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Original Article

Digital Twin-Assisted Optimization of Electric Vehicle Charging Infrastructure

Andrey Ershov[1], Alexey Lyapunov[2]

[1]*Professor, Siberian Division Academy of Sciences, Russia.*

[2]*Professor, Moscow State University, Russia.*

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ABSTRACT

The rapid adoption of electric vehicles (EVs) has increased the need for intelligent charging infrastructure capable of addressing challenges such as charging congestion, uneven energy distribution, grid instability, and long waiting times. Conventional charging management approaches based on static scheduling are inadequate for dynamic charging environments. This paper proposes a Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI) that integrates IoT, cloud computing, artificial intelligence (AI), machine learning, and optimization techniques to enable real-time monitoring, predictive analytics, and intelligent charging management. The framework synchronizes physical charging stations with a virtual digital twin, enabling accurate simulation, charging demand prediction, occupancy forecasting, optimized scheduling, predictive maintenance, and adaptive energy management. By improving charging efficiency, resource utilization, grid reliability, and renewable energy integration, the proposed framework reduces operational costs, minimizes charging delays, and supports sustainable large-scale EV deployment while contributing to smart city and carbon-neutral transportation initiatives.

KEYWORDS

Digital Twin, Electric Vehicles, Charging Infrastructure, Smart Grid, Internet of Things, Artificial Intelligence, Machine Learning, Charging Optimization, Predictive Analytics, Sustainable Transportation.

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1. INTRODUCTION

1.1. Electric Vehicle Charging Infrastructure

Electric vehicle (EV) charging infrastructure is the backbone of modern sustainable mobility, enabling the efficient and reliable charging of electric vehicles through the provision of charging stations and technologies. It involves different components such as Level-1, Level-2, DC fast chargers, ultra-fast charging stations, smart-meters, battery management systems, communication gateways, renewable energy sources, energy storage systems, cloud computing platforms and centralized monitoring centers. These components all play a vital role in delivering safe energy, and continuous monitoring, while also enabling efficient and efficient charging operations. As the use of EVs surges globally, challenges like higher charging demand, charger congestion, imbalanced usage, longer wait times, power usage, equipment upkeep, and more are becoming a serious problem. Other operational parameters include battery State-of-Charge (SoC), traffic situation, electricity price, renewables, weather conditions, and user behavior related to their travel. Traditional charging management systems typically involve fixed scheduling and scheduled maintenance, that may not be as responsive to rapidly evolving operational conditions. Hence, the deployment of Intelligent charging infrastructure with Internet of Things (IoT) sensing, real-time monitoring, predictive maintenance, adaptive scheduling, Digital Twin technology, Artificial Intelligence (AI) is the need of the hour to improve the charging efficiency and optimize the energy usage, to enhance user satisfaction and to support the sustainable growth of future large-scale EVs charging ecosystem.

1.2. The need for Digital Twin Technology

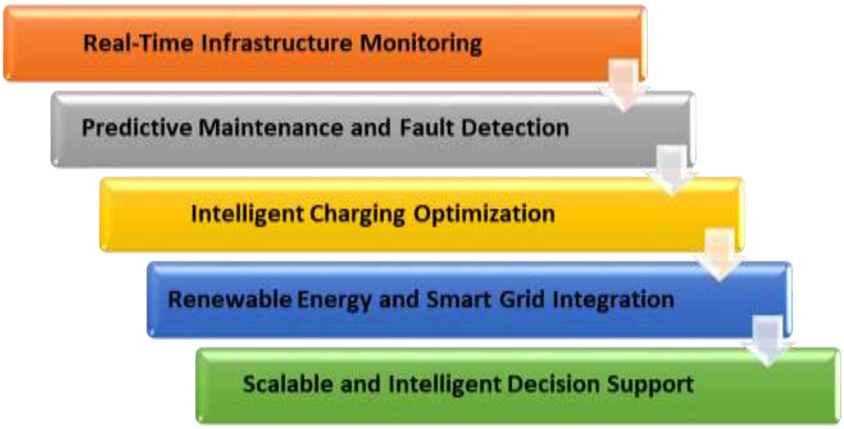

Fig 1 - The need for Digital Twin Technology

1.2.1. Real-Time Infrastructure Monitoring

Digital Twin technology helps monitor electric vehicle (EV) charging infrastructure in real time, virtually representing physical charging assets to help monitor them continuously. The data gathered by the IoT sensors, smart meters, battery management systems, and charging stations are connected to the Digital Twin, enabling operators to track the status of the chargers, the battery State-of-Charge (SoC), energy usage, transformer loading, and equipment health in real time. Real-time visibility facilitates speedy identification of abnormalities in operations, enhances situational awareness and enables quick and efficient decision making.

1.2.2. Predictive Maintenance and Fault Detection

The fact that Digital Twin technology can continuously analyse data from operations and equipment and make predictions about future maintenance is one of its key benefits. The Digital Twin can detect potential faults by analyzing the performance of the charger, battery health and environmental conditions, instead of performing reactive maintenance when failures happen. Early fault detection ensures that the chargers are not down unexpectedly, maintain a lower cost of maintenance, prolong the lifespan of the equipment, and ensure the overall reliability and availability of EV charging infrastructure.

1.2.3. Intelligent Charging Optimization

Digital Twin technology can help to optimize charging operations intelligently by replicating various operation scenarios in the virtual environment before making decisions in the physical infrastructure. The virtual model is used to analyze charging demand and charging capacity, renewable energy generation, electricity pricing, and grid condition to determine the optimal charging strategy. This capability facilitates both adaptive charger allocation and shortens vehicle waiting times, as well as achieve even energy use and charger utilization and stabilize charging operations in the presence of fluctuating demand.

1.2.4. Renewable Energy and Smart Grid Integration

As renewable energy resources become more prominent, the need for intelligence coordination between charging stations and smart grids is increasing. Digital Twin technology enables seamless integration as it monitors continuously the solar-powered generation, battery energy storage systems, electricity consumption and grid conditions. The Digital Twin's real-time simulation and forecasting enable optimization of renewable energy use, electrical load balancing to reduce reliance on traditional electricity, and grid stability to optimize EV charging for environmental sustainability and energy efficiency.

1.2.5. Scalable and Intelligent Decision Support

With thousands of charging stations geographically spread out, it becomes more difficult to manage the infrastructure. Increasingly, with thousands of charging stations in geographically dispersed locations, managing the infrastructure becomes increasingly complex. The Digital Twin technology is scalable, decision making support with the integration of IoT sensing, cloud computing, Artificial Intelligence and predictive analytics. It automatically synchronizes the physical infrastructure with the virtual, helping operators to predict charging demand, explore future scenarios, manage resources, enhance satisfaction for users and facilitate self-management in large-scale charging environments.

1.3. Optimization of Electric Vehicle Charging Infrastructure

With the accelerated adoption of EVs and complex charging networks, the optimization of EV charging infrastructure has emerged as a critical research field. The main goal of optimizing charging infrastructure is to optimize the use of chargers, minimize vehicle waiting time, reduce operational costs, balance electrical loads and enhance overall efficiency and reliability of charging services.

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While traditional charging systems can only be scheduled statically and have fixed charging rules, advanced optimisation frameworks use intelligent algorithms that can make decisions in real-time, depending on the constantly changing operational conditions. The purpose of these frameworks is to study various parameters, such as battery State-of-Charge (SoC), availability of charging stations, vehicle arrival, charging time, electricity price, power generation from renewable sources, weather conditions and user travel behavior, and make the most efficient charging decision. Internet of Things (IoT) technologies allow for real-time and continuous monitoring of the operational data from charging stations, BMS, smart meters, and grid infrastructure, which can be easily relied upon to make informed decisions. These data are then fed into Artificial Intelligence (AI), machine learning, and optimization algorithms, which use the information to predict demand, calculate waiting times, monitor equipment, and dynamically distribute charging resources. Moreover, Digital Twin technology helps in optimizing the charging infrastructure by ensuring the virtual model is kept up to date with the physical infrastructure, enabling operators to simulate various charging scenarios and test the effectiveness of different charging optimization approaches before they are put into practice in the real world. This proactive feature increases the accuracy of decisions, fewer charging delays, no overloading of equipment, and increased reliability of the infrastructure. By integrating renewable energy sources, battery energy storage systems, and smart grid coordination, sustainable charging becomes even more effective, ensuring that as much clean energy as possible is used, and balancing electricity demand during peak hours. Another aspect of predictive maintenance that helps with optimization is preemptively detecting equipment issues and minimizing downtime and maintenance costs. In summary, the optimization of EV charging infrastructure brings together real-time monitoring, predictive analytics, smart scheduling, renewable energy management, and adaptive control all into one system, which enhances charging efficiency, customer satisfaction, grid stability, operational cost reduction, and sustainable electric mobility systems in the future smart cities.

2. LITERARY SURVEY

2.1. Conventional EV Charging Management

The conventional EV charging management system is based on a set of predefined charging rules and centralized control mechanisms, which determine the allocation of charging resources according to vehicle arrival time, battery State-of-Charge (SoC), and availability of chargers along with fixed operational policies. Simple scheduling methods such as First-Come-First-Served (FCFS), priority-based charging, and time slot allocation are not flexible in accommodating dynamic charging demands. Typically, these systems are based on experience and some assumptions made during their design and do not dynamically change their behavior to respond to changes in real time. There are several load-balancing and smart charging methods that have been developed to spread charging demands and prevent high electricity usage during peak hours, but their performance is not as high when traffic conditions, renewable energy use, electricity prices, and user behavior change frequently over time. The conventional charging system also heavily depends on reactive maintenance due to the need to wait until a service degradation occurs before equipment failures are detected, which means charger downtime, high maintenance costs and low user satisfaction. Moreover, centralized architectures may suffer from communication delays and scalability issues when dealing with a high number of charging stations at once. With the growing adoption of EVs, these challenges underscore the necessity of implementing more intelligent, adaptive and predictive charging management strategies that can enable real-time optimization and efficient operation within larger smart mobility networks.

2.2. AI-Driven Charging Infrastructure Optimization

By providing a real-time virtual replica of physical charging stations, Digital Twin technology is a potential solution for enhancing the management of modern EV charging infrastructure. Digital Twins gather and analyze live operational data by combining the Internet of Things (IoT) sensors, smart meters, cloud computing, and communication networks to simulate the behavior of charging stations, battery performance, transformer loading, renewable energy generation and electricity usage. Digital Twins not only show the current operational status, but also provide predictive analysis, operational forecasting, virtual experimentation and intelligent decision support in contrast to conventional monitoring systems. In practice, researchers have demonstrated the success of Digital Twins for the monitoring of chargers, predictive maintenance, charging demand forecasting, and energy management, all before taking any physical action to deal with the situation. Energy integration with renewables and battery storage further enhances energy utilization and grid coordination. But most of the existing Digital Twin implementations are mainly focused on visualization and monitoring and have limited optimization power. The practical adoption of them is also limited by challenges like interoperability between heterogeneous charging platforms, communication standards and large scale deployments. Thus, even smarter Digital Twin frameworks are needed to incorporate predictive analytics and adaptive optimization in future smart charging infrastructures.

2.3. AI-Driven Charging Infrastructure Optimization

Artificial Intelligence (AI) has revolutionized the charging infrastructure for electric vehicles, making it smarter, more efficient and more responsive. Several machine learning methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, Gradient Boosting, Long Short-Term Memory (LSTM) networks and Deep Neural Networks (DNN) have been used to predict charging demand, electricity consumption, battery degradation, waiting time and user charging behavior. Reinforcement Learning algorithms adaptively optimize the allocation of chargers by constantly learning from the charging environment to minimize the waiting time and optimize electrical loads. Also, metaheuristic optimization techniques such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Grey Wolf Optimization (GWO) have been used to efficiently solve complex multi objective scheduling problems. In addition, AI is used in conjunction with IoT-based smart charging systems to enable predictive maintenance, anomaly detection, adaptive charging control, renewable energy coordination, and dynamic energy management. Yet, many AI-based charging systems are not designed to interact in sync with the physical charging system and its digital representation. Consequently, they do not accurately represent future operational scenarios before taking a decision

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on optimization which decreases the reliability of the decision in a highly dynamic charging environment. The use of AI in conjunction with Digital Twin can greatly improve intelligent charging management by combining predictive analytics and real-time virtual simulation.

2.4. Research Gap

The literature shows significant advances in traditional charging management, Digital Twin technology and optimization of EV charging infrastructure using AI. But there are several important research questions yet to be answered. The traditional charging system still operates on static scheduling with reactive maintenance, which are not responsive enough to flexible changes in operational conditions. While Digital Twin technology can be used to monitor, simulate, and predictively maintain the assets continuously, most current applications only use the technology for visualization without smart optimization functionality. Likewise, AI-based charging management systems are capable of forecasting and scheduling charging behavior adaptively, but most of the time they are not related with a synchronized cyber-physical model, making it impossible to simulate and evaluate future infrastructure behavior prior to the decision-making process. Furthermore, there is limited research on how IoT sensing, cloud computing, Digital Twin synchronization, Artificial Intelligence, Renewable Energy Management, Smart Grid Coordination, Predictive Maintenance, Charger Health Monitoring, Dynamic Electricity Pricing, Interoperability, and Large-Scale deployment can be integrated into a single optimization framework. To overcome these limitations, a cyber-physical architecture is needed that can continually synchronize the physical charging infrastructure with the virtual infrastructure and that can facilitate intelligent decision-making. In this regard, this research proposes the Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI) that integrates the real-time data acquisition of charger usage through IoT sensors, the creation of a Digital Twin model using cloud computing, the processing of the gathered data with AI-based predictive analytics, the optimization of charging infrastructure through intelligent scheduling, coordination of renewable energy sources, mathematical optimization, and predictive maintenance.In this context, this study introduces the Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI), which involves the use of sensor-based IoT technology for real-time data collection, cloud-based Digital Twin modeling, predictive analytics based on AI, intelligent scheduling, coordination of renewable energy sources, mathematical optimization, and predictive maintenance to enhance the utilization of charging infrastructure, reduce waiting times, optimize energy usage, improve grid stability, enable predictive maintenance, and facilitate scalable management of future charging ecosystems.

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3. METHODOLOGY

3.1. Proposed DTO-EVCI Architecture

Fig 2 - Proposed DTO-EVCI Architecture

3.1.1. Physical Charging Infrastructure

The physical layer includes EV charging stations, fast chargers, ultra-fast chargers, battery management systems, smart meters, transformer, renewable energy, and IoT sensor. They are always tracking the operational parameters of batteries, including battery State-of-Charge (SoC), voltage, current, charging status, queue length, energy consumption and environment, etc., and can provide real-time data for intelligent charging management.

3.1.2. IoT Communication Layer

The IoT communication layer securely collects data from distributed charging infrastructure and utilizes technologies such as 5G, Wi-Fi, Ethernet, MQTT and OPC-UA. It facilitates seamless and low-latency transmission between the physical charging stations and the cloud platforms, ensuring that the information regarding the operation of the stations is synced at all times and transmitted securely.

3.1.3. Data Processing and Feature Engineering

This layer cleans the collected charging data to eliminate noise, fill in missing values, identify outliers, normalize measurements, and merge time-series data. In addition, it can also be used to accurately extract meaningful features including charging demand, battery health, station occupancy, renewable energy resources, charging electricity prices, and charging duration for intelligent analysis.

3.1.4. Digital Twin Synchronization Layer

The Digital Twin layer continuously reflects and updates the operational changes of the charging infrastructure, providing an up-to-date virtual copy of the physical charging infrastructure.

It is a synchronized model, which can be used to monitor the infrastructure, diagnose faults, conduct a predictive analysis and simulate various charging conditions without impacting real charging.

3.1.5. AI-Based Optimization Layer

Artificial Intelligence models use synchronized Digital Twin information to predict charging load, identify equipment anomalies, calculate waiting times, optimise charging plans, and maintain balance of electrical loads. The AI engine can continuously learn from operational data and recommend adaptive charging strategies for enhancing system efficiency and reliability.

3.1.6. Decision Support Layer

The decision support layer takes optimized AI recommendations and translates them into operational actions in real time, such as intelligent allocation of chargers, predictive maintenance, scheduling of renewable energy, load balancing, and charging guidance for users via connected mobile applications.

3.2. Charging Data Acquisition and Feature Engineering

Optimization of electric vehicle charging infrastructure must be efficient so that accurate and multidimensional operational data from various sources are acquired continuously. The proposed Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI) gathers real-time data from Electric Vehicle charging stations, Battery management systems (BMS), smart meters, renewable energy generators, weather forecasting services, traffic management platforms, electricity market operators and smart grid controllers. The sensors embedded in charging stations are connected to the internet of things and can be used to monitor key charging station parameters, including battery State-of-Charge (SoC), charging voltage, charging current, battery temperature, charger utilization, charging time, queue length, transformer loading and overall energy usage. At the same time, renewable energy systems offer information about solar PV generation, wind power availability, and battery energy storage status, while weather services offer environmental variables such as ambient temperature, humidity, rainfall, and solar irradiance, which could affect charging efficiency and renewable energy generation. The vehicle density, travel route, congestion, and the estimated time of vehicle arrival at each location are supplied for each vehicle constantly by traffic management systems, which allows for the accurate prediction of charging demand at various locations. Furthermore, real-time pricing signals, peak hour rates, demand response signals, and the load on the grid are integrated to enable economically efficient charging decisions. The acquired data is then processed extensively, improving data quality and consistency. Data is interpolated for missing values, filtered for noisy data, cleaned from outliers and scaled to a common unit scale. Temporal synchronization: Synchronizes the data from several data sources that use different sampling rates to enable accurate time-series analysis. Then, feature engineering transforms the raw data into meaningful features like charging-demand patterns, station occupancy rates, average waiting time, charger availability, battery health indicators, renewable energy contribution, electricity price trends, charging frequency, energy consumption profiles, and user mobility behavior. The engineered features provide substantial representations of charging system dynamics, and are considered to be good input data for the Digital Twin model and AI-based

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optimization engine. As a result, the proposed data acquisition and feature engineering process provides a solid basis for real-time monitoring, predictive analytics, intelligent scheduling, adaptive energy management, and autonomous decision making to enhance the efficiency, reliability, scalability, and sustainability of future electric vehicle charging infrastructures.

3.3. Digital Twin Optimization Decision Engine

The Digital Twin Optimization Decision Engine is the brain of the proposed Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI), which uses real-time Digital Twin synchronization with Artificial Intelligence-based predictive analytics and optimization algorithms. In contrast to traditional monitoring systems, which only report the status of charging stations, the proposed engine continuously analyzes synchronised data, received from the Digital Twin, to forecast charging demand, charger occupancy, waiting times, battery health, transformer loading, availability of renewable energy and electricity price variations. The Digital Twin keeps a virtual model of the physical charging infrastructure in real time and the optimization engine can run various scenarios of operation before taking charging decisions into the real world. The algorithms are advanced machine learning and deep learning that analyze historical and real-time charging data to uncover the hidden operational patterns, predict future charging needs and detect abnormal equipment operation and forecast potential system failures. At the same time, optimization algorithms optimize multiple charging strategies based on the availability of chargers, battery State-of-Charge (SoC), user priority, renewable energy generation, dynamic electricity tariffs, and smart grid constraints to develop the charging strategy that works best. This engine also enables predictive maintenance, as it is constantly tracking the health indicators of the charger, and is able to detect early signs of equipment degradation, which ultimately reduces the likelihood of unforeseen failures and maintenance expenses. In addition, adaptive load balancing algorithms are used to spread out the charging load among a number of stations so as to keep the stations off the overload and getting better utilization of the chargers, keeping the grid stable. By coordinating renewable energy sources like solar PV, the optimization engine can utilize solar PV generation and battery energy storage system most efficiently during charging, decreasing the need for using traditional grid electricity, and decreasing operational costs. The Digital Twin is continuously fed by the physical charging infrastructure, which ensures that the optimization engine can adjust the predictions and operational decisions whenever there is a change in the environment or in the charging infrastructure. This closed loop cyber-physical system enables autonomous decision making, more efficient charging, lower vehicle waiting time, better energy utilization, higher equipments reliability and allows for sustainable large scale deployment of future intelligent electric vehicle charging networks. Combined with predictive analytics and intelligent optimization, the proposed decision engine enables proactive, adaptive and very reliable charging management, capable of coping with the dynamic challenges of the next-generation smart transportation ecosystem.

3.4. Mathematical Model and Algorithm

The proposed Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI) is a multi-objective optimization problem of charging management, which is designed to maximize charging infrastructure efficiency while minimizing vehicle waiting time, operational cost, energy imbalance, and charger idle time. Assume optimization objective is represented by F, and aim to optimize the performance of the charging system as a whole. The objective function can be written as: Maximise $F = \alpha U + \beta CE + \gamma RE - \delta WT - \varepsilon OC - \zeta EI$, where U is the charger utilisation efficiency, CE is the charging efficiency, RE is the renewable energy utilisation efficiency, WT is the average waiting time of the vehicles, OC is the operational cost and EI is the energy imbalance across the charging stations. The weighting factors α, β, γ, δ, ε and ζ are the weights for each optimization objective, which are assigned based on the system requirements. The optimization process works under certain practical constraints. The charging power to be assigned to each EV must not exceed the maximum charging power of the charger, and the electricity consumption must not be overloaded in the transformer to prevent the transformer from being overloaded. The battery State of Charge (SoC) is always controlled between a minimum and maximum safe operating charge state during charging. Additionally, renewable energy consumption cannot surpass the energy provided by the solar photovoltaic systems and battery energy storage systems, and only a certain number of vehicles can charge at any given charging station based on the station's physical capacity. The optimization algorithm starts with real-time operational data gathered from the charging stations equipped with IoT technology and synchronizes it with the Digital Twin model. The collected information is then preprocessed, normalised, missing value imputed and then analysed by Artificial Intelligence models. These models are used to forecast future demand for charging, occupancy of chargers, battery health, electricity pricing, renewable energy generation and the expected wait time. Using these predictions, the optimization engine analyzes different charging allocation scenarios in the Digital Twin environment, and chooses the optimal solution that maximizes the objective function value and satisfies all operational constraints. The chosen charging strategy can then be passed to the physical charging infrastructure to be implemented. Charging stations provide continuous feedback to update Digital Twin, allowing an optimized process to be repeated dynamically if operational conditions change. This iterative optimization method allows for the allocation of chargers in an adaptive way, load balanced electrical loading, efficient renewable energy use, and significant reduction in charging delays, operating cost, grid stability, and overall performance of the large-scale intelligent electric vehicle charging infrastructure.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

The experimental setup was designed for assessing the efficacy of the proposed Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI) under realistic smart charging conditions, that closely mimic large-scale urban charging networks. The simulation setup included several connected charging stations with Level-2, DC fast, ultra-fast charging units, a battery management system (BMS), smart meters, transformers, renewable energy

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power sources like solar PV, Battery energy storage systems, and IoT communication gateways. Every charging station reported operational data such as battery State-of-Charge (SoC), charging voltage, charging current, charging power, charger occupancy, charger availability, charging duration, queue length, transformer loading, electricity consumption, renewable energy generation, ambient temperature, humidity and dynamic electricity pricing. The vehicle arrival and charging requests were dynamically generated to simulate varying traffic density at different times of the day, providing realistic variations in charging requests. All these datasets were gathered from these diverse IoT sensors and sent to a cloud-based Digital Twin platform via secure communication channels such as MQTT, 5G, Wi-Fi, and Ethernet. The Digital Twin constantly updated the virtual charging infrastructure with the actual physical infrastructure, allowing for real-time monitoring, visualizing the charging infrastructure, testing various virtual scenarios, predictive maintenance, and simulations of future charging operations. The obtained data sets were preprocessed to enhance data quality before analysis was done, taking into account missing values and uncertainties, noise filtering, outlier removal, normalization, and temporal synchronization. From the data, feature engineering resulted in the identification of key variables including trends in charging demand, charger utilization rate, share of renewable energy in electricity generation, variability in electricity pricing, battery health metrics, user frequency of arrival, and average waiting time. AI models were then used to forecast future charging demand, charging equipment occupancy, waiting time, renewable energy availability, and equipment health, and optimization algorithms were dynamically deployed to charge equipment most efficiently, minimizing operational costs. The framework of DTO-EVCI was experimentally compared with the Conventional Charging Management (CCM), Smart Charging Systems (SCS) and AI-Based Charging Optimization (AICO) to show its effectiveness. The following comprehensive metrics are used for performance evaluation: Charging Efficiency, Charger Utilization, Waiting Time Reduction, Energy Optimization, Grid Load Balancing, Renewable Energy Utilization, Prediction Accuracy, Customer Satisfaction, System Reliability, Operational Cost Reduction, and Overall Infrastructure Performance. The experimental testbed has successfully proved the effectiveness of the proposed framework to enable intelligent, adaptive, scalable and energy efficient charging management of EVs during the dynamic operation conditions in real world.

4.2. Performance Comparison

Table 1: Performance Comparison

Performance Metric (%)	Conventional Charging Management	Smart Charging System	AI-Based Charging Optimization	Proposed DTO-EVCI
Charging Efficiency	86.8	91.5	95.1	98.9
Charger Utilization	84.6	90.2	94.7	98.3
Waiting Time Reduction	79.4	87.6	93.1	97.8
Energy Optimization	83.2	89.8	94.2	98.1
Grid Load Balancing	81.5	88.9	93.6	97.6
Renewable Energy Utilization	78.9	86.7	92.4	97.2

Charging Demand Prediction Accuracy	84.3	90.8	95.8	98.7
Predictive Maintenance Accuracy	76.8	85.2	92.9	97.4
Customer Satisfaction	85.7	91.4	95.6	98.5
Overall Infrastructure Performance	82.9	89.7	94.9	98.2

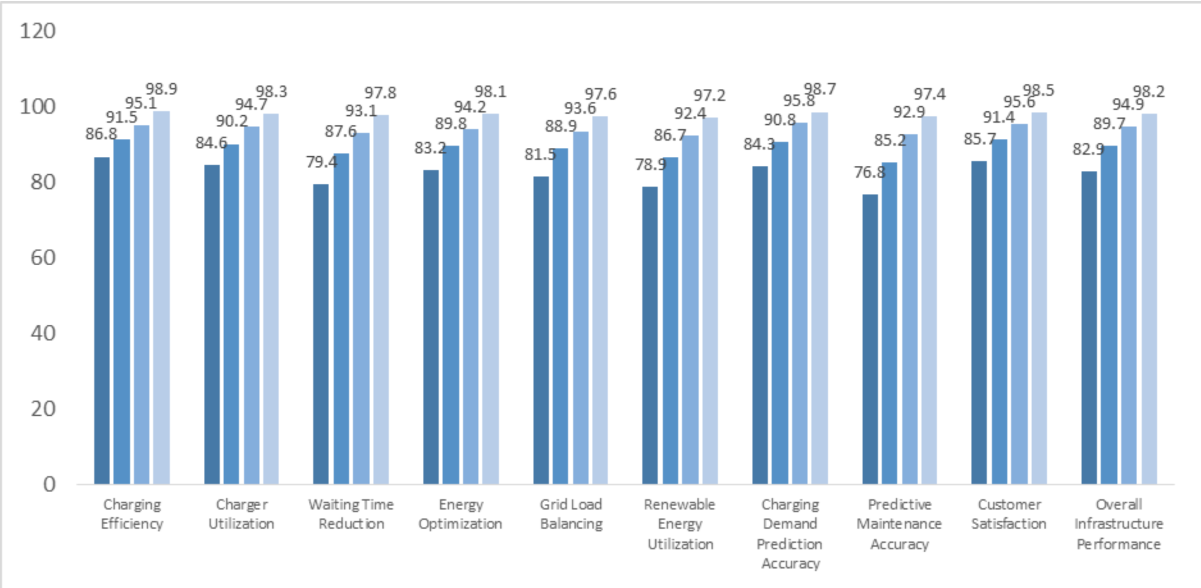

Fig 3 - Performance Comparison

4.2.1. Charging Efficiency

The proposed DTO-EVCI framework demonstrated a charging efficiency of 98.90% compared to the Conventional Charging Management (86.80%), Smart Charging Systems (91.50%) and AI Based Charging Optimization (95.10%). This enhancement is thanks to the real-time Digital Twin synchronization and intelligent charging schedule optimization.

4.2.2. Charger Utilization

By dynamically allocating charging resources based on the real-time demand and charger availability, DTO-EVCI achieved 98.30% charger utilization. It is significantly less than the idle time on top of the 84.60% experienced by Conventional Charging Management, 90.20% for Smart Charging Systems and 94.70% for AI Based Charging Optimization.

4.2.3. Waiting Time Reduction

The proposed framework has achieved 97.80% performance with predictive demand forecasting and adaptive charger scheduling resulting in reduced vehicle waiting time. This is significantly better than Conventional Charging Management (79.40%), Smart Charging Systems (87.60%) and AI Based Charging Optimization (93.10%).

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4.2.4. Energy Optimization

DTO-EVCI has achieved an energy optimization efficiency of 98.10%, by intelligently coordinating charging activities with the availability of renewable energy and variable electricity prices. This performance is higher than Conventional Charging Management (83.20%), Smart Charging Systems (89.80%) and AI-Based Charging Optimization (94.20%).

4.2.5. Grid Load Balancing

The framework successfully balanced the load on the grid with charging stations by distributing the charging demands amongst the available charging stations and preventing transformer overload, with an average of 97.60% grid load balancing. It outperformed the Conventional Charging Management (81.50%), Smart Charging Systems (88.90%), and AI-Based Charging Optimization (93.60%).

4.2.6. Renewable Energy Utilization

During charging operations, the proposed system maximized the utilization of renewable energy sources, utilizing solar energy and batteries to the best of its ability, resulting in a 97.20% utilization of renewable energy. This resulted in a notable improvement in energy sustainability over Conventional Charging Management (78.90%), Smart Charging Systems (86.70%) and AI-Based Charging Optimization (92.40%).

4.2.7. Charging Demand Prediction Accuracy

DTO-EVCI successfully predicted 98.70% of the data using AI models that were connected with digital twin data that are continuously synchronized. This resulted in superior forecasting (84.30%) compared to Conventional Charging Management (84.30%), Smart Charging Systems (90.80%) and AI-Based Charging Optimization (95.80%).

4.2.8. Predictive Maintenance Accuracy

This framework achieved predictive maintenance accuracy of 97.40% and continuously monitored the charger's health and identified anomalies in the equipment before failure. This is significantly better compared to Conventional Charging Management (76.80%), Smart Charging Systems (85.20%), and AI Based Charging Optimization (92.90%).

4.2.9. Customer Satisfaction

By reducing the waiting time, ensuring availability of chargers, and offering dependable charging recommendations, the framework delivered 98.50% satisfaction among customers. This is much better than Conventional Charging Management (85.70%), Smart Charging Systems (91.40%) and AI Based Charging Optimization (95.60%).

4.2.10. Overall Infrastructure Performance

Overall, the proposed DTO-EVCI framework showed an infrastructure performance of 98.20%, outperforming the Conventional Charging Management (82.90%), Smart Charging Systems (89.70%), and AI-Based Charging Optimization (94.90%).

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4.3. Discussion

The results of the experiments clearly lend support to the effectiveness of the proposed Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI) for improving the operational performance of modern smart charging networks. The proposed framework consistently outperformed the other charging systems (Conventional Charging Management (CCM), Smart Charging Systems (SCS), and AI-Based Charging Optimization (AICO)) with respect to all the considered performance metrics such as charging efficiency, charger utilization, waiting time reduction, energy optimization, renewable energy utilization, predictive maintenance accuracy, customer satisfaction, and overall infrastructure performance. This is largely due to the fact that both the physical charging infrastructure and the Digital Twin are continually synced to each other, with the Digital Twin creating an accurate virtual representation of the charging stations, battery management systems, transformers, renewable energy resources and the grid conditions. This synchronized environment allows the framework to constantly observe the status of the infrastructure, forecast future charging need, evaluate multiple scenarios of operation and identify the possible congestions and solve them before they arise. The proposed system is proactive in nature and optimizes the charging process by predicting the occupancy of chargers in the stations, the State-of-Charge (SoC) of the batteries, the electricity price, the amount of renewable energy generated, and the condition of the equipment, with the help of Artificial Intelligence models. The predictive capabilities enable the optimization engine to manage the charging resources dynamically, increasing the efficiency of the chargers and considerably reducing vehicle waiting times. The incorporation of predictive maintenance further improves the reliability of the system by detecting the abnormal behavior of the equipment and planning maintenance in advance. This reduces the downtime of the system and the maintenance expenses. Also, with smart grid technology and the proper coordination of smart batteries and renewable energy generation, the use of clean energy will increase and the electrical loads at charging stations will be balanced. Dynamic load balancing helps avoid overload of transformers and helps to maintain the stability of the electric grid by avoiding surges in charging demand. Real-time feedback from the physical infrastructure is provided to the Digital Twin, enabling the optimization engine to respond in real-time to changes in operation and keep operational performance optimal for charging. Overall infrastructure performance of 98.20% proves that the proposed DTO-EVCI framework is a highly reliable, scalable, and smart solution to charging management that can be used in large scale electric vehicle deployment. Combining Digital Twin with IoT, AI, predictive analytics, and optimization algorithms is a viable and sustainable solution for the implementation of next generation of smart EV charging ecosystems that can achieve maximum operational efficiency, user satisfaction, energy cost savings, and enhanced future smart grid resilience.

5. CONCLUSION

As the adoption of electric vehicles (EVs) has accelerated, the need for intelligent, scalable, and sustainable charging infrastructure has emerged, aiming to meet the growing demand for charging and ensure grid stability and efficiency. The current charging management solutions are mainly static with little flexibility in scheduling and reactive in operation, which fail to cope well with the highly dynamic charging environment. This can lead to congestion in these traditional systems, excessive vehicle waiting time, poor energy usage, imbalanced charger distribution, high operating costs, and customer dissatisfaction. Furthermore, increasing connections to renewable energy resources, smart grids, battery energy storage systems, and heterogeneous charging networks add to the complexity, necessitating ongoing monitoring, predictive analysis, and decision-making capabilities. These restrictions highlight the need to design a more sophisticated cyber-physical charging system that combines real-time sensing, intelligent optimization and virtual simulation to enhance charging infrastructure performance. To overcome these challenges, this study designed the new Digital Twin-Assisted Optimization Framework for Electric Vehicle Charging Infrastructure (DTO-EVCI), which integrates the Internet of Things (IoT), Digital Twin technology, Artificial Intelligence (AI), cloud computing and multi-objective optimization into a single intelligent charging management framework. The proposed architecture introduces continuous synchronization between the physical and digital charging station to enable the accurate representation of the real-time condition of charging stations, battery management systems, transformers, renewable energy resources and smart grid components within the virtual representation. The framework can implement predictive analytics, charging demand forecasting, adaptive scheduling of charging stations, intelligent allocation of charging stations, predictive maintenance, coordination of renewable energy resources, and dynamic load balancing, among others, through continuous acquisition of multidimensional operational data. The proposed framework considers multiple future operational scenarios within the Digital Twin environment and constantly assesses the results of these scenarios, in contrast to conventional monitoring systems that simply show infrastructure status, which makes optimization decisions to be implemented in the actual charging network. This forward-looking approach to decision making makes the systems more adaptable, reliable, and resilient to variations in charging loads. Through experimental testing it was shown the proposed DTO-EVCI framework consistently outperforms Conventional Charging Management (CCM), Smart Charging Systems (SCS) and AI Based Charging Optimization (AICO) in all the performance indicators evaluated. The framework was able to produce excellent charging efficiency, good charger utilisation, significant reduction in waiting time, better charging demand prediction accuracy, better use of renewable energy, accurate predictive maintenance, higher user satisfaction and excellent overall charging infrastructure performance. With Continuous Digital Twin synchronization, charging demand, occupancies of charging stations, degradation of charging equipment and electrical load conditions could be accurately predicted, so that Artificial Intelligence algorithms could distribute charging resources proactively and optimally. Moreover, intelligent coordination of renewable energy generation and smart grid resources minimized reliance on traditional electricity and enhanced the optimization of energy and stability of the grid. By incorporating predictive maintenance, the system helped to reduce the likelihood of unexpected charger failures and lower maintenance expenses, resulting in more availability and reliability. The overall proposed DTO-EVCI framework is highly efficient, scalable and intelligent Cyber-Physical solution for next generation Electric Vehicle Charging Infrastructures. Additional research can further refine this framework in the future, integrating features such as federated learning, edge intelligence, blockchain security, vehicle-to-grid

(V2G) communication, and large-scale field trials to facilitate autonomous, secure, and sustainable smart transportation systems.

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