EVMapSim: A Network-level Electric Vehicle Charging Simulator

Demonstration Track

Prokopis Georgiou
University of Southampton
Southampton, United Kingdom
pg1n23@soton.ac.uk

Jayati Deshmukh
University of Southampton
Southampton, United Kingdom
j.deshmukh@soton.ac.uk

Vahid Yazdanpanah
University of Southampton
Southampton, United Kingdom
v.yazdanpanah@soton.ac.uk

Sebastian Stein
University of Southampton
Southampton, United Kingdom
ss2@ecs.soton.ac.uk

Enrico Gerding
University of Southampton
Southampton, United Kingdom
eg@ecs.soton.ac.uk

ABSTRACT

Long-distance electric vehicle (EV) travel depends critically on charging infrastructure reliability. When stations fail or queues form unexpectedly, drivers face increased range anxiety and risk of getting stranded. In this demonstration paper, we present EVMapSim, a discrete-event simulator for modelling EV navigation and charging behaviour at a national scale. We demonstrate 10,000+ vehicles traversing the UK road network, each making real-time charging decisions while encountering infrastructure failures. EVMapSim supports three failure scenarios, enabling analysis of how infrastructure resilience affects driver outcomes, including wait times, route deviations, and stranding rates.

KEYWORDS

EV charging; agent-based simulation; road network; resilience

ACM Reference Format:
Prokopis Georgiou, Jayati Deshmukh, Vahid Yazdanpanah, Sebastian Stein, and Enrico Gerding. 2026. EVMapSim: A Network-level Electric Vehicle Charging Simulator: Demonstration Track. In *Proc. of the 25th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2026), Paphos, Cyprus, May 25 – 29, 2026*, IFAAMAS, 3 pages. https://doi.org/10.65109/WOKO4552

1 INTRODUCTION AND BACKGROUND

Range anxiety, the fear of depleting battery charge before reaching a charging station, remains a significant barrier to electric vehicle (EV) adoption [13, 14, 16]. While EVs offer substantial environmental benefits, including lower emissions and reduced dependence on fossil fuels, prospective buyers consistently cite concerns about charging availability and journey reliability as key deterrents [4, 16, 17]. This anxiety is acute for long-distance travel, where drivers must plan multiple charging stops and trust that the infrastructure will be operational upon arrival. Surveys confirm that station availability and reliability significantly influence driver behaviour [6, 7]. Yet, existing simulations assume static networks, overlooking the stochastic nature of real infrastructure where failures are inevitable [5, 9]. Empirical studies show that a significant fraction of public chargers may be non-functional due to hardware faults and payment errors, undermining reported availability rates [2, 4, 8, 15, 20].

Within the UK, these challenges are visible. The public charging network has grown rapidly in recent years, with tens of thousands of charge points installed, including rapid and ultra-rapid chargers [1, 3, 19, 21, 22]. Despite this, driver confidence remains fragile. Reports of out-of-order chargers and slow repairs undermine trust in reliable inter-city travel [4, 20]. Infrastructure reliability is not merely installed capacity but sustained operational performance.

We present EVMapSim, a UK-level EV navigation and charging simulator modelling infrastructure failures and large-scale multi-agent interactions to quantify impacts on driver experience. It simulates 10,000+ EVs in a shared resource environment as autonomous agents, making decentralised decisions under uncertainty. EVMapSim captures how stochastic outages and agent interactions drive emergent effects, allowing researchers to study multi-agent phenomena such as resource competition and infrastructure resilience. It provides a scalable experimental platform for infrastructure planners to compare failure patterns and resilience, policymakers to evaluate reliability standards and researchers to test coordination mechanisms and how battery capacity influences stranding risk.

2 EVMAPSIM SIMULATOR

EVMapSim simulates thousands of EV journeys across the UK to answer: *how do charging station failures affect drivers' ability to complete long-distance trips?* The simulator tracks each vehicle's State-of-Charge (SoC), recording when drivers experience anxiety, encounter failed stations, face unexpected queues, or become stranded. By aggregating outcomes across the network, EVMapSim reveals how infrastructure reliability translates into driver experiences. A demo video is available here: https://www.youtube.com/watch?v=MTlZAShsqrE.

2.1 System Components

Network and Data. The simulator constructs a UK road network from ONS geographic data [11], representing 344 wards as graph nodes with distance-weighted edges. Charging station data from OpenChargeMap [12] (27,423 points) is assigned to nearest nodes, including connector types, power, and capacity.

Proc. of the 25th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2026), C. Amato, L. Dennis, V. Mascardi, J. Thangarajah (eds.), May 25 – 29, 2026, Paphos, Cyprus. © 2026 International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org). https://doi.org/10.65109/WOKO4552

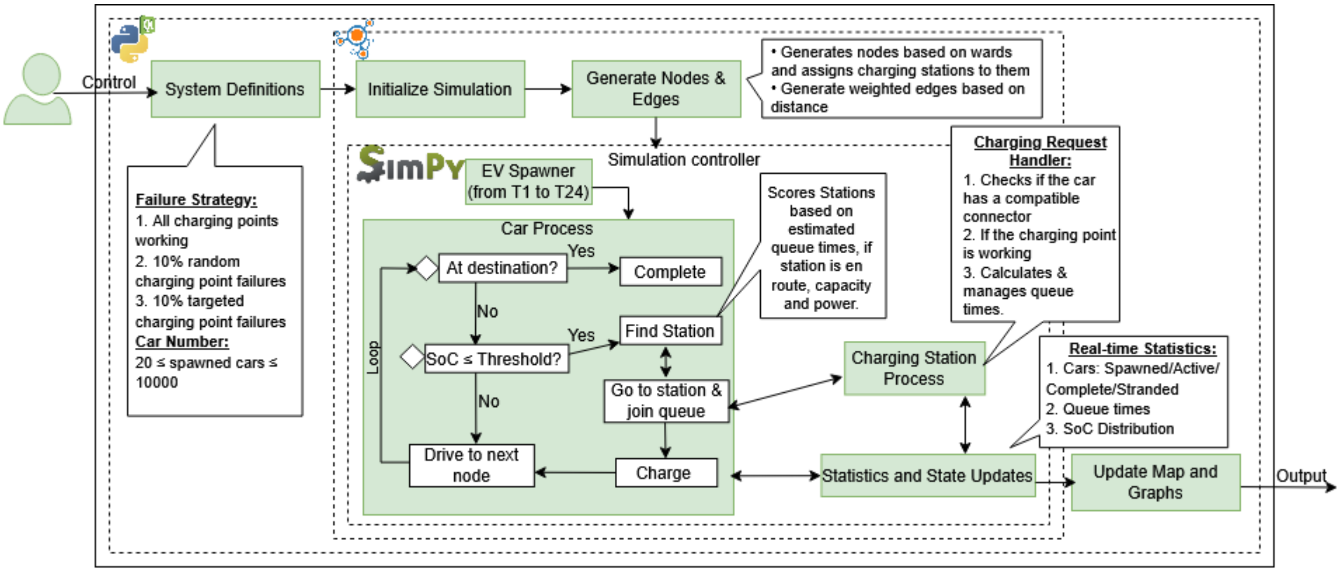
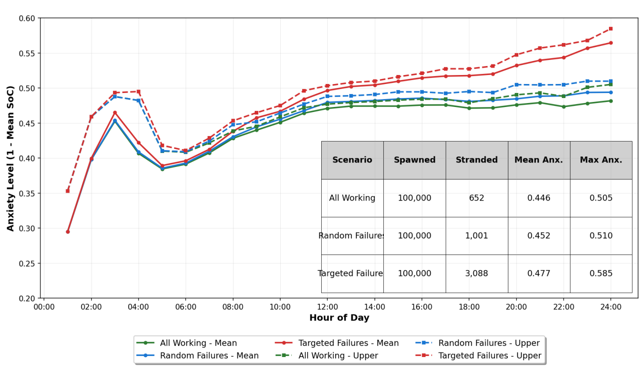


Figure 1: System Architecture of the EV charging simulation framework

Simulation Engine. EVMapSim uses SimPy for discrete-event simulation [10]. Heterogeneous vehicles are spawned as shown in Figure 1, in a 24-hour demand distribution with randomised origin-destination, initial SoC, battery capacity, patience threshold, and connector type (UK distribution). A 10,000 EV simulation run completes in 8 minutes on a 14-core CPU machine with 16 GB RAM.

Driver Behaviour and Charging. Vehicles navigate using shortest-path routing and threshold-based charging decisions. Station selection considers queue length, wait time, charger power, and route deviation. Upon arrival, drivers discover the actual equipment status. Charging duration is based on realistic physics models, accounting for battery capacity, SoC, and efficiency.



Scenario	Spawned	Stranded	Mean Anx.	Max Anx.
All Working	100,000	652	0.446	0.505
Random Failures	100,000	1,001	0.452	0.510
Targeted Failure	100,000	3,088	0.477	0.585

Figure 2: Anxiety levels under different failure scenarios.

2.2 Failure Scenarios and Analysis

EVMapSim supports three failure scenarios: (1) baseline with all charging points operational, (2) 10% random failures distributed uniformly, and (3) 10% targeted failures disabling high-traffic hubs using betweenness centrality.

Figure 2 shows how failure scenarios affect driver anxiety throughout a 24-hour simulation with 10,000 vehicles over 10 simulation runs with different seed values. We adopt a simple anxiety proxy, $Anxiety = 1 - SoC$ [18, 23]. Targeted failures (red) consistently produce higher anxiety than random failures (blue) and baseline (green), and the gap widens as vehicles encounter failed stations at critical nodes and as the number of vehicles increases.

2.3 Visualisation and Statistics

The interface provides real-time visualisation with vehicles colour-coded by SoC and live analytics. The status bar displays live statistics: active vehicles, driving count, charging count, completed journeys, and stranded vehicles. Hover tooltips show individual vehicle details, including current SoC, origin, destination, and personal charging threshold. This provides intuitive evidence for public engagement and policy discussions.

3 CONCLUSIONS AND FUTURE WORK

We presented EVMapSim, a network-level EV charging simulator modelling 10,000 vehicles navigating the UK road network under charging infrastructure failures. EVMapSim quantifies how reliability impacts driver anxiety, route deviations, and stranding risk, providing evidence for resilience planning and reliability standards.

Future work will extend EVMapSim to other countries by adapting charging and geographic datasets, add reinforcement-learning agents that adapt to outages and weather-driven range loss, and study multi-agent coordination via shared station availability, alongside policy experiments comparing charging incentive schemes.

ACKNOWLEDGMENTS

This work is supported through an EPSRC Turing AI Fellowship (EP/V022067/1), the EPSRC FEVER project (EP/W005883/1) and the UKRI SustAI CDT (EP/Y030702/1).

REFERENCES

[1] I Safak Bayram, Ali Saad, Ryan Sims, Anish Babu, Calum Edmunds, and Stuart Galloway. 2023. Statistical characterization of public AC EV chargers in the UK. *IEEE Access* 11 (2023), 70274–70287.

[2] Marie Rajon Bernard, Sonsoles Díaz, Irem Kok, and Uwe Tietge. 2024. Enhancing user experience in public electric vehicle charging. https://zevalliance.org/wp-content/uploads/2024/11/Enhancing-user-experience-in-public-EV-charging_Nov-2024.pdf Accessed: 2026-03-04.

[3] Tianjin Chen, Xiao-Ping Zhang, Jianji Wang, Jianing Li, Cong Wu, Mingzhu Hu, and Huiping Bian. 2020. A review on electric vehicle charging infrastructure development in the UK. *Journal of Modern Power Systems and Clean Energy* 8, 2 (2020), 193–205.

[4] Department for Transport. 2022. Public Electric Vehicle Charging Infrastructure: Consumer Research. Research report. https://assets.publishing.service.gov.uk/media/6234a51f8fa8f540edba36f1/public-ev-charging-infrastructure-research-report.pdf Accessed: 2026-03-04.

[5] Tomislav Erdelić and Tonči Carić. 2019. A survey on the electric vehicle routing problem: variants and solution approaches. *Journal of Advanced Transportation* 2019, 1 (2019), 5075671.

[6] Thomas Franke and Josef F Krems. 2013. What drives range preferences in electric vehicle users? *Transport Policy* 30 (2013), 56–62.

[7] Joachim Globisch, Patrick Plötz, Elisabeth Dütschke, and Martin Wietschel. 2019. Consumer preferences for public charging infrastructure for electric vehicles. *Transport Policy* 81 (2019), 54–63.

[8] Konara Mudiyanselage Sandun Y Konara, Mohan Lal Kolhe, Nils Ulltveit-Moe, and Indika AM Balapuwaduge. 2023. Reliability Enhancement of Fast Charging Station under Electric Vehicle Supply Equipment Failures and Repairs. *Energies* 16, 6 (2023), 2933.

[9] Ilker Kucukoglu, Reginald Dewil, and Dirk Cattrysse. 2021. The electric vehicle routing problem and its variations: A literature review. *Computers & Industrial Engineering* 161 (2021), 107650.

[10] Klaus Müller et al. 2022. SimPy: Discrete Event Simulation for Python. Python package. https://simpy.readthedocs.io/ Accessed: 2026-03-04.

[11] Office for National Statistics. 2023. Open Geography portal. https://geoportal.statistics.gov.uk/. Accessed: 2026-03-04.

[12] Open Charge Map. 2020. Open Charge Map: Global Public Registry of Electric Vehicle Charging Locations. https://openchargemap.org/site/develop/api. Accessed: 2026-03-04.

[13] Dario Pevec, Jurica Babic, Arthur Carvalho, Yashar Ghiassi-Farrokhfal, Wolfgang Ketter, and Vedran Podobnik. 2019. Electric vehicle range anxiety: An obstacle for the personal transportation (R) evolution?. In *2019 4th international conference on smart and sustainable technologies (splitech)*. IEEE, 1–8.

[14] Dario Pevec, Jurica Babic, Arthur Carvalho, Yashar Ghiassi-Farrokhfal, Wolfgang Ketter, and Vedran Podobnik. 2020. A survey-based assessment of how existing and potential electric vehicle owners perceive range anxiety. *Journal of cleaner Production* 276 (2020), 122779.

[15] Bonnie Powell and Caley Johnson. 2024. *Impact of electric vehicle charging station reliability, resilience, and location on electric vehicle adoption.* Technical Report. National Renewable Energy Laboratory (NREL), Golden, CO (United States).

[16] Zeinab Rezvani, Johan Jansson, and Jan Bodin. 2015. Advances in consumer electric vehicle adoption research: A review and research agenda. *Transportation Research Part D: Transport and Environment* 34 (2015), 122–136. https://doi.org/10.1016/j.trd.2014.10.010

[17] Sirapa Shrestha, Bivek Baral, Malesh Shah, Sailesh Chitrakar, and Bim P. Shrestha. 2022. Measures to resolve range anxiety in electric vehicle users. *International Journal of Low-Carbon Technologies* 17 (2022), 1186–1206. https://doi.org/10.1093/ijlct/ctac100

[18] Yang Song and Xianbiao Hu. 2023. Learning electric vehicle driver range anxiety with an initial state of charge-oriented gradient boosting approach. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations* 27, 2 (2023), 238–256. https://doi.org/10.1080/15472450.2021.2010053

[19] Transport + Energy. 2025. Public charge points grow by 22% year-on-year. Online article. https://transportandenergy.com/2025/10/14/public-charge-points-grow-by-22-year-on-year/ Accessed: 2026-03-04.

[20] Versinetic. 2024. Charging on the Go: 2024 Public EV Charging Whitepaper. Whitepaper. https://www.versinetic.com/news-blog/charging-on-the-go-public-ev-charging-whitepaper/ Accessed: 2026-03-04.

[21] Zapmap. 2025. Ultra-fast EV public chargers up by 51% year-on-year. Online article. https://evpowered.co.uk/news/zapmap-ultra-fast-ev-public-chargers-up-by-51-year-on-year/ Accessed: 2026-03-04.

[22] Zapmap. 2025. Zapmap statistics for first half of 2025 show 136 new charging hubs. Online article. https://www.zapmap.com/news/zapmap-statistics-first-half-2025-show-136-new-charging-hubs-start-year Accessed: 2026-03-04.

[23] Junianna Zatsarnaja, Katharina Reiter, Milad Mehdizadeh, Alim Nayum, and Trond Nordfjærn. 2025. Charged up with peace in mind: Unraveling the factors of range anxiety among norwegian electric vehicle drivers. *Transportation Research Part F: Traffic Psychology and Behaviour* 110 (2025), 15–28. https://doi.org/10.1016/j.trf.2025.02.006