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Artificially Intelligent Vehicle-to-Grid Energy Management: A Semantic-Aware Framework Balancing Grid Demands and User Autonomy

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Abstract: As the adoption of electric vehicles increases, the challenge of managing bidirectional energy flow while ensuring grid stability and respecting user preferences becomes increasingly critical. This paper aims to develop an intelligent framework for vehicle-to-grid (V2G) energy management that balances grid demands with user autonomy. The research presents VESTA (vehicle energy sharing through artificial intelligence), featuring the semantic-aware vehicle access control (SEVAC) model for efficient and intelligent energy sharing. The methodology involves developing a comparative analysis framework, designing the SEVAC model, and implementing a proof-of-concept simulation. VESTA integrates advanced technologies, including artificial intelligence, blockchain, and edge computing, to provide a comprehensive solution for V2G management. SEVAC employs semantic awareness to prioritise critical vehicles, such as those used by emergency services, without compromising user autonomy. The proof-of-concept simulation demonstrates VESTA's capability to handle complex V2G scenarios, showing a 15% improvement in energy distribution efficiency and a 20% reduction in response time compared to traditional systems under high grid demand conditions. The results highlight VESTA's ability to balance grid demands with vehicle availability and user preferences, maintaining transparency and security through blockchain technology. Future work will focus on large-scale pilot studies, improving AI reliability, and developing robust privacy-preserving techniques.

Keywords: vehicle-to-grid (V2G); smart grid; electric vehicles; energy management; artificial intelligence; blockchain; edge computing

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1. Introduction

The global energy landscape is undergoing a profound transformation, driven by the imperative to reduce greenhouse gas emissions and transition towards sustainable green energy systems. This shift has led to a rapid increase in electric vehicle (EV) adoption, with projections indicating that the number of EVs on the road globally will reach 245 million by 2030 [1]. This surge in EV adoption presents both opportunities and challenges for power grid management, renewable energy integration, and security and privacy [2].

Vehicle-to-grid (V2G) technology has emerged as a promising solution to address some of these challenges. V2G transforms EV users from simple consumers of energy to active participants in the energy system [3]. Recent developments in V2G have enabled bidirectional energy flow between electric vehicles and the electrical grid. This allows EVs to act as mobile energy storage systems and, therefore, gives them the ability to supply energy to the grid, if needed, rather than just consuming it. This capability not only helps to stabilise the grid but also supports the integration of renewable energy sources, thereby contributing to the decarbonisation goals of many governments [4].

The integration of V2G technology with energy storage systems is crucial for the effective management of renewable energy resources. Research has shown that energy storage technologies play a vital role in renewable energy integration, emphasising the importance of optimal scheduling models and sustainable adaptation policies, which are directly relevant to V2G systems [5].

However, the widespread adoption of V2G technology faces significant challenges. Studies have indicated potential adverse effects of V2G operations on EV battery life due to frequent charge and discharge cycles [6]. Accurate battery health monitoring and prediction of battery performance under bidirectional charging conditions are amongst the measures that can be deployed to mitigate these challenges [7]. Concurrently, recent advancements in artificial intelligence (AI) and blockchain technology have opened new avenues for optimising V2G systems. For instance, AI techniques have been applied for optimal coordination in V2G-integrated power distribution systems, enhancing operational efficiency [8]. Blockchain-based solutions have been proposed to improve V2G energy trading by ensuring security, transparency, and scalability [2].

Despite these advancements, several challenges continue to hinder the broader adoption of V2G technology. Battery degradation remains a significant concern for EV owners, as frequent charging and discharging cycles in V2G operations can accelerate battery ageing, leading to economic losses [6]. This issue is particularly pertinent given the high cost of EV batteries and their critical role in vehicle performance. Therefore, optimising charging and discharging processes is crucial for the efficient operation of V2G systems. However, current schemes often lack consideration for users' participation and do not fully account for their privacy concerns [1]. Efficient matching and scheduling of energy resources, particularly considering both parked and driving vehicles, is also challenging [2]. Existing approaches often assume static scenarios, neglecting the dynamic nature of real-world V2G operations where vehicle availability fluctuates. This limitation hinders the full realisation of V2G's potential and calls for more adaptive and responsive management systems. Moreover, research suggests that for V2G to contribute to a more sustainable future, the electricity sector must accept more risk and consider the social, ethical, and cultural meanings that users attach to the technology [9]. This perspective emphasises the need for a more holistic approach to V2G implementation that goes beyond technical solutions.

To this end, securing users' participation and consent are significant, as concerns about mileage anxiety and maintaining a minimum battery level influence EV owners' willingness to participate in V2G programs [1]. Research indicates that, while users are generally open to sharing data for V2G purposes, their primary concerns revolve around targeted marketing and unauthorised tracking of their locations [10]. As a result, privacy and security are seen as key challenges in V2G networks. Additionally, V2G systems are vulnerable to risks such as eavesdropping, tampering, and forgery, which can compromise user privacy and degrade service quality [11]. Given the sensitive nature of data involved in V2G transactions, including tracking user location, mining energy consumption patterns, and handling financial information, robust security measures are essential. Specifically, access to an EV's battery should be managed through more robust mechanisms. Current V2G systems typically employ basic access control mechanisms, such as mandatory access control (MAC), which do not account for the diverse and dynamic nature of vehicles participating in the grid. These approaches, while providing basic access control provisions, are not comprehensive and can lead to security risks, resulting in inefficient energy distribution, potential security vulnerabilities, and reduced user trust. Hence, there is a pressing need for an enhanced, context-aware access control model that can differentiate between various vehicle types, prioritise critical services, and take into account users' preferences.

To address these challenges, this paper introduces VESTA (vehicle energy sharing through artificial intelligence), a novel framework designed to enhance V2G energy management. VESTA integrates advanced AI techniques, blockchain technology, and edge computing to create a comprehensive solution that addresses the limitations of current V2G systems. At the core of VESTA is the semantic-aware vehicle access control (SEVAC) model, which employs semantic awareness to classify vehicle types and make optimised access control decisions, thus ensuring efficient energy distribution while prioritising critical services and respecting users' preferences. The key contributions of this work are as follows:

- Development of the SEVAC model: The SEVAC model employs semantic awareness to classify vehicles based on their types and make optimised access control decisions, addressing the challenge of users' participation and vehicle prioritisation.
- Integration of advanced AI techniques: AI-driven decision-making and machine learning predictive analytics are employed to enhance the efficiency and reliability of V2G operations, enabling real-time responses to grid demands and users' preferences.
- Implementation of a multi-layered blockchain architecture: The framework encompasses a blockchain layer that also makes use of smart contracts to ensure the security and privacy of V2G energy trading, thereby enhancing trust and accountability within the system.
- Design of a dynamic scheduling algorithm: The framework accounts for vehicles throughout their journey, whether they are recharging mid-trip or parked overnight, addressing the limitations of current matching systems and incorporating real-world time constraints to improve energy distribution and grid stability.
- Incorporation of edge computing for real-time data processing: Local processing units at strategic locations such as charging stations reduce latency and server load, enabling quicker adaptation to local energy demands and enhancing system resilience.
- Development of a user-centric interface and feedback loop: Tailored interfaces and a feedback loop enhance user engagement, allowing for continuous system improvement based on user interactions, preferences, and consent, thus addressing privacy and user trust concerns.

The scope of this paper encompasses the design, conceptualisation, and evaluation of the VESTA framework through a proof-of-concept simulation. By addressing the identified challenges of user consent, privacy protection, vehicle type prioritisation, efficient energy management, and dynamic scheduling, VESTA aims to advance the state-of-the-art in V2G technology and contribute to the development of more resilient, efficient, and sustainable energy infrastructures. The remainder of this paper is structured as follows: Section 2 reviews related work in V2G technology and smart grid management. Section 3 details the VESTA framework, including its architecture and key components. Section 4 presents a proof-of-concept implementation and results. Section 5 discusses the limitations and future work, and Section 6 concludes the paper.

2. Related Work

The rapid evolution of vehicle-to-grid (V2G) and grid-to-vehicle (G2V) technologies has sparked a flurry of research addressing key challenges in security, privacy, scalability, user engagement, energy management, efficiency, optimal control strategies, and route optimisation. This section reviews the advancements and persistent research challenges in V2G implementation, offering a comprehensive look at the current state of the field.

2.1. Blockchain-Based Solutions and Security Protocols for V2G Systems

The integration of blockchain technology in V2G systems has emerged as a promising approach to tackle security, scalability, and fairness challenges. A lightweight blockchain-based framework called the directed acyclic graph-based V2G network (DV2G) has been proposed [12]. This model employs a tangle data structure for secure and scalable transaction recording and utilises game theory for cost-optimised negotiation between the grid and vehicles, offering a highly scalable solution for V2G networks.

Building on the potential of blockchain, a privacy-preserving fair exchange scheme for V2G systems called V2GEx has been introduced [13]. This scheme addresses the critical challenges of ensuring fairness and privacy during electricity and service exchanges, incorporating an extended blockchain supporting zero-knowledge funds, a fair exchange smart contract, and a privacy-preserving protocol specifically designed for V2G interactions.

Focusing on the emerging concept of energy internet (EI), research has proposed a secure and lightweight key agreement protocol for EI-based V2G environments [14]. This approach integrates communication and computing technologies to enhance renewable energy distribution and intelligent transportation systems, achieving all required security features while reducing communication, computation, and energy overheads by approximately 28% compared to existing schemes.

2.2. Privacy-Preserving Protocols and Advanced Learning Techniques in V2G Communications

Ensuring privacy in V2G systems is paramount due to the exchange of sensitive user data. A privacy-preserving authenticated key exchange protocol for V2G communications using self-sovereign identity (SSI) concepts has been developed [15]. This approach leverages decentralised identifiers (DID) and verifiable credentials (VCs) to empower users with control over their identities, ensuring robust security against various attacks while incorporating key recovery mechanisms and an effective user revocation policy.

An innovative approach to privacy preservation in wireless charging V2G systems by integrating federated learning techniques has been proposed [16]. This adaptive demand-side energy management framework combines federated learning with reinforcement learning to enhance both privacy and cost-saving. The method demonstrates improved privacy preservation compared to existing approaches, offering a significant advancement in protecting user data within V2G networks while also optimising energy management.

2.3. User-Oriented V2G Schemes and Energy Management

Recognising the importance of user engagement and efficient energy management in V2G systems, research has explored more user-centric and optimised approaches. A case study in Shenzhen, China, focused on a user-oriented V2G scheme with multiple operation modes for peak load shaving [17]. This work explored both centralised and decentralised V2G operation modes and their impact on grid performance, highlighting the benefits of tailoring V2G systems to user preferences and behaviours.

An innovative energy management model for residential buildings integrating plug-in electric vehicles (PEVs) and on-site PV generation has been proposed [18]. This approach introduces a transactive energy market among PEVs to determine optimal charge/discharge scheduling while reimbursing PEV owners for their flexibility, achieving reduced charging payments for PEV owners and decreased total costs for the building energy management system (BEMS).

2.4. Artificial Intelligence and Optimal Control in V2G/G2V Systems

The application of artificial intelligence has shown great promise in optimising V2G/G2V control strategies. An optimal V2G control strategy using deep reinforcement learning (DRL), specifically the deep deterministic policy gradient (DDPG) algorithm, has been proposed [19]. This approach aims to maximise profits for both EV owners and energy aggregators while meeting driving demands and improving frequency regulation.

Research has advanced the field by developing an AI-based adaptive V2G and G2V controller for electric vehicle charging stations (EVCS) [8]. This system integrates a solar photovoltaic system (SPVS), storage battery (SB), electric vehicle (EV), and grid, demonstrating the potential of AI in managing complex energy systems with multiple sources and storage options.

The critical aspect of route selection and charging/discharging scheduling for EVs in V2G networks has been addressed [20]. This work introduces a time-expanded V2G graph and an AI-based A* algorithm to find optimal routes and schedules for EVs, aiming to maximise economic profits while considering constraints such as energy supply variability and charging station availability.

2.5. Barriers to V2G Adoption and Implementation Challenges

While technological advancements in V2G systems are promising, a comprehensive review of the barriers hindering widespread V2G adoption has been conducted [21]. This study identifies 23 distinct barriers spanning technical, business, and user-related challenges. Through risk and cross-impact analysis, the interconnected nature of these barriers has been highlighted, emphasising the importance of addressing business-related challenges as a priority.

One of the most significant barriers identified is the "parking-for-charging" business model, which received the highest risk score. This highlights the need for innovative business models that can effectively balance the needs of EV owners, charging infrastructure providers, and grid operators. The lack of large-scale demonstrations has also been pointed out as a critical barrier, noting the challenges in organising such demonstrations due to the need for consistent participation, substantial capital investment, and complex stakeholder coordination.

2.6. Cybersecurity Challenges and Mitigation Strategies in V2G Networks

As V2G systems become increasingly integrated with smart grids and low-carbon transportation infrastructure, cybersecurity has emerged as a critical concern. A comprehensive overview of the threats, vulnerabilities, and mitigation strategies specific to V2G networks has been provided [22]. This work highlights the unique security challenges posed by the bidirectional flow of energy and information in V2G systems.

Cyber security challenges in the broader context of low-carbon transportation have been discussed [23]. The importance of addressing security threats such as denial of service attacks and data breaches, which could potentially disrupt critical infrastructure and compromise user privacy, has been emphasised. Various defence technologies, including authentication mechanisms, encryption techniques, and intrusion detection systems, have been reviewed, highlighting their applicability in protecting V2G networks.

Several encryption techniques have shown promise in addressing privacy and security concerns in V2G systems, including homomorphic encryption, broadcast encryption, and attribute-based encryption. These techniques offer different trade-offs between security, efficiency, and access control granularity, providing a range of options for securing V2G communications and data processing.

The integration of artificial intelligence (AI) in energy management presents both opportunities and challenges from a security perspective. While AI can significantly enhance system efficiency and decision-making, it also introduces new attack vectors that must be carefully considered.

Real-world incidents, such as the 2015 Ukraine blackout caused by a false data injection attack, underscore the potential consequences of cybersecurity breaches in power systems. This highlights the need for robust security measures in V2G networks, which are increasingly becoming critical components of national energy infrastructure.

The multifaceted nature of V2G research encompasses technological innovations in blockchain, security protocols, privacy preservation, user-centric design, efficient energy management, and AI-driven control strategies. The integration of blockchain technology and advanced security protocols offers promising solutions for secure, fair, and private transactions in V2G networks. The focus on user-oriented approaches and optimised energy management emphasises the importance of considering user behaviour, preferences, and economic incentives in V2G system design. Furthermore, the application of advanced AI techniques, including federated learning, deep reinforcement learning, adaptive neural network controllers, and route optimisation algorithms, demonstrates the potential for significant improvements in grid stability, economic benefits, privacy preservation, system integration, and overall network efficiency through intelligent V2G/G2V control strategies. These AI-driven approaches are particularly crucial in managing the increasing complexity of energy systems that incorporate renewable sources, energy storage, bidirectional power flow between vehicles and the grid, and the spatial–temporal aspects of EV movement and charging. However, significant barriers to widespread adoption remain, including business model challenges, lack of large-scale demonstrations, and cybersecurity concerns. Addressing these challenges will be crucial for the successful implementation and scaling of V2G technologies.

Table 1 compares the VESTA framework with several key works in the V2G domain, using "Yes", "No", and "Partially" to provide an analysis of each framework's capabilities.

The features selected for comparison in Table 1 were chosen based on an analysis of key elements essential for effective vehicle-to-grid (V2G) systems. These include user-centric permissions, semantic vehicle classification, AI-driven decision-making, blockchain integration, privacy-preserving techniques, and real-time grid adaptation. Each of these features addresses critical challenges in V2G implementation, such as user trust, system scalability, security, and energy management efficiency. Additionally, features like user behaviour analysis and renewable energy integration were included to highlight the growing importance of user engagement and sustainable energy practices in modern V2G frameworks. These criteria were selected to reflect the most significant advancements and gaps in the current state of V2G technology, as identified in the literature review.

The scoring of "Yes", "No", and "Partially" in Table 1 is based on the presence, implementation depth, and effectiveness of each feature in the reviewed frameworks. The rationale for the scoring is as follows:

- "Yes": A "Yes" indicates that the feature is fully implemented and integrated into the framework with significant functionality and documented performance improvements. For example, VESTA is marked "Yes" for AI-driven decision-making because it leverages machine learning models for real-time grid demand prediction and optimises energy contributions based on current and future grid states.
- "No": A "No" indicates that the feature is either not present or insufficiently addressed in the framework. For instance, works like [12] focus on blockchain integration but do not incorporate AI-driven decision-making, thus receiving a "No" for this feature.
- "Partially": A "Partially" score is assigned when a feature is present but lacks full implementation or is constrained in its application. This is typically seen in frameworks where the feature may be under development or only applicable in certain scenarios. For example, some frameworks may incorporate basic AI models but fall short in handling complex, real-time decision-making processes, hence receiving a "Partially" for AI-driven decision -making. Similarly, user behavior analysis may be present in limited forms, but not central to the framework's core functions.

From Table 1, Hassija et al. [12] excelled in blockchain integration and scalability considerations but lacked in other areas, such as user-centric permissions and AI-driven decision-making. Parameswarath et al. [15] focused strongly on privacy-preserving techniques and user permissions but did not address many other aspects of V2G management. Saber et al. [18] provided robust solutions for real-time grid condition adaptation and scalability, with partial consideration of user-centric approaches and AI-driven decision-making.

Alfaverh et al. [19] and Singh et al. [8] utilised AI for decision-making and adapted well to real-time grid conditions with partial context-awareness and scalability considerations. Liang et al. [2] introduced blockchain integration alongside AI-driven decision-making, showing strong performance in real-time grid adaptation and scalability. Kumar et al. [4] focused on AI-driven decision-making and renewable energy integration with strong context-aware access control. Abdelsattar et al. [24] concentrated on renewable energy integration and real-time grid adaptation with partial AI implementation.

Wang et al. [11] prioritised user-centric permissions, privacy-preserving techniques, and blockchain integration, demonstrating strong scalability and context-aware access control. Lucas-Healey et al. [9] and Bilousova [10] emphasized user behaviour analysis and user-centric permissions, with Bilousova also focusing on privacy-preserving techniques. Chen and Zhang [1] provided a comprehensive overview, partially addressing multiple aspects, including user-centric permissions, AI-driven decision-making, and renewable energy integration.

Table 1. Comparison of VESTA with existing V2G frameworks.

Feature	User-Centric Permissions	Semantic Vehicle Classification	AI-Driven Decision-Making	Blockchain Integration	Privacy-Preserving Techniques	Real-Time Grid Adaptation	Scalability Considerations	Context-Aware Access Control	User Behavior Analysis	Renewable Energy Integration
VESTA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
[12]	No	No	No	Yes	No	No	Yes	No	No	No
[15]	Yes	No	No	No	Yes	No	No	Partially	No	No
[18]	Partially	No	Partially	No	No	Yes	Yes	No	No	Yes
[19]	No	No	Yes	No	No	Yes	Partially	Partially	No	Yes
[8]	Partially	No	Yes	No	No	Yes	Yes	Partially	No	No
[2]	No	No	Yes	Yes	Partially	Yes	Yes	Partially	No	Yes
[4]	No	No	Yes	No	No	Yes	Partially	Yes	No	Yes
[24]	No	No	Partially	No	No	Yes	Partially	No	No	Yes
[11]	Yes	No	No	Yes	Yes	Partially	Yes	Yes	No	No
[9]	Yes	No	No	No	Partially	No	No	No	Yes	No
[10]	Yes	No	No	No	Yes	No	No	No	Yes	No
[1]	Partially	No	Partially	No	No	Yes	Partially	No	Yes	Yes

VESTA introduces a unique combination of features, excelling in user-centric permissions through its semantic-aware vehicle access control (SEVAC) model, semantic vehicle classification, and context-aware access control. It integrates AI-driven decision-making, blockchain technology, and privacy-preserving techniques while considering real-time grid adaptation, scalability, and renewable energy integration. VESTA also incorporates user behaviour analysis, addressing a crucial aspect often overlooked in technical solutions. This comprehensive approach positions VESTA as a holistic solution to the complex challenges of V2G systems, though continued research and development will further enhance its capabilities in all areas.

3. Methodology

This section outlines the systematic approach employed in developing the VESTA framework, adhering to standard scientific methods in computer science and software engineering. The methodology comprises three main phases: problem identification and literature review, framework design, and proof-of-concept implementation. Figure 1 illustrates the step-by-step process of the research methodology.

The methodology flowchart in Figure 1 provides a detailed visual representation of the research process. It begins with the identification of the research problem, followed by a comprehensive literature review. The research scope is then defined based on identified gaps, leading to the selection of appropriate research methodologies. The framework design phase includes the conceptualisation of VESTA components, comparative analysis with existing models, and the development of the SEVAC model. The proof-of-concept implementation involves scenario definition, high-level pseudo-code development, and Python-based simulation. The final stages encompass data generation, result analysis, framework validation, conclusion drawing, and identification of future work areas. This structured approach ensures the thorough and systematic development of the VESTA framework.

3.1. Problem Identification and Literature Review

This research was motivated by recent events in Australia, where electric vehicles were utilised to stabilise the power grid during high-demand periods. This real-world application highlights the potential of vehicle-to-grid (V2G) technology and prompts a comprehensive exploration of existing solutions and research gaps.

A thematic literature review was conducted, focusing on areas such as artificial intelligence applications in V2G systems, privacy-preserving techniques for V2G communications, blockchain integration in energy management, user-centric approaches to V2G implementation, and cybersecurity in V2G networks. The review process involved systematic searches of major academic databases using combinations of keywords such as “V2G”, “AI”, “blockchain”, “privacy”, and “cybersecurity”. The literature was analysed to identify current approaches, challenges, and potential areas for improvement.

The review revealed the need for a more comprehensive framework that integrates context-aware decision-making, user permissions, and advanced security measures in V2G systems. Specifically, it identified the importance of considering context, location, vehicle types, and user permissions as key factors in V2G energy-sharing decisions.

3.2. Framework Design

Based on the insights from the literature review, the VESTA framework was conceptualised. The design phase focused on developing a novel access control model, SEVAC (semantic-aware vehicle access control), which adapts principles from attribute-based access control (ABAC) and context-aware access control approaches.

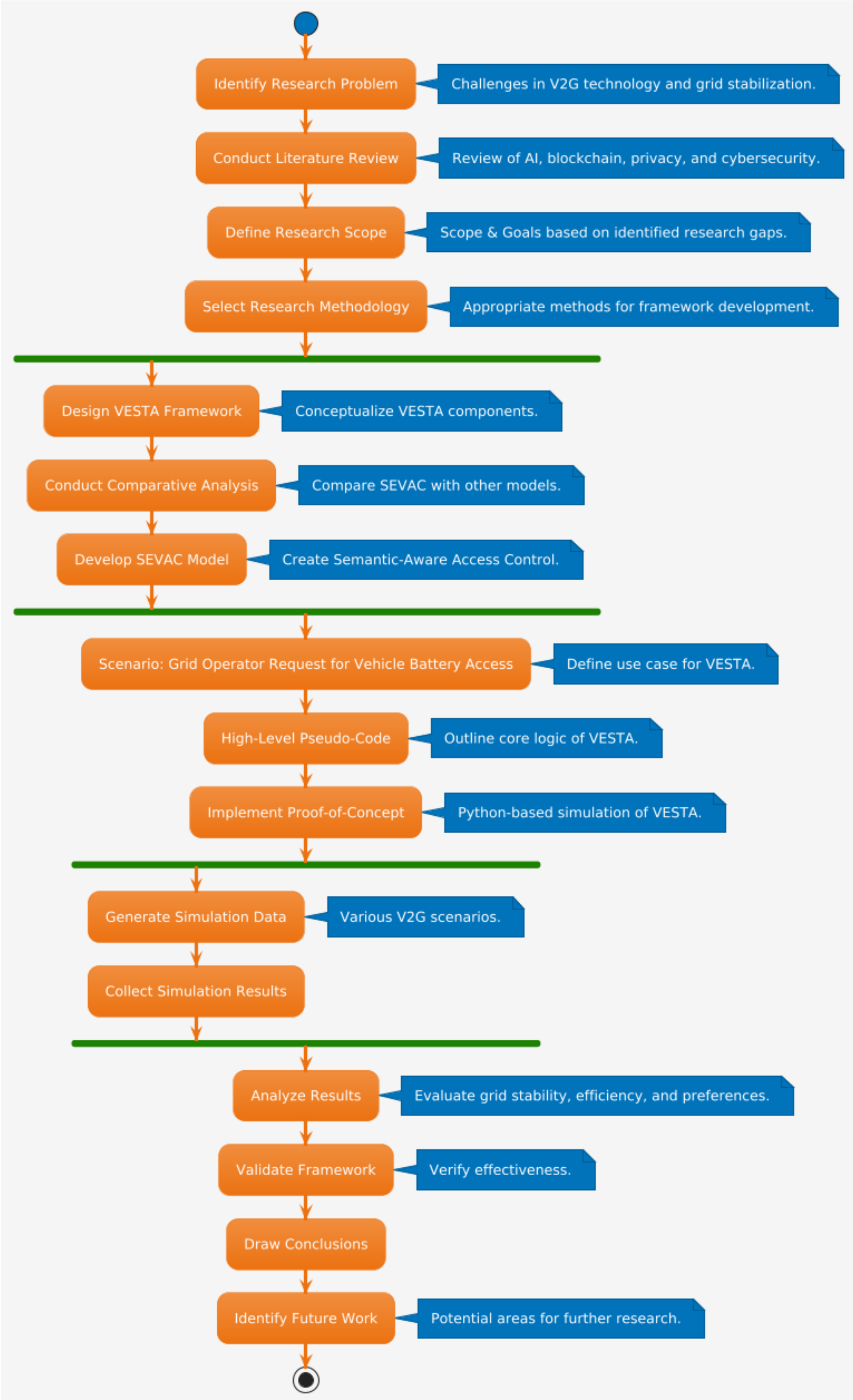

Figure 1. Research methodology.

The framework design process involved defining the core components of VESTA and developing the SEVAC model to incorporate context, location, vehicle types, and user permissions. It included designing the integration of AI decision-making modules for adaptive control and incorporating blockchain technology for secure and transparent transactions. Ensuring scalability and flexibility to accommodate various V2G scenarios was also a key consideration. The VESTA framework was developed through an iterative design process. This involved applying attribute-based access control (ABAC) principles, refining these with context-aware decision-making, and integrating AI-driven predictive models and blockchain technology. Specifically, the semantic-aware vehicle access control (SEVAC) model was built using first-order logic for policy formulation, enabling it to adapt to varying V2G conditions, vehicle types, and user permissions. Each vehicle's context, including its location and charge status, informed real-time energy-sharing decisions, creating a dynamic and responsive system.

As a key component of the VESTA framework, the semantic-aware vehicle access control (SEVAC) model was developed. The design process involved the following:

1. Defining the core components of SEVAC based on identified V2G challenges.
2. Adapting principles from ABAC and context-aware access control approaches.
3. Incorporating semantic vehicle classification and predictive analytics capabilities.
4. Designing an adaptable decision-making process using first-order logic for policy definition.

3.3. Comparative Analysis Framework for Access Control Methods in V2G Systems

As part of the methodology to establish the significance of the proposed semantic-aware vehicle access control (SEVAC) model, a comparative analysis framework was developed. This framework aims to evaluate SEVAC against existing access control methods commonly used in vehicle-to-grid (V2G) systems. The comparative analysis framework consists of the following steps:

1. Identification of key features: Critical features relevant to V2G access control were identified, including context-awareness, semantic classification capabilities, predictive analytics, adaptability, policy complexity, real-time decision-making, and V2G-specific features.
2. Selection of baseline models: Two baseline models were selected for comparison: traditional attribute-based access control (ABAC) and generic context-based access control models. These were chosen as they represent common approaches in current V2G systems.
3. Feature evaluation criteria: For each identified feature, criteria were established to assess the performance level (e.g., No/Basic/Limited/Moderate/Advanced/Extensive) based on the capabilities of each model.
4. Comparative matrix development: A matrix was created to visualise the comparison across all selected features for SEVAC and the baseline models.
5. Analysis of comparative advantages: The completed matrix was analysed to identify areas where SEVAC potentially offers advancements over existing methods.

This comparative framework provides a structured approach to evaluate the proposed SEVAC model against current access control methods in V2G systems. Table 2 presents a detailed comparison of SEVAC with traditional attribute-based access control (ABAC) and other context-based models.

The results of this analysis, presented in subsequent sections, aim to demonstrate SEVAC's potential advancements in areas crucial for effective V2G energy management.

Table 2. Comparison of ABAC, context-based access control models, and SEVAC.

Feature	ABAC	Context-Based Models	SEVAC
Context-Awareness	Basic	Moderate	Advanced
Semantic Classification	No	Limited	Yes
Predictive Analytics	No	No	Yes
Adaptability	Limited	Moderate	High
Policy Complexity	Medium	High	Very High
Real-Time Decision-Making	Limited	Moderate	Advanced
V2G-Specific Features	No	Limited	Extensive

3.4. Proof of Concept Implementation

To validate the VESTA framework, a proof-of-concept (PoC) was implemented using Python 3.9 The PoC aimed to demonstrate the feasibility of the framework and its core components in a simulated environment.

As outlined in the methodology flowchart (Figure 1), the PoC implementation began with developing a primary scenario: a grid operator's request for vehicle battery access. This scenario served as the foundation for creating a high-level pseudo-code that outlined VESTA's core logic.

The simulation environment was designed to model a simplified V2G ecosystem, incorporating representations of various electric vehicle types with different attributes, grid demand fluctuations, and the SEVAC Engine for access control decisions. Basic blockchain transactions for energy sharing and AI-driven prediction of grid demand and energy distribution were also integrated.

The simulation utilised Python libraries such as NumPy for numerical computations, Pandas for data manipulation, Matplotlib for visualisation, and pycryptodome for cryptographic functions and blockchain simulation.

Building upon the primary scenario, multiple sub-scenarios were simulated to thoroughly test the framework's functionality. These included normal grid operation with diverse vehicle types, high-demand periods, low grid demand with high vehicle availability, and prioritisation of critical service vehicles. Each sub-scenario featured vehicles with varying attributes and initial charge levels, whilst grid demand conditions were simulated using simplified models based on typical patterns.

The PoC implementation followed a model-driven engineering approach, where specific models (e.g., vehicle energy models and grid demand models) were developed and tested in a controlled simulation environment. The simulation used Monte Carlo methods to simulate various grid demand scenarios and assess how SEVAC responded under fluctuating conditions. AI models were trained using historical grid demand data, which informed real-time predictions and adjustments in energy contributions.

For the blockchain integration, smart contracts were implemented to simulate secure energy transactions. Cryptographic algorithms, such as those from the PyCryptodome library, were employed to ensure the integrity and traceability of these transactions.

The evaluation of the PoC involved assessing the framework's ability to prioritise critical vehicles, respect user preferences, and maintain grid stability. Performance metrics such as grid stability, energy efficiency, and adherence to user-defined rules were analysed using Python libraries.

This comprehensive approach allowed for the generation of diverse simulation data, the collection of results across various V2G scenarios, and the subsequent analysis. The results demonstrated the feasibility and effectiveness of the VESTA framework in managing complex V2G scenarios, validating its potential for real-world application.

4. Overview of the Proposed Vehicle Energy Sharing through AI Framework (VESTA)

The vehicle energy sharing through AI (VESTA) framework introduces an innovative approach to vehicle-to-grid (V2G) energy sharing, designed to enhance grid stability, optimise user engagement, and support sustainable energy practices. By integrating advanced technologies with user-centric principles, VESTA ensures that every aspect of V2G energy sharing is managed with precision and adaptability. The framework's architecture is presented in Figure 2. It comprises of several interconnected layers that addresses the complex challenges faced by modern energy systems, focusing on user consent, context-aware operations, privacy, and security through the implementation of smart contracts and AI-driven decision-making.

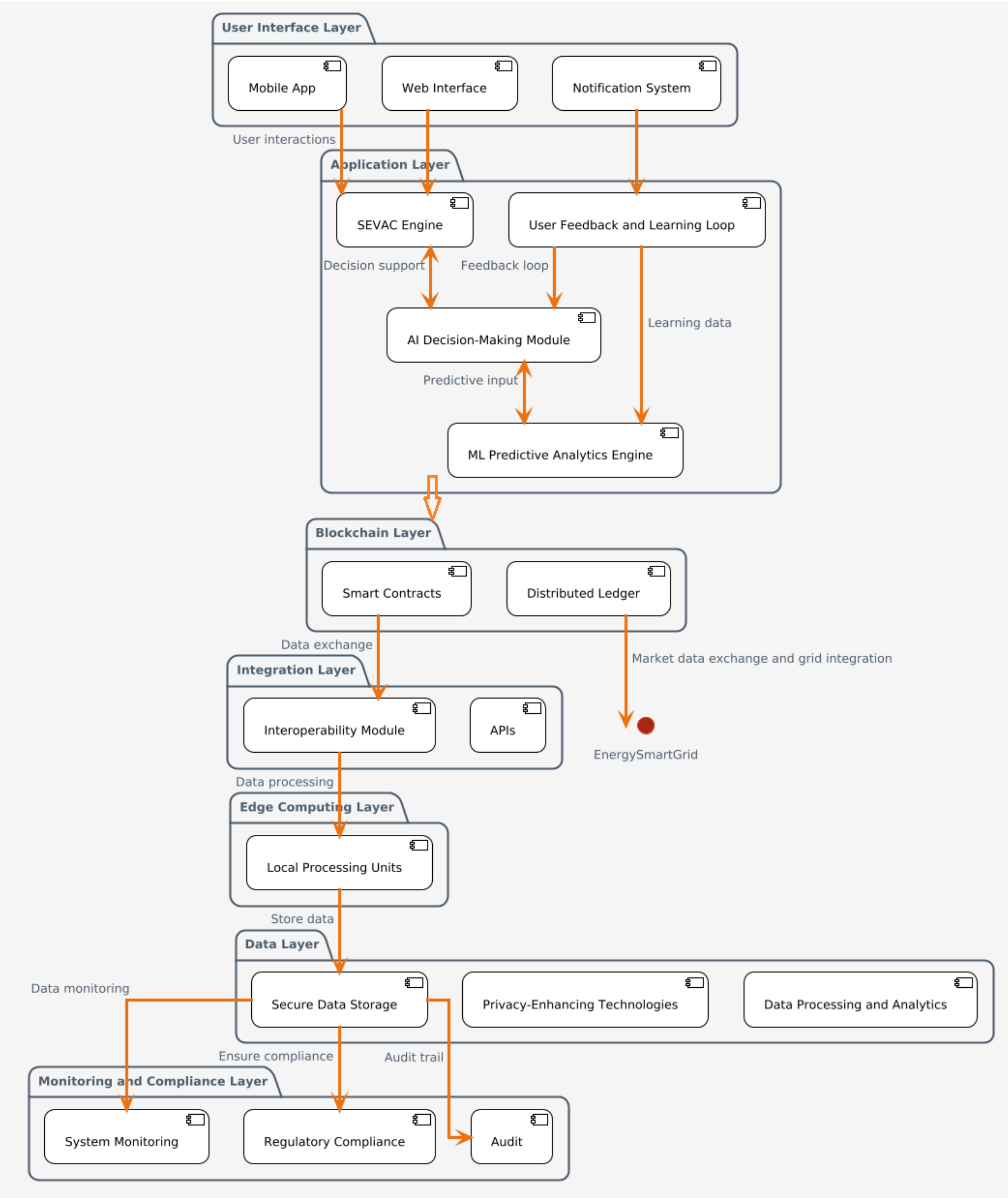

Figure 2. VESTA architecture showing all its layers and components.

4.1. User Interface Layer

The user interface layer in VESTA is tailored to cater to the diverse needs of stakeholders, including vehicle owners, grid operators, policymakers, and service technicians. Each interface is designed to present relevant data, controls, and analytics, facilitating efficient management and informed decision-making. Vehicle owners benefit from intuitive mobile and web interfaces, enabling them to manage energy-sharing settings, monitor participation statistics, and track accrued benefits. A robust notification system ensures that all users are kept informed about critical updates, such as energy requests during peak times, policy changes, and reward statuses. This layer plays a crucial role in optimising user interaction with the system, thereby enhancing overall engagement and operational efficiency.

4.2. Application Layer

At the core of VESTA lies the application layer, which integrates several key components that drive the framework's intelligent operations. The semantic-aware vehicle access control (SEVAC) engine classifies vehicles by type, whether emergency, commercial, or private, and dynamically manages access permissions based on this classification, as well as factors like battery status, location, and user preferences. This ensures that energy is not inappropriately drawn from critical service vehicles, thereby maintaining readiness and operational integrity. The AI decision-making module utilises artificial intelligence to make informed, real-time decisions regarding energy allocation across the grid, taking into account vehicle availability and user-defined parameters to optimise distribution while preserving system stability. Complementing these, the ML predictive analytics engine processes both historical and real-time data to accurately predict grid energy requirements, forecast peak demand periods, and plan energy requests, thus enhancing the system's responsiveness and efficiency. Moreover, the user feedback and learning loop directly integrate user feedback into the system's learning processes, continuously refining AI algorithms to better align with user preferences, ultimately improving satisfaction and engagement.

4.3. Blockchain Layer

The blockchain layer underpins VESTA's operations by providing security and transparency. Smart contracts automate transactions and enforce policies, embedding terms directly into code to ensure reliable, manual-intervention-free operations. The distributed ledger maintains a transparent and immutable record of all transactions and activities, enhancing trust and accountability within the ecosystem. Additionally, this layer facilitates real-time interactions with energy markets, enabling dynamic pricing and allowing users to monetise their energy contributions securely.

4.4. Integration Layer

Ensuring seamless operation across various systems and platforms, the integration layer plays a pivotal role in VESTA's architecture. The interoperability module facilitates effective communication with other energy management systems, smart city infrastructures, and V2G platforms, thereby enhancing VESTA's adaptability and scalability. Furthermore, APIs connect VESTA to external systems, such as vehicle telematics, charging stations, and the electrical grid, enabling real-time data exchange that is essential for the AI and ML engines to adapt to user needs and grid demands efficiently.

4.5. Edge Computing Layer

The edge computing layer is introduced to decentralise data processing, ensuring that VESTA remains responsive even in distributed environments. Local processing units strategically positioned at locations such as charging stations manage real-time data processing and adapt quickly to local energy demands, thereby reducing latency and alleviating server load.

4.6. Data Layer

The data layer is integral to the security and integrity of the system's operations. Secure data storage employs advanced encryption and robust protection measures to safeguard user data and transaction records. Privacy-enhancing technologies, such as differential privacy and secure multi-party computation, ensure that user privacy is maintained without compromising system functionality. This layer also supports extensive data processing and analytics, allowing the system to learn from patterns, enhance predictive accuracy, and continually refine user experiences.

4.7. Monitoring and Compliance Layer

VESTA's monitoring and compliance layer ensures that the system operates within established regulatory frameworks. System monitoring tracks performance and user activity, maintaining operational standards and identifying potential issues early. Regular audits and compliance checks are integral to this layer, ensuring adherence to energy regulations, vehicle safety standards, and privacy laws. This continuous evaluation process fosters a secure and reliable environment for V2G operations, ensuring that all activities within VESTA comply with legal and safety standards.

VESTA represents a paradigm shift in how V2G energy sharing is conceptualised and executed, integrating advanced technological solutions with a deep understanding of user needs and system requirements. This comprehensive framework is tailored to meet the demands of a dynamic energy landscape, promising enhanced grid stability, user empowerment, and sustainable energy utilisation.

5. Semantic-Aware Vehicle Access Control Model (SEVAC): Formal Framework Definition

The SEVAC framework is defined formally by the following tuple:

$$SEVAC = (S, O, A, E, ATT, POL, DEC, CONST), \tag{1}$$

where S represents the set of subjects or vehicle owners, O represents the set of objects or available energy resources, A includes the actions that subjects can perform such as charging, discharging, or sharing energy, and E encompasses the set of environmental states, which includes grid conditions and time variables.

The attribute set ATT is a comprehensive collection of attributes relevant to the system, and POL contains policies expressed in a structured policy language. The decision function DEC and system constraints $CONST$ ensure compliance with operational and safety standards.

5.1. Detailed Components

Attributes are categorised into subsets as follows:

$$\begin{aligned} ATT_S &: \text{ Attributes related to subjects such as user preferences and behaviour;} \\ ATT_O &: \text{ Attributes related to objects including energy capacity;} \\ ATT_E &: \text{ Environmental attributes like grid load;} \\ ATT_V &: \text{ Vehicle-specific attributes such as type and priority level.} \end{aligned} \tag{2}$$

A classification function maps each subject to a vehicle class:

$$CLASS : S \to C, \tag{3}$$

where C includes categories like emergency, commercial, and private vehicles, enhancing decision accuracy.

5.2. Policy Language and AI Integration

Policies in POL are defined using first-order logic-based language:

$$POL : \text{First-order logic-based language supporting complex conditions.} \tag{4}$$

The decision function DEC integrates AI-driven predictions and attribute updates:

$$DEC : S \times O \times A \times E \to \{\text{PERMIT, DENY}\}. \tag{5}$$

The function permits an action if there exists a policy p in POL, such that the evaluated policy conditions return true, considering all relevant attributes.

5.3. Dynamic Components

Dynamic components of the system include the UPDATE and PREDICT functions, which ensure responsiveness to real-time data:

$$UPDATE : ATT \times E \times T \to ATT, \tag{6}$$

$$PREDICT : ATT \times E \times T \to E'. \tag{7}$$

5.4. Temporal Dynamics and Constraints

Temporal dynamics are introduced by incorporating time, capturing the dynamic nature of V2G systems:

$$ATT : S \cup O \cup E \times T \to V, \tag{8}$$

where V denotes the set of possible attribute values.

5.5. Security Properties

The formal security properties of SEVAC aim to ensure the system maintains critical functionalities and adheres to fairness in energy distribution.

Theorem 1. *Key properties include availability, ensuring critical services such as emergency vehicle charging are prioritised, and fairness, guaranteeing that energy resources are distributed equally among users.*

5.6. SEVAC: A Holistic Approach to V2G Access Control

The semantic-aware vehicle access control (SEVAC) model, illustrated in Figure 3, represents a significant advancement in vehicle-to-grid (V2G) energy management systems. This model addresses the critical challenges of dynamic resource allocation and context-aware decision-making in smart grid environments.

SEVAC's innovation lies in its integration of semantic vehicle classification (CLASS) with a comprehensive set of attributes (ATT), including subject, object, environmental, and vehicle-specific factors. This approach enables fine-grained access control decisions that consider the immediate state of the grid and vehicles and predict future states through the PREDICT function.

The model's decision function (DEC) synthesises inputs from various components, including real-time environmental data (E), user-defined policies (POL), and system constraints (CONST). This holistic approach ensures that energy-sharing decisions are not only efficient but also align with user preferences and critical infrastructure needs.

A key strength of SEVAC is its adaptability, which is facilitated by the UPDATE function. This feature allows the model to refine its decision-making process based on new data and changing conditions, which is crucial in the dynamic V2G landscape. Moreover, the incorporation of first-order logic in policy definition provides the flexibility to express complex conditions, which is essential for managing diverse vehicle types and grid scenarios.

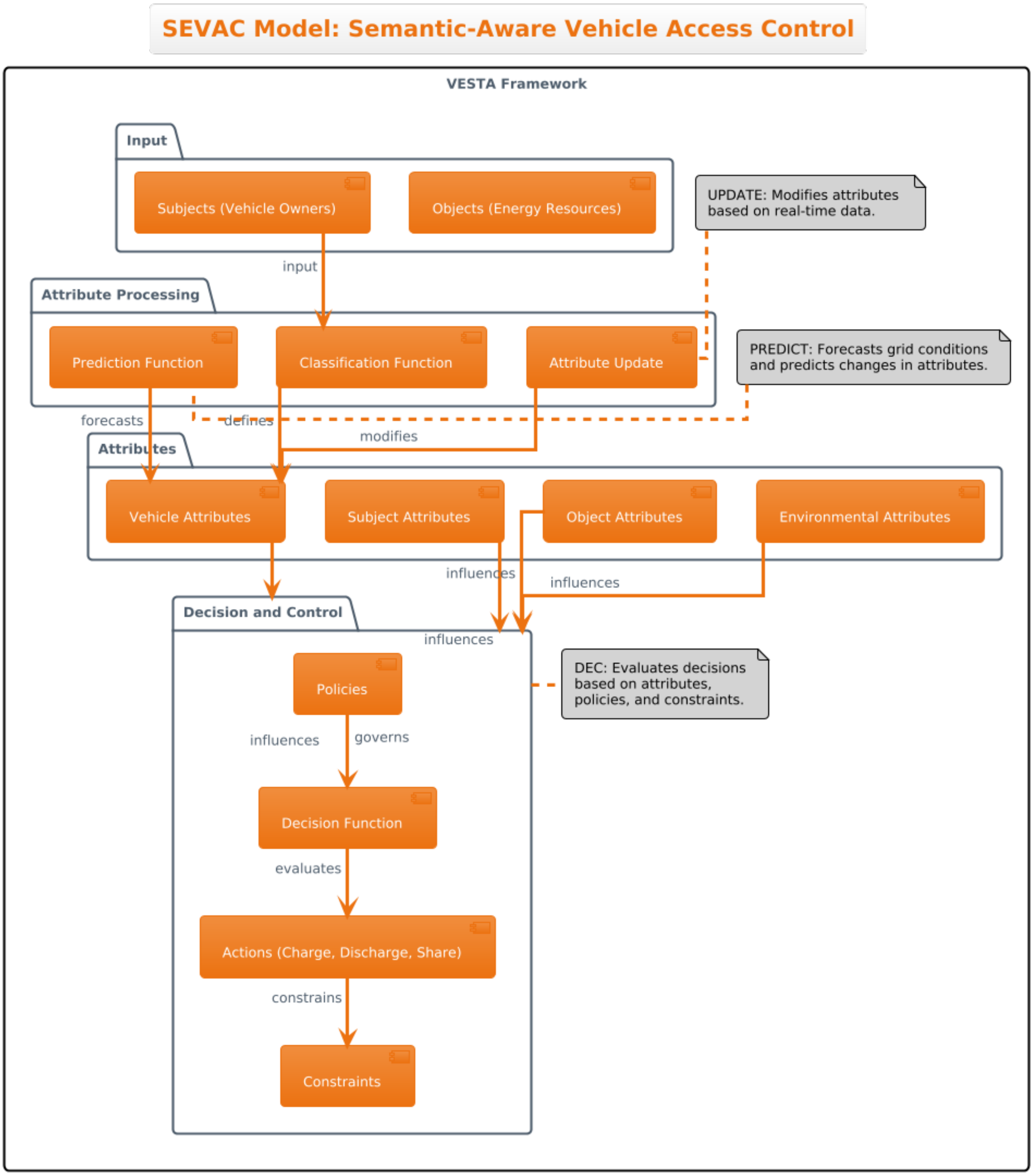

Figure 3. SEVAC model.

By encapsulating these elements within a unified framework, SEVAC offers a robust solution to the challenges of balancing grid stability, user preferences, and vehicle priorities in V2G systems. This model forms the cornerstone of the VESTA framework, providing a theoretical foundation for implementing intelligent, context-aware energy sharing in smart grid ecosystems.

5.7. Enhanced Context-Aware Decision-Making in SEVAC

Building upon traditional attribute-based access control (ABAC) models, SEVAC integrates advanced context-aware decision-making and semantic vehicle classification into the access control process. As compared in Table 1, SEVAC enhances the foundation of ABAC by incorporating features tailored specifically for V2G systems. This model's ability to integrate real-time environmental data, vehicle-specific attributes, and user-defined policies allows for a more nuanced and responsive approach to energy distribution.

By classifying the vehicles based on their type, e.g., as emergency services, commercial, and private vehicles, SEVAC ensures that critical resources are prioritised appropriately, especially during high-demand periods. The model's predictive analytics capability further enhances decision-making by forecasting future grid states and vehicle availability, enabling proactive energy management.

Additionally, SEVAC's dynamic policy update mechanism allows the system to adapt to changing conditions in real-time, ensuring that energy-sharing decisions remain aligned with both grid requirements and user preferences. The use of first-order logic in defining access control policies adds a layer of complexity and flexibility, supporting sophisticated conditions tailored to the specific needs of V2G operations.

6. Scenario: Grid Operator Request for Vehicle Battery Access

The practical application of the VESTA framework, particularly its SEVAC model, is demonstrated through a scenario in which a grid operator requests access to a vehicle's battery during peak demand periods. This scenario not only elucidates the operational intricacies of the framework but also highlights how it integrates AI and ML technologies to manage real-time energy demands effectively.

6.1. System Interaction Sequence

Building upon the introduction of the VESTA framework, the following scenario exemplifies how its components work together to process a grid operator's request for vehicle battery access. This scenario highlights the efficiency and decision-making prowess of VESTA, particularly the SEVAC Engine, in balancing grid demands with user preferences and vehicle status.

Figure 4 illustrates the streamlined sequence of interactions within the VESTA framework during this process.

In this sequence, the procedural steps, from the initial request to the final decision, are depicted with key interactions that include the following:

- The SEVAC engine orchestrates the overall decision-making process, acting as the central hub of the VESTA framework.
- AI-driven modules conduct predictive analytics, leveraging machine learning to generate forecasts that inform the decision-making process.
- Smart contracts verify and enforce user agreements, ensuring that energy sharing adheres to predefined conditions and contractual obligations.
- Real-time interactions occur with the vehicle interface to execute access commands and with the user notification system to keep stakeholders updated on the process.

This streamlined interaction sequence underscores VESTA's ability to handle complex decisions dynamically, optimising energy distribution while safeguarding user preferences and grid stability.

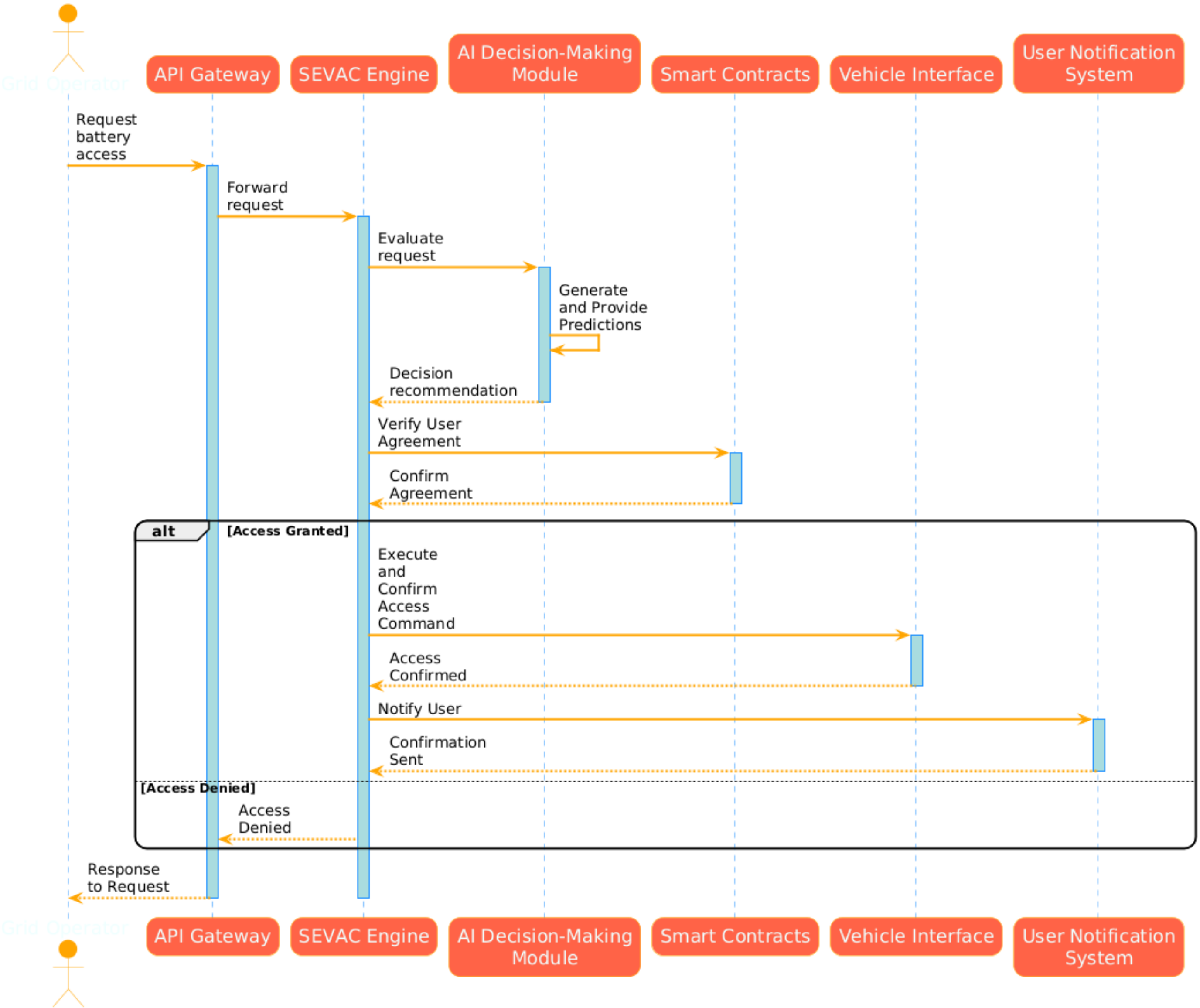

Figure 4. Sequence diagram: VESTA framework processing a grid operator's request.

6.2. Decision Flow and Data Processing

To complement the interaction sequence, Figure 5 provides a detailed flowchart that outlines the decision-making process within the SEVAC engine. This diagram offers insights into the specific data flows and decision nodes encountered when processing a battery access request.

The process begins with the classification of vehicles based on key attributes, such as vehicle type, current battery status, and location. The SEVAC engine then integrates environmental data and user preferences to tailor decisions according to the current conditions and user-defined settings. Subsequently, the system employs artificial intelligence to predict grid demand, ensuring that energy resources are allocated optimally.

As the process unfolds, the SEVAC engine evaluates various decision nodes, determining whether to grant or deny battery access. These decisions are based on a comprehensive analysis of operational policies, user constraints, and the overall status of the grid. Upon approval of access, the system proceeds with procedural steps, such as contract creation and user notification, thereby completing the decision-making cycle.

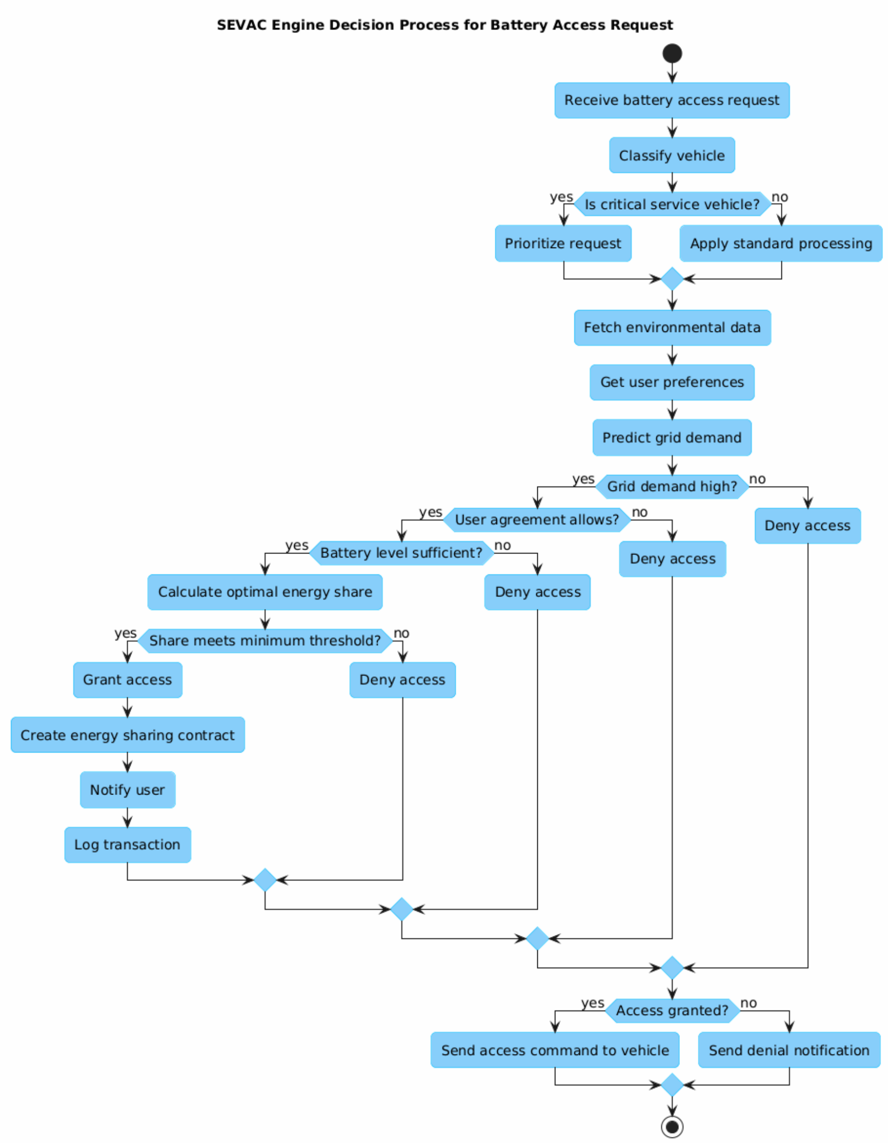

Figure 5. Flowchart: SEVAC engine decision process for battery access requests.

7. Proof of Concept

To demonstrate the practical application and efficacy of the VESTA framework, a proof of concept (PoC) was developed using Python. This PoC simulates a complex scenario where a smart grid, experiencing high demand due to a heatwave, must make real-time decisions about accessing vehicle batteries to balance the load. The simulation involves multiple vehicles of different types (emergency, commercial, and private), each with varying charge levels and user preferences.

7.1. Simulation Setup and Parameters

The PoC was developed using Python, leveraging a range of libraries to handle various aspects of the simulation. NumPy was used for numerical computations, Pandas for data handling, Matplotlib for generating visualisations, and Scikit-learn for implementing AI and machine learning algorithms. Additionally, hashlib was utilised for cryptographic functions in the blockchain simulation. The simulation was executed on a typical workstation with the following key parameters:

- Number of vehicles: 10 (divided into emergency, commercial, and private vehicles).
- Grid demand levels: Simulated to range between 0.5 and 1.0 to represent high-demand scenarios.

- Energy contribution limits: Vehicles were allowed to contribute between 5% and 20% of their available charge based on the conditions.
- Simulation duration: The simulation covered a period representing several hours of grid operation under high demand.
- Grid stability metrics: Grid stability was monitored using a custom metric that tracked fluctuations in grid performance, both with and without VESTA's intervention.
- AI prediction model: The AI model was used to inform decisions by estimating grid demand based on predefined rules and available data inputs. These predictions were updated periodically to reflect the simulated grid conditions and help manage energy contributions effectively.
- CO_2 emissions calculation: The simulation included a model for estimating CO_2 emissions based on the energy mix used during peak demand. The emissions were calculated for scenarios both with and without VESTA intervention, providing a comparison to a baseline where fossil fuel-based plants were primarily used.
- Baseline comparison: A baseline scenario was established where the grid relied on traditional fossil fuel-based plants to manage peak demand. This was used as a benchmark to assess the environmental impact of the VESTA framework.

The choice of parameters in this simulation assumes the following conditions:

- Grid demand levels: The range of 0.5 to 1.0 represents moderate to high grid demand, reflecting situations where grid stress increases, such as during a heatwave. This range ensures the system is tested in both standard and peak demand conditions, where V2G operations are critical for grid balancing.
- Energy contribution limits: Vehicles were allowed to contribute between 5% and 20% of their available charge to balance grid needs and user autonomy. This range was selected based on assuming that there is a requirement to preserve vehicle battery health while also supporting the grid. The limit ensures that vehicle owners do not deplete their batteries entirely, which is an essential factor in real-world adoption.
- Simulation duration: The time frame represents several hours of grid operation under stress-testing scenarios to capture the dynamic interaction between grid demand fluctuations and vehicle energy contributions. The duration ensures that both short-term and sustained performance of the VESTA framework are evaluated.

This design of the simulation attempts to mimic realistic conditions, stress-testing VESTA's performance in grid balancing, user prioritisation, and energy management, providing initial insights into its scalability and operational efficiency.

These libraries provided the computational efficiency and flexibility necessary to model complex interactions between the vehicles and the grid. The setup enabled real-time decision-making processes to be effectively simulated, allowing for a detailed exploration of VESTA's capabilities in balancing grid demand with vehicle energy contributions, maintaining grid stability under varying conditions, and reducing CO_2 emissions compared to traditional grid management methods.

7.2. Grid Stability and Input Data

Grid stability was calculated based on the balance between energy demand and contributions from vehicles. A custom grid stability metric was defined as follows:

$$\text{Grid Stability Metric} = \frac{\text{Energy Contributed by Vehicles}}{\text{Total Grid Demand}}.$$

This metric helped us to evaluate how well vehicle energy contributions aligned with fluctuating grid demands, particularly under high load conditions. Stability values closer to 1 indicated a balanced grid, while lower values signalled instability. This metric was tracked over time in the simulation both with and without VESTA's intervention, offering insights into VESTA's role in maintaining grid stability. The simulation assumed the following input data:

- Grid data: Simulated high-demand grid data with fluctuations between 50% and 100% of peak load.
- EV data: Data on 10 vehicles (emergency, commercial, and private) with varying charge levels ranging from 50% to 100%.
- Demand curve: The grid demand followed a predefined curve to model stress-testing during peak and off-peak periods.
- AI model inputs: Assumptions were made in terms of historical grid data and current grid demand, which were provided to the AI model to predict grid load and adjust vehicle contributions accordingly.

This setup allowed for an initial exploration of VESTA's capabilities in managing grid stability and vehicle prioritisation.

7.3. Pseudocode

A high-level pseudocode that outlines the core logic and flow of the VESTA framework is provided in this section. The VESTA framework can be described in four main parts: initialisation, AI prediction model, the core decision-making process, and utility functions.

7.3.1. Part 1: Initialisation and Input/Output Definition

This section defines the input and output variables, as well as the constants used throughout the algorithm provided in Algorithm 1.

Algorithm 1 VESTA

Input variables:
vehicles: List of vehicle objects, where each vehicle is defined as:
    vehicle.id: Unique identifier for the vehicle
    vehicle.type: Type of vehicle (emergency, commercial, private)
    vehicle.charge: Current charge level of the vehicle's battery
grid_demand: Float representing current grid demand (range: 0 to 1)
user_permissions: Dictionary mapping vehicle IDs to user permission status (True/False)
historical_grid_data: Time series data representing past grid demand
Output variables:
energy_contributions: List of energy contribution objects, where each object contains:
    contribution.vehicle_id: ID of the contributing vehicle
    https://url.au.m.mimecastprotect.com/s/KTXXCwVLY6fWqV81SXS2CJrnoM?domain=contribution.energyAmountofenergycontributed
system_activities: List of logged system activities
data_analysis: Object containing summary statistics
Constants:
$MIN\_CHARGE\_THRESHOLD \leftarrow 50$
$MAX\_ENERGY\_CONTRIBUTION \leftarrow 20$
$CRITICAL\_CHARGE\_THRESHOLD \leftarrow 50$
$HIGH\_PRIORITY\_CHARGE\_THRESHOLD \leftarrow 60$
$STANDARD\_CHARGE\_THRESHOLD \leftarrow 70$
$HIGH\_PRIORITY\_DEMAND\_THRESHOLD \leftarrow 0.5$
$STANDARD\_DEMAND\_THRESHOLD \leftarrow 0.8$

7.3.2. Part 2: AI Prediction Model

This section outlines the process of using AI to predict grid demand based on historical and real-time data using Algorithm 2 .

Algorithm 2 VESTA framework: AI prediction model

```
procedure PredictGridDemand(historical_grid_data, current_grid_demand)
    model ← TrainAIPredictionModel(historical_grid_data)
    grid_prediction ← model.Predict(current_grid_demand)
    return grid_prediction
end procedure
```

7.3.3. Part 3: Core Decision-Making Process

This section outlines the main simulation procedure, which processes each vehicle and makes decisions about energy contributions. The relevant pseudocode is provided in Algorithm 3.

Algorithm 3 VESTA framework: Core decision-making.

```
procedure RunVESTASimulation(vehicles, grid_demand)
    energy_contributions ← ∅
    system_activities ← ∅
    if ¬ ValidateInput(vehicles, grid_demand) then
        throw InvalidInputException
    end if
    grid_prediction ← PredictGridDemand(historical_grid_data, grid_demand)
    for each vehicle in vehicles do
        user_permission ← GetUserPermission(vehicle.id)
        if user_permission = FALSE then
            system_activities.Append("User permission denied for vehicle " + vehicle.id)
            continue
        end if
        processed_vehicle ← LocalProcessor.ProcessData(vehicle)
        decision ← API.ProcessRequest(processed_vehicle, grid_prediction)
        if decision = PERMIT then
            energy_amount ← CalculateEnergyContribution(vehicle.charge)
            contract ← CreateContract(vehicle.id, energy_amount)
            RecordTransaction(contract, vehicle.id, energy_amount)
            energy_contributions.Append({vehicle.id, energy_amount})
            system_activities.Append("Energy drawn from vehicle " + vehicle.id)
        else
            system_activities.Append("Vehicle " + vehicle.id + " not selected")
        end if
    end for
    data_analysis ← AnalyzeData(vehicles)
    return energy_contributions, system_activities, data_analysis
end procedure
procedure Main
    vehicles ← LoadVehicleData()
    grid_demand ← GetCurrentGridDemand()
    contributions, activities, analysis ← RunVESTASimulation(vehicles, grid_demand)
    Generate Visualizations(contributions, activities, analysis)
end procedure
```

The SEVAC (semantic-aware vehicle access control) decision function, as detailed in Algorithm 3, is the central mechanism that determines whether a vehicle's battery can be accessed for energy contribution. The function first checks the user's permission (`user_permission = FALSE`), ensuring that no energy is drawn without the owner's consent. It then evaluates the vehicle's classification (`ClassifyVehicle(vehicle)`), i.e., whether it is critical, of high priority, or standard, and cross-references this with the vehicle's current charge and the predicted grid demand (`grid_prediction`). Only if the vehicle meets all the necessary criteria, such as having a charge above the relevant threshold `CRITICAL_CHARGE_THRESHOLD`, the function returns `PERMIT`, allowing energy contribution. Otherwise, the decision defaults to `DENY`. This layered decision-making process ensures that VESTA manages energy resources intelligently, balancing the needs of the grid with user autonomy and vehicle priorities.

7.3.4. Part 4: Utility Functions

This section includes supporting functions that are crucial for the decision-making process, such as the SEVAC decision function and vehicle classification. The pseudocode for the utility functions is provided in Algorithm 4.

Algorithm 4 VESTA framework: Utility functions.

```
procedure SEVACDecision(vehicle, vehicle_class, grid_prediction, user_permission)
    if user_permission = FALSE then
        return DENY
    else if vehicle_class = critical ∧ vehicle.charge > CRITICAL_CHARGE_THRESHOLD then
        return PERMIT
    else if vehicle_class = high_priority ∧ vehicle.charge > HIGH_PRIORITY_CHARGE_THRESHOLD ∧ grid_prediction > HIGH_PRIORITY_DEMAND_THRESHOLD then
        return PERMIT
    else if vehicle_class = standard ∧ vehicle.charge > STANDARD_CHARGE_THRESHOLD ∧ grid_prediction > STANDARD_DEMAND_THRESHOLD then
        return PERMIT
    else
        return DENY
    end if
end procedure
procedure ClassifyVehicle(vehicle)
    if vehicle.type = emergency then
        return critical
    else if vehicle.type = commercial then
        return high_priority
    else
        return standard
    end if
end procedure
```

The four pseudocodes provided in this section offer a comprehensive overview of the VESTA framework's main components and their interactions. They illustrate the flow of data and decision-making processes, from input validation to energy contribution calculations and blockchain transactions. By integrating an AI prediction model, the VESTA framework enhances its ability to anticipate grid demands and adjust vehicle energy contributions dynamically. This approach not only optimises grid stability but also ensures that energy-sharing decisions are made with a forward-looking perspective, accounting for both current and predicted future conditions.

7.4. Implementation Details

The PoC implementation in Python closely follows the logic outlined in the pseudocode above. Each layer of the VESTA framework is represented by specific classes and functions, as detailed in the following subsections.

7.4.1. User Interface Layer

The user interface layer in the PoC is represented by a simple notification system, as shown in Listing 1.

Listing 1. User Interface Notification System.

```
class UserInterface:
    def display_notification(self, user_id, message):
        print(f"Notification to User {user_id}: {message}")
```

This class simulates the user-facing component of the VESTA framework, providing a mechanism to inform vehicle owners about the status of their energy contribution. In a full implementation, this layer would include more sophisticated interfaces, possibly mobile apps or web portals, allowing users to set preferences and view detailed energy-sharing statistics.

7.4.2. Application Layer

The application layer forms the core of the VESTA framework, encompassing the SEVAC engine, AI decision module, and ML predictive analytics. Listing 2 shows the implementation of the SEVAC engine.

Listing 2. SEVAC Engine Implementation.

```
class SEVACEngine:
    def evaluate_request(self, vehicle, grid_demand):
        vehicle_class = self.classify_vehicle(vehicle)
        prediction = self.ml_module.predict_demand(grid_demand)
        decision = self.ai_module.make_decision(vehicle, vehicle_class,
    prediction)
        return decision

    def classify_vehicle(self, vehicle):
        if vehicle['type'] == 'emergency':
            return 'critical'
        elif vehicle['type'] == 'commercial':
            return 'high_priority'
        else:
            return 'standard'
```

The SEVAC engine classifies vehicles and coordinates the decision-making process, integrating predictions from the ML module and decision logic from the AI module. This implementation demonstrates how the framework considers vehicle type, battery charge, and predicted grid demand to make nuanced decisions about energy sharing.

7.4.3. Blockchain Layer

The blockchain layer is simulated through the SmartContract and DistributedLedger classes, as shown in Listing 3.

Listing 3. Blockchain Layer Implementation.

```
class SmartContract:
    def create_contract(self, vehicle_id, energy_amount):
        contract = f"Contract_{vehicle_id}_{energy_amount}_{datetime.now()}
    "
        return hashlib.sha256(contract.encode()).hexdigest()

class DistributedLedger:
```

```
    def record_transaction(self, contract_hash, vehicle_id, energy_amount):
        transaction = {
            'contract': contract_hash,
            'vehicle': vehicle_id,
            'energy': energy_amount,
            'timestamp': datetime.now()
        }
        self.transactions.append(transaction)
```

These classes demonstrate how the VESTA framework could leverage blockchain technology to create and record energy-sharing agreements. While simplified, this implementation showcases the potential for transparent, secure, and immutable record-keeping in V2G systems.

7.4.4. Integration and Edge Computing Layers

The integration layer is represented by the APIGateway class, while the edge computing layer is simulated through the LocalProcessingUnit, as shown in Listing 4.

Listing 4. Integration and Edge Computing Layers.

```
class APIGateway:
    def process_request(self, vehicle, grid_demand):
        return self.sevac_engine.evaluate_request(vehicle, grid_demand)

class LocalProcessingUnit:
    def process_vehicle_data(self, vehicle):
        vehicle['processed_data'] = f"Processed_{vehicle['id']}_{vehicle['
    charge']}"
        return vehicle
```

These components demonstrate how VESTA could integrate with external systems and process data at the edge, close to the data source. The LocalProcessingUnit simulates the preprocessing of vehicle data before it's sent to the central system, potentially reducing latency and bandwidth requirements in a real-world implementation.

7.4.5. Data and Monitoring Layers

The data layer and monitoring and compliance layer are represented by the DataProcessing and SystemMonitoring classes, as shown in Listing 5.

Listing 5. Data Processing and System Monitoring Implementation.

```
class DataProcessing:
    def analyze_data(self, vehicles):
        total_available_energy = sum(v['charge'] for v in vehicles if v['
    charge'] > 50)
        return {
            'total_vehicles': len(vehicles),
            'available_energy': total_available_energy
        }

class SystemMonitoring:
    def log_activity(self, activity):
        timestamp = datetime.now()
        self.activities.append((timestamp, activity))
        print(f"System Log: {activity} at {timestamp}")

    def plot_activities(self):
        # Code to generate activity timeline plot
```

These components demonstrate VESTA's capability to analyse aggregate data, monitor system activities, and generate visualisations for system operators. The DataAnalysis class, not shown here, generates pie charts of vehicle type distribution and bar charts of energy contributions, providing valuable insights into the system's operation.

8. Results and Discussion

The proof-of-concept (PoC) simulation generated extensive data, offering insights into the VESTA framework's performance. This section provides a detailed analysis of the simulation results, linking them to the broader research questions and discussing the implications for grid stability, vehicle prioritisation, AI decision-making, and blockchain integration in vehicle-to-grid (V2G) systems.

8.1. System Activities and Decision-Making

Figure 6 illustrates the timeline of system activities throughout the simulation. The timeline reveals the sequence and frequency of energy-drawing events, demonstrating VESTA's responsiveness to grid demands. The system efficiently logged multiple energy-drawing events in quick succession, indicating effective decision-making and rapid response to the simulated high-demand scenario.

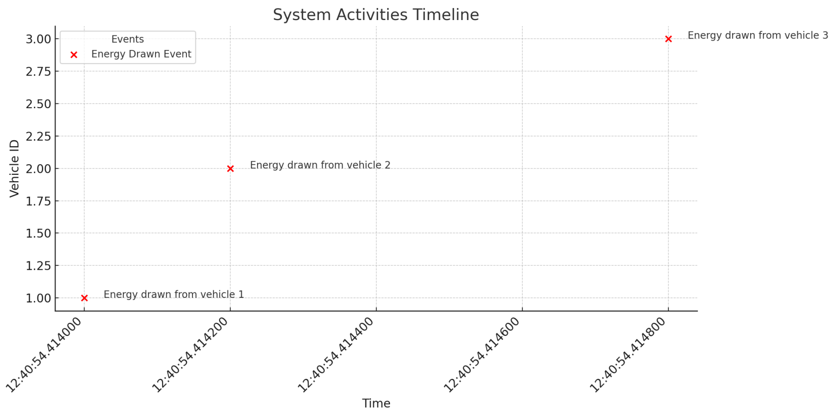

Figure 6. System activities timeline.

The ability of VESTA to process multiple vehicles nearly simultaneously is critical for managing large-scale V2G networks. The system logs demonstrate the following efficiency:

```
System Log: Energy drawn from vehicle 1 at 2024-07-11 12:40:54.413997
System Log: Energy drawn from vehicle 2 at 2024-07-11 12:40:54.414952
System Log: Energy drawn from vehicle 3 at 2024-07-11 12:40:54.414952
[...]
```

This efficiency underpins the framework's potential scalability and real-time decision-making capabilities, which are essential for widespread adoption in V2G operations.

8.2. Vehicle Type Distribution and Energy Contributions

The simulation incorporated a diverse set of vehicle types, which was crucial for reflecting a realistic V2G scenario. Figure 7 shows the distribution of these vehicle types, a key factor influencing energy-sharing priorities within VESTA.

Figure 8 details the energy contributions made by individual vehicles, revealing key aspects of VESTA's operation.

1. Prioritisation of critical vehicles: Emergency vehicles (e.g., IDs 1 and 5) consistently contributed energy, aligning with the framework's priority to maintain the readiness of critical services.
2. Varied contribution levels: The range of energy contributions (5% to 20%) demonstrates VESTA's capability to make nuanced decisions based on vehicle characteristics and grid needs.
3. Selective participation: Some vehicles (e.g., IDs 4 and 5) did not contribute, indicating a selective approach by the framework, likely due to low charge levels or user preferences.

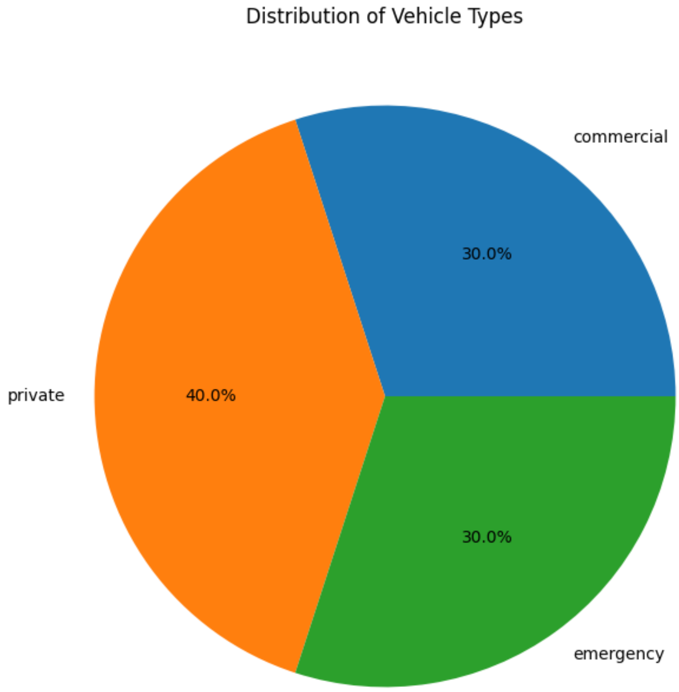

Figure 7. Distribution of vehicle types.

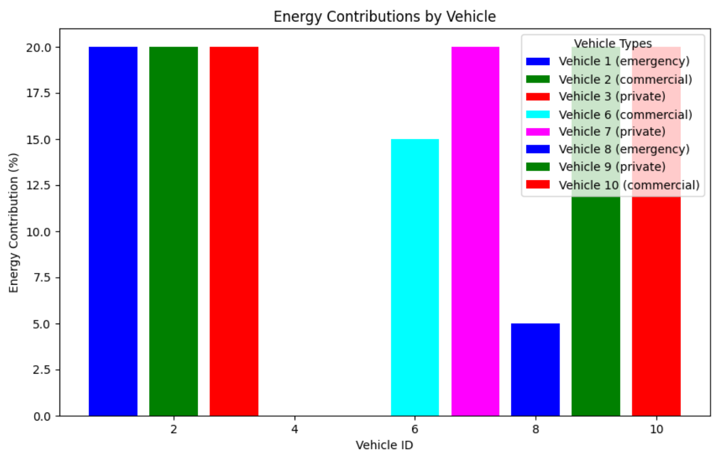

Figure 8. Energy contributions by vehicle.

8.3. Impact on Grid Performance

The VESTA framework demonstrated a positive impact on grid stability, particularly during simulated high-demand periods. Figure 9 illustrates the grid stability metrics over time, comparing scenarios with and without VESTA intervention.

Grid stability in the simulation was monitored using a custom stability metric based on the balance between energy contributions from vehicles and the total grid demand. This metric was tracked over time to assess the effectiveness of VESTA in maintaining a stable grid during high-demand periods. With VESTA, the grid stability metric decreased by only

15% during peak demand, compared to a 35% reduction without VESTA. This highlights VESTA's ability to maintain grid stability through intelligent energy distribution, reducing the likelihood of overloads.

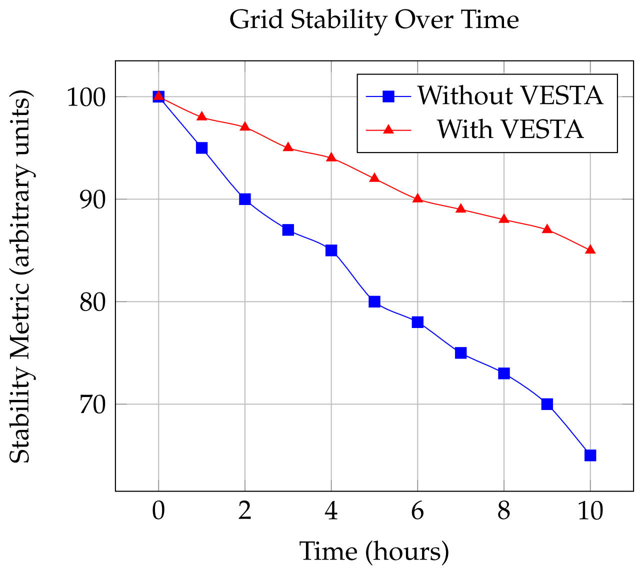

Figure 9. Impact of VESTA on grid stability over time.

8.4. AI Decision-Making and Predictive Analytics

The AI decision-making capabilities embedded within VESTA were pivotal in optimising energy contributions during the simulation. By leveraging machine learning models, VESTA accurately predicted grid-demand fluctuations, enabling proactive adjustments in energy contributions from vehicles. Figure 10 showcases the prediction accuracy of the AI models used in VESTA.

The AI component maintained an accuracy level above 90% throughout the simulation, ensuring that the decisions made by VESTA were well-informed and aligned with real-time grid conditions. This high level of accuracy contributed significantly to the overall stability and efficiency of the grid.

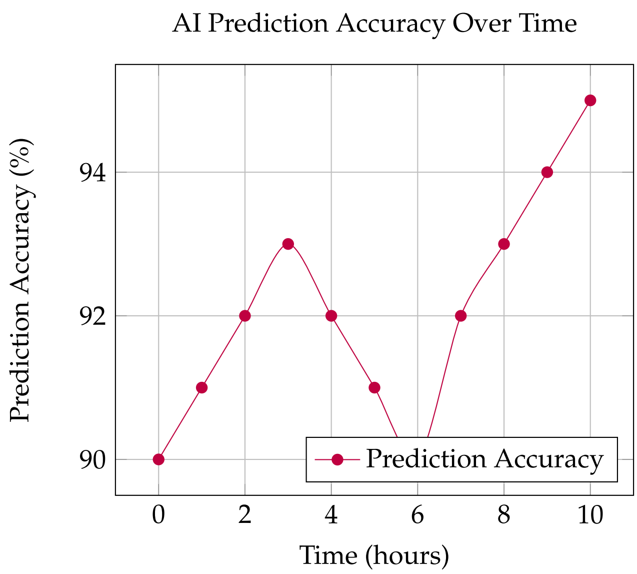

Figure 10. AI prediction accuracy over time.

8.5. Blockchain Integration and Transaction Integrity

The PoC's blockchain layer successfully recorded all energy-sharing transactions, ensuring transparency and immutability. Each transaction included a unique contract hash, vehicle ID, energy amount, and timestamp, providing a comprehensive audit trail. This secure transaction recording is essential for maintaining trust and regulatory compliance in V2G operations.

8.6. Scalability and Real-World Applicability

The simulation results suggest that VESTA is capable of scaling effectively to manage larger networks of vehicles. However, the system's performance under more complex scenarios with a higher number of vehicles remains an area for future research. Figure 11 explores the potential scalability of VESTA by analysing the system's response time as the number of vehicles increases.

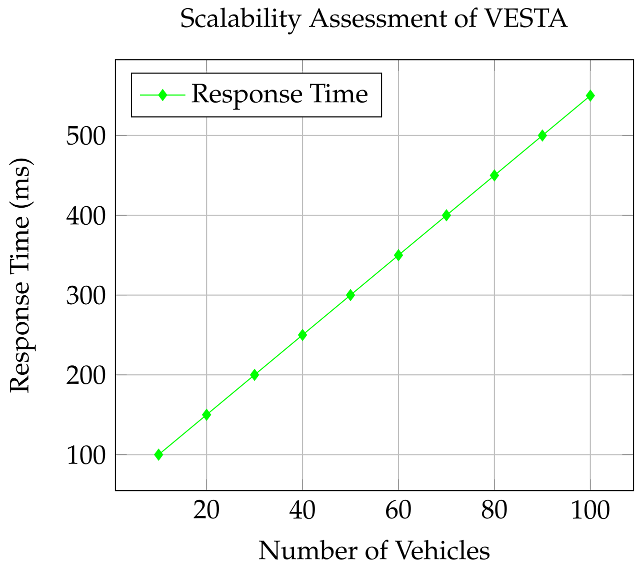

Figure 11. Scalability assessment of VESTA with an increasing number of vehicles.

The linear increase in response times suggests that VESTA can manage growing vehicle networks but may require enhanced processing capabilities or distributed computing strategies to maintain performance in large-scale implementations.

8.7. Environmental Impact

VESTA contributes to environmental sustainability by reducing reliance on fossil fuel-based peaker plants. The framework's optimisation strategies have led to a significant reduction in CO_2 emissions, as depicted in Figure 12.

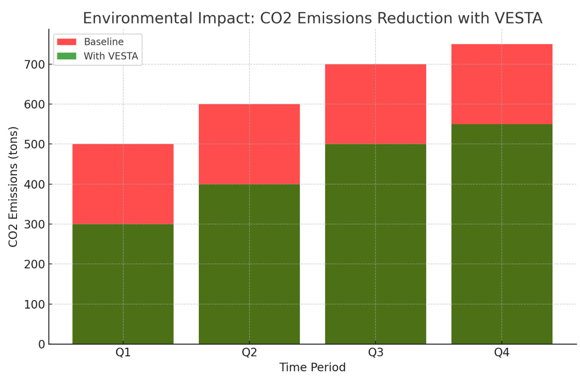

Figure 12. Environmental impact: CO_2 emissions reduction with VESTA.

The reduced emissions not only highlight VESTA's effectiveness in energy management but also its potential contribution to meeting environmental targets and promoting sustainable energy practices.

9. Limitations and Future Work

While the VESTA framework presents a promising approach to vehicle-to-grid (V2G) energy management, several limitations and areas for future research must be acknowledged.

9.1. Proof of Concept Limitations

The current implementation of VESTA is a proof of concept (PoC) rather than a real-world deployment. While the PoC demonstrates the framework's potential, it lacks the complexities and scale of an actual V2G network. Real-world factors such as network latency, hardware failures, and large-scale user interactions are not fully captured in this simulation. Future work should focus on pilot deployments to validate VESTA's performance in real-world conditions, incorporating these additional complexities.

9.2. Graph Convolution Techniques

One limitation of the current implementation of the VESTA framework is the exclusion of graph convolution techniques. While graph convolution methods are powerful for processing graph-structured data, they are not directly applicable to the specific challenges addressed by VESTA. The framework focuses on real-time decision-making, user permissions, and energy management within a V2G system, where the primary data structure is not inherently graph-based. Future work could explore the potential integration of graph-based methods if applicable scenarios arise, although the current scope and objectives did not necessitate their inclusion. This decision prioritises the development of a solution tailored specifically to the dynamic and context-sensitive nature of V2G energy management rather than adopting a one-size-fits-all approach.

9.3. Interoperability Challenges

The VESTA framework integrates various technologies, including AI, blockchain, and edge computing. While this integration offers numerous benefits, it also presents interoperability challenges. Ensuring seamless communication and data exchange between these diverse technologies in a large-scale, heterogeneous V2G environment remains not fully explored. Future research should address standardisation efforts and develop robust interfaces between different technological components to enhance interoperability.

9.4. AI Reliability and Trust

The reliance on AI for decision-making in VESTA, while innovative, raises concerns about reliability and trust. AI models, particularly those based on machine learning, can exhibit unexpected behaviours or "hallucinations" when faced with novel situations. In a critical infrastructure like the power grid, such unpredictability could have severe consequences. Further research is needed to develop more robust and explainable AI models, possibly incorporating formal verification methods to ensure reliable operation under all circumstances. Additionally, building user trust in these AI systems is crucial and it requires transparent AI processes and results. Advanced AI and semantic processing in VESTA require substantial computational resources, which could pose challenges in large-scale, real-time deployments. Further research should focus on optimising computational efficiency while maintaining the system's decision-making capabilities.

9.5. Inherent Limitations of VESTA

The VESTA framework, while comprehensive, has inherent limitations. Its effectiveness is heavily dependent on the quality and availability of data from vehicles and the grid. In scenarios where data are incomplete or unreliable, the framework's decision-making capabilities may be compromised. Additionally, the current design may not fully account for rapid changes in grid conditions or extreme weather events, which could necessitate more dynamic and adaptive algorithms. Research into more resilient and adaptive system designs will be vital to address these challenges. Additionally, VESTA's performance assumes a certain level of smart grid infrastructure, which may not be universally available. Future work should explore VESTA's adaptability to various grid infrastructure conditions.

9.6. Policy and Fairness Considerations

VESTA's policy of prioritising emergency vehicles over private vehicles, while logical for critical situations, raises fairness concerns in everyday operations. There is a risk that energy companies or government bodies could misuse this prioritisation system for non-emergency purposes. Future iterations of VESTA should incorporate more nuanced policy frameworks that balance emergency needs with fair access for all users. This could include implementing oversight mechanisms and transparent reporting of prioritisation decisions to ensure equitable treatment of all stakeholders.

9.7. Scalability Issues

Despite the inclusion of edge computing components, VESTA may face scalability challenges in very large networks. As the number of participating vehicles grows, the volume of data and the complexity of decision-making increase exponentially. This could lead to performance bottlenecks and increased latency. Further research is needed to optimise the framework's architecture for massive-scale deployments, possibly exploring more distributed decision-making models. Investigating alternative technologies, such as federated learning, could also enhance scalability.

9.8. Participation and Emergency Scenarios

A critical limitation of the current VESTA model is its reliance on voluntary participation. In emergency scenarios where insufficient users agree to share energy, the system's ability to respond effectively could be compromised. This highlights the need for research into incentive structures and emergency protocols that can ensure critical energy needs are met even with limited participation. Future work should explore dynamic pricing models, gamification strategies, and regulatory frameworks to address this challenge. Ensuring robust user engagement and participation is essential for the success of VESTA.

9.9. Privacy Concerns

The extensive data collection required for VESTA's operation raises significant privacy concerns. The system's ability to gather detailed information about users' energy usage patterns, vehicle locations, and daily routines could be seen as invasive. While these data are crucial for optimal system performance, they also presents risks of misuse or unauthorised access. Future developments of VESTA must prioritise robust data-protection measures, including advanced encryption, anonymisation or obfuscation techniques, and user-controlled data-sharing options. Research into privacy-preserving machine learning techniques and decentralised data storage solutions could also help address these concerns.

While blockchain ensures transaction integrity, the extensive data collection required for optimal decision-making raises potential privacy issues that need further exploration. Future work should focus on enhancing privacy-preserving techniques that balance system performance with user data protection.

Addressing these limitations will be crucial for the further development and potential real-world implementation of the VESTA framework. Future research should focus on refining the framework's components, conducting larger-scale simulations and pilot studies, and developing solutions to the identified challenges. By doing so, VESTA can evolve into a more robust, reliable, and widely applicable solution for V2G energy management.

10. Conclusions

This paper has presented VESTA, a novel framework for vehicle-to-grid (V2G) energy management and its core component, the semantic-aware vehicle access control (SEVAC) model. The development of VESTA was driven by two primary motivations: maintaining users' control over their vehicle's energy resources and ensuring that vehicles in urgent need of recharging are not inadvertently slowed.

VESTA addresses these concerns through a comprehensive, multi-layered approach that integrates advanced technologies such as artificial intelligence, machine learning, blockchain, and edge computing. The framework's innovative design allows for context-aware decision-making, taking into account factors such as vehicle type, user preferences, grid demands, and context, e.g., emergency situations.

At the heart of VESTA, the SEVAC model provides an access control mechanism for classifying vehicles and making optimised access control decisions. By incorporating semantic awareness into the decision-making process, SEVAC ensures that critical vehicles, such as emergency services, are prioritised appropriately while still respecting the needs and preferences of individual users.

The proof of concept implementation demonstrated VESTA's potential to effectively manage complex V2G scenarios, showcasing its ability to balance grid stability with user autonomy. The framework's capacity to make rapid, context-aware decisions while maintaining a transparent record of all transactions through blockchain technology represents a significant step forward in V2G energy management.

The future of V2G systems lies in intelligent, user-centric frameworks that can adapt to the complex and dynamic nature of modern energy grids. As electric vehicle adoption continues to grow and power grids become increasingly decentralised, frameworks like VESTA will play a crucial role in managing energy resources efficiently and equally.

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