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Potential Energy Saving of V2V-Connected Vehicles in Large-Scale Traffic ⋆

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Abstract: Most studies evaluating the energy efficiency of connected and automated vehicles (CAVs) in car-following scenarios have considered a few preceding vehicles communicating with the controlled CAVs. However, considering rapidly evolving technologies in CAVs, extended vehicle-to-vehicle (V2V) connectivity over large-scale traffic needs to be considered in estimating CAVs' energy benefits. This paper investigates the potential energy saving of V2V-connected vehicles in large-scale downstream traffic by adopting a human driver model generating stable car-following trajectories for many consecutive vehicles. The energy-efficient driving of a CAV is demonstrated based on an optimal controller minimizing the longitudinal acceleration by forecasting an immediately preceding vehicle's trajectory over a fixed prediction horizon. Various traffic scenarios are considered by applying different simulation parameters, including the distribution of vehicle time gaps, the number of connected vehicles, and prediction horizon lengths. Furthermore, a comprehensive analysis is conducted to discover the relationships between the parameters of interest and system performance, including prediction and control. Our findings from the parameter study are validated by evaluating the realistic energy consumption of a vehicle in a simulation platform operating high-fidelity powertrain models.

Keywords: optimal control, electric vehicles, connected and automated vehicles, intelligent transportation, modeling and simulation of transportation systems

1. INTRODUCTION

The advent of advanced communication technologies, such as the fifth-generation (5G) mobile network, makes cellular-based vehicle networks available over extended ranges with less delay (Wang et al. (2017)). As faster and broader communication becomes available on the road, the potential energy saving of CAVs has been increasing in recent years. Specifically, CAVs can minimize energy consumption by optimizing driving maneuvers such as steering, throttling, and braking, also known as *eco-driving control* in previous literature (Sciarretta et al. (2015)). Amongst various eco-driving control strategies, constrained optimal control in car-following scenarios has attracted considerable attention because the presence of a preceding vehicle is common in the real world (Sciarretta et al. (2020); Bae et al. (2019)).

In the car-following scenarios, forecasting the preceding human-driven vehicle's trajectory plays an important role in reaching the maximum energy efficiency of a CAV as well as avoiding collisions (He and Orosz (2017)). Thus, many studies have developed prediction techniques using CAV technologies to enhance prediction accuracy (Moser et al. (2015); Jing et al. (2015)). The prediction accuracy and consequent optimal control performance, however, could be significantly dependent on the driving environment including V2V penetration rates, car-following aggressiveness and heterogeneity. (Vahidi and Sciarretta (2018)). For example, the accuracy of predictors using V2V information as their input features might be degraded under limited V2V connectivity (Hyeon et al. (2019)). In addition, when following aggressive drivers, an eco-driving controller may bring larger energy benefits because aggressive driving demands more fuel consumption (Liu et al. (2016)). Moreover, employing acceptable system parameters is critical for maximizing the benefits of using eco-driving control systems. Moreover, the eco-driving control system can internally maximize its benefits by optimizing key parameters and adding control complexity. For example, using an insufficient length of prediction horizons may limit the energy saving allowed to the system, while an excessively long horizon makes the system waste computational resources (Prakash et al. (2016)).

To our best knowledge, most previous studies have assessed CAVs' energy saving in limited domains; the number of connected vehicles is not more than 10, and road participants have similar driving styles by sharing the

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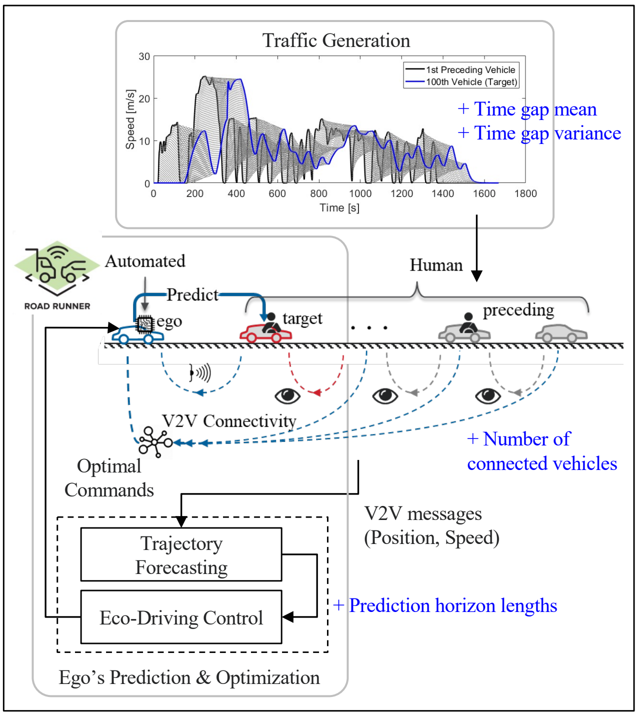


Fig. 1. Schematic overview of this work.

same model parameters (Hyeon et al. (2019)). Considering extended connectivity from rapidly evolving vehicle communication technologies, analyzing the CAVs' energy-saving performance in a large-scale traffic environment is necessary. However, it is challenging to generate the realistic car-following trajectories of a large number of consecutive vehicles for extensive traffic generation.

In order to address the aforementioned issue, this paper adopts a novel human driver model developed by Han et al. (2022), which has high fidelity and reliability toward extensive traffic generation. By employing this human driver model, the performance of our eco-driving control system is investigated in large-scale downstream traffic. Fig. 1 shows the schematic overview of this work. First, large-scale traffic scenarios are generated with the various distributions of time gaps between vehicles. Then, the car-following of a CAV driven by an eco-driving controller is simulated with various simulation parameters, including (1) the time gap between vehicles to address car-following styles, (2) the number of connected vehicles representing V2V connectivity, and (3) prediction horizon length indicating look-ahead ability. Our eco-driving controller minimizes longitudinal acceleration while avoiding collisions from a preceding vehicle, where a V2V-enabled predictor estimates its future trajectories proposed in Hyeon et al. (2021). Next, a comprehensive analysis is conducted by evaluating the performances of both the controller and predictor and discovering their relationships. Furthermore, trajectory predictors not using V2V information are implemented in the same scenarios and their performances are compared with the V2V-enabled predictor to evaluate the performance reliability over the different levels of V2V connectivity. Finally, realistic energy consumption is computed by implementing the same scenarios in a high-fidelity traffic and vehicle simulation software to validate our findings.

The paper is organized as follows: In Section 2, the eco-driving control system used for this work is described including a control algorithm and various approaches for forecasting the target vehicle's trajectories. Section 3 explains simulation settings for the parameter study and the traffic model used for generating large-scale traffic. Section 4 presents and discusses the results of the parameter study. The parameter study is extended by using the high-fidelity vehicle simulator to compute realistic energy consumption, where the results are summarized in Section 5. Finally, Section 6 concludes this paper.

2. ECO-DRIVING CONTROL SYSTEM

This section concisely explains the eco-driving control system used in this paper by summarizing the eco-driving controller and trajectory predictors developed in our previous work. In order to avoid confusion, the following terminologies are used to indicate vehicles in this paper: the *ego vehicle* is the CAV controlled by the eco-driving controller introduced in Section 2.1; the *target vehicle* is the vehicle immediately in front of the ego vehicle and the prediction target of the ego vehicle, and the *preceding vehicles* are all the vehicles driving in front of the target vehicle. The definitions of these terminologies are visualized in Fig. 1.

2.1 Eco-Driving Controller

This work uses an eco-driving controller developed in our previous work Han et al. (2020). This controller minimizes acceleration to reduce energy consumption indirectly. The eco-driving controller has a two-level approach to provide the reference states of the next time step in a model predictive control fashion: (1) The upper level selects the desired driving mode assuming free flow and plans speed accordingly, and (2) the lower level is aware of the target vehicle's existence and plans speed to maintain the desired distance gap from the target vehicle. The lower level uses the target vehicle's estimated final position and speed at the end of the prediction horizon to optimize the final position and speed of the ego vehicle. Then, the state-constrained trajectories are produced by considering the predicted trajectory of the preceding vehicle. This analytical approach guarantees that the real-time computing capability of the eco-driving control algorithm does not suffer from the increase in the prediction horizon.

2.2 Vehicle Trajectory Predictor

To estimate the final position of the target vehicle, four types of predictors are implemented and compared:

(1) Accurate preview ("perfect"): the target vehicle's accurate final position is given.
(2) Constant speed ("CS"): the current speed of the target vehicle is propagated to compute the target vehicle's final position.
(3) Constant acceleration ("CA"): the current acceleration of the target vehicle is propagated to compute the target vehicle's final position.
(4) V2V predictor ("V2V"): V2V information transmitted from preceding vehicles is used to calculate target vehicle's future position.

The V2V predictor proposed by Hyeon et al. (2021) estimates the future speed profile of the target vehicle based on a locally weighted polynomial regression (LWPR) algorithm. This predictor uses the preceding vehicles' current speed and position as its input features. We assume that these types of information can be delivered to the ego vehicle via V2V communication according to Dedicated Short Range Communications Technical Committee (2016).

3. SIMULATION SETTINGS

This section presents simulation settings for the parameter study. Amongst various system parameters, this work focuses on the following four parameters:

(1) The mean of time gaps between vehicles (μ_τ),
(2) The standard deviation of time gaps (σ_τ),
(3) The length of prediction horizons (T), and
(4) The number of connected vehicles (N_{cv}).

A time gap between vehicles is regulated because short time gaps could cause oscillations in vehicles' speed profiles leading to more energy consumption. In this study, we assume that time gaps between vehicles follow a normal distribution. The mean of time gaps (μ_τ) is selected as 0.5, 1, and 1.5 s—considering the characteristics of real-world driving according to Winsum and Heino (1996). In addition, the standard deviation of the time gap (σ_τ) is set to 0 s and 1 s to address homogeneous and heterogeneous time gaps, respectively.

The logic behind choosing the third and the fourth parameters is well described in Section 1. The prediction and control horizons are synchronized in this work, chosen from 10, 20, 50, and 100 s. The number of connected vehicles is selected from 8, 20, 50, 80, and 100.

3.1 Traffic Model

A traffic model that can handle many consecutive vehicles' trajectories is necessary to generate large-scale traffic. This work adopts an analytical anticipative optimal drivability model (A2ODM) proposed by Han et al. (2022). The A2ODM can capture dynamic car-following behavior while maximizing driving comfort without collisions with high computational efficiency. Moreover, the A2ODM has higher accuracy than an intelligent driver model developed by Treiber et al. (2000), one of the most commonly used traffic models for simulating human drivers' car-following behavior. In the A2ODM, the following vehicle's equation of motion is characterized by the acceleration optimizing drivability. The acceleration is the function of states and parameters, including desired time gap from a preceding vehicle, desired speed and acceleration, and safety distance. In this study, only the first lead vehicle's drive cycle is given, and the A2ODM generates the trajectories of the rest of the vehicles. A total of a hundred vehicles are simulated where the first lead vehicle drives the UDDS cycle for this study.

3.2 Performance Metrics

To measure the optimal control performance, we used *acceleration energy* because our controller minimizes acceleration in its formulation. In other words, acceleration energy indicates the smoothness of trajectory computed by the following:

$$E_{\mathrm{a}} = \frac{1}{2}\sum_{k=0}^{N_{\mathrm{trip}}} a^2(k) \tag{1}$$

where a is longitudinal acceleration (and deceleration) that the ego vehicle employs, and N_{trip} is the total number of time steps in a trip. Realistic energy consumption is assessed in the later section.

Since the controller uses the predicted position of the target vehicle at the end of the prediction horizon to compute state constraints, the root-mean-squared error of the target vehicle's final position estimates is selected as the predictor's performance metric.

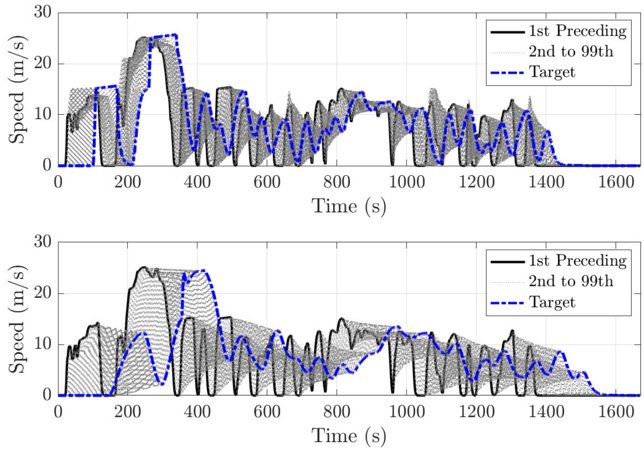


Fig. 2. Speed profiles of the first lead vehicle, target vehicle, and the vehicles between them (dotted lines) with the time gap mean of 0.5 s (top) and 1.5 s (bottom).

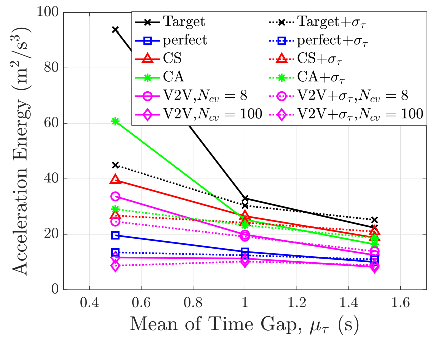
4. SIMULATION RESULTS AND DISCUSSION

The eco-driving simulation results from varying the parameters selected in Section 3 are presented in this section. The following sections discuss the impacts of each parameter on prediction and control performances.

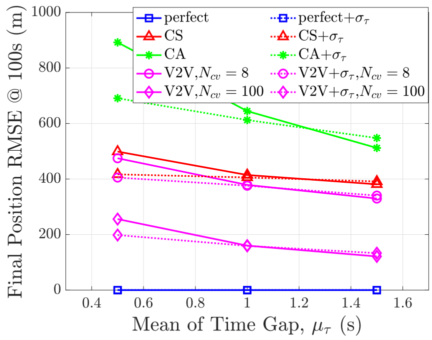
4.1 Mean and Standard Deviation of Time Gap

Fig. 2 compares the A2ODM simulation results with 100 vehicles using the different mean values of the time gap distributions. In this analysis, the prediction horizon length is fixed at 100 s to focus on the effect of the time gaps in traffic. The results show that having the mean of time gaps of 1.5 s results in the smoother speed profiles of the following vehicles compared to 0.5 s. This phenomenon occurs because keeping a longer gap from its preceding vehicle gives a longer reaction time, especially under the preceding vehicle's abrupt braking.

As shown in Fig. 3a, acceleration energy generally decreases with the mean value of the time gap for all the ego vehicles, regardless of the prediction methods and the target vehicle. The dotted lines indicate the results tested in the traffic with the standard deviation of the time gap of 1 ($\sigma_\tau = 1$). The results show that the impact of mean of time gaps is attenuated in the heterogeneous traffic. This phenomenon is caused because as time gap values

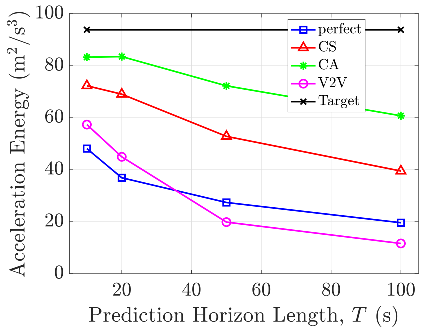


(a) Acceleration energy

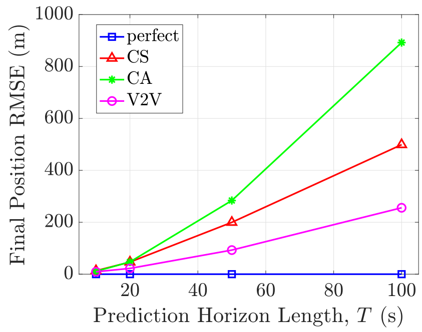


(b) Root-mean-squared errors of final position estimates

Fig. 3. Comparison of acceleration energy and final position accuracy resulted from different mean and standard deviation of the A2ODM time gap parameter.



(a) Acceleration energy



(b) Root-mean-squared errors of final position estimates

Fig. 4. Comparison of acceleration energy and prediction accuracy over various prediction horizon lengths applied to the predictors and controller.

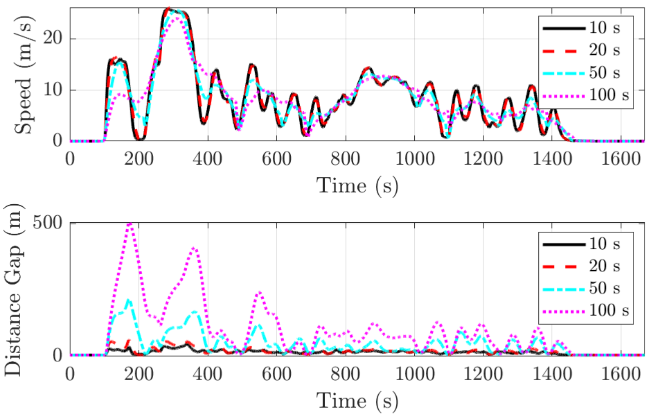


Fig. 5. Ego vehicle's speed and distance gaps from the target vehicle when using the V2V predictor with different prediction horizon lengths.

are mixed in traffic over various ranges, the impacts of the different time gaps are blended.

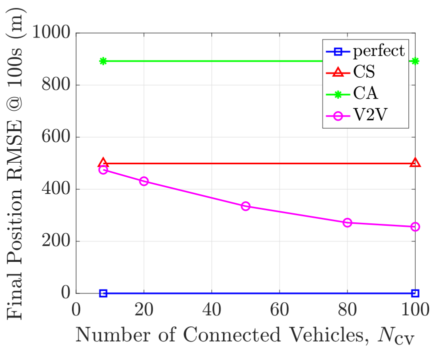
Overall, the eco-driving controller with the V2V predictor reduces acceleration energy more than the CS and CA predictors due to its improved prediction accuracy. Another notable finding is that the V2V predictor produces reliable performance regardless of the mean of time gaps when the number of connected vehicles is 100.

4.2 Prediction Horizon Length

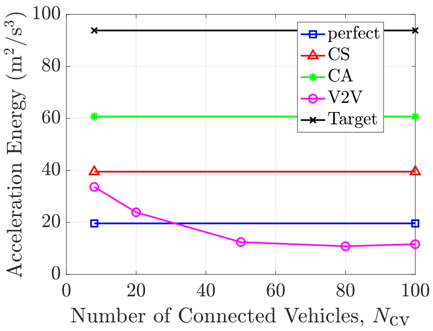
The acceleration energy from applying different prediction horizon lengths to the controller is compared in Fig. 4a. These results are produced with the homogeneous car-following scenarios with $\mu_\tau = 0.5$ s and $\sigma_\tau = 0$, where all vehicles are connected, $N_{\text{cv}} = 100$. The results show that the ego vehicle can reduce acceleration energy compared to the target vehicle for all the predictor types. The reason for this result is well visualized in Fig. 5. In the figures, the speed and distance gap trajectories of the ego vehicle using the V2V predictor are plotted with different prediction horizon lengths. When the horizon length is 10 s, the ego vehicle closely follows the target vehicle with less flexibility. When applying a longer prediction horizon, the controller can produce better optimal solutions by looking ahead further. Hence, applying a longer prediction horizon results in a smoother speed trajectory overall. This conclusion might not be consistent under limited V2V connectivity, which will be further studied in our future work.

4.3 Number of Connected Vehicles

The influence of the number of connected vehicles on the performance of the V2V predictor is analyzed in this section. In Fig. 6a, the RMSE of the target vehicle's final position estimates are plotted for varying numbers of connected vehicles, where the prediction horizon length is 100 s, and the same time gap parameters with Fig. 4 are used. The RMSE of the V2V predictor decreases as the number of connected vehicles increases. Note that when the number of the connected vehicles is limited to 8, the RMSE of the V2V predictor is similar to the CS predictor



(a) Root-mean-squared errors of final position estimates



(b) Acceleration energy

Fig. 6. Comparison of prediction accuracy and acceleration energy using different numbers of connected vehicles.

due to the strategy the V2V predictor adopts: When the V2V information for interpolating the entire horizon is limited, the CS prediction is employed, using the current speed of the farthest connected preceding vehicle. The impact of the number of connected vehicles on the V2V predictor's accuracy directly leads to acceleration energy, as shown in Fig. 6a. The acceleration energy savings significantly increases as the V2V predictor's accuracy is improved with the maximum V2V connectivity.

5. ENERGY CONSUMPTION EVALUATION

5.1 Simulation Setting

To validate the findings from our the parameter study in realistic environment, we implement RoadRunner (Kim et al. (2018)). RoadRunner is a multi-vehicle simulation platform in which each vehicle has a high-fidelity powertrain model and reacts to the surrounding environment (e.g., preceding vehicle, intersections). To avoid heavy computational load, the ego and target vehicles' driving are only simulated in RoadRunner environment, while the rest of the preceding vehicles are virtually existed. The V2V messages transmitted from the preceding vehicles are delivered to the ego vehicle in RoadRunner online. The preceding vehicles' trajectories are adopted from the A2ODM traffic generation conducted in the MATLAB environment. In this analysis, homogeneous car-following scenarios is considered where the most front vehicle drives the UDDS cycle. The energy consumption of ego vehicles is evaluated using a battery electric vehicle model provided in RoadRunner. The total mass of the vehicle is 1784 kg. The maximum power and torque of the vehicle are 123.9 kW and 393.7 Nm, respectively. The wheel radius is 0.3 m, and the battery energy is 59.89 kWh. Finally, the gear and the final drive ratios are 1.6 and 3.5, respectively.

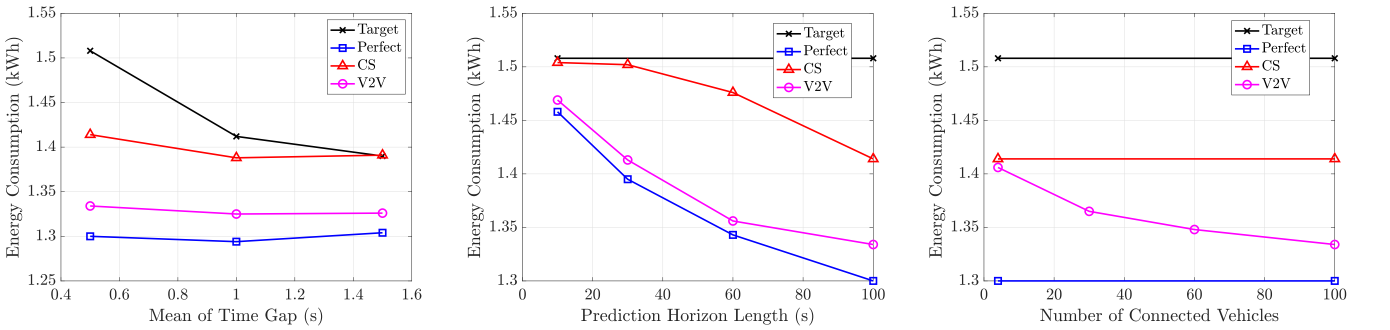
5.2 Results and Discussion

The RoadRunner simulation results with various combinations of parameters are plotted in Fig. 7. Battery energy consumption is reduced when a longer time gap is applied in the traffic generation (Fig. 7a). This trend coincides with the trend in the acceleration energy presented in Fig. 3a. In addition, the target vehicle's battery energy consumption decreases with the time gap due to the smoothed speed profile, which weakens the benefit of using V2V communication. Fig. 7b and Fig. 7c show battery energy consumption depending on the prediction horizon lengths and number of connected vehicles, respectively. These further battery energy savings are correlated to reduced acceleration energy, as shown in Fig. 4a and Fig. 6b. The V2V predictor enables the ego vehicle to decrease its battery energy consumption and reach the minimum closer to the perfect predictor, as it elongates its prediction horizon while guaranteeing higher accuracy using richer V2V information. The 2% performance gap between the perfect and V2V predictors still exists and could be filled by future-intent sharing between connected vehicles. Note that when the number of connected vehicles is limited ($N_{\mathrm{cv}} = 4$), the energy savings from using the V2V predictor is similar to that of using the CS predictor.

6. CONCLUSION

This paper investigates the potential energy saving of a V2V-enabled eco-driving control system. The eco-driving controller optimizes driving speed based on the target vehicle's future driving behaviors, predicted by an LWPR algorithm using connected vehicles' states obtained via V2V communication. The performance of the predictor and controller is assessed by varying the mean and standard deviation of time gap parameters, the number of connected vehicles, and the prediction horizon length. Simulation results show that vehicles consume less energy when traffic maintains longer time gaps, while randomness in time gaps weakens this trend. In addition, our system can achieve near-benchmark energy efficiency with the prediction horizon of 100s if a sufficient number of connected vehicles is available. This study will be extended by analyzing the cross impacts between parameters, for instance, finding the effective length of prediction horizons under the different combinations of time gaps and the number of connected vehicles. Furthermore, the different levels of cooperative driving automation will be implemented in large-scale traffic simulations for performance comparison.

DISCLAIMER



(a) Time gap (b) Prediction horizon length (c) Number of connected vehicles

Fig. 7. Energy consumption produced by RoadRunner with the various system parameters.

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