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Modeling Driving Experience in Smart Traffic Routing Scenarios: Application to Traffic Multi-Map Routing

ALVARO PARICIO AND MIGUEL A. LOPEZ-CARMONA
Departamento de Automatica, Universidad de Alcala, Escuela Politecnica Superior, Campus Externo de la UAH, 28807 Alcala de Henares, Spain
Corresponding author: Alvaro Paricio (alvaro.paricio@uah.es)

ABSTRACT The effectiveness of user-oriented traffic routing applications to mitigate traffic congestion in Intelligent Transportation Systems depends on their degree of adoption, which usually evolves depending on subjective and exogenous factors. This paper proposes a user experience and social dynamics model to analyze and evaluate traffic routing methods, based on fuzzy rules and discrete choice theory. The model has been applied to the optimal Traffic-Weighted Multi-Maps (TWM) routing method to evaluate the adoption dynamics and analyze convergence towards the system optimum. Route unfairness and resistance to change are also considered in the model. Experimental results are obtained simulating the evolution of the drivers' population behavior. Simulation is carried over synthetic and real networks, using optimized TWM maps. The experimental results show how the TWM system evolves to a stationary System Optimum, improving overall traffic congestion and showing how User Equilibrium variability is bounded as it depends on user routing choices influenced by behavioral patterns.

INDEX TERMS Dynamic traffic assignment, multi-map routing, fuzzy logic, evolutionary algorithms, discrete choice modeling, traffic simulation, vehicle routing, traffic weighted multi-maps.

I. INTRODUCTION

The efficiency and impact of routing software applications (routing apps) in Intelligent Transportation Systems (ITS) to mitigate traffic congestion depend not only on the quality of the routing solutions proposed to the drivers but also on their adoption rate [1]–[3]. This adoption rate depends on individual factors, public policies and regulation, and social influence [4], [5].

There is a considerable amount of route choice, and traffic information management proposals focused on congestion mitigation and travel-time improvement using static or dynamic methods [6]. From a macroscopic perspective, they try to reach the right balance on Wardrop's principles of User Equilibrium (UE) and System Optimal (SO) [7], [8]. These proposals consider that most users are free to decide the route they would take for their trips, using a subjective evaluation of objective data and status information such as travel time forecast, network traffic status, previous routing choices, social information, and other individual parameters. Multi-criteria and imprecise traveler behavior is usually approached with Utility theory (UT), Prospect Theory (PT), and Regret Theory (RT), together with Discrete Choice Methods (DCM) and Fuzzy Methods (FM) [9], [10].

In an environment with multiple routing apps available which are not usually interoperable and interfere between them [11], [12], drivers first need to decide which app to use [13]. User experience, perception and trust, and social influence are key concerns [14], [15].

Discrete choice methods with multinomial logit models (MLM) have been widely applied to route choice problems [1], [16] as they consider mutually exclusive alternatives. Individual trip routing decisions are taken after considering and comparing the utilities of every routing strategy. The utility evaluation is a subjective process that considers the available (fuzzy) knowledge of the considered parameters. It can be processed and weighted employing fuzzy (behavioral) rules.

The effectiveness of traffic routing applications depends on their user adoption rate (adherence). This ITS adherence must be considered as a time-dependent process [12], [17]. Successive trip planning iterations have different ITS

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adherences as user experiences evolve. ITS adherence has a double impact on total travel time (TTS) and congestion: even with low adoption levels, the whole network gets improved as the most used routes receive less traffic assignment, and thus non-adopters are also positively impacted. Nevertheless, SO-oriented ITS have a well-known issue that needs to be addressed: a fraction of the drivers may be penalized on behalf of the majority improvement. This effect is called route unfairness (RU), which has been studied by [18]–[20].

Fuzzy modeling of the route choice problem has been described in [21] and [22], and later works have developed and enriched this approach as in [23] that proposed a multi-criteria framework for route generation, evaluation, and selection. These models propose calibrated fuzzy sets for traffic variables and fuzzy rules to make routing decisions. They require that the drivers have imprecise knowledge of the status of the network to make their decisions, and from a global perspective, UE and SO cannot be guaranteed.

User utility functions defined as fuzzy methods have been used to model decision-making processes as shown in [24] and [25]. These approaches have also been applied to the transportation problem in [26] where a multi-criteria route choice model for driver utility is proposed. Risk-averse decisions are also taken into account in the route choice fuzzy models as described in [27]–[29]. Risk-aversion and user's perceived utility are in the basis of Prospect Theory which has also been applied to route choice under uncertain information [30], [31].

Other fuzzy-based proposals have also been applied as a heuristic approach to the Traffic Assignment Problem (TAP) [32], proving a macroscopic routing perspective. This fuzzy macroscopic approach has been exposed by [33] considering fuzzy costs for the traffic network links and applying the model to the TAP. Fuzzy cost sets can be biased to avoid the Independence from Irrelevant Alternatives (IIA) from the Logit based models. In the same way, user inertia in decision making is a well-known effect that needs to be considered as resistance to change [34]. Hassan *et al.* [35] have recently proposed a two-level approach for modeling transit-path travel strategies and route choice in transit paths, where fuzzy sets are used to calibrate a discrete choice model.

Our work proposes a method to estimate and simulate ITS adoption by modeling driver's behavior under multi-criteria and uncertainty. It is used to study how SO-oriented ITS approaches behave over time in terms of global adoption considering individual fuzzy decision criteria. Will the drivers use the system considering their fuzzy utility criteria? Will the ITS adherence converge to stable values that fulfill the global SO objectives? It uses a two-level approach similar to [35] that combines fuzzy rules and discrete choice methods to model ITS adoption dynamics considering their utilities. Multiple concurrent ITS usage may converge to a system optimum, evolving towards a stationary global adoption status.

The main contributions of this paper include:

1) A driver experience evaluation model that describes the utility of using different routing strategies, based on a fuzzy parameter model and rule-set behavior evaluation.
2) An individual trip routing decision model based on the subjective utility set using a multinomial logit model and considering the inherent resistance to change.
3) A study of the traffic system evolution in time, considering the adherence to a concrete smart routing application (Traffic Multi-Map Routing, TWM), and the convergence and stability of the system optimum for global travel time.
4) Simulation study on temporal system dynamics, validating how SO-oriented principles can be evaluated in ITS and smart apps for congestion mitigation.

The routing strategy developed with the Traffic Weighted Multi-Maps (TWM) routing system has been previously introduced in [36] and [37], and it essentially relies on the design, distribution, and adoption of complementary network views that decouple the physical road network layout from the logical perspective of the network usage. These views are created by applying different weights to the links between connected roads or street junctions. It induces the routing applications to select different minimum-cost routes depending on the received map. It can be thought as if traffic were colored depending on the received map. The application of TWM to complex traffic scenarios may lead to significant improvements in terms of global travel time, congestion mitigation, emissions reduction, incident avoidance, per fleet routing, time-based routing, and others. One of the main benefits of TWM is the ability to be easily integrated with existing traffic control frameworks as a traffic map server.

In [38] it is discussed how to create optimal TWM distributions depending on the network topology, the planned traffic demand, and various optimization criteria. These optimal TWM distributions can be generated by heuristic optimization algorithms where multiple criteria can be applied to reduce complexity, and leading to pseudo optimal solutions. This optimal TWM provides static traffic assignment scenarios very close to the system optimum (SO) in terms of total travel time (TTS), though other optimality criteria may also be added in TWM calculus. Other similar works have appeared later, presenting a similar idea with randomized maps applied to different traffic networks [39].

In our work, we consider a dynamic traffic assignment with daily stable traffic demands (flows). The utility model assumes that every driver takes individual routing decisions (planning) before starting a trip by considering the following aspects:

1) Social awareness of TWM: knowledge of the existence of the TWM app.
2) Qualified user of TWM: considering if the driver has ever used the system (registered user).
3) Comparison against the optimal travel time that would be achieved when a free-flow scenario is considered.
4) Current network status information and travel time forecast for the next trip.

5) Previous driving experiences using TWM: positive or negative compared to the congested or non-congested situation.
6) TTS improvement or worsening in the latest driving experience, considering TWM usage or not.

These aspects are modeled as fuzzy rules generating probability distributions that estimate the utility of using TWM. This utility model feeds the final decision-making process that makes the routing decision. This process is implemented with a Multinomial Logit Model (MLM) taken from discrete choice theory. Specifically, in this work, the selection process is focused on choosing between the route generated by the shortest-path algorithm and the route provided by TWM. MLM has been widely used to model human behavior in route selection models [1] and other areas such as economics or evacuation scenarios [40]–[42]. The main advantages of the proposed model are its generality, versatility, open and flexible character, its ability to be adapted to empirical values obtained from direct feedback from users, and that it can be easily simulated.

Simulation experiments are conducted in synthetic and real urban traffic networks under congestion conditions. Synthetic traffic networks allow a fast model development isolating the utility model assumptions and policies from the real network constraints. The real urban traffic network is then used for empirical validation and traffic prediction. The experiments allow us to measure:

- How the TWM adherence evolves, and how long it takes its convergence.
- Which are the most valuable fuzzy rules and their relevance in time.
- How social awareness affects ITS adoption.

The rest of the paper is organized as follows. Section II describes the user utility model, the multiple ITS evaluation rules for route choice, and their application to the optimal traffic multi-maps (TWM) routing mechanism. Section III describes the experimental use cases and results, and finally, Section IV points out conclusions and future research lines.

II. MODELING THE UTILITY OF ROUTING APPS

Given a certain number of traffic routing policies or applications $\{\mathbb{R}_n\}$ available, drivers need to choose between them at the planning time of the trip to decide which route to take. This choice can be expressed as a combination of beliefs (including the available information), obligations, intentions, and desires, in the so-called BOID model, described in the classical intelligent agent approaches [43], which can be extended to a BOID+S model if it is expected that social media may have a relevant impact on user adherence. In our approach, each driver takes a strategical routing decision combining a fuzzy logic model with a discrete choice method. The sequence of steps involved are:

1) Collect the necessary observations for the accounted variables.
2) Fuzzy evaluation of these variables using fuzzy membership functions.
3) Application a fuzzy behavior rule-set to obtain the utility values for the considered routing strategies $\{\mathbb{R}_n\}$, showing how useful would be any of the available choices when the driver's decision is taken. A global rule-set wrapping function is used to aggregate the utility value obtained from all the rules together with their relevance (weight).
4) A discrete choice model is then applied to obtain the usage probability of the routing strategies $\{\mathbb{R}_n\}$. A previous linear scaling is required to adapt utilities to the probability ranges.
5) A stochastic decision is then taken, where the driver selects which routing strategies $\{\mathbb{R}_n\}$ to use.
6) Differentiation between decision making and execution is then applied, as users experience resistance to change. It is modeled using a stochastic process.
7) Select the appropriate routing method R_i for the next trip.

This section covers the utility model and its application to the TWM routing strategy.

A. FUZZY UTILITY MODEL

A routing strategy, method, or application $\{\mathbb{R}_n\}$ is supposed to provide a particular utility value $\left[U_n^k\right] = \left[U_1^k, U_2^k \dots U_n^k\right]$ to the driver k at a specific time ($[U_n]$ from now on), which considers the experience gained by the driver in previous trips. Discarding those vehicles that have fixed routes such as regular urban buses, it is reasonable to consider that drivers use at least one routing policy when planning a trip. Thus, we define the standard trivial routing method $\mathbb{R}_0$ that considers the minimum cost route under free-flow conditions, ignoring or not knowing the traffic status. Its utility is represented by $\overline{U}$ (no ITS usage).

Utility values $[U_n]$ are independently evaluated considering BOID+S components represented by the variables $[X_i]$. They can be implemented as fuzzy variables, which can be multi-valued with the value sets $\left[c_{ij}\right]$, which numerically represent the membership to the fuzzy categories $\left[C_{ij}\right]$ specific to each variable. The values $\left[c_{ij}\right]$ are obtained through fuzzy-set evaluation functions $\left[m_{ij}\right]$ (1):

$$X_i \to x_i \approx \left[c_{ij}\right], \; c_{ij} \to m_{ij}(x_i) \tag{1}$$

For instance, let us consider the driving factor $X_{FF-ITTS} \approx$ *"Individual Last-Trip to Free-Flow Travel time Similarity"* (X_1), which measures the ratio between the individual free-flow travel time (best possible travel time using the minimum cost route) and the previous travel time experience. It may be evaluated by the fuzzy categories $[C_{11}, C_{12}, C_{13}] \approx$ *{ "optimum", "acceptable", "bad" }* depending on the ratio value obtained for a given vehicle at a specific time. Every fuzzy category has its membership function $[m_{11}, m_{12}, m_{13}]$, so from the fuzzy perspective, any X_1 value x_1 is evaluated by the evaluating tuple $[m_{11}(x_1), m_{12}(x_1), m_{13}(x_1)]$, for example: $x_1 = 0.8915 \approx [0.99, 0.23, 0.01]$.

TABLE 1. TWM adoption rule R_3.

Rule	Trigger condition		Evaluation		Weight
R_3	WHEN	The free-flow individual travel time similarity IS *bad* (very long travel time compared to free-flow) AND The driver IS an *unregistered TWM user* AND TWM popularity IS *high*	THEN	Utility of TWM routing IS *high* AND Utility of standard routing (non-TWM) IS *low*	WEIGHT=0.5

In the same way, the utility variable set $[U_n]$ is also described by fuzzy variables which also are multi-valued value sets $\left[u_{nj}\right]$ that represent the membership to the fuzzy categories $\left[UC_{ij}\right]$ using fuzzy-set evaluation functions $\left[um_{ij}\right]$ (2):

$$U_n \rightarrow u_n \approx \left[u_{nj}\right],\ u_{nj} \rightarrow um_{nj}(U_n) \tag{2}$$

Following the previous example, the utility of using TWM, U_{TWM}, may be modeled as *{"high","mid", "low", "very low"}* and also $\overline{U}$ may be modeled as *{"great","normal", "small"}* (they do not need to map to the same categories).

Driver behavior is modeled by evaluation rules $\{R_r\}$that estimate the utility values $[U_n]$ considering the driver and context variables $[x_i]$ and their fuzzy categories $\left[C_{ij}\right]$. Rule evaluation is done by the rule processing method $\mathcal{F}$ (3). The BOID+S model is implemented by multiple rules, each one returning its own evaluation set $[u_i]_r$, so it is necessary to provide unique evaluation values to a rule-set wrapping method $\mathbb{Q}$ (4), considering the returned utilities and the corresponding rule weights w_i:

$$R_r : [u_n]_r \rightarrow \mathcal{F}([x_i]) \tag{3}$$

$$[u_i] \rightarrow \mathcal{Q}([[u_n]_r, w_r]), \quad \forall R_r \tag{4}$$

For instance, using our behavior fuzzy rules we can easily define the rule described in Table 1.

Fuzzy engines offer multiple evaluation strategies that could be used depending on the problem to be solved. We use an additive resolution model, considering that utility is usually an additive process. The fuzzy utility model returns normalized values in the [0,1] range that needs to be linearly scaled before the probability calculus for traffic routing method $\mathbb{R}_i$, generating $\left[u_i^*\right]$.

B. DISCRETE CHOICE MODEL

Once the utility values have been obtained, a discrete choice model based on random utility theory is applied [1], [44], [45] under the following assumptions:

1) Individuals belong to a homogeneous population in terms of objectives (mainly reduce travel time), use perfect information about the traffic status and previous experiences, and make rational decisions (based on behavior rules).
2) There is a predefined set of routing $\{\mathbb{R}_n\}$ ITS alternatives expressed by value attributes $\left[c_{ij}\right]_k$ for every individual. Individuals need to make choices considering these valued attributes.
3) Utility perceived by each driver k over each routing alternative is expressed by the expression (5,6) that combines the systematic evaluation of the attributes and an ε_n^k observational error.

$$u_n^k = v_n^k + \varepsilon_n^k \tag{5}$$

$$v_n^k = \sum \beta_{ij} * x_{ij}^k \tag{6}$$

4) The travelers select the maximum utility alternative when $v_n^k - v_m^k \geq \varepsilon_m^k - \varepsilon_n^k$ and then the probability $P(u_n^k)$ of choosing the alternative n is described by (7):

$$P(u_n^k) = Prob\left\{\varepsilon_n^k \leq \varepsilon_m^k + (v_n^k - v_m^k), \forall U_m\right\} \tag{7}$$

When the observational errors ε_n^k are independent and identically distributed (IID), the Weibull/Gumbel distribution can be used (Extreme Vale Type I), and the Multinomial Logit Model (MLM) can be applied [46]. It provides a simplified expression to calculate the probabilities $P(u_i^k)$ that a driver will use a traffic routing method $\mathbb{R}_i$ at a time (8):

$$P(u_i^k) = \frac{exp(u_i^k)}{\sum_k exp(u_k^k)} \tag{8}$$

Calibration of logic models with fuzzy reasoning mechanisms applied to transportation scenarios is discussed in [47] and [48]. More recently, [35] describes a dual fuzzy-logit model calibrated with user data.

In this paper, we use MLM to model the routing method choice of a driver at time t, which is then achieved using the probability distribution $\left[P(u_n^k)\right]$ for a stochastic experiment that returns the usage of a specific routing method or app $\mathbb{R}_k^t$. Resistance to change is modeled independently of the routing method choice model. This final decision-making process decides whether to apply $\mathbb{R}_k^t$ or stay using the previous routing method $\mathbb{R}_k^{t-1}$.

C. USER EXPERIENCE PARAMETERS

The BOID+S model is a fuzzy model described by the fuzzy input variables $[X_i]$, the fuzzy output utilities $[U_n]$, the fuzzy reasoning rules $\{R_r\}$ together with their weights, the rule evaluation policies $[\mathcal{F}, \mathbb{Q}]$ and the user resistance to change Y.

The fuzzy input variables $[X_i]$ considered are:

- *Individual Last-Trip to Free-Flow Travel Time Similarity* (X^t_{FF-TTS}): represents how close has been the previous travel time to the ideal free-flow minimum value. It is measured by the ratio (9) between the individual free-flow travel time (best possible travel time using the minimum cost route) and the previous travel time experience (TT^t_k). It is described by the categories (10).

$$X^t_{FF-TTS} = \frac{TT^{FF}_k}{TT^t_k} \tag{9}$$

$$C_{FF-TTS} \in \{\text{"}Optimum\text{"}, \text{"}Acceptable\text{"}, \text{"}Bad\text{"}\} \tag{10}$$

- *Individual Last-Trip Travel Time Experience* (X^t_{LT-TT}): represents the most influencing short-term experience, comparing the two latest experiences and checks if the latest decision was worthy. It compares the latest trip TT^t_k improvement over the previous one TT^{t-1}_k. Improvement (11) is effective when its value is over a certain subjective threshold δ. X_{LT-TT} categories are described in (12).

$$X_{LT-TT} = \left(TT^t_k < TT^{t-1}_k * (1-\delta)\right) \tag{11}$$

$$C_{LT-TT} \in \{\text{"}Yes\text{"}, \text{"}No\text{"}\} \tag{12}$$

- *Individual Awareness of ITS R_k* (X^t_{RU-K}): reflects if a user actively knows about the routing method $\mathbb{R}_k$. This knowledge can be measured by the vehicle's registration status in the routing application or by the individual memory flag recording if it has been ever used. It is described by the categories described in (13).

$$C_{RU-K} \in \{\text{"}NoUser\text{"}, \text{"}PotencialUser\text{"}, \text{"}ActiveUser\text{"}\} \tag{13}$$

- *Individual Mean Travel Time Experience using ITS R_k* (X^t_{MTT-K}): reflecting the mid-term individual perception about R_k usage. It is measured as the ratio of trips that improved their travel time using $\mathbb{R}_k$ in the latest m executions (14). It is described by the categories (15).

$$X^t_{MTT-K} = \frac{\sum_i X^i_{LT-TT}}{m}, i \in [t-m, t] \tag{14}$$

$$C_{MTT-K} \in \{\text{"}Improved\text{"}, \text{"}Neutral\text{"}, \text{"}Worsened\text{"}\} \tag{15}$$

- *Last-Trip Has Used ITS $\mathbb{R}_k$* (X^t_{LTU-K}): expresses if an ITS routing mechanism has been used in the previous trip. Previous trip experience is critical, and the routing method that has been used needs to be evaluated to make the next decision. It is measured as a yes/no option for the $\mathbb{R}_k$ routing methods (16).

$$C_{RU-K} \in \{\text{"}Yes\text{"}, \text{"}No\text{"}\} \tag{16}$$

- *ITS $\mathbb{R}_k$ Social Influence* (X^t_{SOC}): reflecting the influence of the driver's community over the individual decision. This parameter aggregates all the social influencing factors. It can be initially approached as the adoption ratio of the routing method in the global population (17): percentage of drivers using R_k, where N is the number of drivers. It is described by the categories (18).

$$X^t_{SOC} = \frac{\sum X^t_{LTU-K}}{N} \tag{17}$$

$$C_{SOC} \in \{\text{"}Low\text{"}, \text{"}Mid\text{"}, \text{"}High\text{"}\} \tag{18}$$

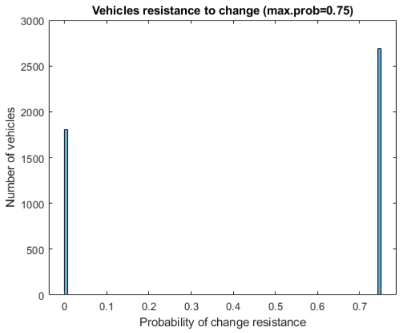

FIGURE 1. Strict distribution of driver resistance to change, $Y_{bin} \rightarrow 0.75 * binary(0.6)$.

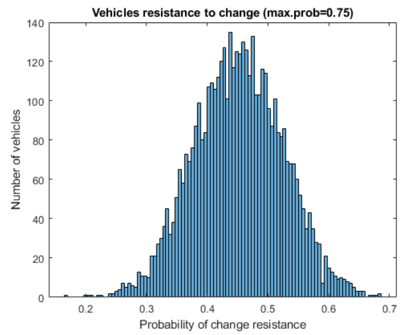

FIGURE 2. Normal distribution of driver resistance to change, $Y_{norm} \rightarrow 0.75 * norm(0.6, 0.1)$.

The fuzzy output variables are the utility values $[U_n]$ obtained from the fuzzy rules evaluation. They are evaluated by the fuzzy engine (4), and are described by the categories $[C_U]$ (19):

$$C_U \in \{\text{"}Low\text{"}, \text{"}Mid\text{"}, \text{"}High\text{"}\} \tag{19}$$

Besides the fuzzy variables, the *Individual Resistance to Change* (X_{RC}) is also considered. It reflects the personal attitude to maintain the previous routing method decision taken. Resistance to change is modeled over the vehicle population, assigning a certain probability for X_{RC} to every vehicle with a p_{max} maximum probability. Several probability distributions may be used. Our work is focused on:

- The strictly receptive model where the driver simply accepts or rejects the routing decision to be taken with probability $Y_{bin} : p_{max}, m \rightarrow p_{max} * binary(m)$ where $binary(m)$ is a [0, 1] experiment for the m percentage of vehicles. Figure 2 illustrates the probability values distribution for X_{RC} where only *60%* of the vehicles may

TABLE 2. Weight categories for the fuzzy rules.

Category	Very High	High	Normal	Low
Weight	1	0.75	0.50	0.25

have a X_{RC} probability of *0.75*. Values are randomly assigned to the vehicles.
- The normal resistance mode, where ability to adopt changes is modeled with a normal distribution $Y_{norm} : p_{max}, m, d \rightarrow p_{max} * norm(m, d)$, where $norm(m, d)$ is the normal random distribution with mean m and standard deviation d. Figure 2 shows the X_{RC} histogram for the whole population with $p_{max} = 0.75$, $norm(0.6, 0.1)$.

If the resulting decision at the trip planning stage is a change of routing criteria, then a probabilistic experiment is executed with the individual X_{RC} probability to decide whether to change or not. The flexibility of our BOID+S model allows easy definition of new parameters. We are mainly focused on travel-time related factors, but other parameters may be added directly, such as:

- Trip length, comparing $\mathbb{R}_k$ use or not, both in short-term and mid-term experiences.
- Congested areas traversal, in percentage ratio of total trip length.
- Freeways usage.

D. USER EXPERIENCE RULES

For the sake of conciseness and understanding, we will limit ourselves to describing the rules that affect the existence of a single routing method$\mathbb{R}_{TWM}$. All the fuzzy rules are evaluated at every driver decision-making iteration, whose relative impact is weighted as shown in Table 2. The rules are shown in Table 3, which are grouped by their similar behavior into the following rule-sets:

1) TWM non-users behavior (rules 1-5): when the driver is not a TWM user, depending how valuable is the last-trip experience compared to the free-flow driving conditions, and the social acceptance of TWM, the utility of using TWM (U_{TWM}) or not using it ($\overline{U}$) will vary. The TWM utility condition the new-adopters policy.
2) TWM users behavior considering short-term experience (rules 6-15): when the driver is a TWM user (registered user or has ever used it), last-trip experience conditions if it was worthy TWM usage or not, considering if the travel time has improved or not. Social acceptance of TWM is less important here. This rule-set controls if the driver keeps using TWM or rejects using depending the traffic experiences when adoption is increasing and congestion conditions evolve.
3) TWM users behavior considering mid and long term experience (rules 16-19): when the driver is a TWM user, mid and long term experience using TWM is valuable to represent driver's confidence to the routing method. Regardless of what has happened on the driver's last trip, he learns from other previous experiences. These rules limit as well oscillations in the decision process.

The traffic routing adoption model is very open and new rules can be easily added referring to the existing fuzzy variables or to new add-ons.

E. OPTIMAL TWM ROUTING OVERVIEW

Traffic Weighted Multi-Maps (TWM) is a routing technique based on the usage and distribution of complementary views (maps) of the traffic network to create alternative paths for the planned trips. It was introduced in [36] and [37], where its application was applied to global travel times, individual mean travel time, and congestion reduction.

TWM decouples the physical topology of the traffic network from the logical usage view of the network (map), assuming that it is based on traffic logical rules, constraints, and recommendations. TWM is based on the generation of a set of static link weights that the drivers use to calculate route costs. TWM provides differentiated views (maps) to the vehicles with specific link weights, inducing them to select scattered routes. TWM maps are selectively distributed to the traffic groups through standard traffic services. It assures backward compatibility with other traffic routing services, as their core is always based on a network map. TWM is compatible with centralized and distributed traffic routing mechanisms.

Use cases studied so far with TWM are congestion mitigation, per fleet differential routing, real-time incident management [36], and more recently, optimal traffic assignment [38]. This latest work demonstrates that it is possible to apply optimization algorithms to generate TWM map-sets that provide quasi-optimum traffic assignment when the traffic demand is estimated in advance and a certain usage ratio (adherence) is considered.

Explored TWM optimization mechanisms are based on evolutionary algorithms, where link weights in the traffic maps are distributed to achieve minimum global travel time (TTS) for a given demand. TWM optimization uses static traffic assignment models, using volume-delay functions (VDF) [49]. VDF provides a macroscopic approximation of the travel time and traffic flows.

The most commonly used VDF function is (20) defined by the Bureau of Public Research [50] that describes link travel times as a function of the free-flow travel time tt_0, link capacity q_{max} and link usage q.

$$tt_i = (tt_o + \alpha * (\frac{q}{q_{max}})^{\beta}) \tag{20}$$

Considering the k-shortest paths (KSP) for the traffic flows, it can be defined traffic routing areas containing the KSP nodes and all the link-connected nodes at a distance d from them. This algorithm is called Extended Flow-Path Optimal TWM (EFP-TWM) [38]. Optimal TWM designed for these routing areas has lower complexity since they use a much smaller volume of links to optimize, focusing on the

TABLE 3. TWM adoption rules.

Group	Id	Description	Weight	x_{FF-TTS}	x_{MTT-K}	x_{RU-K}	x_{LTU-K}	x_{SOC}	x_{LT-TT}	U_{TWM}	$\overline{U}$
Never used TWM	1	TWM non-users. Good routing experience. No need to change.	Very high	Optimum		NoUser	No			very low	high
	2	TWM non-users. Could improve routing performance. May change.	Normal	Acceptable		NoUser	No			low	mid
	3	TWM non-users. Bad routing performance. TWM unknown. Hardly change.	Normal	Bad		NoUser	No	low		very low	mid
	4	TWM non-users. Bad routing performance. TWM mid-popular. Could change.	Normal	Bad		NoUser	No	mid		low	mid
	5	TWM non-users. Bad routing performance. TWM very popular. Try to change.	Normal	Bad		NoUser	No	high		high	mid
TWM users	6	TWM user. Recently improved relative experience with TWM. Keep using.	High			ActiveUSer	Yes		improved	high	low
	7	TWM user. Recently worsened relative experience using TWM. Reject using.	Normal			ActiveUSer	Yes		worsened	very low	high
	8	TWM user. Didn't use recently TWM, and had good experience. Reject using.	Normal			ActiveUSer	No		improved	very low	high
	9	TWM user. Didn't use recently TWM, and had poor experience. Return to TWM.	Normal			ActiveUSer	No		worsened	high	low
	10	TWM user. Recently good absolute results with TWM. Keep using.	Normal	Optimum		ActiveUSer	Yes			high	low
	11	TWM user. Recently good absolute results without TWM. Reject using.	Very High	Optimum		ActiveUSer	No			low	mid
	12	TWM user. Recently mid absolute results with TWM. Indifferent.	Normal	Acceptable		ActiveUSer	Yes			low	low
	13	TWM user. Recently mid absolute results without TWM. Detractor.	Normal	Acceptable		ActiveUSer	No			low	mid
	14	TWM user. Recently poor absolute results with TWM. Strong detractor.	Normal	Bad		ActiveUSer	Yes			low	high
	15	TWM user. Recently poor absolute results without TWM. Promoter.	Very High	Bad		ActiveUSer	No			high	low
TWM Mean Usage	16	TWM user. Latest TWM experiences are good. Promoter	High		Improved	ActiveUSer	Yes			high	low
	17	TWM user. Latest TWM experiences are good, even if last day didn't use it. Promoter.	High		Improved	ActiveUSer	No			high	low
	18	TWM user. Latest TWM experiences are bad. Detractor	High		worsened	ActiveUSer	Yes			very low	high
	19	TWM user. Latest TWM experiences are bad, even if last day didn't use it. Detractor.	High		worsened	ActiveUSer	No			very low	high

most relevant links. EFP-TWM distributions provide traffic assignment distributions very close to the system optimum at a reasonable computing cost.

F. USING THE FUZZY UTILITY MODEL WITH TWM ROUTING

The effectiveness of the optimal TWM distributions depends mainly on the driver's adherence to TWM usage. Nevertheless, adherence evolves depending on several factors, especially when previous experiences are taken into account, including social TWM awareness. For system optimum traffic assignment, some of the vehicles will inevitably be harmed for the benefit of the majority. This is called the route unfairness effect [18]–[20]. So, TWM usage will have promoter and detractor driver profiles, considering these drivers that improved or worsened their planned trips. Despite having received a TWM routing recommendation, some drivers may decide not to change their routing strategies due to behavioral inertia or a biased utility perception [13], [34].

TWM adherence can be studied considering repetitive traffic flows such as regular daily trips, considering the peak hour. This simplification of the problem is acceptable as there could be time-framed TWM sets distributed to the vehicles. So, for the sake of conciseness and simplicity, we will consider repetitive traffic flows during the peak hour and study the dynamics of driver adherence concerning the global travel time.

Our utility model provides two main variables $\left[U_{TWM}, \overline{U}\right]$, representing the utility of using TWM routing or not using it, thus using the standard method $\mathbb{R}_0$ (21).

$$[U_n] = \left[U_{TWM}, \overline{U}\right] \tag{21}$$

According to the MLM expression described in (8) for the probability of TWM usage, we obtain (22)

$$P(U_{TWM}) \rightarrow \frac{exp(U_{TWM})}{exp(U_{TWM}) + exp(\overline{U})} \tag{22}$$

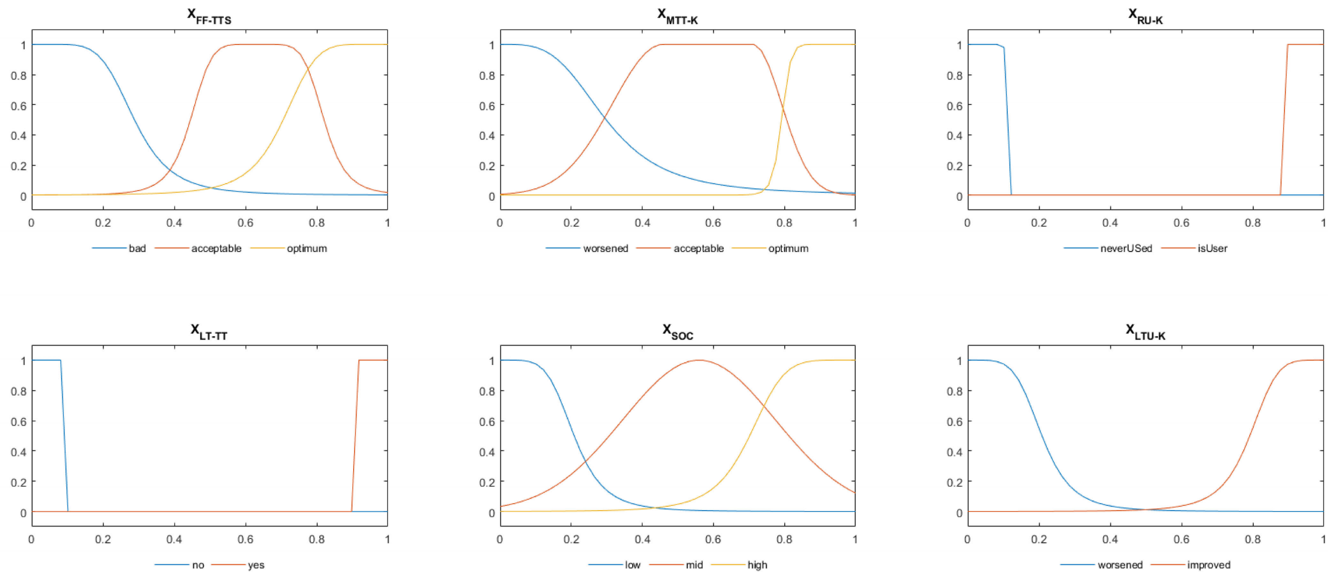

FIGURE 3. **$[X_i]$ evaluation functions for TWM.**

The evaluation functions for the $[X_i]$ to $[C_i]$ categories are shown in Figure 3, using mainly Gaussian distributions to represent user behavior. The specific values for the parameters of the functions are taken from the extensive experiments that have been developed in the study, though they may be taken from real data usage or user surveys. $\left[U_{TWM}, \overline{U}\right]$ evaluation functions are shown in Figure 4.

III. EXPERIMENTS

Deploying new ITS applications in a massive scope is a complex task that requires intensive research, testing, investment, and marketing effort. To validate the effectiveness of new ITS systems, existing traffic simulation software plays a pivotal role by enabling simulating diverse traffic demand and driver behavior conditions, including the simulation of advanced ITS applications.

In our work, two different simulation scenarios are studied:

1) A synthetic reference traffic network, where traffic demand generates congested links and nodes. Synthetic scenarios allow a fast model development isolating the utility model assumptions and policies from the real network constraints.
2) A real urban traffic network is fed with a synthetic traffic demand to reproduce congestion conditions, used to validate results.

A. SIMULATION ENVIRONMENT

The experimental results are evaluated in Matlab R2020b (update 5) [51] together with some python 3.7 scripts to process map formats. The Matlab environment uses the Simulink package and the Matlab Fuzzy Logic Toolbox [52] which is used to model the driver's fuzzy utility model. Optimization of TWM maps is achieved by means of the Matlab's package for Genetic Algorithm processing [53]. The whole simulation runs in a Window10 hosted Intel iCore7 quad-core architecture with 16Gb RAM.

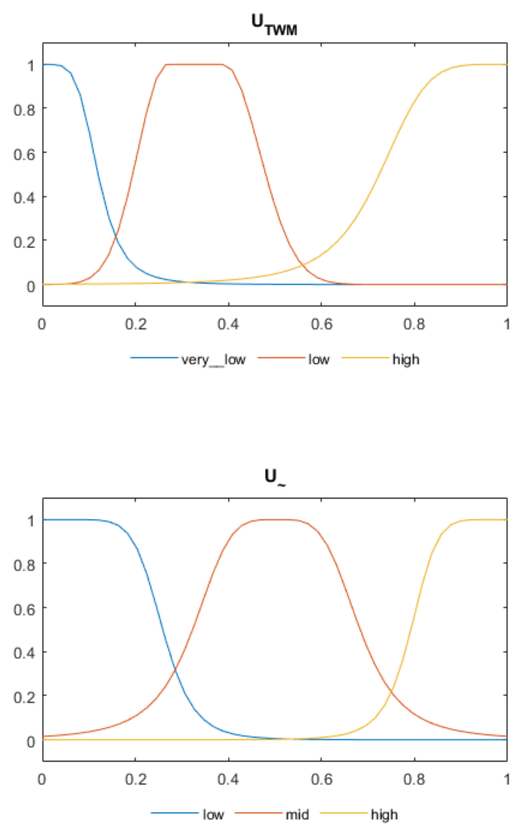

FIGURE 4. **$\left[U_{TWM}, \overline{U}\right]$ evaluation functions.**

B. EXPERIMENTAL SETUP

Experiments are focused on how ITS adoption evolves, attending to the BOID+S model for the driving experience. We consider a specific traffic demand formed by the origin-destination flows that are repeated every day. These flows correspond to a congested time frame where drivers are looking for routing alternatives to reduce travel time.

The experiments model the evolution of the first D days, starting from an empty adoption distribution and considering a specific resistance to change, following a probabilistic distribution. A time frame of $D = 50$ labor days is considered, though real experiences could differ in time extension depending on concrete circumstances.

Every day, drivers take the routing decision considering the BOID+S model, and, at the end of the trip, they register how was the driving experience considering the observed parameters. In the same way, the traffic authority takes daily snapshots on global traffic parameters: global adherence to TWM, total travel time, and others. The authority may take some action to influence TWM adherence.

At the beginning of the simulation period, an optimized TWM map is generated. It uses the traffic network and the traffic demand forecast, which is known in advance. With the TWM generation process, a TWM distribution policy for every vehicle is selected among the available policy set: pure random assignment, random per flow, sequential per flow, or some other. Our experiments use the pure random assignment policy for simplicity.

To be able to make consistent comparisons between simulation scenarios the homogeneous parameter sets are considered. Optimal TWM map sets are based on a TWM-3-2-2 schema [38]: 3 weighted network maps in the TWM, two shortest-paths based on the free-flow minimal cost paths, and consideration of 2-distance radius from the KSP paths. The shortest paths are obtained based on Dijkstra's algorithm with the implementation proposed by Yen [54].

For the optimum TWM generation, a static traffic assignment criteria is used, using the volume-delay function (VDF) (20) using $\alpha = 0, 15$ and $\beta = 4$. Link capacities are adapted from [55] and [56].

The genetic algorithm (GA) that computes the optimal TWM map uses 50 individuals and 500 evolutionary generations, bounding maximum and minimum weight variation between [-50% of the original weights. Details of the GA can be found in [38].

We used two different user resistance to change models: the binary mode Y_{bin} and the normal mode Y_{norm} with $p_{max} = 0.5$. These are shown in Figures 5 and 6. Different values $p_{max} \in [0, 1)$ values are considered for the maximum probability amplitude in the normal distribution. Value 0 provides the zero resistance to change.

The simulations consider that the drivers have a mid-term memory of the last 10 executions.

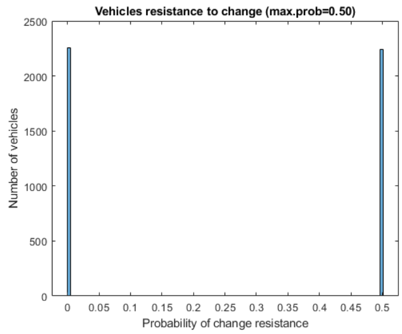

FIGURE 5. Strict distribution of driver resistance to change, $Y_{bin} \rightarrow 0.5 * binary(0.5)$.

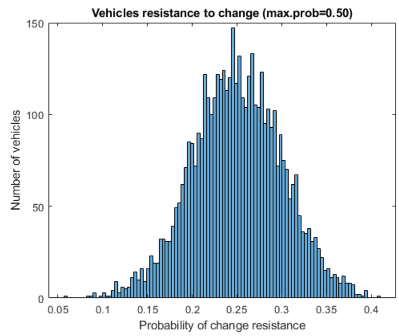

FIGURE 6. Normal distribution of driver resistance to change, $Y_{norm} \rightarrow 0.5 * norm(0.5, 0.1)$.

TABLE 4. GRID64: O/D matrix.

Source/Destination	N_{73}	N_{75}	N_{77}
N_{23}	1000	500	1000
N_{26}	500	1000	500

C. SYSTEM DYNAMICS IN THE GRID64 SYNTHETIC NETWORK

The synthetic scenario selected for experimental simulation is the GRID64 described in [38], where the different algorithms and criteria for obtaining an optimal TWM distribution are detailed for a particular traffic demand. We refer to this work for the calculation details.

GRID64 is a rectangular grid-shaped network defined by 8×8 nodes $[N_{xy}]$ connected by bi-directional links. It contains 64 nodes and 224 bidirectional links whose weights are randomly assigned in the [4, 12] range (uniform) (Figure 7). Traffic demand is formed by 6 traffic flows $\mathbb{T} = [f_1, f_2 \ldots f_6]$ connecting 3 traffic origins and 2 traffic sinks. Total traffic payload contains 4.500 vehicles (Table 4). An initial adoption rate of 0.1% of TWM adherence is assumed.

1) TWM ADOPTION EVOLUTION

For this experiment the Extended Flow-Path for TWM algorithm has been used [38], using a 3 maps structure with 3 shortest-paths, and a distance radius $d = 2$ for the KSP routing area (EFP-KSP-3-2-2). Optimal TWM distribution is

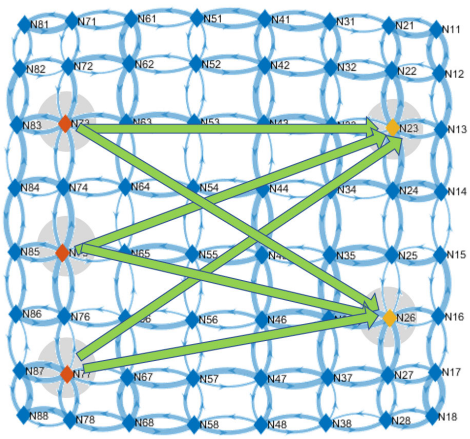

FIGURE 7. GRID64: traffic network and demand flows.

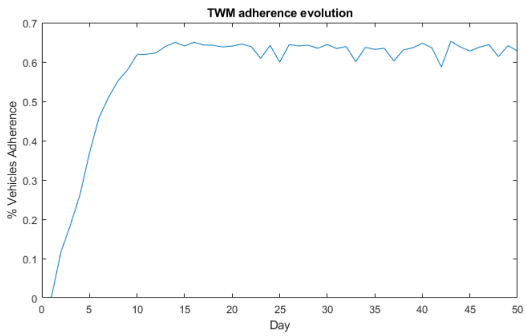

FIGURE 8. GRID64: Evolution of TWM adherence with $Y_{norm}(0.5, 0.5, 0.1)$.

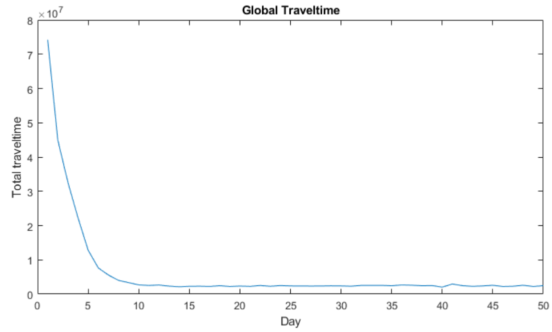

FIGURE 9. GRID64: Evolution of TTS $Y_{norm}(0.5, 0.5, 0.1)$.

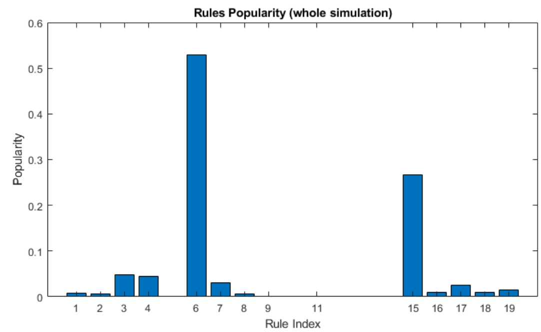

FIGURE 10. GRID64: popularity of BOID+S rules.

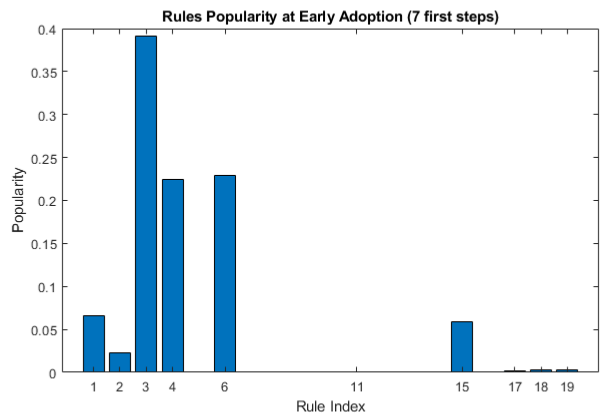

FIGURE 11. GRID64: popularity of BOID+S rules in early times.

generated with the Matlab Genetic Algorithm package using an evolutionary population of 50 members and 500 generations. TWM creation process converges quickly providing an optimal TWM distribution.

Figure 8 shows the adherence using $rc_{norm}(0.5, 0.5, 0.1)$. As we can see, travel time differences during congestion scenarios force the drivers to look for alternative routing methods (TWM in this case), which is initially almost unknown. The drivers that start using it find that the travel time experience with the new routes is much better than the travel time with the shortest path under current traffic conditions. This usage reinforces TWM usage for the future, and they keep on using it.

Regardless of how TWM adherence behaves, it is interesting to observe in Figure 9 that TTS gets stationary, close to the system optimum, despite the changes of decision that the vehicles are taking. For the selected simulation, at period 15, TTS stabilizes.

The Fuzzy Utility Rules popularity is shown in Figure 10. Rule 6 states that those vehicles using TWM and obtaining a good result in travel time will keep on using this routing method. In the same situation, rule 15 states that those vehicles that are qualified TWM users, and on the last day did not use it obtaining poor results, will retake TWM usage.

It is interesting to deep dive into the early adoption phase, where the most used rules are 3, 4, and 6. Rule 3 states that under low TWM popularity, non-TWM users will not use the new routing method. Rule 4 states that when TWM popularity raises, drivers will slightly tend to use it. Of course, as has been already pointed, rule 6 states that if TWM provides reasonable solutions, drivers will keep on using it.

After an initial period of early adopters (up to day 15), the drivers' community observes that TWM adoption is relevant, and new drivers are attracted by this new method, quickly reaching 65% usage. At this point, many users are selecting the same alternative routes, so some of them return to the original routing strategy. Figure 12 shows how the fuzzy rules are fired for a concrete individual.

Figure 13 outlines how TWM usage decisions affect the individual travel times, where the impact of changing the

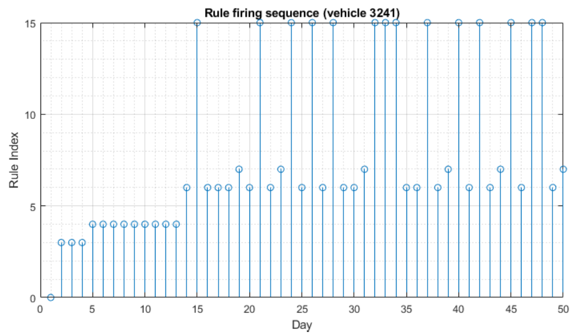

FIGURE 12. **GRID64: Individual fuzzy decision sequence.**

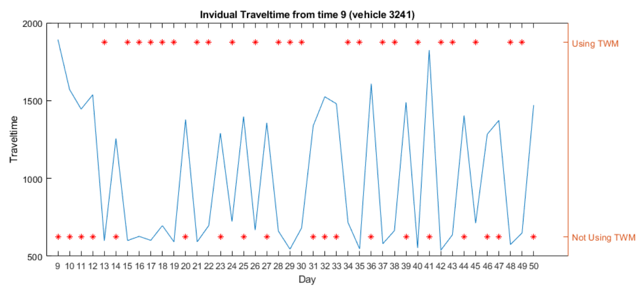

FIGURE 13. **GRID64: Travel time evolution related to TWM usage.**

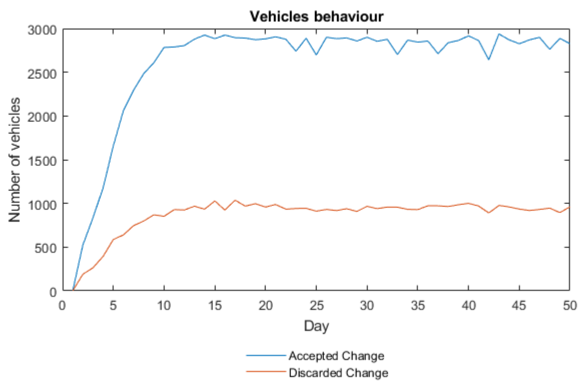

FIGURE 14. **GRID64: Drivers resistance to change.**

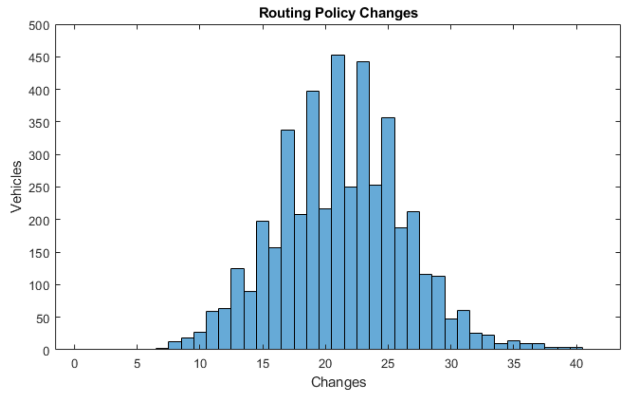

FIGURE 15. **GRID64: Number of vehicles changing routing strategy.**

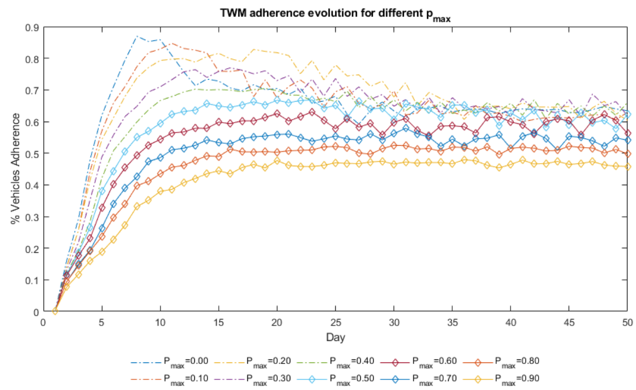

FIGURE 16. **GRID64: TWM adherence evolution at different p_{max} values $Y_{norm}(p_{max}, 0.5, 0.1)$.**

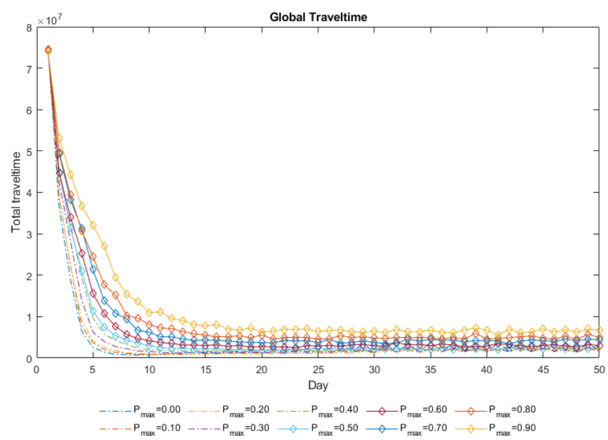

FIGURE 17. **GRID64: global travel time evolution at different p_{max} values $Y_{norm}(p_{max}, 0.5, 0.1)$.**

routing decision is exposed. Drivers that start using TWM and decide to change their decision suffer a travel time penalty that forces them to roll back their decision.

Considering the user resistance to change (Figure 14), we can observe that the distribution of drivers that should have changed the routing strategy is divided into the distribution of drivers accepting changes (blue) and drivers deciding not to change their actual routing strategy.

Figure 15 represents the number of vehicles that have changed their routing decision during the whole simulation, where we can see how previous decisions and their impact on travel experience make them change and adapt their subsequent decision to a subjectively better scenario.

It can be observed in Figures 16 and 17 that the system has a strong tendency to converge towards stable values, besides the effect of user resistance to change. Several probabilities of change are used, ranging from 0 to 0.9. Interestingly, when drivers are prone to accept changes, they use alternate traffic methods depending on the concrete traffic conditions. After several peak adoption oscillations, TWM adoption converges towards a system optimum status.

D. SYSTEM DYNAMICS IN A REAL TRAFFIC NETWORK

A real traffic network scenario is shown in Figure 18 describing the new district of Las Tablas in the north of Madrid,

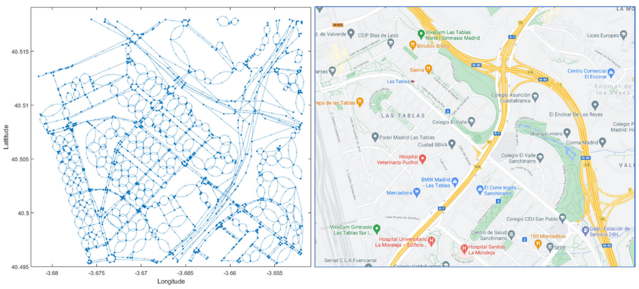

FIGURE 18. Madrid-Las Tablas traffic network and Google maps view.

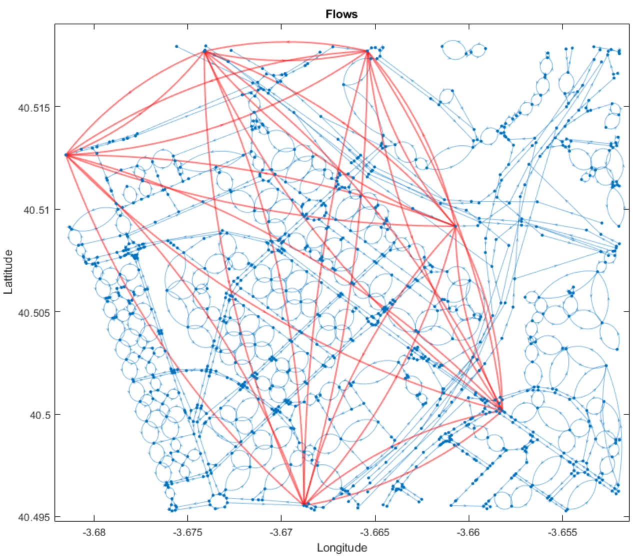

FIGURE 19. Las tablas main traffic flows.

Spain. This district, with more than 24,300 hectares, occupies almost half of the municipal term of Madrid. Added to this particularity, its 30,000 inhabitants make it, by demographic weight, the city's third district. It also contains large business and financial centers that cause significant inbound and outbound traffic during business hours. The district is bounded by large expressways to the north, south, and east, while to the west, it is blocked by railways.

A synthetic traffic demand of 15,000 vehicles is created for the experiment, crossing the network and creating congested areas. They are grouped in 30 flows of 500 vehicles and are represented in Figure 19. The traffic network contains 971 nodes and 1583 links. The GA that creates the optimal TWM for the traffic demand selects a sub-network of 420 nodes and 691 links when an EFP-KSP-3-2-2 strategy is considered (3 traffic maps, 2 shortest paths, and 2 node-distance for alternative routing area). It takes 160 evolutionary generations to converge. An initial adoption rate of 0.1% of TWM adherence is assumed.

1) TWM ADOPTION EVOLUTION

Figure 20 shows how TWM adherence evolves depending on the resistance to change selected for the vehicle population, while Figure 21 shows global travel time evolution.

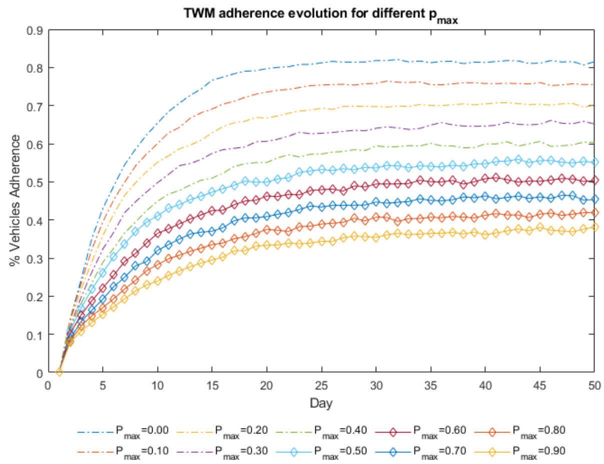

FIGURE 20. Madrid las tablas: TWM adherence evolution at different p_{max} values $Y_{norm}(p_{max}, 0.5, 0.1)$.

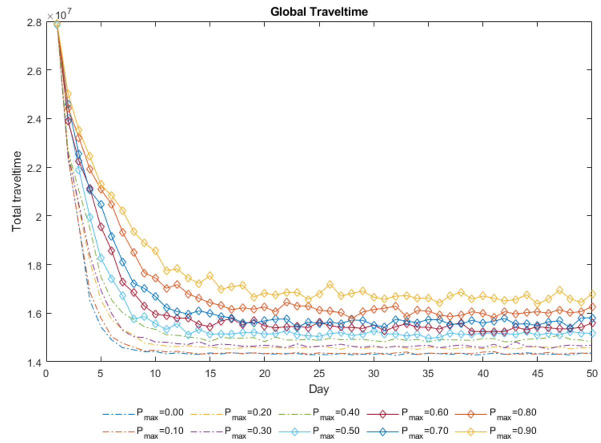

FIGURE 21. Madrid las tablas: global travel time (TTS) evolution at different p_{max} values $Y_{norm}(p_{max}, 0.5, 0.1)$.

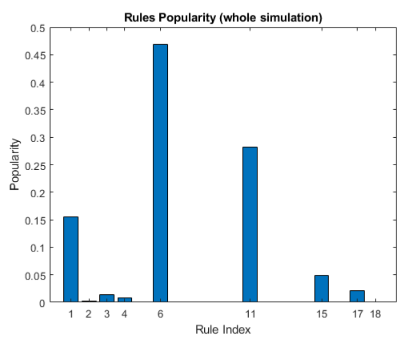

FIGURE 22. Madrid las tablas: popularity of BOID+S rules.

TWM adherence evolves to a quasi-constant value that varies considerably depending on the propensity to change of the population. Nevertheless, it can be observed that global travel time optimization is quickly achieved, and what is most interesting, it hardly depends on the resistance to change. It is enough that a small of the population adopts TWM to obtain a highly significant value of TTS for the majority.

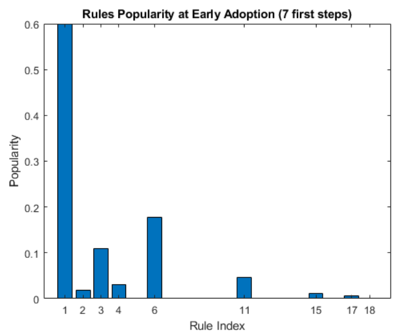

FIGURE 23. **Madrid las tablas: popularity of BOID+S rules in early times.**

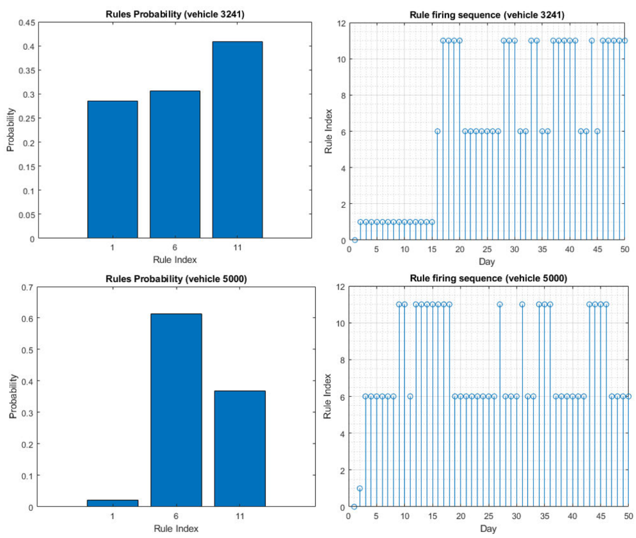

FIGURE 24. **Madrid las tablas: behavior of individuals 3241 and 5000.**

Figure 22 show BOID+S rules popularity for the whole simulation, while Figure 23 shows the same concept during the seven first TWM deployment days. Results are consistent with those obtained in the synthetic scenario: those drivers adopting TWM and experiencing a significant improvement in their travel time will keep using it. Early adoption is limited by the knowledge of the drivers about TWM.

If we analyze individual behavior, Figure 24 shows two different behaviors for individuals 3241 and 5000. The first individual habitually uses a route with good travel times (rule 1 is elicited). Eventually, this individual becomes a TWM user (rule 6) and gets a new route, but the experience is not so good as the previous, so this driver uses the standard non-TWM routing mechanism (rule 11). On the other hand, individual 5000 suffers congestion regularly, so this driver quickly starts using TWM (rule 6) and keeps on using it as a preferred strategy. Sometimes, the route gets affected by others' decisions and tries back to the standard routing strategy (rule 11), but returns quickly to TWM when it is noticed that it provides better routes (rule 6).

IV. CONCLUSION AND FUTURE WORK

Our study proposes a flexible framework for modeling and evaluating driving experience in Intelligent Transportation Systems (ITS). When a traffic population is offered a set of traffic routing applications, drivers individually use their subjectively better app to select the recommended route. The paper considers driver behavior as a set of beliefs, obligations, intentions, desires, and social influences (BOID+S), evaluated through multi-valued fuzzy criteria.

Individuals evaluate the fuzzy utility of each routing strategy for each trip. So, when these fuzzy subjective utilities are available, then a discrete choice over the routing alternatives can be applied. A Multinomial Logit Model (MLM) is suitable to estimate the probabilities of making routing decisions.

This behavioral routing decision model poses a reasonable concern about the convergence and stability over time of the ITS strategies that are considered. If they propose subjectively good routing alternatives, such app adoption would increase in time and lead to a system optimum.

The adoption rate (adherence) to ITS in the traffic population determines the effectiveness of their algorithms. However, this adherence evolves, where the decisions made by the rest of the population constantly change the decision-making processes.

Our paper applies the ITS evaluation model to the Traffic Multi-Map Routing with optimal link weights (TWM) described in [38], using a concrete set of travel-time related parameters and fuzzy rules.

TWM adherence convergence, stability, and global travel times obtained are studied over two different network scenarios:

- A reference synthetic grid-based network that enables detailed analysis of the BOID+S model.
- A real urban traffic network where the same TWM strategy is applied.

The experimental results are consistent between them, showing that optimal TWM usage provides a good traffic solution that significantly impacts the global travel time of the traffic network from the system optimum perspective. Traffic network performance evolves based on individual decisions that lead to a constant TWM adoption rate.

Macroscopic convergence of TWM adoption is based on the microscopic individual behavior model. Individuals make their own decisions considering their circumstances that are modeled by fuzzy rules.

The main advantages of the proposed analysis model are its generality, its versatility, its open and flexible character, its ability to be adapted to empirical values obtained from direct feedback from users, and that the results can be easily simulated:

- It can be applied to any traffic routing strategy, not only to traffic-weighted multi-maps. Moreover, multiple traffic routing strategies can be used and compared at the same time based on user experiences.
- The user utility model is very flexible, where multiple utility objectives can be added and managed efficiently. The fuzzy utility modeling approach decouples value categories from the numerical evaluation functions.

- The user behavior model is open, where new variables, as user considerations, can be added and managed easily. As well, its fuzzy modeling provides a natural way to express behaviors decoupled from their numerical expressions.
- User decisions are modeled as weighted fuzzy rules that can also be easily edited and managed, adding generic behaviors and specific constraints when required.

It is worth noting that using fuzzy rules in conjunction with discrete choice methods (in this case, using a multinomial logit model) may be easily linked to field analysis based on user experience surveys or application feedback methods. The users can directly inform the user utility variables and expectations on the routing methods. This study is left for future field research work, together with the analysis of other user impact variables such as trip distances, tolls, electric recharge stations, and other factors.

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ALVARO PARICIO received the double M.S. degree in computer science and communications from the Universidad Politecnica de Madrid, Madrid, Spain, in 1992. He is currently pursuing the Ph.D. degree in information and communications technologies with the Universidad de Alcala (UAH), Madrid. He is a Lecturer in computer science with UAH and a Lecturer in digital transformation with the Escuela de Organizacion Industrial, depending of the Spanish Ministry of Industry. He has developed a wide professional career in private held companies. He joined Telefonica Research and Development, in 1994, as an AI Expert. In 1999, he is a co-founded the Company IAPsolutions (Spain, USA) a technology startup for an AI agents, the IoT and edge-computing leading the company as the CTO. In 2014, he joined SecuritasDirect, a global leader for home-security, as the Development Director for EMEA and LATAM. Since 2017, he leads Digital Transformation Offices with the Telecom Group MasMovil, the fastest growing telecom operator in Europe, since 2017. His main research interests include optimization algorithms, traffic routing optimization, safety and evacuation strategies, the IoT architectures, and massive data analytics.

MIGUEL A. LOPEZ-CARMONA received the B.S. degree in electronics engineering from the University of Alcala, in 1994, the M.S. degree in telecommunication engineering from the Polytechnic University of Madrid, in 1999, and the Ph.D. degree in telecommunication engineering from the University of Alcala, in 2006. From 1995 to 2000, he held positions in Logytel and Alcatel as the Project Manager and a Research Scientist in the areas of railways and defense. Since 2000, he has been an Associate Professor with the Department of Computer Engineering, University of Alcala. From 2010 to 2017, he was the Vice-Dean of the Polytechnic School, University of Alcala. He has been a Visiting Researcher with the Center for Collective Intelligence, Massachusetts Institute of Technology (MIT), where he did research in complex automated negotiations and optimization of complex networks. His research interests include intelligent transport systems, safety and evacuation strategies, automated negotiation, multi-agent systems, and optimization of complex networks.