Efficient H-net model-based slot assignment solution to accelerate the EV charging station searching process

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Abstract* — The extensive growth in the manufacturing of lithium-ion batteries and their usage in electric vehicles has led to a surge in the sales of electric vehicles, surpassing previous records. Electric vehicles offer numerous advantages over fossil fuel vehicles, including decreased air and noise pollution, lower maintenance costs, among other benefits. However, there are also growing issues associated with this, such as the unavailability of EV charging stations when they are needed. To address this issue, there are numerous mobile applications that can locate the closest EV charging stations based on their proximity to GPS coordinates. Very few of the systems consider the availability of the charging slots along with the nearest stations. However, there are only a few systems that rely solely on finger counting to allocate slots at EV charging stations effectively. Therefore, this paper proposes utilizing the H-Net model, a Hungarian neural network, to allocate EV charging slots efficiently, enabling the charging of more vehicles in a single day and preventing congestion. This method, in conjunction with shortest distance estimation, quickly identifies the nearest EV charging station with an available slot, thereby enhancing the congestion-free charging process.

Keywords: Neural Networks, EV Charging station location, Slot Allocation, Hungarian neural network, Euclidean distance.

I INTRODUCTION

Efforts to reduce emissions of greenhouse gases and increase the use of renewable energy sources have led to the development of electric vehicle technology in recent years. One important step toward lowering CO2 emissions in urban areas is the widespread use of electric vehicles (EVs) powered by renewable energy sources that greatly supplement existing transportation infrastructure. As a result of several nations shifting their focus away from fossil fuels and toward energy needs, the use of electric vehicles is quickly growing in the 21st century. Long charging times, high costs, and limited driving range are the three biggest problems with electric vehicles. Reduced charging efficiency, unknown charging locations, insufficient power, arbitrary procedures, and increases in the maximum demand of the grid are additional challenges to the mobility of electric vehicles. The solution to this problem is the widespread installation of public charging stations in places with heavy pedestrian traffic, such highways, retail centers, gas stations, and parking lots. Problems with charging time, cost, scheduling, the distance travelled by EVs to reach their destination, incorrect information management, and other associated issues may occur as a result of the multiple charging stations (CS). A scheduling system based on VANETs can be employed to improve charging time and guarantee grid stability .It finds the best time to charge each electric vehicle by analyzing real-time data on charging demand and the availability of charging infrastructure. To ensure that electric vehicles receive quick charging, it can adapt the charging schedule on the fly in response to unforeseen circumstances. Data from a variety of sources, including vehicles, charging stations, the grid, and more, are used by this VANET system's machine learning (ML) algorithms to schedule charging stations. Due of high-dimensional data, ML algorithms make the VANET system more complex, which in turn decreases scheduling performance. In order for ML approaches to function, a process known as Feature Selection (FS) must be carried out. FS entails extracting essential characteristics and removing unnecessary ones.When ML classifiers are trained with the right features, they perform better. Search stop criteria, validity, evaluation, and feature subset search are the four main components of the FS process.

To enhance the working of the charging station location slot assignment at EV charging station is the most important task that eventually reduces the congestion at EV station. To allocate the slot at EV charging station Hungarian Network (Hnet) is used. To resolve assignment issues, the Hungarian Network (Hnet) employs deep learning to execute the Hungarian algorithm. Harold Kuhn created the Hungarian algorithm in 1955 as a combinatorial optimization method. The contributions of Dénes Kőnig and Jenő Egerváry, two mathematicians from Hungary, form its foundation. Thanks to Hnet, the

Hungarian method can be used in conjunction with other deep-learning tasks that demand PIT. As a result, PIT is unnecessary for training. When it comes to assignment difficulties, the Hungarian loss algorithm was created with profit maximization in mind. By subtracting each element's maximum value from the cost matrix, we can transform it into a profit matrix.

[1] In order to assess the financial viability of a BESS functioning in distribution networks, luca argiolas et al. introduced a mixed-integer linear model. The evaluated case study, which is representative of the Dutch energy market, demonstrates that a PV-FCS coupled with a 500 kW/500 kWh BESS is economically advantageous. Actually, the 95ke is the computed system NPV. In addition, the system NPV can be extended to 108 k€ by adding the service to the third party, the FCS. The maximum power exchange at the grid connection point can be reduced by coupling BESSs with PV-FCSs, as previously mentioned, which flattens their generation and load profiles. As power markets become less appealing in the future, it will become the primary revenue generator. According to the results, the case study's participants—the owner of the BESS, the owner of the FCS, and the local DSO—are able to indirectly reap economic and technical benefits from this setup.

[2] When planning electric vehicle charging stations, qiao ma et al. emphasis on finding a middle ground between competing interests. The trip chain theory-based charging demand model for a single EV is first created, taking into account both the spatial and temporal dimensions. Also provided is the nodal EV charging wait model, which may be used to assess charging congestion. Using the Monte Carlo method, author were able to calculate the whole electric vehicle charging demand. A multi-objective optimization model for an electric vehicle charging station is then suggested, taking into account the interests of many stakeholders. In order to improve power quality and system stability, the author plans to focus future research on the dispatch of energy from electric vehicle batteries.

[3] Abdul Hafeez et al. should think about the worrying scenario caused by vehicles on the road with internal combustion engines and other greenhouse gas emissions. This document presents a detailed plan for a micro grid that is connected to electric vehicles and uses data to regulate demand. The MG-related loads were anticipated with the help of the deep learning time-series technique. Information gathered from a power substation was used to train the DL technique. Additionally, a data-driven technique was used to model PV connected to the MG. By treating it as a standalone power source, author were able to model the EVCS and predict the accompanying EV battery's system on a chip (SoC) using deep learning. Since the LSTM model outperformed the VARIMA model in terms of validation efficiency (99.51%), it was chosen for SoC estimation. author can enhance EVCS utilization by bringing it closer to real-world circumstances through future research that combines this more realistic model with other intelligent operational models.

Section 2 of this paper details the previous research, while Section 3 details the process of implementing the suggested model with the help of the H-Net neural network. The research concludes in section 5, after discussing the acquired results in section 4. Section 5 throws light on future work of this topic.

II LITERATURE SURVEY

[4] In order to obtain performance, v. manoj kumar et al. presented the CHHO charge scheduling algorithm and validated it in various scenarios. Current methods, such as HHO and FCFS, were compared to the obtained findings. Electric vehicle charging is typically thought of as a tedious task, which is why many people choose for more traditional automobiles due to their convenience. However, the CHHO algorithm has shown promise in tackling the problems of electric vehicle charging scheduling, which has led to shorter wait times. Using a recently created fitness function and recasting the problem as a multi-objective optimization issue, the CHHO method can efficiently determine the ideal charging schedule. The next step for this project is to incorporate real-time data, such traffic and charging station status updates, to further improve performance.

[5] By combining TOPSIS and BGP, eiman elghanam et al. offer a thorough MCDM framework for WCL optimal allocation. To determine the best places to put the charging lanes and how long they should be, this framework takes into account financial limitations in addition to social, environmental, and geographical factors. Infrastructure planners and strategy makers can use this method, which is both computationally efficient and practically useful, to size up and choose locations for mobile wireless EV charging infrastructure. The research technique and data gathering process are detailed here so that we can learn

about the various locations' characteristics using accurate geospatial data and internet resources Additionally, to alleviate range anxiety and increase demand coverage, cities should strategically place wireless EV charging lanes throughout the city fabric. This will provide for on-the-go charging possibilities for existing and future EV customers.

[6] Efficient smart charging (SC) applications are in high demand due to the rising demand for electric vehicles (EVs), as described by Kaleb Phipps et al. But SC is fine as long as the EV user's mobility needs and risk preferences are met—that is, if their EV has enough juice to go where they're going. In order to meet these criteria and accommodate various risk preferences, the SC application needs to think about how long it will take to park at a specific spot and how uncertain that prediction is. Consequently, this research offers various methods to tailor the uncertainty quantification of parking length estimates for SC applications that focus on EV users. The parking length forecast mistakes are broken down by the author into two parts: one that leads to undercharging and the other that is less critical. Integrating the tailored uncertainty quantification offered in this paper into stochastic optimization problems or applying it to identify anomalous behaviour should also be the focus of future research.

[7] Dias de Lima Tayenne et al. Additionally, the suggested model was assessed by optimizing for either carbon tax or planning cost separately. By spending more in PV units and presenting the lowest value of CO_2 emissions compared to the other case studies, the risk-averse planning linked with the carbon tax achieved the best benefits from an environmental perspective. Nevertheless, compared to the other scenarios, this plan's anticipated cost is higher. Carbon dioxide emissions are greatest in the alternative approach that solely accounts for CVaR associated with planning costs. Future studies should tailor decentralized planning to the needs of various EDS players, including distribution system operators, DER investors, and EVCS investors.

[8] The dependability probability evaluation methodology, developed by K. vaishali et al., was used to assess the failure rate of electric vehicle charging stations that utilized a mix of uniform and non-uniform port layouts. The 36-port charging station configuration has been introduced for commercialization in consideration of a 50-350 kW distribution system. A mix of 20 uniformly arranged ports and 16 non-uniformly arranged ports makes up the 36-ported charging station layout that has been proposed. Following the criteria of MILHBK-217F with the mathematical extension of binomial probability, the methodology of dependability estimation for each port involved in each configuration according to the port arrangement has been analyzed. Analysis of the proposed system's failure rates led to the conclusion that the 20-ported uniform configuration can supply the charging facilities with a 2% failure rate and an expected probability of 0.625/106 Hours.

[9] For drivers setting out on extended road trips in electric vehicles, the new routing algorithm suggested by S. PRIYA et al. is incredibly valuable. Given the current situation in autor’s nation, where the number of CSs along the route is limited, it is essential to prepare the timetable in advance. In terms of time management and the best places to stop at charging stations, this plan might be a real lifesaver for drivers. The program uses machine learning to find the vehicle's range and fuzzy logic to figure out how much it will cost to get to each charging station. Each hop along the way, it chooses the one with the lowest cost. Cost is determined mostly by the distance to the destination from the CS, the amount of time spent waiting at the CS, and the energy required to reach the CS. A few steps will be done in the future to make the routing algorithm that was built using a Kaggle random dataset more reliable. There will be a first step in gathering real-world data on EV routes. Data collected from electric vehicle manufacturers in India will be included in these databases.

[10] Youngmin Gong et al. state that the study's approach was created to aid in the development of policies for the deployment of electric vehicle charging stations by recommending which stations should be prioritized. This will allow future stations to be placed in areas where there is projected to be a greater demand for charging. This is anticipated to enhance the charging convenience for electric vehicle customers and reduce the cost of EV charging stations. The case study of the Republic of Korea was presented in this article. The Republic of Korea's high concentration of electric vehicles and other vehicles provides a useful case study for other nations facing a comparable challenge, as discussed in this paper. Nevertheless, there are a number of caveats to this research. To begin with, there may be other socioeconomic factors that impact the amount of

charging energy at EV charging stations; secondly, the study only used current data, so it doesn't represent the trend of increasing EV penetration in the future.

[11] Based on their analysis of the "vehicle-station-grid," Hongwei Li et al. present a model for optimizing the placement and capacity of electric vehicle charging stations in metropolitan areas. [12] Using biogas and biomass as a resource, Sekar palanisamy et al. charged electric vehicles. Scenario-6, which included BG+PV+WT, was the most technically, economically, and ecologically viable of the six possible hybrid system configurations studied. An impressive 2,009,492 kWh of electricity and 30,199 kg of hydrogen are produced annually by this top-tier system.

[13] The dramatic increase in the demand for electric vehicles necessitates the installation of more effective charging infrastructure, as Ahmed O. Elmeligy et al. explain. But conventional charging techniques have lengthy downtimes and add to range anxiety since people worry they won't have enough juice to get to the next charging station in time. Mass adoption of electric vehicles is impeded by this. The greater deployment costs when compared to stationary charging methods must be minimized through appropriate planning of the DWC infrastructure. In addition, to avoid overloading and maintain grid stability, it is important to consider the non-negligible impact that DWC systems have on the electricity grid. In order to find the best spots in Sharjah, UAE, to install DWC lanes, this study proposes a DWC infrastructure planning model. Allocating DG resources optimally to prevent overloading and minimize overall system costs (capital expenditure and operating expenses included) is the goal of the proposed model, which employs traffic simulations with optimal power flow analysis and metaheuristic GA optimization to find the best places, lengths, and charging powers for DWC lanes. Revenue increased by 4.62% and net profit by 23% as a direct result of the author's efforts.

[14] Using derivative-free charging scheduling methods, ZIA ULLAH et al. presented a distributed consensus-based approach to optimal power sharing between the power grid and EVCSs. Optimal power sharing between the electrical grid and EVCSs is the goal of the proposed effort. Optimal power-sharing as proposed here both meets the demand for affordable EV charging and lowers the overall energy costs of the network. Lessening the load on the main power grid, the proposed solution not only cuts energy costs but also drastically lowers the grid's average daily power usage. Investigations reveal that the suggested system attained an energy cost balance of 0.10$/kWh across all EVCSs, and the system is designed to accommodate both small and large electric vehicles. Assuming all goes according to plan, the next step will be to refine the suggested method while incorporating demand response and multi-objective power sharing.

[15] Taking into account the interconnection between the transportation and electric distribution networks, S. Muthukannan et al. presents a thorough framework for the construction of EVCS infrastructure. Author improve the sites of charging stations by developing a dynamic user equilibrium model that captures the route preferences of EV users. In the future, the model might be enhanced to include additional origin-destination pairs, take battery state into account to determine charging demands, and incorporate other charging providers. Efficiently integrating electric cars into urban transportation networks while guaranteeing grid stability and cost-effectiveness is promoted by the CoRTED framework, which offers a holistic approach to EVCS infrastructure planning.

[16] The environmental catastrophe, according to Carmen Calvo-Jurado et al., is prompting governments to push for anti-pollution laws that gradually limit the usage of fossil fuels. In this light, there has been a recent uptick in research into the possibility of integrating EVs in an effort to cut down on pollution from traffic. An extensive charging network must be put in place in order to ease the switch from gas-powered to electric automobiles. In order to find the best spots to add more electrical charging stations to the existing network, this article offers a numerical plan. In order to achieve this, the main framework will be Voronoi diagrams that are built utilizing the current charging stations as the structure's point generators.

[17] In their descriptive statistics, Ahmed İhsan Şimşek et al. examine electric car charging station locations and the links between research according to author, country, citation, and incidence. Scientists will be able to collect comprehensive data for their investigations into the placement of charging stations for electric vehicles in this way. From 2011 until 2022, 212 papers were analyzed in the "Web of Science" database. This study used Vos viewer and R to perform network analysis. First, author offer descriptive data

in this context. Basic study information is presented in the descriptive statistics section, which also includes yearly scientific output, most productive countries, total citations per country, country collaboration, most productive authors, and total citations per country. Publications about the optimal placement of charging stations for electric vehicles have been on the rise since the middle of 2010. China, India, and the United States appear to have dominated research on the optimal placement of charging stations for electric vehicles.

II PROPOSED METHODOLOGY

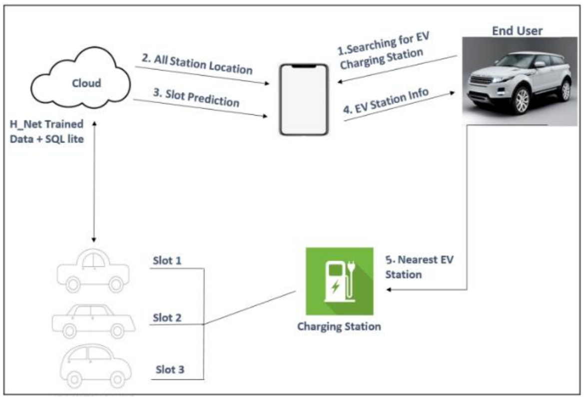

Figure 1: Proposed model Design

Below is a description of the procedures involved in the designed model for the location of electric vehicle charging stations in metropolitan locations, with the goal of reducing congestion and meeting the demand.

Step 1: User Request processing – The designed model is developed as a mobile application using the cross-platform language codename One. This application provides a panel for EV charging owners to register station information by providing some basic details, like the number of slots, GPS coordinates, detailed address, etc. On the other hand, the end user must install the application on their respective mobile devices in order to utilize the EV charging station locator services while on the go. The system receives the user's request to locate the closest EV charging station using their current GPS coordinates. The designed model accesses all the listed EV charging station names and their locations in a list to compute the nearest one from the registered database. To estimate the nearest EV charging station for the current user, the designed model uses the Euclidean distance as depicted in equation 1.

The model computes the distance between each EV charging station location and the user's location using the respective latitude and longitude. We then store the obtained distances in the list by sorting them into ascending order. This list is used to estimate the availability of the slot of the EV charging station. On the other hand, each EV charging station is equipped with the H-net model to catalyze the allocation of the charging slot to reduce the congestion.

Step 2: Generating Hungarian Neural network (H-net) training Data for slot assignment - As stated in the previous phase, the EV Charging owner must enters each slot type and their load capacity in the system. The Hungarian neural network uses this to handle slot allocation. The Hungarian Network (Hnet) is the name of the Hungarian method that uses deep learning to help solve the assignment problem. This method may be applied to additional deep learning tasks that require permutation invariant training (PIT) by using a deep learning neural network. This manner, we can train the deep learning tasks without requiring PIT at all. Permutation invariant training is required for deep learning applications like slot separation and multi-slot assignment.

In order to train the H-net for multi- slot assignment , we must first generate the following data using the load predicted values obtained from EV charging station owner's input. We create a dataset with a training split of specific distance matrices D and their matching association matrices A in order to train the Hnet. 10% of the training split's size is allocated to validation. The highest number in the dataset, Nmax = 2, determines the fixed dimensions of D and A, which are the identical. By selecting reference and forecast load Direction of arrivals of EV vehicles at random from spherical equiangular grids with resolutions of 1, 2, 3, 4, 5, 10, 15, 20, and 30 slots, we sample an equal number of D matrices. The dataset equally represents all possible combinations of (number of predictions, number of slots) such as (0,0), (0,1), (1,0), (1,1), (1,2), (2,1), and (2,2). The distance pairs in D are formed using Euclidean distances as shown in equation 1.

$$\boldsymbol{ED} = \sqrt{(\boldsymbol{x1} - \boldsymbol{x2})^2 + (\boldsymbol{y1} - \boldsymbol{y2})^2} \qquad (1)$$

Where,

ED- Euclidean distance of a specific row.

x1, x2, y1, and y2 are the labeled value of load direction of arrivals(DoA)

Random high distance values are assigned to the corresponding inactive entries due to padding D to Nmax _Nmax dimensions even when Mt;Nt < Nmax, making it easier for Hnet to determine the precise number of active load slots and their relationships. Thus Hnet obtains an F-score of >99% on any D data produced using the above specified specifications following training.

Step 3: H-net Training - The cornerstone of the proposed training technique based on differentiable tracking is known as Hnet. It estimates a dimension's association matrix {A, which is the same as the input distance matrix D. To train Hnet quickly and effectively, we choose a simpler design, as illustrated in Fig. 2, with three losses, as opposed to the deep Hungarian network . We employ a 128-unit gated recurrent unit (GRU) input layer, which interprets one of the input matrix D's two dimensions as the time-sequence and the other as the feature length. To find the time steps with the right associations, a single-head self-attention network is fed the GRU output time-sequence. A fully-connected network with sigmoid non-linearity processes the self-attention layer's output and estimates ~A as a multiclass, multilabel classification task.

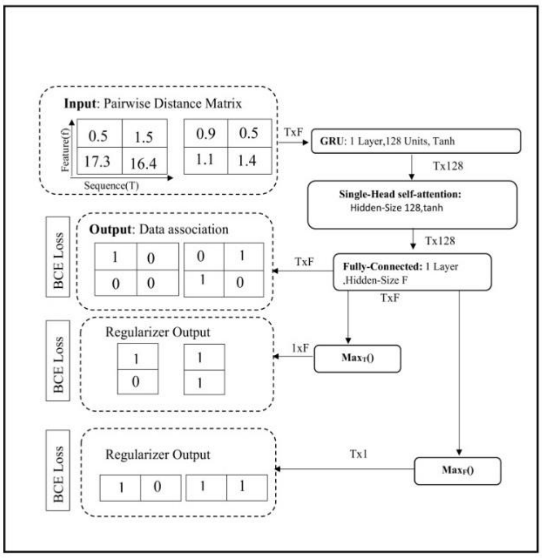

Figure 2: Block Diagram of Hungarian network

Furthermore, we perform max-operation on the fully-connected network's output (prior to the sigmoid non-linearity used to compute "A") along both the temporal (maxT()) and feature (maxF()) axes in order to direct the network to predict a maximum of one association per row and column, as is expected for associations resulting from the Hungarian algorithm. As multiple classes may be active in an output instance, we apply sigmoid non-linearity to their outputs. Lastly, using weighted combinations of the three losses—which are each calculated using binary cross-entropy between the predictions and the goal labels of A, maxT(A), and maxF(A)—the Hnet is trained in a multi-task framework. Tanh Activation function is used to train the model as mentioned in equation 2 and 3.

f(x)= $\tanh(x) = \frac{2}{1+e^{-2x}} - 1$ ____(2)

tanhx $= \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$ _______(3)

Where ,

X is the input to a neuron

$f(x) = Tanh\ Activation\ Function$

e= Euler's Number

A sequence list for the available slots with the load factor is the result of the Hungarian neural network obtained in this step.

Step 10: Decision tree for slot allocation – This sequence list for the slot is the outcome of a comprehensive and innovative integration of the Hungarian task allocation system with the H-net neural network. We will employ the sequence list during this phase of the procedure to achieve better slot allocation results. This is a crucial statistic that will aid in the real-time customization of the scheduling technique used to find the closest EV charging station. The decision-tree technique is employed to take the decision to check the available slots for the nearest EV charging station from the sorted list obtained in phase 1. After allocating the nearest charging station, the system creates a direction map and displays it on the customer's mobile panel, indicating the direction on the Google ma to reach the EV charging station.

III RESULTS AND DISCUSSIONS

The Codename One framework, the Java programming language, and the NetBeans integrated development environment were utilized in the process of developing the proposed method for locating the nearest charging station and slot availability for electric vehicles. In addition to this H-net model is deployed in python programing language and its trained file is stored in the AWS cloud and connected to the mobile application using the end point. Development machine is equipped with a Primary memory of 16 GB an Secondary memory with 1 TB.

For the purpose of database management, the SQLite database is utilized. Taking into consideration a great deal of different factors, the practicability of the strategy that was recommended has been thoroughly evaluated. This section provides a description of the results obtained from the experimental inquiry.

Analysis of Scalability of H-net Slot allocation

By feeding different numbers of slots into the H-net, we evaluate the scalability of slot allocation at EV charging stations. We are conducting a thorough investigation to achieve this goal, including several tests on the H-Net model to assess its performance in allocating slots within the given timeframe. Some experiments are carried out by feeding the increasing number of slots along with their capacity time. Based on these two parameters, H-net forms the permutation matrix, and then the trained model predicts the slot allocation for the next request. We record and graph the time for each request to create the plot and tabulation in Figure 3 and Table 1, respectively.

Number of Input slots	Time taken to predict the Slot number by H-Net (In Millseconds)
5	52
10	69
15	57
20	71
25	65

Table 1: H-Net time performance records

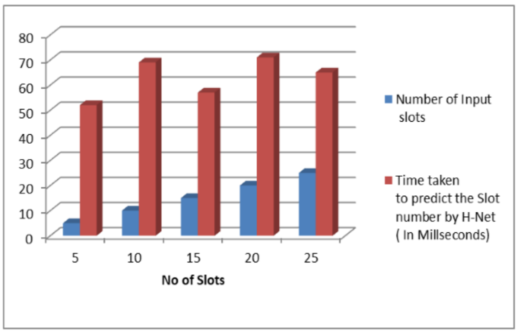

Figure 3: H-Net performance chart

Using the information in table 1, we may generate the bar graph which we can see in Figure 3. The chart successfully shows the relationship between the number of slots and the time required to assign them using the H-net model. A better understanding of the methodology and its application in constrained settings is provided by the study's findings. It can be clearly seen that as the number of slots increases in the input, the time required to estimate the slot is not directly proportional to the number of slots. This demonstrates that the H-net model was effectively used to allocate the slots for the forthcoming booking. The results shed light on how improving the efficiency of H-nets can improve the functioning of the EV-Charging station finder app.

IV CONCLUSION AND FUTURE SCOPE

This paper proposes the use of slot assignment techniques to enhance the efficiency of EV charging stations, thereby preventing congestion and ensuring prompt service delivery to customers. In order to optimize slot assignments, we implemented the H-Net neural network, which utilizes the Hungarian scheduling algorithm to assign slots to various terminals, thereby minimizing EV vehicle congestion at charging stations. To implement H-Net initially charging slots time, their type is taken into consideration to form a double-dimension list, which is then used to scrutinize the slots permutations to achieve the best slot timings by ensembling with a deep learning model. Experiments clearly demonstrate that the H-net model's prediction time for the number of slots does not directly correspond to the input number of slots. This clearly indicates that the H-net model's deployment is accurate only on the first attempt.

In the future of this research, we may consider multiple factors to assign the slots, like car type, battery type, manufacturer, traffic status, weather status, and many more by inducting a transfer learning mechanism.

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