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Artificial Intelligence based semi-autonomous control system for military vehicle

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Abstract

All over the world traffic accidents are a major concern for society. According to studies carried by the World Health Organization, approximately 1.24 million people died in car accidents only in 2010. The decade 2011-2020 was declared the "Decade of Action for Road Safety" by the UN, which evidences this preoccupation.

Accidents involving vehicles are mostly caused by drivers who have poorly controlled their vehicles. When it comes to military vehicles, the risks are amplified due to the threats they are exposed to (improvised explosives, anti-tank weapons, etc.), and also the unstructured environment in which they are employed. It is therefore clear that new technologies can be used in order to reduce these risks, with the development of vehicular applications for that.

In this paper we propose a semi-autonomous control system capable of providing assistance to the driver by correcting or canceling risky performance in a military vehicle. In this system, the driver's behavior, the presence of external threats and the vehicle's tendency to evolve to instability are treated as inputs and processed through Artificial Intelligence techniques (Artificial Neural Networks and Fuzzy Logic), resulting in the weighting of control inputs from the driver and from an automatic controller, trying to keep the vehicle under safe operating conditions.

Introduction

Increasing safety on roads is a goal that has been pursued by various governmental or non-governmental agencies on the leading nations of the world. In [1], a detailed study on safety on roads was developed by the World Health Organization (WHO), at the request of many governments around the world. That report has served as a tool for assessing progress in this area and for the development of public policies aiming to reduce traffic risks.

Many factors can increase the probability of a car accident occurrence. However it is a common sense that, in general, the drivers of the vehicles are primarily responsible for the accidents, whether by imprudence, incompetence or incapacity for direction.

Accident risks can become even greater when military vehicles are taken into account. This is because, in addition to the risks inherent to the direction and behavior of drivers, during a military operation the vehicles are exposed to enemy threats (e.g. Improvised Explosive Devices - IED, LASER sight anti-tank weapons, etc.). For that reason, in order to mitigate these risks and to maximize the safety in military vehicles, innovative technological solutions with the use of inertial and external threats sensors are necessary. These solutions can be based on the strategy of providing assistance to the driver, correcting or canceling any unsatisfactory performance by implementing systems that can enable the capability of shared control (or semi-autonomous control) of the vehicle in question.

While it has been considered that the unmanned military ground vehicles will be the main weapon of the armies in the XXI century (as stated in [2]), it is likely that this evolution may take place gradually, so that the military vehicles shall incorporate technological innovations of driver assistance slowly, as it have been happening with the passenger and commercial cars. Recent studies have shown a tendency to solutions of this type ([3], [4], [5], [6] and [7]), and will be analyzed in more detail on the next sections.

The objective of this work is to propose a Semi-autonomous Control System for use in military vehicles, implemented through the use of Artificial Intelligence techniques. Among these techniques, we can highlight the inference systems based on Fuzzy Logic and the design of control systems with the utilization of Neural Networks. This Semi-autonomous Control System shall be used in a dynamic model of a 6x6 armored vehicle, and shall take into account the following input parameters: (i) the driver's behavior; (ii) the presence of external threats; and (iii) the tendency of the vehicle to evolve to instability.

This work has its text organized as follows: the second section contains some details about the Semi-autonomous control of vehicles with a little description of the related work and the Artificial Intelligence approach for the problem. The mathematical models used on the development are presented on the following section. We present some simulation results on the fourth section, which is followed by a little section for comments and conclusions. The descriptions of the Fuzzy Inference Systems used in this work are presented on the Appendix.

Semi-autonomous (or shared) control of vehicles

The design of a "middle-term" control system that stands between the extremes of manual control and full automatic control has been extensively explored as a research topic, specially on the development of some theories like supervisory control or telerobotics

[8]. However, recent research efforts indicate the growth of importance of shared control systems, in which the main characteristic is the blending and application of control inputs from a human and a controller on a specific process or plant.

Related work

Several Active Safety Systems or Advanced Driver Assistance Systems (ADAS) for increasing the safety in vehicles have been developed and studied by researchers, encouraged by industry and the scientific community. As stated by Nilsson in [9] and reinforced by Chen et al. in [10], the systems can be divided into three categories, organized on the Table 1.

Table 1. ADAS Categories and main characteristics.

Information/Warning Systems	Systems that provide information through different modalities and by different emergency levels, warning the driver of potential hazards.
Active assistance/semi-automation Systems	Systems designed to assist drivers in their driving tasks (acceleration, braking, steering, etc.).
Full/high automation Systems	Systems designed to take over the control of the vehicles and act automatically during driving.

The system proposed in this work can be classified as an **Active assistance/semi-automation system**. In general, these systems can also be divided into two types: (i) **Reactive Systems**, when the states of the dynamic system (in this case, the vehicle) are approximating to some critical stability boundary, which may lead to dangerous operation or accidents; and (ii) **Predictive Systems**, which also consider the forecast evolution of the states of the dynamic system, and estimates undesired disturbances from the environment.
Among the examples of existing solutions, in [11] Anderson et al. presented a method for the control of vehicles that included the evaluation of collision threats and planning trajectories. The result was the generation of an optimal path (from the vehicle stability point of view) on the safer region of the terrain.
This method was based on the development of a framework for active safety (presented in [3]), which allowed the identification of obstacles (so they could be avoided) and vehicle stability control. For both studies, they used optimal control techniques for the system design, and an intervention law was generated from the minimization of threats identified by a Model Predictive Controller (MPC). This work also generated subsidies to [12] and [13].

Another employment of a shared control system was proposed by Yu et al. in [14], where the problem of helping the elderly on their mobility tasks was adressed. In their work, the level of control authority between the human user and a controller was adjusted in proportion to the user's performance. Their approach, however, was essentially reactive, which makes it inappropriate for high speed applications such as automotive or robotics.

In a more recent work ([4]), Storms and Tilbury demonstrated the effectiveness of using similar techniques for teleoperated mobile robots control at high speed. That paper justifies itself by the fact that, in many applications, human operators are essential in the control loop ("human in the loop"), due to their knowledge as specialists.

The strategy used to define how that authority allocation is carried out varies, but is generally related to finding ways to minimize an "undesired" objective function, such as: collision threat level; deviation between the inputs provided by the driver and those provided by the controller; or some abstract function that considers both.
From the assessment of some of these metrics and an optimization method, a parameter $K \in [0,1]$, representing the best level of controller or human intervetion is generated. This parameter is then used for the weighting of the inputs to be applied to the dynamic system, resulting on a total input given by

$$u = K\, u_c + (1 - K)u_h, \qquad (1)$$

where u_c is the input desired by the controller and u_h is the input desired by the human driver.

In this work, we propose that the real-time choice of this value K is made by an Artificial Intelligence (AI) based system, such as a Fuzzy Inference System drawn up in order to take into account some relevant inputs for the safe and confortable driving, but also other important inputs for the military operations context.

AI approach

As stated above, our approach for achieving the blending of the control inputs from the controller and the human driver shall be obtained by the deployment of AI techniques for processing some considerable attributes, such as: the external threats which the vehicles are exposed to; the drivers behavior; and the tendency of the vehicle to become instable. To quantify these attributes, we must consider:

1. The magnitude of the difference between the inputs provided by the driver and the controller;
2. The calculation of the Stability Moments (SM), and then the generation of a representative measurement of the tendency to rollover of the vehicle as well (The Stability Moment was defined in [15], and will be briefly discussed on next sections and subsections), also considering the employment of ideal inertial sensors on the vehicle, as accelerometers and gyroscopes; and,
3. The presence of ideal military sensors in the vehicle. These sensors must be able to identify whether the vehicle is being illuminated by a LASER sighting device and also the existence of IED on the ground in which it is used.

A general, high-level architecture is proposed in the next topic, where it is described.

Proposed architecture

Figure 1 shows a closed control loop where a controller can be identified. This controller (and its design), considered the main element in the loop, essentially represents our goal within the development of this work. To achieve this, we propose the controller architecture illustrated on Figure 2, formed by two main sub-elements (the Fuzzy Ponderer and the Sub-controller).

One can observe that the inputs for this controller are strictly related to the attributes enumerated above, in a sense that they must be quantified with measurements of the driver's inputs, of the stability parameter and of an external threats parameter.

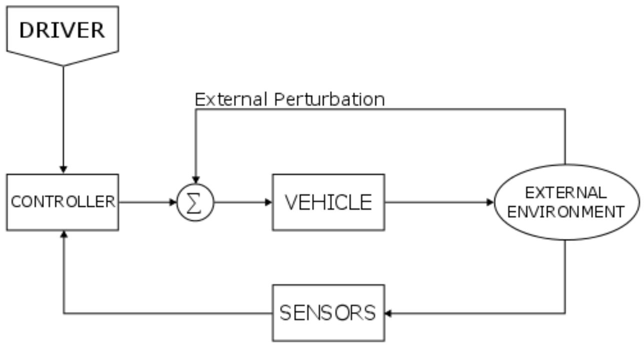

Figure 1. Semi-autonomous (or shared) control loop proposed, where the controller (on the left) is the main element.

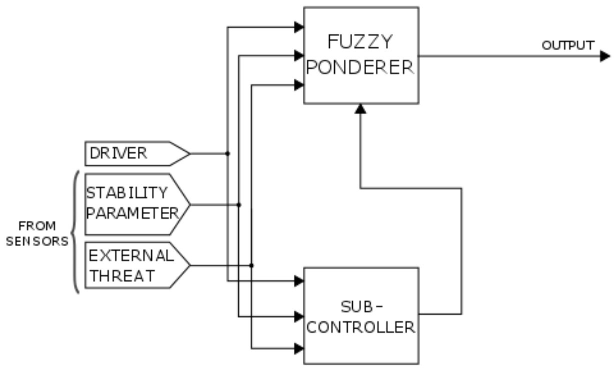

Figure 2. Architecture of the controller, with the two sub-element (Fuzzy Ponderer and Sub-Controller).

Mathematical Modeling

For achieving the development of the proposed semi-autonomous controller, one can divide the problem in minor parts, as the calculation of the necessary input parameters for the Fuzzy Ponderer (mainly the stability parameter); the implementation of the Fuzzy Ponderer itself; and a mathematical model of the vehicle (in this case, the dynamic system to be studied) that could be used for the Sub-Controller design.

Stability Parameter

As mentioned before, in order to quantify the tendency of the vehicle to evolve into a rollover condition and generate a metric for stability, we used the "Stability Moment" proposed by Peters and Iagnemma in [15]. However, the metric (similar to the "load transfer" metric) defined by

$$R_{SM} = \frac{SM_l - SM_r}{SM_l + SM_r}, \quad R_{SM} \in [-1,1], \tag{2}$$

was used for measuring the total destabilizing factor for the vehicle. With this parameter, if

$$R_{SM} \to -1 \; or \; R_{SM} \to 1 \tag{3}$$

the vehicle is tending to a rollover about the left or right tipover axes. Clearly, if

$$R_{SM} \to 0, \tag{4}$$

the vehicle tends to keep itself stable, with roll angle near zero.

In the simulation environment, a subsystem has been implemented to perform the calculation of these parameters, allowing the metric defined in (2) to be used as an input variable for the Fuzzy Ponderer proposed.

Fuzzy Ponderer

In Figure 2, we observed that the Fuzzy Ponderer should be proposed taking into account the following antecedents:

1. Driver;
2. Stability Parameter; and
3. External threats.

The architecture of the Fuzzy Ponderer is illustrated with more details in Figure 3. To describe the attributes mentioned above, the following input variables were used:

- Δu - Difference between the input provided by the driver and the automatic controller;
- $|R_{SM}|$ - Absolute value of the stability metric defined in (2);
- $D_{a,i}$ - Relative distance between the vehicle and the i^{th} shooter's line of sight;
- $V_{a,i}$ - Relative velocity between the vehicle and the i^{th} shooter's line of sight;
- $D_{e,i}$ - Relative distance between the vehicle and the i^{th} IED; and,
- $V_{e,i}$ - Relative velocity between the vehicle and the i^{th} IED.

Besides these, we also used the following intermediate variables:

- $A_{e,i}$ - External threat posed by the i^{th} IED;
- $A_{e,i}$ - External threat posed by the i^{th} shooter;
- A_t - Total external threat; and,
- B_{Motr} - Driver's behavior.

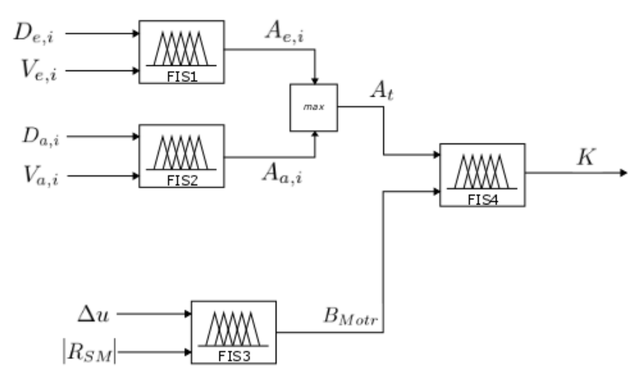

Figure 3. Architecture of the Fuzzy Ponderer, with the listed input and intermediate variables and the generation of K.

With those input variables, we developed a system capable of generating the intervention variable K (system output). However, as the number of variables is considerably large, the system is designed so that it took four Fuzzy Inference Systems (FIS), generating the intermediate variables shown.

The FIS used to develop this architecture are described on the Appendix.

Sub-Controller

The “Sub-Controller”, shown in the block diagram of the Figure 2, is the element of the controller responsible for the generation of control signals that will be weighted with the control inputs desired by the driver. As a goal of this research work, its development and design method shall be presented in the near future. Anyway, to achieve this a mathematical model that could represent the vehicle’s dynamic behavior with good accuracy must be used. At this point of the research, the two most promising implementation proposals for this mathematical model are the vehicular system identification using Artificial Neural Networks (ANN) or the modeling from the equations of motion of the multibody system.

Vehicular system identification

The control systems theory encompasses a lot of different techniques used to control dynamical systems. For the most part of them, those techniques become truly effective when you have prior knowledge about the mathematical modeling of the dynamical system to be controlled. Because of the difficulties inherent to the analysis and modeling of certain physical systems, as they may be non-linear or time-varying, system identification procedures are performed to allow the synthesis of models for the representation of its dynamic behaviors.

The utilization of ANN for the identification of nonlinear models is considered appropriate, mainly for its interpolation or universal approximation characteristics. In [16], mathematical statements are presented that Dynamic Recurrent Neural Networks (DRNN, illustrated on Figure 4) are able to approximate the dynamic behavior of systems. This capability is illustrated by the identification of a nonlinear system of multiple inputs and multiple outputs (MIMO) evaporator. Also in [16], the Neural Network training was conducted through a hybrid algorithm involving an evolutionary stage, as the backpropagation algorithm have been considered computationally expensive and impractical. In [17], however, the evaporator of the same identification problem was addressed by training the network through an Automatic Differentiation (AD) algorithm.

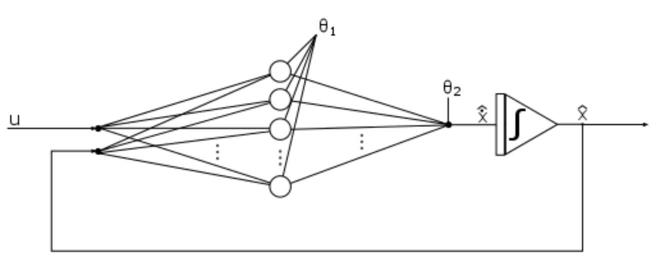

Figure 4. Classical DRNN topology for dynamic systems identification.

The continuous recurrent networks can approximate nonlinear dynamical systems represented by

$$\begin{cases} \dot{x} = f(x,u) \\ y = g(x) \end{cases}, \tag{5}$$

implementing systems given by

$$\begin{cases} \dot{\hat{x}}(t) = \hat{f}(\hat{x}(t), u(t), \theta) \\ \hat{y}(t) = C\,\hat{x}(t) \end{cases}, \tag{6}$$

where, in both equations (5) and (6) we have $u(t)$ as the external input vector consisting of n_u variables, $x(t)$ is the state vector consisting of n_x variables, $y(t)$ is the output vector comprising n_y variables. The variables marked with “hat” (̂) indicate their approximations. The vector θ is the network parameters and C is the matrix given by

$$C = \left[I_{n_y \times n_y} \quad \emptyset_{n_y \times n_x - n_y} \right], \tag{7}$$

which indicates that the system outputs are the first n_y variables of the vector.

6x6 vehicle models from the equations of motion

The equations of motion of a simplified multibody system can lead to an useful mathematical model for the proposed sub-controller’s implementation. From some basic information of an Armored Personal Carrier (APC) vehicle of the GUARANI family obtained in technical documentation [18], a mathematical model was conceived.

This mechanical model has a total of twelve degrees of freedom (DOF), represented by its Euler angles (three DOF), the position of a reference point (three DOF) considered the roll center of the sprung mass (rigid body of the vehicle) and the position of the mass points representing each of the six tire-suspension assemblies (six DOF). In Addition, we considered that the longitudinal acceleration of the vehicle is zero, and that the slip angle cannot be neglected. Figures 5 and 6 illustrate the considered simplifications.

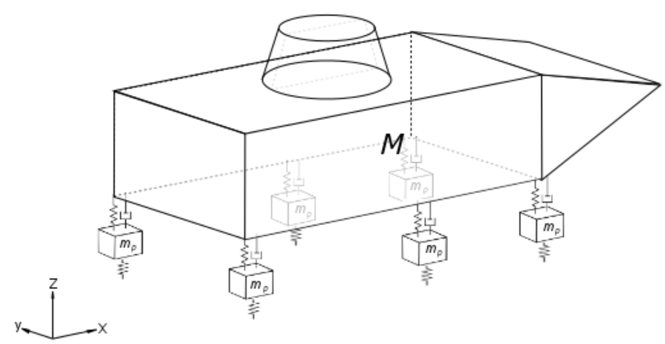

Figure 5. Simplified schematic for the 6x6 vehicle (perspective view).

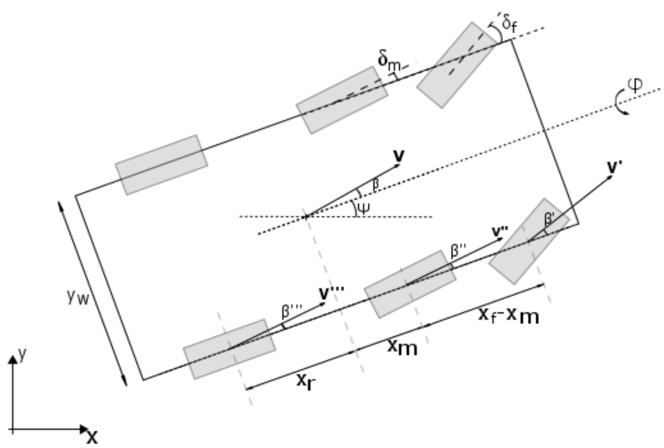

Figure 6. Simplified schematic for the 6x6 vehicle (top view).

Looking at Figure 2, we can reach the equations of motion on the vertical axis for both the sprung mass M and the mass blocks m_p (relative to their centers of gravity). The equations will be given by

$$\sum_{m_{p,i}} \boldsymbol{F} = m_{p,i}\ \ddot{z}_i \ \Rightarrow$$

$$m_{p,i}\,\ddot{z}_i =$$

$$k_p[h_0 - (z_i - r_i)] - k_i\left[l - \left(z \pm \frac{y_w}{2}\,\varphi \pm x_r\theta - z_i\right)\right]$$

$$- b_i\left[-\left(\dot{z} \pm \frac{y_w}{2}\,\dot{\varphi} \pm x_r\,\dot{\theta}\right) + \dot{z}_i\right] - m_{p,i}\,g\,,$$

$$(i = 1,2,\dots,6), \qquad (8)$$

where the parameters represent the following: $m_{p,i}$ is the mass block representing the i^{th} tire-suspension assembly; z_i is the (time-varying) height of the mass block $m_{p,i}$; k_p is the stiffness of the spring representing each of the vehicle's tires; h_0 is the height where the mass blocks $m_{p,i}$ would be if there were no gravity; r_i is the height at the point of contact of the i^{th} tire with the ground; k_i the spring stiffness of the i^{th} suspension; l is the distance between the sprung mass center of gravity and the height of the mass blocks $m_{p,i}$ if there were no gravity; z is the (time-varying) height of the center of gravity of the sprung mass M; b_i the damping constant of the ith suspension; y_w and x_r are the distances indicated in Figure 2; φ the (time-varying) roll angle the sprung mass; θ the (time-varying) pitch angle the sprung mass; and g the gravitational acceleration.

In equation (8), all terms that are proportional to φ and θ were labeled with $\pm$ because their signals vary according to each of the 6 tire-suspension assemblies.

For the sprung mass M we can also write

$$\sum_{M} \boldsymbol{F} = M\ddot{z} \ \Rightarrow$$

$$M\ddot{z} = \sum_{i=1}^{6} F_i - Mg\,, \qquad (9)$$

where

$$F_i = k_i\left[l - \left(z \pm \frac{y_w}{2}\,\varphi \pm x_r\theta - z_i\right)\right]$$

$$+ b_i\left[-\left(\dot{z} \pm \frac{y_w}{2}\,\dot{\varphi} \pm x_r\dot{\theta} - \dot{z}_i\right)\right]. \qquad (10)$$

Considering the top view illustrated on Figure 6 one can obtain a bicycle type model for the vehicle, which can be represented by the equation

$$\sum \boldsymbol{F}_y = M_t\ddot{y} - Mh[\ddot{\varphi}\ \cos\varphi$$
$$- \ \dot{\varphi}^2 \sin\varphi]\cos\psi, \qquad (11)$$

where $M_t = M + 6\,m_p$ e h is the distance between the center of gravity of the sprung mass and its roll center.

Taking into account that in this work we will consider only situations where no longitudinal acceleration is applied to the vehicle, we can observe that

$$\begin{cases} \dot{x} = V\cos(\psi + \beta)\,; \\ \dot{y} = V\sin(\psi + \beta) \end{cases},$$

therefore

$$\begin{cases} \ddot{x} = -V\sin(\psi + \beta)(\dot{\psi} + \dot{\beta})\,; \\ \ddot{y} = V\cos(\psi + \beta)\,(\dot{\psi} + \dot{\beta}) \end{cases},$$

from where one could conclude that

$$M_t\,V\cos(\psi + \beta)\,(\dot{\psi} + \dot{\beta}) =$$

$$Mh[\ddot{\varphi} - \ \dot{\varphi}^2\ \sin\varphi]\cos\psi + \ 2\,F_f\cos(\delta_f + \psi)$$
$$+ \ 2\,F_m\cos(\delta_m + \psi) - 2\,F_r\cos\psi, \qquad (12)$$

The forces F_f, F_m and F_r are calculated in a similar way from that presented in [3], with the cornering stiffness C_f, C_m and C_r of the tires, by the expression

$$\begin{bmatrix} F_f \\ F_m \\ F_r \end{bmatrix} = \begin{bmatrix} C_f & 0 & 0 \\ 0 & C_m & 0 \\ 0 & 0 & C_r \end{bmatrix} \begin{bmatrix} \alpha_f \\ \alpha_m \\ \alpha_r \end{bmatrix}, \qquad (13)$$

where α_f, α_m and α_r are the angles between the longitudinal axis of the tires on the front, intermediary and rear axis and their velocity vectors. Therefore it can be said that

$$\begin{cases} F_f = C_f(\delta_f - \beta') \\ F_m = C_m(\delta_m - \beta'')\,, \\ F_r = C_r(\beta''') \end{cases} \qquad (14)$$

where the angles β', β'' and β''' are approximated by

$$
\begin{cases}
\beta' = \beta + \frac{x_f}{V}\dot{\psi} \\
\beta'' = \beta + \frac{x_m}{V}\dot{\psi} \\
\beta''' = \beta - \frac{x_r}{V}\dot{\psi}
\end{cases} \tag{15}
$$

The moments of the forces can be addressed as

$$
\begin{bmatrix} \sum M_x \\ \sum M_y \\ \sum M_z \end{bmatrix} = \begin{bmatrix} I_{xx} & -I_{xy} & -I_{xz} \\ -I_{xy} & I_{yy} & -I_{yz} \\ -I_{xz} & -I_{yz} & I_{zz} \end{bmatrix} \begin{bmatrix} \ddot{\varphi} \\ \ddot{\theta} \\ \ddot{\psi} \end{bmatrix}, \tag{16}
$$

where we shall have

$$
\sum M_x = 2\, F_f h\, \cos\delta_f + 2\, F_m h\, \cos\delta_m - 2\, F_r h + Mgh\, \sin\varphi - \frac{y_w^2}{4}\varphi \sum_{i=1}^{6} k_i - \frac{y_w^2}{4}\dot{\varphi} \sum_{i=1}^{6} b_i, \tag{17}
$$

$$
\sum M_y = (F_3 + F_4)x_r - (F_2 + F_5)x_m - (F_1 + F_6)x_f, \tag{18}
$$

and

$$
\sum M_z = 2\, F_f\, x_f\, \cos\delta_f + 2\, F_m x_m \cos\delta_m + 2F_r x_f. \tag{19}
$$

The model resulting from these equations was implemented on a numerical simulation environment and it generated good results, similar to those illustrated in [18], which makes this a valuable model to be used for the development of sub-controller proposed.

Simulation Results

Although the proposed control system has not been fully implemented, one of its two main elements (i.e., the Fuzzy Ponderer) had its development already initiated. At this point of our research it was possible to carry out some simulation tests, so that three test scenarios (where the control system action would be required) were suggested. The scenarios and the results are detailed on the next subsections. On Table 5, the parameters used for the mathematical model and for these simulations are presented.

Test scenarios

In order to check the operation of the Fuzzy Ponderer, simulations were performed in the following three test cases:

1. Hostile environment: In this case, the vehicle is in a simulated hostile environment where there are an IED and an enemy sniper equipped with an anti-tank weapon. With this simulation, we try to check the Fuzzy Ponderer behavior on the evaluation of external threats.

2. Hazardous maneuver: In this situation, we simulate the behavior of the car and of the Fuzzy Ponderer facing a reckless behavior of the driver, where an input (steering wheel angle) is provided to the system, generating a hazardous maneuver and increasing the values of stability parameters shown in equation (2). With this simulation, we try to check the Fuzzy Ponderer's behavior when varying the driver's performance evaluation.

3. Hazardous maneuver in hostile environment: In this situation we tried to mix the two previous situations. However, we tried to check the operation of the Fuzzy Ponderer in a case, which the driver had presented a "bad" behavior, but in an extremely dangerous situation. According to the design presented, in those situations, the level of intervention is expected to decrease.

The test scenarios schematics are illustrated by the trajectories shown on Figures 7, 8 and 9.

Results

From the simulations, we can obtain the evolution curves of the time-varying intervention variable K. It should be noted that in this study, only the Fuzzy Ponderer behavior is analyzed. No control action is applied to the dynamical system, which makes it impossible to be compared with other systems from the literature.

Figures 7, 8 and 9 show the evolution curves for the variable K in the first, second and third simulated test situations.

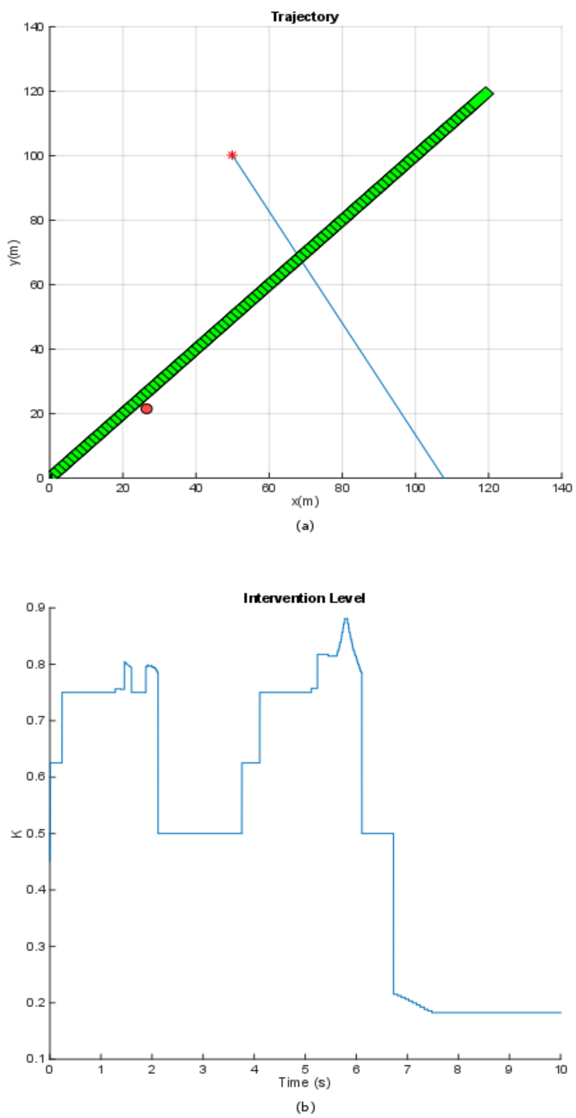

Figure 7. Trajectory (a) and intervention level's evolution (b) for the hostile environment scenario.

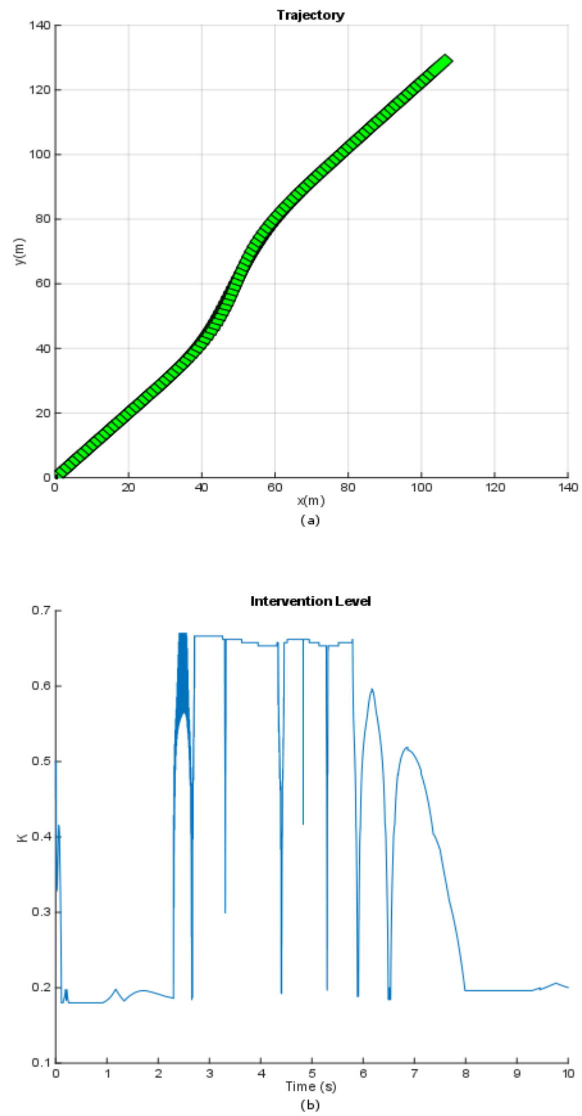

Figure 8. Trajectory (a) and intervention level's evolution (b) for the hazardous maneuver scenario.

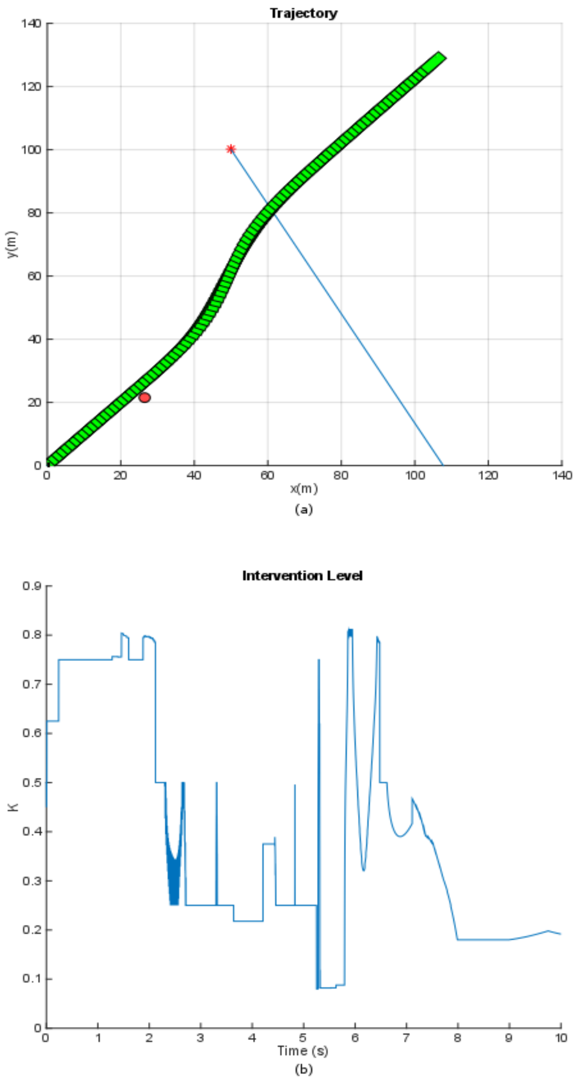

Figure 9. Trajectory (a) and intervention level's evolution (b) for the hazardous maneuver in hostile environment scenario.

It can be seen that the evolution of the variable K is given as expected, due to the fact that the vehicle is being used at a high-risk environment while the driver provides inputs that cause the system to perform a dangerous maneuver (where a sudden stroke is applied to the steering wheel even with the vehicle having a longitudinal speed of 60km/h). However, in the third scenario, we can also note a fall on the value of K at about 6s, which can be explained by the fact that on a situation of extreme danger in the same time of a highly unexpected behavior of the driver, the intervention level should decrease (as stated on the fuzzy rules presented on Table 4), increasing the driver's control authority. The fuzzy rules are defined this way so that urgent tactical maneuvers desired by the military drivers are not disturbed or modified without their will.

Summary/Conclusions

In this paper we proposed a semi-autonomous control system based on artificial intelligence techniques to be deployed in military vehicles. This proposed system shall be composed of two main subsystems, which are a "Fuzzy Ponderer" and a "Sub-controller", to be developed from mathematical models that were also presented here. Basic concepts about the semi-autonomous control of vehicles were presented, as well as the architecture of the proposed system. Mathematical modeling of important parameters (as the stability parameter) for the development of the system as well as the modeling of the subsystems were shown, creating subsidies for carrying out simulations that allowed the analysis of Fuzzy Ponderer behavior. The results obtained from three different simulated test situations were presented. It was not possible to compare the results of this semi-autonomous control system with other from the literature, since no control action was in fact applied to the dynamic system itself.

As future work, we intend to continue the development of the system, using the Fuzzy Ponderer as the generator of the intervention variable K that shall be used to blend the control inputs desired by the driver and that of the Sub-controller, including the comparison of the results to be obtained with those from other semi-autonomous controllers available.

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Definitions/Abbreviations

AD	Automatic Differentiation
ADAS	Advanced Drive Assistant Systems
AI	Artificial Intelligence
ANN	Artificial Neural Networks
APC	Armoured Personel Carrier
DOF	Degree Of Freedom
DRNN	Dynamic Recurrent Neural Networks
FIS	Fuzzy Inference Systems
IED	Improvised Explosive Device
LASER	Light Amplification by Stimulated Emission of Radiation
MIMO	Multiple Input Multiple Output
WHO	World Health Organization

Appendix

Fuzzy Ponderer's FIS's description

As illustrated on Figure 3 (and mentioned before), the Fuzzy Ponderer is a system composed by four FIS's, with two input variables and one output variable for each one. Those variables were listed on subsection "*Fuzzy Ponderer*". Their universes of discourse and the fuzzy rules for each of the FIS's are described below.

FIS 1 and FIS 2

Input variables

Distance $D_{e,i}$ and velocity $V_{e,i}$ (or $D_{a,i}$ and $V_{a,i}$), as illustrated on Figures 10 and 11.

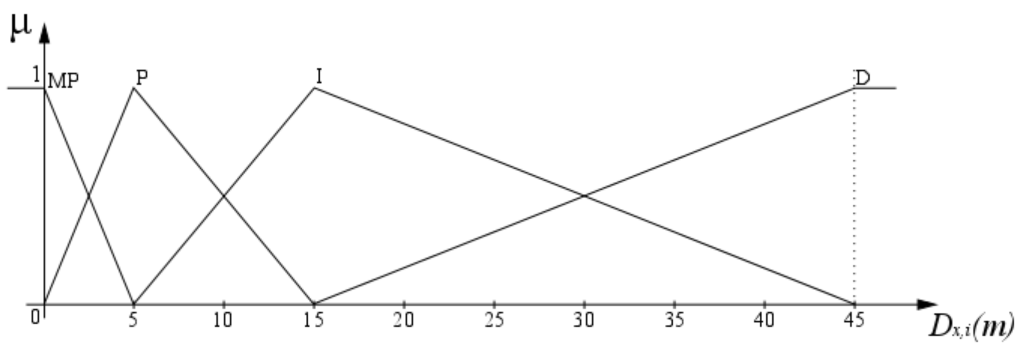

Figure 10. Universe of discourse for the variable $D_{e,i}$ (or $D_{a,i}$).

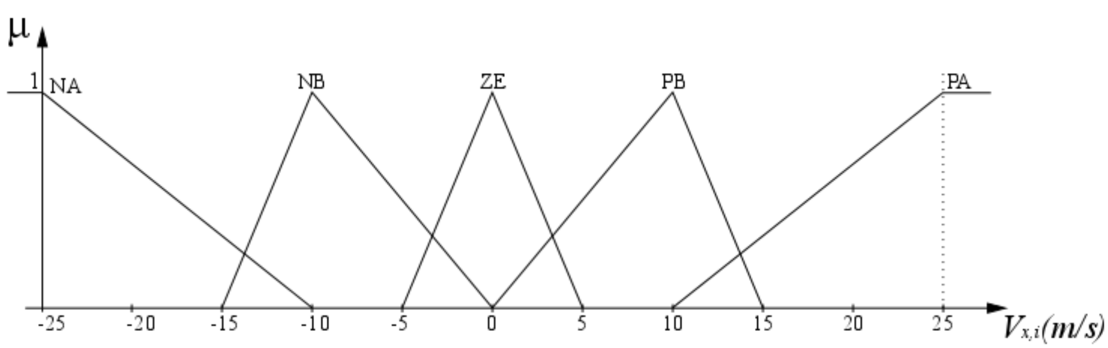

Figure 11. Universe of discourse for the variable $V_{e,i}$ (or $V_{a,i}$).

Output variables

External threat $A_{e,i}$ (or $A_{a,i}$), as illustrated on Figure 12.

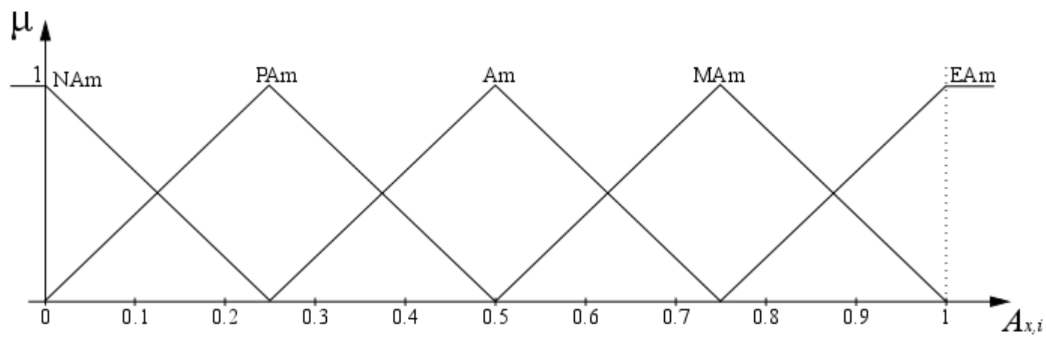

Figure 12. Universe of discourse for the variable $A_{e,i}$ (or $A_{a,i}$).

Defuzzification method

Center of Gravity (CoG).

Fuzzy rule base

Presented on Table 2.

Table 2. Fuzzy rule base for FIS 1 (and FIS 2).

		$D_{e,i}$ (or $D_{a,i}$)			
		MP	P	I	D
$V_{e,i}$ (or $V_{a,i}$)	NA	EAm	Am	MAm	Am
	NB	EAm	MAm	Am	PAm
	ZE	EAm			
	PB	EAm		PAm	NAm
	PA	EAm			NAm

Where:

- MP - Very close
- P - Close
- I - Intermediary
- D - Distant

- NA - Negative high
- NB - Negative low
- ZE - Zero
- PA - Positive high
- PB - Positive low

- NAm - No threat
- PAm - Low threat
- Am - Medium threat
- MAm - High threat
- EAm - Extreme threat

FIS 3

Input variables

Driver's and Controller's inputs difference Δu and stability metric's absolute value $|R_{SM}|$, as illustrated on Figure 13 and 14.

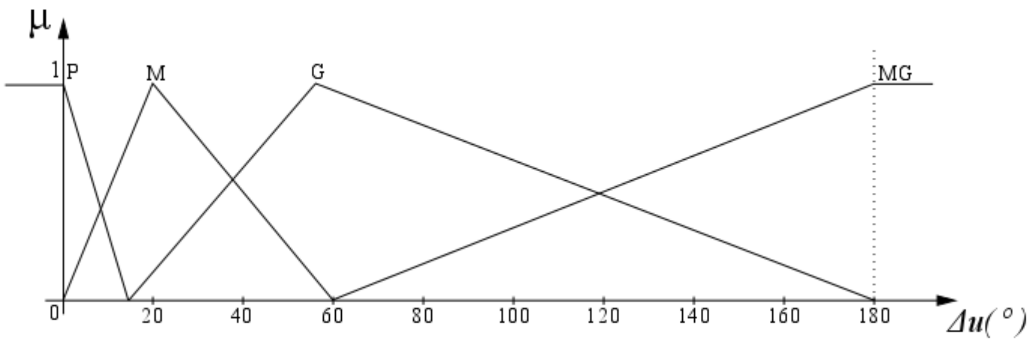

Figure 13. Universe of discourse for the variable Δu.

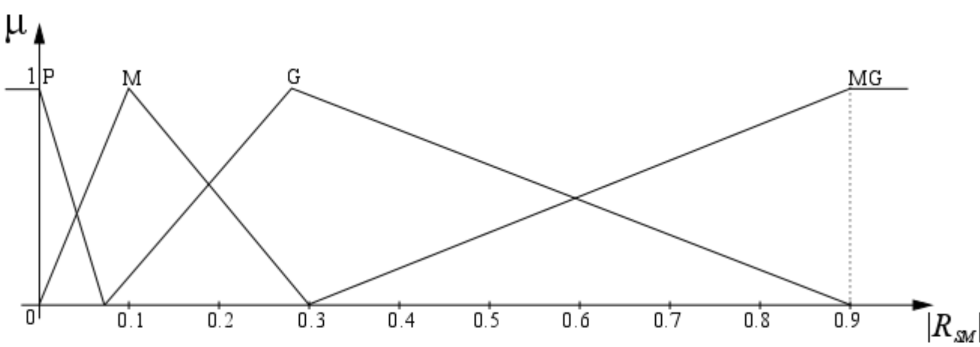

Figure 14. Universe of discourse for the variable $|R_{SM}|$.

Output variables

Driver's behavior B_{Motr}, as illustrated on Figure 15.

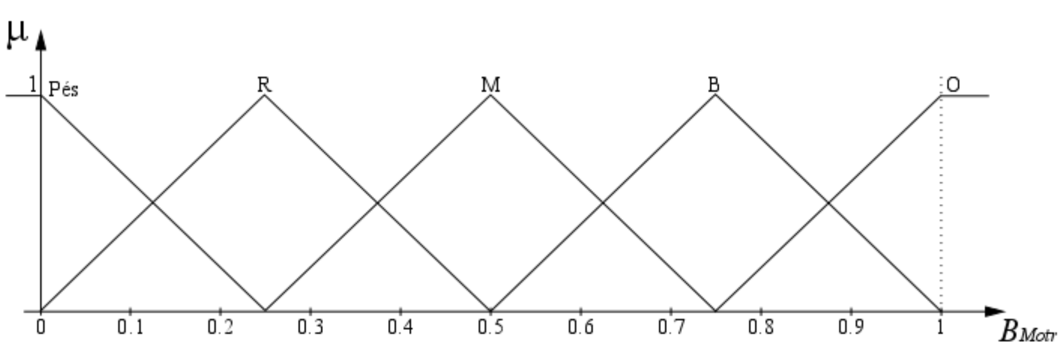

Figure 15. Universe of discourse for the variable B_{Motr}.

Defuzzification method

Center of Gravity (CoG).

Fuzzy rule base

Presented on Table 3.

Table 3. Fuzzy rule base for FIS 3.

		Δu			
		P	M	G	MG
$\lvert R_{SM} \rvert$	P	O	O	B	B
	M	B	M	M	R
	G	M	R	R	$Pés$
	MG	R	R	$Pés$	$Pés$

Where:

- P - Small
- M - Medium
- G - Big
- MG - Very big
- O - Very good
- B - Good
- R - Bad
- $Pés$ - Very bad

FIS 4

Input variables

Total External threat A_T, as illustrated on Figure 12 ($A_{e,i}$, $A_{a,i}$ and A_T have the same universe of discourse) and Driver's behavior B_{Motr}, as illustrated on Figure 15.

Output variables

Level of intervention K, as illustrated on Figure 16.

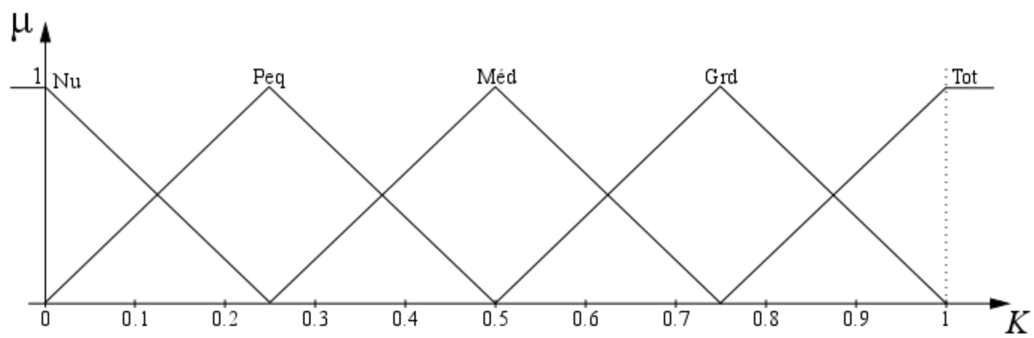

Figure 16. Universe of discourse for the variable K.

Defuzzification method

Center of Gravity (CoG).

Fuzzy rule base

Presented on Table 4.

Table 4. Fuzzy rule base for FIS 4.

		B_{Motr}				
		$Pés$	R	M	B	O
A_T	NAm	Tot	Grd	$Méd$	Nu	Nu
	PAm	Grd	$Méd$	Peq	Peq	Peq
	Am	$Méd$	Peq	$Méd$	$Méd$	$Méd$
	MAm	Peq	Nu	Grd	Grd	Grd
	EAm	Nu	Nu	Tot	Tot	Tot

Where:

- Nu - Null
- Peq - Small
- $Méd$ - Medium
- Grd - Big
- Tot - Total

Note: In case of two or more IED or sniper threat, one should use as many FIS 1 (or FIS 2) as necessary. The outputs of these systems must be connected to the max operator already illustrated in Figure 3.

Model and Simulation parameters

Table 5. Model and Simulation parameters' values and descriptions.

Parameter	**Value**	**Description**
V	60 km/h	Longitudinal velocity of the vehicle.
g	9.81 m/s^2	Gravitational acceleration.
M	15,539.0 kg	Sprung mass of the vehicle.
m_p	421.16 kg	Tire-suspension assembly's mass.
C_f	2.05 kN/deg	Frontal tires' cornering stiffness.
C_m	2.33 kN/deg	Intermediary tires' cornering stiffness.
C_r	2.70 kN/deg	Rear tires' cornering stiffness.
x_f	1.986 m	Longitudinal distance between the center of gravity and the frontal axis.
x_m	0.286 m	Longitudinal distance between the center of gravity and the intermediary axis.
x_r	1.714 m	Longitudinal distance between the center of gravity and the rear axis.
y_w	2.260 m	Vehicle's width.
r_p	0.575 m	Tires' radius.
k_p	1.25 kN/mm	Tires' stiffness.
k_1	0.207 kN/mm	Frontal-left suspension stiffness.
k_2	0.260 kN/mm	Intermediary-left suspension stiffness.
k_3	0.349 kN/mm	Rear-left suspension stiffness.

k_4	$0.200\ kN/mm$	Rear-right suspension stiffness.
k_5	$0.250\ kN/mm$	Intermediary-right suspension stiffness.
k_6	$0.334\ kN/mm$	Frontal-right suspension stiffness.
$b_1 = b_2 = b_3$	$27.7\ Ns/mm$	Left suspensions' damping.
$b_4 = b_5 = b_6$	$10\ Ns/mm$	Right suspensions' damping.
h	$1.033\ m$	Distance between the center of gravity of the sprung mass and its roll center.
I_{xx}	$15{,}800.0\ kg\ m^2$	Inertia tensor components.
I_{xy}	$-1{,}186.0\ kg\ m^2$	
I_{xz}	$3{,}794.0\ kg\ m^2$	
I_{yy}	$64{,}670.0\ kg\ m^2$	
I_{yz}	$-52.25\ kg\ m^2$	
I_{zz}	$65{,}270.0\ kg\ m^2$	

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