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Cascade Adaptive MPC with Type 2 Fuzzy System for Safety and Energy Management in Autonomous Vehicles: A Sustainable Approach for Future of Transportation

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Citation: Phan, D.; Amani, A.M.; Mola, M.; Rezaei, A.A.; Fayyazi, M.; Jalili, M.; Ba Pham, D.; Langari, R.; Khayyam, H. Cascade Adaptive MPC with Type 2 Fuzzy System for Safety and Energy Management in Autonomous Vehicles: A Sustainable Approach for Future of Transportation. *Sustainability* **2021**, *13*, 10113. <https://doi.org/10.3390/su131810113>

Academic Editor: Bilal Farooq

Received: 14 July 2021

Accepted: 2 September 2021

Published: 9 September 2021

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Abstract: A sustainable circular economy involves designing and promoting new products with the least environmental impact through increasing efficiency. The emergence of autonomous vehicles (AVs) has been a revolution in the automobile industry and a breakthrough opportunity to create more sustainable transportation in the future. Autonomous vehicles are supposed to provide a safe, easy-to-use and environmentally friendly means of transport. To this end, improving AVs' safety and energy efficiency by using advanced control and optimization algorithms has become an active research topic to deliver on new commitments: carbon reduction and responsible innovation. The focus of this study is to improve the energy consumption of an AV in a vehicle-following process while safe driving is satisfied. We propose a cascade control system in which an autonomous cruise controller (ACC) is integrated with an energy management system (EMS) to reduce energy consumption. An adaptive model predictive control (AMPC) is proposed as the ACC to control the acceleration of the ego vehicle (the following vehicle) in a vehicle-following scenario, such that it can safely follow the lead vehicle in the same lane on a highway. The proposed ACC appropriately switches between speed and distance control systems to follow the lead vehicle safely and precisely. The computed acceleration is then used in the EMS component to find the optimal engine torque that minimizes the fuel consumption of the ego vehicle. EMS is designed based on two methods: type 1 fuzzy logic system (T1FLS) and interval type 2 fuzzy logic system (IT2FLS). Results show that the combination of AMPC and IT2FLS significantly reduces fuel consumption while the ego vehicle follows the lead vehicle safely and with a minimum spacing error. The proposed controller facilitates smarter energy use in AVs and supports safer transportation.

Keywords: autonomous vehicle; cascade control; adaptive model predictive control; interval type 2 fuzzy logic; autonomous cruise control; sustainable circular economy; complex system

1. Introduction

Greenhouse gas emission is the greatest concern of our future life [1]. Despite social and political movements towards electrification, transportation is still responsible for 24% of CO₂ emissions [2]. This means that we need a deep restructure in the transport sector in order to achieve the goals of the Paris Climate Accords. To address these concerns, some transportation researchers have begun to align their R&D efforts with the sustainable

circular economy principles: reduce, reuse, recycle and replace (RRRR) [3,4]. In this context, the autonomous vehicle (AV) is a promising technology [5].

Recently, autonomous vehicles (AVs) have been at the center of attention in automotive engineering research [6]. The AV technology has equipped conventional vehicles with the ability to move without a human driver, using only state-of-the-art image processing and machine vision techniques which is a complex systems [7,8]. Despite exempting humans from driving duties, which is indeed potentially dangerous, it can improve vehicle safety and energy efficiency [6]. The AV technology is set to be life-changing since it can lead to a reduction in the number of crashes, road congestion, energy consumption and CO₂ emissions of conventional vehicles. It is predicted that vehicle manufacturers will have a USD 7 trillion annual revenue stream from the AV market by 2050 [9]. Previous studies on user adoption of driverless vehicles have focused on safety [5]. However, energy management in conventional autonomous vehicles is still challenging and demanding. In addition to conventional AVs which are only based on Internal Combustion Engines (ICE), hybrid AVs, in which ICE and an electric motor drive the vehicle jointly, have been studied in [9]. Research activities successfully show that most vehicle crashes happen during maneuver driving such as: accelerating, decelerating, changing lanes, merging and overtaking [10]. These operations mainly form the objectives of autonomous cruise control (ACC) – also known as adaptive cruise control or intelligent cruise control technology, which is widely regarded as a crucial component of AVs and is an extension of conventional cruise control. It is mainly responsible for controlling the speed of a vehicle and its relative distance with the lead vehicle by using sensor data [11].

In a reasonable driving condition, a vehicle equipped with an ACC travels at a driver-set velocity by controlling the throttle, exactly similar to conventional cruise controllers. In the case of detecting a leading vehicle, the ACC system needs to determine whether the vehicle is still able to safely travel at the set speed. If not, ACC sends signals to the engine or braking system to decelerate the vehicle. Vehicle manufacturers have employed many advanced algorithms, such as PID [12], fuzzy logic control [13], linear quadratic optimal control [14], recurrent control [15] and model predictive control [16–18], to adaptively control the throttle, brakes and gear shifting. Recently, with advancements in connected vehicles, the concept of cooperative ACC is introduced which improves the ACC performance through communications among vehicles [19,20].

Model predictive control (MPC) is an advanced process control technique based on optimal control theory. It works based on running an optimization problem over a finite time-horizon and applies the resulted optimal action only for the current timeslot. It then repeats the same process for shifted time-horizons to the end of the process [11]. Using this mechanism, MPC gains the ability to anticipate future events and act accordingly. Constraints can also be plugged into the MPC optimization process to ensure that the selected action remains valid in the problem context [13]. The MPC's predictive capability comes at a high computational cost since it requires solving one optimization problem at each time step.

MPC algorithms have been successfully applied to cruise control (CC) and ACC systems. Kural et al. [21] used MPC for the ACC problem and tested their achievements using a nonlinear vehicle model. They utilized MPC in a hierarchical architecture and applied quadratic programming techniques for solving the real-time optimization problem. Angle et al. [22] also used MPC for ACC where drivers' decisions, expressed by mathematical formulation, were considered as constraints. Designing energy-optimal ACC based on MPC was studied in [23] where prior knowledge of the route was used to compute an energy-optimal speed trajectory using dynamic programming. They utilized MPC to control the vehicle speed while ensuring constraints such as a safe distance to a preceding vehicle. Miftakhudin et al. [24] proposed an ACC by solving a so-called “multistage MPC”, where the square of errors between the anticipated values of the vehicle velocity and the safe distance was minimized.

Adaptive model predictive control (AMPC) is a type of MPC where the control algorithm is re-tuned based on the behavior of the system, such as variation of the vehicle model. This feature helps ACC designers to accommodate a vehicle lateral dynamics model [25] or the road condition [26]. As the control system is adapted to current system conditions, AMPC performance is robust against uncertainties.

Despite the aforementioned advances in ACC to improve safety, it is not the only concern about AVs from a sustainability perspective. Transportation, as a complex system, has challenges such as capacity, transfer, reliability, integration to reduce time and energy consumption [27]. Energy management systems (EMSs) are control systems aiming for energy efficiency in AVs. Numerous methods have been proposed to improve engine efficiency, such as regenerative braking protocols [28], rule-based reduction of energy consumption [29,30] and intelligent approaches [31–33]. Among these approaches, intelligent control algorithms, such as fuzzy systems, show a great potential to deal with the nonlinearities of this problem in vehicles [31]. Many of the existing fuzzy logic-based EMS has been designed based on a type 1 fuzzy logic system (T1FLS) [29,34–36]. The set of rules and membership functions of a T1FLS are formulated based on the knowledge of human beings. However, the linguistic and numerical uncertainties, inherited from the driving conditions, could not be solved and addressed comprehensively by using explicit membership functions in a T1FLS [37–39]. To overcome these disadvantages, interval type 2 fuzzy logic systems (IT2FLS) have been introduced [40]. By offering fuzzy membership functions (MFs), they can accommodate the insufficiency related to the changes of the driving conditions. The MFs of IT2FLS are three-dimensional, in opposition to the two-dimension MFs in T1FLS, and therefore offering one additional degree of freedom. IT2FLS can precisely achieve membership grades in practical problems with high levels of uncertainty [41]. Our recent research [42] showed that IT2FLS is more effective than T1FLS in reducing energy consumption in an autonomous vehicle.

In this paper, we integrate an AMPC-based ACC with an IT2FLS fuzzy logic-based EMS to achieve a cascade control system. It has two different objectives simultaneously: obtaining a safe distance with the lead vehicle and reducing the energy consumption of the ego vehicle. A lead-ego vehicle-following scenario (see Figure 1), which is when a lead vehicle is being followed by an ego vehicle in the same lane, is considered. The ego vehicle is appropriately equipped with a combining radar measurement using an extended object tracker, and the LiDAR measurements using a joint probabilistic data association tracker are used. Then these tracks are fused by using a track-level fusion algorithm to measure the distance and velocity relative to the lead vehicle.

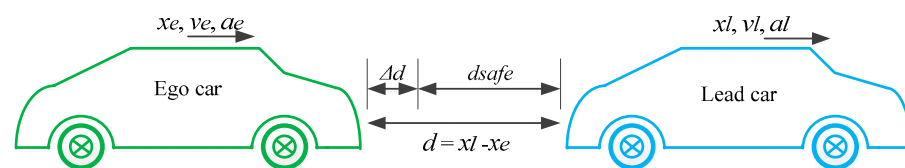


Figure 1. The lead-ego scenario to keep a safe distance between the lead and ego vehicles.

We show that by using this combination, the distance between two vehicles is kept safe while energy consumption is reduced. The main contributions impact on implementation of the technology of this study are useful for the future of transportation and can be highlighted as follows:

An AMPC algorithm is applied as ACC to control the safe operation of the ego vehicle under combined loads. In this algorithm, the objective function of the MPC algorithm is adapted based on ego-lead distance.

Energy management of vehicles in cascade with the AMPC is established based on the IT2FLS method which can handle the uncertainties of driving conditions.

Prediction safety control is used to control a vehicle while satisfying a set of vehicle and road geometry constraints.

The rest of the paper is organized as follows: Section 2 illustrates the vehicle dynamics and power model required for the ego vehicle. Our integrated control system is presented in Section 3. Section 4 illustrates simulation results, including a discussion. Finally, the work is concluded in Section 5.

2. Vehicle Dynamics and Require Power

In this article, a longitudinal model is considered for the ego vehicle as shown in Figure 2. Using Newton's law, the total driving force of a vehicle is:

$$ma = F_t - F_r - F_w - F_g \quad (1)$$

where F_t , F_r , F_w and F_g are the total driving force, the rolling resistance force, the aerodynamic resistance force, and the component of gravity along the road surface, respectively, m is the mass of the vehicle and a shows its acceleration. Forces are calculated using the following formulas:

$$F_r = \mu_r \cdot mg \cos \theta \quad (2)$$

$$F_w = c_a \cdot \frac{1}{2} \rho \cdot A \cdot (v_t + v_w)^2 \quad (3)$$

$$F_g = mg \sin \theta \quad (4)$$

where μ_r is the road friction coefficient, θ is the slope of the road, c_a is the aerodynamic resistance coefficient, ρ is the air density, A is the cross-sectional area, v_t is the velocity of the vehicle, v_w is the velocity of the wind, g is gravity, and a is the acceleration of the vehicle. By Substituting (2), (3) and (4) into (1), the total driving force is

$$F_t = \mu_r mg \cos \theta + c_a \cdot \frac{1}{2} \rho \cdot A \cdot (v_w + v_t)^2 + mg \sin \theta + ma \quad (5)$$

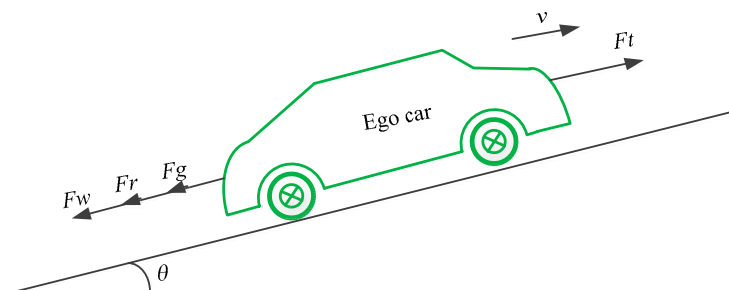


Figure 2. Longitudinal dynamics of the ego vehicle.

Using F_t , we can define the required power of the vehicle as,

$$P = F_t \cdot v_t + P_{accessory} \quad (6)$$

where $P_{accessory}$ is the air conditioning (AC) power consumption. In this paper, the AC model, introduced in [43], is considered. As the vehicle travels along the road, the power consumption exploited by an AC system changes dynamically. It can increase the power usage of the vehicle by 12–17% [44]. Other supplementary powers are quite modest in comparison with the overall power consumption of the vehicle. Thus, in this work, only the AC's power consumption is considered, and the rest are consolidated in the mechanical losses. For the AC power we have:

$$P_{accessory} = \frac{dW_{ac}}{dt} = MC_{room} \frac{dT_{room}}{dt} \quad (7)$$

where M is the air mass in the cabin, T_{room} and C_{room} are the cabin temperature and the temperature constant.

To achieve the vehicle power (P) in Equation (6) and considering the power train model explained in [45], the following fuel consumption rate is required

$$\dot{m}_{fuel} = \frac{P}{q_{combustion} \cdot \eta_{mechanical} \cdot \eta_{engine}} \quad (8)$$

where $q_{combustion}$ is the combustion energy, $\eta_{mechanical} = 0.9$ [46] is the mechanical efficiency and η_{engine} is the engine efficiency. The engine efficiency graph (see Figure 3) is normally illustrated by a contour plot as a function of torque [Nm] and the engine speed [rpm]. These contours are derived using the experimental characterization of the engine in real performing conditions. The highest obtainable efficiency for an ICE is 34%, due to thermodynamic limitations.

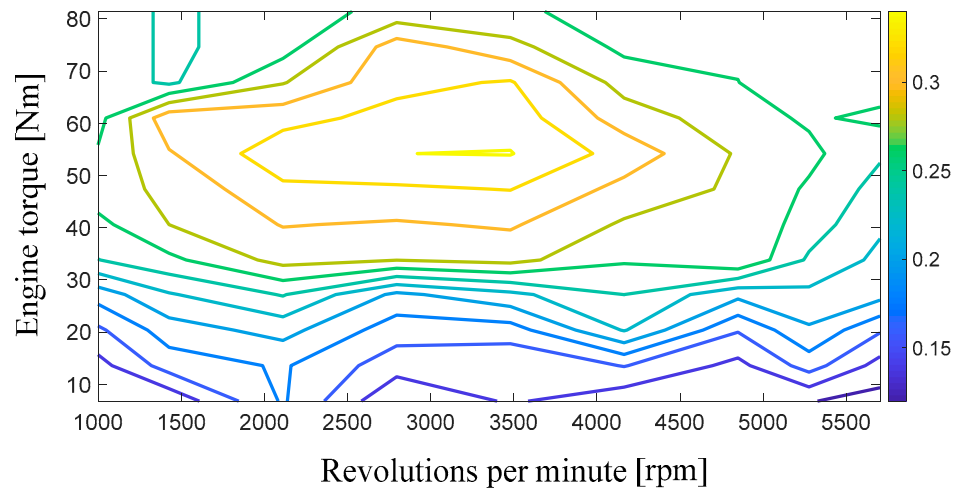


Figure 3. Engine efficiency map of Honda Insight (2004) 1.0i VTEC-E SI from ANL test data.

3. Proposed Control System for the Ego Vehicle

The block diagram of the control system for the ego vehicle is shown in Figure 4. This is a cascade control structure, including an ACC in series with an EMS. The control objectives are as follows.

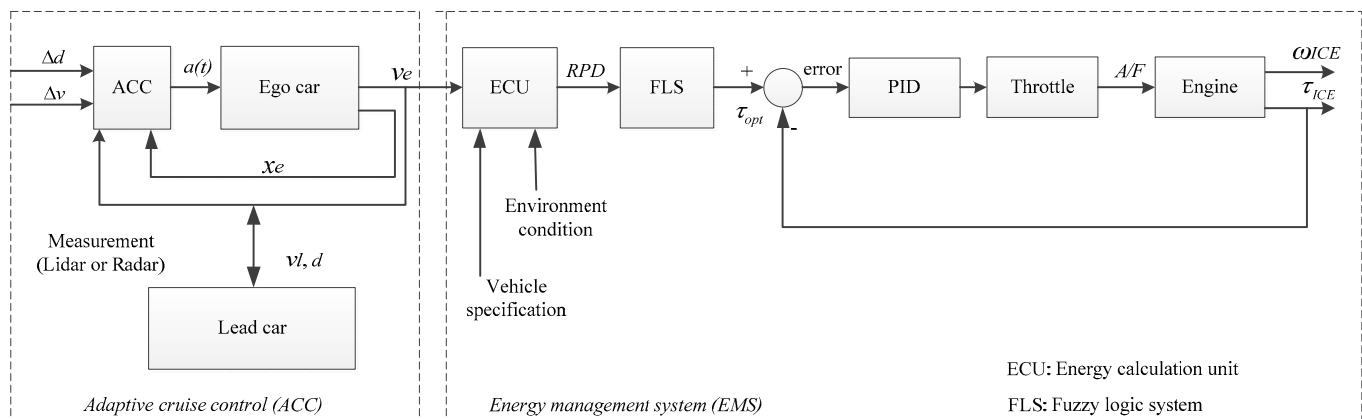


Figure 4. Integrated control system architecture.

- The spacing error between two vehicles, i.e., $\Delta d = d - d_{safe}$ is always maintained greater than zero, where d and d_{safe} are the actual and safe distances between the lead and ego vehicles, respectively.
- The energy consumption for the ego vehicle is optimized using an EMS.

3.1. Adaptive Cruise Control

Generally, an ACC controller has a hierarchical structure, including an upper-level controller and a lower-level controller [47]. The upper-level controller typically determines the desired acceleration for the ego vehicle based on the relative speed and the relative distance from the lead vehicle. The lower-level controller determines the throttle and brake actions to follow the acceleration/deceleration commands from the upper-level controller. In this paper, by assuming that the lower-level controller is well-designed, our focus is more on the design of the upper-level controller. The ACC model of the vehicle can be defined as follows [16].

$$\tau \frac{d\ddot{x}(t)}{dt} + \ddot{x}(t) = u(t) \quad (9)$$

where τ refers to the time lag corresponding to the finite bandwidth of the lower-level controller and u depicts the acceleration command applied by the upper-level controller. x , $\dot{x}$, $a = \ddot{x}$ are the position, speed and acceleration of the ego vehicle, respectively. Using a first-order approximation, the discrete-time expression of (9) can be shown as,

$$a(k+1) = \left(1 - \frac{T_s}{\tau}\right)a(k) + \frac{T_s}{\tau}u(k) \quad (10)$$

where T_s refers to the sampling period, $a(k)$ is the acceleration of the ego vehicle at the sampling time k . The safe distance between the lead vehicle and ego vehicle can be calculated based on the velocity of the ego vehicle, shown below.

$$d_{safe} = d_{default} + t_{gap} \cdot v_e(k) \quad (11)$$

where t_{gap} is the constant time headway. $d_{default}$ is a safe distance and is fixed when the vehicle travels at a low speed or is completely stopped. In other words, d_{safe} is adjusted based on the speed of the ego vehicle $v_e(k)$. The relative speed between the lead and the ego vehicle v is,

$$v(k) = v_l(k) - v_e(k) \quad (12)$$

where $v_l(k)$ is the speed of the lead vehicle at sampling time k . Therefore, equations of motion of the ego vehicle can be represented using the following state-space model:

$$\begin{cases} x(k+1) = \begin{bmatrix} 1 & T_s & -\frac{1}{2}T_s^2 \\ 0 & 1 & -T_s \\ 0 & 0 & 1 - \frac{T_s}{\tau} \end{bmatrix} x(k) + \begin{bmatrix} 0 \\ 0 \\ \frac{T_s}{\tau} \end{bmatrix} u(k) \\ y = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} x(k) + \begin{bmatrix} -d_{default} \\ 0 \\ 0 \end{bmatrix} \end{cases} \quad (13)$$

where $x = [\Delta d, v, a]^T$ is the state vector of the system.

Despite these linear equations, ACC deals with the strongly nonlinear powertrain system, for which equations will come later. The control objective for the ego vehicle is to maintain its speed close to the lead vehicle while their relative distance is safe, i.e., $\Delta d \rightarrow 0$ and $v(k) \rightarrow 0$ as k reaches to infinity. To achieve this objective, an adaptive model predictive control (AMPC) is used. Acceleration of the ego vehicle should be adaptively changed in order to regulate Δd . The acceleration command is calculated by solving the following constrained optimization problem during each sampling period.

$$\min_u J = \sum_{k=1}^p \{z_{t+k}^T Q_t z_{t+k} + \Delta u_{t+k}^T R_t^{\Delta u} \Delta u_{t+k} + u_{t+k}^T R_t^u u_{t+k}\} \quad (14)$$

$$\text{s.t.} \begin{cases} \Delta d \geq 0 \\ v_{\min} \leq v_e(k) \leq v_{\max} \\ a_{\min} \leq a(k) \leq a_{\max} \\ u_{\min} \leq u(k) \leq u_{\max} \end{cases} \quad (15)$$

where t is the current time, p is the prediction horizon and Δu is the increment of the control input. Q_t , $R_t^{\Delta u}$, and R_t^u refer to the weight matrices for the following error, change rate and magnitude of the control input, respectively.

As a normal ACC, the MPC control objective should be distance control, i.e., $z = \Delta d$ in Equation (15). However, we will show in simulations that the performance of such a controller is poor when the ego vehicle falls behind for any reason. To solve this issue, an AMPC is considered in which the control objective is adaptively changed based on the distance Δd between ego and lead vehicles. When Δd is large, i.e., the ego vehicle is far behind the lead one, AMPC switches to speed control system. Therefore, $z = v$ in the optimization problem (15) which results in accelerating the ego vehicle to fill its gap with the lead. However, when Δd becomes reasonably close to $d_{default}$, the control system switches to distance control and $z = \Delta d$. In this case, the ego vehicle follows the driving profile of the lead by increasing and decreasing longitudinal acceleration such that $\Delta d \rightarrow 0$. It is worth noting that if the relative speed between the lead and the ego vehicle is not precisely measurable, the controller goes to the distance control mode to preserve safety.

This adaptive behavior makes the control algorithm robust against undesired disturbances. For example, if the ego vehicle fails in achieving $\Delta d \rightarrow 0$ for any reason, such as sudden action of the lead driver or loss of sensor signals, it will be easily compensated by switching to the speed control mode for a while.

3.2. Energy Management System

In this work, an EMS is integrated with ACC to reduce fuel consumption while the vehicle performance is kept satisfactory. The EMS system has two main components: A fuzzy logic system (FLS) and a PID controller. FLS is employed to generate the optimal torque by considering the required power for the vehicle. A PID controller is exploited to govern the engine to follow the optimal torque created by FLS.

3.2.1. Fuzzy Logic System

The FLS uses the required power of the vehicle as input and generates the optimal torque for the engine. To calculate the required power, described in Equation (6), all data about the behavior of the driver (e.g., the speed of the vehicle using data fusion), environmental conditions and vehicle specification are collected and passed through the energy calculation unit (ECU) in Figure 4.

The environmental conditions, such as road and wind profiles, vary during the driving process. Road profiles are generated with statistical characteristics of real roads using the method presented in [48]. A Poisson distribution is used to create the number of road segments. The length of each road segment is obtained by using an exponential distribution. Rayleigh distribution is employed to model the height of up and down hills of the road. The left and the right bend of the road are acquired using Gaussian distribution. A wind profile is also obtained from the model in [48]. It is a collection of regions of different lengths, the speed of the wind and its direction. The length, wind speed and direction are modelled using the exponential, Weibull and uniform distributions, respectively. All the parameters used to calculate the required power of the vehicle are shown in Table 1.

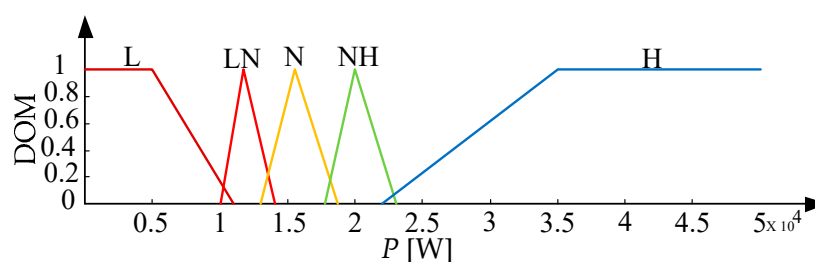
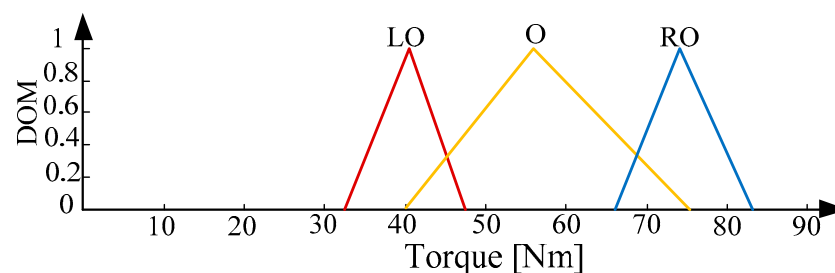
Table 1. Inputs used to calculate the required power of the vehicle.

Description	Symbol	Value
Coefficient of road friction	μ_r	0.015
Gravity acceleration	g	9.81 [m/s ²]
Velocity of the vehicle	v	ACC command
Mass (vehicle + equivalent rotating parts + passengers)	m	1280 [kg]
Aerodynamic resistance coefficient	c_a	0.335
A cross-sectional area	A	$1.9 * 1 / \cos(\phi)$
Air density	ρ	1.225 [kg/m ³]
Combustion energy	$q_{combustion}$	38,017 [kJ/kg]

After achieving the required power of the vehicle, FLS is used to produce the desired engine torque. FLS is considered a reasoning method which resembles human reasoning. FLS is designed based on two methods: T1FLS and IT2FLS.

Part I. Type 1 Fuzzy Logic System

The membership functions of T1FLS are designed based on our previous work [34]. Five membership functions for the input (the required power of the vehicle) are formulated, including L, LN, N, NH, H (Figure 5). The membership function of the output (the engine torque) is split into three groups: LO, O, RO (Figure 6). Fuzzy rules are constructed so that the engine state is regulated to operate on its optimal area to elevate energy efficiency. These rules cover five different conditions and are shown in Table 2. In summary, if the required power is in L or H range of Figure 5, the T1FLS generates LO and RO signals related to low and high torque values, respectively. Otherwise, it generates an O signal.

**Figure 5.** T1FLS membership functions for the input, the required power of the vehicle.**Figure 6.** T1FLS membership function of the output, the engine torque.**Table 2.** Fuzzy logic system rules.

Condition Number	If Required Power	Then Engine Torque
1	L	LO
2	LN	O
3	N	O
4	NH	O
5	H	RO

Part II. Interval Type 2 Fuzzy Logic System

The IT2FLS is a new algorithm that accommodates unique characteristics to overcome the limitations of T1FLS in coping with the uncertainties. An IT2FLS is represented in Figure 7, including five components: fuzzifier, rule-based, fuzzy inference, type-reducer and defuzzifier.

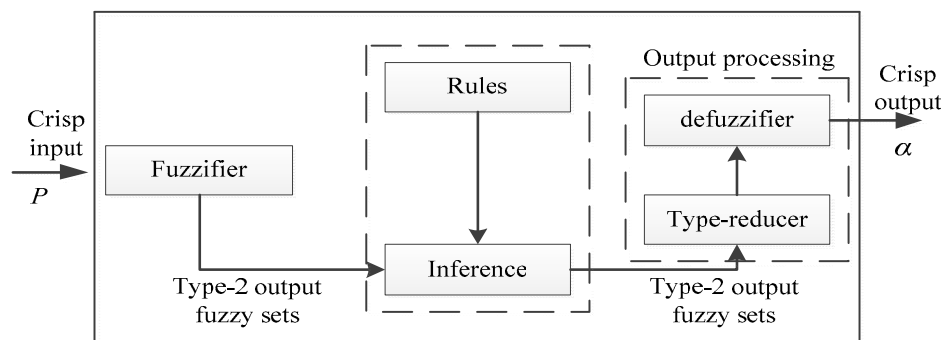


Figure 7. Block diagram of a type 2 fuzzy logic system.

The notable discrepancies between IT2FLS and the type 1 counterpart are that interval type 2 fuzzy sets are exploited and used in IT2FLS. Therefore, the IT2FLS has an extra process that is known as the type reduction [37,49,50]. An interval type 2 set ($\tilde{A}$) is determined with a type 2 membership function $\mu_{\tilde{A}}(x, u)$ as below.

$$\tilde{A} = \int_{x \in D_{\tilde{A}}} \int_{u \in J_x} \frac{\mu_{\tilde{A}}(x, u)}{(x, u)} \quad (16)$$

where J_x is the primary membership of x , while $\mu_{\tilde{A}}(x, u)$ is a type 1 fuzzy set known as the secondary set [37,49,50].

$$\mu_{\tilde{A}}(x = x', u) \equiv \mu_{\tilde{A}}(x') = \int_{u \in J_{x'}} \frac{f_{x'}(u)}{u} \quad (17)$$

$$0 \leq f_{x'}(u) \leq 1 \quad (18)$$

A region called footprint of uncertainty (FOU) is formulated to evaluate the uncertainty in the primary membership of an interval type 2 fuzzy set $\tilde{A}$, as depicted in Figure 8. It can be defined as follows.

$$\text{FOU}(\tilde{A}) = \bigcup_{x \in X} J_x = \{(x, u) | u \in J_x \subseteq [0, 1]\} \quad (19)$$

where J_x presents the primary membership of $\tilde{A}$.

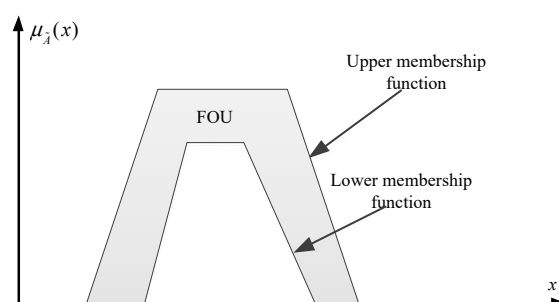


Figure 8. The FOU (shaded area), UMF and LMF of IT2FLS.

An upper membership function (UMF) and a lower membership function (LMF) are also introduced to represent the FOU. They can be represented as below.

$$\underline{\mu}_{\tilde{A}}(x) = \text{LMF}(\tilde{A}) = \inf\{u \mid u \in [0, 1], \mu_{\tilde{A}}(x, u) > 0\} \quad (20)$$

$$\bar{\mu}_{\tilde{A}}(x) = \text{UMF}(\tilde{A}) = \sup\{u \mid u \in [0, 1], \mu_{\tilde{A}}(x, u) > 0\} \quad (21)$$

The uncertainty of driving conditions is handled by the antecedents and consequents interval type 2 fuzzy sets, which utilize FOUs to cover the linguistic and numerical uncertainties associated with changing unstructured environments. The interval type 2 fuzzy sets compound a huge amount of embedded type 1 fuzzy sets to solve the various uncertainties as well [51].

In this study, the fuzzy MF in T1FLS is exploited as initial values to build the FOU of the fuzzy MF of IT2FLS. In interval type 2 MFs, the FOU is achieved by defining the bounding upper and lower type 1 MFs [49,52]. The resulting MFs for IT2FLS are illustrated in Figure 9. The set of rules shown in Table 2 are also used for this case.

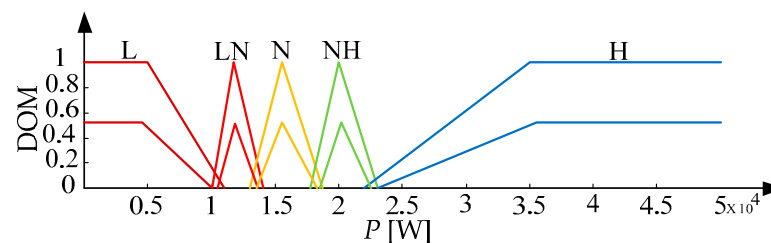


Figure 9. IT2FLS membership functions for the input, the required power of the vehicle.

3.2.2. PID Controller

A PID controller is used to control the operation of the engine to track the torque generated by the FLS. The PID controller regulates the engine operation by adjusting the air to fuel (A/F) ratio into the cylinder of the engine. The error between the generated torque and actual torque is considered as the input of the PID controller. The output of the PID controller is a function of the A/F ratio, which affects the engine actual torque directly.

The actual torque, provided by the internal combustion engine, can be derived using the power train model explained in [45].

$$\tau = \frac{C_T \cdot AFI(\lambda) \cdot SPI(\delta) \cdot V_{disp} \cdot P_m \cdot \eta_{vol}}{4\pi \cdot R \cdot T} \quad (22)$$

where C_T is the torque constant, $AFI(\lambda)$ depicts a function of air to fuel ratio, $SPI(\delta)$ represents the ignition time, V_{disp} shows the engine volumetric displacement, η_{vol} is the engine volumetric efficiency, P_m illustrates the manifold pressure. $AFI(\lambda)$ can be adopted as follows [45]:

$$AFI(\lambda) = \cos(7.3834(A/F) - 13.5) \quad (23)$$

where A/F is the air to fuel ratio.

The desired torque is achieved by adjusting the air mass entering the cylinder of the engine to have an appropriate A/F ratio. The A/F ratio is managed using the proportional, integral and derivative actions in PID controller. PID regulator is described as follows.

$$u(t) = k_p e(t) + k_I \int e(t) dt + k_D \frac{de(t)}{dt} \quad (24)$$

where k_p , k_D and k_I are proportional, derivative and integral parameters, respectively. These parameters are tuned manually in MATLAB Simulink to provide the best results, i.e., the error between the generated torque by the FLS and the actual torque after the PID controller converges to zero.

4. Simulations and Discussion

4.1. Simulations

In this section, for the ego vehicle, we compare the performance of three different alternatives for the control structure, mentioned in Table 3. The powertrain model which has been introduced in [45], is summarized by Equations (23) and (24). This model is used during all scenarios in these simulations. It assumes a continuously variable transmission (CVT) system as an automatic transmission that can change seamlessly through a continuous range of gear ratios.

Table 3. Structures of the control system compared in this paper.

	ACC	EMS
Alternative 1	AMPC	-
Alternative 2	AMPC	T1FLS
Alternative 3	AMPC	T2FLS

Alternative 1: For this structure, the EMS block in the model of Figure 4 is bypassed. The ego vehicle follows the lead vehicle for a period of 766 s, equal to 16.5 km of travel distance using an ACC. Through this journey, the lead vehicle follows a standard driving cycle (HWFET). The ego vehicle, equipped with ACC based on AMPC, travels with the initial velocity of 0 m/s. The relative distance between the two vehicles at the beginning is 200 m. In the simulation, the controller's sampling time is 0.1 s, the constant time headway is 1.4 s, the prediction horizon $p = 30$ and the standstill default spacing is 10 m. MATLAB Simulink and model predictive control toolbox [53] are used in the simulations. The required power of the ego vehicle is produced by the energy calculation unit.

Alternative 2: This simulation is conducted under the same conditions as the Alternative 1. However, the EMS block is activated and works based on the T1FLS, which is introduced in Section 3.2.1 Part I.

Alternative 3: This simulation is conducted under the same conditions as the Alternative 1. However, an EMS based on IT2FLS is considered. This allows to evaluate the controller's performance in handling enormous uncertainties of driving conditions, especially in the vehicle-following process. The IT2FLS MATLAB/Simulink toolbox designed by [54] is applied to execute the third simulation.

4.2. Discussion

4.2.1. Safety

Figures 10 and 11 compare the performance of our proposed AMPC with the conventional MPC which focuses only on the distance control, i.e., $z = v$ in Equation (15). Figure 10 shows how switching between speed and distance control mode happens based on Δd . When $\Delta d > 0$, i.e., when the distance between the lead and ego cars is larger than the safe threshold, the controller switches to speed control to compensate for the gap between vehicles. However, it activates the distance control mode when $\Delta d < 0$, i.e., when the distance between vehicles is not safe. In Figure 11, it is assumed that the ego car starts falling behind the lead vehicle at $T = 200$ s. It can be seen in Figure 11a that the normal MPC algorithm fails to bring the distance between two vehicles in an acceptable region. It means that, using this control technique, the gap between cars cannot be compensated if Δd becomes too large for any reason. However, our proposed AMPC successfully controls the distance and keeps it in a safe range (Figure 11b). In addition, our study shows that the normal MPC consumes about 0.2 L/100 km more fuel than the proposed AMPC in this maneuver. In other words, the AMPC works more robustly against any uncertainties which results in increasing Δd . Figure 11b also shows a smooth variation of the spacing Δd during the whole scenario which means that excessive high braking and accelerating are avoided. Consequently, not only the risk of crashes is reduced, but also the comfort of driving is improved significantly.

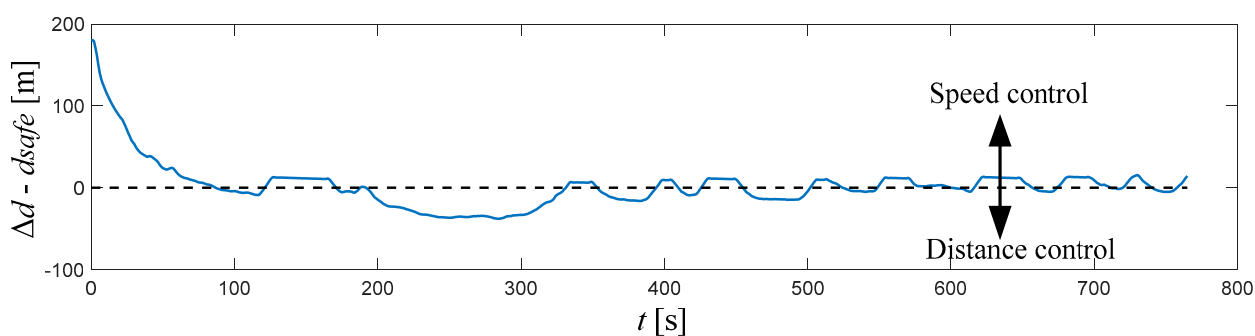


Figure 10. Switching between speed and distance control systems.

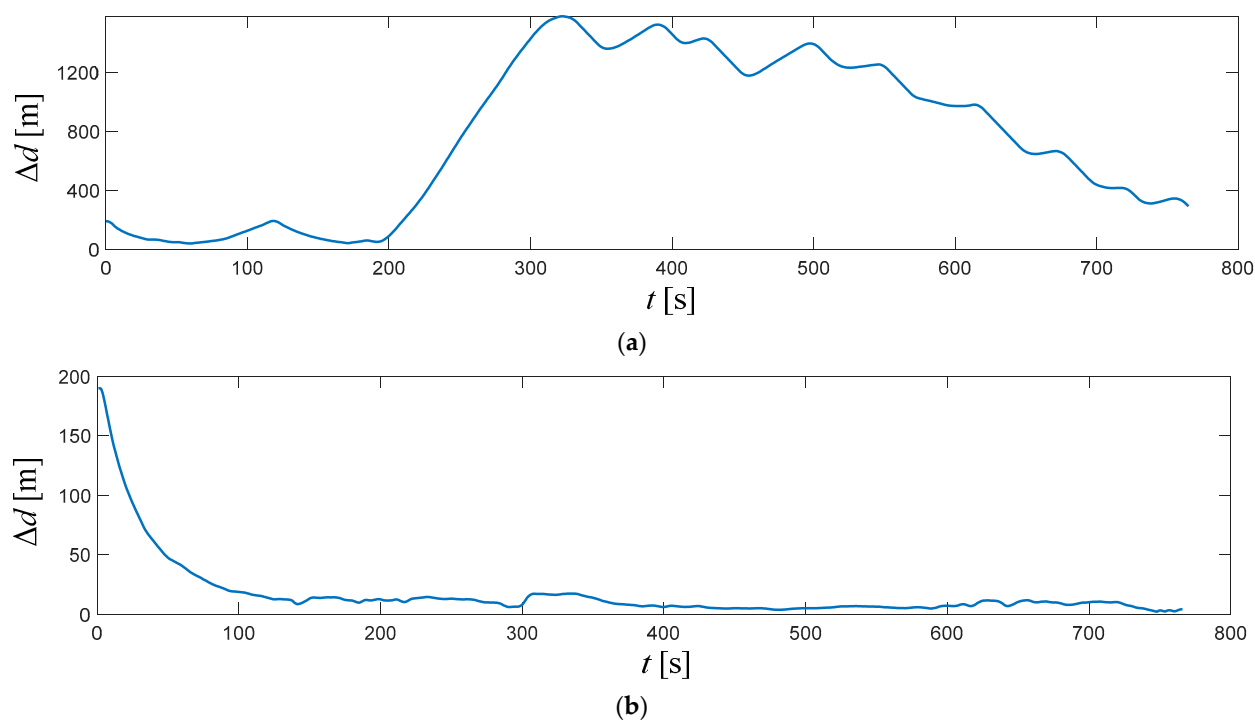


Figure 11. Distance variation between ego and lead cars in the presence of (a) MPC for distance control only and (b) the AMPC.

4.2.2. Fuel Economy

In this section, performances of three alternatives for the ACC+EMS control structure, introduced in Table 3, are compared. Results of comparing A/F ratio, revolutions per minute, torque of the engine, fuel efficiency and fuel consumption rate in these three control structures are compared in Figures 12–16, respectively.

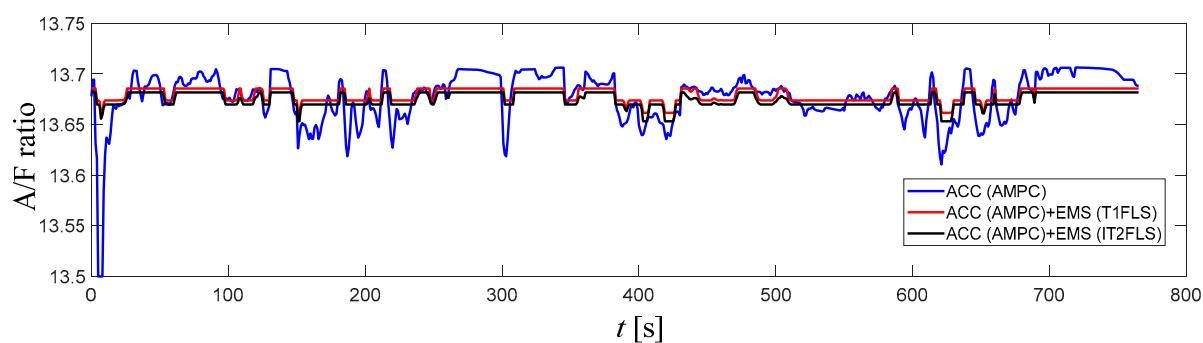


Figure 12. The A/F ration of the engine.

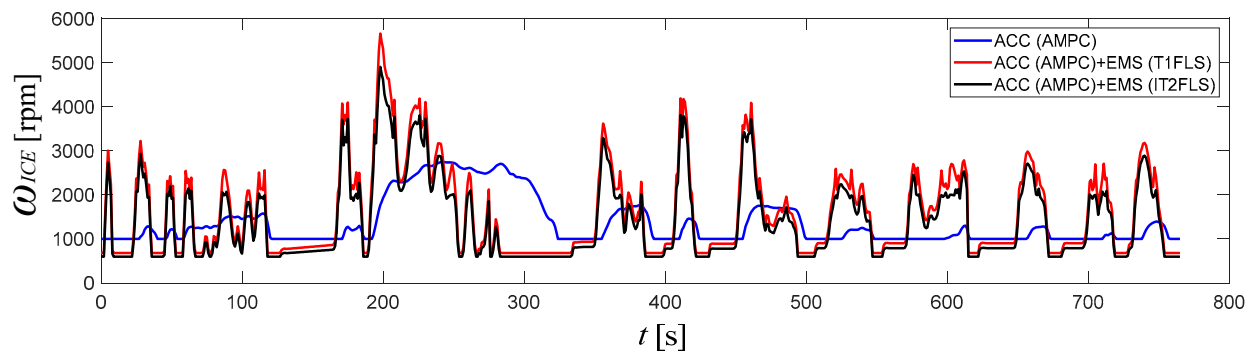


Figure 13. The revolutions per minute of the engine.

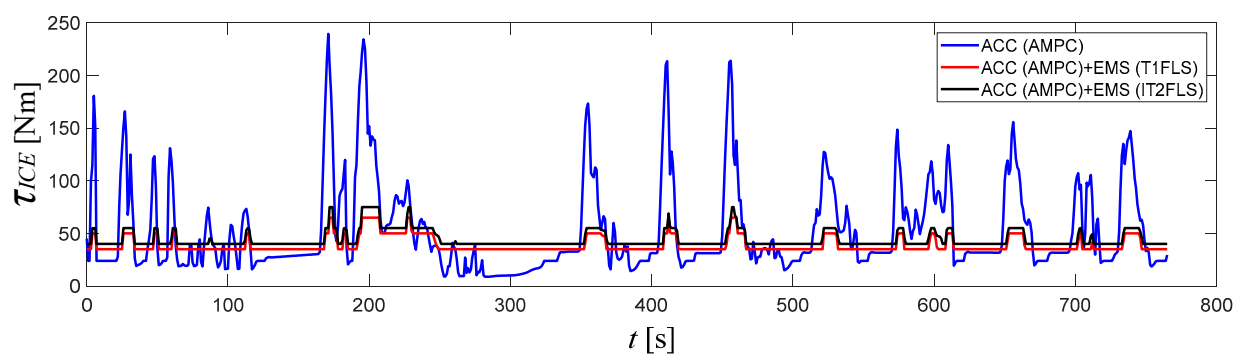


Figure 14. The torque of the engine.

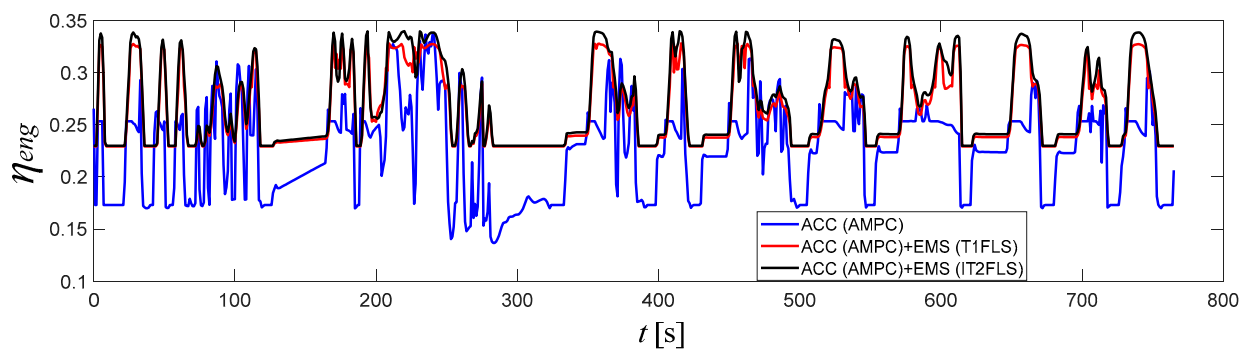


Figure 15. The efficiency of the engine.

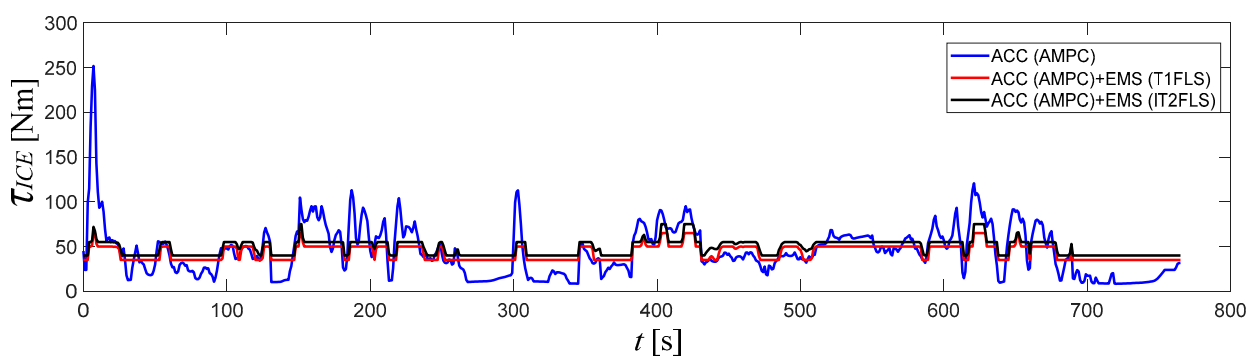


Figure 16. The fuel consumption rate of the engine.

Alternative 1: In this case, the engine operates in a region that has low energy efficiency as the engine torque is elevated and the RPM is low (compare blue lines in

Figures 13 and 14). The average proficiency of the engine in this control structure is 25.31%. Therefore, the fuel usage of the vehicle can be estimated as 7.21 L/100 km.

Alternative 2: In this simulation, the EMS based on T1FLS is applied to save the fuel consumed by the ego vehicle. Figure 14 shows that with the proposed system, the engine is regulated to produce a torque within the range of 35–65 [Nm]. In this case, a suboptimal range of engine torque is considered, referring to Figure 3. Thus, the efficiency of the engine increases to 29% on average (see Figure 15). Consequently, the vehicle consumes 6.88 L/100 km which is less than Alternative 1.

Alternative 3: In this structure, the engine is controlled to supply the torque and the speed within ranges 40–75 [Nm] and 1000–3800 [rpm], respectively, based on Figures 13 and 14. Therefore, the working area of the engine shifts to a more optimal regime, referring to Figure 3. The engine efficiency is escalated to 29.78% on average (see Figure 15), which is the result of a reduction in fuel consumption to 6.68 L/100 km.

These results are also compared with the adaptive cruise control look ahead (ACC(LA)) system [13] in Table 4. The ACC(LA) was designed based on the adaptive neuro-fuzzy inference system. The system calculated the fuel usage of the vehicle under combined dynamic loads as well. A look-ahead approach was involved in the model to anticipate the slope of the road in the future.

Table 4. Fuel consumption of different ACC system.

Model	Average Efficiency	m_{fuel} (L/100 km)
ACC (LA)	-	7.95
ACC (AMPC)	25.31%	7.21
ACC (AMPC) + EMS (T1FLS)	29.00%	6.88
ACC (AMPC) + EMS (T2FLS)	29.78%	6.68

A comparison of these three alternatives shows that the combination of AMPC as ACC and T2FLS as EMS provide the best engine performance for the vehicles and results in less fuel consumption. It also inherits robustness of MPC, which is a crucial requirement in the uncertain environment of AVs. We see an example of this robustness in Figure 11 when uncertainty in Δd happens.

5. Conclusions

Unlike previous research activities which were mainly focused on the autonomous cruise control (ACC) – also known as adaptive cruise control or intelligent cruise control of autonomous vehicles (AVs), this paper considered the joint ACC-energy management systems (EMS) problem to address both safety and energy management simultaneously, thus providing a sustainable solution for AVs. We proposed integrated adaptive model predictive control (AMPC) and interval type 2 fuzzy logic systems (IT2FLS)-based EMS for improving energy efficiency in conventional vehicles in a vehicle-following scenario while a safe driving condition is achieved. To this end, we utilized a cascade control structure with an ACC on the outer loop and an EMS on the inner one. An AMPC approach was used to design ACC in which the control objective was appropriately switched between speed and distance. This resulted in compensation for the gap between vehicles in a reasonable amount of time if the ego vehicle fell behind for any reason. The AMPC is accompanied by an IT2FLS-based EMS, which was originally proposed to manage model uncertainties. The control system was conducted in a MATLAB/Simulink environment to empirically test the performance in a lead-ego vehicle-following scenario. Simulation results for an HWFET drive cycle showed safe driving in a vehicle-following process in all scenarios. Meanwhile, the fuel consumption per hundred kilometres for the ego vehicle was improved by 13.45% using the T1FLS-based system and by 15.97% using an IT2FLS EMS. That means by applying advanced EMS algorithms, robust against nonlinearities of the energy efficiency problem, and combining them with advanced ACC, can result in a significant energy saving and emission reduction toward a sustainable circular economy.

Moreover, the AMPC+IT2FLS method assists AVs to make a smarter use of energy and support a safer transportation.

Author Contributions: Conceptualization, Ideas, Methodology, Management, Conducting, D.P. and H.K.; Software and Development and Data Curation, A.M.A., M.M., A.A.R., M.F., M.J. and R.L. Conducting a research and Investigation process supervision D.B.P.; Project administration H.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. *The Sustainable Development Goals Report*; United Nations: New York, NY, USA, 2019.
2. *Tracking Transport 2020*; International Energy Agency: Paris, France, 2020.
3. Khayyam, H.; Naebe, M.; Milani, A.S.; Fakhrhoseini, S.M.; Date, A.; Shabani, B.; Atkiss, S.; Ramakrishna, S.; Fox, B.; Jazar, R.N. Improving energy efficiency of carbon fiber manufacturing through waste heat recovery: A circular economy approach with machine learning. *Energy* **2021**, *225*, 120113. [\[CrossRef\]](#)
4. Cugurullo, F.; Acheampong, R.A.; Gueriau, M.; Dusparic, I. The transition to autonomous cars, the redesign of cities and the future of urban sustainability. *Urban Geogr.* **2020**, 1–27. [\[CrossRef\]](#)
5. Acheampong, R.A.; Cugurullo, F.; Gueriau, M.; Dusparic, I. Can autonomous vehicles enable sustainable mobility in future cities? Insights and policy challenges from user preferences over different urban transport options. *Cities* **2021**, *112*, 103134. [\[CrossRef\]](#)
6. Xie, J.; Xu, X.; Wang, F.; Tang, Z.; Chen, L. Coordinated control based path following of distributed drive autonomous electric vehicles with yaw-moment control. *Control. Eng. Pract.* **2021**, *106*, 104659. [\[CrossRef\]](#)
7. Khayyam, H.; Javadi, B.; Jalili, M.; Jazar, R.N. Artificial Intelligence and Internet of Things for Autonomous Vehicles. In *Nonlinear Approaches in Engineering Applications*; Springer: Basingstoke, UK, 2020; pp. 39–68. [\[CrossRef\]](#)
8. Marzbani, H.; Khayyam, H.; To, C.N.; Quoc, D.V.; Jazar, R.N. Autonomous Vehicles: Autodriver Algorithm and Vehicle Dynamics. *IEEE Trans. Veh. Technol.* **2019**, *68*, 3201–3211. [\[CrossRef\]](#)
9. Lancot, R. Accelerating the future: The economic impact of the emerging passenger economy. *Strategy Anal.* **2017**, *5*.
10. Noh, S. Decision-Making Framework for Autonomous Driving at Road Intersections: Safeguarding Against Collision, Overly Conservative Behavior, and Violation Vehicles. *IEEE Trans. Ind. Electron.* **2018**, *66*, 3275–3286. [\[CrossRef\]](#)
11. Duraisamy, B.; Schwarz, T.; Wöhler, C. Track level fusion algorithms for automotive safety applications. In Proceedings of the 2013 International Conference on Signal Processing, Image Processing & Pattern Recognition, Innsbruck, Australia, 12–14 February 2013; pp. 179–184.
12. Milanes, V.; Villagra, J.; Godoy, J.; Gonzalez, C. Comparing Fuzzy and Intelligent PI Controllers in Stop-and-Go Manoeuvres. *IEEE Trans. Control. Syst. Technol.* **2011**, *20*, 770–778. [\[CrossRef\]](#)
13. Khayyam, H.; Nahavandi, S.; Davis, S. Adaptive cruise control look-ahead system for energy management of vehicles. *Expert Syst. Appl.* **2012**, *39*, 3874–3885. [\[CrossRef\]](#)
14. Liang, Z.; Ren, Z.; Shao, X. Decoupling trajectory tracking for gliding reentry vehicles. *IEEE/CAA J. Autom. Sin.* **2015**, *2*, 115–120. [\[CrossRef\]](#)
15. Lin, C.-M.; Chen, C.-H. Car-Following Control Using Recurrent Cerebellar Model Articulation Controller. *IEEE Trans. Veh. Technol.* **2007**, *56*, 3660–3673. [\[CrossRef\]](#)
16. Bageshwar, V.; Garrard, W.; Rajamani, R. Model Predictive Control of Transitional Maneuvers for Adaptive Cruise Control Vehicles. *IEEE Trans. Veh. Technol.* **2004**, *53*, 1573–1585. [\[CrossRef\]](#)
17. Magdici, S.; Althoff, M. Adaptive Cruise Control with Safety Guarantees for Autonomous Vehicles. *IFAC-PapersOnLine* **2017**, *50*, 5774–5781. [\[CrossRef\]](#)
18. Takahama, T.; Akasaka, D. Model Predictive Control Approach to Design Practical Adaptive Cruise Control for Traffic Jam. *Int. J. Automot. Eng.* **2018**, *9*, 99–104. [\[CrossRef\]](#)
19. Mahdini, I.; Arvin, R.; Khatkhat, A.J.; Ghiasi, A. Safety, Energy, and Emissions Impacts of Adaptive Cruise Control and Cooperative Adaptive Cruise Control. *Transp. Res. Rec. J. Transp. Res. Board* **2020**, *2674*, 253–267. [\[CrossRef\]](#)
20. Shladover, S.E.; Nowakowski, C.; Lu, X.-Y.; Ferlis, R. Cooperative adaptive cruise control: Definitions and operating concepts. *Transp. Res. Record* **2015**, *2489*, 145–152. [\[CrossRef\]](#)
21. Kural, E.; Güvenç, B.A. Model Predictive Adaptive Cruise Control. In Proceedings of the 2010 IEEE International Conference on Systems, Man and Cybernetics, Cordoba, Spain, 1–4 June 2010; pp. 1455–1461.
22. De Madrid, A.P.; Mañoso, C.; Romero, M. Fundamentals of the MPC approach to stop-and-go Adaptive Cruise Control. In Proceedings of the 2014 13th International Conference on Control Automation Robotics & Vision (ICARCV), Singapore, Singapore, 10–12 December 2014; pp. 175–180.

23. Weißmann, A.; Görges, D.; Lin, X. Energy-Optimal Adaptive Cruise Control based on Model Predictive Control. *IFAC-PapersOnLine* **2017**, *50*, 12563–12568. [\[CrossRef\]](#)
24. Miftakhudin, M.I.; Subiantoro, A.; Yusivar, F. Adaptive Cruise Control by Considering Control Decision as Multistage MPC Constraints. In Proceedings of the 2019 IEEE Conference on Energy Conversion (CENCON), Yogyakarta, Indonesia, 16–17 December 2019; pp. 171–176.
25. Bujarbaruah, M.; Zhang, X.; Borrelli, F. Adaptive MPC for Autonomous Lane Keeping. In Proceedings of the 14th International Symposium on Advanced Vehicle Control (AVEC), Beijing, China, 16–20 July 2018.
26. Wang, X.; Guo, L.; Jia, Y. Road Condition Based Adaptive Model Predictive Control for Autonomous Vehicles. In Proceedings of the Dynamic Systems and Control Conference (DSCC), Atlanta, GA, USA, 30 September–3 October 2018.
27. Khayyam, H. *Automation, Control and Energy Efficiency in Complex Systems*; MDPI Books: Belgrade, Switzerland, 2020; p. 245.
28. Koot, M.; Kessels, J.J.; De Jager, A.B.; Bosch, P.P.V.D. Fuel reduction potential of energy management for vehicular electric power systems. *Int. J. Altern. Propuls.* **2006**, *1*, 112. [\[CrossRef\]](#)
29. Khayyam, H.; Kouzani, A.Z.; Khoshmanesh, K.; Hu, E.J. A.Z.; Khoshmanesh, K.; Hu, E.J. A rule-based intelligent energy management system for an internal combustion engine vehicle. In *TENCON 2008-2008 IEEE Region 10 Conference*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2008; pp. 1–5.
30. Khayyam, H.; Kouzani, A.Z.; Hu, E.J.; Nahavandi, S. Coordinated energy management of vehicle air conditioning system. *Appl. Therm. Eng.* **2011**, *31*, 750–764. [\[CrossRef\]](#)
31. Phan, D.; Bab-Hadiashar, A.; Lai, C.Y.; Crawford, B.; Hoseinnezhad, R.; Jazar, R.N.; Khayyam, H. Intelligent energy management system for conventional autonomous vehicles. *Energy* **2020**, *191*, 116476. [\[CrossRef\]](#)
32. Won, J.-S.; Langari, R. Intelligent Energy Management Agent for a Parallel Hybrid Vehicle—Part II: Torque Distribution, Charge Sustainance Strategies, and Performance Results. *IEEE Trans. Veh. Technol.* **2005**, *54*, 935–953. [\[CrossRef\]](#)
33. Khayyam, H.; Nahavandi, S.; Hu, E.; Kouzani, A.; Chonka, A.; Abawajy, J.; Marano, V.; Davis, S. Intelligent energy management control of vehicle air conditioning via look-ahead system. *Appl. Therm. Eng.* **2011**, *31*, 3147–3160. [\[CrossRef\]](#)
34. Marano, V.; Rizzoni, G.; Tulpule, P.; Gong, Q.; Khayyam, H. Intelligent energy management for plug-in hybrid electric vehicles: The role of ITS infrastructure in vehicle electrification. *Oil Gas Sci. Technol. Rev. d'IFP Energies Nouv.* **2012**, *67*, 575–587. [\[CrossRef\]](#)
35. Phan, D.; Bab-Hadiashar, A.; Hoseinnezhad, R.; Jazar, R.N.; Date, A.; Jamali, A.; Pham, D.B.; Khayyam, H. Neuro-Fuzzy System for Energy Management of Conventional Autonomous Vehicles. *Energies* **2020**, *13*, 1745. [\[CrossRef\]](#)
36. Naranjo, J.E.; Sotelo, M.A.; Gonzalez, C.; Garcia, R.; De Pedro, T. Using Fuzzy Logic in Automated Vehicle Control. *IEEE Intell. Syst.* **2007**, *22*, 36–45. [\[CrossRef\]](#)
37. Tan, W.W.; Chua, T.W. Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions. *IEEE Comput. Intell. Mag.* **2007**, *2*, 72–73. [\[CrossRef\]](#)
38. John, R. Type 2 Fuzzy Sets: An Appraisal of Theory and Applications. *Int. J. Uncertain. Fuzziness Knowl. Based Syst.* **1998**, *6*, 563–576. [\[CrossRef\]](#)
39. Bi, Y.; Lu, X.; Sun, Z.; Srinivasan, D.; Sun, Z. Optimal Type-2 Fuzzy System for Arterial Traffic Signal Control. *IEEE Trans. Intell. Transp. Syst.* **2017**, *19*, 3009–3027. [\[CrossRef\]](#)
40. Vaezipour, A.; Rakotonirainy, A.; Haworth, N. Reviewing In-vehicle Systems to Improve Fuel Efficiency and Road Safety. *Procedia Manuf.* **2015**, *3*, 3192–3199. [\[CrossRef\]](#)
41. Khooban, M.-H.; Gheisarnejad, M.; Vafamand, N.; Boudjadar, J. Electric Vehicle Power Propulsion System Control Based on Time-Varying Fractional Calculus: Implementation and Experimental Results. *IEEE Trans. Intell. Veh.* **2019**, *4*, 255–264. [\[CrossRef\]](#)
42. Phan, D.; Bab-Hadiashar, A.; Fayyazi, M.; Hoseinnezhad, R.; Jazar, R.N.; Khayyam, H. Interval Type 2 Fuzzy Logic Control for Energy Management of Hybrid Electric Autonomous Vehicles. *IEEE Trans. Intell. Veh.* **2021**, *6*, 210–220. [\[CrossRef\]](#)
43. Khayyam, H. Adaptive intelligent control of vehicle air conditioning system. *Appl. Therm. Eng.* **2013**, *51*, 1154–1161. [\[CrossRef\]](#)
44. A Lambert, M.; Jones, B.J. Automotive Adsorption Air Conditioner Powered by Exhaust Heat. Part 1: Conceptual and Embodiment Design. *Proc. Inst. Mech. Eng. Part D* **2006**, *220*, 959–972. [\[CrossRef\]](#)
45. Cho, D.-I.; Hedrick, J.K. Automotive Powertrain Modeling for Control. *J. Dyn. Syst. Meas. Control.* **1989**, *111*, 568–576. [\[CrossRef\]](#)
46. Michael, P.; Anthony, M. *Engine Testing Theory and Practice*; SAE International: Warrendale, PA, USA, 1999.
47. Rajamani, R.; Zhu, C. Semi-autonomous adaptive cruise control systems. *IEEE Trans. Veh. Technol.* **2002**, *51*, 1186–1192. [\[CrossRef\]](#)
48. Khayyam, H. Stochastic Models of Road Geometry and Wind Condition for Vehicle Energy Management and Control. *IEEE Trans. Veh. Technol.* **2012**, *62*, 61–68. [\[CrossRef\]](#)
49. Liang, Q.; Mendel, J.M. Interval type-2 fuzzy logic systems: theory and design. *IEEE Trans. Fuzzy Syst.* **2000**, *8*, 535–550. [\[CrossRef\]](#)
50. Mendel, J.M.; Liu, X. Simplified Interval Type-2 Fuzzy Logic Systems. *IEEE Trans. Fuzzy Syst.* **2013**, *21*, 1056–1069. [\[CrossRef\]](#)
51. Karnik, N.N.; Mendel, J.M.; Liang, Q. Type-2 Fuzzy Logic Systems. *IEEE Trans. Fuzzy Syst.* **1999**, *7*, 643–658. [\[CrossRef\]](#)
52. Mendel, J.; Karnik, N.; Liang, Q. Connection admission control in ATM networks using survey-based type-2 fuzzy logic systems. *IEEE Trans. Syst. Man Cybern. Part C* **2000**, *30*, 329–339. [\[CrossRef\]](#)

-
53. Bemporad, A.; Morari, M.; Ricker, N.L. *Model Predictive Control Toolbox User's Guide*; The Mathworks: Portola Valley, CA, USA, 2010.
 54. Taskin, A.; Kumbasar, T. An open source Matlab/Simulink toolbox for interval type-2 fuzzy logic systems. In Proceedings of the 2015 IEEE Symposium Series on Computational Intelligence, Cape Town, South Africa, 8–10 December 2015; pp. 1561–1568.