Eco-Driving of Connected and Autonomous Vehicles with Sequence-to-Sequence Prediction of Target Vehicle Velocity

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Abstract: The Eco-Driving control problem seeks to perform fuel efficient speed planning for a Connected and Autonomous Vehicle (CAV) that can exploit information available from advanced mapping, and from Vehicle-to-Everything (V2X) communication. The ability of an Eco-Driving strategy to adapt in real time to variable traffic scenarios where surrounding vehicles can be either connected or unconnected is critical for further development and deployment of this technology in the transportation sector. In this work, the Eco-Driving strategy, formulated as a receding-horizon optimal control problem, is integrated with a target vehicle speed prediction model and solved via Dynamic Programming (DP) to determine the optimal speed trajectory in the presence of a human-driven target vehicle. An encoder-decoder architecture analyzes the patterns in the target vehicle velocity recorded over a historic window using a Gated-Recurrent-Unit (GRU) based encoder and generates an estimate of the future velocity trajectory using the GRU based decoder. A sensitivity study is done to analyze the effect of the historical and prediction windows on the accuracy of the velocity predictor. The proposed Eco-Driving controller is evaluated through microscopic simulations using a traffic simulator.

Keywords: Connected and Autonomous Vehicles, Eco-Driving, Model Predictive Control, Dynamic Programming, Driver Behavior Prediction, Gated Recurrent Unit Encoder-Decoder

1. INTRODUCTION

The recent advancements in Connected and Automated Vehicles (CAVs) technologies have the potential to increase safety, driving comfort as well as fuel economy, by exploiting information on driving conditions ahead that become available via advanced navigation systems, Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication (Guanetti et al. (2018)). Intuitively, the availability of such technologies could be exploited in a predictive controller to plan a speed trajectory that minimizes unnecessary acceleration and braking events, thereby improving driver comfort and fuel-efficiency (Xu and Peng (2018)). Furthermore, information on future driving conditions could enhance energy efficiency gains in electrified powertrain, by optimally scheduling the use of the electric motors and onboard battery pack (Guzzella et al. (2007)).

In this scenario, Eco-Driving aims at exploiting information on future driving conditions to optimize speed planning and powertrain control for improving the fuel efficiency between an origin and destination. However, Eco-Driving algorithms pose challenges for the design of a predictive (“look-ahead”) controller, especially in presence of uncertain traffic environment (Alam and McNabola (2014)). Another limitation of the existing literature in Eco-Driving is that the problem of speed trajectory optimization and powertrain control is often treated as two decentralized problems to reduce the computational complexity. In this case, the speed trajectory prediction of the target vehicle is incorporated in the speed planning problem, and the resulting ego vehicle speed trajectory is utilized as an external input for the sub-problem of powertrain control optimization (Firoozi et al. (2018)).

For real-world implementation of Eco-Driving controls, it is crucial to predict the presence of target vehicles as additional dynamic states, and incorporate them into the trajectory planning process. While some work has been done to incorporate a velocity prediction for a fully or partially connected target vehicle (see for instance Sun et al. (2014); Kanal et al. (2015)), however such assumptions might not be realistic in a partially connected environment where the ego vehicle might have access to only the current value of the target vehicle velocity.

In addition, forecasting the speed trajectory of a human-driven vehicle (no automation) in urban driving is a very difficult task, as the vehicle’s maneuvers may be affected by various dynamic factors, for instance traffic light Signal Phasing and Timing (SpaT), driver’s experience, weather, etc. Earlier studies have assumed simple but unrealistic speed trajectories, such as constant speed and constant acceleration when no information is available (for example, Lefèvre et al. (2014)). Auto-regressive models proved to be
powertrain control exploiting V2X technology in presence of partially connected, human-driven target vehicle.

This work proposes a unified Eco-Driving framework that performs co-optimization of vehicle velocity and powertrain control, as shown in Fig. 1. The proposed architecture acquires various information from multiple data resources, including route information (speed limits, road grade, position of route markers such as traffic lights and stops signs) from an advanced navigation system, SPaT information from a Dedicated Short Range Communication (DSRC) unit, and target vehicle velocity data from V2V communication or on-board detection system (comprises of radar and camera unit). A simpler but faster variant of LSTM namely Gated Recurrent Unit (GRU) is used to build an Encoder-Decoder (ED) network that provides an estimate of the future target vehicle speed trajectory. Existing literature has shown that GRU’s are faster, compact and ideal for short-term predictions (Altché and de La Fortelle (2017)). Although LSTM have proven to have high accuracy, they generally require large training time and are ideal for long-term prediction (Altché and de La Fortelle (2017)).

Prediction of target vehicle velocity is essential for efficiently applying Eco-Driving in urban traffic conditions. Most of the work published to date assume that the target vehicle is either connected to the infrastructure or to the ego vehicle. Since this assumption is rather limiting, the prediction here developed considers that only the current value of the target vehicle velocity is available at each time step. This represents the most general case of an ego vehicle equipped with an object detection system.

The short term planning of a typical human driver with respect to traffic conditions is generally represented as a time-varying, nonlinear time-series in terms of speed and acceleration (Toledo et al. (2007); Gupta et al. (2019)).

Fig. 2. Block Diagram of 48V P0 Mild-Hybrid Drivetrain.

2. MILD HYBRID ELECTRIC VEHICLE MODEL

A forward-looking parallel mild-Hybrid Electric Vehicle (HEV) is considered, as shown in Olin et al. (2019). A P0 HEV powertrain with a Belted Starter Generator (BSG) performs torque assist, regenerative braking and start-stop functions over real-world routes. The BSG is connected to the crankshaft of a 1.8L turbocharged gasoline engine and a 48V battery pack.
Despite the flexibility and power of Deep Neural Networks (DNNs), they are not ideal for sequences, since they require the dimensionality of input and output to be known and fixed (Sutskever et al. (2014)). In this work, the time-dependent nature of the driver behavior is captured by using sequence-to-sequence modeling via a Gated Recurrent Unit Encoder-Decoder.

3.1 Gated Recurrent Unit Encoder-Decoder Architecture

The concept of Gated Recurrent Unit (GRU) was originally proposed by Chung et al. (2014) to overcome the vanishing gradient problem in Vanilla RNNs (Pascanu et al. (2013)) and make each recurrent unit adaptively capture temporal dependencies of sequential data. A GRU network has two gating units: a reset gate \( r_t \) and an update gate \( z_t \) that modulate the flow of information inside the unit. The reset gate determines how much of the past information to forget, and the update gate determines how much of the past information needs to be passed along to the future. Even though GRUs do not explicitly contain separate memory cells as in LSTM (Hochreiter and Schmidhuber (1997)), the memory is introduced in the network by the hidden state vector \( h_t \), which is unique for each input sequence. This makes the GRU relatively fast and compact, suitable for short-term predictions (Gao et al. (2020)).

In this work, a GRU-Encoder-Decoder (GRU-ED) architecture has been used to perform sequence-to-sequence prediction of the target vehicle velocity. In literature, GRU-ED has been extensively used in machine translation tasks (Cho et al. (2014)). GRU-ED is a sequentially connected 3-layer arrangement comprising of an encoder, hidden and decoder layer, as shown in Fig. 4. The encoder layer contains GRU cells that read input sequences one time step at a time to obtain a large fixed-dimensional encoder vector that intrinsically learns the representation in the input sequence. The encoded vector is then fed as input to another sequence of GRU cells contained in the Decoder layer that generates the predicted sequence.

### 3.2 Driving Features

The crucial step in developing a vehicle speed prediction model is the selection of a set of input features that are representative of real-world driving. In this work, the input features were selected to be easily measured from ego vehicle’s on-board detection system, without requiring the target vehicle to broadcast its position and velocity. However, it is assumed that V2I communication exists, and more specifically that signalized intersections can broadcast SPaT messages to the ego vehicle within a predetermined transmission range. The longitudinal motion of any vehicle on a straight and flat road over the next time step \( \Delta t \) can be determined by the velocity \( v_t \) and acceleration \( a_t \) at the current time \( t \):

\[
v_{t+1} = v_t + a_t \Delta t. \tag{2}
\]

This means that the pair \([v_t, a_t]\) is used to develop non-linear car-following longitudinal models (Gupta et al. (2019); Rajakumar Deshpande et al. (2020)). Furthermore, it is necessary to predict the target vehicle’s behavior near a signalized intersection, as shown in Gupta et al. (2020). This implies that the driver behavior near an intersection can be expressed as a non-linear function of velocity, acceleration and distance to the traffic light \( d_{TL,t} \).

Finally, the feature set \( F = \{ v_t, a_t, d_{TL,t} \} \) can comprehensively represent human driving on a straight road and near signalized intersections. Note that the assumption of a human driving and no connectivity in the target vehicle does not allow the ego vehicle to incorporate...
a car-following behavior in the feature set, for example as done by Hyeon et al. (2021). However, even without V2V connectivity, the distance of the target vehicle to the traffic light $d_{TL,t}$ can be evaluated from the assumption of the ego vehicle receiving V2I communication within a communication range, as shown in Fig. 5. Outside this range, $d_{TL,t}$ is arbitrarily set to 500m:

$$d_{TL,t} = \begin{cases} 
  d_{gap,t} - d_{DSRC}, & d_{TL,t} < 500m, \\
  500m, & \text{otherwise}
\end{cases}$$

where $d_{TL,t}$ refers to the distance of the ego vehicle to the intersection obtained via V2I communication (position of upcoming intersection is broadcasted by the V2I modem); $d_{gap,t}$ refers to the relative distance between the ego and target vehicle, obtained via on-board radar unit.

### 3.3 Methodology

A comprehensive vehicle trajectory dataset, Next Generation Simulation (NGSIM), was collected by U.S. Federal Highway Administration (FHWA) in 2005 and is widely used in transportation research, especially in traffic flow analysis and modelling, traffic-related estimation and prediction, and vehicular ad hoc network-related studies (Kovvali et al. (2007)). In this paper, a subset of the dataset is adopted to train the GRU-ED network.

The GRU-ED network is trained over approximately 18 hours of NGSIM driving data using TensorFlow and the Keras API package. To access the learning performance of the model and its ability to generalize over different drivers, the considered data-set is split into 70% for training the GRU-ED and 30% to validate and test the trained model. For better generalization over the different features, the feature set $F$ is normalized between 0 and 1 using the sci-kit learn toolbox in Python. Custom functions are designed to split the data into a historical window and prediction window of time duration $T_h$ and $T_p$ respectively during the training phase. To evaluate the performance of the prediction model, Root Mean Square Error (RMSE) is computed between the predicted speed ($\hat{y}_t$) and the actual speed ($y_t$):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_t - \hat{y}_t)^2}$$

### 3.4 Evaluation

To analyze the effect of both $T_h$ and $T_p$ on the accuracy of prediction, a sensitivity study was performed where the GRU-ED network is trained and tested over several combinations of $[T_h, T_p]$ pairs, as shown in Table 1.

For a given $T_h$, increasing the length of prediction window increases the RMSE. For instance, the pair $[T_h, T_p] = [5s, 5s]$ produces the lowest RMSE and as the length of prediction window increases for fixed $T_h$, the RMSE increases. However, for a given $T_p$, increasing the length of $T_h$ decreases the RMSE but the difference is not very large. This signifies that the network’s accuracy is more sensitive to the length of prediction window but less sensitive to the length of historical window.

| $[T_h, T_p]$ [s,s] | [5,5] | [5,10] | [5,20] | [10,10] | [10,20] | [20,20] |
|-------------------|-------|-------|-------|--------|--------|-------|
| RMSE [m/s]        | 0.77  | 1.85  | 3.45  | 1.83   | 3.44   | 3.36  |

Fig. 6 and Fig. 7 show the actual and predicted velocity comparison and the correlation plot respectively for $[T_h, T_p] = [5s, 5s]$. Clearly, the predictor is able to forecast most of the acceleration/deceleration/cruise events, but it diverges for small durations at points where the vehicle abruptly switches from an acceleration to a deceleration maneuver (or vice-versa). This is understandable, since the velocity predictor relies only on the current values of velocity and acceleration, hence large variations in magnitude and sign of the vehicle acceleration (for example occurring during a rapid transition from acceleration to braking) are impossible to predict with the available features. Nonetheless, the network converges to the actual velocity within the span of few seconds.
where $s$ is the discrete position, $u_s$ is the control input, $\gamma$ is a weighing factor between the fuel consumption and the travel time, and $\dot{m}_f(s)$ is the fuel flow rate. $\Delta t_s := \frac{\Delta d_s}{\dot{v}_s}$ is the travel time per step, $\Delta d_s$ is the distance step (i.e. $\Delta d_s = d_{s+1} - d_s$) calculated from the distance traveled ($d_s$) along the route at position $s$, and $\bar{v}_s = \frac{v_{s} + v_{s+1}}{2}$ is the average velocity. The state and action space are subject to a set of constraints, as described in Olin et al. (2019).

To incorporate time-based information such as SPaT and presence of other vehicles, time is added as an additional state variable in the OCP formulated in the spatial domain. In previous work, Zhu et al. (2021) formulated a 3 state OCP with time as one of the states to incorporate the SPaT information into the Eco-Driving controller, assuming a traffic-free environment. However, the effectiveness of this controller would reduce in presence of a target vehicle, particularly near signalized intersections. In this work, the target vehicle velocity predicted by the GRU-ED network is integrated with the Eco-Driving OCP and solved over a receding horizon of $N_H$ horizon, which varies as a function of the ratio of average lead and ego vehicle velocity evaluated over a distance step. If $\bar{v}_k < \bar{v}_e$, the target vehicle is faster than ego vehicle and the $d_{gap,k+1} > \hat{d}_{gap,k}$. On the other hand, if $\bar{v}_k > \bar{v}_e$, the target vehicle is slower than ego vehicle and the $d_{gap,k+1} < \hat{d}_{gap,k}$. This logic can be used by the Eco-Driving controller to modulate the ego vehicle velocity such that the $\hat{d}_{gap,k} > d_{safe,k}$ which is defined as the safe car-following distance (Brackstone and McDonald (1999)):

$$d_{safe,k} = d_0 + v_{e+1}T_{gap} + \frac{v_{e+1}^2 \Delta v_{e+1}}{2 a_{max} b_{max}}$$

where $d_0$ refers to the safe distance gap at stand still, $T_{gap}$ refers to the time gap, $\Delta v_{e+1}$ refers to the relative velocity between target and ego vehicle, $a_{max}$ and $b_{max}$ refers to the maximum acceleration and deceleration respectively. Assume that the discretized state dynamics for the Eco-Driving problem has the following form:

$$x_{s+1} = f_s(x_s, u_s), \quad s = 1, \cdots , N - 1.$$
actions respectively. In this work, the state variables are the vehicle velocity \((v_s)\), battery SoC \((\xi_s)\) and travel time \((t_s)\). The control actions are the engine torque \((T_{\text{eng},s})\) and BSG torque \((T_{\text{bsg},s})\). The equations describing the state dynamics \(f_s(x_s, u_s)\) have been derived in prior work (Gupta (2019)).

As mentioned above, the Eco-Driver optimization problem is formulated as a receding horizon optimal control problem where the full route of \(N\) steps is solved over a reduced horizon \(N_H<< N\). At a given position \(s = 1, \ldots, N - N_H\), the optimization problem is formulated as:

\[
J^*(x_s) = \min_{\{\mu_k\}_{k=s}^{s+N_H-1}} \sum_{k=s}^{s+N_H-1} c_T(x_{s+N_H}^k) + c(x_k, \mu_k(x_k)),
\]

where \(\mu_k : \mathcal{X} \rightarrow \mathcal{U}\) is the admissible control policy of the controller at the step \(k\) in the prediction horizon; \(c : \mathcal{X} \times \mathcal{U} \rightarrow \mathbb{R}\) is the stage cost function defined as the weighted average of the fuel consumption and travel time; \(c_T : \mathcal{X} \rightarrow \mathbb{R}\) is the terminal cost function. The state space and action space are subject to following constraints:

\[
\begin{align*}
  v_k &\in [v^\text{min}_s, v^\text{max}_s], \quad (10a) \\
  \xi_k &\in [\xi^\text{min}_s, \xi^\text{max}_s], \quad (10b) \\
  t_k &\in T_{\text{G,k}}, \quad (10c) \\
  a_k &\in [a^\text{min}, a^\text{max}], \quad (10d) \\
  d_{\text{gap},k} &\in [d_{\text{safe}}, d_{\text{radar}}] \quad (10e) \\
  T_{\text{eng,k}} &\in [T^\text{min}_{\text{eng}}, T^\text{max}_{\text{eng}}(v_k)], \quad (10f) \\
  T_{\text{bsg,k}} &\in [T^\text{min}_{\text{bsg}}, T^\text{max}_{\text{bsg}}(v_k)], \quad (10g)
\end{align*}
\]

where \(v^\text{min}_s, v^\text{max}_s\) are the minimum and maximum route speed limits respectively, \(\xi^\text{min}_s, \xi^\text{max}_s\) are the static limits applied on battery SoC, \(a^\text{min}, a^\text{max}\) represent the limits imposed on the acceleration for comfort, \(d_{\text{safe}}\) is obtained from Eqn. 7, \(d_{\text{radar}}\) refers to the radar range (assumed to be 250m), \(T^\text{min}_{\text{eng}}(v_k), T^\text{max}_{\text{eng}}(v_k)\) are the minimum and maximum engine torque limits, and \(T^\text{min}_{\text{bsg}}(v_k), T^\text{max}_{\text{bsg}}(v_k)\) are the minimum and maximum BSG torque limits, respectively. To ensure SoC neutrality over the entire itinerary, a terminal constraint \(\xi_1 = \xi_T\) is applied to the battery. \(T_{G,s}\) represents the feasible set of travel time for passing-at-green at signalized intersections (Zhu et al. (2021)).

The receding horizon OCP is solved using Approximate Dynamic Programming (ADP), such that an approximate terminal cost used in the receding horizon OCP (named “Short-term Optimization” in Fig. 1) is obtained from the offline solution of a full-route optimization under partial information (termed “Long-term Optimization”).

5. SIMULATION AND EVALUATION OF RESULTS

To illustrate the proposed approach, a mixed-urban route in Columbus, OH (USA) was selected for the simulation and analysis. As shown in Fig. 9, the route is 7km in length and comprises 5 traffic lights and 2 stop signs (start and end of the trip).

To simulate the presence of a target vehicle, a time-varying vehicle velocity profile is generated using Simulation of Urban MObility (SUMO) for a given departure time. The vehicle velocity profile generated in SUMO is used as the source for the velocity predictor integrated into the Eco-Driver controller. The velocity profile is segmented into historical data using a moving window of 10s, then fed to the trained GRU-ED network to predict the target vehicle velocity within the receding horizon OCP that determines the optimal speed and battery SoC profiles for the ego vehicle (Eqn. 9 and 10). Note that this framework is reasonable for this study, since the vehicle motion in the simulation is limited to a single lane and the SPaT sequences obtained from SUMO are post-processed to be consistent with the departure time of the target vehicle.

Fig. 10 shows the velocity trajectory and time-space plot of the lead and ego vehicle over the route shown in Fig. 9. The ego vehicle is able to pass all the traffic lights, except the second, at a green phase even in the presence of a target vehicle. Within the V2I communication range of the first, fourth and fifth traffic lights (located at approximately 1300, 3600, 3800m), the Eco-Driver controller is aware of the time remaining in the green phase. This information, combined with the GRU-ED network predicting the target vehicle to cruise (based on the historical data and distance to traffic light), is exploited by the Eco-Driver controller to either hold the ego vehicle speed or accelerate to pass the signalized intersections during the green phase. This is also evident from the Fig. 11, where the relative distance either remains the same or decreases.

Moreover, while approaching the second traffic light, the Eco-Driver controller knows “a priori” that the time remaining in the red phase is small and the GRU-ED network predicts the target vehicle will decelerate (based on the initial deceleration of the target vehicle while approaching the intersection). Using this information, the controller lowers the ego vehicle’s speed to allow the signal to change to green, while at the same time avoiding a collision with the target vehicle. At the third traffic light, since the time remaining in the red phase is large, the Eco-Driver controller decides to stop, to avoid a collision with the target vehicle at the intersection. It should be noted that even during stand-still, the ego vehicle maintains a safe gap from the target vehicle.
Further, the forecast of target vehicle velocity over the prediction horizon allows the ego vehicle to pass-at-green at most of the intersections when compared against the baseline case reducing overall travel time.

6. CONCLUSIONS

In this work, an Eco-Driving strategy formulated for a connected and automated mild-HEV with an on-board detection system, V2I communication and longitudinal automation was augmented with a prediction-based target vehicle velocity estimator. A sequence-to-sequence velocity predictor, based upon a Gated Recurrent Encoder-Decoder (GRU-ED) network was trained to forecast the target vehicle velocity trajectory based upon historic data, and was then integrated with the Eco-Driving controller by designing a dynamic model of the relative distance between the target and the ego vehicle. Compared to previous studies where the target vehicle is assumed to be fully connected, the methodology proposed in this paper is applicable to the more general case of a target vehicle with partial or no automation, and without the ability to broadcast velocity and acceleration.

The Eco-Driving problem was cast as a receding horizon optimal control problem with three states, namely vehicle velocity, battery SoC and travel time. The problem was solved using Approximate Dynamic Programming and implemented in a Model Predictive Control (MPC) framework. It is worth mentioning that the formulation presented in this paper integrates all elements of the Eco-Driving problem (speed planning and powertrain set-points optimization) into a single controller. Simulation results indicate that the Eco-Driving controller is able to intelligently pass the signalized intersection in green phase, by forecasting the target vehicle velocity. Future work will address the development of a co-simulation platform where the optimization is performed in a parallel implementation developed with CUDA programming on a GPU to reduce the computational requirement from inclusion of additional states and allow to perform Eco-Driving in presence of multiple surrounding vehicles in a multi-lane scenario.

ACKNOWLEDGEMENTS

The authors acknowledge the support from the United States Department of Energy, Advanced Research Projects Agency – Energy (ARPA-E) NEXTCAR project (Award Number DE-AR0000794).

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