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5G OPPORTUNITIES AND IMPACT OF ELECTRIC VEHICLE PERFORMANCE WITH ARTIFICIAL INTELLIGENCE TOWARDS THE SMART CITIES

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Abstract - This research aims to evolve the National Clean Air Program (NCAP) Operational Strategy, as announced by the Government of India in 2017; the wide-ranging epidemiological synecdoche is to resolve the air contamination concern at a 20% to 30% target of reduction in 2024. According to public authority guidelines, it is compulsory to convert approximately 25% of existing vehicles into electric vehicles by 2024. In the car area, vehicle planning and maintainability are focused on using Electric Vehicle innovation with zero discharge and the minimization of carbon. Electric Vehicles are more eco-accommodating along their lifecycle than traditional petroleum derivative vehicles, particularly on the off chance that they are powered with clean power. Further, current advancements like AI (Artificial Intelligence) and IoT have likewise improved the plan and development of Electric Vehicle manufacturing and battery charging innovation. The fundamental goal of computer-based intelligence is to provide closed-loop enhancement of electric vehicles in the areas of quick charging conventions for batteries, output control, monitoring, and preservation of force with an inspired way to a superior sustainable environment. The proposed work enumerates in detail the features of electric vehicles with the influence on 5G-IoT (Internet of Things) and comprehends advancement strategies of AI and ML to improve the highlights of EV in frequency band analysis with SNR and downlink power utilization.

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Introduction

It is anticipated that continued total population growth and further industrialization will result in greater levels of energy demand, and global energy consumption is predicted to increase. by 50% from 2018 to 2050. A large portion of this energy demand is satisfied by non-renewable energy sources, all of which are detrimental to the climate, and the overall global energy consumption is likely to increase by 50% from 2018 to 2050 [1]. The use of non-renewable energy sources contributes to the discharge of gases that are deleterious to the environment, which, in turn, jeopardizes human health and causes climate change via greenhouse gases. These reasons necessitate the use of non-electric energy resources, among which solar, wind, running water, and geothermal energy are the most useful resources. The sun is acknowledged to serve as the principal or secondary source for all renewable energy sources, except geothermal energy. Among all renewable energy sources, solar energy is the most promising because it can capture as much energy as the entire world's annual requirement in less than an hour [2]. After solar energy, wind energy is the most promising renewable energy source for satisfying the world's energy requirements.

Environmentally friendly power assets have irregular negative effects, which can be countered by fuel sources with various capacity-enhancing techniques. Continuous energy can be generated from these fuel sources. As noted in [3], writing has several described examinations of different energy systems for a green and sustainable world. Most claims in the writing focus on integrating renewable energy into electrical loads. However, supplying electrical loads with renewable energy is not the only solution for a sustainable future, as approximately 29% of the world's greenhouse gases are emitted from mobile vehicles [4]. Therefore, in addition to electrical loads, eco-friendly power sources should be provided for mobile vehicles.

For this study, a hydrogen fuel cell vehicle, in which hydrogen is derived from water using sustainable power-controlled electrolysis, as depicted in Fig.1, was used for transportation. Moreover, it must be emphasized that other methods exist for producing hydrogen. However, the rest involve the burning of fossil fuels and are still highly greenhouse gas-emitting [5]. Thus, they are probably not a solution for a sustainable and environmentally friendly future.

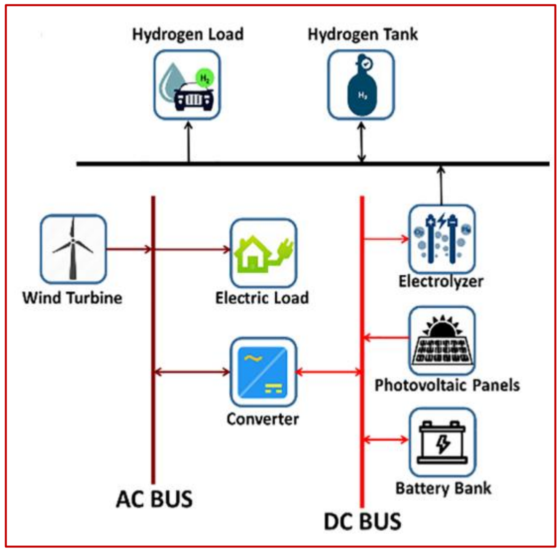

Fig.1: Hybrid system architecture incorporating several power sources

The transportation sector accounts for roughly 69% of all greenhouse gases produced by road transport, 37% of which comes from light-duty vehicles and 21% from heavy-duty vehicles. According to the 2015 Transport White Paper, for the EU to achieve its long-term target, a 71% reduction in these emissions must be achieved by 2045 [6]. Hence, the EU and other international entities are incentivizing national governments to increase the implementation of electric vehicles. However, the rapid advancement of these technologies in the transport field may pose more problems and call for new, refined approaches [7]. Unrestricted ad-hoc charging of EVs creates heavy, sustained demand for electricity and can lead to blackouts. However, the charging demand from EVs can be flexible, and paradoxically, EVs may increase grid stability by providing electricity (via V2G) and demanding electricity when the grid is overloaded. Moreover, EVs can instantaneously discharge their stored electricity to the grid to relieve demand peaks and can provide their full capacity (discharge all stored electricity) to the grid when the demand is persistently high. Thus, EVs can be classified as flexible and dischargeable (grid) resources [8]. EVs' steering takes control of the vehicle steering issue (VSI), which should characterize the operational characteristics of such vehicles. In this context, new choice problems arise, as the steering of electric vehicles (EVs) should not only consider VSI trademark information (e.g., time windows, service times, distances, and travel times) but also information about charging stations, charging times, and energy costs. In this chapter, the focus is on the problem of optimally scheduling cargo transportation services provided by EVs, for which a new decision model is proposed. In general, Vehicle Service Institutions (VSIs) are responsible for assigning transportation requests to available vehicles and determining service routes in a specified order to optimize one or more predefined objectives [9]. The Green Vehicle Routing Problem

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(GVRP) was introduced to address the complexities of managing a fleet of environmentally friendly vehicles. The GVRP is defined as the task of designing optimal trip schedules for a set of eco-friendly vehicles, considering their energy consumption and the potential need for additional stops to refuel or recharge [10]. Problem (EVRP), one facet of which is the deployment of a fleet of Electric Vehicles (EVs) that leave a depot to serve a predetermined customer set while also factoring in a potential need to visit a charging station to maintain battery charge levels to complete the trip [11].

The rapid growth of urban populations and the accelerating shift toward smart cities necessitate innovative solutions to address escalating energy demand and environmental challenges. Electric Vehicles (EVs), powered by clean energy sources, are at the forefront of this transformation, offering a sustainable alternative to conventional fossil-fuel-based transportation. However, the successful integration of EVs into urban ecosystems depends not only on advancements in battery and vehicle technologies but also on the development of intelligent systems capable of efficiently managing energy consumption and grid interactions. AI algorithms further empower predictive analytics for battery health, charging demand forecasting, and adaptive energy distribution. Moreover, the integration of AI and 5G supports advanced features, such as autonomous vehicle navigation and intelligent routing, which contribute to reduced emissions and improved traffic management. Despite these technological advances, challenges remain in scaling the infrastructure, managing stochastic charging behaviors, and ensuring equitable access to smart charging facilities. Addressing these issues requires a multidisciplinary approach encompassing energy storage optimization, grid modernization, and policy frameworks that incentivize the adoption of EVs and smart systems. This study explores these interconnected domains, emphasizing the role of AI-driven 5G-enabled platforms in enhancing EV efficiency and sustainability in smart cities. By leveraging emerging technologies with intelligent control systems, this study aims to contribute to a cleaner, more resilient urban transportation network aligned with global environmental targets.

5g Based IOT Architecture with Inference and Bandwidth Allocations

The Web has transformed over time and has developed in complexity and structure from a simple hierarchical design to a fully functioning, intricately meshed network of interconnections and organizations. Cost management, greater control over internal organizational relationships to guarantee quality Internet services, and the addition of new web use cases all contributed to this evolution. Most traffic at the interdomain or core level of the Internet is exchanged among autonomous systems (ASs) operated by different organizations through two primary mechanisms: transit and peering. Under a transit agreement, a customer AS connects to an upstream transit provider that offers access to the full set of Internet routes and carries all traffic on behalf of the customer's network. In contrast, peering involves the direct exchange of traffic between an AS and one or more other networks. Peering can be public or private. Public peering occurs at an Internet Exchange Point (IXP), where multiple networks interconnect, whereas private peering relies on a dedicated Point of Interconnection (POI) that links two networks directly.

Large-scale entities, such as major media platforms and content delivery organizations (CCOs), commonly exchange traffic with top-tier Web Access Supplier (WAS) networks through Paid Interconnection Arrangements (PNIs). At the same time, these organizations also leverage IXPs to interact with numerous smaller networks. Transit services remain an available option for exchanging traffic. Overall, global interdomain traffic flows through a mix of interconnection models, chiefly transit networks, Internet exchange points (IXPs), and private network interconnections (PNIs). The specific route chosen for traffic is typically determined by commercial and policy-driven factors.

For any given client network, technical design choices and business strategies dictate the preferred blend of interconnection types and the volume and nature of traffic allocated to each. A comprehensive worldwide overview of interdomain traffic distribution remains unavailable, largely because such an effort would require full transparency and collaboration from all operators of the interdomain infrastructure. Nonetheless, the prevailing view within the interconnection research community suggests that PNIs likely account for a somewhat larger fraction of the total global interdomain traffic than IXPs.

Ultimately, IXPs serve a crucial function as interdomain infrastructure, with a large IXP acting as a central hub for traffic consolidation that facilitates the interchange of substantial amounts of interdomain traffic within a singular, concentrated framework. Conversely, PNIs are dispersed throughout interdomain infrastructures, both in their placement within the architecture of the Web and in their physical locations. In 2016, the German government designated major Internet Exchange Points (IXPs) with over 300 connected networks as critical infrastructure, highlighting their significance to the modern Internet.

Percentage of all interdomain traffic on a worldwide scale compared to IXPs, Electric Vehicles Run by Batteries That Tap into the Power Grid and Use 5G Networks

In the 1990s, a proposal to harness the battery reserve of electric vehicles as a power storage facility to back up the electric power system was introduced [12]. The focus of this approach is on the vehicle-to-grid (V2G) system. Because most (92%) private cars are not in transit, V2G can be expanded to provide extra buffering or ancillary services to grid employees. On the other hand, V2G is the Vehicle Electric (EV) business model system [13]. Several studies have been devoted to the possibility of bidirectional coupling of EVs to low-voltage grids. The state-of-the-art technology for primary bidirectional EV charging/discharging stations, coupled with the mandatory

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capacity of EV batteries, is not mature. Meanwhile, the primary control of Variable Renewable Energy Sources (VRES), which in some cases have a strongly intermittent generation profile [14], is becoming of paramount importance. Power system operation, transmission, and storage pose significant challenges.

V2M, which offers 100% RE inventories, has potential value in power generation. This is followed by the VRE's strategic positioning and significant contribution to the public power supply in Germany [15]. The challenges inherent in accommodating more VRE generation within a given electrical system are generally manageable by modifying consumption profiles, adding new transmission lines, or expanding storage. For the supply of a public grid, the ability to exchange power with neighboring countries is a contributory factor to the low outflow of the public power supply [16].

Given the overall population of the EV market, a specific development rate was predicted. A remarkable learning curve was forecasted based on the number of 35,000 EVs in the public German market in 2019, 5.5 million in 2025, and 19 million in 2045. In **Fig.2**, the total number of EVs is displayed alongside the total battery size used. Most innovative Li-Air batteries, predicted to be compatible [17] in 2032, are currently being tested. Based on the information provided, apart from the predicted technological advances, the year 2035 is also expected to add a small acceleration to the predicted total battery size curve. This study considered only Light Electric Vehicles (LEVs), as the presence of EV trucks or buses is unlikely. In this study, the terms LEV and EV are used interchangeably to describe electric vehicles operated by private individuals or companies that are not designed predominantly for transporting goods or are part of a public transport system.

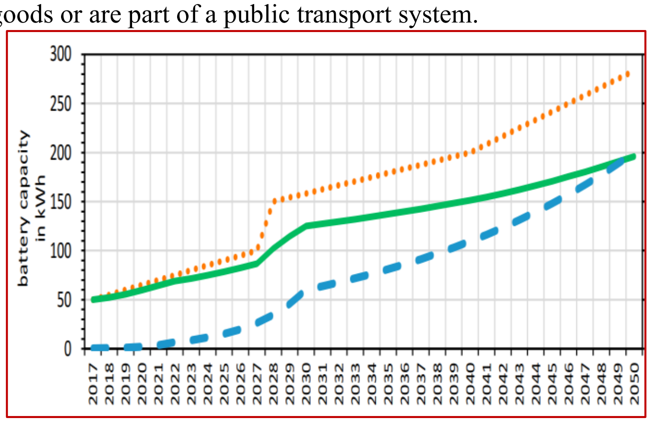

Fig.2: Power utilization by electric vehicle in year wise distribution scale

Every user of Electric Vehicles (EVs) has the opportunity to maintain a minimum balance of 30% in their battery system. This is vital for satisfying individual mobility demands [18]. System users can unilaterally decide whether they want to participate in the V2G scheme. It is assumed that, on average, 90% of users will opt for the V2G system. In addition, average user profiles are assumed, except certain hours of the day for V2G, which affect hours with a presumed high degree of individual mobility, such as commuting to and from work during workdays [19].

A) Diverse Energy Storage Capabilities for Electric Vehicle Grid with Power Distribution Factor Evaluation

The widespread adoption of battery-powered transport has the potential to create substantial technical issues and serious negative consequences for the infrastructure in place if utilities cannot keep up with the rapid increase in demand for charging. Consequently, both primary and secondary infrastructure will require substantial and expensive upgrades. In a 2020 report, researchers determined that the low-voltage EV charging level can cause quality degradation of the electric power system owing to the overloading of transformers [20]. In addition, to ensure safety, on-grid charging for EVs must be controlled; this must be done by predicting demand, scheduling charging, and controlling access, which is often impractical to enforce and thus unpredictable. EVs, when charged exclusively by the grid, do not provide substantial benefits to the ecosystem; however, if coupled to a solar charger, the system significantly aids in the reduction of CO2 emissions per km. Therefore, the installation of charging stations that draw from decentralized renewables is the most optimal strategy to allow for the continued adoption of EVs globally, while lessening the burden on overstressed power systems [21].

Nevertheless, off-grid charging stations equipped with RES are still unable to provide a continuous electric power supply because of the intermittency and unpredictability of the renewable energy sources.
Variation in biomass energy availability depends on seasonal temperatures, wind speeds, and sunlight availability during the evening and in cloudy weather. These factors are also critical in the design of energy systems, including wind and solar PV systems [22]. The incorporation of several renewable energy systems in parallel should mitigate the issues of energy availability and complement each other. To further improve the system, reliable optional energy storage systems (electrochemical, thermochemical, and nuclear) should be included. Several studies, including this one, have utilized solar photovoltaic and wind energy technologies, either alone or together. To produce the requisite energy for electric vehicle charging, a case study investigated a predictive control technique for the integration of a multifunctional photovoltaic system and battery storage, and a zoned HVAC system was investigated. The goal was to flatten peak shaving while maintaining the thermal comfort of the occupants [23]. The average load was reduced by 23% from the predicted operational load baseline, demonstrating the effectiveness of the proposed controller. A previous study proposed further research

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incorporating EV charging and wind turbines, both of which are included in this chapter [24].

In addition, a load-shedding response strategy was engineered for a grid-connected household energy system incorporating passive solar and wind technologies, designed to reduce energy expenses and tackle the issue of fragmentation typical of hybrid renewable energy systems. Three load types were considered, each of which had to be supplied with a defined service reliability: interruptible, flexible, and non-interruptible. The system was designed to optimize the integration of renewable energy by load shifting and storage, thereby minimizing the energy costs associated with the grid to maximize power exchange [25].
Global interest in the use of biomass as a sustainable resource for electricity has been growing over the past few years. Biomass-based electricity generation has numerous advantages, such as sustainability, effective waste management, and independence from price volatility, among others. Within the last decade, global biomass electricity generation has more than doubled, from 319 TWh in 2010 to over 751 TWh by 2020 [26]. Biomass consists of waste streams such as Municipal Solid Waste (MSW), animal waste, food waste, and aquatic plants, especially algae. Thermal and chemical methods for the conversion of biomass into energy have been developed over the past 40 years as replacements for fossil fuels. Energy is generated through four main methods: combustion, pyrolysis, gasification, and anaerobic digestion, as illustrated in **Fig.3**. The first three methods are thermochemical, whereas the last is biological [27]. During combustion, biomass is burned in a furnace, and the heat generated is used to produce steam, which is then used to drive a steam turbine for generating electricity.

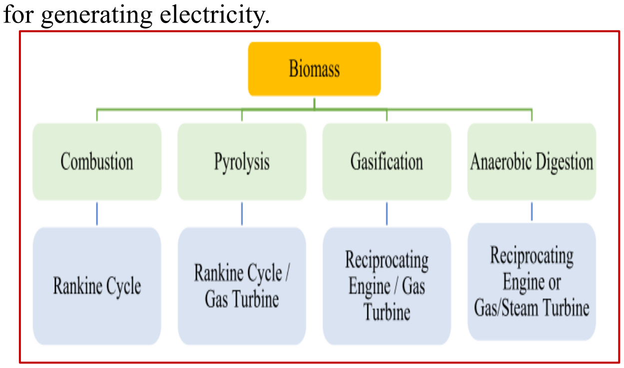

Fig.3: Alternative energy resources from biomass with diverse streaming types for automotive applications [27].

Owing to the temperature and potential ramifications of the steam generated by biomass boilers, which may attain 512 ◦C and 98 bar, steam Rankine cycle facilities have been incorporated with CPV/T subsystems in several studies to enhance their efficiency.[28].
From the cooperation strength perspective, it is possible to hybridize CPV/T and biomass ignition advancements, which combine several studies within the analytical literature that have pioneered the empirical dependability of this combination to furnish energy, primarily for remote regions with neutral biomes on the order of kW to GW scale.
A parametric file on solar-based energy allocation for a 6.2 MW cross-breed solar biomass electricity plant was developed [29]. The steam temperature increased from 287 to 598 °C, accompanied by a 1.2-fold increase in energy output and a boost in energy conversion efficiency from 18.4% to 32%. In addition, a solar–biomass hybrid Rankine cycle plant with a capacity of 34 MW was analyzed, and the results indicated that hybridization enhanced the plant capacity utilization from 31% to 52%. Comparative assessments between hybrid solar and biomass configurations and stand-alone biomass systems revealed that the combined approach reduced biomass consumption and land requirements by approximately 31%, with associated costs ranging from 7.9 to 25.1 $/GJ/a. However, the availability of solar radiation is restricted to daylight periods and favorable weather conditions, and solar electricity production is further constrained by the performance limits of photovoltaic panels, as illustrated in Fig. 4 [30].

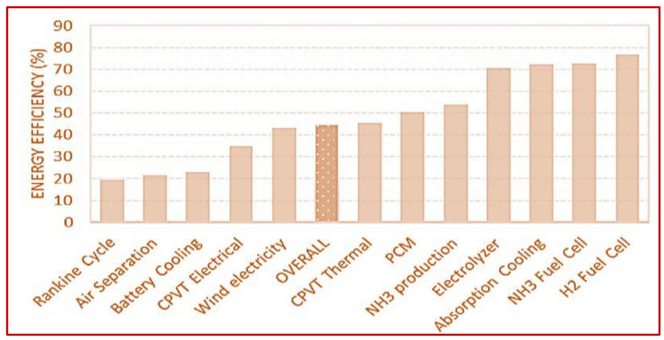

Fig.4: The performance energy efficiency of multiple energy resources for the electric vehicle functioning [30]

Moreover, one of the main characteristics of the EV charging request is its stochastic nature, resulting in the underutilization of the energy produced by the PV system during the day because of the smaller number of EVs available for charging compared to the energy available.
To address the challenges posed by the abnormal strengths exhibited by PV arrays and the stochastic demand for electricity by EVs, additional supplementary renewable energy sources (RES) and appropriate energy storage systems (ESS) are required for effective and consistent energy delivery. Nuclear energy is considered one of the most promising potential energy storage systems, particularly when it is stored as cheap or passive heat, which, in the case of SCM, is recoverable depending on the conditions. The incorporation of phase-change materials (PCM) into nuclear energy (TES) systems has been the focus of several studies to enhance the effectiveness of PV systems. In the case of a CPV/T system, it is possible to use the stored nuclear energy to enhance the overall system performance, particularly when the system is designed for full operational capability. Additionally, the incorporation of SCM into CPV/T systems mitigates the temperature fluctuations caused by solar irradiance [32]. In

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general, TES systems provide better overall performance, require lower total costs, and have a higher potential than other alternatives.

Another dominant away strength is placing away undersized imitated stockpiling, where strength and electric devices are produced, and electricity is produced. H2 and NH3 are examples of these frameworks. The strength recovery electrochemically convertible systems have efficiencies as high as 69%. Electrochemically convective systems are other potential sources of away strength, where electricity can be obtained instantaneously when the potential is coupled with a load. Batteries are considered the most celebrated thermal systems. In battery thermal energy storage, the net round-trip efficiencies are as high as 95% [33].

Electric Vehicle Performance Simulation Model Using Artificial Intelligence

The electric components of vehicles have been advanced and refined by automakers, alongside digital and electric improvements and a constant stream of new offerings. Automakers further advance and refine vehicles by adding more electronic components and improving the vehicle's safety, comfort, reliability, and special features. Therefore, an imbalance may occur in the interaction between the creation and utilization of collectors, generators, and electric energy loads in a vehicle's energy system. The integration of the outputs of the generator, battery, and power components is the most important starting point in designing a vehicle power system. If it is not properly balanced, it affects the efficient functioning of vehicles. Furthermore, neural networks are based on the behavior of interconnected neurons in the brain. Neural networks have remarkable capabilities for predictive and nonlinear learning [34]. A well-structured neural network that can learn through the adaptive mechanism of neural networks can determine the design of the neural network. This is the main reason why neural networks serve as excellent default mathematical models for any nonlinear function. The neural organization's ability to nonlinearly envisage structure-function relations might be unexplainable in the current version, and the indirect pathways that scheme information and yield facts would have to be situated somewhere in the neural organization. The ability of neural organization to nonlinearly envisage structure-function relationships is shown in **Fig.5** [35].

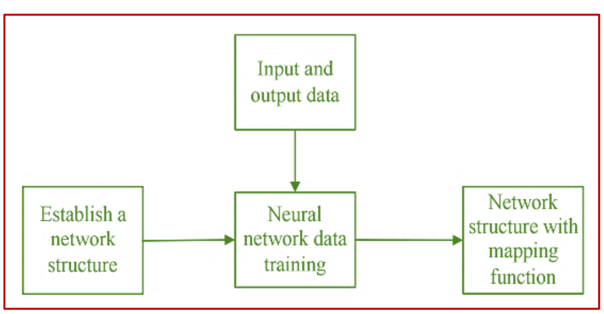

Fig.5: Neural architecture for the analysis of electric vehicle load variation with power [35]

The vehicle electrical balance refers to the vehicle's power interrelating the battery, alternator, and power drain with the instantaneous processing of the interdependent use of the shared capacity. When the alternator is marginally deficient in power production, the battery and alternator discharge to the electric load; when the alternator is marginally sufficient in power, the alternator discharges to the electric loads simultaneously with the battery [36]. The alternator model configuration in this study incorporated the alternator-assessed active model and the full-load active model. According to a considerable number of studies conducted by companies or OEMs, the compelling evidence needed to justify is obtained, and the data are processed by the neural network device of the compartment to construct the associated nonlinear function map.

Research focusing on the reuse of retired batteries in stationary energy applications has grown, yet the number of studies incorporating a full supply chain perspective remains limited. This lack of a comprehensive system perspective has likely resulted in an unreasonably positive assessment of the impact of battery reuse on Distributed Energy Systems (DES). There remains a significant gap in knowledge regarding the interactions of DES with its immediate upstream and downstream systems. In this context, the used batteries of the DES supply chain, system impacts, market size, and technological maturity are pivotal. In addition, the used batteries of the DES supply chain impact system, market size, and technological maturity are sufficiently interrogated [37].

To mitigate these challenges, this study presents, for the first time, an integrated framework aimed at depicting the supply chain evolution and formulating DES recycling strategies for retired EV batteries. These configurations are critical in the future of energy transitions and for establishing a vital circular-resource conduit of used EV batteries in stationary storage systems. In addition, a game-theoretic model integrated with a DES optimization structure serves to examine the interactions of various supply chain constituents, such as the government, EV and battery manufacturers, DES operators, and D&R.

As shown in **Fig. 6** [38], the proposed model combines a supply chain profit allocation model and a DES planning model. Part of the profit allocation model deals with the routing of retired EV batteries to large-scale storage incorporated within DES units and the latter's D&R sector. The focus is to maximize overall supply chain profit while ensuring that profit equity is sustained through a Nash equilibrium. Equity is defined as a condition in which each sector can obtain a reasonable share of the total profit. Meanwhile, the DES planning model, in the course of the 20-year horizon of the project, determines the cost-optimal network design, meso (or system) configuration, and system deployment route, in the use of either new or retired batteries [39]. The analysis also goes beyond the ordinary "renewables

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+ storage" system configuration of the study to explore the system-level consequences of the inclusion of new and retired batteries within generalized DES planning.

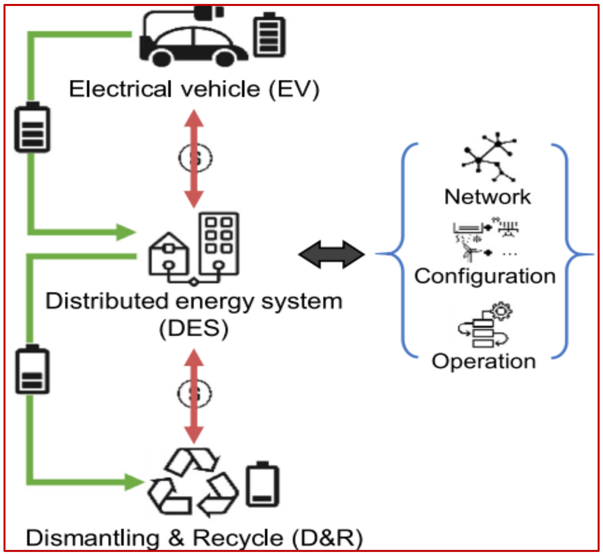

Fig. 6: Network synchronization with the DES system [38]

This is accomplished by improving the DES development model to include both renewable and conventional energy sources, energy management activities, and integrated supply and demand planning to satisfy the electricity, heating, and cooling demands of a region with a heterogeneous building stock [40].

Neural networks applied to the domain of autonomous vehicles are particularly impactful. Unlike other technological domains, the relevant data are continuously monitored, analyzed, and refined by sophisticated artificial intelligence. Predictive algorithms indicate an increasing demand for battery-electric vehicles, outpacing that for conventional hybrids. The diverse energy resources available within modern EV technologies suggest that electric vehicles are likely to be one of the primary enablers of cutting-edge mobility and an essential element in the ecosystems of future intelligent cities.

A) Artificial Intelligence Impact in the 5 G-supported Electric Vehicle World

The role of Artificial Intelligence in developing and managing more advanced electric vehicles, complex power systems, and transport systems is of tremendous importance in the future. The combination of advanced AI algorithms and computing power, along with the increase in data volume, has opened the field of forecasting battery capacity and electric vehicle charging demand to AI [41]. The integration of AI with electric vehicles to solve complex problems, such as smart charging and vehicle-to-grid (V2G), allows the real-time management of power consumption and generation from heterogeneous actors. The ability to gather information from heterogeneous sensors and devices and codify the information in real time is a crucial function of the smart battery management and battery charging control systems. The systems incorporated into smart EV charging infrastructure can have a considerable impact on energy consumption. Rapid advancements in artificial intelligence (AI) and deep learning algorithms are facilitating technological advancements in electric vehicles. The contribution of AI in the management of complex electrical power systems is becoming increasingly important.

While the energy system undergoes rapid changes with the increase in electric vehicles and renewable energy, integration with other technologies, such as charging electric vehicles with renewable energy and increasing power demand, has been developed [42-44].

The integration of Artificial Intelligence (AI) technologies and 5G mobile networks helps reduce the susceptibility of the framework to the variable and intermittent nature of renewable energy sources and improves system integration. If AI is to assist in the advancement of Electric Vehicles (EVs) and impact the efficient operation of energy (EN) systems, then the construction of a strategy to diversify policy frameworks on AI is critical. However, there is limited empirical research on the application and effectiveness of AI over long periods and its impact on the technological advancement of EVs. Previous research on AI has centered on the advancement of Artificial Intelligence (AI) technology using patents as the sole data and then classifying AI technology in a certain field [45]. However, the AI Technology under the class is restricted, as it cannot simulate the sophisticated behavior of AI technology and algorithms, as the identification and analysis of patent data is purely based on the AI technology class. Research has focused on the application of 5 G-based AI on Electric Vehicles (EVs) for the prediction of battery state of charge, battery charging and discharging cycles, energy management, battery materials, battery system optimization, and battery operational performance [46-49]. With an increase in recurrence, the age of the signal and the engendering of the sign become more difficult. An electric vehicle with 5G connectivity demonstrated a reduction in air pollutants up to 2 THz and dry air of 5 g of THz and 5 g of THz and 5 g of THz with 5 g of THz under ground-level climate conditions and ITU-R P.676-9. **Fig. 7** also shows downpours of 4, 16, and 50 mm/h, corresponding to moderate, heavy, and torrential downpours, respectively.

ITU-R P.838-3 is a guideline for evaluating the specific attenuation caused by rain at frequencies up to 1 THz, including considerations for polarization. The guideline indicates that the general behavior of rain attenuation within the frequency range of 1 to 998 GHz is an increasing function with a rate of increase that is maximum at approximately 98 GHz and then levels off. **Fig. 8** shows the

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three principal nearby maxima in the THz range of up to 499 GHz. These maxima occurred at 298.31 GHz with 41.23 dB/km, 312.45 GHz with 198.79 dB/km, and 502.78 GHz with 443.57 dB/km, respectively. Although Fig. 8 shows a detailed consideration of the attenuation components below the THz range, increased focus is directed towards the specific attenuation within the interval of 301 GHz to the third local maximum at 502.124 GHz in the THz frequency band. The attenuation value at 301 GHz is 3.987 dB/km, while the adjacent local minimum of the three THz band local maxima occurs at 298 GHz with 11.23 dB/km and at 503.69 GHz with 21.54 dB/km.

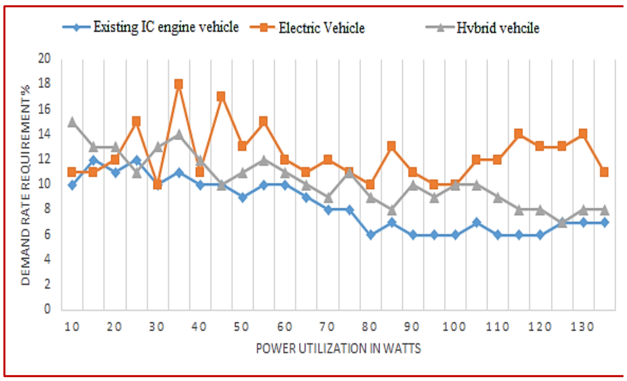

Fig.7: Requirement rate with power utilization generated by the neural network

If we define transmission windows as spanning a low-THz band with a 4.5 dB/km loss differential to its surrounding local minimum, the first three such windows above 325 GHz are shown in great detail in **Fig.8**.

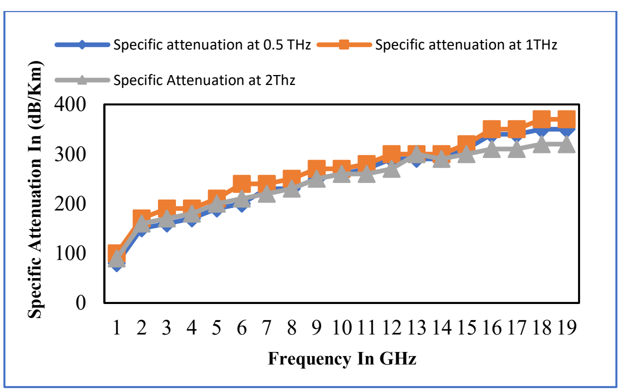

Fig. 8: Characterization of specific attenuation in 5G mobile networks through investigation of the 298-305 GHz interval under local window limitations

The higher frequency limit of next-generation mobile networks is undoubtedly increasing, with extensive field measurements at 41, 59, and 82 GHz being carried out in addition to theoretical expectations. However, to date, very little research has been conducted on channel estimation and propagation modeling in the low-THz band [50], as analog and digital transmission studies are being conducted. To our understanding, only one THz indoor channel model has been examined in the existing literature so far. **Fig.9** is to scale and demonstrates the theoretical SNR values achieved in the electric vehicle operational scenario, thus validating the simulations conducted [51]. The highest SNR value of 3.92 dB corresponds to a BER of 2.5 *10-3 obtained with the practical implementations of PSSK and quadrature PSK modulated transmissions.

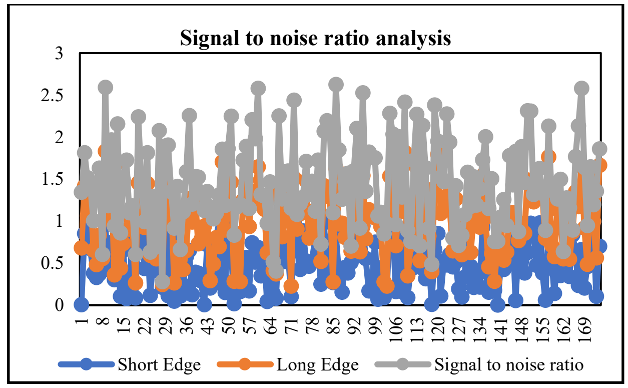

Fig.9: SNR estimation on the electric vehicle floorspace analysis

Fig. 10 describes the standard downlink transmission power of the base station as a function of client density, assuming a cell coverage area of Ai=π*350 m2, Bandwidth B=120 MHz. In addition, it describes the standard downlink transmission power as a function of base station density with user density=10-2 user/m2 and B=45 MHz [52]. The user downlink transmission power has a defined user density, as follows: The mean downlink user transmission power diminishes with an increase in base-station density. A comparison of the simulation and analytical results verified the reliability of the experimental 5G coverage model for electric vehicles. The model developed from the group's earlier studies offers a stochastic solution for calculating the frequency range of 347.25–398.75 GHz. All parameters for a given channel transmission, namely, amplitude, polarization, time delay, phase, frequency shift, angle of arrival, and angle of departure, were included. However, the model was incomplete. The proposed variable sets are determined by a specific use case, and due to time limitations, the outcomes of ray-tracing simulations are utilized instead of actual channel measurements.

Mirrored wave stage turns show a consistent dispersion with an increase of 270°–340 °, thus lacking specific information. The dispersion of the elevation and flight angle was also measured, but this is due to the area's layout and the locations of the transmitters (TXs) and receivers (RXs), rather than the dispersion of the electromagnetic wave itself. The model's accuracy is significantly compromised due to the requirement to modify it with beam steering for each changing weather situation. Overall, notwithstanding its IEEE designation, the channel model represents a

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significant advancement towards a novel paradigm of wireless communication.

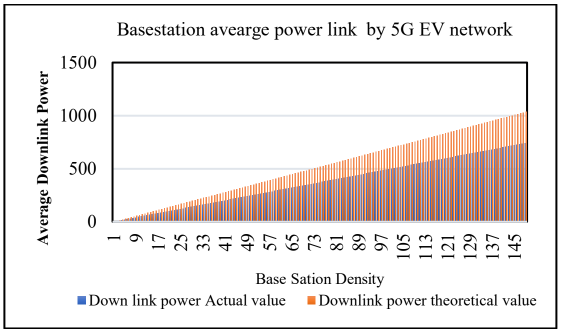

Fig.10: Base station power link usage analysis for the electric vehicle 5G coverage platform

CONCLUSIONS

In light of the global transition toward a digitally oriented energy landscape, the integration of vehicle-to-grid (V2G) systems with 5G technology constitutes a strategic response to the increasing variability associated with renewable energy sources, such as photovoltaic and wind generation. V2G yields substantial net benefits for both energy production and distribution entities, as well as private consumers. Importantly, the optimal rating for a bidirectional V2G charging pole was identified at approximately 6.9 kW, indicating that this configuration was not designed to operate as a high-speed charging solution. Rather, charging and discharging durations in the range of 5–12 h, achievable with standard low-voltage "wall-box" technologies, are considered appropriate.

Under these operational assumptions, the capital costs associated with bidirectional charging infrastructure are not expected to be prohibitive, particularly given their projected role as foundational ICT components in smart grid architectures. This stands in contrast to conventional fast-charging infrastructure, which is typically linked to medium-voltage networks and incurs significantly higher costs, with limited potential for price variation at such grid connection points. Consequently, V2G systems place minimal emphasis on rapid charging, as the primary users of these systems generally exhibit extended vehicle idle periods, rendering slower grid-integrated charging cycles both suitable and efficient..Considering this, the vehicle-to-grid (V2G) concept alters the perception of EV charging and use. V2G no longer revolves around the concept of queuing at a petrol station. In the context of V2G and 5G mobile networks, one can think of a concept associated with consumer electronics: charging is no longer an action undertaken voluntarily by the user, but rather performed continuously and, at the same time, offers ancillary services (load generation balancing, provision of energy storage systems) to the grid.

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