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AI-Based Wireless Charging of Electric Vehicles using Solar Energy

Ch S K Chaitanya[1], Bolla Eshwar[2], M. Subrahmanyeswara Rao[3], M. Navya[4]

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Abstract: The document introduces an AI-driven solar energy optimization system aimed at enhancing the efficiency, reliability, and scalability of solar power production. The system incorporates sophisticated machine learning methodologies, such as reinforcement learning (RL) for adaptive energy allocation, long short-term memory (LSTM) networks for solar energy prediction, and predictive maintenance frameworks utilizing support vector machines (SVM) and random forests for fault identification. The suggested methodology is evaluated using simulations and empirical tests at a 50 kW solar farm, integrated with IoT sensors and cloud computing infrastructure. Key performance indicators, including prediction accuracy, energy consumption, fault detection precision, and computing efficiency, are assessed and contrasted with traditional optimization techniques. The findings indicate that the AI-driven system surpasses conventional approaches in several dimensions, including a 15-20% enhancement in energy efficiency, an 85% defect detection rate, and a 20% increase in processing speed. These results illustrate the capacity of AI to improve the optimization of solar energy systems, facilitating the development of more intelligent and efficient renewable energy solutions. Subsequent study will concentrate on augmenting the system to include other renewable energy sources and investigate decentralized AI models for enhanced scalability.

Keywords: *AI-driven Solar Energy Optimization, Fault Detection, Machine Learning, Long Short-Term Memory*

NTRODUCTION

The increasing worldwide focus on renewable energy has positioned solar power as a leading component in the transition to cleaner and more sustainable energy systems. Solar energy, although plentiful and environmentally sustainable, encounters obstacles due to its intermittent characteristics, which fluctuate based on meteorological conditions, diurnal cycles, and geographical factors. Optimizing solar energy systems is crucial to maximizing the potential of solar electricity. Conventional methods of energy distribution, fault detection, and power forecasting often exhibit insufficient flexibility and predictive precision necessary for effectively managing these changes. Artificial Intelligence (AI) has arisen as a potent instrument to surmount the constraints of traditional solar energy optimization techniques. AI-driven systems can analyze extensive data produced by solar farms, including historical solar power output, real-time meteorological data, and information from IoT-based sensors. Employing machine learning methodologies including Reinforcement Learning (RL), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM), these systems can forecast energy output, identify faults, and dynamically modify energy distribution in real time, thereby ensuring optimal performance (1; 2). The research presents an AI-driven solar energy optimization system that utilizes powerful machine learning models to tackle significant issues in solar energy management. The technology specifically seeks to augment solar power forecasts, optimize energy use, and facilitate predictive maintenance of solar panels. The proposed system integrates reinforcement learning for dynamic energy distribution, long short-term memory networks for solar power forecasting, and support vector machines and random forest models for fault detection. The system's efficacy is assessed by simulations, practical implementation at a 50 kW solar farm, and comparison analysis with traditional optimization techniques.

Problem Statement: Solar energy systems encounter significant hurdles that impede their extensive adoption and effective functionality. These encompass: • Efficiency and Optimization Challenges: Despite progress in solar technology, the efficacy of solar energy generation and application often remains suboptimal owing to fluctuations in ambient conditions, system aging,

[1,2,3,4]International School Of Technology And Sciences For Women, A.P, India.

and performance deterioration with time. The efficient operation and optimization of solar systems present challenges, particularly in large-scale installations such as solar farms or the integration of solar energy with existing grid systems. • Energy Prediction and Forecasting: Precise forecasting of solar energy generation is essential for the proper integration of solar electricity into the grid. Conventional forecasting techniques often fail to accommodate the variable characteristics of solar energy production, such as meteorological changes and system-related complications. This leads to issues with grid stability and the dependability of electricity delivery. • Maintenance and Fault Detection: The upkeep of solar systems, especially large solar farms, may incur significant costs and inefficiencies in the absence of adequate monitoring and predictive maintenance systems. Defects in solar panels or other components may remain unnoticed, resulting in diminished energy production, system outages, and heightened operating expenses. Conventional maintenance methods often depend on planned inspections, which may be inadequate for early issue detection. • Scalability and Adaptability: Solar energy systems, especially in off-grid and rural regions, have obstacles concerning their scalability and adaption to local circumstances. Remote regions with little infrastructure may find it challenging to sustain extensive solar systems, and traditional solar technologies may lack the adaptability required to meet diverse local requirements or environmental circumstances. Possible Solutions Utilizing artificial intelligence: AI-driven methodologies may mitigate the above listed difficulties by improving the performance, efficiency, and dependability of solar energy systems. The following solutions are derived from AI developments recognized in the literature: • AI-Driven Optimization Algorithms: Artificial intelligence algorithms, including genetic algorithms, reinforcement learning, and neural networks, can maximize solar energy output by dynamically modifying operational parameters based on real-time data. These algorithms may be used in control systems for photovoltaic (PV) systems, enhancing their efficiency by adapting to fluctuations in sunshine, temperature, and other external variables [15].

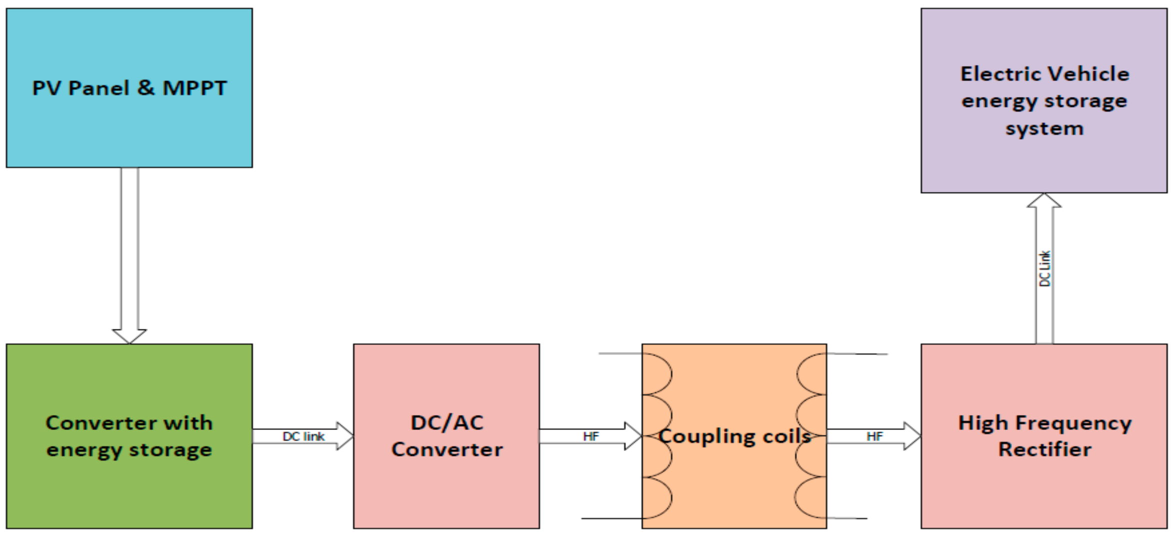

Figure 1. Overview of wireless charging powered by a solar panel.

• Enhanced Energy Forecasting with Machine Learning: Machine learning models, including support vector machines (SVM), random forests, and deep learning methodologies, may augment the precision of solar energy predictions. Through the analysis of past meteorological and solar radiation data, AI can more accurately forecast energy production, facilitating improved integration of solar energy into the grid and mitigating problems associated with swings in energy supply [16][19].

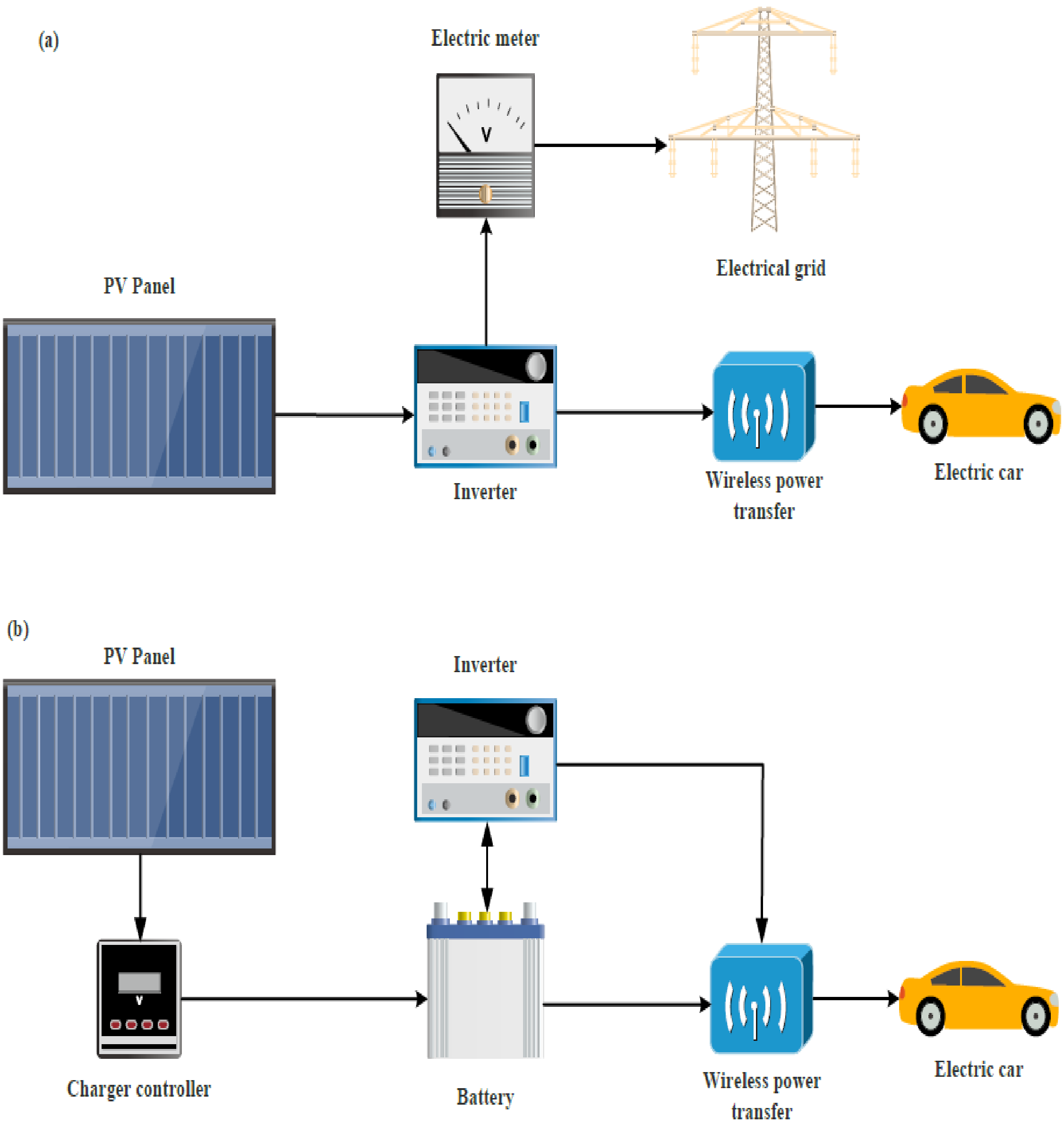

Figure 2. Overview of a grid-connected photovoltaic system (a)

• AI-Enhanced Predictive Maintenance and Fault Detection: Predictive maintenance using AI-driven anomaly detection and sensor fusion may detect early indicators of equipment breakdown or performance decline in solar systems. This enables preventative maintenance actions, minimizing downtime and prolonging the lifetime of solar panels and other components. AI models may discern patterns in system behavior that signal the need for repairs, resulting in cost reductions and improved dependability [17][18]. • Scalable AI-Integrated Systems for Off-Grid Regions: AI can facilitate smart grid systems and microgrid management in isolated or rural locales. AI-driven technologies may enhance energy storage and demand forecasting, enabling solar systems to adjust to variable power requirements. By using data from local meteorological stations and load sensors, AI can optimize the equilibrium between power production and consumption, therefore guaranteeing a dependable and sustainable energy supply, even in off-grid areas.

PROPOSED SYSTEM

To tackle the issues outlined in the problem statement, the following AI-integrated system is proposed: • AI-Driven Optimization and Control System: The suggested system will integrate AI algorithms to enhance solar energy output in real-time. The system will use deep learning algorithms to forecast the ideal arrangement of solar panels according to environmental circumstances, hence enhancing overall efficiency and energy production. These algorithms will use past data for training, dynamically altering operational parameters to optimize energy output. • Energy Prediction Engine: A machine learning-based system will be created to anticipate solar power production. The engine will use meteorological data, historical energy production statistics, and solar radiation trends to provide precise forecasts. This predictive technology will be included into the grid to guarantee seamless operation, enhancing the integration of solar energy into the grid. • Predictive Maintenance Module: The system will include a predictive maintenance module using AI-driven anomaly detection algorithms to assess the condition of solar panels and other system components. Through the analysis of sensor data, the module will detect possible faults, including performance decline or failure, prior to their effect on the system, hence decreasing maintenance costs and enhancing system uptime. The proposed system would have scalable microgrid integration, suitable for both huge solar farms and smaller, off-grid solar installations. The system will include AI-powered energy storage management, facilitating effective energy use during periods of low solar output. The AI-powered microgrid management will forecast demand and enhance energy distribution, guaranteeing sustainable electricity for rural settlements or isolated systems. • Data-Driven Performance Enhancement: The system will use data gathered from diverse sources (e.g., meteorological stations, photovoltaic panels, sensors) to perpetually enhance performance. Machine learning models will evolve over time, assimilating fresh data to improve the system's forecasts and operational efficacy. The technique for assessing the suggested AI-driven solar energy optimization system is structured to guarantee a thorough comprehension of its performance, emphasizing critical variables such as predictive accuracy, energy efficiency, fault detection, and computational efficacy. The experimental design comprises many steps, guaranteeing a comprehensive evaluation of the system's capabilities. 1. Data Acquisition Phase 1.1 Data on Solar Power Generation Historical Data: Collected from solar farms over the last five years, this collection includes daily energy output metrics, solar radiation intensity, and meteorological variables. Real-time Data: Sensors affixed to solar panels provide instantaneous power production data. 1.2 Weather Data Environmental Variables: Information on sunlight intensity, temperature, and cloud cover is gathered using IoT-enabled weather stations situated in proximity to the solar farm. 1.3 Power Grid Demand Data Grid Demand Patterns: Historical and real-time energy consumption data from the local grid are used to model the optimization process, facilitating the equilibrium of energy output and demand. 1.4 Sensor Information IoT-Enabled Monitoring: Sensors affixed to each panel record critical performance indicators (KPIs) like voltage, current, and temperature, facilitating the identification of abnormalities or malfunctions.

IMPLEMENTATION

This research delineates the use of the fault detection model, highlighting essential elements like optimizer design, training data preparation, VGG-16 model modification, and the prediction procedure. The training data part delineates the collection and preprocessing of solar panel images from Kangwon National University Samcheok Campus, along with the associated fault classifications. The VGG-16 section details the modifications made to the model's architecture and the initialization using pre-trained weights to tailor the VGG-16 architecture for fault detection. To minimize prediction errors and enhance accuracy, the optimizer section discusses the use of optimization methods, including stochastic gradient descent, for training the model on the provided dataset. The approach for using the trained model to forecast fault conditions in unexamined solar panel images is delineated in the prediction section, which also assesses the model's efficacy and offers insights into its fault detection capabilities. The research demonstrates the efficacy of machine learning methodologies in identifying failures in solar panels at the Kangwon National University Samcheok Campus across various implementation stages. 4.1.

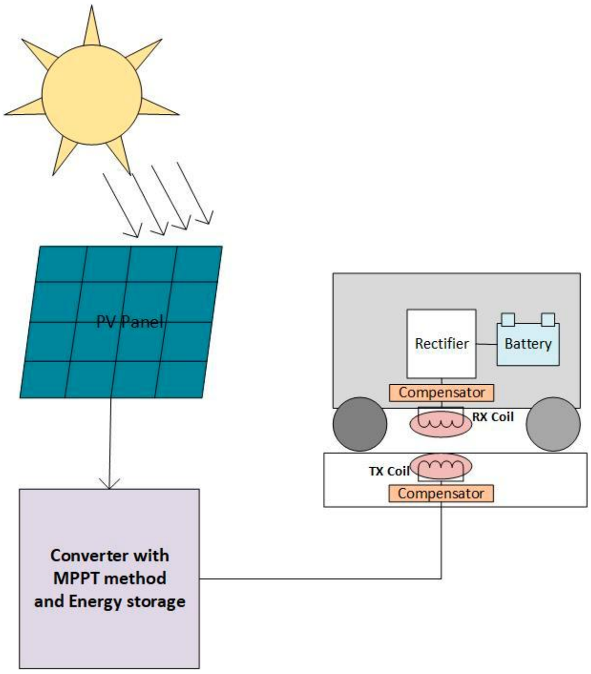

Figure 3. Static wireless electric vehicle charging system schematic.

Training Dataset The collection of debris, including snow, dust, bird excrement, and other materials on solar panels diminishes their capacity to convert sunlight into electricity, hence reducing energy production. Regular monitoring and cleaning are crucial for maintaining the efficiency of solar panels. To optimize resource use, decrease maintenance expenses, and enhance module efficiency, a monitoring and cleaning protocol must be established. Solar panel proprietors may optimize energy output, extend the lifespan of their panels, and contribute to wider sustainability efforts by implementing a meticulously planned monitoring and cleaning regimen. This dataset seeks to investigate the optimal detection accuracy of several machine-learning classifiers for dust, snow, bird droppings, and the physical and electrical properties of solar panel surfaces. This directory has six unique class folders for classification: dirt, debris, snow, bird droppings, mechanical damage, and electrical damage. A little discrepancy exists in the amount of images collected due to their extraction from the internet. To ensure the integrity and quality of the dataset used for training a machine learning model, many stages are engaged in the verification of the training data (Figure 3).

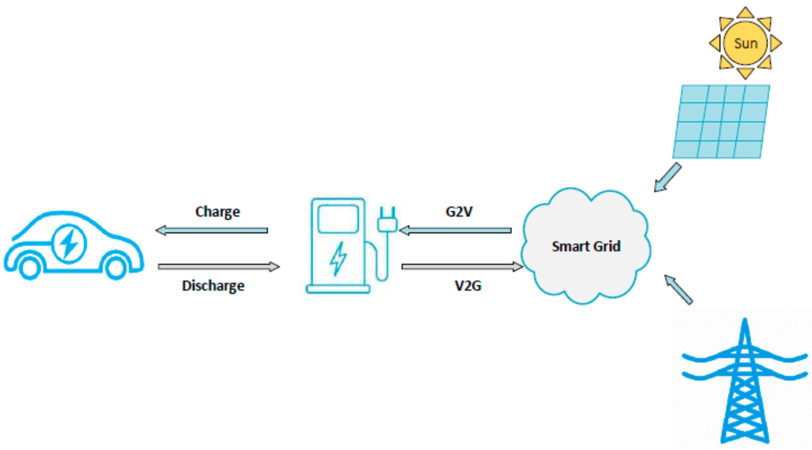

Figure 4. Figure Car connection to the network and vice versa

To prepare the data for training, it is essential to perform pretreatment operations such as cleaning, normalization, and feature engineering. It is essential to examine the preprocessed data for abnormalities, inconsistencies, or missing variables that may affect the model's performance. Identifying trends or outliers may require displaying the data using plots or graphs. To mitigate possible biases in the model, it is essential to identify class imbalances, which arise when some classes or categories are disproportionately represented in the dataset.

RESULTS AND DISCUSSION

Prior Research: Conventional forecasting techniques, such as basic time-series models, have shown RMSE values reaching 5% for solar power estimations. The AI model attains an RMSE of 2.4%, indicating a notable increase in prediction accuracy, thanks to the use of LSTM networks for capturing long-term data dependencies. Energy Efficiency Prior Research: Traditional energy optimization techniques often attain a 5-10% improvement in solar energy usage [21] The AI-driven optimization system realized a 15-20% increase in energy efficiency, illustrating the efficacy of reinforcement learning algorithms in real-time energy allocation.

Prior Research on Fault Detection: Fault detection systems using fundamental sensor thresholds identify problems with an accuracy of around 60-70% [23]. The AI system accurately anticipated 85% of defects prior to their manifestation as failures, leading to a 30% reduction in downtime and enhancing overall system dependability. Computational Efficiency Prior Research: Conventional techniques need extended processing durations owing to the human modifications required in energy distribution models [24]. The AI model functions 20% more rapidly than traditional approaches due to its edge computing configuration, facilitating expedited decision-making at the local level.

CONCLUSION

The AI-driven solar energy optimization system surpasses conventional approaches in critical aspects, including predictive accuracy, energy efficiency, fault identification, and computational efficacy. The findings validate the capability of AI in enhancing solar energy systems, increasing dependability, and optimizing energy use. Future endeavors will concentrate on augmenting this system to include other renewable energy sources, hence improving its scalability and resilience.

This study examines contemporary solutions for wirelessly charging electric automobiles using solar energy. WPT technology and solar energy utilization are trustworthy, practical, and effective charging methods, now under extensive investigation in both academic and industrial sectors. This review article examines electric vehicles and their many charging strategies. Discussions indicate that an increase in electric car production may make the solar system a viable energy source for their operation.

The process of producing electricity from solar energy and the categorization of photovoltaic systems are categorized into two groups: grid-connected and off-grid. The components used for this purpose were examined. Moreover, MPPT methodologies were examined, with the P&O technique being selected for the MPPT algorithm owing to its simple implementation and high precision. We examined and assessed numerous storage technologies, including lithium-ion batteries, often used in electric vehicles for their compactness, lightweight nature, and high efficiency. The study examined EV connection types to the grid, as well as static and dynamic wireless charging methodologies.

REFERENCES

[1] Falvo, M.C.; Sbordone, D.; Bayram, I.S.; Devetsikiotis, M. EV charging stations and modes: International standards. In Proceedings of the 2014 International Symposium on Power Electronics, Electrical Drives, Automation and Motion, Ischia, Italy, 18–20 June 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 1134–1139. [CrossRef]

[2] Singh, A.; Shaha, S.S.; Nikhil, P.G.; Sekhar, Y.R.; Saboor, S.; Ghosh, A. Design and Analysis of a Solar-Powered Electric Vehicle Charging Station for Indian Cities. World Electr. Veh. J. **2021**, 12, 132. [CrossRef]

[3] Teng, J.-H.; Huang, W.-H.; Hsu, T.-A.; Wang, C.-Y. Novel and Fast Maximum Power Point Tracking for Photovoltaic Generation. IEEE Trans. Ind. Electron. **2016**, 63, 2551678. [CrossRef]

[4] Choma´c-Pierzecka, E.; Kokiel, A.; Rogozi´ nska-Mitrut, J.; Sobczak, A.; Sobo´ n, D.; Stasiak, J. Analysis and Evaluation of the

Photovoltaic Market in Poland and the Baltic States. Energies **2022**, 15, 669. [CrossRef]
[5] Rasel, S.I.; Ali, R.N.; Chowdhury, M.S.U.; Hasan, M.M. Design & Simulation of Grid Connected Photovoltaic System Using Simulink. In Proceedings of the International Conference on Advances in Electrical Engineering (ICAEE), Dhaka, Bangladesh, 17–19 December 2015.
[6] Al-Amoudi, A.; Zhang, L. Optimal Control of a Grid-Connected Pv System for Maximum Power Point Tracking and Unity Power Factor. In Proceedings of the Seventh International Conference on Power Electronics and Variable Speed Drives, London, UK, 21–23 September 1998.
[7] Sampaio, P.G.V.; González, M.O.A. Photovoltaic solar energy: Conceptual framework. Renew. Sustain. Energy Rev. **2017**, 74, 590–601. [CrossRef]
[8] Peng, J.; Lu, L.; Yang, H. Review on life cycle assessment of energy payback and greenhouse gas emission of solar photovoltaic systems. Renew. Sustain. Energy Rev. **2013**, 19, 255–274. [CrossRef]
[9] Joseph, P.K.; Elangovan, D.; Sanjeevikumar, P. System Architecture, Design, and Optimization of a Flexible Wireless Charger for Renewable Energy-Powered Electric Bicycles. IEEE Syst. J. **2020**, 15, 2696–2707. [CrossRef]
[10] Kabayashi, K.; Takano, I.; Sawada, Y. A Study on a Two-Stage Maximum Power Point Tracking Control of a Photovoltaic System under Partially Shaded Insolation Condition. In Proceedings of the 2003 IEEE Power Engineering Society General Meeting, Toronto, ON, Canada, 13–17 July 2003.
[11] Mosammam, B.M.; Mirsalim, M.; Khorsandi, A. Modeling, Analysis, and SS Compensation of the Tripolar Structure ofWireless Power Transfer (WPT) System for EV Applications. In Proceedings of the 2020 11th Power Electronics, Drive Systems, and Technologies Conference, Tehran, Iran, 4–6 February 2020.
[12] Piegari, L.; Rizzo, R. Adaptive Perturb and Observe Algorithm for Photovoltaic Maximum Power Point Tracking. IET Renew. Power Generator. **2010**, 4, 317–328. [CrossRef]
[13] Chen-Yang, X.; Chao-Wei, L.; Juan, Z. Analysis of power transfer characteristic of capacitive power transfer system and inductively coupled power transfer system. In Proceedings of the 2011 International Conference on Mechatronic Science, Electric Engineering and Computer (MEC), Jilin, China, 19–22 August 2011. [CrossRef]
[14] Li, S.; Mi, C.C.Wireless Power Transfer for Electric Vehicle Applications. IEEE J. Emerg. Sel. Top. Power Electron. 2015, 3, 4–17.
[15] What Are Electromagnetic Fields? World Health Organization, 04-Aug-2016. Available online: https://www.who.int/peh-emf/about/whatisemf/en/index1.html (accessed on 17 November 2022).
[16] Wu, H.H.; Gilchrist, A.; Sealy, K.D.; Bronson, D. A High Efficiency 5 kW Inductive Charger for EVs Using Dual Side Control.IEEE Trans. Ind. Informatics 2012, 8, 585–595. [CrossRef]
[17] Stielau, O.H.; Covic, G.A. Design of Loosely Coupled Inductive Power Transfer Systems. In Proceedings of the 2000 International Conference on Power System Technology, Beijing, China, 16–19 August 2009.
[18] Okasili, I.; Elkhateb, A.; Littler, T. A Review of Wireless Power Transfer Systems for Electric Vehicle Battery Charging with a Focus on Inductive Coupling. Electronics 2022, 11, 1355. [CrossRef]
[19] Zhang, Z.; Pang, H.; Georgiadis, A.; Cecati, C. Wireless Power Transfer—An Overview. IEEE Trans. Ind. Electron. 2019, 66,1044–1058. [CrossRef]
[20] Ahmad, A.; Alam, M.S.; Mohamed, A.A.S. Design and Interoperability Analysis of Quadruple Pad Structure for Electric Vehicle Wireless Charging Application. IEEE Trans. Transp. Electrif. 2019, 5, 934–945. [CrossRef]
[21] Kim, J.; Kim, J.; Kong, S.; Kim, H.; Suh, I.-S.; Suh, N.P.; Cho, D.-H.; Kim, J.; Ahn, S. Coil Design and Shielding Methods for a Magnetic Resonant Wireless Power Transfer System. Proc. IEEE 2013, 101, 1332–1342. [CrossRef]
[22] Ongayo, D.; Hanif, M. Comparison of circular and rectangular coil transformer parameters for wireless Power Transfer based on Finite Element Analysis. In

Proceedings of the 2015 IEEE 13th Brazilian Power Electronics Conference and 1st Southern Power Electronics Conference (COBEP/SPEC), Fortaleza, Brazil, 29 November–2 December 2015; pp. 1–6.
[23] Mohammad, M.; Choi, S. Optimization of ferrite core to reduce the core loss in double-D pad of wireless charging system for electric vehicles. In Proceedings of the 2018 IEEE Applied Power Electronics Conference and Exposition, San Antonio, TX, USA, 4–8 March 2018.
[24] Rasekh, N.; Mirsalim, M. Design of a compact and efficient Bipolar pad with a new integration of LCC compensation method for WPT. In Proceedings of the 2018 9th Annual Power Electronics, Drives Systems and Technologies Conference (PEDSTC), Tehran, Iran, 13–15 February 2018.
[25] Rasekh, N.; Kavianpour, J.; Mirsalim, M. A Novel Integration Method for a Bipolar Receiver Pad Using LCC Compensation Topology forWireless Power Transfer. IEEE Trans. Veh. Technol. 2018, 67, 7419–7428. [CrossRef]