Check for updates

TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Research Article

Transportation Research Record
1–13
© National Academy of Sciences: Transportation Research Board 2020
Article reuse guidelines: sagepub.com/journals-permissions
DOI: 10.1177/0361198120941508
journals.sagepub.com/home/trr
SAGE

Long-Term Vehicle Speed Prediction via Historical Traffic Data Analysis for Improved Energy Efficiency of Connected Electric Vehicles

Mohammad Reza Amini[1], Yiheng Feng[1], Zhen Yang[1], Ilya Kolmanovsky[1], and Jing Sun[1]

Abstract

Connected and automated vehicles (CAVs) are expected to provide enhanced safety, mobility, and energy efficiency. While abundant evidence has been accumulated showing substantial energy saving potentials of CAVs through eco-driving, traffic condition prediction has remained to be the main challenge in capitalizing the gains. The coupled power and thermal subsystems of CAVs necessitate the use of different speed preview windows for effective and integrated power and thermal management. Real-time vehicle-to-infrastructure (V2I) communications can provide an accurate speed prediction over a short prediction horizon (e.g., 30 s to 60 s), but not for a long range (e.g., over 180 s). Therefore, advanced approaches are required to develop detailed speed prediction for robust optimization-based energy management of CAVs. This paper presents an integrated speed prediction framework based on historical traffic data classification and real-time V2I communications for efficient energy management of electrified CAVs. The proposed framework provides multi-range speed predictions with different fidelity over short and long horizons. The proposed multi-range speed prediction is integrated with an economic model predictive control (MPC) strategy for the battery thermal management (BTM) of connected and automated electric vehicles (EVs). The simulation results over real-world urban driving cycles confirm the enhanced prediction performance of the proposed data classification strategy over a long prediction horizon. Despite the uncertainty in long-range CAVs' speed predictions, the vehicle-level simulation results show that 14% and 19% energy savings can be accumulated sequentially through eco-driving and BTM optimization (eco-cooling), respectively, when compared with normal driving (i.e., human driver) and conventional BTM strategy.

In addition to enhancing safety and mobility, connected and automated vehicles (CAVs) can exploit vehicle speed prediction and planning to improve energy efficiency at the individual vehicle level, as well as the traffic network level. While abundant evidence has been accumulated showing substantial energy saving potential of the CAVs by up to 20%, uncertainties associated with vehicle speed forecast in real-world traffic consisting of human-driven and automated vehicles can degrade these benefits (*1–7*). The reason for such degradation in the energy consumption benefits is that energy management strategies are often based on economic optimization solutions that aim at operating the vehicle powertrain system at its maximum efficiency while enforcing power and thermal constraints. In the presence of traffic preview uncertainties, the risk of violating those constraints increases, forcing the energy management system to take more aggressive and less efficient actions to ensure the viability of the vehicle powertrain system, for example, prevent battery overheating in electrified vehicles.

For electrified vehicles, including hybrid electric vehicles (HEVs), plug-in HEVs (PHEVs), and fully electric vehicles (EVs), while traction power demand is the major power consumption source, thermal management of the electric battery, cabin air, engine, and exhaust aftertreatment system can have a significant impact on the electric battery energy consumption, as well as the overall energy efficiency of the vehicle (*8–12*). As an example, for EVs with relatively large battery packs, the electric battery is

[1]College of Engineering, The University of Michigan, Ann Arbor, MI

Corresponding Author:
Mohammad Reza Amini, mamini@umich.edu

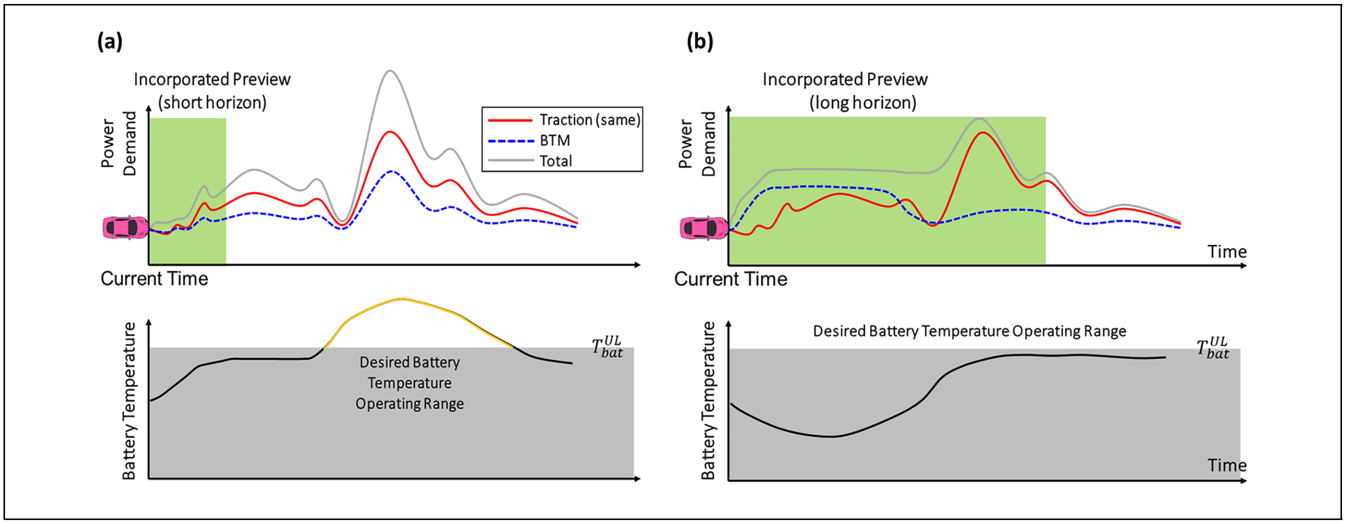

Figure 1. The importance of prediction horizon length on battery thermal management (BTM) system performance: (*a*) short prediction horizon and (*b*) long prediction horizon.

the only source of power to satisfy the driving demand, that is, traction power, and auxiliary loads, including those for powering the electric compressor of the air conditioning (A/C) system. In typical EVs, the battery thermal management (BTM) system rejects the generated heat from the battery to the refrigerant of the A/C cooling loop to maintain the battery temperature within the safe region. Eventually, the A/C compressor consumes the battery power to reject heat from the A/C refrigerant. Therefore, the operation of the BTM system introduces extra load on the battery. As it has been reported in the literature, the BTM and A/C systems can consume a substantial amount of energy in hot weather, and reduce the EV driving range by 50% (*13–16*). Therefore, optimization of the thermal management system operation is essential for improving the overall energy efficiency of electrified vehicles. While reducing the traction power losses through CAV-based technologies (e.g., eco-driving, platooning, cooperative adaptive cruise control) have been investigated heavily in the last decade (see Vahidi et al. and Guanetti et al [*1, 2*]) and the references therein), leveraging these connectivity technologies for efficient thermal management has been the subject of only a few recent studies (*8, 13, 16–18*).

The reason for the opportunities of thermal management optimization not being fully capitalized on is the challenges associated with thermal systems. Thermal systems, as compared with electrical current/voltage and mechanical dynamics, have relatively slow dynamic responses. Thus, vehicle speed forecasts with a relatively long time horizon are required for the optimization of the thermal system responses to achieve the best energy efficiency. This concept has been visualized in Figure 1, where the performance of a hypothetical optimization-based EV's BTM system is shown for a given traction power profile, along with the associated BTM power consumption. As can be seen, while the traction power demand is flat during the first part of the trip (e.g., driving in a city with low speed), it includes a high-demand period (e.g., driving in a highway) in the middle of the trip. For an economic optimization-based BTM controller designed with a short prediction horizon (Figure 1*a*), initially the controller is not aware of the upcoming highway driving period, pushing the battery temperature to its upper limit ($T_{\mathrm{bat}}^{\mathrm{UL}}$) to minimize the battery energy consumption. As a result, when the vehicle enters the highway, since the temperature is already close to its limit and the traction power demand rises suddenly, the temperature limit is violated. With a short prediction, the BTM system does not have enough lead time to enforce the constraint as the battery temperature dynamic responds slowly. Once the prediction horizon is extended (Figure 1*b*), the BTM controller detects the highway driving period early on, thus, pre-cooling the battery before entering the highway. The longer lead time allows the BTM controller to enforce the temperature constraint, see Amini et al. for further details (*8*).

To be useful for efficient thermal management, the long-term vehicle speed forecasts need to be sufficiently accurate, which is difficult to achieve with the existing connectivity-based vehicle speed prediction approaches. This is because vehicle-to-infrastructure (V2I) communications, which are often used for speed forecast/planning in CAVs through eco-driving, can only provide accurate short-range predictions.

Eco-driving at signalized intersections typically involves eco-arrival and eco-departure (EAD), where trajectories of one or more vehicles are optimized given the signal timing by controlling, or through the advisory of, vehicle speeds, with the purpose of reducing energy consumption. EAD studies can be classified into several categories based on the number of vehicles considered in the model, the number of intersections, whether surrounding traffic is considered, and the solution method. Most of the previous studies have addressed one vehicle approaching/departing one intersection without the consideration of surrounding vehicles (*19, 20*). Some other studies have considered multiple intersections, but they treated each intersection independently when planning vehicle speed trajectories (*21, 22*).

The surrounding traffic has a considerable impact on the ego-vehicle trajectory. The development of EAD algorithms which account for traffic queuing dynamics at the intersections has been addressed in other studies (*23–25*). A parsimonious shooting heuristic (SH) algorithm has been proposed in other studies to construct the trajectories of all the vehicles in the traffic network with considerations of the vehicle kinematic limits, traffic arrival patterns, car-following safety, and signal operations (*26, 27*). Almost all the EAD models mentioned above, as discussed earlier, generate short-term vehicle trajectories (e.g., over a time interval of 30 s to 60 s in duration). Furthermore, only one or two close-spaced intersections are considered in these studies over the planning horizon. On the other hand, while some studies have investigated long-term vehicle speed profile prediction, they have focused on predicting the average speed of the vehicle at the road segment level, or on estimating vehicle speed at a fixed location (*28–30*). Overall, high-resolution (i.e., capturing the main traffic events) and long-term vehicle speed forecasting has not been sufficiently addressed. The lack of long-term speed preview prohibits full exploitation of the CAVs' technology benefits in enhancing the thermal efficiency of electrified vehicles.

With the aforementioned challenges in the optimization-based thermal management of EVs and long-term vehicle speed forecast, this paper aims at answering the following questions:

- How to extend the traffic and vehicle speed forecasts beyond the current V2I-based technologies?
- How to integrate the long-term speed forecast with the short-range V2I-based eco-trajectory planning algorithms?
- How to leverage the long-term traffic preview for efficient thermal management of connected and automated electrified vehicles?
- How sensitive is the optimization-based thermal management strategy to the uncertainties in the long-term look-ahead preview?

To address these questions, a novel approach is proposed for long-term vehicle speed prediction using historical big traffic data analysis. At the same time, an eco-trajectory planning algorithm from the authors' previous work is adopted for short-term speed planning/prediction, and it is integrated with the data-driven long-term preview (*25*). To demonstrate the benefits of such multi-range speed prediction in enhancing the energy efficiency of CAVs, the BTM of EVs is focused on. To this end, an economic model predictive controller (MPC) is designed with incorporated speed preview. The performance of the designed BTM controller is studied with and without traffic preview uncertainty, and the advantages of the proposed long-term speed predictions with enhanced accuracy will be discussed in detail. Note that the application of the proposed long-term traffic forecast is not limited to the BTM problem, and can be used in numerous vehicular energy management solutions. Figure 2 summarizes the authors' efforts on integrated power and thermal management of CAVs, and distinguishes the new contributions of this paper. Other studies give a broader overview (*1, 2, 31*).

Multi-Range Vehicle Speed Prediction

In this section, the short-range eco-trajectory planning process which accounts for queuing dynamics is reviewed first. Then, the traffic data classification approach for long-range prediction of the CAVs speed profiles will be discussed.

Short-Range: Eco-Trajectory Planning for CAVs

The authors' previous work proposed an eco-trajectory planning approach which accounts for queuing dynamics along congested corridors (*25*). In this model, the eco-vehicle receives traffic signal and queue length information via V2I communications and generates a speed profile with the objective to minimize energy consumption. The queue length is predicted based on the trajectories of connected vehicles inferred from basic safety messages (BSMs) and from loop-detectors installed at the infrastructure side.

The queuing process is modeled based on the shockwave profile model (SPM) to provide a green window for eco-driving trajectory planning (*35*). In this paper, the green window is defined as the time interval during which an ego-vehicle can pass through a given intersection. Since the original SPM can only estimate the queue length after the signal cycle and after the vehicles have been already discharged, a modified algorithm was proposed in the authors' previous work which is able to predict the queuing dynamics and estimate the green window before the eco-driving vehicle arrival at an intersection (*35*).

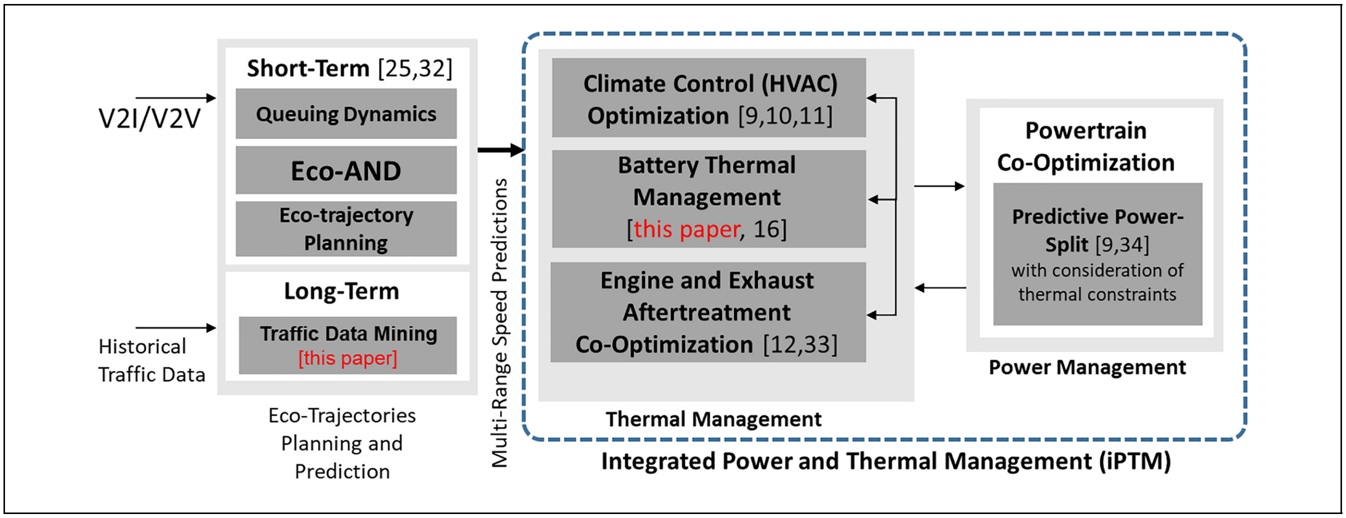

Figure 2. Research background on integrated power and thermal management of connected and automated vehicles (CAVs) (*9–12, 16, 25, 32–34*).
Note: HVAC = heating, ventilation, and air conditioning; V2I = vehicle-to-infrastructure; V2V = vehicle-to-vehicle.

Following the approach in authors' previous work (*25*), a six-intersection corridor on Plymouth Road in Ann Arbor, Michigan, U.S., has been modeled, which will be used in the simulations in the remainder of this paper. The stretch of the road represented in the simulations is about 2.2 miles long and has two lanes in each direction. This stretch is one of the busiest local commuting routes, connecting US23 to the North Campus of the University of Michigan and downtown Ann Arbor. A microscopic traffic simulation software VISSIM was used to build the road network and simulate background traffic (*36*). To calibrate the simulation model and represent a congested traffic condition, real-world data were collected during afternoon (PM) peak hour (4:00–5:00 p.m.), including traffic volume, turning ratio, and traffic signal timing at each intersection. The volume to capacity (v/c) ratios vary from different intersections and approaches with an average of around 0.85. Moreover, the traffic signals are under SCOOT (Split, Cycle, and Offset Optimization Technique) adaptive signal system. Figure 3 shows the arterial Plymouth corridor in Ann Arbor, along with the six considered intersections (red circles). Vehicles in VISSIM are programmed to broadcast BSMs. Additionally, all the traffic signals are programmed to broadcast signal status in real-time. All vehicle and signal data are sent to the queuing profile algorithm for prediction. Finally, the predicted green window is sent to the trajectory planning algorithm.

The predicted green window specifies a time interval during which the eco-driving vehicle should arrive at the intersection. The vehicle speed trajectory is then generated. The planning horizon of the vehicle speed trajectory starts from the time instant the eco-driving

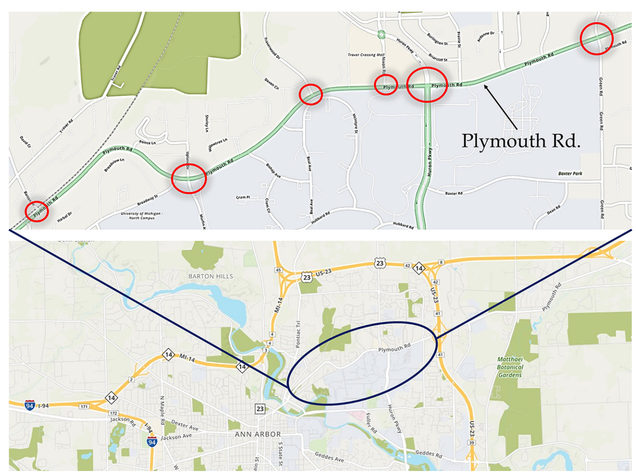

Figure 3. Plymouth corridor in Ann Arbor, Michigan, for traffic modeling and simulation.

vehicle enters the communication range until it departs from the intersection. To ensure a smooth trajectory and reduce the energy consumption, a trigonometric speed profile from Bath et al. (*21*) is used which has the following form,

$$v_{\mathrm{veh}}(t) = \begin{cases} v_p - v_r \cos(\mathrm{mt}), t \in [0, t_p) \\ v_p - v_r \dfrac{m}{n} \cos[n(t + \dfrac{\pi}{2n} - t_p)], t \in [t_p, t_q) \\ v_p + v_r \dfrac{m}{n}, t \in [t_q, t_{\mathrm{arr}}), \end{cases} \quad (1)$$

where $v_p = d_{\mathrm{stop}}/t_{\mathrm{arr}}, v_r = v_p - v_0$, $v_{\mathrm{veh}}(t)$ is the vehicle speed at time t, v_0 is the initial vehicle speed, d_{stop} is the distance to stop bar (i.e., to the end of the vehicle queue), t_{arr} is the time of arrival at the intersection given by $t_{\mathrm{arr}} = t_g + h$, t_g is the beginning of the green window estimated by the queue length prediction algorithm, and h is the saturation headway between two vehicles in seconds. At the time instant t_p, the speed of the eco-driving vehicle reaches the average speed v_p. After t_q, the vehicle speed does not change and the vehicle will cruise to the stop bar. The variables m and n are model parameters calculated based on maximum acceleration, maximum deceleration, and jerk constraints. These parameters determine the shape of the trigonometric profile and are set to reach the cruise segment as soon as possible, subject to the above constraints, as this reduces energy consumption. Note that $[0, t_{\mathrm{arr}})$ is the planning window. The trajectory planning ends when the vehicle passes the intersection.

The short-range eco-trajectory planning is executed once the CAV enters the communication range (i.e., 300 m) of an intersection and receives the traffic signal and queuing information. The planning algorithm is re-triggered if the traffic condition changes, for example, if the signal timing is changed or the green window is changed. Note that for normal driving (i.e., human drivers), the internal driving model in VISSIM is used, see Bath et al. and Yang et al. for more details (*21, 25*).

Based on the relationship between the predicted green window, current signal status, and the remaining time, the eco-driving vehicle may choose one of the following four types of speed profiles: "slow down," "speed up," "cruise," or "stop." All speed profiles except for "cruise" are informed by the trigonometric profiles with different parameters, while the "cruise" speed profile maintains a constant speed to pass the intersection. In this paper, the minimum cruise speed is set to be 70% of the speed limit. Following the analysis in Liu et al. (*37*), Figure 4 shows the distribution of the acceleration data for 50 CAVs simulated with and without the eco-trajectory strategy at different speeds. All these 50 CAVs pass through the entire corridor, that is, none of them exit the corridor before the last intersection. It can be seen that the eco-trajectory planning, by making the speed profiles of the CAVs smoother, reduces the aggressiveness in driving and limits the absolute maximum of the acceleration/deceleration to 2 m/sec^2. See Amini et al. and Yang et al. for a detailed analysis of the proposed eco-driving strategy impact on the energy consumption of HEVs (*9, 12, 25*).

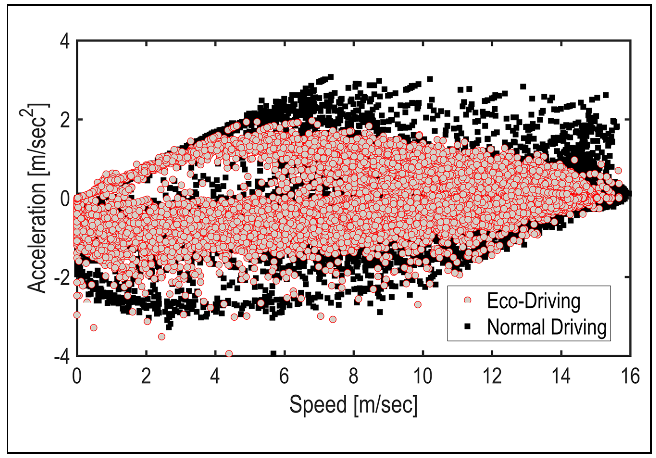

Figure 4. Distributions of acceleration/deceleration for 50 connected and automated vehicles (CAVs), with and without eco-trajectory planning incorporated at different vehicle speeds.

Long Range: Traffic Data Classification

In some previous studies, the extensive coverage of the cellular network, GPS-based position and velocity measurements, and the communication infrastructure of cellphones have been exploited to estimate the traffic flow speed (v_{flow}) for energy management of electrified vehicles (*38–40*). While the study in Herrera et al. has shown that traffic flow data can be extracted from a GPS-based traffic monitoring system and be used for long-term vehicle speed predictions for energy management of electrified vehicles, the main focus of these studies is for highway driving (*39*). Urban driving scenario with congestion and multiple intersections is not considered. The main challenge in the latter case is that the average GPS-based speed data cannot represent the traffic flow dynamics.

To demonstrate the aforementioned challenge, the same six-intersection corridor shown in Figure 3, and modeled in VISSIM (*36*) is recalled. The model is run for 4 hours, and the trajectories of mixed traffic (1,531 vehicles in total: 1,481 driven by human, 50 eco-driving) are collected. It should be noted that the total number of vehicles in the background traffic is more than 1,531, as some vehicles enter/exit the considered corridor at different intersections. In this section, only the data from those vehicles that pass through all the six intersections (i.e., 1,531 vehicles) is considered. In this study, the penetration rate of eco-vehicles is less than 4%, thereby the overall pattern of the traffic is dominated by the vehicles with human drivers. Additionally, it is assumed that all the simulated vehicles are connected and they can communicate their speed and position data. To reduce the uncertainties brought by the adaptive traffic signals, the SCOOT system is replaced by a coordinated fixed-time signal timing policy with a cycle length of 100 s in all intersections.

Figure 5*a* shows the overall average and standard deviation of the aggregated speed profiles of all the simulated vehicles along the Plymouth corridor. Since the

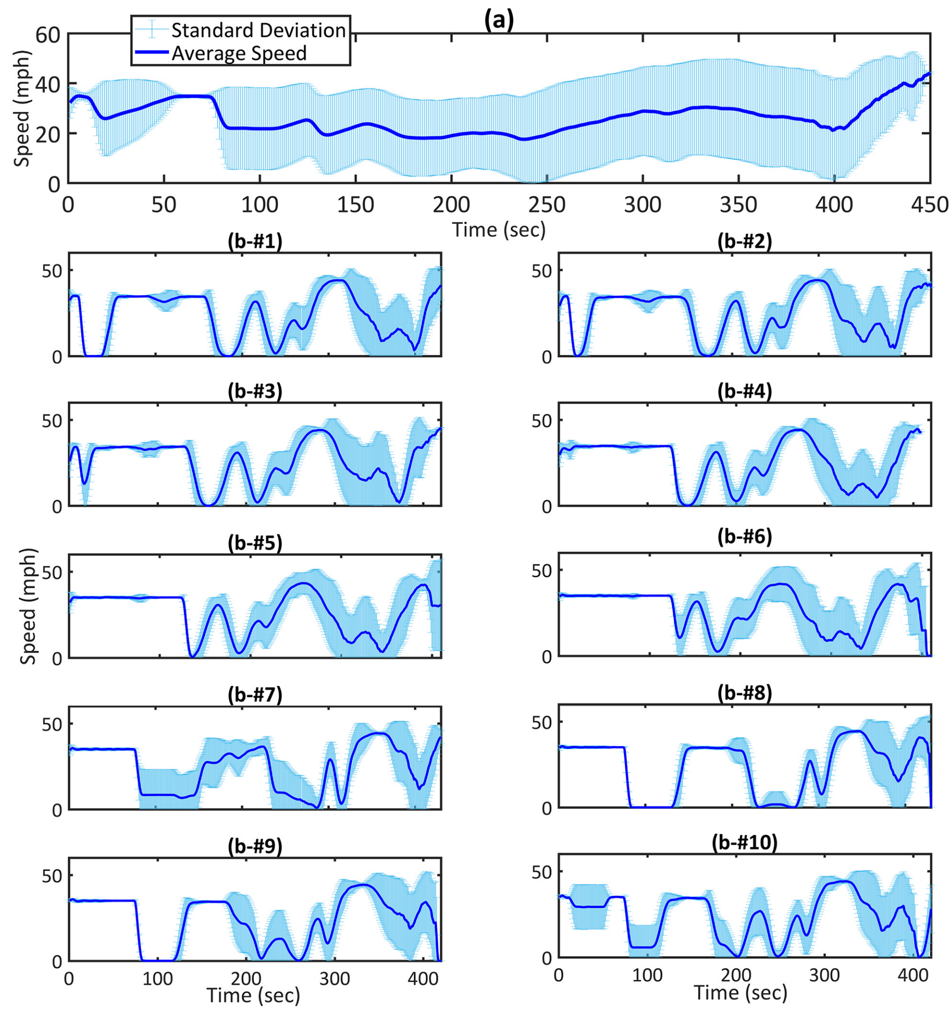

Figure 5. (*a*) The overall average and standard deviation of the 1,531 simulated vehicles over the Plymouth Rd, and (*b*-#1–10) average and standard deviation of the "classified" speed profiles in 10 bins.

simulation model is calibrated against real-world data, it is considered as the ground truth in this study. It can be seen that, despite having six intersections and multiple stop-and-go behaviors in the majority of the vehicles (i.e., it is very unlikely that one vehicle passes the entire corridor without stopping at one of the intersections), the average of all the vehicles trajectories does not provide insightful information about the traffic flow and the location and time of the stops at the signalized intersections. Moreover, the standard deviation of data shown in Figure 5*a* is large, showing a large variation in the behavior of the vehicles traveling through Plymouth Rd corridor. This aggregated average speed, if used for long-range vehicle speed predictions, will result in large error for MPC-based energy management strategies. Operating the system at its limit with an uncertain speed preview will increase the chances of constraint violations. While violation of hard physical constraint could be safety-critical and unacceptable, violation of soft constraints is usually associated with efficiency and other performance degradation.

The large variance in the aggregated data suggests that a data classification/fusion is needed to get clearer patterns in the speed profiles to improve the long-range demand preview for predictive energy management (*41–45*). The traffic signals on arterial corridors dictate the traffic flow with the stop-and-go feature. If the traffic signal information is known, it is possible to classify the trajectories based on the signal timing plans. To this end, a rule-based data classification algorithm is applied to the collected vehicle trajectories. All vehicles are categorized into 10 bins based on their arrival time at the first intersection. One signal cycle of 100 s, which begins with the signal turning red, is divided equally into 10 intervals and each interval consists of 10 s corresponding to one bin. For example, if a vehicle arrives at the intersection 45 s after the signal turns to red, the vehicle is classified into bin 5 (i.e., 40–50 s). Note that, intuitively, two bins can be considered based on the signal's red and green intervals. The analysis showed that, because of the effects of the queuing dynamic, two bins cannot capture the long-term patterns of the traffic flow, calling for more bins (i.e., >10) to achieve acceptable speed prediction accuracy.

The average and standard deviation of the vehicle speed profiles clustered into these 10 bins are shown in Figure 5*b*-#1–10. Compared with Figure 5*a*, 5*b* confirms that the signal timing-based classification improves the prediction accuracy significantly. Since the vehicle classification is done only based on the arrival time at the first intersection, the speed variations increase spatially. Note that, while the average speed of the classified vehicles captures the approximate trend of the traffic flow, Figure 5*b* shows that the speed variations are different for different bins. Overall, once the bin number for the ego-vehicle is determined, the associated average long-term speed preview is assigned to that vehicle based on the data shown in Figure 5*b*.

Figure 6 shows the average and standard deviations of the two selected bins (i.e., #8 and #7) from the total 10 classified bins. Figure 6*a* shows that while the traffic data classification is done only based on the arrival time at the first intersection (shown in Figure 3), the associated speed variation over the first 3 minutes of the trip is less than 5 mph in bin #8. On the other hand, for the second bin (i.e., #7) shown in Figure 6*b*, the variation increases after the first intersection. The reason for picking ego-vehicles in bins #7 and #8 is that they respectively represent the bins with the highest and lowest standard deviations in the speed preview. Such selection makes it possible to investigate the performance of the optimization-based BTM system in the best- and worst-case scenarios.

Case Study: Electric Vehicle (EV) Battery Thermal Management (BTM)

To demonstrate the effectiveness of the proposed traffic data classification in improving the efficiency and robustness of MPC-based energy management of CAVs, a BTM problem for connected EVs is considered in this section. The battery is the only source of power for traction (P_{trac}) in EVs, and its efficient thermal management is important for safe and efficient operation of the battery, as well as the vehicle (*13*). EVs have relatively bigger batteries as compared with HEVs, thus a liquid-based BTM system with higher cooling capacity is often utilized to effectively manage the thermal loads of the battery. The liquid-based BTM system uses the A/C refrigerant to reject heat ($\dot{Q}$) from the battery and introduces extra load on the A/C compressor (P_{BTM}). The auxiliary power for operating the A/C compressor can be up to 2.5 kW from the battery (*13*).

Conventional BTM is designed to maintain the battery temperature (T_{bat}) within the desired range by tracking a constant or variable temperature setpoint well below the upper temperature limit (*46*). The tracking-based BTM strategy, however, results in a conservative design and reduces the EV's range because of the excessive energy being consumed for BTM purpose. On the other hand, optimization-based BTM solutions with trip "preview" information can maintain the battery temperature within the desired limits (e.g., $T_{\text{bat}}^{\text{LL}} - T_{\text{bat}}^{\text{UL}}$) efficiently (*13*). An economic MPC-based BTM solves the following finite-time (i.e., N) optimization problem:

$$
\begin{aligned}
\min_{\dot{Q}(\cdot|k)} \quad & \sum_{i=0}^{N} P_{\text{BTM}}(i|k), \\
\text{s.t.} \quad & T_{\text{bat}}(i+1|k) = f_{T_{\text{bat}}}(i|k), i = 0, \cdots, N, \\
& \text{SOC}(i+1|k) = f_{\text{SOC}}(i|k), i = 0, \cdots, N, \\
& T_{\text{bat}}^{\text{LL}} \leq T_{\text{bat}}(i|k) \leq T_{\text{bat}}^{\text{UL}}, i = 0, \cdots, N, \\
& -\dot{Q}_{\max} \leq \dot{Q}(i|k) \leq 0, i = 0, \cdots, N-1, \\
& T_{\text{bat}}(0|k) = T_{\text{bat}}(k), \text{SOC}(0|k) = \text{SOC}(k),
\end{aligned} \tag{2}
$$

where $(i|k)$ denotes the prediction for the time instant $k + iT$ made at the time instant k. $f_{T_{\text{bat}}}$ and f_{SOC} are the nonlinear models used for predicting the battery temperature (T_{bat}) and battery state-of-charge (*SOC*) over the prediction horizon N, respectively (*8*):

$$
f_{\text{SOC}}(k) = \text{SOC}(k) - T\left(\frac{U_{\text{oc}}(k) - \sqrt{U_{\text{oc}}^2(k) - 4R_{\text{bat}}(k)(P_{\text{trac}}(k) + P_{\text{BTM}}(k))}}{2C_{\text{nom}}R_{\text{bat}}(k)}\right), \tag{3}
$$

$$
f_{T_{\text{bat}}}(k) = T_{\text{bat}}(k) + T\left(\frac{\frac{\left(U_{\text{oc}}(k) - \sqrt{U_{\text{oc}}^2(k) - 4R_{\text{bat}}(k)P_{\text{trac}}(k) + P_{\text{BTM}}(k)}\right)^2}{4R_{\text{bat}}(k)} + \dot{Q}(k)}{m_{\text{bat}}C_{\text{th,bat}}}\right), \tag{4}
$$

with T being the sampling time, and R_{bat}, U_{oc}, C_{nom}, $C_{\text{th,bat}}$, m_{bat} being battery internal resistance, open-circuit voltage, nominal capacity, thermal capacity, and mass, respectively. The optimization problem in Equation 2 is to minimize the power spent for battery thermal management, $P_{\text{BTM}} = a_c\dot{Q}$, over the prediction horizon N, while

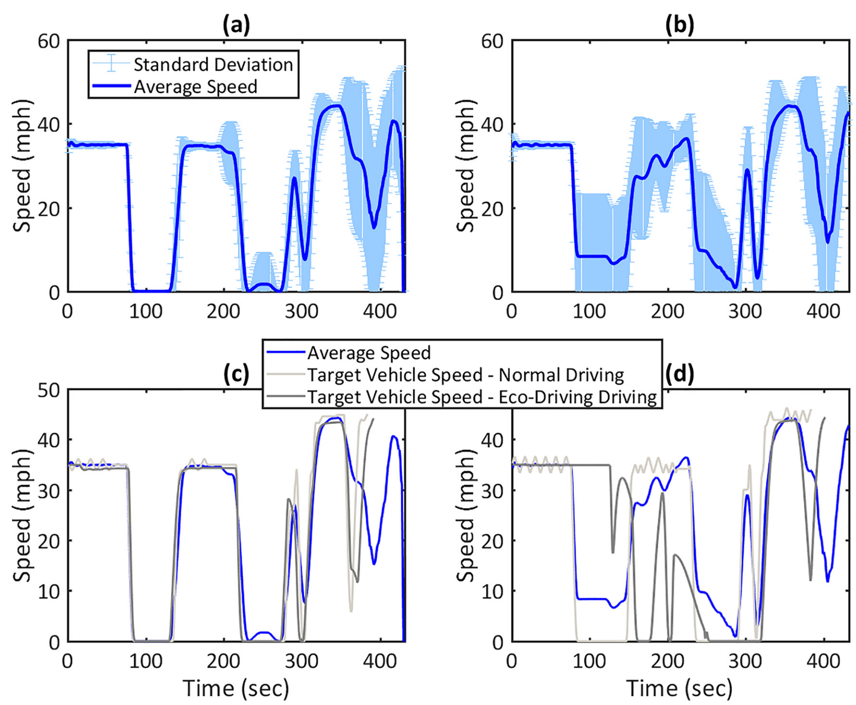

Figure 6. Average and standard deviation of the "classified" speed profiles: (*a*) bin #8, (*b*) bin #7, and speed profiles of two target vehicles with normal driving and eco-driving in bin #8 (*c*), and bin #7 (*d*).

enforcing the state and input constraints (*16*). In Equation 2, T_{bat}^{UL} and T_{bat}^{LL} are set to 40°C and 20°C, respectively (*46*). Note that $\dot{Q}$ is always non-positive for battery cooling scenario with a_c being constant. The parameters of the battery T_{bat} and *SOC* models, as well as the vehicle longitudinal dynamic (to compute P_{trac} as a function of the vehicle speed) are adopted from the library of Autonomie* software for an EV, and can be found in studies by Amini et al. and Halbach et al. (*8, 16, 47*).

The optimization problem is solved at every time step, then the horizon is shifted by one step (T), and only the current control is commanded to the system ($\dot{Q}(k) = \dot{Q}(0|k)$). The closed-loop simulations are carried out on a desktop computer, with an Intel® Core i7@2.60 GHz processor, in MATLAB®/SIMULINK® using YALMIP (*48*) for formulating the optimization problem, and IPOPT for solving the optimization problem numerically (*49*). The BTM using the MPC in Equation 2 with speed preview (via P_{trac}) is referred to as "eco-cooling" in this paper (*16*).

*Autonomie® is a MATLAB®/Simulink®-based system simulation tool for vehicle energy consumption and performance analysis developed by Argonne National Laboratory (ANL) [*47*].

Simulation Results

Intuitively, the MPC in Equation 2 leads the battery temperature to the upper limit T_{bat}^{UL} to reduce the BTM power consumption (similar to the concept shown earlier in Figure 1). Unlike the traction power demand with a relatively fast responding dynamic, the battery temperature responds slowly. The slow thermal dynamics of the battery calls for a long prediction horizon so that the MPC (Equation 2) can maintain the temperature within the desired limits. Two sample vehicles from bins #8 and #7 are selected, and their normal-driving and eco-driving speed trajectories are shown in Figure 6*c* and 6*d*, respectively. Figure 7*a* and 7*b* show the results of BTM with the MPC with prediction horizons of $N = 30$ (30 sec with sampling period of $T = 1$ sec) and 180 (180 sec) for these two target vehicles, in which they follow the eco-trajectories (i.e., with eco-driving) shown in Figure 6*c* and 6*d*.

First, the case where the exact speed previews are known a priori is considered. Figure 7*a* and 7*b* show that, while the battery temperature upper limit (T_{bat}^{UL}) is enforced for both target vehicles with a long prediction horizon (e.g., $N = 180$), the battery temperature constraint is violated when a short horizon (e.g., $N = 30$) is used, specifically toward the end of the driving cycle. Next, the impact of uncertainty in vehicle speed preview

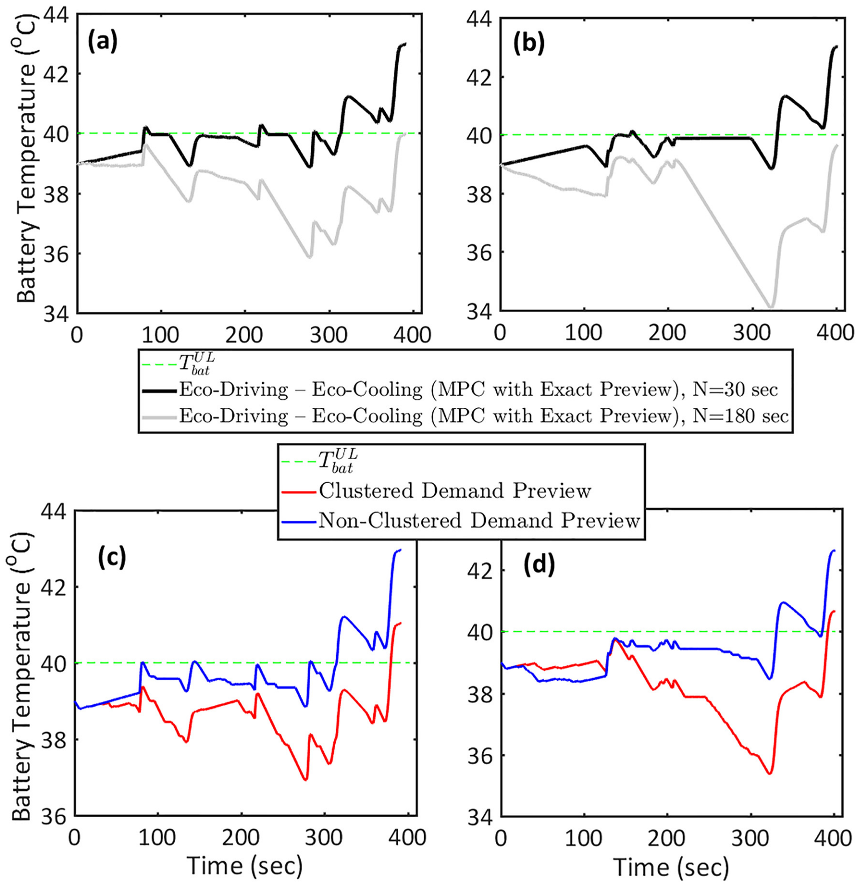

Figure 7. Time histories of the battery temperature with the model predictive control (MPC) in Equation 2 for prediction horizons of $N = 30, 180$ for the eco-vehicles in bin #8 (*a*) and #7 (*b*). Subplots (*c, d*) show the MPC-based battery thermal management (BTM) results for $N = 180$ with clustered (i.e., classified) and non-clustered speed previews for eco-vehicles in bin #8 and #7, respectively.

is shown in Figure 7*c* and 7*d*, where the non-clustered speed preview is based on the aggregated speed average as in Figure 5*a*, and the clustered ones are based on the average speed of the vehicles in bin #8 and #7. Figure 7*c* and 7*d* show that an uncertain speed preview can deviate the performance of the BTM controller. It is also observed from Figure 7*c* and 7*d* that a rule-based traffic data classification helps to significantly improve the performance of MPC-based BTM system with fewer constraint violations. It is noted that, even with an improved speed preview through traffic data classification, enforcing the battery temperature constraint over the entire driving cycle cannot be guaranteed. This is because the long-range speed prediction is based on the arrival time at the first intersection; thus, the speed variation increases as the distance of the ego-vehicle from the first intersection increases.

It was shown in Figure 7 that traffic data classification helps significantly improve the robustness of the MPC-based BTM strategy in relation to the battery temperature constraint violation. These results are consistent with previous studies (*16*) over EPA driving cycles (e.g., Urban Dynamometer Driving Schedule [UDDS] and New York City Cycle [NYCC]) that have investigated the impact of prediction horizon length on the MPC-based BTM performance (*16*). The energy consumption results of three cases for the two selected target vehicles in bins #7 and #8 are compared in Figure 8. Figure 8 shows that with normal BTM cooling (i.e., conventional battery temperature setpoint tracking), eco-driving reduces the vehicle-level energy consumption by 19.7% and 18.6% for the target vehicles in bin #8 and #7, respectively, as compared with the baseline case with normal driving and normal battery cooling. Note that the eco-driving, even without an optimized BTM, decreases the BTM energy consumption by 12.4% (#8) and 21.2% (#7). Upon applying the eco-cooling strategy, the BTM energy consumption is further reduced by 30.2% (#8)

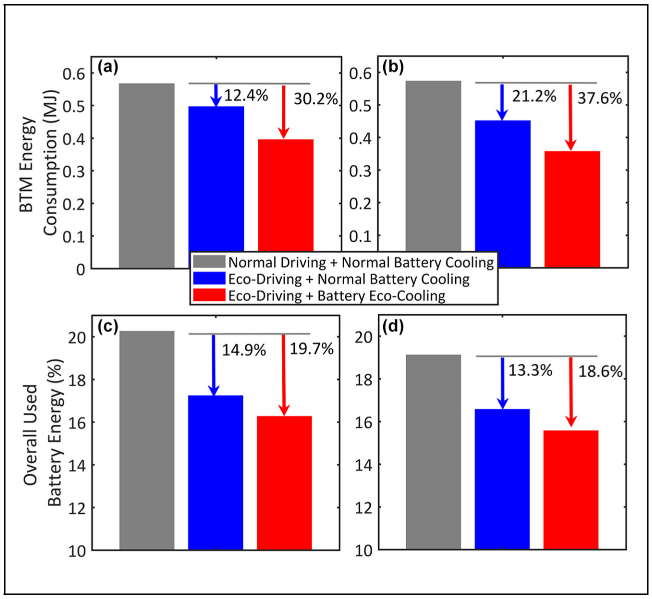

Figure 8. Battery thermal management (BTM) and vehicle-level energy saving results through eco-driving and eco-cooling based on the long-range speed preview for the target vehicles from bin #8 (*a*, *c*) and #7 (*b*, *d*), and the initial battery temperature of 39°*C*.

and 37.6% (#7), which are translated into further energy savings results of up to 19.7% (#8) and 18.6% (#7) at the vehicle level. It is worth noting that these savings are achieved despite the uncertainties in long-range vehicle speed predictions.

Finally, the MPC-based BTM strategy with long-term uncertain speed preview is compared with the ideal case, where the exact speed preview is known a priori, and the results are summarized in Figure 9. Figure 9 shows that, because of the mismatch between the actual and the estimated speed preview, the performance of the BTM controller varies slightly from the ideal case. While for the target vehicle in bin #7 (Figure 9*b*) the overall energy consumption increases by 1%, for the vehicle in bin #8 (Figure 9*d*), with much lower speed variation as shown in Figure 6, the overall consumed energy is decreased by 1.1%.

Conclusion

A big data analytic framework for CAVs, integrated with a V2I-based speed trajectory planning algorithm, was

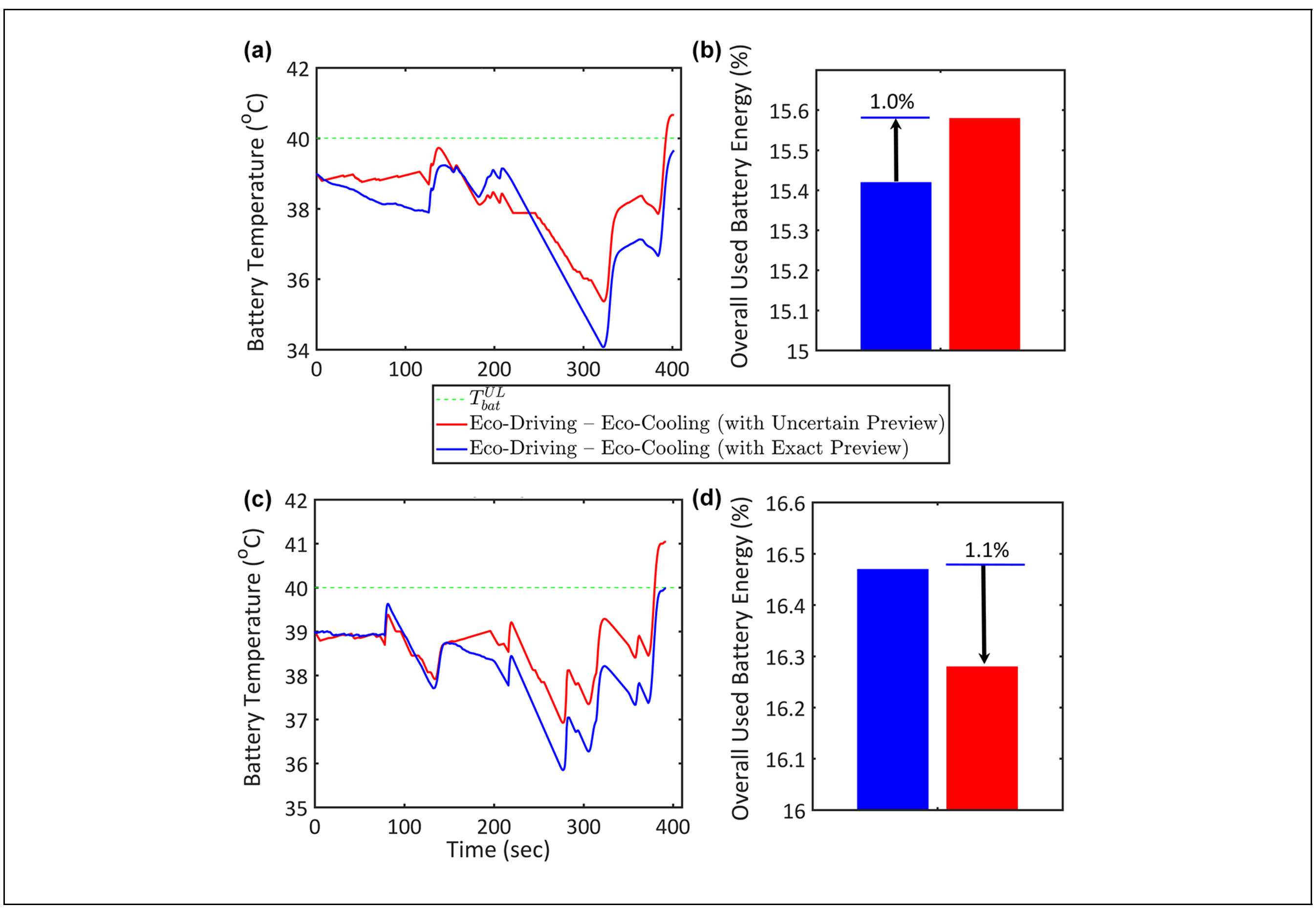

Figure 9. Time histories of the battery temperature and vehicle-level energy saving results through eco-cooling with exact and approximate (uncertain) speed previews for the target vehicles in bin #7 (*a*, *b*) and #8 (*c*, *d*) for initial battery temperature of 39°*C*.

developed in this paper to provide short- and long-range speed previews for optimization-based energy management of electrified CAVs:

- Over the short prediction horizon, an eco-trajectory speed planning algorithm is used with consideration of the queuing dynamics at the intersections.
- Over the long prediction horizon, by leveraging the data collected from an urban traffic network, a big data classification algorithm was developed to mine historical traffic data and predict the vehicle speed.
- Integrating the short- (and accurate) and long- (and approximate) range speed forecasts creates a multi-range speed preview which allows for optimizing (fast) power and (slow) thermal dynamics of EVs through predictive optimization schemes.
- The application of the proposed CAV speed prediction strategy was studied for BTM of connected EVs. It was shown that, compared with the baseline EVs with normal driving, an average energy saving of up to 14% can be achieved through eco-driving.
- The simulation results over real-world urban driving cycles showed that by using the proposed traffic speed prediction scheme substantial energy can be saved via the "eco-cooling" strategy for BTM of connected EVs, as compared with more traditional energy management techniques without consideration of vehicle speed preview.
- While the data classification approach enhances the preview accuracy, the forecast is still subject to uncertainties. For BTM application, with a relatively slow dynamic, this approximate long-term preview is still valuable and can be leveraged to enhance the energy consumption of EVs by 4%–5%.

This paper aimed at modeling the early deployment stage of CAVs where the penetration rate is very low (e.g., 4%). The results showed significant fuel benefit of being "connected," which can incentivize the deployment of CAVs. Investigating the impact of CAVs' penetration rate on the traffic flow and energy efficiency is left to future works. The authors will also focus on enhancing the data classification algorithm accuracy, which currently is formulated based on the arrival times at the first intersection of the considered arterial corridor. To this end, advanced spatiotemporal data analytic algorithms will be adopted to take into account the randomness of the traffic data in a highly stochastic urban driving environment with different penetration rates of CAVs (*6*). This allows for updating the long-term speed preview after passing the first intersection based on the new observation and data collected from the traffic network in real-time (i.e., rolling prediction horizon versus fixed prediction horizon). Moreover, the application of the proposed framework will be studied for more complex power and thermal management of the CAVs, with consideration of the combustion engine and cabin thermal management. In addition, similar to the approach in Yeon et al. (*50*), it is of interest to conduct a comparative analysis between model-based approaches and recently rising learning-based approaches in relation to eco-speed profile generation and prediction.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M. Amini, Y. Feng, Z. Yang, J. Sun, I. Kolmanovsky; data collection: Z. Yang, Y. Feng; analysis and interpretation of results: M. Amini, Y. Feng, Z. Yang, J. Sun, I. Kolmanovsky; draft manuscript preparation: M. Amini, Y. Feng, Z. Yang, J. Sun, I. Kolmanovsky. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This material is based on the work supported by the United States Department of Energy (DOE), ARPA-E NEXTCAR program under award No. DE-AR0000797.

References

1. Vahidi, A., and A. Sciarretta. Energy Saving Potentials of Connected and Automated Vehicles. *Transportation Research Part C: Emerging Technologies*, Vol. 95, 2018, pp. 822–843.
2. Guanetti, J., Y. Kim, and F. Borrelli. Control of Connected and Automated Vehicles: State of the Art and Future Challenges. *Annual Reviews in Control*, Vol. 45, 2018, pp. 18–40.
3. Borek, J., B. Groelke, C. Earnhardt, and C. Vermillion. Economic Optimal Control for Minimizing Fuel Consumption of Heavy-Duty Trucks in a Highway Environment. *IEEE Transactions on Control Systems Technology*, Vol. 28, No. 5, 2020, pp. 1652–1664.
4. Robinette, D., E. Kostreva, A. Krisztian, A. Lackey, C. Morgan, J. Orlando, and N. Rama. *PHEV Real World Driving Cycle Energy and Fuel and Consumption Reduction Potential for Connected and Automated Vehicles*. SAE Technical paper 2019-01-0307. Society of Automotive Engineers, Detroit, 2019.
5. Xu, C., S. Geyer, and H. Fathy. Formulation and Comparison of Two Real-Time Predictive Gear Shift

Algorithms for Connected/Automated Heavy-Duty Vehicles. *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 8, 2019, pp. 7498–7510.
6. Li, Y., S. Shekhar, P. Wang, and W. Northrop. Physics-Guided Energy Efficient Path Selection: A Summary of Results. *Proc., 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. Seattle, WA, 2018.
7. Sangjae, B., Y. Kim, J. Guanetti, F. Borrelli, and S. Moura. Design and Implementation of Ecological Adaptive Cruise Control for Autonomous Driving with Communication to Traffic Lights. *Proc., American Control Conference*, Philadelphia, PA, 2019.
8. Amini, M., I. Kolmanovsky, and J. Sun. Two-Layer Model Predictive Battery Thermal and Energy Management Optimization for Connected and Automated Electric Vehicles. *Proc., 57th IEEE Conference on Decision and Control*, Miami Beach, FL, 2018.
9. Amini, M. R., X. Gong, H. Wang, I. Kolmanovsky, and J. Sun. Sequential Optimization of Speed, Thermal Load, and Power Split in Connected HEVs. *Proc., American Control Conference*, Philadelphia, PA, 2019.
10. Wang, H., I. Kolmanovsky, M. R. Amini, and J. Sun. Model Predictive Climate Control of Connected and Automated Vehicles for Improved Energy Efficiency. *Proc., American Control Conference*, Milwaukee, WI, 2018.
11. Amini, M., H. Wang, X. Gong, D. Liao-McPherson, I. Kolmanovsky, and J. Sun. Cabin and Battery Thermal Management of Connected and Automated HEVs for Improved Energy Efficiency using Hierarchical Model Predictive Control. *IEEE Transactions on Control Systems Technology* Vol. 28, No. 5, 2020, pp. 1711–1726.
12. Amini, M., Y. Yiheng, H. Wang, I. Kolmanovsky, and J. Sun. Thermal Responses of Connected HEVs Engine and Aftertreatment Systems to Eco-Driving. *Proc., 3rd IEEE Conference on Control Technology and Applications*, Hong Kong, China, 2018.
13. Bauer, S., A. Suchaneck, and F. León. Thermal and Energy Battery Management Optimization in Electric Vehicles using Pontryagin's Maximum Principle. *Journal of Power Sources*, Vol. 246, 2014, pp. 808–818.
14. Neubauer, J., and E. Wood. Thru-Life Impacts of Driver Aggression, Climate, Cabin Thermal Management, and Battery Thermal Management on Battery Electric Vehicle Utility. *Journal of Power Sources*, Vol. 259, 2014, pp. 262–275.
15. Jeffers, M., L. Chaney, and J. Rugh. *Climate Control Load Reduction Strategies for Electric Drive Vehicles in Warm Weather*. SAE Technical paper 2015-01-0355. Society of Automotive Engineers, Detroit, 2015.
16. Amini, M., I. Kolmanovsky, and J. Sun. Hierarchical MPC for Robust Eco-Cooling of Connected and Automated Vehicles and Its Application to Electric Vehicle Battery Thermal Management. *IEEE Transactions on Control Systems Technology*, 2020. https://doi.org/10.1109/TCST.2020.2975464.
17. Masoudi, Y., A. Mozaffari, and N. Azad. Battery Thermal Management of Electric Vehicles: An Optimal Control Approach. *Proc., ASME Dynamic Systems and Control Conference*, Columbus, OH, 2016.
18. Masoudi, Y., and N. Azad. MPC-Based Battery Thermal Management Controller for Plug-in Hybrid Electric Vehicles. *Proc., American Control Conference*, Seattle, WA, 2017.
19. Rakha, H., and R. Kamalanathsharma. Eco-Driving at Signalized Intersections using V2I Communication. *Proc., 14th International IEEE Conference on Intelligent Transportation Systems*, Washington, D.C., 2011.
20. Guan, T., and C. Frey. Predictive Fuel Efficiency Optimization using Traffic Light Timings and Fuel Consumption Model. *Proc., 16th International IEEE Conference on Intelligent Transportation Systems*. The Hague, The Netherlands, 2013.
21. Barth, M., S. Mandava, K. Boriboonsomsin, and H. Xia. Dynamic ECOdriving for Arterial Corridors. *Proc., IEEE Forum on Integrated and Sustainable Transportation System*, Vienna, Austria, 2011.
22. Xia, H., K. Boriboonsomsin, and M. Barth. Dynamic Eco-Driving for Signalized Arterial Corridors and Its Indirect Network-Wide Energy/Emissions Benefits. *Journal of Intelligent Transportation Systems*, Vol. 17, No. 1, 2013, pp. 31–41.
23. Wu, X., X. He, G. Yu, A. Harmandayan, and Y. Wang. Energy-Optimal Speed Control for Electric Vehicles on Signalized Arterials. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 16, No. 5, 2015, pp. 2786–2796.
24. He, X., H. Liu, and X. Liu. Optimal Vehicle Speed Trajectory on a Signalized Arterial with Consideration of Queue. *Transportation Research Part C: Emerging Technologies*, Vol. 61, 2015, pp. 106–120.
25. Yang, Z., Y. Feng, X. Gong, D. Zhao, and J. Sun. Eco-Trajectory Planning with Consideration of Queue along Congested Corridor for Hybrid Electric Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2019. 2673: 277–286.
26. Ma, J., X. Li, F. Zhou, J. Hu, and B. B. Park. Parsimonious Shooting Heuristic for Trajectory Design of Connected Automated Traffic Part II: Computational Issues and Optimization. *Transportation Research Part B: Methodological*, Vol. 95, 2017, pp. 421–441.
27. Zhou, F., X. Li, and J. Ma. Parsimonious Shooting Heuristic for Trajectory Design of Connected Automated Traffic Part I: Theoretical Analysis with Generalized Time Geography. *Transportation Research Part B: Methodological*, Vol. 95, 2017, pp. 394–420.
28. Park, J., Y. Murphey, R. McGee, J. G. Kristinsson, M. L. Kuang, and A. M. Phillips. Intelligent Trip Modeling for the Prediction of an Origin–Destination Traveling Speed Profile. *IEEE Transactions on Intelligent Transportation Systems* Vol. 15, No. 3, 2014, pp. 1039–1053.
29. Jiang, B, and Y. Fei Vehicle Speed Prediction by Two-Level Data Driven Models in Vehicular Networks. *IEEE Transactions on Intelligent Transportation Systems* Vol. 18, No. 7, 2016, pp. 1793–1801.
30. Ma, X., Z. Tao, Y. Wang, H. Yu, and Y. Wang. Long Short-Term Memory Neural Network for Traffic Speed Prediction using Remote Microwave Sensor Data.

Transportation Research Part C: Emerging Technologies, Vol. 54, 2015, pp. 187–197.

31. Zhang, F., X. Hu, R. Langari, and D. Cao. Energy Management Strategies of Connected HEVs and PHEVs: Recent Progress and Outlook. *Progress in Energy and Combustion Science*, Vol. 73, 2019, pp. 235–256.
32. Feng, Y, Z. Yang, M. R. Amini, Q. Hu, and J. Sun. Eco-Trajectory Planning Considering Cut-In Intention for Hybrid Electric Connected Vehicles. Presented at 99th Annual Meeting of the Transportation Research Board, Washington, D.C., 2020..
33. Hu, Q., M. Amini, Y. Feng, Z. Yang, H. Wang, I. Kolmanovsky, J. Sun, A. Wiese, Z. Qiu, and J. B. Seeds. *Engine and Aftertreatment Co-Optimization of Connected HEVs via Multi-Range Vehicle Speed Planning and Prediction*. SAE Technical Paper 2020-01-0590. Society of Automotive Engineers, Detroit, MI, 2020.
34. Gong, X., H. Wang, M. Amini, I. Kolmanovsky, and J. Sun. Integrated Optimization of Power Split, Engine Thermal Management, and Cabin Heating for Hybrid Electric Vehicles. *Proc., 3rd IEEE Conference on Control Technology and Applications*, Hong Kong, China, 2019.
35. Wu, X., and H. X. Liu. A Shockwave Profile Model for Traffic Flow on Congested Urban Arterials. *Transportation Research Part B: Methodological*, Vol. 45, No. 10, 2011, pp. 1768–1786.
36. PTV Group. *PTV Vissim 9.0 User Manual*. PTV AG, Karlsruhe, Germany, 2016.
37. Liu, J, K Kockelman, and A Nichols. Anticipating the Emissions Impacts of Smoother Driving by Connected and Autonomous Vehicles, using the MOVES Model. Presented at 95th Annual Meeting of the Transportation Research Board, Washington, D.C., 2016.
38. Herrera, J., D. Work, R. Herring, X. J. Ban, Q. Jacobson, and A. M. Bayen. Evaluation of Traffic Data Obtained via GPS-Enabled Mobile Phones: The Mobile Century Field Experiment. *Transportation Research Part C: Emerging Technologies*, Vol. 18, No. 4, 2010, pp. 568–583.
39. Sun, C., F. Sun, X. Hu, J. K. Hedrick, and S. Moura. Integrating Traffic Velocity Data into Predictive Energy Management of Plug-In Hybrid Electric Vehicles. *Proc., American Control Conference*, Chicago, IL, 2015.
40. Sun, C., S. Moura, X. Hu, J. K. Hedrick, and F. Sun. Dynamic Traffic Feedback Data Enabled Energy Management in Plug-In Hybrid Electric Vehicles. *IEEE Transactions on Control Systems Technology*, Vol. 23, No. 3, 2014, pp. 1075–1086.
41. Hosseini, S. A. *Data-Driven Framework for Modeling Deterioration of Pavements in the State of Iowa*. PhD thesis. Iowa State University, 2020.
42. Mehran, B., and M. Kuwahara. Fusion of Probe and Fixed Sensor Data for Short-Term Traffic Prediction in Urban Signalized Arterials. *International Journal of Urban Sciences*, Vol. 17, No. 2, 2013, pp. 163–183.
43. Jenkins, J., D. Lewis, and S. A. Hosseini. Does Practicing One Steering Task Improve Performance on a Subsequent Steering Task? *Proc., Road Safety and Simulation International Conference*, Orlando, FL, 2015.
44. Jenkins, J., and S. A. Hosseini. Real-Time Data Extraction Program for Research Simulators. *Proc., IMAGE Conference*, Dayton, OH, 2015.
45. Hosseini, S. A. *Extracting Real-Time Data from a Driving Simulator*. Master thesis. Cleveland State University, 2015.
46. Zolot, M., A. Pesaran, and M. Mihalic. *Thermal Evaluation of Toyota Prius Battery Pack*. SAE Technical paper 2002-01-1962. Society of Automotive Engineers, Detroit, 2002.
47. Halbach, S., P. Sharer, S. Pagerit, A. P. Rousseau, and C. Folkerts. *Model Architecture, Methods, and Interfaces for Efficient Math-Based Design and Simulation of Automotive Control Systems*. SAE Technical paper 2010-01-0241. Society of Automotive Engineers, Detroit, 2010.
48. Lofberg, J. YALMIP: A Toolbox for Modeling and Optimization in MATLAB. *Proc., 2004 IEEE International Conference on Robotics and Automation*, New Orleans, LA, 2004.
49. Wächter, A., and L. Biegler. On the Implementation of an Interior-Point Filter Line-Search Algorithm for Large-Scale Nonlinear Programming. *Mathematical Programming*, Vol. 106, No. 1, 2006, pp. 25–57.
50. Yeon, K., K. Min, J. Shin, M. Sunwoo, and M. Han. Ego-Vehicle Speed Prediction using a Long Short-Term Memory Based Recurrent Neural Network. *International Journal of Automotive Technology*, Vol. 20, No. 4, 2019, pp. 713–722.