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Review

A Review on Emerging Communication and Computational Technologies for Increased Use of Plug-In Electric Vehicles

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Abstract: The electric vehicle (EV) industry is quickly growing in the present scenario, and will have more demand in the future. A sharp increase in the sales of EVs by 160% in 2021 represents 26% of new sales in the worldwide automotive market. EVs are deemed to be the transportation of the future, as they offer significant cost savings and reduce carbon emissions. However, their interactions with the power grid, charging stations, and households require new communication and control techniques. EVs show unprecedented behavior during vehicle battery charging, and sending the charge from the vehicle's battery back to the grid via a charging station during peak hours has an impact on the grid operation. Balancing the load during peak hours, i.e., managing the energy between the grid and vehicle, requires efficient communication protocols, standards, and computational technologies that are essential for improving the performance, efficiency, and security of vehicle-to-vehicle, vehicle-to-grid (V2G), and grid-to-vehicle (G2V) communication. Machine learning and deep learning technologies are being used to manage EV-charging station interactions, estimate the charging behavior, and to use EVs in the load balancing and stability control of smart grids. Internet of Things (IoT) technology can be used for managing EV charging stations and monitoring EV batteries. Recently, much work has been presented in the EV communication and control domain. In order to categorize these efforts in a meaningful manner and highlight their contributions to advancing EV migration, a thorough survey is required. This paper presents existing literature on emerging protocols, standards, communication technologies, and computational technologies for EVs. Frameworks, standards, architectures, and protocols proposed by various authors are discussed in the paper to serve the need of various researchers for implementing the applications in the EV domain. Security plays a vital role in EV authentication and billing activities. Hackers may exploit the hardware, such as sensors and other electronic systems and software of the EV, for various malicious activities. Various authors proposed standards and protocols for mitigating cyber-attacks on security aspects in the complex EV ecosystem.

Keywords: PEVs; V2G; G2V; IoT; Zigbee; machine learning; big data and blockchain; V2G; V2X; charging station

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1. Introduction

Governments and automobile manufacturers of various countries are promoting electric vehicles (EVs) as a vital technology for zero carbon emissions for climate change [1]. EVs are very climate-friendly when compared to vehicles that run on gasoline and diesel [2]. Most automotive manufacturers aim to stop selling new gasoline-powered vehicles and trucks by 2035 and will manufacture battery-powered vehicles [3]. The worldwide EV market size will be increased to 34,756 thousand units by 2030, at a compound annual growth rate of 26.8% [4]. Vehicles are connected to everything nowadays. Vehicle-to-everything (V2X) is a wireless communication technology that is extensively used for vehicle-to-pedestrian, vehicle-to-infrastructure, vehicle-to-vehicle (V2V), and vehicle-to-infrastructure communication (V2I). V2V technology allows vehicles to share relevant information within a specific limit. V2I technology can be used to communicate with various infrastructures, such as the grid, traffic lights, and municipal authorities. This technology can also be used in autonomous vehicles to navigate urban areas. Vehicle-to-pedestrian technology can send traffic status alerts to pedestrians' cell phones and warn them in order to avoid accidents. Various sensors, electronic systems, communication protocols, and standards are being used in the technologies mentioned above and have been implemented successfully. Various important parameters of the EVs, such as the driving range, monitoring the battery status of the vehicle, receiving billing information after battery charging and discharging, and receiving alerts from vehicles and other infrastructure, are to be implemented effectively. Due to the pressing need for the technological advancement of EVs, various protocols, communication standards, and computational technologies have emerged and have been utilized effectively for the improved performance of various EVs. Only a few papers addressed EVs' standards, protocols, communication, and computational technologies.

Vendor-independent, open, and international EV charging standards pliable for infrastructure operators and EV drivers have been discussed in [5]. In [6], the author discussed various open protocols used in Europe and USA for the EV industry. However, [5,6] authors have not discussed anything related to the IoT, Zigbee, and other communication standards used for V2I, vehicle, and personal communication. In [7], the author discussed the communication protocols and standards of EV-grid messaging. Various protocols, such as openADR, OCPP, and ISO15118, have been discussed. The paper also proposed methods for selecting messaging protocols. James Mater et al. [7] did not focus on wireless communication technologies such as LoRa, LoraWAN, and 5G for V2X communication. Various standards and communication protocols for different purposes for EVs have been discussed in [8,9]. Authors in [9] discussed communication standards and technologies for EVs and smart grid applications. The authors discussed wireless communication standards such as Wi-Fi, Zigbee, and LTE, and the use cases were compared. In [10], The authors proposed various electric vehicle smart charging technologies and strategies to provide solution for charging demand.The authors did not focus on computational and communication technologies like IoT, ML and blockchain for EVs. Myriam Neaimeh and Peter Bach Andersen et al. [11] discussed the open communication protocols for vehicle-to-grid (V2G) integration. The authors did not focus on the communication and computational technologies required for V2X communication.

Vidhya et al. discussed the electrical aspects of EVs, such as the drive system and electrical machine design [12]. The authors focused more on control techniques and converter topologies and did not mention the computational and communication-related protocols. In [13], the authors presented a literature review on plug-in EVs, focusing more on EVs' charging and technical aspects but not on the computational and communication technologies. In [14], the authors presented a literature review on EVs that focuses on the problems and solutions of PEV deployment and integration into the grid in the United States. They mentioned much about the hurdles in the deployment of PEV. Liao et al. [15] presented a comprehensive literature review on EV consumer preferences. They compared EVs' psychological and economic aspects to give direction to research.

In [16], the authors focused more on the moderators and mediators for EV adoption, which would be helpful to policy makers and researchers. The authors did not mention any literature review on computational technologies. In [17], the authors thoroughly mentioned various technologies for EV battery management, technologies related to the charging process of EVs, and EV battery management. In [18], the authors presented a paper on the interaction of EVs with power distribution systems. They presented a chronological survey showing the interactions between the electric grid and EVs. The authors did not mention anything about computational and communication technologies. The need for EVs is growing daily, and we can see a drastic increase in migration to EVs, cars, and buses in every country [19,20]. In the future, every EV should communicate with the infrastructure, vehicle, and person. Communication technologies are very much required to ensure efficient and secure inter and intra-vehicular communication [21]. Computational technologies such as machine learning and big data can be used to predict charging station deployment. Blockchain technology can be used to make the billing and transactions of PEVs more transparent and secure. Few authors focused on the open communication standards of EVs, and some authors discussed only wireless communication technologies. The number of published papers on communication and computational technologies taken from the Scopus database is shown in Figure 1.

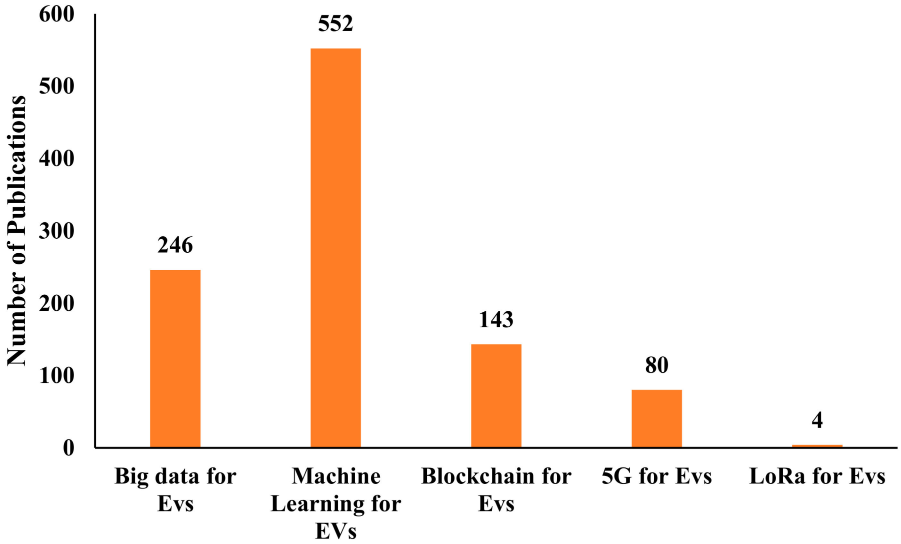

Figure 1. Publication statistics on emerging technologies for EVs.

The above statistics show that emerging technologies are yet to be adequately exploited to enhance EVs' utility. This paper discusses the open communication standards, communication technologies, and computational technologies required for the PEV industry. The works of various authors have been discussed in the sections. In this paper, Section 2 describes various open standards for plug-in EV charging and infrastructure development. Use cases and the purpose of various open communication standards are discussed. Section 3 is about the communication technologies used in V2X communication. The work of various authors related to communication technologies used in IoEV is discussed. Various communication technologies' speed, range, and frequencies are compared. Applications of disruptive computational technologies such as machine learning, big data, and blockchain are discussed in Section 4. The purpose of various machine learning techniques and big data tools is also discussed in Section 4. This survey will be helpful for those working in the EV industry, building the architectures for EV charging stations, and establishing communication among the EVs and infrastructure. This paper discusses various applications of EVs with the above-mentioned disruptive communication and computational technologies.

2. Protocols and Standards for EVs

As EVs have become an integral part of the transportation system, there is an increased demand for charging stations. Protocols are rules and guidelines certifying smooth communication and data exchange between various entities in the EV industry. Charging station operators and service providers are facing challenges regarding the protocols and regulations of their networks.

Protocols and standards are rules and guidelines used to provide efficient communication between various entities, such as plug-in EVs, smart grids, and charging point stations. Various global organizations and research institutes designed and developed open source and proprietary protocols to meet the ever-increasing EV demands and requirements. One of the challenges in the design of plugin EVs is interoperability. The increased usage of battery EVs is associated with challenges such as efficient energy management in the grids, battery management, and providing authentication of data transfer. Specifications and details of all of the EVs protocols have been published [6] by ElaadNL, an innovation center in the Netherlands.

Very important protocols and standards for EVs have been discussed in [5,6] and are summarized in Table 1 and in Figure 2. The protocols discussed in this paper are open standards.

Table 1. PEV industry protocols use cases.

Reference	Protocol/Standard	Use Cases
[5,6]	OCPP	Authorize charging session, Billing, Managing grid, Operating charge point, Reservation, Smart charging
[5,6]	OCHP	Providing charge point information, Reservation, Roaming, Authorizing charging sessions, Smart charging.
[5,6]	OCPI	Providing charge point information, Reservation, Smart charging, Authorizing charging sessions, Roaming.
[5,6]	OSCP	Handing out capacity budgets, Managing grid capacity using these budgets, Smart charging by communicating capacity forecasts.
[5,6]	OpenADR	Managing grid, Smart charging, Handling registrations
[5,6]	eMIP	Providing smart charging features, Authorizing charging sessions, Billing, Roaming.
[5,6]	ISO15118	Authorizing charging sessions, Schedule-based charging, Certificate handling.
[5,6]	IEEE2030.5	In-house smart grid solutions, Demanding response/load control, Exchanging metering data, Providing tariff information, Sending text messages, Providing actual usage and billing information, Energy flow reservation.
[5,6]	IEC 61850	Communication parameter modeling, Message structure standardization, Plug-and-play for different applications, such as charging station–EV coordination, Virtual power plant operation

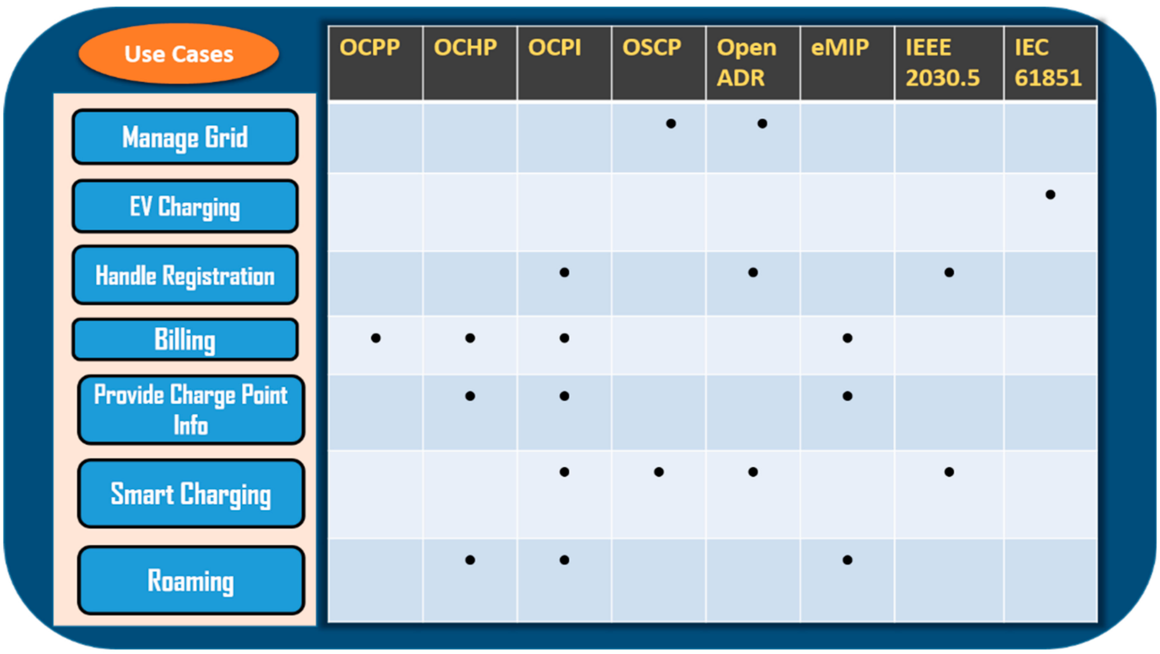

Figure 2. Use cases of different EV protocols and standards.

The V2G industry is not yet fully evolved. The standardization of the protocols is critical for meeting new requirements of the EV communications infrastructure when incorporating the capabilities of EVs into grid operations management effectively [6]. IEEE 2030.5-has recently been updated to incorporate the CA Rule 21 and IEEE 1547-2018 functionality in the standard. It is an application layer standard based on web services with built-in security and is designed to use the modern Internet to transport its messages between devices. It is emerging as the preferred industry standard for DER communication [7]. Several standards related to the DC fast charging option are under development by the International Electrotechnical Commission (IEC). The IEC 61851-23 standard represents the requirements for communication architecture and grid connections for fast charging. The use cases and purpose of various communication protocols and standards used in EVs are provided in the figure below.

In addition, the IEC 61850 standard has been constantly improved to incorporate EVs and their respective operations [22]. There have been efforts to link different standards, such as IEEE WAVE and IEC 61850, to successfully manage ad hoc vehicle fleets and the charging burden [23,24]. The initial results have been very promising, although the connectivity between different EVs in an ad hoc manner raised privacy concerns. In order to address these concerns, there have been studies on securing these message exchanges [25,26]. Another effort that combines standard harmonization and addressing security concerns is presented in [27], where the IEC 61850 communication of EVs in a system is performed via XMPP. Such schemes have also been tested in real-life testing conditions via hardware-in-the-loop testing, where standard messages are exchanged to perform power system control [28].

IoEV is all about connecting the EVs through the Internet to control and manage the data and energy transfer for V2X. As this is an emerging area, some standards are under development or published. When the EV is being charged, the vehicle has to follow certain communication standards and protocols, which The Society of Automotive Engineers (SAE) has defined. The standards have been described in [29,30] and are summarized in Table 2. In [31,32] authors communication models based on IEC 61850 are created for the grid energy management system, PV, EV, and home energy management systems. Additionally, communication message flows have been built, and utilising various communication technologies, their performance has been examined. Hussain et al. [33] proposed a method which uses cognitive radio to establish communication during emergencies and the simulation results shows the viability of modeling.

Table 2. Communication standards when EV is being charged.

Standard	Purpose
SAE J2293	Architectures and functionality required for EV to transfer energy
SAEJ2836/1& J2847/1	communications between EVs and the power grid, and defines energy transfer
SAEJ2836/2& J2847/2	Provides the essentials for the communication between EV and off-board DC charger.
SAEJ2836/3& J2847/3	Defines essentials and use cases for energy (DC) transfer from the grid-to-EV and grid-to-vehicle energy transfer.
SAE J2931	Provides digital communication essentials between off-board device and EV.
SAE J2931/2	Provides the essentials for physical layer communication with in-band signaling between EVSE and EV.

3. Emerging Communication Technologies for EVs

The autonomous vehicle number has increased significantly over the past few years. Reliable and efficient V2X communication is integral to smart cities and autonomous driving vehicles. Energy-efficient and low-latency architectures are required to implement V2X communication [33]. V2X communication includes communication from the vehicle to the pedestrian, vehicle, network, and infrastructure, as illustrated in Figure 3. The main challenge in V2X communication is data exchange from vehicles to other units at high speed without losing data packets.

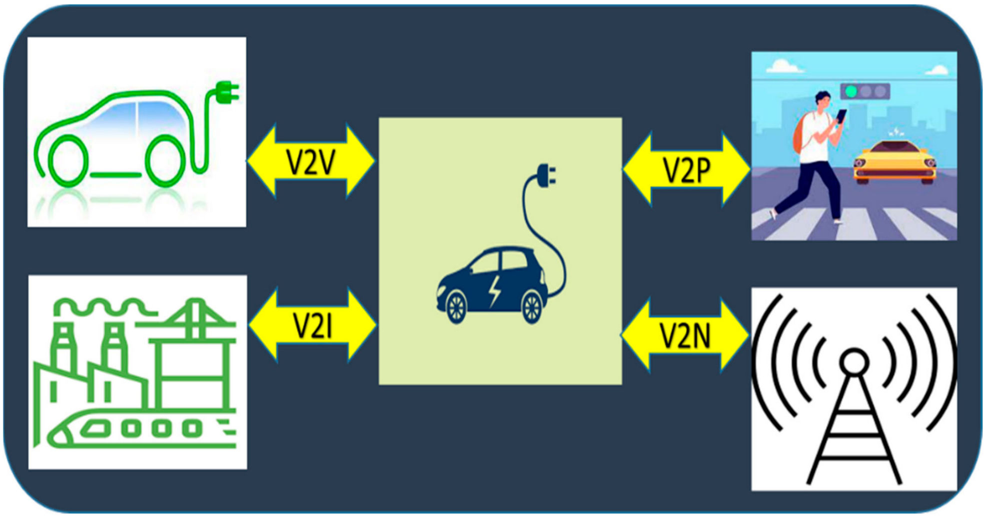

Figure 3. V2X communication of EVs.

The electronic units of the vehicle and the other infrastructure must respond to the requests sent by one another without causing much delay. Emerging technologies such as IoT, 5G, and LoRa are extensively used for V2X communication.

Using the Internet of Things (IoT) for EVs offers various advantages and flexibility. Various authors proposed different types of charging management systems using the IoT. An improved decentralized charging mechanism is proposed to coordinate the charging of large-scale EVs in various residential buildings [34]. EV batteries need to estimate an accurate charging status to enhance their lifespan. A battery management system using the Coulomb method and MQQT for communication has been proposed [35].

IoT helps communication between the vehicle and pedestrian and V2V. MQQT and COAP protocols are extensively used to transfer messages from machine to machine or machine to human beings. Bilateral communication, data gathering, and response control are the key features of IoT. Wired and wireless communication standards include Zigbee, Bluetooth low energy (BLE), LoRa, Wi-Fi, and cellular. Some of the IoT communication technologies are shown in Figure 4. A comparison of parameters of various communication technologies has been given in Table 3.

Table 3. Popular communication standards used in IoEVs.

Communication Technology	Standard	Speed	Range	Frequency Spectrum
Zigbee	IEEE 802.15.4	250 Kbps	100 m	2.4 GHz
LoRa/LoRaWAN	IEEE 802.15.g	27 Kbps	10 Km+	865–926 MHz
WiMAX	IEEE 802.16	70 Mbps	50 Km+	2–11 GHz
Wi-Fi	IEEE 802.11	100–250 Mbps	100 mts+	2.4, 5 GHz
GSM/GPRS	ETSI	114 Kbps	35 Km+	1800, 1900, 900 MHz
LTE	3GPP	0.1–1 Gbps	28 km/10 Km	700–2600 MHz

Many authors have proposed architectures and frameworks designed with the technologies mentioned above. Customers can visualize the energy consumption through energy management units (EMUs). EMUs help customers in power grid interactions. EMU connects to EV supply equipment (EVSE) via Zigbee (802.15.4) and other WLAN technologies. Most smart home ecosystem providers use Zigbee as a full stack solution [36].

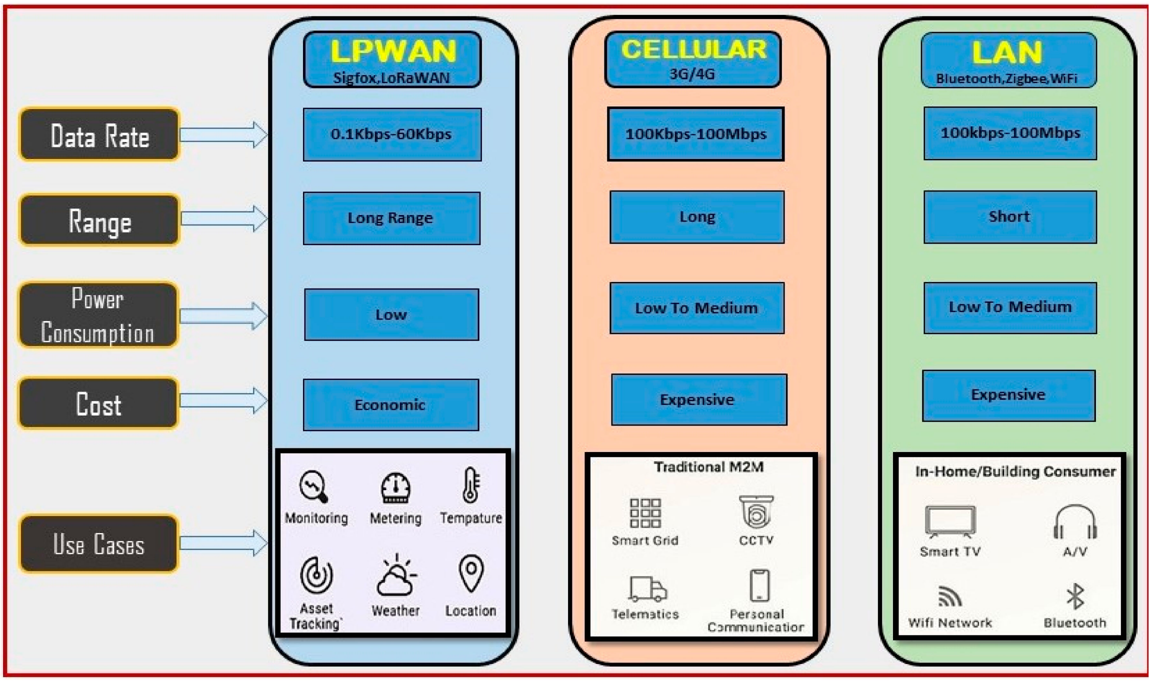

Figure 4. Types of communication technologies used in IoT.

Cellular communications with different operators offer services for smart grid applications. EMU and power meter manufacturers embed digital communication modules to enable garage charging. Application data such as energy consumption and prices are exchanged periodically. Most popular cellular networks have various advantages: (1) cellular communication technologies such as 5G are advanced enough to meet the requirements of smart grids; (2) since almost all of the cellular networks operate on a licensed spectrum, there is no need to use unlicensed bands in the spectrum; (3) all of the cellular networks are reasonably scalable in order to connect many EVs.

Mukarram A. M. Almuhaya et al. [37] discussed various trends, opportunities, and simulation tools for LoRa technology. The authors compared popular simulation tools to analyze the network performance of LoRa/LoRaWAN. The authors also classified the LoRa/LoRaWAN performance in terms of network scalability, network coverage, energy consumption, quality of service, and security. The various wireless communication standards used in EVs are given in Table 4.

Table 4. Various wireless communication standards used in EVs.

Reference	Objective	Wireless/Cellular Communication Standard	Solutions/Results	Advantages
[38]	Modeling and simulation of centralized EV charging station	Zigbee	Simulation of AODV routing protocol for EVCS using NS-2 simulator	The packet loss rate is significantly lower
[39]	Communication between PHEV and smart grid	Zigbee	Hardware modules such as Arduino boards were used, along with XCTU software for communication	Provides architectures to meet the interest of vehicle owners and grid operator
[40]	An EV charging system	Zigbee	Zigbee energy dispenser (ZED) with onsite charging hotspot subsystem and backend web portals subsystem was developed	Coordinates the dataflow among utility information systems and charging hotspot

Table 4. *Cont.*

Reference	Objective	Wireless/Cellular Communication Standard	Solutions/Results	Advantages
[41]	EV alarm regionalization management control system	Zigbee	Developed alarm system and tested multi-sensor information with data collection.	Strong robustness and high practicability
[42]	RFID mesh network design for EV smart charging infrastructure.	Zigbee	WINSmartEV four-channel smart charging infrastructure	Cost efficient to identify and authorize vehicles for charging
[43]	Heterogenous LPWAN communication for EV charging infrastructure	LoRa	Simulation of SNR characteristic of LoraWAN and hardware for communication is proposed	better noise performance, which extends to −20 dB with a BER performance of 10^{-5}
[44]	Implementation of smart energy meter using a LoRa network	LoRa	Residential electricity metering networks and an electrical variable measuring device for households using LoRa were created	Low power consumption and robustness
[45]	Vehicle charging architecture based on LoRa	LoRa	Developed LoRa protocol between EV and energy management	Vehicles obtain information on charging station before actually arriving there
[46]	Energy analysis of LoRaWAN technology for traffic sensing applications	LoRa	The adaptive algorithm was used to transmit sensor data collected over user-defined time intervals	Preventing data loss and better energy efficiency
[47]	Privacy protection model for V2X	5G	Intelligent vehicle-dispatching model	Optimizing the distributed power system to make up for the EV
[48]	Cyber security issues in 5G enabled EVCS	5G	Simulation of the FDI attack and DDoS attacks on 5G enabled remote (SCADA) system that controls the EV controller of the EVCS	Could safeguard the EVCS and its stakeholders from possible cyber threats
[49]	EV public charging network based on 5G	5G	Using forward and backward algorithms for optimizing the charging mode of EVs	Testing and processing 5G and big data EV public charging network research.
[50]	EV charging behavior analysis using hybrid intelligence	5G	Cloud-computing-based hybrid computing architecture with applications in the 5G-based vehicle-to-grid networks	EVs can be accurately identified with the classification method

Charging stations are evolving into much more than just a charger by utilising Wi-Fi to wirelessly interact between the electric vehicle, the user, and the infrastructure for charging. Wi-Fi is becoming the most effective method for controlling the charging process in both wired and wireless charging settings [51]. The wireless communication standards such as Zigbee and LoRa have been extensively used for developing the applications of EVs, such as the simulation of EVCS, network design for EV smart charging infrastructure, and implementation of smart energy meters using the LoRa network, etc., which are given in Table 5.

Table 5. Applications of communication standards in IoEVs.

Standard	Application in IoEVs
Zigbee (802.15.4)	Charging sub-system, The interaction between PEVs and grid, EVSE to EMU communication
LoRa, LoRaWAN	EV charging architectures, Data exchange between EMS and PEV
3G/4G/LTE/5G	Public charging of PEVs, Energy trading, Garage charging, EMU-to-grid and mobile-PEVs-to-control-center communication
Wi-Fi, WiMAX	Public charging, Load shifting, EMU-to-grid and mobile-PEVs-to-control-center communication

4. Computational Technologies for EVs

For the past few years, computational technologies such as artificial intelligence, big data, and blockchain have revolutionized many sectors, such as health care, education, defense, finance, agriculture, and banking. Artificial intelligence technologies such as machine learning and deep learning have been applied to many data sets for predicting and forecasting the results. Machine learning is a subset or branch of artificial intelligence that mimics human behavior. Supervised machine learning algorithms such as regression and classification can be applied to labeled data for analysis. Unsupervised machine learning algorithms such as dimensionality reduction, association, and clustering are extensively used in biology and target marketing applications. Reinforcement algorithms are extensively used in vehicle navigation applications. Reinforcement algorithms are also used in robotics for industrial automation.

Deep learning techniques are a subset of artificial intelligence that can be applied to unstructured data and facilitates computational models to learn features steadily from data at various stages. Deep learning techniques are extensively used in ADAS. Tools such as PyTorch, Keras, and tensor flow are used in research for deep learning applications.

Big data is a term that describes large, ever-increasing, complex, and hard-to-manage volumes of both structured and unstructured data, and it is difficult or impossible to process using traditional methods. With the growth of IoT, a huge volume of data are being generated by sensors, RFID tags, and smart meters, driving the need to analyze and draw insights from the big data. Specialized tools such as Apache spark and Hadoop are the popular big data technologies used for big data processing and analytics.

Blockchain technology records the transactions in a digital ledger, and it is impossible to change or hack the system [52]. The record is added to the participant's digital ledger whenever a new transaction happens. Blockchain uses a cryptographic signature, which is immutable and called a hash in distributed ledger technology in which transactions will be recorded. Bitcoin and Ethereum are the most popular crypto currencies that make use of blockchain's distributed ledger technology. The various computational technologies used for IoEVs are shown in Figure 5.

4.1. Machine Learning for Plug-In EVs

Machine learning is a subset of artificial intelligence popular for data science and computer vision applications. Machine learning technology can be used in EV-related applications to leverage the performance that enables the EV's success. As EV sales have rapidly increased, implementing infrastructure such as EVSE and managing the EVs effectively is tedious. EVs are chosen for energy sustainability. Machine learning technology can be used for managing and orchestrating EVs. Machine learning comprises three types of algorithms: supervised, unsupervised, and reinforcement as given in Table 6. The steps involved in applying machine learning algorithms to EVs is illustrated in Figure 6.

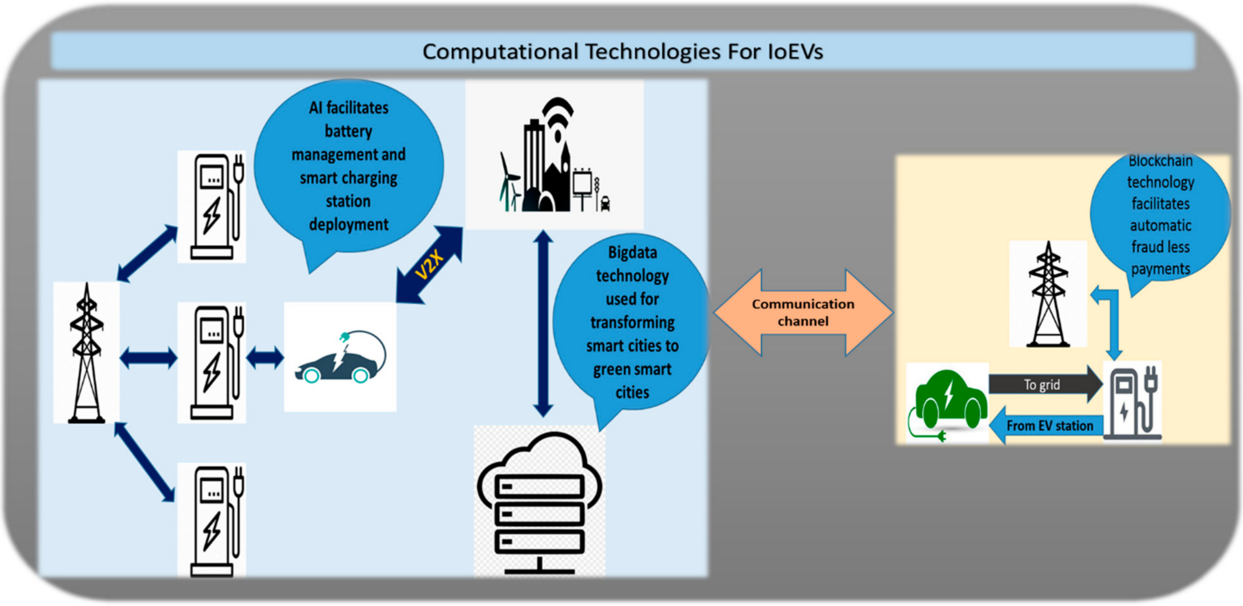

Figure 5. Computational technologies for IoEVs.

Table 6. Types of machine learning.

Machine Learning Type	Purpose
Supervised	Classification, Regression, Forecasting
Semi-Supervised	For labeled and unlabeled data
Unsupervised	Association, Clustering, Dimensionality reduction
Reinforcement	ANN, RNN

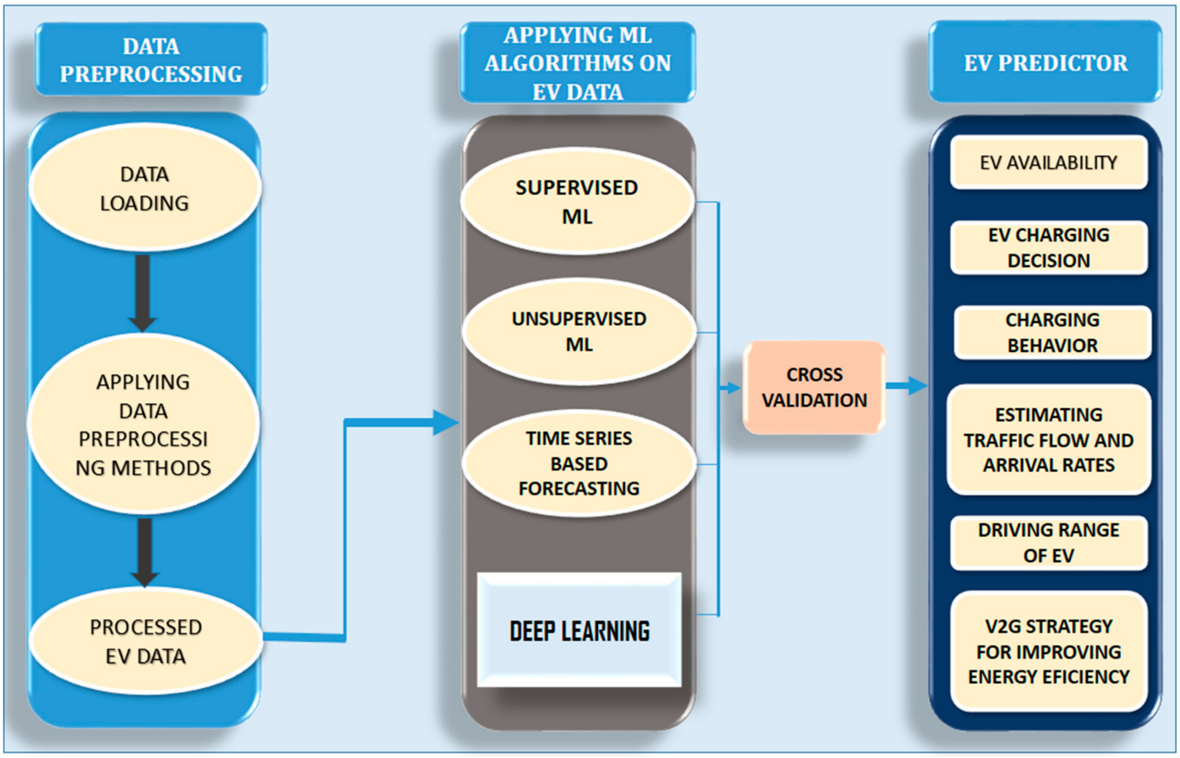

Figure 6. Applying ML algorithms for predicting EV.

Many researchers have developed EV charging recommendation systems for EVs. The recommendation system considers multiple spatiotemporal factors for recommending charging stations to the public

Unsupervised machine learning methods such as k-nearest neighbors, random forest, and decision trees have been used for load forecasting. The driving range of EVs is predicted inaccurately, and a better battery management system is required to estimate the energy left for further travel. Yong Wanga et al. proposed an efficient decision-tree-based gradient boosting algorithm (LGBM) to precisely predict the driving range of EVs. In this model, the feature importance scores are provided to discover the relationship. Donovan Aguilar-Dominguez et al. proposed a model to predict the availability of an EV providing the vehicle-to-home services [53]. Machine learning algorithms have been applied to the data related to distinct vehicle usage profiles, differentiated by the number of trips made per week to predict the availability of EVs. Rafael Basso et al. proposed a time-dependent EV routing problem with chance constraints (EVRP-CC) based on a Bayesian-based probability model [54]. A summary of different machine learning models used for predicting charging behavior is given in Table 7.

Table 7. Types of machine learning models used for predicting charging behavior.

Source	Predicting Term	Learning Model Type
[55]	EV charging departure time	Supervised ML (XG Boost and LR)
[56]	Energy consumption at a charging outlet on University campus	Supervised ML (KNN)
[57]	Daily charging times charging capacity	Supervised ML (Random Forest)
[58]	Charging behavior based on clustering	Unsupervised ML (K-Means)
[59]	User charging behavior based on distinct clusters	Unsupervised ML (GMM)
[60]	Charging demand of parking lot based on expected departure and arrival times	Time-Series-Based Forecasting (ARIMA)
[61]	Public charging station hourly load prediction	Deep Learning (RNN)
[62]	EV arrival rates and traffic flow estimation	Deep Learning (CNN)
[63]	Charging behavior based on labels obtained using clustering	Deep Learning (ANN)

In [55], O. Frendo et al. used XGBoost and LR to predict the EV departure time in order to improve smart charge optimization. An MAE of 82 min for departure was achieved. In [56], the supervised ML model KNN was used to predict energy consumption, resulting in 15.27% SMAPE. In [57], Y. Lu et al. used a random forest algorithm to predict the charging times and charging capacity, resulting in 9.76% MAPE.

S.Venticinque et al. in [58] used k-means and KNN algorithms to find the charging behavior and classify the data into clusters. In [59], J.R Helmus et al. used the unsupervised Gaussian mixture model to find unique user charging behavior for nonresidential charging. In [60], J.Zhu et al. used recurrent neural network (RNN)-based models to predict the hourly charging load of a public charging station. X. Zhang et al., in [61], used a convolutional neural network (CNN) to estimate traffic flow and arrival rates. In [62], Y.Xiong et al. used artificial neural networks (ANN) for predicting the charging behavior using clustering along with labels, resulting in a 78% accuracy.

In [64], Shuai Sun and Jun Zhang used machine learning and fuzzy-logic-based methods to drive the range prediction model to improve the prediction accuracy. In [65], Marina Dorokhova et al. used reinforcement learning approaches for routing EVs with intermediary charging stations. They used a reinforcement machine learning approach that aims to produce possible energy paths for EVs from the source to the target. Xue Lin et al. [66] proposed energy management in a hybrid EV to minimize total operating costs based on machine learning. The authors used the inner loop reinforcement learning process and outer loop adaptive learning to minimize the fuel usage and battery replacement cost. In [67], Connor Scott, Mominul Ahsan et al. used Holt–Winters and neural networks to improve the public buildings' energy performance. K-nearest neighbors, random forests, and decision trees have been used extensively by many researchers in the EVs domain for load forecasting and energy monitoring. The driving range and energy consumption of EVs using machine learning technology was discussed in [68]. Weijia Zhang et al. [69] proposed a multi-agent spatio-temporal reinforcement learning framework. It is a multi-objective and multi-agent reinforcement learning system. D. Cao et al. [70] proposed a prediction module for forecasting the dynamic charging load using machine learning (ML) techniques. A. Mathew et al. [71] discussed various approaches to deep learning algorithms, such as recurrent neural networks (RNN) and artificial neural networks. Deep learning is a method of clustering, classifying, and predicting things using different types of neural networks trained on huge amounts of data [72]. Many standard CNN models, such as AlexNet, GoogleNet, Inception-ResNet, VGG, etc., are available today to solve complex problems. Renesas company has designed a r-Car development framework to accelerate deep learning development for ADAS and automotive driving applications [73,74]. K.Lopez et al. [75] proposed the demand side management of EV smart charging using deep learning techniques. The authors used various deep learning techniques to manage smart charging.

4.2. Big Data Technology for EVs

Big data refers to the huge volume, complex, and variety of data that are difficult to process using traditional methods. Unstructured data such as text documents, emails, videos, and audio are part of big data [76]. EVs have made a massive impact on carbon-free transportation. EVs are the producers of data that are generated from various sources, such as onboard sensors and off-board sensors of various infrastructure, which communicate with PEVs. Once the big data are stored in the cloud databases, they can be used for developing algorithms, strategies for siting charging stations [77], and various policies for battery management systems. Big data technology facilitates EV manufacturers and policymakers to turn these challenges into opportunities. The real-time recharge data of EVs enable the companies to know how many EVs are using charging points in the vicinity [78]. IBM company and car manufacturer Peugeot teamed up to develop new connected car services, such as analyzing drivers' data to help retailers and car dealerships. IBM's big data and analytics platform allow Peugeot to analyze a wide range of driver and vehicle data for safe transportation. The data collected can improve road building decisions and ease traffic conditions in smart cities [79]. Streaming data can help drivers adapt to driving conditions and avoid dangerous situations.

The volume of the data has doubled every two years. Recent advances in IoT have increased the data's volume, variety, and velocity. The vast amount of data generated by buildings, EVs, and smart grids with the highest data transmission rates lead to big data. The difference between traditional data and big data is given in Table 8. Big data analytics uses innovative analytical techniques using large, different datasets containing distinct sizes of non-structural and structural data from various sources [80]. Various sensors inside and outside of the vehicle continuously transmit and receive data from infrastructure, pedestrians, vehicles, etc., leading to the generation of huge volumes of data. Harnessing this big data requires specialized data analytic tools to retrieve intelligent and meaningful insights. Apache spark and Hadoop are the two big data analytics tools available to solve the potential challenges of big data [81]. Big data analytics is essential to handle the huge volume of data generated by ESEVs, smart meters, and intelligent electronic devices [82]. Every EV consists of sensors and electronic subsystems to monitor the battery's driving behavior and energy level.

The amount of information generated by various sources can be stored and analyzed by various tools. One must distinguish big data from normal data before using the tools for drawing insights. Distinct strategies and tools are deployed for big data and traditional data [83]. Analytic tools used for traditional data may not support analyzing big data. Hadoop and Spark frameworks are extensively used for big data processing and analytics.

Table 8. Comparison of big data and traditional data.

	Big Data	Traditional Data
Data Type	Structured, semi-structured, unstructured	Structured
Data Structure	Distributed	Centralized
Relationship of Data	Complex	Uncertain
Data Volume	Petabytes and zettabytes	Terabytes

Apache Hadoop is a scalable and reliable distributed computing framework that can be used for processing large data sets across clusters of computers. The framework is designed to scale up from a single server to multiple servers. The framework also detects and handles failures at the application layer. The Apache framework includes modules such as Hadoop Common, HDFS, Hadoop YARN, and Hadoop MapReduce. The distributed file system is the core of the HDFS framework and provides a high throughput. Hadoop YARN and MapReduce are used for the cluster resource management and parallel processing of large data sets. The other related projects include Ambari, Cassandra, Hbase, Hive, etc. [83]. Apache Spark is another popular framework for executing data-science-related projects on single-node clusters. The key features of Apache Spark are real-time streaming data processing, SQL analytics, and machine learning. SQL queries can be executed quickly with Apache Spark for dashboarding and ad hoc reporting [84]. Apache Spark can be integrated with various machine learning and analytics frameworks.

A comparison of Hadoop and Spark frameworks can be seen in Table 9. Hadoop is best for batch processing, using the MapReduce feature to divide large data across clusters for parallel processing. In contrast, Spark is extensively used for live streaming data analysis. Apache Hadoop is extremely secure and supports LDAP, ACLs, etc. Spark relies on Hadoop for necessary security. The other big data tools and their purpose is given in Table 10.

Table 9. Comparison of Hadoop and Spark frameworks.

Parameter	Hadoop	Spark
Cost	Open-source platform	Open-source platform
Scalability	Using nodes and disks for scalability	Tough to scale because it depends on random access memory for computations.
Data Processing	Suitable for batch processing	Best for repetitive and live-stream data analysis
Ease of Use and Language Support	Java or Python can be used for MapReduce apps.	Application programming interfaces can be written in Python, Spark SQL, and Java.
Machine Learning		
Performance	Performance is lower because it depends on disk write and read speeds of secondary storage	High performance due to in-memory computations with reduced disk operations.

The data from PEVs, infrastructure, and charging stations comprise the big data of EVs, which require big data analytic tools running on the cloud platform. Mobile apps designed by automobile manufacturers can be used to monitor the vehicle's charging levels. Data are mainly generated from electronic units and the sensors on the vehicle. Authorized government enterprises can use big data to install charging stations based on the charging behavior and patterns of EV owners. The huge volumes of generated data with variety can be stored in the cloud for future projects.

Table 10. Purpose of various big data tools.

Big Data Tools	Purpose
Hadoop and HBase	To optimize the charging via job scheduling
Hadoop, Pig script, MySQL	To improve the interoperability of heterogeneous chargers
Cassandra and MongoDB	NoSQL DBMS for managing large databases
Hadoop and R statistical package	To improve the accuracy of the battery consumption model
J48 and M5 algorithms from Weka platform	To provide decision support for power system operators

Big data analytics is useful for applications such as battery monitoring, finding the better letter for installing charging stations, and PEV status tracking. Traditional statistical methods and algorithms are not useful for drawing actionable insights from big data. The challenges faced in using different big data tools is summarized in Table 11.

Table 11. Objectives and challenges in various big data applications.

Reference	Technology	Subdomain	Objectives	Challenges
[85]	Big data	IoEVs	Proposed a categotization of big data in IoV.	Extracting insights from multidimensional data generated from heterogeneous objects
[86]	Big data and ML	Driving Parameters	Proposed and developed a system prototype for improving the driver-braking style through visual elements	Gathering the data from in-vehicle sensors and components
[87]	Big data	Smart Cities	Highlighted the feature of edge computing that supports BDA activities in smart grid to EV integration in smart cities.	Integrating security features into design and development of edge architectures
[88]	Big data	IoEVs	Framework for EV range estimation	Gathering real-time and historical data of all standards
[89]	Big data	Intelligent Transportation	Big data analysis on EV data using fuzzy means and k means clustering algorithms	Gathering the data based on different traffic conditions.
[90]	Big data	Driving Parameters	Analyzing the energy consumption and driving range of EVs	Collecting driving patterns data from GPS data loggers.

In [85], Ansif Arroj et al. explored the key features of big data in the vehicle domain. The authors explored that conventional data gathering and analyzing methods are insufficient in yielding optimal results in big data applications. Giovanni Delnevo et al. [86] used big data and machine learning technology to improve the driver's braking style. The authors conducted tests with simulated and real data. Dr. Mo-Yuen Chow and Habiballah Rahimi-Eichi, in [88], proposed a framework for EV range estimation. The authors used various historical and standard data related to the driving range for big data analytics. Gebeyehu M. Fetene et al. [90] used big data technology to analyze the energy consumption rate (ECR) and driving range of battery vehicles. The authors collected the driving patterns of 741 drivers over two periods. Based on the research, the authors found that the performance of battery EVs (BEV) is highly dependent on weather conditions and driving patterns. In [91], W. Wei et al. proposed a model that processed data in parallel using

MapReduce over the Hadoop framework. Their model uses grid demand, an EV battery, a user, a charging station, and data from a local distribution system. The authors developed an optimized charging model, the multi-level feedback queue. Further studies are required to evaluate the performance using Hadoop and other framework works.

In [92], Lee et al. used the R statistical package and Hadoop framework for the proposed spatio-temporal analysis of EV data. The authors conducted time series analysis to predict the EVs battery consumption using the R Language package. J. Lee et al. proposed a framework to implement meter management for streaming EV data [93].

Bolly J. Springer et al. [94] used a pre-processing stage to eliminate duplicates and inconsistencies in the data. The authors extracted and transformed raw EV data into classified buckets. The authors took more than ten features of 200 EVs into consideration. The authors used Hadoop and MapReduce to process the unstructured data. Weka and Hadoop-based platforms can be considered for distributed data mining and streaming big data analytics.

One of the challenges in big data is the lack of publicly available real-time data on EVs and infrastructure. Efficient and secure data analytics approaches and tools are required for the real-time interaction of the EVs with the other infrastructure.

4.3. Blockchain Technology for EVs

A blockchain is a distributed digital ledger shared across a private or public computing network that nullifies the role of central authority to verify transactions between two or more parties [95]. Transactions will be encrypted mathematically and added as a new block to the chain of records, authenticated by multiple consensus protocols before being added to the ledger. Blockchain technology can be used in EVs for efficient payment processing. Blockchain transactions are recorded with a hash called SHA 256, which is used to verify the transaction's authenticity. Blockchain is a disruptive technology for cyber security, healthcare, and finance.

Blockchain technology can cause a massive impact on the EVs domain [96]. The publication statistics for the use of blockchain for EVs is shown in Figure 7.

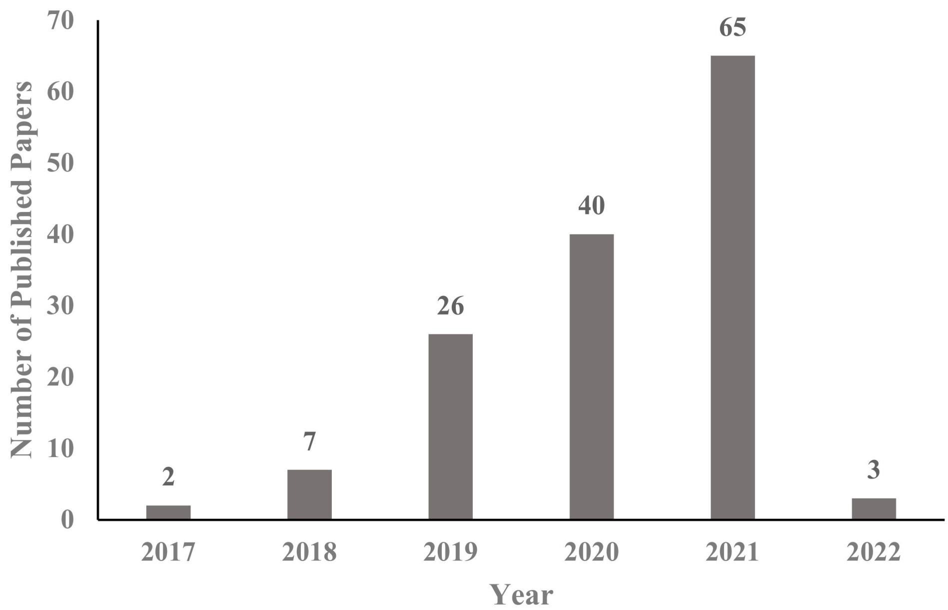

Figure 7. Publications on blockchain for EVs.

In addition, it shows an increasing trend, indicating its popularity for EV applications. The general architecture of blockchain for EV applications is shown in Figure 8.

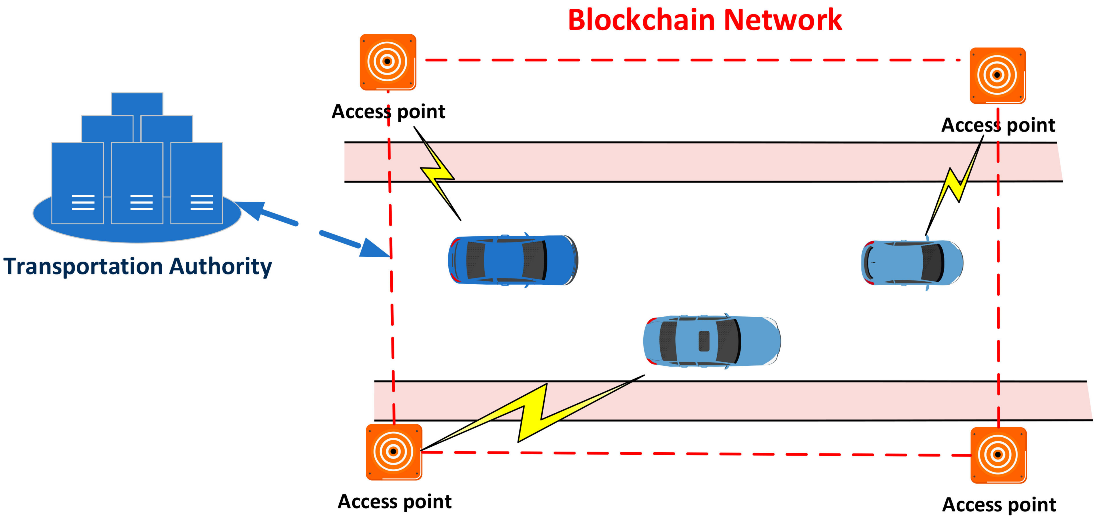

Figure 8. Blockchain architecture for EV applications.

Leveraging blockchain technology for EV-related applications will boost the development of the EV industry. The above figure represents the architecture of blockchain for EV infra. V2X commutations such as vehicle-to-access-point mechanisms are extensively used in blockchain architecture. Each EV in the architecture is a mobile entity and will have a unique ID. Nodes or access points are the electronic units capable of receiving the data from EVs, so nodes or access points are to be placed at regular intervals. Sensors embedded in the EVs continuously monitor the status of various parameters, such as the battery status, vehicle status, bill payment for charging, etc., and send them to the access points using various wireless communication technologies. The access points communicate among themselves either by wired or wireless communication technology. The access points in the blockchain network consider the data as blocks, and each access point must validate the transaction to ensure transparency. The transport authorities access the blockchain network to continuously monitor the status of the EVs and send personalized recommendations to the EV user.

The benefits of using blockchain technology for EVs are that payments can be verified instantly by automatic confirmations, and the payments of EVs can be processed automatically, executing contracts directly with the station based on user convenience [96]. Various blockchain platforms are available to build blockchain applications. The popular blockhead platforms are the XDC network, Ethereum, Hyperledger Fabric, R3Corda, Ripple, etc., and are summarized in Table 12 [97].

Table 12. Blockchain platforms based on industry and ledger type.

	XDC Network	Ethereum	Hyperledger Fabric	R3 Corda	Ripple
Industry Type	Cross-Industry	Cross-Industry	Cross-Industry	Financial Services	Financial Services
Ledger Type	Permission-less	Permission-less	Permissioned	Permissioned	Permissioned

Ethereum is a peer-to-peer decentralized blockchain platform that establishes a network that securely executes and verifies an application code, called smart contracts. Extremely flexible decentralized applications can be built using the solidity scripting language and Ethereum virtual machine [98]. Smart contracts are the application codes written in Solidity and Vyper that reside at a specific address on the blockchain. A transaction in Ethereum refers to a signed data package that stores a message to be sent from an externally owned account [99]. Financial and semi-financial applications can be designed on top of Ethereum. Hyperledger Fabric is the first distributed platform supporting smart contracts written in Go, Java, and Node.js programming languages [100]. The Fabric platform is permissioned, which means that the participants may not fully trust one another, but a governance model is built off of what trust exists between participants [93]. Hyperledger Fabric uses pluggable management identity protocols such as LDAP or OpenID connect. In [101], problems such as a lack of transparency in trading systems can be mitigated with blockchain technology. Blockchain can be used for automatic payment processing at toll stations. Many companies are developing e-wallets for payment processing. Users of PEVs can sell the excess electricity to charging stations through smart contracts and pay the bills through e-wallets [102]. A comparison of Hyperledger Fabric and Ethereum are shown in Table 13.

Table 13. Comparision of Hyperledger Fabric and Ethereum frameworks.

	Hyperledger Fabric	**Ethereum**
Public vs. Private	Private	Public
Governance	Federated	Decentralized
Permissions	Permissioned	Permissionless
Smart Contract Languages	Go, Java, Javascript (Node.js)	Solidity, Vyper
Private Transactions	Yes	No
Consensus Mechanism	Pluggable BFT	Proof-of-Work
Speed	3000 Tps	15 Tps

In [101], Prince Waqas Khan et al. proposed a payment method for energy trading and charging for EVs based on blockchain technology. The authors developed an automatic payment system for EVs using the Hyperledger Fabric platform. The proposed scheme will reduce human interaction and increase EV users' transparency, privacy, and trust. The authors also assessed the latency and throughput of resource utilization.

Javed et al. [102] used blockchain technology to provide a solution for the secured scheduling of the charging system. They introduced V2V and V2G charging strategies. In [103], Pustiek et al. introduced the concept of blockchain-independent negotiation. In [104], Xiang et al. used blockchain technology to provide automated demand response solutions for EVs.

In [105], Shang et al. used Multi-Objective Gray Wolf Algorithm to build charging and discharging model on blockchain. The article by Duan et al. [106] used IoT and blockchain-based smart contracts to propose charging methods for EVs. In [107], Khan et al. used blockchain technology for vehicle networking applications, mainly considering the decentralized big data storage and security. Authors defined different nodes, such as road networks and vehicles, to form different blockchain subnets

A summary of the various works on blockchain for EVs is given in Table 14.

P. Bhattacharya et al. proposed a trusted and secure energy trading scheme for EVs based on blockchain technology [108]. The authors used 5G-enabled software-defined networks (SDN), which allow the V2I nodes to handle multiple requests with a lower response time, which is a secure and trusted energy trading scheme for trusted EVs based on blockchain technology. The authors used 5G-enabled software-defined networks (SDN), allowing V2X nodes to handle multiple requests with a minimum response time. Furqan Jameel et al. in [109] proposed an efficient mining cluster selection for V2X communications based on blockchain technology. Their work showed an improved performance over the conventional nearest mining cluster selection technique. MyeongHyun Kim et al., in [111], proposed a charging system for EVs to resolve the security flaws, such as privileged insider attacks and a distributed denial of service. The proposed charging system ensures secure mutual authentication, security of key, and perfect forward secrecy. The authors also compared computation and communication costs with previous schemes.

Table 14. Challenges of blockchain technology in the EV domain.

Reference	Objectives	Subdomain	Technologies	Solution	Advantages	Challenges
[108]	Efficient energy trading scheme for V2X communications	V2X communications	Blockchain and 5G	Adopting a game-theoretic approach to efficiently unload the mining tasks to the mining clusters	The block convergence time is less, with minimal computation and good data transfer rates to maintain the fairness of the vehicles in the unloading process	Scalability of the data chains within the blockchain and the impact of data security in the process of downloading data into EVs
[109]	Efficient mining cluster selection for V2X communications	Secure V2X communications	Blockchain and named data networking (NDN)	Deploying a novel framework with finite block length architecture	Good data transmission rates and maintaining fairness among offloading vehicles	Without the right cluster, the secure V2X sequence does not help in improving network performance
[110]	Energy trading and charging payment system for EVs	Demand side management for smart grid	Private blockchain	Opportunistic scheduling algorithms to reduce electricity cost	Real-time pricing for unpredictable energy consumption trends	Development of a priority enabled scheduling algorithms based on constraints
[111]	EV charging system	Charging system model	Hyperledger Fabric blockchain platform	A secure and practical EV charging system	Proved secure mutual authentication between EV and EAG	Developing schemes for mutual authentication and key agreement to provide security
[112]	A review of Ethereum blockchain platform	Application of Ethereum blockchain platform	Ethereum Blockchain platform	Application in finance	Efficiency and security	Techniques to improve the efficiency of public and private Ethereum chain

In above table, various authors worked on their objectives and provided solutions using different blockchain platforms, such as Ethereum and private platforms. Advantages and challenges are also mentioned in above table. In [113], Danda et al. proposed a framework for privacy-aware V2X communications by using named data networking (NDN) and blockchain. The authors did not use the confidential information of the vehicle owners and pedestrians in their work. The authors claim that the overall network performance can be improved by clustering the users. In [95], the authors proposed a broad methodology for designing blockchain-based systems and show how to apply it to EVs.

In [114], Ayesha Sadiq et al. used blockchain technology to work on data and energy trading in IoEV. The authors also used an inter-planetary file system (IPFS), which provides reliable and fault tolerant data storage for overcoming failures. The authors also produced results that explain the efficacy of their proposed data and energy trading scheme in IoEV. Ahmed S. Musleh et al. [115] proposed frameworks for key smart grid blockchain-based applications. The authors also reviewed different prospects and technical challenges in utilizing blockchain technology for smart grid applications. Marina Dorokhova et al. [116] proposed an Ethereum-based framework for the charging management of EVs. The proposed framework enables the reliable and secure accounting of energy exchanges in a network, thus facilitating EV charging through private charging infrastructure. Al-Saif Nasser et al. [117] provided various opportunities, requirements, and challenges in their work. There are various opportunities of blockchain in EV energy trading, such as stakeholder reputation-aware energy trading, streamlined billing and payments, automatic energy auctioning, and automated vehicle-to-grid energy trading. The authors discussed various blockchain opportunities in energy trading in detail with respective designs. The authors also discussed various research projects by research organizations and companies.

Various technological and organizational challenges may affect the adoption of blockchain technology for EVs. The main challenges for adopting blockchain technology in EVs are scalability, interoperability, privacy, and security. Godwin C. Okwuibe et al. [118] proposed a blockchain-based smart charging infrastructure. The maximum duration of the charging event and charging of the EV user will provide the demand. The authors simulated the charging system with different loads and achieved an acceptance rate of EV users that increased by more than 50 percent. Blockchain technology can reduce a company's production costs with the blockchain track-and-trace feature. This feature allows manufacturers to track materials, such as wolframite and cobalt, as they are brought for production [119]. Blockchain also allows manufacturers to monitor the discrepancies while materials are brought into the factory for EV production. Various authors proposed frameworks and policies related to EV energy trading systems using blockchain technology. Machine learning and deep learning technologies can be used along with blockchain technology for a better analysis and prediction with transparency.

4.4. Security Aspects of EVs

EVs are being used by many people currently in the urban and semi-urban areas of the world because of their ease of use. Various automobile manufacturers have been manufacturing plug-in EVs for the past few decades. EVs have low greenhouse gas emissions and lower maintenance and operating costs. The EV users can generate revenue by selling the electricity stored in their car's batteries to the grid. The disadvantages of using EVs are the cost of batteries, swapping the batteries at the right time, charging station availability while travelling farther places, and an overload on electric grids during charging at peak hours. Every EV, whether a BEV (battery EV) or plug-in EV, contains various electronic systems and relevant system software to interact with the sensors and other infrastructure inside and outside of the vehicle. Providing security for EV hardware and software is essential for mitigating its risks. EVs can communicate with pedestrians, vehicles, and infrastructure by sending messages and signals.

A certain level of risk is involved in the connected devices. Connected cars send essential information about the driver and other systems of the vehicle to the other infrastructure with the Internet. In 2019, the number of cyber-attacks on connected cars increased to seven times [120]. Most EVs and connected cars rely on embedded software to efficiently manage and operate the systems. A hacker can exploit the security vulnerabilities, such as disabling the brakes, taking control of steering, disabling cameras, sensors, electronic control units (ECUs), and accessing the personal information of the vehicles and other infrastructure [121]. Most connected cars and EV users use mobile applications to control infotainment systems and other Bluetooth-technology-related operations, which may increase the security risk. The EV charging security is the main concern currently because an application is very much needed to communicate with EV supply equipment (EVSE) for charging. One must focus on the components of EVSE, such as firmware updates, physical access points, the communication channel between the vehicle and EVSE, and the mobile application that the vehicle driver uses for tracking the charging [121].

Various automotive industries are practicing various coding standards for EV security. ISO21434 is the automotive standard used by auto makers to reduce cyber security risks [121]. Because of the complex ecosystem of the EVs and EVSE, it is challenging to mitigate some of the issues regarding the cyber security risks. The important challenges are limitations of the devices and communication channels, identity and communication management, and access and authorization control. Various types of attacks, such as denial of service, a delay attack, and a Sybil attack on EV infrastructure show a social, physical, and cyber impact. Using the above attacks, the hackers can break the communication either at a broader or aggregate level; requesting power at incorrect timings may cause breakdowns; and the hackers can copy ID tokens for various purposes [122]. Security researchers have proposed authentication protocols to protect data exchange between the charging station and EV. In [123], the authors discussed various aspects of security, threats, and the threat model in the EV charging system. The authors also compared various security protocols that offer authentication, secure payment, and billing facilities. Farooq et al. [124] proposed an authentication protocol that provides direct authentication mechanisms between different components. Hamouid et al. [125] designed a protocol for EV charging systems. The protocol hides the location of the EV during the entire charging process and also provides other features, such as fast authentication and anonymity. Various researchers proposed security-related protocols for various purposes to mitigate the cyber security risks in the smartgrid domain [126–130].

5. Conclusions

EVs are the future of reliable and carbon-emission-free transportation. Unlike traditional vehicles, EVs directly interact with the electricity grid. Their impact on the grid operation exponentially increases as their numbers rise. Therefore, researchers have focused on developing solutions to efficiently communicate with EVs and control their behavior, not only to minimize their negative impacts on the grid but also to make them contribute to grid stability and reliability. The authors discussed various communication and computational standards and their applications in the EV domain. Applications of EV industry protocols and standards in various scenarios, such as authorizing charging sessions, billing, managing the grid, operating the charge point, reservation, and smart charging use cases, have been emphasized. Communication standards during charging for various purposes, such as grid-to-vehicle and vehicle-to-grid energy transfers and communication between the EV and off-board DC charger, have been discussed. Various wireless communication technologies, such as Zigbee, BLE, Wi-FI, and LoRa, are used for V2X communication for efficient data transfer and security. Use cases of communication technologies in the IoEV domain were discussed in the paper. Computational technologies such as ML and neural networks are used to predict the charging behavior and find the optimum location of charging stations. Apart from the above two use cases, machine learning algorithms can monitor the battery status and driver habits. The paper also discusses applying bigdata tools in the EV domain for the generated data. Authors have also discussed the work of different authors who have carried out work on the security aspects of EVs, such as authentication, secure payment, and billing facilities. The authors have conducted an extensive literature survey on computational and communication technologies to meet the needs of authors and researchers to find the gap in the EV research domain and pursue their research successfully. For efficient communication, various protocols and standards are available for vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-person communication. Machine learning and deep learning can be used for decision making and predictive analytics for EV-charging control. Blockchain technology can be used for energy-trading systems for EVs for transparent and secure transactions. All of the technologies mentioned above and communication standards can be used in the EV industry for building frameworks, architectures, and policies for better future prospects. Only in this fashion can a full-scale migration to EVs be possible.

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Abbreviations

AI	Artificial Intelligence
ADAS	Advanced Driver-Assistance Systems
ANN	Artificial Neural networks
AODV	Ad hoc On-demand Distance Vector
BLE	Bluetooth Low Energy
CNN	Convolutional Neural Network
COAP	Constrained Application Protocol
DDoS	Distributed Denial-of-Service
DER	Distributed Energy Resources
EV	Electric Vehicle
EVCS	EV Charging Station
eMIP	eMobility Protocol Inter-Operation
EMU	Energy Management Unit
EVSE	EV Supply Equipment
IBM	International Business Machines
IEC	International Electro technical Commission
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IoEV	Internet of EVs
LoRa	Long Range
IoV	Internet of Vehicles
LPWAN	Low-Power Wide-Area Network
ML	Machine Learning
MQQT	Message Queuing Telemetry Transport
OCHP	Open Clearing House Protocol
OCPI	Open Charge Point Interface
OCPP	Open Charge Point Protocol
OpenADR	Open Automated Demand Response

OSCP	Open Smart Charging Protocol
PEV	Plug-in EV
LTE	Long-Term Evolution
RFID	Radio Frequency Identification
RNN	Recurrent Neural Network
SAE	Society of Automotive Engineers
SCADA	Supervisory Control And Data Acquisition
SQL	Structured Query Language
V2G	Vehicle-to-Grid
V2I	Vehicle-to-Infrastructure
V2P	Vehicle-to-Pedestrian
V2X	Vehicle-to-Anything
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local-Area Network
ZED	Zigbee Energy Dispenser

References

1. EV Sales Surge in 2021. Available online: https://www.power-technology.com/news/electric-vehicle-sales-surge-in-2021/ (accessed on 15 September 2021).
2. Alternative Fuels Data Center: Emissions from EVs. Available online: https://afdc.energy.gov/vehicles/electric_emissions.html (accessed on 9 August 2022).
3. How Green Are EVs? Available online: https://www.nytimes.com/2021/03/02/climate/EVs-environment.html (accessed on 10 April 2022).
4. Why the Future of EVs Appears Promising in India. Available online: https://www.eletimes.com/ (accessed on 10 April 2022).
5. EV Charging Industry Protocols and Standards. Available online: https://driivz.com/blog/ (accessed on 10 April 2022).
6. Available online: https://www.elaad.nl/uploads/downloads/downloads_download/EV_related_protocol_study_v1.1.pdf (accessed on 10 April 2022).
7. James, M.; Myers, E.; Ealey, B.; Wey, V. Communication Protocols for Managed EV Charging and V2G Applications. In Proceedings of the 33rd EV Symposium (EVS33), Portland, OR, USA, 14–17 June 2020.
8. EVs Charging Equipment's Technical Report; Pike Research: 2011. Available online: https://www.ecmweb.com/content/article/20885651/pike-research-report-on-ev-charging-equipment (accessed on 10 April 2022).
9. Selim Ustun, T. (Ed.) *Advanced Communication and Control Methods for Future Smartgrids*; IntechOpen: Rijeka, Croatia, 2019. [CrossRef]
10. Sadeghian, O.; Oshnoei, A.; Mohammadi-ivatloo, B.; Vahidinasab, V.; Anvari-Moghaddam, A. A Comprehensive Review On Electric Vehicles Smart Charging: Solutions, Strategies, Technologies, And Challenges. *J. Energy Storage* **2022**, *54*, 105241. [CrossRef]
11. Neaimeh, M.; Andersen, P.B. Mind the Gap-Open Communication Protocols for Vehicle Grid Integration. Available online: https://energyinformatics.springeropen.com/track/pdf/10.1186/s42162-020-0103-1.pdf (accessed on 10 April 2022).
12. Vidhya, H.; Allirani, S. A Literature Review on EVs: Architecture, Electrical Machines for Power Train, Converter Topologies and Control Techniques. In Proceedings of the IEEE 2021 International Conference on Computational Performance Evaluation (ComPE), Shillong, India, 2–4 July 2021; pp. 565–575.
13. Zhang, F.; Zhang, X.; Zhang, M.; Edmonds, A.S. Literature Review of EV Technology and Its Applications. In Proceedings of the IEEE 2016 5th International Conference on Computer Science and Network Technology (ICCSNT), Changchun, China, 10–11 December 2016; pp. 832–837. [CrossRef]
14. Plug-in-Electric-Vehicles-Literature-Review. Available online: https://www.c2es.org/wp-content/uploads/2011/07/plug-in-electric-vehicles-literature-review.pdf (accessed on 15 February 2022).
15. Liao, F.; Molin, E.; van Wee, B. Consumer Preferences For EVs: A Literature Review. *Transp. Rev.* **2016**, *37*, 252–275. [CrossRef]
16. Kumar, R.R.; Alok, K. Adoption of EV: A Literature Review and Prospects for Sustainability. *J. Clean. Prod.* **2020**, *253*, 119911. [CrossRef]
17. Sanguesa, J.A.; Torres-Sanz, V.; Garrido, P.; Martinez, F.J.; Marquez-Barja, J.M. A Review on EVs: Technologies and Challenges. *Smart Cities* **2021**, *4*, 372–404. [CrossRef]
18. Arias-Londoño, A.; Montoya, O.D.; Grisales-Noreña, L.F. A Chronological Literature Review of EV Interactions with Power Distribution Systems. *Energies* **2020**, *13*, 3016. [CrossRef]
19. Ustun, T.S.; Zayegh, A.; Ozansoy, C. EV Potential in Australia: Its Impact on Smartgrids. *IEEE Ind. Electron. Mag.* **2013**, *7*, 15–25. [CrossRef]
20. Begwani, A.K.; Ustun, T.S. Electric bus migration in Bengaluru with dynamic charging technologies. *AIMS Energy* **2017**, *5*, 944–959. [CrossRef]
21. ElGhanam, E.; Hassan, M.; Osman, A.; Ahmed, I. Review of Communication Technologies for Electric Vehicle Charging Management and Coordination. *World Electr. Veh. J.* **2021**, *12*, 92. [CrossRef]

22. Ustun, T.S.; Ozansoy, C.R.; Zayegh, A. Implementing Vehicle-to-Grid (V2G) Technology with IEC 61850-7-420. *IEEE Trans. Smart Grid* **2013**, *4*, 1180–1187. [CrossRef]
23. Hussain, S.S.; Ustun, T.S.; Nsonga, P.; Ali, I. IEEE 1609 WAVE and IEC 61850 Standard Communication Based Integrated EV Charging Management in Smart Grids. *IEEE Trans. Veh. Technol.* **2018**, *67*, 7690–7697. [CrossRef]
24. Nsonga, P.; Hussain, S.S.; Ali, I.; Ustun, T.S. Using IEC 61850 and IEEE WAVE standards in ad-hoc networks for EV charging management. In Proceedings of the IEEE Online Conference on Green Communications, Piscataway, NJ, USA, 14 November–17 December 2016; pp. 39–44.
25. Farooq, S.M.; Hussain, S.S.; Ustun, T.S. A Survey of Authentication Techniques in Vehicular Ad-Hoc Networks. *IEEE Intell. Transp. Syst. Mag.* **2021**, *13*, 39–52. [CrossRef]
26. Farooq, S.M.; Hussain, S.S.; Kiran, S.; Ustun, T.S. Certificate Based Security Mechanisms in Vehicular Ad-Hoc Networks based on IEC 61850 and IEEE WAVE Standards. *Electronics* **2019**, *8*, 96. [CrossRef]
27. Aftab, M.A.; Hussain, S.S.; Ali, I.; Ustun, T.S. IEC 61850 and XMPP Communication Based Energy Management in Microgrids Considering EVs. *IEEE Access* **2018**, *6*, 35657–35668. [CrossRef]
28. Ustun, T.S.; Hussain, S.M.S.; Syed, M.H.; Dambrauskas, P. IEC-61850-Based Communication for Integrated EV Management in Power Systems with Renewable Penetration. *Energies* **2021**, *14*, 2493. [CrossRef]
29. SAE Vehicle Electrification Standards. Available online: http://www.sae.org/smartgrid (accessed on 12 June 2022).
30. Gowri, K.; Pratt, R.G.; Tuffner, F.K.; Meyer, K. *Vehicle to Grid Communication Standards Development, Testing and Validation: Status Report*; Technical Report; Pacific Northwest National Laboratory: Richland, WA, USA, 2011.
31. Ustun, T.S.; Hussain, S.M.S.; Kikusato, H. IEC 61850-Based Communication Modeling of EV Charge-Discharge Management for Maximum PV Generation. *IEEE Access* **2019**, *7*, 4219–4231. [CrossRef]
32. Ustun, T.S.; Ozansoy, C.; Zayegh, A. Extending IEC 61850-7-420 for distributed generators with fault current limiters. In Proceedings of the 2011 IEEE PES Innovative Smart Grid Technologies, Perth, Australia, 13–16 November 2011; pp. 1–8.
33. Hussain, S.M.S.; Aftab, M.A.; Ali, I.; Ustun, T.S. IEC 61850 based energy management system using plug-in EVs and distributed generators during emergencies. *Int. J. Electr. Power Energy Syst.* **2020**, *119*, 105873. [CrossRef]
34. Yao, L.; Chen, Y.-Q.; Lim, W.H. Internet of Things for EV: An Improved Decentralized Charging Scheme. In Proceedings of the 2015 IEEE International Conference on Data Science and Data Intensive Systems, Sydney, Australia, 11–13 December 2015. [CrossRef]
35. Asaad, M.; Ahmad, F.; Alam, M.S.; Rafat, Y. Department of Electrical Engineering, Aligarh Muslim University, IoT enabled EV's Battery Monitoring System. In Proceedings of the 1st EAI International Conference on Smart Grid Assisted Internet of Things, Marie, ON, Canada, 11–12 July 2017; pp. 1–10. [CrossRef]
36. Zigbee Alliance. Available online: http://www.zigbee.org/ (accessed on 10 April 2022).
37. Almuhaya, M.A.M.; Jabbar, W.A.; Sulaiman, N.; Abdulmalek, S. A Survey on LoRaWAN Technology: Recent Trends, Opportunities, Simulation Tools and Future Directions. *Electronics* **2022**, *11*, 164. [CrossRef]
38. Liu, C.; Zhou, Q.; Hu, J.; Xu, H.; Zhang, H. International Conference on Advances in Computational Modeling and Simulation. *Procedia Eng.* **2021**, *31*, 746–750. [CrossRef]
39. Rao, K.; Bobba, P.B. Communication between PHEV's and Smart Grid using Zigbee Protocol. In *E3S Web of Conferences*; EDP Sciences: Les Ulis, France, 2019. [CrossRef]
40. Lam, K.L.; Ko, K.Y.; Tung, H.Y.; Tung, H.C.; Tsang, K.F.; Lai, L.L. ZigBee EV Charging System. In Proceedings of the IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 9–12 January 2011.
41. Zeng, Z.; Sun, X. EV regional management system based on the BSP model and multi-information fusion. *Syst. Sci. Control Eng.* **2021**, *9* (Suppl. 1), 114–121. [CrossRef]
42. Chung, C.Y.; Shepelev, A.; Qiu, C.; Chu, C.-C.; Gadh, R. Design of RFID Mesh Network for EV Smart Charging Infrastructure. In Proceedings of the IEEE International Conference on RFID-Technologies and Applications (RFID-TA), Johor Bahru, Malaysia, 4–5 September 2013. [CrossRef]
43. Aiju, T.; Eldhose, N.V. Heterogeneous LPWAN Communication for Electric Vehicle Charging Infrastructure. *Int. J. Innov. Technol. Explor. Eng.* **2019**, *9*, 2060–2067. [CrossRef]
44. Francisco Sánchez, S.; Ortega, A.C.; Hernández, J.C. Design and Implementation of a Smart Energy Meter Using a LoRa Network in Real Time. *Electronics* **2021**, *10*, 3152. [CrossRef]
45. Ouya, A.; De Aragon, B.M.; C'ecile, B.; Habaulty, G. An Efficient EV Charging Architecture based on LoRa Communication. In Proceedings of the IEEE International Conference on Smart Grid Communications, Dresden, Germany, 23–27 October 2017; pp. 23–26.
46. Mathur, S.; Sankar, A.; Prasan, P.; Iannucci, B. Energy Analysis of LoRaWAN Technology for Traffic Sensing Applications. In Proceedings of the ITS World Congress, Montreal, QC, Canada, 29 October–2 November 2017.
47. Xu, C.; Wu, H.; Liu, H.; Li, X.; Liu, L.; Wang, P. An Intelligent Scheduling Access Privacy Protection Model of EV Based on 5G-V2X. *Sci. Program.* **2021**, *2021*, 1198794.
48. Manoj, B.; Hasan Ali, M.D. Exploring Cybersecurity Issues in 5G Enabled EV Charging Station with Deep Learning. *IET Gener. Transm. Distrib.* **2021**, *15*, 3435–3449. [CrossRef]
49. Yao, W.; Zhang, C.; Deng, G.; Ke, W.; Zhang, D.; Li, L. Research on Urban EV Public Charging Network Based on 5G and Big Data. *J. Phys. Conf. Ser.* **2021**, *2066*, 012045. [CrossRef]

50. Yi, S.; Wei, F.; Feng, Y.; Kadoch, M. EV Charging Behavior Analysis Using Hybrid Intelligence for 5G Smart Grid. *Electronics* **2020**, *9*, 80. [CrossRef]
51. Wi-Fi Takes EV Charging Infrastructure Next Level. Available online: https://www.u-blox.com/en/blogs/insights/ (accessed on 10 January 2022).
52. Hussain, S.M.S.; Farooq, S.M.; Ustun, T.S. Implementation of Blockchain technology for Energy Trading with Smart Meters. In Proceedings of the Innovations in Power and Advanced Computing Technologies, Vellore, India, 22–23 March 2019; pp. 1–5.
53. Dominguez, D.A.; Ejeh, J.; Dunbar, A.D.F.; Brown, S.F. Machine learning approach for EV availability forecast to provide vehicle-to-home services. In Proceedings of the 5th Annual CDT Conference in Energy Storage & Its Applications, Virtual, 12–13 January 2021. [CrossRef]
54. Basso, R.; Kulcsárb, B.; Diazc, I.S. EV routing problem with machine learning for energy. *Transp. Res.* **2021**, *145*, 24–55. [CrossRef]
55. Frendo, O.; Gaertner, N.; Stuckenschmidt, H. Improving Smart Charging Prioritization by Predicting EV Departure Time. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 6646–6653. [CrossRef]
56. Majidpour, M.; Qiu, C.; Chu, P.; Gadh, R.; Pota, H.R. Fast prediction for sparse time series: Demand forecast of EV charging stations for cell phone applications. *IEEE Trans. Ind. Inform.* **2015**, *11*, 242–250. [CrossRef]
57. Lu, Y.; Li, Y.; Xie, D.; Wei, E.; Bao, X.; Chen, H.; Zhong, X. The application of improved random forest algorithm on the prediction of EV charging load. *Energies* **2018**, *11*, 3207. [CrossRef]
58. Venticinque, S.; Nacchia, S. *Learning and Prediction of E-Car Charging Requirements for Flexible Loads Shifting in Internet and Distributed Computing Systems*; Springer Nature: Berlin/Heidelberg, Germany, 2019; pp. 284–293.
59. Helmus, J.R.; Lees, M.H.; van den Hoed, R. A data driven typology of EV user types and charging sessions. *Transp. Res. C Emerg. Technol.* **2020**, *115*, 102637. [CrossRef]
60. Amini, M.H.; Kargarian, A.; Karabasoglu, O. ARIMA-based decoupled time series forecasting of EV charging demand for stochastic power system operation. *Electr. Power Syst. Res.* **2016**, *140*, 378–390. [CrossRef]
61. Zhu, J.; Yang, Z.; Guo, Y.; Zhang, J.; Yang, H. Short-term load forecasting for EV charging stations based on deep learning approaches. *Appl. Sci.* **2019**, *9*, 1723. [CrossRef]
62. Zhang, X.; Chan, K.W.; Li, H.; Wang, H.; Qiu, J.; Wang, G. Deep-Learning-Based probabilistic forecasting of EV charging load with a novel queuing model. *IEEE Trans. Cybern.* **2021**, *51*, 3151–3170. [CrossRef]
63. Xiong, Y.; Wang, B.; Chu, C.-C.; Gadh, R. EV driver clustering using statistical model and machine learning. In Proceedings of the 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, USA, 5–10 August 2018; pp. 1–5.
64. Sun, S.; Zhang, J.; Bi, J.; Wang, Y. A Machine Learning Method for Predicting Driving Range of Battery EVs. *J. Adv. Transp.* **2019**, *2019*, 4109148. [CrossRef]
65. Dorokhova, M.; Ballif, C.; Wyrsch, N. Routing of EVs With Intermediary Charging Stations: A Reinforcement Learning Approach. *Front. Big Data* **2021**, 33. [CrossRef]
66. Lin, X.; Bogdan, P.; Chang, N.; Pedram, M. Machine Learning-Based Energy Management in a Hybrid EV to Minimize Total Operating Cost. In Proceedings of the IEEE/ACM International Conference on Computer-Aided Design, Austin, TX, USA, 2–6 November 2015. [CrossRef]
67. Scott, C.; Ahsan, M.; Albarbar, A. Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings. *Sustainability* **2021**, *13*, 4003. [CrossRef]
68. Wang, Y.; Wei, C.; He, H. Estimating the Energy Consumption and Driving Range of EVs with Machine Learning. In Proceedings of the International Conference on Information Technology and Intelligent Control (CITIC 2021), Guilin, China, 23–25 July 2021; Volume 2005.
69. Zhang, W.; Liu, H.; Wang, F.; Xu, T.; Xin, H.; Dou, D.; Xiong, H. Intelligent EV Charging Recommendation Based on Multi-Agent Reinforcement Learning. In Proceedings of the Web Conference 2021, Ljubljana, Slovenia, 19–23 April 2021. [CrossRef]
70. Cao, D.; Lerch, J.; Stetter, D.; Neuburger, M.; Wörner, R. Application and machine learning methods for dynamic load point controls of EVs. In *E3S Web of Conferences*; EDP Sciences: Les Ulis, France, 2020. [CrossRef]
71. Amitha, M.; Amuda, A.; Sivakumar, S. Deep Learning Techniques: An Overview. In Proceedings of the International Conference on Advanced Machine Learning Technologies and Applications, Manipal, India, 13–15 February 2020; pp. 599–608. [CrossRef]
72. Introduction-to-Deep-Learning. Available online: https://training.ti.com/sites/default/files/docs/introduction-to-deep-learning.pdf (accessed on 5 March 2022).
73. Renesas Accelerates Deep Learning Development for ADAS and Automated Driving Applications | Renesas. Available online: https://www.renesas.com/us/en/about/press-room/renesas-accelerates-deep-learning-development-adas-and-automated-driving-applications (accessed on 9 August 2022).
74. Available online: https://www.sas.com/en_gb/insights/articles/analytics/machine-learning (accessed on 10 March 2022).
75. López, K.; Gagné, C.; Gardner, M.A. Demand-Side Management Using Deep Learning for Smart Charging of EVs. *IEEE Trans. Smart Grid* **2018**, *10*, 2683–2691. [CrossRef]
76. Big Data: What It Is and Why It Matters. Available online: https://www.sas.com/en_in/insights/big-data/what-is-big-data.html (accessed on 9 August 2022).
77. Big Data Analytics for Optimizing EVs Chargers. Available online: https://soulpageit.com/big-data-analytics-for-optimizing-electric-vehicles-chargers/ (accessed on 18 October 2019).

78. Available online: https://www.wipro.com/blogs/wipro-insights/big-data-helps-electric-vehicles-shift-gears/ (accessed on 10 June 2022).
79. Jackson, A. EVs Connect Drivers and Generate Big Data. Available online: https://www.smartdatacollective.com/all-electric-future-how-big-data-will-vital-transition/ (accessed on 2 March 2018).
80. Abdulali, S.; Abdulali, A.; Gültepe, Y. Big Data Tools and Technologies. *Res. J. Mass Commun. Inf. Technol.* **2020**, *6*, 53–58.
81. Li, B.; Kisacikoglu, M.C.; Liu, C.; Singh, N.; Erol-Kantarci, M. Big Data Analytics for EV Integration in Green Smart Cities. *IEEE Commun. Mag.* **2017**, *55*, 19–25. [CrossRef]
82. Precisely. Big Data Definition: Big Data vs Traditional Data. *What Defines Big Data?* Available online: https://www.precisely.com/blog/big-data/big-data-definition-data-what-defines-big-data (accessed on 17 November 2019).
83. Apache Hadoop. Available online: https://hadoop.apache.org/ (accessed on 9 August 2022).
84. Apache SparkTM—Unified Engine for Large-Scale Data Analytics. Available online: https://spark.apache.org/ (accessed on 9 August 2022).
85. Arooj, A.; Farooq, S.; Akram, A.; Iqbal, R. Big Data Processing and Analysis in Internet of Vehicles: Architecture, Taxonomy, and Open Research Challenges. *Arch. Comput. Methods Eng.* **2021**, *29*, 793–829. [CrossRef]
86. Delnevo, G.; Lena, P.D.; Mirri, S.; Prandi, C.; Salomoni, P. On combining Big Data and machine learning to support eco-driving behaviours. *J. Big Data* **2019**, *6*, 64. [CrossRef]
87. Hussain, M.M.; Sufyan, M.M.; Alam, M.S.; Laskar, S.H. Big Data Analytics Platforms for EV Integration in Transport Oriented Smart Cities. *Int. J. Digit. Crime Forensics* **2019**, *11*, 833–854. [CrossRef]
88. Rahimi Eichi, H.; Chow, M.-Y. Big-Data Framework for EV Range Estimation. In Proceedings of the Annual Conference of the IEEE Industrial Electronics Society (IECON2014), Dallas, Texas, USA, 29 October–1 November 2014.
89. Lv, Z.; Qiao, L.; Cai, K.; Wang, Q. Big Data Analysis Technology for EV Networks in Smart Cities. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 1807–1816. [CrossRef]
90. Fetene, G.M.; Kaplan, S.; Mabit, S.L.; Jensen, A.F.; Prato, C.G. Harnessing big data for estimating the energy consumption and driving range of EVs. *Transp. Res. Part D: Transp. Environ.* **2017**, *54*, 1–11. [CrossRef]
91. Wei, W.; Ai, M.; Chen, N.; Ge, X.; Pu, T. Multi-Level Feeder Queue Optimization Charging Model of EV and its Implementation of MR Algorithm. *Int. J. U-E-Serv. Sci. Technol.* **2016**, *9*, 199–208. [CrossRef]
92. Lee, J.; Park, G.L.; Cho, Y.; Kim, S.; Jung, J. Spatio-Temporal Analysis of State-of-Charge Streams for EVs. In Proceedings of the 14th International Conference on Information Processing in Sensor Networks, Seattle, WA, USA, 13–16 April 2015; pp. 368–369.
93. Lee, J.; Park, G.-L. EV Charger Management System for Interoperable Charging Facilities. *J. Teknol.* **2018**, *78*, 5–8.
94. Bolly, V.; Springer, J.; Dietz, E. Using Open Source NOSQL Technologies in Designing Systems for Delivering EV Data Analytics. In Proceedings of the 121st ASEE Annual Conference, Indianapolis, IN, USA, 15–18 June 2014; pp. 24–1339.
95. Appasani, B.; Mishra, S.K.; Jha, A.V.; Mishra, S.K.; Enescu, F.M.; Sorlei, I.S.; Bîrleanu, F.G.; Takorabet, N.; Thounthong, P.; Bizon, N. Blockchain-Enabled Smart Grid Applications: Architecture, Challenges, and Solutions. *Sustainability* **2022**, *14*, 8801. [CrossRef]
96. CEEW, CEF. Block Chain Technology and Its Impact on EVs. Available online: https://www.ceew.in/cef/masterclass/explains/blockchain-technology-and-its-impact-on-electric-vehicles (accessed on 9 August 2022).
97. Takyar, A. Top Blockchain Platforms of 2022 for Blockchain Application. Available online: https://www.leewayhertz.com/blockchain-platforms-for-top-blockchain-companies/ (accessed on 12 June 2018).
98. What Is Ethereum? | AWS Blockchain. Available online: https://aws.amazon.com/blockchain/what-is-ethereum/ (accessed on 9 August 2022).
99. Ethereum Whitepaper. Available online: https://ethereum.org (accessed on 9 August 2022).
100. Hyperledger-Fabric. Available online: https://hyperledger-fabric.readthedocs.io/_/downloads/en/release-2.0/pdf/ (accessed on 12 June 2022).
101. Khan, P.W.; Byun, Y.C. Blockchain-Based Peer-to-Peer Energy Trading and Charging Payment System for EVs. *Sustainability* **2021**, *13*, 7962. [CrossRef]
102. Javed, M.U.; Javaid, N. Scheduling charging of EVs in a secured manner using blockchain technology. In Proceedings of the 2019 International Conference on Frontiers of Information Technology (FIT), Islamabad, Pakistan, 16–18 December 2019; pp. 351–3515.
103. Pustišek, M.; Kos, A.; Sedlar, U. Blockchain based autonomous selection of EV charging station. In Proceedings of the 2016 International Conference on Identification, Information and Knowledge in the Internet of Things (IIKI), Beijing, China, 20–21 October 2016; pp. 217–222.
104. Xiang, K.; Chen, B.; Lin, H.; Shen, Y.; Du, Y.; Yan, T. Automatic demand response strategy of local pure EV with battery energy storage system based on blockchain technology. In Proceedings of the 2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2), Beijing, China, 20–22 October 2018; pp. 1–6.
105. Shang, X.; Li, Y.; Huang, R. A Charging And Discharging Model For Electric Vehicles Based On Consortium Blockchain Using Multi-Objective Gray Wolf Algorithm. *Recent Adv. Electr. Electron. Eng. (Former. Recent Pat. Electr. Electron.Eng.)* **2022**, *15*. [CrossRef]
106. Duan, B.; Xin, K.; Zhong, Y. Optimal dispatching of EVs based on smart contract an Internet of things. *IEEE Acces* **2019**, *8*, 9630–9639. [CrossRef]
107. Khan, P.W.; Byun, Y.C. Secure transactions management using blockchain as a service software for the internet of things. In *Software Engineering in IoT, Big Data, Cloud and Mobile Computing*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 117–128.

108. Bhattacharya, P.; Tanwar, S.; Bodkhe, U.; Kumar, A.; Kumar, N. EVBlocks: A Blockchain-Based Secure Energy Trading Scheme for EVs Underlying 5G-V2X Ecosystems. *Wirel. Pers. Commun.* **2021**, 1–41. [CrossRef]
109. Jameel, F.; Javed, M.A.; Zeadally, S.; Jantti, R. Efficient Mining Cluster Selection for Blockchain-Based Cellular V2X Communications. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 4064–4072. [CrossRef]
110. Rasheed, M.B.; Javaid, N.; Ahmad, A.; Awais, M.; Khan, Z.A.; Qasim, U.; Alrajeh, N. Priority and Delay Constrained Demand Side Management in Real-Time Price Environment with Renewable Energy Source. *Int. J. Energy Res.* **2016**, *40*, 2002–2021. [CrossRef]
111. Kim, M.; Park, K.; Yu, S.; Lee, J.; Park, Y.; Lee, S.W.; Chung, B. A Secure Charging System for EVs Based on Blockchain. *Sensors* **2019**, *19*, 3028. [CrossRef]
112. Buterin, V. Ethereum Platform Review—Opportunities and Challenges for Private and Consortium Blockchains—Full Review. *J. Br. Blockchain Assoc.* **2016**. Available online: https://staticl.squarespace.com/static/55f73743e4b051cfccOb02cf/ti57506f387da24ff6bdecb3c1/1464889147417/Ethereum_Paper.pdf (accessed on 10 April 2022).
113. Rawat, D.B.; Doku, R.; Adebayo, A.; Bajracharya, C.; Kamhoua, C. Blockchain Enabled Named Data Networking for Secure Vehicle-to-Everything Communications. *IEEE Netw.* **2020**, *34*, 185–189. [CrossRef]
114. Sadiq, A.; Javed, M.U.; Khalid, R.; Almogren, A.; Shafiq, M.; Javaid, N. Blockchain Based Data and Energy Trading in Internet of EVs. *IEEE Access* **2021**, *9*, 7000–7020. [CrossRef]
115. Musleh, A.S.; Yao, G.; Muyeen, S.M. Blockchain Applications in Smart Grid-Review and Frameworks. *IEEE Access* **2019**, *7*, 86746–86757. [CrossRef]
116. Dorokhova, M.; Vianin, J.; Alder, J.M.; Ballif, C.; Wyrsch, N.; Wannier, D. A Blockchain-Supported Framework for Charging Management of EVs. *Energies* **2021**, *14*, 7144. [CrossRef]
117. Al-Saif, N.; Ahmad, R.W.; Salah, K.; Yaqoob, I.; Jayaraman, R.; Omar, M. Blockchain for Electric Vehicles Energy Trading: Requirements, Opportunities, and Challenges. *IEEE Access* **2021**, *9*, 156947–156961. [CrossRef]
118. Okwuibe, G.C.; Li, Z.; Brenner, T.; Langniss, O. A Blockchain Based EV Smart Charging System with Flexibility. In Proceedings of the 21st IFAC World Congress, Berlin, Germany, 11–17 July 2020. [CrossRef]
119. Joshi, N. The Role of Blockchain in the Development of the EV Industry. Available online: https://www.forbes.com/sites/naveenjoshi/2021/12/21/the-role-of-blockchain-in-the-development-of-the-ev-industry/ (accessed on 9 August 2022).
120. Data Security in Connected Cars | Uswitch. Available online: https://www.uswitch.com/guides/car-insurance/data-security-in-connected-cars/ (accessed on 10 August 2022).
121. Britton, J. EV Security Overview. Available online: https://www.perforce.com/blog/sca/electric-vehicle-security (accessed on 10 August 2022).
122. Securing the EV Charging Infrastructure. Available online: https://arxiv.org/pdf/2105.02905.pdf (accessed on 10 April 2022).
123. Babu, P.R.; Palaniswamy, B.; Reddy, A.G.; Odelu, V.; Kim, H.S. A Survey on Security Challenges and Protocols of EV Dynamic Charging System. *Secur. Priv.* **2022**, 5. [CrossRef]
124. Farooq, S.M.; Hussain, S.M.S.; Kiran, S.; Ustun, T.S. Certificate Based Authentication Mechanism for PMU Communication Networks Based on IEC 61850-90-5. *Electronics* **2018**, *7*, 370. [CrossRef]
125. Hamouid, K.; Adi, K. Privacy-Aware Authentication Scheme for EV In-Motion Wireless Charging. In Proceedings of the 2020 International Symposium on Networks, Computers and Communications (ISNCC), Montreal, QC, Canada, 20–22 October 2020; pp. 1–6. [CrossRef]
126. Ustun, T.S.; Hussain, S.M.S. Secure Communication Modeling for Microgrid Energy Management System: Development and Application. *Energies* **2020**, *13*, 68. [CrossRef]
127. Ustun, T.S.; Hussain, S.M.S.; Ulutas, A.; Onen, A.; Roomi, M.M.; Mashima, D. Machine Learning-Based Intrusion Detection for Achieving Cybersecurity in Smart Grids Using IEC 61850 GOOSE Messages. *Symmetry* **2021**, *13*, 826. [CrossRef]
128. Hussain, S.S.; Farooq, S.M.; Ustun, T.S. Analysis and Implementation of Message Authentication Code (MAC) Algorithms for GOOSE Message Security. *IEEE Access* **2019**, *7*, 80980–80984. [CrossRef]
129. Ustun, T.S.; Farooq, S.M.; Hussain, S.M.S. A novel approach for mitigation of replay and masquerade attacks in smart grids using IEC 61850 Standard. *IEEE Access* **2019**, *7*, 156044–156053. [CrossRef]
130. Nadeem, F.; Aftab, M.A.; Hussain, S.M.S.; Ali, I.; Tiwari, P.K.; Goswami, A.K.; Ustun, T.S. Virtual Power Plant Management in Smart Grids with XMPP Based IEC 61850 Communication. *Energies* **2019**, *12*, 2398. [CrossRef]