

Developing Adaptive Driving Route Guidance Systems Based on Fuzzy Neural Network

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Abstract—This paper proposes a route guidance system which can be moldable by drivers based on using fuzzy neural network. The self-learning system has become a hot issue in the field of Driving Route Guidance. However, most of the researches didn't pay attention to the relationship between the route choice and the driver's vague perception. Even though with the same starting and destination points, different drivers typically do not go through the same path as they make choices of routes based on different attributes and weighting of the attributes. The adaptive-network-based fuzzy inference system (ANFIS) is used to learn the decision logic with vague attributes from the past driving records of the drivers to make the guidance system adaptive. By integrating this intelligent adaptive capability, a driving route guidance system should be able to adapt to driver's behavior in generating routes teller-made for individual drivers.

Keywords—route guidance system, route choice criteria, intelligent adaptive system, fuzzy inference system, TSK inference system, ANFIS

I. INTRODUCTION

Because of the rapid advancement of Advanced Traveler Information Systems (ATIS), information such as route distances, expected travel time, and congestion degree can be acquired and transmitted to drivers through a great variety of devices. Such information along with other personal considerations and preferences of the drivers can be incorporated for supporting their choices of routes to the destination. Many existing literatures have shown that different people choose routes based on different decision perspectives and criteria. A driver considers not only the distance but also on other factors—familiarity of the route, traffic condition, weather condition, personal preference, and so on—from the experience and/or the purpose of the trip. While a direct and fast route is important for business travelers, comfortable and pleasant scenery is probably more preferred for leisure travelers. With such diverse needs of travelers, it is unlikely to exist an “optimal” route for all the drivers at all time. However, none of the existing systems can learn from driver's route choice behavior automatically and make modification of the route guidance system based on the departure from the recommended route. Furthermore, these needs and preferences

are mostly uncertain and vague, and thus are required to be modeled differently.

Most of the current route guidance systems provide the route recommendation for drivers based on either the shortest distance or the shortest time. Some systems would also provide real-time information on congestion or accidents of the roads for the drivers to move away from their planned routes manually. With more data available for analysis, a broader notion of “optimum” as well as its analysis has been gradually adopted in various literatures. Models such as LOGIT models (a widely used stochastic discrete choice model), fuzzy hierarchical analysis process, probabilistic-possibilistic methodology, or others were applied. Some researchers used fuzzy logic on the shortest path problem with fuzzy arc lengths, or to model driver's route choice behavior. However, they only focus on individual fields, either the shortest path problem or simulation of drivers' decision logic. Some systems can only be executed when there are alternative routes.

The limitation of applicability and adaptability of the existing routing systems motivates our study to develop an adaptive driving route guidance system. Fuzzy logic provides a means to model vague attributes by transforming variables between crisp and linguistic values. The attributes considered in route guidance can be classified into three categories: route characteristics, driver perceptions, and situation factors. Fuzzy inference system can be used to simulate a driver's decision-making logic based on the variables and rule base, and then derives the cost for each link. The optimum route is recommended through computing the least cost path from the starting point (origin) to the intended destination by approaches such as the Dijkstra's algorithm. If a driver does not like the recommended route and drives through a different route, the system can learn from this behaviour, adapt these changes of conditions, and hopefully provide a better recommendation next time. This adaptive mechanism can be achieved by using ANFIS. Repeating the above steps continuously will make this adaptive driving route guidance system more comprehensive and conform to individual driver's route choice behavior.

II. ADAPTIVE ROUTE CHOICE SYSTEM

Due to the inclusion of advanced technologies in ATIS, such as communications, microelectronics, sensors, and information technology, the provision of real-time information on traffic conditions to drivers has become possible. For drivers, using ATIS can make travel planning, route choice, and way finding much easier. Driver route choice decisions are significantly affected by their past experience, perception, subjective interpretation of the traffic information provided, situational factors (time-of-day, weather conditions, and trip purpose), and more. These quantitative and qualitative factors in driver routing decisions make it complex to accurately model a driver's preference towards alternative routes. Furthermore, decisions may also be made in real time. Therefore, en-route and pre-trip information on traffic and drivers' decisions is equally important to intelligent route choice systems.

Most of the existing route guidance systems compute the "best" route for drivers either on the shortest driving distance or the least amount of time. Some systems would provide real-time information on the congestion status of the road. Moreover, qualitative factors, such as familiarity, safety, and scenery of the road, are uncertain and vague and need to be captured properly in the model.

A. System Structure

Different route choices are not limited to the difference among drivers. Even for the same driver, his/her preference varies under different circumstances.

For example, time is typically the most important factor for route choice; yet it could be less significant while taking a leisure trip. In order to support the learning of drivers' route choice rationale in different scenarios to provide different yet better recommendations to the drivers, the proposed route guidance system is constructed in two layers, as shown in Fig. 1.

The first layer, namely "scenario layer", is built to distinguish the scenarios according to driver. Each scenario will lead to a different execution layer and result in a different route choice model with different weights on the criteria. With this division, each scenario will also correspond to a learning system. The second layer, called "execution layer", includes the fuzzy inference system, the shortest path problem, and the behavior learning system (ANFIS).

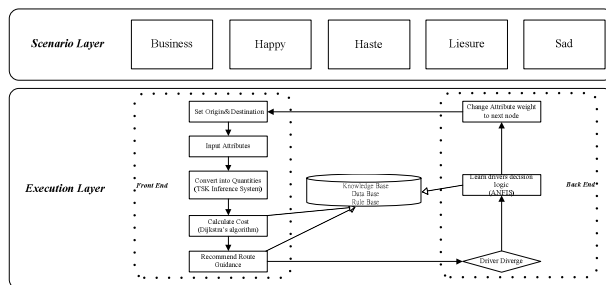


Figure 1. System structure

B. Execution Structure

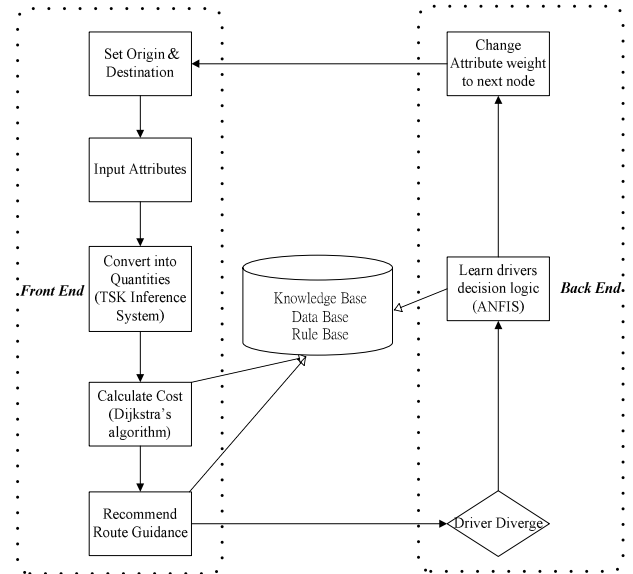


Figure 2. Execution structure

Fig. 2 illustrates the adaptive system structure. First, driver should set a pair of origin and destination. Then the route choice model converts the quantitative perception and qualitative idea into fuzzy value. After that, this system can give a recommended route automatically. When driver does not follow the recommended way, this system can learn the driver's decision logic by ANFIS. In the last, system change the origin to the next node, which is the end of the current link.

When driver uses this system, parts of the model are executed at the front end. Drivers can see or enter data at the front end, including setting origins and destinations, selecting the preferred attribute values, modifying the rule base or the database, and at the end displaying the recommended route. The other parts are executed at the back end, including judging whether the driver is diverging from the recommended route. This kind of learning system though very important does not need to be exposed to drivers.

III. ADAPTIVE MODEL FORMULATION

The adaptive driving route guidance system is established based on the following assumptions:

- All of the information can be transmitted to the system immediately. And the operations of Takagi-Sugeno-Kang (TSK) inference system, Dijkstra's algorithm, and ANFIS can be done in time for the route choice decision.
- The driver will either follow the recommended path or select a more suitable path by himself. However, the driver will not take a wrong route which is neither the recommended path nor the path he wants to take.

A. Attributes

Peeta and Yu [6] proposed to classify criteria for route choice decisions into three categories:

- **Driver attributes:** socio-economic characteristics, network familiarity, confidence in information, sensitivity to delay, and personal preferences.
- **Route characteristics:** travel time, travel distance, toll, facility type, route complexity, and location type.
- **Situational factors:** weather conditions, time-of-day, and trip purpose.

B. TSK Inference system

Peeta and Yu [4][5] proposed a hybrid probabilistic-possibilistic framework where the quantitative variables are directly incorporated and the qualitative variables are converted to fuzzy variables to incorporate the day-to-day and within-day dynamics of driver route choice decisions under real-time information provision, shown as follows:

$$U_n = V_n + \alpha_n = \sum_l \beta^l X_n^l + \sum_m \gamma^m \Omega_m(V_n^m) + \alpha_n \quad (1)$$

where U_n is the utility of route i for driver n , V_n is the systematic utility of route i for driver n , β^l and γ^m are coefficients of the variables, X_n^l is the value of quantitative or adjusted quantitative variable l on route i for driver n , V_n^m is the value of qualitative variable m on route i for driver n , $\Omega_m(V_n^m)$ is the transformation function to determine the fuzzy value of qualitative variable m , and α_n is the disturbance term for route for drivers.

A typical two-input, one-output example rule of the TSK method used in the research is [8].

$$\text{If } x \text{ is } A_i \text{ and } y \text{ is } B_j, \text{ then } Z_k = ax + by + c \quad (2)$$

where a , b and c are constant, $i=0,1,\dots, r_1$, $j=0,1,\dots, r_2$, and $k=0,1,\dots, n$ ($n=r_1 * r_2$). The if-parts of the rule “ x is A ” and “ y is B ” are called the antecedent or premise, while the then-part of the rule “ $z=ax+by+c$ ” is called the consequent or conclusion.

The cost function is similar to the linear consequent (2) of the TSK Method, where A_i are numerical constant, C_{ij} is the output level. Let’s expand the cost function to a complete TSK inference system, and integrate it with the shortest path algorithm and ANFIS. Then a route choice model is created in execution layer as shown in Fig. 2. In this model, driver should set a pair of origin and destination first, and then the route guidance system will give him a recommended route automatically.

After setting the origin and the destination, all attributes of each link are set to be input variables of TSK inference system. In this research, based on the driver’s perception of the conditions of the routes, their corresponding attributes are characterized by fuzzy values represented by trapezoidal membership function specified as follows by four parameters $\{a, b, c, d\}$.

$$\mu_{V_{ik}}(V_i) = \begin{cases} 0, & \text{for } x \leq a \\ \frac{x-a}{b-a}, & \text{for } a \leq x \leq b \\ 1, & \text{for } b \leq x \leq c \\ \frac{d-x}{d-c}, & \text{for } c \leq x \leq d \\ 0, & \text{for } x \geq d \end{cases} \quad (3)$$

where V_{ik} represents the k th linguistic values of attribute i and $k=1, 2, \dots, s_i$. Fig. 3 illustrates an example of a trapezoidal membership function. It is popular with fuzzy logic researchers and is widely used in fuzzy control.

Then, through the fuzzy implication and the rules of TSK inference system, the membership values resulting from input values and membership functions are combined by the min operator to generate the firing strength (rule weight) of each rule. Finally, based on the firing strength, the system generates the linear consequent (output membership function) of each rule and subsequently derives a single output value, which is the cost of the link

C. Route Choice Decision Process

Henn [9] proposed a fuzzy choice model and compared it with the LOGIT model which represents cost as a random variable. He also proved that these two models can achieve the same result. With these assumptions, to build an adaptive driving route guidance system based on driver’s behavior; all influencing attributes need to be first normalized. It can be observed that the values of the attributes—such as distance, time, toll, route complexity, risk factor, weather condition, and time-of-day—should be as small as possible for an ideal route.

These seven attributes can therefore be considered as “unfavorable attributes,” which are normalized and represented by $\Gamma^-(V_i) = V_i/d$, where d is the maximal span of the values. In other words, the collection of these attributes is to be minimized as they act in accordance with the cost. Attributes for flow rate, scenery, familiarity and personal preference, on the other hand, would be as large as possible and are thus called “favorable attributes”. Since the cost decreases as the values of these attributes increase, the normalization of the favourable attributes is represented by the function $\Gamma^+(V_i) = -(V_i/d) + 1$. The normalized values of these attributes can then be considered as the cost of the link with respect to the criteria at a fixed set of conditions.

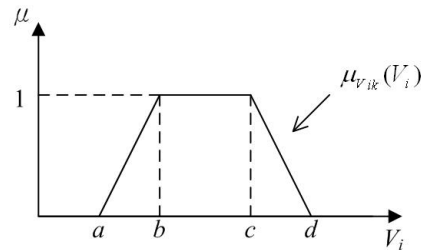


Figure 3 Example of the trapezoidal membership function

It can also be perceived that some attributes of a feasible route are dynamic while others are static. The dynamic ones may include flow rate, familiarity, personal preference, risk factor, weather condition, and time-of-day. The static ones are those such as distance, time, toll, route complexity, and scenery. Then cost function C_j for each link j based on the normalized attributes can be established for each driver,(4).

$$C_j = \sum_i a_i \Gamma^+(A_{ij}) + \sum_l a_l \Gamma^-(A_{lj}) \quad (4)$$

where $\Gamma^+(A_{ij})$ = normalized favorable attribute i on link j , $\Gamma^-(A_{lj})$ = normalized unfavorable attribute l on link j , a_i = scaling coefficient of attribute i , a_l = scaling coefficient of attribute l .

D. ANFIS System

Teodorovic and Kikuchi [2] were first to model the complex route choice problem using approximate reasoning model and fuzzy inference. This model considers only the approximate travel time and cannot make inference to multiple routes easily. In order to analyze the interactions between a driver's existing perception and the real-time traffic information. Lotan and Koutsopoulos [8] have also proposed a rule-based fuzzy model based on the driver's route choice behavior. Radojevic and Petrovic [1] used fuzzy sets and reasoning to simulate human preference structure by modeling Birmingham-Belgrade route choice. Pang et al. [3] used a fuzzy inference system to model driver route choice behavior and adjust the membership function parameters by neural network.

Because ANFIS will be used to train the TSK inference system, it is constrained that different rules cannot share the same output membership function. In other words, the number of output membership functions must be equal to the number of rules. Assume that each attribute has up to s_i linguistic values. Therefore there should be Πs_i rules in the rule base after arrangement. Before starting to use the route guidance system, all of the linear consequences are set to equal the initial cost function, which means that all coefficients of the normalized values of attribute i , a_i are the same. The values will most likely become different after training by ANFIS.

IV. MODEL SIMULATION

Now simulate an example based on self-learning system with situational factors, driver perceptions and route characteristics by using ANFIS System and TSK Inference System.

A. Define Attributes

- **Route characteristics:** distance, time, toll, flow rate, route complexity, and scenery.
- **Driver perceptions:** familiarity, personal preference, and risk factoy.
- **Situational factors:** weather condition, time-of-day.

B. Convert Attributes into Fuzzy Value

At beginning, there are 18 fuzzy if-then rules shown in Table 2 with antecedent and consequent. Antecedents consist of linguistic values of each attribute after arrangement. All

initial consequents are costs derived from the same initial cost function, (5).

$$C = \Gamma^+(D) + \Gamma^-(V) + \Gamma^-(S) \quad (5)$$

After establishing the TSK inference system, the values and the normalized values of attributes on each link at time t shown in Table I can be normalized and put into the system.

C. Calculate Cost

For ease of illustration, additional assumptions are made for the adaptive driving route guidance system: 1) only three attributes, distance, flow rate, and scenery, are used in the example. 2) The distance is the actual length of each link ranging from 0 to 500 km. The flow rate of each link predicted by the traveler information system—the congestion degree—ranges from 0 to 120 km/hr. The scenery is gathered from drivers are represented by a value ranging from 0 to 10.

A hypothetic network is given in Fig. 4—with 13 nodes, 18 links, and one expressway through nodes 1, 2, 3, 4, 5, and 6—to illustrate the procedure of the system. The values of the three attributes of each link are given in Table II where it is assumed to be at time t with the flow rate and scenery being dynamic and distance static.

Hence the cost function can be constructed as (6). Then, the cost of each link will be derived as shown in Table II.

$$C_j = a_1 \Gamma^+(D_j) + a_2 \Gamma^-(V_j) + a_3 \Gamma^-(S_j) \quad (6)$$

where $\Gamma^+(D_j)$ is the normalized distance on link j ; $\Gamma^-(V_j)$ is the normalized flow rate on link j ; $\Gamma^-(S_j)$ is the normalized scenery on link j ; and a_i is the scaling coefficient of the normalized attribute i ($i = 1\sim 3$).

Three scaling coefficients are set to one initially, which means that all of the attributes are of the same importance for the driver. For normalization, each favourable attribute should be divided by its upper limit, and each unfavourable attribute should be divided by its minus upper limit and plus 1. So the initial cost function of each link can be written as (7).

$$\begin{aligned} C_j &= 1 \times \Gamma^+(D_j) + 1 \times \Gamma^-(V_j) + 1 \times \Gamma^-(S_j) \\ &= 1 \times \left(\frac{D_j}{500} \right) + 1 \times \left(-\frac{V_j}{120} + 1 \right) + 1 \times \left(-\frac{S_j}{10} + 1 \right) \end{aligned} \quad (7)$$

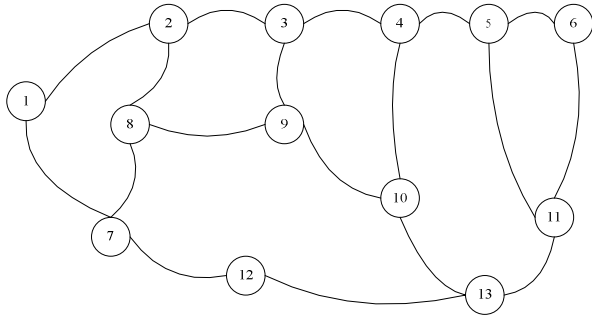


Figure 4 An example network

TABLE I. FUZZY IF-THEN RULES BEFORE TRAINING

No.	Antecedent (if-part of the rule)			Consequent (then-part of the rule)
	<i>D</i>	<i>V</i>	<i>S</i>	<i>Cost</i>
1	s	s	u	$C=\Gamma+(D)+\Gamma-(V)+\Gamma-(S)$
2	s	s	b	$C=\Gamma+(D)+\Gamma-(V)+\Gamma-(S)$
...
18	l	f	b	$C=\Gamma+(D)+\Gamma-(V)+\Gamma-(S)$

Table II INITIAL VALUES OF ATTRIBUTES ON EACH LINK

links	Distance		Flow rate		Scenery		Cost
L(1,2)	250	0.5	110	0.08	0	1	1.58
L(1,7)	280	0.56	60	0.50	5	0.5	1.56
L(2,3)	180	0.36	110	0.08	0	1	1.44
L(2,8)	200	0.4	60	0.50	6	0.4	1.30
L(3,4)	230	0.46	90	0.25	0	1	1.71
L(3,9)	200	0.4	60	0.50	6	0.4	1.30
L(4,5)	180	0.36	70	0.42	0	1	1.78
L(4,10)	260	0.52	50	0.58	4	0.6	1.70
L(5,6)	190	0.38	70	0.42	0	1	1.80
L(5,11)	260	0.52	20	0.83	2	0.8	2.15
L(6,11)	270	0.54	30	0.75	2	0.8	2.09
L(7,8)	170	0.34	50	0.58	10	0	0.92
L(7,12)	330	0.66	70	0.42	7	0.3	1.38
L(8,9)	200	0.4	50	0.58	10	0	0.98
L(9,10)	270	0.54	50	0.58	10	0	1.12
L(10,13)	180	0.36	50	0.58	8	0.2	1.14
L(11,13)	190	0.38	50	0.58	3	0.7	1.66
L(12,13)	310	0.62	70	0.42	7	0.3	1.34

D. Learn by ANFIS

As shown in Fig. 5, if a driver wants to go from node 1 to node 11 for business, the system will execute Dijkstra's algorithm and recommend a least cost route from node 1, through nodes 7, 12, and 13, to 11. But if the driver diverted from the recommended route (the solid line) and instead took the expressway to node 11 for business (the dotted line), the

system will learn from this driver's decision-making logic and adopted it for further planning.

ANFIS is used to training the TSK inference system. At the beginning, by referring to the costs of the links on the recommended route, the cost of the forecasted adopted links taken by the driver will be updated by the equations (7). Let α be 0.1. Then, the training data of ANFIS will be the input and output values of the links on the forecasted adopted route and the recommended route with modification of $C_L(1,2)$ from 1.58 to 0.85, $C_L(2,8)$ from 1.3 to 0.7, $C_L(8,9)$ from 0.98 to 0.53, $C_L(9,10)$ from 1.12 to 0.6, and $C_L(10,13)$ from 1.14 to 0.61.

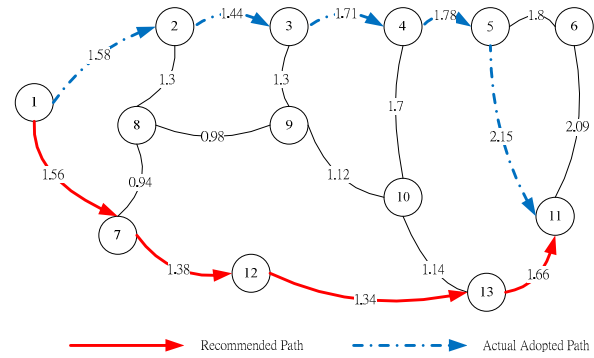


Figure 5 Recommended and adopted routes

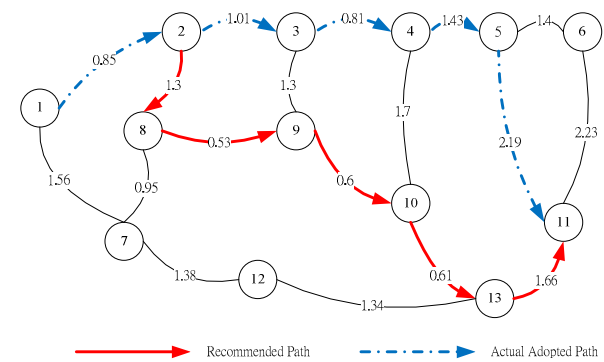


Figure 6 The route after first training

In order to make the system stable and balanced, eighteen training data derived from fuzzy if-then rules are added. While input values are mean linguistic values whose membership functions reach the maximum, output values are costs calculated by the TSK inference system. Set error tolerance equal to 0 and epochs 30 and begin training the database and the rule base of the TSK inference system.

E. Analysis of the result

After training, the membership functions will be the same as the original ones, but the consequents of rules in Table II will be different. The scaling coefficients a_i will be changed every time after training. The costs of the links derived from the TSK inference system with updated rule base after training

are shown in Fig. 6 and the recommended route can be derived by Dijkstra's algorithm. Because the driver still diverts from the recommended route, the origin will be changed from node 1 to node 2 and the training the system continues.

When the driver arrives the destination node 11, the system would have been trained for three times. All of the training data will be retained as the driver's knowledge base or experience base. Next time when the driver goes from node 1 to node 11 under the same conditions, the system will guide him through the route via nodes 2, 3, 4, and 5. Clearly, this adaptive route guidance system will fit in with the driver's needs increasingly with more training data from all the trips taken by the driver. Optionally, if the training data is sufficient in quantity, the part of the training data used to balance the TSK inference system can be eliminated. Next time when the driver travels on an unfamiliar network, he will trust the route recommended by this personalized adaptive route guidance system.

V. CONCLUDING COMMENTS

This research modeled the dynamics of driver route choice decisions under advanced traveler information systems by adapting fuzzy inference systems, the shortest path algorithm, and neuro-fuzzy systems. It enables the update of driver decision criteria by updating the membership functions and if-then rules in different scenarios. This newly developed driving route guidance system has the capability of supporting the driver in deciding an optimum route based on individual preferences and behaviours. The main contributions of this study comparing with other solutions are as follows.

- The proposed system can deal with multiple uncertain and vague decision attributes from the driver's decision behaviour through the TSK inference system.
- It can provide one route based on the driver's route choice behaviour between arbitrary origins and destinations without alternatives through Dijkstra's algorithm.
- The system is adaptive, which learns the driver's route choice logic automatically through adaptive-network-based fuzzy inference system without any need of user intervention.

For future research, the core adaptive framework of the established system can be adopted while more sophisticated and realistic attributes—such as efficiency, similarity, degree of difficulty—considered and implemented. Moreover, many other methodologies can be adopted to solve the fuzzy inference system, the shortest path problem, and the learning system. These methodologies should be experimented if not proved to ensure that they enable faster, more adaptive, or

better performance. Continuing research will enhance the system and make the system more applicable in the real world, which in turn enhances the functionality of the intelligence transportation system.

Furthermore, there exists many other inherently imprecise concepts or variables, which are uncertain and vague and cannot be expressed in crisp models but can be handled by fuzzy logic. For example, in e-learning, the order in which teaching materials are provided to individual students can be based on the characteristics of the materials and/or the students. Such sequencing requirements can be derived through similar adaptive frameworks so that the best arrangement of the materials can be generated and delivered to different students.

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