Behavior Evaluation of Vehicle Platoon via Different Fuzzy-X Tuned Controllers

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Abstract*—Over the past few decades, Intelligent Transportation System (ITS) has become a topic of considerable interest for transportation development. One of the significant applications of ITS is vehicle platooning, which is described as a string of fully or partly automated vehicles traveling together at closely controlled inter-vehicular distances while preserving a set speed without violating safety restrictions. Control studies of a platoon of vehicles moving in a single dimension has recently attracted extensive research interest. The platoon control challenge relies on the adaptation of the predefined vehicle's speed while keeping a safe gap between each two successive vehicles. This study investigates intelligent unidirectional decentralized control approach based on Fuzzy Logic Control (FLC). The performance of the controller is tuned using three different techniques through the hybridization of FLC with two approaches; Genetic Algorithm (GA) and Proportional-Integral-Derivative (PID) and the adaptation of FLC with Neural Networks (NN) forming Fuzzy-X tuned controllers to control the follower vehicles to achieve their objective. In order to accomplish the goal of the study, each vehicle is represented through a longitudinal vehicle dynamic model. A reference velocity trajectory is built for the vehicles to follow. Simulations are conducted to evaluate the performance of each controller in terms of spacing error convergence and desired velocity tracking. Results show that the desired tracking performance and gap control are achieved by all the controllers with certain limitations that are discussed through out the study.

***Index Terms*—Vehicle platoon; Fuzzy Logic Control (FLC); Tuning; Genetic Algorithm (GA); Proportional-Integral-Derivative (PID); Neural Network (NN).**

I. Introduction

Over the past few years, Intelligent Transportation System (ITS) has become a topic of considerable interest for transportation development in terms of safety and efficiency. ITS includes myriad of applications that serve as promising solutions for several critical issues of today's transportation such as enhance road capacity and safety, lower fuel consumption and other environmental impacts [1].

Besides, Cooperative-ITS (C-ITS) is considered to be the latest technology initiated by IT systems. It depends on information exchange and interaction between several vehicles, road infrastructure and pedestrians [2]. One of its significant applications is vehicle platooning, which is described as a string of fully or partly automated vehicles traveling together at closely controlled inter-vehicular distances while preserving a predefined speed without violating safety restrictions as shown in Fig. 1. This organization increases the road throughput, reduces the air drag resisting the motion of the vehicles, which in return reduces fuel consumption as well as CO_2 emissions [4].

Fig. 1: 1D platoon structure of a string of 4 trucks [3]

Moreover, for the successful implementation of a platoon in real world, some challenges were addressed by various previous studies. One of the major challenges is to control the platoon to follow a certain trajectory to reach its desired destination. One of the most important research directions in this field relies on the adaptation of the predefined vehicle's speed while maintaining a safe inter-vehicular spacing distance gaps. Previous researches proposed different controllers to solve this problem as in [5]–[7], however, these controllers have several drawbacks as the incapability of coping with complicated nonlinear models, the high level of mathematical computations and the need of a reasonably good model of the system to be able to control it successfully.

Thus, the focus of this study is to investigate intelligent unidirectional decentralized control approach based on Fuzzy Logic Control (FLC) on the platoon vehicles which is a robust non-specialized controller that deals only with input and output variables without requiring any prior knowledge of system dynamics. The relationship between input and output variables are expressed by a set of sentences (rules) that mimic human behavior, which makes FLC be an intelligent control approach with a convenient and faster response [8]. One of the main challenges of the FLC is designing and tuning its input and output functions as they mainly rely on field exports' knowledge without depending on any mathematical

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or analytical procedure.

Thus, in this paper three distinctly tuned FLC are applied on the platoon follower vehicles to control their speeds and relative spacing distances to their preceding vehicles. The performance of FLC is tuned through the hybridization of FLC with two approaches; Genetic Algorithm (GA) and Proportional-Integral-Derivative (PID) and the adaptation of FLC with Neural Networks (NN) forming Fuzzy-X tuned controllers to control the follower vehicles to achieve their control objectives.

In order to accomplish the goal of the study, each vehicle is represented through a longitudinal vehicle dynamic model. A reference velocity trajectory is built for the vehicles to follow. Moreover, the three tuned fuzzy-logic controllers are implemented, simulated and compared in terms of spacing error convergence and desired velocity tracking performance.

The remainder of this paper is organized as follows: Section II represents the vehicle longitudinal dynamics studied. Section III represents the platoon control architecture followed by this study. Sections IV and V introduce the FLC implemented on the leader and follower vehicles including the various tuning methods used. Section VI validates the techniques presented through simulations and results' discussions. Finally, section VII summarizes the work of the paper, as well as recommends future work of this study.

II. Longitudinal Vehicle Dynamics

In this study, a platoon of homogeneous vehicles is considered; all vehicles are uniform having identical dynamics and controlled with the same control approach. The platoon consists of a leader vehicle and N follower vehicles as shown in Fig. 2. The leader's position and velocity are symbolized as x_0 and v_0 respectively, while x_i and v_i resembles the position and velocity of the i^{th} follower vehicle studied.

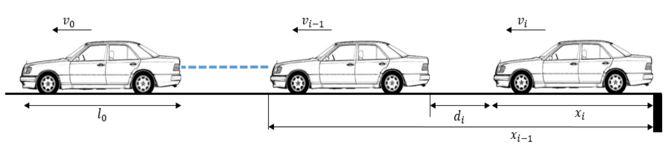


Fig. 2: Longitudinal platoon structure of a string of vehicles [1]

The main objective of the leader vehicle is to guide the whole platoon to a desired destination while preserving a predefined speed. Moreover, the intention of all other vehicles is to follow their preceding $(i-1)^{th}$ vehicle while preserving the same speed and controlling the relative spacing gap d_i between each two successive vehicles, to reach the desired gap d_{ref}. d_i is calculated at a certain time t as:

$$d_i = x_{i-1} - x_i - l_{i-1} \tag{1}$$

where l_{i-1} is the length of the preceding vehicle.

In order to model a platoon of vehicles, a single vehicle nonlinear dynamic model is demonstrated that serves as the basis for the control formulation exhibited for each platoon vehicle in the upcoming sections. The model depends on considering the longitudinal forces acting on a vehicle on an inclined road as shown in Fig. 3.

At a certain time t, the host i^{th} vehicle is exposed to a set of external forces which includes the traction force $F_{traction_i}$ provided by the engine to propel the vehicle forward, the braking force F_{brake_i} decelerating or stopping the vehicle, the resisting forces as aerodynamic drag force F_{drag_i} which is the streamlined impact of wind resistance acting on the vehicle and rolling force F_{roll_i}. In addition to the gravitational force $F_{gravity_i}$ which can be either assisting or resisting force depending on the road inclination shown as angle θ [1].

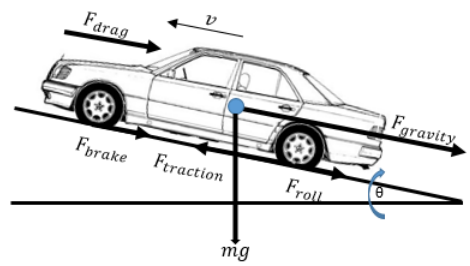


Fig. 3: Longitudinal forces acting on the i^{th} vehicle in the platoon [1]

The vehicle's longitudinal dynamics equation of motion is formulated based on Newton's second law of motion, depending on the longitudinal forces acting on the host vehicle shown in Fig. 3 [9], [10] as:

$$m\ddot{x}_i = F_{traction_i} - F_{brake_i} - F_{drag_i} - F_{roll_i} - F_{gravity_i} \tag{2}$$

Each force is calculated based on the following equations:

$$F_{drag_i} = \frac{1}{2} C_{drag} \rho A_f (\dot{x}_i + v_{wind})^2 \tag{3a}$$

$$F_{roll_i} = C_{roll} mgcos(\theta) \tag{3b}$$

$$F_{gravity_i} = mgsin(\theta) \tag{3c}$$

where C_{drag} and C_{roll} are the coefficients of aerodynamic drag and rolling resistances, respectively. The air density is given by ρ, A_f is the frontal area of the vehicle, $\dot{x}_i$ is the velocity of the i^{th} vehicle, v_{wind} is the wind speed and g is the acceleration due to gravity. The longitudinal traction force of the host vehicle $F_{traction_i}$ resembles the force that acts between the vehicle tyres and the road. The model provided is simple having the motor torque T_m as the input of the system affected by the effective radius of the tyres R, the gear ratio G and the motor efficiency η. Thus, an equation is used to calculate to $F_{traction_i}$ from the given input torque [11] as:

$$F_{traction_i} = \frac{T_m \times G \times \eta}{R} \tag{4}$$

After presenting the adopted vehicle model, the overall control architecture of the system is presented.

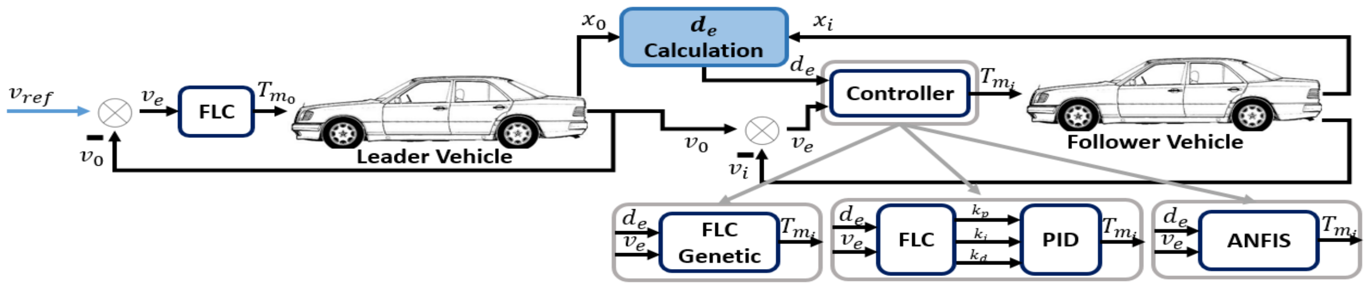


Fig. 4: Schematic representing closed control loop of platoon vehicles

III. Platoon Control Architecture

In this paper, the platoon control system architecture is based on decentralized unidirectional control approach. This approach enables each platoon vehicle to be controlled through its own separate controller, by monitoring only the behaviour of its preceding vehicle and take actions accordingly.

In this study, the Fuzzy Logic Control (FLC) is examined on the platoon vehicle. FLC is considered to be an intelligent control approach that mainly apply knowledge to manipulate the environment and learning from experience without depending on the system model equations. It aims to emulate the human driver behaviours, their experience and mimicking their actions through relating the inputs and outputs of the system by a set of expressions (rules).

A pure FLC is used to control the speed of the leader vehicle to follow a desired speed trajectory. Moreover, three distinctly tuned FLCs are applied to the follower vehicles. Each of which has as input the relative distance error d_e which is calculated based on the host vehicle and its predecessor position information, as well as the speed error v_e between the host vehicle and its predecessor. The controller is used to manage the followers inter-vehicular distance and the speed of each vehicle to preserve the same speed as that of the leader. The tuning is obtained through the adaptation of FLC with Neural Networks (NN) and hybridization of FLC with two approaches; Genetic Algorithm (GA) and Proportional-Integral-Derivative (PID) forming Fuzzy-X tuned controllers to control the follower vehicles to achieve their objective. A schematic representing the mentioned platoon control architecture of the leader and follower vehicles is shown in Fig. 4.

In the upcoming sections, the leader and follower vehicles controllers are further illustrated.

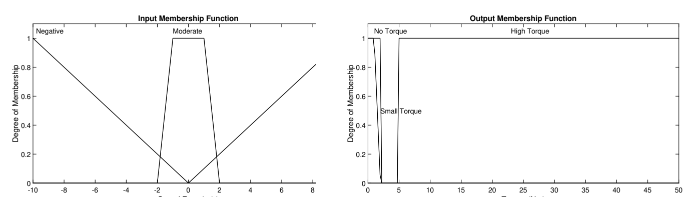
IV. Leader Vehicle Control

The leader vehicle is required to track a reference speed trajectory, therefore its controller acquires the error between the desired speed v_{ref} and the actual speed of the vehicle v_0 and outputs the desirable torque needed to navigate the vehicle with the desired speed. In this study, a unified pure FLC controller is used to control the leader vehicle. This FLC takes as an input the velocity error and converts this crisp (numerical) value into a linguistic variable through the fuzzification process of FLC based on an input membership function shown in Fig. 5a.

This membership function is represented by three sets; two triangular sets; the Negative set [-10,0] m/s indicating that v_0 is greater than v_{ref} and the Positive set [0,10] m/s indicating the v_0 is lower than v_{ref} and finally a trapezoidal Moderate set [-2,2] m/s indicating the moderate region of the velocity error including zero error (desired speed). Each set is activated by a certain percentage that activates a set of rules in order to obtain the required torque to be applied to the system. The fuzzy inference rules used for this problem are:

- **IF** $v_e = Positive$, **THEN** $T_{m_0} = High \quad Torque$
- **IF** $v_e = Moderate$, **THEN** $T_{m_0} = Small \quad Torque$
- **IF** $v_e = High$, **THEN** $T_{m_0} = No \quad Torque$

From the activated rules, the output torque is obtained through the de-fuzzification process to get the torque's numerical value using the output membership function presented in Fig. 5b which has three trapezoidal sets; the No Torque set [0,2] Nm, the Small Torque set [0,2] Nm and the High Torque set [5,50] Nm. The sets of input and output membership functions are obtained by trial and error taking into consideration the system specifications.



(a) Input membership function (b) Output membership function

Fig. 5: Membership functions of the leader vehicle

V. Follower Vehicles Control

The adaptation and hybridization of FLC with other approaches is considered in this study to enhance the control of the platoon follower vehicles through the re-shaping of the membership functions based on tuning algorithms or hybridization of other control algorithms with the FLC to get a desirable system response [12].

In this section, the approaches used to designate the Fuzzy-X controllers are discussed. The proposed techniques used for this study are Fuzzy-Genetic by which the fuzzy sets and rules are optimized based on Genetic Algorithm (GA), Fuzzy-PID by which the fuzzy sets are used to obtain the desired PID gains for PID controller to act as the lower level controller of the system and Fuzzy-Neural by which the sets and rules are determined based on Adaptive Neural Networks (ANN).

A. Fuzzy-Genetic Control

Genetic Algorithm (GA) is adopted for optimal tuning of the platoon fuzzy logic longitudinal controller. GA is a stochastic optimization method that is based on the genetics evolutionary concepts. GA technique is designated to simulate the genetic process required for natural populations evolution based on the survival of the fittest principle [13].

In order to solve the optimization problem using GA, each candidate solution is represented as an individual. This individual is also named as a chromosome which contains the decision variables that are considered as genes [14]. A fitness function is designated to represent the fitness of each candidate solution and evaluate its chance to survive and reproduce.

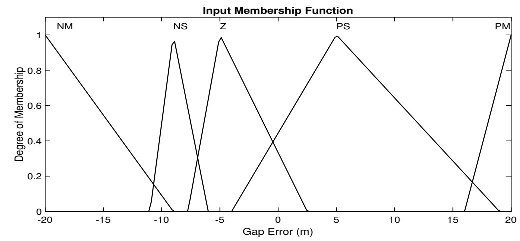
The algorithm starts by initializing a population of randomly generated chromosomes. The algorithm evolve these chromosomes throughout a number of iterations called generations. Throughout each generation, three main stages are performed; crossover which is responsible to create new generations by selecting parent chromosomes to be crossed with each other for offspring production, mutation which alter some of the chromosome's genes to have better chance of survival in the next generations and elite member selection which the method of selecting the best chromosome in the population depending on the fitness function value to continue as a chromosome in the next generation. The combination of the previously discussed operators is the procedure followed by the GA to accomplish optimization. In this study, GA is used to optimize the FLC input and output membership functions.

The GA algorithm used consists of 50 generations of 100 chromosomes each; every chromosome represents FLC input and output sets encoded using "Value Encoding" by which each set is represented as a string of double values. Every value corresponds to a vertex of the set. The selection process used is the Elitism process having 10 elite members. The crossover percentage is 80% and the mutation percentage is 20%. These values are obtained by trial and error with a multitude of tests with different fitness functions to obtain the most suitable results. The most suitable fitness function used which decides the best cost solution in the population is proposed to be:

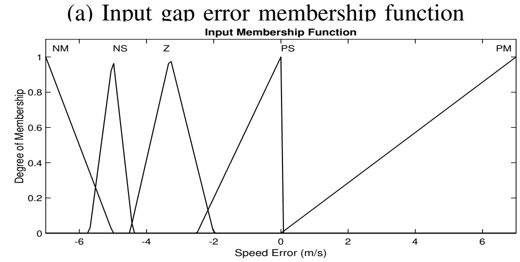
$$F = \frac{1}{4}\left(\frac{1}{\sum_{t=1}^{T} E^2(t)} + \frac{1}{\sum_{t=1}^{T} \dot{E}^2(t)} + \frac{1}{MAE} + \frac{1}{RMSE}\right) \quad (5)$$

where T is the simulation time of each individual, E is the spacing distance gap error, $\dot{E}$ is the speed error, MAE and $RMSE$ represent the maximum absolute error and the root mean square error of the spacing gap, respectively.

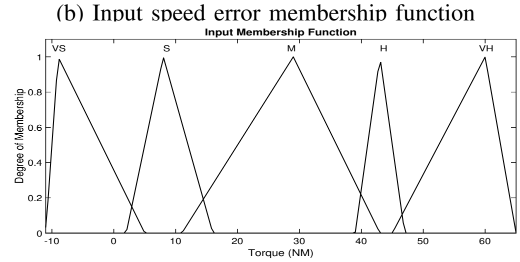
The tuned input and output membership functions of the FLC using GA are presented in Fig. 6. The input sets are classified as Negative Medium NM, Negative Small NS, Zero Z, Positive Small PS and Positive Medium PM sets. The output sets are classified as Very Small VS, Small S, Moderate M, High H and Very High H. The rules used to specify the output of the FLC are given by I.



(a) Input gap error membership function



(b) Input speed error membership function



(c) Output torque membership function

Fig. 6: Membership functions of Fuzzy-GA controller

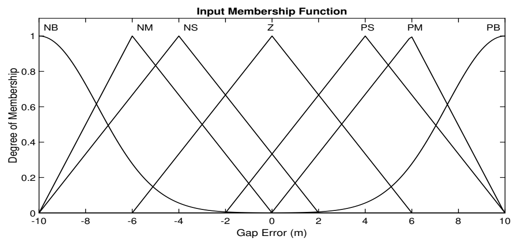
TABLE I: Fuzzy-GA rules matrix

$d_e \mid v_e$	NM	NS	Z	PS	PM
NM	VS	S	M	H	VH
NS	VS	VS	S	M	H
Z	VS	VS	VS	S	M
PS	VS	VS	VS	VS	S
PM	VS	VS	VS	VS	VS

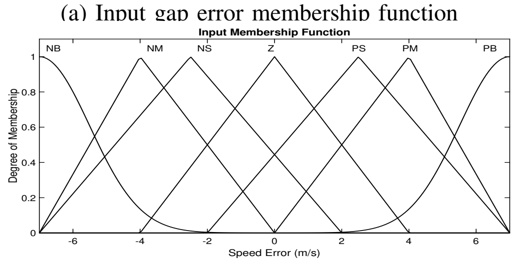
B. Fuzzy-PID Control

The suggested controller in this section is the Fuzzy-PID control algorithm, in which the control signal is generated from the conventional PID controller. However, the knowledge base and fuzzy inference mechanism are used to tune the proportional, integral and derivative gains k_p, k_i and k_d respectively, through fuzzy inference engines on an online manner. Given the spacing distance error and the speed error as the inputs to the controller and produce three outputs which are the corresponding PID gains. The input membership functions used are shown in Fig. 7 where the sets are classified as Gaussian and triangular sets named as Negative Big NB, Negative Medium NM, Negative Small NS, Positive Big PB, Positive Medium PM, Positive Small PS and Zero set Z. The output membership functions have the same sets shape and notation, however with different ranges. As for the first follower, the ranges are $k_p = [-35, -20]$, $k_i = [-1.6, 0]$

and $k_d = [-40, -20]$, while the second follower ranges are $k_p = [-20, -10]$, $k_i = [-0.5, -0.25]$ and $k_d = [-40, -20]$. The fuzzy sets and rules are developed based on theoretical analysis and expert experience by the help of previous research [15]. Each parameter of PID has its own control rule that is shown in Table II.



(a) Input gap error membership function



(b) Input speed error membership function

Fig. 7: Input membership functions of Fuzzy-PID controller

C. Fuzzy-Neural Network Control

Adaptive Neuro-Fuzzy inference system (ANFIS) is a type of artificial neural network (ANN) that is based on Takagi-Sugeno fuzzy inference system [16]. It captures the benefits of both neural networks and fuzzy logic principles in a single framework. ANFIS architecture is composed of five layers as shown in Fig. 8. The 1^{st} layer is the input layer that passes the external crisp input signal to the 2^{nd} layer (inputmf) which is the fuzzification layer, where crisp inputs are converted to their corresponding membership values. Then comes the rule-base layer; the 3^{rd} layer where each element corresponds to a single Sugeno-type fuzzy rule.

Each rule receives inputs from the respective fuzzification elements and calculates the normalized firing strength of the rule it represents. The 4^{th} layer (outputmf) is the de-fuzzification layer that converts the normalized output membership values back to a crisp values which are then summed together through the 5^{th} summation layer to produce the overall ANFIS output of the system.

A training process took place by providing inputs and output data in a specific time range to the NN; the inputs are the spacing distance and speed errors and output is the corresponding torque required. After performing the training process, the NN structure and the membership functions are created; the input sets are presented through Figs. 9a and 9b; the sets have same notation as mentioned in previous controllers, however with different shapes and ranges. The corresponding output values for the given input sets is presented through the surface shown in Fig. 9c.

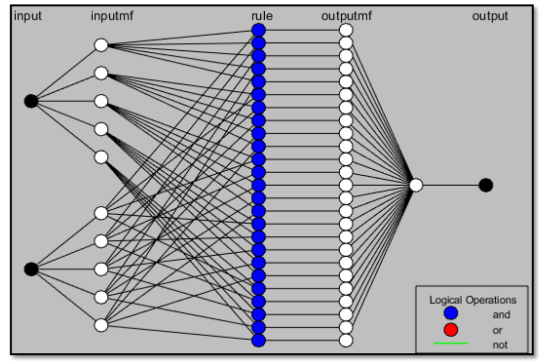
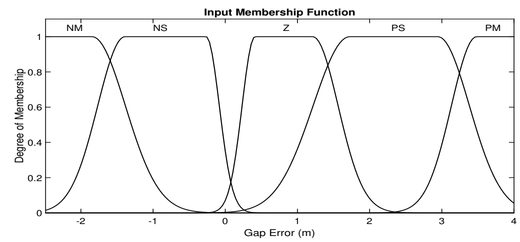
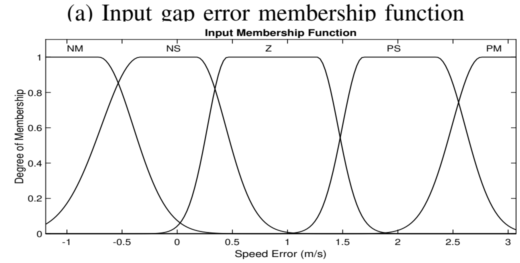


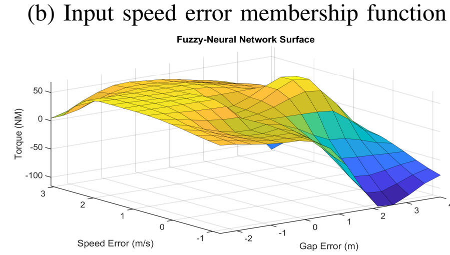
Fig. 8: Layered ANFIS architecture



(a) Input gap error membership function



(b) Input speed error membership function



(c) Output surface

Fig. 9: Input membership functions and output surface of Fuzzy-NN controller

VI. Simulation Results

In order to validate the performance of the presented control algorithms, numerical simulations are carried out for a homogeneous platoon of one leader and two follower vehicles. The prime intention of the leader vehicle is to build a trajectory to assist the platoon to a certain destination, while maintaining a predefined speed. Furthermore, the aim of other vehicles is to follow the leader with the same speed while preserving a specific spacing distance to their preceding vehicle.

In this section the testing environment including the simulation platform used and vehicles' inherited parameters are

TABLE II: Fuzzy-PID rules matrix

d_e / v_e	NB	NM	NS	Z	PS	PM	PB
NB	$PB \mid NB \mid PS$	$PB \mid NB \mid NS$	$PM \mid NM \mid NB$	$PM \mid NM \mid NB$	$PS \mid NM \mid NB$	$Z \mid Z \mid NM$	$Z \mid Z \mid PS$
NM	$PB \mid NB \mid PS$	$PB \mid NB \mid NS$	$PM \mid NM \mid NB$	$PS \mid NS \mid NM$	$PS \mid NS \mid NM$	$Z \mid Z \mid NS$	$NB \mid Z \mid Z$
NS	$PM \mid NM \mid Z$	$PM \mid NM \mid NS$	$PM \mid NS \mid NM$	$PS \mid NS \mid NM$	$Z \mid Z \mid NS$	$NB \mid PS \mid NS$	$NB \mid PS \mid Z$
Z	$PM \mid NM \mid Z$	$PM \mid NM \mid NS$	$PS \mid NS \mid NS$	$Z \mid Z \mid NS$	$NB \mid PS \mid NS$	$NM \mid PM \mid NS$	$NM \mid PM \mid Z$
PS	$PS \mid NM \mid Z$	$PS \mid NS \mid Z$	$Z \mid Z \mid Z$	$NB \mid PS \mid Z$	$NB \mid PS \mid Z$	$NM \mid PB \mid Z$	$NM \mid PM \mid Z$
PM	$PS \mid Z \mid PB$	$Z \mid Z \mid PS$	$NB \mid PS \mid PS$	$NM \mid PS \mid PS$	$NM \mid PM \mid PS$	$NM \mid PB \mid PS$	$NS \mid PB \mid PB$
PB	$Z \mid Z \mid PB$	$Z \mid Z \mid PM$	$NM \mid PS \mid PM$	$NM \mid PM \mid PM$	$NM \mid PM \mid PS$	$NS \mid PB \mid PS$	$NS \mid PB \mid PB$

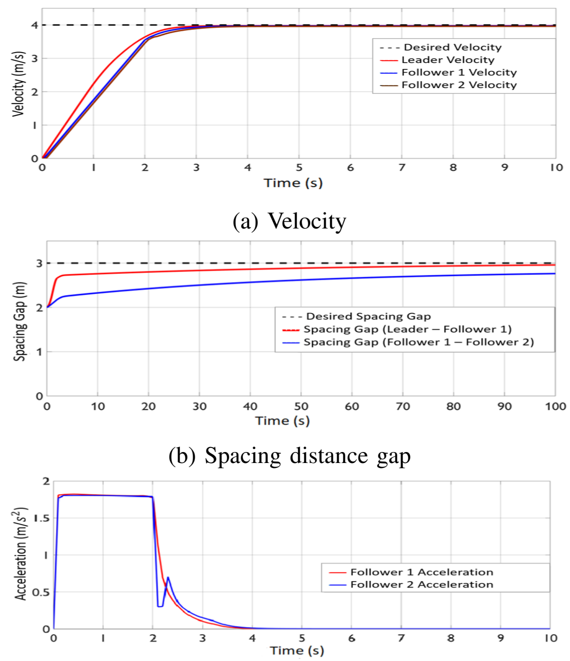
presented. Moreover, the controllers presented are compared in terms of desirable performance and control effort revealing the comfort of passengers.

A. Testing Environment

MATLAB/Simulink 2019b provided as the simulation platform for testing the dynamic platoon model and controllers. Simulink blocks and MATLAB functions are used to implement dynamic equations and control algorithms of each vehicle. The vehicle parameters used for simulation are shown in Table III. All model parameter are inherited from the villager 4 golf car for simulations.

TABLE III: Villager 4 vehicle parameters

Parameter	Numerical Value
Maximum torque (T_{max})	46.7 (Nm)
Mass (M)	544.5 (kg)
Frontal area (A_f)	2.088 (m^2)
Tyre radius (R)	0.2286 (m)
Air density (ρ)	1.225 (kg/m^3)
Aerodynamic drag coefficient (C_{drag})	1.05
Rolling coefficient (C_{roll})	0.015
Motor efficiency (η)	0.8
Gear ratio (G)	12.32



(a) Velocity

(b) Spacing distance gap

(c) Acceleration

Fig. 10: Fuzzy-GA results

B. Results and Discussion

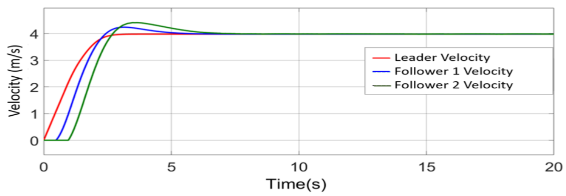
The desired spacing distance gap is set as $d_{ref} = 3m$ and the desired velocity is set to a constant value of $v_{ref} = 4m/s$ for simulations. The three Fuzzy-X tuned are simulated and compared through the upcoming paragraph.

For the Fuzzy-GA, all the vehicles reaches the desired speed within $4s$ with almost no steady state error and zero overshoot, which indicates the adaptability of Fuzzy-GA in controlling the platoon speed as shown in Fig. 10a with appropriate acceleration profile shown in Fig. 10c.

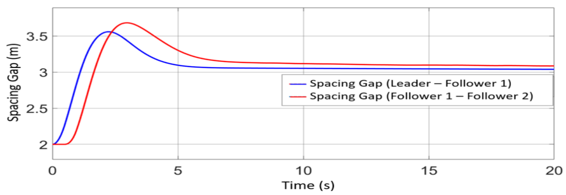
However, the Fuzzy-GA yields disappointing responses after controlling the gaps between the vehicles. The gap between the vehicles is maintained after very large settling time (more than $100s$) as shown in Fig. 10b. However, the maintained gaps have large steady state error which deprives the platoon of its desired advantage.

In regards of the Fuzzy-PID, the desired velocity is reached in about $6s$, however with a slight overshoot in the response as shown in Fig. 11a. Fig. 11b shows that the system undergoes an overshoot of about $0.5m$ till reaching the desired spacing gap, along with an increased overshoot in case of introducing additional vehicle to the platoon as seen in the second follower vehicle response. Accordingly, the acceleration of the first follower is stable. However, the second follower vehicle undergoes a series of oscillations at a small range of acceleration due to propagated error on the second follower as shown in Fig. 11c. This shows that Fuzzy-PID does not support platoon stability if more vehicles are introduced to the platoon, providing the desired control objective for a limited number of platoon vehicles.

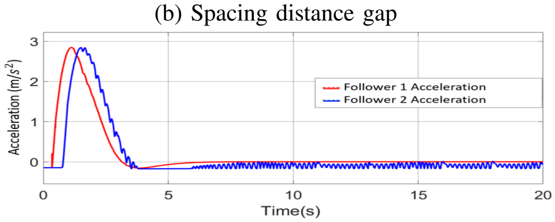
Finally for the Fuzzy-NN, the desired velocity is reached in about $5s$ with no overshoot in the response for both followers as presented through Fig. 12a. The corresponding acceleration response does not indicate any error propagation as both the follower vehicles' responses are identical and have no oscillations as shown in Fig. 12b. The corresponding gap control response between the vehicles in the platoon is presented through Fig. 12b. It is indicated that the follower vehicles have the same gap control response. This shows that the system is stable and the error induced between the vehicles is negligible. The overall controllers spacing distance gap comparison is represented through Table IV.



(a) Velocity

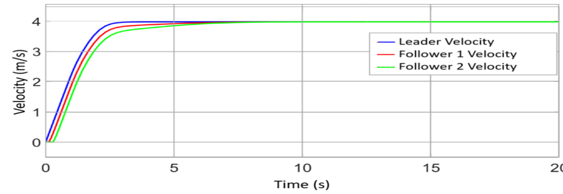


(b) Spacing distance gap

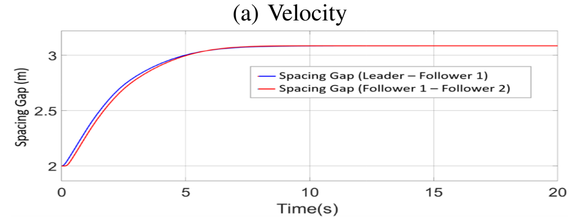


(c) Acceleration

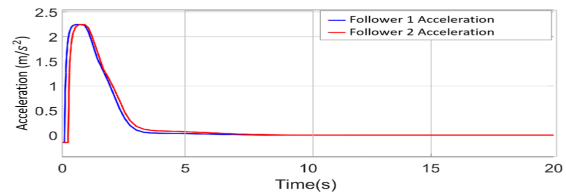
Fig. 11: Fuzzy-PID results



(a) Velocity



(b) Spacing distance gap



(c) Acceleration

Fig. 12: Fuzzy-NN results

TABLE IV: Spacing gap comparison

Controller	Settling Time	Steady State Error	Overshoot
Fuzzy-GA	$> 50s$	$\approx 0.5m$	$\approx 0m$
Fuzzy-PID	$\approx 5s$	$\approx 0.1m$	$\approx 0.5m$
Fuzzy-NN	$\approx 10s$	$\approx 0m$	$\approx 0m$

VII. Conclusion and Future Recommendations

The use of various control algorithms to control the distance gap between platoon vehicles is presented. A detailed nonlinear longitudinal vehicle dynamic model is introduced. Three optimized fuzzy logic controllers are implemented on each follower vehicle in the platoon, i.e. Fuzzy-GA, Fuzzy-PID and Fuzzy-NN. Analyzing the provided results, it is concluded that the Fuzzy-NN controller outperformed the other introduced controllers in terms of spacing distance gap convergence. It maintained a relevant and stable response on both of follower vehicles. On the other hand, Fuzzy-PID managed to control the system properly, but it revealed a propagation of gap control error when more than one follower vehicle is introduced to the platoon. In conclusion, Fuzzy-GA provided a stable response, however, it managed to reach the desired gap in more than $100s$ which indicates a slow control response.

For future endeavors it is recommended to test the provided intelligent controllers on a simulation platform, as well as implement them on a hardware application to visualize the control response in a better manner. It is also advised to implement other controllers and compare their results to the optimized fuzzy controllers. In addition to widening the dynamics of the vehicles by including the lateral dynamics to analyze the controller response on a more complex and generalized vehicle model. Moreover, it is urged to study the controllers' behavior on an unlimited platoon vehicles.

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