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An Advanced Simulation Framework of an Integrated Vehicle-Powertrain Eco-Operation System for Electric Buses

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***Abstract*—Activities of transit buses traveling along arterial roads and city streets consist of frequent stops and idling events at many predictable occasions, e.g., loading/unloading passengers at bus stops, approaching traffic signals or stop signs, and going through recurrent traffic congestion, etc. Besides designing transit buses with electric powertrain systems that can save a noticeable amount of energy thanks to regenerative breaking, this urban traffic environment also unfolds a number of opportunities to further improve their energy efficiency via vehicle connectivity and autonomy. Therefore, this paper proposes a complete and novel simulation framework of integrated vehicle/powertrain eco-operation system for electric buses (Eco-bus) by co-optimizing the vehicle dynamics and powertrain (VD&PT) controls. A comprehensive evaluation of the proposed system on mobility benefits and energy savings has been conducted over various traffic conditions. Simulation results are presented to showcase the superiority of the proposed simulation framework of the Eco-bus compared to the conventional bus, particularly in terms of mobility and energy efficiency aspects.**

***Index Terms*—Simulation framework; Connected and automated vehicles (CAV); Eco-Bus; Vehicle dynamic; powertrain characteristics; energy efficiency.**

I. Introduction

The advancement towards vehicle connectivity and autonomy offers many potentials and opportunities in developing innovative eco-driving systems and applications to leverage the energy efficiency. Specifically, a very promising example is eco-driving at signalized intersections, where the signal phase and timing (SPaT) information is shared with vehicles to optimize the vehicle dynamics, avoid the unnecessary or abrupt acceleration/deceleration, and reduce the idling period [1]–[3]. From a broader perspective, the positive impacts of eco-driving applications can be attributed to the highly predictable location and the high penetration of signalized intersections that may require vehicles to make complete stops.

Within this scope, the energy efficiency of transit buses have large potentials to improve, as compared to standard passenger cars, since they are initially designed to make much more frequent and predictable stops, such as the loading/unloading of passengers at bus stops. In addition, the bus routes are commonly designed in densely populated areas, which also gives rise to a higher probability of encountering traffic jams. Therefore, a significant amount of energy savings can be anticipated with the connected eco-driving, provided that the operating state of the preceding vehicle can be shared and communicated to effectively optimize the vehicle dynamics. Moreover, electric vehicles (EV) generally have better energy efficiency in the urban areas than the rural areas thanks to the regenerative braking, which slows down the vehicle via an energy recovery mechanism to convert the kinetic energy back to the electric energy. Therefore, an accurate and robust control of the EV powertrain can maximize the energy restored and further boost the energy efficiency.

However, early development and deployment of connected eco-driving technology mainly focused on optimizing vehicle dynamics (VD) [4]–[8] and powertrain (PT) [9] operation independently, and therefore there exists untapped potential to further improve vehicle fuel efficiency through a simultaneous optimization of both VD&PT control. Therefore, this paper proposes an advanced simulation framework of an integrated vehicle-powertrain eco-operation solution for an electric bus with state-of-the-art Connected and automated vehicles (CAV) technologies, aiming at improving vehicle energy efficiency and reducing tailpipe emissions. The overall simulation framework incorporates a two-layer vehicle optimal trajectory planning module that seamlessly integrates a graph-based trajectory planning algorithm and a deep neural network, with the simulation settings and parameters calibrated using real-world electric bus data from the Riverside Transit Agency (RTA) bus trajectories. The optimal trajectory can be generated with the proposed innovative VD&PT eco-operation control module embedded in a microscopic simulation tool – PTV Vissim [10], and its energy-saving performance is validated with different test scenarios against the baseline driving strategies.

II. System Framework

Connected and automated vehicles (CAV) have the potential to excel at efficient driving because of their increased situational awareness and ability to execute more complex maneuvers more precisely [9]. In order to comprehensively optimize the operation maneuver of electric

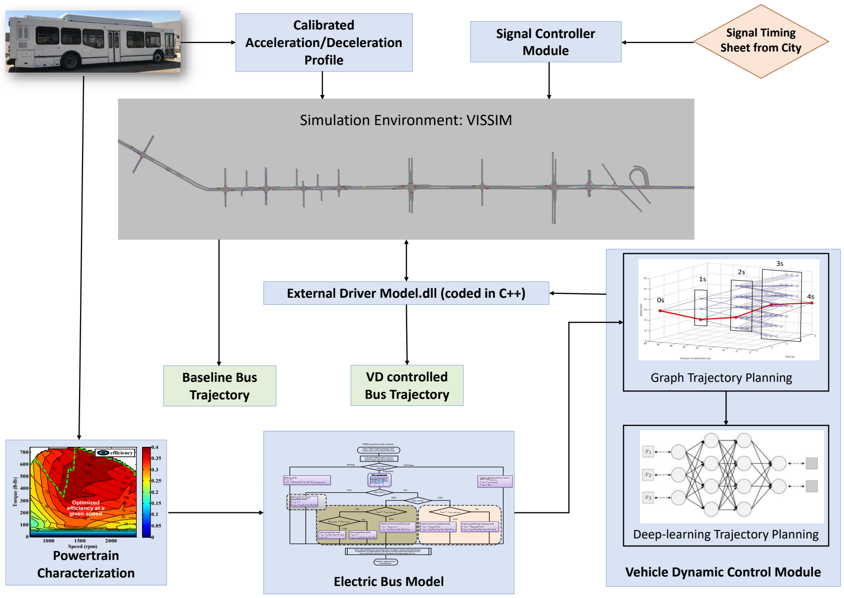


Fig. 1. System Framework

buses to improve the fuel efficiency, this paper proposes an advanced electric bus simulation framework integrating vehicle dynamics and powertrain operations. Specifically, this framework is established with real-time optimal trajectory planning under (VD&PT) control interacting with a calibrated environment using real-world data. The overall simulation framework develops traffic network modeling, embedded vehicle dynamic control, and real-world data calibration with PTV Vissim. In the simulation environment, a programable energy-efficient speed trajectory can be generated, optimizing with many parameters and data after the initial calibration process, including signal phase and timing (SPaT) information from upcoming intersections, the state variables of the preceding vehicle, and the vehicles dynamics in the network. The optimized trajectory is generated with the innovative vehicle-powertrain eco-operation control module that we developed and embedded in a VISSIM application programming interface (API).

Fig. 1 illustrates the system framework of the advanced simulation framework for developing the connected Eco-Operation system for electric buses. In this framework, the baseline bus control is based on the embedded car-following logic in VISSIM, and its acceleration and deceleration behavior has been calibrated to match real-world acceleration/deceleration versus speed profiles of RTA bus trajectories. In addition, both the powertrain characteristics and the efficiency map are generated from the real-world testing data. To evaluate the specific energy consumption, a simplified electric bus model with a powertrain-related function of speed, acceleration and road grade is developed and applied to a built-in graph-based trajectory planning algorithm. This integrated mechanism will be used to evaluate the energy consumption of both the baseline bus trajectory and the integrated Eco-Bus trajectory.

In addition, a signal control module was developed to implement SPaT messages from signalized intersections along the simulation corridor based on the real-world signal timing sheet obtained from the City of Riverside. In the developed external driver model, the SPaT messages is obtained within the dedicated short-range communications (DSRC) range [11] and decoded into signal phase and countdown information. The vehicle dynamic control module contains a two-layer vehicle optimal trajectory planning: 1) a graph-based trajectory planning algorithm and 2) deep neural networks (DNN) [12]. Specifically, the first layer of trajectory planning algorithm is based on a graph model, which takes the energy consumption as the cost function to optimize the transit path. The second layer employs a DNN to expedite the calculation of the optimal target speed of an Eco-bus for the next time step. Then the output external driver model can effectively reinforce an energy-efficient trajectory for an electric bus. Similarly, this advanced simulation framework is able to generate the optimized output driver model for any user-specified traffic conditions and vehicle powertrain characteristics, which makes this framework very convenient to further evaluate any customized EV eco-operation system interfacing with the traffic network, via this integrated vehicle-powertrain approach.

III. Simulation Study

A detailed description of the simulation setup, traffic network development, bus characteristic calibration, as well

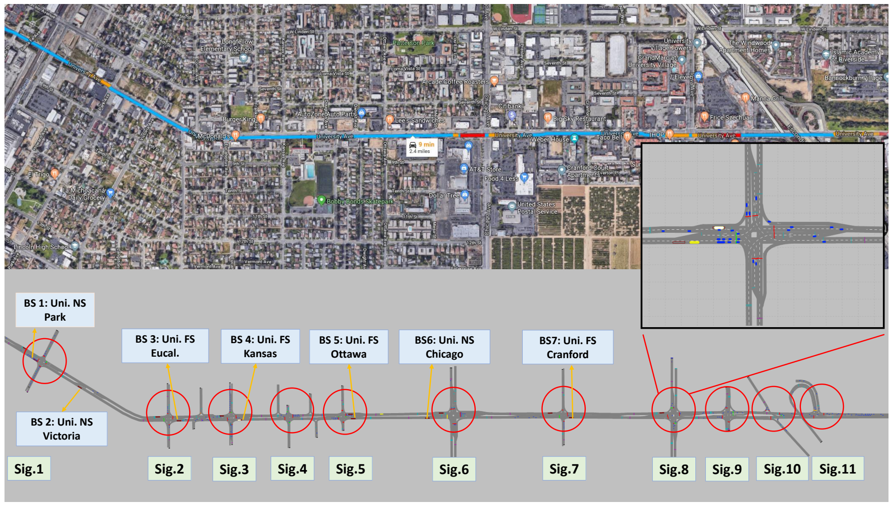


Fig. 2. Simulated Network on University Ave with Signal Control and Bus Stops

as other scenario settings are presented in this section.

A. Simulation Tools

In this study, PTV Vissim [10] is employed as a microscopic traffic simulation tool for traffic network modeling, bus characterization, External Driver Model.dll development with integrated vehicle-powertrain optimal trajectory planning using the Vissim API, as well as Eco-bus mobility and energy performance evaluation. As a leading-edge microscopic traffic simulator, Vissim is capable of modeling private transport, commodity transport and road- or rail-bound public transport down to pedestrians, simulating the wireless communication network, and calibrating with real-world data. In addition, Vissim provides two types of add-on programming interface, namely the Component Object Model (COM) and the External Driver Model DLL. Specifically, COM interface is written in script that can be used to work as an Automation Server, modify the underlying simulation models, access the model outputs, and provide advisory longitudinal and lateral maneuvers. However, limitations exists on directly controlling the driving behavior in the simulation, as well as a high computation load while accessing a large scaled network with many vehicles under control. In this study, we used the External Driver Model DLL Interface of Vissim to replace the inherent driving behavior model by a fully user-defined behavior embedded in the vehicle dynamic control module.

The External Driver Model DLL Interface of Vissim is developed to access signal information and sensor measurements, it is also capable of integrating an innovative VD&PT control system to obtain the most energy efficient bus trajectory through multiple signalized intersections. The vehicle dynamic control module, as shown in Fig. 1, is implemented in a DLL written in C++. During a simulation execution, Vissim calls the External Driver Model DLL code for the targeted electric bus in each simulation time step, which is able to obtain the current vehicle state, determine its next optimal speed, and then pass this updated vehicle state back to Vissim.

B. Simulation Network Model

The real-world traffic network used in this study is a 3-mile signalized corridor along the University Ave with its westbound beginning from the Riverside Canal and its eastbound ending in Canyon Crest Dr at Riverside, CA, USA, as shown in Fig. 2. The simulated network consists of eleven signalized intersections and seven bus stops on the eastbound bus route (see Fig. 2). Based on the real-world signal timing sheets at each intersection from Riverside City, we decoded the information to design the Signal Controller with the consistent SPaT message. The transit buses differ from the private vehicles or heavy-duty trucks in a sense that their trajectories are not only associated with the traffic light and the recurrent congestion, but they also need to comply with the specific bus stop schedule from Riverside Transit Agency (RTA). Therefore, the arrival time is estimated at each bus stop along the RTA bus EB route based on its specific schedule on two main stops. Then, the Public Transport module in Vissim id calibrated to match the assigned arrival time at each bus stop along the simulated network. In addition, the bus acceleration/deceleration profile in the simulation is also calibrated using real-world data from RTA bus trajectories. In summary, the network is well calibrated using the real-world signal controls, traffic inputs and bus trajectories data. Therefore, the results and observation from the proposed simulation framework should accurately represent the mobility and energy efficiency performance of an Eco-bus with the integrated VD&PT control.

C. Simulation Scenarios

To gain an in-depth insight into the integrated vehicle dynamic and powertrain Eco-operation performance, a variety

TABLE I
ROUTE 14 EB STOPS ALONG UNIVERSITY AVENUE.

Stop Name	Latitude	Longitude	Estimated Arrival Time	Estimated Departure Time	Distance from Previous Stop (m)	Simulated Arrival Time
University FS Brockton				07:28:00 (Actual)		
East University NS Lemon	33.980889	-117.372455	7:30:44	7:30:54	660	
University NS Park	33.977343	-117.364859	7:34:02	7:34:12	804	7:31:47
University NS Victoria	33.976519	-117.363105	7:34:55	7:35:05	182	7:33:14
University FS Eucalyptus	33.975493	-117.364859	7:36:35	7:36:45	384	7:34:18
University FS Kansas	33.975538	-117.356839	7:37:36	7:37:46	220	7:35:32
University FS Ottawa	33.875565	-117.349528	7:39:20	7:39:30	404	7:38:00
University NS Chicago	33.975545	-117.349528	7:40:34	7:40:44	276	7:38:46
University FS Cranford	33.975603	-117.343839	7:42:47	7:42:57	528	7:40:40
Iowa FS Blanie			7:48:00 (Actual)		1240	
Route travel time			0:08:45			0:08:53
Route travel time (min)	8.8					8.9
Percentage Difference						1.5%

of traffic conditions were simulated under different system settings. Here, we used v/c ratio to quantify the congestion level based on Highway Capacity Manual [13]. The traffic volume with the real-world traffic count is categorized as the Light Traffic condition with v/c ratio as 0.35. The other three traffic conditions are No Traffic, Moderate Traffic and Heavy Traffic condition with v/c ratio as 0.17, 0.7 and 1, respectively. Note that for Heavy Traffic case the actual traffic in the network is less than the input traffic demand in the OD matrix, as vehicles may be blocked out of the network at the first intersection due to over-saturation. For each simulation scenario, 10 runs were executed with a simulation duration of 3,600 seconds. All experiments are carried out using a computer with Intel i7 CPU with 2.80 GHz and 16 GB RAM.

IV. POWERTRAIN MODEL FOR EVS

In the energy consumption model for the electric bus powertrain, we assume the instantaneous vehicle speed is v and it is operating under the traction mode, then the motor speed ω can be written as

$$\omega = n \cdot v \tag{1}$$

where n is the "lumped" gear ratio calibrated from the real world data.

Considering only a vehicles longitudinal motion governed by Newtons second law of motion [9], the acceleration of the vehicle depends on the traction/brake force, the rolling resistance force impacted by road grade, and the aerodynamic drag

$$ma = F - \left(mg\sin\theta + \mu mg\cos\theta + \frac{1}{2}C_D\rho_a A v_i^2 \right) \tag{2}$$

where m is the vehicle mass (kg), g is the gravity constant, θ is the road slope (rad), μ is the rolling resistance coefficient, C_D is the aerodynamic drag coefficient, ρ_a is the air density (kg/m^3) and A is the vehicle frontal area (m^2).

The above equation also indicates the critical acceleration rate when the vehicle is coasting (i.e. $F = 0$):

$$a_{coast} = -g\sin\theta - \mu g\cos\theta - \frac{1}{2m}C_D\rho_a A v_i^2 \tag{3}$$

When the vehicle is under coasting or braking mode, i.e. $a \le a_{coast}$, we assume the fuel consumption rate is a constant Q_i which equals to the consumption rate while idling.

When the vehicle is under traction mode $a > a_{coast}$, the traction force based on motor torque τ (in Nm) is formulated as

$$F = \eta\tau n \tag{4}$$

where η is the overall efficiency of powertrain. We can derive the torque expression in the steady-state $(a = 0)$ in terms of speed and acceleration as:

$$\tau = \frac{1}{\eta n}\left(ma + mg\sin\theta + \mu mg\cos\theta + \frac{1}{2}C_D\rho_a A v^2 \right) \tag{5}$$

The energy consumption of the electrical motor can be derived based on the motor speed, torque and motor efficiency map.

As an electric vehicle is capable of converting kinetic energy into electric energy that can recharge the battery during braking, the regenerated braking power is formulated as

$$W_{reg} = \tau v \cdot \eta_{wh}\eta_{fd}\eta_{mot}\eta_{batt} \tag{6}$$

where η_{wh} is the wheel drive efficiency, η_{fd} is final drive efficiency, η_{mot} is motor efficiency, and η_{batt} is battery efficiency. The efficiency map is reconstructed from a real-world electric bus data from the Riverside Transit Agency (RTA).

V. SIMULATION EVALUATION AND ANALYSIS

This section presents results of the default bus acceleration/deceleration profile, the bus schedule calibration, and the sensitivity analysis of the VD&PT controlled Eco-Bus performance in terms of mobility and energy savings under various traffic conditions.

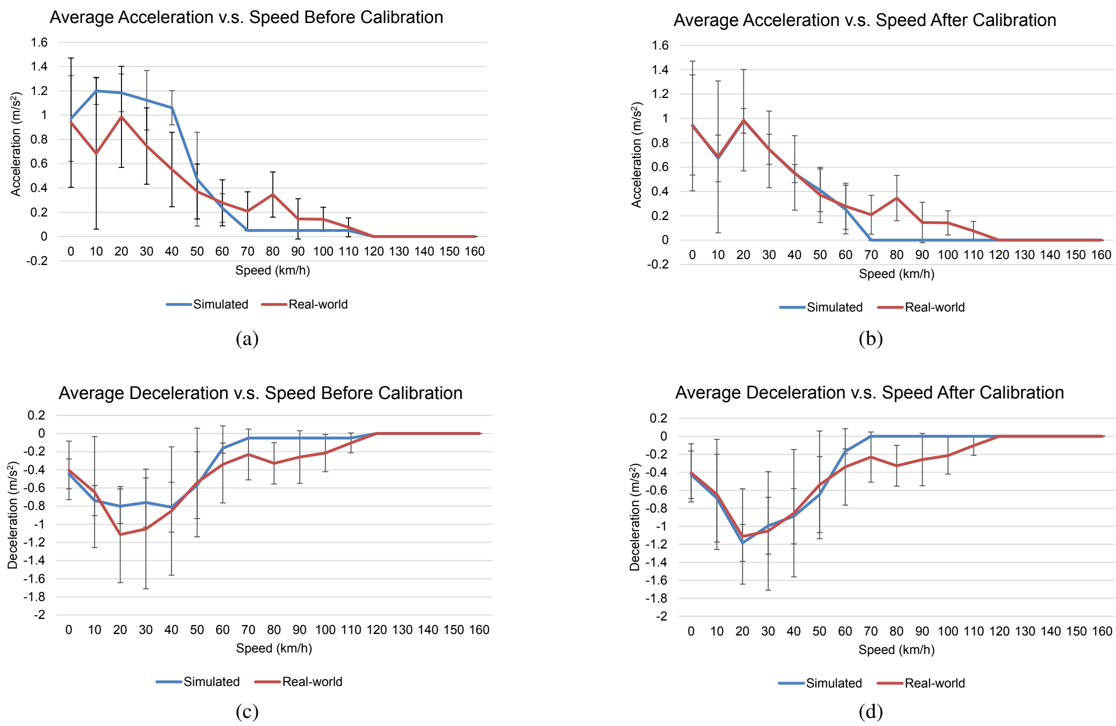


Fig. 3. Average acceleration and deceleration before and after calibration.

TABLE II
COMPARATIVE RESULTS ON ENERGY SAVINGS AND MOBILITY BENEFITS.

	No Traffic	Light Traffic	Moderate Traffic	Heavy Traffic
Relative Improvement on Energy Consumption	26.68 %	27.34 %	27.08 %	24.69 %
Relative Improvement on Average Speed	46.98 %	41.85 %	33.20 %	23.85 %

A. Calibration Results

The subplots of Fig. 3 compare the bus average acceleration and deceleration profile over speed, before and after performing calibration with real-world RTA bus data. It is demonstrated that the simulated acceleration/deceleration profile under the default bus characteristics in Vissim pretty much violates the real-world conditions. After fitting the bus characteristics settings in an iterative manner, much more acceleration/deceleration profile can be generated comparing to the real-world bus (see Fig. 3 (b)(c)).

Based on the RTA Route 14 time table available on [14], we first identified the Time Points (i.e., key bus stop for planning the schedule) that bracket our test route, which are University @ Brockton (western) and Iowa @ Blaine (eastern). By looking up the time table, we realized the scheduled arrival times at these two Time Points are 07:28 a.m. and 07:48 a.m., respectively, for the simulation period (i.e., between 07:00 a.m. and 08:00 a.m.). The bus departure time and average speed (or total route travel time) were then calibrated to match with the associated bus schedule. Table I summarizes the calibration results where the difference in departure time is 10 second and the total route travel time is off by only 1.5%, which is considered to be acceptable.

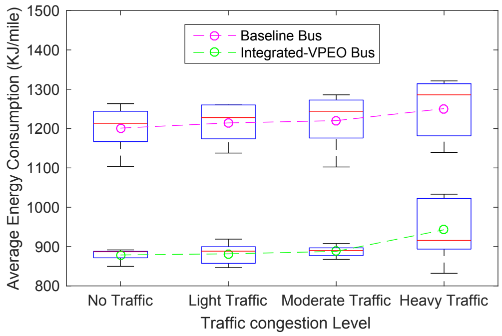
B. Energy Consumption Evaluation

The energy consumption factor (EF, energy consumption in unit distance, KJ/mile) can be obtained by:

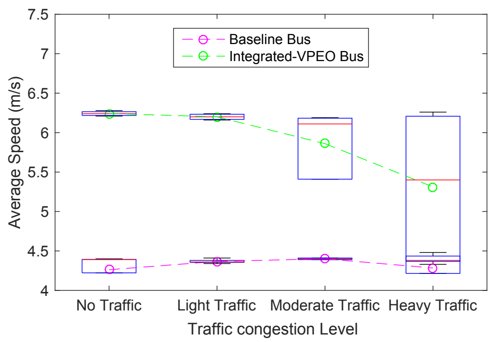
$$EF = \frac{\Sigma_{i=1}^{n} \Sigma_{t=1}^{T_i} energy_{i,t}}{\Sigma_{i=1}^{n} \Sigma_{t=1}^{T_i} VMT_{i,t}} \quad (7)$$

where $energy_{i,t}$ is the energy consumption rate for vehicle i at time t, in KJ, and $VMT_{i,t}$ is the vehicle miles traveled for vehicle i at time zt.

The boxplot and error bars of the average energy consumption of baseline bus and Integrated Vehicle-Powertrain Eco-bus (VPEO-bus) over different traffic congestion levels are shown in Fig. 4(a). It illustrates the average energy consumption of the VPEO-bus are 878 KJ/mile, 881 KJ/mile, 887 KJ/mile and 942 KJ/mile under no traffic, light traffic, moderate traffic and heavy traffic condition, respectively. However, the average energy consumption of the baseline bus are all above 1200 under different traffic conditions.



(a)



(b)

Fig. 4. Comparative results of at various traffic conditions: (a) the average energy consumption and (b) the average speed.

C. Mobility Analysis

The mobility benefits are quantified by average travel time and average speed of vehicle, provided as

$$\bar{v} = \frac{\Sigma_{i=1}^{n}\Sigma_{t=1}^{T_i} VMT_{i,t}}{\Sigma_{i=1}^{n}\Sigma_{t=1}^{T_i} VHT_{i,t}} \tag{8}$$

$VMT_{i,t}$ = vehicle miles traveled for vehicle i at time t,
$VHT_{i,t}$ = vehicle hours traveled for vehicle i at time t.

According to Fig. 4(b), as the traffic congestion level increases, average speed of the Eco-bus is decreasing with a larger variance. Overall, the average speed of Eco-bus is higher than the baseline bus with higher mobility benefits when traffic condition is lighter.

D. Improvements

Based on the prior analysis, the percentage improvements of mobility and energy efficiency of the Eco-bus under VD&PT control are demonstrated in TABLE. II. It is not surprising to observe that the relative improvement on vehicle average speed is increased the most under No Traffic condition with 46.98%, and this improvement would decrease with the traffic condition getting intensified, reducing to only 23.85% in the Heavy Traffic condition. On the contrary, the improvement on energy saving is kept within a stable range of around 24% to 27%, showcasing the its robust performance and good adaptability under all traffic conditions.

VI. Conclusion

This paper proposes an advanced simulation framework of the integrated vehicle/powertrain eco-operation system for Eco-bus by co-optimizing VD&PT controls. The comprehensive results under different traffic scenarios showcase the superiority of the proposed Eco-bus simulation framework compared to a conventional bus, particularly in terms of increased mobility and energy efficiency.

Acknowledgment

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