Design, Implementation, and Evaluation of an Innovative Vehicle-Powertrain Eco-Operation System for Plug-In Hybrid Electric Buses

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***Abstract*—Transit buses serve a vital role in sustainable transportation systems, providing mobility to millions of passengers daily. These buses primarily operate on fixed routes in urban areas, leading to frequent stops at bus stops and traffic signals, which contribute to them having low fuel economy. In recent years, hybrid electric buses and plug-in hybrid electric buses (PHEBs) have gained significant interest in transit applications. However, the energy efficiency of early HEBs and PHEBs is limited as they rely primarily on simple charge sustaining strategies. This paper presents the design, implementation, and validation of a Connected Eco-Bus system that utilizes connected and automated vehicle technology to improve the energy efficiency of a power-split PHEB. The system co-optimizes the PHEB's vehicle dynamics and powertrain controls by leveraging connectivity and partial automation (Level 1) capability. A case study is conducted with the Connected Eco-Bus system operating on a typical urban route where its performance is evaluated through both microscopic simulation and Dynamometer-in-the-Loop testing. The results demonstrate that the Connected Eco-Bus system can achieve energy efficiency improvements of up to 32.4%, which would thereby contribute to a more sustainable transportation system.**

***Index Terms*—plug-in hybrid electric bus, connected and automated vehicle, vehicle dynamics, powertrain controls, partial automation, Dynamometer-in-the-Loop**

I. Introduction and Motivation

Public transit has long been recognized as a key component of urban transportation systems, providing mobility to millions of people worldwide on a daily basis. Although it is considered a sustainable transportation mode due to its relatively high occupancy, there is still much room for improvement in its operational and energy efficiencies. For example, electrification of transit buses has emerged as a promising solution, with many cities and transit agencies adopting hybrid electric buses (HEBs) and plug-in hybrid electric buses (PHEBs) in their fleets. However, the operation of these buses is unlikely to be optimized for energy efficiency, and simply relies on heuristic charge sustaining strategies without fully considering the unique operating characteristics of transit buses and prevailing traffic conditions along the route. Therefore, innovative approaches are needed to improve the energy efficiency of electrified transit buses to fully realize their environmental benefits.

The emergence of connected and automated vehicle (CAV) technology has opened up opportunities for developing innovative applications that can improve vehicle energy efficiency [1]. Optimizing vehicle dynamics is the primary approach among these applications, involving the estimation of downstream traffic states using shared information from connected vehicles and connected infrastructure, and calculation of an energy-efficient longitudinal trajectory of target vehicles. Eco-Approach and Departure is a promising example of this approach for urban scenarios as it enables drivers to receive signal phase and timing (SPaT) information in advance to avoid unnecessary acceleration and deceleration, resulting in reduced fuel consumption and emissions along signalized corridors. However, despite the potential benefits of Eco-Approach and Departure, the development and deployment of connected eco-driving technology is still in its early stages, with the focus primarily on vehicle dynamic control. The lack of consideration for detailed powertrain operation limits the ability to fully utilize the advantages of a hybrid drivetrain. Although powertrain-specific eco-driving applications have been developed in previous studies, vehicle dynamics (VD) and powertrain (PT) operation are usually optimized separately [2]. In this paper, we propose a system that co-optimizes both vehicle dynamics and powertrain operation to further enhance the system's performance in terms of energy efficiency. In addition, current simulation platforms are usually adopted for single resolution modeling and analyses (e.g., microscopic traffic simulation, vehicle dynamic simulation, and powertrain simulation), which may not be adequate to evaluate the system's performance in real-world settings, particularly in urban areas. To address this limitation, we have devised an advanced simulation framework that integrates all of these components. Furthermore, we have established a Dynamometer-in-the-Loop (DiL) platform to replace the powertrain simulation section, which enables a more practical and direct assessment of the system's efficiency. This approach allows us to evaluate the eco-operation system's effectiveness across a broad range of traffic scenarios, offering insights into the potential energy efficiency and emission reduction impacts.

In summary, this paper makes the following contributions:

- We have modified a compressed natural gas (CNG) bus into a PHEB with a parallel hybrid powertrain configuration and developed a comprehensive model of this PHEB to estimate its energy consumption and performance.
- By leveraging CAV technologies, we have designed an integrated eco-operation system that co-optimizes vehicle dynamics and powertrain control. This system takes into account real-time traffic information and powertrain performance to calculate an energy-efficient dynamic power split strategy for the PHEB.
- We have evaluated the proposed eco-operation system through simulation-based and dyno-in-the-loop testing, demonstrating significant improvements in energy efficiency for the PHEB operating on a typical urban route.

The remainder of this paper is organized as follows:

In Section II, we introduce our efforts to convert a CNG-powered bus into a PHEB and the comprehensive model developed for it. Section III describes the method of vehicle dynamics optimization enabled by CAV technology. Section IV details the design of a powertrain operation strategy informed by vehicle dynamics, followed by the evaluation and testing of the proposed system in Section V. Finally, Section VI presents conclusions and future directions.

II. The Design and Model of PHEB

A. PHEB Design, Key Components, and Modeling

In this research, a CNG bus was converted into a PHEB with a parallel hybrid configuration, as presented in Figure 1. The PHEB, modified by US Hybrid, employs a Cummins ISB6.7 G 240 CNG engine, yielding 240 horsepower, and peaking at 300 with electric assist. Its dimensions are: 34,760 lb in weight, 44 ft 10 in length, 102 in width, and 134 in height, including CNG tanks.

The powertrain model includes various key components such as the driver model, chassis, wheel, final drive, transmission, clutch, engine, motor/inverter, battery, electrical accessories, and starter. The detailed modeling procedure is explained in a previous study [3], [4]. Both physics-based and data-driven methods were used to model each component, and the model was evaluated over eco-driving cycles using advanced CAV technologies.

B. Component Energy Efficiency Database (CEED)

To comprehend and improve the control strategy of the PHEB, we conducted a detailed evaluation of each module and tabulated the performance characteristics into a database [5], referred to as CEED. The CEED was created by developing optimal performance tables for the hybrid powertrain, with multiple power sources. It identifies the range of available wheel torque for the PHEB at each speed level while also considering the vehicle weight and road grade. The operating envelope takes into account the power, torque, and speed outputs from the engine and motor, both individually and combined. Based on the PHEB engine, motor/inverter, and transmission data maps, the CEED was used to: 1) generate optimal operation for engine-only- and motor-only propulsion modes, 2) provide optimized powertrain performance efficiency maps as functions of vehicle speed and wheel torque, and 3) provide the corresponding transmission maps for the selection of gear ratio. It also developed a set of optimal operation maps for combined engine and motor operation in a power split mode (under heavy-load conditions), and for combined engine and generator operation during periods of light loads such as idling.

III. Vehicle Dynamics Optimization

Figure 2 demonstrates the various vehicle dynamics optimization applications being developed for eco-operation of the PHEB using CAV technologies. Apart from the Eco-Approach and Departure (EAD) application at signalized intersections, the system also includes the Eco-Stop and Launch (ESL) application, which calculates the most energy-efficient speed profile for the bus to approach (with deceleration) and accelerate from bus stops and stop signs, and the Eco-Cruise (EC) application, which identifies the most energy-efficient cruising speed for the bus by considering factors such as the speed limits on the road, look-ahead traffic and terrain conditions (such as road grade), and vehicle characteristics.

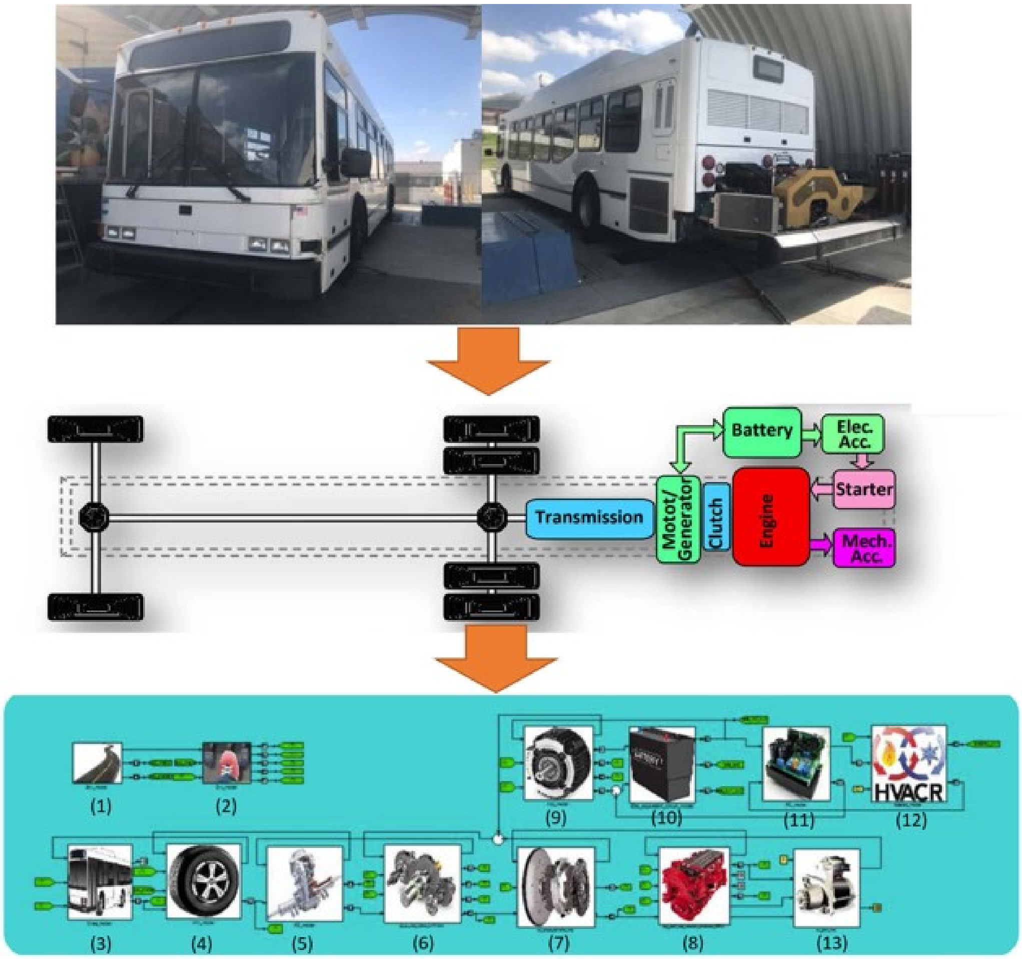

Fig. 1. Modified PHEB, parallel pre-transmission configuration schematic, and its forward-looking model, which includes sub-models for (1) driving environment, (2) driver model, (3) chassis, (4) wheel, (5) final drive, (6) transmission, (7) clutch, (8) engine, (9) motor/inverter, (10) battery, (11) power converter, (12) electrical accessories, and (13) starter. [2]

Figure 3 outlines the structure of the vehicle dynamics optimization framework, which consists of three main components: the real-time queue prediction module, the graph-based trajectory planning algorithm (GTPA) module, and the deep learning-based trajectory planning algorithm (DLTPA) module. The real-time queue prediction module predicts the downstream traffic situation based on information shared among CAVs. The GTPA module formulates the trajectory planning problem by constructing a graph that encodes the state space, with trajectory planning represented as a shortest-path problem. The DLTPA module leverages the knowledge from the GTPA module, obtained through offline simulation and training, to ensure real-time performance.

A. Dynamic Queue Prediction Module

To determine the optimal eco-driving strategy at an intersection, it is critical to understand the dynamics of the downstream queue, specifically the states of the preceding vehicle. Therefore, we propose an adaptive framework [6] for predicting queues at different levels of connectivity and with on-board sensor information. Our approach uses Lighthill-Whitham-Richards shockwave theory [7] and time headway measurements, where the discharge rate is calibrated from historical data at the target intersection.

B. Graph-based Trajectory Planning Algorithm (GTPA) Module

We formulate a graph to represent the feasible spatio-temporal states of the PHEB, which are determined by translating trajectory and signal data into boundary values for trajectory planning [8], [9]. The weighted directed graph model is defined as $G = (V, E, C)$ where V, E, and C represent the set of nodes, edges, and costs, respectively. As shown in Figure 3, time and space are discretized into grids with fixed time steps ΔT and distances ΔX. In the proposed algorithm, a node is only considered valid if its distance from the intersection is greater than the sum of the distance of the preceding vehicle and a safe gap. The graph includes all possible vehicle states in a discretized vehicle-time-distance space, with transition costs representing energy consump-

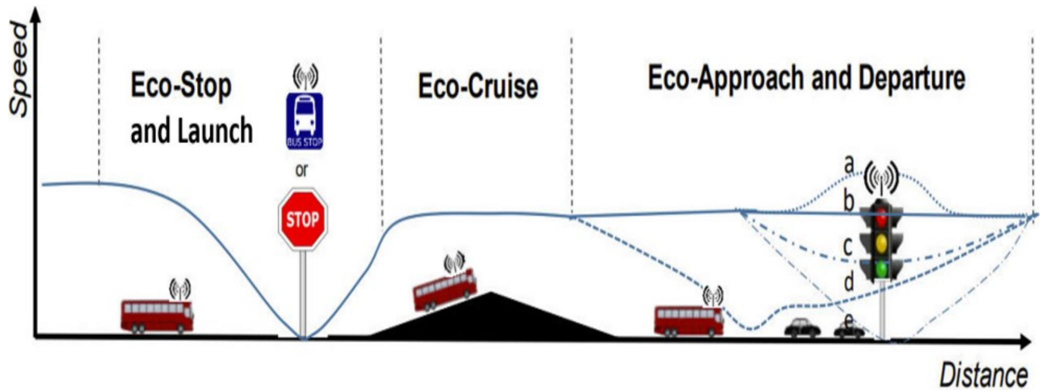

Fig. 2. Illustration of CAV-enabled vehicle dynamic optimization applications: Eco-Stop and Launch, Eco-Cruise, and Eco-Approach and Departure. [10]

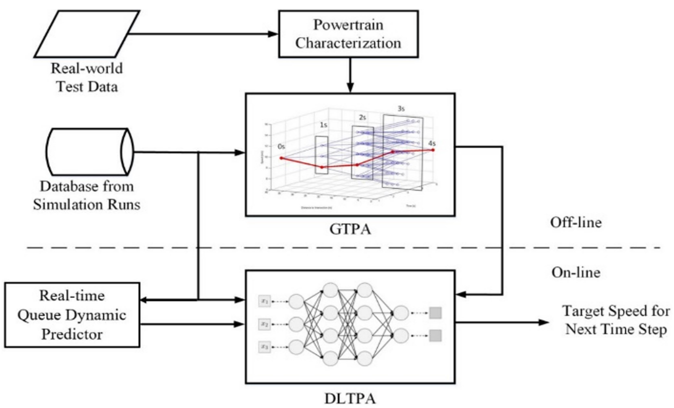

Fig. 3. System Architecture of Deep Learning-based Queue-Aware Eco-Approach and Departure System. [9]

tion rate. The cost is calculated based on the PHEB model presented in the previous section. The trajectory planning algorithm combines traffic/signal boundary conditions from the information integration module, target states information from the scenario identification module, and energy costs from the powertrain module. We then use a graph model to find the shortest path from the source node, $V_s(0, X, v_s)$, to the destination node, $V_d(T, 0, v_d)$, with constraints on target travel time (T), target distance (X), initial speed (v_s), and target speed (v_d). This allows us to formulate an energy consumption minimization problem into a path-finding problem. We apply Dijkstra's algorithm to solve the single-source shortest path problem in the graph G, where the computational complexity is $O(\log(N) \times E)$.

C. Deep Learning-based Trajectory Planning Algorithm (DLTPA) Module

The main drawback of the GTPA module is its inefficiency in computation and inability to handle infeasible states, as its computation time increases significantly with the planning horizon. This reduces its effectiveness in adapting to dynamic environments in complex urban driving scenarios, where the ego-vehicle needs to adjust its strategies quickly. To address this issue, we adopt a hybrid approach by combining offline training and online inference. More specifically, for the offline process, the GTPA module calculates the optimal solution to generalized simulation scenarios. Its outputs are used to train a deep neural network (DNN), called the DLTPA module, in a supervised learning manner to find the optimal speed for the next time step based on the current vehicle state and traffic inputs from the queue prediction model. In other words, the input features and output target state pairs for the DLTPA module are derived from the GTPA module during training. A large dataset can be generated by mapping every possible dynamic state to its corresponding optimal speed. The DLTPA module utilizes a fully connected DNN to capture this state transition mapping. Training and testing sets for the DNN are randomly selected from this dataset, and cross-validation is employed to improve hyperparameters and reduce overfitting.

It is noted that the DNN consists of three types of perceptron layers: an input layer with a feature vector consisting of the current state of the vehicle, constraints, distance to the intersection, and target arrival time interval; two hidden layers utilizing the rectified linear unit (ReLU) activation function for computational efficiency and reducing the chance of vanishing gradient; and dropout layers placed after each hidden layer to prevent overfitting. The output layer comprises a single node with a linear activation function that determines the optimal vehicle speed in the next time step. Once the DLTPA module is well trained offline, it can be used for online implementation purposes, i.e., to compute the optimal speed trajectory and interact with other vehicles in a microscopic traffic simulator. The DLTPA module updates the input features based on the predicted queue length, allowing the ego-vehicle to quickly adapt to changes in the dynamic environment. For more details regarding the algorithm, please refer to [10].

IV. Powertrain Operation Model and Co-optimization

In this section, we present the methods used to deeply integrate the vehicle dynamics and powertrain control system of the PHEB. Firstly, we suggest a rule-based approach to

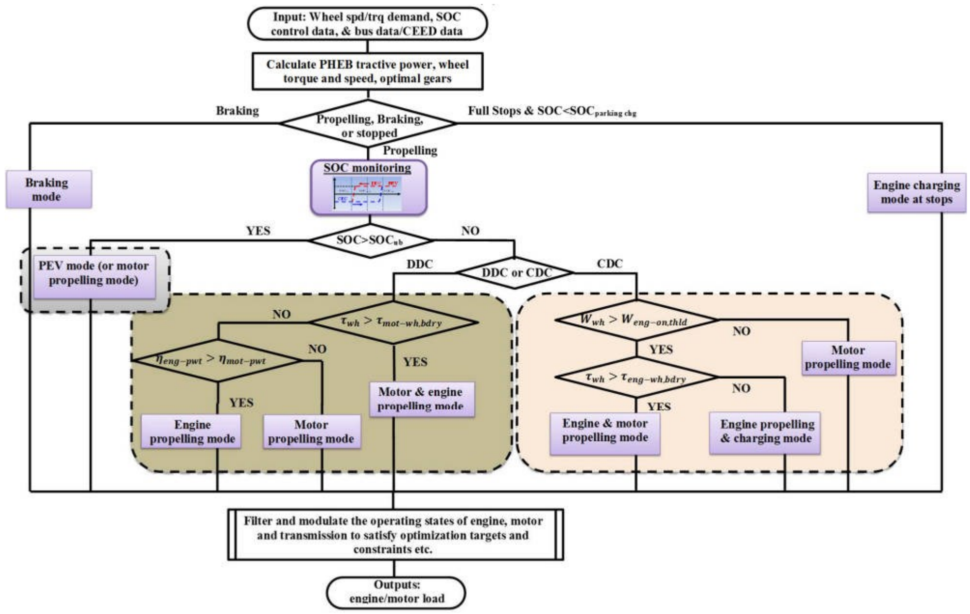

Fig. 4. SOC control and engine and motor torque demand in all modes. [2]

determine the power split between the motor and engine while simultaneously ensuring that the State of Charge (SOC) remains at an optimal level. Following this, we describe an iterative scheme to co-optimize the final optimal control from both the VD and PT models.

A. SOC Supervisory Powertrain Model

The SOC supervisory control strategy uses CEED data, vehicle speed, and tractive torque demand related to instantaneous driving conditions to optimize the motor and engine operating state and provide maximum overall powertrain efficiency. The SOC supervisory control is based on regulating the SOC level to elaborate complex powertrain operations consisting of charge-sustaining (CS) control and charge depletion (CD) control. Specifically, the engine and motor propulsion modes under CS control are regrouped into discharge-dominant control (DDC) and charge-dominant control (CDC) operating regimes. Based on the upper and lower boundaries of SOC management (i.e., SOC_{ub} and SOC_{lb}), the supervisory strategy considers three propulsion control processes: CD, DDC, and CDC. When $SOC > SOC_{ub}$, the supervisory strategy runs under a CD process. Once the SOC drops below SOC_{ub}, the operation is in charge-sustaining mode, and the controller switches between the DDC and CDC processes whenever the specified values of SOC_{ub} and SOC_{lb} are reached, ensuring safe and reliable battery operation. For example, if $SOC \leq SOC_{lb}$, the control strategy adopts CDC; once SOC increases above SOC_{ub}, the control strategy switches CDC to CD/DDC as shown in Figure 4.

In addition, the braking mode, with regenerative braking, occurs at all CDC, DDC, and CD processes once the PHEB decelerates. Also, the control enables the engine charging mode at parking stops if $SOC \leq SOC_{parking,chg}$: the engine will run at the operational condition with maximal efficiency. Meanwhile, a comprehensive approach was developed to filter and modulate operating states of the engine, motor, and transmission based on the actual usage to achieve acceptable vehicle drivability and real-time component operation within normal functional limits. Therefore, this powertrain control strategy enables the powertrain efficiency to be optimized in real time via smart and reliable management of electrical and mechanical paths as well as SOC, while adopting efficiency-driven battery charging.

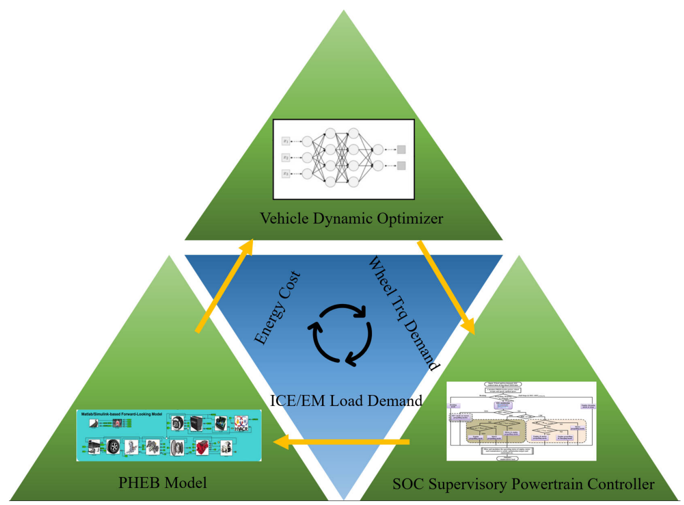

Fig. 5. Co-optimization: integrated vehicle dynamics and powertrain control.

B. Integrated VD/PT Co-Optimization Strategy

Figure 5 presents the co-optimization flowchart, comprising three main components in the system [11]. The PHEB model at the bottom left provides the cost for optimizing the vehicle dynamics, while the trajectory planning module (e.g., DLTPA) is located in the top block. The fine-grained powertrain control module is in the bottom right block. A loop is formed where the input of each module depends on the output of the previous module. For example, the vehicle model requires a full speed profile as the input driving cycle to calculate energy cost per second based on the instant state. To address this problem, we propose an alternative approach for deep algorithm integration by solving the problem iteratively:

1) Based on the key logic of the powertrain control strategy, a simplified PHEB powertrain model is developed and put into our vehicle dynamic optimization module as the edge cost to derive the theoretical optimal speed profile.
2) The powertrain control module takes that speed profile as the initial driving cycle, fine-tunes it if it is not valid in engineering practice, and computes the powertrain parameters and energy consumption for the whole process under the optimal powertrain strategy.
3) The process can be repeated to find the optimal solution with high validity and energy efficiency. However, the number of iterations is mainly determined by the real-time performance requirement.

V. Evaluation

A. Simulation-based Evaluation

A range of numerical and simulation tools have been developed to evaluate intelligent transportation systems (ITS), each with their own limitations. Microscopic traffic simulators struggle to accurately model vehicle dynamics and autonomous behaviors, while vehicle simulators struggle to integrate interactions with other road users and infrastructure. To address these issues, we utilized PTV VISSIM as a microscopic traffic simulation tool to model traffic networks, characterize buses, and develop an External Driver Model Dynamic Link Library (DLL) for integrated vehicle-powertrain optimal trajectory planning [12]. VISSIM is a leading-edge simulator that can model various types of transport, simulate wireless communication networks (to some extent), and calibrate general driver behaviors with real-world data. The study employs the External Driver Model DLL Interface of VISSIM to replace the inherent driving behavior model with a fully user-defined behavior embedded in the vehicle dynamic control module. During a simulation execution, VISSIM calls the External Driver Model DLL code for the targeted PHEB 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.

The real-world traffic network used in this study is a 3-mile segment of University Ave. in Riverside, California, a signalized corridor with 11 signalized intersections and 7 bus stops. Based on the real-world signal timing plan at each intersection from Riverside City, we code the information into the signal control module with a consistent SPaT message. Unlike passenger vehicles or heavy-duty trucks whose trajectories are only associated with the traffic light and recurrent congestion, transit buses need to also 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 eastbound route based on the specific schedule of two main stops along the route. Then, the Public Transport module in VISSIM is calibrated to match the assigned arrival time at each bus stop. In addition, the bus acceleration/deceleration profile in the simulation is also calibrated using real-world data from RTA bus trajectories. The study simulates different traffic conditions under different system settings and uses volume/capacity (v/c) ratios to quantify the congestion level based on the Highway Capacity Manual [13]. The traffic volume with the real-world traffic count is categorized as the Light Traffic condition with a v/c ratio of 0.35. The other three traffic conditions are No Traffic, Moderate Traffic, and Heavy Traffic conditions with v/c ratios of 0.17, 0.70, and 1.00, respectively. For each simulation scenario, 10 runs are executed with a simulation duration of 3,600 seconds.

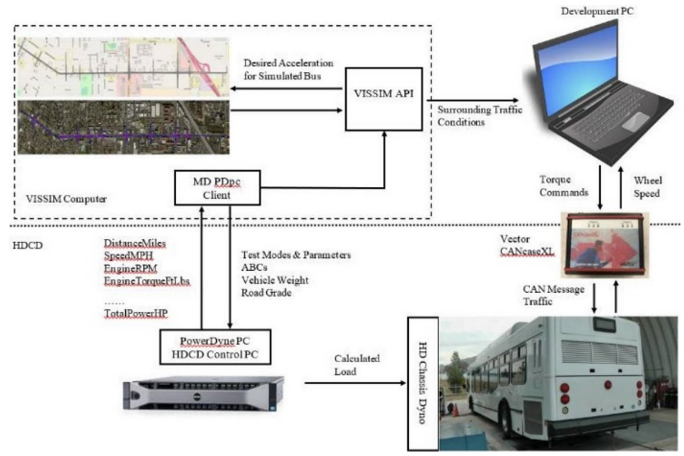

Fig. 6. DiL setup with automatic control. [13]

B. DiL-based Evaluation

In order to conduct system evaluations that involve an actual PHEB and human operator, we utilize an innovative DiL development and testing platform [14], which enables us to perform more realistic evaluations. The platform contains both a physical world and a simulation world, eliminating the need for a costly dedicated testing track. Additionally, different roadway networks and traffic scenarios can be created for modeling and evaluation in the simulation world. The platform is ideal for environment-oriented emerging technologies, such as CAV-based eco-driving, as it balances model accuracy and evaluation scalability. It is considered a cost-effective

TABLE I
SUMMARY OF EVALUATION RESULTS

Technology	Energy Efficiency Improvement	Trip Time Penalty	Notes
Eco-Approach and Departure	10.5% – 20.9% (simulation)	negligible	Varies with congestion levels and CAV MPR
	9.6% – 22.9% (real-world DiL)	negligible	
Eco-Stop and Launch	10.9% - 17.1% (simulation)	3s per stop	Numerical simulation was used to evaluate this separately
Eco-Cruise	0% - 12.8% (simulation)	negligible	Numerical simulation was used to evaluate this separately
Combined Powertrain Optimization	13.7% – 18.0% (simulation)	negligible	Varied with congestion levels and CAV MPR
	8.5% – 10.5% (DiL and projected from simulation)	negligible	-
Total Integrated (VD & PT)	20.2% – 29.4% (simulation)	negligible	Varied with congestion levels and CAV MPR
	19.4% – 32.4% (DiL and projected from simulation)	negligible	-

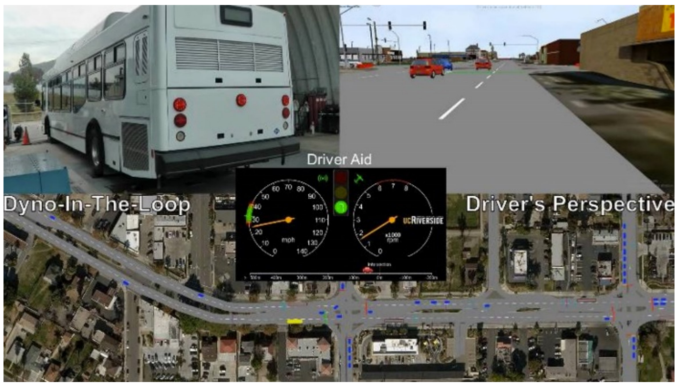

Fig. 7. PHEB on Heavy-duty Chassis Dynamometer (HDCD) (upper-left panel); driver's perspective (upper-right panel); bird's-eye view of the road network (lower panel); advisory information on driver-vehicle interface (middle panel). [13]

approach, which allows for testing on a limited scale to gauge effectiveness and then being extrapolated to a larger scope.

As shown in Figure 6, the physical world of this DiL platform contains a chassis dynamometer and a test vehicle that is equipped with various systems for data acquisition, monitoring, and control. The test vehicle is connected to the chassis dynamometer through an Application Programming Interface (API), and the information from both the test vehicle and the dynamometer can be transmitted to a microscopic traffic simulator in the simulation world. In the simulation world, a virtual version of the test vehicle is created and synchronized with the real test vehicle in terms of vehicle dynamics. The simulation engine controls the behavior of other road users, the operation of traffic signals, and interactions between road users. The DiL platform is flexible in modeling and evaluation under different roadway networks and traffic conditions, and it can also be used to test different market penetration rates of emerging technologies by modifying the behavior of other vehicles through APIs. Figure 7 illustrates the developed mixed-reality environment where the driver's perspective, bird's-eye view of the roadway in the simulation environment, and the advisory information shown on the driver-vehicle interface (i.e., on-board display) are presented. To maintain realistic driving behavior from the driver, the latency between the driver's input and simulation response needs to be minimized.

C. Results

The Connected Eco-Bus was evaluated on a typical bus route in Riverside, California. The operation of the bus was evaluated under a number of conditions, including different levels of traffic (i.e., none, light, moderate, heavy, and very heavy traffic conditions) and different levels of connected vehicle penetration (i.e., 0% and 20% penetration rates). The original plug-in hybrid electric bus platform (with no improvements to the vehicle dynamics and powertrain operation) was first tested to serve as a baseline for subsequent comparisons. The evaluation process involved conducting multiple tests to assess the integrated vehicle dynamics speed trajectory planning (VD), the efficiency-based powertrain controls (PT), and combined VD and PT. The tests were conducted both in simulation and using the DiL methodology, and the results are shown in Table I.

VI. CONCLUSIONS AND FUTURE WORK

In this study, we developed, implemented, and assessed a novel vehicle-powertrain eco-operation system to improve the efficiency of a PHEB, which was converted from a CNG bus. We conducted a comprehensive analysis of its powertrain system component-by-component. To determine the optimal operation ranges for the motor and the engine, we devised the CEED. We also proposed a CAV-based approach for optimizing vehicle dynamics in three applications—EAD, ESL, and EC—and used a combination of graph-based and deep-learning-based algorithms to solve for an optimal speed profile for the PHEB in real-time. To co-optimize the powertrain operation and the vehicle dynamics, we first introduced a rule-based SOC supervisory powertrain model and optimized its parameters based on the CEED. We then utilized an iterative scheme to identify the most efficient power split to achieve optimality for both vehicle dynamics and powertrain controls. To evaluate the vehicle-powertrain eco-operation system, we first developed an advanced simulation framework that allows for the simulation of the co-optimized vehicle dynamics and powertrain control in the traffic simulation environment of the VISSIM traffic simulator for simulation-based evaluation. Moreover, we implemented the system in the actual PHEB, and developed a dyno-in-the-loop testing platform to further evaluate the system under more realistic conditions. The results demonstrate that by using only VD optimization, the energy efficiency of the PHEB can be improved by up to 18.0%. However, with the integrated VD and PT optimization, the vehicle-powertrain eco-operation system can achieve energy efficiency improvements by up to 32.4%.

Although the proposed model is highly effective in real-time optimization of vehicle dynamics and powertrain operation, there is still potential for improvement in: a) the accuracy of the powertrain model, b) SOC supervisory control strategy, and c) power split logic. In the future, with the integration of vehicle-to-everything (V2X) communication, on-board sensing, and artificial intelligence, there will be unprecedented opportunities for data-driven, customized VD and PT co-optimization. To mitigate cybersecurity issues and enable predictive maintenance, control strategies should be enhanced by detecting abnormal signals. We also plan to conduct road tests to evaluate the system's performance in a real-world environment.

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