Developing a Data-driven Modularized Model of a Plug-in Hybrid Electric Bus (PHEB) for Connected and Automated Vehicle Applications

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***Abstract*—Shared Electric Connected and Automated Vehicles have the potential to improve transportation safety, mobility, and energy efficiency. A plug-in hybrid electric architecture is well suited for developing connected and automated vehicle (CAV) applications, allowing for vehicle dynamics management and powertrain control. In this paper, we developed a data-driven modularized modeling approach for a plug-in hybrid electric bus (PHEB), thereby allowing for a wide range of connected and automated vehicle applications. Instead of using an end-to-end learning approach to model the PHEB, our modularized modeling approach considers the physical connection of each component of PHEB, which provides various signals and dynamics of each subsystem for testing use or controller design. The plug-and-play (PnP) feature allows us to customize the bus model and update each individual module in a flexible manner. The modules include human driver behavior, energy management system, internal combustion engine, electric motor(s), transmission, and powertrain dynamics. For each module, a Long Short-term Memory (LSTM) network is utilized to learn each modules' behavior and dynamics using the data from extensive dynamometer-in-the-loop (DiL) testing.**

I. Introduction

A. Motivation

Transportation energy consumption and environmental impacts have been a long-term concern for decades. To address this issue, a wide range of emerging technologies and research has been developed from different perspectives. There are several examples of this: 1) traffic management strategies like ramp control systems [1] can reduce congestion and speed fluctuation at the microscopic level; 2) Vehicle dynamic optimization strategies like Cooperative Adaptive Cruise Control (CACC) [2] and Eco-Approach and Departure (EAD) [3] can also be used to plan more efficient trajectories for vehicles to follow; and 3) Powertrain optimization strategies like intelligent energy management [4] can improve the energy utilization ratio. All of these technologies coupled with vehicle electrification, connectivity and automation, make the vehicle system increasingly eco-friendly while more complex. Understanding the vehicle dynamics, including not only the speed response but also the detailed operating status, can assist researchers to design, test and validate the aforementioned strategies. To carry this out, it is essential to have an accurate, complete, and flexible model to perform a wide variety of intelligent transportation system (ITS) applications.

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Benefiting from numerous strategies for energy management, hybrid electric vehicles (HEV) have a significant advantage in reducing energy consumption and emissions. These savings rely on the following reasons: 1) when a vehicle is powered by both an electric motor (EM) and an internal combustion engine (ICE), a smaller ICE engine can be used; 2) both EM and ICE can be designed to operate only in their most efficient regions; 3) regenerative braking can recapture a significant amount of energy that would have otherwise been wasted. A transit bus is a good target for hybridization since it plays an important role in the cities' public transportation system. Specifically, a plug-in hybrid electric bus (PHEB) can achieve a 28-48 percent fuel economy improvement [5]. However, the modeling and controller design of a PHEB is challenging because this type of heavy-duty vehicle usually has a low power to mass ratio and large actuator delays [6]. In addition, the combination of both internal combustion engine (ICE) and electric motor (EM) makes the vehicle dynamics even more complicated. Further, the different powertrain configurations with different mechanical properties, Vehicle Control Unit (VCU)-level power, and battery management logic (e.g., parallel hybrid and series hybrid) also complicate the modeling process. As a result, a physics-based modeling approach does not accurately capture the detailed features of individual components or processes, such as regenerative braking, engine drive, torque converters, and transmission.

B. Literature Review

Studies on vehicle modeling have been well established over several decades. The physics-based modeling approach has been dominating, with simple physical principles to represent dynamical changes for vehicle states [7]. Roughly speaking, the physics-based model aims to reconstruct the relationship between driver's command and vehicle reaction based on vehicle's tractive force (e.g., engine torque output), road resistance (e.g., rolling resistance and aerodynamics drag), and inertia (e.g., vehicle mass and shaft moment of inertia). However, to describe the necessary transients, a more detailed representation of the mechanical properties of the vehicle powertrain components is required. McMahon et al. [7][8] presented the physics-based model building upon engine model, torque converter, and transmission mechanics, targeting the longitudinal control of a platoon of automated vehicles. Since then, a number of researchers have proposed a series of sophisticated or succinct models for different control purposes. Based on those methodologies, Rajamani [9] provided comprehensive coverage of vehicle modeling and control design. By modeling the detailed vehicle components such as anti-lock brake systems (ABS), and semi-active suspension, the book introduced the control design for multiple purposes, like adaptive cruise control, and automated lane-keeping. However, most of the above research only modeled the passenger car or general-purpose vehicle. According to Lu and Hedrick's [10] research, heavy-duty vehicles have their own characters compared to passenger cars due to different power to mass ratios and mechanical setups. With the vehicle electrification, modeling an electric vehicle becomes another hot topic. Among them, Mohd el al. [11] proposed a methodical model for electric vehicles on the Matlab-Simulink platform to investigate the energy flow and efficiency of the EV drivetrain. Mapelli et al. [12] and Liu et al. [13] analyzed and modeled plug-in hybrid electrical vehicle (PHEV) and power-split hybrid vehicle. Lin et al. [14] modeled medium-duty hybrid electric truck using a feed-forward simulation tool and provided a power management control algorithm to mimic the behavior of a dynamic-programming optimization scheme. Maia et al. [15] used a fuzzy logic model approach to capture the regenerative braking feature of the electric vehicle while considering the vehicle's acceleration and jerk, as well as road grade as input variables. As the vehicle structure becomes increasingly complicated, it is difficult for a conventional model approach to capture all the details. A data-driven/learning-based approach is attractive due to its ability to represent nonlinearities. Thompson et al. [16] used a neural network to model the emission performance of a heavy-duty diesel engine. Albeaik el al. [6] presented an end-to-end learning method for the longitudinal dynamics of heavy-duty trucks. Further, vehicle model simulation tools, such as ADVISOR [17] and Autonomie [18] have been used to develop models of different types of vehicles.

Deep neural networks (DNN) have become increasingly popular among the field of transportation modeling due to its advantage in fitting complex non-linear dynamics using a large amount of data. Ma et al. [19] proposed a large-scale traffic speed model by using 2D traffic flow images and a convolutional neural network (CNN). The Recurrent neural networks (RNN) was developed based on CNN specifically to process sequential data. Tan et al. [20] identified the nonlinear dynamic model of the throttle body processes in an automotive engine using RNN. The LSTM model solved the problem of vanishing gradient problem which was often found in RNN by using a memory cell that can maintain information in memory for long periods of time. Wu et al. [21] proposed an LSTM based traffic flow prediction model, which made full use of weekly/daily periodicity and spatial-temporal characteristics to improve the prediction accuracy. Albeaik et al. [6] modeled the heavy duty truck using LSTM and controlled the longitudinal dynamics using deep reinforcement learning.

C. Contribution of this Paper

Although there are numerous studies on vehicle dynamics and powertrain modeling, very few studies have investigated a plug-in hybrid electric bus. In this study, we propose a data-driven modularized modeling approach for a PHEB using extensive testing data from our Dyno-in-the-Loop (DiL) platform [22]. Our model and approach are innovative in the following aspects:

- The PHEB model is modularized based on the physical structure which can provide accurate prediction of detailed system states of different modules.
- Deep learning with LSTM networks has been adopted to depict the extensive dynamics of the PHEB.

D. Paper Organization

The remainder of this paper is organized as follows: In Section II, we introduce the testbed and the method of data collection. Section III explains the system structure and modeling methodology. Section IV presents the evaluation of the model including both stand-alone performance of each module and the cascaded vehicle model, compared with the real data. Finally, Section V concludes the paper and discusses possible directions for future work.

II. Data Collection

A. Testbed

In this research program, a compress natural gas (CNG) transit bus has been hybridized as shown in Figure 1. This vehicle uses a power-split hybrid approach where the internal combustion engine (ICE) and the electric motors (EM) are coupled so that they are able to power the vehicle either individually or together. The power-split logic is programmed into the onboard computer (VCU) to select proper torque output with a different proportion from both ICE and EM. In addition, through such a hybrid system, battery management strategies like regenerative braking have been adopted. Negative torque can be generated from the EM to charge the battery when the driver pushes the brake pedal.

For the testing, the PHEB is tested on a Mustang heavy-duty chassis dynamometer (HDCD), which is capable of absorbing continuous loads of 600 hp, with vehicle inertia simulated in the weight range of 10,000-80,000 lb. The major components of our HDCD include rollers, load absorbers (e.g., brake), a power supply, and monitoring and control systems, in addition to a structural steel frame and auxiliary systems (e.g., cooling system).

Figure 1. PHEB as tested on heavy-duty chassis dynamometer

B. Data Acquisition

A data acquisition system from Vector Informatik (CANCaseXL) is connected with an on-board computer installed with Vector CANAlyzer [23] to retrieve J1939 messages from the in-vehicle network bus (and create desired CAN messages if needed).

To collect the data for training our PHEB model, thirty scenarios at different traffic conditions, including no traffic, light traffic, moderate traffic, heavy traffic, and very heavy traffic, are tested. For each test, the speed profile and instantaneous speed are delivered to the driver through a driver-vehicle interface (DVI) mounted on the vehicle dashboard. Through the acceleration pedal and brake pedal, the longitudinal control is handled by the driver. Lateral controls are not considered in this study. We select sixteen signals out of the whole set of J1939 messages to build our model. In Table I, the signal and their abbreviations are listed.

In addition to the signals in the J1939 message, the suggested speed profile (shown on DVI) is also available for modeling. The overall system takes the suggested speed as input. Combined with initial states, the system updates all the relevant vehicle states (e.g., SOC and actual speed) for the next time step. Then the vehicle sends actual speed feedback to the beginning of the model (i.e., human driver module), forming a closed loop. To evaluate the model's performance, the dataset is divided into two portions: one for training, and the other for validation.

TABLE I. SIGNAL SELECTED FROM J1939 MESSAGE

Name	Abbreviation (unit)
Vehicle Actual Speed	Veh_Spd (mph)
Acceleration Pedal Position	Acc_Pdl (pct)
Brake Pedal Position	Brk_Pdl (pct)
Battery State of Charge	SOC (pct)
Electric Motor Torque Command	EM_Trq_Cmd (Nm)
Electric Motor #1 Speed	EM1_Spd (rpm)
Electric Motor #2 Speed	EM2_Spd (rpm)
Electric Motor #1 Torque	EM1_Trq (Nm)
Electric Motor #2 Torque	EM2_Trq (Nm)
Engine Command Percent Torque	ICE_Trq_Cmd_Pct (pct)
Actual Engine Percent Torque	ICE_Trq_Act_Pct (pct)
Engine Speed	ICE_Spd (rpm)
Engine Throttle Valve Position	ICE_Thrtl_Val_Pos (pct)
Engine Fuel Rate	ICE_FR (lph)
Transmission Actual Gear Ratio	Trns_GR_Act
Transmission Selected Gear Level	Trns_GLvl_Sel

III. DATA-DRIVEN MODULARIZED PHEB MODELING

In this section, we introduce the methodology of the proposed data-driven modularized modeling approach for our PHEB.

A. System Structure

Figure 2 illustrates the system structure of our modularized PHEB model. All the modules modeled in this study are shown in the dashed boxes. The Human Driver module considers the interaction between the driver and DVI. Based on the suggested speed and current vehicle actual speed, the

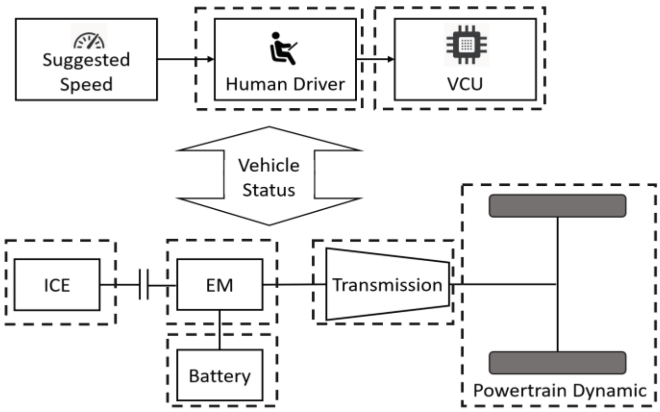

Figure 2. System Struction, modules modeled are shown in dashed boxes

driver responds by pushing the acceleration pedal or the brake pedal. Then based on current vehicle status and the positions of two pedals, VCU calculates the power split logic and sends it to ICE and EM. A clutch is used to govern the transition between different modes (e.g., ICE-only, electric-only, and hybrid). For example, in the electric-only mode, the clutch is released; in the ICE-only mode, the clutch is engaged, and the EM provides zero torque output; in the hybrid mode, the clutch is engaged, and both ICE and EM respond to their command torques accordingly. Because of physical constraints and some low-level controller logic (e.g., idle-speed controller), the actual response varies from the torque command. Therefore, the ICE module and the EM module depict the torque response based on torque command and vehicle status. Next, battery dynamics can be updated according to the usage or charging mode of the EM. Afterwards, the transmission module reconstructs the automatic transmission shift schedule. With all the above vehicle status predicted, the powertrain dynamic module mimics the key states including vehicle actual speed, ICE speed, and EM speed. Finally, the predicted actual speed is sent back to the human driver module for the next iteration. To conclude, the input/output signals of each module refer to Table II. Although there are two separate electric motors, both of them are linked together and respond to the command in the same manner. Therefore, they are modeled as a whole.

B. LSTM Network for each Module

Given the nonlinearity nature of modeling PHEB dynamics, the LSTM neural network is chosen to be the training algorithm because of its significant ability of fitting complex dynamics with a large amount of sequential data. The complexity of the neural network has an impact on model accuracy. In general, the higher the complexity, the easier it is to fit the training data, but it is more likely to overfit and reduce the model generalizability.

TABLE II. INPUT/OUTPUT SIGNALS, NETWORK STRUCTURE, AND STAND-ALONE PERFORMANCE OF EACH MODULE IN THE SYSTEM

Module	**Input**	**Output**	**Structure**	**MAE/Accuracy**	**NMAE**
Human Driver	Ref_Speed	Acc_Pdl	LSTM(300) × 2 FC(300) × 2 FC(1)	7.829	0.0752
	Veh_Spd	Brk_Pdl		2.899	0.0445
VCU	Veh_Spd	EM_Trq_Cmd	LSTM(200) × 2 FC(200) × 3 FC(1)	47.299	0.0217
	SOC				
	Acc_Pdl				
	Brk_Pdl	ICE_Trq_Cmd_Pct		1.058	0.0106
	Trns_GR_Act				
	ICE_Thrtl_Val_Pos				
EM	EM_Trq_Cmd	EM1_Trq	LSTM(200) × 2 FC(200) × 3 FC(1)	8.182	0.0092
		EM2_Trq		7.997	0.0090
ICE	ICE_Trq_Cmd_Pct	ICE_Trq_Act_Pct	LSTM(400) × 2 FC(400) × 3 FC(1)	4.134	0.0413
	Acc_Pdl	ICE_Thrtl_Val_Pos		4.024	0.0613
	Brk_Pdl	ICE_FR		1.311	0.0249
	ICE_Spd				
Battery	EM1_Spd	SOC	LSTM(400) × 2 FC(400) × 2 FC(1)	1.548	0.0356
	EM2_Spd				
	EM1_Trq				
	EM2_Trq				
	Initial_State_1				
Transmission	EM1_Spd	Trns_GR_Act	LSTM(300) LSTM(200) FC(200) FC(100) FC(6)	90.34%	--
	EM2_Spd				
	EM1_Trq				
	EM2_Trq				
	ICE_Trq_Act_Pct				
	Acc_Pdl				
Powertrain Dynamics	EM1_Trq	Veh_Spd	LSTM(400) × 2 FC(400) × 3 FC(1)	0.731	0.0151
	EM2_Trq				
	ICE_Trq_Act_Pct	EM1_Spd		78.711	0.0450
	Acc_Pdl				
	Brk_Pdl	EM2_Spd		78.684	0.0449
	Trns_GR_Act				
	Initial_States_2	ICE_Spd		67.317	0.0382

At time step t, each module in the system receives the input from the current time step, hidden and cell states from previous time step $t-1$, initial state of the output, and predicts the output at the next time step $t+1$, which can be described as the mapping below:

$$y(t+1) = f(x(t), c(t-1), h(t-1), y_0)$$

where x and y are the input/output vectors that vary according to different modules, c and h are the cell state and hidden state, respectively, produced by the LSTM layers to store the memory from previous time steps, y_0 is the initial state of the output, and f represents the mapping function.

The neural network consists of LSTM layers, fully connected layers (FC), dropout layers, and nonlinear activation layers. A dropout layer is adopted with dropout ratio of 0.2 after each LSTM layer to prevent over-fitting. Rectified linear (ReLU) unit is chosen to be the nonlinear activation layer for the network. The detailed structure shows in Table II.

For each module, we train a network for every category of output. LSTM(n) represents the number of hidden units in the LSTM layer and FC(n) represents the output size of the fully connected layer. The structure for each module is described in the Table II.

$$ReLU(x) = \begin{cases} x & x > 0 \\ 0 & \text{otherwise} \end{cases}$$

For the Transmission module, since there is a one to one correspondence between Transmission Actual Gear Ratio and Transmission Selected Gear Level, Trns_GLvl_Sel is selected to be the network output in training. Because the transmission gear level has only six possible values, a classification layer is used as the last layer instead of a regression layer.

The network is implemented using MATLAB. The training process takes 1000 iterations with a preset early stop criterion to avoid over-fitting. The trainable parameters are updated using an adaptive moment estimation (Adam) optimizer with an initial learning rate 5×10^{-3}. All the model training, validation, and testing are performed on a PC with six-core 3.70 GHz CPU, 32 GB of RAM, and Nvidia GeForce GTX 1080 TI GPU.

IV. PHEB MODEL EVALUATION

A. *Stand-alone Module Evaluation*

Each module is trained and tested separately using the data collected from the PHEB. The collected data is resampled to 10 Hz and grouped into sequential series of 500 time steps each. The full dataset is split into training, validation, and testing separately. To evaluate the performance of the proposed system, mean absolute error (MAE) and normalized MAE (NMAE) are calculated for all modules except the transmission where the accuracy of the transmission gear level was used as the performance index. The stand-alone testing results are summarized in Table II. The MAE and NMAE are defined as below:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n}$$

$$NMAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n \times |\max(y) - \min(y)|}$$

where y is the ground truth value and $\hat{y}$ is the predicted value. The NMAE normalizes the error to be between 0 and 1. As can be seen from the table, all the NMAE values are smaller than 0.1, and the prediction accuracy of the transmission selected gear level reaches over 90%, indicating the excellent performance of all modules in the system.

B. *Cascaded Vehicle Model Evaluation*

1) *Simulation setup:* The experiments showed in this subsection are conducted through our DiL testbed and Matlab Simulink is used to evaluate the effectiveness of the proposed model. First, a random trajectory is selected as the suggested speed profile for both the driver and the proposed model. Next, using the DiL platform, the driver tries to follow this speed profile as accurate as possible. The criteria for the driver in this test are the same as the one when collecting the training dataset, which is to follow the provided speed profile as close as possible. The speed response and other aforementioned data are collected to be the ground truth. The cascaded vehicle model is built at the Simulink platform. Each module corresponds to a block in Simulink, and the blocks are connected based on their input-output relationships. Only the suggested speed profile and the necessary initial state are required for the simulation.

2) *Simulation results:* This section presents and analyzes the simulation results for the proposed model. The simulation results are shown in Figure 3. All the results in the same module are shown in the red dashed boxes. The blue curves show the ground truth, while the red curves show the predicted value from the proposed model. In general, the cascaded vehicle model successfully predicts signals with the correct trend and acceptable approximate value. Among them, the negative torque provided by EM presents a good example of regenerative braking. The ICE outputs (ICE_Act_Trq, ICE_FR, and ICE_Thrtl_Val_Pos) converging from low value to a higher one depicts the idle-speed control and torque convert precisely. However, the prediction from the Human Driver module at the very first 20 seconds is inaccurate. As the upstream module of the cascaded system, it influences the prediction of those downstream ones. An upshift-downshift maneuver is predicted inaccurately by the transmission module, and the powertrain dynamics module miscalculates the zero speed.

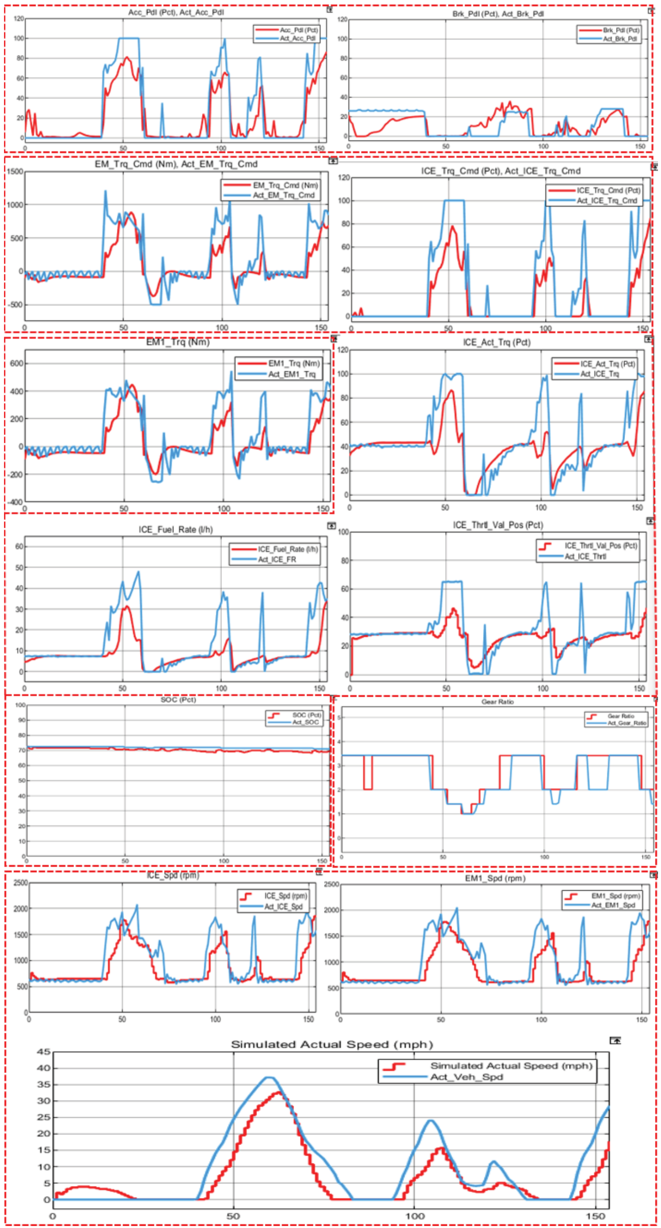

Figure 3. Simulation Results for Stand-alone Modules

V. CONCLUSIONS AND FUTURE WORK

Conventionally, modeling vehicles is based on the understanding of the physical attribution of the vehicle. Numerous of ODE is used to depict the vehicle dynamics. However, due to the heavy-duty vehicle's slow dynamics, the nonlinearity is usually hard to be captured accurately. Also, as the vehicle structure becomes increasingly complicated, part of the vehicle dynamics evolving preprogrammed automatic control logics (e.g. automatic transmission scheduling and intelligent power management strategies for HEV) are difficult to be considered without prior data. To address this, numerous researchers have turned to learning-based modeling approaches. Although offering relatively good performance in modeling the vehicle speed response, most of the end-to-end learning-based models lose too much detailed information that is essential for designing and validation of powertrain control and power and battery management strategies planning. In general, only few research has been done on modeling PHEB.

In this paper, we proposed a data-driven modularized model for PHEB using the deep learning approach with LSTM networks. We design the modular structure according to the physical architecture of the vehicle platform and the LSTM networks based on the properties of each module. The performance validation of the stand-alone modules shows great accuracy in modeling the vehicle subsystems. The cascaded vehicle model is able to predict numerous signals and depicts the vehicle dynamics with the correct trend and approximate value. The results show that given the initial states, without update any ground truth information, the error of the model does not grow alone time. Moreover, the availability of the key signals such as SOC, engine fuel rate, and transmission shift schedule provide potent support for testing use or controller design.

Although the presented model is accurate, there is still room for improvement. As the property of the cascaded system, the inaccurate signal transmitting along modules may magnify the error. For example, the insufficient predicted acceleration pedal position may lead to insufficient torque from both ICE and EM and also cause the gear-level prediction error. As a result, the speed estimation would be relatively small compared with the ground truth. Therefore, fine-tuning of the networks to emphasize the performance of certain key signals could further improve the accuracy.

Besides, taking advantage of the presented model, an ongoing research direction is to develop a reinforcement learning-based eco-friendly control algorithm that can optimally split the power of ICE and EM to track giving trajectories.

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