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IMPROVING TRAFFIC CONGESTION ASSESSMENT BY USING FUZZY LOGIC APPROACH

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ABSTRACT

In a smart transport context, traffic density can usually only be calculated by monitoring traffic conditions in real time using heavy and expensive technical installations. In this paper, we present a new method for estimating traffic density based on a fuzzy logic approach. In addition, our method will allow the integration of urban planning aspects (built environment) in the planning of intelligent transportation initiatives. Indeed, the system we propose will allow to estimate the traffic density of an area through its urban characteristics. To do so, we will use three urban characteristics, namely distance to public transit, job accessibility, and land use distribution, as inputs for our fuzzy system. Our work confirms that urban form can perform an important role in reducing traffic density and thus minimizing the risk of congestion.

Keywords: *Smart Transport, Fuzzy logic, Urban form, Congestion, Traffic Density*

1. INTRODUCTION

Nowadays, traffic congestion is considered as the major concern of the leaders of most cities in the world. This situation is due, in part, to urban sprawl caused by the rapid urbanization of populations (growth in urban population, drivers, and vehicles) without being followed by the evolution of transport infrastructure or transport alternatives other than the car. Base on [1] we can define traffic congestion as a phenomenon of variable duration, caused by a mismatch between demand and supply of transport infrastructure, which induces an overflow of the road's capacity. Congestion has serious consequences on the economy (increase energy consumption, loss of time, reduced income, reduce production) and the environment (pollution, greenhouse gases). It can also lead to a loss of personal comfort and well-being and a reduction in mobility [1]. Figure 1 gives the main causes of congestion and classifies them into two categories. Recurring congestion, typically happens regularly during peak hours and can be predicted. It requires a planning of possible solutions to minimize it. And non-recurring congestion that happens when there are perturbations in the flow of traffic. Perturbation caused by unusual circumstances like crashes, special events, etc. It requires real-time control and monitoring of facilities and the road network in order to make the appropriate decision in the event of an incident

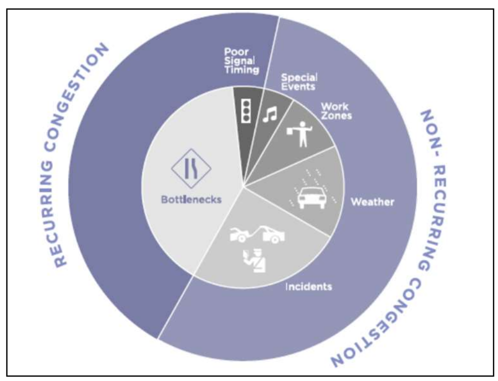

Figure 1 : Causes of Congestion [2]

To deal with this situation, several approaches have been adopted, including increasing the capacity of the infrastructure by building new roads but does not necessarily reduce traffic congestion [1]. The most cited approach in the last decade is the one based on new information technology, which aims at optimizing existing infrastructures and making it more efficient. This approach, based on technical installations, has emerged as a magic solution within the framework of what is commonly known as Smart Transport [3]. The principle is based on the observation of traffic conditions and the optimization of the use of infrastructures by regulating traffic at intersections, at traffic lights and on specific sections of roads. In this perspective, transport operators as well as city decision-makers have focused on the implementation of several families of traffic control and management solutions: intersection control and traffic management, emergency car prioritization, infrastructure monitoring and others [4]. However, the problem of congestion has many causes and cannot be solved just by monitoring and optimizing the infrastructure. Indeed, several studies particularly in the field of urban planning, have shown the existence of a direct or indirect relationship of interdependence between the urban form of the city (or region) and the travel behaviour of its residents [5][6]. Beyond the technical solutions for monitoring and regulating traffic, city decision-makers also need to understand the problem of congestion in all its aspects, to know its causes and how they can act on them to deal with the problem. This led us to ask the following questions: what are the causes of congestion? And to what extent can one act on these causes to address the issue?

In order to participate in answering these questions, we tray in this paper to study the relationship between the urban structure of the city and its traffic condition and we propose a method that express the traffic condition as a function of the variables defining the urban structure of each area.

In order to catch the concept of congestion and due to the absence of direct measures, proxy measures are used such as level of service, ratio of traffic volume to physical capacity and traffic density. This proxy measures are used in different smart transport application in order to allows transport managers to understand how easily people can reach their destinations; predict travel conditions on roads with a view to improving the reliability of road networks.

In our study, we will use traffic density as a proxy measure of traffic congestion because there is an interdependent relationship between congestion and traffic density [1]. In fact, the measurement of traffic density is a key element that will be combined with other parameters to determine the strategy to be adopted to avoid or minimize the risk of congestion in different areas of the city. Usually traffic density can only be calculated by monitoring real time traffic conditions using technical installations based on different families of sensors. The objective of this article is to provide a model that will allow to estimate the traffic density of each city area based only on its urban characteristics and without having to install any technical facilities. In this paper we propose a reference framework for mapping the traffic density of different city areas according to their urban characteristics. On the one hand, this approach will give city managers and transport operators a useful tool to deal with the urban growth and development and the related issues, particularly those concerning transport, by guiding urban planning and design. On the other hand, decisions will be more relevant and comprehensive (integrate urban characteristics into transport planning and investment decisions) making investment in Smart Transport Initiatives more effective and efficient.

The method we propose uses one of the tools of Artificial Intelligence (AI), namely Fuzzy Logic. This method deals with the uncertain and inaccurate data that characterises the handling of the issue of traffic density (it changes in a dynamic way which makes it very difficult, even impossible to estimate it in an exact way). What we propose here is based on expert knowledge in the fields of urban planning and transport. The aim of our work is to show that by using fuzzy logic we can estimate the traffic density in each city area considering its urban characteristics that define or influence the traffic conditions, particularly: distance to public transport, job accessibility and land use mix.

This article will try to help to answer the following questions: By knowing the urban characteristics of each city area can we identify the critical areas where the risk of congestion is important? And how useful can this knowledge be for city managers to address transport issues? How the city can be designed in such a way as to minimise the need to travel by private car and therefore minimise the risk of congestion?

2. METHODOLOGY

The aim of my work is to give city managers and transport operators a way to estimate the traffic density in their city and to help them in their decision-making regarding Smart Transport Initiatives. To do so, I will start with a brief overview of the Smart Transport concept and the importance of traffic condition assessment as one of the purposes of Smart Transport solutions and at the same time a factor that will determine the traffic regulation strategies to be implemented. Then I will introduce the main methods used to calculate this traffic density and show how these methods will be constraining and costly for the city. We will then present the main urban characteristics cited in scientific literature, as well as the main studies which demonstrate the extent to how these characteristics can influence the travel behaviour of city dwellers and consequently the state of traffic in the city. This

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will lead us to propose a method for estimating traffic density using one of the AI techniques which is Fuzzy Logic and taking as inputs the urban characteristics previously defined. In order to do so, we will first present the LF concept, its principles and rules of use, then we will define the input and output variables according to the needs of our study, the membership functions, the linguistic values, the result graphs and finally a simulation will be made. Then a discussion of the result will be given to highlight the advantages of this method without forgetting to cite its limitations. Finally, a conclusion will be drawn, opening up the perspectives of this research.

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3. RESULTS

3.1. Smart Transport a Response to City's Transport Problems

Urban growth poses many challenges for citizens and actors involved in the management of cities. These challenges can be grouped into the following categories: economy, governance, environment, health, education, security, transport and quality of life [3]. This rapid urbanisation trend will put a heavy strain on the city's transport infrastructure due to the growing need for people to travel (work, leisure, etc.), for goods transport and the increase in the number of vehicles.

However, cities are not in a position to install or build new facilities or roads to meet these needs, that lead to recurrent congestion and inadequate transport supply [1]. As a result, and given that cities' resources are limited and cannot keep up with the demands, the only remaining possibility is to make the existing infrastructure more efficient and effective [7]. That's where the Smart Transport concept fits in. Indeed, the principle of Smart Transport is to find out how, by exploiting the opportunities made available by ICT, we can make the facilities more efficient and traffic flow more smoothly and more safely.

For this purpose, it seems clear that the knowledge and assessment of the traffic conditions becomes an imperative to set up adequate strategies for traffic regulation. As described in [8], traffic estimation consists of an estimation of three main traffic parameters, namely speed, density and flow, based on traffic variables measured through one or more sensors. In addition, Road traffic density estimation provides important information for road planning, intelligent road routing, road traffic control, vehicular network traffic scheduling, routing and dissemination [9]. It is also clear that the risk of road congestion is closely linked to high traffic density. [10].

It is clear that traffic density (The congestion proxy measures that will be considered in this paper) is a factor that must not only be considered when designing smart transport solutions, but must also be continuously evaluated and monitored after their implementation. Traffic density is an important information to know before and after the implementation of a Smart transport solution. Before In order to identify the problems, we want to answer and after to adapt the strategies of control or regulation of the traffic in real time and also to follow and schedule the evolutions of these solutions.

3.2. Assessing Traffic Density: Methods and Discussion

3.2.1. Methods for assessing traffic density

In the context of any Smart transport project, the measurement of traffic density is a crucial parameter for choosing the transport management strategy to be implemented. Its calculation can be done by implementing solutions that monitor roads and collect data that can then be used to estimate this density. However, this method of estimation requires substantial installations in terms of the infrastructure required to collect the necessary data, various types of sensors, communication networks and software to process the data collected as well as the related installation costs. In this section we present a state of the art of the methods used to calculate this density. According to [4] we can categorize methods of density estimation in two main families:

The first family: based on fixed devices or sensors embedded in or beside the roadway. Different types of sensors are used (Doppler radar, infrared, inductive loop-based, ultrasonic sensor, roadside cameras) to count the number of vehicles passing through a given point. For example, the author in [13] provides real-time traffic density estimation using a smartphone equipped with a camera. In [14] the author presents an image-based learning method and a deep Convolutional Neural Network for density estimation. In [15] using video recordings of traffic, the author proposes a method for estimating average traffic density using a second-order divided difference Kalman Filter. We also can estimate the global density of an area (region or city) based on the calculation of the local density (in well identified places) using sensors. For example, in [12] the author proposes a method for estimating the traffic density (in large-scale urban freeway) of the entire road network based on the traffic flow theory by

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installing the sensors at specific points on the road network to collect local traffic information

The second family is relying on vehicular ad hoc networks (VANET) consisting of the exchange of information on the traffic conditions around probe cars equipped with wireless connections [7]. In [11] the author proposes the use of a probe vehicle that will allow, by communicating with neighbouring cars, to collect the necessary information to calculate the local traffic density. In [10] using the same method of the probe car the author provides a way of estimating global density based on the information collected from a vehicle cluster.

3.2.2. Discussion of methods

One can discuss on two axes. Firstly, as we have seen, most of the research attempts to measure traffic density in real time, which requires the setting-up of infrastructures and technical installations (sensors, communication networks, etc.) to collect traffic information and the setting-up of calculation platforms or image or video processing platforms to estimate traffic parameters (density, speed and flow). However, this type of solution is highly sensitive to technical failures and also affected by environmental conditions [16] [13], which may compromise their ability to provide reliable information. In addition, such systems require heavy and expensive installations and constant maintenance, and their large-scale deployment requires extremely large investments in communication and sensor infrastructure [17]. Secondly, in the case of solutions using probe cars, this assumes that the cars are equipped with VANET technology, which is not always possible, which limits the use of this method.

In a Smart Transport approach, the objective is not to implement technical solutions to calculate traffic density and apply strategies to deal with it. But it is necessary to combine this with a wider and deeper research of the causes and factors that determine this density to understand the transport issues as a whole and to allow city managers to be more aware of the interrelation between transport and the different fields, in particular urban planning. In addition, the emphasis on the technical aspect not only neglects important aspects of land use and transport relationships, but can also lead to the reduction of transport issues to technical problems. The objective of this article is to respond to this need and to propose a method for estimating traffic density that considers the urban characteristics (land use, built environment) that are likely to influence traffic conditions. This is what we will try to do in the next section.

3.3. Urban Form and Transport Relationship

Since the 1980s, extensive and sophisticated studies have focused on the impact of urban development (land use) on transport and, in particular, on the travel behaviour of city dwellers have multiplied [6]. These studies have focused on assessing the impact of the different components of urban form (individually or in a grouped manner) on the travel behaviour of residents. The aim of these studies is to demonstrate the extent to which urban development and urban planning can influence the travel behaviour of the residents of a city or region and thereby contribute to the improvement of the traffic conditions and its sustainability. In order to understand the relationship between these two domains (land use/urban form and transport), it was necessary to define measures and attributes which characterizes each area. In the literature, urban form has been expressed by five main attributes or variables (Density, Diversity, Design, Destination Accessibility and Distance to Transit). The description of these variables is resumed in table 1.

Table 1: Built Environment Variables ([6] and [18])

Variable	Definition
Density	Measured as the variable of interest (Population, employment) per unit of area
Diversity	Refers to the number of different land uses in a given region
Design	Involves the characteristics of the road network in a surface (block size, average street widths, numbers of pedestrian crossings)
Destination accessibility	Measures the convenience of travel to a destination. It may be regional (central business district, jobs) or local (school, retail shop).
Distance to transit	Is measured as the shortest distance to nearest transit stop. it may be measured as transit route density, distance between transit stops, or the number of stations per unit area

The oldest and most cited study is the one conducted by Newman and Kenworthy [19], which analysed 32 cities worldwide (10 in the USA and 22 worldwide) and showed that car use declines exponentially as urban density increases. In 1999 Kenworthy and Laube [20] had extended the study to include 46 cities, which showed that car use (in terms of kilometres travelled) is inversely related to urban density (person per hectare). In [21] the authors have shown that it is possible to reduce car dependency, but by ensuring a certain minimum urban intensity of 35 per hectare (inhabitants and jobs). In [22] the

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study has shown that there are potential benefits in reducing car travel through planning and design practices promoted by new forms of development like new urbanism (in neighbourhood scale) and smart growth (in city scale). These forms of development are characterised by "the intensification of urban development and attempts to limit growth beyond the urban edge. It encourages increases in density; mixed-use and cluster developments; a variety of housing types beyond detached units; protection of open space, agricultural lands and ecologically sensitive areas; the reduction in use of private and motorized forms of transport; the promotion of public transport systems; and the design and redesign of areas to support such use" [23]. In the meta-analysis of the existing literature in 2009 [6], authors found that destination accessibility (both for Job or downtown) combined with dense and compact development is the variable that substantially influences the VMT and encourages walking, which in other words limits car use. In [24] Ewing et al. extending the scope of the study (157 urban areas) and taking more variables into account, showed that the local neighbourhood density in the so-called compact urban areas alone cannot explain the decrease in VMT, but it is the accessibility of these neighbourhoods to the rest of the region. This implies that these variables have to be considered at both local and metropolitan or regional levels. They introduced another comprehensive metric which is compactness/ sprawl index widely used in the planning literature and measured by four factors—density, mixed use, degree of entering, and street connectivity—has a stronger relationship to per capita VMT. The travel impacts of neighbourhood characteristics are found to be significant in many studies even after controlling for the influence of residential self-selection [25]. In [26] after studying 127 of the major urban areas in the USA, the authors concluded that a centralised population and mezzo scale job-housing balance as well as a higher population density can significantly reduce VMT and CO2 emissions.

Through these studies, we have been able to observe the potential role that urban planning can play in reducing car dependency and consequently minimising traffic congestion. We have also observed that most of his research is based on statistical tools (principal component analysis (PCA), structural equation modelling, regression, correlation, elasticity). In the same perspective, and in order to explore the relationship between urban planning and transport we will propose another method based on one of the tools of artificial intelligence, which is the flow logic. In the following section, we present the fuzzy logic and its different components

3.4. Presentation of Fuzzy Logic

The concept of fuzzy subsets was first introduced by Professor Lofti A. Zadeh (University of California, Berkeley) in 1965. It was introduced as a tool to take into account the lack of strict specifications in many problems, uncertainties in knowledge and inaccuracies in measured quantities. [27]. It began to be used from the 1970s in the fields of industry and medicine, and then saw its widespread use in the 1990s in all sectors (automatic control systems, decision-making, diagnostics and robotics).

Fuzzy logic is based on the principle of fuzzy subsets. Its basic characteristics are linguistic variables, the universe of discourse, the function of membership and finally fuzzy subset as described in figure 2.

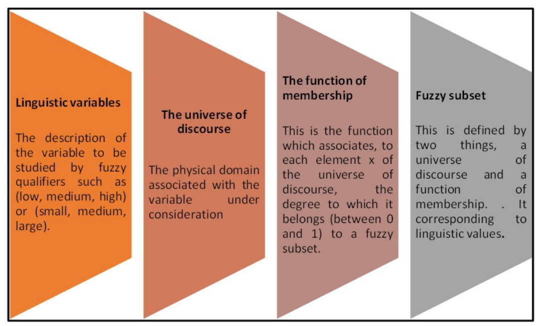

Figure 2: Basic characteristics of Fuzzy logic (developped by the author)

The components of a fuzzy logic system can be represented as followed (figure 3). In other word he operating principle of a fuzzy logic system consists of three phases, fuzzification, fuzzy inference engine and defuzzification.

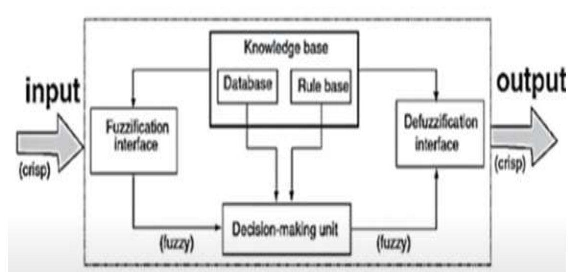

Figure 3: Fuzzy Inference System [28]

3.4.1. The fuzzification

This phase consists of transforming the real variables to be studied (input and output) into linguistic variables by assigning them degrees of membership to fuzzy subsets. In other words, it means matching and linking all possible inputs to fuzzy sets by associating degrees of membership to them. This operation allows the inputs of a system to be modelled in the form of curves called membership functions. In our case, we have four fuzzy subsets for input and output data. In the case of the "medium" fuzzy subset, this means that it is a density zone, which starts at 26 vehicle per Km, is fully realised between 32 vehicle per Km and 36 v/Km, and ceases at 42 v/Km and above (Figure 4).

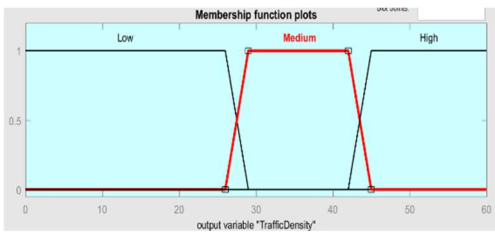

Figure 4: Example of Membership Function

3.4.2. The Fuzzy Inference engine

This is the phase that will generate the fuzzy outputs from the fuzzy inputs. This is the phase where we can most notice the presence of human reasoning in the fuzzy logic approach. Indeed, in a general way, this engine is built on knowledge bases which constitutes the basis of the inference rules [29]. These rules use linguistic variables to draw conclusions using the following syntax:

If Premises (Input) then Conclusion (Output).

Exemple: If the urban density is high then the traffic density is high.

The degree of truth of the consequence is calculated from that of the antecedent. If a rule has several antecedents, a fuzzy operator (And, OR) is used to obtain a single number that represents the degree of truth of the consequence. This is then applied to the membership function of the consequence.

After aggregating all the rules of the fuzzy system, the consequences obtained are fuzzy facts with degrees of membership. The result obtained is a composite membership function that does not correspond to any defined linguistic variable [27].

3.4.3. Defuzzification

Since the end result must be a concrete decision and the result of the inference is a fuzzy set, this fuzzy set must be transformed into a single net result that represents the output of the fuzzy system. This process is called Defuzzification [30]. Several methods are then applicable and some of the most commonly used include the method of the average of the maxima and the centre of gravity method. The first one refers to the average mean value of all the maxima of the output fuzzy set. The second one corresponds to the abscissa of the centre of gravity of the surface of the result curve.

3.5. Our Method of Traffic Density Estimation

Usually the traffic density is calculated after implementing ST technical solutions (installation of cameras, processing and calculation software) for the purpose of monitoring and regulating the traffic. However, knowing, studying and understanding the traffic situation (in our case the traffic density) in an urban area before the implementation of a ST solution, seems to us to be of paramount importance as it makes it possible to clearly identify the various factors that define or influence the traffic situation in the city on the one hand. On the other hand, it will enable us to clearly define and understand the problems of transport in the city by integrating all the aspects of the city (social, urban planning, economic, etc.). Therefore, the ability to understand this interaction between urban form and traffic density is paramount and crucial for any smart transport strategy. This is an essential step in order to better design a governance solution. The methods used so far only give an overall estimate of density, our method, which considers the structure and dynamics of the city, has the advantage of offering an understanding of the problem of congestion in relation to the different urban aspects of the city.

In this article we will introduce a new method for the calculation of traffic density at the level of an urban area based on fuzzy logic. In this paper we will use the terms "low", "medium" and "high" to describe the intensity of land use and the quality of public transport means in several fuzzy subsets and to derive the traffic density values according to the use of the urban area. We have seen in the literature how the five variables of urban form can significantly influence residents travel decisions, in particular car dependency. For our study, we will group these five variables into three factors: Distance to Transit, Destination Accessibility and Compactness, which is combination of the last three variables (density, diversity and design). Our aim is to assist the impacts of this three factors on congestion outcomes (density of traffic as proxy of congestion). Traffic density will be considered as indicator for the impact of land-use development and policy plans on resident travel behaviour and on traffic conditions in general. In the following we will describe these factors in more detail. These three dimensions of urban form provide an excellent framework for understanding how the physical characteristics of a neighbourhood can affect residents travel decisions, hence minimizing a problem of congestion.

3.5.1. Distance to Transit

Distance to Transit, Proximity to transit or Accessibility to transit, all of these three variables give the same signification: the availability of public transport in residence places as well as in workplaces. This reflects the ease with which local people can access public transit service and how it connects them to work and other services. It may be measured as transit stops (bus, train, etc.) density, transit route density, distance between transit stops or by distance to transit stops [18]. In our study we will use the further as a metric. This metric captures the amount of jobs, population, trip origins, or trip destinations within a certain radius of a transit stop. The radius often represents a reasonable distance that people are willing to walk to and from transit stops, typically between ¼ mile (400m) and ½ mile (800m) [31][32]. We have choose the following subset:

- ✓ High Distance to transit: when most of population and employment are located more than 10 min walking of transit stop (> 800 m).
- ✓ Medium Distance to transit: when most of population and employment are located between 8 min walking of transit stop (between 400 and 800 m)
- ✓ Low Distance to transit: when most of population and employment are located less than 5 min walking of transit stop that (<400 m)

3.5.2. Destination accessibility

As defined in [33] Accessibility refers to people's overall ability to reach desired services and activities (together called opportunities), and therefore the time and money that people and businesses must devote to transportation. The accessibility is focused on making it easier for individuals to reach destinations where they can meet daily needs such as work, recreation, shopping, and other forms of social exchange. It is a concept that is used by several scientific fields in particular transport planning, urban planning and geography. Accessibility is determined by both the transportation system and the land use pattern [34]. Thus, destination accessibility can be expressed differently from these two perspectives. From a transportation perspective, accessibility by the concept of mobility that refer to the actual movement of people (i.e., the actual distances travelled or the actual number of trips made) [34]. From the land use perspective, accessibility is represented by the concept of proximity that refer to the distances between destinations. In other word improving mobility - via automobile, transit, or any other travel mode - means facilitating faster travel speeds. And improving proximity means shortening distances between trip origins and destinations. According to [32] Destination accessibility can be measured in terms of travel time with which travellers can access their destinations from home or from a given point of departure. Thus, in this paper, destination accessibility is measured in terms of the time (travel time) it takes to get to the essential destinations (Job, Health care facilities, Schools, Supermarkets) to which households regularly travel in transit mode. In developing countries, the majority of travel is for work reasons. Therefore, we will restrict our study on accessibility to jobs and we will use 45 min from origin location as a travel time threshold based on [30] who define this value through the observation of the travel behaviour. It is clear that accessibility decrease as travel time increase. We have choose the following subset:

- ✓ High Transit time to Job: a trip that require more than 45 min in transit
- ✓ Medium Transit time to Job: a trip that require above 30 min in transit
- ✓ high Transit time to Job : a trip that require above 15 min in transit

3.5.3. Land use mix

In the last two decades, there has been a new trend against modernist urban forms and urban sprawl, both of which are heavily car-dependent, pedestrian-unfriendly and environmentally non-sustainable [35]. Indeed, the 'smart growth' [23] movement has promoted the creation of a more compact and integrated urban development. It encourages, among other things, mixed-use developments; the reduction of the use of private and motorised modes of transport and the promotion of public transport systems. Therefore, mixed-use development become an important concern in town and country planning considerations. The purpose of mixed-use development is to design land uses in a complementary manner that are close to each other. Complementary uses can encompass residential, retail, public facilities, workspaces and service uses destinations to which people regularly travel [36]. We choose in our study to use this variable because many studies [18][37][38][39] in urban planning have shown that a high degree of land use mix (bringing activities closer together) can reduce the length of journeys, allowing people to walk and cycle rather than drive, and increasing the possibilities for combining journeys. In addition, facilitating access to employment and shopping through walking and cycling reduces the need to own a car for personal mobility [36]. Measures of Land use mix refer to the number of different land

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uses in a given area and their degree of balance and the method of measurement depends in part on the scale of analysis. There are several measures of land use mix, a full discussion is provided in [40] and the references therein. In this paper, we use Balance Index measure. Balance Index measures the extent to which two different types of land uses or activities are in balance with each other in an area. In our study we chose to use the ratio of Job to housing as proxy of land use mix. By fitting the Balance Index (BI) equation of [40] to our case, we obtain the following formula (1):

$$BI = 1 - \frac{|H-J|}{H+J} \tag{1}$$

Where H is amount of Housing in considered area and J is amount of jobs in considered area. The Balance Index ranges from 0 to 1 with higher values associated with greater land use mix, i.e. greater levels of balance [40]. It is clear that have the same level of job and housing make land use mix higher.
For this factor we have choose the following subset:

- ✓ High Land use mix: when BI is high than 0,8
- ✓ Moderate Land use mix: when the BI amount 0,6
- ✓ Low Land use mix: when the BI is low than 0,4

3.5.4. Traffic Density

Congestion is can be defined as the mismatch between the capacity of the road and the flow of traffic through it. In other words, congestion occurs when the number of vehicles wanting to pass through a road exceeds its capacity. For this reason, we have considered that the measure of traffic density is the most representative attribute of traffic conditions and congestion in particular. The output variable of our study is traffic density. Based on [16] and [2], density traffic can be defined as a number of vehicles occupying a length of roadway. It is obvious to note that if the density is low, then the traffic is smooth. The following Table 2 summarises the three categories of traffic conditions.

Table 2: Traffic Flow Conditions (Adapted from [16])

Traffic density (vehicle/line-Km)	Flow conditions
0-26	Uncongested
26-42	Near capacity
42-62 or higher	Congested

So fuzzy subsets for our output will be as follow:

- ✓ Low density : from 0 to 26 vehicles per line-Km
- ✓ Medium density: from 26 to 42 vehicles per lane-Km
- ✓ High density: higher than 42 vehicles per lane-Km

3.5.5. Overview of our Fuzzy System

Through the above, we built our fuzzy system. Fuzzy subset of our system have the linguistic expression: High, Medium and Low. Corresponding membership functions of input and variables are represented in the Figure 5 and Figure 6 give an example of some inference rules of our fuzzy system.

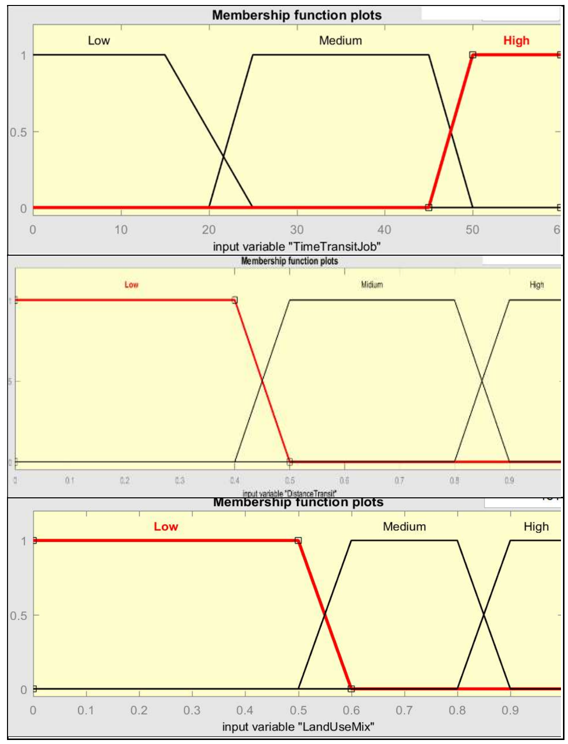

Figure 5 Exemple of Membership Functions

4. If (DistanceTransit is Low) and (TimeTransitJob is Medium) and (LandUseMix is Low) then (TrafficDensity is Medium) (1)
5. If (DistanceTransit is Low) and (TimeTransitJob is Medium) and (LandUseMix is Medium) then (TrafficDensity is Low) (1)
6. If (DistanceTransit is Low) and (TimeTransitJob is Medium) and (LandUseMix is High) then (TrafficDensity is Low) (1)
16. If (DistanceTransit is Midium) and (TimeTransitJob is High) and (LandUseMix is Low) then (TrafficDensity is High) (1)
17. If (DistanceTransit is Midium) and (TimeTransitJob is High) and (LandUseMix is Medium) then (TrafficDensity is Medium) (1)
18. If (DistanceTransit is Midium) and (TimeTransitJob is High) and (LandUseMix is High) then (TrafficDensity is Medium) (1)
19. If (DistanceTransit is High) and (TimeTransitJob is Low) and (LandUseMix is Low) then (TrafficDensity is Medium) (1)
20. If (DistanceTransit is High) and (TimeTransitJob is Low) and (LandUseMix is Medium) then (TrafficDensity is Medium) (1)
21. If (DistanceTransit is High) and (TimeTransitJob is Low) and (LandUseMix is High) then (TrafficDensity is Low) (1)

Figure 6 Exemple of Inference Rules

4. DISCUSSION

4.1. Results interpretation

After building our inference system, we will now be able to read, interpret and analyse the results of the defuzzification. The interpretation of the graphs will allow us to understand the relationship between the three urban form variables that we have chosen for our study and the traffic density. In order to do this we will comment on the three following use cases.

4.1.1. Use case N°1: Average TimeTransitJob

We will analyse the reaction of our system if we assign the "job accessibility" factor an average value (30 min). The goal of this case is to see to what extent each of the two remaining factors can have an individual and collective impact on car dependency and consequently on traffic density.

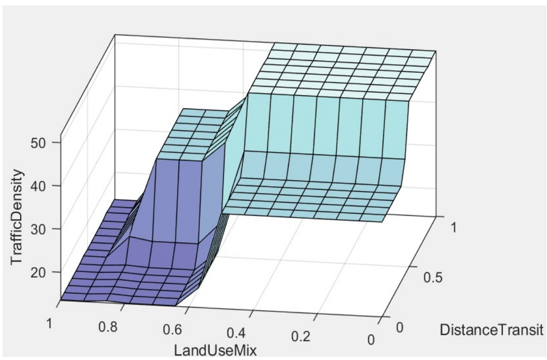

Figure 7: Surface View for Use Case N°1

According to the figure 7, we can see that there are three stages. The first one (stage 1) is in the case where the traffic density is low. This case is characterized by a high land use (whatever the distance to transit) or a medium land use but with short distance to transit. The second stage (stage 2) is the case where the density is medium.

This situation is conditioned by the fact that the land use is medium or low but with a short distance to transit as well. The last stage (Stage 3) represents the case where the density is high. This case occurs when we have a low land use mix combined with a medium or high distance to transit. The following Table 3 summarizes this discussion.

Table 3: Traffic Density Stages For Use Case N°1

Land Use Mix / Distance to Transit	Low	Medium	High
Low	Stage 2	Stage 1	Stage 1
Medium	Stage 3	Stage 2	Stage 1
High	Stage 3	Stage 2	Stage 1

As we can see in the Figure 8, when the land use mix is high the density tends to remain in the low values (amount 24) whatever the distance to transit is high. This use case shows the crucial role of the mix of uses. Indeed, quality transport with access to transport cannot lead to a significant decrease in traffic density unless there is a reasonable (average) mix of uses, otherwise the risk of congestion is always high.

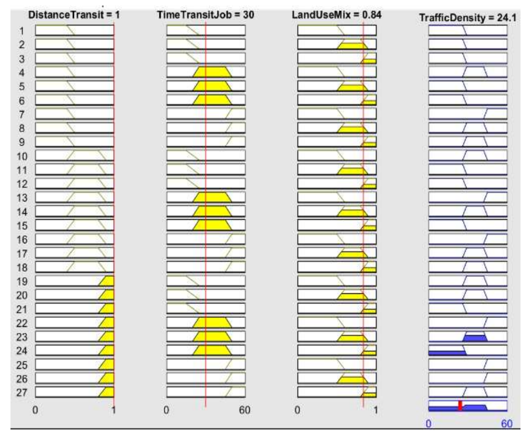

Figure 8: Rules View for High Both LandUseMix and DistanceTransit

4.1.2. Use case N°2: average DistanceToTransit

We will analyse the reaction of our system if we assign the "Distance to Transit" factor an average value (600 m).

As can be seen in Figure 9 and summarized in Table 4, this case study also presents three very salient stages. Indeed, when land use mix is high and the time transit job remains low or medium the traffic density remains low. However, contrary to use case N°1, when the time transit job is high, the traffic density increases and becomes medium. When the land-use is medium, two situations arise if the time transit job is short, then the traffic density remains low. Otherwise the density passes to the second level (about 35). When the land-use is low then the density can only be medium or high; medium in the case where the Time Transit Job is short and high when the time transit job becomes medium or high.

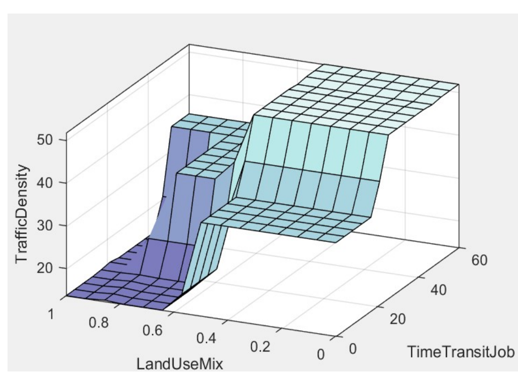

Figure 9: Surface View of Use Case N°2

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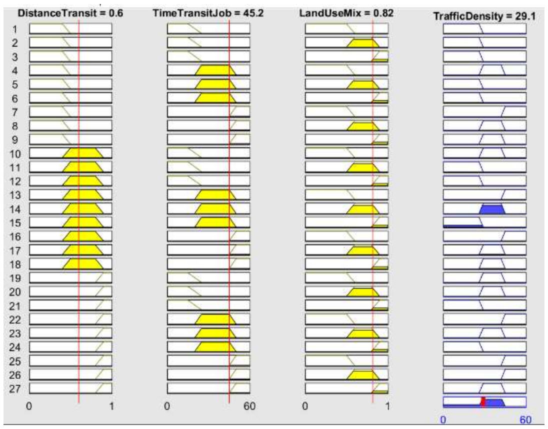

Figure 10: Rules View for High LandUseMix and TimeTransitJob

As we mentioned in the first case, the mixture of land use promotes what we so-called soft modes of transport (walking and biking). If we combine this with a correct level of accessibility to work via transit, we can say that the use of private cars will be greatly reduced, thus reducing the risk of congestion.

Table 4: Traffic Density Stages For Use Case N°2

TimeTransit Job \ Land Use Mix	Low	Medium	High
Low	Stage 2	Stage 1	Stage 1
Medium	Stage 3	Stage 2	Stage 1
High	Stage 3	Stage 2	Stage 2

In this use case, we note that as soon as the values of the two factors "Land use mix" and "Time transit job" are averaged, traffic density tends to remain medium. But when the variable land use mix is a somewhat high, as we can see in the figure 10, then even if the distance to job is a slightly high (around 45 min), the density remains in the low subgroup (about 29).

4.1.3. Use case N°3: Average Land Use Mix

We will analyse the reaction of our system regarding to the variable of the land use mix.

When the jobs are located far from the residences, two cases may arise in order to get to the workplace. The first one is to use transit, but in this case the two other variables of our study must support this choice. In other words, the transit time to job must be acceptable (in the medium subset) and at the same time the distance to transit must also be acceptable and accessible by walking or cycling. As we can see in Figure 11, in this case we can expect to have a traffic density in the high-range of the low subset. In the second case- Figure 12-, if transport quality is low (high transit time to job) and accessibility to transit is low also (high distance to transit), then the remaining choice is the use of the private car, which induces high traffic density, that represents a very high risk of traffic congestion.

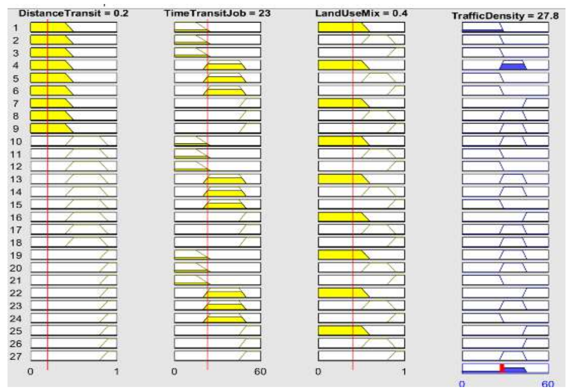

Figure 11: Rules View for Low LandUseMix and Good TimeTransitJob

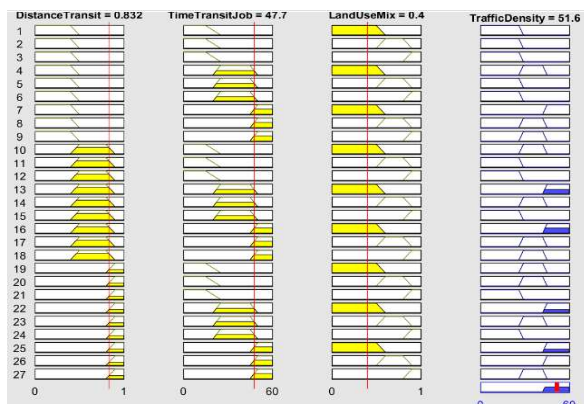

Figure 12: Rules View for Low LandUseMix and Low TimeTransitJob

As we can see in in Figure 13 and as we summarised in table 5, when we set the variable land use mix to a medium value (0.7), we can note as long as the remaining two variables (Job and transit accessibility) have low or medium values, the traffic density remains low. Even when one of them take high values, the traffic density also remains medium.

Table 5 : Traffic Density Stages For Use Case N°3

Time Transit Job \ DistanceTo Transit	Low	Medium	High
Low	Stage 1	Stage 1	Stage 2
Medium	Stage 1	Stage 1	Stage 2
High	Stage 2	Stage 2	Stage 3

However, when both of them have very high values at the same time then the traffic density takes a high value. We can state that an area with an average land use mix can expect a very average or even low traffic density as long as the two other variables do not take very high values at the same time.

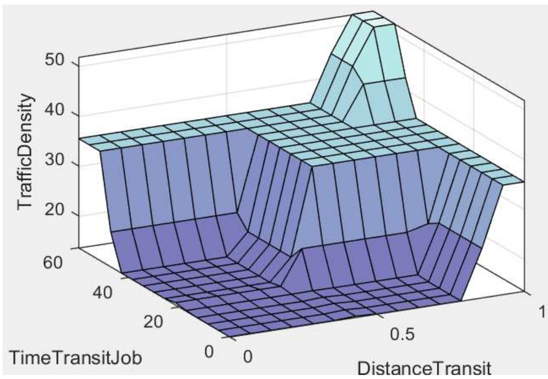

Figure 13: Surface View of Use Case N°3

Our result is in accordance with several studies in particular [18] and [36]. Indeed, when places of employment and residence are close to each other, people will be encouraged to use gentler modes of transport, walking and cycling to work, which improves traffic conditions and minimizes car dependency.

From the above we can conclude that a compact city or the mix of population, jobs, activities and facilities, as well as a neighbourhood accessibility can reduce the number of journeys, encourage walking and biking and consequently reduce the use of the private car. This finding is supported by research results [34][36] which state that the mix of uses favours walking and biking which reduces car dependency and also by [21] that notice that an increased number of jobs compared to the resident population was associated with reporting a reduction in car use.

4-2 The contribution and limitations of our paper

In most cases, the traffic density is calculated based on observation of road conditions using different techniques (for observation) and different methods for calculation [section 3-2]. There are causes of congestion which will have technical solutions, however there are others which can only be resolved through spatial planning solutions for areas, activities (mixed use, urban design, construction of new roads) or temporal (adjustment of the schedules of certain activities). The originality of our method for estimating traffic density is, firstly, that it can be useful upstream for any Smart Transport initiative. Secondly, it is not satisfied with merely observing and recording traffic but goes beyond them and takes into account several factors (to understand the sources of high density) and to predict traffic density. Finally, it allows the mapping of this density according to the urban characteristics of the zone.

The objective is not to limit itself to observing and reacting to this situation, but to go further and be proactive by identifying the different factors that determine or influence the level of traffic density and to study how the combination of these factors can define and influence the traffic conditions. This will give city managers a holistic view on the management of their city, and will allow them to develop Smart Transport and Planning policies by:

- ✓ encouraging sustainable modes of transport (walking and cycling) that are environmentally friendly ;
- ✓ improving the health of citizens by promoting walking and cycling, which will enable them to engage in physical activity while travelling;
- ✓ improving the use of public transport;
- ✓ Promoting mixed activities and social inclusion by mixing different types of housing and activities;
- ✓ Redeveloping less densely populated areas to encourage the settlement of residents and companies;
- ✓ Reorganization/ redevelopment of areas to create a balance in the need for mobility between different areas of the city.

Through our work, we can say that if the city is able to offer opportunity for transit, walking and cycling it could lead to changes in travel behaviour of dependence on the car. In other words, the urban environment influences the attitude of travel and mobility [36]. Our work can advise decision-makers on the forms of urban development which may lead to a limitation of travel by private car and consequently reduce congestion.

However, our work was limited by the fact that we did not consider all urban characteristics that the scientific literature has shown to have a proven influence on travel behaviour. We only studied three of the five; in addition, we only dealt with one aspect of each variable. For the first variable, distance to transit, we have processed only the distance to the nearest stop while the variable can be considered by the density of stops in a zone. For the second variable, we have considered that access to work via transit while the variable can be used for other activities (work, administration, school, shop,..) as well as for other modes of transport (car, bicycle, walking, carpooling). For the land use mix, we have limited ourselves to the work-housing mix, this same variable can consider different types of land use (job, housing, leisure, commerce, health, school, etc.) from two perspectives, in terms of quantity and proximity.

5. CONCLUSION AND PERSPECTIVES

City planning and transport management is not an easy task. It has to be of great importance, it has to think about planning the city in such a way as to minimise the risk of congestion by implementing an intelligent transport strategy that deals with the transport problem as a whole and its interaction with the other areas of the city: social, urban planning, economic and others. In this paper, we presented existing solutions that seek to optimize the use of infrastructure and showed their limitations in that they require costly technical installations and do not offer city decision-makers the opportunity to understand the sources of the congestion problem and the factors that determine and promote it. Then we have presented the studies that show the relationship between urban characteristics (5Ds) and traffic conditions in an urban area. In order to reconcile the two domains (transport and urban planning), we have proposed a framework that will allow city decision-makers to have a global understanding of the traffic problem, before embarking on heavy investments under the name of the Smart Transport Initiative. This work aims also to liberate the concept of smart transport from the technical domination by opening it up to other and more exhausting horizons. In this perspective, the Smart transport concept can include not only the technical aspects but also environmental, social, urban and other aspects. To do this we have use a very powerful tool of Artificial Intelligence that is the Fuzzy Logic. We built an inference system that allowed us to assess to what extent urban features influence traffic conditions. We used three urban variables as inputs to our system, namely distance to Transit, Job Accessibility (Time Transit to Job) and land use mix. Our system provides us with the traffic density as an output. As a result, we were able to observe that a mix of land uses, as well as a high accessibility to job and a low distance to transit can not only favour the use of soft modes (walking and cycling), but minimize the use of the private car, and therefore minimize the risk of traffic congestion. Our work offers city decision-makers an alternative way of thinking about the city in order to make it smart in terms of transportation by reducing the dependence of city dwellers from the private car and promoting public transportation and sustainable modes of transport.

In perspective and to give more completeness to our current work, our next work will focus on the integration of other urban variables on the one hand. On the other hand, we will try to test the robustness of our fuzzy model as a tool for quantifying traffic density by comparing it with an empirical model.

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