RESEARCH PAPER

Artificial Intelligence Algorithm Executions in Charge Controlling of a Renewable Energy integrated Electric Vehicle System

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ABSTRACT
While photovoltaic (PV) generation is sporadic and seldom corresponds with charging demand, the expansion of electric vehicles (EVs) raises demand on the power grid. The design and implementation of a reinforcement-learning (RL) based charge controller for a PV-powered EV charging station with a static battery and a grid connection are presented in this study. Tabular Q-learning, which learns whether to charge the EV as well as when to charge or discharge the station battery under a time-of-use tariff, stochastic solar output, and a departure-time energy demand, is used to solve the charging problem, which is formulated as a Markov Decision Process (MDP). The controller is trained over 600,000 simulated days and tested on 1,000 unseen days once the system is formally modelled. The learnt controller meets the EV energy target on each test day while increasing PV self-consumption from 64.4% to 90.6% and reducing average daily operating costs by 19.1% when compared to uncontrolled charging. Additionally, it is 14.9% less expensive than a manually adjusted rule-based controller.
Keywords: electric vehicle, photovoltaic, charge control, reinforcement learning, Q-learning
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INTRODUCTION

One important way to reduce carbon emissions is through transportation electrification, however unregulated EV charging causes strong demand peaks and transfers emissions rather than eliminates them when the grid is dominated by coal. This is addressed by matching charging stations with nearby renewable energy sources, primarily rooftop or carport PV. The challenge is that electricity prices fluctuate throughout the day, solar power is erratic and unpredictable, and EV arrival and departure times are set by the driver. These cannot all be handled at once by a set rule.

The assessed energy-management techniques are based on the sequential decision-making framework of reinforcement learning (RL). An agent adopts a policy by engaging with an environment and maximizes

cumulative reward, according to Sutton and Barto's standard formulation [2]. A key model-free approach in this context is Q-learning [1]. Without using a model of the dynamics of the system, it learns action values directly from experience. Mnih et al. [3] integrated Q-learning with deep neural networks in the Deep Q-Network (DQN), demonstrating that agents may learn efficient control policies from high-dimensional inputs, while tabular approaches scale poorly to huge state spaces. DQN can only be used in discrete action spaces. The Deep Deterministic Policy Gradient (DDPG), an actor-critic technique for continuous control, was developed by Lillicrap et al. [4] to address this. The majority of deep reinforcement learning (DRL) applications to energy systems, where choices like battery dispatch and charging power are often continuous, are based on these two advancements.

Because energy problems are uncertain and stochastic—prices, renewable generation, occupant behavior, and arrival times are difficult to estimate precisely—model-free DRL works well. After reviewing RL algorithms and modeling approaches for demand response, Vázquez-Canteli and Nagy [7] come to the conclusion that RL can adjust to changing circumstances without the need for explicit system models. In order to accommodate varying EV charging arrival times and costs, Wan et al. [5] use DRL for real-time EV charging scheduling without a model of the underlying uncertainty. Online building energy optimization using DRL is addressed by Mocanu et al. [6], who demonstrate that learnt rules may control consumption in real time under dynamic circumstances.

DRL has been applied to household and microgrid energy management in more recent work. For home energy management, Liu et al. [8] suggest a DRL-based optimization technique that schedules household resources to save costs while taking user needs into consideration. Model-free DRL is extended to microgrid energy management by Talab and Avci [9], where several components must coordinate generation, storage, and load. By integrating renewable generation, storage, and EV charging demand into a single control issue, Baskaran [10] uses DRL to optimize energy in a solar-battery hybrid EV charging station. Of the works surveyed, this one is the most similar to systems that combine renewable energy sources with electric vehicle loads.

The construction and optimization of home energy management systems (HEMS) are covered in a body of work in addition to the DRL literature. The principles, setups, and scheduling techniques of smart HEMS are reviewed by Zhou et al. [11]. In their review of IoT for the smart home, Stojkoska and Trivodaliev [12] discuss the problems related to the sensing and communication infrastructure that HEMS rely on. An intelligent HEMS architecture is suggested by Shakeri et al. [13] for effective demand response in the smart grid. Residential demand-side management designs, strategies, optimization models, and techniques are surveyed by Esther and Kumar [14]. Foresee, a user-centric HEMS that prioritizes demand response and energy efficiency while taking occupant preferences into consideration, is introduced by Jin et al. [15]. Alam et al. [17] examine computational techniques for domestic energy cost optimization in smart grids, and Chavali et al. [16] provide a distributed algorithm for home energy management specifically for appliance scheduling. When taken as a whole, these studies create the optimization-based standard that DRL methods are typically evaluated against. Model-free approaches are motivated by the fact that they usually rely on precise models, forecasts, or extensive computation.

The physical design of renewable energy systems and storage is the subject of another set of research. In order to achieve total energy self-sufficiency in residential structures, Chegari et al. [18] investigate the best energy management practices of a hybrid system of PV, wind, pumped hydro storage, and batteries. Power management and control of a stand-alone DC microgrid that combines PV, hydro, biomass, and battery sources are covered by Biswal et al. [20].

In their comparison of integration topologies for sodium-sulfur (NaS) batteries in hybrid renewable systems, Das et al. [21] demonstrate how system performance is impacted by storage selection and integration. In order to enhance solar energy capture, Deepika et al. [19] introduce a hybrid weather station and solar tracking system. This complementing strategy raises generation at the source rather than maximizing its utilization.

Three categories comprise the literature. General RL and DRL algorithms make up the first [1]–[4]. The second includes DRL applications for microgrids, houses, buildings, and EV charging [5]–[10]. HEMS architectures, optimization-based demand-side management, and hybrid renewable and storage system design make up the third [11]–[21]. While hybrid renewable research [18]–[21] concentrate on system configuration, sizing, and conventional control, conventional HEMS and optimization approaches [11]–[17] manage scheduling effectively but rely on models and forecasts.

While DRL research [5]–[10] demonstrate that model-free learning may manage uncertainty, the majority focus on a specific domain, such as microgrid dispatch, household appliances, or EV charging. Few use a learning-based controller to simultaneously handle battery storage, renewable energy, and EV charging needs under dynamic situations. The goal of the current study is to close this gap.

2. Description of the proposed system

A PV array feeds a common DC bus via a boost (MPPT) converter, a stationary lithium-ion battery on the DC bus via a bidirectional DC-DC converter, an EV charger (DC-DC stage) providing power to the electric vehicle, and a bidirectional AC-DC inverter that connects the bus to the utility grid and a local base load make up the suggested system (Figure 1). After reading measurements (PV power, battery SoC, EV SoC, time, and tariff), a supervisory AI controller gives the converters power set-points.

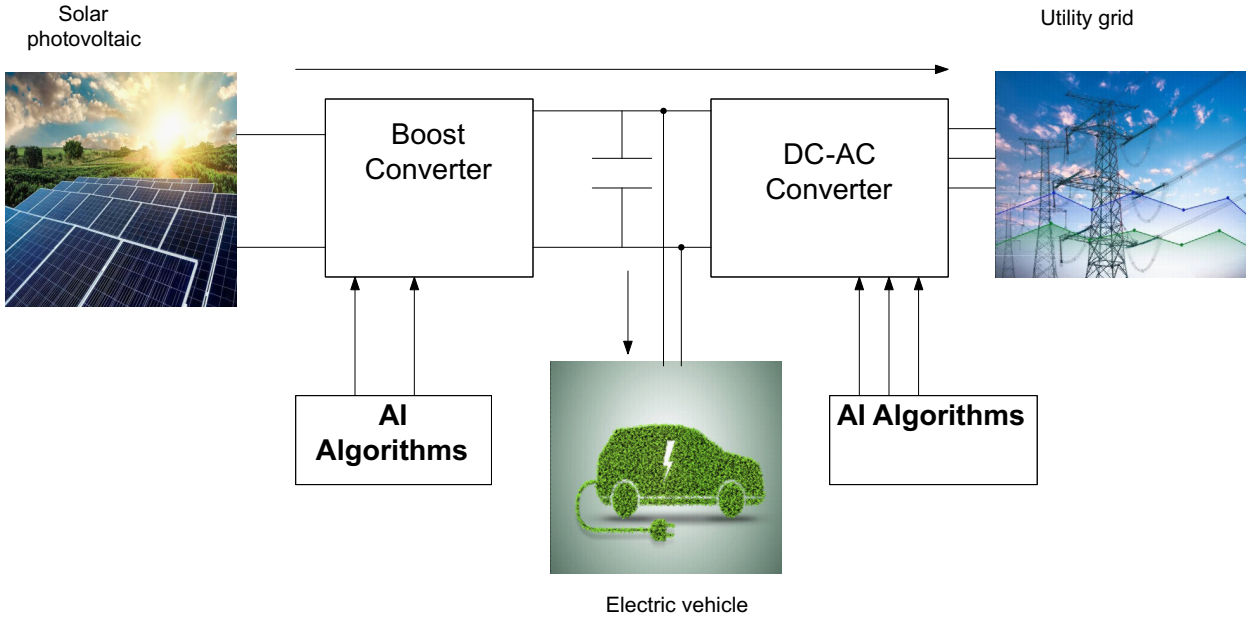

Figure 1. Proposed PV, battery and EV charging system with the AI supervisory controller.

3. Mathematical Modelling

The time step is $\Delta t = 1$ h and the horizon is one day, $t = 0, 1, \ldots, 23$.

3.1 PV generation. A physical PV model is

$$P_{pv}(t) = \eta_{pv} \cdot A \cdot G(t) \cdot [1 - \beta (T_c(t) - 25)] \quad (1)$$

$$T_c(t) = T_a(t) + (NOCT - 20)/800 \cdot G(t) \quad (2)$$

where G stands for irradiance (W/m2), A for array area, η_{pv} for efficiency, β for temperature coefficient, and Tc for cell temperature. The daily PV profile, which is a bell-shaped clear-sky curve scaled by a daily cloud factor and compounded by noise, is artificially created in the simulation:

$$P_{pv}(t) = P_{pv,max} \cdot s \cdot \exp(-(t + 0.5 - 12.5)^2 / (1.3 \cdot 3^2)) \cdot \xi_t \quad (3)$$

3.2 Station battery. With charging power $P_b^+ \geq 0$ and discharging power $P_b^- \geq 0$:

$$SoC_b(t+1) = SoC_b(t) + [\, \eta_b \cdot P_b^+(t) - P_b^-(t)/\eta_b \,] \cdot \Delta t / E_b \quad (4)$$

$$0.1 \leq SoC_b(t) \leq 0.9, \qquad P_b^+, P_b^- \leq P_{b,max} \quad (5)$$

3.3 Electric vehicle. The EV is plugged in from arrival time tarr = 08:00 to departure tdep = 18:00:

$$SoC_{ev}(t+1) = SoC_{ev}(t) + \eta_c \cdot P_{ev}(t) \cdot \Delta t / E_{ev} \quad (6)$$

$$P_{ev}(t) \in \{0, 3.7, 7.4, 11\} \text{ kW for } t_{arr} \leq t < t_{dep}, \text{ else } 0 \quad (7)$$

$$SoC_{ev}(t_{dep}) \geq SoC^* = 0.90 \quad (8)$$

3.4 Power balance. The net grid power (positive = import, negative = export) is

$$P_g(t) = P_{ev}(t) + P_L + P_b^+(t) - P_b^-(t) - P_{pv}(t) \quad (9)$$

where PL = 2 kW is the constant base load. Battery discharge to the grid is not allowed, so $P_b^- \leq P_{ev} + P_L$.

3.5 Cost function. The daily operating cost to be

minimised is

$$J = \Sigma t \left[\lambda imp(t) \cdot Pg^{+}(t) \cdot \Delta t - \lambda exp \cdot Pg^{-}(t) \cdot \Delta t + cd \cdot (Pb^{+} + Pb^{-}) \cdot \Delta t \right] + \rho \cdot Eev \cdot \max(0, SoC^{*} - SoCev(tdep)) - \lambda T \cdot Eb \cdot (SoCb(24) - SoCb(0)) \quad (10)$$

4. AI Controller based Q-Learning

4.1 State: st = (t, SoCev, SoCb, Ppv), discretized into 5 PV levels, 21 EV-SoC levels, 9 battery-SoC levels, and 24 hourly slots. 22,680 states result from this.

4.2 Action: at = (Pev, Pb) with Pev ∈ {0, 3.7, 7.4, 11} kW and Pb ∈ {−5, 0, +5} kW, yielding 272,160 Q-values and 12 actions.

4.3 Reward: rt = −ct, which is the negative of the step t cost in Equation (10).

4.4 Transition: the PV profile is stochastic and is controlled by Equations (3)–(9).

4.4 The learning rule. It updates the action-value function by

$$Q(st, at) \leftarrow Q(st, at) + \alpha k \left[rt + \gamma \cdot \max_a' Q(st+1, a') - Q(st, at) \right] \quad (11)$$

discount γ = 1, learning rate αk = max(0.03, 0.3(1 − k/N)), and an ε-greedy exploration rate εk = max(0.02, 1 − k/(0.8N)), where N = 600,000 and k is the episode number. The initial value of the Q-table is zero, which promotes exploration and is optimistic for cost-only return.

Following training, the supervisory controller stores the greedy policy as a look-up table. The controller (i) measures PV power and two SoCs at each control interval, (ii) maps them to discrete states, (iii) reads the optimal action from the table, and (iv) translates the power commands to converter references, such as Iev = Pev / Vdc for the charger current loop.

Because inference is a table look-up, the technique may operate on a cheap microcontroller and has very little processing cost. Regardless of the policy outcome, the battery and charger management systems impose safety limitations (SoC bounds, current and voltage limits, and charger rating).

Table.1 Specification of parameters of solar and electric vehicle

Parameter	Value
PV rating	8 kW peak
Station battery	20 kWh, ±5 kW, ηb = 0.95, SoC 10–90 %
EV battery	40 kWh, charger efficiency 0.92
Charger power levels	0, 3.7, 7.4, 11 kW
EV plug-in window	08:00–18:00, SoC target 90 % at departure
Initial EV SoC	Uniform 20–50 %
Base load	2 kW constant
Training	600,000 simulated days
Testing	1,000 unseen days (fixed random seed)

A comparison is made between three controllers. **Uncontrolled:** battery idle; charge at 11 kW as soon as you arrive till you reach the goal. **Rule-based:** the battery charges from PV excess and discharges in the evening; the battery is charged at the power that corresponds to the PV surplus, but never below the power required to meet the deadline. The learned greedy policy, or **Q-learning**, was proposed.

5. Results and Discussion

5.1 Learning behavior

The average daily cost while training is displayed in Figure 2. When ε is big and the agent explores extensively, it first rises somewhat. As exploitation increases, it declines progressively from a peak of approximately 425 to about 300 each day. Near the end of training, it flattens, signifying convergence. Because the exploration noise is included in training values, the greedy policy reduces the cost on the test set.

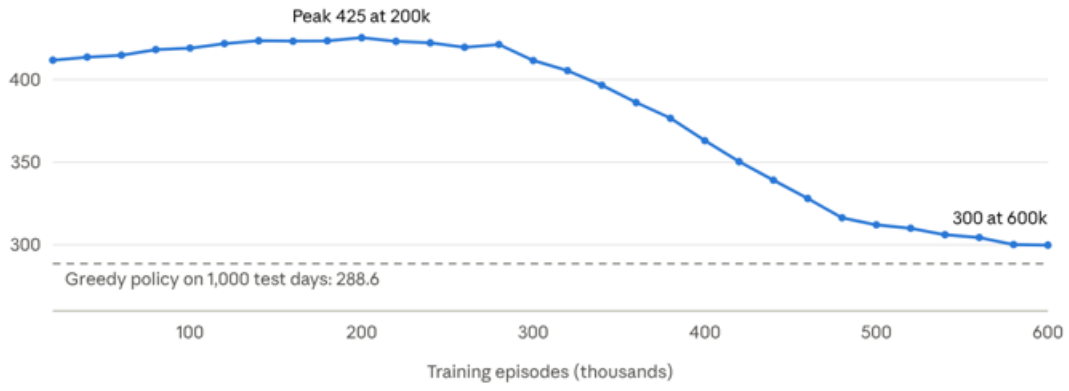

Figure 2. Learning curve of the Q-learning controller; the dashed line is the cost of the trained greedy policy on unseen days.

5.2 Daily operation

A typical test day (medium PV, initial EV SoC 30%) is depicted in Figure 3. The unregulated charger consumes up to 11.7 kW from the grid before the sun rises, starting at 11 kW at 8:00. In order to reach the 90% target, the learnt policy waits until 9:00, charges primarily at 3.7 kW via the solar window, uses a brief 7.4 kW period near the end, charges the battery at nite using cheap grid electricity, and empties it during the evening peak (Figure 4). On this day, Q-learning costs 293 per day, while uncontrolled and rule-based charging cost 380 and 364, respectively.

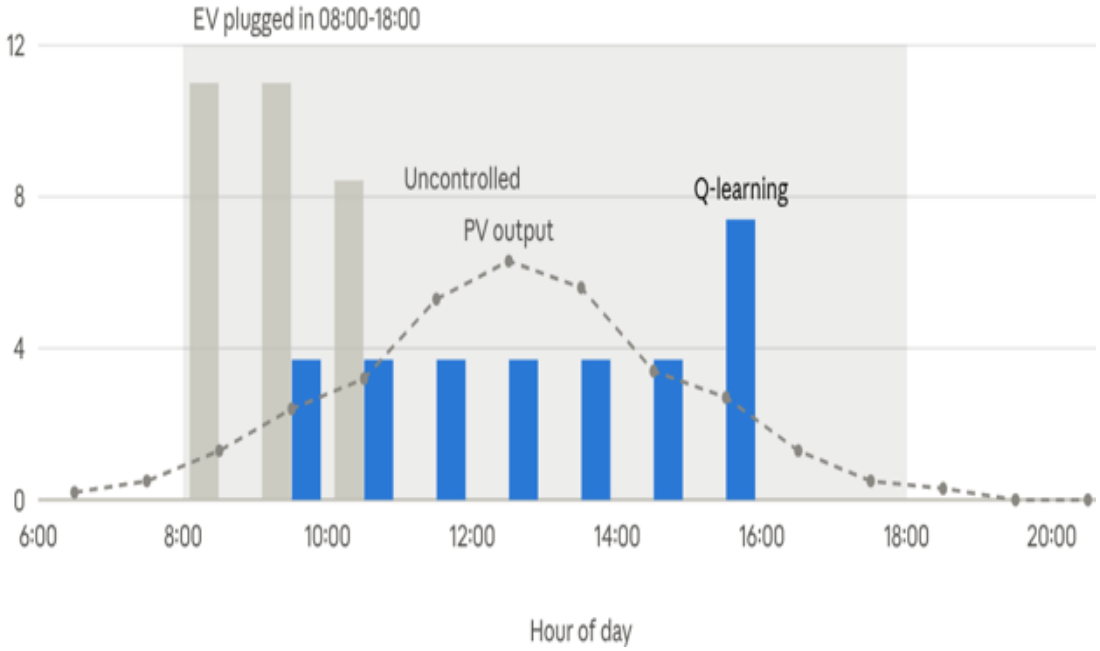

Figure 3. EV charging power of the uncontrolled and Q-learning controllers against PV output on a representative test day.

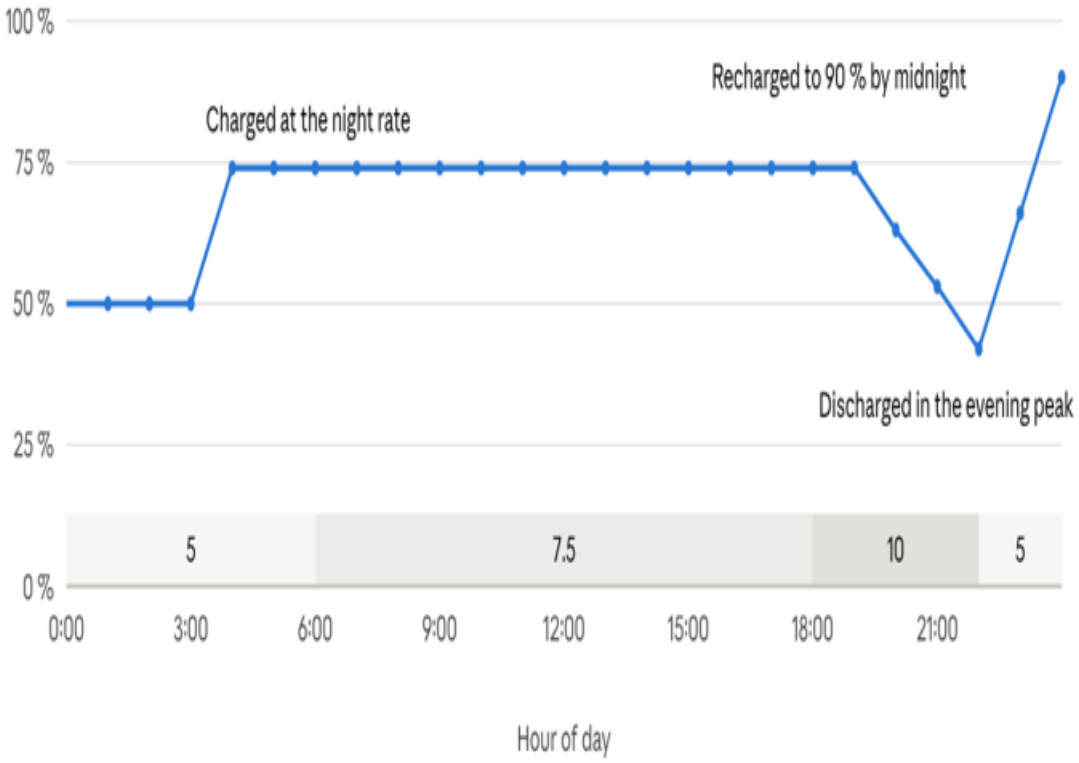

Figure 4. Battery state of charge under the Q-learning policy on the same day, against the time-of-use tariff.

Table 2. Performance on 1,000 test days

Metric	Uncontrolled	Q-learning
Average daily cost ($)	0.99	1.03
Cost reduction	7.8%	13.9 %
Grid import (kWh/day)	39.6	56.9
PV export (kWh/day)	5.9	3.6
PV self-consumption	88.6 %	91.9 %
Mean peak grid import (kW)	4.9	9.8
Mean EV SoC	0.96	0.95

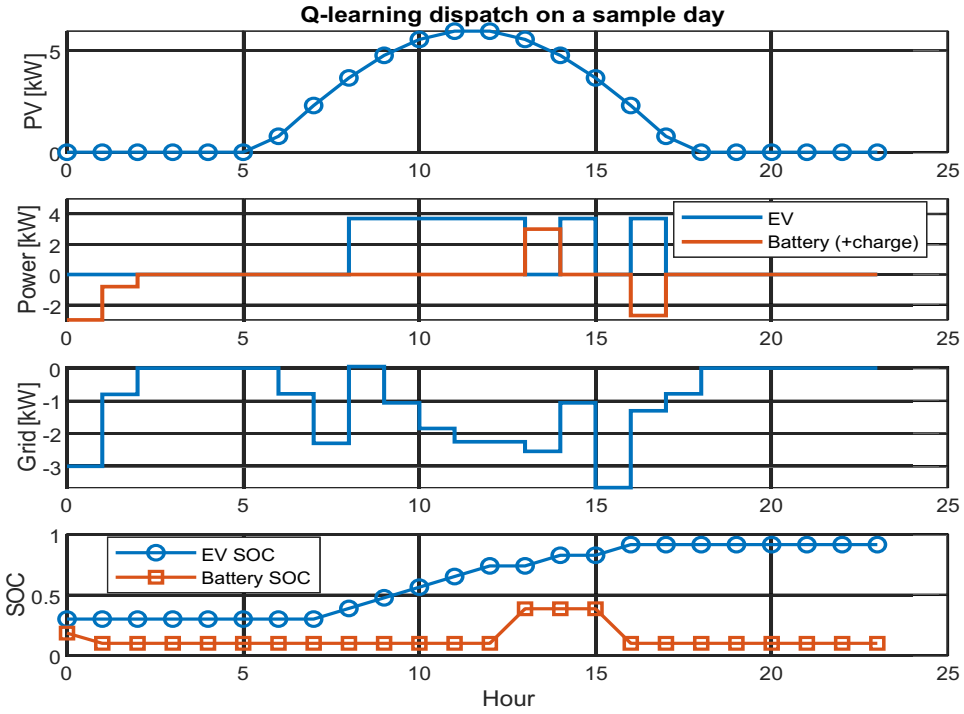

Figure 5. Variation of various performance parameters over the time

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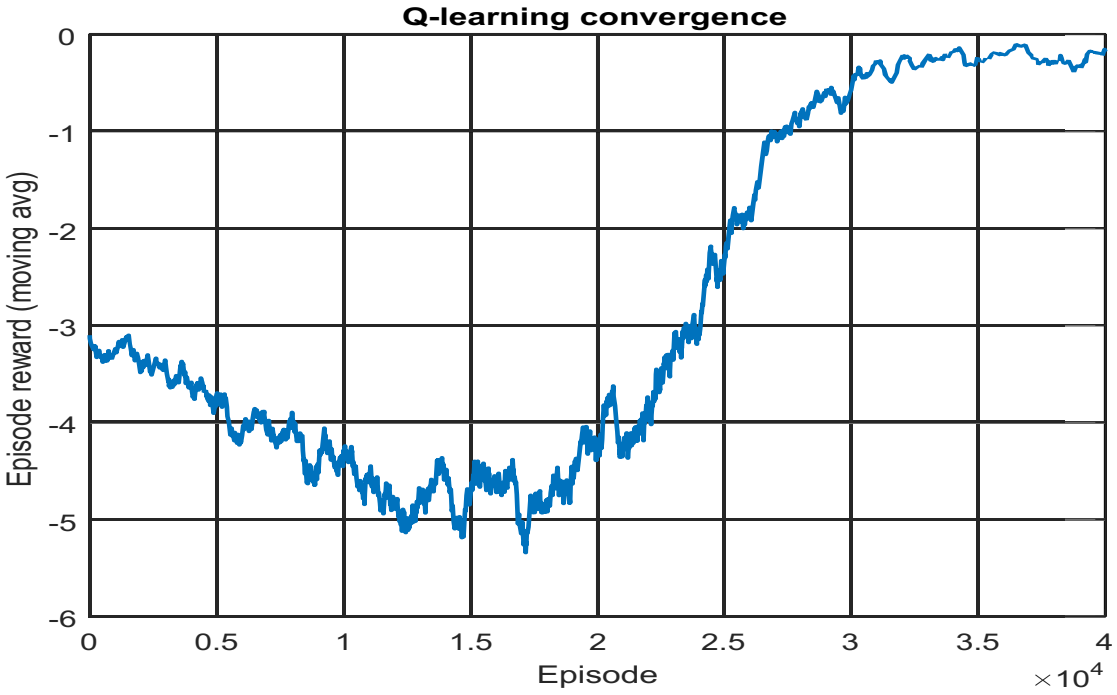

Figure 6. Variation of various episode reward over the episode

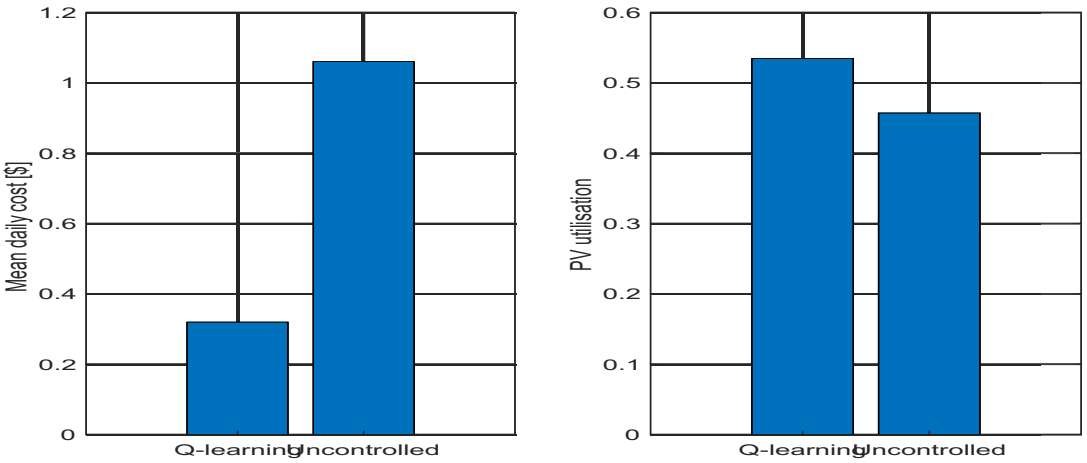

Figure 7. Measurement of mean daily cost and PV utilization with Q learning and uncontrolled

The variation of performance parameters like SPV power, battery power, grid power, SOC over the time period with Q-learning is shown in Fig.5. The Variation of various episode reward over the episode is shown in Fig.6 while the variation of mean daily cost and PV utilization with Q learning and uncontrolled is shown in Fig.7

6. Conclusion

In order to charge an EV from a PV, battery, and grid system, this paper built a model and an RL controller. The Q-learning agent learnt to consistently meet the departure deadline, move EV charging into the solar window, and use the battery for energy exchange. With 90.6% PV self-consumption, it lowered operating costs by 19.1% against uncontrolled charging and 14.9% against a rule-based controller on 1,000 unseen days. Future research will focus on hardware-in-the-loop validation, deep reinforcement learning, vehicle-to-grid operation, numerous vehicles with random arrivals, and actual irradiance data.

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