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Explainable Quantum AI for optimizing vehicular energy management in smart cities

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ABSTRACT

In rapidly growing cities, the move toward Autonomous Electric Vehicles (AEVs) is challenging the current Energy Management Systems (EMS). The goal in smart cities is to reduce emissions and improve efficiency by optimizing vehicular energy; however, it remains challenging to address real-time decisions, complex AI, and extensive computing requirements for this task. Although AI and optimization are regularly used, they cannot be trusted in safety-related situations due to issues with complexity, scalability, and lack of clarity in their actions. To achieve transparent, smart energy systems in future transportation, it is crucial to address these issues. This research proposes an Explainable Quantum AI (XQAI) model that combines the computational capabilities of Quantum Machine Learning (QML) with the interpretability of Explainable AI (XAI). With QML, dealing with complex vehicular data is more efficient, and the model uses Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) to ensure transparency and interpretability in the model's decision-making process. This proposed model is developed using data from real cities, encompassing a wide range of features, to predict vehicular energy consumption across various trip types accurately and to provide insight into the reasons behind these predictions. According to simulation results, the proposed XQAI model is effective, as the Hybrid Classical–Quantum Regressor shows superior prediction performance with an R^2 score of 0.8439. Furthermore, using LIME revealed a confidence score of 0.95, further establishing its credibility, interpretability, and reliability. The results demonstrate that the model meets the needs for scalable, understandable, and regulated vehicular energy forecasting in smart cities.

1. Introduction

The global shift toward sustainable transportation has made Electric Vehicles (EVs) a key component of modern transportation, as they can significantly reduce greenhouse gas emissions and help address climate change [1]. With smart electric transit, drivers are now switching from old Internal Combustion Engine (ICE) vehicles to new electric cars that are both environmentally friendly and more affordable [2,3]. The growing need for vehicles to last longer and use less energy has prompted the need for advanced thermal and energy systems for sustainability [4]. Therefore, transportation now consumes more energy than any other sector, which has motivated efforts to develop dependable, rapidly deployable, and eco-friendly methods for EVs [5,6].

Although EVs have great potential, persistent challenges prevent their widespread adoption. Developing suitable powertrain designs that meet vehicle purposes while balancing performance and cost remains crucial. Apart from that, EMS must integrate critical hybrid components, such as electric motors, converters, and energy storage systems, to enable vehicles to perform well in all driving conditions [7]. The representative schematic in Fig. 1 demonstrates how both ICE Vehicle (ICEV) and EV systems are blended in a hybrid vehicular powertrain.

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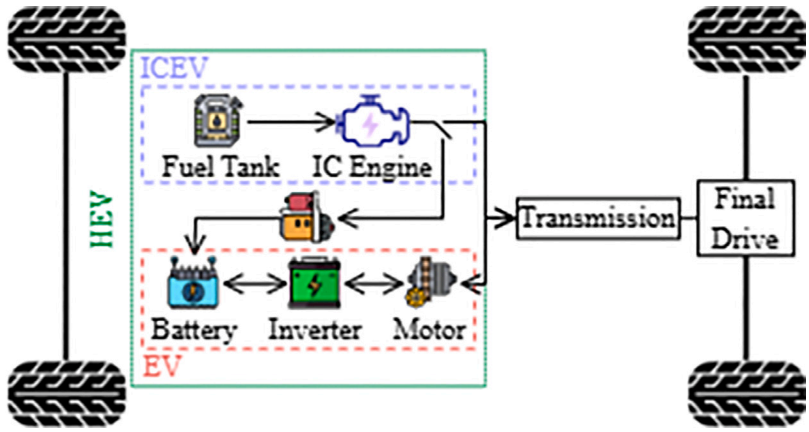

Fig. 1. AEV architecture [8].

It points out that both the fuel tank and battery combine their energy using a standard transmission system to control the output.

Fig. 1 demonstrates the arrangement of a Hybrid EV (HEV) that uses both an ICEV and an EV. It shows that today's vehicles have many power sources, and it is vital to manage their energy efficiently. In the field of smart cities, these architectures require intelligent energy management enabled by data, making them a key focus for AI researchers. Connecting EVs to smart and microgrids, as part of the decentralization of infrastructure, poses additional challenges and requires ensuring the grid remains stable [9]. Furthermore, battery design and storage limitations affect essential aspects of vehicle performance, including weight, range, and acceleration [10].

To overcome these challenges, computational strategies such as stochastic dynamic programming, Reinforcement Learning (RL), and game theory have been widely explored for EMS optimization [11, 12]. Still, these models have limitations: they are difficult to adapt to large-scale problems, require real-time data, and incur high computational overhead. Most importantly, because they are black-box systems, they are not sufficiently transparent to be used in safety-critical situations [13,14]. These limitations underline the urgent need for advanced frameworks that are not only efficient and adaptive but also interpretable and trustworthy.

QML combines key concepts from quantum computing and classical machine learning to fix optimization and prediction challenges more efficiently [15]. Unlike traditional algorithms, QML leverages quantum superposition and entanglement to process high-dimensional data spaces with significantly reduced computational overhead. In the context of vehicular energy management, QML offers the potential to model and optimize highly nonlinear energy consumption patterns driven by real-time variables such as traffic conditions, route elevation, vehicle load, and battery health [16]. By enabling faster convergence and enhanced generalization on small datasets, QML-based models are particularly well-suited for embedded smart vehicle systems operating within dynamic urban environments. This layered QML-based energy optimization workflow is visually represented in Fig. 2.

Fig. 2 shows a two-layered architecture for intelligent energy optimization in smart vehicular systems. The lower part, labeled as the AEV Data Layer, captures real-time operational data from the internal components of an AEV, including its hybrid powertrain and environmental interactions. This data is then transmitted upward to the QML layer, where complex, high-dimensional inputs are analyzed using quantum-enhanced algorithms to generate adaptive and energy-efficient control strategies.

While machine learning models have demonstrated strong predictive capabilities in energy management [17], their opaque decision-making processes often hinder their acceptance in safety-critical transportation systems. XAI addresses this gap by providing transparent, human-interpretable justifications for model outputs. LIME and SHAP help stakeholders, including engineers, policymakers, and system operators, easily identify which aspects of a system contribute to energy consumption predictions [18–20]. In AEVs, such interpretability is essential for validating model behavior, ensuring operational accountability, and building trust in intelligent EMS deployments. Consequently, integrating XAI into vehicular systems not only enhances transparency but also supports regulatory compliance and real-time decision assurance.

The integration of QML [21] and XAI provides a reliable solution to key problems in vehicular energy management, combining computational efficiency with interpretability. QML quickly and accurately handles changing energy in cities, and XAI is transparent, building public trust as decisions are made. By cooperating, they help develop a smart, scalable, and trustworthy EMS model for the next generation of AEVs that work well in smart cities.

2. Literature review

Numerous studies have developed methods for analyzing and predicting vehicular energy consumption under varying operational conditions. Predictive energy modeling is considered a cornerstone for enhancing energy efficiency, particularly in electric and hybrid vehicles. By anticipating energy demands based on contextual inputs such as speed, route, traffic, and load, these models enable intelligent decision-making within EMS. However, many existing approaches remain limited in scalability, real-time adaptability, and transparency.

In [22], researchers proposed a hybrid framework that integrates quantum computing and AI to address key challenges in energy optimization and load balancing within smart grid environments. Specifically, the research targets issues such as real-time adaptability, energy waste reduction, and computational inefficiency—common barriers in traditional EMS implementations. To overcome these challenges, the authors designed a quantum-enhanced model that combined the Quantum Approximate Optimization Algorithm (QAOA) with Quantum Annealing (QA) for discrete optimization tasks. Additionally, AI techniques were employed to predict energy demand and support dynamic resource allocation. Simulation results demonstrated a 25% improvement in load-balancing efficiency, a 30% reduction in energy waste, and a 20% decrease in peak energy demand, alongside a 40% reduction in computational complexity compared to conventional optimization methods. These outcomes highlighted the model's effectiveness in improving grid stability and decision-making speed in dynamic conditions. However, the study's focus on grid-level energy systems may limit its direct applicability to decentralized or vehicular contexts, where system constraints and mobility introduce additional layers of complexity.

In this study [23], it was suggested that machine learning can improve cost planning for charging and discharging Plug-in HEVs

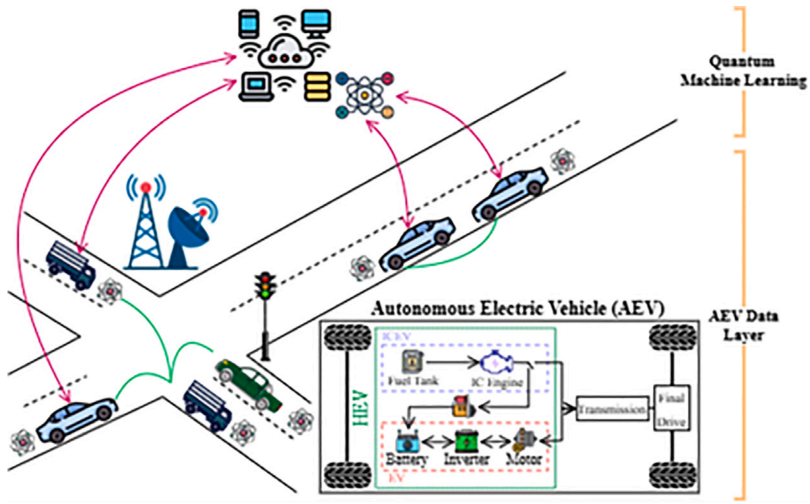

Fig. 2. QML-based energy optimization in AEVs.

(PHEVs) within smart city infrastructure. The research is designed to integrate PHEVs with the Intelligent Transportation Systems (ITS) using smart grid and communication between vehicles and infrastructure. To address issues of efficiency and user recharging, the authors developed a decision-tree-based model for a fog computing platform. It allows charging stations to make quick adjustments by analyzing current energy consumption and available charging stations, aiming to boost charging savings and increase energy efficiency for transport. The evaluation showed that the proposed system outperformed traditional methods, making intelligent energy management more feasible for city traffic. Moreover, the study points out that how the system handles real-world challenges and grows needs to be appropriately tested for future use.

The research [24] outlined plans to integrate EVs into smart grids and introduced an updated EMS to improve optimization. The system combines a Genetic Algorithm (GA) for setting optimal charging schedules worldwide, a Gated Recurrent Unit (GRU) for predicting user demand, and RL for handling flexible payment of energy costs. The approach helps reduce strain on the grid and eases the addition of renewable energy. While the study shows promising results from simulations, it suggests that the new approach should be tested with different grid types and large numbers of EVs.

In [25], advanced deep learning techniques have been developed to optimize energy consumption in smart cities, highlighting their role in enhancing efficiency and sustainability. The paper reviews a range of methods, including RL for adaptive power distribution, CNNs and Recurrent Neural Networks (RNNs) for spatial–temporal demand forecasting, and GANs for simulating energy scenarios and anomaly detection. Additionally, Federated Learning is explored as a privacy-preserving solution for decentralized energy systems. These models collectively support real-time load balancing and predictive control across urban infrastructures. While promising, the authors highlight challenges such as high computational demands and call for comparative evaluations to guide the deployment of scalable, energy-efficient AI solutions.

According to the research [26], an AI-based optimization framework was designed to enhance user demand forecasting and energy distribution in EV charging systems. The framework leverages a variety of machine learning models, including Random Forest, SVR, Gradient Boosting, XGBoost, LightGBM, and LSTM, to predict charging needs and optimize allocation strategies. Among these, XGBoost outperforms the others, achieving the lowest MAE and RMSE and a 15% reduction in prediction error. The system incorporates proportional and priority-based energy allocation strategies to minimize energy shortfalls and maintain balance between supply and demand. The results demonstrate improved grid efficiency and responsiveness, supporting more sustainable EV infrastructure. However, the study notes that model generalizability across different real-world conditions remains an area for further exploration.

According to [27], a deep learning-based EMS utilizing RNNs was proposed to minimize CO_2 emissions in PHEVs. By validating the approach in a digital setting, scientists found it yields better fuel savings than standard rule-based methods. The findings indicate that rule-based techniques and RL are still used in EMS design, with algorithms such as Q-learning and Deep Deterministic Policy Gradient (DDPG) assisting in support decision-making. They enable the training of controllers as power flows occur in real-time. Additionally, methods such as Mixed-Integer Programming and Gaussian Mixture Models are applied to distinguish driving situations and generate suitable control instructions. Despite the rise of other optimization strategies, the paper confirms that meta-heuristic algorithms are vital for optimizing EMS, as they are flexible in handling the complex decisions that arise in hybrid vehicle actions.

Researchers in [28] claim that Proton Exchange Membrane Fuel Cells (PEMFCs) could provide a zero-pollution, efficient, and very quiet solution for vehicles. The research focuses on improving fuel cell performance in Fuel Cell HEVs (FCHEVs) by designing an EMS in which the fuel cell is the primary power source and the battery serves as backup. Authors have introduced a novel solution to address frequent on/off cycles and rapid load breakdowns, which promote fuel cell wear. This hybrid technique enables adaptive control under dynamic driving conditions, effectively reducing operational stress on the fuel cell system. The approach enhances the stability and longevity of FCHEVs, making it a promising direction for emission-free urban mobility.

In [29], a Quantum SWARM-based dynamic scheduling method was proposed to optimize EV charging in disordered, rapidly changing traffic environments. The approach accounts for both individual vehicle competition and group collaboration, enhancing real-time allocation efficiency. Simulation results demonstrate an 87% reduction in error and convergence within a single iteration for 100 randomly selected charging clients, validating the algorithm's effectiveness. The method also supports optimal charging station planning and introduces a control logic framework adaptable to swarm-intelligent autonomous vehicles, suggesting broader applications in smart urban mobility systems.

According to [30], quantum computing posed significant threats to current V2X cryptographic systems, prompting the need for quantum-resistant security algorithms (QRSAs). The authors propose a Service & Computation Orchestrator (SCO) to manage secure communication and optimize QRSA performance. They evaluate Toom–Cook and Karatsuba parallel computation methods under varying CPU loads and highlight ongoing standardization efforts. The study highlights the importance of securing V2X systems in anticipation of potential post-quantum threats.

This research [31] explored AI-driven approaches to optimize energy consumption in EVs within the Industry 5.0 framework. The paper integrated IoT and AI to develop smart, user-aware charging systems aligned with renewable energy goals. A key contribution is the use of an enhanced Generative Adversarial Network (GAN) to generate realistic synthetic EV charging data, which supports ensemble machine learning models for predicting energy demand. To improve model transparency, XAI techniques such as SHAP are utilized to interpret the influence of individual features. The statistical validation of synthetic data, as measured by skewness and Kurtosis, further confirms its reliability. Overall, the study offers a consumer-centric, sustainable AI framework for intelligent EV energy management.

According to [32], SVM-based linear regression was utilized to improve autonomous roadside infrastructure and traffic management in smart cities. By leveraging vehicular networks and real-time data analytics, the approach enhances Vehicle-to-Vehicle (V2V) communication, supporting more informed decision-making for both city planners and road users. The method demonstrates improved performance over traditional traffic control systems.

Many researchers have proposed intelligent approaches to enhance vehicular energy optimization and traffic management. For example, energy-aware fuzzy logic schemes have been developed for efficient routing in flying ad hoc networks [33]. At the same time, congestion-avoidance and path-detection methods have been applied to improve vehicular management systems [34]. Reinforcement learning has also attracted significant attention, with surveys and intersection-based Q-learning protocols highlighting its role in intelligent transportation and energy optimization [35,36]. More recently, weighted explainable federated learning has been introduced to enable scalable and privacy-preserving energy optimization in autonomous vehicular networks [37]. While these approaches show considerable progress, they are often limited by computational overhead, lack of transparency, and difficulty in adapting to large-scale, real-time deployments—underscoring the need for hybrid frameworks that balance efficiency and interpretability, as proposed in this study.

Table 1 provides a comparative overview of existing energy management approaches for AEVs, revealing that while several models achieve strong optimization and predictive performance, most lack explainability, regulatory alignment, or scalability. The proposed XQAI framework uniquely addresses these gaps by integrating QML with XAI techniques, offering a transparent, efficient, and adaptable solution for next-generation smart mobility systems.

2.1. Limitations of existing approaches

Evaluating existing vehicular energy management and optimization models reveals critical limitations that compromise their transparency and scalability in smart city environments.

1. **Limited Explainability and Transparency**
   Most models, such as [24,27,33–39], rely on black-box AI architectures without integrating XAI techniques like SHAP or LIME. This lack of interpretability reduces stakeholder trust, complicates model validation, and hinders alignment with emerging regulatory frameworks. While [30,32] demonstrate progress, explainability remains absent mainly in most reviewed works.
2. **High Computational Overhead and Poor Scalability**
   Approaches, including DRL-based EMS [24], quantum annealing methods [22], and neural-evolutionary optimizers [28], impose high computational loads. Their complexity limits real-time deployment in embedded or large-scale vehicular energy infrastructures, hindering scalability and responsiveness.

2.2. Contribution of the proposed model (addressing limitations)

The proposed XQAI model addresses these limitations by delivering a scalable, interpretable, and computationally efficient solution for energy optimization in smart urban mobility systems.

1. **Enhancing Explainability and Transparency**
   XQAI integrates SHAP and LIME within its decision pipeline, enabling clear insight into the contributing features of each energy prediction. This interpretability supports auditing, regulatory compliance, and public trust, addressing the opacity observed in prior works, such as [24,27,38].
2. **Achieving Quantum-Efficient Scalability**
   The use of QML allows the proposed model to efficiently handle high-dimensional vehicular data by lowering training and inference overhead. This resolves scalability and performance bottlenecks observed in models such as [22,24], and [28], making XQAI suitable for real-time embedded deployment in large-scale vehicular networks.

3. Proposed methodology

AEVs encounter significant real-world challenges in smart cities, including adapting to traffic shifts, varying road slopes, changes in energy usage, and limited real-time optimization capabilities. In addition, interpretability issues in traditional AI-driven EMSs hinder the system's compliance with rules, its trustworthiness within the community, and its wider adoption. Addressing these issues is essential for ensuring efficient, transparent, and adaptive energy management in next-generation mobility ecosystems. To address these challenges, this study proposes an XQAI model that combines the computational efficiency of QML with the interpretability of XAI techniques such as LIME and SHAP. The model processes high-dimensional vehicular data to generate accurate, transparent predictions of energy consumption while ensuring real-time adaptability and scalability. Unlike traditional black-box systems, XQAI enables regulation-compliant, auditable decision-making and is well-suited for deployment in complex smart city environments. Fig. 3 illustrates the system architecture and operational flow of the proposed framework. Fig. 3 illustrates the workflow of the proposed XQAI-based energy management model for AEVs. The model is initialized with the AEV Data Input Layer, where vehicular information, such as Vehicle ID, Trip Distance, Time of Day, and Total Voltage, is collected from the dataset for further processing. The dataset [40] presented in Table 2 is carefully preprocessed, trained, and validated to build the proposed XQAI model, which aims to improve intelligent energy management in AEVs.

The dataset contains 10,151 trip samples collected from AEVs operating in a real urban environment. Telemetry measurements such as Current, Voltage, GPS coordinates, and Speed were recorded at a sensing frequency, and this real-world dataset [40] captures mixed driving conditions, including congestion, peak/off-peak hours, and varied trip durations. This data enters the Preprocessing Layer, which performs critical operations, including missing-value detection, feature scaling, categorical encoding, feature selection, outlier handling, and re-normalization tailored for quantum encoding.

Fig. 4 displays box plots of normalized features (Trip Distance, Time of Day, Current, Total Voltage, and Trip Time Length), highlighting variability and potential outliers, particularly in Trip Distance and Current. This step ensures data consistency and effective normalization, reducing the impact of anomalies and supporting reliable downstream QML and XAI modeling. Outlier thresholds were quantified using the $1.5 \times IQR$ rule (capping <2% of values per feature), and continuous variables were normalized to the range $[-\pi/2, \pi/2]$ for quantum rotation encoding. This ensures stable gradient propagation in the variational circuit while preserving the statistical distribution of vehicular parameters for reliable model convergence.

Table 1
Comparative analysis of the existing approaches.

Ref	Method	Objective	Preprocessing technique	Predictive model	QML	XAI	Reg.	Veh.	Strengths	Limitations
[22]	QAOA + Quantum Annealing with AI	Energy optimization and load balancing in smart grids	Not explicitly stated	AI + QAOA + QA	Yes	No	No	No	Reduced energy waste, peak demand, and computational complexity	Limited applicability to vehicular systems
[23]	Decision Tree + Fog Computing	Cost optimization for PHEV charging/discharging	Not explicitly stated	Decision Tree	No	No	No	Yes	Real-time, mobility-aware optimization	Scalability needs validation
[24]	GA + GRU + RL	EV charging schedule optimization	Not explicitly stated	GA, GRU, RL	No	No	No	Yes	High accuracy (97.56%), cost reduction	Needs real-world testing
[25]	RL + CNN + RNN + GAN + FL	Energy optimization in smart cities	Not explicitly stated	Hybrid DL + FL	No	No	No	Yes	Privacy-aware, decentralized control	High computational cost
[26]	Ensemble AI Framework	User demand prediction for EV charging	Not explicitly stated	RF, SVR, XGBoost, LSTM	No	No	No	Yes	15% error reduction, real-time allocation	Limited generalizability
[27]	RNN + RL + MIP	CO_2 reduction in PHEVs	Not explicitly stated	RNN, Q-learning, DDPG	No	No	No	Yes	Fuel savings, adaptive EMS	Virtual environment only
[28]	NN + GA	FCHEV lifespan improvement	Not explicitly stated	Neural Network + GA	No	No	No	Yes	Reduced degradation, adaptive control	Focused on PEMFC only
[29]	Quantum SWARM Algorithm	Dynamic EV charging optimization	Not explicitly stated	Quantum SWARM	Yes	No	No	Yes	87% error reduction, fast convergence	Scalability not discussed
[30]	SCO + QRSA	Post-quantum V2X security	Not explicitly stated	QRSA + Parallel Crypto	Yes	No	Yes	No	Secure V2X resilience	No energy optimization
[31]	GAN + SHAP + Ensemble ML	Explainable EV energy prediction	GAN-based synthetic data	XGBoost + SHAP	No	Yes	No	Yes	Transparency, XAI validation	Limited real-time analysis
[32]	Autonomous Roadside Infrastructure	Traffic flow optimization	SVM-based regression	SVM Linear Regression	No	No	No	Yes	Improved roadside efficiency	No QML/XAI integration
[38]	YOLO + DQN	Vision-based EMS and car-following	Image + distance data	YOLO + DQN	No	No	No	Yes	Embedded feasibility, vision-based control	Simulation-based only
[39]	LSTM + PCA + A-V2X-ECMS	Predictive EMS with V2X	PCA on energetic indices	LSTM + ECMS	No	No	No	Yes	SoC-aware adaptation	No real-world deployment
Proposed	**XQAI model**	**Interpretable smart mobility optimization**	**Real vehicular data**	**QML + LIME/SHAP**	**Yes**	**Yes**	**Yes**	**Yes**	**Quantum efficiency with explainability**	**Needs further operational validation**

Table 2
Dataset features description [40].

Sr. No.	Feature	Description/Data type
1	Trip Energy Consumption	float64
2	Vehicle ID	int64
3	Trip Distance	int64
4	Time of Day	float64
5	Day of the Week	int64
6	Longitude	float64
7	Latitude	float64
8	Speed	float64
9	Current	float64
10	Total Voltage	float64
11	Maximum Cell Temperature of Battery	float64
12	Minimum Cell Temperature of Battery	float64
13	Trip Time Length	int64

Fig. 5 presents histograms of normalized features (Trip Distance, Time of Day, Current, Total Voltage, and Trip Time Length), illustrating frequency distributions and skewness. Trip Distance and Current show heavy right-skew, while Time of Day is more evenly distributed, reflecting temporal usage patterns. These insights support effective normalization, feature engineering, and reliable QML modeling for energy forecasting.

Fig. 6 illustrates the pairplot of normalized features, providing distributions along the diagonal and pairwise relationships in the off-diagonal scatterplots. For instance, Trip Distance and Trip Time Length exhibit a positive association, reflecting that longer trips are associated with higher energy use. This analysis helps detect outliers, assesses multicollinearity, and confirms the suitability of features for QML-based modeling.

To ensure efficient quantum encoding, feature selection was guided by correlation analysis and physical relevance. As seen in Fig. 7, Trip Distance has the strongest relationship with energy consumption ($r \approx 0.92$), while Trip Time Length, Current, and Total Voltage also directly affect electrical load and propulsion. Time of Day was retained to capture temporal traffic patterns. Features such as Vehicle ID, Latitude, and Longitude exhibited negligible correlation and were removed. Although Speed and battery temperature are physically relevant to vehicular energy dynamics, further correlation analysis revealed that Speed is strongly dependent on Trip Distance and Trip Time Length, while battery temperature parameters are closely coupled with electrical load indicators such as Current and Total Voltage due to thermoelectric behavior. Speed and battery temperatures, although relevant, were highly

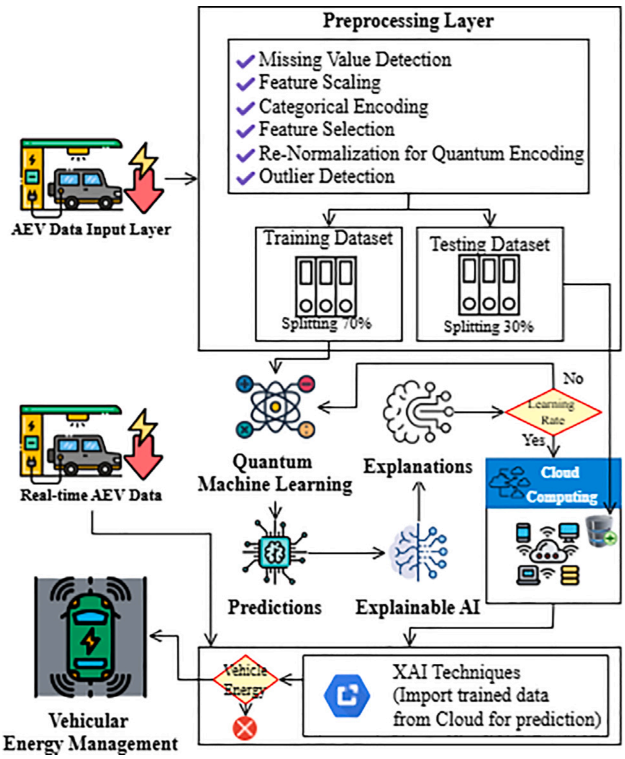

Fig. 3. Proposed XQAI-based energy management model for AEVs.

collinear with the selected features and offered limited additional predictive gain. Including these features would increase feature redundancy and quantum circuit complexity without improving predictive performance. Therefore, the five most informative and non-redundant features—Trip Distance, Time of Day, Current, Total Voltage, and Trip Time Length—were selected for qubit mapping to balance physical representativeness with quantum efficiency, ensuring a shallow, stable, and hardware-efficient PQC design.

Fig. 8 shows the density distributions of key vehicular features (Trip Distance, Time of Day, Current, Total Voltage, and Trip Time Length) using Kernel Density Estimation (KDE). Trip Distance and Trip Time Length display right-skewed distributions, while Time of Day shows a near-uniform or mildly bimodal pattern reflecting trip activity across different hours. Current and Total Voltage exhibit sharp peaks, indicating consistent electrical behavior. These distributions confirm that normalization preserved the statistical integrity of the data, ensuring the features are ready and relevant for quantum encoding and predictive modeling.

For reproducibility, the dataset was partitioned using scikit-learn's train_test_split with a 70/30 train–test ratio and a fixed random state (random_state = 42), ensuring that the same samples are used for training and testing across all quantum and hybrid models.

The preprocessed dataset (samples = 10 151) is then split into training (70%) and testing (30%) subsets to develop and validate the model. The QML module comprises multiple models, including the Variational Quantum Regressor (VQR), Hybrid Classical–Quantum, Hybrid CNN–Quantum, and Quantum-Inspired Dense Regressor (QDenseReg), which are trained on a 70% training subset to learn complex, high-dimensional patterns in vehicular energy consumption. Among these, the Hybrid Classical–Quantum Regressor demonstrated superior performance. This model fuses classical dense layers for initial feature transformation with a Parameterized Quantum Circuit (PQC) that enhances representational expressiveness through quantum entanglement and non-linearity.

In the proposed setup, each classical input feature is normalized and mapped to a qubit using angle (rotation-based) encoding. The circuit employs five qubits, corresponding to the five selected vehicular features: Trip Distance, Time of Day, Current, Total Voltage, and Trip Time Length. Two layers of variational gates (RY, RZ) are alternated with nearest-neighbor CNOT entanglement to balance circuit expressivity and trainability while avoiding barren-plateau gradients. This ansatz structure was finalized after multiple trials to ensure stable convergence and interpretability of encoded vehicular patterns.

The choice of two variational layers ($L = 2$) was empirically validated. A comparison with $L = 1, 2,$ and 3 showed that $L = 1$ underfitted the data ($R^2 \approx 0.83$), while $L = 3$ provided negligible accuracy gain (<0.003) but increased training time by >40%. $L = 2$ offered the best accuracy–complexity trade-off ($R^2 = 0.8439$), making it the optimal depth for stable and efficient training. To make this accuracy–complexity trade-off more explicit, a concise quantitative comparison of variational circuit depth is summarized in Table 3.

Each input feature vector $x = [x_1, x_2, \ldots, x_n] \epsilon R^n$ is first mapped to a quantum state using rotation-based encoding:

$$|\psi_0(x)\rangle = \mathrm{RY}(x_1)\,\mathrm{RY}(x_2)\ \ldots\ \mathrm{RY}(x_n)\,|00\cdots 0\rangle \tag{1}$$

Here, each feature x_i controls a RY gate applied to the ith qubit, creating a data-encoded quantum state. This state is then passed through a variational quantum circuit (θ), comprising trainable gates such as $RY(\theta_j)$, $RZ(\theta_j)$, and entangling operations like CNOTs. The CNOT topology connects adjacent qubits, enabling controlled entanglement between vehicular parameters and allowing the model to capture inter-feature dependencies, such as the joint influence of trip distance and current on energy consumption. The output quantum state becomes:

$$|\psi_\theta(x)\rangle = U(\theta)\,|\psi_0(x)\rangle \tag{2}$$

A scalar prediction $\hat{y}$ is then obtained by measuring the expectation value of a Pauli-Z operator on the readout qubit:

$$\hat{y} = \langle \psi_\theta(x) \mid Z \mid \psi_\theta(x)\rangle \tag{3}$$

Circuit parameters θ are initialized uniformly within $[-\pi, \pi]$ and optimized using the Adam optimizer with a learning rate of 0.005, as this configuration provided the most consistent convergence in simulation. Gradients are computed using the parameter-shift rule implemented in PennyLane, ensuring analytical precision and stability during training. The number of parameters and circuit depth are deliberately kept low to maintain computational efficiency and prevent overfitting. To more accurately describe optimization behavior, we monitored gradient norms during training and observed values consistently between 10^{-3} and 10^{-1} across 300+ epochs, indicating stable, non-vanishing gradients. This aligns with findings that shallow circuits with structured entanglement exhibit reduced barren-plateau risk. Accordingly, the manuscript now states that the design reduces the risk of barren plateaus rather than fully avoiding them. For clarity, the variational quantum circuit can be interpreted as a compact nonlinear transformation that captures interactions among vehicular features using a shallow architecture. In simple terms, barren plateaus denote training regions with very small gradients; in this work, their impact is reduced by limiting circuit depth and employing structured entanglement, ensuring stable and efficient optimization for readers less familiar with quantum computing.

The model is trained by minimizing the Mean Squared Error (MSE) over the training data. MSE was chosen because vehicular energy consumption is a continuous-valued regression task, and MSE directly penalizes squared deviations between the predicted and ground-truth energy values, yielding a smooth optimization surface for gradient-based learning. For reproducibility, the variational circuit employed two layers of rotation gates (RY, RZ) with nearest-neighbor CNOT entanglement, $\langle Z_0\rangle$ as readout, and five qubits aligned with the selected features (Trip Distance, Time of Day, Current, Total Voltage, Trip

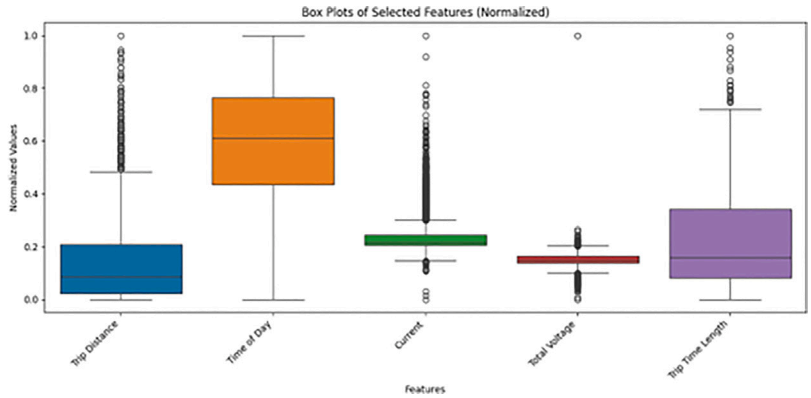

Fig. 4. Box plots of selected features.

Table 3
Effect of variational circuit depth on model performance.

Variational layers (L)	Test R^2	Relative training cost	Interpretation
$L = 1$	0.83	Low	Underfitting due to limited expressivity
$\mathbf{L = 2}$	**0.8439**	Moderate	**Best accuracy–complexity balance**
$L = 3$	0.846	High (+40%)	Marginal gain with increased complexity

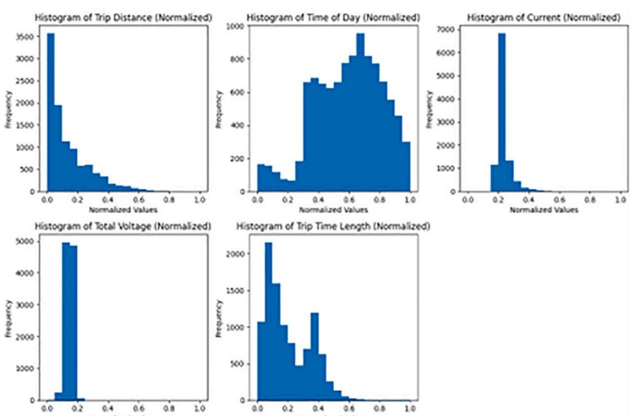

Fig. 5. Histograms of normalized features.

Time Length). Parameters were initialized uniformly in $[-\pi/2, \pi/2]$ and optimized using Adam ($lr = 0.005$).

A 5-qubit PQC is utilized with rotation-based data encoding and two variational layers ($L = 2$). Data encoding applies $RY(x_i)$ to qubit i ($i \in \{0, \dots, 4\}$). Each variational layer consists of element-wise $RY(\theta_i^l)$, $RZ(\phi_i^l)$ on all qubits, followed by a nearest-neighbor CNOT ring ($q_0 \rightarrow q_1 \rightarrow q_2 \rightarrow q_3 \rightarrow q_4 \rightarrow q_0$).

The qubit-feature mapping is q^0: Trip Distance, q^1: Time of Day, q^2: Current, q^3: Total Voltage, and q^4: Trip Time Length. Prediction is the Pauli-Z expectation $\langle Z_0 \rangle$ on qubit q^0 after the final layer; $\{\theta, \phi\}$ are initialized $\mathcal{U}[-\pi/2, \pi/2]$ and trained with Adam optimizer (0.005). This explicit design strikes a balance between expressivity and trainability, aligning with the feature dimensionality, as shown in Fig. 9.

$$\mathcal{L}(\theta) = \frac{1}{m} \sum_{i=1}^{m} \left(y_i - \hat{y}_i \right)^2 \tag{4}$$

where y_i is the ground-truth energy consumption for the sample i, and $\hat{y}_i$ is the predicted value from the quantum model.

Once trained, this model is evaluated on the test subset and deployed for predictions on real-time AEV data. The XAI module then processes these predictions, which apply LIME and SHAP to deliver

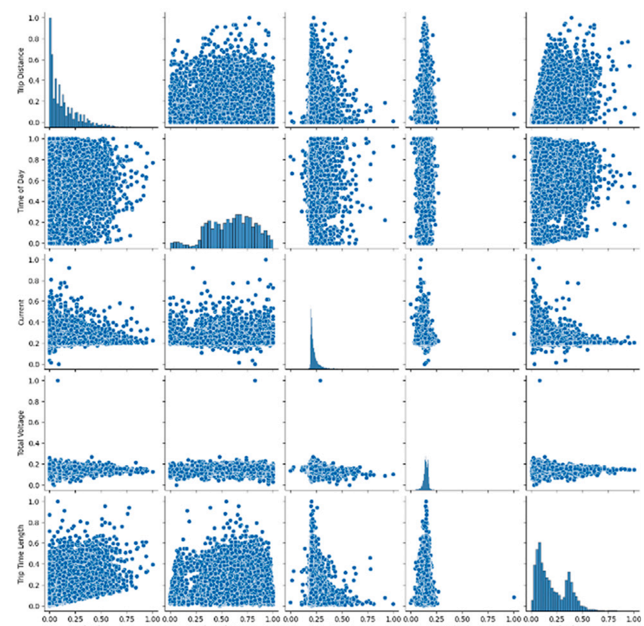

Fig. 6. Pairplot of selected features.

human-interpretable insights. The SHAP and LIME modules are applied post-hoc to the hybrid quantum model's classical outputs, ensuring that feature-level interpretability remains consistent with standard XAI frameworks. LIME provides local instance-based explanations for individual trips, whereas SHAP quantifies the global contribution of each feature across all trips, reinforcing accountability and transparency.

- **LIME** approximates the original complex model f in the neighborhood of an input x using a simpler interpretable model g. The approximation is obtained by minimizing:

$$\hat{h}(x) = \arg\min_{g \in G} \left[L(f, g, \pi_x) + \Omega(g) \right] \tag{5}$$

Here, L ensures local fidelity between f and g, π_x defines the locality around x, and $\Omega(g)$ penalizes the complexity of g. This

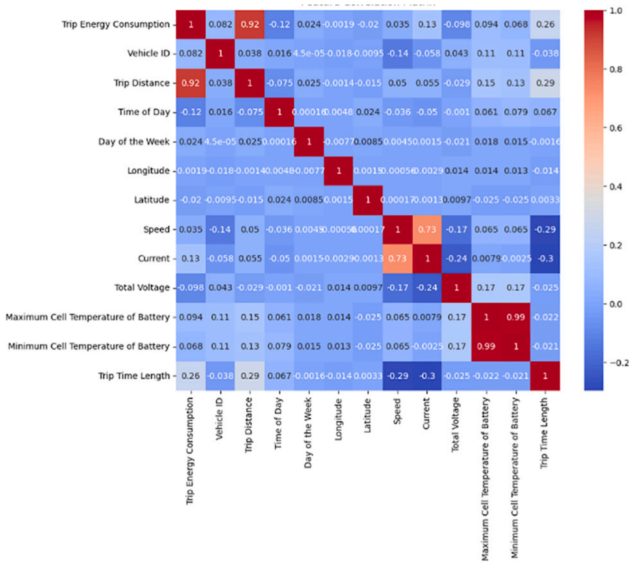

Fig. 7. Feature correlation matrix.

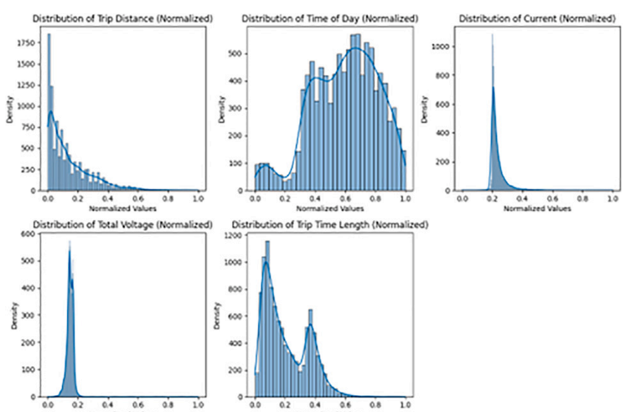

Fig. 8. Density distributions of features.

enables stakeholders to comprehend the local decision boundaries surrounding specific AEV predictions.

- **SHAP** values, derived from cooperative game theory, provide a global explanation by distributing the prediction score across all features. The Shapley value for the feature i is calculated as:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \tag{6}$$

where F is the set of all features, and S is a subset excluding i.

This quantifies the marginal contribution of the feature i to the final prediction, thereby enhancing transparency and compliance with model accountability standards. By combining these two interpretability methods, the proposed XQAI model bridges quantum efficiency with explainability, fulfilling the transparency requirements essential for regulatory and safety-critical smart mobility systems. By combining quantum-enhanced prediction and interpretable AI, this integrated model not only improves energy forecasting accuracy but also enhances trust, auditability, and regulatory compliance, a crucial advancement for deploying AI systems in real-time, safety-critical smart mobility infrastructures.

The predictions and their corresponding explanations are first evaluated to ensure they meet predefined performance thresholds. If the model's learning rate or prediction quality falls short, the deep learning phase is re-initialized and retrained on the training subset. If the criteria are satisfied, the validated patterns and XAI-generated explanations are uploaded to a cloud-based system for secure storage and future referencing.

Algorithm 1 Pseudocode of the proposed model

Start: Initialize the XQAI energy optimization process for autonomous electric vehicles (AEVs).
Data Input Layer: Collect vehicular data as a feature vector

$\mathbf{x} = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^n$

Features include Trip Distance, Time of Day, Voltage, Current, Trip Time Length, etc.
Data Preprocessing: Missing value detection, Feature scaling, Categorical encoding, Feature selection, Outlier handling, Re-normalization tailored for quantum encoding, Split the data
Quantum Data Encoding: Encode each feature x_i as a rotation on qubit q_i using $RY(x_i)$ gates.
PQC Construction: For $L = 2$ variational layers:

- Apply $RY(\theta_i^l)$, and $RZ(\phi_i^l)$ gates on each qubit
- Implement CNOT ring entanglement $(q_0 \to q_1 \to q_2 \to q_3 \to q_4 \to q_0)$

Quantum Model Training:

- Encode classical features into a quantum state:

  $|\psi_0(\mathbf{x})\rangle = RY(x_1) \cdot RY(x_2) \cdots RY(x_n)|00\ldots0\rangle$

- Apply the PQC:

  $|\psi_\theta(\mathbf{x})\rangle = U(\theta)|\psi_0(\mathbf{x})\rangle$

Prediction Phase:

- Generate predictions using Pauli-Z expectation:

  $\hat{y} = \langle\psi_\theta(\mathbf{x})|Z|\psi_\theta(\mathbf{x})\rangle$

- Optimize parameters by minimizing the loss function:

  $\mathcal{L}(\theta) = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2$

XAI

- Compute SHAP value for each feature i:

  $\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$

- Train LIME surrogate model:

  $\hat{h}(\mathbf{x}) = \arg\min_{g \in G} \left[L(f, g, \pi_x) + \Omega(g)\right]$

Model Evaluation: Evaluate performance on the test set to ensure prediction quality meets the threshold.
Cloud Storage: Upload trained model M^* and explanations (SHAP, LIME) to the cloud.
Storage and Feedback Completion: Store interpretable predictions and model updates for future reference.
Real-Time Prediction and Fault Detection: Use a trained model to assess incoming real-time AEV data

$P(\text{fault} \mid S') = h(M^*(t+1), S')$

Decision Making: If fault probability exceeds threshold δ, apply energy optimization:
if $P_{\text{fault}}(S') > \delta$ **then**
    Discard prediction
elseOtherwise, transmit it to AVN for execution.
end if
Stop: Terminate the process.

The predictions $\hat{y}$ and their corresponding explanations are first evaluated to ensure they meet predefined performance thresholds. Formally, the prediction confidence or failure risk can be modeled as:

$$P(\text{fault} \mid S') = h\big(M^*(t+1),\ S'\big) \tag{7}$$

where S' is the real-time input vector and $M^{*(t+1)}$ is the final trained interpretable model. If the fault probability exceeds the predefined safety threshold δ, the interpretable prediction is stored on the cloud for future referencing; otherwise, the model is retrained to improve its prediction accuracy.

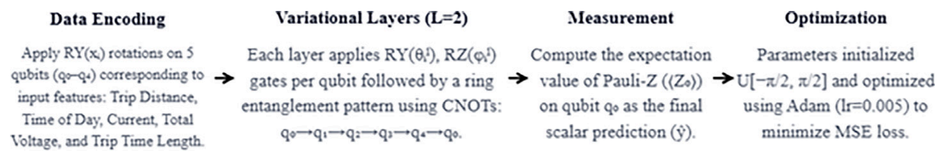

Fig. 9. Two-layer 5-qubit VQC architecture.

In the subsequent Validation Phase, the trained model is deployed on real-time vehicular data, and the relevant XAI modules are retrieved from the cloud to interpret the predictions. Upon successful validation, predictions are transmitted to the Autonomous Vehicular Network (AVN) for final decision-making. The transmission condition is:

$$\text{If } P_{\text{fault}}(S') > \delta \Rightarrow \text{ discard prediction} \quad (8)$$

Otherwise, predictions are accepted and transmitted to AVN for execution.

This end-to-end process ensures that the AVN is guided by accurate, interpretable, and trustworthy insights derived from both real-time and historical data, thereby enhancing vehicular safety, efficiency, and transparency in dynamic urban environments. Algorithm 1 presents the step-by-step pseudocode of the proposed XQAI-based energy management model for AEVs. It outlines data preprocessing, quantum model training, XAI integration, and real-time decision logic for transparent and optimized vehicular energy control.

4. Simulation results

The increasing integration of AEVs into smart urban infrastructures introduces critical challenges in energy consumption modeling, interpretability, and computational efficiency. While traditional AI-based energy prediction models are helpful, they often struggle with real-time data processing and lack the transparency required by regulatory bodies. To address these limitations, this study proposes an XQAI-based model that integrates the computational efficiency of QML with the interpretability of XAI. Simulations were executed in Google Colab using PennyLane's default.qubit simulator backend under Python 3.12 with TensorFlow 2.15 to ensure reproducibility and numerical stability without physical quantum hardware. The experiments used 5 qubits, 2 variational layers (L = 2), and a Tesla T4 GPU (16 GB VRAM), with an average runtime of 42 s per epoch. The dataset was split into 70% training and 30% test sets, and model performance was evaluated using MSE, RMSE, and R^2. Interpretability was validated using SHAP and LIME to ensure transparent, trustworthy decision support.

All QML models were implemented using PennyLane's default.qubit simulator (5 wires) and integrated into TensorFlow via the KerasLayer interface. Training was performed using the Adam optimizer (lr = 0.005), a batch size of 32, and a fixed 20% validation split. The VQR model was trained for 30 epochs, while the Hybrid Classical–Quantum, Hybrid CNN–Quantum, and QDenseReg models used 50 epochs under the same fixed-epoch schedule. A consistent train–test split was maintained using random_state = 42 to ensure reproducibility. Due to the computational cost of quantum circuit simulation, we employed a single 70/30 split with internal validation rather than full k-fold cross-validation. The close alignment of training and testing metrics (Table 4) demonstrates stable generalization and indicates that the results are not dependent on a specific data partition. Although k-fold cross-validation can provide more robust performance estimates, its use in quantum simulation-based learning significantly increases computational cost due to repeated optimization of parameterized quantum circuits. Therefore, a single 70/30 train–test split was adopted as a practical and widely accepted compromise in quantum machine learning studies. The use of a fixed random seed and the close agreement between training and testing metrics further support the reproducibility and stability of the reported results.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad (9)$$

where y_i represents the actual energy consumption, $\hat{y}_i$ denotes the predicted energy value, and n is the total number of samples. A lower MSE indicates improved prediction accuracy and model generalization.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad (10)$$

This metric provides an interpretable measure of prediction error in the same units as energy consumption, enhancing the comparability and reliability of quantum and hybrid models. Coefficient of Determination (R^2R Score):

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \quad (11)$$

Here, $\bar{y}$ is the mean of actual energy values. An R^2 score closer to 1 signifies a strong correlation between predicted and actual values, indicating the model's effectiveness in capturing the underlying patterns of vehicular energy dynamics. As illustrated in Table 4, all QML models show competitive training performance. The Hybrid Classical–Quantum Regressor yields the lowest training MSE (0.0028) and RMSE (0.0531), and the highest R^2 score (0.8574), suggesting strong learning capacity. Similarly, both the Hybrid CNN–Quantum and VQR demonstrate efficient training behaviors, with R^2 values of 0.8544 and 0.8517, respectively. The Quantum-Inspired Dense Regressor performs relatively lower, with a higher MSE of 0.0033 and an R^2 of 0.8324, indicating a slightly weaker fit on the training data.

During testing, all models maintain consistent performance. The Hybrid Classical–Quantum Regressor continues to perform well, achieving an R^2 score of 0.8439 with a minimal RMSE of 0.0557. The Hybrid CNN–Quantum Regressor and VQR also yield stable, comparable results, with test R^2 values of 0.8436 and 0.8433, respectively. Meanwhile, the Quantum-Inspired Dense Regressor exhibits the lowest R^2 score of 0.8219 and the highest RMSE of 0.0595, suggesting reduced generalization ability under real-world conditions. The slight difference between training (R^2 = 0.8574) and testing (R^2 = 0.8439) scores confirms that the proposed model generalizes well without overfitting, supported by its shallow two-layer circuit design and constrained parameter initialization, which act as implicit regularization mechanisms.

Based on both training and test performance outlined in Table 4, the Hybrid Classical–Quantum Regressor stands out as the most effective model, offering the best trade-off between learning accuracy and generalization, making it an optimal choice for real-time deployment in smart vehicular EMSs. To further enhance transparency and trustworthiness, the interpretability of this model was analyzed using SHAP and LIME, as shown in Figs. 10–13.

Fig. 10 illustrates the SHAP summary plot, showing the contribution of each input feature to the proposed XQAI model's prediction outcomes. The horizontal spread of points reflects the magnitude and direction of each feature's impact on model output, while the color gradient represents the original feature values. Notably, Trip Distance

Table 4
Performance comparison of QML models on training and testing.

QML model	Training			Testing		
	MSE	RMSE	R^2	MSE	RMSE	R^2
Variational Quantum Regressor (VQR)	0.0029	0.0542	0.8517	0.0031	0.0558	0.8433
Hybrid Classical–Quantum Regressor	0.0028	0.0531	0.8574	0.0031	0.0557	0.8439
Hybrid CNN–Quantum Regressor	0.0029	0.0537	0.8544	0.0031	0.0558	0.8436
Quantum-Inspired Dense Regressor	0.0033	0.0576	0.8324	0.0035	0.0595	0.8219

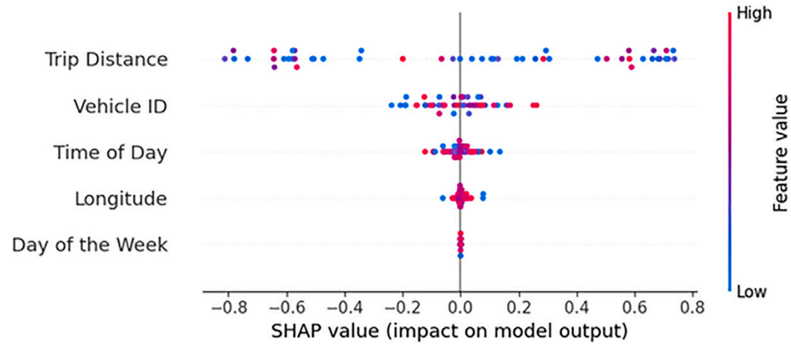

Fig. 10. SHAP summary plot highlighting each feature's influence on energy consumption predictions.

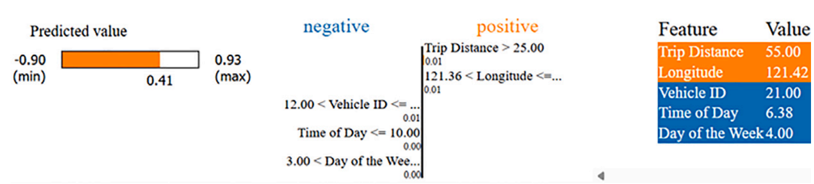

Fig. 11. LIME plot showing top features influencing a single XQAI framework prediction.

emerges as the most influential variable, with high SHAP values indicating its substantial role in determining energy consumption. Vehicle ID also shows moderate variability, suggesting that individual vehicle characteristics affect prediction patterns. In contrast, features such as Time of Day, Longitude, and Day of the Week exhibit narrower SHAP distributions, indicating a relatively lower impact. This visualization not only confirms the model's reliance on key physical and contextual parameters but also enhances transparency by enabling interpretable, feature-level insight into the model's decision-making, supporting auditability, trust, and regulatory alignment in smart vehicular energy systems. These SHAP patterns align with physical behavior: longer trips and higher electrical load naturally increase energy demand. Their dominance confirms that the model captures meaningful vehicle dynamics rather than noise, helping engineers identify energy-intensive operating conditions.

Fig. 11 presents a LIME visualization for an individual prediction made by the proposed XQAI framework. The explanation yields a local confidence score of 0.93, reflecting strong agreement between the interpretable surrogate model and the underlying quantum regression predictor. Features such as Trip Distance (>25.00) and Longitude (>121.36) were identified as key positive contributors to the predicted energy consumption. At the same time, Vehicle ID, Time of Day, and Day of the Week had minimal or negative impact. This level of interpretability reinforces model transparency, supports regulatory alignment, and validates the framework's practical utility in real-world autonomous vehicular energy forecasting.

Fig. 12 presents a LIME visualization for another prediction generated by the proposed XQAI framework. The explanation reflects a local confidence score of 0.94, indicating strong fidelity between the interpretable surrogate model and the core quantum regression predictor. In this case, Time of Day (>10.00) and Trip Distance (<8.00) emerged as positive influences on the predicted energy consumption, whereas Day of the Week (>5.00), Longitude (<121.36), and Vehicle ID (>35.00) contributed negatively. This interpretability supports model accountability and enhances stakeholder trust, making it suitable for deployment in real-time smart mobility systems.

Fig. 13 illustrates a LIME for a specific prediction generated by the XQAI framework. With a local confidence score of 0.95, the explanation confirms a high level of alignment between the surrogate interpretable model and the underlying quantum regression-based predictor. Among the input features, Vehicle ID (>35.00), Time of Day (>10.00), Trip Distance (<8.00), and Day of the Week (<1.00) contributed positively to the predicted energy consumption, while Longitude (≤121.23) had a minor negative influence. This interpretable breakdown affirms the framework's transparency and supports its deployment in safety-critical EMSs for AEVs.

The three LIME-based visual explanations (Figs. 10–12) collectively demonstrate the interpretability and reliability of the proposed XQAI framework by highlighting how different contextual features—such as Trip Distance, Longitude, Time of Day, and Vehicle ID—contribute to energy consumption predictions across varying scenarios. Consistently high local confidence scores (ranging from 0.93 to 0.95) confirm strong alignment between the interpretable surrogate models and the underlying quantum predictor, reinforcing the model's transparency, explainability, and suitability for real-time deployment in intelligent vehicular EMSs. For comparative benchmarking, classical baseline models (RF, KNN, Ridge Regression, MLP, LSTM, and Ensemble methods) from prior studies [41–46] were used, with similar evaluation metrics (MSE, RMSE, R^2), to contextualize the performance of the proposed XQAI model. Among these, the explanation in Fig. 12 stands out with the highest confidence score of 0.95, indicating the strongest local fidelity and most stable model interpretability. SHAP and LIME results

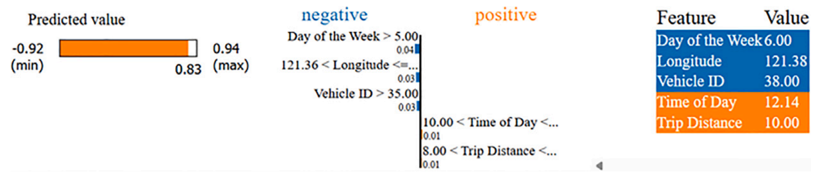

Fig. 12. LIME plot showing top features influencing a single XQAI model prediction.

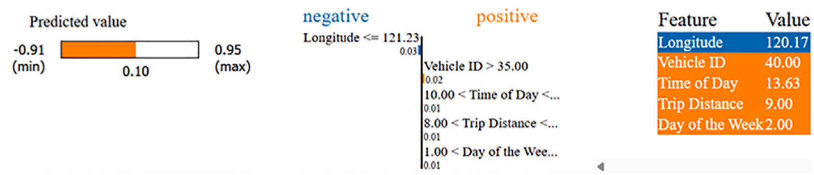

Fig. 13. LIME plot showing top features influencing a single XQAI model prediction.

Table 5
Comparative analysis of the proposed XQAI model with previous works.

Ref	Model	MSE	RMSE	R^2
[41]	RF	0.0007	0.026	0.83
[41]	KNN	0.0008	0.027	0.81
[42]	RF	15.8	3.97	0.74
[42]	CatBoost	11.7	3.42	0.80
[43]	Ridge Regression	13.2877	3.645	0.8342
[43]	MLP	48.8066	6.986	0.3909
[47]	Voting Ensemble	30.69	5.54	0.69
[47]	Stacking Ensemble	30.25	5.50	0.70
[44]	ANN	24.68	4.9680	0.8168
[45]	LSTM	233.05	15.2662	0.6696
[46]	IRLA (Commercial, Private)	C = 1310.44 P = 1428.84	C = 36.2 P = 37.8	C = 34.5 P = 35.6
[46]	MDP (Commercial, Private)	C = 1989.16 P = 4816.36	C = 44.6 P = 69.4	C = 41.3 P = 67.8
[45]	RNN	290.05	17.0308	0.5888
[45]	GRU	278.11	16.6769	0.6057
[45]	LSTM	256.99	16.0310	0.6311
Proposed	**Hybrid Classical–Quantum Regressor**	**0.0031**	**0.0557**	**0.8439**
Proposed XQAI	Hybrid Classical–Quantum Regressor	Confidence score = 0.95		

align closely, consistently highlighting Trip Distance and Current as key predictors, confirming the XQAI model's reliability and physical validity.

Across multiple instances, LIME consistently highlighted similar features (e.g., Trip Distance, Current), indicating stable and non-contradictory explanations suitable for real-time decision support. For example, in one inefficient trip, both SHAP and LIME attributed higher energy usage to prolonged stop-and-go traffic and elevated Current. Such insights help operators adjust routes or schedules to reduce energy waste.

To contextualize the performance of the proposed QML approach, we benchmarked it against widely used classical models reported in existing literature. Table 5 presents comparative results for Random Forest, KNN, CatBoost, Ridge Regression, MLP, ANN, LSTM, RNN/GRU, and ensemble methods [41–46], which constitute state-of-the-art baselines for electric vehicle energy prediction. These classical methods achieve R^2 values typically between 0.67 and 0.83, whereas the proposed Hybrid Classical–Quantum Regressor attains an R^2 of 0.8439 with an additional interpretability confidence of 0.95 via LIME. This demonstrates that the QML-based XQAI framework not only matches or surpasses classical baselines but also provides transparent explanations, a feature essential for trustworthy and safety-critical smart mobility applications.

Table 5 highlights the variability of classical methods across different datasets and modeling contexts. While several models [41–46] such as RF, Ridge Regression, and ANN achieve reasonable performance ($R^2 \approx 0.74$–0.83), others—including MLP, LSTM, and RNN-based architectures—show notable instability and reduced generalization, particularly on nonlinear and high-variance energy consumption patterns. This variability can be attributed to structural limitations of classical models when handling complex, nonlinear interactions among multiple vehicular features, such as dynamic traffic conditions, heterogeneous trip characteristics, and fluctuating electrical load. Tree-based models rely on fixed partitioning strategies that may struggle under rapidly changing conditions, distance-based learners like KNN are sensitive to noise and feature scaling, and deep sequential models such as LSTM and RNN typically require large volumes of temporally consistent data to maintain stability and avoid overfitting. These inconsistencies reflect the limitations of purely classical models in capturing complex multi-factor interactions in AEV energy behavior. In contrast, the proposed Hybrid Classical–Quantum Regressor achieves robust performance ($R^2 = 0.8439$) while maintaining a consistent interpretability confidence of 0.95 via LIME. Rather than focusing solely on numerical improvements, the XQAI model's strength lies in combining strong predictive accuracy with transparent feature-level explanations. By encoding nonlinear feature interactions within a compact quantum representation and complementing them with XAI-based interpretability, the proposed framework offers improved robustness under complex energy patterns while ensuring traceable, auditable, and regulation-compliant decision-making. This alignment between quantum representations and XAI insights provides a practical advantage for safety-critical settings, enabling traceable, auditable, and regulation-compliant energy management decisions—capabilities that traditional black-box models generally lack.

5. Conclusion

The rapid expansion of AEVs within smart city environments has intensified the demand for efficient vehicular energy management. Factors such as fluctuating traffic conditions, variable trip characteristics, and nonlinear energy consumption patterns pose significant challenges to ensuring optimal energy use. Traditional machine learning approaches often lack transparency, adaptability, and scalability, making them unsuitable for real-time, safety-critical smart mobility applications. To overcome these limitations, this study introduced an XQAI-based model that integrates the computational strength of QML with the interpretability of XAI techniques such as LIME and SHAP. The proposed Hybrid Classical–Quantum Regressor model achieved notable performance with an R^2 score of 0.8439 and a local confidence level of 0.95, outperforming conventional models [41–46] while offering interpretable insights. The simulations demonstrate that the model reliably provides trustworthy, clear, and practical information on the energy use of AEVs in changing city environments. While the results are encouraging, further validation in large-scale, real-world deployments is necessary before the model can be considered ready for operational use.

5.1. Limitations

While the model demonstrates encouraging results, some limitations, such as scalability, may be constrained by the computational cost of quantum simulations. The practical deployment of quantum simulations on noisy real hardware remains challenging. Furthermore, broader testing on diverse vehicular datasets is necessary to confirm the model's robustness and generalizability.

5.2. Future work

In the future, Federated Learning (FL) will be integrated to further enhance data privacy protection by training models on decentralized devices. Efforts will also explore quantum model compression and lightweight deployment strategies to ensure scalable, real-time performance in smart vehicular environments. Additionally, the computational complexity and scalability implications of quantum-enhanced regressors will be systematically analyzed to evaluate their feasibility for real-time vehicular deployment. Since the present study was implemented on quantum simulators, future work will also focus on adapting the framework to real quantum hardware as it becomes more stable and mature.

6. Practical implications

The proposed framework can be applied in smart city infrastructures, particularly for large-scale EV fleet management, intelligent charging optimization, and dynamic energy routing. The framework can further support real-time decision-making and energy-aware route planning in autonomous vehicular systems. Key barriers include computational overhead, IoT integration, and the immaturity of quantum hardware for large-scale deployment. By emphasizing these specific real-world applications, addressing these challenges through cloud–edge integration strategies, scalable deployment mechanisms, and real-world pilot validation, along with collaboration with industry stakeholders, will be essential to transition from proof-of-concept to operational deployment.

CRediT authorship contribution statement

Muhammad Saleem: Writing – original draft, Validation, Methodology, Conceptualization. **Muhammad Sajid Farooq:** Writing – review & editing, Validation. **Khan Muhammad Adnan:** Writing – review & editing, Validation, Methodology, Conceptualization. **Muhammad Nadeem Ali:** Writing – review & editing, Validation, Data curation. **Adeel Munawar:** Writing – review & editing, Validation, Resources. **Byung-Seo Kim:** Writing – review & editing, Validation, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Kashem MA, Shamsuddoha M, Nasir T. Sustainable transportation solutions for intelligent mobility: A focus on renewable energy and technological advancements for electric vehicles and flying cars. Future Transp 2024;4(3):874–90.
[2] Liu H, Yu S, Wang T, Li J, Wang Y. A systematic review on sustainability assessment of internal combustion engines. J Clean Prod 2024;141996.
[3] Khedr AM, El-Adawy M, Ismael MA, Qador A, Abdelhafez A, Ben-Mansour R, Habib MA, Nemitallah MA. Recent fuel-based advancements of internal combustion engines: Status and perspectives. Energy Fuels 2025;39(11):5099–132.
[4] Petri M, Chomiak I. Towards a sustainable future: The use of electrical energy in smart cities. In: European conference on artificial intelligence. Springer Nature Switzerland; 2023, p. 216–22.
[5] Dik A, Omer S, Boukhanouf R. Electric vehicles: V2G for rapid, safe, and green EV penetration. Energies 2022;15(3):803.
[6] Jha RK, Neupane S. Securing the future of mobility: Electric vehicle charging infrastructure protection. J Inf Technol Digit World 2023;5(3):291–309.
[7] Mittal V, Shah R. Energy management strategies for hybrid electric vehicles: A technology roadmap. World Electr Veh J 2024;15(9):424.
[8] Oyucu S, Doğan F, Aksöz A, Biçer E. Comparative analysis of machine learning approaches for li-ion battery performance prediction in EVs. Appl Sci 2024;14(6):2306.
[9] Prianka YM, Sharma A, Biswas C. Integration of renewable energy, microgrids, and EV charging infrastructure. Control Syst Optim Lett 2024;2(3):317–26.
[10] Rawat S, Choudhury S, Saini DK, Gupta YC. Integrated system architectures of lithium-ion batteries for electric mobility. World Electr Veh J 2024;15(9):394.
[11] Xu B, Rathod D, Zhang D, Yebi A, Zhang X, Li X, Filipi Z. Reinforcement learning optimized energy management strategy for a hybrid electric vehicle. Appl Energy 2020;259:114200.
[12] Zou W, Li J, Yang Q, Duan Z. Improved max–min game theory control of fuel cell and battery hybrid systems. IEEE J Emerg Sel Top Power Electron 2022;11(1):78–87.
[13] Tekkesinoglu S, Habibovic A, Kunze L. Advancing explainable autonomous vehicle systems: A comprehensive review. ACM Trans Hum Robot Interact 2025;14(3):1–46.
[14] Broekman N. Toward safe and scalable autonomy: Technologies and challenges in autonomous driving. Trans Comput Sci Methods 2025;5(4).
[15] Shankar KP, Chandraprabha K, Raja KS, Kanmani P. Foundations of quantum computing and machine learning. In: Quantum computing and artificial intelligence: the industry use cases. 2025, p. 225–46.
[16] Tresca L, Pulvirenti L, Rolando L, Millo F. Deep Q-learning energy management system for hybrid electric vehicles. Transp Eng 2024;16:100241.
[17] Khan MA, Sabahat Z, Farooq MS, Saleem M, Abbas S. Smart home energy management using machine learning. Discov Sustain 2024;5(1):430.
[18] Machlev R, Heistrene L, Perl M, Levy KY, Belikov J. Explainable AI techniques for energy and power systems. Energy AI 2022;9:100169.
[19] Khan MA, Farooq MS, Saleem M, Shahzad T, Ahmad M, Abbas S, Abu-Mahfouz AM. Smart buildings: Federated learning-driven secure, transparent and smart energy management system using XAI. Energy Rep 2025;13:2066–81.
[20] Malik AZ, Naz NS, Ahmed F, Saleem M, Farooq MS, Rehman AU, Ismael WM, Khan MA. Enhancing smart city mobility through real-time explainable AI in autonomous vehicles. Sci Rep 2025;15(1):42118.
[21] Bai Y, Sui Y, Deng X, Wang X. Quantum-inspired robust optimization for coordinated scheduling of PV–hydrogen microgrids. Sci Rep 2025;15(1):29589.
[22] Manasa M, Tlajiya F, Chavan S. Optimizing energy management and load balancing through AI-driven quantum approximate optimization. In: Proc. 4th international conference on mobile networks and wireless communications. ICMNWC, IEEE; 2024, p. 1–7.

[23] Neelakantam G. Machine learning-based decision making for charging/discharging cost optimization of PHEVs in smart cities. In: Proc. international symposium on parallel computing and distributed systems. PCDS, IEEE; 2024, p. 1–6.
[24] Zhao X, Liang G. Optimizing electric vehicle charging schedules using an integrated GA–GRU–RL approach. Front Energy Res 2023;11:1268513.
[25] Rojek I, Mikołajewski D, Galas K, Piszcz A. Advanced deep learning algorithms for energy optimization of smart cities. Energies 2025;18(2):407.
[26] Shern SJ, Sarker MT, Haram MHSM, Ramasamy G, Thiagarajah SP, Al Farid F. Artificial intelligence optimization for user prediction and efficient energy distribution in EV smart charging. Energies 2024;17(22):5772.
[27] Millo F, Rolando L, Tresca L, Pulvirenti L. Neural network-based energy management system for plug-in hybrid electric vehicles. Transp Eng 2023;11:100156.
[28] Min D, Song Z, Chen H, Wang T, Zhang T. GA-optimized neural network for fuel cell hybrid electric vehicle energy management. Appl Energy 2022;306:118036.
[29] Zhang G, Dai M, Zhao S, Zhao P. Dynamic charging scheduling optimization for electric vehicles based on quantum SWARM algorithm. In: Proc. Asia-Pacific conference on intelligent robot systems. ACIRS, IEEE; 2022, p. 154–7.
[30] Zeydan E, Turk Y, Aksoy B, Tasbag YY. Post-quantum era in V2X security: Convergence of orchestration and parallel computation. IEEE Commun Stand Mag 2022;6(1):76–82.
[31] Mohanty PK, Reddy KH K, Panigrahy SK, Roy DS. Leveraging generative and explainable AI for electric vehicle energy. IEEE Access 2024.
[32] Naveed SA, Farooq U, Raza MA, Rehman ZU, Saleem M, Ghazal TM. Enhancing traffic flow and congestion management in smart cities using SVM-based linear regression. J Transp Technol 2024.
[33] Lee SW, Ali S, Yousefpoor MS, Yousefpoor E, Lalbakhsh P, Javaheri D, Rahmani AM, Hosseinzadeh M. Energy-aware predictive fuzzy logic routing in flying ad hoc networks. IEEE Access 2021;9:129977–30005.
[34] Noussaiba M, Razaque A, Rahal R. Heterogeneous algorithm for efficient-path detection and congestion avoidance. Sensors 2023;23(12):5471.
[35] Lansky J, Rahmani AM, Hosseinzadeh M. Reinforcement learning-based routing protocols in VANETs: A survey. Mathematics 2022;10(24):4673.
[36] Khan MU, Hosseinzadeh M, Mosavi A. Intersection-based routing using Q-learning in vehicular ad hoc networks. Mathematics 2022;10(20):3731.
[37] Saleem M, Arishi A, Farooq MS, Khan MA, Adnan KM. Weighted explainable federated learning for energy optimization in autonomous vehicular networks. Egypt Inform J 2025;31:100758.
[38] Tang X, Chen J, Yang K, Toyoda M, Liu T, Hu X. Visual detection and deep reinforcement learning-based car following and energy management. IEEE Trans Transp Electrification 2022;8(2):2501–15.
[39] Pulvirenti L, Rolando L, Millo F. Energy management system optimization using LSTM-based vehicle speed prediction. Transp Eng 2023;11:100160.
[40] Liu Yang. Electric vehicle trip energy consumption data. ETS-Data; 2023, Dataset.
[41] Ullah I, Liu K, Yamamoto T, Zahid M, Jamal A. Electric vehicle energy consumption prediction using stacked generalization. Int J Green Energy 2021;18(9):896–909.
[42] Ullah I, Liu K, Yamamoto T, Zahid M, Jamal A. Prediction of EV charging duration using ensemble learning and SHAP. Int J Energy Res 2022;46(11):15211–30.
[43] Hussain I, Ching KB, Uttraphan C, Tay KG, Noor A. Evaluating machine learning algorithms for EV energy consumption prediction. Sci Rep 2025;15(1):1–20.
[44] Zhu J, Yang Z, Mourshed M, Guo Y, Zhou Y, Chang Y, Wei Y, Feng S. Electric vehicle charging load forecasting: A comparative study. Energies 2019;12(14):2692.
[45] El-Latif A, Eman I, El-dosuky M. Explainable energy consumption and speed prediction in sustainable cities. Neural Comput Appl 2025;1–17.
[46] Alshammari A, Chabaan RC. Metaheuristic optimization-based ensemble learning for EV charging time prediction. Sustainability 2023;15(8):6684.
[47] Shahriar S, Al-Ali AR, Osman AH, Dhou S, Nijim M. Prediction of EV charging behavior using machine learning. IEEE Access 2021;9:111576–86.