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Research on EV Charging Cost Optimisation and Pricing Assumptions

This report explores how recent academic literature models EV-charging prices when real-world tariff data are unavailable. Eleven open-access studies were identified (preference was given to UK-focused or European studies but global work was included when relevant). For each paper, we extract its citation, regional focus, pricing model assumptions (particularly how missing tariff data were handled), and provide a brief remark on how pricing uncertainty was tackled.

Papers and how they handle charging-price assumptions

1. Electric vehicle charging route planning for shortest travel time using an improved ant-colony algorithm (2024)

- **Citation:** Wei Gong, Haixin Cheng, et al., *Sensors*, 2024.
- **Region focus:** China (simulated road network and charging stations).
- **Pricing assumptions:** The system separates modules for EVs, electric grid, charging stations and the Internet-of-Vehicles (IoV). The electric-grid module **provides electricity price information**, and each station updates its price based on grid data and its own status and sends this to the IoV [1]. Thus charging prices are assumed to be available in real time; the model does not address missing or unknown tariffs.
- **Handling pricing uncertainty:** Price data are treated as known inputs; there is no discussion of default values or assumptions when price information is missing. The study focuses on minimizing travel time rather than cost.

2. Routing of electric vehicles with intermediary charging stations: a reinforcement-learning approach (2021)

- **Citation:** Daniel Pesquier et al., *Frontiers in Big Data*, 2021.
- **Region focus:** Generalised (experimental grid scenario). No country-specific tariff data used.
- **Pricing assumptions:** The paper notes that electricity price is one of several factors affecting station choice but focuses on energy efficiency and travel time [2]. No tariff data are used; charging is not cost-optimised.
- **Handling pricing uncertainty:** Prices are acknowledged qualitatively but not modelled; there are no assumptions about missing price data.

3. Dynamic pricing for electric-vehicle charging—A literature review (2019)

- **Citation:** Avizoua Nadera et al., *Energies*, 2019.
- **Region focus:** Review of U.S. and international tariff schemes.
- **Pricing assumptions:** Summarises various tariff types—flat rates, time-of-use (TOU), real-time prices, session-based fees and membership fees—used by utilities and public charging networks [3] [4]. It notes that states differ in whether per-kWh billing is allowed and that many public stations charge per minute or offer free charging.

- **Handling pricing uncertainty:** As a review, it does not propose a model but highlights that real-time and dynamic prices increase billing variability. It provides context for selecting default tariff types when actual data are unavailable but does not present explicit substitute values.

4. Optimal electric-vehicle charging with dynamic pricing, customer preferences and power-peak reduction (Cahiers du GERAD report, 2024)

- **Citation:** Mohammadi, Moeini & Benedikt Woltsche, *Cahiers du GERAD*, 2024.
- **Region focus:** Generic; no specific country used. Simulation parameters are adjustable.
- **Pricing assumptions:** The provider chooses charging prices from a discrete set and each customer has a **reserve price (maximum willingness-to-pay)**. A **fictitious station** is introduced so that if all stations exceed a customer's reserve price, the customer remains unserved [5]. There is no use of real tariff data; instead, the price set is a modelling parameter.
- **Handling pricing uncertainty:** Prices are decision variables rather than inputs. Missing tariffs are not an issue because the model allows operators to select price levels; the fictitious station prevents unrealistic price escalation.

5. Electric-vehicle charging and discharging algorithm based on reinforcement learning under dynamic pricing (2020)

- **Citation:** Song Yu et al., *Energies*, 2020.
- **Region focus:** Simulation using typical dynamic pricing schemes.
- **Pricing assumptions:** The study considers **time-of-use (TOU) and real-time pricing** schemes and treats them as given price signals. It notes that reinforcement-learning algorithms can be trained with historical price data and do not require explicit mathematical models [6]. The authors acknowledge that many studies assume fixed arrival/departure times and rely on historical price data.
- **Handling pricing uncertainty:** When future prices are unknown, they recommend training reinforcement-learning agents on historical price sequences; they do not propose default values but highlight that unrealistic user behaviour assumptions can distort results.

6. Optimal charge scheduling using war strategy optimization (2024)

- **Citation:** Shin et al., *Scientific Reports*, 2024.
- **Region focus:** South Korea (simulated grid and charging stations).
- **Pricing assumptions:** The paper's literature review notes that many existing scheduling models assume **fixed charging prices that vary with comfort levels, power demand and grid peak periods** [7]. The authors use a dynamic scheduling algorithm but do not explicitly model pricing; they focus on reducing waiting time and cost under a fixed price scheme.
- **Handling pricing uncertainty:** Prices are assumed constant during simulations. The study acknowledges that dynamic pricing models exist but does not address missing price data.

7. Firm-level optimisation strategies for sustainable and cost-effective EV workplace charging (2025)

- **Citation:** Catherine D. Middleton et al., *npj Sustainable Mobility and Transport*, 2025.
- **Region focus:** United Kingdom (workplace charging using UK electricity tariffs).
- **Pricing assumptions:** The model uses the **Octopus Agile** time-of-use tariff and public data for **grid-carbon intensity** to compute charging costs and emissions [8]. Three objectives—peak minimisation, cost minimisation and carbon minimisation—are tested.

- **Handling pricing uncertainty:** Real tariff data are available; no default rates are needed. The study demonstrates trade-offs between low-cost charging and peak management but does not discuss missing price data.

8. Deep reinforcement learning for charging scheduling considering distribution-network voltage stability (2023)

- **Citation:** Guoxing Liu et al., *Sensors*, 2023.
- **Region focus:** Simulation (likely Chinese network).
- **Pricing assumptions:** The simulation uses a **fixed TOU price schedule**—valley price 0.295 USD/kWh, peak price 0.845 USD/kWh and flat price 0.56 USD/kWh [9]. These are exogenous inputs.
- **Handling pricing uncertainty:** Prices are treated as known constants; no method is provided for missing data or forecasting.

9. Optimizing EV charging stations and power trading with deep learning and path optimisation (2025)

- **Citation:** Qing Zhu, *PLOS One*, 2025.
- **Region focus:** China (five-region power system).
- **Pricing assumptions:** The path-optimization component defines a **cost function combining travel cost and a charging fee based on price per kWh plus service fees** [10]. Regional power trading is optimised using **locational marginal prices (LMPs)**. LMP data come from simulated supply–demand imbalances; no missing data issues are discussed.
- **Handling pricing uncertainty:** Prices are taken from simulations of regional markets; there is no procedure for missing tariff data, but the model integrates dynamic price differences across regions.

10. Optimizing electric-vehicle charging costs using machine learning (2024)

- **Citation:** Yasin Mohammed et al., *Ingénierie des Systèmes d'Information* (IIETA), 2024.
- **Region focus:** Canada; data sources include Ontario electricity market and Winnipeg vehicle-usage surveys.
- **Pricing assumptions:** Because driving habits, electricity prices and fuel costs **were not available for the same city**, the authors combined data from multiple sources and made explicit assumptions: (1) the dataset is not affected by the electricity rate; (2) electricity price is closely related to consumption; and (3) gasoline costs more than electricity [11]. Public datasets (Ontario hourly load and gasoline prices) were used as proxies for electricity prices [11]. Missing values were handled through preprocessing and feature engineering [12].
- **Handling pricing uncertainty:** The study builds an information system that fuses public data on electricity prices, demand, driving habits and weather. When local price data were unavailable, **default relationships between electricity consumption and price** were assumed and gas prices were used as an upper bound [11]. The model uses reinforcement learning and dynamic programming to learn optimal charging strategies.

11. Optimization of electric charging infrastructure: integrated model for routing and charging coordination (2024)

- **Citation:** Hamid R. Sayarshad, *npj Sustainable Mobility and Transport*, 2024.
- **Region focus:** Generic model with examples from North America.
- **Pricing assumptions:** The integrated model estimates **bidding prices for day-ahead and intra-day electricity markets** and includes renewable generation. Charging stations decide

how much electricity to bid and at what price to minimize costs [13]. Real-time pricing adjustments are incorporated to adapt to market conditions.

- **Handling pricing uncertainty:** Prices are not assumed known; instead, the model **optimises bidding quantities and prices** using market forecasts. This indirectly addresses price uncertainty by adjusting bids rather than relying on fixed tariffs.

12. Impact and optimisation of vehicle-charging scheduling on regional clean-energy power supply networks (2025)

- **Citation:** Penghui Xu, Xiaobo Wang & Zhichao Li, *Energy Informatics*, 2025.
- **Region focus:** China (regional clean-energy grid).
- **Pricing assumptions:** The model uses a **Long Short-Term Memory (LSTM) network to forecast electricity prices** and integrates reinforcement learning to update dispatch decisions based on real-time prices, clean-energy availability and grid capacity [14]. The state vector includes station electricity price and other network variables [15].
- **Handling pricing uncertainty:** Uncertainty is addressed by **predicting the next period's electricity price** and using reinforcement-learning feedback to update the model when actual prices differ from forecasts [14]. The approach does not assume missing data but relies on continuous price forecasting to adapt to volatility.

Recommended papers for modelling charging prices when tariff data are unavailable

For a reinforcement-learning thesis that needs to model charging prices without reliable tariff data, the following papers are especially pertinent:

1. **Optimizing electric-vehicle charging costs using machine learning (IIETA 2024)** – This paper directly tackles missing pricing data by combining datasets from different locations and making explicit assumptions about the relationship between electricity consumption and price and the relative cost of gasoline [11]. It provides a practical example of how to build a proxy pricing model when local tariff data are unavailable.

2. **Optimization of electric charging infrastructure (npj 2024)** – The integrated model estimates day-ahead and intra-day bidding prices rather than assuming a fixed tariff [13]. It demonstrates how to incorporate dynamic electricity-market prices into routing and charging decisions, an approach that can be adapted when actual charging tariffs are uncertain.

3. **Optimal electric-vehicle charging with dynamic pricing, customer preferences and power-peak reduction (Cahiers du GERAD 2024)** – By selecting prices from a discrete set and introducing a fictitious station to ensure no customer is priced out, this paper avoids reliance on actual tariff data and offers a flexible pricing mechanism that can be tuned during optimisation [5].

4. **Dynamic pricing for electric-vehicle charging—A literature review (Energies 2019)** – Although not a modelling paper, this review summarises common pricing schemes and highlights the variety of flat, time-of-use and real-time tariffs [3]. It is useful for selecting a default pricing structure when data are missing and understanding how pricing models affect cost optimisation.

5. **Electric-vehicle charging and discharging algorithm based on reinforcement learning (Energies 2020)** – This work shows how reinforcement-learning agents can learn optimal charging schedules using historical price data and dynamic pricing schemes [6]. When future prices are unknown, model-free RL can adapt to price uncertainty.

6. **Optimizing EV charging stations and power trading with deep learning and path optimisation (PLOS One 2025)** – The study integrates locational marginal prices and charging fees into the route-planning cost function [10]. It provides an example of combining travel cost and charging cost in routing when regional price differences matter.

These papers collectively provide methods ranging from proxy price assumptions and dynamic pricing strategies to bidding-price estimation and reinforcement-learning adaptations. Together they offer a foundation for modelling charging costs in situations where real tariff data are incomplete or volatile.

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[1] Electric Vehicle Charging Route Planning for Shortest Travel Time Based on Improved Ant Colony Optimization
https://www.mdpi.com/1424-8220/25/1/176

[2] Routing of Electric Vehicles With Intermediary Charging Stations: A Reinforcement Learning Approach - PMC
https://pmc.ncbi.nlm.nih.gov/articles/PMC8187862/

[3] [4] Dynamic Pricing for Electric Vehicle Charging—A Literature Review
https://www.mdpi.com/1996-1073/12/18/3574

[5] G-2024-42.pdf
https://www.gerad.ca/fr/papers/G-2024-42.pdf

[6] Electric Vehicle Charging and Discharging Algorithm Based on Reinforcement Learning with Data-Driven Approach in Dynamic Pricing Scheme
https://www.mdpi.com/1996-1073/13/8/1950

[7] Optimal electric vehicle charge scheduling algorithm using war strategy optimization approach
https://www.nature.com/articles/s41598-024-72428-6.pdf

[8] Firm level optimisation strategies for sustainable and cost effective electric vehicle workplace charging
https://www.nature.com/articles/s44333-025-00032-w.pdf

[9] Deep Reinforcement Learning for Charging Scheduling of Electric Vehicles Considering Distribution Network Voltage Stability - PMC
https://pmc.ncbi.nlm.nih.gov/articles/PMC9920735/

[10] Optimizing EV charging stations and power trading with deep learning and path optimization | PLOS One
https://journals.plos.org/plosone/article

[11] [12] Optimizing Electric Vehicle Charging Costs Using Machine Learning | IIETA
https://www.iieta.org/journals/isi/paper/10.18280/isi.290326

[13] Optimization of electric charging infrastructure: integrated model for routing and charging coordination with power-aware operations
https://www.nature.com/articles/s44333-024-00004-6.pdf

14 15 Impact and optimization of vehicle charging scheduling on regional clean energy power supply network management | Energy Informatics | Full Text
https://energyinformatics.springeropen.com/articles/10.1186/s42162-025-00476-x