Embedding a Neuro-Fuzzy Mode Choice Tool in Intelligent Agents

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Abstract

Increasing road traffic levels in urban areas require actions and policies to manage and control the number of road users. Travelers' choices of transport modes, particularly private cars, that generate the main share of road traffic levels, depend on many factors, which include both personal preferences and level-of-service variables. Understanding how travelers choose transport modes according to the above factors is an important challenge in order to adopt the most suitable policies and facilitate a sustainable mobility. In the literature, behavioral models have been mainly proposed in order to both estimate mode choice percentages and capture travel behaviors by suitable estimation of some parameters associated to the above factors. However, behavior is complex in itself and the mechanisms underlying user behavior might be difficult to be captured by traditional models. In this paper, a neuro-fuzzy approach is proposed to extract mode choice decision rules by evaluating different sets of rules and different membership functions of the neuro-fuzzy model. Particularly, to determine which inputs are the most relevant in such decision process, fuzzy curves and surfaces have been considered in order to take into account nonlinear effects. The neuro-fuzzy model proposed in this paper has been thought to be embedded in an agent-based methodological framework where user agents – representing travelers – make travel choices based on the rules learnt by means of the neuro-fuzzy system.

Keywords

Agent System, Fuzzy System, Mode choice, Neuro-Fuzzy Inference, Rule Learning

1. Introduction

Traffic flow conditions in urban road networks are the consequences of several user's choices – from the decision to own a private vehicle to the decision to use it for commuting or to move between origin/destination pairs, at different periods, along some paths. In the last decades, road vehicle traffic levels have been constantly increasing due to – among the others – better economic conditions, which has led to an increasing number of personal vehicles, and increasing number of urban inhabitants, which has implied a continuous growth of urban mobility.

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The consequences of increasing vehicular traffic levels are well-known, ranging from traffic jams, loss of time and economic resources – which affect the quality of life of citizens – to environmental effects both as a direct consequence of mobility (i.e., air pollution) and indirectly for the use of environmental resources from production to end-of-life of a vehicle [1, 2, 3, 4].

Different strategies have been adopted at different levels (e.g., local, national and supranational) to manage such effects, mainly by providing solutions based on transit modes and new technologies [5, 6, 7, 8]. However, suitable policies aimed at balancing private vehicular traffic against shared transportation modes require prediction of mode users' choices based on both level-of-service variables and personal preferences [9, 10]. In addition, user's path choices affect the way in which vehicular congestion spreads across the transportation network [11]. From one hand, the choice to use a private vehicle involves also mobility choices (e.g., having a guide license, owing a vehicle) [12], on the other hand, once the private vehicle has been chosen as modal alternative, users will get their trip destinations from given trip origins by following a sequence of road facilities, which identify paths on the transportation networks [13, 14, 15].

As well known, ultimately path choices will lead to traffic flow levels on road links [16, 17]. Then, the sequence transport mode–path choices has important consequences, both directly on the transportation network conditions (e.g., travel times, pollution, monetary costs) and indirectly on the territorial system (e.g., environmental impacts, life quality).

Analysis and prediction of users' choices – mainly mode choices - are considered fundamental both for the knowledge of travel demand on the available transport modes and for deciding how to vary the level-of-service variables of the transportation supply in order to achieve sustainable mobility and better quality of life [18].

Every day users perform several choices about their trips (e.g., destination, travel mode and path), which depend on the combination of policy measures (e.g., traffic restrictions, access fees to Limited Traffic Zones, parking fares, cost of public transport), external issues (e.g., fuel price) and new forms of mobility like car-sharing, car-pooling, and, as expected in the next future, shared connected and autonomous vehicles [19, 20]. To realize their trips most users still prefer to use private mobility rather than transit opportunities. In other words, individual drivers are reluctant to change their habits regardless of the policies adopted and the additional costs involved in using private mobility. Therefore, it is clear that one key issue is to understand user's travel behavior more in-depth as well as the factors that influence it.

Understanding users' choice behavior is becoming a pressing need and many models and approaches have been used to this aim, from random utility models [21, 22, 23] to stated preferences (SP) [24] techniques and artificial intelligent agents [25]. Random utility models associate a utility value to each available alternative depending on some attributes that characterize the alternative itself. Then, it is assumed that users choose the alternative having the maximum perceived utility, which is in fact a stochastic variable whose distribution function leads to several discrete choice models (for example, Logit, Nested Logit and Probit models [23, 26, 27], the derived Dogit Logit [28] and Logit Box-Cox transformation [29, 30], as well as the the Cross-Nested Logit or the Generalized Nested Logit models [31, 32]). Such models are often based on compensatory approaches [33] where negative attributes (e.g., times or costs) balance positive attributes (e.g., reliability or comfort), both suitably weighted by parameters that result from calibration procedures exploiting user's choice data. A promising alternative to random utility approaches is represented by neuro-fuzzy models [34, 35, 36], which represent a class of adaptive networks that combine the ability to generate a fuzzy inference system (FIS) with a linear relationship in input-output data given by the neural network. Neuro-fuzzy models are known for their ability to capture the vagueness and ambiguity inherent in human decision-making processes.

Additionally, in recent years there has been an increasing use of intelligent software agents (hereafter simply agents) in the transportation domain, to cover manifold aspects and provide effective and efficient solutions for Intelligent Transportation Systems (ITS) [37, 38, 39] as, for instance, to obtain trip choice probabilities [40] or to estimate perceived travel time [41] among the others. In particular, agents are designed with learning, cooperative and adaptive behaviors capabilities [25, 42, 43], often based on Artificial Intelligence (AI) techniques [44], which make them suitable to simulate a great variety of complex human behaviors and agent-to-agent interactions at different levels of detail [45, 46, 47] and abstraction [48]. Neuro-fuzzy systems can be embedded into software agents that need to make decisions by simulating human behavior.

In this perspective, this paper proposes to adopt a neuro-fuzzy component able to both identify the main key factors and model user's mode choice behavior [49, 50, 51, 52], which is expected to be used as input for modular agents simulating travelers' behaviors. More in detail, the paper proposes a neuro-fuzzy network approach to identify behavioral rules that will be used by agents in a cascading structure. Although the article focuses only on the neuro-fuzzy model and its results to understand and model travel mode choice behavior, the modular structure of the agent will also be described in order to provide the methodological framework in which the proposal was developed. Some simulations have been carried out to estimate the performance of the proposed neuro-fuzzy component. The obtained results are satisfactory and the designed neuro-fuzzy component to simulate the transportation modal choice has the undeniable advantage of making explicit in a clear and unequivocal way the users' behavioral rules, which otherwise would have remained embedded in the parameters of the traditional models. Explicitly understanding behavioral rules that lead users to some travel choices will make it possible, on the one hand, to meet better user's expectations in terms of transport services, and, on the other, to meet the requirements of sustainable mobility.

The rest of the paper is organized as follows. The next Section introduces the agent-based approach in a modular framework perspective. Section 3 describes the neuro-fuzzy modeling while Section 4 gives an overview on the adopted methodology. Finally, in Section 5 the neuro-fuzzy based module is validated and in Section 6 some conclusions are drawn.

2. The Agent-based Approach: Modular Framework

This Section provides the agent-based methodological framework in which the neuro-fuzzy model is embedded. The basic idea underlying this simulator is that traffic flows on several specific transportation mode (e.g., private, public and pedestrian) might be simulated in an integrated way starting from mode choices made by travelers based on both socio-economic and transport supply features, while usually they are simulated in a separated way.

As introduced in Section 1, mode choices affect urban traffic levels in terms of next path choices, which are linked to the features of the transportation supply mainly in terms of level of service variables. As mode choices generally depend on user socio-economic characteristics other than on mode supply features, here agents have been associated with users rather than vehicles. Starting from this perspective, the decision-making process – described in the following sections – autonomously performed by the users (i.e., user agents) to choose a specific transportation mode to accomplish their trips has been modelled mainly based on these two groups of variables - i.e., socio-economic and transport supply variables. The agent-based approach simulates the travel decision process starting from the first step, i.e. learning behavioral rules for being able to make mode choices. It overcomes some limits of a previous simulator developed by the Authors, which even though has a high versatility (it was used also to simulate *Urban Air Mobility* (UAM) for point-to-point connections [53, 54]), from the other hand does not allows further progresses like investigating on users' behavior.

The hypothesis of "rationality" has been assumed, similarly to random utility models, which implies that each user agent is able to make a choice based on the advantages and disadvantages of each available alternative. Figure 1 represents the block-scheme of the user agent. More in detail, the initial information, which refers to behavioral rules learnt by means of a neuro-fuzzy model, is provided by the (*Input Data*) block, whose task is to collect information (e.g., trip origin and destination, time, comfort, user's preferences, etc.) and sent to the *Mode Choice Module* block. This block simulates the user's selection of the transportation mode (here private, public and pedestrian modes have been considered). For each available transportation mode, a dedicated module (e.g., the agent module *Private Driving Module* for the private car mode) will interact with the corresponding transportation network (i.e., the *Private Transportation Network*, set as exogenous system where other user agents that are active on that network at a given time interact among them). Finally, the *Feedback Module* will release a feedback about information concerning the travel features on the given network experimented during the journey between the origin/destination pair. Such feedback will be used by the user agent to modify, if it is the case, his/her mode choices based on both the experiences and the set of rules learnt at the beginning and provided by the *Input Data* block [55].

Currently, we are developing the *Mode Choice Module* that equips the user agent and will realize the first task carried out by the user agent. In the adopted cascading structure, this module influences all the other simulations of the transportation network and, therefore, it represents the most critical component to simulate urban mobility by using an agent approach. This component will be explained in detail in the following.

3. The Neuro-based Fuzzy Inference System

In mathematics, a set is defined as a collection of objects independently by their number. In 1965, Lotfi Zadeh [56] proposed the idea of fuzzy set as a set to which objects can belong with different degrees of membership. The confidence that the element belongs to the fuzzy set is represented by a membership function whose values can range from 1 (absolutely true) to 0 (absolutely false) and that can assume different shapes (e.g., triangular, trapezoidal, gaussian, sigmoidal, etc.). Here, we will apply the fuzzy theory to sets of descriptive words, where the degree of membership identifies the confidence in the descriptor (i.e., its weight), often set by the analysts.

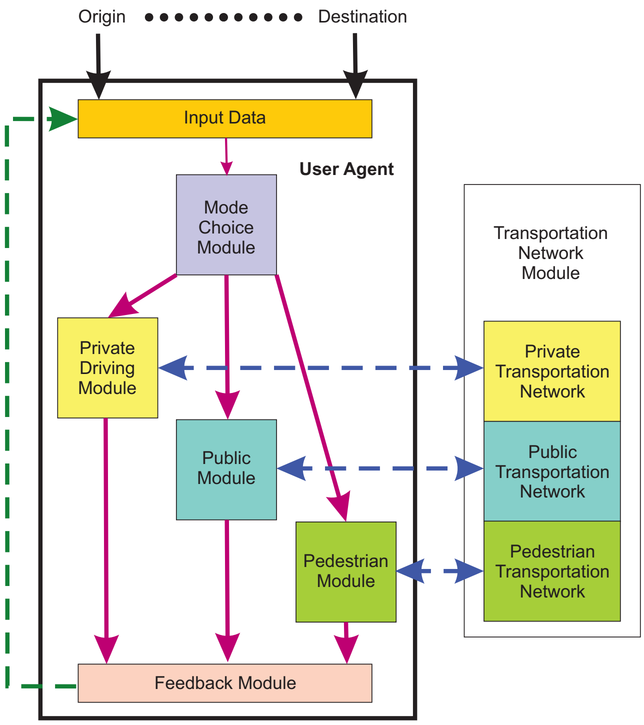

Figure 1: User Agent - Block scheme.

More in detail, a Fuzzy Inference System (FIS) is a set of fuzzy membership functions and rules to generate an output using fuzzy set theory, thus mapping an input space into an output space. The structure of a fuzzy inference system [57] includes three conceptual components:

1. a selection of fuzzy rules;
2. a catalog of membership functions exploited in the fuzzy rules;
3. a reasoning method, which executes the inference procedure (i.e., the fuzzy reasoning introduced earlier) by using the rules and a given condition to produce a logical output or conclusion.

In addition, the basic FIS can receive both fuzzy and crisp[1] inputs, returning (usually) fuzzy sets as output, but sometimes it is necessary that a crisp output (representative of the fuzzy set) is returned. In particular, when a FIS receives and returns crisp data, it makes a nonlinear mapping from the input space to the output space.

This mapping is made explicit through a set of fuzzy *if-then* rules. Each rule is referred to a local behavior of the mapping, where the antecedent of the rule delimits a fuzzy area of the input space, while the consequent refers to the associated outputs [58]. Various types of inference are described in the literature [59], but due to its flexibility in terms of writing, Sugeno

[1]Crisp inputs are assimilated to fuzzy singletons with degree of membership 0 everywhere except at specific points where degrees of membership are 1.

inference [60, 61] will be adopted (see below) since it provides a systematic approach to obtain fuzzy rules for a given set of input-output data. More specifically, a generic fuzzy Sugeno rule has the form:

if x **is** A **and** y **is** B **then** z

where the antecedent consists of the fuzzy sets A and B, while the consequent is given by $z = f(x, y)$, where $f(\ )$ is a crisp function of x and y.

Generally, the process to make a FIS, usually called fuzzy modeling, consists of four steps:

1. *Fuzzification* - This process associates the degree of membership of an input data to a fuzzy set by means of special functions, called membership functions, defined on the range of possible values in the domain [0;1];

2. *Fuzzy operator* - A fuzzy operator (*AND* or *OR*) is used to combine the set of antecedents of each rule;

3. *Implication* - This method builds the consequential part of each rule;

4. *Defuzzification* - The aggregator and defuzzifier blocks to set a FIS are represented by the weighted sum operator.

A FIS allows a fast modeling of input-output relationships by extracting a set of rules able to model the nature of the data. Several variations/adaptations to the standard FIS process exist for improving the performance of the model. In particular, the centers and standard deviations of Gaussian membership functions can be adaptively modified to better fit the training data. In addition, an artificial neural network (ANN) can be trained to estimate the error even based on a small number of inputs used for the FIS [62]. Finally, a further stage may introduce also automatically new rules and corrections (based on expert knowledge) to the rules previously included in the FIS process.

In particular, neuro-fuzzy modeling exploits neural network-based learning techniques to have the FIS. In this case, a trial-and-error process, that stops when the desired accuracy is reached, is used to set decision rule sets. The fuzzy rule set is obtained by covering the input-output space of the samples with overlapped patches, where each patch represents a fuzzy rule. Note that a total coverage of samples is generally impossible to achieve since it is almost impossible to have a patch for each sample. In other words, the goal is to implement a technique that is as simple and efficient as possible for estimating the optimal number of clusters and the initial values of their centers in multivariate data. Then, from this information, an iterative optimization algorithm attempts to minimize a cost function that maintains the quality of the original data. Once the optimal configuration of clusters is selected then each cluster center is made to correspond to a fuzzy rule.

To implement the above process we used the GENFIS toolbox of Matlab [63]. This toolbox allows the extraction of fuzzy membership functions (FMFs) based on input/output pairs. Moreover, the Fuzzy Logic toolbox of Matlab include the *Adaptive Neuro-Fuzzy Inference System* (ANFIS) function [64, 65] for tuning the neuro-fuzzy inference system on the basis of some collections of input–output data. Therefore, a GENFIS+ANFIS approach was used in this work.

4. The Adopted Methodology

The above-described approach has been used to analyze users' decision criteria when choosing a transportation mode, which can be expressed by simple *if-then* rules fitting with fuzzy logic like:

if the time on mode M_1 **is** less than the time on mode M_2 **then** the mode M_1 is chosen

However, the decision processes underlying modal choices are usually more complex and more similar to:

if $t_{M_1} < t_{M_2}$ ***and*** $t_{ac/eg,M_1} < t_{ac/eg,M_2}$ ***and*** $K_{M_1} > K_{M_2}$ ***and*** $\cdots$ ***then*** the mode M_1 is chosen

which, in words, can be expressed in the form "if the travel time of M_1 is less than that of M_2 and the access/exit time of M_1 is less than that of M_2 and the comfort of M_1 is greater than that of M_2 and $\cdots$ then the user chooses the mode M_1".

In particular, in the random utility theory, a set of decision rules can be expressed as:

$$U_{M_1} = \beta_1 \cdot t_{M_1} + \beta_2 \cdot t_{ac/eg,M_1} + \beta_3 \cdot K_{M_1} + \cdots + \epsilon_{M_1} \tag{1}$$

$$U_{M_2} = \beta_1 \cdot t_{M_2} + \beta_2 \cdot t_{ac/eg,M_2} + \beta_3 \cdot K_{M_2} + \cdots + \epsilon_{M_2} \tag{2}$$

where the variables associated with the various transportation modes (e.g., t, $t_{ac/eg}$, K, etc.) are weighted by the set of parameters β obtained by a calibration procedure [9, 66]. In addition, a random term (ϵ) is also considered to take into account information and simplification in both model assumptions and mathematical formulations.

A further problem is the estimation of attributes referring to non-chosen transportation modes or qualitative attributes (e.g. comfort, etc.); in all these cases such attributes should be estimated by the analysts. Moreover, the number of variables to be taken into account in order to represent the behavior of users might be very large and then the calibration process could be time-consuming.

In the user's decision-making process some variables characterizing each transportation mode are relevant while other are just marginal. It is worthwhile to note that modeling user's behaviors should focus on identifying the set of variables that influence significantly the user's behavior. This aspect also meets one of the constraints of the FIS technique represented by the need to limit the number of variables in order to avoid a combinatorial explosion of the rule catalog. Therefore, the selection of the most representative variables (i.e., inputs) is an important stage with respect to both utility and FIS models.

In this work, a fuzzy curve approach was used to select the variables to be used as inputs to the FIS procedure, taking into account nonlinear effects [67, 68]. More in detail, with respect to a multiple-input single-output system (MISO), a travel mode is characterized by a set of variables x_i, with $(i = 1, \cdots, m)$ where m is the number of available travel modes, while y will denote the travel mode chosen by the user. For the k-th user and the t training patterns, the fuzzy curve c will be computed as:

$$c_i(x_i) = \frac{\sum_{k=1}^{t} y_k \cdot F_{i,k}(x_i)}{\sum_{k=1}^{t} F_{i,k}(x_i)} \quad \text{with } F_{i,k}(x_i) = e^{-\left(\frac{x_{i,k}-x_i}{s}\right)}$$

where F_{ik} is a Gaussian function $F_{ik}(x_i)$, with x_i and s, respectively, being the mean and the standard deviation of the i-th coordinate of the k-th training pattern. This method consists in assessing the flatness of the fuzzy curve (c_i) because if it is too flat then the output will be weakly affected by inputs [51, 69].

The relevance of the input is determined based on a figure of merit, defined as the range of the fuzzy curve that is usually a fraction of the domain of the corresponding output variable (i.e., y) over the entire dataset of examples. More in detail, we subdivide the intervals of input and output in overlapped regions (consequently, also the fuzzy curve will be subdivided in overlapped regions) and label the corresponding value of the variable with fuzzy values. From each of the regions in which the fuzzy curve is partitioned it will be possible to derive a rule (with simple antecedent) that describes the input-output relationship for that region and, therefore, it will be possible to obtain a set of rules that approximates the fuzzy curve. In this way, the application of fuzzy patches (and thus fuzzy rules) is easier, although one must neglect possible correlations between input variables since there are as many fuzzy curves as the input-output pairs. Since there are no fuzzy curves for multiple simultaneous inputs, it is then necessary to use fuzzy surfaces to solve the problem. Fuzzy surfaces [70, 71] can be assumed as an extension of fuzzy curves. More formally, a fuzzy surface can be represented as:

$$c_i(x_i, x_j) = \frac{\sum_{k=1}^{t} y_k \cdot F_{i,k}(x_i) \cdot F_{j,k}(x_j)}{\sum_{k=1}^{t} F_{i,k}(x_i) \cdot F_{j,k}(x_j)} \quad \text{with} \quad F_{i,k}(x_i) = e^{-\left(\frac{x_{i,k}-x_i}{s}\right)}$$

$$\text{and} \quad F_{j,k}(x_j) = e^{-\left(\frac{x_{j,k}-x_j}{s}\right)}$$

In this case, the fuzzy rules have a double antecedent whose connective is *AND* since there are two inputs involved in the rule that approximates the fuzzy surface. Trivially, a fuzzy surface can generate countless fuzzy curves and for this reason extracting a catalog of rules directly from fuzzy surfaces is convenient. In fact, the use of fuzzy surfaces allows reducing the cardinality of the system (thanks to the presence of rules with double antecedent) and, moreover, the rules extracted from fuzzy surfaces trivially contain those extracted from fuzzy curves. Note that the use of fuzzy surfaces in the transportation domain is not new, for instance, in [72, 73] where a FIS leveraged to simulate and predict the future behavior of a vehicle by considering human factors of driving or in [74] to predict the level of congestion in heterogeneous networks by considering the flow and capacity of each arc of the network as input variables and the level of congestion as output. 75 rules and fuzzy surfaces have been employed to this purpose.

5. Modal Choice Module Validation

In this section we will show the performance of the modal choice module we designed. To this aim, a database obtained through the use of revealed preference techniques [9], has been used. The sample considered in the validation process consisted of 200 users for the training dataset and 500 users to realize the test dataset for home-work trips. The travel modes considered are walking (A), motorcycle (B), car-driver (C), car-passenger (D), and bus (E). Table 1 shows the percentages of users for the two different travel purposes and for the five travel modes.

The main variables considered in the surveys can be classified into; *i*) socio-economic variables (e.g., income, sex, age, private mode availability and so on) and *ii*) level of service variables (e.g., travel time, monetary costs, parking availability and so on) referred to the characteristics of the transportation network (see [9]). The input data are considered as fuzzy variables and each fuzzy variable, referred to a linguistic description, is characterized by a measure of membership in each of the considered linguistic properties.

In particular, the steps of the process to model a FIS are:

1. *Inputs Fuzzification* - Here the inputs membership degree to the relevant fuzzy sets are determined. The input is always a crisp value ranging in the domain of the input variable, while the output is a fuzzy degree of membership in the [0;1] domain. Consequently, we know the belonging degree of each antecedent with respect to each rule.

2. *Fuzzy Operators Application* - The fuzzy operator is applied to obtain a representative value of the antecedent result (simple or composed) for that rule to be applied to the output functions. The input fuzzy operator consists of two or more membership values derived from the fuzzification of the input variables, while the associated output consists of a single truth value.

3. *Outputs Aggregation* - In this step, the fuzzy outputs produced by each rule are unified into a single fuzzy set, ready to be defuzzified, by graphical superposition. In the aggregation process, the input is the set of membership functions (stopped or scaled), resulting from the implication process on each rule, while the output is represented by a fuzzy set for each output variable.

4. *Output Defuzzification* - In input this process receives the aggregated fuzzy outputs and in output returns a crisp value obtained by calculating the barycenter of the geometrical

Travel Modes	Code	%
Walking	A	10.8
Motorcycle	B	9.2
Car-driver	C	56.4
Car-passenger	D	6.2
Bus	E	17.4

Table 1
Percentage of transport mode usage for the exploited datasets.

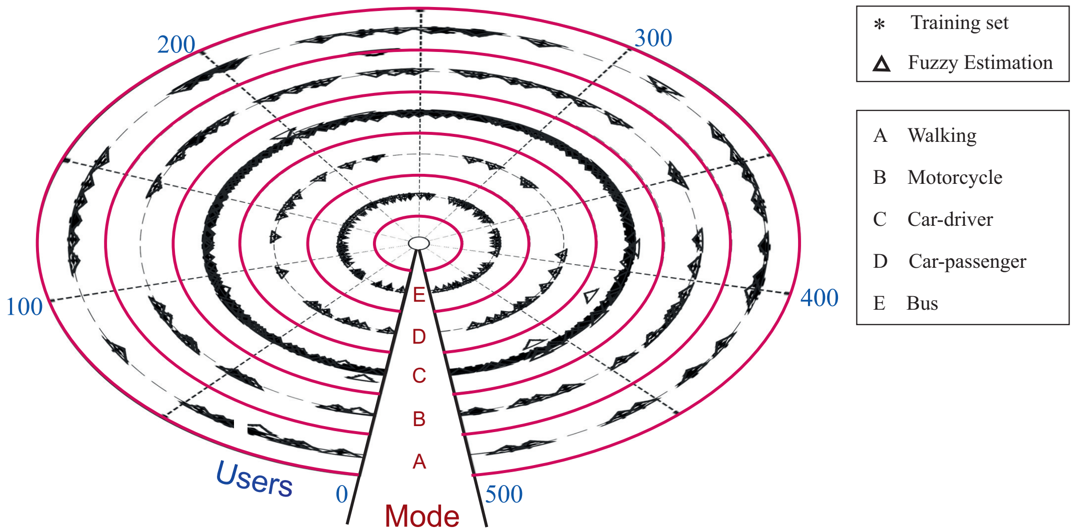

Figure 2: Accuracy of the neuro-fuzzy approach in predicting users' mode choices.

shape derived from the aggregation of the outputs. Moreover, by adopting Sugeno's FIS, peaks (or singletons) are used as consequents then simplifying the defuzzification process. Accordingly, the main features of the FIS generated by GENFIS can be summarized in 12 inputs representing the qualitative variables reported in the database used for the validation of the module (i.e., the attributes of the travel modes available to users such as time, monetary costs, vehicle ownership, saturation ratio of parking facilities at destination, etc.), 16 rules and a single output for each user, represented by the chosen travel mode.

Based on the input-output patterns, a conventional FIS was first designed without making use of any learning techniques and, as expected, unsatisfactory performance have been obtained. Subsequently, the toolbox GENFIS and the function ANFIS were used to improve the performance of the initial FIS. In particular, the neural network used by ANFIS is made by five layers, namely, the first layer for the input, the second layer for the membership functions associated with each input, the third layer for the implication constructs, the fourth layer for the aggregation operation and, finally, the fifth layer for the output. Note that the membership functions, after learning, may be overlapped even in significant numbers

The predictions calculated after the training phase by applying the proposed methodology to the test dataset for home-work trips are represented in Figure 2, for both the users and the various transport modes. Each marker identifies the prediction accuracy between a user's choice and a transport mode (identified from A to E), while not aligned markers identify incorrect predictions. In other words, the closer the markers are to the red line, the worse is the prediction; conversely, the closer the markers are to the dotted line (where each dotted line identifies a transportation mode), the more accurate the prediction is. From Figure 2, it is evident that the proposed neuro-fuzzy approach has a high degree of accuracy in correctly predicting the transport mode chosen by the user in most cases. The neuro-fuzzy approach is wrong only in presence of users characterized by very specific attributes (which can considered as outliers). The high level of accuracy indicates the capability of the rules calibrated by the model to simulate the real behavior of users, thus confirming the basis of many economic theories that the behavior of users can be inferred from their choices. Further analyses of the results show that users primarily give a high value to travel time with respect to, for example, travel costs and prefer private transport modes such as cars and motorcycles, except when the ratio of vehicles in the family versus the number of its members is much less than 1.

Although the degree of accuracy of the modal choice predictions is satisfactory, further refinements (mainly in terms of better understanding users' behavior) would be possible if additional qualitative information such as user information systems, comfort, privacy, etc., not present in the dataset used, were available.

Note that with quantitative data, the two methods, random utility models and fuzzy methods, arrive at the same results in terms of predictions, but differ on the basis of the specific information provided (e.g., semantic rules versus parameter values). Differently, the presence of qualitative variables does not change the operation and predictions produced by the proposed neuro-fuzzy approach (e.g., semantic rules are considered with both quantitative and qualitative variables), while random utility models require a conversion from qualitative to quantitative variables to be operated on the basis of a conversion scale. In the latter case, it is evident how the correctness of the predictions is affected by the conversion scale adopted. Finally, the feedback released in the last step (see Section 2) should ensure the agent's ability to adapt its mode choices over time as conditions change.

6. Conclusions

This paper proposed a neuro-fuzzy model to feed a more complete agent-based structure where travel choice behavioral rules are embedded. More in detail, the paper has focused on the learning step of user agents, based on fuzzy logic approaches, to recognize the most important rules taken into account by users when they choose a transport mode.

Among the relevant features of fuzzy logic approaches, there are the use of linguistic variables either in place or in addition to numerical variables; the identification of associations among variables by using fuzzy conditional statements; the implementation of complex relationships by using fuzzy-based algorithms.

In this work, experimental data have been used to find linguistic rules in the form *if-then* whose antecedents and consequents utilize fuzzy sets instead of crisp numbers. The fuzzy inference models derived from the previous rules allow understanding user's mode choice behavior and provide user agents with such knowledge. Particularly, behavioral rules make user agents not only able to simulate traveler's choices but also to modify their choices according to such rules in case of variations in the transportation system – mainly level of service variable variations.

The main advantages of the fuzzy approach are: *i*) opportunity to obtain rules with direct interpretation; *ii*) simple use of such results also by generalist analysts; *iii*) opportunity to improve the model by adding further information of the experts in the field (expert judgments).

In addition, the fuzzy model does not require high computing complexity, particularly for the on-line applications, and its "network" structure facilitates the implementation of a hardware system with relatively little costs. The main disadvantage is the limited number of inputs required by the fuzzy model to work efficiently, which implies data-compression techniques and suitable reduction of the inputs.

The results obtained in this study are very promising, not only they are comparable with other known approaches (e.g., random utility models), but they offer greater opportunity for simulating user behavior in a more complete user agent framework addressed to simulate transportation systems. Particularly, feedback obtained at the last step - as a result of the interactions with the *Transportation Networks Module* in the user agent framework - might be used to feed learning steps, which could be improved continuously.

Finally, as a further development, we note how the performance of the designed *Mode Choice Module* makes it also suitable to be embedded in a personal agent assistant to support users in their daily travel activities

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