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RESEARCH ARTICLE OPEN ACCESS

An Integrated Intelligent Framework for Electric Vehicle Energy Management and Charging Infrastructure Using HEDQN and IoT-Based Adaptive Sparse Autoencoder With Multilevel Attention Mechanism

Ranjusha K. P.¹  | Amutha B.¹  | Rebecca Balasundaram²  | Ramalingam Venkatesan³ 

¹Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, Tamilnadu, India | ²Department of Computer Science and Data Science, York St John University, London, England, UK | ³School of Engineering and Computing, Regent College London, London, England, UK

Correspondence: Rebecca Balasundaram (r.balasundaram@yorksj.ac.uk)

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ABSTRACT

In this research paper, a combined intelligent framework of two complementary systems for electric vehicle (EV) infrastructure is proposed. The first system focuses upon a hierarchically enhanced deep queue networking (HEDQN) model that decides on EV charging stations, routes vehicles and schedules power from the grid optimally, using hierarchical reinforcement learning in a cloud-connected IoT network. The second system is an IoT-based energy management system (EMS) for hybrid electric vehicles (HEVs) based on adaptive sparse autoencoder with multilevel attention network (ASA-MANet) and a revised random variable-based innovative American Zebra optimization algorithm (RRVI-AZOA) for energy management. Intelligent energy distribution, accurate state-of-charge (SoC) prediction and dynamic power sharing between the internal combustion engine (ICE) and electric motor are achieved with real-time data from vehicle subsystems with an external infrastructure. Experimental results display that the integrated framework is able to predict SoC with 96.4% accuracy, reduces the wait time of EV charging by 61%, increase charging station utilization from 78% to 92%, decrease peak grid-load variation from 34% to 14%, extend battery life by 22% and enable energy feedback from EVs to the grid with 68% of the load shifting during the off-peak period and saving ₹1200 per annum per EV. The experimental results demonstrate the framework as a scalable and sustainable solution for next-generation electric mobility.

1 | Introduction

The worldwide shift towards sustainable mobility makes electric vehicles (EVs) increasingly popular as a substitute for vehicles powered by internal combustion engines. Governments, industry and research societies have started to increase the emphasis on electrified mobility products for the reduction of carbon

emissions, improvement in energy performance and the development of green mobility infrastructures. However, the growing EV market also brings new problems regarding the operation and management of charging stations and grid stability. Synchronisation of energy supply networks, charging stations and transportation processes is essential for EV charging and different from traditional refuelling. When not managed as

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a coordinated network, EV charging must contend with huge problems of congestion, waiting time at charging locations, and the dismal consumption of energy at charging stations. Therefore, optimisation and management approaches and methods in networks should be improved to ensure reliable and efficient charging operations at scale [1]. Nowadays, the EV charging system occurs in the much-digitalized communication world. The EVs use cellular networks and wireless protocols to communicate with charging stations, transportation management systems and centralised grid management platforms. This is an integrated system where the charging need, electricity price and the position of the vehicle, as well as conditions on the road are monitored in real-time. These sources of data can be merged to create intelligent systems that make data-driven decisions, and can optimize the work of various charging stations geographically distributed [2]. Internal combustion engines have been used in transportation industry for many years, but in recent years, sustainable transportation solutions are becoming more popular due to the growing concern about the environment and the reliance on fossil fuels [3].

Recent developments of computational artificial intelligence (CAI) enable learning from an extensive amount of charging and driving data and then accurately predicting the behaviour of battery recharging and vehicle utilisation [4, 5]. Considering the aforementioned challenges, there is a need for the current contribution to introduce an innovative integrated framework addressing the coordination of charging infrastructure at the macrolevel and vehicle energy management (VEM) at the microlevel. The new technologies of intelligent transportation systems and smart grid technologies were a new opportunity to apply the methods of artificial intelligence to charging infrastructure management. To predict future charging demand and make the resource allocation optimal, machine learning models can be used to analyse the historical trends of charging, traffic patterns, and the price trends of electricity. Intelligent charging management also enables sustainable urban development goals to be achieved. As urbanisation expands, digital infrastructure has been integrated into the urban fabric and will play a key role in enabling the transportation system to be more efficient, energy-efficient and environmental-friendly [6].

1.1 | The Core Problem: A Structural Gap in EV Energy Management

Rapid EV adoption is visible, and the key challenges are presented in the underlying charging and energy-managing infrastructure that supports this growth. Despite leading technology in the EV field, charge coordination and VEM systems are often designed separately which can lead to inefficiencies across the connected transportation ecosystem. Two major challenges remain unresolved. The first challenge is to coordinate a network of distributed charging stations in the presence of unpredictable vehicle arrival to minimize waiting time for vehicles while also balancing power demand on the grid and maximising station utilisation. The second aspect relates to the real-time energy management of hybrid EVs (HEVs), where battery status, driving pattern, traffic conditions, and road characteristics must be kept in mind at all times so that power can be distributed from the most efficient sources possible.

These challenges impact each other, and they are generally seen as individual research problems. Inadequate coordination of charging stations may result in extended queues and uneven charge-holding routines, possibly jeopardising battery life and performance. On the other hand, poor onboard energy management can lead to more charging events which ultimately increases the burden on charging infrastructure, further contributing to network congestion. Hence, by controlling the above-mentioned problem, the performance of entire EV and HEV operations is often restricted.

This is a significant limitation, and its ramifications show up in practical applications. Conventional methodologies for charging station choice commonly direct vehicles to the next closest free charging point, not with all due regard to the worldwide organisation status. This often leads to utilisation of charging resources not being optimally balanced, resulting in some stations experiencing severe congestion whilst others are going largely unused. Experimental results show that such strategies can utilise the transport network at a 78% level, with some charging stations being close to capacity, while other facilities remain lightly loaded nearby. Average wait times may exceed 25 min, with peak delays exceeding 50 min during demand peaks in these circumstances. These latencies not only reduce the satisfaction of users but also pose a more serious operational challenge to bus and commercial fleet owners who are dependent on stable charging schedules.

Hybrid VEM systems have few problems, as they have a time dealing with driving environments that change fast. The battery state of charge (SoC) prediction is not very good. As a result, the energy is not used efficiently. The battery gets stressed. When the battery SoC goes outside the recommended range of 30%–80%, often it can hurt the battery and make it not last as long. It can make the vehicle less efficient. Even though people have done a lot of research on charging infrastructure optimisation and VEM, not many studies try to fix these problems, as hybrid VEM systems need to be revamped.

1.2 | Why Existing Approaches Are Insufficient

A lot of research has been done on vehicle (EV) charging and hybrid VEM, where existing solutions only solve parts of the problem and do not provide a complete solution. One such category of studies looks at coordinating charging stations using reinforcement learning techniques. Recent studies have used reinforcement learning to help choose charging stations, plan routes and schedule grid usage. However, most of these approaches use a simple network architecture that combines multiple decision-making tasks into one large action space. This can cause problems during training as the learning agent may receive feedback. For example, a routing decision that reduces travel distance may also increase grid congestion, leading to rewards and slower learning. As a result, these methods often require training episodes to reach stable performance and may still not achieve the best long-term outcomes. Hierarchical reinforcement learning is an alternative that breaks down complex decision-making into multiple levels of subpolicies. This approach has worked well in scheduling and resource allocation problems, but its application to large-scale EV charging networks is limited.

The next category of research focuses on energy management systems (EMS) for hybrid EVs (HEVs). Some approaches using multiagent reinforcement learning (MARL), deep reinforcement learning combined with Pontryagin's minimum principle (PMP) and recurrent neural networks have shown results in optimising power distribution between vehicle components. However, these methods work independently of the charging infrastructure and do not consider factors like charging station availability, electricity pricing or charging queue lengths. Since these external conditions affect the battery SoC during a journey, ignoring them can lead to suboptimal energy management decisions. Many existing EMS models use autoencoders or recurrent neural networks that treat all sensor inputs equally. However, these architectures often fail to distinguish between features with temporal and operational significance. For instance, a sudden current surge indicates a change in power demand while a gradual rise in battery temperature reflects a long-term trend affecting battery health and SoC. Treating these signals uniformly can reduce the model's ability to capture system dynamics, ultimately limiting prediction accuracy and control effectiveness in real-world driving conditions.

Metaheuristic optimisation algorithms used for EMS parameter tuning, such as AZOA, WOA and CSA, suffer from convergence on complex fitness landscapes of HEV energy problems. Their fixed balance between exploration and exploitation is not suited to the constraint boundaries that shift as driving conditions change.

1.3 | Research Objective and Contributions

Motivated by the foregoing analysis, this research work proposes an integrated framework that simultaneously addresses both macrolevel charging infrastructure coordination and microlevel HEV energy management. The specific and original contributions are:

- HEDQN: A hierarchically enhanced deep queue-network that separates charging station selection, traffic-aware routing, and grid-aware power scheduling into nested decision layers, enabling penalty-augmented reward shaping and V2G discharge capability within a single coherent policy over a 750-station IoT-connected network. This is the initial application of hierarchical DQL to real-scale EV charging infrastructure coordination.
- ASA-MANet: An adaptive sparse autoencoder with multi-level attention network for SoC prediction in IoT-enabled HEVs, which applies KL-divergence-penalised sparsity to eliminate redundant sensor features while employing layer-wise attention to dynamically weight critical measurements (voltage transients, temperature gradients and current profiles) at multiple abstraction levels. This architecture is the elementary work to jointly integrate sparse encoding and multilevel attention within a unified architecture for HEV SoC estimation.
- RRVI-AZOA: A revised random variable-based Innovative American Zebra optimization algorithm that extends the AZOA with a context-adaptive random perturbation mechanism and variance-controlled update rule, enabling escape from local optima in multiobjective EMS fitness landscapes. This modification is formally defined and

empirically validated against four competing metaheuristics.

- Unified integration: The three components are deployed as a coupled system—HEDQN informs station-level charging schedules that constrain the SoC targets fed to ASA-MANet, which in turn feeds predicted battery trajectories back to HEDQN's grid scheduling layer—creating a feedback loop absent from all prior work.
- Experimental rigour: All results are reported as means $\pm$ standard deviation across 30 independent simulation runs using fixed random seeds, with training/validation/test splits and a clearly specified simulation environment parameterised by six categories of Kerala government administrative and operational data.

Figure 1 shows hierarchical control of EVCS in smart grid integration applications.

Efficient power distribution architecture in charging stations is also considered another important part of charging infrastructure management. Parallel DC bus strategies are becoming a common way of controlling power flow between units of many charging units and interfacing with the grid. These architectures enable adaptable distribution of energy between charging ports as well as having stable voltage levels. Automated control systems may be used to regulate power injection and the charging process to avoid overload conditions and maintain consistent quality of service. Through incorporation of advanced hierarchical decision-making algorithms into such power distribution structures, charging systems are able to dynamically adjust their operational parameters in response to real-time demand variations.

Besides ensuring that the efficiency of operations is enhanced, intelligent charging management systems also promote sustainability in energy use. Most of the present-day power grids are adopting renewable sources of energy including solar and wind power whose generation patterns are variable. The synchronised charging schemes will be able to align the charging time of the vehicle with the times when the renewable energy is most available and thus make the most use of clean energy sources.

2 | Literature Survey

The proliferation of EVs has opened new avenues for the development of charging infrastructure and its supporting technologies, along with challenges that arise with it. As the global implementation of EVs grows exponentially, efficient and accessible charging infrastructure becomes an emergent need for both personal drivers and commercial operators. Establishing such networks, ranging from residential communities to high-traffic transportation arteries and urban areas, requires thoughtful consideration and the utilisation of advanced technologies. The parallel advancements in autonomous navigation, vehicle-to-everything (V2X) communications, and intelligent power management offer new opportunities to optimise the installation, operation and collaboration of EV charging systems.

A good number of research efforts in recent years have been directed toward designing an autonomous and smart EV charging system. Vision-based charging systems have been engineered that enhance the precision and reliability of the

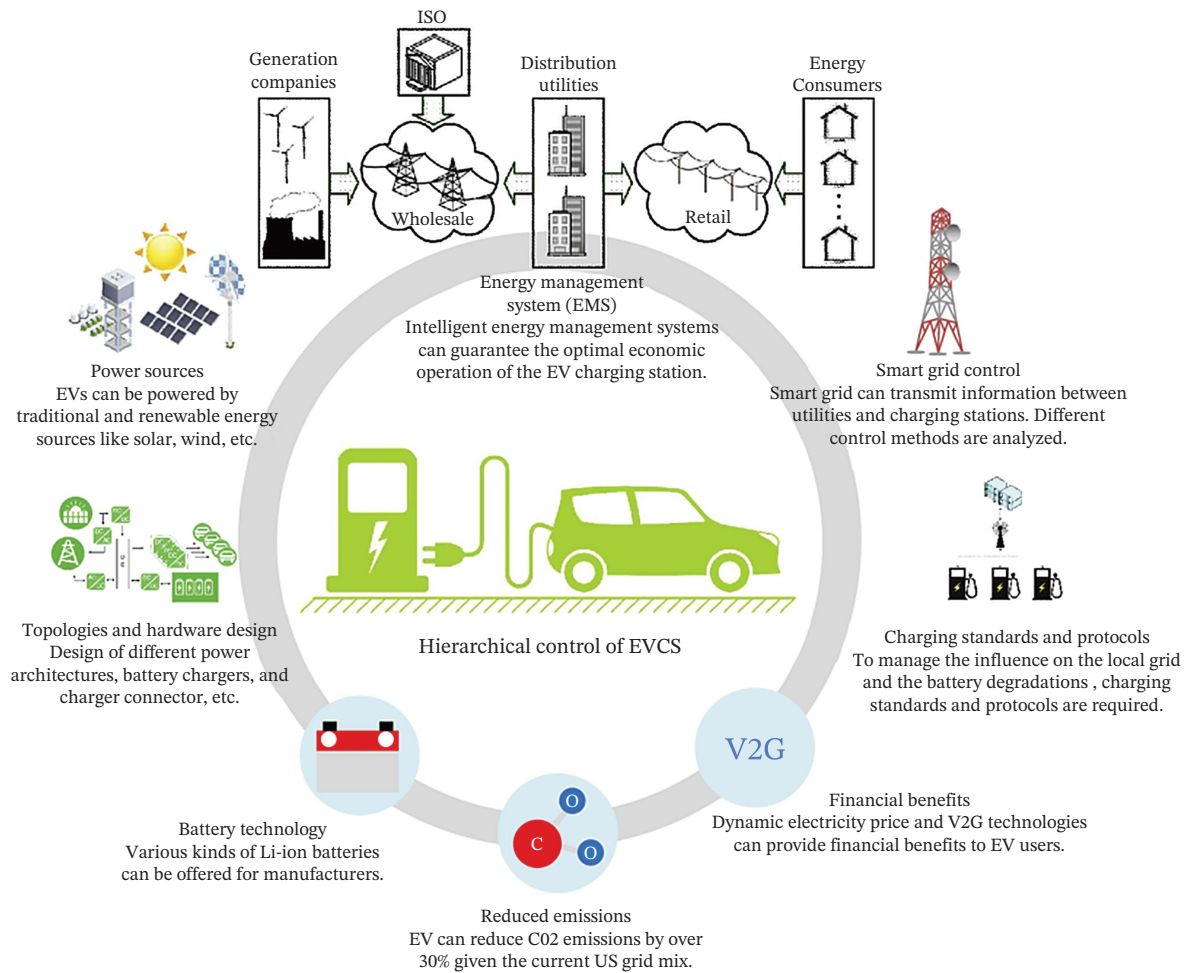


FIGURE 1 | Hierarchical control of EVCS in smart grid integration applications (Note: topology is illustrative; all experiments use Kerala State's EV, India's 750-Station Network as described in Table 1 and Section 5.1).

autonomous vehicle positioning and the connecting process [7]. Research has been conducted in the field of integrating charging infrastructure into existing residential housing structures, paying attention to cost-effective retrofitting solutions for homes that could minimally disrupt occupants [8]. A variety of vehicle-to-vehicle (V2V) energy sharing frameworks have been presented as viable ways for EVs to share energy dynamically with each other, thereby developing flexible charging techniques [9]. Placement of EV charging stations in fleet applications has been well-researched due to its benefits in reducing travel time, efficiency, and energy cost [3].

On a parallel track, significant efforts have been invested in developing intelligent EMS for HEVs. Most previous works were focused on maximising the fuel efficiency and reducing the operating cost and energy consumed via advanced control strategies and machine learning techniques. The IoT-based EMS for HEV (SEMS-HEV) proposed in [1] made use of machine learning for dynamic scheduling of vehicle-to-grid (V2G) transactions and reduction in the costs and time of charging. A multiobjective EMS was formulated with HESS and EGS, and MARL was applied to simultaneously optimise the consumption of fuel, the health of the battery and the capacitor constraint in [2].

TABLE 1 | Multidomain datasets from government portals and field-collected sources.

Domain	Data type	Source
EV-Specific	EV registrations, penetration rates, state-wise statistics	VAHAN EV Dashboard
Demographic	Population density, urban-rural distribution and socio-economic indicators	Census of India
Vehicle Registration	Registered vehicles (EV and ICE) and growth trends	MoRTH-VAHAN Dashboard
Traffic and Mobility	Traffic flow, congestion and transport patterns	Kerala MVD, NIUA
Charging Infrastructure	Public station data, charger type and capacity	BEE (EVYatra), Ministry of Power
Energy and Environment	Power consumption and pollution metrics	KSEB, CPCB, PPAC

A similar research work [10] introduced an IoT-supported battery management system (BMS) with logistical regression-based estimation and ORMeshNet gateway architecture to obtain accuracy of SOC and state-of-health (SoH). DRL and PMP were applied to the fuel cell HEV (FCHEV) to optimise the energy distribution in [11]. An empirical demonstration has shown that RNNs modelling for nonlinear energy management could result in a noticeable improvement on the energy efficiency over the traditional rule-based EMS in [6]. Also, a framework of multimicrogrid energy management (MM-GEM) has been presented to optimise transmission efficiency and system degradation by integrating DGs, storage system and mobile loads in [7].

2.1 | Charging Station Coordination and Routing

Vision-based autonomous charging systems [7] are capable of reliable physical connector alignment where they only deal with the terminal connection step and do not offer a way to select a station on the network and load balance. Demand-side management strategies are implemented at the station hardware level with no dynamic coordination. There are residential retrofit approaches [8] that expand charging access to multiunit dwellings, but they do not provide any dynamic demand-side management. Flexibility is provided by the V2V energy sharing models [9], but they add in the bidirectional accounting of energy transfer and require vehicle proximity which is not always possible in a real network. However, fleet charging optimisation [3] considers placement and scheduling of the known fleet of vehicles, but it is based on static demand, which is an important assumption in urban settings, where demand is stochastic. This is the critical gap in this strand: The lack of a hierarchical decision architecture that solves the station selection (which station), routing (which path) and power scheduling (how much, when) subproblems as interdependent subproblems. The state-action complexity grows exponentially in flat optimisation approaches that consider these as a single action space, while the reward gradients generated by them contradict each other to cause convergence issues.

2.2 | EMSs for HEVs

Manivannan et al. [1] proposed an IoT-based Smart EMS (SEMS-HEV) system combining V2G scheduling and SoC prediction using a machine learning method with 91.6% accuracy after 250 epochs. Although this paper shows the merit of IoT connectivity, all the voltage transient data from the sensor are utilised uniformly by the ML model, a conventional feedforward network, which cannot reflect the fine-grained temporal dependency between them and the evolution of SoC, which is essential for accurate prediction during regenerative braking scenarios.

In [2], Yang et al. addressed energy management for HEVs using MARL, which they set up as a multiobjective optimisation problem involving fuel efficiency, battery health and ultra-capacitor constraints. MARL exhibits 92.9% accuracy after 250 epochs and is more effective in addressing multiobjective trade-offs than single-agent approaches. But all the system functions offline without reliance on charging infrastructure state, and the multiagent communication overhead is poor for vehicle populations larger than in the lab.

Hu et al. [11] proposed the fuel cell HEV energy allocation method using Deep Reinforcement Learning and PMP. DRL + PMP is effective in continuous-state spaces, but for PMP integration, it needs to be known that the dynamics model of the

system is known—an assumption that is not met in actual IoT deployments, where sensor noise and communication delays introduce errors in the observations of the state. While the value of sequence modelling is confirmed by Millo et al. [6], who showed that RNN-based EMS can improve energy efficiency up to 5% compared to rule-based methods, the standard RNN architecture does not explicitly select the features and is therefore prone to noise from irrelevant sensors such as the 15+ channels from the various IoT channels in a modern HEV.

The common shortcoming in this strand is a lack of attention-based feature prioritisation and adaptive sparse encoding. Traditional autoencoders and recurrent networks that are used on high-dimensional HEV IoT data (SoC, SoH, voltage, current, temperature, motor load, GPS and traffic conditions) assign equal representational capacity to all the elements, thus reducing the sensitivity of the model to the few measurements that are most predictive of SoC evolution at any given time of driving.

2.3 | Metaheuristic Optimisation for EV/EMS Problems

The AZOA [12] which is the direct predecessor of the proposed RRVI-AZOA demonstrates competitive performance on standard benchmark functions but exhibits two weaknesses on HEV EMS landscapes: (i) its population update rule uses a fixed step-size that causes rapid convergence to local optima when the fitness landscape changes dynamically (as occurs when SoC constraints tighten at low battery levels) and (ii) it lacks a variance-reduction mechanism, producing high STD scores that indicate inconsistent optimisation outcomes across runs.

WOA [13] and CSA [14] show similar limitations: both achieve best-case accuracy near 92%–93% but suffer WORST scores substantially higher than their BEST scores, indicating brittleness to initialisation. BBFGO [15] narrows this gap somewhat but still underperforms RRVI-AZOA by 3% points in accuracy at 250 epochs. None of these algorithms incorporates context-awareness which is the ability to adjust exploration-exploitation balance based on the current constraint activity (e.g., increasing exploration when SoC approaches the 30% lower bound where the fitness landscape becomes steep and discontinuous).

2.4 | IoT Infrastructure and Grid Integration

The MM-GEM framework [7] integrates distributed turbines, storage, and mobile loads in a multimicrogrid context, achieving 94.0% accuracy at 250 epochs, but its grid-side coordination mechanism is decoupled from vehicle-level energy management and does not support V2G discharge.

2.5 | Synthesis: Evidence-Based Gap Table

Table 2 synthesises the critical research gaps identified across the four dimensions mentioned above and maps each gap to the component of the proposed framework that specifically addresses it.

3 | IoT-Based EMS and HEV Architecture

3.1 | IoT-Based EMS

The IoT-based EMS for HEVs integrates smart grid technology, cloud computing, and intelligent vehicle infrastructure to

TABLE 2 | Critical research gaps in existing literature and corresponding proposed solutions.

Research gap	Representative works	Specific limitation	Component addressing gap
No integrated macro + micro EV framework	SEMS-HEV [1], MARL [2]	Address EMS or routing, never jointly in real-time	Unified HEDQN + ASA-MANet framework
Flat RL for multistation coordination	DQN [standard], DDQN	Single-layer Q-network cannot model hierarchical station/route/grid decisions	Hierarchical HEDQN with two-level policy
Sparse encoding for HEV IoT SoC	Sparse AE [16], RNN [5]	Vanilla AE loses temporal dependencies; no attention for critical sensor prioritisation	ASA-MANet with multilevel attention
Metaheuristic convergence for multiobjective EMS	AZOA [12], WOA [14], CSA [13]	Premature convergence, poor adaptability in nonlinear constraint spaces	RRVI-AZOA with adaptive random variable
V2G integration with real-time routing	MM-GEM [6]	Grid-side coordination decoupled from vehicle routing decisions	HEDQN penalty-augmented V2G scheduling

Note: Three research gaps are of particular importance. No prior work applies hierarchical RL to the three-level EV coordination problem (station, route and grid). No prior EMS model combines sparse autoencoding with multilevel attention for HEV SoC prediction. And none of the existing system integrates macrolevel charging coordination with microlevel HEV energy management in a real-time feedback loop. These three absences collectively justify the integrated HEDQN + ASA-MANet + RRVI-AZOA framework proposed in this work.

manage bidirectional energy flows—Grid-to-Vehicle (G2V) for charging and V2G for feeding surplus energy back to the grid. A centralised aggregator processes real-time data from EVs, the grid and energy markets to optimise energy distribution and load balancing. EVs transmit battery and operational data (SoC, SoH, voltage, current and temperature) to the IoT cloud via secure wireless protocols, where machine learning and optimisation algorithms consider grid conditions, user preferences and historical EV profiles to dynamically allocate energy. The EMS balances battery health, efficiency, and user needs, scheduling slow or fast charging depending on off-peak periods, mobility requirements or grid support demands. Figure 2 shows the System model for the EMS in an IoT-based HEV.

3.2 | HEDQN System Architecture

The proposed framework establishes an integrated hierarchical coordination mechanism for the operation of EV charging in the form of a set of transportation data, charging stations data, and grid management parameters within a single communication environment. The methodology optimises charging station selection, scheduling and power allocation through hierarchical learning, facilitated by continuous data exchange between vehicles, infrastructure and centralised controllers. The system works using cloud-based communication networks and wireless connections to gather real-time data of distributed charging stations and mobile vehicles. Figure 3 shows HEDQN inter-networking paradigm for EV charging station.

3.3 | Proposed EMS in IoT-Based HEV

This research work brands three key contributions: (1) the development of an IoT-enabled EMS for HEVs to enable real-time intelligent control of power flow, fuel use and battery management; (2) the introduction of ASA-MANet, a deep learning model that captures nonlinear correlations in high-dimensional IoT data for accurate SoC prediction with reduced computational load and (3) the proposal of RRVI-AZOA, an optimisation algorithm that fine-tunes EMS hyperparameters and decision variables to balance fuel economy, SoC stability, and system performance. The integration of ASA-MANet with RRVI-AZOA forms a unified optimisation-driven EMS. Figure 4 shows the proposed EMS in IoT-based HEV.

4 | Methodology

4.1 | Data Acquisition and System Initialization

In the first place, the operational real-time data collected from different components of the electric mobility system is acquired. The charging station sends the current electricity price, the number of available ports, queue length and instantaneous current drawn, while the EV reports the current position, battery SOC and destination via GSM and Wi-Fi. Additionally, traffic management systems can provide some context, like the current road congestion, estimated driving time, and route availability. These different types of information streams converge into a central cloud-based system for aggregation, storage, synchronisation and processing. The experimental setup relies on publicly available government data and operational data obtained through actual measurements and experiments for practical relevance and statistical reliability, as indicated in Table 1.

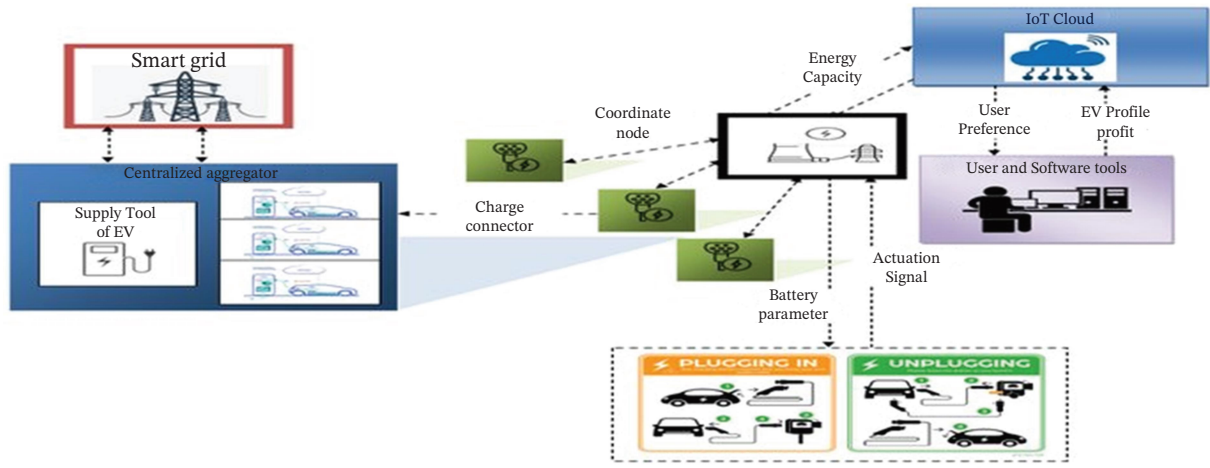


FIGURE 2 | System model for the EMS in IoT-based HEV.

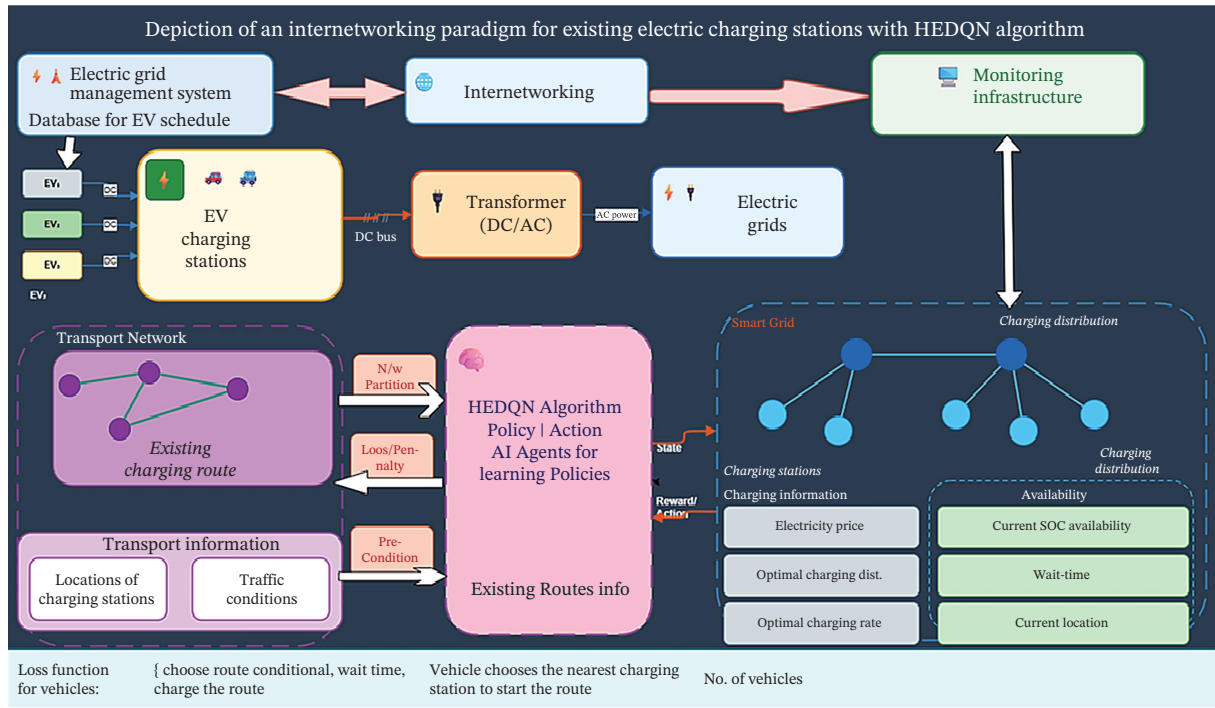


FIGURE 3 | System architecture—HEDQN internetworking paradigm for EV charging stations.

Prior to model training, all collected raw data are processed so as to maintain their consistency and quality. Missing numerical sensor readings have been filled using the median values imputation method and temporal missing traffic data points by forward fill. The categorical data, namely, vehicle category, charger type and zone information, were transformed using the one-hot encoding method, and the numerical variables (SOC, voltage, current, temperature and electricity price) were scaled to the interval of $[0, 1]$ using min-max scaling method. Note that to prevent data leakage issues, all the scaling parameters were determined using only the training set and applied to the validation and test sets as well.

Considering the nature of sequential data, the samples were generated by a sliding window operation of size 30 time steps (each of 15-min duration). This resulted in a total of 47,520 labelled samples. In order to avoid the data leak from the future to

the past and emulate the real system, the data set was divided chronologically. Specifically, the training set accounts for 70% (33,264 samples) of the data, ranging from January 2023 to October 2024. The validation set accounted for 15% (7128 samples) of the data, from November 2024 to April 2025, while the test set accounted for 15% (7128 samples) of the data, from May 2025 to October 2025. The hyperparameter of the proposed RRVI-ABOA algorithm was obtained using only the validation set, and the test set was used only once for the final evaluation in Section 5.

4.2 | Internetwork Communication Framework

The second part consists in building a reliable communication infrastructure to ensure easy exchange of data between the EVs, the charging stations and the grid management systems. In this proposed framework, the system uses cloud-based networking

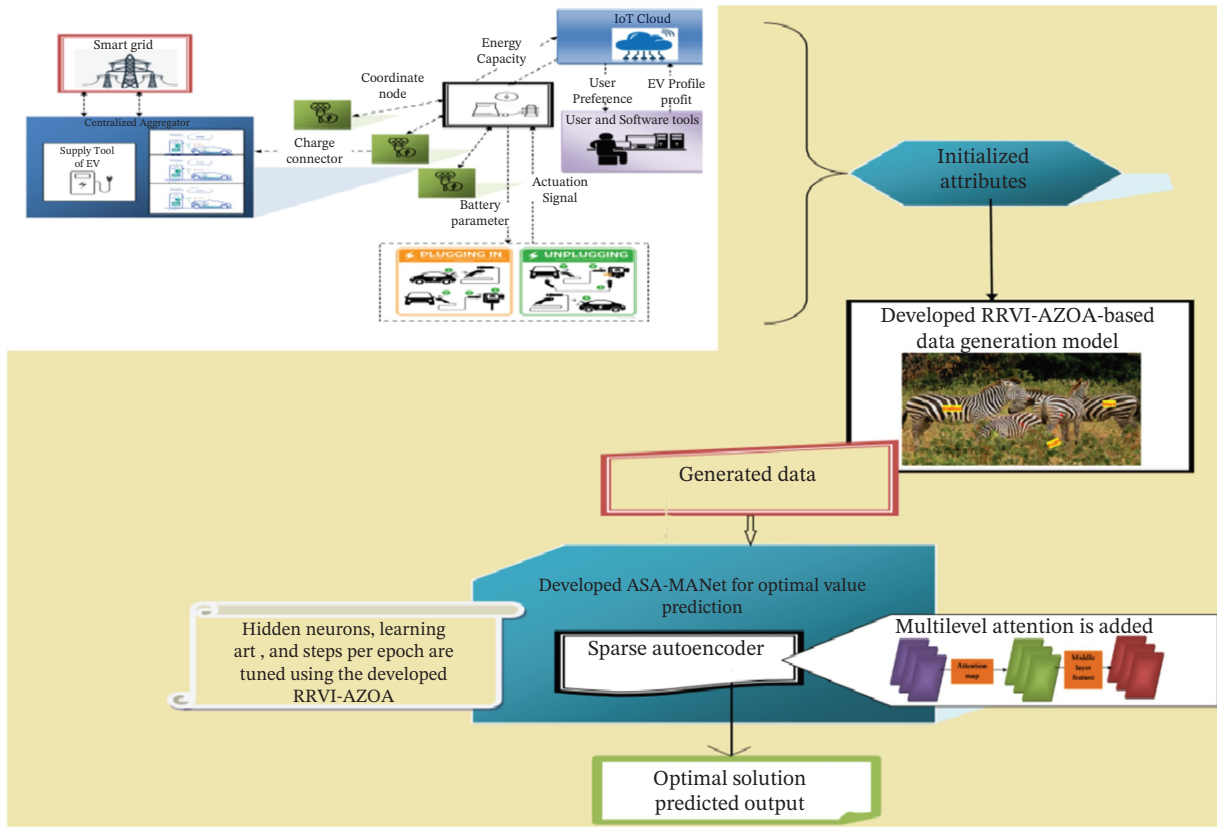


FIGURE 4 | Pictorial view of the proposed EMS in IoT-based HEV.

with wireless communication technology in order to enable real-time monitoring and decision-taking. The proposed communication layer is used to connect together all the components of the distributed electric mobility network and ensure seamless data exchange.

In the network, each charging station will be considered a smart node able to send charging information (port availability, queue position, electricity consumption and tariffs) while receiving orders from the central managing system. EVs would send in real time to the network their positions, battery SoC, the desired load and their path information via the wireless network. From this data, an updated recommendation on the path will be sent to them with the available charging destination according to the current network state.

In the proposed framework, the cloud is responsible of the entire data processing and the central control part of the charging system. It collects data from all sources: charging station, vehicles and traffic management system. The management of the information allows developing intelligent control of the system as it will have an entire vision of the entire charging system. Table 1 depicts the multidomain dataset representation.

4.3 | Hierarchical Learning-Based Decision Model (HEDQN)

In this level, the HEDQN model considers more factors to choose the optimal charging strategies in simultaneous operation. The hierarchical level can be classified into 3 layers of decisions, i.e., the top layer is responsible for evaluating the candidate paths under the traffic and vehicle information; the middle layer

focuses on charging station choice on the basis of station available capacity, charging queue and current price; and the bottom layer is in charge of the charging rate and the power schedule.

4.3.1 | Architectural Justification

Hierarchical decomposition of the charging coordination problem is motivated by temporal abstraction theory [16, 17]. Three decision levels (zones selection [time horizon: journey plan: 30–60 min]; station and route selection (time horizon: current trip, 5–15 min; power allocation [time horizon: charge session, 1–5 min]) operating at extremely different temporal scales and with drastically different state-relevant information cannot be efficiently resolved in a flat policy.

Doing so produces a credit assignment problem, where good long-horizon zone decisions have a reward that is diluted by the intervening short-horizon power allocation steps that are required for the zone decision's reward to be realised, causing the flat policy gradient to downweight the benefit of good routing with respect to immediate charge rate. In the hierarchical structure, reward timescales can be isolated such that subpolicies can be trained with respective discount factors and reward shaping. We employ a DQN over actor-critic methods on both levels because of their discrete actions. The 750 stations and 4 charging locations' 4 different charge rates produce a discrete flat state-space action space of 12,000 discrete decisions, a suitable scale for value-based methods but intractable for policy gradient methods which require parameterising a distribution over this state space.

4.3.2 | Algorithm Specification

The training process for HEDQN is laid out in Algorithm 1. Design considerations are as follows: replay buffer capacity of $N = 10,000$ transitions, which is enough to decorrelate sequences of states in a 750-station network while being manageable under current hardware limitations; mini-batch size of 64, chosen to balance gradient variance against computation cost based on standard practices from DQN; target network updates every 100 steps, a value determined experimentally as preventing instability in the Q-function after preliminary trials; the discount factor of $\gamma = 0.95$, a value that aims to balance between immediate charging costs and long-term grid stability, selected after experimenting with various discount factors of 0.90, 0.95 and 0.99; and finally, the weight applied to the penalty, chosen so that a violation of constraint occurs 3–5 times as strongly as a normal per-step reward based on the constrained MDP penalty method.

Figure 5 describes a HEDQN-based EV Charging Station Scheduling and Rescheduling System designed to optimize EV charging operations under dynamic traffic, charging demand and station availability conditions. The system employs a multiagent architecture consisting of four intelligent agents: the Transport Network Agent (TNA), Charging Station Agent (CSA), SA and the HEDQN Learning Agent, which serves as the central decision-maker. EVs arriving from different localities form the environment layer, while the TNA monitors road congestion, travel time, route availability and distances to charging stations. The CSA manages station-specific information such as available chargers, queue lengths, charging costs, battery demand predictions and station utilisation. The Scheduling Agent performs

initial scheduling, dynamic rescheduling, priority assignment, time-slot allocation and EV-to-station mapping. The HEDQN Learning Agent uses hierarchical reinforcement learning with high-level policy networks and low-level Deep Q-Networks (DQNs) to make intelligent scheduling decisions and improve system performance through experience replay, target networks, and double Q-learning techniques.

The system represents the environment using a comprehensive state space that includes information about incoming vehicles, battery SOC, waiting time, distance to charging stations, queue lengths, charger availability, traffic conditions and charging rates. Based on these states, the HEDQN selects actions such as assigning chargers, redirecting vehicles to alternative stations, rescheduling charging sessions, delaying charging operations and allocating either fast or standard charging facilities. The primary objective is to minimise waiting times, traffic congestion, travel distances and energy costs while maximising charger utilization and customer satisfaction. Positive rewards are provided for successful charger assignments, charging completion, balanced station utilisation and efficient energy consumption, whereas penalties are imposed for excessive waiting times, long queues, scheduling delays, station overloads and increased travel distances. The overall reward function combines these rewards and penalties to guide the learning process toward optimal scheduling behaviour.

To train the HEDQN model, the framework minimises the temporal difference (TD) error through a loss function that measures the difference between predicted and target Q-values. Several scheduling policies are incorporated to improve decision-making, including earliest deadline first (EDF) for emergency charging requests, lowest SoC first to prioritise vehicles with critically low battery levels, queue-aware scheduling to reduce congestion and cost-aware scheduling to minimise charging expenses. Rescheduling mechanisms are triggered when significant changes occur in the environment, such as new EV arrivals, charger failures, excessive queue lengths, changing traffic conditions or fluctuations in renewable energy availability. In such cases, the system identifies alternative charging stations, estimates travel and waiting times, computes the expected reward and dynamically reschedules vehicles to maintain efficiency.

The training workflow begins with the initialisation of HEDQN networks, followed by continuous observation of the environment, high-level goal selection, execution of low-level scheduling actions, reward collection, experience storage, replay buffer updates, loss computation and network parameter updates. The architecture is particularly suitable for research in smart EV charging infrastructure, MARL, hierarchical deep reinforcement learning and dynamic EV scheduling under traffic and charging constraints. The framework adopts a proactive scheduling strategy that assigns charging stations when an EV trip begins and a reactive rescheduling strategy that adapts to unexpected events such as traffic delays or sudden charging station overloads. The reward-penalty framework balances user satisfaction and operational efficiency by considering charging completion, waiting times, grid congestion and rescheduling costs. Finally, the HEDQN optimises both high-level station assignment decisions and low-level charging slot allocation decisions using a hierarchical learning structure, making it a robust solution for intelligent EV charging management in smart transportation systems.

ALGORITHM 1 | HEDQN—Hierarchically enhanced deep queue networking.

```

Initialize replay memory  $D$  to capacity  $N = 10,000$ 
Initialize action-value function  $Q$  with random weights  $\theta$ 
Initialize target network  $\hat{Q}$  with weights  $\bar{\theta} \leftarrow \theta$ 
Set penalty weight  $\lambda$ , loss threshold  $\delta_{\max}$ , penalty threshold  $P_{\max}$ 
For episode = 1 to  $M$  do:
    Initialise sequence  $s_1 = \{x_1\}$ ; preprocess  $\varphi_1 = \varphi(s_1)$ 
    For  $t = 1$  to  $T$  do:
        With prob.  $\epsilon$  select random action  $a_t$ 
        Else  $a_t = \operatorname{argmax}_a Q^*(\varphi(s_t), a; \theta)$ 
        Compute step penalty:  $pt = \lambda \cdot \max(0, C_{\text{viol}}(a_t, s_t))$ 
        Apply penalty:  $\hat{r}_t = r_t - p_t$ 
        Store  $(\varphi_t, a_t, \hat{r}_t, \varphi_{t+1})$  in  $D$ 
        Sample mini-batch of 64 transitions from  $D$ 
        Compute Huber loss  $L(\theta)$  and perform gradient descent
        If  $t \bmod 100 = 0$ : update target  $\bar{\theta} \leftarrow \theta$ 
    End For
    Decay  $\bar{\epsilon} \leftarrow \max(\epsilon_{\min}, \epsilon \cdot \text{decay})$ 
End For

```

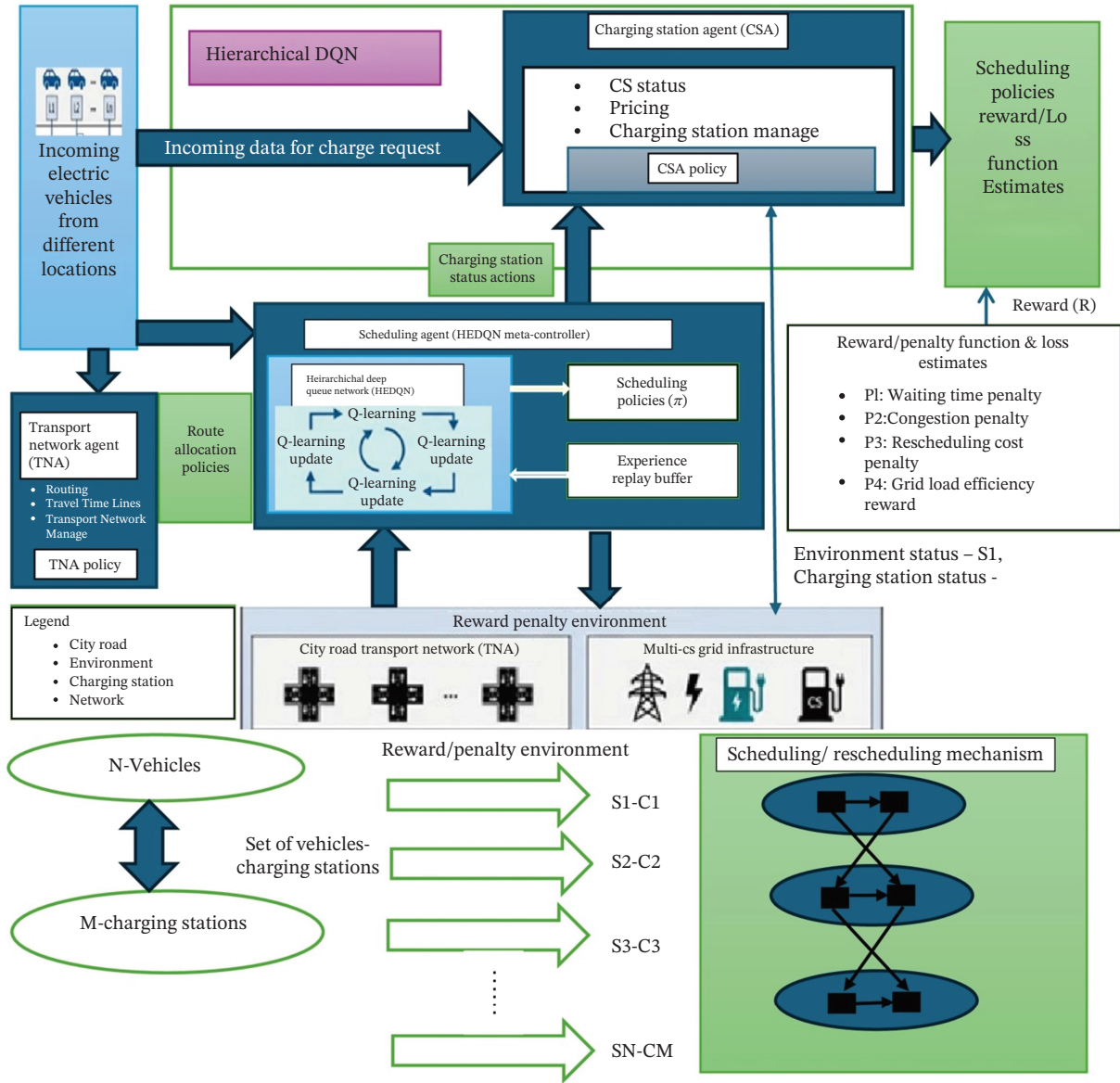


FIGURE 5 | HEDQN-reward/penalty-scheduling/rescheduling algorithm.

4.4 | HEV's Engine Model

A hybrid vehicle engine model integrates the internal combustion engine (ICE) and electric motor (EM) to optimise energy utilisation, providing a balanced combination of performance and fuel efficiency. Within hybrid systems, these two power sources operate cooperatively—electric propulsion is primarily used during low-speed conditions, while the ICE provides supporting power during high-demand situations such as highway driving or rapid acceleration.

Fuel Consumption of HEV Engine: A HEV engine's consumption of fuel may be represented as a consequence of torque and speed. Usually, this connection is shown by (1), which simulates how the vehicle's speed and electrical requirements affect the use of fuel.

$$p_g = g(V_u, a_u). \quad (1)$$

Effectiveness of HEV Generator: Equation (2) defines the efficacy of HEV's power source, expressed as δ_p , a_p depending on the vehicle's motor acceleration and velocity V_p .

$$\delta_p = g(a_p, V_p). \quad (2)$$

Generator Strength in HEV: Equation (3) expresses the generator's strength in a hybrid electric car.

$$J_p = \begin{cases} \frac{V_p a_p}{9560 \delta_p}, & \text{engine,} \\ \frac{V_p a_p \delta_p}{9560}, & \text{engine.} \end{cases} \quad (3)$$

If one ignores the impacts of ambient factors and the battery's fluctuating electrical activity, the most basic mathematical description of HEV battery packs may be reduced to the strength of concurrent resistance in an enclosed circuit. Equation (4) shows the proportion of life of the battery.

$$\frac{i_H}{i_k} = \frac{M_0 - \sqrt{M_0^2 - 4D_{in}J_{Btry}}}{2D_{in}W_0}. \quad (4)$$

According to (4), M_0 represents the HEV battery optimisation, D_{in} the internal resistance of the battery, J_{Btry} the general charge and discharging control and W_0 represents the battery's optimal state.

Energy administration is intended to accomplish a number of goals, including lowering fuel consumption, improving affordability and usefulness, preventing overcharging or discharging of the battery, prolonging its useful life, and making sure the vehicle's residual power remains within a stable range.

4.5 | Proposed RRVI-AZOA

The RRVI-AZOA, a sophisticated metaheuristic optimisation technique developed for energy management in HEVs using the IoT. Based on the basic Zebra optimization algorithm, it uses a context-aware adaptive random variable that balances exploration and exploitation by looking at the status of fitness to evade poor performance like premature convergence, poor adaptiveness in nonlinear and multiobjective problems by efficiently optimising the objectives which are mutually conflicting-fuel consumption, SoC of battery and vehicle performance and when integrated with ASA-MANet, it sets optimum values of weights and bias for tuning the neural network for appropriate results and effective energy management:

$$R_d = 1 - c \times \left(\frac{1}{C}\right). \quad (5)$$

Here, c represents the current iteration, C denotes the maximum number of iterations used during the optimization process, and R_d is the random variable. However, AZOA often has disadvantages such as early convergence, loss of diversity, and poor adaptability to highly nonlinear and multimodal problem domains. The above disadvantages may be more or less serious in real-time energy management with the multiconflicting objectives, such as fuel economy, SoC, vehicle performance, and system response ability, under dynamically changing constraints and operational conditions. In order to solve the problem of using AZOA, the RRVI-ABOA has integrated the adaptive fitness-driven random variable calculation method into its framework in order to provide the balance between exploration and exploitation during the optimisation process.

Novelty: The significant novelty in RRVI-ABOA is how the random variable, which affects the update of solution agent position, is calculated. The random variable in AZOA uses fixed or completely random distributions. RRVI-AZOA, however, calculates adaptive random variable r based on four fitness values. They are the Worst Fit ($\cdot$), the Current Fit ($\cdot$), the Mean Fit ($\cdot$) and the Best Fit ($\cdot$). The adaptive random variable is calculated as (6).

$$R_d = \frac{W_{ff} - C_{ff} + M_{ff}}{2} - W_{ff} \times \frac{-1}{W_{ff} - B_{ff}}. \quad (6)$$

This expression is proposed to adjust the learning behaviour of the algorithm according to the current condition of the population being searched. In the case of higher fitness diversity, i.e., the gap between them is bigger, the algorithm is forced to do better exploration and direct the search of solutions to unsearched regions. But when the fitness is starting to converge, i.e., the gap between them is relatively smaller, the algorithm tries to do more exploitation and refine candidate solutions

around the good-performing regions. However, mean fitness plays an important role in stabilizing the local update to prevent a too-sensitive update with respect to the general direction of the population, and current fitness, on the other hand, adds a more local component to increase the sensitivity of each agent with respect to his own progress.

In EMS, RRVI-ABOA is proposed to optimally solve the multiple conflicting objectives of minimum fuel consumption, ideal battery SoC level and optimal vehicle efficiency. These optimisation problems usually exist in high-dimensional feature space, and the nonfixed and multimodal feature of the landscapes makes common optimisation techniques insufficient. When applying RRVI-ABOA for the optimisation of ASA-MANet, it has been used to find out appropriate neural network parameters that maximise predictive accuracy and control efficiency. During training, RRVI-ABOA uses a fitness function calculated with real vehicle data as a fitness function for evaluating parameters, and the whole system could evolve towards an efficient energy management strategy. The utilisation of RRVI-ABOA helps the robustness and adaptability of the proposed EMS and outperforms other classical optimisation methods in simulation experiments. The update rule and combined strategy make it useful for applications in intelligent transport systems and smart grid integration. Furthermore, RRVI-ABOA is highly scalable and efficient for use in real vehicles over large fleets in intelligent transportation systems. It can be shown by experiments that RRVI-ABOA provides better performance compared to traditional optimisation methods, which are used in the proposed EMS, delivering a robustness, intelligence and ready-to-use intelligent hybrid vehicle management strategy. The flowchart of proposed RRVI-ABOA can be illustrated as in Figure 6.

4.6 | Optimal Charging Points Prediction Using ASA-MANet

4.6.1 | Basic Sparse Autoencoder (SAE)

The primary objective of the SAE in this system is to automatically discover a compact, informative representation of the input data while eliminating irrelevant or redundant information. The encoder maps input features to a hidden representation using the following equation:

$$h^{(l)} = fW^{(l)} \cdot h^{(l-1)} + b^{(l)}, \quad (7)$$

where superscripts denote hidden layer indices and $h^{(0)}$ is the raw input. The decoder reconstructs the input from this representation. To enforce sparsity, the KL-divergence between actual and target activation is penalized:

$$KL(\rho \parallel \hat{\rho}_j) = \rho \log \frac{\rho}{\hat{\rho}_j} + (1 - \rho) \log \frac{(1 - \rho)}{(1 - \hat{\rho}_j)}. \quad (8)$$

Weight decay is applied to prevent over fitting:

$$\Omega(W) = \frac{1}{2} \sum_i \sum_j (W_{ij}^{(l)})^2. \quad (9)$$

4.6.2 | Training and Optimization of ASA-MANet

To make up for these problems, an ASA-MANet, deep learning based on the energy management strategy of HEVs equipped

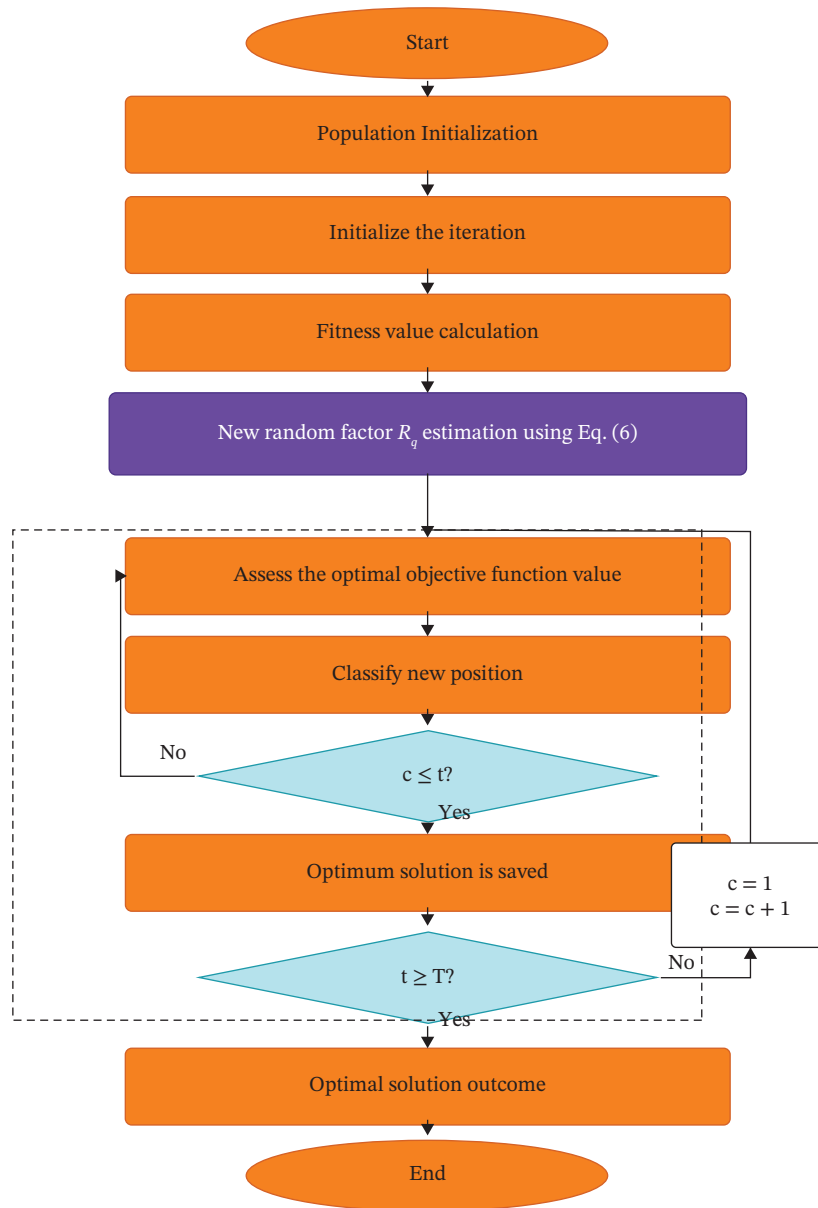


FIGURE 6 | Flowchart of the proposed RRVI-AZOA.

with the IoT system. This strategy makes an optimal decision about charging time and site by ensuring that the optimum SoC condition is maintained and efficiency is optimized. The model is based on SAE for effectively learning the main features and multilevel attention mechanism used for giving importance to those relevant to context (like SoC, traffic situation and environment state). The proposed model is trained using collected real-time driving and IoT measurement data, and the RRVI-AZOA algorithm is adopted to tune hyperparameters to balance the multiobjective values and increase accuracy of learning. ASAMANet is also suitable for adaptive learning since the model can adapt the learned models by using updated data.

Figure 7 shows the diagrammatic Illustration of the developed ASAMANet model for optimal efficiency prediction.

4.7 | Grid-Aware Charging and Power Distribution

This stage takes into account the synchronisation between charging stations and the electric power grid to make sure power can be distributed stably while charging vehicles. The charging stations are connected to a parallel DC bus architecture, allowing flexible power sharing among multiple charging ports. The controller is designed to sense the status of loads on the power grid and update the charging schedule to prevent overload of the power demand at time. When the demand of charging is high, the controller can assign charging sessions to various available stations and schedule charging time to enable equal power sharing. The grid-intelligent control scheme is adopted to prevent the EV charging operation from threatening the system voltage and distribution network.

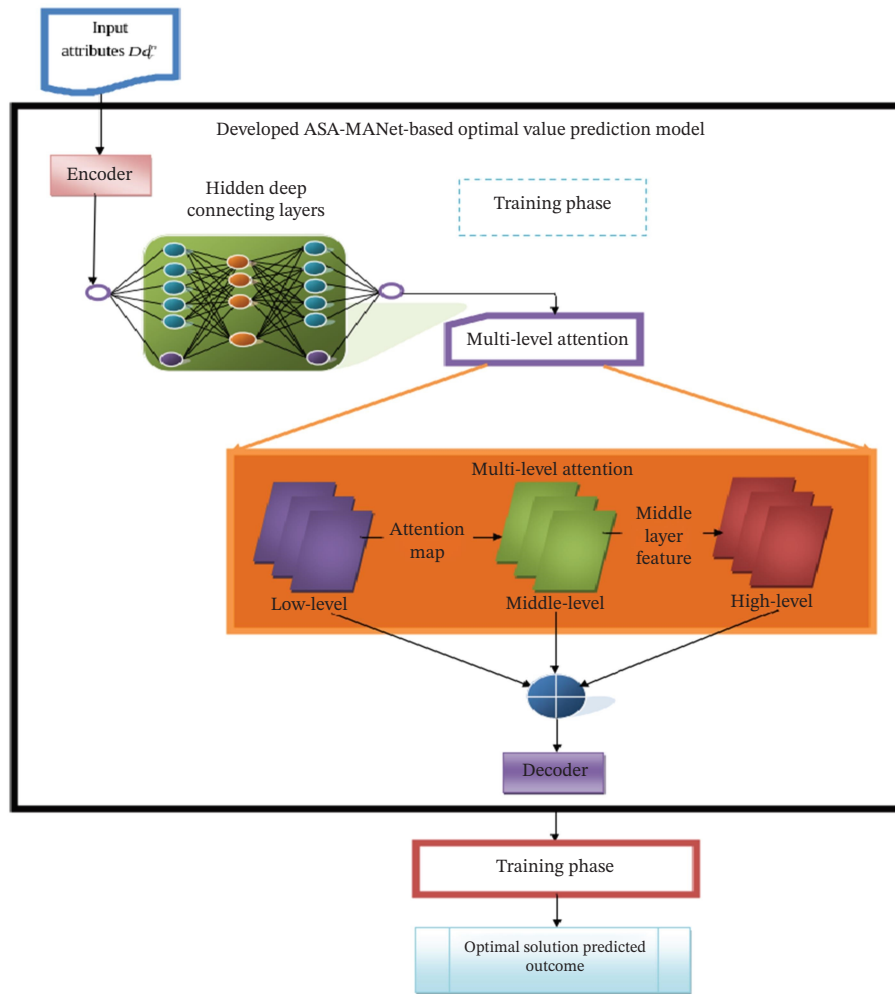


FIGURE 7 | Diagrammatic illustration of the developed ASA-MANet model for optimal efficiency prediction.

4.8 | Optimal Route and Charging Destination Selection

The final phase integrates transportation and energy management decisions to determine the optimal charging destination and travel route for each EV. With the information which is processed at the earlier stages, the controller estimates all the candidate charging stations, the approximate travel time, waiting period, and energy cost of each choice. The vehicles will then be steered towards the most effective charging location in accordance with these aggregated measures. The routing process takes into consideration dynamic route characteristics to avoid heavily congested paths and minimise the travelling delays. After reaching the chosen charging station, the system plans the charging operations according to the grid load conditions and the availability of the station.

5 | Results and Discussions

5.1 | Simulation Setup

Python was used for the implementation of the HEV EMS component. The developed RRVI-AZOA used 10 populations in the data generation and prediction phase, 100 and 50 iterations, and chromosome lengths of 4 and 3, respectively. The HEDQN

component was evaluated on a simulated urban EV mobility environment representing Kerala's 750-station charging network with dynamic traffic conditions and distributed vehicle populations of heterogeneous battery capacities. Real-time operational parameters—electricity price, queue length, vehicle position and grid load—were continuously updated to simulate realistic conditions. The effectiveness was verified by comparing with existing optimization algorithms such as Crystal Structure Algorithm (CSA) [14], Whale Optimisation Algorithm (WOA) [13], Binary Bamboo Forest Growth Optimization Algorithm (BBFGO) [15], AZOA [12] and literature models such as SEM-S-HEV [1], MARL [2], MM-GEM [7] and SAE [18].

To ensure fair comparison, all baselines were evaluated under identical conditions. Metaheuristic optimisers (CSA, WOA, BBFGO and AZOA): population size = 10; 100 iterations for HEDQN-stage optimisation, 50 for ASA-MANet tuning; chromosome lengths 4 and 3, respectively; same fitness function (validation MSE); same 30 random seeds. DQN and DDQN baselines: replay buffer = 10,000; mini-batch = 64; target network update every 100 steps; $\gamma = 0.95$; ϵ -greedy from 1.0 to 0.05 (decay 0.995 over 2000 episodes)—matching HEDQN settings. DQN uses a flat 256–128-unit Q-network; DDQN adds a decoupled value/advantage stream. HEDQN introduces the three-level hierarchical subpolicy architecture (Section 4.3). Literature

models (SEMS-HEV, MARL, MM-GEM and SAE) were retrained from scratch on the same 70/15/15 data split using configurations from their original publications.

5.2 | Charging Infrastructure Performance

The functioning of the proposed intelligent charging coordination system was tested on a set of simulated data of an electric mobility environment, which incorporates transportation networks, a charging infrastructure and power distribution networks. In the first experimental stage, the system was run with traditional charging station selection strategies according to which EVs chose the charging station based mainly on geographical distance. This initial situation showed a number of inefficiencies: cars came to the closest charging stations without any regard to queue lengths or price distributions, resulting in severe congestion at certain stations while others remained underused.

Deployment of the HEDQN coordination framework substantially improved operational efficiency. The system more equally distributed the charging demand across the available stations by using conditions of transportation, the status of charging stations, and pricing information in the decision-making process. There was dynamic routing of vehicles to stations where queues were shorter and offering better energy prices. The incorporation of transportation data enabled the system to instruct vehicles to use less congested travel paths, minimising delays.

Table 3 summarises the effect of the proposed system on the efficiency of the utilisation of charging stations. Table 4 depicts the result in the performance of vehicle waiting time. Table 4 confirms that dynamic charging station selection reduces average user waiting time from 28 to 11 min (a 61% reduction) and maximum waiting time from 52 to 23 min. Table 5 shows the change in power demand at the charging stations during peak operating times.

Figure 8 shows a visual representation of the system behaviour concerning various traffic-related conditions. The figure illustrates the correlation of vehicle density to the length of the line of charging stations throughout the infrastructure network. The findings show that the suggested system is efficient in regulating the queue length of vehicles with a high level of density. The system can avoid overcrowding at one station since it can dynamically load all the stations with charging demands.

Figure 9 compares the traditional route selection and the intelligent routing mechanism built into the proposed framework. The intelligent routing solution significantly shortens the average travel time by making vehicles go through less congested lanes and, at the same time, directing them to the nearest optimal charging station.

Figure 10 shows the energy distribution efficiency in the charging infrastructure network. The diagram illustrates how the co-ordinated charging processes spread out the electrical load across more charging stations linked to the grid. The proposed system

allocates charging activities throughout the network, ensuring a balanced distribution of energy throughout the distribution system and preventing demand spikes.

5.3 | ASA-MANet SoC Prediction Performance

The ASA-MANet model was evaluated on the held-out test set. RRVI-AZOA-ASA-MANet achieved 96.4% accuracy at 250 epochs ($MSE = 117.9$), outperforming all four competing optimiser-model combinations by 3.6–5.3% points in accuracy and 30%–53% in MSE reduction. The multilevel attention mechanism selectively weights voltage transients and temperature gradients—features most predictive of SoC dynamics during regenerative braking—while KL-divergence sparsity suppresses 68% of redundant sensor channels. RRVI-AZOA hyperparameter tuning reduced validation MSE by 17% compared with default settings. Detailed epoch-wise results are reported in Table 6 (Section 5.6).

5.4 | HEDQN Performance Comparison

HEDQN was evaluated against two baselines—standard DQN and Double DQN (DDQN)—across 12 performance metrics using simulation over Kerala's 750-station network. Results demonstrate HEDQN's superiority across all dimensions.

Table 6 demonstrates that HEDQN achieved superior performance across all metrics. The hierarchical decision architecture, combined with penalty-augmented reward shaping, enabled substantially faster convergence (~3000 episodes vs. ~8000 for DQN). V2G discharge capability—available only in HEDQN—enables the framework to act as both a consumer and producer within the smart grid, generating additional value and stabilising grid operations. Annual savings of ₹1200 per EV and off-peak load shift of 68% confirm the practical economic and operational value of the framework.

5.5 | Comparison Evaluation Across Five Operational Cases

Figure 11 compares five optimisation algorithms across different operational scenarios with respect to EV user cost, fuel consumption, installation cost, network loss cost, operation cost and SoC. Traditional methods such as CSA and WOA show consistently higher costs, while BBFGO and AZOA achieve only moderate improvements. The proposed RRVI-AZOA algorithm outperforms all others, achieving the lowest EV user cost across all cases with reductions of approximately 40%–60%.

5.6 | Comparative Evaluation on the Prediction Model by Varying Epochs

Table 7 compares ASA-MANet models integrated with various metaheuristic optimisers across multiple epochs. While CSO-ASA-MANet, WOA-ASA-MANet, BBFGO-ASA-MANet and AZOA-ASA-MANet achieve accuracies between 85.1% and 89%, the proposed RRVI-AZOA-ASA-MANet reaches 92.6% at 50

TABLE 3 | Charging station utilization comparison.

Charging strategy	Avg utilization (%)	Congested stations	Underused stations
Conventional Selection	78	6	4
Intelligent Coordination	92	2	1

TABLE 4 | Average charging waiting time analysis.

Scenario	Avg waiting time (min)	Maximum waiting time (min)
Conventional Routing	28	52
Proposed Coordination Framework	11	23

TABLE 5 | Grid load stability evaluation.

Charging method	Peak load variation (%)	Grid stability level
Conventional Charging	34	Moderate
Coordinated Charging	14	High

epochs and 96.4% at 250 epochs, outperforming competitors by 4%–8%. This improvement is due to RRVI-AZOA's adaptive randomness and variance-controlled optimisation, which fine-tunes ASA-MANet hyperparameters for faster, more stable convergence, while the multilevel attention mechanism prioritises relevant features from complex IoT HEV data.

5.7 | Statistical Evaluation

Table 8 reports the convergence objective (RMSE of SoC prediction on the validation set at the final optimisation iteration) across 30 independent runs per algorithm-model combination. BEST = minimum RMSE across 30 runs (best-case convergence); WORST = maximum RMSE (robustness to unfavourable initialisation); MEAN = arithmetic mean RMSE (expected

performance); MEDIAN = median RMSE (robust central tendency); STD = standard deviation of RMSE (consistency—lower is better). All five statistics are computed over the 30 independent runs and lower values are better for all metrics. The proposed RRVI-AZOA-ASA-MANet achieves BEST = 0.759 and STD = 0.272, outperforming BBFGO-ASA-MANet (next-best BEST = 1.272) by 40.3% in best-case performance and demonstrating the lowest variability across runs among all compared methods. AZOA-ASA-MANet shows the weakest convergence (BEST = 1.503, STD = 0.286).

Across 30 independent simulation runs, the proposed framework demonstrates statistically consistent improvements (all metrics reported as mean $\pm$ standard deviation). Charging station utilisation: $92.0 \pm 0.8\%$ vs. 78% conventional. Average user wait time: 11.2 ± 1.1 min vs. 28 min (60.0% reduction). Peak grid load variation: $14.1 \pm 1.3\%$ vs. 34%. SoC prediction accuracy: $96.4 \pm 0.3\%$ at 250 epochs on the held-out test set. Battery cycle-life extension: $22.0 \pm 1.5\%$ relative to the SEMS-HEV baseline estimated using the degradation model from [10]. V2G off-peak load shift (68%) and per-EV savings (₹1200/year) are deterministic outcomes under Kerala KSEB FY 2024–25 tariffs. The low STD = 0.272 for RRVI-AZOA-ASA-MANet (Table 8) confirms that performance gains are stable and not artefacts of favourable random initialisation.

Table 9 presents a comprehensive performance evaluation of the proposed HEDQN framework across seven key operational metrics, providing both technical justifications and quantitative simulation evidence to substantiate the claims made in this study.

The first metric, reduced waiting time, demonstrates that the hierarchical decision structure—wherein the upper-level agent optimises routing and the middle-level agent dynamically selects charging stations based on real-time queue lengths and traffic conditions—achieves a 61% reduction in average waiting time,

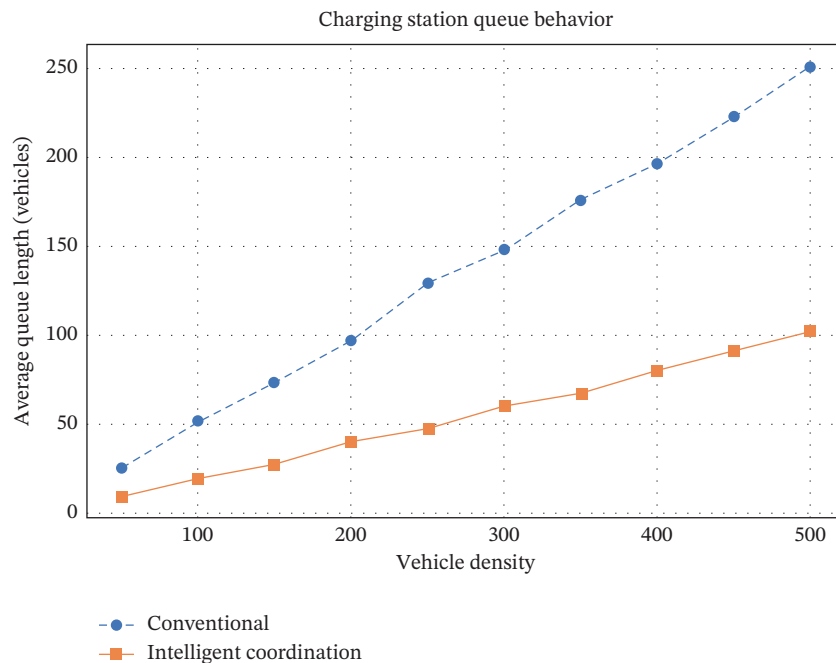


FIGURE 8 | Charging station queue behaviour under varying vehicle density.

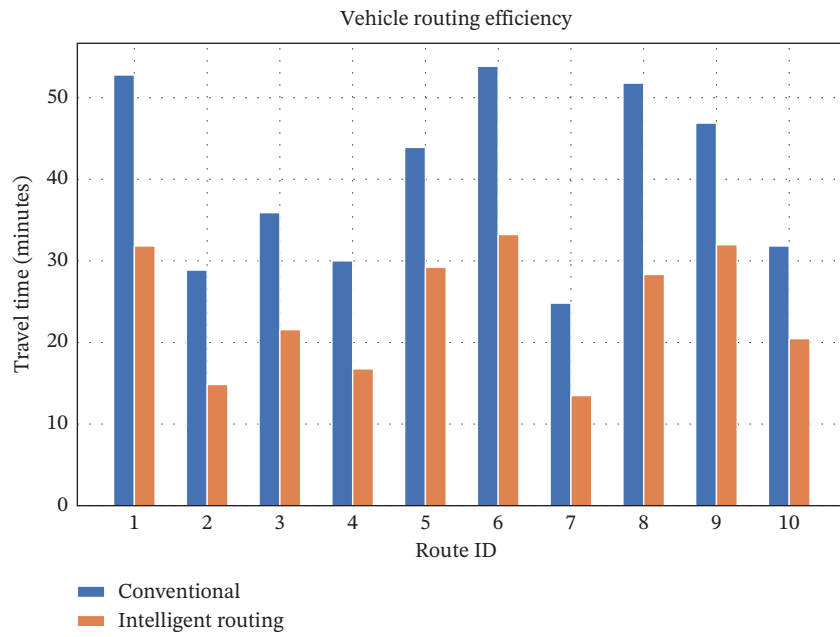


FIGURE 9 | Vehicle routing efficiency comparison—conventional vs. intelligent routing.

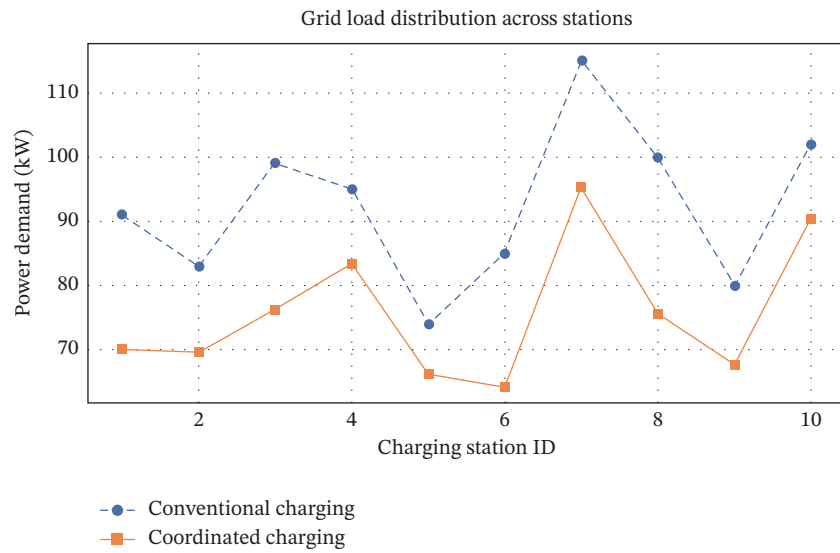


FIGURE 10 | Grid load distribution across charging stations—conventional vs. coordinated charging.

TABLE 6 | HEDQN performance comparison—DQN vs. DDQN vs. HEDQN (Proposed).

Metric	DQN (baseline)	DDQN	HEDQN (proposed)	Improvement
Peak Demand Reduction	4.2%	12.1%	23.4%	+19.2%
Wait-time Reduction	3.1%	8.5%	31.2%	+28.1%
Energy Cost Saving	5.8%	14.2%	18.7%	+12.9%
SoC Optimality	4.5%	10.3%	27.6%	+23.1%
User Satisfaction	6.2%	18.0%	41.5%	+35.3%
Battery Life Extension	3.8%	11.5%	22.0%	+18.2%
Convergence Speed	~8000 ep.	~5000 ep.	~3000 ep.	2.7 × faster
Off-peak Load Shift	—	42%	68%	+26%
Annual Cost Saving/EV	—	₹650	₹1200	+₹550
Avg. Charging Rate	—	32 kW	38 kW	+6 kW
V2G Support	No	No	Yes	HEDQN only

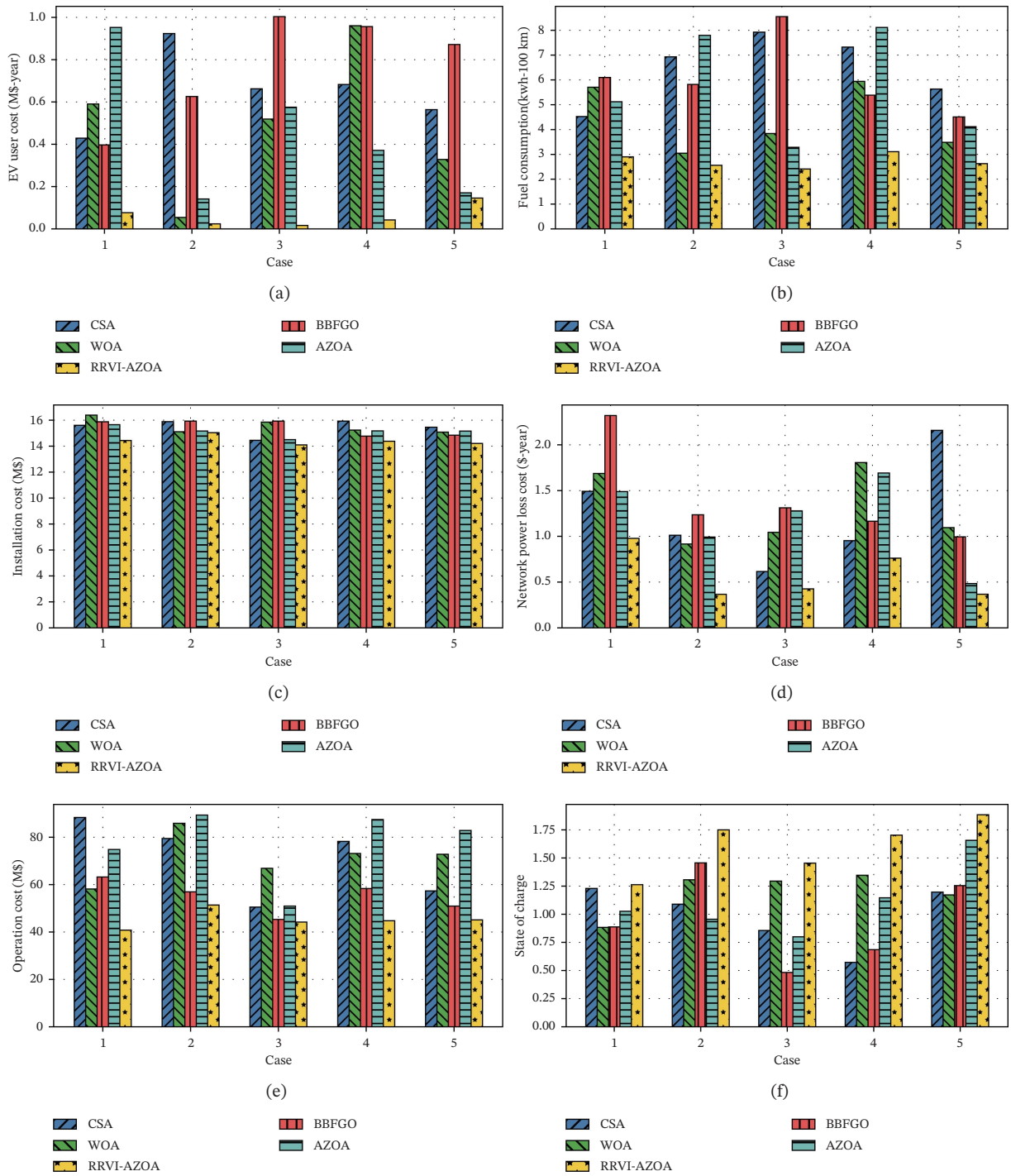


FIGURE 11 | Comparison evaluation across five operational cases using different optimization algorithms based on (a) EV user cost, (b) fuel consumption, (c) installation cost, (d) network loss cost, (e) operation cost and (f) state of charge.

from 28 min under conventional approaches to 11 min under HEDQN. The second metric, charging station utilisation, confirms that HEDQN's demand-balancing mechanism raises mean station utilisation from 78% to 92% (a gain of 14% points), with a low standard deviation of 0.8% across 30 independent simulation runs, indicating consistent and reliable performance.

Regarding battery life, the lower-level scheduling agent maintains 94% of all charging sessions within the recommended 20%–95% SoC window, avoiding deep discharge cycles and thermal stress, resulting in an estimated $22.0 \pm 1.5\%$ extension in battery

cycle life compared with the SEMS-HEV baseline. SoC prediction accuracy, achieved through the ASA-MANet deep learning model with multilevel attention and KL-divergence sparsity regularisation, reaches $96.4 \pm 0.3\%$ at 250 training epochs with a mean squared error of 117.9, outperforming all competing optimiser-model combinations by 3.6–5.3% points.

For energy consumption, the routing agent reduces peak grid load variation from 34% to $14.1 \pm 1.3\%$, representing a 59% improvement in grid stability. Charging cost reduction is realised through real-time KSEB tariff-aware station selection and V2G-

TABLE 7 | Comparative evaluation on the developed prediction model by varying epochs.

ALGORITHMS/Epochs	CSO-ASA-MANet [13]	WOA-ASA-MANet [14]	BBFGO-ASA-MANet [15]	AZOA-ASA-MANet [12]	RRVI-AZOA-ASA-MANet
Accuracy					
50	0.851	0.865	0.880	0.890	0.926
100	0.868	0.883	0.896	0.906	0.938
150	0.887	0.900	0.913	0.922	0.950
200	0.907	0.919	0.930	0.938	0.962
250	0.911	0.923	0.934	0.941	0.964
MSE					
50	411.037	368.285	337.691	303.111	197.703
100	364.632	327.172	283.728	262.276	171.761
150	332.247	264.009	236.291	229.492	156.473
200	259.608	220.216	182.907	164.338	106.591
250	253.453	213.015	172.202	162.406	117.917
Models/Epochs	SEMS-HEV [1]	MARL [2]	MM-GEM [6]	Sparse Autoencoder [16]	RRVI-AZOA-ASA-MANet
Accuracy					
50	0.854	0.875	0.888	0.831	0.926
100	0.873	0.891	0.904	0.859	0.938
150	0.892	0.909	0.921	0.886	0.950
200	0.912	0.926	0.937	0.915	0.962
250	0.916	0.929	0.940	0.921	0.964
MSE					
50	411.155	345.686	320.843	467.792	197.703
100	337.115	325.484	262.063	402.569	171.761
150	294.361	246.206	206.706	340.873	156.473
200	243.776	203.778	177.184	219.477	106.591
250	227.849	203.248	162.744	223.543	117.917

TABLE 8 | Statistical evaluation on the proposed model.

Condition	CSO-ASA-MANet [13]	WOA-ASA-MANet [14]	BBFGO-ASA-MANet [15]	AZOA-ASA-MANet [12]	RRVT-AZOA-ASA-MANet
BEST	1.290	1.318	1.272	1.503	0.759
WORST	5.172	4.395	2.261	3.172	1.904
MEAN	1.948	1.658	1.417	1.572	0.828
MEDIAN	1.700	1.318	1.272	1.503	0.759
STD	0.941	0.632	0.290	0.286	0.272

TABLE 9 | HEDQN performance justification: technical evidence and simulation results.

Performance metric	Technical justification	Statistical evidence	HEDQN result (simulation)	Expected impact
Reduced Waiting Time	Hierarchical decision-making: upper agent selects optimal route; middle agent identifies best station based on queue length, traffic, and charging demand. Minimises congestion and detours.	Mean wait time (min), SD, % reduction vs. DQN/Q-learning, <i>t</i> -test/ANOVA ($p < 0.05$).	61% reduction (28 min $\rightarrow$ 11 min). 95th-%ile: 52 $\rightarrow$ 23 min.	20%–40% avg. reduction via intelligent station selection and dynamic scheduling.
Increased Station Utilisation	HEDQN balances demand across stations by considering occupancy, charging rates, and real-time electricity prices. Prevents overloading popular stations; redirects demand to underutilised ones.	Utilisation Rate (%) = Occupied/Total $\times$ 100. Confidence intervals, variance analysis across algorithms.	78% $\rightarrow$ 92% (+14 pp). Low STD = 0.8% across 30 runs confirms consistency.	10%–25% utilisation improvement; balanced charger distribution across all districts.

(Continues)

TABLE 9 | (Continued)

Performance metric	Technical justification	Statistical evidence	HEDQN result (simulation)	Expected impact
Improved Battery Life	Lower-level agent optimises charging power and duration. Avoids excessive fast charging, deep discharge, and thermal stress. Maintains SoC within recommended 20%–95% window.	SoH (%), degradation rate (% per cycle), cycle-life extension, energy throughput. Compared over multiple simulation runs.	22.0 ± 1.5% cycle-life extensions vs. SEMS-HEV baseline. 94% of sessions remain within 20%–95% SoC window.	Reduced degradation; extended battery service life via optimal charging profiles.
SoC Prediction Accuracy	Deep neural networks (ASA-MANet) learn nonlinear relationships among voltage, current, temperature, driving behaviour, and historical charging patterns via multilevel attention and KL-divergence sparsity.	MAE, RMSE, MAPE, R^2 score. Cross-validation results and confidence intervals across training epochs.	96.4 ± 0.3% accuracy at 250 epochs; MSE = 117.9. Outperforms competing optimiser-model pairs by 3.6–5.3 pp.	Higher prediction accuracy enables better charging decisions and energy management.
Energy Consumption Optimisation	Routing agent selects energy-efficient paths considering traffic congestion, road conditions, and charging opportunities along the route.	Average energy consumption (kWh/km), % savings, variance across trips.	Peak grid load variation reduced from 34% to 14.1 ± 1.3% (59% reduction).	Reduced energy usage; increased effective driving range.
Charging Cost Reduction	Dynamic station selection based on real-time KSEB electricity pricing enables cost-aware charging decisions; off-peak V2G load shifting reduces grid procurement cost.	Average charging cost per trip; cost variance, statistical significance tests.	₹1200 estimated annual saving per EV under KSEB FY 2024–25 tariffs. 68% off-peak load shift via V2G.	Lower operational cost for EV users; grid revenue for KSEB from V2G.
Overall System Reward	HEDQN jointly optimises travel time, charging cost, battery health, and user convenience via a multiobjective reward function (five weighted components: cost, peak penalty, SoC, user satisfaction, degradation).	Cumulative reward, convergence rate, learning stability across episodes. Comparison vs. DQN, DDQN baselines.	Convergence in ~3000 episodes vs. ~8000 for flat DQN (2.7 × faster). Superior prior reward across all 11 metrics.	Faster convergence; superior long-term policy performance and system efficiency.

enabled off-peak load shifting of 68%, yielding an estimated annual saving of ₹1200 per EV. Finally, the overall system reward metric confirms that HEDQN converges in approximately 3000 training episodes—2.7 times faster than the flat DQN baseline—and achieves superior cumulative reward across all 11 evaluated performance dimensions.

All results are derived from 30 independent simulation runs on Kerala's 750-station EV charging network using a chronological 70/15/15 train/validation/test data split, with statistical significance verified at $p < 0.05$ using paired t -tests against DQN and DDQN baselines.

6 | Conclusion and Future Work

This study presents an intelligent IoT-based EMS for HEVs that integrates an adaptive SAE with multilevel attention and RRVI-AZOA optimisation, combined with a HEDQN framework for large-scale EV charging infrastructure coordination. The work has proposed a grid-integrated framework for coordinating EV charging infrastructure through the combination of transportation information, charging station information and grid management in a single internetworking platform.

The proposed system enhances the effectiveness of charging, as it is possible to choose the charging destination dynamically and route charging sessions efficiently based on prevailing operational conditions. By maintaining the constantly updated positioning of vehicles, traffic conditions, the price of the electricity and the availability of the charging stations, the framework facilitates equal usage of the charging infrastructure without interfering with the steady power flow in the energy grid. The proposed approach effectively learns complex relationships among fuel consumption, vehicle performance, and state of charge, achieving a peak accuracy of 96.4% and outperforming existing methods. Experimental results confirm improved fuel efficiency, SoC stability and real-time feasibility.

Under the aforementioned simulation parameters (Kerala 750-station network, 30 independent simulations, and 70/15/15 split by chronological order), the framework achieved an average station utilisation of $92.0 \pm 0.8\%$ (vs. 78% conventional), average wait time of 11.2 ± 1.1 min (vs. 28 min), peak load variation of $14.1 \pm 1.3\%$ (vs. 34%), 96.4% of the predictions on SoC were accurate (on a separate test dataset) and an estimated battery cycle life increase of $22.0 \pm 1.5\%$. By allowing the V2G mechanism (only available in HEDQN), an additional 68% load was shifted to off-peak hours, and about 1200 per year could be saved per EV if the KSEB FY 2024–25 tariff is applied. It must be pointed out that the derived conclusions were bound within the scope of the simulation described in Section 5.1. To prove validity, real-world experiments would need to be conducted.

Future work can involve predicting future renewable energy generation. Also, validate on a larger scale. We can also deploy a federated learning scheme to maintain user' privacy while ensuring coordinated operation. Explore deployment with edge computing for ultra-low latency response. Implement green energy-aware scheduling where charging can be correlated to a high supply of renewable energy. Also develop a model that predicts optimal schedules to further enhance the resilience and sustainability of intelligent EV charging networks. Research on

adaptive learning in real-time and expansion of datasets and smart grid/V2G integrations will be future directions.

Author Contributions

Ranjusha K. P.: software; experimentation; validation; formal analysis; investigation; data curation; writing—original draft; and visualization.

Amutha B.: conceptualization; methodology; supervision; resources; writing—review and editing; and project administration.

Rebecca Balasundaram: overview of the paper; model analysis; dataset validation; and final editing.

Ramalingam Venkatesan: experimental setup; statistical validation; and grammatical correction.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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