Research Article

ELECTRIC VEHICLES AND INTERNET OF THINGS ENABLED IN SMART CITIES

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ABSTRACT
The convergence of Electric Vehicles (EVs) and the Internet of Things (IoT) has emerged as a transformative force in the development of smart cities. This paper explores the integration of EVs and IoT technologies, examining their synergies and the potential impact on urban sustainability, transportation efficiency, and overall city management. In the context of smart cities, EVs play a pivotal role in reducing carbon emissions and enhancing energy efficiency. The adoption of IoT in conjunction with EVs introduces a dynamic layer of connectivity, enabling real-time data exchange and smart decision-making. This paper delves into the various facets of this integration, emphasizing the benefits and challenges associated with the fusion of these two technologies.

Keywords: Electric vehicles (EVs), smart cities, EV Charge Scheduling, PEV and PHEV charging

1.INTRODUCTION

The ubiquity of electric vehicles (EVs) in future smart cities demands efficient and intelligent charge scheduling techniques. Smart grids, on the other hand, are equipped with sensors and meters that significantly assist in the supervision and control of the charge scheduling process. Thus, integrating both EVs and smart grids in a larger IoT entity can facilitate the vast deployment of EVs towards a green and intelligent transportation era. Conventional motor vehicles mostly depend on the energy of fossil fuels. At the present time, fossil fuels are considered as the worlds' primary energy resources. All technological advancements in the fields of agriculture, transportation, industry, etc., depend heavily on fossil fuels. Global transportation is one of the major sources of fossil fuel consumption such as gasoline, petrol, diesel, etc. Moreover, fossil fuels are considered as non-renewable energy resources which may eventually run out in the near future. Therefore, it is necessary to take serious steps to reserve fossil fuelresources for a stable energy future. Due to the aforementioned reasons, people arenow moving towards the diversification of energy resources, particularly for daily transportation needs. According to the US Climate Action Report in 2010 [29], approximately 28% of the total greenhouse gas (GHG) emissions in the USA comes from the transportation sector that includes cars, buses, motorcycles, aircrafts, ships, trains, etc. Burning fossil fuels is the largest source of GHG due to the emission of carbon dioxide, CO_2. Moreover, it negatively affects global warming that is impacting theentire ecosystem on the planet. For instance, there has been a phenomenal increasein the observed temperature during the second half of the twentieth century, solelybecause of the GHG emissions. Furthermore, carbon monoxide, nitrogen oxide, and hydrocarbons are released when fuel is burned by the internal combustion engine (ICE) inside vehicles and emitted into the atmosphere through the vehicle's tailpipe. In addition to the detrimental impact on health, motor vehicle pollution also contributes to the formation of acid rains. Figure 1 depicts the GHG emission in Delhi, India, and shows that the transportation sector accounts for 62% of GHG emissions.

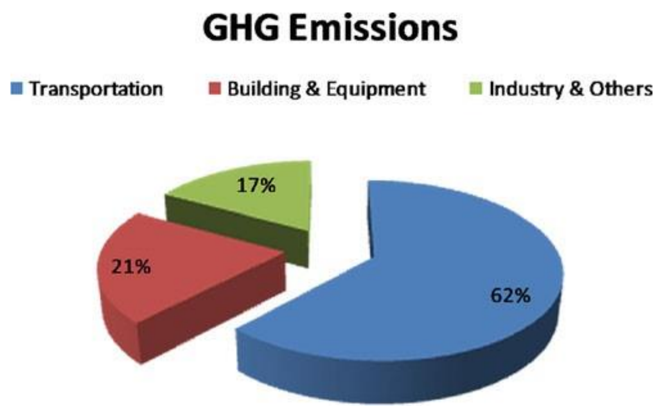

Fig. 1 Greenhouse gas emissions in Delhi, India

One way to significantly reduce the pollution incurred by motor vehicles is the usage of green EVs instead of conventional ICE vehicles. On the other hand, electricity is a clean form of energy that can be easily and effectively transformed from one energy form to another. Nowadays, most researchers focus their intensions and objectives towards the vehicles driven by electric motors instead of ICEs. An EV is basically driven by electric energy that is stored in a rechargeable battery (or series of batteries). Currently, EVs are gaining considerable popularity in many developed countries. However, EVs are still used in small scale due to the challenges related to charging efficiency and cost. These challenges can be considerably resolved by the careful scheduling of EV charging and placing charging stations along the serviceareas. The advantages of using EVs can be summarized as follows:

- **CLEAN ENVIRONMENT:** EVs are environmentally friendly and operate without emitting GHGs that impact the health of humans and other living organisms.
- **ECONOMIC PERFORMANCE:** EVs, which use electricity for propulsion instead of fossil fuels, are considered as more economical since the price of electricity is less than that of fossil fuels.
- **QUIET VEHICLES:** EVs produce less noise and help reduce the noise pollution.

There are many pros and cons to be considered about EVs. For instance, EVs havefaster acceleration but less capability for long distances. Moreover, they produce no exhaust but, however, require long charging times. Moreover, EVs can offer more time flexibility in charging and discharging by introducing the concept of vehicle-to- Grid (V2G). V2G is defined as the capability of returning stored electric energy to the grid from the vehicle's battery. In other words, an EV acts as both a controllable load and distributed storage device. By connecting unused EVs to the electric grid, the batteries of these EVs can provide energy during peak load times, and thus increase the reliability of the grid [57].

2.EV CHARGE SCHEDULING AND CHARGING TECHNIQUES

Charge scheduling (charging and discharging strategies) is essential to avoid grid congestion. Efficient scheduling ensures proper operation of the distribution system. The goal of scheduling is to allocate energy from available resources to where the energy is needed while maintaining the optimal operation of the system without overloading or congesting the main grid [28]. Therefore, scheduling in smart distribution systems helps minimize the operational costs by reducing the electricity bills. Furthermore, smart scheduling plays a significant role in establishing the intelligent transportation system (ITS), where both communication and computingmeet in vehicles and charge stations to maintain efficient and reliable performanceregarding energy and cost [19]. The central cloud in the Internet of Vehicles (IoV) paradigm will have a holistic view about energy availability and charging demands to optimize the charging process in stations and vehicles.

Different types of EVs are available such as the Plug-in EV (PEV), Plug-in Hybrid EV (PHEV), Hybrid EV (HEV), Sensor Vehicle (SV), Battery EV (BEV), and Plug-in Electric Train (PET). PHVs and PHEVs are EVs with rechargeable batteries that provide power to operate the vehicle. These batteries can be fully recharged by connecting to an external power supply. However, PHEVs have bothICE and electric motors for propulsion.

The research area of EVs has been extensively studied recently. In [10], a scheduling scheme is presented to decrease the peak electricity demand and reducethe electricity bill using SVs and PHEVs. In [11–15], the authors developed tech- niques for minimizing the peak hour electricity demand by allowing communication between PEVs and the electric grid. The authors in [16, 17] considered that existing power infrastructure will be affected by the increase in the number of the EVs. In [68], the authors introduced a method for achieving maximum fuel economy and minimizing the environmental pollution using HEVs.

Charging and discharging techniques can be classified as vehicle-to-grid (V2G), grid-to-vehicle (G2V), vehicle-to-vehicle (V2V), vehicle-to-home (V2H), and home-to-vehicle (H2V). V2G describes a system in which plug-in EVs suchas BEVs and PHEVs communicate with the electric grid to exchange services such as buying or selling electricity from/to the grid with variable charging rates. Research in this field of study involves several categories of objective functions regarding charging and discharging. The major categories include maximizing profit and generating revenue, minimizing cost and power loss, charging station placement, scheduling of EV charging, minimizing pollution, peak clipping and valley filling, and V2G power flow. In [17, 18, 19–24], the authors proposed V2G for discharging EVs through the main grid. Using this technique, customers can generate revenue by selling power to the grid, and help provide power duringpeak hours. In [25], a system architecture is designed for efficient control of load balancing in EVs at charging stations using V2G technology. In [26], a method forthe optimal placement of charging stations in smart cities using V2V is proposed. Furthermore, combining wind power generation with V2G technology helps reduce the intermittency of wind power and lead to more sustainable development [24]. The EVs in a parking garage can be utilized as a dynamic energy storage facility to compensate for the variability of renewable energy resources [27].

Integrating the massive number of vehicles into the power grid might incur other issues and challenges. A stochastic model based on queuing theory for PEV and PHEV charging demands is studied in [28]. This study highlighted the impact of the large-scale integration of EVs on the power grid. An integrated rapidcharging strategy that considers both traffic conditions and status of the power grid is introduced in [29]. However, rapid charging could degrade the power system performance especially during peak hours.

Minimizing the operational cost of EV charging has been considered by severalresearchers using different approaches such as scheduling [27] and shifting the peak load to valley areas where the real-time pricing is low [30]. Moreover, sellingelectricity to the power grid using V2G can bring profit to vehicle owners. However, this requires efficient energy management in regard with available renewable energy resources [20], operational costs and energy losses [22], and parking lot allocation [21]. In [20, 22], load management approaches are presented using peak clipping (i.e., avoiding EV charging during peak hours) and valley filling (i.e., incentives on charging during off-peak hours). In this manner, customers can generate revenue by selling power to the grid through discharging their EVs and using renewable energy during peak hours. Similarly, during off-peak hours customers get incentives for charging EVs within a prescribed time limit.

Scheduling algorithms have been proposed to minimize costs and peak electricity demands by considering the factors of fuel pricing, electricity demand, and vehiclecharacteristics [30]. In addition, the accurate placement of charging stations plays a significant role in improving the performance of EV charging by serving more EVs in less amount of time [23–25].

3.RENEWABLE ENERGY FOR EV CHARGING

The most common renewable energy resources are the wind and solar energy. However, other energy resources such as the motion of water, the carbohydrates in plants, and the warmth of the earth can also be exploited to satisfy the energy demands in a sustainable manner. Future EVs need to be fast in both speed and charging time. Current technologies allow EVs to be recharged within a couple of hours. Although this time seems to be short for an EV, it is still very long comparedto traditional vehicles. A fast-charging mechanism can be envisioned as follows: when a car comes to recharge, a robotic system removes the discharged battery from the car and places it on a conveyer belt. This belt takes the battery to an underground battery recharging unit and replaces it with a fully charged battery. The whole process is done in a couple of minutes which seems very promising.

Scheduling can be achieved either in a centralized or decentralized manner. Thecentralized model for EV scheduling is effective in reducing the total cost and peak- to-average ratio of load. A decentralized system is the one in which the entry of peers is not regulated, i.e., any peer can enter or leave the system at any time. However, in a decentralized system, there is no centralized authority that makes decisions on behalf of all parties. Instead, each party, also called a peer, makes local and autonomous decisions towards its individual benefits which may possibly conflict with other peers. Moreover, peers can directly interact with each other and share information or provide services.

3.1SMART DISTRIBUTION SYSTEMS

In real life, a number of constraints are involved in the charging of EVs. Some of these constraints are listed below:

- Maximum and minimum output power limits
- Grid capacity
- Charging limit in batteries
- State-of-charge (SOC) of the battery and the charging rate
- Intermittent supply of renewable energy resources

To cope with the aforementioned constraints, developing smart scheduling schemes is essential to dynamically allocate power for EVs taking into account thecharging duration, battery limit, grid conditions, and costs. Moreover, integrating these constraints in the IoT paradigm will make the entire charging process more efficient and reliable. In this section, the problem of EV scheduling in smart distribution systems is presented.

3.2SMART EV SCHEDULING: A CASE STUDY

The goal of using smart distribution systems is to optimize the scheduling of EV charging. There is different cost associated with different charging levels. For instance, the cost of slow charging is very low but, however, takes more time than other charging levels. Whereas the cost of very fast charging is higher than that of other charging levels but, however, requires much less time. The difference in charging times is due to the amount of charging power, i.e., the more the charging power, the less the time required to charge the vehicle. The system model for EV scheduling is shown in Fig. 2.

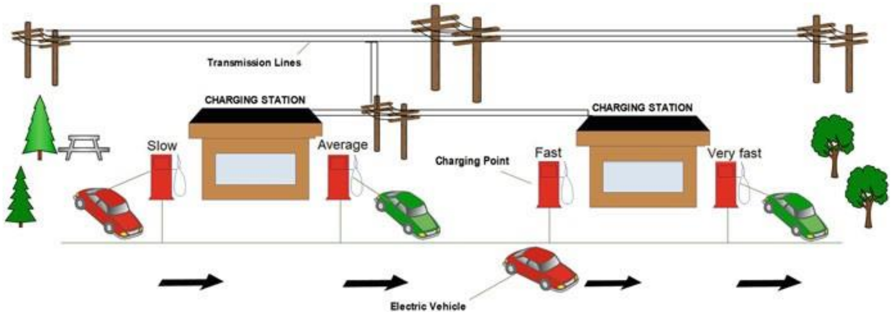

Figure. 2 Electric vehicles scheduling system model

Different charging levels depending on the desired charging time are listed below:

- Level 1 (L-1) charging is the slow charging and the vehicle battery is charged by applying 120VAC/16A for a 1.92-kW charging power using the on-board battery charger. The charging time required for full capacity is about 10 h [76]. EV charging that takes place at homes can be considered as level 1 charging, where the charging process is completed during the night.
- Level 2 (L-2) charging is called the standard charging. The vehicle battery is charged by applying 208V-240VAC, 12A-80A for a 2.5–19.2-kW charging power using the on-board battery charger. In L-2 charging, the time required to fully charge an empty battery is 6–8 h. The best implementation of L-2 charging is at places where the user stays for a long time, e.g., at work.
- Level 3 (L-3) is DC fast charging, where charging is done by applying up to 200A for a 75-kW charging power using off-board chargers. The time required for fast charging is about 30 min, whereas the charging price is high [76].
- Level 4 (L-4) is DC very fast charging, where charging is done using up to 400A for a 240-kW charging power using off-board chargers. The very fast charging is required at places where the user cannot wait for a long time, e.g., at public charging stations. The time required for charging is about 15 min with very high pricing [76].

The time horizon T is divided into discrete time slots (15-min time slot), i.e.,the time required for charging an EV with very fast charging is 15 min (one time slot) and the time required for the fast charging is 30 min (two time slots). Similarly, the time required to charge an EV using average charging is 45 min (three time slots) and the time required for slow charging is 60 min (four time slots). We always ensure that the number of time slots is greater than or equal to the number of EVs, otherwise the solution will not be feasible. The table provides an overview of the notations used in the problem formulation.

The EV scheduling problem which is a binary integer linear programming problem aims at maximizing the total profit through the scheduling of slow, average,

Notation overview

Symbol	Description
T	Total time
N_v	Number of electric vehicles
c^s	Cost of slow charging
c^a	Cost of average charging
c^f	Cost of fast charging
c^{vf}	Cost of very fast charging
t^s	Time for slow charging
t^a	Time for average charging
t^f	Time for fast charging
t^{vf}	Time for very fast charging
w_i, x_i, y_i, z_i	Decision variable $w_i, x_i, y_i, z_i \in \{0,1\}$, $\forall$ i $\in \{1,2,3,. \quad N_v\}$
$L-1$	Level 1 Charging power 1.92 kW
$L-2$	Level 2 Charging power 2.5–19.2 kW
$L-3$	Level 3 Charging power 75 kW
$L-4$	Level 4 Charging power 240 kW

fast, and very fast charging levels. This problem is quite similar to a knapsack problem and is an NP-hard (non-deterministic polynomial time hard). The binary integer variables $w_i,x_i,y_i,z_i \in \{0,1\}, \forall i \in \{1, 2, 3, ..., N_v\}$ are considered as the decision variables for the slow, average, fast, and very fast charging levels, respectively. For instance, if w_i is "1," then the EV is under slow charging, andif z_i is "1," then the vehicle is charged using the very fast charging level, etc. Theoptimization problem is formulated as:

min :
wi ,xi ,yi ,zi

Subject to:
Nv
$w_i c^s + x_i c^a + y_i c^f + z_i c^{vf}$
$i=1$
$C_1 : \quad w_i + x_i + y_i + z_i = 1, \qquad \forall i \in \{1, 2, 3, \quad , N_v\}$
Nv
(1) C_2 :
$w_i t^s + x_i t^a + y_i t^f + z_i t^{vf} \leq T$
$i=1$
$C_3 : \quad w_i, x_i, y_i, z_i \in \{0, 1\},$

where c^s, c^a, c^f , and c^{vf} represent the cost of slow, average, fast, and very fast charging, respectively. N_v denotes the total number of EVs available for charging. t^s, t^a, t^f, and t^{vf} denote the time required for slow, average, fast, and very fast charging, respectively. It means that the service provider must ensure that all the EVs and batteries are charged before that time limit. The objective is to maximize the total profit as shown in (4.1) by optimally minimizing the cost of charging while

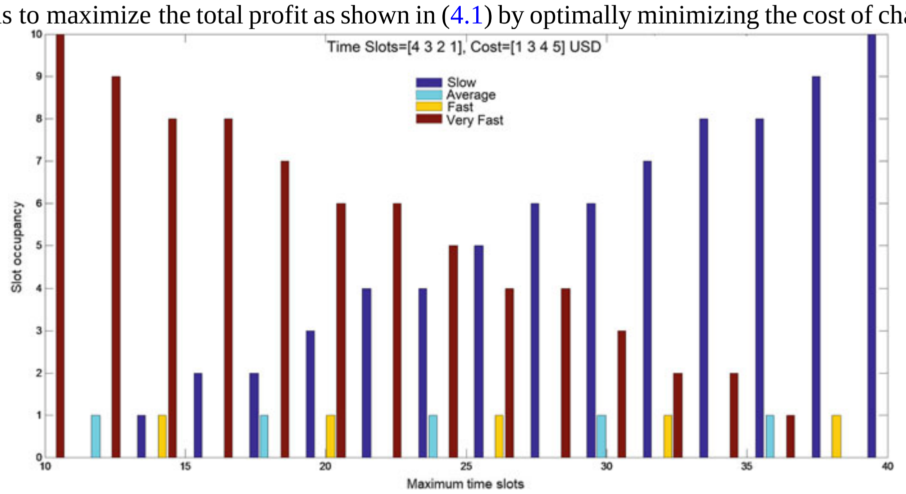

Fig. 3 Slot occupancy versus maximum time slot for different charging systems

satisfying all customers. The constraint C_1 shows that only one charging level can take place. C_2 ensures that the total charging time should be less than or equal to the total time T . C_3 indicates that variables representing the charging levels can beeither 0 or 1. Assume that we have 10 EVs to be charged. The rates for different charging levels are as follows:

- For slow charging, 4 time slots costs 1 $
- For average charging, 3 time slots costs 3 $
- For fast charging, 2 time slots costs 4 $
- For very fast charging, 1 time slot costs 5 $

Solving the optimization problem yields the optimal scheduling of slow, average, fast, and very fast charging for EVs at different time slots as shown in Fig. 3. Itis noticed that slot occupancy is high in the case when the maximum number of available slots is large. On the other hand, slot occupancy is high when the maximum number of available slots is small. This is because slow charging needs more slots to complete charging. The result shows the optimal number of slot occupancy for different charging types for the given number of maximum available slots.

4.CONCLUSION

The world's fossil fuel supply is diminishing rapidly, and the transportation sector is one of the major consumers. Further, to make our cities green and pollution-free, EVs must dominate the transportation sector in the future, and to successfully incorporate EVs into the intelligent transportation and IoT systems, optimal scheduling paradigms need to be developed to ensure optimal charging performance with lower prices. This paper presented a scheduling approach to maximize total profit.

REFERENCE

[1]. Delsing , J. (2021). Smart city solution engineering . *Smart Cities* 4 (2): 643 – 661 .
[2]. Zand , M. , Nasab , M.A. , Hatami , A. et al. (2020). Using adaptive fuzzy logic for intelligent energy management in hybrid vehicles . In: *2020 28th Iranian Conference on Electrical Engineering (ICEE)* , 1 – 7 . IEEE . https://doi.org/10.1109/ICEE50131.2020.9260941.IEEE Index.
[3]. Ahmadi-Nezamabad , H. , Zand , M. , Alizadeh , A. et al. (2019). Multi-objective optimization based robust scheduling of electric vehicles aggregator . *Sustainable Cities and Society* 47 : 101494 .
[4]. Zand , M. , Nasab , M.A. , Sanjeevikumar , P. et al. (2020). Energy management strategy for solid-state transformer-based solar charging station for electric vehicles in smart grids . *IET Renewable Power Generation* 14 (18): 3843 – 3852 . https://doi.org/10.1049/iet-rpg.2020.0399 IET Digital Library.
[5]. Ghasemi M , Akbari , E. , Zand , M. et al. (2019). An efficient modified HPSO-TVAC-based dynamic economic dispatch of generating units , *Electric Power Components and Systems* , 47 (19–20), 1826 – 1840 . https://doi.org/10.1080/15325008.2020.1731876 .
[6]. Nasri , S. , Nowdeh , S.A. , Davoudkhani , I.F. et al. (2021). Maximum Power point tracking of Photovoltaic Renewable Energy System using a New method based on turbulent flow of water-based optimization (TFWO) under Partial shading conditions . In: *Fundamentals and Innovations in Solar Energy* , 285 – 310 . Singapore : Springer . ISBN: 978-981-336-456-1.
[7]. Rohani , A. , Joorabian , M. , Abasi , M. , and Zand , M. (2019). Three-phase amplitude adaptive notch filter control design of DSTATCOM under unbalanced/distorted utility voltage conditions . *Journal of Intelligent & Fuzzy Systems* 37 (1): 847 – 865 . https://doi.org/10.3233/JIFS-201667 .
[8]. Zand , M. , Nasab , M.A. , Neghabi , O. et al. (2019). Fault locating transmission lines with thyristor-controlled series capacitors By fuzzy logic method . In: *2020 14th International Conference on Protection and Automation of Power Systems (IPAPS), Tehran, Iran* , 62 – 70 . https://doi.org/10.1109/IPAPS49326.2019.9069389 .
[9]. Zand , Z. , Hayati , M. , and Karimi , G. (2020). Short-channel effects improvement of carbon nanotube field effect transistors . In: *2020 28th Iranian Conference on Electrical Engineering (ICEE), Tabriz, Iran* , 1 – 6 . https://doi.org/10.1109/ICEE50131.2020.9260850 .
[10]. Tightiz , L. , Nasab , M.A. , Yang , H. , and Addeh , A. (2020). An intelligent system based on optimized ANFIS and association rules for power transformer fault diagnosis . *ISA Transactions* 103 : 63 – 74 . ISSN 0019-0578. https://doi.org/10.1016/j.isatra.2020.03.022 .
[11]. Zand , M. , Neghabi , O. , Nasab , M.A. et al. (2020). A hybrid scheme for fault locating in transmission lines compensated by the TCSC . In: *2020 15th International Conference on Protection and Automation of Power Systems (IPAPS)* , 130 – 135 . IEEE . https://doi.org/10.1109/IPAPS52181.2020.9375626 .
[12]. Zand , M. , Azimi Nasab , M. , Khoobani , M. et al. (2021). Robust speed control for induction motor drives using STSM control . In: *2021 12th Power Electronics, Drive Systems, and Technologies Conference (PEDSTC)* , 1 – 6 . IEEE . https://doi.org/10.1109/PEDSTC52094.2021.9405912 .
[13]. Padmanaban , S. , Zand , M. , Nasab , M.A. et al. (2021). Spider community optimization algorithm to determine UPFC optimal size and location for improve dynamic stability . In: *2021 IEEE 12th Energy Conversion Congress & Exposition – Asia (ECCE-Asia)* , 2318 – 2323 . https://doi.org/10.1109/ECCE-Asia49820.2021.9479149 .
[14]. Azimi Nasab , M. , Zand , M. , Eskandari , M. et al. (2021). Optimal planning of electrical appliance of residential units in a smart home network using cloud services . *Smart Cities* 4 : 1173 – 1195 . https://doi.org/10.3390/smartcities4030063 .
[15]. Azimi Nasab , M. , Zand , M. , Padmanaban , S. et al. (2022). An efficient robust optimization model for the unit commitment considering of renewables uncertainty and pumped-storage hydropower . *Computers and Electrical Engineering* 100 : 107846 .
[16]. Nasab , A. , Mortez , Z. , Mohammad , P. et al. (2021). Simultaneous long-term planning of flexible electric vehicle photovoltaic charging stations in terms of load response and technical and economic indicators . *World Electric Vehicle Journal* 2021 : 190 . https://doi.org/10.3390/wevj12040190 .
[17]. Zand , M. , Nasab , M.A. , Padmanaban , S. , and Khoobani , M. (2022). Big data for SMART sensor and intelligent electronic devices–building application . In: *Smart Buildings Digitalization* , 11 – 28 . CRC Press .
[18]. Panda , D.K. and Das , S. (2021). Smart grid architecture model for control, optimizationand data analytics of future power networks with more renewable energy . *Journal of Cleaner Production* 301 : 126877 .
[19]. Ali , Z.H. and Ali , H.A. (2021). Towards sustainable smart IoT applications architectural elements and design: opportunities, challenges, and open directions . *The Journal of Supercomputing* 77 : 5668 – 5725 .
[20]. Asadi , A.H.K. , Jahangiri , A. , Zand , M. et al. (2022). Optimal design of high density HTS-SMES step-

shaped cross-sectional solenoid to mechanical stress reduction . In: *2022 International Conference on Protection and Automation of Power Systems (IPAPS)* , vol. 16 , 1 – 6 . IEEE .

[21]. Kabir , M.H. , Hasan , K.F. , Hasan , M.K. , and Ansari , K. (2022). Explainable artificial intelligence for smart city application: a secure and trusted platform . In: *Explainable Artificial Intelligence for Cyber Security* , 241 – 263 . Cham : Springer .

[22]. Oladipo , I.D. , AbdulRaheem , M. , Awotunde , J.B. et al. (2022). Machine learning and deep learning algorithms for smart cities: a start-of-the-art review . *IoT and IoE Driven Smart Cities* 143 – 162 .

[23]. White , R. (2021). *Global Harms and the Natural Environment* , The Palgrave Handbook of Social Harm , 89 – 114 . Cham : Palgrave Macmillan .

[24]. Golla , Naresh Kumar , and Suresh Kumar Sudabattula . Impact of Plug-in electric vehicles on grid integration with distributed energy resources: A comprehensive review on methodology of power interaction and scheduling . *Materials Today: Proceedings* (2021).

[25]. Chen , Y. , Peng , X. , Xu , X. , and Wu , H. (2021). Deep reinforcement learning based applications in smart power systems . *Journal of Physics: Conference Series* 1881 (2): 022051 . IOP Publishing.

[26]. Lu , Q. , Chen , Y. , and Zhang , X. (2022). *Smart Power Systems and Smart Grids: Toward Multi-Objective Optimization in Dispatching* . Walter de Gruyter GmbH & Co KG .

[27]. Li , C. et al. (2021). Data-driven planning of electric vehicle charging infrastructure: a case study of sydney, australia . *IEEE Transactions on Smart Grid* 12 : 3289 – 3304 .

[28]. Sivaraman , P. and Sharmeela , C. (2021). Power quality problems associated with electric vehicle charging infrastructure. *Power Quality* . *Modern Power Systems* 151 – 161 .

[29]. Alghamdi , T.G. , Said , D. , and Mouftah , H.T. (2021). Profit maximization for EVSEs-based renewable energy sources in smart cities with different arrival rate scenarios . *IEEE Access* 9 : 58740 – 58754 .

[30]. Dashtaki , M.A. , Nafisi , H. , Pouresmaeil , E. , and Khorsandi , A. (2020). Virtual inertia implementation in dual two-level voltage source inverters . In: *2020 11th Power Electronics, Drive Systems, and Technologies Conference, PEDSTC 2020*.