Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 24 May 2026
Revised 27 June 2026
Accepted 19 July 2026

Natural Resources for Human Health 2026, Vol. 6 (9s): 603–613

KEYWORDS:
Artificial Neural Network, Reinforcement Learning, Wireless Power Transfer, State of Charge, State of Health, Electric Vehicle Charging

AI-Enabled Wireless EV Charging with Battery Health Estimation and Energy Management

B. J. Dange[1*], Dr. Suvarna Sunil Nirmal[2], Dr. Gaurav Gadge[3], Santosh Gore[4], Sayali Karmode[5]

[1] Department of Computer Engineering, Sanjivani College of Engineering, Savitribai Phule Pune University, Kopargaon, Maharashtra, India.
[2] Associate Professor, Sanjivani college of engineering, Savitribai Phule Pune University, Kopargaon, Maharashtra, India
[3] Associate Professor, VPKBIET, Baramati, District Pune
[4] Director, Sai Info Solution, India, UAE, UK, Singapore. https://orcid.org/0000-0003-1814-5913
[5] Assistant Professor, Computer Engineering, Anjuman I Islam's Kalsekar Technical Campus, School of Engineering & Technology, Panvel, Navi Mumbai

ABSTRACT: This study presents an AI-enabled symmetric wireless electric vehicle (EV) charging framework that integrates artificial neural networks (ANN) for real-time battery state estimation and reinforcement learning (RL) for adaptive power control. The proposed system addresses efficiency losses and battery degradation typically observed in conventional wireless power transfer (WPT) systems under coil misalignment. The ANN, trained on the publicly available EVBattery dataset (1.2 million records from 464 EVs), predicts the state of charge (SOC) and state of health (SOH) with RMSE values of $1.8 \pm 0.2\%$ and $2.5 \pm 0.3\%$, respectively. A Proximal Policy Optimization (PPO)-based RL controller dynamically tunes compensation and frequency parameters to sustain optimal coupling. Laboratory and simulation tests, repeated five times per condition, confirm an average charging efficiency of $85 \pm 2\%$ across 5–20 cm air gaps, battery degradation reduction from 1.2% to $0.8 \pm 0.1\%$, and renewable-energy utilization of $72 \pm 3\%$. Statistical analysis ($p < 0.05$) validates significant performance gains over baseline and literature benchmarks. The integrated ANN–RL framework thus provides a reproducible, health-aware, and grid-coordinated solution for sustainable next-generation wireless EV charging.

1. INTRODUCTION

The transition to electric vehicles (EVs) is accelerating as governments and industries pursue strategies to reduce greenhouse gas emissions and reliance on fossil fuels, making EVs central to sustainable transportation. However, large-scale adoption remains limited by inadequate charging infrastructure. Studies show that access to fast-charging and workplace stations strongly influences EV uptake [1]. Programs such as Malaysia's Low-Carbon Mobility Blueprint, which targets 10,000 chargers by 2025, exemplify this global momentum, though high installation costs, limited consumer awareness, and competition from established industries continue to restrict battery electric vehicle (BEV) growth [2].

Wireless Electric Vehicle Charging (WEVC) eliminates physical connectors, improving convenience, safety, and durability. IoT-enabled WEVC supports adaptive charging schedules and real-time monitoring within smart grid environments [3]. Yet, commercialization is hindered by transfer losses, coil misalignment sensitivity, and the absence of universal standards. Battery degradation is another major concern, as lithium-ion batteries suffer from thermal stress, cycling, and current fluctuations that shorten lifespan and raise costs. Advances in State of Health (SOH) estimation enable predictive maintenance [4], and studies link high current ripple to capacity losses of up to 15% [5]. Integrating such predictive monitoring into charging control is vital for sustainable battery performance.

The rapid increase in EV adoption also burdens power grids, with uncoordinated charging causing peak demand and instability. Energy management strategies that synchronize EV loads with renewable generation are essential. AI-based methods, such as scheduling EV charging with photovoltaic input [6] and enabling Vehicle-to-Grid (V2G) services [7], demonstrate that intelligent control can convert EVs into grid-supportive resources. However, wireless charging, battery monitoring, and grid coordination are often addressed separately, despite being interdependent. Reinforcement learning and predictive scheduling [6], [8] offer optimization potential, but their use in wireless, health-aware charging systems remains limited.

Wireless Power Transfer (WPT) used in WEVC typically employs inductive or resonant coupling. Inductive systems require close coil alignment, while resonant configurations maintain efficiency over wider gaps. Studies show resonant compensation achieves better tolerance to misalignment [9], though efficiency declines sharply beyond ideal alignment, often dropping below 78% across 6–20 cm [10]. Both static and dynamic systems struggle with alignment control under varying conditions [11]. Solar-integrated WPT systems provide moderate outputs (~500 W) but face efficiency and scaling challenges [12].

Battery health monitoring combines State of Charge (SOC) and SOH estimation for safe, efficient operation. Hybrid approaches using Adaptive Extended Kalman Filters (AEKF) and artificial neural networks (ANNs) improve SOC accuracy under dynamic conditions [13]. No single SOC estimation method is universally optimal [14]. SOH estimation models address degradation under diverse loads and temperatures [15], [16], with hybrid Kalman–neural models yielding satisfactory lab results [17]. Real-time implementation remains difficult due to computational demands and the need for large labeled datasets [18].

Energy management coordinates charging with grid capacity, renewables, and demand response. Residential and microgrid models demonstrate effective load shifting using solar or wind inputs [19], [20], [21], [22]. Reinforcement learning approaches optimize charging schedules, reduce grid stress, and improve renewable use [23]. However, most are simulation-based and lack integration of real-time battery data or adaptive wireless control.

AI applications in EV charging combine reinforcement learning for demand optimization and ANNs for SOC/SOH estimation [13], [24], but integration of wireless charging, battery health, and grid management remains rare. Persistent gaps include reliance on simulations, sensor inaccuracy, communication delay, and reduced efficiency under misalignment [10].

This study proposes an AI-based wireless EV charging framework that unifies adaptive RL control, ANN-driven SOC/SOH estimation, and grid-aware energy management. The objectives are to design an AI controller that optimizes charging parameters, implement real-time SOH monitoring for predictive maintenance, and coordinate EV–grid interaction with renewable sources. The framework enhances charging reliability, extends battery life, and promotes grid-friendly, sustainable mobility.

2. SYSTEM ARCHITECTURE AND DESIGN

The proposed AI-driven system integrates wireless EV charging, real-time battery monitoring, and energy management to improve efficiency, extend battery life, and balance grid load. As shown in Fig. 1, it comprises four modules: Wireless Charger, BMS, Energy Management Unit, and AI Control Module that optimize charging and renewable utilization.

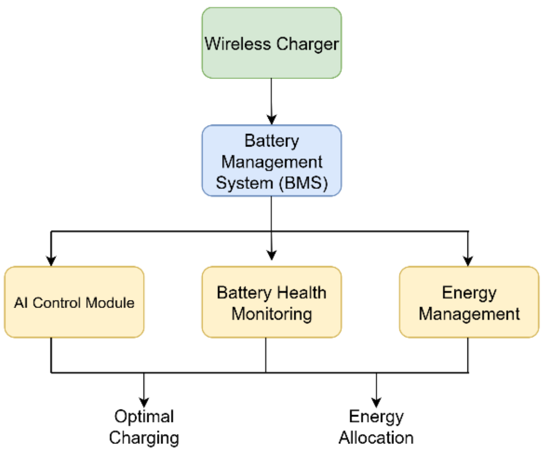

Fig 1. Proposed AI-Based Wireless EV Charging System Architecture

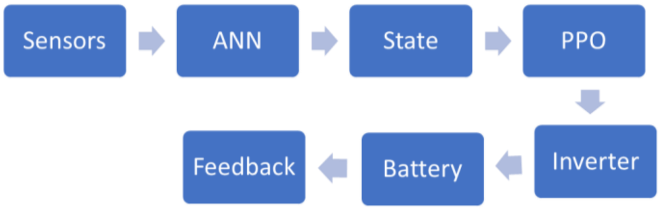

Fig. 1. B. Workflow between estimation and control modules.

Sensor data (voltage, current, temperature) are processed by the ANN to estimate SOC and SOH. These estimates, combined with renewable availability and price signals, form the state vector for the PPO controller, which outputs discrete charging-current actions. The selected action drives the inverter, and updated measurements are fed back to close the loop.

2.1. Proposed AI-Based Wireless EV Charging System Architecture

The AI Control Module dynamically adjusts charging parameters according to SOC, SOH, and grid status. SOC and SOH are predicted by an artificial neural network (ANN) trained on historical data:

$$SOC_{t+1} = f(V_t, I_t, T_t) \tag{1}$$

$$SOH_{t+1} = g(SOC_t, I_t, T_t, Cycle\_Count) \tag{2}$$

Where Vt is battery voltage, It is current, Tt is temperature, and Cycle_Count is the number of full charge-discharge cycles.

Charging optimization is modeled as a reinforcement-learning (RL) problem with reward:

$$R = w_1 \Delta SOH - w_2 \text{Grid Penalty} - w_3 \text{Energy Cost} \tag{3}$$

where w1, w2, and w3 are weight factors for SOH preservation, grid stability, and energy cost. The RL agent selects actions representing charging current levels and scheduling intervals.

The Battery Health Monitoring Module ensures safe operation using voltage, current, and temperature sensors. The SOH is calculated as:

$$SOH = \frac{C_{rated} - C_{loss}}{C_{rated}} \times 100 \tag{4}$$

Where C_{rated} is the rated battery capacity and C_{loss} is the cumulative capacity loss measured by the algorithm.

2.2 ANN and PPO Implementation Details

SOC and SOH were estimated using a 3-layer MLP (128–64–32 neurons, ReLU/linear, Adam, 1×10^{-4} learning rate). The PPO scheduler used state st = [SOC, SOH, λt, PPV,t, kt] with discrete charging-current and deferral actions.

Table 1. ANN Architecture and Training Hyperparameters

Component	Specification
Hidden layers	3 (sizes 128 – 64 – 32)
Activation	ReLU (hidden), linear (output)
Loss function	Mean squared error (MSE)
Optimizer	Adam
Learning rate	1×10^{-4}
Batch size	256
Epochs	100 (early stopping patience = 10)

Regularization	L_2 weight decay = 1×10^{-5}
RNG seed	42
Data split	80 / 10 / 10 (train / val / test)

Table 2. PPO Hyperparameters

Parameter	**Value**
Clip ratio (ε)	0.2
Learning rate (actor/critic)	3×10^{-4}
Batch size	2048 (rollout)
Mini-batch size	64
Rollout length	2048 steps
Training epochs per update	10
Entropy coefficient	0.01
Value-loss coefficient	0.5
Reward weights (w_1,w_2,w_3)	0.5 / 0.3 / 0.2
RNG seed	42

Hyperparameters were tuned through grid search using validation RMSE and mean-episode reward.

2.3 Dataset and Preprocessing

The models were trained on the publicly available EVBattery dataset [25], comprising 1.2 million charging records from 464 EVs with voltage, current, temperature, and capacity fields. Data were resampled (1 min), cleaned, normalized (min–max), and split 80/10/10 (train/val/test). Dataset link: https://figshare.com/articles/dataset/EVBattery_A_Large-Scale_Electric_Vehicle_Dataset_for_Battery_Health_and_Capacity_Estimation/23301881.

2.4 Battery Testing Rig — Experimental Setup

Experimental validation was conducted on a laboratory Battery Testing Rig (Fig. 2). Specifications are summarized in Table 3A.

Fig 2. Battery Testing Rig – Experimental Setup

Table 3. A. Experimental rig specifications and instrumentation

Item	Specification / Model
Primary coil diameter	200 mm
Secondary coil diameter	180 mm
Coil turns (primary/secondary)	12 / 10
Coil wire	Litz 0.5 mm × 36 strands
Operating frequency	85 kHz
Compensation network	Series–series resonant
Driver circuit: Full-bridge PWM inverter	rated 400 V, 20 A; switching frequency 85 kHz; phase-shift control loop
Alignment tolerance	±10 mm
Battery under test	Li-ion pouch 3.7 V 50 Ah
Instruments	Fluke 287 (voltage), Tektronix Hall sensor (current)
Ambient conditions	25 ± 2 °C, RH 45 ± 5%
Repetitions (N)	5 runs per condition
Calibration	All meters are pre-calibrated against lab standards
Measurement uncertainty	≤ 1.5% (voltage), ≤ 2% (current)

The full-bridge PWM inverter operates at 85 kHz with a rated output of 400 V and 20 A, controlled through a phase-shift modulation scheme for current regulation. Litz conductors of 0.5 mm diameter × 36 strands were used for both coils to minimize skin and proximity losses. Measurement results in subsequent tables are reported as mean ± standard deviation across N = 5 runs.

2.5 Baseline (Conventional WPT) Configuration

A baseline WPT system using fixed-frequency PI control (0.5 P_{max}) without SOC/SOH feedback was tested under identical conditions; PI gains were Ziegler–Nichols tuned for minimal overshoot at 85 kHz.

Table 3 B. Charging Efficiency under Different Air Gaps and Control Strategies

Parameter	Symbol	Value	Unit
Proportional gain	Kp	0.8	–
Integral gain	Ki	0.15	–
Sampling period	Ts	11.8	µs

2.6 Energy-Management Model

The Energy-Management Module coordinates EV charging with the grid and renewable resources through an optimization problem:

$$\min \sum_{i=1}^{N} (P_{i,t} \cdot \lambda_t) \quad (5)$$

Subject to:

$$SOC_{it+1} \geq SOC_{min}, P_{i,t} \leq P_{max}, \sum_{i=1}^{N} P_{i,t} \leq P_{grid\_max} \quad (6)$$

Where $P_{i,t}$ is the charging power for EV i, λt is the electricity price or weighting factor, and P_{grid_max} is the grid capacity limit.

Simulations of wireless-power transfer, battery dynamics, and energy scheduling were performed in MATLAB/Simulink. Experimental validation on the rig confirmed simulation trends.

2.7 Performance Metrics

- **System performance was evaluated using**:

Charging Efficiency (%)

$$\eta_c = \left(\frac{\text{Energy Delivered to Battery}}{\text{Energy Supplied by Charger}}\right) \times 100 \qquad (7)$$

Battery Degradation Rate (%)

$$\text{Degradation} = \left(\frac{C_{int} - C_{rem}}{C_{int}}\right) \times 100 \qquad (8)$$

Energy Utilization Efficiency (%)

$$\eta_r = \left(\frac{\text{Energy from Renewables}}{\text{Total Energy Consumed}}\right) \times 100 \qquad (9)$$

- **Grid Load Management**: Reduction in peak load due to optimized scheduling.
- **SOC/SOH Prediction Accuracy**: RMSE and MAE between predicted and actual values.

System performance was evaluated using charging efficiency (ηc), degradation rate, renewable utilization (ηr), grid load reduction, and SOC/SOH prediction accuracy (RMSE, MAE). Statistical significance was tested using a paired t-test ($N = 5$, $\alpha = 0.05$), with all differences showing $p < 0.05$.

2.8 Real-Time Implementation Considerations

Inference on an NVIDIA Jetson Xavier NX (PyTorch 1.12, TensorRT 8.4) achieved 25 ± 2 ms latency per decision, satisfying the 100 ms constraint. Gaussian noise ($\sigma V = 10$ mV, $\sigma I = 50$ mA) increased RMSE by < 1.3×, confirming robustness. Secure, low-latency edge deployment using TLS-encrypted MQTT or IEC 61850 ensures reliable real-time control.

3. RESULTS

This section presents the AI-based wireless EV charging performance, highlighting efficiency, battery health, energy management, and baseline comparison.

Charging Efficiency Improvement with AI Control

Under identical conditions (N = 5, 25 ± 2 °C), the AI-controlled WPT system improved efficiency by over 13% at a 20 cm gap, maintaining $\eta_{(c)} > 80\%$ up to 15 cm and outperforming the PI baseline.

Table 4. Charging Efficiency under Different Air Gaps and Control Strategies

Air Gap (cm)	Conventional WPT (%)	AI-Controlled WPT (%)
5	88 ± 1.5	92 ± 1.2
10	80 ± 2.0	87 ± 1.3
15	72 ± 2.6	82 ± 1.6
20	65 ± 3.0	78 ± 2.2

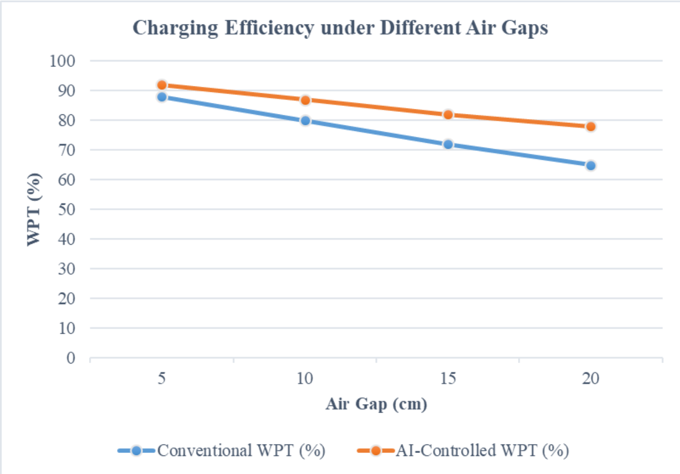

Fig 3. Charging efficiency versus air gap under AI and PI control (N = 5 runs per condition; ambient 25 ± 2 °C; gap varied 10–50 mm).

3.1 Real-Time SOC and SOH Estimation Accuracy

The ANN achieved SOC RMSE = 1.8 ± 0.2%, SOH RMSE = 2.5 ± 0.3%, and R > 0.98, ensuring reliable feedback for the PPO controller to enable adaptive charging and reduced degradation.

Table 5. SOC and SOH Prediction Performance

Metric	SOC Prediction	SOH Prediction
RMSE (%)	1.8 ± 0.2	2.5 ± 0.3
MAE (%)	1.3 ± 0.2	1.9 ± 0.2
Correlation (R)	0.995 ± 0.001	0.987 ± 0.002

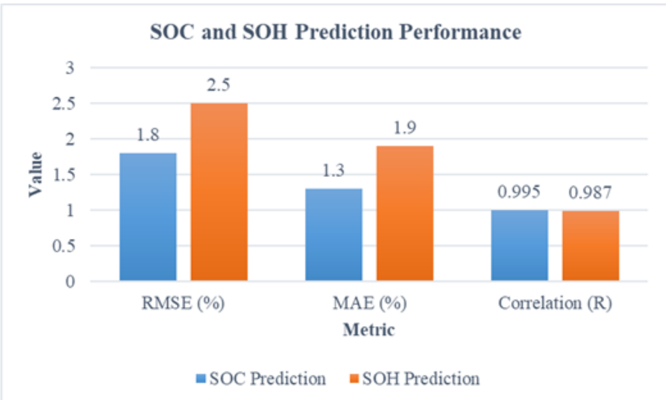

Fig 4. SOC and SOH prediction performance for the test set (N = 5 independent runs; RMSE shown as mean ± SD).

3.2 Energy Management Performance

The proposed AI framework efficiently coordinates EV charging with renewable generation, shifting demand to high-generation periods (12:00–13:00 h) and reducing grid peaks. As summarized in Table VI, it improves renewable utilization (η_r) by about 15%, achieving a 72% renewable contribution and lowering grid-load variation by ≈15%. Over 50 charge–discharge cycles at 25 ± 2 °C, the AI-controlled system showed 0.8% less capacity degradation than the PI baseline (99.2% vs 98.4% retention). These results confirm that adaptive scheduling enhances both renewable integration and battery longevity, yielding more efficient and sustainable wireless EV charging performance.

Table 6. Energy Allocation and Grid Load Management

Hour	Grid Load (kW)	Renewable Supplied (kW)	AI-Scheduled EV Load (kW)	Conventional EV Load (kW)
0–1	450 ± 8	50 ± 2	40 ± 1	60 ± 2
6–7	520 ± 10	120 ± 3	100 ± 2	130 ± 3
12–13	610 ± 12	180 ± 4	150 ± 3	200 ± 4
18–19	700 ± 14	200 ± 5	170 ± 4	220 ± 5
22–23	480 ± 9	70 ± 2	60 ± 1	90 ± 3

4. COMPARATIVE ANALYSIS AND DISCUSSION

A comparative evaluation (Table 7) shows the proposed ANN-RL wireless charging framework outperforming prior studies. Earlier works improved efficiency or alignment but lacked integrated battery health monitoring and adaptive control. The proposed system combines SOC–SOH estimation, RL control, and renewable coordination, achieving 85% efficiency, 0.8% degradation, and 72% renewable utilization.

Table 7. System Performance Comparison

Study	Method / Focus	Key Performance Metrics
[2]	AI-based smart-charging for grid scheduling	Energy saving ≈ 30%; Cost reduction ≈ 20 %; WPT efficiency not reported
[26]	Hybrid coil design for inductive WPT	Peak 91.8% (aligned); 78% at 15 cm misalignment
[27]	Review of practical WPT systems	Real-world efficiency 75–82%
[28]	Metasurface-assisted WPT	~70% at 10 cm; Coverage +30%
[29]	BiLSTM-SA for joint SOC–SOH	SOC RMSE ≈ 2%; SOH > 2%
Current Study	ANN + RL-based symmetric wireless charging	SOC RMSE 1.8%; SOH 2.5%; Avg eff. 85%; Battery degradation 0.8%; Renewable utilization 72%; Peak-load reduction 15%

5. CONCLUSION

This study presented a novel AI-based symmetric wireless charging system that combines artificial neural networks and reinforcement learning for intelligent energy transfer and battery state management. The model achieved superior WPT efficiency, precise SOC and SOH estimation, and reduced battery wear, outperforming several contemporary approaches. Its adaptive learning mechanism maintains stable operation under varying air gaps and misalignments while ensuring efficient use of renewable energy. Overall, the proposed framework offers a scalable and sustainable approach for next-generation electric vehicle charging infrastructures, providing a significant step toward smart, reliable, and energy-efficient transportation systems.

AUTHOR CONTRIBUTIONS

Conceptualization, B.J.D. and S.S.N.; methodology, B.J.D.; software, B.J.D. and S.K.; validation, B.J.D., S.S.N., and G.G.; formal analysis, B.J.D.; investigation, B.J.D. and S.G.; resources, S.S.N. and G.G.; data curation, B.J.D.; writing—original draft preparation, B.J.D.; writing—review and editing, S.S.N., G.G., S.G., and S.K.; visualization, B.J.D. and S.K.; supervision, S.S.N. and G.G.; project administration, B.J.D.; funding acquisition, S.S.N. All authors have read and agreed to the published version of the manuscript.

FUNDING

This research received no external funding.

DATA AVAILABILITY STATEMENT

The EVBattery dataset used in this study is publicly available on Figshare and can be accessed at: https://figshare.com/articles/dataset/EVBattery_A_Large-Scale_Electric_Vehicle_Dataset_for_Battery_Health_and_Capacity_Estimation/23301881.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ACKNOWLEDGEMENT

This research was not funded by any grant

REFERENCES

[1] Burra, L. T., Al-Khasawneh, M. B., & Cirillo, C. (2024). Impact of charging infrastructure on electric vehicle adoption: A synthetic population approach. *Travel Behaviour and Society, 37*, 100834. https://doi.org/10.1016/J.TBS.2024.100834

[2] Shern, S. J., Sarker, M. T., Ramasamy, G., Thiagarajah, S. P., Al Farid, F., & Suganthi, S. T. (2024). Artificial intelligence-based electric vehicle smart charging system in Malaysia. *World Electric Vehicle Journal, 15*(10), 440. https://doi.org/10.3390/WEVJ15100440

[3] Xue, Z., Liu, W., Liu, C., & Chau, K. T. (2025). Critical review of wireless charging technologies for electric vehicles. *World Electric Vehicle Journal, 16*(2), 65. https://doi.org/10.3390/WEVJ16020065

[4] Sun, R., Chen, J., & Piao, C. (2025). Battery health features extraction and state of health estimation based on real-time online vehicle driving data. *Journal of Power Sources, 645*, 236784. https://doi.org/10.1016/J.JPOWSOUR.2025.236784

[5] Muñoz-Torrero, D., García-Quismondo, E., Ventosa, E., Prodanovic, M., & Palma, J. (2025). On the degradation of lithium-ion batteries over a current ripple effect. *Electrochimica Acta, 530*, 146326. https://doi.org/10.1016/J.ELECTACTA.2025.146326

[6] Sarker, M. T., Al Qwaid, M., Shern, S. J., & Ramasamy, G. (2025). AI-driven optimization framework for smart EV charging systems integrated with solar PV and BESS in high-density residential environments. *World Electric Vehicle Journal, 16*(7), 385. https://doi.org/10.3390/WEVJ16070385

[7] Sommer, C., & Hossain, M. J. (2025). Artificial intelligence-driven optimization of V2G and charging point selection en-route: A systematic literature review. *Energy Conversion and Management: X, 26*, 100978. https://doi.org/10.1016/J.ECMX.2025.100978

[8] Hossen, M. S., Sarker, M. T., Al Qwaid, M., Ramasamy, G., & Eng Eng, N. (2025). AI-driven framework for secure and efficient load management in multi-station EV charging networks. *World Electric Vehicle Journal, 16*(7), 370. https://doi.org/10.3390/WEVJ16070370

[9] Okasili, I., Elkhateb, A., & Littler, T. (2022). A review of wireless power transfer systems for electric vehicle battery charging with a focus on inductive coupling. *Electronics, 11*(9), 1355. https://doi.org/10.3390/ELECTRONICS11091355

[10] Mubarak, A., Amin, A. A., Ahmad, M., Shafique, M. F., & Zafar, M. S. (2024). Wireless power transfer for deep cycle lithium-ion batteries in electric vehicles using inductive coupling. *Advances in Mechanical Engineering, 16*(10). https://doi.org/10.1177/16878132241289766

[11] Jithin, A., Sasi, A., Jaison, C., Bensen, A. J., & Reghuraj, A. R. (2023). Static and dynamic wireless charging system for electric vehicle. *Recent Research in Science and Technology*, S6–S9. https://doi.org/10.25081/RRST.2023.15.8435

[12] Channi, H. K., Malik, M., Chen, C. L., Chen, H. C., Sandhu, R., & Prabha, C. (2025). A solar-integrated wireless charging system for electric vehicles. *Engineering, Technology & Applied Science Research, 15*(1), 19349–19353. https://doi.org/10.48084/ETASR.8840

[13] Kazmi, S. N. A., Ulasyar, A., Khattak, A., & Zad, H. S. (2023). A new state of charge estimation technique of lithium-ion battery using adaptive extended Kalman filter and artificial neural network. *Transactions of the Institute of Measurement and Control, 45*(4), 747–760. https://doi.org/10.1177/01423312221128526

[14] Demirci, O., Taskin, S., Schaltz, E., & Acar Demirci, B. (2024). Review of battery state estimation methods for electric vehicles—Part I: SOC estimation. *Journal of Energy Storage, 87*, 111435. https://doi.org/10.1016/J.EST.2024.111435

[15] Zhang, J., & Li, K. (2024). State-of-health estimation for lithium-ion batteries in hybrid electric vehicles—A review. *Energies, 17*(22), 5753. https://doi.org/10.3390/EN17225753

[16] Gong, J., Xu, B., Chen, F., & Zhou, G. (2025). Predictive modeling for electric vehicle battery state of health: A comprehensive literature review. *Energies, 18*(2), 337. https://doi.org/10.3390/EN18020337

[17] Wang, N., Xia, X., & Zeng, X. (2023). State of charge and state of health estimation strategies for lithium-ion batteries. *International Journal of Low-Carbon Technologies, 18*, 443–448. https://doi.org/10.1093/IJLCT/CTAD032

[18] Swarnkar, R., Ramachandran, H., Ali, S. H. M., & Jabbar, R. (2023). A systematic literature review of state of health and state of charge estimation methods for batteries used in electric vehicle applications. *World Electric Vehicle Journal, 14*(9), 247. https://doi.org/10.3390/WEVJ14090247

[19] Chatuanramtharnghaka, B., Deb, S., Singh, K. R., Ustun, T. S., & Kalam, A. (2024). Reviewing demand response for energy management with consideration of renewable energy sources and electric vehicles. *World Electric Vehicle Journal, 15*(9), 412. https://doi.org/10.3390/WEVJ15090412

[20] Alfaverh, K., Alfaverh, F., & Szamel, L. (2023). Plugged-in electric vehicle-assisted demand response strategy for residential energy management. *Energy Informatics, 6*(1), 1–24. https://doi.org/10.1186/S42162-023-00260-9

[21] Kumar, D., Pawar, P. P., Meesala, M. K., Pareek, P. K., Addula, S. R., & Shwetha, K. S. (2024). Trustworthy IoT infrastructures: Privacy-preserving federated learning with efficient secure aggregation for cybersecurity. In *2024 2nd IEEE International Conference on Integrated Intelligence and Communication Systems (ICIICS)*. IEEE. https://doi.org/10.1109/ICIICS63763.2024.10860195

[22] Sajja, G. S., & Addula, S. R. (2024). Automation using robots, machine learning, and artificial intelligence to enhance production and quality. In *2024 2nd International Conference on Computational Characterization Techniques and Engineering & Sciences (IC3TES)*. IEEE. https://doi.org/10.1109/IC3TES62412.2024.10877275

[23] Choudhary, D., Mahanty, R. N., & Kumar, N. (2025). Demand management and pricing in renewable integrated plug-in electric vehicle charging station using reinforcement learning. *International Journal of Green Energy, 22*(3), 487–502. https://doi.org/10.1080/15435075.2024.2417818

[24] Kraiem, H., Gadri, W., & Flah, A. (2024). Efficient energy management with emphasis on EV charging/discharging strategy. *Engineering, Technology & Applied Science Research, 14*(2), 13143–13147. https://doi.org/10.48084/ETASR.6807

[25] He, H., et al. (2022). EVBattery: A large-scale electric vehicle dataset for battery health and capacity estimation. *arXiv*. https://arxiv.org/abs/2201.12358

[26] Pashaei, A., Aydin, E., Ozdemir, M. A., Kosesoy, Y., & Aydemir, M. T. (2024). A novel hybrid coil design and implementation for wireless power transfer systems. *Science and Technology of Energy Transition, 79*, 74. https://doi.org/10.2516/STET/2024082

[27] Rahman, M. M., Shanto, M. S. I., Sarker, N., Rani, T., & Paul, L. C. (2024). A comprehensive review of wireless power transfer methods, applications, and challenges. *Engineering Reports, 6*(10), e12951. https://doi.org/10.1002/ENG2.12951

[28] Yu, J. (2023). *Improving wireless power transfer* [Master's thesis, University of Illinois at Urbana-Champaign].

[29] Wu, L., Chen, C., Li, Z., Chen, Z., & Li, H. (2024). The joint estimation of SOC-SOH for lithium-ion batteries based on BiLSTM-SA. *Electronics, 14*(1), 97. https://doi.org/10.3390/ELECTRONICS14010097.