of peak traffic of the participants by about 60%.
24	Kumar, V. & others (2016)	2006	Netherlands	SP/RP	Reward	Authors presented a detailed analysis and modeling to understand how incentives affect traveler choices, where the scheme included monetary or credit towards obtaining a smartphone with a view to motivate commuters to change their departure time choice out of the peak period. The study founded that incentives are effective in changing behavior and can overcome inertial effects.

Tables (4&5) provide an in-depth analysis of the variables studies in the literature affecting WTP and ATE, respectively.

Table 4: WTP Demographic & Other Variables in Literature

No	Source	Demographic variables										Other Variables												
		Age	Gender	uca-tion	ry Size	/ho ly	In- e of	Res cu-	na g	hou (dri	ver Typ e of	tion	cost tim	e ing	(Fla s	(fue g	char ra-	tion na-	tive par-	ture ion	(cit ing	(Pe es	al- ght	of
1	Tillema, T. (2007)	x	x	x	x	x	x		x		x													
2	Ubbels, B. (2006)	x	x			x	x		x	x	x													
3	Mabrouk, A. & Abdenaddher, C (2016)	x	x			x		x		x														
4	Ettema, D. (2006)																							
5	Hess, S. & Borjesson, M. (2017)					x																		
6	Vrtic, M. & others (2010)	x	x		x	x	x	x		x														
7	Di Ciommo, F. & others (2013)					x		x		x														
8	Bhat, C. & Castelar, S. (2002)	x	x			x		x		x														
9	Borjesson, M. (2008)																							
10	Vrtic, M. & others (2007)	x	x			x	x	x		x														
11	Golob, T. (2001)	x	x	x	x	x				x														
12	Jou, R. & others (2007)	x	x	x	x	x				x														
13	Karlstrom, A. & Franklin, J. (2009)	x	x			x		x																
14	Kockelman, K. & Kalmanje, S. (2005)	x	x	x	x	x				x														
15	Li, Z. & others (2010)	x	x	x	x	x				x														

16	Arentze, T. & Timmermans, H. (2007)	x	x	x	x	x				x									
17	Saleh, W. & Farrell, S. (2005)																		

("x" indicates that the variable included within study, red, yellow and green colors indicates degree of significance of included variable, red is the most).

Table 5: ATE Demographic & Other Variables in Literature

		Demographic variables								Other Variables								
No	Source	Age	Gender	Education level	Family Size/household	Monthly Income	Work statues and place	occupation	Car ownership	Type of trip	No. Working days	Amount of Reward	Type of reward	Times of rewarding	Departure time	Travel time	Alternative mode	Travel distance
1	Ben-Elia, E.; Ettema, D. (2009)	x	x	x	x	x	x			x								
2	Peer, S. & others (2016)	x	x	x		x		x										
3	Leblanc, R. & others (2013)	Mentioned but not determined																
4	Zhou, L. & others (2009)																	
5	Bie, J. & others (2010)	x	x	x		x			x									
6	Ettema, D. & others (2010)	x	x	x	x													
7	Kumar, V. & others (2016)	x	x	x	x	x			x									

("x" indicates that the variable included within study, red, yellow and green colors indicates degree of significance of included variable, red is the most).

The above literature review indicates that the following are the most significant variables influenced traveler's behavior and attitude towards WTP and ATE:

- Congestion toll (cost).
- Amount of reward.
- Travel time change/savings.
- Departure time.

To measure commuters' both WTP and ATE and how this will affect their behavioral change towards addressing traffic congestion; a number of scenarios is designed for that purpose. These scenarios are developed to expose participants to multiple hypothetical environments where they have to make a "choice" stating their preference in each of these environments. In each scenario, three variables are presented with several levels/scales for each, as follows:

- For WTP scenarios: Toll, travel time savings, and departure time, and
- For ATE scenarios: Reward, travel time savings, and departure time.

For WTP scenarios, three variables with three values for each lead to 27 distinct scenarios using a full factorial design. This is indeed a large number of scenarios to be presented to respondents, so by using fractional factorial design the number of scenarios could be reasonably reduced to only 9 scenarios. To keep the most essential scenarios that directly relate to the significant variables identified earlier, this study applied a procedure by eliminating strongly dependent variables/decisions based on the literature – for example - combining no toll scenario with earlier departure time is a case to encourage respondents to change their behavior. Similarly, for ATE scenarios, four values for reward points (no reward, 1 point, 2 points, 3 points) are presented in addition to three values each for of the other two variables (departure time, travel time savings). Considering the full factorial design, the combination of these values results in 36 different scenarios which is also a large number to be presented. Performing a fractional factorial design reduced this number to 9 only, and further elimination of strongly dependent variables resulted in 7 scenarios only for respondents. Tables (6, 7) summarize the final scenarios for each scheme which are then designed / presented within survey.

Table 6: WTP Final Scenarios' Variables and Values

No.	Variables			Will You Choose this Scenario?	
	Toll	Travel Time Saving	Departure Time	Yes	No
1	No toll	%15	30 mins. later		
2	LE 10	%20	30 mins. earlier		
3	LE 20	%25	Same as usual		
4	No Toll	%25	30 mins. earlier		
5	LE 10	%15	30 mins. later		
6	LE 20	%20	Same as usual		

Table 7: ATE Final Scenarios' Variables and Values

No.	Variables			Will You Choose this Scenario?	
	Reward (Points)	Travel Time Saving	Departure Time	Yes	No
1	1 point	%25	30 mins. earlier		
2	2 points	%20	30 mins. later		
3	3 points	% 15	30 mins. later		
4	1 point	%15	30 mins. later		
5	2 points	%25	30 mins. earlier		
6	3 points	%20	30 mins. earlier		
7	No Reward	-	Same as usual		

After completing the survey statements, it was presented to specialists for arbitration, and necessary modifications were performed. Such modifications include adding/deleting some statements, sequence of questions, scale of questions (e.g. 3-point vs 5-point scale), clarifying some jargons, developing visualizes for each scenario by means of graphs and other important modifications. On the next step, an online form of the survey was designed in both Arabic and English languages, including two introductory educational movies to congestion pricing and peak-avoidance rewards; besides presenting scenario by means of dynamic graphs to visually engage participants (refer to Figure 10 as an example). Prior to fully launching the survey, a polit survey was conducted among 10 selected researchers and

experts in this field. The purpose of this pilot is to evaluate the questionnaire in both languages (i.e. identify any source of errors in the survey and/or, any concerns regarding the clarity of questions), and estimate the length of the survey / time to complete the survey. It should be noted that all participants had no prior knowledge of the study nor designing the questionnaire to avoid any biased feedback.
After addressing the feedback from the pilot, the survey was programmed and made available online on for a period of three months (Jan 2018 - April 2018). The online survey was distributed via a combination of the following methods: email invitation, regular follow-up phone calls, social media groups' members to participate in the survey; and Facebook invitations. The results of the survey and data analysis are discussed in the next section.

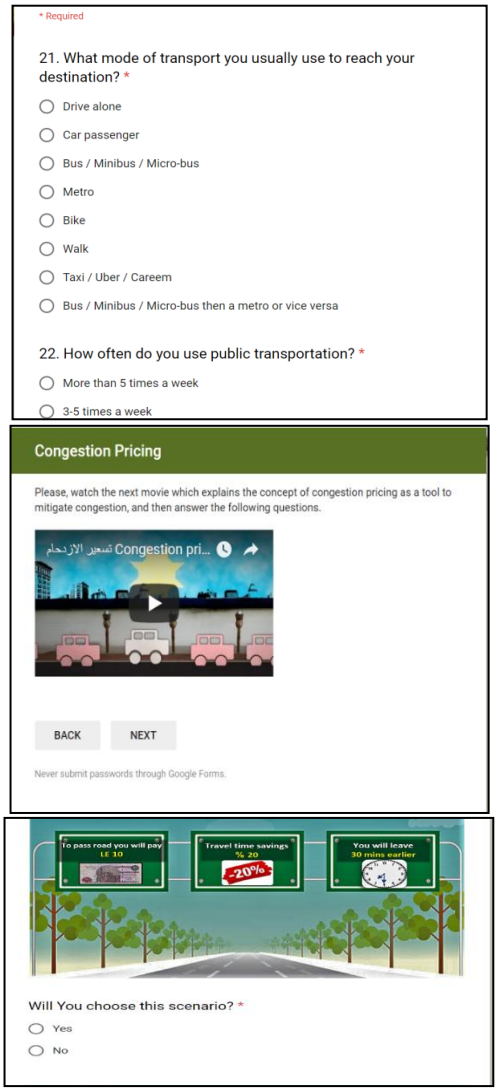


Fig. 10: Sample Visuals from the Online Survey.

4. Data analysis and modeling

4.1. Data analysis

4.1.1. Demographic characteristics of respondents

A total of 885 responses were collected in both Arabic (701) and English (184) versions. These responses are the completed responses with no missing or N/A statements. The study's sample size was observed to capture 59.4% males vs 40.6% females -as depicted in Figure (11). Participants ages show a healthy mix between 25 - 34 years (about 36%) constituting the majority of responses, followed by 29.2% between 18 - 24 years, and 27.8% between 35 - 44 years old; and just 1.7% prefer not to mention their ages.

Most participants are working full time (about 59.5%) while 22.8% of them are students at various levels (undergraduate and graduate students). Also, about 8% of respondents are working part time while 2.7% of them are working from home, with about 7% of participants un-employed (refer to Figure 12).

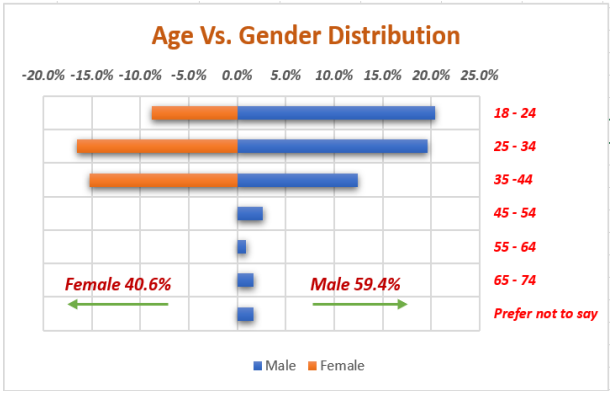


Fig. 11: Gender vs. Age Distribution.

The household distribution of respondents indicates 34% of size 4 persons per family, and about 29.3% of families contain 5 persons, while 18% of these families contain 3 persons. A few families report 1, 2, 6 or more than 6 persons per each family (refer to Figure 13). In terms of holding a driving license, most of respondents have a driving license (70% of them), while the rest have not (Figure, 14). With regards to car ownership, the majority of participants (about 53.4%) own one car, while 27.5% of respondents have no cars relying on other means of transportation (refer to Figure 15). The monthly income distribution indicates a wide range of income levels from 2000 LE to 20,000 LE with majority (29%) earn between 2,000-5,000. It is worth noting that respondents in general tends to underreport income levels (refer to Figure 16).



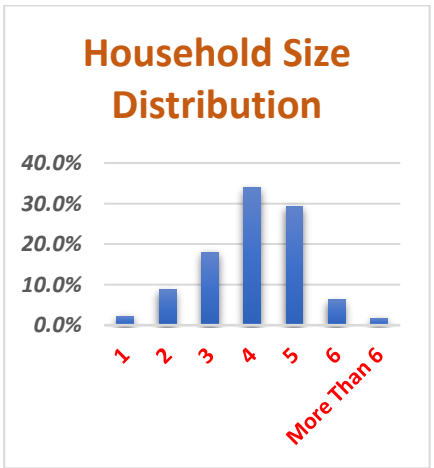
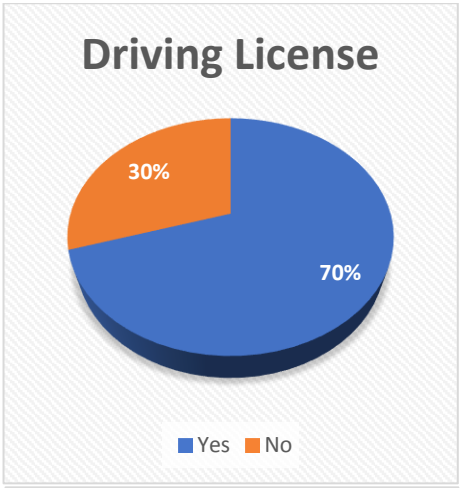


Fig. 12: Employment Statue Fig. 13. Household Size.



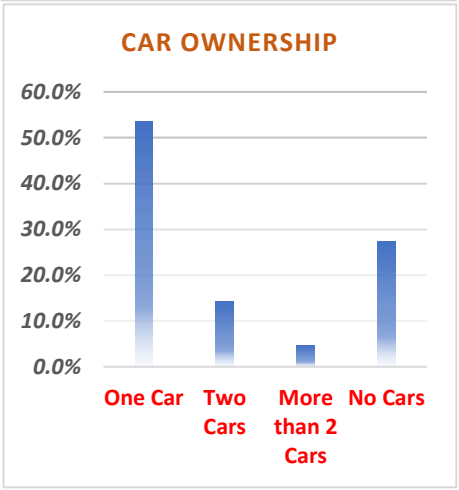


Fig. 14: Driving License Ownership Fig. 15. Car Ownership.

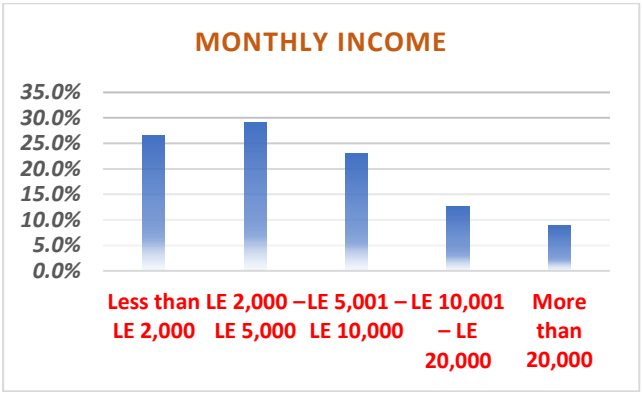


Fig. 16: Monthly Income.

4.1.2. Understanding respondents' perception of traffic congestion

The results obtained indicate a severe congestion problem in Cairo where respondents report its notable impact on work vs home location choice. The known vibrant nature of the city is no more attractive as the city comes to a halt at peak hours leaving residence with no choice except to look for quitter / less intimidating environments. On the other hand, the inadequate public transportation network is a key contributing factor to congestion, followed by lack of enforcement, reckless driving behavior and heavy trucks. Figure (17) summarizes analysis of respondents' reaction with traffic congestion.

Respondents' reaction to daily congestion in Cairo varies considerably ranging from adjusting their departure and arrival times, to making productive use of time in congestion, to use technology / their own knowledge to determine best routes within their trips. One interesting finding from the responses indicate that majority of people are genuinely willing to contribute to congestion mitigation measures if logical solutions are properly introduced and strictly enforced.

Furthermore, respondents' opinions regarding usual departure times, delays, and peak times varied indicating that the majority believes that Thursday is the most congested day of week, and 4:00-6:00pm is the common peak time faced during the day.

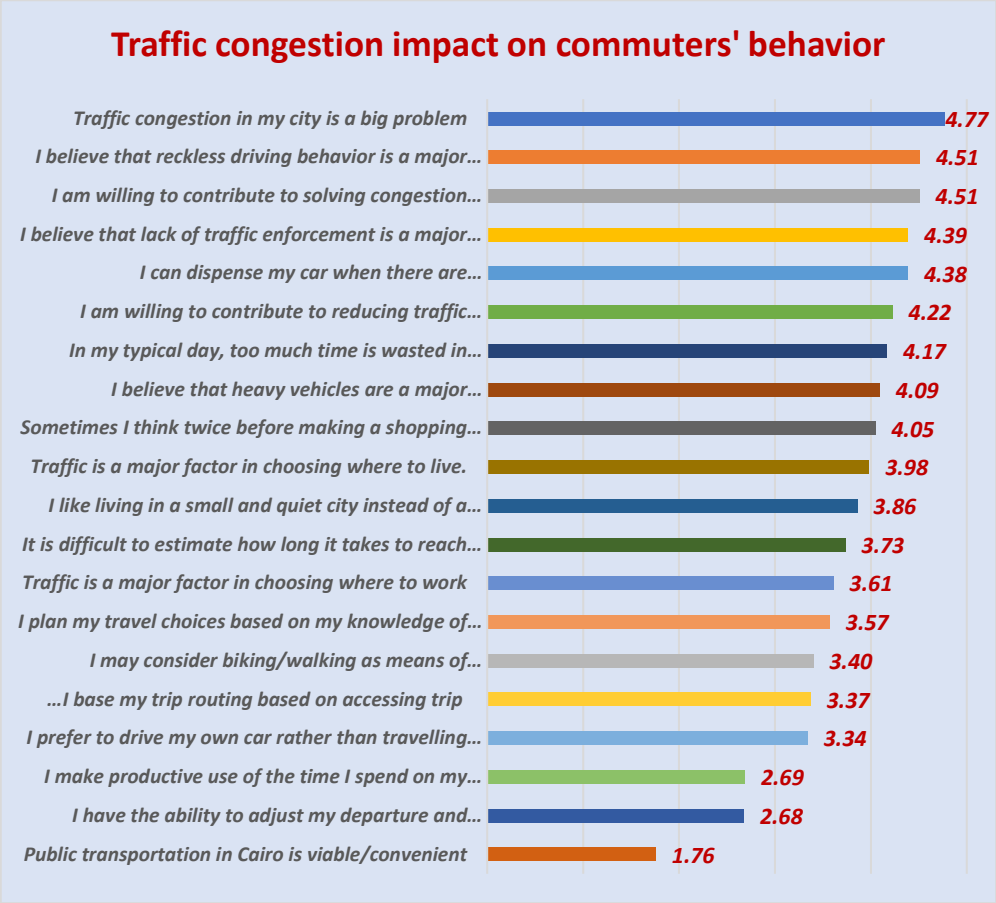


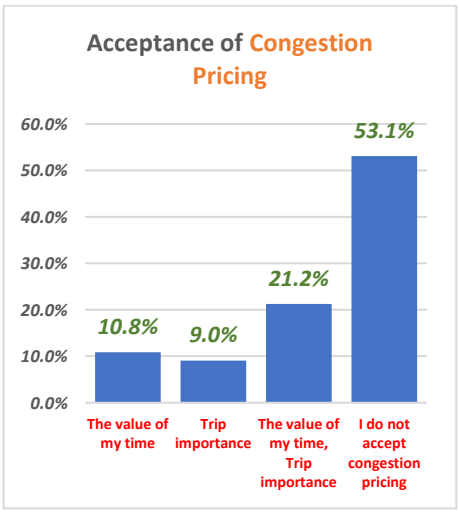
Fig. 17: Statements Mean Values Distribution for Respondents' Reaction with Congestion.

As expected, and because of the unique human nature which endorses motivations more than punishment, about half of respondents do not accept the concept of congestion pricing, and will seek other alternatives like avoiding congestion or finding other routes if applied. On the other hand, people are most likely to prefer receiving a reward if they avoid peak times, majority of them will avoid congestion to get rewarded by means of free fuel cards or by any other types (Figures 18-20).

As indicated before, the public transit network in Cairo is not adequate nor convenient, so respondents believe that the best way to reinvest the collected fees if congestion pricing is applied is to rehabilitate and improve this network. Improving public transportation; not only addresses traffic congestion along busy routes / corridors but would encourage mode shift given the abandoning fuel subsidy strategy the country is adopting. This was confirmed by the survey results as 15-20% would consider using public transit in the case of congestion pricing or a rewarding program.



Fig. 18: Reasons of Pricing Acceptance Fig. 19. Desire of Rewarding.



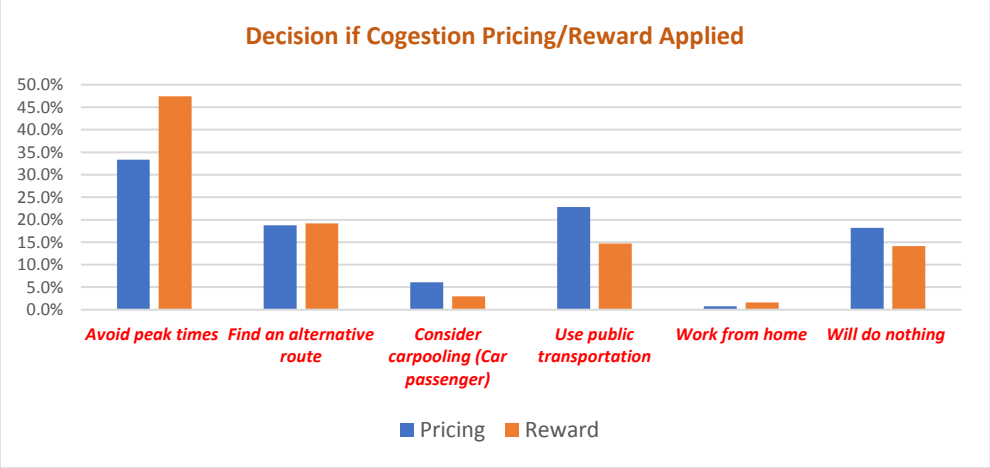


Fig. 20: Act If Pricing/Rewarding Applied.

4.2 Data modeling

4.2.1. WTP model (congestion pricing acceptance)

Respondents within this study were exposed to 6 hypothetical scenarios. In each scenario, they were asked whether to change their behavior or not in response to 3 variables: toll [no toll, LE10, LE20], time savings [15%, 20%, 25%] and departure time [depart 30 minutes later, depart same as usual and depart 30 minutes later].

By using the SP data collected from the 885 respondents, and according to the nature of data and choices pattern, a binary choice model is estimated where the obtained SP data were treated and analyzed as panel data. Each record within obtained data represents one individual respondent with six choice observations. It is worth noting that different model structures were tested using SPSS modeling package, and the final data model - presented in Table (8) - produces the best fit to the observed data. Thirteen parameters were estimated for individuals' choices across the six SP variables. The log-likelihood for model is observed to be -5374.7, while the reported R-squared value, as a measure of goodness-of-fit, is 0.26. Although there are no strict guidelines on what constitutes a -good-R-squared value, it is deemed that values between 0.2 and 0.4 are indicative of particularly good model fits within the context of this study (29). All the reported parameters are estimated with the expected signs and found to be statistically significant at the 95% confidence interval.

Table 8: WTP Variables Definitions and Parameter Estimation Results

Variable	Estimate	Standard Error	t-value *
Constant (Intercept)	-1.586	0.145	0.205
Toll (LE)			
No toll	2.459	0.069	11.692
LE10 toll	-0.782	0.086	0.458
LE20 toll	-1.825	0.065	0.161
Time Savings (%)			
15% time saving	0.442	0.060	1.556
20% time saving	-1.441	0.072	0.237
25% time saving	0.804	0.060	2.234
Departure time			
Departing 30 minutes earlier	0.829	0.060	2.292
Departing same as usual	-1.477	0.072	0.228
Departing 30 minutes later	0.442	0.060	1.556
Demographic			
Gender	0.039	0.058	1.040
Age	0.049	0.024	1.050
Employment statues	-0.034	0.028	0.967
Monthly income	0.014	0.023	1.014

*Significant at 95% confidence interval.

By examining the estimated model parameters - presented in Table (8) - the following findings can be stated:

Value of Toll:

No toll: As expected, and from the observed descriptive analysis, a significant number of individuals within this study do not accept the concept of congestion pricing as a mitigation policy in Cairo; therefore, the (no toll) variable is observed to have a very strong impact on the choice of commuting behavior for respondents.

Low toll (LE 10): The low toll variable has also a negative impact on the choice of respondents' behavior since it has a value of (-0.782) which means that there is an inverse relationship between low toll variable and commuting behavior, and hence low WTP.

High toll (LE 20): High toll variable is observed to has a strong impact on respondents WTP and hence their commuting mode choice, it has a value of (-1.825) which indicates an inverse high relationship between high toll and individual's WTP.

Time Savings:

Low time savings (15%): Based on the model outcomes it is observed that low time savings has no significant impact on respondents' choice since it has a value of (0.442), the t-statistics for this variable is recorded to be (1.556) which indicates a weak relationship between this variable and individuals' WTP.

Medium time savings (20%): This variable is observed to have a significant impact on commuters' behavior since it has a value of (-1.44) which refers to an inverse relationship between this variable and commuting choice.

High time savings (25%): high time savings' variable is recorded to has a strong impact on commuting choice since it has a value of (0.804), this reflects respondents' high value of time and their desire to minimize trip time as possible according to their desires to maximize their utility of trip.

Departure Time:

Departing 30 minutes earlier: Reporting a high value for this variable (0.829), it obviously indicates a strong impact on respondents' behavior, the high positive relationship reflects a high desire of commuters to depart earlier and hence avoiding peak times.

Depart same as usual: Respondents are observed not to prefer departing as usual, the value of (-1.47) indicates that there is a strong inverse impact on commuting behavior. Within this context, it is worth to mention that this variable is combined with high toll variable among presented scenarios, and this is intentionally assigned to encourage people to change their departure time and hence avoiding congestion.

Depart 30 minutes later: Departing later is observed to have no significant impact on choosing commuting choice since it has a value of (0.442).

Gender: The gender distribution of study sample size is recorded to have a value of (0.039), which indicates a low impact on responses choice.

Age: Age categories variable of our sample size has also a low impact on commuting choice scenario, a value of only (0.049) is recorded for that.

Employment Statue: As the last two variables, employment statue has also a low impact on choosing commuting mode, it records a small value of (-.034).
Monthly Income: Similar to the above discussion on employment status, it was not expected that the monthly income of respondents does not affect the choose of commuting mode, it just records a value of (0.014).
Finally, and referring to previous explanation and results, respondents in our study generally have a negative WTP desire (Utility constant = -1.586), as they do not prefer to pay to utilize a space on the road during peak hours, however, respondents have a high desire to change their departure times to avoid congestion. The good news is that majority of respondents feel that they are so interested in time saving during their usual trip, and they are able to change their behavior to gain more time. These results are aligned with findings from the descriptive analysis presented earlier.

4.2.2. ATE Model (peak-avoidance rewards acceptance)

On the other hand, respondents within this study were exposed to 7 hypothetical scenarios to address ATE. In each scenario, they were asked whether to change their behavior or not in response to 3 variables: reward [no reward, one point reward, two points reward and three points reward], time savings [15%, 20%, 25%] and departure time [depart 30 minutes earlier, depart same as usual and depart 30 minutes later].
As discussed above, a binary choice model is also estimated for the ATE model. It is worth noting that different model structures were tested using SPSS modeling package, and the final data model - presented in Table (9) - produces the best fit to the observed data. Fourteen parameters were estimated with each record represents individuals' choices across the seven SP variables. The log-likelihood for model is observed to be -7874.22, while the reported R-squared value, as a measure of goodness-of- fit, is 0.1.the reported low R-square value reflects the high variability in data; indicating that results shall be cautiously interpreted. However, such the results obtained are somehow comparable with results from models for other cities [15] [32]. All the reported parameters are estimated with the expected signs and found to be statistically significant at the 95% confidence interval.

Table 9: ATE Variables Definitions and Parameter Estimation Results

Variable	Estimate	Standard Error	t-value *
Constant (Intercept)	1.412	0.292	4.103
Reward (Points)			
No Reward	-0.474	0.073	0.623
One-point reward	-0.439	0.057	0.645
Two points reward	0.284	0.057	1.329
Three points reward	0.452	0.058	1.571
Time Savings (%)			
15% time saving	-0.821	0.057	0.440
20% time saving	0.562	0.058	1.755
25% time saving	0.566	0.058	1.761
Departure time			
Departing 30 minutes earlier	0.960	0.054	2.612
Departing same as usual	-0.474	0.073	0.623
Departing 30 minutes later	-0.700	0.052	0.497
Demographic			
Gender	0.469	0.052	1.598
Age	-0.178	0.022	0.837
Employment statues	-0.141	0.025	0.868
Monthly income	-0.056	0.020	0.946

*Significant at 95% confidence interval.

By examining the estimated model parameters - presented in Table (9) - the following findings can be stated:
Value of Reward:
No reward: As expected, and from the observed descriptive analysis performed earlier, a reasonable number of individuals within this study accept the concept of peak- avoidance rewards as a mitigation policy in Cairo, therefore, the (no reward) variable is observed to have a moderate negative impact on the choice of commuting behavior for respondents with a value of (-0.474).
Low reward (one point): The low reward variable has also a moderate impact on the choice of respondents' behavior since it has a value of (-0.439) which means that there is an inverse relationship between low reward variable and commuting behavior, and hence low ATE for low reward values.
Medium reward (two point): At this point, the sign of B-value is shifted from negative to positive with a low impact on commuting mode choice, since it records a value of only (0.284).
High reward (three points): High reward variable is observed to has a moderate impact on respondents ATE and hence their commuting choice, it has a value of (0.452) about one and half times the value of medium reward which indicates a positive moderate relationship between high reward and individual's ATE.
Time Savings:
Low time savings (15%): From the model results, it is observed that low time savings has a significant impact on respondents' choice since it has a value of (-0.821), which indicates a high inverse relationship between this variable and individuals' ATE.
Medium time savings (20%): This variable is observed to have a moderate impact on commuters' behavior since it has a value of (0.562) which refers to a positive relationship between this variable and commuting mode.
High time savings (25%): high time savings' variable is recorded to has a moderate impact on commuting choice since it has a value of (0.566) closer to medium time saving.
Departure Time:
Departing 30 minutes earlier: Recoding a high value for this variable (0.960), it obviously indicates a strong impact on respondents' behavior, reflecting a high desire of commuters to depart earlier and avoid peak times.
Depart same as usual: Respondents are observed not to prefer departing as usual, the value of (-0.474) indicates that there is a moderate inverse impact on commuting behavior. Within this context, it is worth to mention that this variable is combined with no reward variable among presented scenarios, and this is intentionally assigned to test whether respondents are willing to change their departure time to avoid congestion.
Depart 30 minutes later: Departing later is observed to have a significant impact on choosing commuting choice since it has a value of (-0.700), this indicates a high inverse relationship between this variable and commuters' ATE. This result indicates that respondents are likely to adopt to earlier departing times than later.
Gender: The gender distribution of study sample size is estimated to have a value of (0.469), which indicates a moderate impact on responses choice, and higher comparing with that obtained from WTP model.
Age: Age categories variable of our sample size has also a low impact on commuting choice scenario, a value of only (-0.178) is estimated.
Employment Statue: As the previous variable, employment statue has also a low impact on choosing commuting mode, it records a small value of (-0.141).
Monthly Income: Monthly income variable has a low impact also on commuters' behavior since it records a value of (-0.056).
As a summary of the above modelling results, respondents' in this study generally have a positive ATE (Utility constant = 1.412) when compared to WTP (Utility constant = -1.586) in response to congestion mitigation measures; regardless of their socio-economic characteristics. Generally, a notable preference to avoid peak hours and gain rewards is observed particularly for early departure times to avoid congestion. Additionally, most respondents are interested in travel time saving during their usual trip and they are able to change their behavior to gain more time and rewards.

5. Conclusions

Due to accelerated growth of population in Cairo – and in most vibrant metropolitan areas- roads expansion strategies have proven to fall short in coping with the population growth and urban sprawl. So, decision makers have to think out of box to find meaningful/logical solutions for such the escalated traffic congestion problem by harnessing untraditional techniques. The core of this study attempts to find a solution to alleviate traffic congestion in vibrant cities – with Cairo as a case study - and hence better management of infrastructure networks, by means of applying "stick & carrot" technique. In other words, applying both congestion pricing and peak-avoidance rewards to trace and model the change of commuters' behavior especially during peak hours.

A mixed stated preference/revealed preference survey was created and distributed online among several channels to investigate the effect of congestion on commuters' daily life, and to understand their willingness to alter their behavior by exposing them to multiple hypothetical scenarios and to make choices on their daily commutes.

The modelling results confirmed that there is a soaring congestion problem in Cairo with inadequate public transportation network, lack of enforcement in the city streets, and reckless driving behavior. Almost all participants have indicated serious endeavors to participate in any plausible mitigation measures if logical solutions are introduced, even if few others have not. On the other hand, about half of respondents did not accept the concept of congestion pricing, while they were most likely to prefer rewarded if they avoid peak times and alter their behavior.

Furthermore, two binary logit models were developed and estimated from the SP data obtained from the survey; where the first one was to measure respondents' WTP, and the other was for their ATE. It was found that respondents generally have a negative WTP desire, they do not prefer to pay to use a road during peak hours, however, respondents have a high desire to change their departure times to avoid congestion, while they had a positive ATE desire since they prefer to avoid peak hours and collect rewards.

6. Research contributions

The main Contributions of this study could be summarized as follows:

- Investigation of traffic congestion problem in Cairo, and how it affected the daily life decisions of its residents, and their perception towards congestion.
- Introducing of "Stick & Carrot" technique as a new approach for congestion mitigation, which could lead to better management of infrastructure network.
- Measuring respondents both WTP and ATE behavioral change after introducing them to multiple scenarios of congestion pricing and peak-avoidance rewards.
- Modeling the behavioral change of respondents by means of representing logit models for both WTP and ATE, and determining utility function parameters for each one to be maximized up to their decision.

References

[1] Lieu, H., Gartner, N., Messer, C. J., & Rathi, A. K. (1999). "Traffic flow theory". Public Roads, Volume 62, pp.45-47.

[2] Knoop, V. L., & Daamen, W. (2017). "Automatic fitting procedure for the fundamental diagram". Transport metrica B: Transport Dynamics, Volume 5 (2), pp.129-144. https://doi.org/10.1080/21680566.2016.1256239.

[3] http://www.worldbank.org/en/country/egypt/publication/cairo-traffic-congestion-study-executive-note - access date 15.3.2018

[4] Small, K. A., & Gómez-Ibáñez, J. A. (1997). "Road pricing for congestion management: the transition from theory to policy", Transport Economics, pp.373-403.

[5] Tillema, T., Ben-Elia, E., Ettema, D., & van Delden, J. (2013). "Charging versus rewarding: A comparison of road-pricing and rewarding peak avoidance in the Netherlands", Transport Policy, Volume 26, pp.4-14. https://doi.org/10.1016/j.tranpol.2012.01.003.

[6] Tillema, T. (2007). Road pricing: a transport geographical perspective, Geographical Accessibility and Short and Long-Term Behavioral Effects, NWO/Connekt VEV project, Urban and Regional research centre Utrecht, Faculty of Geosciences, Utrecht University.

[7] Ettema, D., & Timmermans, H. (2006). "Costs of travel time uncertainty and benefits of travel time information: conceptual model and numerical examples", Transportation Research Part C: Emerging Technologies, Volume 14 (5), pp.335-350. https://doi.org/10.1016/j.trc.2006.09.001.

[8] Swamy, H. S., & Sinha, S. (2014). Urban Transport Developments in India under NUTP and JnNURM.

[9] Börjesson, M. (2008). "Joint RP–SP data in a mixed logit analysis of trip timing decisions", Transportation Research Part E: Logistics and Transportation Review, Volume 44 (6), pp.1025-1038. https://doi.org/10.1016/j.tre.2007.11.001.

[10] Ubbels, B. J. (2006). Road Pricing. Effectivenss, Acceptance and Institutional Aspects, NWO/Connekt VEV project, Urban and Regional research centre Utrecht, Faculty of Geosciences, Utrecht University.

[11] Ben-Elia, E., Bierlaire, M., & Ettema, D. (2010). "A behavioural departure time choice model with latent arrival time preference and rewards for peak-hour avoidance". In European Transport Conference.

[12] Ben-Elia, E., & Ettema, D. (2009). "Carrots versus sticks: Rewarding commuters for avoiding the rush-hour—a study of willingness to participate", Transport policy, Volume 16 (2), pp.68-76. https://doi.org/10.1016/j.tranpol.2009.03.005.

[13] Bie, J., van Arem, B., & Igamberdiev, M. (2010, January). "Using economic incentives to influence drivers' route choices for safety enhancement: A cost-benefit analysis and the results from an empirical study", In Compendium of Papers TRB 89th Annual Meeting. DVD, Mira Digital Publishing.

[14] Peer, S., Knockaert, J., & Verhoef, E. T. (2016). "Train commuters' scheduling preferences: Evidence from a large-scale peak avoidance experiment", Transportation Research Part B: Methodological, Volume 83, pp.314-333. https://doi.org/10.1016/j.trb.2015.11.017.

[15] Leblanc, R., & Walker, J. L. (2013). "Which is the biggest carrot? comparing nontraditional incentives for demand management", In Proceedings of the Transportation Research Board 92nd Annual Meeting (No. 13-5039).

[16] Kumar, V., Bhat, C. R., Pendyala, R. M., You, D., Ben-Elia, E., & Ettema, D. (2016). "Impacts of incentive-based intervention on peak period traffic: experience from the Netherlands", Transportation Research Record: Journal of the Transportation Research Board, Volume 2543, pp.166-175. https://doi.org/10.3141/2543-20.

[17] Santos, G. (2008). London congestion charging. In G. Burtless and J. Rothenberg Pack (eds.), Brookings Wharton Papers on Urban Affairs: 2008, The Brookings Institution, pp.177–207.

[18] http://thisbigcity.net/five-cities-with-congestion-pricing - access date 17.3.2018

[19] Chu, J. (2011, October 28). Searching for balloons in a social network. Retrieved June 2016, from MIT News: http://news.mit.edu/2011/red-balloons-study-102811

[20] SETS North Africa (2016). "Towards wise cities: A data-driven approach for sustainable mobility", progress report, Dec, 2016, EG1609_Rep_En_00_Rev.1

[21] Abdulhai, B. (2013). Congestion Management in the GTHA: Balancing the Inverted Pendulum, an independent study, residential and civil construction alliance of Ontario (RCCAO)

[22] ECMT (2004), Assessment and Decision Making for Sustainable Transport, European Conference of Ministers of Transportation, Organization of Economic Coordination and Development

[23] Litman, T. (2007). "Developing indicators for comprehensive and sustainable transport planning", Transportation Research Record: Journal of the Transportation Research Board, pp.10-15. https://doi.org/10.3141/2017-02.

[24] Saleh, W., & Farrell, S. (2005). "Implications of congestion charging for departure time choice: work and non-work schedule flexibility", Transportation Research Part A: Policy and Practice, Volume 39(7-9), pp.773-791. https://doi.org/10.1016/j.tra.2005.02.016.

[25] Small, K. A. and Verhoef, E. T. (2007). The Economics of Urban Transportation. Abingdon, Oxon, England: Routledge. https://doi.org/10.4324/9780203642306.

[26] Hensher, D.A. and Button, K.J. (2000). "Handbook of Transport Modelling", Elsevier Science Ltd., Oxford, U.K., pp. 1-10.
[27] Khan, O. A. (2007). Modelling passenger mode choice behaviour using computer aided stated preference data, Doctoral dissertation, Queensland University of Technology.
[28] Ben-Akiva, M. E., Lerman, S. R., & Lerman, S. R. (1985). "Discrete choice analysis: theory and application to travel demand", MIT press, Massachusetts, U.S.A., Volume 9.
[29] Louviere, J.J., Hensher, D.A., Swait, J.D., (2000). Stated Choice Methods: Analysis and Application. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511753831.
[30] http://thisbigcity.net/five-cities-with-congestion-pricing - access date 17.3.2018
[31] http://inrix.com/press-releases/scorecard-2018-us - access date 19.3.2019
[32] Ettema, D., Knockaert, J., & Verhoef, E. (2010). "Using incentives as traffic management tool: empirical results of the" peak avoidance" experiment", Transportation Letters, Volume 2(1), pp.39-51. https://doi.org/10.3328/TL.2010.02.01.39-51.