Cooperative Adaptive Cruise Control: A Gated Recurrent Unit Approach

# Cooperative Adaptive Cruise Control: A Gated Recurrent Unit Approach

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***Abstract*- Embedded artificial intelligence solutions are promising controllers for future sustainable and automated road vehicles. This study presents a deep learning-based approach combined with vehicle communication technology for the design of a real-time cooperative adaptive cruise control (CACC). A particular type of recurrent neural network has been selected, namely a gated recurrent unit (GRU). GRU exhibits improved learning performance in control problems such as the CACC since it avoids the vanishing gradient problems that characterize long time series. A GRU has been trained using ad-hoc CACC datasets build-up according to an optimal control policy, i.e. dynamic programming (DP), for a battery electric vehicle. In particular, DP optimizes the longitudinal speed trajectory of the Ego (Following) vehicle in CACC so to achieve energy savings and passenger comfort improvement. Results demonstrate that the Ego vehicle controlled by the trained GRU can achieve an eco-friendly driving in CACC without compromising passenger comfort and safety requirements. Unlike DP, GRU holds strong real-time potential. The performance of the proposed GRU approach for CACC is verified by benchmarking with the optimal performance obtained off-line using DP in several driving missions.**

## I. INTRODUCTION

To achieve the so-called sustainable mobility, governments established a series of objectives to be achieved in the short term, with environmental implications as well as improvements in terms of transport efficiency. One example is the introduction at a regulatory level in newly homologated vehicles of advanced driving assistance systems (ADASs), specifically designed to support the driver by ensuring safer, more efficient, and more ecological driving. Adaptive cruise control (ACC), lane keeping (LK), and emergency brake assist are some basic examples. Although some of these are by now consolidated features, the growing possibilities dictated by vehicle-to-everything connectivity have led to redefine their characteristics, paving the way for an interconnected mobility. The potential benefits deriving from ADAS technologies are manifold [1]. Improvements in energy consumption, in passenger safety and comfort along with reduced travel times are among the mainly demonstrated in the literature [2], [3]. The cooperative adaptive cruise control (CACC) often connected to the concept of eco-driving, allows for adapting the driving trajectory using the information received from other vehicles or from the infrastructure. To this end, several technologies can be used. Vehicle communication technologies such as vehicle-to-everything (V2X) or on-board sensors (RADAR, LiDAR etc) are some examples. They supply time series data information that can be used to consequently adjust the vehicle longitudinal trajectory. However, managing the powertrain according to the condition of the vehicle as well as the activity of the external environment is a complex task. Recent studies have shown the increasing real-time potential of artificial intelligence techniques [4], [5]. Therefore, the present study aims at using a deep learning-based approach to control vehicle acceleration based on information from the vehicle immediately ahead in the same carriageway. Specifically, we propose the use of a gated recurrent unit (GRU), i.e. a variant of recurrent neural network designed to avoid vanishing gradient problem linked to long time series. GRU can extract the main information of the time series and it is capable to find the nonlinear interconnection between the input features and the output ones. In this study the output information refers to the longitudinal control of the battery electric vehicle considered based on the information relative to the vehicle in front.

## II. BACKGROUND

In the literature there are several works related to the cooperative adaptive cruise control application. Targets achievable through this system include energy saving, comfort and safety enhancement along with improvements in traffic throughput. A variety of algorithms can be considered in the definition of the vehicle longitudinal trajectory. Controllers based on model predictive control (MPC) are widely used [6]–[9]. As an example, a learning-based stochastic MPC is developed and validated in [8] for several driving scenarios, including cut-in manoeuvres handling. In [9], a robust MPC approach is considered to evaluate CACC system performance in case of packet loss information. The choice of an MPC-based control derives mainly from its retroactive nature; however, the accuracy of the system and the related calculation times are depending on the selected type of MPC (i.e. linear, adaptive, non-linear, robust). Another not trivial point related to MPC-based models lies in the definition of the state equations, especially when trade-off solutions between accuracy and computational times are considered because in general, they require linearization of the main systems considered (not only in dynamics equations but also in components map). To overcome these problems, machine learning techniques were considered as a possible alternative. In 2011, Desjardins et al [10] presented a reinforcement

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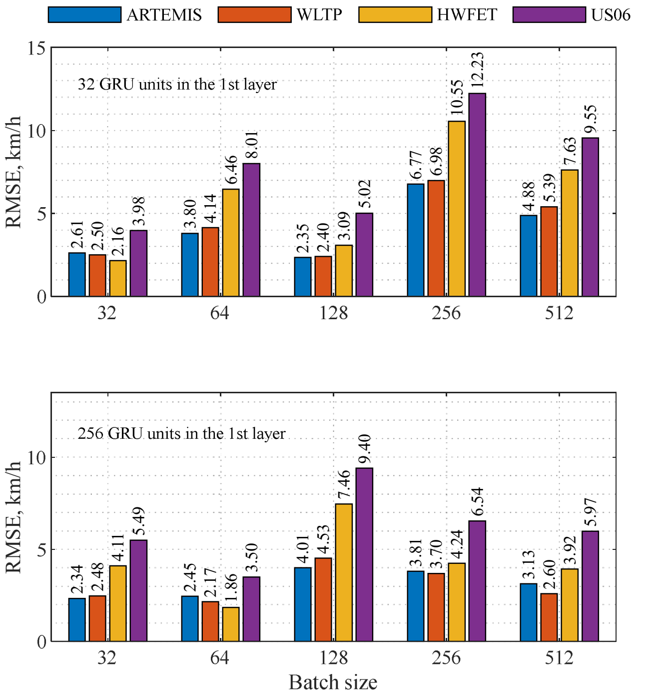


Fig. 1 RMSE results with respect to DP profiles for different batch sizes and driving cycles considering different GRU units in the 1st layer i.e 32 GRU units (upper part) and 256 (bottom part).

TABLE 2
MAIN CHARACTERISTICS OF TRAINING AND TESTING DATASETS

| | Duration (s) | Distance (km) | Average Speed (km/h) | Max speed (km/h) |
|---|---|---|---|---|
| ARTEMIS URBAN | 993 | 4.87 | 17.7 | 57.3 |
| ARTEMIS RURAL | 1082 | 17.3 | 57.5 | 111.1 |
| ARTEMIS MOTORWAY | 1068 | 29.6 | 99.6 | 150 |
| US06 | 596 | 12.8 | 77.9 | 129 |
| WLTP | 1800 | 23 | 46.5 | 131.3 |
| HWFET | 765 | 16.45 | 77.7 | 97 |

TABLE 3
GRU ARCHITECTURE AND SETTINGS

| **Layer (Type)** | **Units** | **Settings** | |
|---|---|---|---|
| GRU | m | Dropout rate | 0.2 |
| Dropout | - | GRU's Unit values range | 32-512 |
| GRU | m | Batch size range | 32-512 |
| Dropout | - | # of samples (in the past) | 5 |
| GRU | m/2 | Optimizer | Adam |
| Dropout | - | Loss | MSE |
| Dense | 1 | Metrics | MSE, MAE |

TABLE 4
RESULTS COMPARISON BETWEEN THE PROPOSED GRU APPROACH AND DP

| | | Lead Vehicle | Ego Vehicle (GRU) | Ego Vehicle (DP) |
|---|---|---|---|---|
| WLTP | Energy consumption (kWh/100km) | 17.46 | 16.55 | 16.55 |
| | RMS of vehicle acceleration (m/s^2) | 0.52 | 0.37 | 0.34 |
| HWFET | Energy consumption (kWh/100km) | 17.05 | 16.86 | 16.75 |
| | RMS of vehicle acceleration (m/s^2) | 0.3 | 0.28 | 0.27 |
| US06 | Energy consumption (kWh/100km) | 21.31 | 20.71 | 20.28 |
| | RMS of vehicle acceleration (m/s^2) | 0.99 | 0.64 | 0.61 |

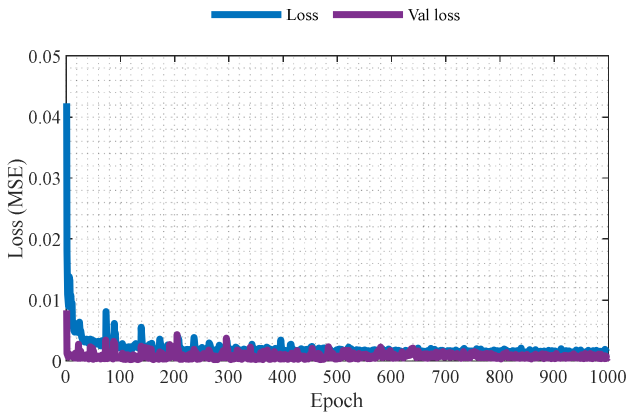


Fig. 2 Train and Validation loss trends. Simulation settings: ARTEMIS cycle for training, WLTP for validation, 32 GRU units in the 1st layer, 1000 # of epochs

The term *RMS of vehicle acceleration* refers to the ride quality evaluated based on the root mean square of acceleration signal [22], [23]. The results shown underline the potential in terms of generalization capacity of the neural network on the test datasets (HWFET and US06) as well as on those used in the training phase. However, several challenges and limits remain open and will need to be analysed in future works. Among the main ones, the proposed network should be implemented within a medium-fidelity simulation environment to be able to check the IVD signal between the two vehicles and re-evaluate the speed prediction in the event of any deviations from the established constraints. This consideration is especially true for long driving cycles that show a deterioration in performance towards the end of the cycle, as can be seen in the lower part of Fig. 3 for the WLTP cycle after 1200s.

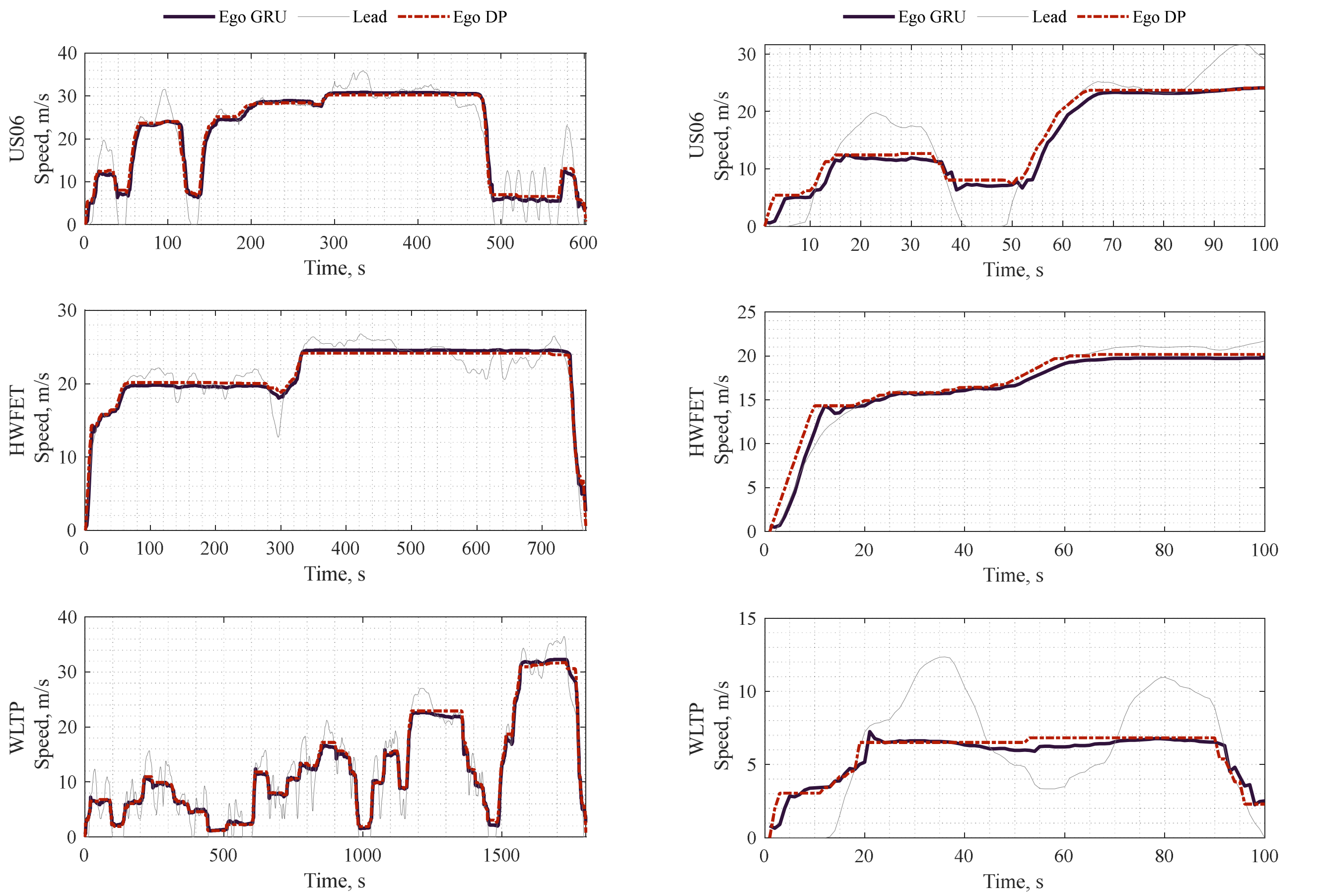


Fig. 3 Results comparison between the proposed GRU approach and DP in terms of speed for the test and validation datasets (left side of the figure), i.e. US06 (upper part), HWFET (middle) and WLTP (bottom part). On the right, a zoom of the first 100s. Simulation settings: ARTEMIS cycle for training, WLTP for validation, batch size 32, GRU units in the 1st layer 32, # of epochs 1000

This deterioration may be explained by the lack of an index indicating the remaining time to travel. However, introducing a feature to represent this information would lead to other considerations related to the user's need to always select a route on the GPS, opening further challenges beyond this work. In addition, the performance obtained in terms of ride comfort does not seem optimal. This lack is attributable to a choice of non-optimal input features to the model as well as a depth of the architecture that may require further investigation. It is worth recalling that depth of architecture refers to the number of layers in the neural network.

## V. CONCLUSIONS AND FUTURE WORKS

In this paper, a gated recurrent unit approach for the design of a real-time cooperative adaptive cruise control has been presented. The GRU has been trained using ad-hoc datasets build-up according to an optimal control policy, namely dynamic programming. The latter has been formulated to account for passenger comfort as well as energy saving enhancement. The GRU control was applied to a two-vehicle string and was found to efficiently mimic optimal trajectory determined through DP simulation. The problem was addressed using a regression approach with the aim of predicting the speed of the ego vehicle. A similar approach to vehicle ego acceleration would have been unsatisfactory given the nervous nature of the acceleration signal. The results shown highlight the potential of such an approach for solving the CACC problem achieving an eco-friendly driving without compromising passenger comfort and safety requirements. Unlike DP, GRU holds strong real-time potential: once trained, it can make predictions in real time (on the order of microseconds in a low fidelity simulation environment). However, there are still several limitations that will need to be addressed in future work. Among these, the need to improve performance in terms of comfort and accuracy in the final part of the mission without introducing any temporal features are the most challenging. Future works might include real driving missions to achieve a human-aware cooperative adaptive cruise control by training the GRU on user driving cycles so as to achieve a customized CACC.

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