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Hybrid powertrain control with dynamic traffic prediction based on real-world V2X information

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***Abstract*— A priori information about the future traffic conditions along the planned route can be essential for optimal hybrid powertrain energy management. However, due to the limited sensor range of a single vehicle, it cannot be acquired locally. In recent time, V2X (decentralized wireless vehicle to everything) has been receiving much attention as a way to obtain and share information from different distributed sources. V2X data can provide updated information on traffic at different locations. Still, this information will be obsolete when the corresponding positions are reached due to changing traffic, and an optimal strategy based on outdated information may not bring the full benefit. Against this background, we propose a method based on a velocity prediction approach which utilizes V2X data currently available in the market in combination with historical data, to obtain a prediction of the expected traffic conditions at in the close future. Actual measurements on a city highway in Linz, Austria, are used to estimate the potential of the approach. Even for rather mild changes in traffic conditions, a reduction of up to 4% in terms fuel consumption over this track was found, confirming the potential benefit of this method.**

I. Introduction

Hybrid electric vehicles (HEV) are widely regarded as a key element for the future of green mobility [1]. The HEV is powered by a combination of two types of energy kinds, typically chemical and electrical. A large number of researches have been conducted to exploit the potential of energy savings in hybrid powertrain, trying to find the most reasonable power split. This can be achieved especially well if future power demand is known a priori, using optimization methods such as Dynamic programming (DP) [2].

However, in reality traffic uncertainties can impact the traction power significantly. It is difficult to derive optimal or even feasible solutions if the actual power demand is not as expected. Therefore, a lot of work has been conducted to predict future traffic. Usually a prediction model is built, using either parametric methods or non-parametric methods [3]. In the former group, the analytical form of driving pattern is determined first, and the model parameters can be then learned from the collected data [4], [5]. The limitation of this approach is that it may only function well in specific scenarios. The second approach does not fix the analytical function beforehand, but learns from data instead, for example using Auto-regressive models [6] and Neural Networks [7]. This approach is more useful in modelling complicated systems of which underlying physics are not well understood. Although the model-based methods are prevailing, a large number of data is the prerequisite. However the data is not rich everywhere. Also the traffic behaviours depend on local habits largely, which are hardly covered by generic models.

Concerning the scope of prediction, most of work focuses on short-term horizon (from next few seconds to minutes). Long-term information (for minutes or even the length of the whole trip) like traffic states is usually used in macroscopic traffic management instead of energy management of single vehicle. However, long-term information can also be critical in overall energy savings for a single vehicle, especially for hybrid vehicles to plan their state of charge (SOC) profile. For instance, if there is a traffic jam, it is better to preserve the battery for it to avoid inefficient engine operation. On the contrary, in a hilly area, it can be more efficient to deplete the battery before the vehicle drives downhill, because the battery can be recharged downslope. However, the information far away cannot be obtained directly by the vehicle's own sensors. Luckily, with the development of intelligent transportation systems (ITS), and in particular with V2X communication [8], distant traffic information can be acquired rather easily. V2X information has been shown positive in improving fuel economy. For example, [9], [10] use V2X and V2I information to predict the velocity periodically and use it for energy management; [11], [12] make use of traffic light signals to assist eco-driving; [13] developed a real-time capable controller that utilizes V2X information and integrates traffic prediction, vehicle dynamics and powertrain operation optimization.

Still, long-term traffic prediction using V2X information attracted much less attention except for a few pioneering publications. [14] developed a vehicle routing strategy based on the information of neighboring vehicles to avoid congestion; [15] proposed a strategy to estimate the average speed of road segments considering the chain reactions from upstream segments, but its benefit in energy savings has not been covered. Moreover, most of the work construct their prediction models based on simulated/assumed V2X data, or tested driving cycles in simulators, which may not be representative for all real-world cases. Also, most of the work only uses current V2X information. In case of a long drive, the traffic condition is very likely to fluctuate, for example it was expected to have a jam, but the jam has already been away when the vehicle really arrives there. Therefore, the use of "static" V2X information requested in the beginning of a trip may lead to unsatisfactory results in terms of powertrain action planning.

To fill these gaps, this paper presents a new model-free approach to predicting traffic by utilizing real-world V2X

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information currently available in the market, and considering the future dynamics of V2X information. This prediction is then also adopted in powertrain control with real driving cycles. The benefit in terms of fuel consumption is shown in the end of our work.

II. Problem description

We assume a hybrid electric vehicle equipped with V2X communication devices. This vehicle is required to complete a journey at the minimum cost in terms of fuel consumption, with a controller acting on the powertrain level (gear, clutch and power split), while coping with traffic disturbances. This work focuses on powertrain control, thus we do not conduct velocity optimization. We assume, that for short-terms the actual velocity is given, and corresponding power requests need to be fulfilled by backward modelling.

A. Control scheme

The powertrain control scheme is based on our previous work [16], as depicted in fig. 1. The control scheme consists of both a remote and an on-board part. The remote cloud has a strong computational ability, and the remote V2X provider offers live V2X data. We use HERE Developer [17] as our V2X provider. When requested, the HERE Developer API (application programming interface) returns topology information and the estimated speed profile based on current traffic constraints of the requested route. It represents the real-time general traffic condition of each road segment. One example can be seen in the top plot in fig. 2.

B. Change of V2X information (traffic)

The changes of traffic is illustrated in bottom three figures of fig. 2. The red curve is a real drive. The blue curve is the information requested from HERE Developer at different times during the drive. It can be observed that the traffic condition kept changing along the drive. It implies that using the "static" V2X information for trip planning can bring poor results.

C. Control process

The general steps of the proposed scheme are:

1) Before departure, the on-board controller sends an estimated speed profile $\hat{v}_{pre}(s)$ and its vehicle model to the cloud.
2) The cloud computes an globally optimal powertrain action immediately (using DP) and sends this optimal solution $x_r^*(s)$ to the vehicle controller (here we use Model Predictive Control, MPC). $x_r^*(s)$ includes the distance-based optimal signals of the states of the powertrain.
3) The MPC then follows this global reference $x_r^*(s)$ while doing local optimization under the constraints of actual traffic, and gives final actions to the powertrain.

About $\hat{v}_{pre}$:

1) If the V2X service is not available: we use a past/typical trip trajectory, which can reflect the route information to some extent.
2) If the V2X service is available: the vehicle will request a live speed profile $\hat{v}_H$ from HERE Developer. $\hat{v}_H$ goes through the predictor (predicting + post-processing since $\hat{v}_H$ is discrete), and is then sent to the cloud.

Apparently, the more accurate $\hat{v}_{pre}$ is, the better the reference the cloud can calculate, and the better the performance of the MPC. The prediction processed will be explained in section IV.

III. Models

The driving cycles are taken from real measurements on a city highway in Linz, Austria. It is $14\mathrm{km}$ long, and contains two signals: geographic altitude $h(s)$ and velocity profile $v(s)$ in terms of distance s as shown in Fig.3. The drives were on different days and times to get various traffic environments.

A. Vehicle model

We assume no wheel slip and a stiff powertrain. The traction force F_p, depending on the driving cycle, can be computed by

$$\begin{aligned} F_p &= F_r(\phi, v) + \lambda^{(j)} m a \\ F_{\mathrm{r}}(\phi, v) &= m g \left(c_{\mathrm{r}} + \sin\left(\phi(s)\right)\right) + \frac{c_{\mathrm{d}} \rho_{\mathrm{air}} A}{2} v^2 \end{aligned} \tag{1}$$

where F_{r} is the resistance force, m the vehicle mass, a the vehicle acceleration, j the selected gear and $\lambda^{(j)}$ the factor accounting for the rotational inertia, g the gravitational constant, c_{r} the rolling resistance, $\phi(s)$ the road grade angle, c_{d} the drag coefficient, ρ_{air} the air density, A the front area of the vehicle. Due to the page limit, the parameters values can be seen in our previous work [16].

The engine speed ω_{e} can be related to the vehicle speed v through

$$\omega_{\mathrm{e}} = \frac{\gamma^{(j)}}{r} v \tag{2}$$

where $\gamma^{(j)}$ is the gear dependent transmission ratio and r is the wheel radius. By using equation 1 and 2, the power demand P can be calculated by

$$P = F_p \cdot v \tag{3}$$

B. Powertrain model

Fig. 4 illustrates the structure of the P2 parallel hybrid powertrain studied in this work. The wheels are connected to brake and gearbox. P is provided by either the battery P_b, the engine P_e, or both, and this power split is decided by the torque coupler, i.e $P + P_L = P_e + P_b$, where P_L accounts for the loss power from the powertrain components.

Engine model: The engine model is given by

$$\tau_{\mathrm{eff}} = \tau + J \cdot \dot{\omega}_{\mathrm{e}}, \quad q_{\mathrm{f}} = q_{\mathrm{f}}(\omega_{\mathrm{e}}, \tau_{\mathrm{eff}}) \tag{4}$$

where τ is the engine torque, J the inertia, ω_{e} the engine speed, and q_{f} the fuel flow rate.

Electric machine: The electrical power is determined based on a power map using effective torque and speed.

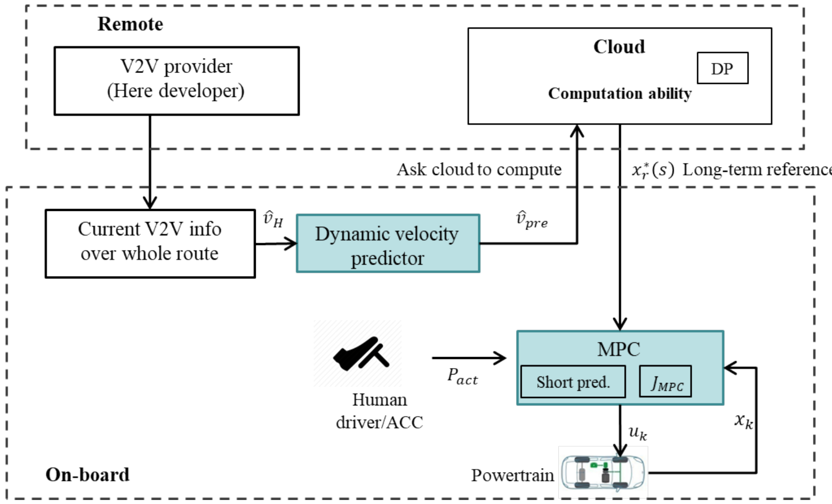

Fig. 1. Structure of the control scheme

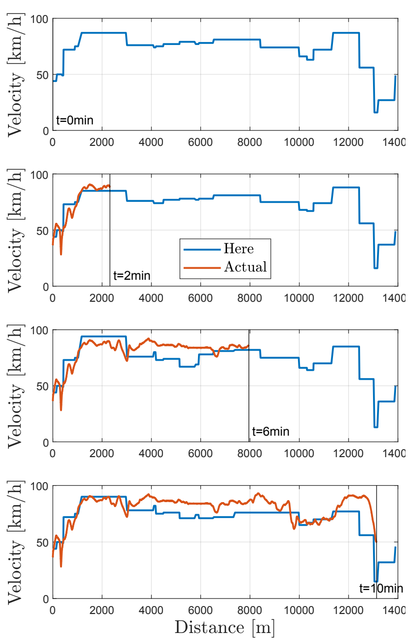

Fig. 2. V2X information changed with time during the measurement

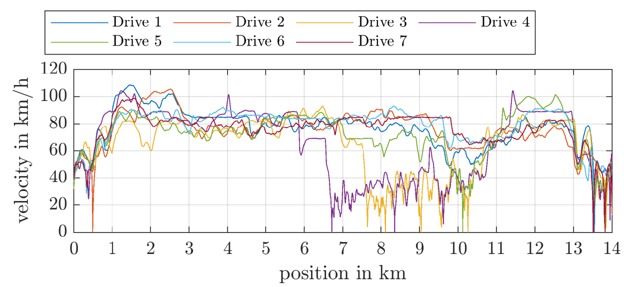

Fig. 3. Measurements(velocity profiles) on different days and times

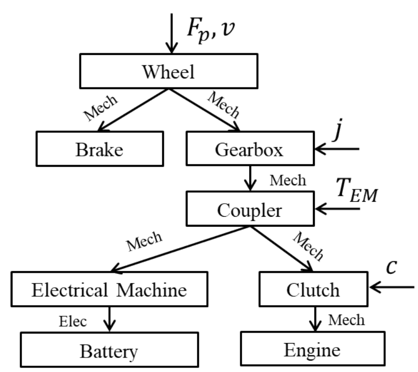

Fig. 4. P2 parallel hybrid structure

Battery model: The state of charge (SOC) ξ is described by [18]:

$$
\begin{aligned}
\dot{\xi} &= \frac{1}{Q_n} \cdot I_b(\xi, P_b) \\
I_b(\xi, P_b) &= \frac{-U_{oc}(\xi) + \sqrt{U_{oc}(\xi)^2 - 4P_b R_i}}{2R_i} \\
U_b &= U_{oc} + R_i \cdot I_b \\
U_{oc}(\xi) &= \left(E_0 - \frac{K}{\xi} + Ae^{(B(\xi-1))} Q_n \right)
\end{aligned} \tag{5}
$$

where Q_n is the nominal charge, I_b the battery current, U_{oc} the open circuit voltage, E_0 the battery constant voltage, and K the polarisation voltage. A and B are model constants, U_b is the battery clamp voltage, and R_i is the internal resistance.

IV. Prediction Methods

We would like to include the future possible changes in V2X information, in other words, we would like to predict "What would the traffic situation be, if we request V2X service in y minutes?". The key idea is first to build a database of speed profiles of the given route, and then, for any new profile, find the closest trajectories in the database, and take their future information as a base for the prediction. There are other possible ways of prediction, for example Bayesian or neural networks, etc. Since we were not able to get sensible results based on limited amount of data, the database searching method is adopted.

A. Data collection

The speed trajectory $\hat{v}_H(s)$ of the route in our driving cycle has been requested and collected from HERE Developer every $\Delta t = 2\text{min}$, 24/7 for two months. All the trajectories form a chronological database until the current time point n:

$$\begin{aligned} \text{Database:}\ \{\vec{s}, \hat{v}_{H,k} \quad & \forall k = 0, ..., n-1; \Delta t\} \\ \vec{s} = \{& s_0, s_1, ..., s_{end}\} \end{aligned} \tag{6}$$

where $\vec{s}$ is a equally-spaced distance vector, with $\Delta s = 100\text{m}$.

B. Prediction model

For any new profile $\hat{v}_{H,n}$ downloaded currently, its past information in the database is available, i.e.

$$\vec{\hat{V}}_{H,n}(n_{prev}) = \begin{bmatrix} \hat{v}_{H,n} \\ \hat{v}_{H,n-1} \\ ... \\ \hat{v}_{H,n-n_{prev}} \end{bmatrix} \tag{7}$$

is known. n_{prev} is the number of previous steps taken into account. Then, we find q pieces of data in the database, that have the most similar past information as $\hat{v}_{H,n}$, and these datasets are denoted as $\hat{v}_{H,k_i}(i = 1, ..., q)$. For each $\hat{v}_{H,k_i}$, the corresponding future information can be found in the database:

$$\vec{\hat{V}}_{H,k_i}(n_{next}) = \begin{bmatrix} \hat{v}_{H,k_i} \\ \hat{v}_{H,k_i+1} \\ ... \\ \hat{v}_{H,k_i+n_{next}} \end{bmatrix} \tag{8}$$

where n_{next} denotes the prediction steps. The interval between the steps is Δt. Then, the mean value of eq. (8) for all q datasets is used as our prediction matrix.

1) Variants of prediction: We considered three ways of prediction: Similarity Selective Prediction (SSP), Similarity Selective Prediction with moving Window (SSP_W), and Time Selective Prediction (TSP). Constant preservation of the initial HERE-request – referred to as Zero Order Hold (ZOH) – serves as a reference method.

- ZOH: Serves as a benchmark, for this method the initial HERE-request is kept over time. It performs already very well as there are usually not many dynamics over short time horizons
- SSP: Searches the database for situations (for the whole track) similar to the current one (high Pearson correlation in the spatial dimension, low deviation in terms of velocity and similar coefficient of variance in terms of time) and takes the mean of their respective future (which is known) to predict the future in the present situation
- SSP_W: Relies on the same principles as SSP, but in this case only a small spatial window is compared that yields the future for the spatial position in the center of the window. This window is then shifted along the whole route
- TSP: Makes use of velocities at similar days and times, it simply searches the database for entries with the same weekday and time of the day and calculates the mean which then serves as the predicted value

2) Transform to distance-based speed profile $\bar{v}_H(s)$: The time-space prediction matrix needs to be translated to a single space-based speed vector. Since every Δt a new information from HERE Developer can be acquired, we assume that the speed profile remains on the same estimated trajectory $\bar{v}_{H,i}$ during one Δt. As soon as Δt has passed (at distances $d_1, ..., d_{end}$), we switch to the next available velocity reference. The corresponding distance points $\vec{d}$ where the speed changes can be found by:

$$\begin{aligned} d_k &= \sum_{i=1}^{m_k} \left(\frac{\Delta s}{\bar{v}_{H,0}(i)} \right) > \Delta t \quad \forall k \in \{1, 2, \dots\} \\ v_{pred} &= \text{concatenate}(\bar{v}_{H,0}(0...d_1), \bar{v}_{H,1}(d_1...d_2), ...) \end{aligned} \tag{9}$$

The illustration can be seen in fig. 5.

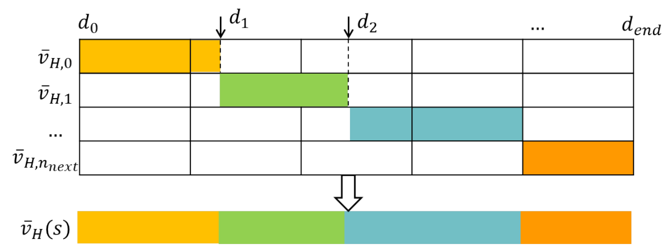

Fig. 5. Process of translating time-space prediction matrix to a space-based vector

C. Prediction results evaluation

The database is split into a training dataset (70% of all data) and a validation dataset (30%). Each profile in the validation dataset is validated compared with their real changes in the next k steps. The following error analysis (fig. 6) represents the average errors from all validation data.

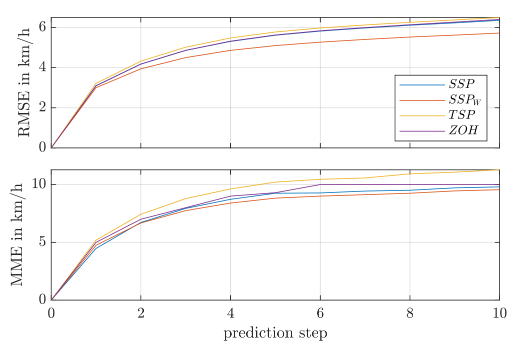

Fig. 6. Error analysis of different prediction variants

It is clearly visible from fig. 6, that the prediction method SSP_W is superior – compared to all other methods – both in terms of RMSE (Root Mean Square Error) and MME (Median Maximum Error), which represents the median of the maximum absolute prediction errors for all validations.

Therefore, it can be said, that a prediction method SSP_W was found, that is capable of delivering better results for future HERE-data than the case where the first request is simply hold for the whole track (ZOH). The ZOH approach still performs quite well in this examination, as the HERE-dynamics in terms of time is usually very low and sometimes even constant. This is also the reason why there are only small differences in terms of prediction performance.

V. Case Study

To show the benefit of the proposed velocity prediction method in powertrain energy management, we conducted a following case study. Since the predicted profiles are piece-wise constant, which is unrealistic in powertrain control, the predicted profiles were smoothed using Fourier transform to eliminate the high frequency parts.

In the control scheme of fig. 1, there are two optimizations: global optimization in the cloud using DP and local optimization using MPC. Both optimizations have three inputs: gear command u_j, clutch action u_c , and power split (i.e. P_b) and three states: gear position j, clutch position c, and SOC ξ.

A. Optimization problem formulation

1) Cloud layer: The main goal is, to minimize fuel consumption and avoid frequent actions of gear and clutch. A charge-sustaining control is required. The cost function and constraints of cloud DP are:

$$J_{\text{gen}} = \sum_{k=0}^{N-1} \left[q_{\text{f}}(k) T_s + \beta_1 z_j(k) + \beta_2 z_c(k) \right] \quad (10)$$

$$\begin{aligned} &\omega_{\text{e,min}} \leq \omega_{e,k} \leq \omega_{\text{e,max}} \\ &j_k \in \{1, \ldots, N_{\text{gear}}\}, \qquad u_{j,k} \in \{-1, 0, 1\} \\ &\xi_{\text{min}} \leq \xi \leq \xi_{\text{max}}, \qquad \xi_N \in [\xi_{\text{min,N}}, \xi_{\text{max,N}}] \\ &c_k \in \{0, 1, 2\}, \qquad u_{c,k} \in \{0, 1, 2\} \end{aligned} \quad (11)$$

where T_s is the sampling time, β_1, β_2 are weighting factors, $z_j = \sum_{k=0}^{N-1} |u_j|$ is the gear shifts $z_c = \sum_{k=0}^{N-1} |u_c|$ the clutch shifts, and N the total number of time steps. The clutch has three states: open, slip, and closed. The gear action can only be up shifting, down shifting, or remaining unchanged. The specific parameters can be seen in our previous work [16].

B. Local layer – MPC

A prediction horizon N_p of 10s is used. We assume the actual power demand P_{act} within this prediction horizon is known. Then the cost function of the MPC is

$$J_{\text{MPC}} = \sum_{k=t}^{t+N_p} \left[m_1 \Delta \xi_k^2 + m_2 \Delta j_k^2 + m_3 \Delta c_k^2 + m_4 q_{\text{f,k}} T_s \right] \quad (12)$$

where Δ refers to the deviations between the current value of states and reference. m_1, m_2, m_3, m_4 are weighting factors.

Apart from the tracking errors, an additional cost term q_{f} is added to handle uncertainties. If the reference is not optimal, the controller can still try to achieve a local optimum (in terms of fuel) while trying to follow the general trend. It prevents unreliable results from MPC, resulting in simply following an inaccurate reference.

C. Case description

Referring to fig. 3, we assume the actual driving cycles to be the driving cycles 6 and 7 respectively, and driving cycles $1-5$ were the past drives. For comparison purposes, for each driving cycle, we consider the following approaches:

1) The V2X information is not available: the vehicle follows the powertrain reference based on past drive $1-5$ respectively. The results are denoted as $r_1 - r_5$.
2) The V2X is available, and use it directly: follow the powertrain reference based on the smoothed trajectory from HERE Developer, the result is denoted as ($HERE$)
3) The V2X is available, and we combine it with prediction: follow the powertrain reference based on the prediction profile: SSP, SSP_W, and TSP respectively.
4) To set a baseline, we assume the actual velocity profile is known, and the vehicle follows the powertrain reference based on this perfect prediction profile.

D. Results and discussion

The signals of approach 3. (SSP_W) are shown in fig. 7. In general, the MPC tracks the reference x^*_{r,SSP_W} well, especially for gear and clutch. There is small deviation between reference SOC and MPC values. This is because the MPC has to first meet the actual power demand, which is different from the prediction. The DP solution is also plotted for comparison. Since the prediction based on the mean value reflects less fluctuations in speed compared to real speed profiles, namely less acceleration/deceleration, the x^*_{r,SSP_W} also has less actions in clutch, which means x^*_{r,SSP_W} considers less switching between engine power and battery power.

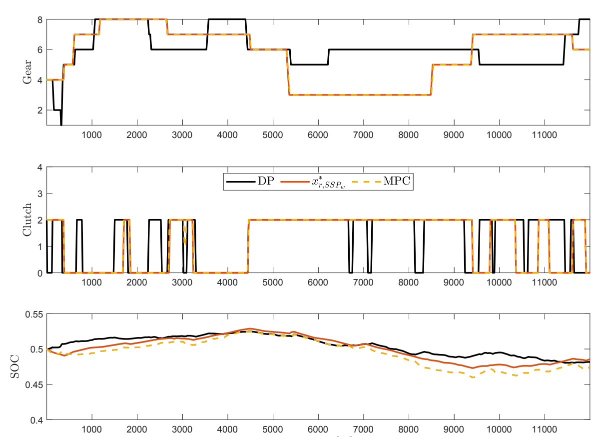

Fig. 7. Simulation results – signals of approach 3 (using SSP_W for prediction)

The deviation of from perfect prediction (additional fuel consumption compared to the baseline solution) for both driving cycles is plotted in fig. 8. For driving cycle 6, by following the references from past information, i.e. "outdated" reference, can lead to $11.8-17.2\%$ additional fuel consumption ($r_1 - r_5$), with an average of 13.7%. When using V2X information ($HERE, SSP, SSP_W, TSP$), the additional q_f is in the range of $9.4-9.8\%$, with an average of 9.5%, which is 4.2% lower than the case without V2X information. The results are similar for driving cycle 7. Following the reference based on live V2X information leads in general to 1.17% less additional fuel consumption compared to following past/typical references. Of course, the performance depends on how close the past speed profile is to the current profile. For example, the drive 3 and 4 are most different from drive 6 and 7 as shown in fig. 3. Therefore, following r_3 and r_4 results in worst fuel efficiency. In general, utilizing V2X long-term information can improve the fuel efficiency, especially in the cases of significant changes in traffic.

Among the results with V2X information, it is to notice, that SSP_W does not always behave the "best" like it is in section IV-C. This is due to following reasons. Firstly, the V2X data we used reflects only the general behaviour of all the vehicles, not the single vehicle's behaviour. Secondly, the V2X speed profiles give discrete values, where the dynamics of vehicles are not shown. Although they are smoothed, the specific dynamics (acceleration, deceleration) can not be fully created, and these dynamics play an important role in fuel consumption. The third point is, that a drive of $14\mathrm{km}$, around $12-18\mathrm{min}$ could be not long enough to show the significant changes of traffic, and thus not able to show the full potential of dynamic predictions. Last but not least, due to limited time of collection, the database is far from rich enough. We only have V2X information for drive 6 and 7, otherwise more driving cycles could be tested and some statistics could be shown. In other words, the results shown are rather conservative estimates, which are however promising.

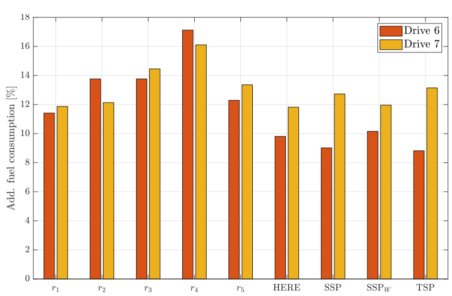

Fig. 8. Case study results — additional fuel consumption and additional total cost

VI. Conclusion and Outlook

The paper introduces a new way of utilizing currently available V2X information in long-distance traffic prediction, and the corresponding fuel saving benefits are illustrated. In general, with V2X information, the vehicle can better plan the trip before departure and outperform the cases without V2X information in terms of energy efficiency.

Future works could focus on updating the V2X information along the drive to get a timely correction of the predicted velocity profile. The ways of translating average V2X information to natural velocity profiles based on diversified driving styles are worth investigating. This could be probably achieved by combing short-term V2X data. Furthermore, a longer route could be chosen to further show the benefits of the proposed methods.

VII. Acknowledgements

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