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On-line Test of a Real-Time Velocity Prediction for E-bus Energy Consumption Estimation

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***Abstract*—To facilitate dynamic vehicle scheduling for battery electric city buses, a real-time on-line energy consumption prediction model is proposed. The model utilizes the current vehicle velocity and position, combined with knowledge of the remaining route, to predict the total trip energy. The model consists of a remaining velocity profile predictor and a longitudinal dynamics model. The algorithm is demonstrated in a Hardware-in-the-Loop experiment with a battery electric bus. The model has an average error of 3.1% with respect to the total trip energy and adapts in real-time to unexpected acceleration and deceleration events.**

***Index Terms*—Electric Vehicle, Battery Electric Bus, Energy Consumption, Prediction, Hardware-in-the-Loop (HiL)**

I. INTRODUCTION

Battery Electric Buses (BEBs) are increasingly used for inner-city public transport. The vehicles emit no local pollutants and potentially offer a lower total cost of ownership (TCO) because of relatively low running expenses. However, adaptation is still relatively low, partially because compared to conventional diesel vehicles BEBs have a smaller driving range due to the limited energy density of their batteries [1]. Additionally, the driving range is uncertain, because it can vary as function of road, weather and vehicle conditions and the performed drivecycle [2]. This results in BEB schedules being conservative, sometimes even including redundant vehicles.

Dynamic vehicle scheduling offers a possible solution by no longer fixing time tables in advance, but rather making them flexible based on traffic conditions [3], electricity pricing [4] or battery degradation [5]. In the dynamic version of this vehicle scheduling problem, the schedule is based on both current information as well as predictions regarding the future [3]. In order to make optimal dynamic schedules for BEBs, it is beneficial to have up-to-date and accurate predictions regarding the energy that will be consumed for a trip and the remaining driving range.

Previous research indicates that using route information can be useful to predict the future energy consumption of an electric vehicle [6]. The same study also indicates that it is beneficial to include up-to-date estimations of rolling resistance and mass during driving to give a more accurate prediction during the trip. The same is suggested by [7]. However, most of this research focuses on predicting certain parameters of the vehicle model, based on the observed difference between measured and modeled energy consumption, while omitting the effect of the current vehicle velocity has on the prediction. While other studies do focus on online prediction of the future velocity [8], [9], many of these methods are data-driven and cover a limited horizon.

This paper presents an on-line method to predict the future vehicle velocity, based on the current vehicle velocity and route data, and uses this information for the energy consumption prediction (ECP) on a BEB. The method is tested by implementing a MATLAB Simulink model in Vector CANoe and performing real-time Hardware-in-the-Loop (HiL) tests.

This paper is organized as follows. In Section II the method applied to predict the future velocity and energy consumption are explained. In Section III the experimental setup of the HiL test is explained, including route details and vehicle specifications. The results of this test are presented and discussed in Section IV. Conclusions are given in Section V.

II. FUTURE ENERGY CONSUMPTION PREDICTION

To predict the future energy consumption using a physics-based approach, the model works in two steps. Firstly, the velocity that will be driven along the remaining part of the route is predicted. Secondly, a physics-based energy consumption model calculates the energy that is required to drive this velocity profile.

A. Future Velocity Profile Prediction

The future velocity profile prediction is based on route information and the current position and velocity of the vehicle. The entire route is discretized, consisting of N points. For each of these points $i = 1, ..., N$ along the route, the following information is assumed to be known:

- GPS coordinates $p_i \in \mathbb{R}^2$ [deg.]
- Cumulative distance from start d_i [m]
- Legislated maximum velocity $v_{leg,i}$ [m/s]
- Local road curvature c_i [1/m]
- Boolean indicating (bus)stops b_i [-]

During operation, a vehicle will start at the beginning of the route, near p_1, and will subsequently pass all the points along the route, until arriving at the end of the route p_N. To make a prediction regarding the remaining part of the route, it is imperative to know the current position of the vehicle with respect to the route. To this end, a map matching algorithm is applied.

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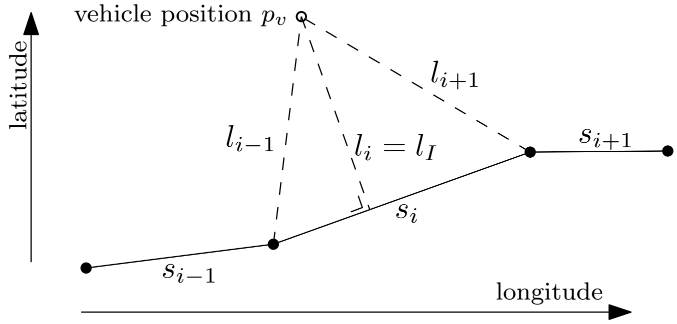

Fig. 1. Map matching: Schematic view of the shortest Euclidian distances (l_i) between the vehicle position and several route segments (s_i).

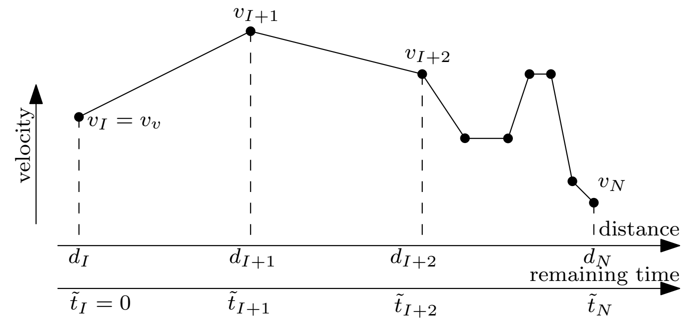

Fig. 2. Predicted future velocity at the route points defined both as function of distance and remaining time.

1) Map Matching: The route is represented by $N-1$ segments, indicated by s_i in Fig. 1. Each segment s_i is defined by its vertices p_i and p_{i+1}. A straight-forward, computationally efficient map-matching algorithm is applied, which identifies the segment the vehicle is currently traversing by calculating the shortest Euclidian distance l_i between the most current GPS measurement p_v and each of the segments s_i, as shown in Fig. 1. The segment for which this distance l_i is shortest, is assumed to be the one where the vehicle is currently driving. This index, specifying the current location of the vehicle, is expressed as I;

$$I = \operatorname*{argmin}_i l_i \ . \tag{1}$$

2) Velocity Prediction Algorithm: Given the vehicle is currently at position p_I, the challenge is to predict the velocity v_i for all remaining route points $i = I, ..., N$. As first step, the velocity limitations due to corners are included by considering a maximum lateral acceleration $a_{y,max}$. This corner-limited velocity is determined as

$$v_{curv,i} = \sqrt{\frac{a_{y,max}}{|c_i|}} \quad \forall \quad i = I, ..., N \ . \tag{2}$$

Secondly, the vehicle is assumed to make a full stop at every bus stop. Therefore, the stop-limited velocity is described as

$$v_{stop,i} = \begin{cases} 0 & b_i = 1 \\ \infty & b_i = 0 \end{cases} \quad \forall \quad i = I, ..., N \ , \tag{3}$$

where no velocity limitations ($v_{stop,i} = \infty$) are imposed on the points that are not stops.

Lastly, the vehicle is assumed to adhere to the legislated maximum velocity $v_{leg,i}$. Therefore, together with (2) and (3), a maximum velocity envelope v_{max} can be described;

$$v_{max,i} = \min(\, v_{leg,i}, \, v_{curv,i}, \, v_{stop,i} \,) \quad \forall \quad i = I, ..., N \ , \tag{4}$$

which the vehicle is assumed to never exceed.

This maximum velocity envelope is discontinuous, which is unrealistic, because the longitudinal vehicle acceleration and deceleration are finite. Therefore the velocity profile has to be adapted to include the finite acceleration. This is realized by step-wise forward time-integration of the profile with a limited longitudinal acceleration $a_{x,acc}$;

$$v_{i+1}^{acc} = \min \left\{ \int_{t_i}^{t_{i+1}} a_{x,acc} dt + v_i^{acc}, v_{max,i+1} \right\} \ \forall \ i = I, ..., N-1 \ . \tag{5}$$

Important here is that the currently measured velocity v_v is used as starting point for this procedure, i.e.

$$v_I^{acc} = v_v \ , \tag{6}$$

thereby including the current vehicle velocity in the prediction. Similarly, backwards time-integration is performed, starting at $v_N = 0$, to ensure that the decelerations do not exceed a maximum value $a_{x,dec}$;

$$v_{i-1} = \min \left\{ \int_{t_i}^{t_{i-1}} a_{x,dec} dt + v_i, \, v_{i-1}^{acc} \right\} \quad \forall \quad i = N, ..., I+1 \ . \tag{7}$$

After applying (5) and (7) to v_i^* described by (4), v_i represents a future velocity profile defined at each of the route points $v(p_i)$, and thus also as function of distance $v(d_i)$.

3) Distance-Time Conversion: For each of the future route points $i = I, ..., N$, the expected arrival time $\tilde{t}$ with respect to the current time t_I is calculated:

$$\tilde{t}_i = \sum_{k=I}^{i-1} \frac{2\,(d_{k+1} - d_k)}{v_k + v_{k+1}}, \quad \forall \quad i = I+1, ..., N \tag{8}$$

which is based on the assumption that the acceleration is constant between two route-points, as seen in Fig. 2. Note that, because p_I signifies the current position of the vehicle, $\tilde{t}_I = 0$. Now, the velocity profile for all the future route points is defined as function of the remaining time: $v(\tilde{t}_i)$.

B. Remaining Energy Consumption Prediction

A physics-based model is applied to predict the energy required to drive the future velocity profile $v(\tilde{t}_i)$. Because the model relies on knowledge regarding the acceleration, the calculations are performed per route-segment s_i. Therefore, velocity $v_{s,i}$ and acceleration $a_{s,i}$ are calculated for every route segment $i = I, ..., N-1$:

$$v_{s,i} = 0.5\,(v_i + v_{i+1}) \quad \text{[m/s]} \tag{9}$$

$$a_{s,i} = \frac{(-v_i + v_{i+1})}{(-\tilde{t}_i + \tilde{t}_{i+1})} \quad \text{[m/s}^2\text{]} \ . \tag{10}$$

By modelling the longitudinal dynamics of the vehicle, the average driving force at the wheels can be determined as

$$F_{wheel,i} = m_{eff} a_{s,i} + c_r \, m \, g + c_a v_{s,i}^2 \; , \tag{11}$$

where m_{eff}, m, c_r, and c_a are vehicle parameters described in Table I. Note that, due tot the characteristics of the route described in Section III-B, no road slope component is considered. From $F_{wheel,i}$, the electric power delivered by the traction inverter is determined as

$$P_{inv,i} = F_{wheel,i} v_{s,i} \; + \; P_{loss} \left(v_{s,i}, F_{wheel,i} \right) \; , \tag{12}$$

where P_{loss} represents a previously measured powertrain losses map [10]. By summing the inverter power over the remaining route, the remaining energy consumption is determined to be

$$E_{remaining} = \sum_{i=I}^{N-1} P_{inv,i} \cdot \left(\tilde{t}_{i+1} - \tilde{t}_i \right) \; . \tag{13}$$

1) Trip Energy Consumption Prediction: Simultaneously, the consumed powertrain energy

$$E_{consumed} = \int_{t_0}^{t_I} U_{HV,measured} \, I_{HV,measured} \, dt \; . \tag{14}$$

is recorded by the model based on the measured traction inverter Direct-Current (DC) voltage $U_{HV,measured}$ and current $I_{HV,measured}$. The total trip energy is determined by combining this measured energy with the predicted remaining energy:

$$E_{trip} = E_{consumed} + E_{remaining} \; . \tag{15}$$

III. Case Study: Bus Trip

The on-line ECP algorithm, as described in Section II, is implemented in MATLAB Simulink, and interfaced via Vector CANoe to the CAN-bus of a battery electric city bus, as seen in Fig. 3. This HiL setup allows for real-time reading and processing of several sensor signals including:

- GPS position $p_v \in \mathbb{R}^2$ [deg.]
- Vehicle velocity v_v [m/s]
- Estimated vehicle weight m_{ECAS} [kg]
- Traction inverter voltage $U_{HV,measured}$ [V]
- Traction inverter current $I_{HV,measured}$ [A].

A. Test vehicle

The vehicle used for this test is a series-production 12 m battery electric city bus equipped with a 170 kW central motor and a 288 kWh battery pack. The vehicle is fitted with the factory-default set of sensors, and an additional GPS-sensor.

The vehicle features an Electronically Controlled Air Suspension (ECAS) that uses pressure measurements in the air-bellows to estimate the current weight of the vehicle. This estimate m_{ECAS} is used as indicated in Table I. The estimated weight provided by the ECAS can vary incorrectly due to vehicle acceleration or suspension kneeling. Therefore a processed signal $\tilde{m}_{ECAS}$ is created that only registers the ECAS vehicle weight if the vehicle is 1) standing still, 2) not kneeled, and 3) the accelerator pedal is not pressed. The effective mass of

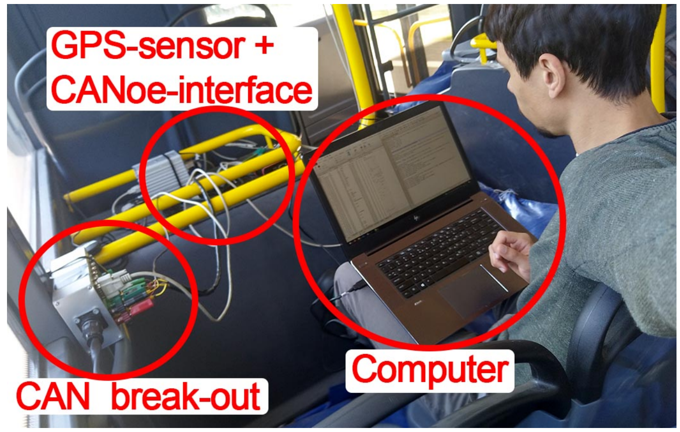

Fig. 3. Photo of the HiL-setup in the vehicle.

TABLE I
Parameters used in the on-line ECP model.

Parameter	Symbol	Value	unit
Vehicle weight	m	$\tilde{m}_{ECAS}$	kg
Effective vehicle mass	m_{eff}	1.02 m	kg
Aerodynamic coefficient	c_a	3.36	kg/m
Rolling resistance coefficient	c_r	0.007	-
Acceleration limit in prediction	$a_{x,acc}$	0.9	m/s^2
Deceleration limit in prediction	$a_{x,dec}$	-0.8	m/s^2
Lateral acceleration in prediction	$a_{y,max}$	1.5	m/s^2

the vehicle is defined as 102% of the vehicle weight. During the measurements, the vehicle is loaded with sand bags to half of its maximum capacity to simulate passenger load.

Except the mass, all further vehicle parameters are assumed constant, as listed in Table I. The rolling resistance coefficient c_r and aerodynamic coefficient c_a originate from coast-down tests performed with a similar vehicle [10]. The table also shows the assumed acceleration limits $a_{x,acc}$, $a_{x,dec}$, and $a_{y,max}$ used in the prediction of the remaining velocity profile. These are based on previously measured velocity profiles of the same vehicle.

B. Route Information

For the HiL test, a route is defined to represent a typical city bus trip. The route is shown in Fig. 4 and features several legislated maximum velocities ranging from 30 km/h to 60 km/h. Apart from the start/stop point, there are two further bus stops. At each of these stops, the driver is instructed to make a full stop, open the doors of the vehicle, and wait for 7 seconds before resuming the trip. In the on-line ECP algorithm, the 8.725 km route is discretized into $N = 1285$ points, resulting in an average segment length $||s_i||$ of 6.8 m. The route is nearly flat, therefore no road slope component is included in (11).

The route is located in a rural area, to minimize the effect of traffic. Nevertheless, some disturbances due to oncoming vehicles or cyclists are observed. The driver is instructed to drive the route as he would normally assuming passengers

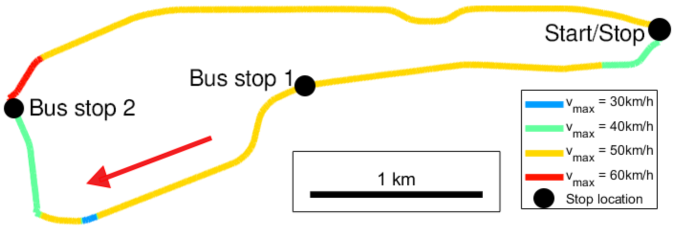

Fig. 4. The used test route, driven clockwise, with bus stops indicated as black dots and the legislated maximum velocity indicated by color.

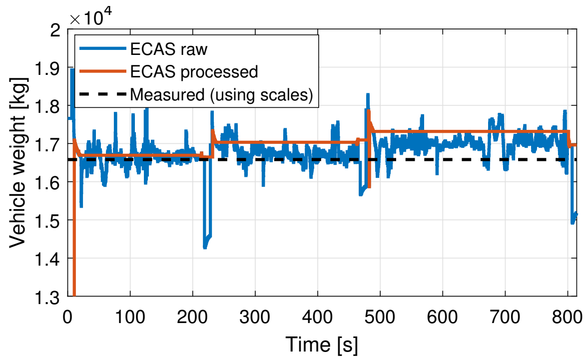

Fig. 5. Vehicle weight according to the ECAS system for trip #4.

are onboard, while adhering to the specified maximum velocities and stopping at the abovementioned bus stops. Before the start of the series of tests, the vehicle is driven for at least 20 minutes to achieve steady-state temperatures in the powertrain and tires.

IV. Results and Discussion

The route specified in Section III-B is driven six consecutive times, where the on-line ECP algorithm is restarted at the beginning of every route. This section discusses the detailed results of trip #4.

A. Vehicle Weight Estimation

Fig. 5 shows the estimated value indicated by the ECAS system together with $\tilde{m}_{ECAS}$ as described in Section III-A. Also indicated is the actual weight of the vehicle, as determined prior to the test by placing the vehicle on scales. The results show that the ECAS weight estimate varies during the trip and slightly over-estimates the actual weight by 1.9%. The processed ECAS weight $\tilde{m}_{ECAS}$ remains constant during driving, with an average error of 2.9%, and only varies during a stop, around $t = 220$ s and $t = 480$ s. The fact that $\tilde{m}_{ECAS}$ provides an over-estimate will results in more conservative energy predictions. Nevertheless, the processed signal is considered useful, because it greatly reduces unwanted fluctuations in the predicted trip energy.

B. Velocity Profile Prediction

During the experiment, the on-line model is repeatedly predicting the remaining velocity profile $v(d_i)$ as described in Section II-A. All these calculations are happening on-line on a computer onboard the vehicle.

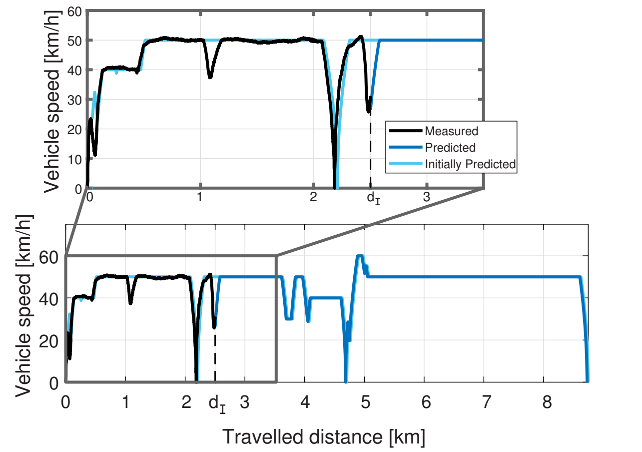

Fig. 6. Measured and predicted velocity profile when the vehicle is at a travelled distance of $d_I = 2.5$ km along the route for trip #4.

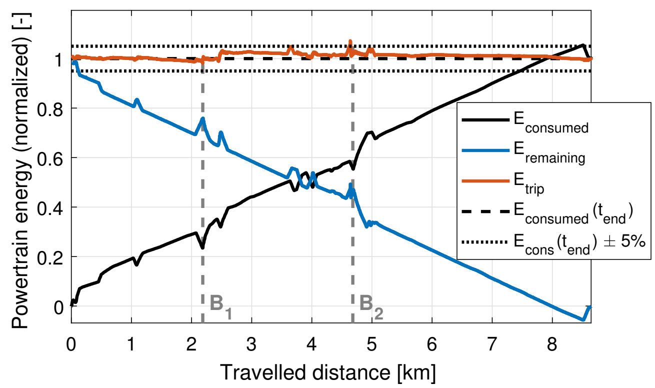

Fig. 7. Measured and predicted energy consumption as function of travelled distance for trip #4. Bus stops are indicated by B_1 and B_2.

Fig. 6 shows the results of this prediction at a point in time where the vehicle is 2.5 km along the route. In this situation, the velocity profile of the past 2.5 km is known, as indicated by the black line. For the remaining 6.2 km the velocity is predicted, based on the available route information and current vehicle velocity.

The results in Fig. 6 indicate that the predicted velocity generally matches the measured velocity along the trip. Nevertheless, deviations due to unmodelled effects, such as traffic, can occur. In this case, the on-line ECP model predicts that the vehicle will accelerate before resuming the originally predicted profile, as demonstrated at $d_i = [2.5, 2.6]$ km by the steeply increasing blue line. Note that prediction here does not include any future influence of traffic, and will always assume unobstructed driving from $\tilde{t}_I = 0$ onwards.

C. Energy Consumption Prediction

The predicted remaining energy, as described in Section II-B, is visualised for this same trip #4 in Fig. 7. This figure shows that dips in $E_{consumed}$, due to deceleration events, are largely compensated by peaks in $E_{remaining}$, ultimately resulting in a smooth estimate E_{trip} that generally stays within the 5% of the actually consumed energy. When the trip is

TABLE II
WEIGHTED AVERAGE PREDICTION ERROR (WAPE) FOR SIX TRIPS.

Trip #	1	2	3	4	5	6	**Average**
PE(d_1) **[%]**	2.0	6.2	1.1	0.4	9.0	7.8	**4.4**
WAPE [%]	1.6	3.4	2.4	1.2	5.1	4.7	**3.1**

finished, the predicted and measured energy consumption are per definition equal.

In case of an unexpected deceleration event, for instance at $d_I = 2.5\,\text{km}$, E_{trip} increases to compensate for the acceleration expected after the deceleration. Likewise, in the last 0.6 km of the trip in Fig. 7, E_{trip} remains lower than $E_{consumed}$, because the prediction already accounts for the energy regenerated during the final braking action of the route. This illustrates the predictive capabilities of the on-line ECP model.

D. Weighted Average Prediction Error

In order to quantify the observed difference, the Prediction Error (PE) is introduced for a route point i, according to

$$\text{PE}(d_i) = \frac{|E_{trip}\,(d_i) - E_{consumed}(t_{end})|}{E_{consumed}(t_{end})} \qquad (16)$$

The trip energy becomes easier to predict as the vehicle progresses along the route, because the prediction only concerns the remaining part of the trip. Therefore the error is weighted by remaining distance, resulting in the Weighted Average PE;

$$\text{WAPE} = \frac{\sum_{i=1}^{n} w_i\ \text{PE}(d_i)}{\sum_{i=1}^{N} w_i}, \text{ where } w_i = 1 - \frac{d_i}{d_N} \qquad (17)$$

are the weight factors that decrease linearly as function of travelled distance d_i. This way, the prediction error at the start of the trip is weighted more than the predictions near the end of the trip. Calculating this value reveals that the WAPE is 1.2% for the measurement presented in Fig. 7. This is partially the results of the fact that the model parameters Table I seem to match particularly well for this trip.

The WAPEs for further trips are indicated in Table II and range between 1.2% and 5.1% among the various trips. This variation could be caused by influences that are not considered in the current algorithm, variation in the occurance of traffic between the individual trips or unmodelled dynamics in the longitudinal vehicle model. Also the variability introduced by the ECAS weight estimator is expected to have an influence on the end results. Nevertheless, on average the WAPE is 3.1%, and is shown to be generally lower than the offline prediction error that is made at the beginning of the trip PE(d_1).

V. CONCLUSIONS

This paper presents an on-line energy consumption prediction model that in real-time predicts the remaining energy required to complete a trip. The results show that by using the current position and velocity of the vehicle, a future velocity profile can be determined that accounts for future acceleration and deceleration events in the route. The remaining energy consumption predicted basted on this velocity profile complements the consumed energy to arrive at a predicted total trip energy that is close to the consumed energy. The results of a Hardware-in-the-Loop test show that the weighted average prediction error is 3.1% over six observed trips. This indicates that the proposed methodology could provide a reliable, real-time energy consumption prediction for future dynamic planning algorithms.

Future work includes further testing of the on-line model with more vehicle loading conditions, different drivers, varying weather conditions, and a route that includes road slope. In a realistic scenario, where passenger occupancy can change at each bus stop, an improved method for weight estimation, that could even predict vehicle weight changes at future stops, would be beneficial. Moreover, possibilities exist to make the algorithm adaptive by including online driver characterization via nonconstant acceleration limits $a_{x,acc}$ and $a_{x,dec}$ and an adaptive longitudinal dynamics model that iteratively estimates the rolling resistance coefficient c_r as function of distance.

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REFERENCES

[1] S. Bakker and R. Konings, "The transition to zero-emission buses in public transport - The need for institutional innovation," *Transp. Res. Part D Transp. Environ.*, vol. 64, pp. 204–215, Oct. 2018. [Online]. Available: https://doi.org/10.1016/j.trd.2017.08.023

[2] K. Kivekas, J. Vepsalainen, K. Tammi, and J. Anttila, "Influence of Driving Cycle Uncertainty on Electric City Bus Energy Consumption," in *2017 IEEE Veh. Power Propuls. Conf.* Belfort, France: IEEE, Dec. 2017. [Online]. Available: https://doi.org/10.1109/VPPC.2017.8331014

[3] X. Tang, X. Lin, and F. He, "Robust scheduling strategies of electric buses under stochastic traffic conditions," *Transp. Res. Part C Emerg. Technol.*, vol. 105, pp. 163–182, Aug. 2019. [Online]. Available: https://doi.org/10.1016/j.trc.2019.05.032

[4] G. Wang, X. Xie, F. Zhang, Y. Liu, and D. Zhang, "bCharge: Data-Driven Real-Time Charging Scheduling for Large-Scale Electric Bus Fleets," in *2018 IEEE Real-Time Syst. Symp.* IEEE, Dec. 2018, pp. 45–55. [Online]. Available: https://doi.org/10.1109/RTSS.2018.00015

[5] J. Wang, L. Kang, and Y. Liu, "Optimal scheduling for electric bus fleets based on dynamic programming approach by considering battery capacity fade," *Renew. Sustain. Energy Rev.*, vol. 130, p. 109978, Sep. 2020. [Online]. Available: https://doi.org/10.1016/j.rser.2020.109978

[6] J. Wang, I. J. M. Besselink, and H. Nijmeijer, "Battery electric vehicle energy consumption prediction for a trip based on route information," *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.*, vol. 232, no. 11, pp. 1528–1542, Sep. 2018. [Online]. Available: https://doi.org/10.1177/0954407017729938

[7] S. Sautermeister, F. Ott, M. Vaillant, and F. Gauterin, "Reducing range estimation uncertainty with a hybrid powertrain model and online parameter estimation," in *2017 IEEE 20th Int. Conf. Intell. Transp. Syst.* IEEE, Oct. 2017, pp. 1–6. [Online]. Available: https://doi.org/10.1109/ITSC.2017.8317633

[8] Y. Li, H. He, and J. Peng, "An Adaptive Online Prediction Method With Variable Prediction Horizon for Future Driving Cycle of the Vehicle," *IEEE Access*, vol. 6, pp. 33 062–33 075, 2018. [Online]. Available: https://doi.org/10.1109/ACCESS.2018.2840536

[9] J. Hou, D. Yao, F. Wu, J. Shen, and X. Chao, "Online Vehicle Velocity Prediction Using an Adaptive Radial Basis Function Neural Network," *IEEE Trans. Veh. Technol.*, pp. 3113–3122, Mar. 2021. [Online]. Available: https://doi.org/10.1109/TVT.2021.3063483

[10] C. J. J. Beckers, I. J. M. Besselink, J. J. M. Frints, and H. Nijmeijer, "Energy consumption prediction for electric city buses," in *13th ITS Eur. Congr.* Brainport, The Netherlands: ERTICO, Jun. 2019. [Online]. Available: https://research.tue.nl/en/publications/energy-consumption-prediction-for-electric-city-buses