scientific reports

Check for updates

OPEN

Optimizing demand response and load balancing in smart EV charging networks using AI integrated blockchain framework

Arvind R. Singh[1], R. Seshu Kumar[2]✉, K. Reddy Madhavi[3], Faisal Alsaif[4], Mohit Bajaj[5,6,7]✉ & Ievgen Zaitsev[8,9]✉

The integration of Electric Vehicles (EVs) into power grids introduces several critical challenges, such as limited scalability, inefficiencies in real-time demand management, and significant data privacy and security vulnerabilities within centralized architectures. Furthermore, the increasing demand for decentralized systems necessitates robust solutions to handle the growing volume of EVs while ensuring grid stability and optimizing energy utilization. To address these challenges, this paper presents the Demand Response and Load Balancing using Artificial intelligence (DR-LB-AI) framework. The proposed framework leverages Artificial intelligence (AI) for predictive demand forecasting and dynamic load distribution, enabling real-time optimization of EV charging infrastructure. Furthermore, Blockchain technology is employed to facilitate decentralized, secure communication, ensuring tamper-proof energy transactions while enhancing transparency and trust among stakeholders. The DR-LB-AI framework significantly enhances energy distribution efficiency, reducing grid overload during peak periods by 20%. Through advanced demand forecasting and autonomous load adjustments, the system improves grid stability and optimizes overall energy utilization. Blockchain integration further strengthens security and privacy, delivering a 97.71% improvement in data protection via its decentralized framework. Additionally, the system achieves a 98.43% scalability improvement, effectively managing the growing volume of EVs, and boosts transparency and trust by 96.24% through the use of immutable transaction records. Overall, the findings demonstrate that DR-LB-AI not only mitigates peak demand stress but also accelerates response times for Load Balancing, contributing to a more resilient, scalable, and sustainable EV charging infrastructure. These advancements are critical to the long-term viability of smart grids and the continued expansion of electric mobility.

Keywords Blockchain, Artificial intelligence, Demand response, EV charging stations, Load balancing

In recent years, the push towards the smart grid paradigm has been driven by a combination of political, economic, technological, and environmental factors. Governments worldwide are setting ambitious targets for decarbonization and renewable energy integration to combat climate change, while economic incentives are emerging from the need to optimize energy efficiency and reduce operational costs. Technological advancements such as digitalization, IoT, AI, and advanced data analytics are also enabling more sophisticated monitoring, control, and automation of power systems. In parallel, the rise of distributed energy resources (DERs), electric

[1]School of Physics and Electronic Engineering, Hanjiang Normal University, Shiyan, P. R. China. [2]Department of EEE, Vignan's Foundation for Science Technology and Research (Deemed to be University), Guntur, Andhra Pradesh 522213, India. [3]Department of Artificial Intelligence and Machine Learning, Mohan Babu University, Tirupati 517102, India. [4]Department of Electrical Engineering, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia. [5]Department of Electrical Engineering, Graphic Era (Deemed to be University), Dehradun 248002, India. [6]Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan. [7]College of Engineering, University of Business and Technology, Jeddah 21448, Saudi Arabia. [8]Department of Theoretical Electrical Engineering and Diagnostics of Electrical Equipment, Institute of Electrodynamics, National Academy of Sciences of Ukraine, Beresteyskiy, 56, Kyiv-57, 03680 Kyiv, Ukraine. [9]Center for Information-Analytical and Technical Support of Nuclear Power Facilities Monitoring, National Academy of Sciences of Ukraine, Akademika Palladina Avenue, 34-A, Kyiv, Ukraine. ✉email: seshumouni@gmail.com; mb.czechia@gmail.com; zaitsev@i.ua

vehicles (EVs), and energy storage solutions are further reshaping the energy landscape. As a result, not only is the architecture of the power system undergoing a significant transformation, but the entire approach to planning, operating, and managing these systems is being revamped to ensure reliability, sustainability, and resilience. The power system is shifting from a centralized to a more decentralized structure, driven by strategic policies, regulations, and initiatives aimed at economic liberalization and reducing carbon emissions. These changes are leading to the gradual phasing out of large-scale oil and coal-powered plants and promoting the adoption of local grid management systems, which are more effective at integrating renewable energy sources. As a result, to maintain a stable and cost-efficient energy supply, the future power grid will need to leverage the flexibility and adaptability provided by all stakeholders. Recent trends show that global renewable energy capacity increased by over 9% in 2023, emphasizing the growing importance of decentralized systems to meet climate goals. This adaptability will be crucial as countries work toward achieving net-zero emissions by mid-century[1]. A significant transformation in electricity system management is shifting from a traditional top-down structure to a more decentralized, bottom-up approach. This transition involves transferring responsibilities from centralized authorities to distributed entities, empowering grid users to take a more active role[2,3]. Decentralized energy systems are particularly advantageous as they enhance the overall efficiency of the electricity grid by utilizing distributed resources locally[4]. Recent literature has introduced innovative methods that enable grid users to contribute actively to maintaining a reliable and secure power supply. Additionally, recent studies have shown that decentralized systems can improve energy efficiency by up to 30%, while reducing transmission losses by 20%, further solidifying their importance in modern energy infrastructure[5]. Recent improvements in grid infrastructure and the progression toward smart grid (SG) systems have enabled the smooth integration of EVs into grid networks, both in individual and coordinated setups[6]. The unidirectional and bidirectional control capabilities of EVs, along with their ability to manage power flow, have allowed grids to optimize efficiency and offer more flexible usage patterns[7,8]. This participation of EVs in grid services contributes to a more reliable and dynamic energy system. The rapid rise in global energy demand, coupled with the urgent need for greener alternatives, has driven significant interest in electric vehicles (EVs) as a key solution to reducing emissions and improving sustainability[9,10]. As a result, enhancing EV technologies has become a top priority in addressing environmental, economic, and sustainability challenges. While initial concerns about EV systems once posed significant obstacles, many of these issues have now diminished to minor inconveniences, making EVs more economically feasible over time. Alongside the advancements in electric vehicle integration, demand-side management (DSM) and energy management play an essential role in improving grid reliability and overall efficiency. DSM focuses on regulating energy consumption patterns among users, ensuring a better distribution of energy during peak and non-peak times. With recent breakthroughs in DSM technologies—such as automated Demand Response systems and AI-powered energy management tools—users can now adjust their energy usage dynamically and in real-time. This not only alleviates strain on the grid during periods of high demand but also helps consumers reduce energy costs. Additionally, the increasing deployment of smart meters and IoT-enabled devices allows for continuous monitoring and control of energy consumption, giving users more flexibility and engagement in energy services. By integrating these technologies with decentralized energy systems and EV participation, a more efficient and responsive energy network is created. The schematic representation of intelligent grid integrated with EV and DSM Programs is represented in Fig. 1 respectively.

The integration of electric vehicles (EVs) into demand-side management (DSM) can be effectively utilized in two key areas: enhancing energy efficiency and implementing load-shifting strategies[11–13]. One of the main challenges in power system operations is managing fluctuating load demands and ensuring supply meets demand during peak periods. However, without proper planning, the widespread adoption of EVs can intensify these challenges. By leveraging the flexible consumption patterns of EVs and treating them as shiftable loads, DSM-EV integration offers a promising solution to mitigate these concerns[14–16]. This approach helps balance energy demand, especially during peak usage, improving overall grid stability. Research suggests that smart EV charging could reduce peak loads by 10–15%, making the grid more resilient and efficient. With the integration of electric vehicles (EVs) into the smart grid (SG) ecosystem, the vast potential they offer can be harnessed to enhance energy management strategies through demand-side management (DSM) and Demand Response (DR) programs. These initiatives can be embedded into various layers of the SG framework, provided there is robust infrastructure and synchronized operational management, as depicted in Fig. 2 respectively. Through strategic coordination, such programs not only optimize energy distribution but also increase grid flexibility, alleviating pressure during peak demand periods. Research highlights that well-implemented DSM-DR initiatives within smart grids can drive down energy expenses by as much as 20%, while significantly bolstering grid reliability and efficiency[17].

A comparable control and operational framework are depicted in Fig. 3 highlights the interactions between the various components involved in the EV-DSM system. A key step forward is selecting the most effective DSM programs for seamless EV-DSM integration, based on data sourced from different usage patterns and behaviors. To develop optimized DSM strategies, it is essential to thoroughly assess factors such as grid load fluctuations, EV charging trends, and energy price signals. Recent research indicates that incorporating EVs into DSM can alleviate grid strain by as much as 25%, especially during peak demand times, and potentially lower electricity costs for consumers by 15–20%. The achievement of DSM-EV program objectives is dependent on addressing uncertainties, constraints, and the availability of resources. Additionally, as vehicle-to-grid (V2G) technology evolves, its ability to offer ancillary services enhances the importance of advanced DSM strategies in the modern energy grid.

Literature survey

The widespread adoption of electric vehicles (EVs) is transforming the energy sector, but it also brings with it substantial challenges in terms of managing energy demand. As the number of EVs connected to the grid

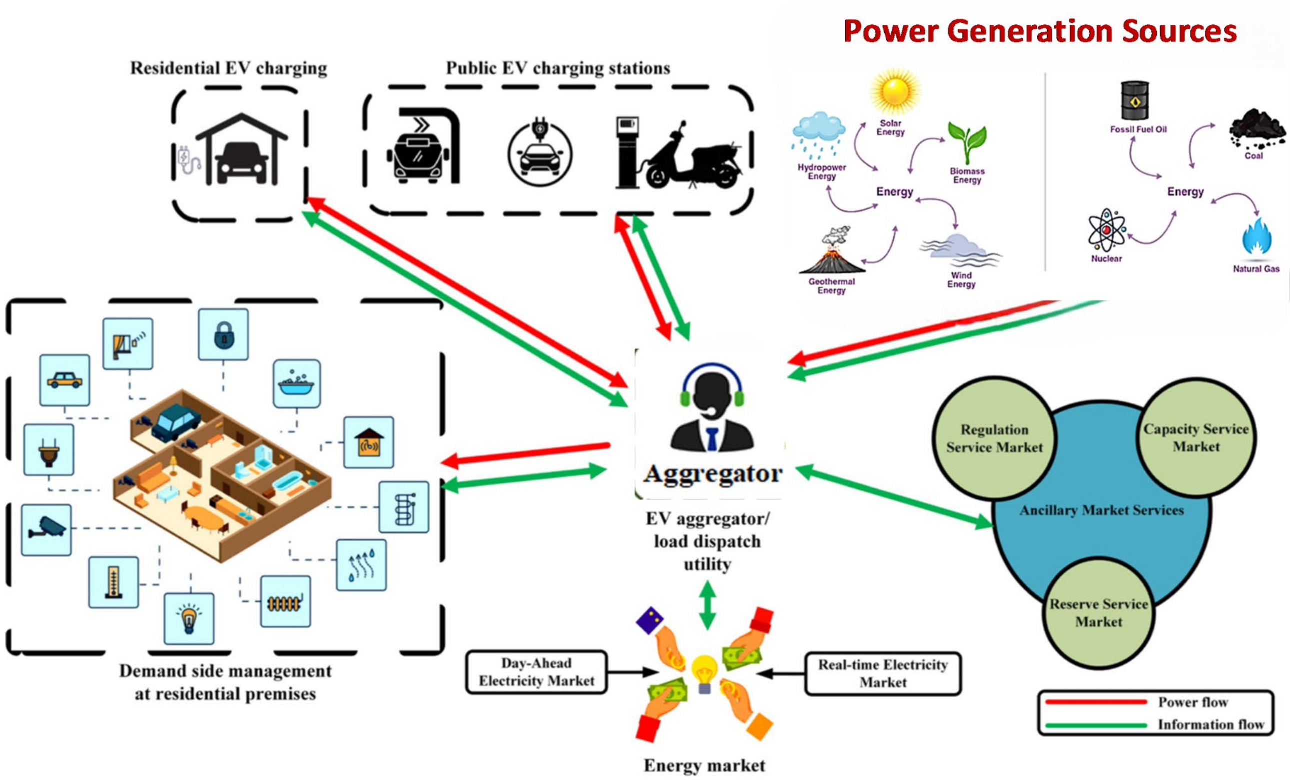

Fig. 1. Schematic representation of smart grid architecture integrated with EV and DSM Programs.

grows, so too does the strain on power systems, particularly during times of peak usage. Conventional energy management techniques may not be equipped to handle these increasingly variable loads, potentially resulting in inefficiencies and disruptions. Consequently, it is crucial to consider innovative approaches that can both address these challenges and optimize energy consumption. Demand Response (DR) management presents one such approach, offering a means for energy users to adjust their consumption patterns in response to changes in price or grid conditions. DR not only helps ease the burden on the grid but also allows consumers to benefit from cost-saving opportunities. In the case of EVs, DR is especially promising, as it empowers users to modify their charging behaviour based on real-time price signals and grid requirements. The energy managing and consumption in distributed electric vehicles is particularly challenging due to their growing usage[18]. One viable solution is Demand Response (DR) management, which can be applied to EVs to allow users to adjust their charging habits based on cost[19]. Demand Response (DR) empowers consumers to play an active role in the energy grid by adjusting or decreasing their power usage during peak periods, in response to time-sensitive pricing or other financial incentives[20]. As an alternative strategy for balancing supply and demand, many electric system operators employ DR programs[21]. These initiatives can lead to a reduction in overall energy prices in the market by encouraging more efficient energy consumption. Participants in energy markets can utilize various time-based pricing mechanisms such as critical peak pricing, variable peak pricing, time-of-use tariffs, and real-time pricing to engage in Demand Response[22]. Although DR research is still in its early stages, there are several notable challenges associated with implementing DR in smart grids[23]. In connection with the previously discussed point on the application of DR in electric vehicles (EVs)[19], the integration of DR in the EV ecosystem allows for the adjustment of charging habits in response to real-time price signals, helping to optimize both grid stability and energy costs. As the use of DR continues to evolve, its potential to mitigate grid stress and lower energy prices becomes increasingly apparent. However, overcoming the current obstacles, such as the need for advanced infrastructure and improved consumer participation, remains essential for fully realizing the benefits of DR within smart grids and EV systems.

Moreover, one of the significant challenges in the implementation of DR in electric vehicles (EVs) is the lack of adequate security and privacy measures to prevent the transmission of malicious or inaccurate data[24]. Additionally, there are insufficient incentives for prosumers those who both produce and consume energy to enrol in DR programs[25]. EV owners are often hesitant to participate in large-scale trading networks without substantial compensation due to concerns about accelerated battery degradation and other associated costs from frequent discharging[26]. When conventional cloud-based storage and management systems are applied to EVs, several challenges arise, including issues related to mobility, low latency requirements, network complexity, and the heterogeneity of systems[27]. These factors suggest that a more decentralized, distributed, interoperable, and scalable data storage infrastructure may be needed to accommodate the future expansion of EVs, ensuring both efficiency and flexibility[28]. Furthermore, the potential of Artificial intelligence (AI) in optimizing DR programs has been recognized. Although AI has already been explored in various domains of power systems,

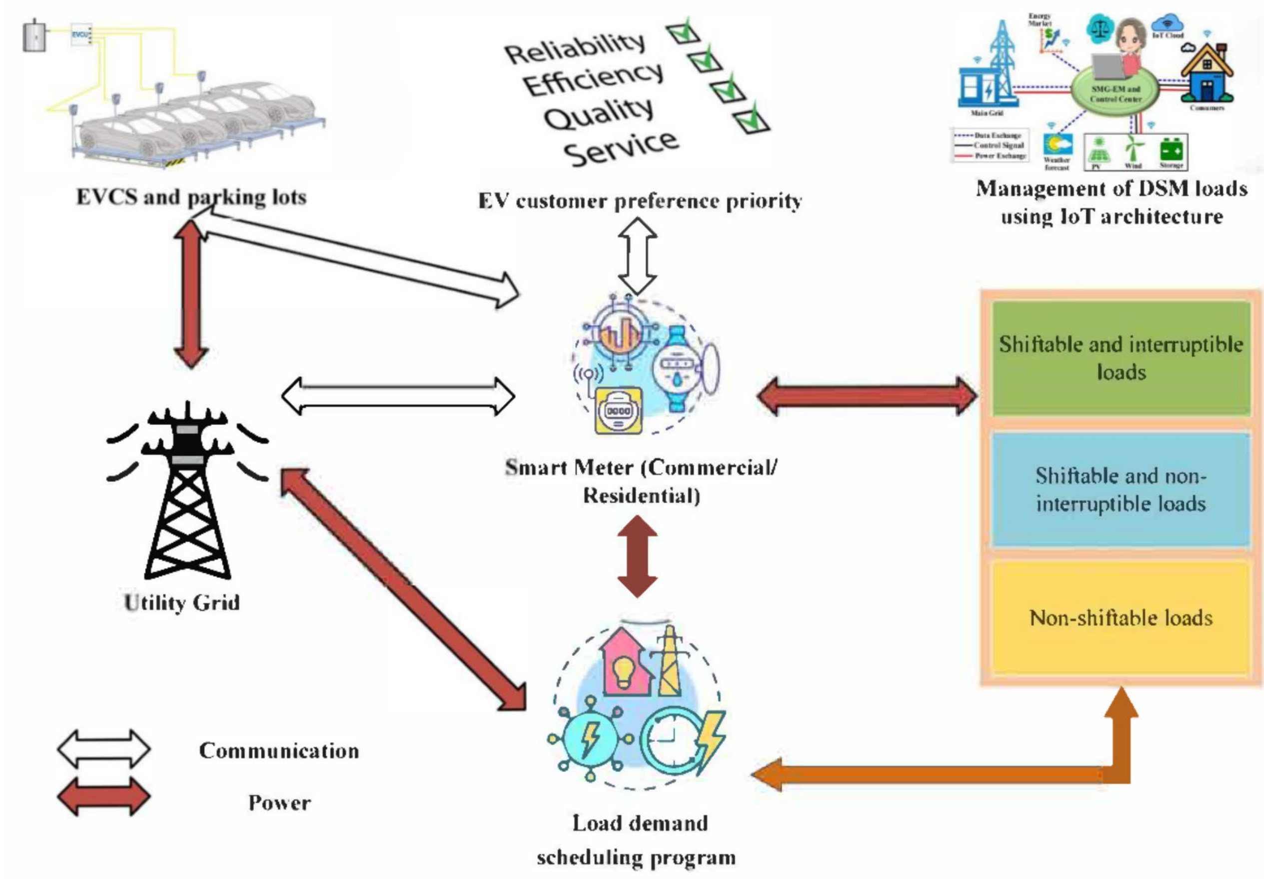

Fig. 2. Generic EV operation integrated with DSM Programs.

its application in Demand Response could further enhance the efficiency and effectiveness of these systems[29]. Addressing these challenges is essential for integrating DR into EV systems and realizing the full benefits of smart grid advancements. Given that Demand Response (DR) has proven to be a highly effective strategy for increasing demand flexibility in power systems, it is essential for power system operators to expand the scale and scope of these initiatives[30]. To ensure the efficiency of disaster recovery mechanisms, it is critical to develop an automated system that can adapt to changing conditions and continuously learn from past experiences[31]. Artificial intelligence (AI) is becoming a pivotal factor in the future success of DR programs, as it can automate processes and personalize them based on consumer preferences[32].For this architecture to be sustainable, incorporating AI-driven techniques into demand-side management is crucial[33]. As a result, a detailed review of the AI algorithms currently employed across various DR applications is becoming increasingly necessary[34]. Building on previous discussions about AI's role in optimizing DR, its ability to process data, forecast trends, and streamline operations will be key to the widespread implementation and effectiveness of DR strategies in the modern power grid. Researchers have recently focused on AI's potential use in Demand Response are tabulated in Table 1 respectively. Despite the fact that AI technologies have been explored and used in several power system applications across various domains for quite some time. Given that DR has been identified as a viable strategy to enable increased demand flexibility in the power system, it is crucial for operators of the power system to increase the size and breadth of these projects. An automated framework with more context-awareness and learning capabilities is required for DR schemes to operate effectively.

Some of the research works collectively contributed on advancing smart and sustainable energy systems and communication technologies. In[43], the focus on cooperative spectrum sensing for cognitive radio vehicular ad hoc networks (CR-VANETs) highlights the importance of efficient spectrum utilization and addresses key research gaps. Building on this in[44] introduced a decentralized electricity trading framework (DETF) leveraging blockchain and machine learning to optimize profit margins for connected electric vehicles (CEVs), which complements the security-focused work of[45] on a machine learning-based false data injection detection protocol for P2P energy transactions. This transition from sensing and trading to security creates a robust foundation for addressing modern energy challenges. Expanding into demand-side management, in[46] examined the role of ICT in enhancing grid efficiency, proposing actionable solutions to improve energy management. Finally, in[47] tackled photovoltaic power forecasting for smart micro-grids, emphasizing sustainability and the development of intelligent forecasting methods. These works are connected through their shared aim of optimizing energy systems, integrating advanced technologies, and addressing the challenges of security, efficiency, and

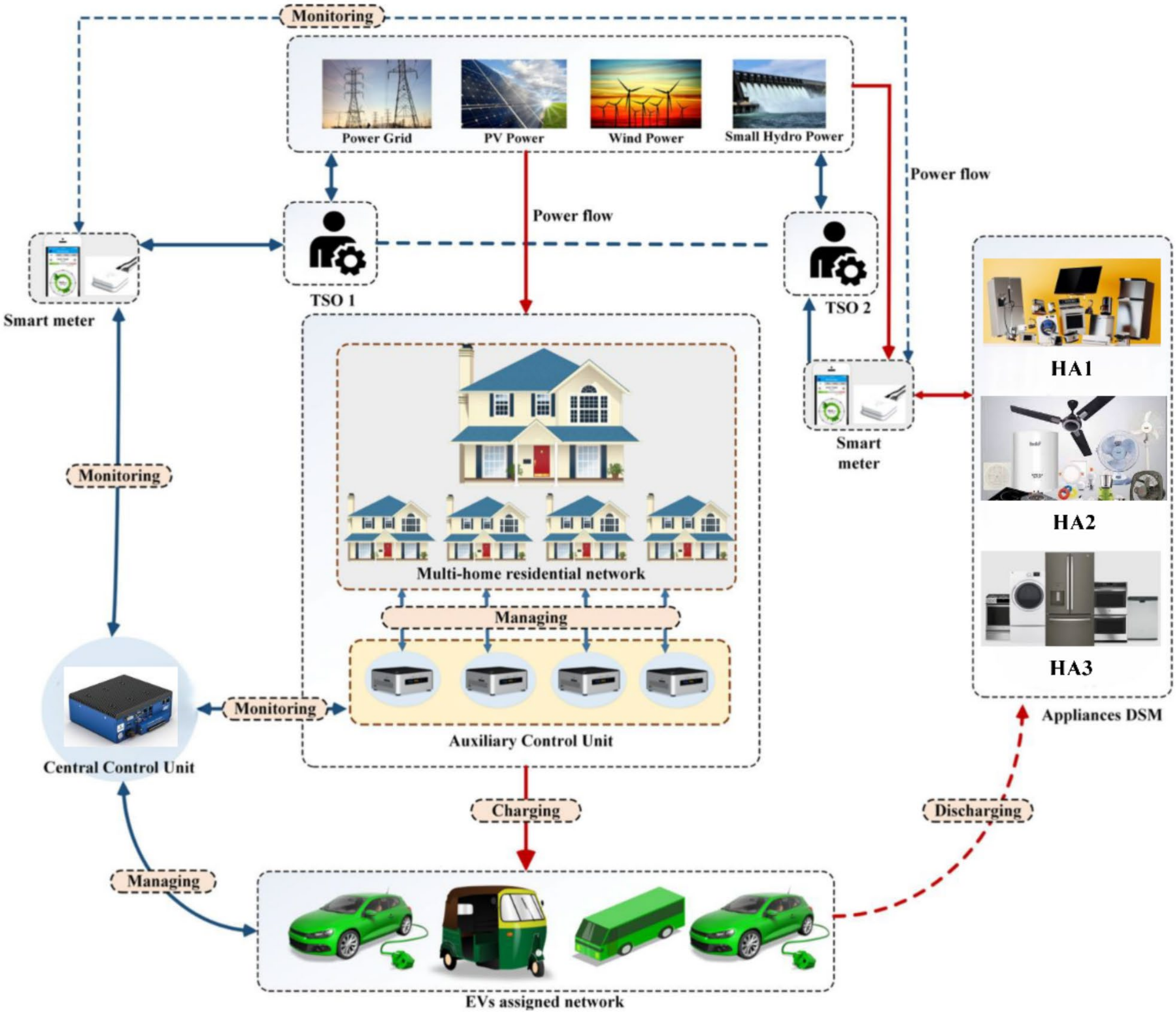

Fig. 3. Operational structure of EV integrated with DSM Programs.

Ref. No	Methods	Advantages	Limitations
35	AI-Based Smart Grid Systems (AI-SMS)	Enhances self-healing properties; integrates distributed energy resources.	Requires significant infrastructure changes; dependency on advanced technologies. Higher peak demand stress
36	AI Enabled Machine Learning (AI-ML)	Optimizes real-time decision-making; improves consumer engagement and Demand Response; adjusts pricing.	High data management complexity; needs substantial computational resources.
37	AI and Big Data Analysis (AI-BDA)	Strengthens grid security; improves system planning; facilitates safe microgrids.	Challenges with scalability and integration; potential security risks in big data handling. Lower scalability
38	Blockchain-Based Federated Learning Technique (BC-FLT)	Reduces communication delays; improves system efficiency; enhances EV energy prediction accuracy.	Communication overhead; potential latency issues; complexity in implementation.
39	IoT Enabled Blockchain Approach (IoT-BC)	Secures energy management through Blockchain; uses IoT sensors for real-time data.	Reliant on robust IoT infrastructure; potential privacy concerns with sensor data.
40	Blockchain Using Deep Learning Technique (BC-DLT)	Optimizes EV scheduling; leverages advanced deep learning and Blockchain technologies.	High computational requirements; potential security vulnerabilities.
41	AI-Based Support Vector Machine (AI-SVM)	Enhances resilience to cyber-attacks; provides accurate demand management.	Limited by the quality of data; may not address all types of cyber threats effectively.
42	Fuzzy Logic Using Blockchain Technology (FL-BCT)	Improves cybersecurity; integrates fuzzy logic for risk analysis; secure data transmission with Blockchain.	Complexity in integrating fuzzy logic with Blockchain; potential performance overhead.

Table 1. A comprehensive literature review.

sustainability within modern smart grids. The integration of Electric Vehicles (EVs) into modern power grids introduces multifaceted challenges that demand immediate attention for sustainable energy management. Limited scalability and inefficiencies in handling fluctuating demand strain traditional power systems, particularly during peak periods, leading to grid overload and instability. Conventional centralized systems amplify these issues by being vulnerable to data breaches, manipulation, and hacking, which compromise both security and transparency in energy transactions. Additionally, the lack of incentives for prosumers, concerns about battery degradation due to frequent discharging, and insufficient consumer participation further impede the adoption of demand response programs. The heterogeneity of systems and the complexity of mobility and latency requirements exacerbate inefficiencies, calling for decentralized, interoperable, and secure frameworks. Furthermore, as EV adoption accelerates, the absence of robust predictive demand management and dynamic pricing strategies limits the grid's ability to adapt to real-time variations, resulting in inefficient energy utilization and increased operational costs. These challenges emphasize the need for innovative approaches that leverage advanced technologies like Artificial Intelligence (AI) and Blockchain to enhance scalability, ensure secure and transparent energy transactions, and optimize load balancing in EV charging networks[48–52].

In summary, modern energy management is being revolutionised by the incorporation of cutting-edge technology into smart grid systems. AI-SMS improves system resilience by using smart grids for bidirectional power and data transfers. To respond to demand-side requests and engage customers in real-time, AI-ML uses machine learning. When it comes to grid safety and efficiency, AI-BDA investigates how AI, Blockchain, and big data can work together. BC-FLT prioritises Blockchain technology for federated learning to reduce communication delays in predicting EV energy. Secure EV energy management is made possible with the help of IoT-BC, which makes use of IoT sensors in conjunction with Blockchain technology. BC-DLT optimises EV scheduling using deep learning and Blockchain technology. When it comes to cybersecurity, AI-SVM employs support vector machines for cyber-attack resistance, whereas FL-BCT mixes fuzzy logic with Blockchain.

Motivation

Managing the effect of EVs on power networks is becoming more challenging as their use becomes more widespread. The need for sophisticated solutions is underscored by the fact that conventional approaches have problems with scalability, data security, and real-time demand management. The development of novel technological solutions to these problems is what drives us. Our goal is to improve the reliability and performance of electric vehicle charging networks by combining Blockchain technology for secure, decentralised communication with Artificial intelligence (AI) for dynamic demand forecasting and Load Balancing. This method guarantees data integrity, promotes the sustainable expansion of electric mobility, and optimises energy distribution while simultaneously reducing peak load stress. Problems with current Demand Response systems' scalability, ineffective real-time management of charging loads, and security holes in centralised data processing are only a few of the obstacles that fast EV integration into power grids brings. There is a risk of overloading during peak hours and decreased system stability since current approaches cannot keep up with the rising demand on the grid. Energy transaction integrity is also called into question because to the absence of safe and transparent data management. To solve these problems, improve data security and transparency, guarantee grid stability, and efficiently manage EV charging demands a new strategy combining cutting-edge technology is required.

The main contribution of this paper is as follows:

- To accurately forecast the need for electric vehicle charging and to dynamically balance loads throughout the grid, the DR-LB-AI architecture employs Artificial intelligence. Improved real-time management and reduced peak load stress are the results of this preventative measure, which leads to more reliable and effective power distribution.
- The framework offers a decentralised and immutable mechanism for managing data and energy transactions by using Blockchain technology. Addressing concerns about centralised data processing and promoting confidence among stakeholders, this integration enhances security, privacy, and transparency.
- This technology successfully optimises energy distribution and balances demands, which allows EV charging networks to scale. By combining AI with Blockchain, the grid becomes more resilient and can handle the growing number of electric vehicles on the road without sacrificing efficiency or stability.

Mathematical modelling and proposed frameworks

Blockchain technology and AI are helping EV charging networks to change themselves, thereby enhancing security, efficiency, and scalability. This leaning is altering the charging systems. Apart from other purposes, AI-powered systems might provide dynamic pricing policies, enhance Load Balancing, and estimate energy usage. These elements allow real-time energy management to be provided. Concurrently guaranteeing the availability of these features, Blockchain technology enables safe, transparent interactions between consumers and energy suppliers. Several practical charging topologies for Artificial intelligence driven electric vehicles are presented in this paper. Among other topics, these ideas deal with Demand Response systems, Blockchain-based secure energy trading platforms, dynamic load prediction, and real-time optimisation. When these technologies are used in the context of modern electric car charging networks, the ultimate goal is to provide a scalable, long-term efficient solution.

Proposed framework and methodology for AI-driven predictive demand analysis

The research work presents an AI-based approach to routinely predict network of electric vehicle demand for charging. By use of machine learning, forecasting of energy consumption enables the system to dynamically balance loads and effectively distribute energy. The system's potential arises from its ability to forecast patterns of energy usage. This precautionary action increases the transparency and openness of energy management across charging stations, therefore reducing the possible grid overload potential in times of maximum demand. Figure 4 shows a very sophisticated network charging electric cars using smart technology. This network optimally uses Artificial intelligence to optimise Blockchain-based Demand Response and Load Balancing, therefore attaining effective energy management. System design considers both personal needs of drivers of such electric cars and charging station needs for numerous nodes. Load distribution and real-time energy use help to accomplish this. The brains underlying Artificial intelligence Demand Response optimisation are found in most significant component of the system. The purpose of this section or system is real-time data entry including trends in energy use and charging needs. The system generates a reliable estimate of future energy consumption by use of a Load Prediction Model using past and present data.

A "dynamic pricing model" is a strategy used to modify prices based on peak and off-peak demand therefore influencing customer behaviour. Then, the Demand Response Decision process modifies the load and price to maximise energy distribution efficiency. The Blockchain-based Load Balancing System guarantees distributed, decentralised and secure energy transactions, therefore supporting smart contracts for energy distribution, user identification, and payment processing. A distributed ledger is one way one may get to this goal. Safe data transactions let consumers, electric vehicle stations, and energy suppliers build lines of contact. At end, Grid Management and Energy Supply aggregates centralised grids, renewable energy sources, energy storage technologies, and other similar features. Feedback loops enable consumers to be always in continual contact with one another, the grid, electric vehicle stations, and so on. Efficiency therefore improves and real-time system optimisation is maintained. Charging your electric automobile using this method will be a safe, hassle-free, ecologically friendly experience.

$$y'\ (k-1) + By\,(u-z) = K\,(h-1)\,,\ u \equiv\ St\,(u-1) \tag{1}$$

The Eq. (1), $y'\ (k-1)$ indicates the rate of a shift in system output from the previous state, whereas $By\,(u-z)$ accounts for the consumer response based on departure from a desirable state $u \equiv\ St$. The $K\,(h-1)$ reflects external forces impacting the system at the moment before, and the state $t\,(u-1)$ depicts the charging load is modified over time, by real-time demand estimates for balancing. This equation facilitates AI-driven modifications in the system to preserve stability.

$$< g > := \frac{1}{R} * M\,(k-1) * Cd\,(mk - r^{np}) \approx\ Range\ (B-1) \tag{2}$$

Equation (2) represents the past energy use, where $M\,(k-1)$. The term $Cd\,(mk - r^{np})$ represents variations $\frac{1}{R}$ in demand that is affected by power use $Range\ (B-1)$ and scaling factors $< g >$. The practical working

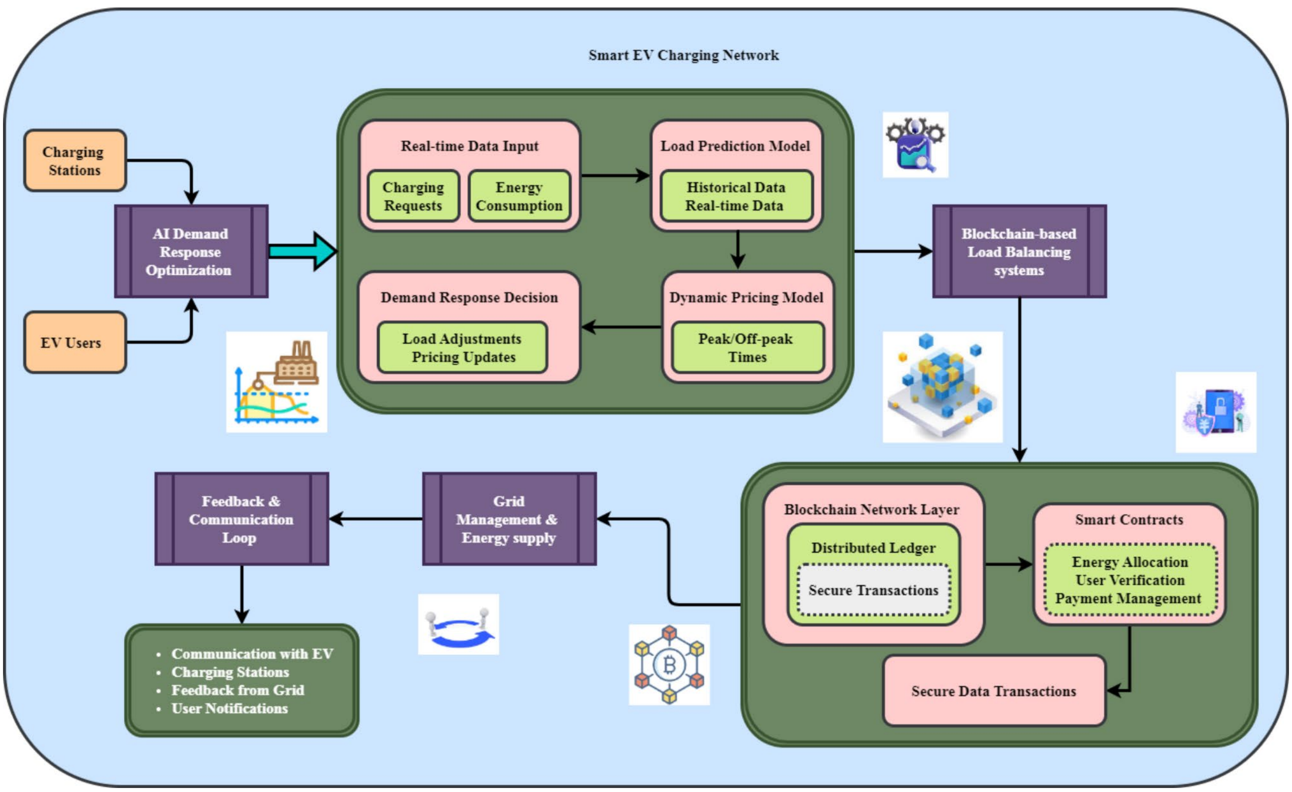

Fig. 4. AI-Driven Smart EV Charging Network with Blockchain-Based Load Balancing.

range for regulating charging loads, which is crucial for minimizing grid strain during peak demand times, is approximated by this Eq.

$$bY_c\,(u-1) + y'\,v\,(m-1) + Cy_b\,(n-1) = G\,(p-k)\,,\; E \equiv\; \partial\, q \tag{3}$$

Dynamic variations in grid demand are modelled by $y'\,v\,(m-1)$ and the impact of past charging load $Cy_b\,(n-1)$ is represented by the Eq. (3), $bY_c\,(u-1)$. Variations in Load Balancing at various stations are accounted for by $G\,(p-k)$. The grid conditions from the outside, whereas the equation $E \equiv\; \partial\, q$ denotes changes to the energy flow. This equation exemplifies how AI optimizes grid stability by continually adjusting charging demands using both historical data and current circumstances.

$$\frac{1}{4} *\; R_v\,(p-2) * [m_1\,(u-k) +\; z_2\,(n)] = 1[Y_{n-z} * P\,((q-1)] \tag{4}$$

Previous recharging sessions $R_v\,(p-2)$ and present load $z_2\,(n)$ are captured by the equation $m_1\,(u-k)$, while the resistance or load limits by the Eq. (4), $[Y_{n-z}]$ two steps earlier. The predicted need and access to energy sources are shown on $P\,((q-1)]$. This equation shows performance by dynamically adjusting Load Balancing based on historical use and predicted energy consumption. Figure 5 illustrates a distributed power trade and charging system connected with Blockchain technology for electric automobiles. Driven by Artificial intelligence, control and prediction algorithms let this system increase the efficiency of energy management techniques. Among the main components of the system are a Blockchain Power Trading Platform.

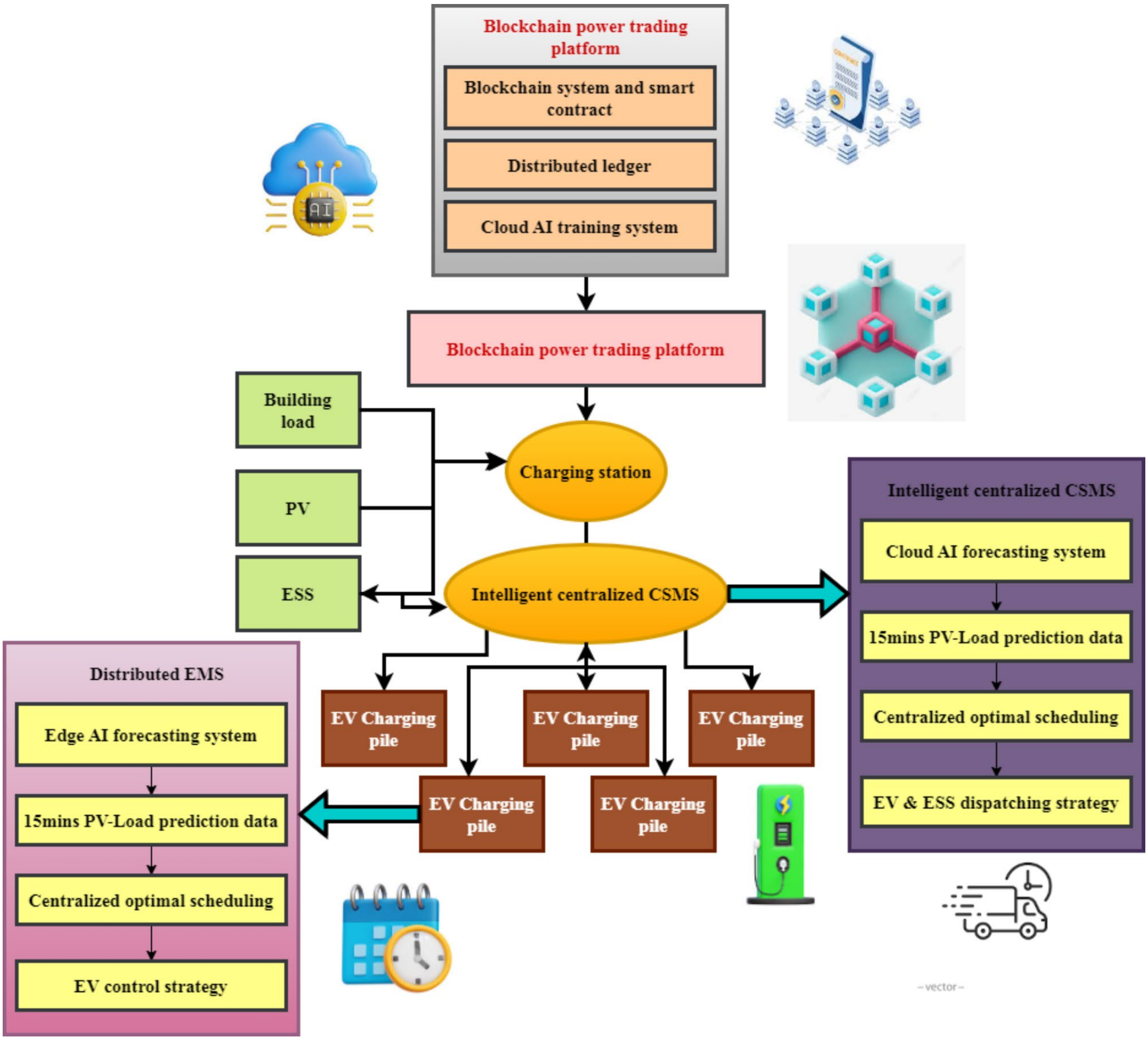

Fig. 5. Blockchain-based intelligent CSMS platform block diagram.

Through smart contracts and a distributed ledger, this platform works to guarantee the security of financial transactions. Another component of this specific solution is the Cloud AI Training System as it helps one to make sensible decisions. Linked with an Intelligent Centralised Charging Station Management System, or CSMS for short, are energy sources like Building Load, Photovoltaic (PV) Panels, and Energy Storage Systems (ESS). Apart from aggregating data from different sources, the CSMS is additionally in responsibility of providing power to many charging stations for electric automobiles. Effective energy distribution helps the platform to guarantee the use of renewable energy and storage. This increases energy usage efficiency. EMS featuring an Edge Artificial intelligence forecasting system is the one in charge of generating 15-minute PV-Load Prediction Data. The data in issue aids for centralised optimum scheduling and offers information to control systems for electric automobiles, thus enabling efficient prioritisation of demand and balancing the energy load. CSMS is an Artificial intelligence forecasting tool centrally focused. By way of a single scheduling approach, this technology provides real-time data for PV load projection and helps to operate ESS and electric cars. This system uses distributed energy management, Blockchain technology, and Artificial intelligence prediction models to offer charging for electric automobiles in a scalable and safe manner rather than merely efficient one. Moreover, this technology helps to increase the sustainability of the power source and the grid's stability. $[d\left(F_2\left(z-1\right)\right)-H\left(r_3\left(v'-v''\right)\right)]=\ M_2\left(y\left(z-1\right)*Qw\right)$ (5)

The change in demand for electricity from a previous state is represented by the Eq. (5), $d\left(F_2\left(z-1\right)\right)$ while fluctuations in voltage or rates of charging are accounted for by $H\left(r_3\left(v'-v''\right)\right)$. The energy required to stabilize $*Qw$ the system based on previous load and power factors is captured by $M_2\left(y\left(z-1\right)\right)$. To achieve optimal Load Balancing, AI-driven Demand Response adjusts to variations in voltage and demand, as shown in this Eq.

$$R_1\left(u_v-Pk\right)+\ Y_2\left(km-n^3q\right)=D,\ R_t\left(u-k'\right)=0 \tag{6}$$

This Eq. (6), denoted as $R_1\left(u_v-Pk\right)$above, reflects the resistance $D,\ R_t$ of the system to the charging load $\left(u-k'\right)$, which is affected by power consumption, and $Y_2\left(km-n^3q\right)$ models the demand, which is affected by charging stations, and grid load. This illustrates the function of AI in maintaining grid dependability and efficient Demand Response by dynamically balancing network loads.

$$Z_2\left(u-1\right)+\ v_2\left(st-2\right)=Min\left(y_1\left(u-1\right)+\ Z_v\left(k-1\right)\right) \tag{7}$$

The total earlier energy consumption $y_1\left(u-1\right)$ and grid load $v_2\left(st-2\right)$ is sought to be minimized by the Eq. (7), $Z_2\left(u-1\right)$ which represents time-adjusted demand $Z_v\left(k-1\right)$ and previous charging states Min, respectively. This exemplifies analysing historical demand and current data to guarantee minimum energy waste and maximum efficiency.

$$h_1\left(u-1\right)+\ R_2\left(z-1\right):Y-\left(m\left(u-1\right)+z\right)*Fp,\ z\equiv\ \forall\mathtt{C} \tag{8}$$

Here, the Eq. (8), $h_1\left(u-1\right)$ and $R_2\left(z-1\right)$ represent the charging load and demand from the past, while $Y-\left(m\left(u-1\right)+z\right)$ represents the energy output $Fp,\ z$ of the system as $\forall\mathtt{C}$, less the weighted charging demand. This equation shows the AI may combine historical data with real-time circumstances.

Proposed framework and methodology for secure and decentralized transactions

Blockchain technology would help us to ensure that energy transactions will be distributed and manageable by including into the suggested DR-LB-AI architecture. Smart contracts and distributed ledgers help to allow increasing degrees of trust and openness among all the engaged parties. This secure strategy offers advantages in terms of reduced network vulnerabilities, less danger related with centralised data processing, and so on in reliable energy trading. The Artificial intelligence architecture, as depicted in Fig. 6, consists of five key modules, all supported by a central EVI data lake. This data lake ensures the comprehensive storage of data inputs, operational outputs, and intelligent processes associated with these modules. Its purpose is to facilitate the creation of a knowledge layer that reflects both ongoing and prospective activities, thus enabling the representation of both current and future states. This knowledge layer can be utilized for hierarchical as well as lateral communication within the smart grid framework. The five primary modules of the AI system include: Electric Vehicle (EV) charge-demand profiling, EV data augmentation, charge-demand forecasting, forecast explainability, and EV charge optimization.

Figure 6 also illustrates the flow of information and insights between these modules, as well as the cyclic structure of the system, where the charge optimization feedback is integrated into the demand profiling for subsequent iterations of EVI usage. Each module employs a range of AI capabilities, including association, profiling, prediction, and optimization. These are implemented using methods like the k-means algorithm, Gaussian Mixture Models (GMM), multivariate regression, and deterministic optimization.

$$H\left(Y_1\left(z_1\left(m-kv\right)\right)*Pr\right)=G\left(mk-nv'\ \left(rw-2q\right)\right) \tag{9}$$

The Eq. (9), HY_1 shows the demand in the past z_1, modified by factors such as the charging load $m-kv$ and the pricing factor Pr, and the load on the grid $rw-2q$, modified by power consumption G and demand variations is shown by $mk-nv'$. Ensuring efficient energy equation emphasizes the significance of AI in demand forecasting and Load Balancing based on real-time and predictive data.

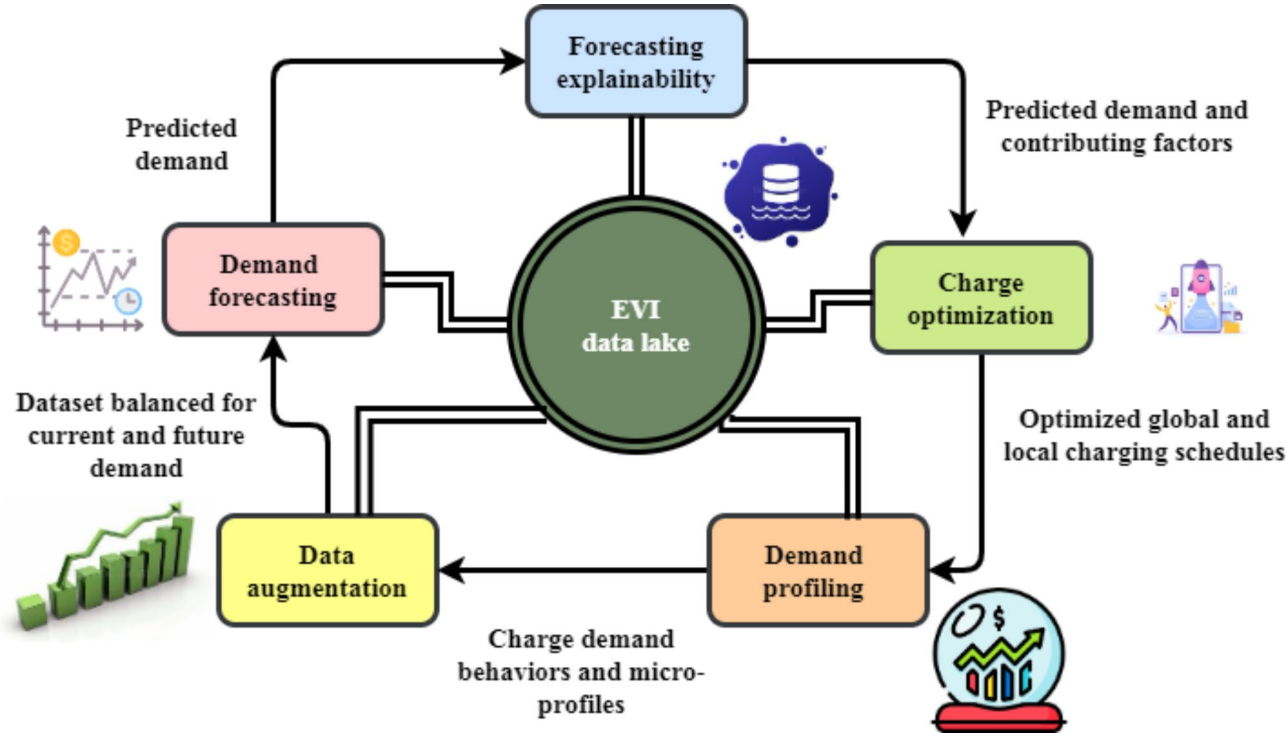

Fig. 6. Design of an AI system for EVS Infrastructure.

$$H * (Y_2 (p-1)) = H (z_2 (m-kt)) = < Hk >,\ u \equiv [1, T-uq] \tag{10}$$

The system is considered to be in equilibrium when the Eq. (10), $H * (Y_2 (p-1))$ and $H (z_2 (m-kt))$ represent the past energy consumption Hk and the real-time charging demand u, respectively. The phrase $[1, T-uq]$ describes an argument for load adjustment that depends on time. An important aspect of AI demand management and Load Balancing in EV charging networks is shown by this Eq.

$$y + \{m (k-1) + < r >\} vd (n-1) = y - y_1 (0) + z_1 (n-2) \tag{11}$$

The current system output is represented by the Eq. (11), y, and changes $y - y_1 (0)$ based on historical demand $< r >$ and real-time data vd are taken into consideration by $m (k-1)$. The shift in energy demand from starting points $z_1 (n-2)$ and earlier modifications. To keep EV charging networks stable and efficient, AI updates Load Balancing on the go, as seen in this Eq.

$$z - \{v (n-1) + < D (E^r - nk) >\} = y - z_2 \left(1 - mk^{n-2}\right) \tag{12}$$

Here, the Eq. (12), z denotes the present demand, and $v (n-1)$ takes into consideration modifications depending on past data $y - z_2$ and factors for variance $1 - mk^{n-2}$. The energy production is represented by $D (E^r - nk)$ about the demand and load modifications that have come before. To ensure optimal allocation of energy across EV charging networks, AI optimizes Load Balancing using both real-time and historical data, as shown in this equation.

Figure 7 shows for a smart electric vehicle charging station a whole, multilayered design driven by Artificial intelligence. The intelligent charging system aims to enhance the charging operation efficiency and energy management capacity. The primary layer acting as the basis is data collecting one. Among other things, it is in charge of compiling real-time data from several sources including grid energy statistics, electric vehicle charging stations, and meteorological conditions. Data is then handled at the Data Processing Layer, where it is aggregated and pre-processed to confirm that it is valid and consistent, therefore preparing it for analysis. This comes after prior layer data processing. The Artificial intelligence and machine learning component of the system is particularly important as it analyses demand using sophisticated algorithms, balances the load, and projects energy usage. This layer guarantees that the system maintains operating efficiency even under dynamic conditions by means of analysis on historical and real-time data. The Optimisation and Control Layer employs a Demand Response controller, load balancer, and decision engine to modify the energy allocation after weighting of these forecasts thereby guaranteeing the greatest possible level of performance. This layer guarantees perfect energy distribution. The layer users interface with while controlling system user interactions is the User Interface Layer. This layer consists of a monitoring dashboard and control panel that let clients observe and regulate the payment operations using the dashboard and control panel. The communication layer is the one in charge of

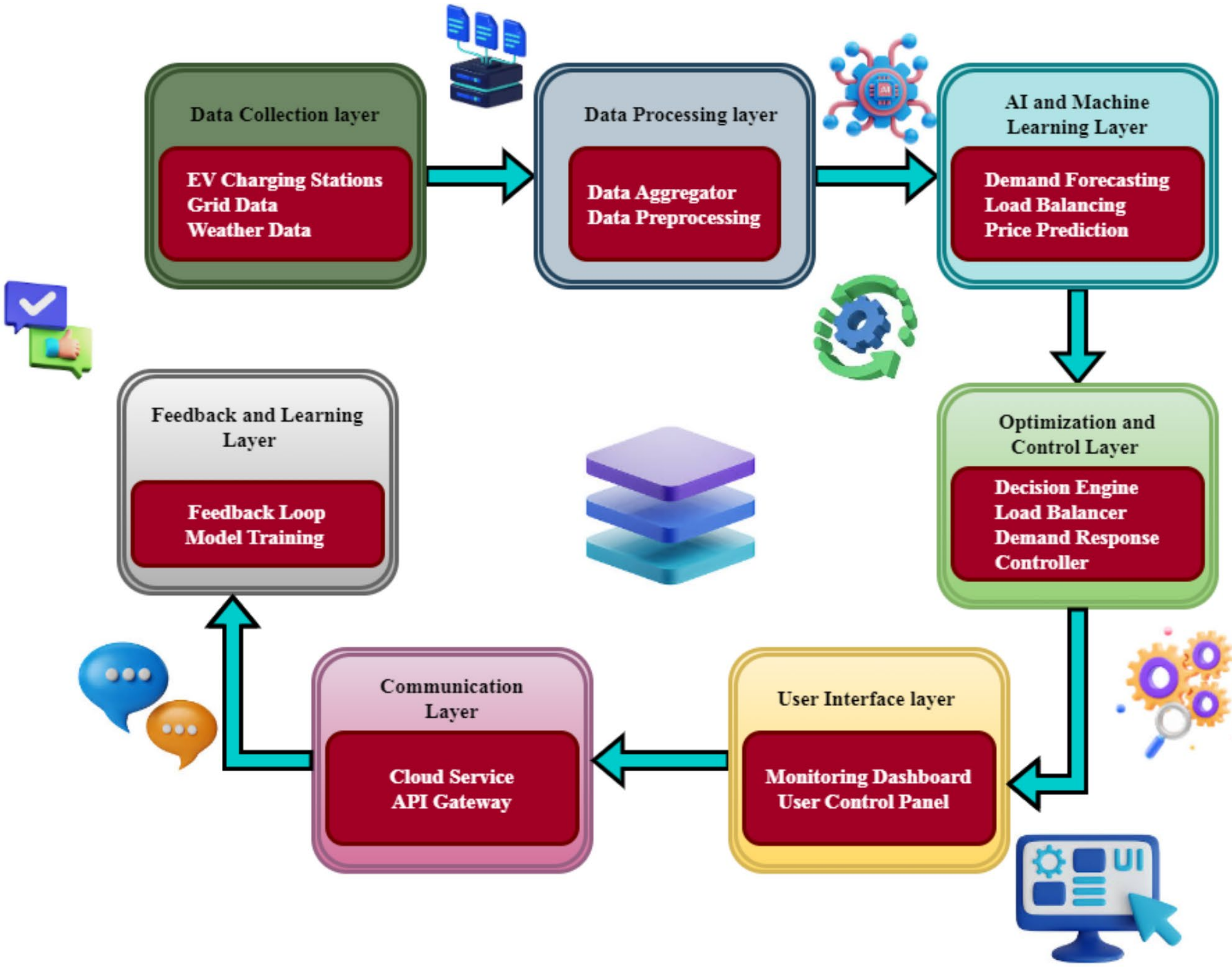

Fig. 7. Layered Architecture for AI-Driven Smart EV Charging System.

allowing the interactions among the many parts of the system. How well this layer functions depends on cloud services and an API gateway. Dubbed the "Feedback and Learning Layer," the final layer operates continuously delivering data back into the system with model training in mind. In this sense, the Artificial intelligence might evolve with time.

$$P_k\left(n-k^{p(n+k)}\right)=D-\ <m\left(n-1\right)>+Y_2\left(z^2-1\right) \tag{13}$$

In terms of power consumption, the demand components P_k and D are reflected in the Eq. (13), $n-k^{p(n+k)}$. The system is adjusted by subtracting the historical demand $Y_2\left(z^2-1\right)$ and adding the change in energy output $m\left(n-1\right)$ from the total. Equation 13 shows load in EV charging networks adjusting the distribution of electricity and Demand Response on the fly.

$$V\left(n-2L\right)=\{y\equiv\ S|y+\ v_{n-1}*SinPq\left(n-kv\right)\} \tag{14}$$

In the previous time step, the voltage was modified by a factor of $V\left(n-2L\right)$, as shown by the Eq. (14), $y\equiv\ S$. The expression represents the connection between the present energy production $y+\ v_{n-1}$ and its modification according to past voltage $SinPq$ and a sine function that symbolizes periodic changes in demand $\left(n-kv\right)$. The equation illustrates the way the machine learning system adjusts to variations in voltage and energy demand.

$$Z\left(k-1\right)+Y\left(2\right)=H\left(z\left(v-2\right)\right)*Evr^{n-kp} \tag{15}$$

The fixed adjustment factor is denoted by $Y\left(2\right)$ and the equation $Z\left(k-1\right)$ reflects previous load data. This Eq. (15) represents the impact of past voltage changes $H\left(z\left(v-2\right)\right)$ and energy variations (Evr^{n-kp}) on the present system, taking into account factors. To optimize load AI system incorporates previous load information and present energy dynamics, as shown in this equation.

Proposed framework and methodology improved scalability and grid stability

Real-time dynamic load management made possible by the DR-LB-AI framework considerably enhances the scalability of electric vehicle charging infrastructure by means of which we can guarantee that the system can handle more electric vehicles without sacrificing grid stability. Smart grids therefore provide a superior long-term sustainability alternative, which is fantastic news for the development of electric vehicles ahead. Figure 8 shows the typical Artificial intelligence powered EV charging network design included within this network are Blockchain technology, predictive demand monitoring, and real-time administration with the objective to increase scalability, security, and efficiency. Usually known as the Data Collection layer, first level data collecting comes from grid sensors and electric car charging stations. Data integration covers the layer known as raw data processing. Centralising the data aggregation and using preprocessing methods enables this layer to ensure appropriate inputs. Using machine learning, the layer on predictive demand analysis generates Load Balancing suggestions, demand prediction, and models. If one wants the best outcomes, energy distribution has to be maximised. Every output this layer generates finds home in the real- time demand management layer. Under present circumstances, this layer's role is to guarantee optimum efficiency of the charging network. This gadget works given that it contains built-in systems for charge control and dynamic adjustment.

Designed by the layer of security and privacy, the security system relies on regulations aimed to prohibit data tampering and data encryption. This layer is in charge of keeping an eye on the safety measures. Two outcomes of using a Blockchain Layer are the use of smart contracts for open and safe transactions and decentralised ledger management. The Blockchain Layer ensures validation of both these results. Real-time data allows a feedback loop involving performance monitoring and model retraining to aid the system to be continuously enhanced. Trust, scalability, security, openness, and simplicity define an efficient and trustworthy electric car charging network most of all. The output of the system guarantees the presence of all these attributes.

$$V_h * Y\,(k-2) = G\,(hj\,(r-1))\,,\ \ u \cong\ [2.u\partial\ -2] \tag{16}$$

The product of the historical voltage V_h and previous load data $Y\,(k-2)$ is represented by the Eq. (16), $G\,(hj\,(r-1))$. The impact of outside forces and modifications on the system is represented by u. For the

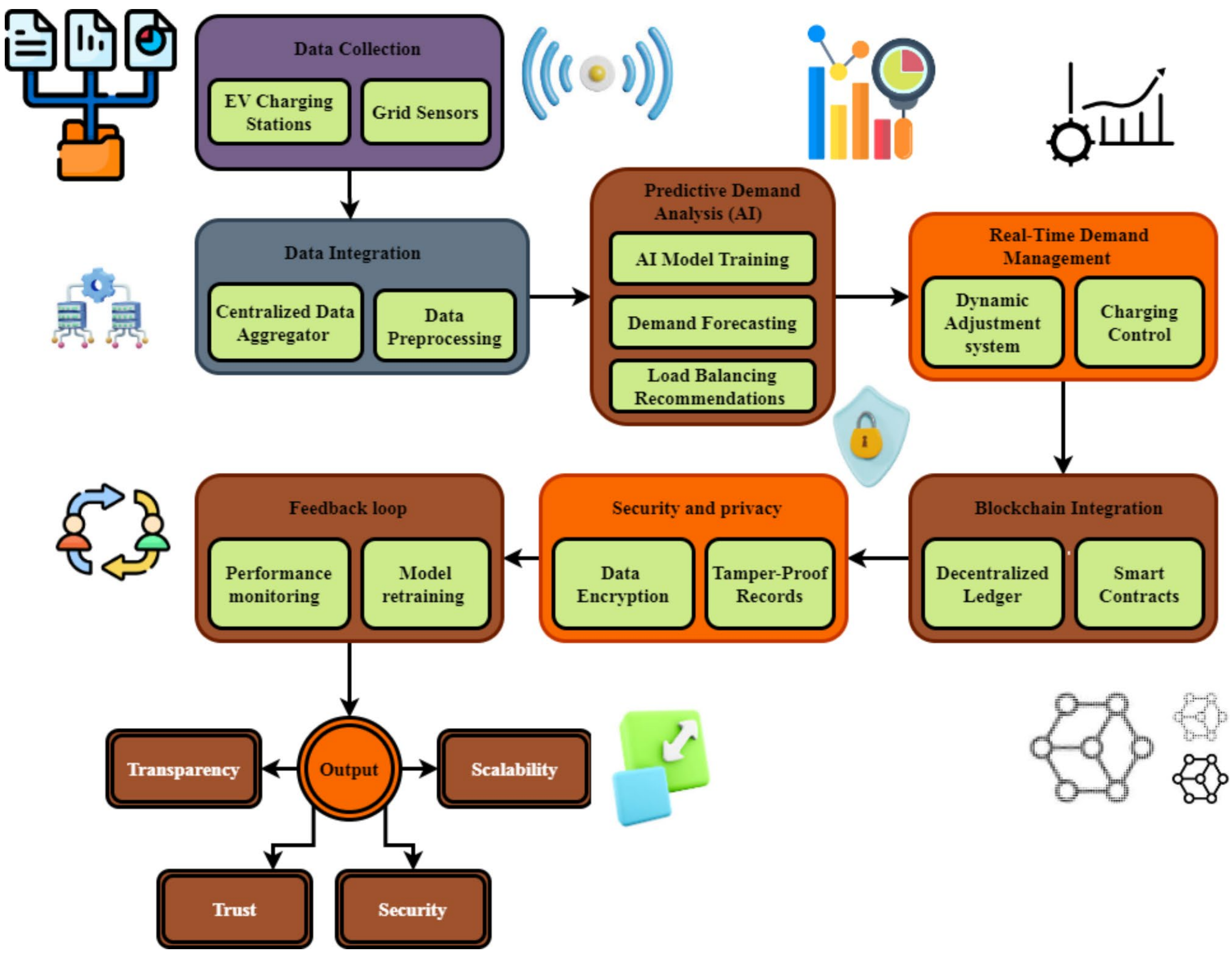

Fig. 8. AI-Driven EV Charging Network with Blockchain and Security Integration.

variable $2.u\partial\ -2$, denotes a range or condition. This formula exemplifies the AI system that maintains EV charging networks' load division and energy distribution at optimum levels on analysis of scalability.

$$< Mt\,(v-1) \geq\ y'\,b\,(k+2) * z'\,n\,(k-vr) + K\,(p\,(v-nk)) \tag{17}$$

Here, the Eq. (17), $Mt\,(v-1)$ incorporates the influence of increased load $y'\,b$, scaling factor $z'\,n\,(k-vr)$, and demand fluctuations $k+2$, and it represents a threshold or needed performance level. The $K\,(p\,(v-nk))$ represents extra adjustments that are dependent on grid conditions balancing workload. AI system makes sure that performance levels reach or surpass standards is shown by this equation on analysis of security.

$$Bm_{n-1} * K\forall\ (n+1) = H\,(v_b\,(f-1p)) * N\left(rT^{n-1k}\right) \tag{18}$$

The scaling factor Bm_{n-1} and the constant $K\forall\ (n+1)$ are multiplied by each other in this Eq. (18), with the demand-based adjustments $N\left(rT^{n-1k}\right)$ indicated by $H\,(v_b\,(f-1p))$ in the equation. To optimize Load Balancing and guarantee optimal utilization of electricity in EV charging networks, the AI system leverages this equation in the analysis of demand management.

$$T\,(Y_0) = Z\,(m:1, n-KT)\,,\ y'{}_2\left(k-Mn^{v-1}\right) \tag{19}$$

While $Z\,(m:1, n-KT)$ accounts for past factors and modifications depending on time, the system's reaction is represented by the Eq. (19), $T\,(Y_0)$ given the initial load $y'{}_2$. The effect of previous load modifications on the current Load Balancing is represented by the expression $k-Mn^{v-1}$. To keep electric vehicle charging networks stable and energy-efficient, this equation demonstrates that the AI system uses both past data and current modifications on low analysis of peak demand stress.

$$B|y\,(v:1, z_2\,(mn\,(k-1))) + Y\left(n:2,\ Y_{n-2}^{k}\right) =\ Ev^{z-\frac{1}{2}} \tag{20}$$

The total adjusted load based on the prior $B|y$ and current energy data $v:1, z_2$ is represented by Eq. (20), $mn\,(k-1)$. The optimized energy value $Ev^{z-\frac{1}{2}}$ taking adjustment variables into account is shown as $Y\left(n:2,\ Y_{n-2}^{k}\right)$. The AI system ensures efficient and reliable distribution of power in EV charging infrastructure by balancing energy loads by this equation on analysis of trust and transparency.

AI displays on a multi-tiered electric vehicle charging station along with explanations. Included with the system is Blockchain technology as well. Important elements include sensor and station data collection for electric cars, Load Balancing under AI, and demand prediction analysis. Blockchain-based solutions support to improve transaction security in the context of the energy market by means of smart contracts and distributed ledges. One can reach this owing to Blockchain technology. Real-time demand control enables affordable energy distribution and protection of data security. This becomes possible with the use of encryption technologies. AI model retraining and performance monitoring guarantees constant system improvement by means of a feedback loop. Combining these advanced technologies enhances sustainability, scalability, and energy management as well as provides owners of electric cars a safe and hassle-free charging experience.

Result and discussion

Efficiency in managing charging demand and grid stability are two issues that have been brought to light by the incorporation of electric vehicles (EVs) into power systems. Inefficiencies and grid overload result from traditional systems' inability to scale, manage demand in real-time, and provide adequate security. This research work focuses on the DR-LB-AI architecture, which integrates Blockchain technology for decentralised and secure data management with AI-driven predictive demand analysis. By improving the openness and safety of energy transactions using Blockchain, the suggested solution optimises energy distribution and reduces peak demand stress through dynamic management of EV charging stations.

Dataset description

Using a field experiment that spanned from November 2014 to October 2015, a group headed by public policy professor Omar Asensio recorded 3,395 instances of electric car charging. Details such as total energy consumed, cost, date and duration of each session, and 85 EV drivers with recurrent use at 105 stations across 25 locations at a workplace charging program are included in the dataset[53].

Analysis of scalability

To handle the increasing demand for EV charging, the suggested DR-LB-AI system has the benefit of being scalable. Because of their inefficiency and grid instability, traditional techniques are ill-equipped to deal with the ever-increasing number of electric vehicles. This is handled by the DR-LB-AI framework, which uses real-time Load Balancing and AI-driven predictive analysis to manage charging stations dynamically according to actual grid demand is explained in Eq. (16). The system can scale up without sacrificing efficiency or grid performance due to this adaptive method, which keeps up with the increasing number of EVs.

By facilitating decentralised data management, eliminating bottlenecks in centralised systems, and enabling safe, transparent communication among an increasing number of parties, Blockchain technology significantly improves scalability. Even as the network grows, the decentralised structure guarantees efficient processing of energy transactions. In the end, the DR-LB-AI framework offers a solution that can be scaled up to accommodate future development, guaranteeing grid stability and efficient energy utilisation even as the demand for electric transportation grows. The scalability ratio is improved by 98.43% is shown in Fig. 9.

To evaluate the performance and convergence of the proposed AI-based model, loss function curves were plotted for both training and testing datasets against iterations. These curves provide critical insights into the model's learning dynamics, ensuring it generalizes well to unseen data without overfitting. As shown in Fig. 10, the training loss decreases consistently over iterations, demonstrating effective optimization of the model. The testing loss curve follows a similar trend but remains slightly higher than the training loss, which is expected in a well-generalized model. The close alignment between the two curves indicates that overfitting has been effectively mitigated through measures such as regularization, dropout, early stopping, and robust validation strategies.

Additionally, the stabilization of the testing loss curve demonstrates the reliability of the model's predictive capabilities on unseen data. The minimal difference between training and testing losses further underscores the robustness of the model, suggesting it can handle variability in real-world data effectively. Moreover, the shape of the loss curves reflects smooth convergence, which can be attributed to the careful selection of hyperparameters such as learning rate, batch size, and optimizer settings. The utilization of advanced optimization techniques was, contributed to the efficient gradient updates, preventing oscillations or divergence. Furthermore, the model's ability to stabilize quickly during training demonstrates its resilience to noisy or redundant data, ensuring computational efficiency and reducing training time. These results validate the proposed model's capability to balance both underfitting and overfitting, providing a reliable and scalable solution for predictive tasks in EV charging networks. The model's learning trajectory highlights its adaptability and effectiveness in leveraging historical and real-time data for accurate predictions, a critical requirement for dynamic energy management systems.

Analysis of security

In Fig. 11, by using Blockchain technology, which fixes several issues with conventional centralised systems, the DR-LB-AI architecture becomes much more secure. Traditional approaches leave data processing and energy transactions open to manipulation, hacking, and data breaches since they are centralised. With the use of Blockchain technology, the DR-LB-AI system decentralises data management, making all transactions in the EV charging network traceable and irreversible is explained in Eq. 17. This increases confidence among stakeholders

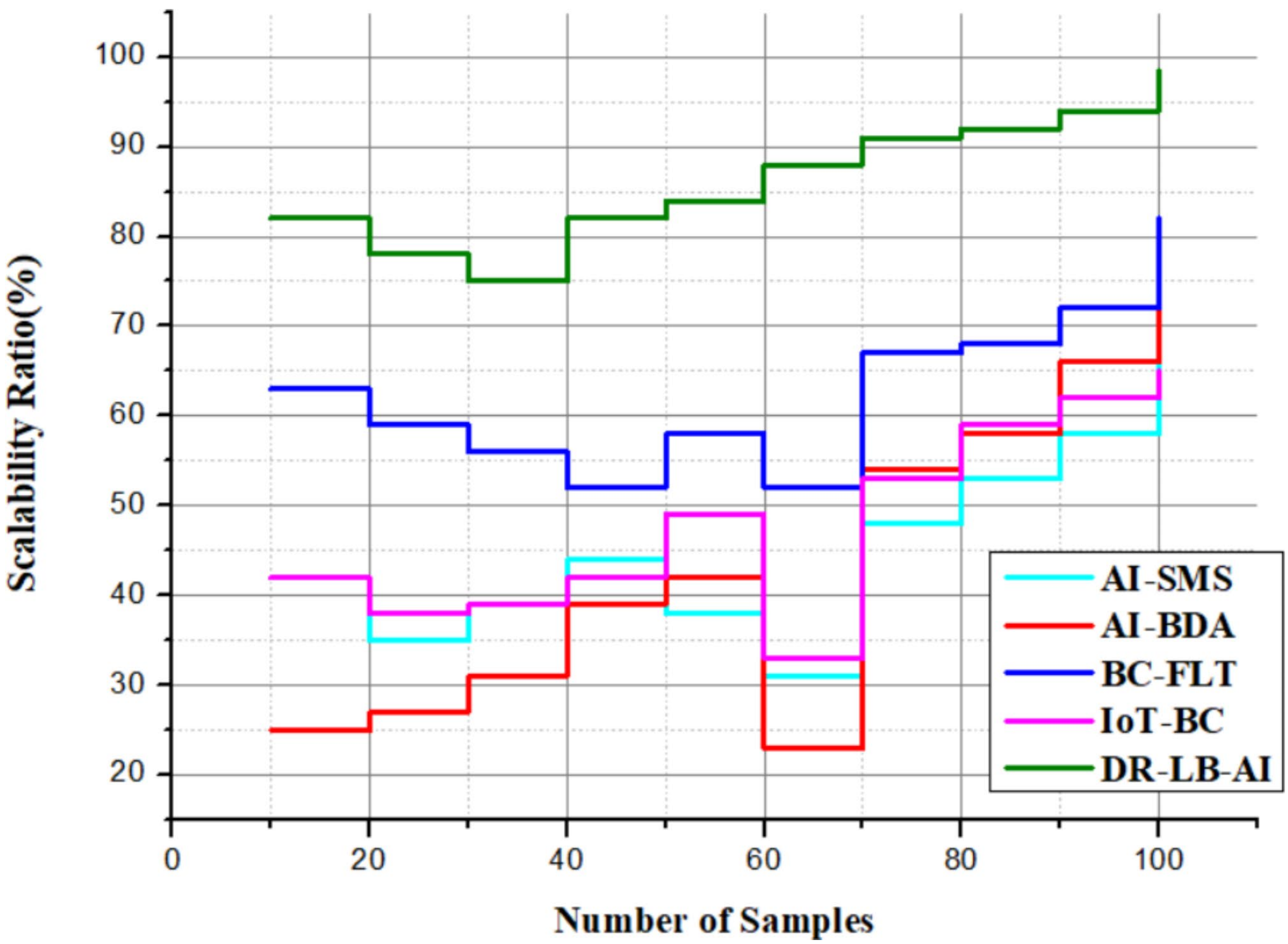

Fig. 9. The Graphical Representation of Scalability.

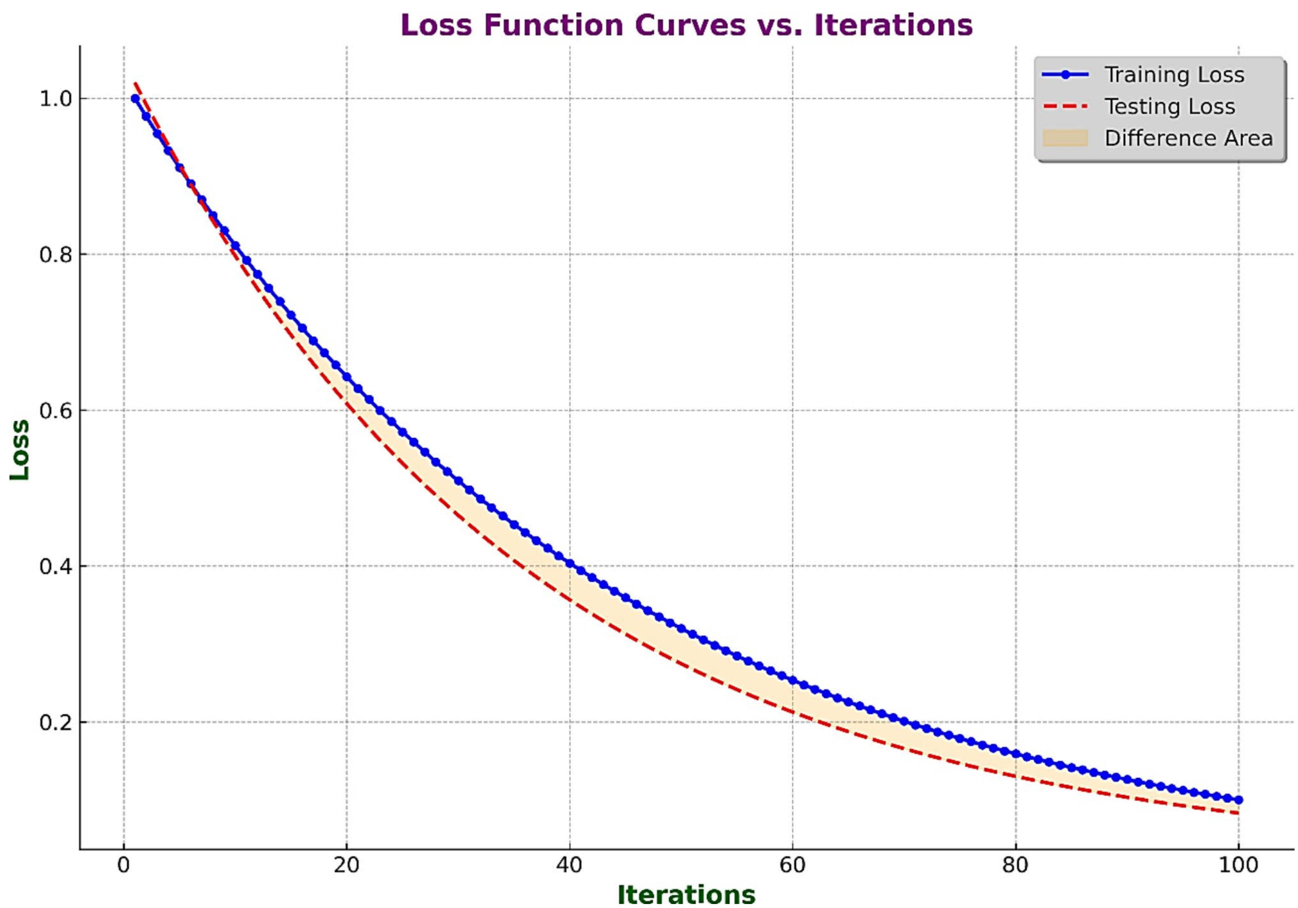

Fig. 10. Loss Function Curves vs. Iterations.

and avoids unauthorised changes. Another benefit of Blockchain is that it lessens the likelihood of catastrophic assaults by eliminating any weak spots in the system. By keeping a constant eye out for any signs of suspicious behaviour or system problems, AI-driven anomaly detection significantly strengthens security. The AI can swiftly react to eliminate dangers if it detects unusual activity, such as possible hacking attempts or system faults. The overall security posture is greatly improved by taking a proactive approach and using predictive analytics to identify and resolve any vulnerabilities before they can be exploited. In this research work the proposed method of DR-LB-AI gained the Security ratio by 97.71%.

Analysis of demand management

When it comes to using the resources of the system in Fig. 12, through Blockchain technology, which solves a number of drawbacks of conventional centralised system, security of the DR-LB-AI architecture is further enhanced. Security concerns with centralized systems allow potential manipulation of data processing – and energy transactions subjects to hacking and data breaches. Unlike the previous DR-LB-AI approach where the management of data was centralised, these new approach technologies the use of Blockchain therefore making it possible to track and make all transactions within the EV charging network unchangeable. This is inculcated by the stakeholders increasing their confidence and doing away with unwarranted interference in this case, system management. This is also another reason that helps restrain the probability of severe attacks, in as much as there are no vulnerabilities in the system. The capability of AI driven anomaly detection further enhances security by providing real time surveillance for the presence of suspicious activities or system fault.

If the AI detects any unusual activity, such as hacking activity or system malfunction, it is capable of acting swiftly to eliminate those threats. A diligent approach towards the security exercise followed by effects that entail the medical administration is taking pre-emptive measures targeting the state of being secure analytics to bolster the security health by reducing the chances of abuses in areas that are usually vulnerable. In the new DR-LB-AI approach, demand management is improved by 96.42% using Eq. (18).

Analysis of peak demand stress

Managing peak demand stress is one of the major problems in operating EV charging networks and is dealt with successfully by the DR-LB-AI system. Due to the rising numbers of electric vehicles (EVs), heavy demand charging patterns can peak during busier periods leading to risks of grid collapse, blackouts and power wastage. The AI component of the system is also important in solving this problem as posed in the Eq. (19) by using

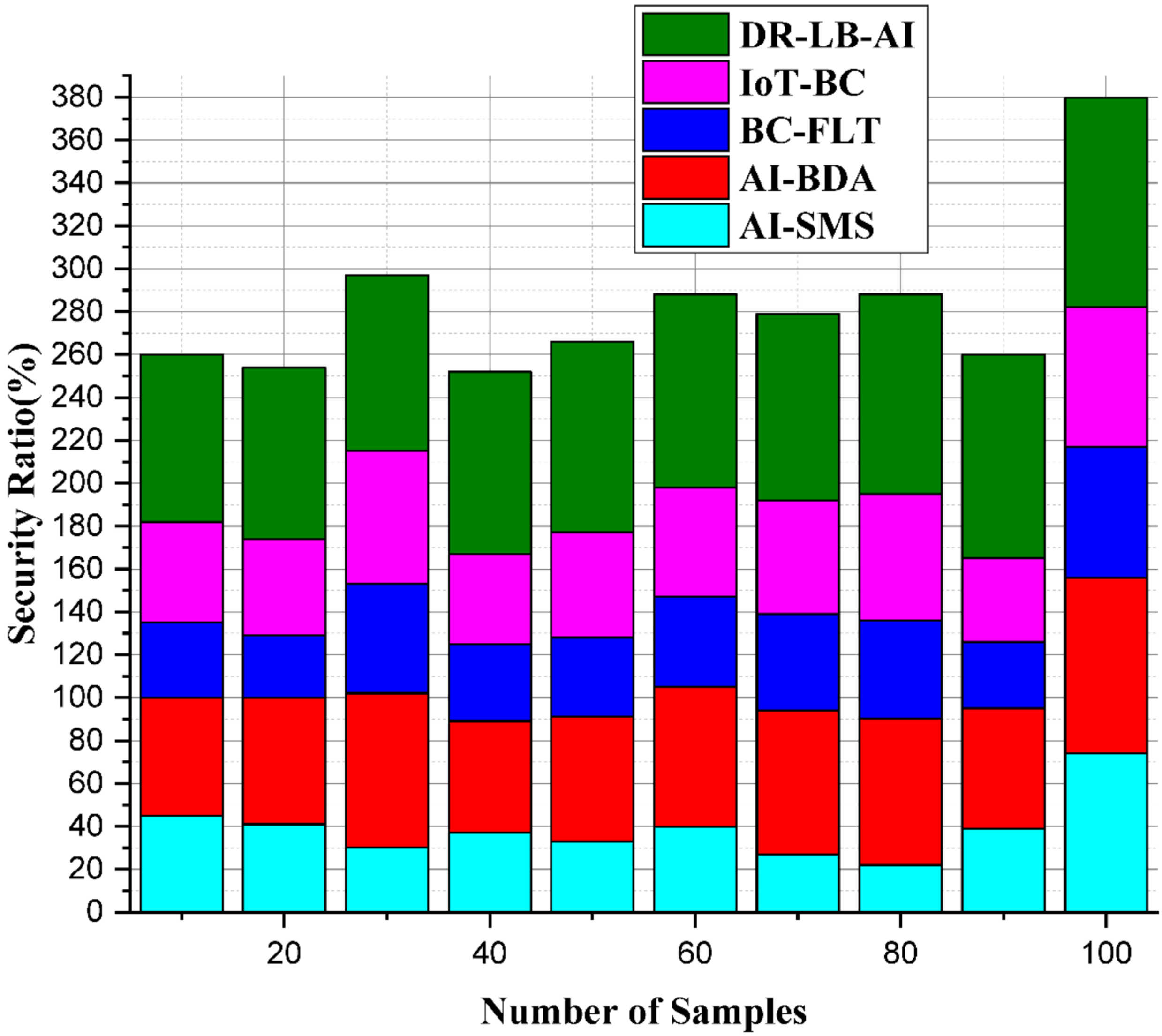

Fig. 11. The Analysis of Security.

predictive demand analysis to anticipate the load curve of systems and providing the appropriate modified loads whenever the real time grid situation calls for such measures.

Smart charging with the aid of an AI-powered technology optimisation can schedule charging time shifts loads to off peak periods when actual energy use is predicted to be low. This reduces the risks of system overload during periods of high energy demand. Similarly, to decongest at the peak time, the system may used varied pricing strategies so that users preferably charge at off peak time. Both improving real-time Load Balancing in an efficient and transparent manner and making the grid stronger with regard to peak stress conditions are made possible collar with the improvement of Blockchain technology which ensures safe, distributed communication and reliable energy exchanges. In Fig. 13, the DR-LB-AI has also been improved with the presented method reducing the peak demand stress by 20%.

Analysis of trust and transparency

As shown in Fig. 14, the implementation of the DR-LB-AI architecture makes the EV charging ecosystem more trusted and transparent with the inclusion of Blockchain technology. The reason for this is because in conventional systems, data and energy transactions are mostly managed through a central entity whereby a large proportion of stakeholders find it hard to establish the integrity and accuracy of such processes which in turn makes such trust to be compromised.

The Blockchain addresses this by allowing for a decentralized approach that allows for all activities with regard to energy transactions and even invoicing to be accounted for within a ledger that can be edited only once after all entries have been completed. Since all these three groups of the energy suppliers, the charging station operators, and the customers participate in the electric vehicle charging network, and this guarantees that every participant has reliable and tamper-proof information is stated in Eq. 20. The removal of third-party

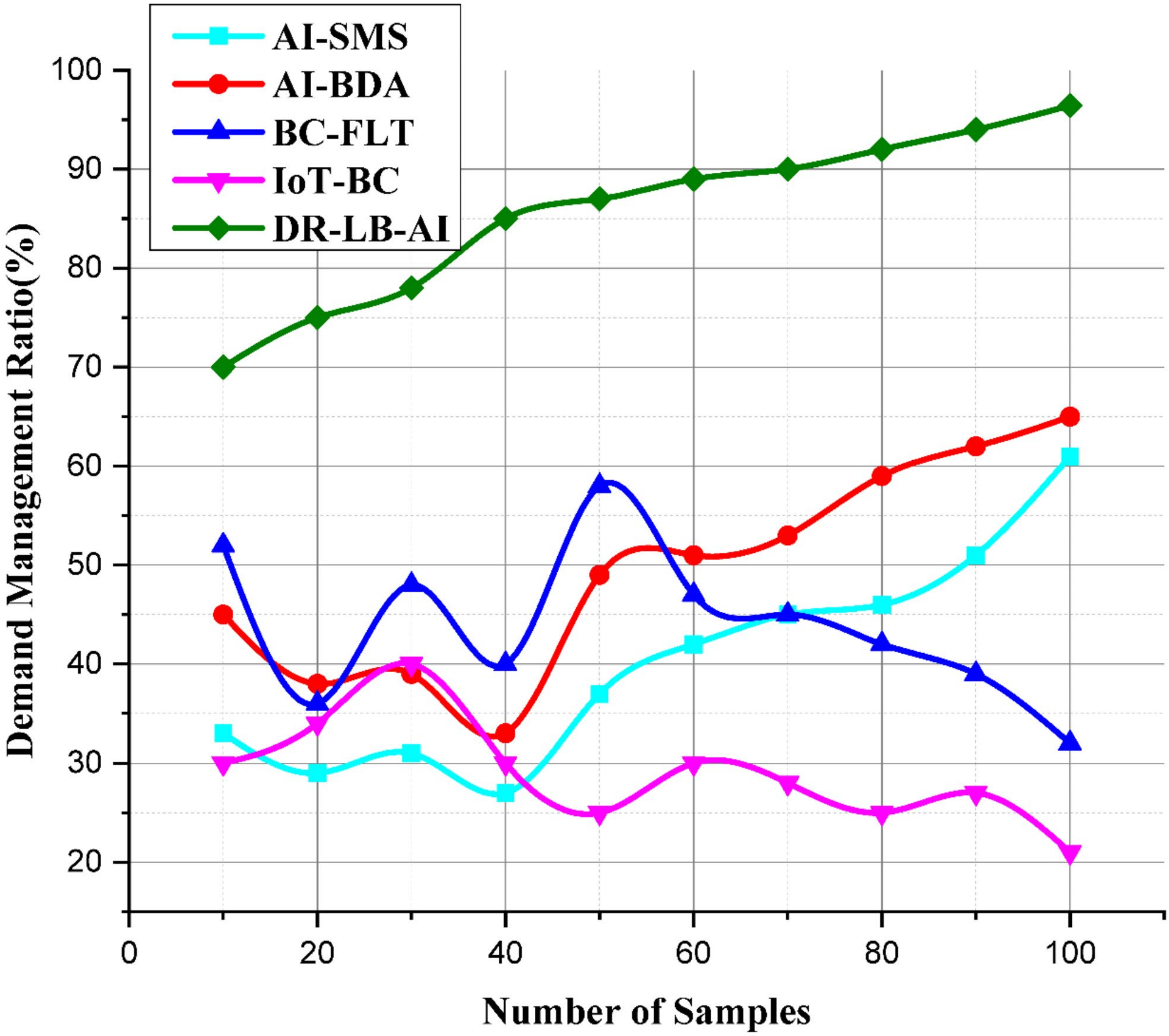

Fig. 12. The Graphical Illustration of Demand Management.

instances is definitively one of the strengths of Blockchain technology, efficacy of which also improves trust and responsibility and decreases the chances of deception or misuse of the information. Also, as an additional layer of trust, AI-driven anomaly detection extends beyond the boundaries of the system by such features as real-time monitoring and rapid response to out-of-the-norm events. As a result of providing active anomaly detection coupled with a clear record-keeping approach to the network, the reliability and security of the network is improved thus boosting the confidence of the users. In this research work the proposed method of DR-LB-AI improves the trust vs. transparency ratio by 96.24%. The overall research findings are compared with existed methods and tabulated in Table 2 respectively.

In summary, by combining AI and Blockchain technology, the DR-LB-AI framework solves important problems associated with EV charging network management. Blockchain guarantees decentralised, transparent, and secure energy transactions, while AI-driven predictive analysis optimises demand forecasting and Load Balancing. With a 20% reduction in peak demand stress and an improvement in dependability of more than 98%, the framework greatly increases the scalability, security, and confidence in the electric vehicle charging ecosystem. A strong contender for smart grids of the future, this technology guarantees grid stability, energy efficiency, and the smooth expansion of electric mobility via proactive anomaly detection and real-time control.

Conclusion

Electrical networks are facing new challenges due to new demands, such as heat pumps, electric cars, and the increasing penetration of distributed energy resources. The tabular results clearly demonstrate that the adoption of the DR-LB-AI framework leads to significant advancements over traditional methods across several critical dimensions. This framework exhibits remarkable scalability, driven by AI-enabled predictive analysis and

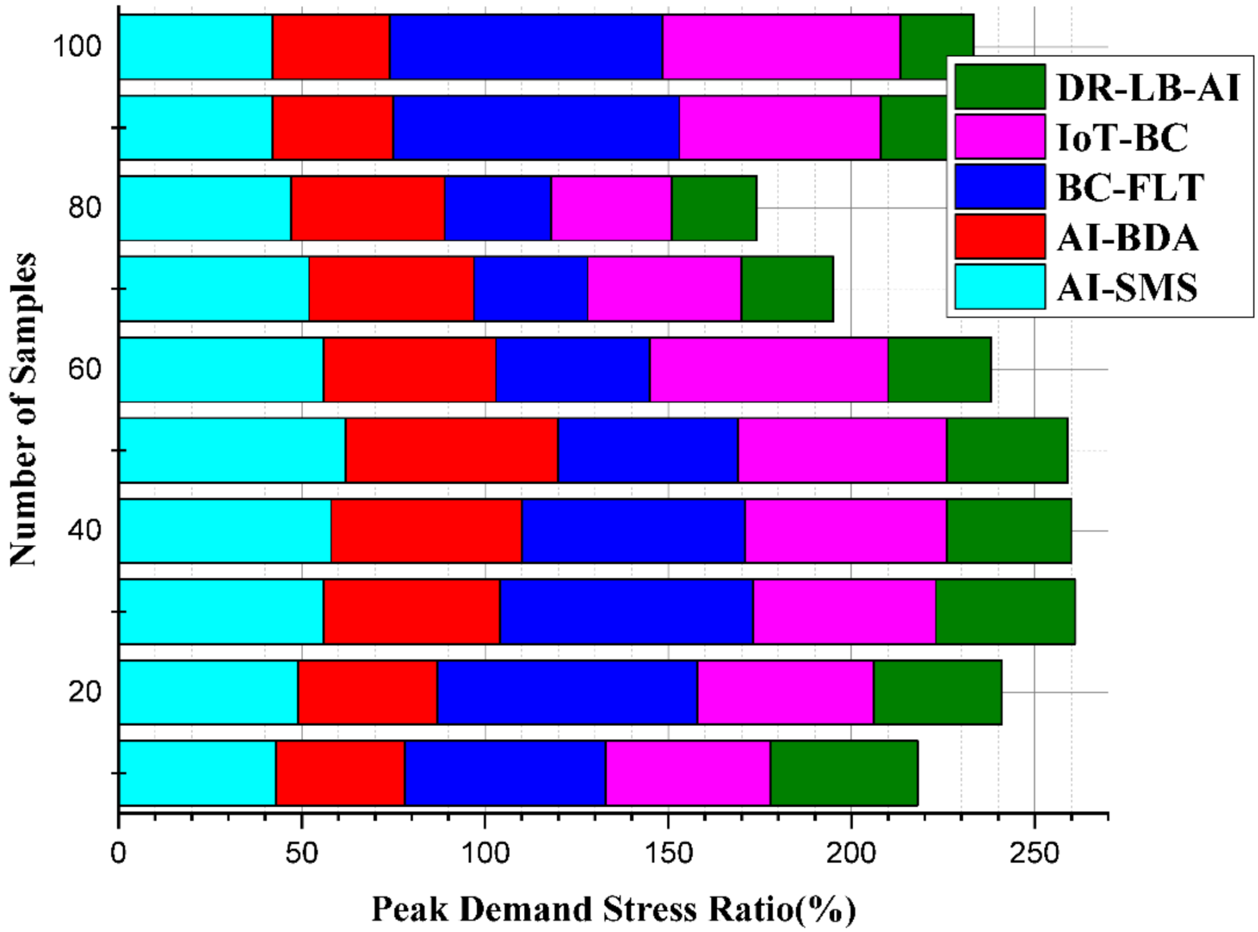

Fig. 13. The Graphical Representation of Peak Demand Stress.

Load Balancing, making it exceptionally efficient at handling the increasing number of electric vehicles (EVs). Specifically, it achieves an improvement rate of 98.43%. Additionally, the integration of Blockchain technology within the framework enhances security by mitigating the vulnerabilities associated with centralized systems, offering a notable 97.71% increase in protection through decentralized and tamper-resistant transactions.

Furthermore, the DR-LB-AI framework shifts from reactive to proactive and predictive demand management, which greatly minimizes the risk of grid overload during peak demand periods, showcasing a 96.42% improvement. The framework also helps alleviate peak demand stress, traditionally a challenge for grid stability, by utilizing AI-based demand distribution and incentivizing off-peak charging, reducing stress by 20%. Finally, the integration of Blockchain technology enhances transparency and stakeholder trust by 96.24%, primarily due to its capability to deliver secure, immutable transaction records. This decentralized ledger system ensures data integrity and traceability, which are critical for maintaining trust in distributed energy management systems.

Future work

To improve sustainability, the DR-LB-AI framework may investigate the possibility of incorporating solar and wind power into the intelligent EV charging infrastructure. Improving demand forecasting and Load Balancing while taking renewable energy supply fluctuations into consideration might be achieved with the help of advanced AI algorithms. To further improve the system's scalability and worldwide acceptance, the Blockchain foundation should be extended to include interoperability between various energy suppliers and cross-border energy trade. To ensure the framework's usefulness and flexibility to changing energy landscapes, it is important to test and refine it under diverse grid situations and increase EV adoption.

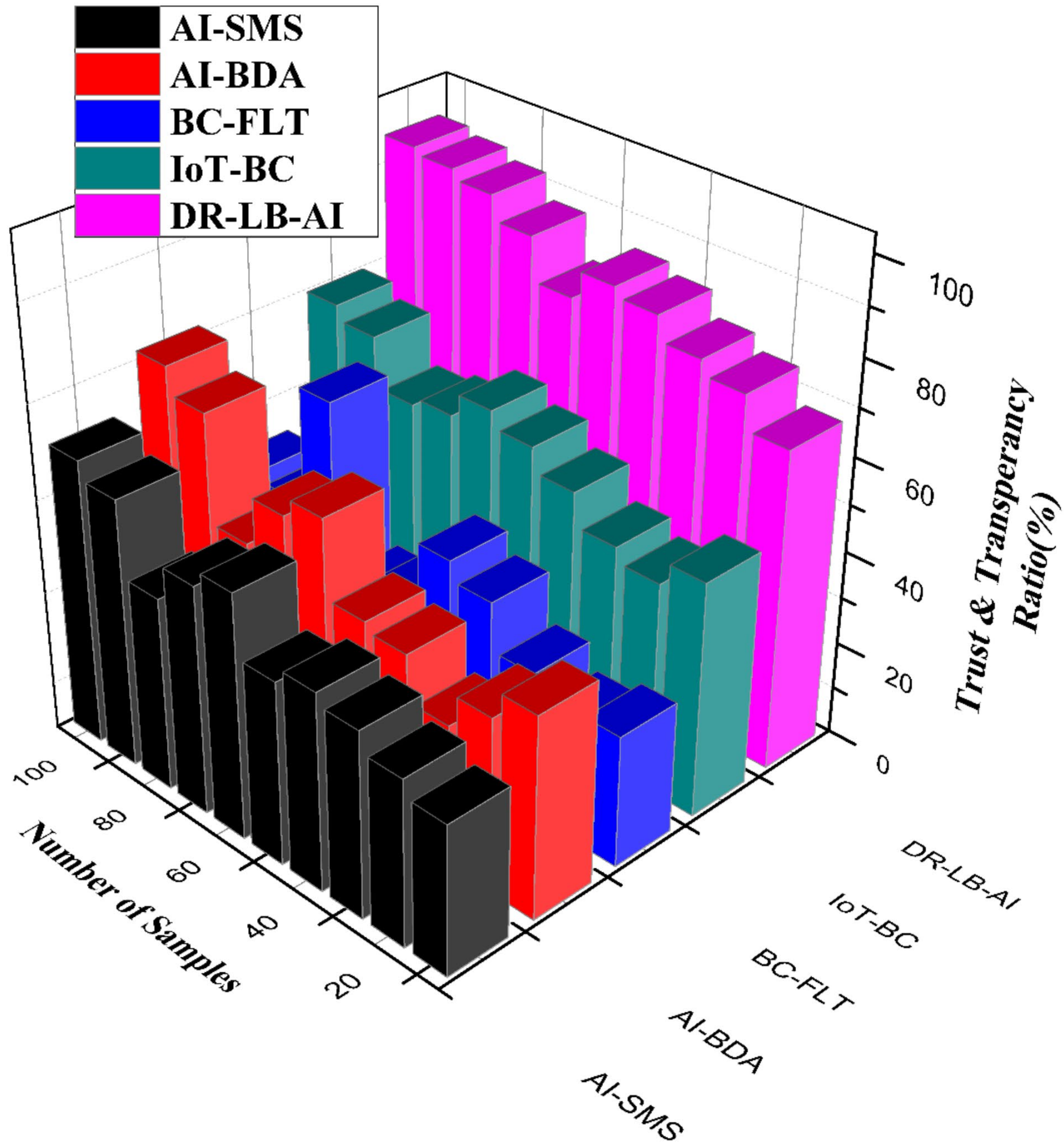

Fig. 14. The Analysis of Trust and Transparency.

S. No	Aspect	Existing Method	DR-LB-AI Framework	Ratio (%)
1	Scalability	Limited scalability; struggle to manage increasing EV numbers.	Highly scalable due to AI-driven predictive analysis and Load Balancing.	98.43
2	Security	Centralized systems are vulnerable to hacking, data breaches, and manipulation.	Blockchain ensures decentralized, tamper-proof transactions, improving security.	97.71
3	Demand Management	Reactive and inefficient, leading to grid overloads during peak demand.	Predictive, proactive demand forecasting and real-time Load Balancing.	96.42
4	Peak Demand Stress	High stress during peak hours, risking grid instability and blackouts.	Reduced through AI-based demand distribution and off-peak charging incentives	20
5	Transparency & Trust	Centralized control with limited visibility for stakeholders, leading to trust issues.	Blockchain provides transparent, immutable records, enhancing trust.	96.24

Table 2. Numerical findings and compared with existed methods.

Data availability

All data generated or analysed during this study are included in this published article [and itssupplementary information files].

Received: 4 October 2024; Accepted: 3 December 2024
Published online: 30 December 2024

References

1. Shayeghi, H., Shahryari, E., Moradzadeh, M. & Pierluigi Siano A Survey on Microgrid Energy Management Considering Flexible Energy Sources *Energies* 12, no. 11: 2156. https://doi.org/10.3390/en12112156 (2019).
2. Sun, G. et al. V2V routing in a VANET based on the Autoregressive Integrated moving average model. *IEEE Trans. Veh. Technol.* **68**(1), 908–922. https://doi.org/10.1109/TVT.2018.2884525 (2019).
3. Sun, G. et al. Bus-Trajectory-Based Street-Centric Routing for Message Delivery in Urban Vehicular Ad Hoc Networks. *IEEE Trans. Veh. Technol.* **67**(8), 7550–7563. https://doi.org/10.1109/TVT.2018.2828651 (2018).
4. Rong, Y. et al. Du-Bus: a Realtime Bus Waiting Time Estimation System based on Multi-source Data. *IEEE Trans. Intell. Transp. Syst.* **23**(12), 24524–24539. https://doi.org/10.1109/TITS.2022.3210170 (2022).
5. Jamil, F., Iqbal, N., Imran, S., Ahmad & Kim, D. Peer-to-Peer Energy Trading Mechanism Based on Blockchain and Machine Learning for Sustainable Electrical Power Supply in Smart Grid, in *IEEE Access*, vol. 9, pp. 39193–39217, doi: https://doi.org/10.1109/ACCESS.2021.3060457 (2021).
6. Ma, K., Yang, J. & Liu, P. Relaying-assisted communications for demand response in Smart Grid: cost modeling, game strategies, and algorithms. *IEEE J. Sel. Areas Commun.* **38**(1), 48–60. https://doi.org/10.1109/JSAC.2019.2951972 (2020).
7. Meng, Q. et al. Enhancing distribution system stability and efficiency through multi-power supply startup optimization for new energy integration. *IET Generation Transmission Distribution* **18**(21), 3487–3500. https://doi.org/10.1049/gtd2.13299 (2024).
8. Liu, Y. & Zhao, Y. A blockchain-enabled Framework for Vehicular Data sensing: enhancing information freshness. *IEEE Trans. Veh. Technol.* **73**(11), 17416–17429. https://doi.org/10.1109/TVT.2024.3417689 (2024).
9. Feng, J., Yao, Y. & Liu, Z. Developing an optimal building strategy for electric vehicle charging stations: automaker role. *Environ. Dev. Sustain.* https://doi.org/10.1007/s10668-024-05326-6 (2024).
10. Fu, Y., Li, C., Yu, F. R., Luan, T. H. & Zhao, P. An incentive mechanism of incorporating Supervision Game for Federated Learning in Autonomous Driving. *IEEE Trans. Intell. Transp. Syst.* **24**(12), 14800–14812. https://doi.org/10.1109/TITS.2023.3297996 (2023).
11. Ravindran, M. A. et al. A Novel Technological Review on fast charging infrastructure for Electrical vehicles: challenges, solutions, and future research directions. *Alexandria Eng. J.* **82**, Pages 260–290, ISSN 1110 – 0168. https://doi.org/10.1016/j.aej.2023.10.009 (2023).
12. Kumar, B. A. et al. A novel strategy towards efficient and reliable electric vehicle charging for the realisation of a true sustainable transportation landscape. *Sci. Rep.* **14**, 3261. https://doi.org/10.1038/s41598-024-53214-w (2024).
13. Kumar, B. A. et al. Hybrid genetic algorithm-simulated annealing based electric vehicle charging station placement for optimizing distribution network resilience. *Sci. Rep.* **14**, 7637. https://doi.org/10.1038/s41598-024-58024-8 (2024).
14. Sidharth Sabyasachi, A. R. et al. Reimagining E-mobility: a holistic business model for the electric vehicle charging ecosystem. *Alexandria Eng. J.* **93**, Pages 236–258, ISSN 1110 – 0168. https://doi.org/10.1016/j.aej.2024.03.004 (2024).
15. Surbhi Aggarwal, A. K., Singh, R. S., Rathore, M., Bajaj, D. & Gupta Revolutionizing load management: a novel technique to diminish the impact of electric vehicle charging stations on the electricity grid. *Sustain. Energy Technol. Assess.*, **65**, 103784, ISSN 2213 – 1388, https://doi.org/10.1016/j.seta.2024.103784 (2024).
16. Kumar, B. A. et al. Enhancing EV charging predictions: a comprehensive analysis using K-nearest neighbours and ensemble stack generalization. *Multiscale Multidiscip Model. Exp. Des.* https://doi.org/10.1007/s41939-024-00457-9 (2024).
17. Patnam, B. S. K. & Pindoriya, N. M. Demand response in consumer-centric electricity market: Mathematical models and optimization problems. *Electr. Power Syst. Res.* **193**, 0378–7796. https://doi.org/10.1016/j.epsr.2020.106923 (2021).
18. Lin, Y. J. et al. Blockchain-based intelligent charging station management system platform. *IEEE Access.* **10**, 101936–101956 (2022).
19. Wang, Z. et al. AEBIS: AI-enabled Blockchain-based electric vehicle integration system for power management in smart grid platform. *IEEE Access.* **8**, 226409–226421 (2020).
20. Kakkar, R., Agrawal, S. & Tanwar, S. A systematic survey on demand response management schemes for electric vehicles. *Renew. Sustain. Energy Rev.* **203**, 114748 (2024).
21. Lin, Y. J. et al. Blockchain power trading and energy management platform. *IEEE Access.* **10**, 75932–75948 (2022).
22. Yahaya, A. S. et al. Blockchain-based energy trading and load balancing using contract theory and reputation in a smart community. *IEEE Access.* **8**, 222168–222186 (2020).
23. Li, J., Herdem, M. S., Nathwani, J. & Wen, J. Z. Methods and applications for Artificial intelligence, Big Data, Internet of things, and Blockchain in smart energy management. *Energy AI.* **11**, 100208 (2023).
24. Samadi, M., Schriemer, H., Ruj, S. & Erol-Kantarci, M. Energy Blockchain for Demand Response and distributed energy resource management. In: *2021 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)* (pp. 425–431). (IEEE, 2021).
25. JAVED, M. U. & AALSALEM, M. Y. SHAFIQ, M., Blockchain-Based Energy Trading and Load Balancing Using Contract Theory and Reputation in a Smart Community.
26. Kakkar, R., Gupta, R., Agrawal, S., Tanwar, S., Altameem, A., Altameem, T., Raboaca,M. S. Blockchain and iot-driven optimized consensus mechanism for electric vehicle scheduling at charging stations. Sustainability **14**(19), 12800. (2022).
27. Kumari, A., Gupta, R., Tanwar, S. & Kumar, N. Blockchain and AI amalgamation for energy cloud management: challenges, solutions, and future directions. *J. Parallel Distrib. Comput.* **143**, 148–166 (2020).
28. Khan, H. & Masood, T. Impact of Blockchain technology on smart grids. *Energies* **15** (19), 7189 (2022).
29. Miglani, A., Kumar, N., Chamola, V. & Zeadally, S. Blockchain for Internet of Energy management: review, solutions, and challenges. *Comput. Commun.* **151**, 395–418 (2020).
30. Hua, W. et al. Applications of Blockchain and Artificial intelligence technologies for enabling prosumers in smart grids: a review. *Renew. Sustain. Energy Rev.* **161**, 112308 (2022).
31. Junaidi, N., Abdullah, M. P., Alharbi, B. & Shaaban, M. Blockchain-based management of demand response in electric energy grids: a systematic review. *Energy Rep.* **9**, 5075–5100 (2023).
32. Ma, R. et al. A blockchain-enabled demand management and control framework driven by deep reinforcement learning. *IEEE Trans. Industr. Electron.* **70**(1), 430–440 (2022).
33. Muthukrishnan, S. K. & Vijayakumar, R. *Demand Side Management Using Blockchain for Peer-to-Peer* (Electric Vehicle Charging Networks, 2021).
34. Teimoori, Z. & Yassine, A. A review on intelligent energy management systems for future electric vehicle transportation. *Sustainability* **14**(21), 14100 (2022).
35. Kumar, N. M. et al. Distributed energy resources and the application of AI, IoT, and Blockchain in smart grids. *Energies* **13**(21), 5739 (2020).

36. Khan, M. A., Saleh, A. M., Waseem, M. & Sajjad, I. A. Artificial intelligence enabled demand response: prospects and challenges in smart grid environment. *Ieee Access.* **11**, 1477–1505 (2022).
37. Mololoth, V. K., Saguna, S. & Åhlund, C. Blockchain and machine learning for future smart grids: a review. *Energies* **16** (1), 528 (2023).
38. Kausar, F., Al-Hamouz, R. & Hussain, S. Energy Demand Forecasting for Electric Vehicles Using Blockchain-Based Federated Learning. *IEEE Access.* **12**, 41287–41298 (2024).
39. Bhaskar, K. B. R., Prasanth, A. & Saranya, P. An energy-efficient Blockchain approach for secure communication in IoT-enabled electric vehicles. *Int. J. Commun Syst* **35**(11), e5189 (2022).
40. Ma, W. et al. New technologies for optimal scheduling of electric vehicles in renewable energy-oriented power systems: a review of deep learning, deep reinforcement learning and Blockchain technology. *Energy Convers. Econ.* **3**(6), 345–359 (2022).
41. Said, D., Elloumi, M. & Khoukhi, L. Cyber-attack on P2P energy transaction between connected electric vehicles: a false data injection detection-based machine learning model. *IEEE Access.* **10**, 63640–63647 (2022).
42. Yang, P. Electric vehicle based smart cloud model cyber security analysis using fuzzy machine learning with Blockchain technique. *Comput. Electr. Eng.* **115**, 109111 (2024).
43. Ahmed, A. A., Alkheir, A. A., Said, D. & Mouftah, H. T. Cooperative spectrum sensing for cognitive radio vehicular ad hoc networks: An overview and open research issues, *IEEE Canadian Conference on Electrical and Computer* Engineering *(CCECE)*, Vancouver, BC, Canada, 2016, pp. 1–4, doi: https://doi.org/10.1109/CCECE.2016.7726681 (2016).
44. Said, D. A Decentralized Electricity Trading Framework (DETF) for Connected EVs: A Blockchain and Machine Learning for Profit Margin Optimization. In: *IEEE Transactions on Industrial Informatics*, vol. 17, no. 10, pp. 6594–6602, Oct. doi: https://doi.org/10.1109/TII.2020.3045011 (2021).
45. Said, D. & Elloumi, M. A New False Data Injection Detection Protocol based Machine Learning for P2P Energy Transaction between CEVs. *IEEE International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM)*, Tunis, Tunisia, 2022, pp. 1–5, doi: https://doi.org/10.1109/CISTEM55808.2022.10044067 (2022).
46. Said, D. A Survey on Information Communication Technologies in Modern demand-side management for Smart grids: challenges, solutions, and opportunities. In: *IEEE Eng. Manage. Rev.*, **51**, 1, pp. 76–107, 1 Firstquarter, https://doi.org/10.1109/EMR.2022.3186154 (2023).
47. Said, D. Intelligent Photovoltaic Power Forecasting Methods for a Sustainable Electricity Market of Smart Micro-Grid, in *IEEE Communications Magazine*, vol. 59, no. 7, pp. 122–128, July doi: https://doi.org/10.1109/MCOM.001.2001140 (2021).
48. Alhija, M. A., Al-Baik, O., Hussein, A. & Abdeljaber, H. Optimizing blockchain for healthcare IoT: a practical guide to navigating scalability, privacy, and efficiency trade-offs. *Indonesian J. Electr. Eng. Comput. Sci.* **35**(3), 1773–1785 (2024).
49. Nidal Turab, H. A., Owida, Jamal, I. & Al-Nabulsi Harnessing the power of blockchain to strengthen cybersecurity measures: a review, *Indonesian Journal of Electrical Engineering and Computer Science*, Vol.35, No.1, July2024, p. 593 ~ 600ISSN: 2502–4752, https://doi.org/10.11591/ijeecs.v35.i1.pp593-600
50. Ullah, N., Al-Rahmi, W. M., Alblehai, F., Fernando, Y. & Alharbi, Z. H. Rinat Zhanbayev, Ahmad Samed Al-Adwan, and Mohammed Habes. Blockchain-powered grids: Paving the way for a sustainable and efficient future. *Heliyon* 10, no. 10 (2024).
51. Al-Sarayrah, N., Turab, N. & Hussien, A. A randomized blockchain consensus algorithm for enhancing security in health insurance. *Indonesian J. Electr. Eng. Comput. Sci.* **34**(2), 1304–1314 (2024).
52. Abu-Rumman, A. et al. Impact of Blockchain Strategy and Information sharing on Digital Operations: empirical evidence from the UAE Banking Industry. In: Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges (475–493). (Springer International Publishing, 2024).
53. Michael Bryant. (n.d.). Electric vehicle charging dataset. Kaggle. Retrieved November 23. https://www.kaggle.com/datasets/michaelbryantds/electric-vehicle-charging-dataset (2024).

Acknowledgements
This work was supported by the Researchers Supporting Project number (RSPD2024R646), King Saud University, Riyadh, Saudi Arabia". In addition, in the Data availability section, please correct the text in brackets as follows: [and its Supplementary information files].

Author contributions
Arvind R. Singh, R. Seshu Kumar, K. Reddy Madhavi: Conceptualization, Methodology, Software, Visualization, Investigation, Writing- Original draft preparation. Faisal Alsaif: Data curation, Validation, Supervision, Resources, Writing - Review & Editing. Mohit Bajaj, Ievgen Zaitsev: Project administration, Supervision, Resources, Writing - Review & Editing.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to R.S.K., M.B. or I.Z.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

© The Author(s) 2024