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OPTIMIZING ELECTRIC VEHICLE CHARGING INFRASTRUCTURE WITH EVGRIDNET BY INTERNET OF THINGS AND MACHINE LEARNING STRATEGIES

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Abstract. In the arena of renewable energy integration for electric vehicle (EV) infrastructure, it is a problem to efficiently use solar power with EV charging, considering grid constraints and user preferences. The current study proposes a new smart charging algorithm that utilizes IoT data for the dynamic optimization of EV charging patterns. A novel aspect of the study was a deep learning model, "EVGridNet", that reliably predicts solar energy output and grid prices. EVGridNet uses deep learning approaches to process accumulated data via IoT devices, facilitating fine-tuned adjustments to charging patterns through predictive analytics. This algorithm receives actual data on the generation of solar energy, the price of grid electricity, and other characteristics set by the user to optimize the usage of solar energy, limit the usage of grid electricity during the peak hours and meet all the needs of the user. The optimization process of the algorithm strategically manages energy sources, uses battery storage systems to exploit solar power effectively and uses grid electricity during low-cost periods, all within user preference parameters. The proposed system has the potential of reducing grid electric use by up to 25% for EV charging, and increasing the renewable energy electricity in EV charging to 40% as per simulation results. This will enable quick EV infrastructure scalability, low carbon emission, and energy independence. EVGridNet is an outstanding innovation in smart charging technology, which is a cost-effective and scalable solution to the renewable energy sector's primary challenge. One of the key aspects of the optimization process is the control of energy sources where battery storage systems allow for flexibility in using solar energy and grid electricity within certain pre-set thresholds.

Key words: EV, grid energy, renewable, IoT, CNN, GRU, dynamic, optimization, rate, infrastructure, data, solar energy.

1. Introduction.

One of the most challenging aspects of the nascent electric vehicle (EV) infrastructure [1] is incorporating renewable sources of energy, such as solar energy [2], into EV charging points. The grid limitations during peak demand times and different user preferences increase the space of non-optimal use of renewable resources in traditional grid-dependent charging models, which is one of the main barriers to achieving more sustainable solutions.

The following study presents Smart EVGridNet to fill this research gap. It is proposed as a smart charging algorithm that employs IoT data [3] to optimize dynamic EV charging patterns. Solar energy generation, grid electricity prices, and user requirements are all taken into account by analyzing real-time data. This is done to enhance the use of solar power, create less reliance on the grid during peak periods, and accept user needs, hence filling the gap left by renewable energy integration as it is currently practiced. The novel EVGridNet model is based on deep learning, in which Convolutional Neural Networks (CNNs) [4] and Gated Recurrent Units (GRUs) are being used, among others coupled with Reinforcement Learning (RL) [5] and dynamic programming for sophisticated prediction of electricity prices and solar outputs. This prediction allows fine-tuning charging patterns in real-time, utilizing energy storage systems, and using the grid effectively when the charges are lowest. The system's ability to turn EV charging into an off-peak hour's activity and renewable energy supremacy is vital in achieving grid-independent and clean EV infrastructure. The impact of the EVGridNet program is not only energy savings; it tells the other story of the speedy expansion of EV infrastructure while lowering the level of carbon emissions and independence in energy. Smart charging [6] can keep up with the dynamics by adopting a holistic approach to decision-making under uncertainty, which allows it to navigate the complexity of the energy matrix and, therefore, becomes the ultimate solution to some of the renewable energy sector's challenges and the significant giant leap towards the establishment of smart charging infrastructure.

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One of the most essential parts of the current research is the use of advanced neural networks for predictive control devices, which helps to improve the efficiency of solar power usage in real-time by controlling the charging patterns. In another way, the decrease in the distribution grid's energy consumption and the improvement of the renewable energy input to the charging system through EVGridNet establishes a basis for clean energy creation. The proposed model could be a significant tool for the transition of the EV charging ecosystem to being more environmentally friendly, cost-effective, and user-oriented. This model should provide support for the rapid development and scaling up of the EV infrastructure while minimizing the carbon emission situation in the process and reinforcing the independence of our local energy resources.Thus, the primary objectives of this study includes:

1. To improve EV charging infrastructure, EVGridNet was utilized, which helped accelerate the incorporation of solar energy and observably decreased non-renewable energy use.
2. To reduce the electricity grid load during peak demand times, the EVGridNet network will help decrease the load on the grid and optimize the charging patterns to take advantage of the off-peak periods and available solar power.
3. To develop a flexible charging infrastructure that could be configured to the inputs of real-time and user-related data.

2. Related Work. The work from [7] addressed EV charging patterns through Functional Data Analysis (FDA) analysis using five years of real-time data from 455 stations in the Kansas City of, Missouri district. The specific approach, the so-called "smooth functions" treatment of the data over time, is exceptional for its flexibility and effectiveness in monitoring daily, station-related usage by customers and energy consumption. The study recognizes the FDA's deficiency in obtaining time series from different periods, which is a significant problem in forming some analytical tools. This work is unique in the sense that the authors succeeded in applying the FDA course to evaluate EVs' charging behavior despite the difficulties involved, whilst the existing data may need to be more consistent. The study from [8] developed a model integrating long-term and short-term planning and decision-making processes to solve the problem of the most efficient placement of charging stations. Their innovative technique exploits a two-stage mixed integer linear programming model to achieve the optimal electricity flow costs, which can then incorporate renewable energy and V2G capabilities. To undermine the complexity of the model, they suggest a mixture of Apriori Progress Hedging And Sample Average Approximation (APH-SAA) algorithms, speeding up the algorithm and making it more efficient. Regardless of its positive side, the study acknowledges that the progressing hedging algorithm has limitations if capitalizing on large-scale problems. Therefore, the study shifts to the heuristic method for a smooth solution. Such research now provides a vital link between various operational factors and charging station planning design, which can be easily replicated for more cost-efficient and environmentally friendly infrastructure development.

Researchers in [9] proposed a solution for optimizing grid operations with growing EVs employing machine learning and the LSTM model. The method puts a great emphasis on the management of electric power demand. Moreover, it decreases losses and fluctuations and drops the economy tariffs, regardless of the charging technologies used. For managing complex and ever-changing loading patterns of the power grid and EVs, LSTM was chosen because of its ability to predict them accurately. The investigation proves that the impact of EV charging on the grid can be effectively managed through simulations; the benefits become apparent, especially during unforeseen load conditions. Notably, the project focuses on ML to improve grids in terms of efficiency and stability, which effectively minimizes challenges posed by the increasing EV acquisition. Conversely, vehicle-to-grid (V2G) technologies might not perform primary operations properly and can cause deep discharging of EVs, which leads to battery degradation and loss of customer satisfaction.

According to the study of [10], using machine learning, primarily deep LSTM, is proposing high-capacity management and routing tools for EV fleets. It measures the uncertainty of load data impact on the EV management system, which is a criterion in showing the LSTM's capacity to handle sudden data. On the other hand, though, this complexity in adopting deep learning approaches for managing the centralized system efficiently emerges as a potential limitation, mainly as more and more EVs come into play. Such growth encompasses larger data sets and affects businesses with parking facilities. As a result, these businesses require advanced technological solutions catering to the emerging EV market.

Researchers in [11] intended to optimize EV charging infrastructure using a genetic algorithm modified

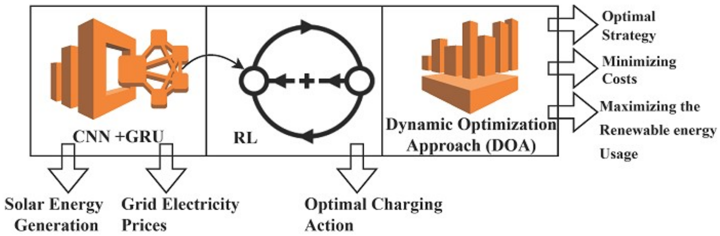

Fig. 3.1: EVGridNet Framework

by neural networks and deep learning architecture, namely data driven multi-objective optimization (DDMO). The main task of the associated framework is to improve these factors, such as the type of charge points, charging location, the amount of charging points and so on. Research consisting of simulation and optimization offers information about the best possible configurations, spatial arrangements and, importantly, the trade-offs between coverage costs and maintaining the target levels. On the one hand, the dependence on data accuracy and model quality for efficient solutions causes the processes to become more computationally complex and take more time. The proposed optimization method is comprehensive. Nevertheless, tuning the parameters is complex and requires efficient handling of computational problems.

The central theme of the study by [12] is a multi-agent-based simulation model for the strategic planning of EV charging facilities on the highways, which predicts user charging patterns and lowers the limitation of the traditional site selection methods by user charging behavioral modeling, and decision-making processes related to charging. The model framework is included in the open-source built-in multi-agent modeling tool MATSim, which simulates the behavior of agents making their travel decisions in a shared network which competes for scarce resources on the highway, like charging facilities. A narrow disadvantage is the belief that EV drivers do not charge at highway facilities while leaving out factors affecting their choice of nearby facilities, leading to significant challenges when simulated in real-world scenarios.

3. Methodology. The methodology integrates Convolutional Neural Networks (CNNs), Gated Recurrent Units (GRUs), and Reinforcement Learning (RL) with a dynamic programming approach to optimize electric vehicle (EV) charging patterns. Initially, it defines the state and action spaces based on time, energy levels in the Energy Storage System (ESS), and possible charging actions.

A policy with parameters α is initialized to guide decision-making. For each episode, the algorithm starts by observing the initial state, which includes the starting time and energy level. As it progresses through each time step, it uses the CNN-GRU framework to predict solar energy generation and grid electricity prices. Based on these predictions and the current state, the RL component determines the optimal charging action according to the policy, executes this action, observes the resulting reward and the next state, and then updates the policy parameters using the policy gradient method to maximize the expected cumulative reward. Simultaneously, the dynamic programming component systematically solves for the minimum cost or optimal strategy by defining a recurrence relation that considers both immediate costs and future outcomes, iteratively computing this for each state.

Finally, it traces back through these decisions to reconstruct the optimal charging strategy, effectively balancing the objectives of minimizing costs and maximizing the use of renewable energy within the operational constraints of the EV charging infrastructure.

This comprehensive approach leverages predictive analytics and decision-making under uncertainty to dynamically adjust and optimize EV charging patterns in a complex, ever-changing energy landscape. Figure 3.1 illustrates the overall framework of EVGridNet model.

3.1. Problem Definition. To formulate the problem of EV charging optimization through dynamic programming, the minimization of cost, the maximization of solar energy utilization, and the constraints are considered. Table 3.1 represents several computational notations for better computations.

Table 3.1: Computational Notations and Definitions

Notations	Descriptions
$T=\{t_1,t_2,\cdots,t_n\}$	Set of discrete time intervals
$S(t)$	Solar energy generation at t
$[G_P(t)]$	Electricity cost in the grid at t
C_{req}	Cumulative energy demand for charging within the horizon
$D_{iot}(t) = \begin{cases} 1, & online \\ 0, & offline \end{cases}$	IoT device status
$\xi(t)$	Energy stored at energy storage system (ESS), $\xi_{min} \leq \xi(t) \leq \xi_{max}$
$G(t)$	Energy utilization for charging ($\mathbb{C}$) at grid

Objective Function. Considering the usage of $S(t)$ and $G(t)$ for charging, the primary objective is to minimize the $G_P\,(t)$ while meeting the user's C_{req} until the end of the optimization horizon is reached.

$$\min \mathrm{Z}{=}\sum\nolimits_{t\in T}[G_P\,(t)\bullet G(t)] \tag{3.1}$$

with three constraints:

$$\sum\nolimits_{t\in T}[G\,(t)+S\,(t)\geq C_{req}] \tag{3.2}$$

$$\xi_{min}\leq\xi(t)\leq\xi_{max} \tag{3.3}$$

$$C(t)\Leftarrow D_{iot}\,(t)=1 \tag{3.4}$$

Equation 3.1, 3.2, 3.3 represents the energy requirement, ESS storage, and IoT device operational constraints, respectively.

The proposed EVGridNet comprises Convolutional Neural Networks (CNNs) for data representation and feature extraction, Gated Recurrent Units (GRUs) for sequence modeling [13], and Reinforcement Learning (RL) for decision-making and action selection. This model aims to leverage the strengths of each component: CNNs for spatial feature extraction (such as weather or temporal patterns), GRUs for capturing short-term trends (e.g., energy generation or market price), and RL for making control decisions (like an optimal charging pattern) which utilizes the dynamic programming algorithm based on specific constraints.

CNN Computations. For instance, processing data along with feature extraction for spatiotemporal data, such as weather conditions that impact solar power generation. The primary computation can be expressed as,

$$f_{cnn}{=}ReLU\,(I\times\omega_{cnn}+e_{cnn}) \tag{3.5}$$

From (3.5), we denote the input, ω and e represent the weight and biases of CNN, respectively with ReLU activation function.

GRU Computations. The comprehension of sequential patterns in solar energy production, grid electricity costs, and energy usage is gained by observation of this time series data. Consecutive readouts after a pass through the network of feature extractions, in combination with historical data on prices, energy generation, and demand, are indispensable to the input system. The operations of update gate (U_t), reset gate R_t), candidate ($\bar{h}_t$)and final activation (h_t) comprise the major processes of GRU in determining the patterns. Thus, the conventional process of GRU can be expressed as,

$$U_t{=}\mu\,([\mathrm{h}_{t-1},i_t]\bullet\omega_U+e_U) \tag{3.6}$$

$$R_t = \mu\left([\mathrm{h}_{t-1}, i_t] \bullet \omega_R + e_R\right) \tag{3.7}$$

$$\widetilde{h}_{tt} = tanh\left([R_t \times i_t, \mathrm{h}_{t-1}] \bullet \omega + e\right) \tag{3.8}$$

$$\mathrm{h}_t = \left(U_t \times \widetilde{\mathrm{h}}_t\right) + \left[(1 - U_t) \times \bar{h}_{t-1}\right] \tag{3.9}$$

From (3.6) to (3.9), i_t and h_t denotes the input and hidden state at time t, and μ signifies the sigmoidal activation function.

RL Computations. At this phase, EVGridNet learns to acquire knowledge of the optimal charging strategy depending on the system's current state and the forecast made by the CNN-GRU framework. The system's present state comprises the efficiency of the ESS, the status of the IoT devices, the estimated solar output, and the price of grids for the given timeframe. Objectives are being achieved via a dynamic optimization approach (DOA) combined with RL decision-making strategies that can ensure the patterns are optimally maintained to minimize grid utilization and maximize solar usage. Thus, the core process of RL is expressed as,

$$\nabla_\alpha f_J(\alpha) = E\left[\nabla_\alpha \log\rho_\alpha (A_t \mid S_t) \times r\ \right] \tag{3.10}$$

From (3.10), ρ_α denotes the policy that was parameterized by α, A_t and S_t indicates the action and state at t, and r represents the reward function with respect to the f_j (objective function) of ρ.

The structured DOA includes four major steps: defining the state, formulating the recurrence relation, determining the base case, solving sub-problems, and reconstructing the optimal solution. Table 3.2 represents the entire computation process of EVGridNet with DOA.

The primary role of the computation procedure of EVGridNet with the DOA is to determine the best patterns for charging a given number of EVs by incorporating the forecasts of the amount of load required in the grid at a given time, reinforcement learning, and dynamic programming. This procedure, which involves the CNN-GRU framework to forecast the generation of solar energy and the price of grid electricity, and RL to identify the optimal charging actions, also involves learning and improving decision-making policies. It strives to reduce costs and enhance the use of renewable energy by determining the best actions for charging using the RL strategy with the best short-term and long-term results. Also, and most importantly, it helps in making sure that the ESS practices a limit of safety through prohibition of its capacity drop to a certain level as well as preventing it from being charged to excess. Therefore, this systematic approach helps manage and optimize the social needs of EVGridNet as an innovation by adapting and guiding the consumption of electricity for charging electric vehicles and ensuring that such usage is efficient for sustainable utilization of energy.

4. Materials and Tools Utilized. For experimental analysis of EVGridNet, Table 4.1 provides a set of hyperparameters along with their optimal values.

An Integrated Energy Management and Forecasting (IEMF) Dataset from [14] is utilized as the lifeblood of the study included in this research work, without which the accuracy of the proposed EVGridNet model cannot be realistically evaluated. The dataset is robust, fragmented, and ranging from Region 1 to Region 5, covering potential EV charging sites positioned along the Chennai-Bangalore highway in India. The specificity of this information - which can be broken down into solar generation, energy consumption, and pricing - is critical for this training and assessment function of EVGridNet. The dataset is dynamic and multi-layered, including the time resolution necessary to capture peak and off-peak fluctuations, spacious variation from varied locations along the highway, and all use cases that can vary in demand. Such a dataset does not only help the decision-making and calibration of the predictive analytics and optimization algorithms run by EVGridNet but also, the model developed from such a dataset operates in the right environment, constitutes a robust substratum for the practical applications, earning the model a chance to scale. EVGridNet utilized the train data and, from IoT devices, collected the attributes that are reflected in Table 4.2.

Overall, this dataset is highly useful for renewable energy management. Understanding the patterns of energy demand and the available supplies assists the operators in forecasting future energy needs. The addition of temperature and weather data also improves the model's ability to predict fluctuations in renewable energy reliability. This forecasting plays an important role in decision-making about energy storage, distribution, and transactions in the energy market.

Table 3.2: Computation Procedure of EVGridNet with DOA

Input: $S(t)$, $[G_P(t)]$, f_{cnn}, C_{req}, $D_{iot}(t)$, $\xi(t)$, $G(t)$, and ρ_α
Output: *optimal policy* $\rightarrow \rho_\alpha^*(A_t\|S_t)$ *and the sequence of actions (charging) for each time interval according to the best-optimized policy:* $G(t_i \in T)$
Initialization • Initialize state space S for a given t and $\xi \in ESS$. • Initialize A based on potential $G(t)$ actions. • Frame policy $\rho_\alpha(A_t\|S_t)$ parameterized by α. $\forall$[episodes $\neq$ convergence] 1: Observe initial S $S_0 = (\xi_0, t_0)$ 2: For $t \rightarrow t_0, t_0+1, \cdots, n-1$: Predict $S(t)$and $[G_P(t)]$ *//using CNN-GRU outcome* Compute A_t based on $\rho_\alpha(A\|S_t)$ Perform $A_t$to observe r_t && S_{t+1} Update $\xi \in ESS \leftrightarrow A_t$ && $S(t)$ *Subject to:* $\xi + S(t) - G(t) \geq \xi_{min}$ *//ensures that ESS will not deplete below its minimum capacity* $G(t) \leq \left[C_{req} - \sum_{t'}^{t}(S(t'))\right]^+$ *//considers the prevention of overcharging beyond* C_{req} 3: Policy Gradient Update $\forall$steps of the episode Compute: $\nabla_\alpha f_J(\alpha) = \mathbb{E}[\nabla_\alpha \log \rho_\alpha(A_t\|S_t) \times r]$ Update α using gradient ascent $\alpha \leftarrow \alpha + \gamma J(\alpha)\nabla_\alpha$ *//$\gamma \rightarrow$ learning rate* 4: Dynamic Optimization 4.1 Defining the state $\Psi(t,\xi)$ represents the minimum cost from t given ξ 4.2 Recurrence Relation $\Psi(t,\xi) = min_{G(t)\geq 0}\{[G_P(t)] \cdot G(t) + \Psi(t+1, min\{s(t) + \xi - G(t), \xi_t\})\}$ 4.3 Base case $\Psi(k,\xi) = 0$; *// $\forall\xi$ at the final step k.* 4.4 Solving Sub-problems Iteratively compute $\Psi(t,\xi)$ using 4.2. 4.5 Reconstruction of optimal solution $G(t) = a[\xi, t]$ *// 'a' denotes the auxiliary array of A to trace back the decisions*

5. Performance Analysis. The realistic assessment for the EVGridNet model is carried out by selecting three state-of-the-art approaches - Dynamic Demand Management Optimization (DDMO), Apriori Progressive Hedging with Sample Average Approximation (APH-SAA) and Long Short-Term Memory (LSTM) networks - that are closely aligned with the main goals of the proposed approach. These approaches provide a solid basis for benchmarking by virtue of their alignment with the intrinsic targets of the electric vehicle charge scheduling optimization, enhancement of renewable energy use, and stabilization of grid interactions, thus supplying the entirety of context for assessing the indicated technological advancements and effectiveness of EVGridNet.

EVGridNet, the proposed EV charging infrastructure optimization model, is a smart technique combining deep learning models (CNNs and GRUs), decision-making technique (RL), and a optimization process (DOA). To evaluate the approach and achieve the work's objectives, the following four metrics and their mathematical computations are considered as a crucial factor of this research. The metrics are solar energy utilization rate (SEUR) [13], grid dependency reduction rate (GDRR) [12], cost savings (CS), and renewable energy utilization Rate (REUR).

SEUR. This metric refers to how much electric vehicle charging power is drawn from solar power. The best way to accomplish that part is to increase (or improve) this rate to wholly correspond with the main objective,

Table 4.1: Hyperparameter Specifications

Hyperparameter	Optimal Value
Learning Rate	0.01
Discount Factor	0.9
Epsilon	0.1
Number of GRU Layers	2
Number of GRU Units per Layer	64
Number of CNN Layers	3
Kernel Size in CNN	3x3
CNN Filters per Layer	32
Batch Size	32
Replay Buffer Size	10000
Policy Update Frequency	5
Training Episodes	1000
ESS Capacity Constraint	100 kWh
Minimum ESS Level	20 kWh

Table 4.2: List of Attributes Utilized in Dataset

List of Dataset Attribute
Timestamp
Solar Power Generation (kWh)
Grid Electricity Price (kWh)
EV Charging Demand (kW)
ESS State of Charge (SoC) (%)
Ambient Temperature (°C)
Weather Conditions
EV Charging Status
User Charging Preferences
Charging Station Utilization

which is to intensify the utilization of renewables for EV charging infrastructure. The primary computation of this metric can be expressed as,

$$SEUR{=}\sum\nolimits_{t\in T} S(T)\bullet G(t)_{solar}/\sum\nolimits_{t\in T} G(t)_{total} \tag{5.1}$$

From 5.1, $S(t)$ denotes available solar power at t, $G(t)_{solar}$ proportion of solar power utilized for charging at t, $G(t)_{total}$ indicates the overall charging power utilized at t.

Figure 5.1 shows that EVGridNet outperforms LSTM, DDMO, and APH-SAA in exploiting solar energy for EV charging under varying scenarios. In scenario 1, while monitoring modest solar availability and regular power demand for EVs, EVGridNet shows performance superiority, with the SEUR of 70% prevailing over the other approaches. Scenario 2 is an ideal situation with high irradiance solar availability and low vehicle demand; EVGridNet comes again on top, achieving a SEUR of 72%. The most underwhelming outcome is Scenario 3, which consists of a low solar availability level and a higher EV demand level, where EVGridNet still provides a SEUR of 75%. Situation 4 indicates that EVGridNet achieves a SEUR of 77% through its ability to apply high solar power efficiently during supply surges. EVGridNet does much better at high SEUR levels in all cases, demonstrating energy system robustness, especially when solar power is in short supply or demand is high. Its adaptability to a broader scope of scenarios is exhibited through changing circumstances. This suggests the smartness and efficiency of EV charging infrastructure management.

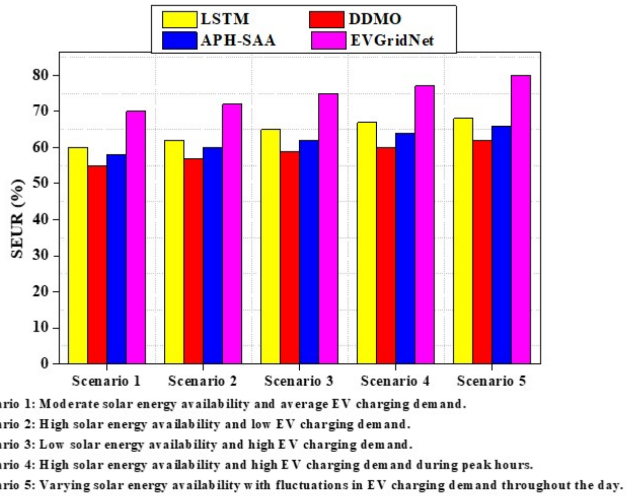

Fig. 5.1: Comparative Evaluation of SEUR across various Scenarios for different Approaches

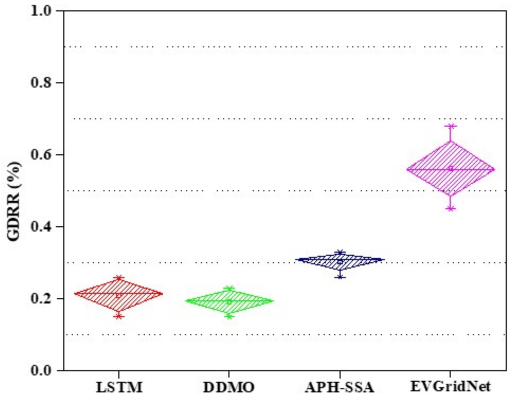

Fig. 5.2: Comparative Evaluation of GDRR across various Scenarios for different Approaches

GDRR. It computes the reduced loading of electricity for EV charging during peak demand periods to minimize the grid's stress duration and maintenance cost. The primary computation process of this metric can be expressed as,

$$GDRR{=}\Delta G_{grid,peak}/G_{grid,peak,baseline} \tag{5.2}$$

From (5.2), $\Delta G_{grid,peak}$ represents the reduction in grid source utilized at peak durations against baseline scenarios, $G_{grid,peak,baseline}$, which indicates the power utilization at peak durations without the induction of EVGridNet processes.

Figure 5.2 shows four EV charging optimization approaches assessed for GDRR metric throughout different scenarios. In Scenario 1, EVGridNet realizes a significant step ahead with the GDRR comprising only 0.6, implying that EVGridNet cuts the grid dependence by 60% during the peak times relative to the baseline scenario. In Scenario 2, EVGridNet narrows this gap further to 0.52, indicating a positive GDRR. Scenario 3 here reveals a relatively tight accordance, at 0.45 levels for EVGridNet and 0.26 levels for APH-SAA. In

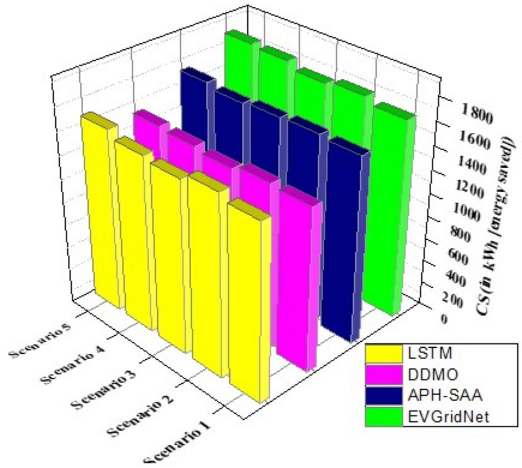

Fig. 5.3: Comparative Investigation of CS across various Scenarios for different Approaches

Table 5.1: Cost Saving Analysis of different Approaches across different Scenarios

Scenario	**CS (in kWh)**			
	LSTM	**DDMO**	**APH-SAA**	**EVGridNet**
Scenario 1	1500	1400	1600	1700
Scenario 2	1550	1420	1620	1750
Scenario 3	1490	1380	1610	1720
Scenario 4	1520	1410	1590	1780
Scenario 5	1580	1430	1630	1800

Scenario 4, the EVGridNet understudies demonstrate the most significant benefit to the network. Thus, it reaches a GDRR of 0.68, and the grid reduction enjoys a 68% decline. In comparison to LSTM (0.18), DDMO (0.23), and APH-SAA (0.33), this result shows that EVGridNet efficiently and effectively manages sources of energy. Overall, EVGridNet has the results of being the better approach in a consistent way, not only relieving grid stress but also optimizing the use of renewable energy for EV charging.

CS. CS ratios encapsulate the savings in charging costs actualized by the dynamic optimization of charging timetables, the application of low-cost grid electricity periods at the right time, and the complete utilization of solar power. The primary computation of CS can be expressed as,

$$CS = \left(\sum\nolimits_{t\in T} G_P\,(t) \bullet G(t)_{baseline}\right) - \left(\sum\nolimits_{t\in T} G_P\,(t) \bullet G(t)_{optimized}\right) \tag{5.3}$$

The $G(t)_{baseline}$ parameters from equation (5.3) states charging power utilized at t in a baseline scenario, and $G(t)_{optimized}$ denote the charging power utilized at t using optimized patterns.

Figure 5.3 and Table 5.1 depict 3D bar chart data and data table of CS metrics (in kWh), respectively, for EV charging optimization methods concerning various scenarios that construct a thought-provoking picture of electricity consumption reduction with the utilization of those methods. This is evident from the data, as EVGridNet takes the lead, starting at scenario 1 with 1700 kWh and ending with 1800 kWh by scenario 5. This reveals that energy efficiency and cost-effectiveness have, to a large extent, increased compared to the other techniques. It is worth noting that although LSTM provides excellent results, the savings are less, ranging from 1500 kWh to 1580 kWh over the exact scenarios. DDMO and APH-SAA came at the middle rates, with

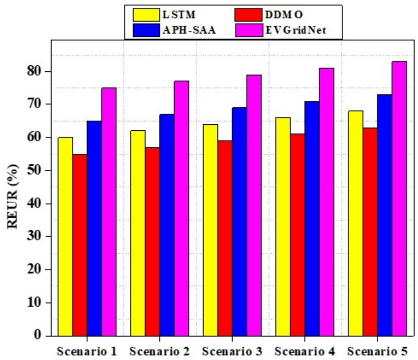

Fig. 5.4: Comparative Evaluation of REUR across various Scenarios for different Approaches

Table 5.2: REUR Analysis of different Approaches across different Scenarios

Scenarios	**REUR (%)**			
	LSTM	**DDMO**	**APH-SAA**	**EVGridNet**
Scenario 1	60	55	65	75
Scenario 2	62	57	67	77
Scenario 3	64	59	69	79
Scenario 4	66	61	71	81
Scenario 5	68	63	73	83

DDMO showing a range from 1400 to 1430 kWh and APH-SAA at a slightly better performance with 1600 to 1630 kWh.

Through Scenario 1 up to Scenario 5, the leap in the amount of savings by EVGridNet illustrates the proactive capacity of the system to effectively manage energy usage, with a high possibility of utilizing renewable sources and periods with low electric rates. The emerging insights in this section suggest that more sophisticated algorithms like EVGridNet make for more sustainable and economical charging facilities. EVGridNet's excellent performance is probably caused by the advanced machine learning techniques in this supervision net, which enables it to predict and adapt to the dynamic of energy generation and demand changes.

REUR. It is quantified as the proportion of renewable energy fed into EV charging, while the entire energy consumed for EV charging during a specific time is taken into consideration. The computation of REUR can be expressed as,

$$REUR{=}\Phi/\tau \tag{5.4}$$

From (5.4), τ denotes the overall energy consumed for EV charging, and Φ indicates the overall renewable energy consumed for EV charging.

Figure 5.4 and Table 5.2 display REUR percentage values for five possible scenarios obtained by applying these strategies for four different EV charging optimization approaches. Despite having a higher REUR percentage (75% to 83%) compared to the other scenarios throughout Scenarios 1 to 5, EVGridNet yields the highest RUE value at all times. Such performance shows a significant correlation, giving an elevated advantage to renewables among EV charging systems.

The results of the LSTM approach are moderate, achieving REUR rates as high as 68% without making any progress better than the previous value of 60%. In contrast, the performance of the DDMO approach is the poorest, with REUR values starting at 55% and only increasing to 63%. The general trend is that APH-SAA's performance is not as good as other neural networks (LSTM and DDMO) in real-life scenarios (accurate EV loads), but it is still better than EVGridNet (REUR varies from 65% to 73%). These outcomes demonstrate the best EVGridNet efficiency, allowing the automatic scheduling of EV charging to raise the amounts of renewable energy that transforms into usable electricity. This fact that it is better compared to the performance of other systems suggests that it can adaptively manage the fluctuating energy sources in the electric system, thus causing efficient and sustainable charging service. The statistics of more than improved REUR percentage from EVGridNet confirm its possible application in a more extensive network, backing its scale and sustainability.

Thus, the usage of renewable energy can greatly increase due to the possibility of the EVGridNet model to optimize the patterns of EV charging by predicting solar energy production and grid prices accurately. It is not only beneficial in lowering the amount of carbon emission but also useful in shaping efficient transport modes. Through more efficient utilization of renewable energy sources, this particular model supports the design of a cleaner and environment-friendly future. At times, when many people return home from work, study, or engage themselves in other tasks, there is typically a significant demand for electricity. To mitigate the effects of this, EVGridNet charges electric cars for other parts of the day. This strategic approach can result in the improvement of the stability of grid operations, a reduction in energy costs and the probability of overloaded circuits, and, in some cases, a complete blackout. Thus, these replacements will drastically improve the grid load management process and, hence, contribute towards a more efficient power distribution system. The available charging times in most areas allow one to take advantage of cheaper night tariffs; thus, owners of EVs can save a lot of money. Such economic benefits may encourage more people to use electric technology cars as a method of transport, thus achieving a faster transition to sustainable transport. This is simple because reducing the cost of owning these cars has remained the most compelling reason for popularizing the use of electric cars in society. The ability of the EVGridNet model to change its structure allows it to be extended successfully to other regions and different conditions of the energy market. This is an important aspect given that the model shall be used in different settings to allow it to be used by many. However, when it comes to the application of smart grid technologies, two critical components should be considered: scalability and the ability to adapt. The blend of deep learning hierarchies [17] with reinforcement learning, along with the dynamic programming in the construction of EVGridNet, provides high technological standards for future advances in smart grid and renewable energy technologies. This approach can spur more advanced and updated research to come up with efficient energy systems as new ideas are discovered.

The effectiveness of the model within the proposed EVGridNet entirely depends on the real-time information obtained from the IoT devices as well as the weather and the energy market data. This means that the performance of the model can be impacted by inadequate or untimely data information, thus the need for correct and timely data information. The main issue to be noted is data dependency, which is a major problem that requires a solution for operations' proper performance. As regards the application of this research, the following are noted as follows:

Optimized EV Charging Infrastructure: Overall, the design of the EVGridNet model can improve the effectiveness and/or sustainability of charging stations for electric vehicles by managing the degree of reliance on the grid during peak hours and utilizing renewable energy resources.

Cost Savings for EV Owners: By shifting charging to off-peak times and utilizing cheaper electricity, the model can help EV owners save on energy costs.

Grid Load Management: The model described in this paper has the potential to revolutionize grid load management. Utility companies can use this model to accurately regulate loads, preventing overloads and reducing the risk of blackouts, thereby ensuring a more reliable and stable energy supply.

Scalability for Diverse Regions: Many such characteristics enable the implementation of the model across diverse regions, which have different energy market characteristics, thus encouraging green transportation solutions.

6. Conclusion and Future Work. The EVGridNet model demonstrates considerable potential in enhancing the efficiency and sustainability of EV infrastructure by integrating renewable energy sources. By addressing the inconsistencies between EV charging supply and demand, EVGridNet shifts charging activities to off-peak hours. This strategic approach not only reduces the reliance on the grid during peak times but also significantly increases the proportion of renewable energy used in the charging process. The simulation results indicate that this methodology can effectively reduce grid strain and optimize energy use, making it a robust solution for current energy challenges. Moreover, EVGridNet's capability to adapt to varying conditions positions it as a foundational technology for developing more eco-friendly and adaptive plug-in vehicle charging systems, thereby promoting a greener and more sustainable transportation future. On the other hand, we are trying to deploy upper-level enhancement models by integrating more exact weather prediction models that can accurately anticipate solar generations. Furthermore, machine learning algorithms implementing adaptive user behavior patterns provide a more personalized charging schedule.

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