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A Comprehensive Study on AI driven Predictive Energy Optimization Frameworks for Electric Vehicle

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Abstract- The fast growing use of electric vehicles creates a larger need for intelligent systems that can adaptively optimize energy use in real time. This paper provides an overview of how AI driven predictive optimization frameworks for EV's are changing the way energy management will be executed. It reviewed the impact of artificial intelligence, machine learning, and deep learning on the limitations of conventional methods for managing and optimizing energy. Advanced algorithms such as Long short term Memory networks, XGBoost, deep reinforcement learning, fuzzy logic, and genetic algorithms allow the predictive modelling of battery performance, power usage, and energy requirements based on an individual route. Utilizing real time data, such as traffic volume, road slope, weather information, and driver behaviour, these systems create a dynamic and context based approach to determining the most effective way to use energy, ultimately resulting in greater distance travelled between recharges and increased battery life. They also explore how Vehicle To Grid Communication (V2G) and model predictive control will work together to optimize energy usage in an operational environment that includes issues, such as sensor reliability and communication dropouts. Some conclusions from this literature review render AI driven energy management systems have excellent performance in controlled traditional environments, but challenges remain in developing standard testing protocols, ensuring data safety from cyberattacks, and the need for onboard real time systems to develop standardised protocols for evaluation and testing. Therefore, in order to use a holistic and multi technology AI structure for predictive analytics, a significant amount of work remains to be done to develop standard operating protocols for energy management of electric vehicles and their associated energy networks.

Keywords: Electric Vehicles, Predictive Energy Optimization, Artificial Intelligence.

I. INTRODUCTION

AI driven predictive energy optimization frameworks are a game changing idea in the world of Electric Vehicle (EV). By this people can make them more efficient and smarter, this will help them to analyze the real time data observed and can give the real time solutions automatically. It can predict things like power required, ways to save the battery life or energy, etc. Overall, this will help them to become reliable and will help them to become better. AI has helped people a lot in many fields,now it's entering the field of EVs. Artificial Intelligence (AI) is turning self driving EVs smarter by predicting the best ways to save energy.

By analyzing real time data like weather of the route, distance, traffic, and road conditions[1], these vehicles can automatically choose the most structured and efficient routes, which will help in managing power or their battery life more efficiently. By this, EVs constantly monitor battery health and power distribution, which will make the working long lasting and also save energy. Electric vehicles are the best option for transportation without polluting or harming the environment, and if they want them to work well, they need a system for that, or they could call it a brain. And that brain is Energy Management System (EMS). It uses AI and power as its most important component in this AI intelligently analyze how much energy is used by the motor and the battery. This model works in such a way as shown in figure (1).

By taking the help of machine learning, this trains the car to adapt to traffic or hills in real time so that energy can be used efficiently and can also reprocess power when the vehicle applies the brakes. This will not overload the power grid and will help in making the battery stay long lasting.

Basically, AI makes them cost and environment friendly and more reliable [2].

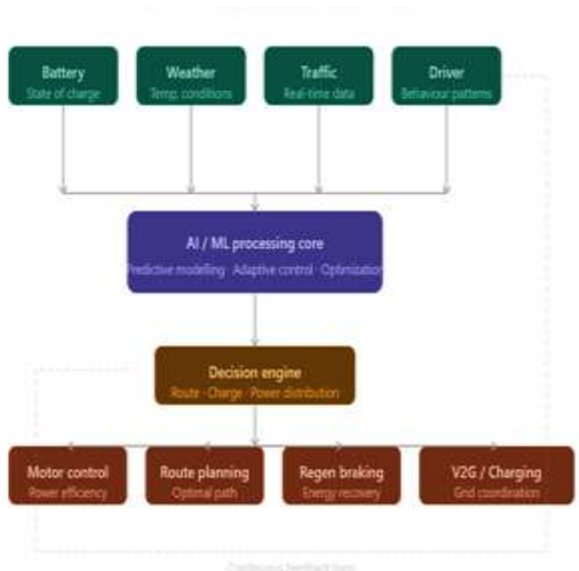

Fig.1. Architectural overview of an AI driven Energy Management System (EMS) for electric vehicles, illustrating real time data inputs, machine learning processing, and output control decisions.

Electric vehicles don't have their own brain AI provides them a brain that makes them smarter and highly efficient. Instead of just using the energy or battery, it uses predictive modeling that will inform about how much energy is needed for the destination and when the vehicle needs a checkup. This helps in keeping the battery safe and healthy and will prevent failures. By using adaptive control, they shift the level of energy usage according to the external conditions, like the ways the user drives and also the traffic that could affect the energy usage.

Genetic algorithms are also used as advanced math is used in them to figure out the best areas or spots for charging up the vehicle and the best way to power it and the fastest way to power it up [3]. And then all of these collectively made EVs efficient, smarter, long lasting, and reliable.

Travel is changing a lot because of vehicles. These electric vehicles work well when they have good systems to manage energy. This means they can make the battery last longer and work with how people like to drive. Electric vehicles are getting smarter. Can even figure out when there might be a problem. They can also send power back to the grid when it is needed.[4] This helps the vehicle last longer and go further. With all the progress that has been made, it is still hard to make these systems work perfectly in real life. Electric vehicles and their energy management systems are very important for a future. Electric vehicles need to be successful so it could have a future.

The EV sector faces some serious challenges in terms of range, charging infrastructure, and government policies, which differ substantially from region to region. The less prominent and emerging markets are also not taken into consideration in this regard. Artificial intelligence, machine learning, and deep learning hold the key to resolving the issues in the management of energy and maintenance of electric vehicles [5] but they have not been employed so far due to certain limitations and hurdles in this regard.

This study will focus on how artificial intelligence and advanced technology can help solve the issues in this regard and how collaboration and cooperation between different stakeholders and government entities can promote the ecosystem of electric vehicles.

Addressing renewable variability and temporal data gaps in EV load forecasting, this study proposes SARLDNet, integrating EMD decomposition, Boruta selection, and a dedicated imputation technique across California charging stations [6]. India's EV sector is growing fast, with authorities targeting a 30% electric share of new vehicle sales by 2030.[7] The primary bottleneck remains charging infrastructure, particularly forecasting station energy demands accurately.

It tackles that through a year long multi vehicle dataset, a GAN based data enhancement model, and ensemble machine learning for precise consumption prediction. SHAP analysis then clarifies each variable's influence on outcomes, giving planners and utility providers a transparent, reliable foundation for deployment decisions. This model works in such a way as shown in figure (2).

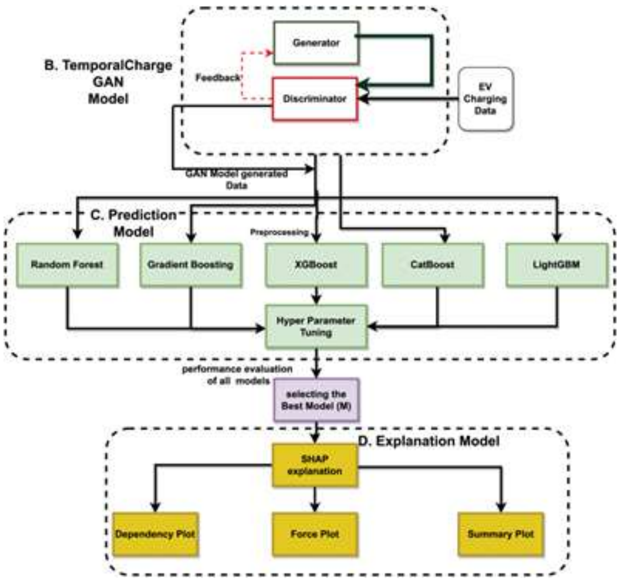

Fig.2. Pictorial Representation of theoretical working of a prediction and explanation model[7]

Most existing EV optimization frameworks fail to account for communication dropout and measurement noise. This integrates a model predictive controller with a convexified polynomial power loss model, validated against NREL datasets, demonstrating robust energy savings under realistic V2V communication conditions [8]. Prior EV energy optimization studies rarely address communication dropout and sensor noise simultaneously. This work also employs a model predictive controller with a convexified polynomial power loss model, incorporating V2V packet loss rates and Gaussian noise to reflect operational uncertainty.[9] Benchmarked across three NREL datasets, the framework demonstrates consistent energy savings under both mild and severe communication degradation scenarios.

Rapid EV uptake has exposed critical shortcomings in conventional demand response frameworks, which lack the flexibility to handle dynamic, real time charging behaviors. [10]. Recalde proposes an AI enhanced framework that predicts charging duration using features such as start time and requested energy, feeding those estimates into an optimization algorithm to flatten the duck curve, reduce peak grid stress, and improve overall load distribution across varying EV integration levels. This section reviews AI based predictive energy management models for electric vehicle batteries based on real time data like traffic conditions/ patterns of movement, weather and road attributes. These models predict the energy consumption of vehicles (potentially hundreds of thousands) and continuously learn new conservation solutions so that demand for energy can be reduced before any wastes occur. They also explore how vehicle to Grid communication (V2G) and model predictive control will work together to optimize energy usage in an operational environment that includes issues, such as sensor reliability and communication dropouts. The combination of artificial intelligence and electric vehicle technology in this context has achieved significant gains in prolongation of battery life, enhancing battery performance, decreasing battery usage and improving vehicle performance thus representing an important advance toward building smarter and greener transportation systems.

II. LITERATURE REVIEW

Fayyazi et al. [11] integrated the fuel cell and battery system which prevented a significant hurdle in the development of hydrogen powered vehicles (FCEV). This was achieved through application of deep reinforcement learning and fuzzy logic, two software applications used to control how much hydrogen the vehicle consumes and how quickly or slowly it would degrade the fuel cell. Ullah et al. [12] when examined machine learning approaches to anticipate energy usage with any other relevant variables 5such as road gradient) or environmental factors (such as temperature), XGBoost and LightGBM came at the top of almost all means of prediction.

Kanagamalliga et al. [13] found out that while AI EMS demonstrates satisfactory performance in controlled experimental settings, benchmark evaluation has not yet been established for scenarios with a mixture of traffic levels, extreme temperature ranges, and various failure modes of sensors. The lack of agreed upon evaluation protocols creates a significant obstacle to conducting cross study comparisons due to slow commercial scale adoption of EVs. Jauhar et al. [14] found out the need to forecast future aggregate power demand based on diverse and growing EV fleets presents a high degree of uncertainty in terms of each forecast's dimensionality, which makes it very difficult for traditional ML forecasting techniques to achieve grid planning level accuracy. Inability to accurately forecast future energy demand results in suboptimal scheduling of the power grid as a whole, under provisioned charging stations, and a loss of confidence in the ability of investors to fund future conversion to electric vehicles.

Diouf, B. [15] studied behavior based learning so they can observe the driving patterns of a fleet of electric vehicles. By doing so, they can develop predictions for the amount of power an electric vehicle will require based on a number of factors, including their current driving patterns, current weather conditions, and the weight of the vehicle. Cavus M et al. [16] studied that transition to Electric Vehicles (EVs) is largely influenced by the combination of Internet of Things (IoT) and big data to actually be able to tell when a part in a vehicle will fail and thus improve how the entire fleet operates, they have access to massive amounts of data generated by the vehicles themselves in real time.

Arif et al. [17] found that a number of manufacturers have expressed newly found interest in a developing new technologies for batteries, and recently new LSTM based networks have been put in place to monitor the use of those batteries (such as number of charge cycles) so that electric vehicles can charge according to the desired life cycles of the end user. Goh et al. [18] was keen to observe that how the complexity of deep learning neural networks (DNNs) and reinforcement learning (RL) agents is incredibly high in operational cost, and implementing these types of models in electric vehicle onboard systems to provide real time decision making (in millisecond response times) concerning braking, fault detection and response, and power distribution has not yet been accomplished within the memory and power constraints of the embedded hardware used in the vehicle.

Devarajan et al. [19] furthermore, continuously executed machine learning inferences against high frequency sensor data with sub millisecond response times to make corrections for power quality which adds to the load on embedded hardware. Up to now, optimizing the speed of the inference processes, the accuracy of the model, and the cost of the hardware has not been done on an industrial scale. Mishra, et al. [20] discovered that upgrades to charging network systems are being made smarter through the use of reinforcement learning and neural network technology. Having the ability to adapt operations based upon changing price structures gives greater capabilities to control when they get the best access to charging stations.

Shern et al. [21] researched that systems using XGBoost and LSTM will be able to predict busy times at charging stations. This will allow for an equitable distribution of loads (scheduling of equipment) during peak load times to prevent grid overload. Gudekota et al. [22] studied that Compounding the difficulty in analyzing energy consumption is the varying amounts of energy wasted depending on how it is utilized. By employing this methodology we are better able to predicate our energy consumption behavior. Khan et al. [23] revealed that there is also a concern about security concerns surrounding AI based EV charging networks this includes problems with adversary manipulation of artificial intelligence (AI) EV software, denial of service attacks on these AI EV systems and federated learning to poison data over time, reducing the effectiveness and accuracy of models. Additionally, a lack of specific EV deployment cybersecurity standards creates additional difficulties in the reliable deployment of AI based charging infrastructure amongst multiple vendors.

Sarker et al. [24] figured out there is evidence from one trial where 800 homes had electricity and used unique, special type electric vehicle charger and it shows they achieved a 31.5% reduction in maximum load on their transformer using a mixture of AI and other techniques, while taking advantage of solar energy. The simulation based performance model for smart EV charging mechanism worked as shown in Fig3. The homes also utilized a solar charger for their electric vehicles in combination with the AI EV support system to enable the household more solar power. Khatib et al. [25] built an AI based infrastructure supporting EVs favors high income individuals while electric vehicle infrastructure also favors high quality smart grids, lower income communities are not adequately covered. The unpredictable nature of user behavior also worsens the ineffectiveness of artificially intelligent demand response (DR) programs.

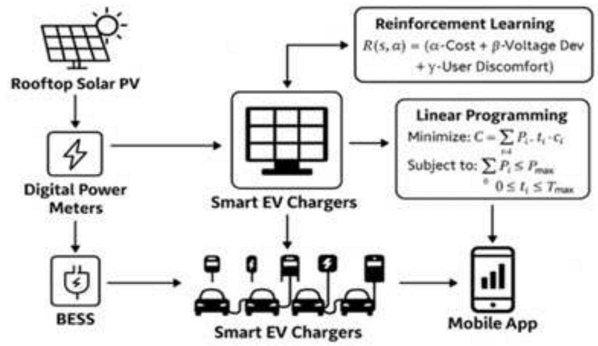

Fig.3. Smart EV charging system as simulation based performance flowchart [24]

Jigyasu et al. [26] Fragmented proprietary protocols and incompatible hardware standards among various manufacturers, grid operators, and charge point suppliers hinder the ability to share data across various types of platforms. They found there will be isolated AI systems without open standards, thus preventing maximising advantages of the use of AI in a network wide manner. Conti et al. [27] Went forward, as EV charging operations must be coordinated with the operational limits of the grid, the integration of renewable energy sources, and the stability of the grid, complexity will continue to increase exponentially. The current infrastructure based, centralised systems cannot handle fleet scale V2G programmes in real time, thus necessitating the construction of novel distributed AI architectures.

Prajapati et al. [28] listed that the factors which limit Solar Based EV metrics mainly associated with Electric Vehicle Charge Point Infrastructure Solutions and one such factor is E Mobility, are the limited amount of available data for complete analysis the difficulty of accessing large volumes of high quality data to train and develop AI systems and the high initial capital costs associated with developing long term EV charging infrastructure. Prakash et al.[29] found out that in addition to traditional navigation systems that provide information on how long it will take a vehicle to travel from point a to point b new navigation Systems (with built in automated charging platform technology) provide real time input of how full the vehicles battery is at any given point the length of time to fully charge the vehicle's battery and, thus, allows users of the EV to better plan for travelling in the city's congested urban core with the knowledge as to where they will find alternative fuel sources during their urban travels. Reddy et al. [30] furthermore discovered that the slow pace for commercial EV roll out has been a result of limited practical application of AI systems to EV Charge Point Infrastructure the high cost for validly testing EVs for all Safety Approval of EVs sold commercially and the multitude of technical hurdles associated with certification of infrastructure equipment used in developing EV Charging Infrastructure.

III. CONCLUSION

This review paper provides an overview of the impact of AI technology on electric vehicle energy management systems based on a comprehensive synthesis of current literature. The findings show that there have been many positive advancements in the ability to optimize energy consumption by various electric vehicle powertrain components through deep reinforcement learning and fuzzy logic, as well as through higher accuracy of consumption forecasts with accumulative classifiers such as XGBoost and LightGBM across different types of road and environmental conditions. Furthermore, advances in long short term memory networks have enabled improved monitoring of battery health and charge cycles, have improved forecasting of energy for charging stations through the augmentation of data using GANs, and have provided more robust energy distribution from the grid by demonstrating the effectiveness of predictive models in conjunction with Vehicle to Grid communication systems under conditions of noise and packet loss.

However, these advancements have introduced several persistent challenges to large scale deployment of AI based EV charging systems. There are no existing evaluation benchmarks which would allow for comparison of results across different studies, many existing algorithms are computationally expensive, making it difficult to implement these algorithms in a real time manner due to hardware limitations, there are numerous cybersecurity vulnerabilities present in AI enabled EV charging systems as a result of adversarial attacks and data poisoning from federated learning environments, the lack of clear standards related to interoperability and the uneven distribution of EV charging infrastructure across different socio economic groups limits the ability to implement AI based EV charging systems at scale.

Future research should focus on improvements to forecasting models based on decomposition forecasting techniques, such as SARLDNet, to enable the deployment of these models in more geographic areas than those covered by existing datasets the continued improvement of GAN based augmentation techniques for the generations of data for use with forecast models with little or no data available and the advancement of neural networks and deep reinforcement learning as techniques to support the development and deployment of predictive models used for vehicle to grid communication systems.

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