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Urban Traffic Routing Using Weighted Multi-Map Strategies

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ABSTRACT Urban traffic routing has to deal with individual mobility and collective wellness considering citizens, multi-modal transport, and fleet traffic with conflicting interests such as electric vehicles, local distribution, public transport, and private vehicles. Different interests, goals, and regulations, suggest the development of new multi-objective routing mechanisms which may improve traffic flow. In this work, *Traffic Weighted Multi-Maps (TWM)* is presented as a novel traffic routing mechanism based on the strategical generation and distribution of complementary cost maps for traffic fleets, oriented towards the application of differentiated traffic planning and control policies. TWM is built upon a centralized control architecture, where a Traffic Management Center generates and distributes customized cost maps of the road network. These maps are used individually to calculate routes. In this research, we present the TWM theoretical model and experimental results based on microscopic simulations over a real city traffic network under multiple scenarios, including traffic incidents management. Experimental evaluation takes into account driver's adherence to the system and considers a multi-objective analysis both for the global network parameters (congestion, travel time, and route length) and for the subjective driving experience. Experimental results deliver performance improvements from 20% to 50%. TWM is fully compatible with existing traffic routing systems and has promising future evolution applying new algorithms, policies and network profiles.

INDEX TERMS Dynamic traffic assignment, traffic control, traffic simulation, vehicle routing, traffic big data, decision making, multi-agent systems, multi-map routing, TWM.

I. INTRODUCTION

Modelling and design of traffic management systems and services have still important challenges to address, such as matching multi-objective demand and resources in an optimal and automated way. In one side *Traffic Control Systems (TCS)* measure and react over the traffic network (resources) to coordinate traffic demand by means of signaling systems, traffic information panels, and regulatory policies and restrictions [36]. In the other side, we have vehicles represented by their traffic agents, that plan routes dynamically, and react in real time to traffic data input: traffic network status, signaling directives and congestion information [35].

The need of individual route generation and dynamic re-planning from a TCS has been addressed by many different approaches and commercial proposals [1], [2], [5], [30]. Many of them require complex architectures and intense computing resources, raising as well important privacy concerns.

From the driver perspective, the main objectives are to reduce and minimize travel time and route cost, considering risk-aversion and time-bounding (predictability). New mobility paradigms for smart-cities and Urban Computing concept [51] also focus on collective objectives considering citizens, multi-modal mobility, and conflicting group interests: safety, electric mobility, car-sharing, air pollution, noise footprint, special fleets requirements, scheduled traffic constraints, geo-fenced policies, event planning and fast reaction, and public transportation.

Optimal traffic planning in TCS must consider and handle all these factors, implementing new multi-objective cost functions and the corresponding control models. This smart mobility management may be enabled by the use of big data techniques [25], [26] that handle the dynamic generation of tons of information from city sensors and mobile agents on devices.

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Our research is based on the fact that a traffic map is not the same as the traffic network but just a representation of it, a view. This view describes both physical features (lanes, distances, lat/long, etc) and logical features that are conventions (lane directionality, speed, time-restrictions, weights, etc). We propose a novel traffic route guidance model called *TWM -Traffic Weighted Multimaps-* based on the generation and distribution of complementary cost maps for traffic collectives (vehicles groups and/or fleets), oriented towards the application of differentiated traffic planning and control policies. TWM takes into account that traffic collectives may have different interests, policies, and constraints, so it makes sense to offer them differentiated network views (maps).

TWM proposes the distribution of multiple maps with different link weights, based not only on speed but also on the result of applying a multi-objective cost function. Optimization in TWM is achieved by a) finding the optimal weight values and map sets for the defined traffic groups, and b) considering that only a percentage of drivers are going to use or follow the recommendations. Individuals belonging to the same group (fleet) share a group of maps. This group and time assignment reduces the computational complexity of the approach. There is a trade-off between individual optimal route and global objectives fulfillment. In our research we show how the aggregation of individual decisions tends to satisfy the predefined control policy.

Traffic Weighted Multimaps approach is shown to be technically feasible and easy to deploy, being compatible with current platforms and navigation systems. It requires few resources to be implemented, and preserves individual's privacy. Compatibility with existing routing frameworks based on route-queries for origin/destination (O/D) is obvious, as TWM can be applied at the TCS back-end when the user asks for a route or an hyper-path.

Global traffic optimization may be then achieved by means of TWM generation algorithms, based on data-driven with machine learning approaches and predictive control techniques. In this paper we focus on the effects of multimaps on travel time and route length using randomly generated weights for traffic dispersion in real urban traffic network. We study both global effects and individual perceptions.

The main contributions of this paper include: (1) a novel traffic route guidance model based on multimap distribution that enable differentiated route selection for individuals and collectives; (2) a microscopic simulation framework for TWM evaluation and algorithm comparisons; (3) impact analysis of TWM in congestion scenarios; (4) TWM usage proposal for incident management, and (5) experimental results based on simulations over a real urban network. The research has promising future evolution applying TWM calculation algorithms, distribution policies and network profiles.

The paper is organized as follows: first we review previous studies and similar references, then we present the conceptual framework that we will use throughout the paper. After that, we present a real traffic network (Alcala de Henares, a Spanish mid-size city) with real multi-fleet demands. The experiments show the TWM positive effects on global network congestion indicators, and on individual driving experiences. To conclude, the paper analyses simulations of traffic incidents in real city scenarios and how they are addressed by ad-hoc multi-maps to avoid congestions and enhance end-user experience. Finally we present our conclusions and show future research lines on the TWM topic.

A. BACKGROUND

We introduced TWM in [38] as a very preliminary proof of concept of congestion mitigation mechanism for a synthetic 16x16 grid network. *TWM* are created by a *TMC (Traffic Management Center)*, which enables intelligent congestion control as a global concern together with individual routing needs.

Global parameters such as pollution level, noise footprint, prioritization of vehicle type, contingency plans, etc, are well described in [8], [9]. Individual intention-aware routing proposals can be found at [13] and [46], that are sometimes used for predictive routing [12] and [16]. There are other works that propose collaborative RGS (Routing Guidance Systems) systems fed by a traffic control center using Big Data mechanisms to compute mobility management policies in both distributed and centralized schemes [27], [40], [44]. They usually require permanent inter-connectivity between vehicles and authorities.

In the same way, there are many multi-agent traffic management proposals such as those reviewed in [7], [10], [35]. They use different approaches such as automatic negotiation, distributed optimization, predictive routing, predictive control, and others [31], [32]. Genetic algorithms are also used for cooperative vehicle coordination as described in [14], [15]. Electric vehicles and their concerns related to charging stations, receive specific attention and several works deal with them [44], [48].

TWM is fully compatible with the hyper-path concept, where individual traffic agents receive for each origin and destination not a single route but a tree of alternatives [11], [23], [34], [41]. Hyper-path route calculus considers the uncertainty and variability of traffic dynamics, and uses mainly historical data as traffic behavior patterns where different analysis methods can be applied [19], [29], [33]. Hyper-path calculus to synthesize the pre-trips require a lot of back-end computing while receiving data streaming for the network and the mobile agents, and also en-route distribution is required to the distribution servers. TWM is complementary to hyper-paths providing different network views for the individuals of any traffic class. This network view can be used for the hyper-path calculus. TWM is multi-purpose and combines individual, group and global policies, in contrast with hyper-path that is conceived for individual risk-averse policies design (minimizing travel-time variance).

TWM relies on a traffic control system architecture which may implement a distributed control in closed loop of routes for the vehicles [30], [37], with capacities of planning

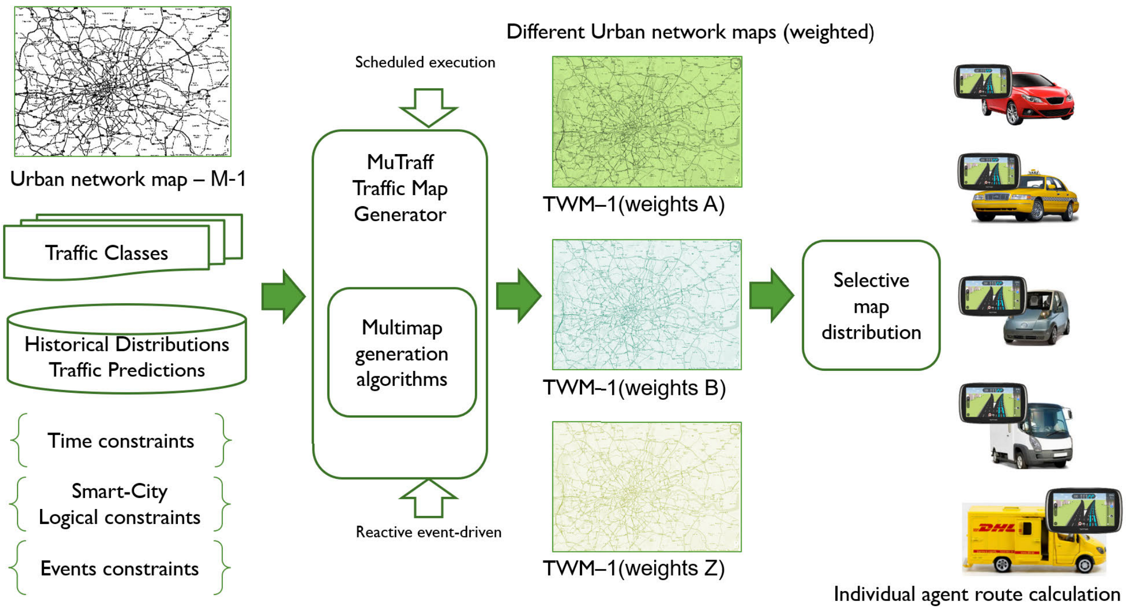

FIGURE 1. Overview of TWM generation and distribution model.

and re-planning. There is no individual feedback about selected route or current trip (no microscopic feedback) but there is mesoscopic feedback collected through standard sensors and cameras that provide measures about traffic congestion and speeds.

Most of the navigation systems (RGS) that operate today suggest the shortest route and hyper-path, derived from real-time traffic density information and historical data [1], [2], [5], [6]. Traffic agents use these recommendations to make their individual decisions based on this common information: they use the same network view and the same traffic data. Agents that are traveling from similar origin/destination or just share common paths will take very similar decisions, causing traffic congestion to be transferred. This is the so-called "*common resource distribution problem*", from which the so-called "*Minority Game*" or "*Farol Bar Problem*" [43] derives. It is therefore clear that there is a need for more precise control of vehicle routes, that requires precise individuals feedback and/or highly distributed sensor networks [24], [42], [50]. This control could be exercised through individualised management at the microscopic level of each route. However, microscopic control entails problems of scalability, deployment and privacy, so TWM proposes an alternative, scalable, non-disruptive control and management methodology with low communication load, limited feedback and thus fewer implications for users' privacy.

Similar strategies have been used with IP routing protocols (MSTP) and SDN networks [18], [22], [28], [39]. These IP traffic engineering techniques assume that the network operators modify link-weights dynamically to achieve routing paths that obtain the required traffic goals (such as latency and congestion).

Our architecture proposal uses a big-data module based on data lake pattern where all the activity is stored in a log-oriented basis. It enables inference of historical traffic patterns that are used to calculate and design TWM. References [17], [21], [45] have recently proposed similar approaches for data-clustering and pattern detection.

II. DEFINITIONS

A. TWM - TRAFFIC WEIGHTED MULTIMAPS

A TMC can generate differentiated network maps for every traffic group of agents (fleets), using cost functions that assign weights to the links of the network, just altering the max speed concept (that is in fact a fixed cost function). Moreover, it could provide time-dependent maps valid only for certain time frames.

These maps can be created considering several sources: historical data, real-time traffic data, real-time events affecting mobility (non-traffic data, but affecting the demand, such as sport events, critical incidents and others), and of course, synthetic data extracted from big-data sources. Figure 1 illustrates the basics for TWM generation.

Instead of having a heavy set of regulation, signaling, geo-fenced constraints that every individual should process, evaluate, and execute, it is easier to have them collected into traffic map collections that are used by the individuals for route selection.

TWM generation is executed in two possible time-policies: 1) in a scheduled way following traffic density loads (daily and hourly in a typical configuration), 2) in a reactive way, conditioned by events (incidental or planned ones).

These multimaps provide a different routing weights set for each fleet at each edge. For instance, a city center will have different network map sets for the fleets taxi, electric vehicles, logistic distributions, and conventional cars. The edge weights will be different for each fleet, promoting or penalizing traffic for each edge. Of course, these maps can be static or time-dynamic, depending on multiple strategies.

O/D route calculation can be generated by the individuals using the network maps and the navigation application, but also can be generated by a TCS that receives the origin-destination requests for route and delivers a set of possible routes [30]. In both cases, multimap approach is valid as it considers optimal route evaluation against a weighted map. It is always the individual who decides which route/path to use.

As stated above, traffic classes are subsets of mobile elements (that we will call fleets) that share similar a) traffic goals, b) network constraints, c) regulations, d) traffic indicators and e) individual behaviors.

Privacy and data protection are main concerns in modern routing systems [20]. TWM prevents individual data exposure, as the traffic agent self-qualifies for a fleet that is used for map selection upon those distributed in the TWM. For the server-side route recommendation mode, the agent should provide its fleet qualification in order to obtain the corresponding TWM for it.

B. MODEL FORMULATION

TWM can be expressed by a formulation including the multimap, routing and agent perspectives. Together with the formulation, we include as well the simulation model that is used in the experimental part of the paper. Table 1 summarizes basic TWM notation.

1) TWM MULTIMAPS

A TWM multimap function Π (1) takes as inputs a traffic network Θ, a set of traffic groups $[\Omega_k]$ (called *fleets*), a set of time constraints $\Gamma_{k,m}$ and a dynamic view Φ of the traffic usage of the network, in order to obtain a set of network maps $[\mu_{k,m}]$.

$$\Pi : \Theta, \quad [\Omega_k], \ [\Gamma_{k,m}], \ \Phi \rightarrow [\mu_{k.m}] \tag{1}$$

In this paper we address static traffic routing with TWM, leaving the dynamic routing based on Φ using different routing algorithms (not only Dijstra) for future works.

In general, each traffic group Ω_k has a set of map instances $[\mu_{k,m}]$ as a customized representation of the traffic network Θ, under certain time constraints $[\Gamma_{k,m}]$. There are two main types of time constraints $[\Gamma_{k,m}]$: those formed by periodic scheduled constraints (i.e. traffic restrictions over certain hours) and eventual time constraints (i.e. works, demonstrations, etc).

Urban areas Θ have a standard traffic network representation (2) formed by a directed graph of geographical nodes η_n connected by edges, being each edge $\epsilon_{i,j}$ a set of links (lanes) that connects nodes η_i and η_j with a weight $\beta_{i,j}^{k,m}$ as expressed by the tuple:

$$\Theta = \{[\eta_n], [\epsilon_{i,j}]\} \tag{2}$$

TABLE 1. Notation summary.

Θ: Urban network representation.
Φ: Traffic density data of the urban network.
Ω_k :Traffic vehicle grouping (fleet) for using TWM.
Ω_0: Generic vehicle group for TWM-unclassified vehicles.
$[\mu_{k,m}]$: TWM multimap for urban network Θ.
$\mu_{k,m}$: Single map instance *(m)* for vehicle group Ω_k. A group may use several maps.
Π: multimap weight evaluation functions.
Π_{std}: Standard map weight evaluation functions.
Π_δ: Traffic weight evaluation function used for TWM creation (*).
(*)δ indicates the weighting factor based on a distribution function, an optimization algorithm, or any other weighting criteria.)
$\Gamma_{k,m}$: Time constraints for map $\mu_{k,m}$.
η_n: Traffic network node for area inside traffic network Θ.
$\epsilon_{i,j}$: Edge connecting nodes η_i and η_j.
$\beta_{i,j}^{k,m}$: Traffic weight for edge $\epsilon_{i,j}$ for map $\mu_{k,m}$.
$S_{i,j}$: max speed for edge $\epsilon_{i,j}$.
$[v_a^k]$: Vehicle population.
Δ_{m}: TAZ, traffic assignment zone.
ψ_k: TWM adherence factor of fleet Ω_k.
W_a^k: Individual trip of vehicle v_a^k from origin O_i to destination D_j.
$[P_a^k]$: Sets of planned stops for the trip W_a^k.
$R_a^{k,m}$: Route selected at vehicle v_a^k for its trip W_a^k using the map $\mu_{k,m}$.
f : Routing algorithm: Dijkstra, A*, etc.
RL_a^k: route length for vehicle v_a^k for its trip W_a^k.
TT_a^k: travel-time for vehicle v_a^k for its trip W_a^k.
STT_a^k: total congested time for vehicle v_a^k for its trip W_a^k.
MTT_a^k: total non-congested time for vehicle v_a^k for its trip W_a^k.
DTD: Ratio of completed traffic demand.
NHD: Halted demand of vehicles.
TTS: Total travel-time spent by the vehicles during the period.
THS: Total halted travel-time spent by the vehicles during the period.
VKT: Cumulative route lengths of trips.
TTC: Individual travel-time improvement when using TWM.
RLC: Individual trip-length improvement when using TWM.

$$\epsilon_{i,j} = \left(\eta_i, \eta_j, \beta_{i,j}^{k,m}\right) \tag{3}$$

Each TWM map $\mu_{k.m}$ is an instance of specific values for each weight $\beta_{i,j}^{k,m}$. As a proof of concept we propose a multi-map Π_{std} that just considers linear scaling α of link-speed $S_{i,j}$ for providing each edge weight $\beta_{i,j}^{k,m}$:

$$\Pi_{std} : [\epsilon_{i,j}], \quad [\Omega_k], \ [\Gamma_{k,m}] \rightarrow [\mu_{k.m}] \mid \beta_{i,j}^{k,m} = \alpha * S_{i,j} \tag{4}$$

In our initial experiments, we have tried normal and uniform functions (5) to create weight distributions that allow traffic dispersion in the network. These perspectives are created scaling weights by a factor δ determined by distribution functions $\delta_{normal} = normal(a, b)$ (a stands for the mean value and b stands for the statistical dispersion amplitude) and $\delta_{uniform} = uniform(a, b)$ (ranging from a to b):

$$\Pi_\delta : [\epsilon_{i,j}], \quad [\Omega_k], \ [\Gamma_{k,m}] \rightarrow [\mu_{k.m}] \mid \beta_{i,j}^{k,m} = \alpha * S_{i,j} * (1 + \delta) \tag{5}$$

Design of optimal TWM weight distribution functions Π_x will be subject of future research, considering factors such as: network topology, vehicle fleets, historical traffic data, real-time traffic information and time constraints.

2) TRAFFIC DEMAND, ROUTING AND AGENTS

We assume a mobile population of $[\upsilon_a^k]$ vehicles grouped by $[\Omega_k]$ fleets. Those vehicles that do not belong explicitly to a fleet are assigned to the standard Ω_0 fleet. The percentage of vehicles that effectively use TWM at any time is called the adherence factor ψ:

$$\psi = \frac{\sum [\upsilon_a^k]_{TWM}}{\sum [\upsilon_a^k]} \tag{6}$$

Vehicles generate $[\mathrm{W}_\mathrm{a}^\mathrm{k}]$ trips during observation epochs. Each trip, as described in (7) is composed by the vehicle identification, the starting timestamp, the starting point (origin node) O_a, the destination point (node) D_a and a tuple with possible intermediate stops $[\mathrm{P}_\mathrm{a}^\mathrm{k}]$:

$$W_a^k = f\left(\upsilon_a^k, t_a^0, O_a, D_a, [P_a^k]\right) \mid \forall \upsilon_a^k \in \Omega_k \tag{7}$$

Traffic demand is grouped by geographical areas called TAZ (traffic assignment zones, Δ_m) that summarize trips as traffic flows, for all the trips starting in the same geo-fenced area.

For the map-distribution approach, depending on each concrete time epoch, each fleet may have a specific navigation map set $[\mu_{k,m}]$. In client-based routing, each map $\mu_{k,m}$ is distributed to its individuals (on-demand or by publication to subscriptions) and in server-based routing the map is used for individual route calculation. Vehicles not classified or in general belonging to standard Ω_0 fleet use the standard map.

The routing agent will calculate for each trip the best route $R_a^{k,m}$ or hyper-path using the corresponding map (standard or ad-hoc received multimap). This calculation uses some of the available routing algorithms $\mathfrak{f}$ (Dijkstra, A*, etc). Presented experiments use Dijstra.

Non-TWM users will use the standard default road map Ω_0 for best-route calculation and the TWM users will use the corresponding map from the offered set according to the selected policy (per fleet for instance) as shown in:

$$R_a^{k,m} = \begin{cases} \mathfrak{f}(O_i, D_a^k, [P_a], \mu_{k,m}) & \upsilon_a^k \in [\upsilon_a^k]_{TWM} \\ \mathfrak{f}(O_i, D_a^k, [P_a], \mu_0) & \upsilon_a^k \notin [\upsilon_a^k]_{TWM} \end{cases} \tag{8}$$

Travel-time TT_a^k taken by each vehicle υ_a^k is the sum of the partial travel times at each edge, and can also be expressed as a composition of congested STT_a^k and non-congested times MTT_a^k. We will use these parameters for individual and global performance:

$$TT_a^k = STT_a^k + MTT_a^k \tag{9}$$

Distance RL_a^k run by each vehicle is expressed as:

$$RL_a^k = \sum length(\epsilon_{i,j}), \quad \epsilon_{i,j} \in R_a^{k,m} \tag{10}$$

For traffic routing performance analysis, we consider at every timestamp t those trips that have been already completed $[\mathrm{W}_\mathrm{a}^\mathrm{k}]_{end}^t$, those that have been started $[\mathrm{W}_\mathrm{a}^\mathrm{k}]_{run}^t$ and not completed $[\mathrm{W}_\mathrm{a}^\mathrm{k}]_{pend}^t$, and those that haven't been started yet (11):

$$[\mathrm{W}_\mathrm{a}^\mathrm{k}]_{total}^t = [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{end}^t \cup [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{run}^t \cup [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{pend}^t \tag{11}$$

3) OPTIMIZATION OBJECTIVES

There are two sets of optimization objectives: global objectives such as congestion or pollution, and individual objectives such as travel-time, trip cost or route length. Individual performance measurement is critical for TWM as it influences drivers' confidence: multiple positive individual adoptions would enable viral adoption of the multimap recommendations.

These variables can be measured and optimized globally for the whole network of by fleet. Some of the objectives can be expressed and measured at every single network edge and are marked with (*).

- *Global network objectives*:
  - *Dispatched traffic demand: DTD^t* as the percentage of routed demand compared against the total traffic demand exposed to the network:

$$DTD^t = \frac{card([\mathrm{W}_\mathrm{a}^\mathrm{k}]_{end}^t)}{card([\mathrm{W}_\mathrm{a}^\mathrm{k}]_{total}^t)} \tag{12}$$

  - *DTD_{TWM} as successfully TWM routed traffic*, as ratio of TWM routed traffic versus incoming traffic:

$$DTD_{TWM} = \frac{card([\mathrm{W}_\mathrm{a}^\mathrm{k}]_{TWM})}{card([\mathrm{W}_\mathrm{a}^\mathrm{k}]_{total})} \mid W_a^k \in [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{end} \mid \upsilon_a^k \in [\upsilon_a^k]_{TWM} \tag{13}$$

  - *TTS^t total time spent by the vehicles* in the traffic network:

$$TTS^t = \sum TT_a^k \mid \mathrm{W}_\mathrm{a}^\mathrm{k} \in [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{end}^t \cup [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{run}^t \tag{14}$$

  - *THS^t, Total Halting Time (Congestion Time, Waiting time) (*)* , as the total sum of halting times of the vehicles in the network:

$$THS^t = \sum STT_a^k \mid \mathrm{W}_\mathrm{a}^\mathrm{k} \in [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{end}^t \cup [\mathrm{W}_\mathrm{a}^\mathrm{k}]_{run}^t \tag{15}$$

- *NHD^t, Number of halted demand (vehicles)* (*):

$$NHD^t = card(\left[v_i^k\right]) \mid \mathrm{W}_{\mathrm{a}}^{\mathrm{k}} \in \left[\mathrm{W}_{\mathrm{a}}^{\mathrm{k}}\right]_{end}^{t} \cup \left[\mathrm{W}_{\mathrm{a}}^{\mathrm{k}}\right]_{run}^{t} \mid speed(v_i^k) <= 0.1 \quad (16)$$

- *VKT total distance traveled* by the vehicles that started their trips in the network:

$$VKT^t = \sum RL_a^k | \mathrm{W}_{\mathrm{a}}^{\mathrm{k}} \in \left[\mathrm{W}_{\mathrm{a}}^{\mathrm{k}}\right]_{end}^{t} \cup \left[\mathrm{W}_{\mathrm{a}}^{\mathrm{k}}\right]_{run}^{t} \quad (17)$$

- *Edge traffic* (*): number of vehicles, mean speed, edge occupancy.
- *Gas Emissions* (*): CO, CO2, HC, PMx, NOx of vehicles (as stated by HBEFA fleet assignments).SUMO simulator provides these edge measures.
- *Consumption* (*): fuel, electricity.
- *Noise emissions* (*). SUMO simulator provides this edge measure.

- *Individual objectives*, comparing how all the individuals[1] are being affected by TWM adoption versus the non-TWM standard situation (marked as experiments *no-TWM* and *TWM*). They are measured using paired statistics in simulations, comparing every individual trip between the standard routing scenario and the TWM routing scenario. Relative change is considered for improvement analysis, though in certain circumstances the absolute value analysis could be relevant from the user's subjective perspective.
  - *TTC_{rel}^k Individual relative travel time change* (as a percentage over original travel time), where $TT_a^k|_{TWM}$ and TT_a^k denote travel-time of a single trip using TWM or not respectively:

$$TTC_{rel}^k = \frac{TT_a^k|_{noTWM} - TT_a^k|_{TWM}}{TT_a^k|_{noTWM}} \quad (18)$$

  - RLC_{rel}^k *Individual route length relative change* (as a percentage over original route length), where $RL_a^k|_{TWM}$ and $RL_a^k|_{noTWM}$ denote route-length of a single trip using TWM or not respectively:

$$RLC_{rel}^k = \frac{RL_a^k|_{noTWM} - RL_a^k|_{TWM}}{RL_a^k|_{noTWM}} \quad (19)$$

  - *Individual consumption*: fuel, electricity.

4) TWM SIMULATION MODEL

The simulation model explores some of the concepts used in the formulation. The following variables are considered for our traffic impact analysis with TWM.

- Network variables:
  - *Topology of urban network* ($\Theta_n = \{[\eta_k^n], [\epsilon_{i,j}]\}$). We consider in our experiments a real city network.
- Traffic demand variables:
  - *Types of urban traffic* (Ω_k) where we distinguish typically fuel-cars, zero-emissions cars, taxis, commercial distribution, buses and motorcycles among others, or even emission models classification such as HBEFA or similar standards.
  - *Traffic zones (TAZ, Δ_m)* to generate in/out and internal traffic inside the network.
  - *Traffic demand density* ($\left[\mathrm{T}_{\mathrm{j}}^{\mathrm{k}}\right]$), expressed by number of trips.
  - *Traffic demand directionality*, where we have tested both crossing and internal traffic. Real scenarios combine both types of traffic.
- Multi-map variables:
  - *TWM enabled/disabled.*
  - *TWM cardinality*, or number of maps to distribute and apply, to check out which number of maps will be the best option for each situation. We use in our experiments 2^n maps $\{0, 1, 2, 4, 8...\}$.
  - *TWM, weight distribution functions Π*, using $\beta_{i,j}^{k,m}$ factor to increase current path weights, and thus impacting route calculus. Current functions implemented are the Π_{std} and Π_δ with normal and uniform distributions. Some weight factors are:
    * No influence: $\beta_{i,j}^{k,m} = 1$.
    * Random Low weight, using $\beta_{i,j}^{k,m} = \alpha * S_{i,j} * (1 + normal(0.5, 0.5))$.
    * Random High impact, that will apply a normal distribution using $\beta_{i,j}^{k,m} = \alpha * S_{i,j} * (1 + normal(2, 0.5))$.
    * Uniform Low and High impact, using the uniform functions instead of the normal ones.
  - *TWM time triggering* ($\left[\Gamma_{k,m}\right]$: Time constraints for TWM $\left[\mu_{k,m}\right]$), reflecting the time instant where the multimaps are applied. This is used to check if maps are used to avoid congestion before it occurs, or used to help congestion clearance while it is occurring. We use:
    * *Always on.*
    * *When-congested*, where the vehicle uses multimap when congestion is detected or forecasted.
    * *On incident* occurrence or clearance.
    * *On schedule* to set time and Geo constraints in the traffic network.
- Routing algorithms:
  - *TWM route selection* algorithm $\digamma$. We support both Dijkstra *and A** for the initial experiments ([23], [47], [49]).

    Route selection, can be used at centralized route delivery where the agent requests the best route to follow, or decentralized where the agent calculates the best route by itself.

[1] Whole vehicle population including TWM and non TWM users

TABLE 2. Traffic fleet composition.

Fleet	%	Traffic mix	Use TWM
Car	44%	random + directional	Yes
Taxi	33%	random + directional	Yes
Bus	11%	random + directional	No
Motorcycle	11%	random + directional	Yes

TABLE 3. Driver adherences.

Adherence	Value
Early adopter	5%
Small confidence	10%
Mid confidence	20%
Big confidence	50%
full adoption	100%

- MTA Agent variables (individual / vehicle):
  - *MTA* multimap *adherence* ψ_n, or n-percentage of vehicles that use TWM in the traffic network. ψ_n is composed by the specific $\psi_{n,k}$ adherences at each fleet Ω_k. In this paper we use the aggregated value ψ_n.

III. APPLICATION OF TWM TO URBAN TRAFFIC

To demonstrate the feasibility of traffic weighted multi-maps, we created a simulation engine that is based on the microscopic simulator SUMO [9] and apply TWM to real urban networks under free-flow and congested conditions.

Considering the traffic demand as a main parameter, several profiles have been created to reproduce situations of low, normal and high levels of traffic congestion. Two types of traffic are used: internal traffic are those trips with random origins and destinations, while directional traffic is formed by trips that cross the whole network.

Several fleets are considered and shown in Table 2. Bus traffic won't use TWM as they follow prefixed routes.

To study TWM impact on traffic use several driver adherences ψ_n as percentage of vehicles effectively using the new routing recommendations. They are shown in Table 3.

For results analysis several diagrams are used:

1) Histograms to represent travel-time distributions, both global and individual. In these histograms we add both mean and median values to show how overall behavior has changed.
2) Evolution of traffic congestion in time, measuring the number of congested traffic nodes, mean network speeds and number of halted vehicles.
3) Histograms to represent individual improvement (positive or negative) of travel-time. It can be absolute or relative, and is zero-centered: positive values show how many vehicles have reduced their travel-time, and negative just those who have been impacted.
4) Cumulative probability of individual travel-time improvement to see the impact of TWM.

TABLE 4. Alcala de Henares TAZ composition.

TAZ	NAME	DESCRIPTION	USAGE
90	Center	Downtown	Residential
91	Espartales	New neighborhoods	Residential
1	E-5	Highway	In+Out+Cross Traffic
2	E-5	Highway	In+Out+Cross Traffic
3	M-100	Road	In+Out+Cross Traffic
4	M-100	Road	In+Out+Cross Traffic
5	M-300	Road	In+Out+Cross Traffic
6	M-300	Road	In+Out+Cross Traffic
7	M-119	Road	In+Out+Cross Traffic
8	M-121	Road	In+Out+Cross Traffic
50	Cuadernillos	Molls & Supermarkets	Commercial
51	La Garena	Molls & Supermarkets	Commercial
60	Universidad	University & Hospital	Services
70	Industrial North	Industry	Industry
71	Industrial West	Industry	Industry

A. REAL CITY NETWORK EXPERIMENTS

We have used the traffic network from Alcala de Henares to test the TWM framework. It is a mid-size city of 250K population, located at 30km north-east of Madrid, Spain.

1) URBAN NETWORK DESCRIPTION

This city is a good experimental scenario as it has a middle-age downtown with heavy traffic restrictions and pedestrian areas, tourism, administrative facilities and residential usages causing high density of internal traffic demand. The city has around the downtown extensive industrial, commercial and citizen service areas (hospitals, wide-area university campus and others). The city is crossed east-west by an intensive highway connecting Madrid and Barcelona. Due to the closeness to the airport and Madrid's business center, there is a heavy daily traffic in and out caused by people going to and from their workplaces. Also, the city has heavy traffic exchange with the surrounding villages.

We have identified the traffic flows in the city using Traffic Area Zones (TAZ) as shown in Figure 2 and in Table 4. We consider TWM adherences of $\psi_{0.1}$, $\psi_{0.2}$, $\psi_{0.5}$ and ψ_1. Traffic types (fleets) distribution is shown in Table 2.

2) CONGESTED TRAFFIC NETWORK USING 16-TWM

Our simulation includes traffic flows between all the TAZ estimated using real data which correspond to heavy traffic hours. Several sources have used for data curation: public APIs, private crowd-sensing and city local traffic service web [3], [4]. Demands estimations are shown in Table 5. We select a 3 hours simulation.

To execute our TWM evaluation, we use a TWM with 16 maps that will be uniformly distributed and used by the fleets with the probability distribution shown in Table 6.

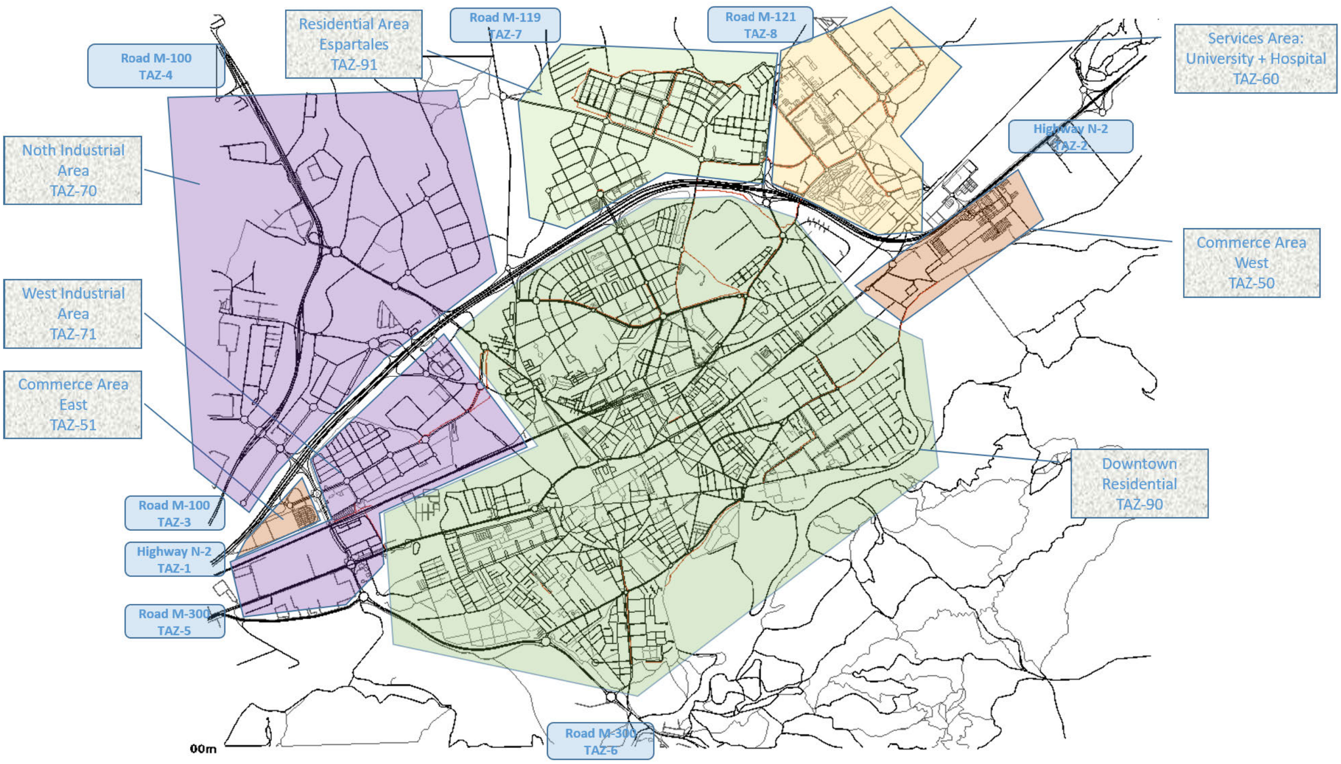

FIGURE 2. Alcala de Henares traffic network and TAZ mapping.

TABLE 5. Alcala de Henares traffic demands.

		TRAFFIC DESTINATION														
		TAZ-90	TAZ-91	TAZ-1	TAZ-2	TAZ-3	TAZ-4	TAZ-5	TAZ-6	TAZ-7	TAZ-8	TAZ-50	TAZ-51	TAZ-60	TAZ-70	TAZ-71
TRAFFIC ORIGIN	TAZ-90	8000	200	800	800	400	400	1000	400	400	400	200	200	200	100	100
	TAZ-91	200	100	300	300	150	150	100	100	100	100	100	100	100	50	50
	TAZ-1	800	500		2000							100	100	200	200	200
	TAZ-2	800	500	2000								100	100	200	200	200
	TAZ-3	400	100	400	400		1000					100	100	100	50	50
	TAZ-4	400	100	400	200	1000						100	100	100	50	50
	TAZ-5	800	100						400			100	100	100	50	50
	TAZ-6	800	100		400			1000				100	100	100	50	50
	TAZ-7	400	100	300	100							100	100	100	50	50
	TAZ-8	400	100	300	100							100	100	100	50	50
	TAZ-50	200	100	100	100	100	100	100	100	100	100			50		
	TAZ-51	200	100	100	100	100	100	100	100	100	100			50		
	TAZ-60	200	50	200	200	100	100	100	100	100					50	50
	TAZ-70	100	50	200	200	50	50	50	50	50	50			50		
	TAZ-71	100	50	200	200	50	50	50	50	50	50			50		

TABLE 6. TWM usage distribution on traffic classes.

Fleet	μ_0	μ_1	μ_2	μ_3	...	μ_{16}
Bus	1.0	0	0	0	...	0
Car	0	0.063	0.063	0.063	...	0.063
Taxi	0	0.063	0.063	0.063	...	0.063
Motorcycle	0	0.063	0.063	0.063	...	0.063
Truck	0	0.063	0.063	0.063	...	0.063
Trailer	0	0.063	0.063	0.063	...	0.063

Buses use map μ_0 for their fixed routes. Routing uses Dijkstra algorithm.

TWM maps have been generated using the Uniform Random High Impact Π_δ. The configuration file is shown in Figure 3.

```
<?xml version="1.0" encoding="UTF-8"?>

<maps>
  <!-- car -->
  <map tag="car" prob="0.0625" file="map.alcalahenares.uni5.rand.1.xml" />
 [...]
  <map tag="car" prob="0.0625" file="map.alcalahenares.uni5.rand.16.xml" />

  <!-- taxi -->
  <map tag="taxi" prob="0.0625" file="map.alcalahenares.uni5.rand.1.xml" />
 [...]
  <map tag="taxi" prob="0.0625" file="map.alcalahenares.uni5.rand.16.xml" />

  <!-- motorcycle -->
  <map tag="motorcycle" prob="0.0625" file="map.alcalahenares.uni5.rand.1.xml" />
 [...]
  <map tag="motorcycle" prob="0.0625" file="map.alcalahenares.uni5.rand.16.xml" />

  <!-- bus -->
  <map tag="bus" prob="1" file="map.alcalahenares.reference.mapR.xml" />

  <!-- truck -->
  <map tag="truck" prob="0.0625" file="map.alcalahenares.uni5.rand.1.xml" />
 [...]
  <map tag="truck" prob="0.0625" file="map.alcalahenares.uni5.rand.16.xml" />

  <!-- trailer -->
  <map tag="trailer" prob="0.0625" file="map.alcalahenares.uni5.rand.1.xml" />
 [...]
  <map tag="trailer" prob="0.0625" file="map.alcalahenares.uni5.rand.16.xml" />

</maps>
```

FIGURE 3. 16-TWM composition.

3) GLOBAL TRAFFIC EVOLUTION USING 16-TWM RANDOM MAPS

We can see the impact of using TWM over travel-times in Figure 4 and Table 7, that compare traffic evolution of a congested scenario under two situations: no TWM usage and TWM usage with certain driver adherence. Travel-time is measured in the simulation for every single trip from departure to arrival. The histograms represent number of trips per travel-time duration. We have selected traffic histograms for the highest adherences as it easier to observe how

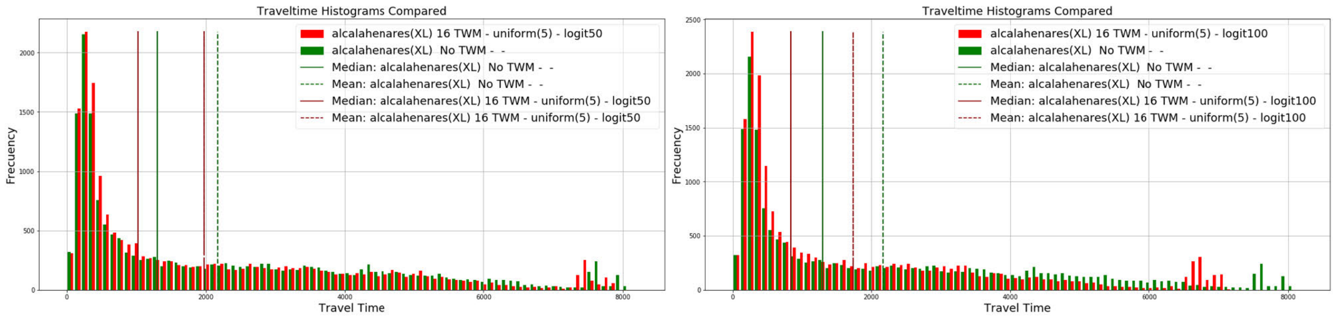

FIGURE 4. Alcala de Henares simulation, TWM impact on TT with $\psi_{0.5}$ and ψ_1 adherences.

TABLE 7. Alcala de Henares simulation, TWM impact with $\psi_{0.1}$, $\psi_{0.2}$, $\psi_{0.5}$ and ψ_1 adherences.

16 maps - uniform05		No TWM	10%	20%	50%	100%
Traffic	Demand	18694	18694	18694	18694	18694
	Using TWM	0	1846	3731	9385	18694
	Routed	17895	17667	18067	18042	18447
	% Routed, DTD	-	-1.27%	0.96%	0.9%	3,08%
Travel time TT	Mean		-3.41%	-4.75%	-9.17%	-19.60%
	Median		-2.93%	-7.25%	-21.28%	-34.70%
Route Length RL	Mean		1.10%	0.73%	1.59%	1.90%
	Median		0.00%	0.00%	2.27%	2.27%

TWM affects travel-time: the number of vehicles with shorter travel-times increases (peaks in the left side). The right side of each histogram shows local peaks where some vehicles are taking longer to complete their trips: TWM adoption moves this peak to the left shortening travel-times. We can also see how mean and median travel-times are reduced, flattening the curves and affecting all the trips in an homogeneous way. Travel-time gets improved when driver's adherence to TWM usage grows, ranging to 19,6% of improvement in the full-adherence scenario. The scenario considers the whole traffic network with many different fleets and types of roads: from small one-way edges to a big crossing high-way with 6 lanes in two senses. Traffic and congestion are strongy heterogeneous in the scenario, and TWM provides routing alternatives for congested edges.

Not only travel-time (TT) is improved but also the routed traffic demand (for the time interval considered): the TWM scenario is routing 3,1% more vehicles. It is the *multimap route clearing effect*: TWM is reducing global congestion when drivers select the alternative best-cost routes.

The penalty of using TWM is reflected in route lengths, which grow slightly due to the fact of using alternative maps, but mean affection is just 1.9%. If we consider the 19.6% reduction in mean travel-time against 1.9% of mean route change we can consider that the balance of using TWM is worthy.

From the previous results we would expect that the global congestion measures get also positively affected in terms of:

- Reducing number of congested edges.

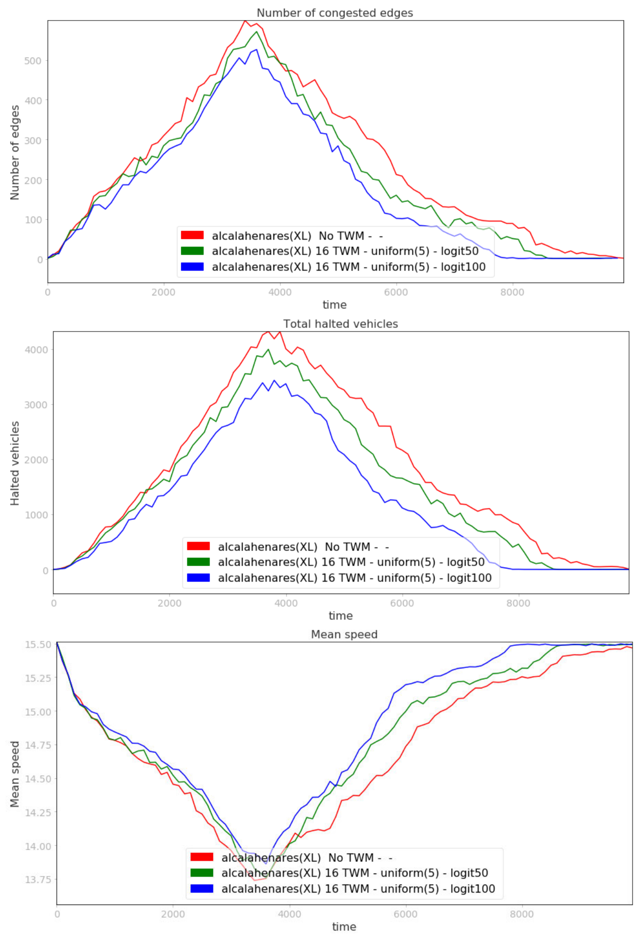

FIGURE 5. 16-TWM number of congested nodes, halted vehicles and mean speed.

- Reducing number of halted vehicles.
- Increasing mean speed in the network.

In Figure 5 we can observe how global network variables evolve in time for different vehicles adherences. The traffic network gets progressively congested while traffic demand is growing being able to route completely at the end of the simulation. The graphs confirm our hypothesis as the three mentioned indicators are significantly improved:

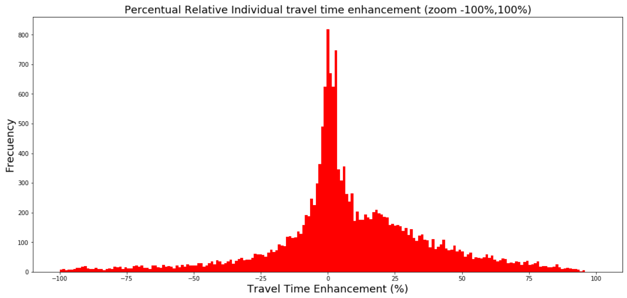

FIGURE 6. Alcala de Henares, TTC_{rel} travel-time relative individual experience with $\psi_{0.5}$.

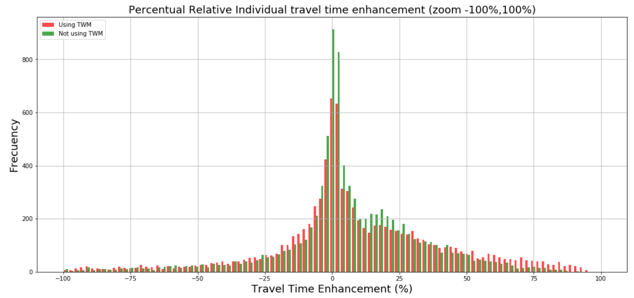

FIGURE 7. Alcala de Henares, comparison of individual experiences for TWM/non TWM users (relative) with $\psi_{0.5}$.

- Congestion peaks (height of figure - number of congested edges and halted vehicles) are significantly lower using TWM.
- Congestion duration (width of figure - time with halted vehicles) is also significantly reduced using TWM.
- Mean network speed is also increased with TWM.

When we consider different TWM driver adherences, we notice that results get improved. Drivers will give positive feedback to the loop, and expectations are that adherence will grow. We can expect that the system will tend to increase adoption in time. This kind of system dynamics is left for future research.

B. INDIVIDUAL DRIVING EXPERIENCE USING 16-TWM

Global statistics hide the individual driver perception that is a key factor for adherence dynamics. To analyze driver's experience we use paired statistics, where we compare single o/d trip of the same vehicle under different scenarios and create travel-time histograms.

In Figure 6 we analyze individual travel time variation with adherence $\psi_{0.5}$ as percentage of affected vehicles over the whole vehicle population. Variations do not follow normal distributions, as confirmed from the results of standard paired tests (T-Test, Shapiro and others).

- 0-Value represents frequency of individuals that do not perceive any significant changes when using TWM.
- Negative values show the percentages of vehicles whose travel time has been penalized. When the TWM assigns a weighted map that differs from the original one, drivers are going to diverge in their decisions from the optimal ones considering just the free-flow empty network. Some of the individual travel-times TT_a^k are negatively affected mainly due to the increments in route lengths RL_a^k and lower speed. For the subjective experience we should also take into account the individual halted time STT_a^k that is reduced.
- Positive values from 0 show percentage of drivers whose travel time has been improved. The higher values, the bigger improvement, and also the main promoters for TWM adoption.

Relative impacts represent better the impact on driver's experience. The driver evaluates how much improved using TWM, when compared to the original non-TWM value. Individual improvement is measured in travel-time, route-length, energy consumption and other parameters. We focus on travel-time which is the main indicator.

At the right side of Figure 6 we find that the subjective improvement is more relevant: a big number of drivers have significantly reduced their travel times respect to the original travel time expectations. They were the previously congested vehicles.

TWM benefits reach all the vehicles, not only for those that use TWM but also the other ones. This is the obvious consequence of routing some traffic out of the preferred paths: the whole network status gets highly improved.

Figure 6 also shows that some vehicles are suffering travel-time penalty as TWM weight adaptation forces evaluation of new optimal routes. Global TWM impact needs to consider the two factors shown in the graph: a) the relative impact for each driver and b) the number of drivers that are reducing travel-time.

1) TWM AND NON-TWM DRIVING EXPERIENCES

If we think in terms of awareness and reward (''What is my reward for using the multimap?'') we need to consider two different populations: those drivers that use TWM and non-using drivers.

Though TWM users achieve the expected benefits, non-TWM users benefit as well, and even more than the TWM users, generating a global improvement. Application of TWM on maps covering the original best-cost routes, derives a significant amount of the traffic out of them, thus triggering a congestion clearance on them: *the multimap route clearing effect*.

Figure 7 compares the variation/improvement for each population where we can see how both populations are being affected by TWM usage in a similar way.

2) MAXIMUM ADHERENCE SCENARIO

We have seen so far the $\psi_{0.5}$ scenario; we study now the scenario where all the vehicles are using TWM, ψ_1. Figure 4 shows the global measures for different adherences, and Figure 8 shows the maximum relative improvements for the traffic network and the considered traffic demand. As expected, we find a right-side slope that reveals that most of the vehicles are having a better driver experience with a

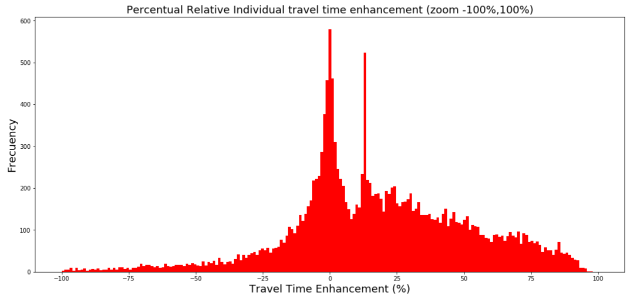

FIGURE 8. Alcala de Henares, TTC_{rel} at ψ_1 adherence.

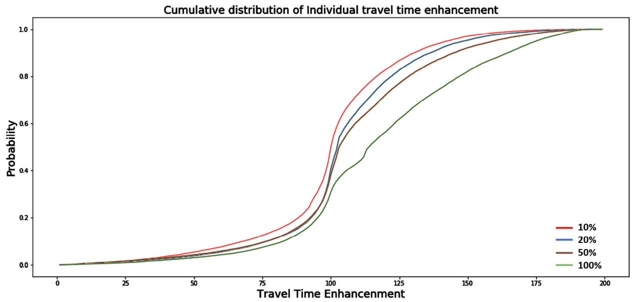

FIGURE 9. Alcala de Henares, cumulative probability distribution for $\psi_{0.1}$, $\psi_{0.2}$, $\psi_{0.5}$ and ψ_1.

wide satisfactory perception. The ψ_1 histogram shows how real bottlenecks are eliminated, represented in the right peaks: previously halted vehicles are now routed.

3) CUMULATIVE PROBABILITY DISTRIBUTION OF DRIVING EXPERIENCE VARIATION

In the cumulative probability distribution for $\psi_{0.1}$, $\psi_{0.2}$, $\psi_{0.5}$ and ψ_1 (Figure 9) we observe how the improvement is achieved. We point out that:

- Starting with very low adherence such as $\psi_{0.1}$ (10%) the probability of being positively impacted is considerable. TWM generate benefits even with a small number of drivers.
- Probability of having improvements increases with the adherence almost linearly with it, and when we reach full adherence, the benefit is maximum.

IV. TWM APPLICATION ON URBAN ROAD INCIDENTS

TWM offers a wide number of use-cases for real application. One of them is to design ad-hoc traffic weighted multi-maps to minimize impacts of traffic incidents. These traffic incidents could be planned works (scheduled) or caused by a real-time event.

In case of incident to be managed by some TWM application, we will follow these steps:

1) Identify the physical coordinates of the incident.
2) Identify the edges and nodes affected by the incident, $\left[\epsilon_{i,j}\right]_x$
3) Create an ad-hoc multi-map $\left[\mu_{k,m}\right]_x$ (20) around the affected edges, within a distance radius of R_x. The multi-map will be valid for a certain time lapse that will typically cover from the incident detection to some time after incident clearance.

$$\Pi_x : [\epsilon_{i,j}]_x, \quad [\Omega_k], \ \left[\Gamma_{k,m}\right], \ R_x \rightarrow [\mu_{k.m}]_x \tag{20}$$

1) Distribute the TWM $\left[\mu_{k,m}\right]_x$ to the adequate fleets. Some fleets may not use it for some possible reasons, for instance, in case of using fixed routes (like buses).
2) In case of supervised routing, where we don't know in advance the time duration of the incident:
   a) Monitoring traffic conditions during the traffic incident.
   b) Restoration of original TWM conditions.

Generated $\left[\mu_{k,m}\right]_x$ maps for incidents are the result of merging edge weights of current $\left[\mu_{k,m}\right]$ that could be currently in use, or the standard map μ_0 if there is no previous TWM usage.

In the creation step of the new $\left[\mu_{k,m}\right]_x$ for the incident, TWM generator allows us to apply several routing policies with different functions Π_δ as we mentioned in the formulation chapter:

- Apply a *fixed weight penalty of value K* to all the edges surrounding the affected edge with N edges of distance.
- Apply a *random weight penalty amplified by value K* to all the edges surrounding the affected edge with N edges of distance. Random distributions allow that different paths will be selected by the vehicles.

Radius R_x is a distance metric that expresses the maximum number of edges belonging to the possible traffic paths that converge into the affected edge $\left[\epsilon_{i,j}\right]_x$. It is not measured in meters nor miles, but in number of edges. This distance calculus is more convenient in urban areas as once the vehicles have entered the edge they should complete the whole edge distance.

A. INCIDENT EXPERIMENT DESIGN

To analyze a realistic scenario, we use the Alcala de Henares traffic network, with ad-hoc traffic demands. Impact of TWM usage in case of traffic incidents has a very different impact depending on the congestion stage of the whole network: highly congested traffic networks are not going to receive the same improvement as other non-congested scenarios.

Our traffic scenario consists on a heavy directional traffic flow that crosses the city (traffic area zones taz5 and taz50). The flow consists on around 2000 vehicles/hour distributed in the first hour. This flow generates some congestion points in the most used edges.

The traffic incident location is shown in Figures (10 and 11). It occurs in an edge belonging to the most selected routes, though it is not at the top congested edges to avoid forcing experimental results. The incident lasts from timestamps 2000 (incident) to 4800 (restore).

Figures 12 and 13 compare both global scenarios of free-flow with or without the incident, showing the evolution of total number of halted vehicles in the network and travel-times of the vehicles using it. The incident creates a

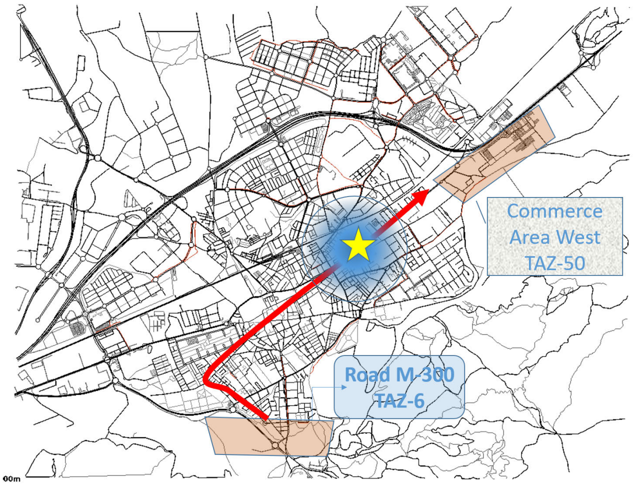

FIGURE 10. Alcala with directional traffic and incident in the main path.


```xml
<?xml version="1.0" encoding="UTF-8"?>

<commands>
  <!-- INCIDENTS SECTION -->
  <!-- Incidents placed in the most occupied edges -->

  <!-- Incident 1-->
  <!-- Avenida Lope de Figueroa -->
  <command time="2000" name="Incident" param="151292453#1" />
  <command time="4800" name="Restore"  param="151292453#1" />

  <!-- COMMAND TO CLEAR CONGESTION IN THE INCIDENTS AREAS -->
  <command time="2000" name="Maps" param="alcalahenares_TWM_timeALL_taz5-taz50XS
_incident3x1-join_01.maps.xml" />
</commands>
```


FIGURE 11. TWM routing command for incident management.

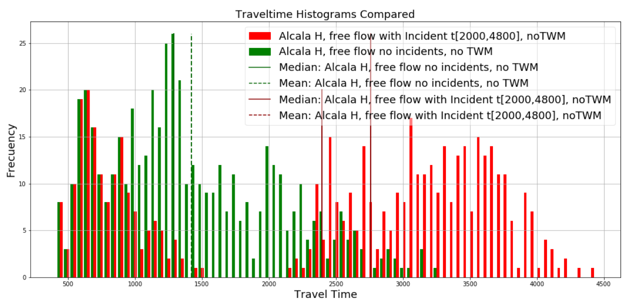

FIGURE 12. Effect of incident on travel-times.

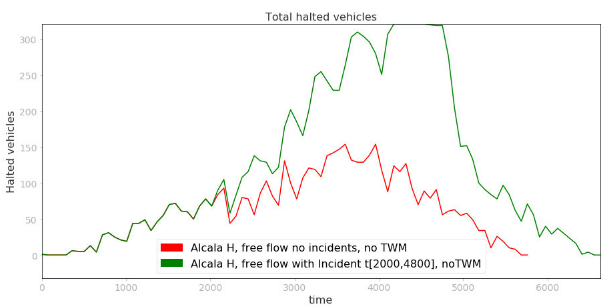

FIGURE 13. Impact of road incident on halted vehicles.

congestion situation as can be seen in the red right side of the histogram where many vehicles are increasing their travel-times. Also it can be observed that total number of halted vehicles raises until incident clearance.


```xml
<?xml version="1.0" encoding="UTF-8"?>

<maps>
  <map tag="car" prob="1" file="alcalahenares.taz5-taz50S.incident3x1.join_map_1
.xml" />
  <map tag="taxi" prob="1" file="alcalahenares.taz5-taz50S.incident3x1.join_map_
1.xml" />
  <map tag="motorcycle" prob="1" file="alcalahenares.taz5-taz50S.incident3x1.joi
n_map_1.xml" />
  <map tag="bus" prob="1" file="alcalahenares.reference.mapR.xml" />
</maps>
```


FIGURE 14. $\Pi_x : \left[\mu_{k,m}\right]_x$ **multi-maps for incident management.**


```xml
<?xml version="1.0" encoding="UTF-8"?>

<config>
  <gmb>
    <mode value="penalty"/>
    <net_file value="xml_maps/alcalahenares.net.xml"/>
    <output_prefix value="map.alcalahenares.taz5-taz50S.incident3x1"/>
    <output_dir value="./alcalahenares.maps/"/>
    <!-- <weight_factor value="abs(1+numpy.random.uniform(0,5))"/> -->
    <weight_factor value="5"/>
    <weight_add value="20"/>
    <num_maps value="1"/>
    <begin value="0"/>
    <end value="10000"/>
    <join_map value="alcalahenares.maps/map.alcalahenares.reference.mapR.xml"/>
    <join_option value="max"/>
    <!-- Set incident point in the biggest occupancy edges -->
    <pen_edges value="151292453#1 "/>
    <pen_edges_steps value="5"/>
  </gmb>
</config>
```


FIGURE 15. Configuration file for the TWM map generator.

B. TWM DESIGN FOR THE INCIDENT

In the experiments, the framework distributes the corresponding multi-map $\left[\mu_{k,m}\right]_x$ with the assumption that the incident is detected in the same time instant that it has been produced, and that the TWM generation and distribution is immediate. This assumption is used for simplicity, as the results will be similar using different times.

The linear multi-map $\left[\mu_{k,m}\right]_x$ used in the experiment is a simple one, that will be used by three of the four fleets; the fourth fleet, buses, is going to use its regular fixed paths.

The linear function Π_{lin} described in (21) is used to create the new weights based on the standard ones based on max speed constraints, setting the new edge weight has a combination of a fixed penalty (parameter a) and a variable scaling factor (parameter b). Our objective is to amplify the edge weights around the incident so that they won't be selected for the new best-route calculation, thus discouraging drivers from using them.

$$
\begin{aligned}
\Pi_{lin} : [\epsilon_{i,j}]_x, [\Omega_k], \left[\Gamma_{k,m}\right], R_x &\rightarrow [\mu_{k.m}]_x \\
| \ \beta_{i,j}^{k,m} = a + b * S_{i,j} | &\begin{cases} a = 20 \\ b = 5 \end{cases} \\
| \ R_x = 5 & \\
| \ \Gamma_{k,m} \in [2000, 4800] &
\end{aligned}
$$

Figure 15 shows TWM map generator configuration, where the parameter *pen_edges_steps=5* indicates that we are using a distance radius of $R_x = 5$ as explained before. Traffic is dispersed around the incident avoiding edges with distance 5 to the incident and re-calculating the best-path to their destination.

The experiments that have been executed, consider different driver's adherences of $\psi_{0.1}$, $\psi_{0.2}$, $\psi_{0.5}$ and ψ_1 for the multi-map adoption.

```xml
<?xml version="1.0" encoding="UTF-8"?>

<meandata>
        <interval begin="0" end="10000" id="whatever">
                <edge id="-378122091" traveltime="74.70482361411086"/>
                <edge id="151292453#0" traveltime="32.478401727861765"/>
                <edge id="151292453#1" traveltime="23.41432685385169"/>
                <edge id="378122091" traveltime="74.76601871850251"/>
                <edge id="23907635#3" traveltime="20.050395968322533"/>
                <edge id="23907635#4" traveltime="21.198704103671705"/>
                <edge id="151292453#2" traveltime="22.14542836573074"/>
                <edge id="-28355546#0" traveltime="22.42260619150468"/>
                <edge id="23907635#2" traveltime="30.00179985601152"/>
                <edge id="28355546#0" traveltime="22.42260619150468"/>
                <edge id="23907635#0" traveltime="26.89704823614111"/>
                <edge id="408924700#4" traveltime="40.72714182865371"/>
                ...
```


FIGURE 16. New $\left[\mu_{k,m}\right]_x$ weights.

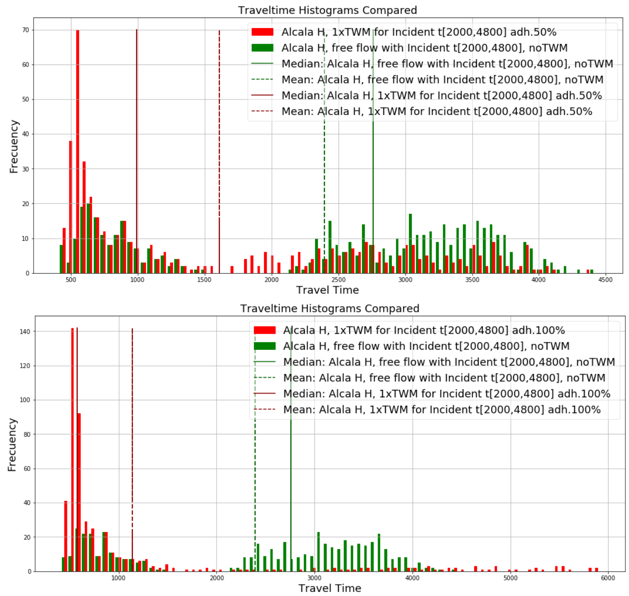

FIGURE 17. Travel-time variation with ad-hoc TWM on incident for $\psi_{0.5}$ and ψ_1.

TABLE 8. Travel-time variation with ad-hoc TWM on incident for $\psi_{0.5}$ and ψ_1.

Incident + 1 TWM, linear a=20, b=5		No TWM	50%	100%
Traffic	Demand	500	500	500
	Using TWM	0	241	500
	Routed	500	500	500
Travel time	Mean		-32,67%	-52,36%
	Median		-64,00%	-79,09%
Route Length	Mean		-0.10%	-1,04%
	Median		0%	0%

Both the linear function used and the selected parameter values are part of basic experiments, and no optimization algorithms have been applied. They will be subject of future research in order to obtain optimal results: optimization function, linear factors, distance radius, number of maps to be used and other parameters that offer a wide range of possibilities.

C. TWM APPLICATION RESULTS

As we can observe at histograms in Figure 17 and Table 8 for $\psi_{0.5}$ and $\psi_1$adherences, the initial congestion is cleared

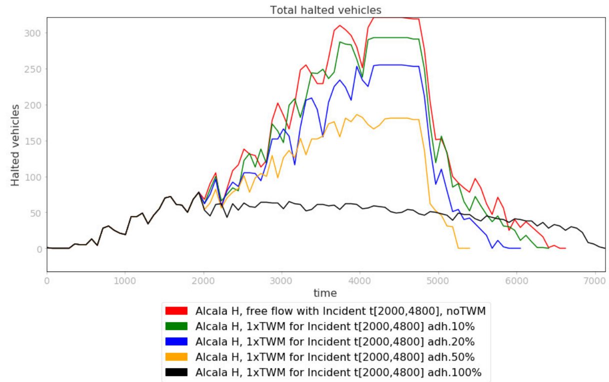

FIGURE 18. Global evolution of incident managed by TWM: Halted vehicles.

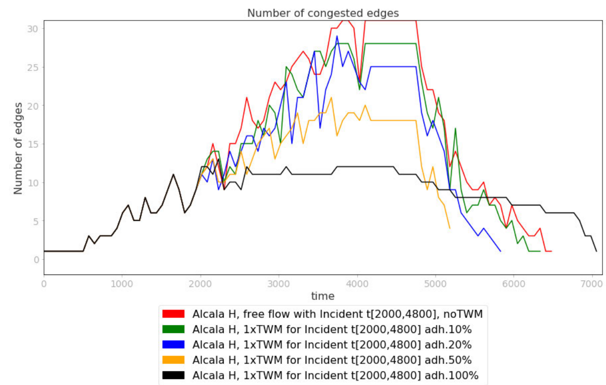

FIGURE 19. Global evolution of incident managed by TWM: Congested edges.

by the TWM, rerouting traffic out of the boundaries of the incident edge. Travel-time variation perceived by the drivers in this case raises up to 79% for a full ψ_1 adherence, but it is clear that this value depends on the incident instant and duration and the route lengths of all the vehicles. Right side of the histograms (green side) show the incident situation where vehicles are blocked by the incident; red left side shows how the vehicles using TWM find alternative paths and get rerouted, thus reducing their travel-times.

Figures 18, 19 and 20 show how global congestion due to the incident is impacted by TWM usage depending on the adherence to the system by drivers:

- Halted vehicles initially collapse the network for the selected paths when the incident appears (red line). Usage of TWM with maximum adherence is able to flatten the curve, reducing to a minimum the impact of the incident (black line). The big gap occurs while jumping from 50% to 100% adherence where the maximum efficiency is achieved.
- Number of edges congested also gets flattened with application of TWM, reducing the congestion peak.
- Mean speed in the network is raised globally while applying TWM.

Subjective individual variation is shown in Figure 21 for ψ_1 adherence where it is clear that vehicles that where initially

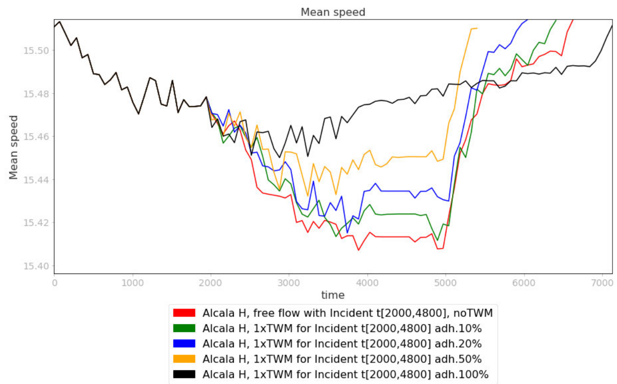

FIGURE 20. **Global evolution of incident managed by TWM: Mean speed.**

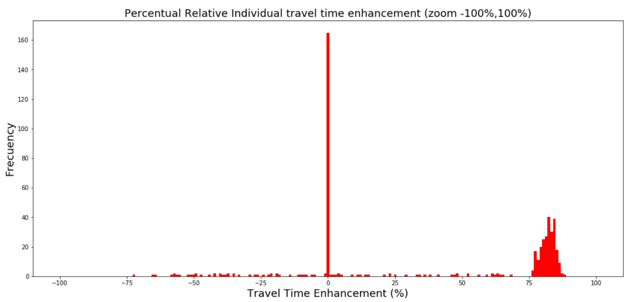

FIGURE 21. **Individual travel-time relative variation.**

blocked by the incident (right-side) have obtained a great reward for using TWM in terms of travel-time. Very few vehicles have been negatively impacted.

V. CONCLUSION AND FUTURE WORKS

Traffic weighted multimaps (TWM) is offering a new approach for both static and dynamic traffic management, as it considers enhancing both global network and individual traffic objectives. It considers the fact that traffic network usually provides multiple paths for the same O/D pair, but traffic agents recommendations usually propose the same routes as they use network and traffic load data, not taking into account the different traffic groups objectives and capabilities.

We have shown with our experiments in a real city traffic network under real traffic conditions, how TWM application can lead to improvements of global travel time indicators between 20% and 30%, depending on scenario conditions, enhancing greatly congestion situations. The penalty paid is using slightly bigger routes. TWM behaves correctly in low and high traffic density scenarios:

- In low-density traffic scenarios, individual improvement has no valuable impact as agents are close to their ideal performance (travel time), but group and global Smart-City indicators are greatly improved.
- In high-density traffic scenarios (close to congested networks), multimap algorithms offer their best performance, as they are able to enhance individual objectives improving also group and global indicators.
- Real-Time response to changes in network such as incidents, is fast and effective, by means of releasing new multimaps sets with link costs adapted to the new situation.

The benefits of TWM include the following:

- The possibility of automating early and real-time decision making for drivers and authorities.
- Generation of an integral model for the application of management and control policies.
- It can be offered as a service (SaaS model), as it uses a non intrusive architecture.
- It is conceived as a evolutionary planning model, based in on traffic feed back and learning cycles.
- Compatible with existing traffic management frameworks and traffic agents.
- Drivers' agents autonomy is preserved as the multimap model takes into account individual freedom of route choice.
- It allows for the articulation of contingency plans and the integration of traffic prognosis models.

TWM stands out from an innovative perspective in the following:

- Offers an integrated planning and re-planning model, extensible and open.
- Enables traffic categorization for application to very different groups and situations: electric vehicle, pay-to-drive and car-sharing fleets, commercial distribution, disabled people, pollutants, dangerous transport, routing due to weather, timetables, etc.
- It is replenished and self-learning.
- Route calculation can use standard optimization algorithms and techniques.
- Uses existing data (Smart-Cities, OpenData) and adds value.
- TWM can be implemented easily in current traffic control systems, creating a new routing module that uses differentiated maps as defined by TWM. It does not require the installation of additional infrastructure.
- TWM does not require V2V communications nor deployment of sensors, panels or communication infrastructures.
- From the user perspective, it is compatible with existing traffic agents, as we will replace the maps they use.
- TWM usage does not require all vehicles to adopt it. May be used in a biased manner (only for certain categories or policies).

There are many open future research works that mainly deal with dynamic traffic assignment with TWM, creating evolutionary algorithms and optimization functions for finding local area minimum for routing maps that can cover eventual time-dependent situations, and also releasing new reference networks, such as radial topologies, roundabouts, etc.

Also modeling user-perspective for influencing the adherence factor that is shown as a key condition for TWM impact is a topic of future research. Generation of hyperpaths based on TWM is a promising research direction, and adding new simulation engines such as mesoscopic ones.

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