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Research Article

# DEEP LEARNING FOR A HEURISTIC OPTIMIZATION STUDY USED FUZZY LOGIC AND GENETIC ALGORITHMS FOR VEHICLE SEAMLESS CONNECTIVITY

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**Abstract**

This paper provides combine algorithms working with fuzzy logic and genetic algorithms, is support seamless connectivity, the algorithms have deep learning for future environmental study, used a heuristic optimization. The genetic algorithms start working based on based equation identified the regulation. The system proposed which is composed of integrated with satellite, Cellular and WIMAX technologies fixed by GPS to support different data rate, the main advantage idea also here the connectivity between vehicle to vehicle (V2V) communication is available based on 802.11p standard distance less than 100m in Local area, and less than 10 km in cellular WIMAX coverage area. Each vehicle equipped with GPS and smart card with Tow interface can be connected on one side interface working to support local network and cellular, another side support virtual connection. Also, this side can reach to connect directly through satellite connection with standers IEEE802.21. In addition, the long-term evaluation (LTE), supporting highest speed up to 400 km/h is different than other technology service coverage. Therefore, study identifies the emerging trends, highlights the technical limitations, and provides a roadmap for future vehicles communication development using robust algorithms with realistic simulations.

**Keywords:** Deep fuzzy system, Fuzzy network, autonomous vehicles (AVs), Deep learning, Traffic optimization.

## INTRODUCTION

Study of the Heuristics are widely used for dealing with complex search and optimization problems Evolutionary Computation (EC). Therefore, methods for Automatic Heuristic Design(AHD), represents the ideas of heuristics in high-performance heuristics on experiments [1], in their survey of the Heuristics are commonly used for tackling complex search and optimization problems among many other methods[2]. These hand-crafted methods have been successfully used in a wide spectrum of real-world applications. However, different applications may require different algorithms and/or algorithm configurations for to adapt issues of the simulation. To address this issue, Automatic Heuristic Design (AHD) has been proposed and become an active research area [3,4]. and frameworks[5], one can tune heuristics or combine different algorithmic components in an automatic manner. Much effort has been made to use machine learning techniques in automatic algorithm design [7-9]. Among them, genetic programming [10,11], provides an explainable approach to algorithm design. However, automotive connectivity stands at the forefront of vehicle design decisions, enabling a wide range of innovative user experiences, value-added services, safety and security enhancements, and new features that are changing the way drivers interact with their vehicles. Therefore, to make these new dimensions possible, cars will need to support a number of wireless technologies, including high-performance Wi-Fi, Bluetooth, Ultra-Wideband(UWB), Near Field Communication (NFC), IEEE 802.11p, and cellular connectivity, in order to enable key use cases, such as advanced in- collection, over-the-air (OTA) updates, vehicle car infotainment and audio systems, secure vehicle access and sharing, intelligent vehicle data diagnostics and health management, tire pressure monitoring systems, vehicle-as-hotspot, and Vehicle-to-Everything (V2X) communications functionality, among others. On this research surveys, will highlight the future of the connected car and discuss how key wireless connectivity technologies will help to enable new innovative use cases within and around the vehicle. Discussion will focus on short-range wireless technologies such as Wi-Fi 6, Bluetooth, V2V, Cellular and WIMAX, as well as on cellular technologies. The research highlights the need support multiple connectivity technologies within the vehicle to effectively address of the existing and emerging use cases and applications. However, including vehicle-to-cloud connectivity and telematics [12],in-vehicle experiences, smart access and shared mobility, and V2X. In addition, it will highlight how new vehicle architectures will be fundamental in ensuring that vehicles of the future will be able to provide secure, robust connectivity. The organization of the paper is structured as follows:

Section 2 presents the background of the selection method, and Section 3describes deep learning algorithms for the fuzzy interference logic system evaluation. Section 4 presents Intelligent seamless model, and Section 5 concludes the paper.

## Background and Related Works

Dhinakaran et al. [13] the objective of their study is to enhance the efficiency, safety, and flexibility of autonomous vehicle navigation systems by employing advanced deep reinforcement learning (DRL) strategies, focusing on real-world adaptability and safety assurance. In this paper [14], authors' main objective is to design and develop a safe reinforcement learning (safe-RL) policy for autonomous vehicles (AVs) to avoid collisions and reduce traffic congestion on highways. The authors in [15] proposed the deep deterministic policy gradient (DDPG)-based framework to deal

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with complex decision-making tasks of autonomous vehicles, such as lane keeping, overtaking, and collision avoidance. The methodology models the AVS as a learning agent that interacts with the dynamic environment and uses a detailed state space incorporating variables such as speed, angle, and distance. Huawei Si et al. [16] proposed a novel reinforcement learning (RL) framework utilizing graph convolutional networks (GCN) to enhance coordination policies among multi-intelligent vehicles in dynamic environments. The approach combines a dynamic coordination graph (CG) model with attention mechanisms to dynamically model and refine interaction relationships between vehicles. Alizadeh et al. [17] introduced a new framework for deep reinforcement learning-based autonomous lane change maneuver improvement in complex highway scenarios. The approach is based on deep Q-learning to train agents in a specially developed simulation environment with realistic vehicle dynamics and intelligent driver models for adaptive cruise control (IDM), and MOBIL, Liu and Yu [18] the research's objective aims to design a trajectory planning method for autonomous vehicles using deep learning techniques, ensuring safe obstacle avoidance while mimicking human driving styles. Karuppasamy Pandiyan et al. [19] the research's objective is to explore and implement deep learning applications in autonomous driving systems, focusing on self-driving car modules such as scene perception, path planning, and motion control. In [20], the authors proposed a solution using a fuzzy neural network in a vehicle braking system that employs an electromechanical actuator. In [21], the authors employed the Takagi–Sugeno–Kang wavelet fuzzy neural network to develop a comprehensive framework dedicated to modeling nonlinear systems by learning from data. Additionally, they utilized Lyapunov stability theory for system optimization. Some authors propose the use of adaptive neural networks to solve the state estimation problem using the fuzzy Takagi–Sugeno model andthe control of nonlinear systems through an adaptive neural network in which the system parameters comply with Markov switching rules [22]. One of the advantages of using fuzzylogic in neural networks is that it accelerates the learning process of the network [23].

## Fuzzy interface system

Fuzzy interface system becomes multi – option has been successfully applied in different fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. In this part the structure using known by different parameters entries for automatic control system for balance transaction. Following diagram show the interface system shown how is every input can fit together.

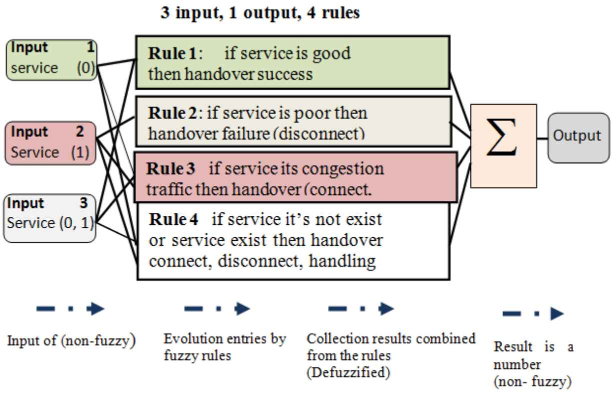



**Figure 1.Fuzzy interference logic system evaluation**

**Step 1 fuzzifier inputs**

The first step is to take the variables parameters input from outside and then combined to the summation rules to determination the evaluation from member sets rules via additional function tasted. In this process of input entries all parameters should be entries in section of fuzzifier to identified the criteria behavior.

**Step 2**

Its logical process combining from set of rules working by logic entries such as (parameters indicator), is refer to service status (good or bad), using "logical operation" AND, OR, NOT to determine the type of parameters depend on inputs variables parameters. If we assume that:

$a$= Strength signals ,$b$=available bandwidth ,and $x$=Service $z$ =high quality $\Delta t = time$, $\theta = speed$ , $x_{i,j} = parameters$ , N= $d = dias\tan ce$ ,

$N = \frac{\Delta d}{\Delta t}$ , $N = \theta = \Theta$ ,

$P = probabilit\,y$ .

IF $x = a + b$ then $x = z$

Suppose that if a = 0 , b = 0, $X$ is variable = 0, 1 , refer to the logic rules ( $a \wedge b$ ) =0, THEN handover is establish a connection in $\Delta t = 0$ or $\Delta t = t - 1$. We assume that the limited time of users to create establishment $\leq$ 0 otherwise NOT. If we assume $\psi =$ poor service, and $\lambda =$ unavailable bandwidth, then $x \neq 0$ , $X = 1$ and $\psi, \lambda \neq 0$ , $\Delta t = t + 1$ and $x_{i,j \in X \approx 0,1}$ , $\psi_X,\ \lambda_X \in X$ , $d = \frac{\Delta d}{\Delta t}$ . We can mention that in the boundary area when users moving and try to establish a connection the formal logic algorithm can be formal at:

Maximize $(\Theta) = \sum_{X=1,0}^{\infty} \forall\ x_{i,j} \leq Z,\ x_{i,j} \in \{0,1\}$

Subject to: $\exists_{X_{i,j}} \leq 0,, x_N = \Theta_{X_{I,J}}$

$$\sum_{N=1,}^{\infty}\sum_{N=0}^{\infty} p_{X i,j}, \exists! \neq 0 \in \{0,1\}$$

Were

$$\psi, \lambda \in X \leq 0 = \{0,1\}, X \geq 0 = x_{i,j} \in X = \{0,1\} \quad \notin \Theta$$

$$\theta = \Delta t = t + 1, t - 1, t = 0$$

$$\psi, \lambda \neq 0 \in X = N \ , \ X = P = \{0,1\}$$

Then

$$\Gamma(t) = \delta(t) d[t + \varepsilon(t)]$$

Were

$\Gamma(t)$ is a signals duration with $T_0, \delta(t)$, amplitude of thesignal and $\varepsilon(time)$ is time error , both $\Gamma(t) and \varepsilon(t)$ are constant .

$$x(t) = \Gamma(t)\sin[\Psi(t+\varepsilon(t))]$$

$$\psi(t) = \frac{2\pi(t)\Psi(t+\varepsilon(t))}{\Phi(t)+\theta(t)}$$

$\psi(t)$ is obtained,

$$2\pi \in (t) = x(t)\sqrt{a^2+b^2} + \phi(t) + \theta(t) = \frac{2}{T}\int_0^{T_0} \Gamma(t)\cos(2\pi(t)dt$$

$X(t) \geq 0$. Can be observed from $\Gamma(t)$. And $\Gamma(t) = \frac{\Delta t}{2\pi}\frac{d\Psi}{dt} = \frac{\Delta t}{2\pi}\frac{d\Phi}{dt} + \frac{d\theta}{dt} = \Theta(\frac{1}{\Delta t})(\frac{1}{2\pi})$

### Interpreting the FUZZY Interface Diagram

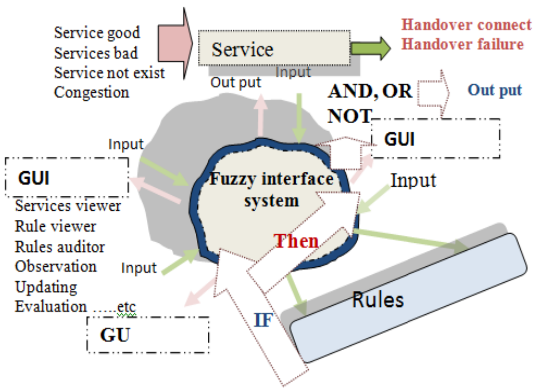



**Figure 2. Describe fuzzy interface system**

The general process of seamless connectivity diagram is organized by different flowchart algorithms service shown in the following figure 3, and Figure 4.

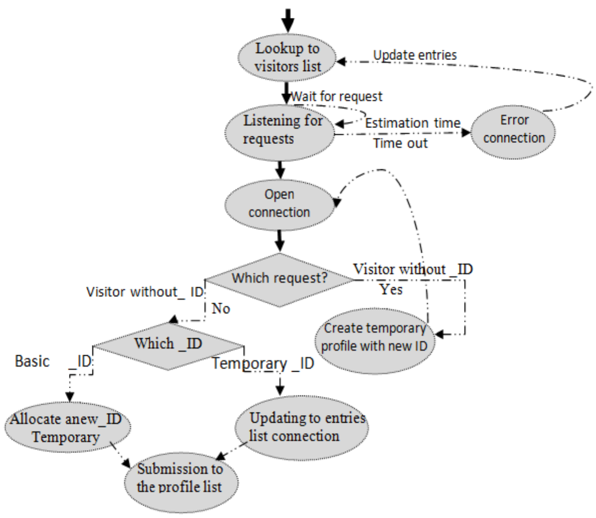



**Figure 3. Describe subscriber entries mechanism process**

### Handover Decision time

The following propose figure is extending intelligent logarithms provide a customer by different class in different level of priority as mention previously in figure 4-44. This combine algorithms working with fuzzy logic and genetic algorithms is support seamless connectivity, Otherwise the handover is a possibility is false and blocked to another period, referring to the proposed algorithms, the algorithms have deep learning for future environmental study used a heuristic optimization, a genetic code according to the population solution distributed randomly. The genetic algorithms start working based on based equation identified the regulation to select groups and individuals on a certain a scheme Figure 4. Is represent the operation process [24].

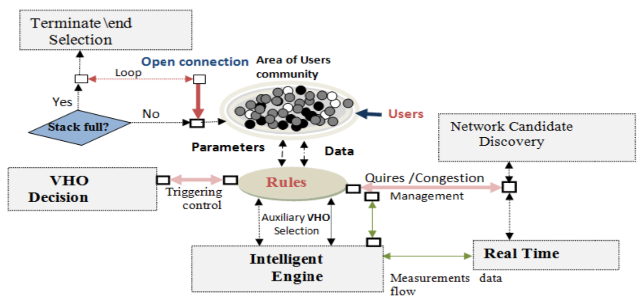



**Figure 4.Genetic algorithms- Handover Rules Decision**

### Algorithms for Stack:

Clear global stack // remove all users and parameters
clear restart operation
while not operations stack is empty DO BEGIN
Select priority queue
Pop;
Push operation queues
Find identified parameters
Repeat
While stack is full
Stop selection queue; waiting until estimation time
Go to step 6and 3
END WHILE

### Counter lookup:

Prefer to look up and accounting to the number of users needed for executing increment operation. The value look up is defined it from parameter lookup on the scope[25].

Public class Counter: users' identification {
Public lookup parameter <value> value parameter {
get {
return (lookup parameter) parameters ["value"];
Get {
return (look up parameter <value>) parameters ["increment"];
Public Counter () {
Parameters. Add (new lookup parameter<"value">));
Parameters. Add (new lookup parameter<"value"> (
" increment",
"Generate the selection value which is already adding"
New value (i++)));
}

### Triggering a handover in a fast moving:

Triggering handover in vehicle is a challenging task when MN is moving rapidly in a heterogeneous wireless network. In this situation there is number of solutions provided to reduce the delay time in the traffic level connection. We suppose that the hierarchical can be divided into three levels for vehicles speed (high speed, medium speed, low speed); we assume that all numbers of the vehicles related to the distance between each other. Our proposed work considers two kinds of communication speed for rural high ways speed and normal speed such as the speed in a city during work day. The major objective of our target here is to provide seamless connectivity with uninterrupted service communication between coverage sources. Most WLAN which provides small coverage led to failure disconnected as in remote areas or in other density of vehicles also scarce lead to packet loss. We can assume expected that WLAN, WIMAX based on IEEE 802.16 standers to have a range up to 50 km and satellite coverage can introduce up to 1000 km. Therefore, in addition to provide mobile users with good services and seamless connectivity, we have integrated develop heuristic hierarchically routing system sub connection working by integrated intelligent system with fuzzy logic equation. The system proposed which is composed of integrated with satellite, Cellular and WIMAX technologies fixed by GPS to support different data rate and cell size such as shown in the following figure. The main advantage idea also here the connectivity between vehicle to vehicle (V2V) communication is available based on 802.11p standard distance less than 100 m in Local area, and less than 10 km in cellular WIMAX coverage area. Assume that each vehicle equipped with GPS and smart card with Tow interface can be connected on one side interface working to support local network and cellular, another side support virtual connection also this side can reach to connect directly through satellite connection with standers

IEEE802.21. In addition, the long-term evaluation (LTE) is supporting highest speed up to 400 km/h is different than other technology service coverage.

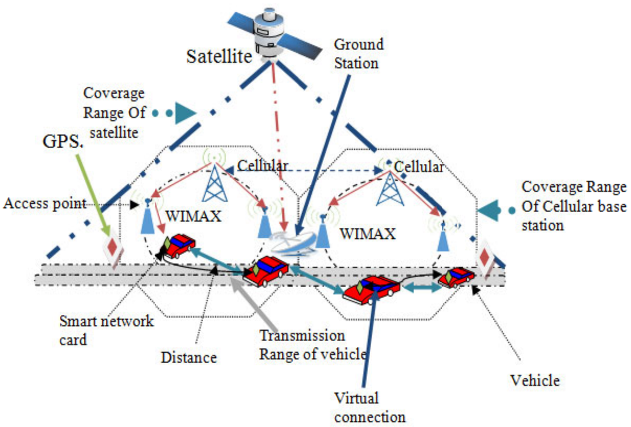



**Figure 5. Source connection with different cellular BS**

## Intelligent seamless model

$$\frac{dv_n, x_{i,j}(t)}{dt} a\left\{1-\frac{v_i(t+\Delta t)}{v_{\max\ speed}}-\frac{\delta}{\Delta x_{i,j}(t)}\right\}$$

$$\frac{dv_n, x_{i,j}(t+\Delta t)}{dt\,(t)} a\left\{\frac{v_i(t)}{v_{\min\ speed}}\right\}+1$$

$$\delta = \Delta x_{\max,\ \min} + \left\{v_n, x_{i,j}(t)T + \frac{v_i(t)\left[v_{i+1}(t), v_{i-1}(t) - v_i(t+\Delta t)^{\frac{1}{2}}\right]}{2\sqrt{\frac{d}{2\pi}}}\right\}$$

Where T is the time duration headway, $\delta$ is safety time in dynamical distance, $\pi$ is the capital area represented by circle. The following algorithm Figure 6, represents the core resource reservation and observation vehicle speed.

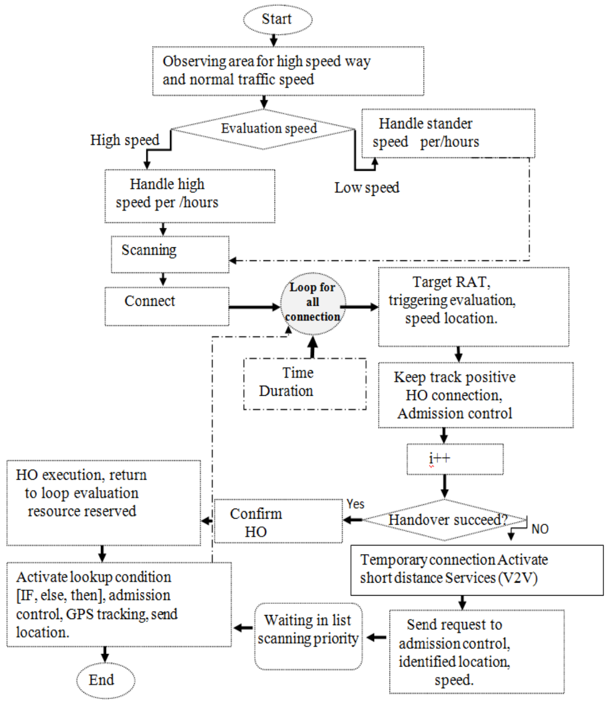



**Figure 6. Flowchart of resource reservation of vehicle Core algorithms speed**

### Fuzzy logic technique

In previous figure vehicles for different speed node that can obtaining the final result by fuzzy logic based a logarithm where multiple parameters evaluated by fuzzy base.

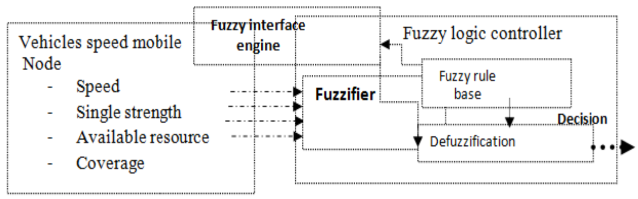



**Figure 7.Fuzzy logic technique**

### Fuzzy rule

Rule 1: IF vehicle speed ≥120 km/h
Rule 2: IF vehicle speed ≤120 km/h
Rule 3: IF the distance in cellular ≤10 km
Rule 4: IF the distance in local network ≤100 m
.
.
Rule n:

### Fuzzy interface system (rules overview)

IF (high speed vehicle in high-speed tracking) THEN (value service is “excellent”)
IF (medium and low speed vehicle in low-speed tracking) THEN (value service is “good”)
IF (distance is short) THEN (service is excellent, service is good)
IF (signals is weak) THEN (value service is “poor”)

End if;

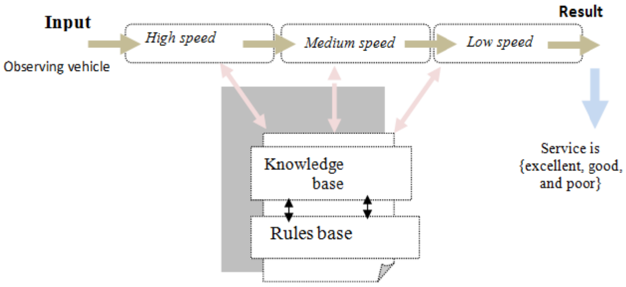
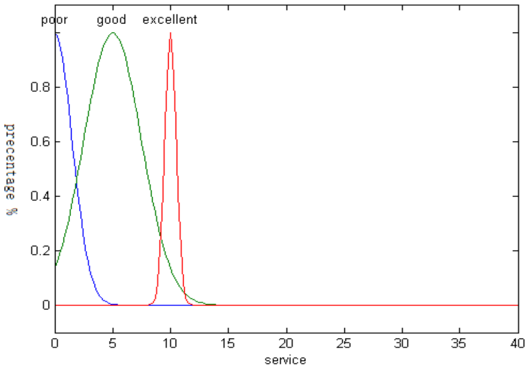
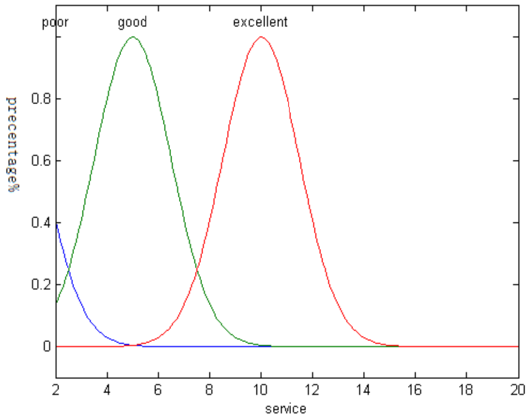



**Figure 8. The following diagram shown demonstrates the service in different vehicle speed with different parameters selection presented in the fuzzy system network. The figure contains knowledge base and rules base for mentoring input parameters. The following simulation results shown in Figure 9, present the fuzzy rules system input.**

## Simulation results and discussion

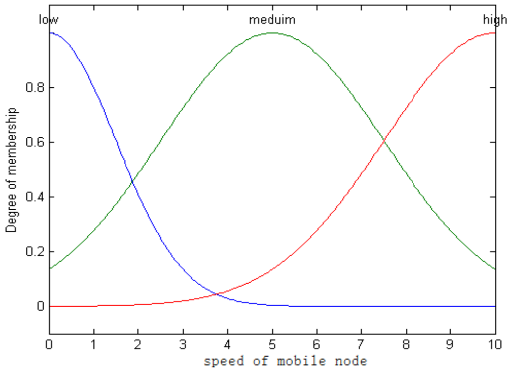



**(a)**

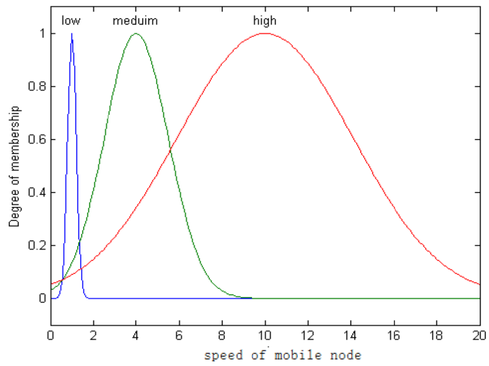



**(b)**

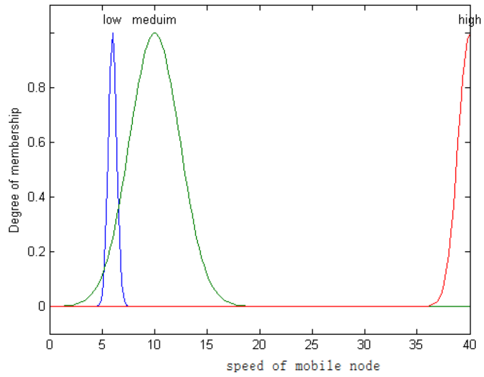
**Figure 9. Represent simulation result of network service, shown different vehicles mobile node speed (a) low, medium mobile node speed, (b) high mobile node speed, medium mobile node speed.**




(a)




**(c)**




**(c)**

**Figure 10. Provide the degree of member ship network service in different vehicles mobile node speed (a, b) low, medium speed and (c) high speed**

## Condition Statement

## The syntax expression IF, else and switch statement

If <expression 1>
% statement (×) will execute if the summation of variable of Boolean expression is true
<Statement (×)>
else
<expression 2>
% statement (×) will execute if the variable of parameters is false
Switch <switch_ expression>

Case
<case_ expression 1>, <case expression 2>
<Statements >
……….
Otherwise
<Statements>
End

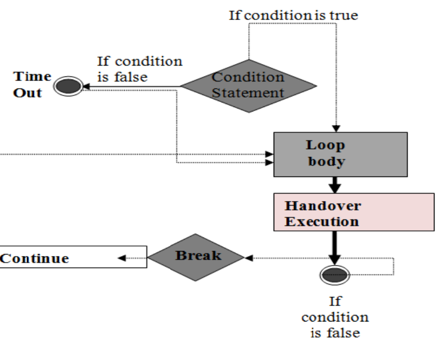



**Figure 11. Flow diagram of decision-making statement**

The figure 11; described Decision making structures required for logical optimization, on criteria of algorithms is more conditions be evaluated to be executed when the condition determined to be in the stage of condition state true or false[25].

**Table 1. IF, else and switch statement**

| Statement | Description |
|---|---|
| If …. statement | Refer to the Boolean expression followed by one or more statement working as in closed time when it's in schedule of condition time. |
| else statement | Any statement can be followed by else statement when the expression of execution time for Boolean expression in state of false. |
| Switch statement | On this stage all variables and parameters should be tasted for equality. |

### Time simulation

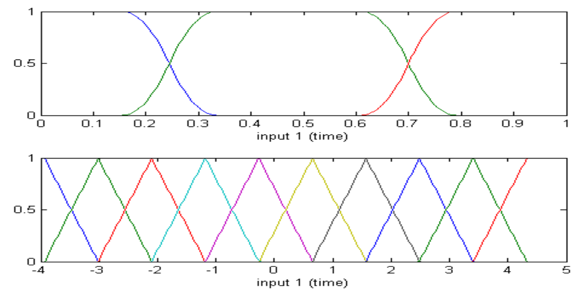
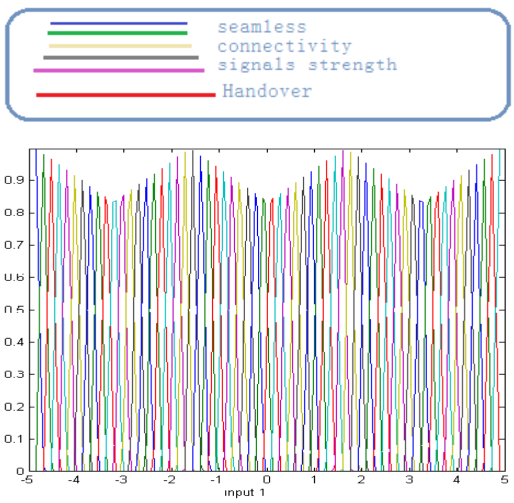
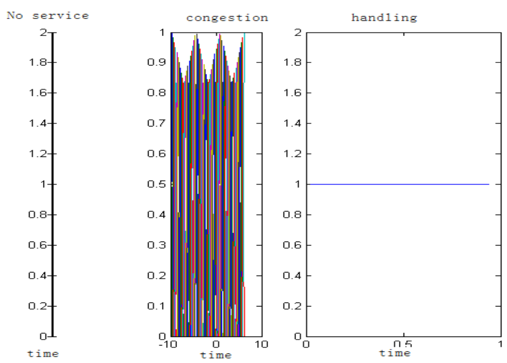



**Figure 12.Service monitoring (seamless, connectivity, signalsstrength, Handover**

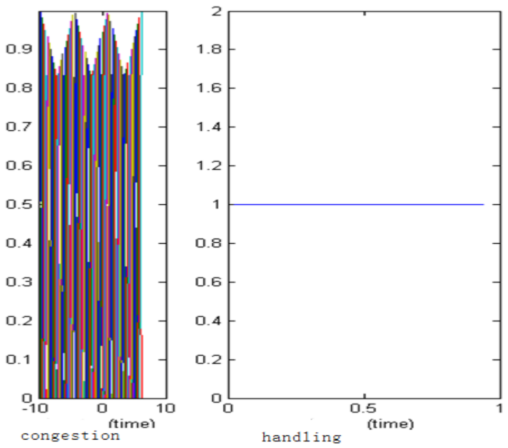



**(a)**




**(b)**

**Figure 13. (a) Service monitoring seamless, connectivity, signals strength, Handover. (b)The graph shown the service graph explaining the rules service is a poor then handover disconnected.**




**(c)**

**Figure 14.(c) graph present rule1, rule2 and rule3, handover disconnect, connect, handling**

## Conclusion

This systematic review has examined the development of the autonomous vehicle algorithm and related simulation frameworks by integrating findings studies in some critical areas, which include decision-making, trajectory planning, object detection, and traffic optimization. On the research surveys, covers optimum methods for how to find a solution in heterogeneous network connection, using some intelligent methods and different algorithms applied with genetic algorithms and fuzzy logic for enhancing a connection between cellular and WIMAX technologies fixed by GPS and wireless satellite networks technologies. The problem faced, its scalability is restricted by the hardware limitations of the Raspberry, and the precision of obstacle detection and navigation in practical situations needs further improvement. This systematic review has examined the development of the autonomous vehicle algorithm and related simulation frameworks by integrating findings from simulation studies in some critical areas, which include decision-making, trajectory planning, object detection, and traffic optimization defines autonomous vehicle (AV) communication types. Each row describes a communication type (e.g.,Vehicle-to-Vehicle, V2V), what it does, and an example usecase. In addition, various communication modalities pertinent to AV technology, from direct vehicle-to-vehicle communication for safety and traffic efficiency enhancement(V2V) to more extensive links with infrastructure networks(V2N), pedestrians and cloud systems (V2C). This gives a brief but detailed picture of the various communication paradigms in the AV scenario.

## Discussion

Discussing traffic optimization strategies in autonomous vehicle communications. Algorithms based on traffic prediction and object detection strategies for recent scientific studies in autonomous vehicles, shown the progress of the handover detection system connection, the simulation result shown the stage of different traffic optimization defines autonomous vehicle (AV) communication types. However, devices standers of the quality reflected the ability of the strength signals of connection to handle dynamic and uncertain environments makes it a preferable choice where real-time decision-making is required.

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