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Article

AI – Driven Reinforcement Learning System for High Traffic Electric Vehicle Charging Station with Linear Optimization Algorithm

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Abstract: Electric Vehicles are thought to be among the best options for lowering gas emissions and oil consumption. EV users can from a charging station with a well-thought-out schedule and price plan. Advanced energy management techniques are required to guarantee the sustainable, dependable, and effective operation of charging infrastructure due to the quick rise in the usage regarding electric vehicle (EV). In light of recent research, current design restrictions as well as the erratic conduct of EV consumers make classic scheduling techniques, such as set costs for Time-of-Use (ToU), insufficient. Uncoordinated charging results Voltage instability caused by transformer overloading, also wasteful utilization of electricity from renewable as EV use rises. AI is becoming more widely acknowledged in a crucial facilitator of scalable, durable, effective EV charging facilities with intelligence. This paper proposes a hybrid AI-based architecture that integrates real-time Traffic pattern, distance of EV, arrival and departure time of EV state of charge as input. Through real-time monitoring and charge optimization, the EVCS enable intelligent EV charging. The AI framework employs a non-uniform Poisson process in order to dynamically assess user demand also enhances schedule of charging. While the charging demand of electric vehicles (EVs) is intrinsically heterogeneous, decentralized, and stochastic, the intermittent and weather-dependent nature of PV power results in considerable output uncertainty. The purpose of the EV Charging Grid Optimization is to facilitate research on AI-driven energy management for EV charging infrastructure. The two proposed optimization algorithm improves the operational effectiveness of EVCS. Using threshold value Reinforcement Learning make the real-time decision that dynamically schedule the EV. Threshold value is determined from customer preferences. The proposed technology demonstrates scalability, durability, and cost-effectiveness and provides a feasible substitute for upcoming metropolitan EV charging system.
Keywords: NA

1. Introduction

Electric vehicles (EVs) include limousines powered through e-motors instead of gasoline engines along with powered via current preserved in electrically charged banks. Jaguars are particularly efficient and typically requiring less maintenance over conventional vehicles due to their compact components, quick braking lack of immediate emission. EVs provide available alternative to traditional gas-powered automobiles worldwide considering the increasing concerns about air pollution and changes in climate. The vehicles are an eco-friendly option for drivers since they run on rechargeable batteries and emit no pollution. Not only are EV environmentally friendly, but they additionally offer quick torque also acceleration, a quiet and comfortable ride, and greatly lower functioning expenses. Because EVs emit zero exhaust, they reduce carbon footprints plus environmental problems. These help combat warming humid and enhance atmospheric superior while lowering reliance upon petroleum-based products. EVs may constitute less expensive to execute and maintain eventually, while occasionally having a higher starting investment. Your repayment period may be as short as three years, depending on your yearly kilometers. Electric charging is generally cost-effective than using petroleum or diesel oil, even if electricity from the sun is utilized. This is considering EVs require little upkeep considering there are lower motors. EVs can be fuelled by alternative sources of energy includes electricity from the sun or wind. Further to having to be fueled by typical reusable electrical source, battery-operated automobiles, or BEVs, run only using electrically. Some are present underneath both recent also ancient cars, and they vary in comparison to moped to 160-tons large trailers. The wheels are driven by an electric motor is powered by power cells, which have been typically built around lithium ions. BEVs must be plugged reflecting outside force supply, including solar energy intersection for powering, standard electrical out let, to be replenished. An engine that burns fuel and a motor driven by electricity are combined in electric plug-in hybrid automobiles. Because they have larger packages of batteries unlike conventional meld cars, plug-in meld electric vehicles are capable of driving farther upon electrically alone. The automobile autonomously shifts either an inline engine as well as a configuration allowing the utilization of combining an engine along with an electrical motor provided batteries has reached its full capacity.

2. Literature Review

Achieving sustainability objectives requires integrating EVs powered by renewable energy sources also smart grids. This review focuses on current research on increasing grid stability, optimizing energy use, and boosting the effectiveness of EV charging infrastructure. EVs and other high-power applications have been suggested for Systems for Wireless Charging. To better power transfer productivity, a range of wired transformer structures are described [2]. Although attempts have been made to incorporate designs based on battery energy storage system (BESS) and photovoltaic (PV) technologies [3] with distribution system requirements, power supply security, dependability, and economics for EV charging stations have not yet been ensured [4]. Simulink-based EV simulation design incorporates artificial intelligence (AI) methods in order to Adaptive Energy Management System (AEMS) also Predictive Maintenance System (PMS). By employing NNs, or neural networks, to track and also accurately anticipate that the power source will be over ninety percent charged. PMS guarantees early identification of battery degradation. AI-powered electric vehicle control system with predictive maintenance and flexible energy administration within the meantime, the AEMS uses Fuzzy Logic Control (FLC) to dynamically optimize energy distribution, increasing driving range by at least 10%. In the meantime, the AEMS uses [5]Fuzzy Logic Control (FLC) to dynamically optimize energy distribution, increasing driving range by at least 10% AI-driven control systems maximize power distribution, regenerative braking, and energy distribution in a variety of driving scenarios. Even in dynamic contexts, deep reinforcement learning allows for adaptable, learning oneself [6] skills when increase power savings as well as prolong power on a single charge. When it comes to power delivery and powering for electric cars, Reinforcement Learning that includes policy iteration methodology [7] also value-iteration methodology performs very well in real-time adaptive decision making. It is investigated artificial intelligence's potential in used to be combat cyber security [8] and security risks in the electric vehicles' energy control systems. This result highlights how artificial intelligence may promote efficiency and creativity in sustainable mobility. ML approaches, such as supervised learning for fault detection, unsupervised learning for [9] anomaly detection, and Reinforcement Learning for maintenance schedule optimization, are a major focus. AI-driven battery management systems designed specifically for electric cars, concentrating on machine [10] learning techniques for state-of-charge (SoC) predictions and predictive maintenance, also battery ailment monitoring. The three types are and solar PV systems EVCS, batteries for EVCS, turbo power plant, and photovoltaic cells. Three potential configurations [11] are evaluated for technological, economical, and environmental viability using meta-heuristic methodologies. The optimization algorithm aims to minimize the energy expenses as well as the overall net current expense while maintaining certain level of likelihood of power supply. An advanced infrastructure for charging EVs is necessary for their flawless rollout. An important consideration is where outlets for rapid powering (FCSs) ought to be positioned. Though consequently, this paper provides a useful [12] way to use the connectivity of Eastern Bay to determine ideal position of FCSs.

An Instantaneous Data Processor, a computerized intelligence -powered incursion authentication mechanism, also Smart Load Balancer (SLB) are the three primary components to improve the system's flexibility, security, and efficiency, these [13]components employ cutting- edge computational learning methods like auto encoders, acquiring through reinforcement and Tensor of Interaction Machines. Smarter strategies that can swiftly adapt while maintaining grid stability and satisfying user charging requirements are becoming more and more necessary EV charging [14] station management uses various approach such as forecasting methodologies, reinforcement-based decision systems, pattern-based learning, and other mixed tactics. Providers can successfully allocate assets by employing forecasting tools to anticipate shifts in charging requirements. Proper forecasting of demand not only helps prevent idle capacity during idle periods but also lessens the likelihood of overflowing charging facilities throughout peak hours. This preventative plan enables broader municipal convergence to utilize environmentally friendly power supplies, thus enhancing the usefulness existing EV [15] hardware simply synchronizing conventional power sources to anticipated refueling requests. The field involves optimizing energy exchange productivity, reducing electrical disposal, as well as minimizing fees for patrons along with suppliers instead of just merely accelerating recharging. AI integration in EV charging [16] technology is the way to make charging systems intelligent and effective since the technology's charge satisfies the needs of both the energy industry as a whole and consumers of futuristic vehicles. However, a lot of models of EV charging stations approach charger configuration also site allocation distinct procedures, which results in inefficient investment, underutilization of infrastructure, and spatial-capacity [17] mismatches. The following research presents AI-powered decision-making method that concurrently maximizes on-site arrangements for chargers and station locations in order to overcome this limitation.[18] The results demonstrate how intelligent charging systems can facilitate the shift to more environmentally friendly modes of transportation while maintaining grid stability and economic feasibility. Nonlinear environmental interactions with urban energy consumption were investigated using MATLAB's Neural Fitting and Regression Learner models.[19] Many preprocessing techniques, including time alignment, smoothing, and outlier removal, were used to preserve the quality of the raw data. The performance measurements revealed a good degree of agreement between the anticipated and measured load profiles, considering an estimated parameter (v1) around 1.56 and mean absolute percentage error (MAPE) of 5.6. Despite our insistence on their use, the ubiquitous the accessibility of charging stations and both the high cost regarding EVs impeding their mainstream adoption. [20] Using QR codes to make payments and storing transaction data in the cloud are two possible solutions to these issues.

3. Proposed System

The suggested a hybrid AI-based architecture Fig 1that combines CSV data, Grid constrains Traffic pattern cost factor as input, and real-time grid-aware scheduling to optimize EV charging stations. Intelligent EV charging is made possible by the EVCs with PV through real-time monitoring and charge optimization. The AI framework uses a reward system based on cost, voltage, and user happiness to improve charging schedules and uses a non-uniform Poisson process to dynamically evaluate user demand. Real-time, flexible, and dynamically aligned decision-making charges using global grid capacity is made possible by artificial intelligence (AI)-based optimization, specifically Linear programming reinforcement learning. The user is provided with mobile app .The decision is made by RL based on grid constraints traffic patterns and the demand's priority

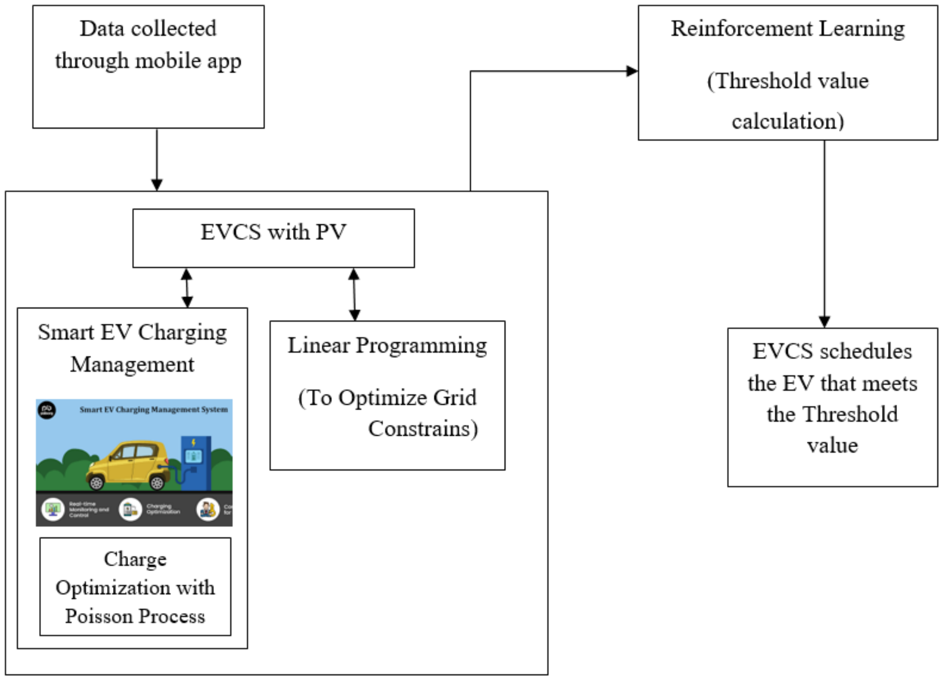

Fig. 1 Frame work of EVCS with RL and Linear Programming

Charge Optimization with Poisson Process

Since the Poisson point process can be seen as a stochastic process, it is frequently defined on the real number line. For instance, it is used in queuing theory to simulate random occurrences that are dispersed over time, like customers arriving at EV charging Station

The counting procedure that is most frequently employed is the Poisson process. It is typically employed in situations where we are counting the instances of specific events that seem to occur at a specific rate but are entirely random (i.e., lacking any particular structure).

A Poisson process is a kind of counting Optimization process $\{M(t), t \geq 0\}$

Where,

M (t) is the total number of events that have taken place by time t.

$$P_x \text{ (M)}=\left\{\frac{e^{-\pi}\pi^{t}}{k\varphi\varphi}\right\}, \text{ for t } \epsilon\ R_x \qquad (1)$$

If $x\sim$ P (φ), EY=φ; Var (Y) =φ Var

If $x_i\sim$ P (φ_i) $EY = \ \varphi_{i,}$; Var (Y) = φ Var

One way to think of the Poisson distribution is as the binomial distribution's limit.

Linear Programming for Grid Optimization

For short-horizon load scheduling, a deterministic Linear Programming (LP) layer is integrated to enhance Grid constraints Optimization. The LP's objective is to lower the overall expense of charging

$$(v_i, r_j)\, D(i(\text{r})) = \sum_{j=0}^{M} \quad v_i r_i \text{ n (r)} \qquad (2)$$

$$\sum_{i=1}^{M} \quad v_i \geq q_{max}, F_i\, q_i\, r_i \geq Ei$$

(3)

Where

Ei - EVs' minimal energy requirements

$D(i($ r)) - pricing signal for energy costs in real time

q_{max} - Transformer capacity limit imposed by the grid.

This LP permits RL to get influence the long-term policy for energy consumption while guaranteeing that grid limits are rigorously maintained. Short-term control hierarchy with two layers viability as well as Two-layered short-term control hierarchy is produced by the interaction of LP and RL.

AI-Driven Reinforcement Learning

Reinforcement Learning (DRL) is used by the hybrid framework's control core to make adaptive decisions in the face of vagueness. The present situation of the network includes loading grid and matrices of customer inquiries.

$$J(r_t, a_t) = -(\beta * C_{elec}(t) + \alpha V(t)^2 + H\ (t) \qquad (4)$$

Where

V (t) - voltage deviation in real time,

H (t) - Index of user annoyance according to a departure with scheduled screens for powering

A and β - Grid simulations to calibrate the hyper parameters

C_{elec}(t) - TOU tariff-based time-varying energy cost function.

Large deviations are penalized more harshly by the squaring of V (t). Cost-effective, grid-friendly, and user-aligned behavior is encouraged by this reward system. Proximal policy optimization (PPO) is used to update policies, guaranteeing training stability and convergence. Determine the Threshold value for the data collected from the EV user.

$$T(S) = \sum J(r_t, a_t \in H(t)\, f(s) \qquad (5)$$

Scheduling the Electric vehicle according to the calculated threshold value is shown below Fig.2

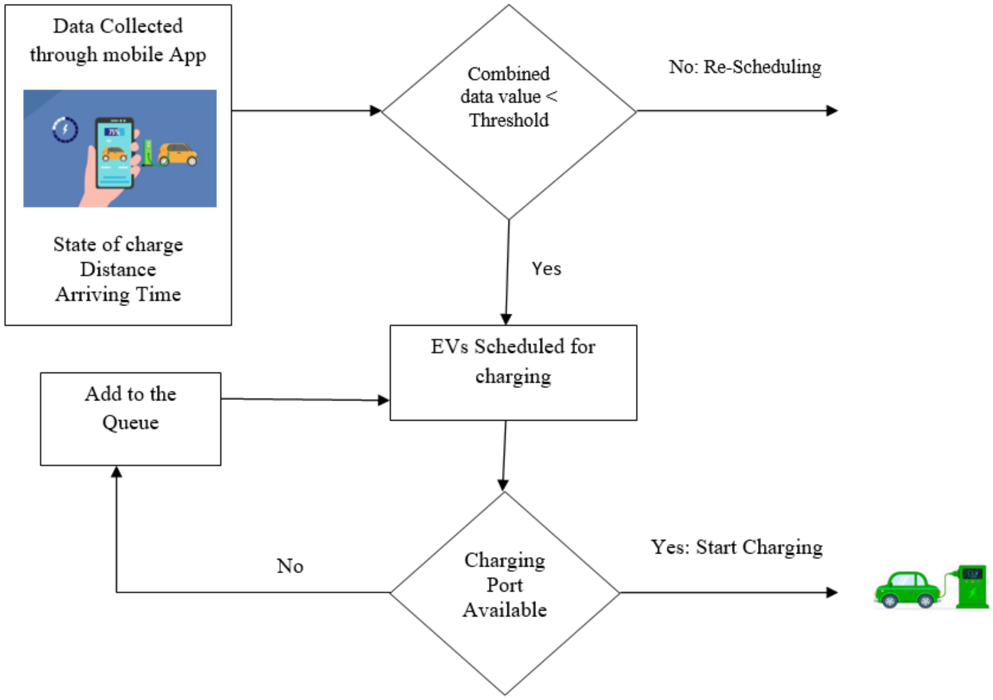

Fig.2 Electric Vehicle Scheduling

Experimental Results and Discussion

The total number of passing Electric Vehicles is the arrival data. The number of EVs that arrive at the charging station and request charging services is modeled using the scaled number of arrival which is shown in Fig. 3.

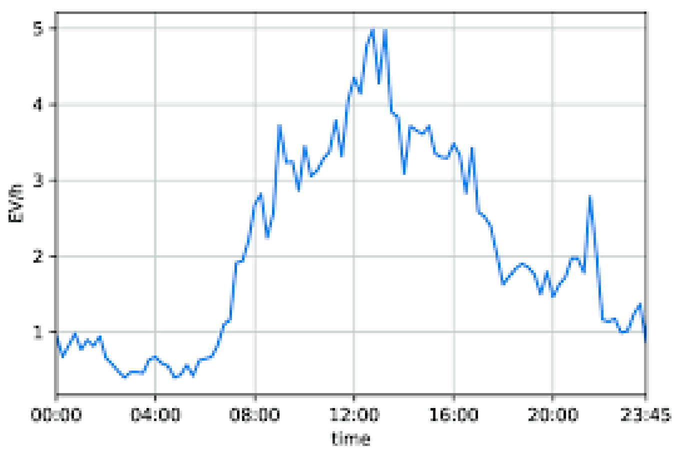

Fig.3 Total Number of Passing Electric

Table1 show the collected data parameters and arriving time for each kind. It stands for the long-term, normal, and emergent users. The parameters used to evaluate demand response are α, and Variance β

Parameter	Normal	Long Term	Emergent
αKw/H	40	100	3.89
β Km/Hr	5	8	4.9

Arriving Time	3.47	30	120
Variance	0.4	15	0.4

The following Fig.4 shows the arrival and departure of various Electric Vehicles under normal demand. Such Normal distributions consider the traffic constraints and availability of resources and allocate the EVCS. Under Normal distribution off- peak load is higher than Light and other users.

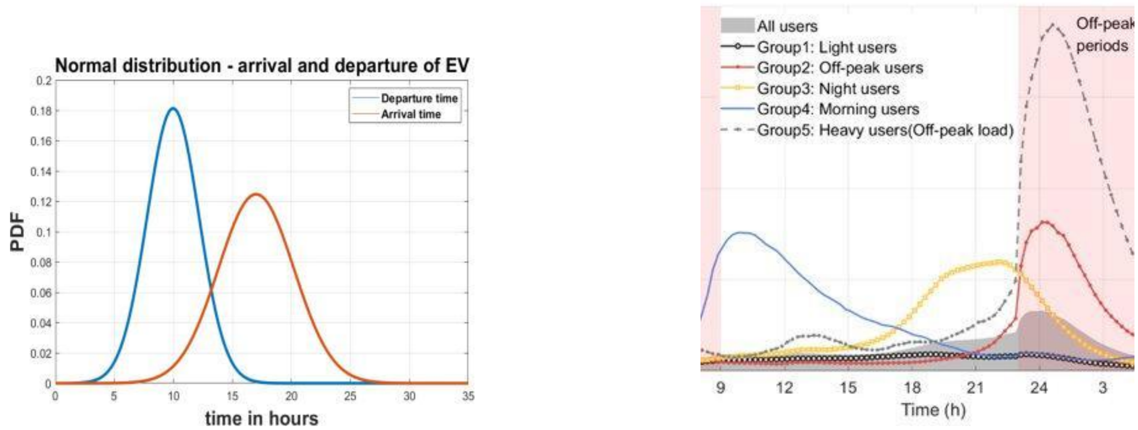

Fig. 4Analysis Result of EV Charging Demand data along with Normal Distribution

The data Such as state of charge, distance and arriving time are collected from the EV users. If the Combined data collected from the EV users is less than threshold value, then the vehicles are allocated for charging if not vehicles get re-schedule notification. Here, fig. 5 the combined data value of vehicle1, Vehicle 2, vehicle 4 and Vehicle 6 are less than threshold, whereas vehicle 3 and vehicle 5 data values are higher than threshold.

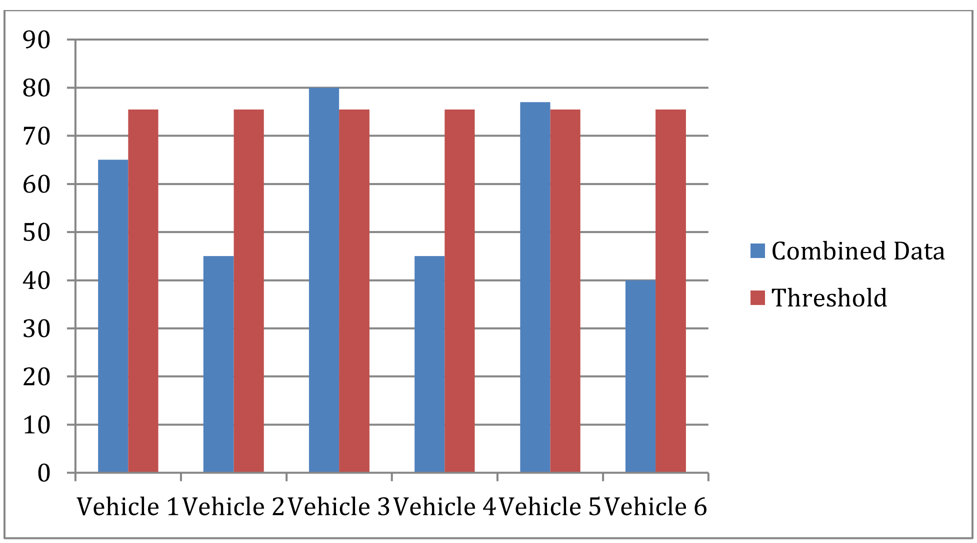

Fig. 5 Comparison of Combined Input Data with Threshold

The following Fig 6 The show a large number of EV are in demand , demonstrating the geographic dispersion of EV users throughout the EVCS, ranging from extremely close to places that are more than 10-40 kilometers away. This variation highlights that the proposed method makes the decision based on the demand of the user in charging slot allocation and scheduling.

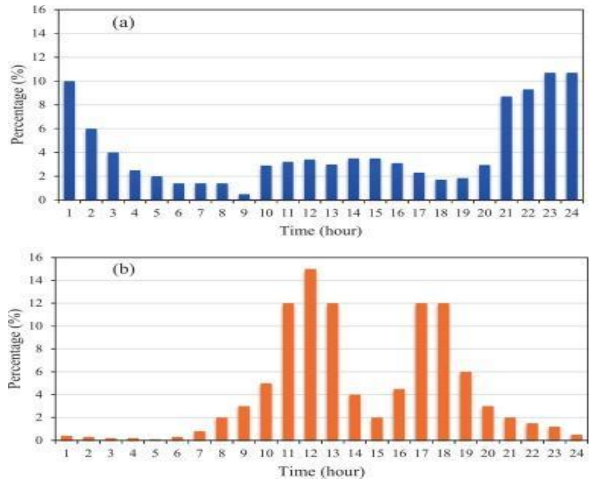

Fig 6 EV slot allocation and scheduling,

4. Conclusion

EV customers and the electrical distribution system can both profit from a charging station with a wellthought out schedule and price plan.Intelligent EV chargig is made possible by the EVCs with PV, which provide realtime m onitoring and charge optimization. The suggested hybrid AI-based architecture for optimal EV charging shows great promise for enhancing load balancing, cutting costs, and using renewable energy. The suggested hybrid framework combines grid-constrained Linear Programming (LP) optimization and Poisson process to dynamically use to assess user demand and optimizes charging schedules reinforcement learning makes the choice based on priority of the EV user

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