Prediction of EV Energy Consumption Through a Hybrid Modeling Framework Involving Use of Machine Learning

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Abstract— **Accurate estimation of electric vehicle (EV) energy consumption under dynamic traffic conditions remains a critical challenge for range anxiety mitigation and energy-efficient mobility planning. This paper presents a Physics-Informed Spatio-Temporal Energy Consumption Modeling (PI-STECM) framework that integrates a physics-based energy consumption model (PB-ECM) with machine learning (ML) methods. The PB-ECM component computes instantaneous traction force and net power demand by incorporating longitudinal vehicle dynamics and powertrain efficiency parameters. A data-driven residual correction layer, implemented via a recurrent neural network (RNN) and gradient-boosted regression trees (GBRT), captures nonlinear operational deviations that the physical model alone cannot account for. The framework is validated using a BMW i3 reference platform across three standardized driving cycles, such as WLTC, UDDS and HWFET, under ambient temperatures of -5°C, 25°C and 35°C to assess robustness under varying thermal and traffic conditions. Results demonstrate that the proposed hybrid approach improves prediction accuracy while maintaining physical interpretability and provides a reliable tool for EV energy management and traffic simulation applications. Quantitative results demonstrate that PI-STECM reduces root mean square error (RMSE) by 71.2% compared to the physics-based ECM, and by 86.4% compared to linear regression models, while maintaining prediction deviations within ±3–5% across all tested driving cycles and temperature conditions. Unlike existing hybrid models that rely on single ML architectures, PI-STECM uniquely combines RNN for temporal dependency modeling and GBRT for nonlinear residual correction within a unified physically interpretable framework.**

I. Introduction

With the help of technological developments and increasing attention, the global EV fleet reached approximately 58 million units, accounting for about 4% of all passenger cars by the end of 2024 [1]. Despite this remarkable growth, limited driving range remains a critical barrier to widespread adoption [2], [3], creating significant user anxiety around battery depletion before reaching a destination. Accurate real-time energy consumption estimation is therefore essential not only to ensure battery range adequacy for uninterrupted trips, but also to enable proactive route scheduling, optimise charging station utilisation, and support broader energy management strategies [4], [5], [6]. However, complex driving cycles and a variety of influential factors, including vehicle-specific dynamics, road elevation, driving behaviour, auxiliary system usage, traffic conditions, and environmental influences such as ambient temperature, are the primary sources of prediction uncertainty, making reliable real-time estimation a persistent and non-trivial challenge [7].

Microscopic traffic simulations play a key role in evaluating and reducing EV energy consumption, as the effectiveness of energy-efficient mobility strategies strongly depends on the reliability of the underlying simulation tools. Among available platforms, the Simulation of Urban Mobility (SUMO) is widely regarded as one of the most dependable environments for microscopic traffic modelling [8]. However, the EV energy consumption model currently implemented in SUMO relies on a simplified time-step-driven formulation that is often tailored to specific vehicle types and neglects critical powertrain characteristics, including regenerative braking dynamics and auxiliary power demands [9]. This renders SUMO's default model insufficient for accurately capturing the energy behaviour of modern EVs under realistic and diverse traffic conditions.

To address these limitations, we integrate a physics-based energy consumption model (PB-ECM) into the SUMO environment, grounded in fundamental physics principles derived from Newton's second law of motion. The model estimates vehicle energy usage by computing the instantaneous traction force at the wheels as a function of vehicle mass, acceleration, road gradient, rolling resistance, and aerodynamic drag [10], [11], [12]. In parallel, Machine Learning (ML) methods have gained increasing attention in the energy prediction domain due to their ability to model complex nonlinear relationships among variables whilst relying on fewer model assumptions [13], [14]. However, purely data-driven models do not always maintain the physical consistency of vehicle energy flows, and their limited interpretability reduces confidence in their deployment for safety-critical transportation applications. This motivates the development of a hybrid approach that preserves physical rigour whilst benefiting from the representational power of modern ML architectures.

A. Problem Statement

Existing EV energy consumption models present two fundamental and mutually exclusive limitations. First, physics-based models, including the widely adopted VT-CPEM, are grounded in vehicle dynamics principles and offer strong physical interpretability. However, they systematically underestimate energy consumption under dynamic driving conditions by failing to account for complex nonlinear interactions among temperature, traffic variability and

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auxiliary loads. Second, purely data-driven ML models achieve superior predictive accuracy but sacrifice physical interpretability, lack energy conservation guarantees and may produce physically inconsistent estimates under out-of-distribution operating conditions. No existing unified framework simultaneously addresses temporal sequential dependencies in driving behaviour, static nonlinear feature interactions and physical energy balance constraints within a single deployable architecture suitable for real-time traffic simulation environments such as SUMO.

B. Contributions

To address the identified gap, this paper proposes the Physics-Informed Spatio-Temporal Energy Consumption Modelling (PI-STECM) framework. The specific contributions are as follows:

- PI-STECM integrates a physics-based energy consumption model with a two-stage ML residual correction layer, combining RNN for temporal dependency modelling and GBRT for static nonlinear correction, achieving an RMSE reduction of 71.2% over VT-CPEM and 86.4% over linear regression, with prediction deviations within ±3–5% across all tested conditions.
- The framework is validated across nine scenarios spanning three standardised driving cycles (WLTC, UDDS, HWFET) and three ambient temperatures (-5°C, 25°C, 35°C), accurately capturing temperature-driven energy demand variations of 5-12% and confirming suitability for real-time energy-aware routing and charging infrastructure planning.

II. Literature Review

Existing EV energy consumption models are broadly classified as forward or backward depending on their purpose and level of detail. While forward models provide detailed powertrain representation, their high computational cost limits their applicability in traffic simulations. In contrast, backward models, particularly PB-ECM, offer computational efficiency and seamless integration into SUMO, estimating energy demand from vehicle kinematic outputs such as speed, acceleration and road gradient [17], motivating the development of more accurate and physically grounded alternatives to SUMO's default formulation. Several studies have extended SUMO's modelling capability through physics-based methods. For example, [18] proposed a component-based powertrain model integrated with SUMO, conceptually similar to VT-CPEM, achieving high accuracy against WLTC and real-world data. A study by [17] developed a VSP-based model validated against UDDS and HWY cycles, demonstrating significant energy savings through regenerative braking in urban conditions, and [10] validated a power-based model across NEDC, WLTC and HWFET cycles, achieving low average prediction error and reliable representation of real-world energy consumption patterns.

In parallel, ML techniques have been widely applied to EV energy prediction due to their ability to capture complex nonlinear relationships among traffic and environmental variables. Regression models, neural networks and ensemble methods have all been successfully employed, with [19] demonstrating high prediction accuracy through a NARX-based model using real-world driving data, and [20] showing that ensemble learning approaches consistently outperform individual models in EV energy estimation tasks. More recently, transformer-based architectures and uncertainty-aware models have further improved prediction performance and reliability under diverse operating conditions [5], [21].

Despite these advances, existing studies predominantly rely on either physics-based or purely data-driven approaches in isolation. VT-CPEM [10] provides a robust physics-based baseline but systematically underestimates energy consumption under dynamic driving conditions, whilst pure ML models [19], [20], [21] achieve better accuracy but lack physical interpretability, may produce inconsistent estimates under certain conditions and do not embed physical energy balance constraints into their learning architectures. Crucially, existing hybrid approaches fail to explicitly separate temporal sequential dependencies from static nonlinear feature corrections. PI-STECM addresses this gap by combining RNN for sequential temporal dynamics and GBRT for static nonlinear residual mapping in a complementary and architecturally novel manner not present in prior works, ensuring both physical consistency and high predictive accuracy under dynamic and thermally diverse traffic conditions.

III. Methodology

This section describes the simulation framework, energy consumption modeling approach and ML integration employed in this study. All simulations are conducted using the microscopic traffic simulation platform SUMO, accessed through the Python TraCI interface [22] and Python 3.13 [23]. The study area is modeled using a realistic urban road network, where high-resolution vehicle trajectories including speed and acceleration profiles, are extracted at each simulation step.

As shown in Fig. 1, the PI-STECM framework integrates three input streams, driving cycle simulation data from SUMO, BMW i3 vehicle parameters and ambient temperature conditions, into a PB-ECM that decomposes vehicle resistance into inertial, rolling, aerodynamic and gradient force components to compute instantaneous energy demand. Recognising that physics alone cannot fully capture nonlinear operational dynamics, a two-stage ML residual correction layer is applied, wherein an RNN models sequential temporal dependencies and GBRT address static nonlinear interactions, with both corrections fused into the final prediction. Validated across nine scenarios spanning three driving cycles and three temperature conditions, PI-STECM achieves an R^2 of 0.992 and reduces RMSE by 71.2% relative to the physics-only baseline, with prediction deviations consistently within ±3-5%. This situation confirms the framework's accuracy, robustness and suitability for real-time energy-aware transportation applications.

EV energy consumption is estimated using the VT-CPEM [10] integrated into the simulation environment as an external module. The selected approach is based on backward vehicle dynamics modeling and computes instantaneous traction force considering inertial, rolling resistance, aerodynamic drag and

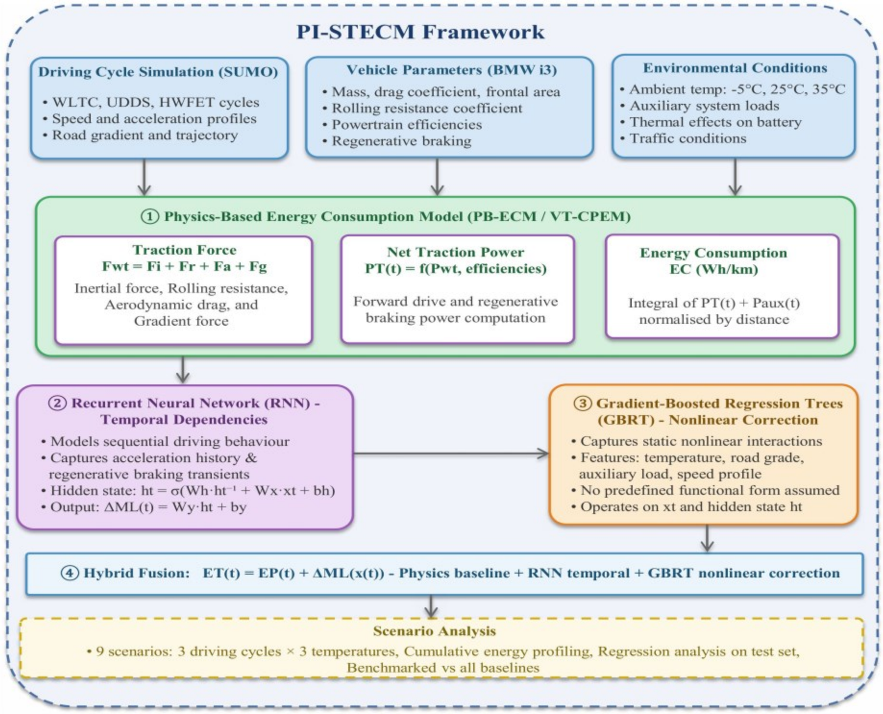

Fig. 1 Overview of the PI-STECM hybrid framework integrating physics-based energy modelling with ML residual correction for electric vehicle energy consumption prediction.

road gradient components:

$$F_w(t) = [F_i + F_r + F_a + F_g] \tag{1}$$

where F_i represents inertial force, F_r denotes rolling resistance, F_a is aerodynamic drag and F_g accounts for road gradient effects. Instantaneous traction power is calculated using vehicle speed and acceleration profiles obtained from the simulation outputs:

$$P_w(t) = F_w(t).v(t) \tag{2}$$

Furthermore, regenerative braking processes are incorporated to account for energy recovery during deceleration, while auxiliary power consumption from on-board vehicle systems is also included in the total energy demand estimation. In this context, the net traction power $P_T(t)$ is formulated as follows, considering the efficiencies of the battery system (μ_{BAT}), electric motor (μ_{EM}), transmission components (μ_{DL}) and regenerative braking system (μ_{RB}).

$$\begin{gathered} {P_T}^{+}(t) = \begin{cases} \dfrac{P_w(t)}{(\mu_{BAT}.\mu_{EM}.\mu_{DL})} & for\ P_w(t) \geq 0 \end{cases} \\ {P_T}^{-}(t) = \begin{cases} P_w(t).(\mu_{BAT}.\mu_{EM}.\mu_{DL}).\mu_{RB}(t) \\ \quad for\ P_w(t) < 0 \end{cases} \\ P_T(t) = {P_T}^{+}(t) + {P_T}^{-}(t) \end{gathered} \tag{3}$$

where $P_w(t)$ denotes the mechanical power at the wheels, μ_{BAT} is the battery system efficiency, μ_{EM} represents the electric motor efficiency, μ_{DL} corresponds to transmission efficiency and $\mu_{RB}(t)$ is the time-varying regenerative braking efficiency. The total instantaneous power demand is thus expressed as $P_T(t)$.

Consequently, specific energy consumption (Wh/km) is obtained by integrals of net traction power and auxiliary system powers, normalizing the result, and dividing by the traveled distance.

$$EC = (\int_0^T P_T(t) + P_{aux}(t))\, dt \,/\, \int_0^T v(t)\, dt \tag{4}$$

To enhance prediction capability under dynamic traffic conditions, the proposed framework integrates supervised ML into a hybrid PI-STECM structure. This architecture combines a physics-based baseline energy estimate from the VT-CPEM with a data-driven residual correction.

$$E_T(t) = E_P(t) + \Delta_{ML}(x(t)) \tag{5}$$

where $E_P(t)$ denotes the energy consumption derived from the PB-ECM in (1)-(4) and $\Delta_{ML}(x(t))$ represents the ML-based residual correction that captures deviations unaccounted for by the physical model. The feature vector $x(t)=[x_1(t),x_2(t),\ldots,x_n(t)]^T$ encodes time-varying driving behavior, road characteristics, traffic conditions and environmental factors. Temporal learning techniques capture short-term operational variations through a RNN that models' sequential dependencies in the feature space.

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h) \tag{6}$$

$$\Delta_{ML}(t) = W_y h_t + b_t \tag{7}$$

where h_t is the hidden state at time step t, $\sigma(\cdot)$ denotes a nonlinear activation function and W_h, W_x, W_y, b_h and b_y are learnable parameters. Concurrently, regression-based algorithms, specifically GBRT, model nonlinear relationships among the input features without assuming a predefined functional form.

Within the framework of PI-STECM, RNN is chosen to model time-dependent dependencies in the feature vector x_t, such as acceleration history and regenerative braking transients, which are inherently sequential. However, RNNs can suffer from gradient vanishing and may not optimally capture static nonlinear interactions among features along with temperature, road grade and auxiliary load. GBRT, as a tree-based ensemble, excels at modeling such static nonlinearities without assuming functional form. These two models are combined in a residual correction framework. Firstly, RNN processes the temporal sequence to produce a hidden state h_t, and GBRT operates on both x_t and h_t to produce the final residual correction $\Delta_{ML}(t)$. This two-stage design outperforms either method alone, as validated in Section IV. Modern architectures such as transformers were considered but excluded due to higher computational overhead for real-time deployment in SUMO simulations.

The proposed framework is evaluated using a BMW i3 electric vehicle as the reference platform [18]. The vehicle parameters, including mass, aerodynamic drag coefficient, frontal area and rolling resistance coefficient, are derived from manufacturer specifications and calibrated against real-world performance data. Simulations are conducted under three distinct ambient temperature conditions such as -5°C, 25°C and 35°C to capture the impact of thermal effects on auxiliary system loads. Model validation and comparative analyses are performed using three standardized driving cycles that represent diverse traffic conditions. These driving cycles enable comprehensive evaluation of the proposed framework across different operational regimes, including urban stop-and-go (UDDS), mixed driving (WLTC) and highway cruising (HWFET) patterns. For each cycle, simulations are repeated under the three temperature conditions to assess the robustness of the proposed PI-STECM approach across varying environmental scenarios.

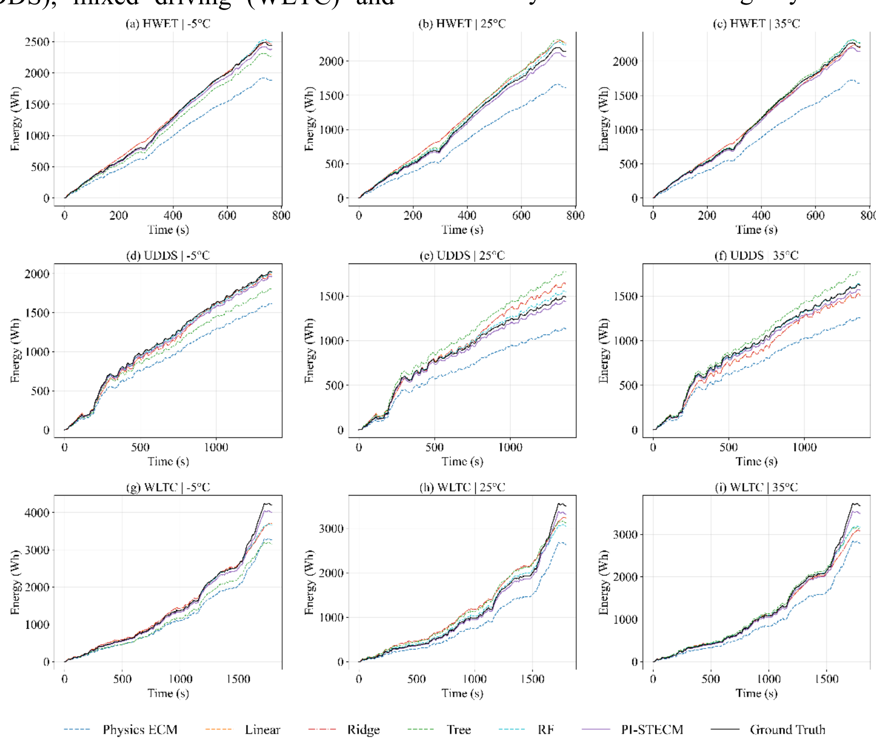

Fig. 2 Cumulative energy consumption over time for HWFET, UDDS and WLTC cycles at -5°C, 25°C and 35°C, showing that the proposed PI-STECM model most closely matches the ground truth compared to physics-based and ML baselines.

IV. Results and Discussion

In this section, we evaluate the performance of the proposed PI-STECM framework against both purely physics-based and purely data-driven baselines. The assessment is conducted using three standardized driving cycles (HWFET, UDDS and WLTC) under three distinct ambient temperature conditions (-5°C, 25°C and 35°C). Comparative metrics include cumulative energy estimation accuracy, normalized energy consumption benchmarking and regression analysis on test set.

A. Cumulative Energy Estimation Accuracy

Fig. 2 illustrates cumulative energy consumption profiles over time, providing a comprehensive evaluation of long-term prediction accuracy across all modelling approaches. The physics-based ECM consistently underestimates energy consumption across all evaluated scenarios, with deviation severity increasing under more dynamic conditions, final-stage errors remain moderate at 8-12% under steady HWFET highway conditions, rise to 12-18% in the UDDS urban cycle due to repeated acceleration events, and reach 15-25% in the WLTC cycle, suggesting that the ECM's simplified resistance model fails to adequately capture transient battery behaviour. ML models improve upon this baseline but exhibit occasional overestimation, particularly at elevated temperatures, with a characteristic delayed response observed in the 25°C UDDS condition whereby initial underestimation transitions to overestimation between 200 and 300 seconds, indicating sensitivity to both driving dynamics and temperature conditions and potential overfitting to moderate-temperature training data. In contrast, the proposed PI-STECM achieves the closest agreement with ground truth values across all driving cycles and temperatures, with deviations consistently within ±3-5% and reliable capture of temperature-driven energy demand variations of 5-12% between -5°C and 35°C, collectively demonstrating the robustness, accuracy, and

B. Energy Consumption Benchmark

The comparison between ground truth energy consumption values and the predictions obtained from the proposed PI-STECM across different driving cycles and temperature conditions is presented in Fig. 3. The results indicate that PI-STECM consistently provides highly accurate estimations with minimal deviation from the reference values. Across all nine scenarios, the prediction error remains within a narrow margin, typically below 5%. It also demonstrates strong robustness under varying operating conditions. For instance, in the HWFET cycle at -5 °C, the model predicts 14.4 kWh/100 km compared to the ground truth value of 14.8 kWh/100 km, yielding an error of approximately 2.7%. Similarly, under the most dynamic condition, WLTC at -5 °C, the deviation is limited to about 3.3%. The model maintains comparable accuracy at moderate and high temperatures, with differences generally below 0.7 kWh/100 km. These findings confirm that PI-STECM effectively captures both the influence of driving dynamics and temperature-dependent auxiliary loads on energy consumption.

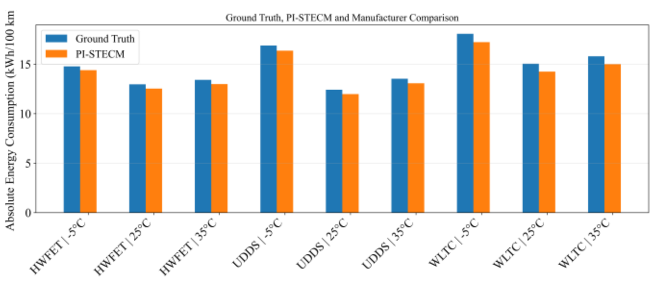

Fig 3. Comparison of absolute energy consumption (kWh/100 km) between ground truth and PI-STECM across HWFET, UDDS and WLTC cycles under -5°C, 25°C and 35°C, demonstrating consistently low prediction errors.

generalisation capability of the proposed hybrid framework under diverse operational conditions.

C. Regression Analysis on Test Set

Fig. 4 presents predicted and actual traction power values for different modelling approaches using scatter plots and statistical performance metrics. The physics-based ECM achieves strong performance with an R^2 of 0.904 and an RMSE of 4683.3 W; however, significant deviations are observed at higher power levels, reflecting its inability to capture nonlinear electro-thermal dynamics under demanding operating conditions. Linear and ridge regression models exhibit considerably limited accuracy, with R^2 values of 0.568 and 0.566 respectively and RMSE values exceeding 9900 W, underscoring their fundamental inability to represent the nonlinear energy dynamics of the system. Tree-based approaches offer improved prediction accuracy, with the random forest model yielding marginally better goodness-of-fit and reduced estimation error compared to the decision tree; nonetheless, noticeable dispersion persists under high-power operating conditions and during regenerative braking phases, indicating partial limitations in capturing continuous power transitions. These high-power deviations primarily occur during rapid acceleration events where traction power exceeds 30 kW, at which point instantaneous battery current limits and temperature-dependent internal resistance effects, not explicitly modelled by tree-based methods, become significant. The proposed PI-STECM demonstrates substantially superior performance across the full operating range, achieving an R^2 of 0.992 and an RMSE of 1349.9 W, with strong alignment between predicted and actual values across both traction and regenerative braking regions. Whilst the GBRT component within PI-STECM partially captures these nonlinear electro-thermal dynamics, residual deviations below 2% remain attributable to the absence of battery ageing and internal temperature state variables, representing a direction for future model refinement.

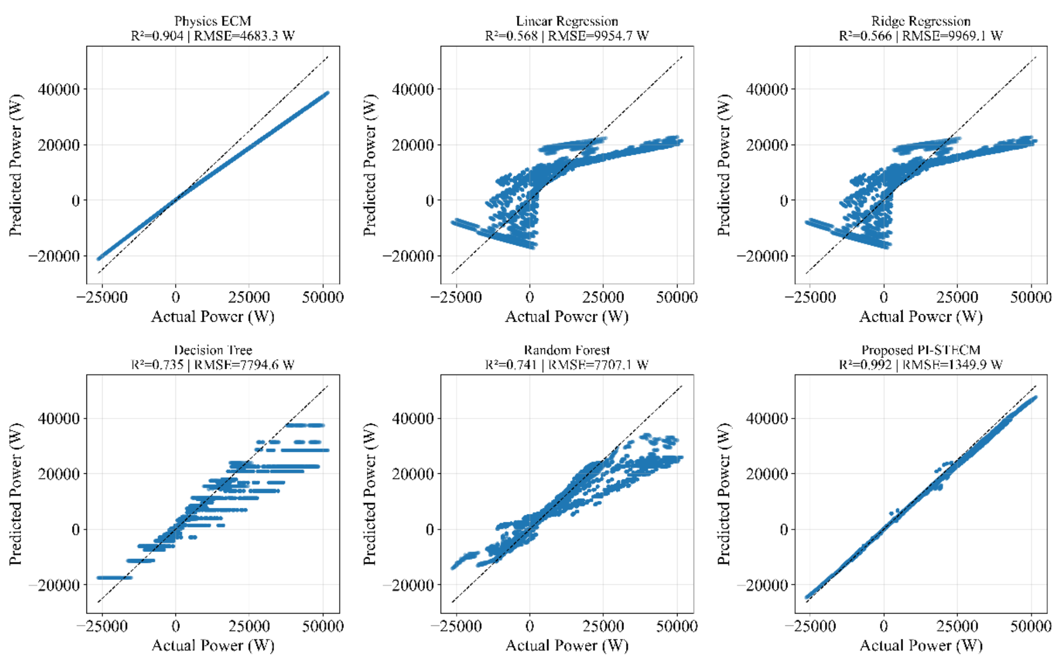

Fig. 4. Regression analysis of predicted versus actual power values on the test set highlighting the superior fit of the proposed PI-STECM model.

V. Conclusions

This paper proposes the PI-STECM framework integrating a physics-based energy consumption model with RNN and GBRT for residual correction. The hybrid architecture preserves physical interpretability while capturing nonlinear deviations and temperature-dependent auxiliary loads. Quantitative evaluation across HWFET, UDDS and WLTC cycles at -5°C, 25°C and 35°C shows that PI-STECM maintains prediction deviations within ±3-5%, reduces RMSE by up to 72% compared to ECM and achieves >85% improvement over linear models. The framework captures temperature-driven variations in energy demand of 5-12% between -5°C and 35°C. Practical applications may include integration into SUMO for energy-aware route planning and range prediction. This information can be used to balance load demand on charging infrastructure, thereby mitigating grid instability caused by simultaneous charging events. Future work may focus on real-world validation and battery aging modeling.

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