IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 5, 2019, accepted January 21, 2019, date of publication January 29, 2019, date of current version February 22, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2895832

In-Vehicle Cognitive Route Decision Using Fuzzy Modeling and Artificial Neural Network

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This work was supported in part by the SEP-CONACyT Research Project under Grant 255387, and in part by the School of Engineering and Sciences and the Telecommunications Research Group, Tecnologico de Monterrey.

ABSTRACT The departments of transportation worldwide are facing various challenges despite introducing and incorporating various vehicular features. One of such challenges is to make vehicles autonomous, intelligent, and capable of self-learning to evolve their knowledge repository. In this paper, human cognition is proposed to be implemented in vehicles so that they can perform human-like decisions. Therefore, the process of vehicular route decision is debated cognitively in order to provide route information intelligently. The in-vehicle routes provided by the GPS are not optimal and lack on-demand user requirements. GPS connectivity issues, in certain conditions, make it difficult for vehicles to take real-time decisions. This leads to the idea of self-decision by the vehicle controller. We propose a cognitive framework for vehicles to make self-decisions that use cognitive memory for storing route experiences. The framework strengthens the existing in-vehicle route finding capability and its provision in a more realistic manner. The user is provided with all available route-related information that is required for the journey. In addition, the route episodes are learned, stored, and accessed inside the cognitive memory for an optimal route provision. The vehicle learns about the routes and matures with route-experience by itself with the passage of time. In simulations, fuzzy modeling is used to validate the impact of cognitive parameters over static/conventional parameters. Moreover, artificial neural networks are used to minimize the error rate in learning to achieve cognitive route decisions. The proposed in-vehicle cognitive framework outperforms the existing route provision system that is inadequate and provokes the user's anxieties during driving. Besides, the proposed scheme gradually gets mature in delivering optimal as well as latest route-related information.

INDEX TERMS VANET, cognition, fuzzy model, artificial neural network, vehicle route.

I. INTRODUCTION

We all use vehicles to reach from one place to another using appropriate routes. To carry out an effective journey in vehicles, the use of Global Positioning System (GPS) [1], [2] is essential as it provides information of routes of all likely infrastructures including universities, schools, traffic lights, junctions, and information about traffic, weather, and conditions of road ways [3]. Route input to global positioning system can be patterns of voice [4] and touch screens for the users. All these features provide good use of the global positioning system, therefore, vehicles are being equipped with in-vehicle GPS navigation systems. Despite having space segment that consist of satellites, control segment that cover ground stations, and user segment that consist of user and its GPS receiver [5] the navigation performed is static and therefore, it provides no updated information once the signals are lost. However, the current onboard GPS navigation system in vehicles functions by receiving signals from the satellites that detects its location by utilizing GPS components. Likewise, the direction sensor detects the direction of the vehicle and the speed sensor detects its travel distance.

The associate editor coordinating the review of this manuscript and approving it for publication was Tao Zhou.

All this information from the sensors and antenna are checked against the map database and displayed on car navigation system screen.

The current route searching mechanism in vehicle is performed when vehicle's current location is identified, destination is searched, route to the destination is checked, recommended route is suggested, directions are provided for the selected route, and finally, route-related information is displayed on screen. It is important to mention that such total dependency on vehicular GPS is not a recommended option. On 25-26th February 2016, the GPS users faced an anomaly in operations [6] when information was broadcasted by multiple satellites for several hours regarding the offset between GPS time, and coordinated time universal (UTC) in a way that did not conform to the GPS signal interface specification (IS-GPS-200) [7], [8]. When communication with third parties does not take place for any reason, this takes us to think about other viable strategies. There are artificial intelligence (AI) approaches to be considered for GPS systems [9], [10], however, these are considered to be within the weak artificial intelligence domain. Recently, artificial intelligence is focusing on stronger strategies such as deep learning [11] and artificial neural networks [12]. However, cognitive science [13] is important for AI developments [14] in the future.

The scheme is to utilize a cognitive approach in the vehicular domain and thus, the use of human cognition in vehicles [15] for provision of optimal route information is much necessary. This scheme overcomes the current weak AI strategies. To utilize human cognition in vehicular domain is, thereby, essential [16] as this overcomes a number of route deficiencies like optimal information, timely delivery, safe and secure routes, and self-decisions. It is not necessary for the optimal route to be the shortest route always, if a longer route is without traffic, it can be chosen instead. There are various aspects of optimal route including safe and secure routes or provision of routes based on user priority, preferences and so on. To move towards our proposed idea of optimal route, routes need to be learned by the vehicular agency. The more a vehicle travels, the more route experience it gets. Cognitive memories are important as every iteration (route) need to be learned and recorded [17]. It utilizes sub-categories of human memory structure [18], [19] in the form of working memory [20], short-term memory [21], long-term memory [22], associative [23], semantic, and episodic memories [24] are essential for rational decision making to provide optimal route information [25], [26].

This paper provides a cognitive framework that delivers up-to-date and optimal route information to the user. The proposed framework facilitates by gathering all possible route information. The information is learned and stored inside cognitive memory for later retrieval. Just like we humans retrieve our past memories and make better decisions based on them, similarly, we suggest for the vehicle regarding route information the same concept. By utilizing cognitive memories, the framework in the vehicle retrieves past route experiences and makes better decisions. In this way, vehicle knowledge repository evolves, however, the evolvement of knowledge takes time and generally depends on vehicle traveling on different routes. The more the vehicle travels, the more it populates the knowledge repository.

II. RELATED WORK

The involvement of cognition in Advanced Driver Assistance Systems (ADAS) identifies driver psychological problems making it hard to collect effective information. The lack of reliable model to measure human mind and enhanced experiments are required to measure variety of driver tolerance levels. Current research in cognition is therefore, debated that involves lateral, longitudinal, and hybrid decision reaction cognition [27]. The usefulness of cognition in VANET research facilitates the network performance as it possess the ability to adapt network variables dynamically. To check the network performance, transmission switching time and transmission frequency are the considered variables in case of cognitive radio. Also, the cognitive radio increases network performance [28]. The cognitive model [29] is essential for a system to possess cognitive ability and the brain-inspired cognitive model for self-driving cars [30] is one of such models to cover perception, memory and attention approaches of humans. The use of permanent memory in cognitive agent for performance enhancement is the future research work [30]. From cognitive perspective, the idea to conceptualize the relationships between mind and the body is important. This leads the research focus toward the theories important for the generation of strong AI systems [31] for different domains. In a car accident, for example, cognitive variables are important to be considered for car driver such as road illusion of going right or left, adaptation with darkness, effects of glare caused by bright objects, expectation of on-coming vehicles, perception, and reaction time during accident [32].

Also, it is essential to provide learning capability in agents so they can learn from their task environment. Domingos *et al.* [33] highlighted the factors necessary for the agent to learn. The factors are: it is not necessary that a single algorithm is going to provide efficiency, relying on data only will not provide the solution, machine learning works by generalizing from examples, variety of machine learning models need to be considered instead of one model, overfitting is experienced in machine learning, and that machine learning works better with fixed length training sets and degrades the performance when the training sets turns huge. Jin *et al.* [34] introduced sparse Bayesian ELM (SBELM)-based algorithm to improve the classification performance of motor imagery. Also, adaptive differential evolution based neural network (ACADE-NN) is investigated [35] for the operator functional state (OFS) prediction. This is important to prevent accidents caused by mental workload, over anxiety and fatigue etc. Designing a dominant classifier with robust generalization capability is an important problem for the development of motor imagery-based brain-computer interface as [36] proposed a multi-kernel ELM (MKELM)-based method for motor imagery electroencephalogram (EEG) classification. Zhou [37] proposed metrics of arrival rate and time efficiency for neural networks, to be trained to perform real-time route planning tasks in a road network. Xue *et al.* [38] proposes new pedestrian model, it utilizes fuzzy logic to a multi-agent system in order to address cognitive behavior to deal with uncertainty and imprecision in decision making. The involvement and significance of fuzzy logic in depicting human cognition is highlighted in different literature to investigate and evaluate human learning ability and the process of cognition [39], [40]. In addition to fuzzy logic, artificial neural network process information like biological nervous system. Artificial Neural Network learn by examples. The learning takes place when synaptic connections are adjusted and it has the ability to learn on the basis of input data [41]. For addressing complex information understanding in cognition, Artificial Neural Network for human cognition is significant [42]. Greene [43] elaborates the usefulness of various aspects of human cognition and memory structuring is one important element. For any cognitive task to perform, the utilization of cognitive memory plays vital role. Moreover, further literature [44], [45], [46], including patent [47] exists to address the vehicle routing problem intelligently, however, none of the related work addresses the vehicle route problem from a cognitive memory perspective. Also, cognitive memory that provides key difference to make a shift toward strong artificial intelligence strategies is not utilized and those datasets that are applied are usually static and without cognitive variables [44]–[47].

Based on literature, we found that there is lack of pure cognitive model for VANET to facilitate strong AI in vehicles. Although different cognitive models are debated now for vehicles but our proposed work relates to vehicle route information by utilizing cognitive memories and learning from experiences in the form of episodes and instances. The proposed framework under discussion is unique as it is not merely focused upon the intelligent decision making (provided by existing relevant solutions), but rather more focused on the continuous learning that resulted into evolution – this cannot be achieved without engaging cognitive memories. As this was not done before therefore, relevant work is split into intelligent routing and agents with cognitive memory, both are cited in the paper.

The literature facilitates our proposed work from cognitive perspective as well as Vehicular Ad hoc Network. Moreover, it also assists in validating our work through Fuzzy model and Artificial Neural Network.

The proposed work with cognitive memory structure is elaborated in section III.

III. PROPOSED WORK

In the proposed route decision module, when incorrect input is provided like improper destination, the module treats the input as *invalid route*. The route input is considered as *existing route* when the vehicle already traveled a route before and has a previous episode of it in its cognitive memory. The route input is taken as *new route* when the vehicle never travelled a route and therefore, do not have any episode of it. Route input can be provided by means of voice patterns, afterwards, initial check is performed to assess the category of the requested route. The proposed work suggests that route provided to the vehicle for expedition falls in the category of existing route i.e., the vehicle already possesses its patterns in its memory. The expedition is completed by utilizing the cognitive memory of the vehicle. The information from cognitive memory is helpful though, however, updated information is important for route provision. For instance, there are chances that new routes might get established with time. Another aspect of the proposed module is when communication system of the vehicle fails for some reason or vehicular node, road-side-unit are not available, in such cases, information from vehicular cognitive memory is utilized. The information although might not be optimal enough, but sufficient enough to carry out vehicular expedition in worst-case scenarios. This raises a question, what if vehicular memory does not have patterns of a route? In that case the route is treated as a new route, and also involvement of vehicular communication system with the third party is required, such as GPS, road-side-units (RSUs) or another vehicular node. The third-party contact is going to gather new route information.

For this purpose, route decision module has been proposed that manages the route categories by interacting with the cognitive memory. This cognitive memory is going to be incorporated in every vehicle as this is going to enhance the manipulation and processing of route related information almost the same way as human perform.

Figure 1 shows the route information as Sources, Destinations, Maps, Routes, etc. and are stored as episodes in Long Term Memory (LTM) due to its future usage. Semantic memory assign meaning to route information whereas Episodic memory stores the entire route information as episodes.

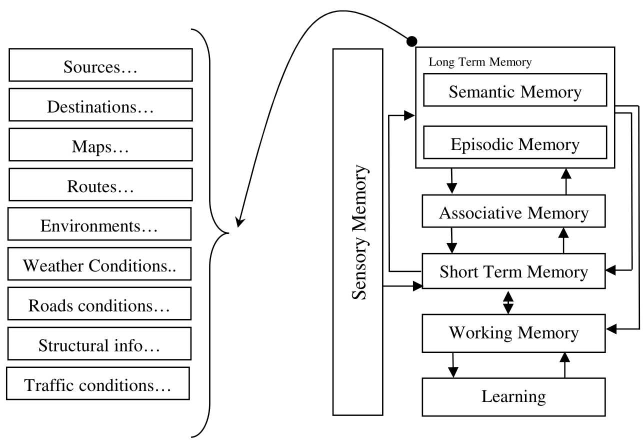

FIGURE 1. Proposed Cognitive Memory Structure containing route information.

Associative memory provides proper association of the required episode for retrieval by making proper associations. Sensory memory senses information and provide to Short

Term Memory (STM) for short intervals. Working Memory processes information in real-time for decision making. This whole process of decision making is learned through transfer function in the learning unit.

Figure 2 shows route decision module that provides route information in optimal manner to the driver. The input route information is received by the on-board computing unit (OBU) of the vehicle. It processes it and the whole module is activated by sending a signal to the route controller. Appropriate naming tags are assigned to source and destination by the route controller and provides the tagged information to the route planner unit. It assesses the provided input whether correct or incorrect and this is performed in comparison to a route profile. The driver is notified in case incorrect input is detected and directs to provide the correct route input. Route controller is updated when correct route input is provided. Category of the correct provided route takes place inside the cognitive memory of the vehicle. The existence of previous route episode is checked by the cognitive memory if any. The route is categorized as existing route if it exists in its knowledge repository, otherwise it is considered as new. The found route category by the cognitive memory is provided to route planner by the route controller. Tagging is performed by the route planner for the purpose of updating the route category. For this purpose, the route controller initializes communication system in the module to communicate with the external entities. This outside intervention with external entities is essential for obtaining up-to-date route information. The vehicle is proposed to be equipped with several wireless technologies as Dedicated Short Range Communication (DSRC), WiFi, cellular as Long Term Evolution (LTE), and satellite communication systems.

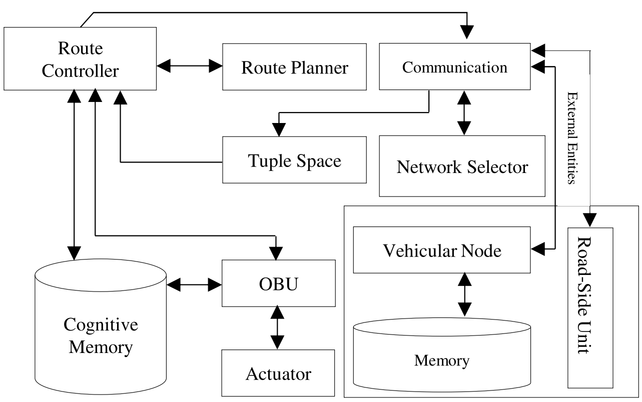

FIGURE 2. Proposed In-Vehicle Cognitive Route Decision Module.

Communication is carried out by the vehicle with the external entities such as RSU(s) or vehicular node(s). Depending on their availability, updated route information is collected. The collected information need to be properly organized before it is stored in the vehicular cognitive memory. The tuple space unit properly organizes the route information accordingly. The updated route information meanwhile is provided to the OBU for decision which notifies the driver via actuator about the updated route. At this stage, the driver of the vehicle views the updated route information. It is the cognitive memory that decides to trigger the process of taking most recent copy of route information from the external entities. This information now resides in the cognitive memory of the vehicle for future decision making. This whole process of route input provision and route update is treated as an episode that is learned and ultimately recorded in the cognitive memory.

Also, if the provided route is categorized as a new route, the cognitive memory of the vehicle follows the following structure:

- Cognitive memory is going to decide on the basis of pre-map information (already stored map information). However, this takes place only when communication component of the vehicle is not functioning for some reason or there are no signals at all and the vehicle is all left alone.
- Cognitive memory decides on the basis of received route information from the external entities (as supervised or semi-supervised stations). This is performed when communication system of the vehicle functions properly.

In case of any route category, the cognitive memory of vehicle avails the most recent route information and stores them as episodes.

Let us examine our proposed cognitive route decision module from process-based functioning with respect to time *t*. This is going to facilitate our proposed vehicular concept of route decisions cognitively.

The OBU processes the provided route input supported by route controller and cognitive memory process. The process flow for proposed module case is presented in Figure 3 that shows its functionality with respect to time intervals t_n. Also, the proposed components in Figure 3 can use different algorithms such as OBU can use preemptive real-time scheduling [48] route planner can make use of ant colony optimization algorithm [49] cognitive memory can utilize

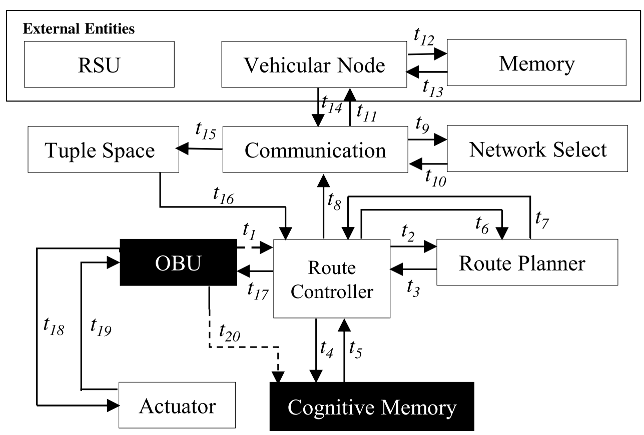

FIGURE 3. Process Flow of the proposed in-vehicle cognitive route decision module.

SURF algorithm [50] and communication controller can use predictive geographic routing protocol [51].

IV. SCENARIO OF EXISTING ROUTE IDENTIFICATION AND COGNITIVE DECISION

In this section, the proposed in-vehicle cognitive route decision module is explained cognitively with a scenario of a person who travels by car from Stratford to Heathrow airport. The vehicle never visited from such route before. When route input is provided, the vehicle's cognitive memory detects the destination as a valid input and route is categorized as new route as it does not have any episode of the route yet. External entities are consulted for fresh route information retrieval and ultimately recorded in the cognitive memory of vehicle. The vehicle provides the most appropriate route as shown in Table 1. However, it took longer to reach the destination because of decelerating, stopping at a book shop, and at ATM which were not located on such route.

TABLE 1. Route provision (Episode 1).

Intersections	Traffic Lights	Traffic	VANET Members	Distance (Km)	Predicted Time	Time Attained
7	12	Less	<50~	88	1 hr 20 min	2 hr

After few weeks, the person has to travel again from Stratford to Heathrow Airport. The vehicle recommends the route as existing route because of having previous route experience in the cognitive memory. It, therefore, knows the last vehicle status: where it decelerated, accelerated, stopped, at what positions and for how long. This information is quite feasible now for decision making in choosing a route, however, for more refined route, cognitive memory triggers route updates from external entities. Predicting the reasons for slowness last time on the basis of its position and timing, updated route provided cognitively is shown in Table 2. This time the vehicle stopped at a specified gas station which was not on the suggested route.

TABLE 2. Route provision after cognitive infusion (Episode 2).

Intersections	Traffic Lights	Traffic	XYZ ATM	Book Store	VANET Members	Distance (Km)	Predicted Time	Time Attained
7	12	Less	4	3	<80~	88	1 hr 30 min	1 hr 35 min

After a few months, the vehicle travels on the route (Stratford to Heathrow airport) once again. The communication system of the vehicle fails to function for some reason. The car is at its own now, however, the vehicle gets route information from its cognitive memory and decision is made on the existence of already stored two episodes and identification of the location of the gas station previously as shown in Table 3.

In the above scenario, three episodes are produced for the route. The generated episodes are learned and ultimately recorded in the cognitive memory. Vehicular memory populated its cognitive memory as the experience is gained with time. This experience facilitates the vehicle to take self-decisions when left independent.

TABLE 3. Route provision by cognitive memory (Episode 2).

Intersections	Traffic Lights	Traffic	MNO Gas Station	XYZ ATM	Book Store	VANET Members	Distance (Km)	Predicted Time	Time Attained
7	12	Less	1	4	3	<80~	88	1 hr 30 min	1 hr 25 min

V. SIMULATION

We have formulated both cognitive and noncognitive variables in order to find out whether their impacts affect the route decisions or not. Therefore, it is essential to elaborate these variables as described in Table 4, and their utilization in Fuzzy Model and Artificial Neural Network simulations. Membership functions and datasets of Fuzzy Model and Artificial Neural Network are presented, respectively, in order to validate our proposed in-vehicle cognitive route decision module. Membership functions and datasets that consist of eleven inputs and a single output are formulated and used in both simulation platforms.

TABLE 4. Fuzzy input output design.

$\tilde{A}$			$\tilde{B}$	
Fuzzy Inputs x_n	**Fuzzy Inputs Range**	**Randomized values for x_n**	**Fuzzy Output Range y_n**	**Desired Value z**
x_1 (Route Input)	0-100	86.9	0-1	Optimal Route Info (Required)
x_2 (Route Profile)	0-100	86.3	0-1	
x_3 (Route Category)	0-100	88.1	0-1	
x_4 (Infrastructure Info)	0-100	80.9	0-1	
x_5 (Error Probability)	0-100	7.26	0-1	
x_6 (Previous Behavior)	0-100	18.3	0-1	
x_7 (Uncertainty)	0-100	16.9	0-1	
x_8 (Protocol Relevancy)	0-100	86.5	0-1	
x_9 (Wifi)	0-100	88.1	0-1	
x_{10} (GIS)	0-100	86.3	0-1	
x_{11} (Data Organizing)	0-100	84.9	0-1	

A. FUZZY MODEL DESIGN SIMULATION

Fuzzy sets A of X and B of Y are functions from the universe of discourse sets X and Y respectively to the unit interval where Z is unknown and required. Fuzzy sets of A and B can be represented as:

$$\tilde{A} : \mathrm{X} \rightarrow \mathrm{x_n} \exists [x_1, x_2, x_3, .., x_{11}]$$

$$\tilde{B} : \mathrm{X} \rightarrow \mathrm{y_n} \exists [y_1, y_2, y_3, y_4, y_5]$$

$$\mathrm{z} \rightarrow [\mathrm{unknown}]$$

F(X) and F(Y) represents the set of all fuzzy sets of X and Y respectively, such as

$$\mathrm{F(X)} = \{\tilde{A} | \tilde{A} : \mathrm{X} \rightarrow [0, 100]\}$$

$$\mathrm{F(Y)} = \{\tilde{B} | \tilde{B} : \mathrm{Y} \rightarrow [0, 1]\}$$

A scale of 0 to 100 is selected for $\mathrm{x_n}$ to measure the level of severity of the defined variables. Random values for $\mathrm{x_n}$ are assigned in order to find out the kind of output value z we get. Also, the value of z is unknown and need to find out with a defined range from 0 to 1. It is required on the basis of the fuzzy effects of x_n and y_n.

Route input (x_1) can be provided with very low voice intensity values (0 0 25) to a possible range of a very high intensity values (75 100 100), its provided value is 86.9 which is high. Route profile (x_2) can be affected by data corruption, thereby, impacting its availability levels in cognitive memory from extremely less values (0 0 25) to its definite availability values (75 100 100), its value is 86.3 and is partially available. Route category (x_3) functions on the information of existing and new route availability in the cognitive memory from very lower values (0 0 25) to its full availability values (75 100 100), its value is 88.1 and is partially available. Infrastructure info (x_4) can be provided with the amount of infrastructure information availability in the cognitive memory from very less availability values (0 0 25) to definite presence of the required information values (75 100 100), the value is 80.9 which is partially available.

Error Probability (x_5) is the amount of error in retrieving $x_1, .., x_4$ and $x_8, .., x_{11}$ from the cognitive memory. The amount of error can be nil with values ranging from (0 0 25) to very high error rate values (75 100 100), the value of 7.26 is assigned which is extremely low. Previous Behavior (x_6) is the amount of previous route episodic experiences. There can be no route episodes or some episodes, thereby, values from (0 0 25) to a definite number of route experiences in the cognitive memory with higher values (75 100 100), its value is 18.3 and is extremely minimal. Uncertainty (x_7) is the unsurely and vagueness of the relevant route information in the cognitive memory. No uncertainty is ideal, however, lower values (0 0 25) are better. Higher values in the range (75 100 100) are problematic, the value of 16.9 is assigned which is extremely low.

Protocol Relevancy (x_8) can be provided with no relevancy or less relevancy values (0 0 25) to appropriate relevancy level with higher values (75 100 100), the value is 86.5 and is partially relevant. Wi-Fi (x_9) can have lower values (0 0 25) representing its unavailability or slight availability to higher values of (75 100 100) representing its full availability, its value is 88.1 and is partially available. GIS (x_{10}) availability for the required route information can have lower values (0 0 25) representing its unavailability, slight availability to higher values of (75 100 100) representing the higher availability of the required information, its value is 86.3 and is partially available. Data Organization (x_{11}) can have lower values (0 0 25) representing no data organization to extremely less and ranging towards higher values (75 100 100) indicating data organization at a maximum level, the value of 84.9 is assigned which is partially organized.

In Table IV, our proposed fuzzy input output design is shown. Fuzzy set A is expressed as inputs x_n with the assigned fuzzy range from 0 to 100. Also, random values for x_n are provided within the provided range. Fuzzy set B is expressed as output y_n with range from 0 to 1. The desired value z is to be achieved.

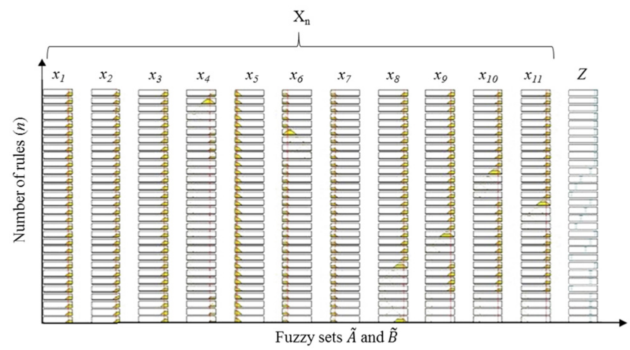

FIGURE 4. Rule viewer indicating the effect of cognitive and non-cognitive inputs on output.

The associated values of fuzzy sets A and B are taken for graph generation to achieve the desired value z in the form of function f as,

$$f : \tilde{A} \rightarrow \tilde{B}$$

Input and output ranges are shown in Tables 5 and 6, respectively. For each input, the range of 0 to 100 range is provided and the output range is 0 to 1.

Table 6 shows the desired output z along with the range values from 0 to 1. Extremely less means the provided route information to the user do not exist, therefore, value 0 is assigned. Very less value of 0.2 states very negligible amount of route information is provided to the user that might be in the form of only route indication. Less value of 0.4 shows that less route information is provided and can be in the form of route indication with few city names. Partial value of 0.6 demonstrates the provided route information is substantial. It can be in the form of route with complete places. Less optimal value of 0.8 reveals the route provided is slightly complete but lacks the updated information. Optimal value of 1 states that the provided route information on the basis of user request is complete and contain all information the user require regarding a particular route (including user preferences as mentioned in Table 1, 2 and 3).

Subsequently, for the inputs and output membership functions as listed in Table 5 and 6 respectively, Fuzzy model is utilized.

In addition, one hundred rules are proposed, and their collective impact is achieved that can be seen in Rule viewer shown in Figure 4.

In Figure 4, the Fuzzy sets A and B are represented horizontally as x_n that ultimately attained z among y_n. The number of generated rules $n$are represented vertically. The Figure 4 indicates when route input detection x_1 is high (86.9), route profile x_2 is partially available (86.3), route category x_3 is partially available (88.1), infrastructure info x_4 is partially available (80.9), error probability x_5 is extremely low (7.26), previous behavior x_6 is extremely minimal (18.3), uncertainty x_7 is extremely less (16.9), protocol relevancy x_8 is partially relevant (86.5), Wi-Fi x_9 is fully available (88.1), GIS data x_{10} is partially available (86.3) and data is partially

TABLE 5. Input range.

Inputs	Description	Range			
x_1: Route Input	Route input provided by the user with different intensities levels from very low to very high.	Very High	75	100	100
		High	50	75	100
		Normal	25	50	75
		Low	0	25	50
		Very Low	0	0	25
x_2: Route Profile	Route Profile might be effected by data corruption, thereby, causing its availability in cognitive memory with extremely less levels to its definite presence of fully available.	Fully Available	75	100	100
		Partially available	50	75	100
		Less	25	50	75
		Very Less	0	25	50
		Extremely Less	0	0	25
x_3: Route Category	Assignment of Route Category on the basis of its information availability in cognitive memory, existing or new route, from extremely less to its full availablity.	Fully Available	75	100	100
		Partially available	50	75	100
		Less	25	50	75
		Very Less	0	25	50
		Extremely Less	0	0	25
x_4: Infrastructure info	Presence of infrastructural information availability, between source and destination, from extremely less to its full availability.	Fully Available	75	100	100
		Partially available	50	75	100
		Less	25	50	75
		Very Less	0	25	50
		Extremely Less	0	0	25
x_5: Error Probability (cognitive)	Chances of error in retieving information (x_1 .. x_4, x_8 .. x_{11}) from cognitive memory due to improper associations. The chances of error rates range from extremely lower values to very high error rate values.	Very High	75	100	100
		High	50	75	100
		Normal	25	50	75
		Low	0	25	50
		Extremely Low	0	0	25
x_6: Previous Behavior (cognitive)	The existence of route episodes inside cognitive memory with extremeily minimal levels to their full existence.	Completely Exist	75	100	100
		Partially Exist	50	75	100
		Minimal	25	50	75
		Very Minimal	0	25	50
		Extremely Minimal	0	0	25
x_7: Uncertainty (cognitive)	Condition when cognitive memory is unclear of getting the designated route episodes from extremely less levels to very high level of uncertainty.	Very High	75	100	100
		High	50	75	100
		Moderate	25	50	75
		Less	0	25	50
		Extremely Less	0	0	25
x_8: Protocol Relevancy	Procedure of appropriate protocol to make communication possible with the external entities with no or extremely less relevancy values to relevant protocol relevancy.	Relevant	75	100	100
		Partially Relevant	50	75	100
		Less	25	50	75
		Very Less	0	25	50
		Extremely Less	0	0	25
x_9: WiFi	Designated communication network with no availability to full availability levels.	Fully Available	75	100	100
		Partially Available	50	75	100
		Less	25	50	75
		Very Less	0	25	50
		Extremely Less	0	0	25
x_{10}: GIS	Required GIS information availability with the external entities from extremely less to full available levels.	Fully Available	75	100	100
		Partially Available	50	75	100
		Less	25	50	75
		Very Less	0	25	50
		Extremely Less	0	0	25
x_{11}: Data Organizing	Proper organization of the GIS data upon fetching from external entities into the cognitive memory.	Fully Organized	75	100	100
		Partially Organized	50	75	100
		Less	25	50	75
		Very Less	0	25	50
		Extremely Less	0	0	25

organized (84.9) x_{11} then the required value of z we get is 0.966 (almost equal to 1). This is an ideal value we get on the basis of x_n values.

TABLE 6. Output range.

Output	Description	Range	
Z: Optical Route Info	Provision of updated route information with user preferences based on cognitive impact that fulfills the need of vehicle user.	Optimal	1.0
		Less Optimal	0.8
		Partial	0.6
		Less	0.4
		Very Less	0.2
		Extremely Less	0.0

The generated 2-Dimensional surface in Figure 5 shows the relation between cognitive input variable and the final output.

The generated plotted graph in Figure 5 indicates the cognitive input x_6 with the specified range from 0 to 100 and the optimal route info Z contains fuzzy values within the defined range from 0 to 1. It indicates that when previous behavior x_6 is extremely minimal i.e., 18.3, optimal route info Z attains the 0.965 value. This indicates the importance of cognitive variable x_6 and its impact on achieving optimal route info Z. The achieved value of 0.965 is very close to 1 which is the ideal case. Ideal case is where the provided route contains the user preferences. It is important to mention that the achieved value is not 1, but a value close to it. The provided value supports the case from the cognitive point of view.

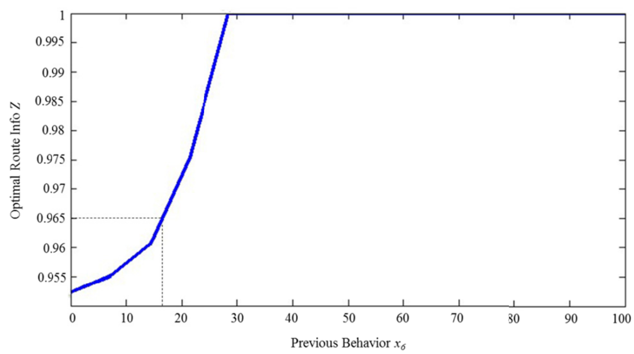

FIGURE 5. Relation between Previous Behavior and Optimal Route Info in a 2D Surface.

The 3D surface plot as shown in Figure 6 indicates the relation between two input variables on the final output.

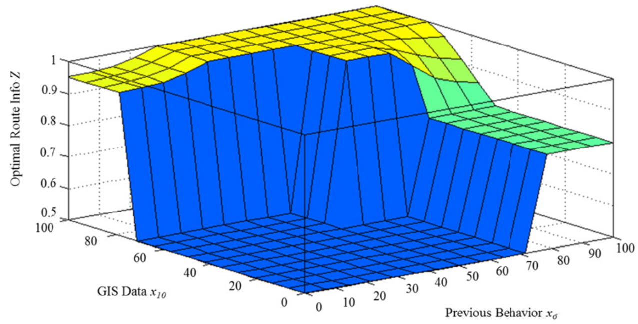

FIGURE 6. Collective impact of Previous Behavior and GIS Data on Optimal Route Info.

Figure 6 shows the cognitive input previous behavior x_6 and noncognitive input GIS Data x_{10} having fuzzy range from 0 to 100 respectively. Both x_6 and x_{10} start impacting the optimal route info Z collectively at values 50 and incrementing almost equal to 1. As the values of x_6 and x_{10} start increasing, accordingly the value of Z attains its peak value as signified in yellow.

B. ARTIFICIAL NEURAL NETWORK SIMULATION

Neural Network (NN) has the tendency to receive complex inputs, processes, learns them and accordingly outputs an appropriate decision. The output is again refined by adjusting the input weights again and again. This process continues until a reasonable output is achieved. NN functions on the basis of supervised and unsupervised learning mechanisms. It is these characteristics of the neural networks that our proposed system uses it for simulation. We utilize the supervised learning mechanism where inputs and output datasets are provided to the ANN software. It receives the inputs, process and trains and learns them according to the learning algorithm and provides a better output. The process continues until a desired output is achieved. Here in our case, the desired value is the output in the form of optimal route info.

The dataset of size 2048 is generated based on cognitive and noncognitive inputs. The error rate is required to get minimize. The dataset is structured as inputs and outputs for Neural network fitting. Static data of 2048x11 matrix is included as inputs 'Case3inputs', 11 elements having samples of 2048. Static data of 2048x1 matrix is included as Targets 'Case3outputs', 1 element having 2048 samples. Samples of size 1434 are designated for training the network and the network is attuned according to its error rate. Samples of size 307 are selected for validating the network and as generalization stops improving, the training is stopped. Samples of size 307 are taken for testing the network for representing independent measure of the performance of network. The selection of hidden neurons is based on achieving performance and low error rate and therefore, its number is specified accordingly.

Consequently, Levenberg-Marquardt back-propagation algorithm [52] is used to train the network with the attained results shown in Figure 7. This algorithm learns the parameters and trains the network for better output and is suggested for big data scenarios. In Figure 7, the Mean Squared Error (MSE) is calculated between outputs and targets. The smaller the MSE, the better the results.

In Figure 7, MSE measures the average of the squared errors and the epoch is single step in training the network. The three lines indicate training, validation and testing data and they already move closer which is what we actually require. The encircle point where the dotted line meet, indicates the attained lowest possible error. Overfitting is a model that models the training data very well. It results in performance degradation so it need to be avoided. One way to come around the problem of overfitting is to use large data sets as proposed. In Figure 7, overfitting might have taken place in case the test line increased significantly. Figure 7 indicates the decrease of error in training, validation and testing data. The error keeps on decreasing and based on training data, best validation performance is attained at epoch 26 which is 0.0010136. As the number of epochs increases, overfitting results to some extent. The attained value at epoch 26 indicates that based on our proposed dataset, learning is achievable with lowest error rate.

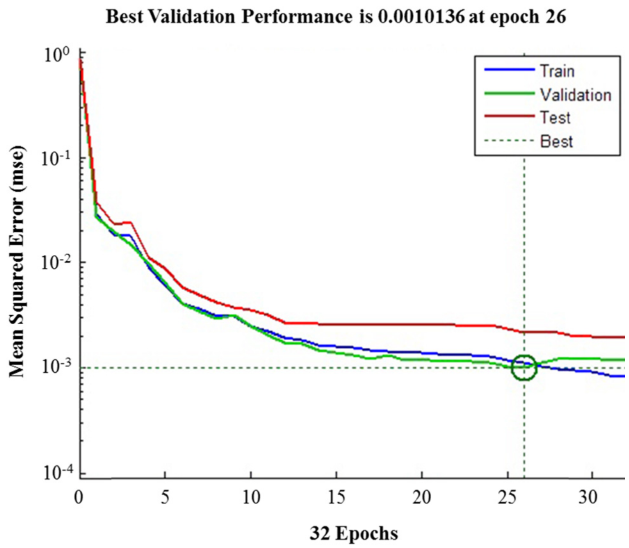

FIGURE 7. Gaining lowest error in the Performance graph.

In Figure 8, the horizontal values are the attained errors and vertical values are the instances. The negative errors are not desirable nor the increased positive values. MSE rates need to be lowest as properly maintained errors are desirable as represented in Figure 8. The bell-shaped structure suggests normal distribution with lowest errors and shown as error histogram.

The error histogram in Figure 8 points out the number of instances (y-axis) with respect to training, validation and

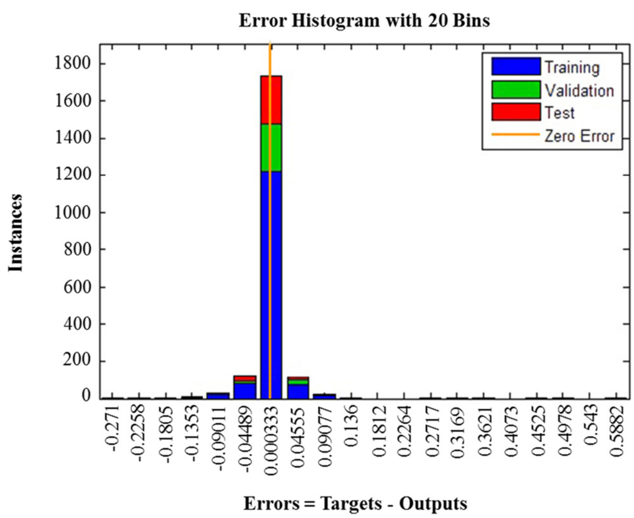

FIGURE 8. Error Histogram indicating error rate with respect to number of instances.

testing on the basis of the provided dataset. Errors are indicated along x-axis which are the difference between target and output values. Neither the negative nor the positive values are better except zero value. It is observed from Figure 8, that minimal error is attained ultimately after 20 bins of operations. This reveals once again that when the network is trained with the proposed dataset, the generated errors are minimized and chance for learning is achievable.

Furthermore, Regression is applied that estimates the relationship between variables. It shows the closeness of the data with respect to the fitted regression line. The R performance of training, validation and test data and overall R performance are indicated in the regression plot and shown in Figure 9.

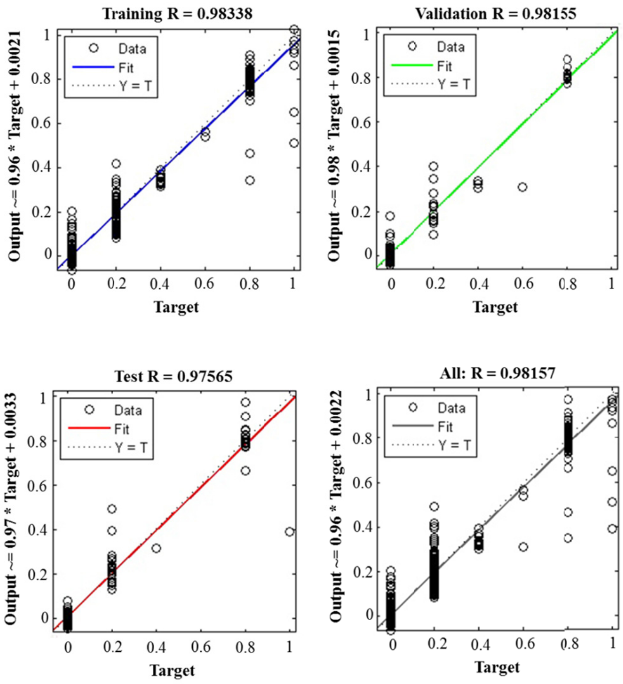

FIGURE 9. **Regression Plot showing different R values.**

Regression R values in Figure 9 measure the correlation between outputs and targets. Horizontal values are target values and the vertical values are outputs. An R value of 1 means a close relationship and 0 shows random relationship. The attained values of R for training, validation and test are 0.98338, 0.98155 and 0.97565 respectively and the overall R value achieved is 0.98157. These all are closer to 1 and thus indicates a close relationship. The results indicate that the proposed dataset fits well with a close relation between outputs and the targets.

VI. CONCLUSION

We found that cognitive memory is important for vehicular route decision process as improved route information is accomplished by the addition of cognitive factors. The decision process, in the form of optimal route provision, can be improved when cognitive variables inside the cognitive memory generates fuzziness upon interaction with noncognitive variables. Furthermore, the decrease in error results to a significant extent is attained which indicates the possibility that vehicular agent can learn by the use of cognitive variables, and it can evolve for better route related decision making with the passage of time. Thereby, gradual shift from supervised learning to unsupervised by vehicle can be attained to take rational route related decisions in any task environment.

From cognitive viewpoint, similar decisions are made by the human mind with information availability and sensory signals. Human mind also assigns classification of events to the processed patterns. Sometimes such event classification might not be always correct due to certain cognitive parameters as uncertainty. Positive results are not always guaranteed as both positive and negative results are part of the experience. From cognitive perspective, the influence of cognitive variables supports the case and the entire process of input route provision till the optimal route information delivery is recorded as an episode in the cognitive memory. This experience is important for the vehicle to take self-decisions with time. The process explained both supervised and semi-supervised learning and the objective is to achieve unsupervised learning in the vehicle. The proposed system has some limitations: the learning is slow and the system matures with time. The more experience the system gains, the more optimal it becomes. Moreover, the vehicle, being cognitive agent, relies on seed knowledge that means cognitive memory must possess key features of the route.

In the future, other characteristics of human cognition, such as emotions, memory structure, need consideration in vehicular domain. The unsupervised learning is another direction to be investigated for making the vehicle self-dependent. We need to address the cognitive episodic memories for storing route instances to overcome the concerned limitations and develop datasets to see the cognitive impact more generically. Just like data mining facilitates routing data, similarly, from cognitive perspective routing episodes having instances need mining strategies.

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