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A Hybrid Framework for Vehicle Parameter Prediction in Heavy-Duty Electric Vehicles for Real-Time Application

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Executive Summary

This paper presents a hybrid framework for real-time parameter prediction in Heavy-Duty Electric Vehicles (HDEVs), combining physics-based simulations & field test data, Machine Learning (ML), and lookup tables. The framework covers gear status classification, linear regression-based estimation in a Bayesian setting and a Physics-Informed Neural Network (PINN) for rolling resistance (C_{rr}), drag coefficient (C_d), and energy consumption prediction. By combining the accuracy of physical models, the speed of ML, and the efficiency of lookup tables, the framework addresses the computational limitations of traditional simulation approaches. Trained on both simulated and real-world data, it achieves over 90% gear classification accuracy and delivers low Root Mean Square Error (RMSE) in energy prediction. Results confirm the hybrid framework's superior performance over conventional methods, supporting its application in real-time backend services and onboard vehicle control systems. Future work will target enhancing generalization across diverse vehicle variants and operating conditions.

Keywords: Heavy Duty electric Vehicles & Buses, AI - Artificial intelligence for EVs, Drive & Propulsion Systems, Modeling & Simulation, Energy management

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1 Introduction

The transportation industry is undergoing a significant transformation toward electrification, with heavy-duty electric vehicles (HDEVs) playing a central role in achieving decarbonization and sustainability goals. In this context, accurate and computationally efficient modeling frameworks for key vehicle parameters are essential for vehicle development, energy optimization, and the deployment of intelligent digital services.

Traditionally, vehicle dynamics are modeled using physics-based methods grounded in Newtonian mechanics. These models provide high-fidelity insights into energy consumption, gear selection, driveline efficiency, and key physical parameters such as rolling resistance (C_{rr}) and aerodynamic drag coefficient (C_d) [1, 2, 3]. However, the high computational cost of these simulations limits their applicability in real-time scenarios, such as fleet energy monitoring, backend services, digital twins, or onboard vehicle control systems.

Machine learning techniques offer a complementary approach by enabling fast predictions after training. However, despite their speed, these models often lack physical interpretability and require extensive datasets for reliable performance. Lookup tables, widely used in embedded systems, provide instant outputs but are restricted to predefined operating conditions, limiting their adaptability to new or unseen scenarios.

Recent research highlights the potential of hybrid modeling approaches that combine physics-based simulations with data-driven learning. Studies such as [4, 5, 6] have demonstrated the effectiveness of hybrid models in improving computational efficiency and predictive accuracy. Furthermore, research in vehicle energy management

[7, 8, 9] has illustrated the benefits of hybrid methods in capturing complex system behaviors. However, most existing efforts rely on data collected under controlled environments with limited vehicle variants and simplified road conditions, which constrains their generalization in real-world applications.

To overcome these limitations, this paper proposes a novel hybrid framework that integrates physics-based simulations, real-world field test data, machine learning methods, and lookup tables. The framework is designed to handle multiple HDEVs configurations and a variety of environmental conditions, such as road surface and weather variability. It has applications on three main parameter estimations: (1) gear status prediction formulated as a classification task, (2) Bayesian linear regression for estimating C_{rr} and C_d, and (3) a Physics-Informed Neural Network (PINN) for nonlinear energy consumption prediction and dynamic parameter estimation.

The proposed framework addresses the challenge of real-time computation and physical interpretability. It offers a promising solution for deployment in backend systems, vehicle control strategies, and digital service platforms.

2 Research Questions

2.1 Gear Selection Prediction

Gear selection is traditionally governed by rule-based logic or physics-driven models, which are limited in their ability to handle large-scale real-time applications. To improve prediction speed while maintaining accuracy, this study considers gear status estimation as a classification problem. In this context, the primary research question becomes:

- Can supervised machine learning models, trained on simulation-generated data, accurately predict gear status across different vehicle configurations, environment conditions, and driving scenarios, while maintaining the interpretability and reliability of traditional approaches?

2.2 Bayesian Linear Regression

As tabular reference values of C_{rr} and C_d, experimentally determined at test sites under various settings, are indicative of the true coefficient values for similar driving conditions, they provide useful information for making predictions about energy consumption. At the same time, various uncertainties that are impossible to account for at test sites may have a significant affect. Therefore, under the assumption that energy consumption is linear in these two coefficients, we set out to test the following:

- Can Bayesian linear regression, with tabular reference values for C_{rr} and C_d as priors, provide an effective hybrid tabular/data-driven approach for identifying the true coefficient values, in order to accurately predict future energy consumption?

2.3 Non-Linear PINN Regression

The vehicle's energy consumption is inherently nonlinear due to dynamic interactions between the driveline, road, weather conditions, and control systems. Classical models struggle to capture these complexities in real-time, prompting a shift toward neural-network-based modeling. This study investigates the use of PINNs to bridge data-driven learning with physical laws. Our core research question is:

- Can a PINN, trained on real-world field test measured data, improve the accuracy and generalization of energy consumption predictions in HDEVs over traditional physics-based models, while enabling faster inference suitable for backend services?

3 Methodology

The proposed hybrid framework for predicting vehicle parameters in HDEVs integrates three modeling approaches: physics-based simulations & empirical field test data, machine learning (ML), and lookup tables. This multilayered architecture is designed to optimize both accuracy and computational efficiency across diverse driving conditions and vehicle configurations.

Figure 1 provides an overview of the framework. It illustrates how field test data and simulations are used to train three levels of ML models: a classification model for predicting gear status and driveline efficiency; a linear regression model for estimating C_{rr}, C_d, and energy consumption; and a nonlinear PINN for high-fidelity energy prediction and dynamic coefficient estimation. Lookup tables complement the ML models by enabling rapid access to calibrated efficiency values in known conditions and tabular reference coefficients.

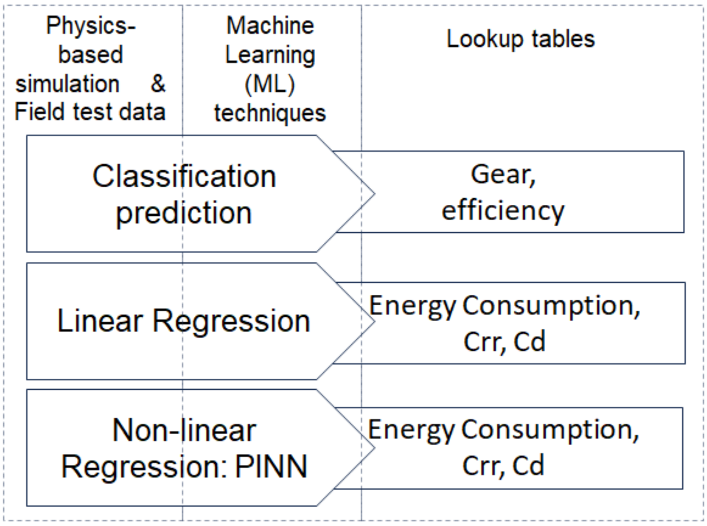

Figure 1: Overview of the hybrid framework.

The following subsections detail the application of this hybrid framework in our vehicle parameter prediction in HDEVs work.

3.1 Gear Selection as a Classification Problem

To predict gear selection in HDEVs, a data-driven classification model was developed using a combination of physics-based simulations and real-world field data. The simulations covered a wide spectrum of vehicle configurations, payloads, road slopes, and operating conditions to ensure comprehensive representation of the driving scenarios. Real-world data was incorporated to capture variability due to weather, surface type, and transient vehicle behaviors that are often underrepresented in simulations.

The key input features included vehicle speed, requested torque, and vehicle mass, selected based on domain knowledge from powertrain control systems. To address class imbalances across gear levels, weighted balancing techniques were applied during model training, ensuring fair representation of all operating modes.

Several classification algorithms were evaluated to identify the best trade-off between accuracy, interpretability, and computational efficiency. Decision trees offered simplicity and transparency through recursive feature partitioning. K-nearest neighbors (KNN) classified samples based on proximity in the feature space without imposing parametric assumptions. Random forests, by aggregating multiple decision trees, enhanced generalization and reduced variance. Gradient boosting machines (GBM) sequentially refined weak learners to minimize prediction errors and ultimately delivered the highest overall performance.

Through systematic hyperparameter optimization and cross-validation, GBM was selected as the final classifier, offering a strong balance between prediction accuracy and computational efficiency.

The performance of the gear prediction module was evaluated using two metrics. First, prediction accuracy was measured by comparing predicted gear classes against ground truth values derived from the simulation model.

Accuracy was defined as:

$$\text{Accuracy} = \frac{\sum_{i=1}^{C} TP_i}{\sum_{i=1}^{C} (TP_i + TN_i + FP_i + FN_i)} \tag{1}$$

where C is the total number of gear classes, and TP_i, TN_i, FP_i, and FN_i represent the true positives, true negatives, false positives, and false negatives for each class i, respectively.

Second, computational efficiency was assessed using wall clock time, representing the total time taken to complete predictions. This metric is particularly important for backend and embedded applications where rapid inference is required.

Once the gear prediction is completed, the estimated gear status is used to reference a detailed lookup table (calibration map) that links speed, torque, and gear to driveline efficiency.

This driveline efficiency estimation is critical for accurate downstream energy consumption prediction, this ensures the hybrid framework is adaptable to both simulated environments and real-world operations, while remaining extensible as new data becomes available.

3.2 Bayesian Linear Regression for Energy Prediction

3.2.1 Vehicle Energy Dynamics Formulation

Accurate and interpretable energy prediction in HDEVs begins with a reliable representation of longitudinal vehicle dynamics. As illustrated in Figure 2, the longitudinal motion of the vehicle is influenced by multiple forces. According to Newton's second law [1], the net force acting on the vehicle is equal to the product of its mass and acceleration, and can be expressed as:

$$F_a = F_w - (F_g + F_r + F_d) \tag{2}$$

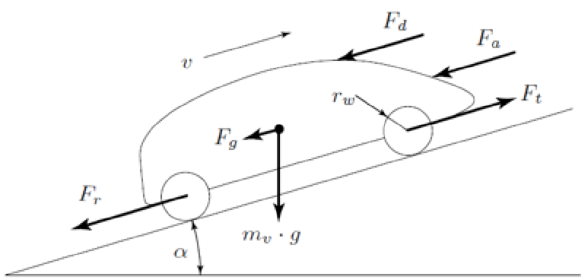

Figure 2: Free-body diagram of a vehicle on an incline showing longitudinal forces.

In this equation, $F_a = ma$ denotes the net acceleration force, where m is the vehicle mass and a is its acceleration. The term F_w represents the traction force generated at the wheels. The gravitational force due to road inclination, F_g, is given by $mg\sin\theta$, where g the gravitational acceleration and θ is the road slope angle. Rolling resistance force F_r is modeled as $mgC_{rr}\cos\theta$, with C_{rr} being the rolling resistance coefficient. Finally, the aerodynamic drag force F_d is expressed as $\frac{1}{2}\rho C_d A v^2$, where ρ is the air density, C_d is the drag coefficient, A is the frontal area, and v is the vehicle velocity.

Substituting these expressions into the original equation yields the total wheel traction force required to maintain or change vehicle speed:

$$F_w = ma + mg\sin\theta + mgC_{rr}\cos\theta + \frac{1}{2}C_d A \rho v^2 \tag{3}$$

This force-based formulation provides the physical foundation for modeling energy consumption. To estimate energy usage over a route, the wheel force is multiplied by the vehicle speed and integrated over time, which corresponds to the distance traveled. For practical implementation, the route is divided into small segments of length d, during which force is assumed constant. The energy required at the wheels over a segment is then calculated as:

$$e_w = mad + mgd\sin\theta + mgC_{rr}d\cos\theta + \frac{1}{2}C_dA\rho d\left(\frac{v_i^2 + v_f^2}{2}\right) \tag{4}$$

where v_i and v_f are the initial and final speeds over the segment, and a is the average acceleration.

The net energy consumption or regeneration e is calculated by incorporating the driveline efficiency η, which accounts for all energy losses from the electric motor through to the wheels. This is expressed as:

$$e = \begin{cases} \frac{e_w}{3600\eta} & \text{if } e_w > 0 \\ \frac{e_w}{3600}\eta & \text{otherwise} \end{cases} \tag{5}$$

Here, η is obtained from gear- and torque-specific calibration maps. The factor of 3600 converts energy from Joules to Watt-hours (Wh), the standard unit for vehicle energy consumption modeling.

3.2.2 Bayesian Linear Regression

Considering the model for vehicle energy dynamics described in 3.2.1, we observe that the energy consumption depend linearly on the coefficients of rolling resistance C_{rr} and air drag C_d respectively. With these values known, we could calculate the energy consumption over a road segment driven retrospectively, given that all other parameters in the model are directly measurable from the vehicle or road. Therefore, these values are important to know in order to make future predictions of energy consumption with the model.

Tabular values for the coefficients, obtained through thorough experiments at test sites, provide a rough estimate of what the values should be. However, the coefficients may also depend on vehicle- and road specific circumstances that such experiments are not able to account for.

As a way of incorporating the knowledge attained through controlled experiments, while also accounting for the uncertainties related to the current vehicle and road conditions, we apply Bayesian linear regression [10] to the problem of determining C_{rr} and C_d.

Compared with ordinary least squares linear regression [11], Bayesian linear regression considers the regression coefficients as random variables. Following the Bayesian framework, these coefficients are reported in terms of posterior probabilities, as a combination of a prior distribution and data samples. This is neat in our case, as it lets us use experimentally determined values for C_{rr} and C_d reported in reference tables to specify the prior means and variances of the coefficients. As we collect data while driving, the coefficient distributions are then updated through calculations of the posterior. Using informative priors as is this case, Bayesian linear regression is generally more robust to noise and outliers in the data, and learns quicker with less data.

To test and evaluate the Bayesian linear regression approach to energy prediction, we consider four different truck models, each with their own experimentally determined C_{rr} and C_d values. Hence, we must learn four different Bayesian linear regression models, one for each truck. We let all of the trucks drive multiple laps around the same test track, providing data for our four models. For each trip, we consider the first half of it as calibration, and use the data collected as training data to fit the corresponding Bayesian linear regression model. Then, for the second half of the trips, we assume that we know what all of the measurable parameters in the energy model in 3.2.1 will be, using their true logged values. Now, we apply the energy model with the (1) values found with Bayesian linear regression and (2) tabular values, to predict what the energy consumption for the second half of the trip will be.

To compare the performance of the two variations, we calculate the Root Mean Square Error (RMSE) on the predictions at a road segment level, and the Percent Error (PE) on the full trip.

RMSE is calculated as

$$RMSE = \sqrt{\frac{\sum_i^N (e_i - \hat{e}_i)^2}{N}}, \tag{6}$$

where e_i is the true and $\hat{e}_i$ the predicted energy consumption, while N is the total number of data points.

3.3 Non-Linear PINN for Energy Prediction

To accurately estimate energy consumption under complex, real-world conditions, this study employs a PINN. For instance, rolling resistance is unlikely to be constant over a whole route, which is assumed in the previously described Bayesian linear regression framework. Unlike purely data-driven models, PINNs incorporate governing physical laws into the training process, allowing for robust predictions that remain consistent with underlying vehicle dynamics. This hybrid learning approach enhances model generalization and mitigates overfitting when data is sparse or noisy.

3.3.1 Physics-Informed Neural Networks

Artificial neural networks are powerful tools capable of approximating complex nonlinear functions, as demonstrated by the Universal Approximation Theorem [12]. This foundational theory states that a sufficiently wide neural network with nonlinear activation functions can approximate any continuous function on a compact domain to arbitrary accuracy [13]. A typical example is shown in Figure 3, where the network receives a vector of input features, processes them through hidden layers using nonlinear activation functions, and updates weights via backpropagation to produce an output.

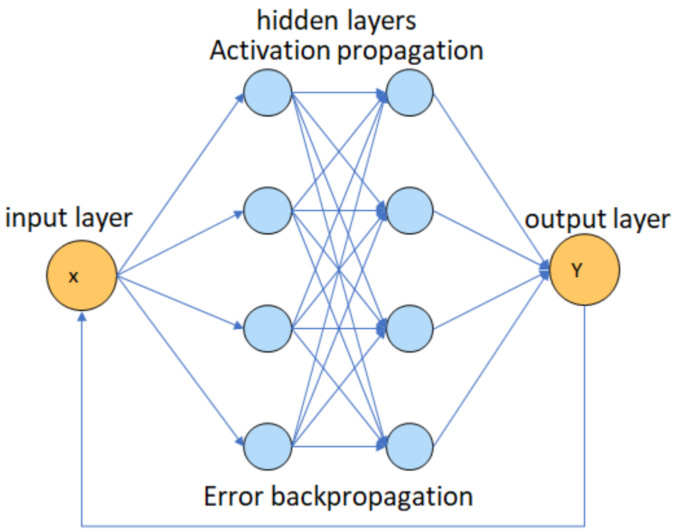

Figure 3: Illustration of a feedforward neural network.

While conventional neural networks serve as flexible function approximators, they often operate as black-box models, lacking transparency and interpretability—especially when applied to systems governed by physical laws. PINNs address this limitation by embedding known physical relationships into the training process. This approach transforms the neural network from a purely data-driven tool into one that respects and reflects the structure of physical systems.

PINNs, introduced by Raissi et al. (2017–2019) [14, 15, 16], bridge data-driven learning and physics-based modeling. Rather than learning solely from data, PINNs are trained using a composite loss function that includes both a data fidelity term and a physics consistency term. This ensures that predictions not only fit observed data but also conform to governing physical laws, such as ordinary or partial differential equations.

By penalizing deviations from these laws during training, PINNs provide a more robust and interpretable learning framework. This integration enhances model generalization, particularly in scenarios with limited or noisy data, and ensures physical plausibility of the outputs. For applications such as vehicle energy prediction, where system dynamics are governed by well-established principles like Newtonian mechanics, PINNs enable accurate and physically consistent modeling that outperforms purely data-driven approaches.

3.3.2 PINN Architecture and Training

The PINN architecture was developed to learn both energy consumptions and physically meaningful coefficients from extensive real-world field test data. To ensure generalization, the model was trained on a diverse dataset that included over 20 truck variants and more than 5,000 routes, representing a wide range of real-world driving conditions and environmental scenarios. Data was at road segment level and collected with constant field data frequency, yielding over 550,000 samples, which were split into 70% training, 15% validation, and 15% test sets.

Key input features were selected through domain-informed feature engineering and include vehicle speed, mass, and road inclination. The primary prediction target is measured energy consumption, while another prediction branch outputs consist of C_{rr} and C_d coefficients.

The network consists of two fully connected hidden layers with 256 and 128 neurons, respectively. Each layer uses ReLU activation, followed by batch normalization and a dropout layer with a dropout rate of 0.1 to prevent overfitting. The model architecture includes two output branches: One for predicting energy residuals and another for predicting physical coefficients.

An overview of the model architecture is shown in Figure 4, which outlines the input layer, hidden layers, dual outputs, and the integrated loss formulation.

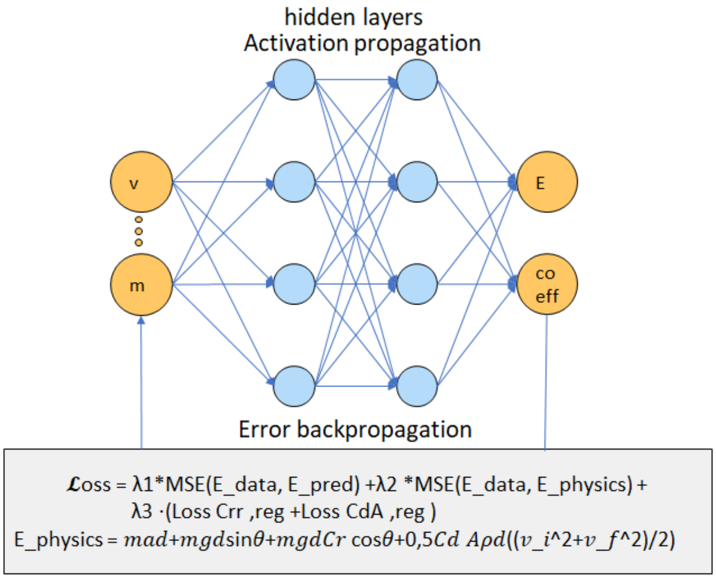

Figure 4: Illustration of the PINN architecture.

The model was optimized using the Adam optimizer with an initial learning rate of 0.005. A ReduceLROnPlateau scheduler was used to dynamically adjust the learning rate based on validation loss. The total loss function incorporates data fidelity, physical consistency, and coefficient regularization:

$$\mathscr{L}_{\text{oss}} = \lambda_1 \cdot \text{MSE}(E_{\text{data}}, E_{\text{pred}}) + \lambda_2 \cdot \text{MSE}(E_{\text{data}}, E_{\text{physics}}) + \lambda_3 \cdot (\text{Loss}_{C_{rr}} + \text{Loss}_{C_dA}) \tag{7}$$

Here, E_{data} is the measured energy consumption, E_{pred} is the energy residual predicted by the network, and E_{physics} is the energy calculated using the physics-based equation (4) using the predicted coefficients C_{rr} and C_dA that incorporates acceleration, gravity , rolling resistance, and aerodynamic drag. The coefficients C_{rr} and C_dA are constrained within physically meaningful bounds: C_{rr} using a scaled sigmoid function within (0, 0.02], and C_dA using dynamic clamping around reference values.

Loss weights were empirically set to $\lambda_1 = 1.0$, $\lambda_2 = 0.1$, and $\lambda_3 = 0.01$ to maintain a balance between fitting observed data and adhering to physical laws.

This architecture enables simultaneous data-driven learning and physics enforcement, offering reliable, real-time energy estimation capabilities for HDEV applications.

To evaluate model performance, two key metrics the same as 3.2.2 were used. RMSE was computed over individual road segments to assess local prediction accuracy, while PE was calculated over complete all trips to measure cumulative deviation from actual energy consumption. These metrics provide a balanced view of both short-term precision and long-term energy estimation performance.

4 Results and Discussion

4.1 Gear Selection Prediction

As discussed in Section 3.1, the GBM algorithm outperformed other classification methods and was selected for deployment due to its strong trade-off between prediction accuracy and computational efficiency. Using the processed dataset, the GBM model achieved over 90% accuracy in predicting gear status, as benchmarked against the physics-based simulation model, which served as the baseline.

Figure 5 compares gear predictions between the physics-based model and the hybrid ML framework, showing high correlation across diverse driving conditions. It is worth noting that predictions were made independently at each time step, rather than as a continuous time-series. Despite this, the model demonstrated robust performance and the system's execution time remained within milliseconds, making it suitable for real-time backend or onboard applications.

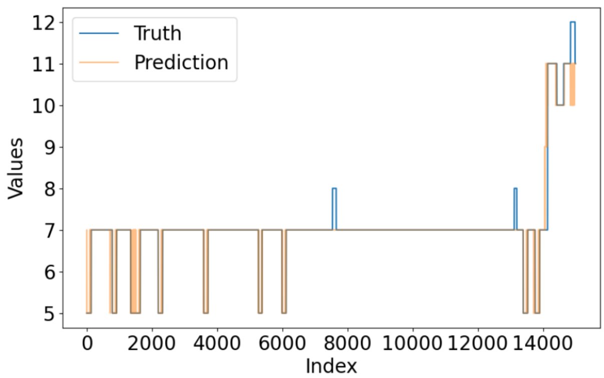

Figure 5: Comparison of gear status between physics-based model and hybrid framework prediction

4.2 Bayesian Linear Regression

The results of the energy consumption prediction using the model described in 3.2.1, using tabular reference values determined through controlled experiments, and Bayesian linear regression respectively, as described in 3.2.2, are shown in table 1.

Table 1: RMSE on road segments, and PE on the full trips, in the prediction of energy consumption using model with C_{rr} and C_d obtained through Bayesian Linear Regression and with tables across four different truck models on a test route.

	Truck Model A		**Truck Model B**		**Truck Model C**		**Truck Model D**	
Metric	**Bayesian**	**Tabular**	**Bayesian**	**Tabular**	**Bayesian**	**Tabular**	**Bayesian**	**Tabular**
RMSE (Wh)	8.69	9.63	5.43	5.19	8.80	9.39	8.98	14.3
PE (%)	0.0540	-15.5	0.173	-5.18	-5.56	-7.25	-5.06	34.1

From the results, we can observe that on a road segment level, the Bayesian linear regression method performs similar to or better than the tabular reference method for 3 of the trucks, as measured by the RMSE . For the 4th truck model, it performs significantly better.

The most striking difference, however, is seen on a full route level, where Bayesian linear regression is shown to result in a much more accurate energy prediction. A reason for the relatively large error for both models on a road segment level is that the rolling resistance coefficient may not be the same for all segments, as the model assumes. It is interesting to note that the Bayesian linear regression method still tend to find good average values, for which the over- and under-predictions cancel out to a large extent for the full trip energy consumption predictions. The same does not appear to be the case for the tabular method with coefficients determined through controlled experiments.

4.3 Non-Linear PINN Regression

The performance of the PINN was evaluated across all HDEV variants introduced in Section 3.3.2. Table 2 presents a comparative summary of energy prediction accuracy between the PINN and two physics-based baselines: one using dynamically predicted coefficients (C_{rr}, C_d), and another using predefined tabular values (C_{rr}^{ref}, C_d^{ref}) derived from controlled tests.

Table 2: Comparison of energy prediction performance across models

Metric	PINN	Physics-Based (Predicted C_{rr}, C_d)	Physics-Based (Tabular C_{rr}^{ref}, C_d^{ref})
RMSE (Wh)	5.78	7.54	11.57
PE (%)	-11.7	-10.0	-40.4

As shown in Table 2, the PINN achieved the lowest RMSE and PE, indicating superior accuracy and generalization across diverse driving scenarios. Notably, both the PINN and the physics-based model using predicted coefficients outperformed the tabular reference model, highlighting the benefit of using dynamic, route-specific parameter estimation.

Beyond energy prediction, the PINN framework also provides interpretable physical parameters. It estimates both the C_{rr} and the aerodynamic drag term (C_dA), offering additional insight into vehicle behavior under varying conditions.

Figure 6 presents the distribution of predicted C_{rr} values for four representative truck models. For Models A and B, many predictions cluster at the upper boundary, suggesting either limitations in model expressiveness or coefficient saturation during training. In contrast, Models C and D show broader distributions and lower medians, indicating better discrimination by the PINN. Compared to fixed reference values (shown in red), the predicted C_{rr} reflects realistic variability due to environmental and operational factors.

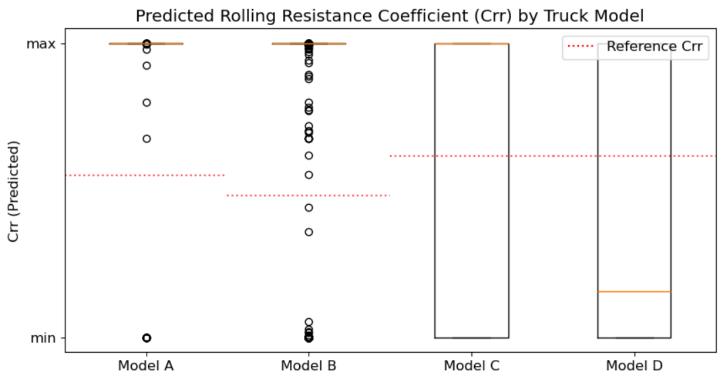

Figure 6: Boxplot of predicted rolling resistance coefficient C_{rr} across four truck models.

Similarly, Figure 7 illustrates the predicted C_dA values across the same truck models. Models A and B tend to produce more conservative estimates compared to the reference. Model C demonstrates higher variance and better alignment with tabular values, while Model D shows a compact distribution with several high outliers. These variations suggest that the PINN effectively captures the influence of factors such as vehicle speed, frontal area, and wind resistance under real-world conditions.

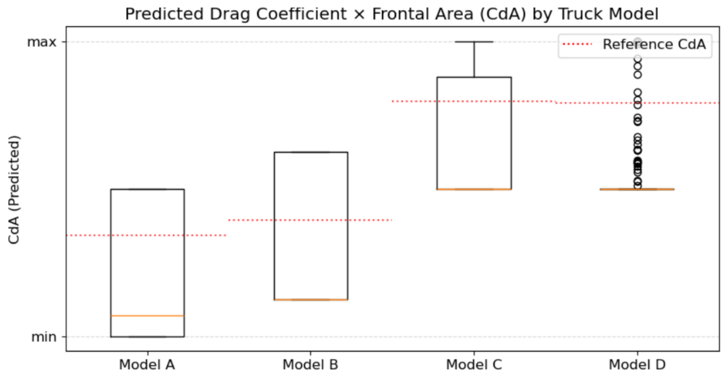

Figure 7: Boxplot of predicted aerodynamic coefficient C_dA across four truck models.

These results demonstrate that the PINN not only provides accurate energy predictions but also yields interpretable physical insights, reinforcing its suitability for real-time, data-driven energy prediction in energy monitoring and vehicle calibration tasks.

5 Conclusion

This paper presented a novel hybrid framework for the classification and estimation of both linear and non-linear vehicle parameters in HDEVs. The framework integrates physics-based modeling, field test data, machine learning, and lookup tables to enable fast and interpretable predictions suitable for real-time applications.

We demonstrated the application of this framework in three key areas: gear selection via classification models, coefficient estimation of C_{rr} and C_d through linear regression, and direct energy prediction using a PINN. Each method was supported by simulation and real-world data, ensuring robustness and physical consistency. In particular, the PINN model effectively bridged physical modeling and data-driven learning, enabling flexible and accurate energy predictions while preserving interpretability.

The results confirmed the strength of the hybrid approach in delivering high prediction accuracy and computational efficiency across various tasks. Future work will explore extending this framework to additional vehicle parameters, such as vehicle mass, and enhancing its generalization across diverse vehicle configurations and operating environments.

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Presenter Biography

Jie Zhong, dual MSE degrees in Mechanical Engineering and Applied AI, is a Specialist System Engineer at Emob Productivity Services, GTT, Volvo Group. She specializes in system simulation, machine learning, and data analysis.

With over 10 years of experience in automotive R&D, her work has focused on energy management for PHEV and BEV vehicles, with a strong emphasis on improving vehicle performance through advanced simulation techniques and data-driven insights.

Hannes Nilsson, MSE, is an Industrial PhD Student at Chalmers University of Technology, and Data Scientist at Emob Productivity Services, GTT, Volvo Group. His work focuses on machine learning methods for forecasting and decision-making.

He has a track-record of publishing theoretical, as well as applied research within AI/ML and the field of transportation.