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Enriching redistribution of power in EV Charging Stations through Deep learning

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Abstract

Extensive population growth and increased usage of electric devices are leading to unprecedented levels of electricity consumption. At times, this consumption can surge significantly during peak hours, leading to power outages in certain areas and occasionally even causing grid failures. Fast electric vehicle charging stations often use more power depending on the number of vehicles charging at a given time. A grid failure during peak hours could significantly impact the overall business of electric vehicle charging station owners, potentially leading to a decrease in the use of electric vehicles among consumers. This could potentially worsen air pollution by increasing the use of fossil fuel-powered vehicles. Therefore, it is crucial to regulate power at charging stations according to slot requirements for efficient charging, ensuring that only a larger number of electric vehicles can be successfully charged during periods of moderate load. Hence, to dynamic redistribution of power among charging ports within a station based on current demand and battery state-of-charge (SoC) is the actually task which can ease the load of electricity properly. This approach not only minimizes user wait times but also maximizes energy utilization, thereby increasing the popularity of electric vehicles among consumers and contributing to the reduction of pollution. The deep learning model Deep belief neural networks, in conjunction with k-nearest neighbor models and decision trees, function as catalysts to determine the dynamic redistribution of power among the slots, taking into account the port's state of charge, thereby enhancing the process. Further, root mean square error measurement shows that the designed model yields an exceptionally lower error rate in the redistribution of power within the station based on current demand and battery state-of-charge.

Keywords: Power Redistribution, K-nearest neighbor, Deep belief neural network (DBN), Decision tree, State of charge.

1. Introduction

Electric vehicles' (EVs) core idea is to be eco-friendly and long-lasting. If we have to construct the whole network of electric vehicle charging stations from the ground up, how environmentally friendly will it be? The electric vehicle business doesn't need to copy the gas station model, which relies heavily on infrastructure.

While the typical American lives just four minutes away from a petrol station, the closest Tesla charging station is thirty-one minutes away. We will require 600,000 charging stations by 2030, according to current estimates. This is a 1400% increase from 2020. It costs Tesla $250K for each supercharging station. Private companies like Tesla, BMW, Volkswagen, etc., and public entities are currently expected to shoulder the financial burden of electric vehicle charging infrastructure. Probably not!

The fact that electric vehicle owners won't have to rely on brand-new external charging infrastructure is one of the biggest advantages of EVs over ICE vehicles. It would be easy and convenient to charge cars at any time using the existing AC power outlets in our homes, just how people charge their phones nowadays. In addition to empowering individuals to take charge of their own vehicle fuelling and charging needs, this would also lessen the burden of constructing a comprehensive EV charging infrastructure from the ground up.

The fact that many people do not have access to garages with electrical outlets is one of the obstacles to this. In addition, the upfront expenses of establishing widespread electric vehicle charging stations in residential areas are currently too high. Installing EV chargers, managing power allocation, preventing power overloads, installing electrical lines, etc. all add up to make it difficult for someone with a fleet of EVs to make use of their existing power infrastructure. Yet, this is evolving at a quick pace. Cyber switching is one of several companies developing power management solutions that will allow homeowners and companies to charge their electric vehicle fleets without constructing expensive and labor-intensive charging infrastructure. Businesses and homeowners may make better use of their current power infrastructure to charge electric vehicles using tools like Cyber switching's EV Management Controller (EVMC). By making optimum use of the current AC power infrastructure, the device takes care of charging the fleet of vehicles automatically. Power usage is monitored, charging is automatically rotated, only cars that need charging are charged, power overload is managed, etc., and peak hour charging is also managed. By doing so, infrastructure and overload costs can be reduced and EV owners can save money by not having to build costly infrastructure on their premises to charge several cars.

Even though fossil fuels power many of our current power systems, we can decarbonize our power grids without EVs. It is projected that by 2050, fossil fuel emissions will have decreased by 75% due to the decarbonization of our power grids through renewable energy sources and the efficient use of our current power infrastructure to charge most of our automobiles. The public, EV manufacturers, and government agencies should all work together to construct this type of charging infrastructure for electric vehicles.

North America's electric vehicle charging infrastructure is now expanding at a rapid pace. In the US and Canada, there are more than 130,000 public charging stations as of 2023, and that number is growing rapidly. Level 2 chargers, which make up the bulk of these stations, can fully charge your device in approximately 4 to 8 hours. The availability of DC fast chargers, which can fully charge a battery in 30 minutes, is, however, on the rise. In North America, EV charging facilities are not evenly distributed. Among the 50 states with the most public charging stations, California ranks first, followed by Florida, New York, and Texas. Other states, like Washington, Oregon, and Colorado, are also investing heavily in electric vehicle charging infrastructure. Electric vehicle (EV) popularity, government incentives, and private investment are all driving forces behind the expansion of EV charging infrastructure. In addition to the Biden administration's target of 500,000 additional EV chargers by 2030, other states have established similarly lofty targets for the rollout of EV charging infrastructure.

The North American electric vehicle charging infrastructure is still in its infancy, but it is expanding at a rapid pace. Electric vehicle charging infrastructure will be in high demand as the number of EVs sold keeps rising. A strong electric vehicle (EV) charging network can be constructed in North America with the correct investments, facilitating the shift to a sustainable transportation future.

Some important developments in North American electric vehicle charging infrastructure are as follows:

- Public charging facilities are proliferating at a rapid pace.
- More and more, electric vehicle charging stations are popping up all throughout North America.
- An increasing number of DC fast chargers are being installed.
- Infrastructure for charging electric vehicles is expanding due to government subsidies.
- Electric vehicle charging stations are also seeing an increase in private funding.

Electric vehicle charging stations in North America have a promising future. A strong electric vehicle (EV) charging network can be constructed in North America with the correct investments, facilitating the shift to a sustainable transportation future.

It may come as a pleasant surprise, but the charging infrastructure in the UK is currently sufficient for anybody who has access to a home charger. The number of ultra-fast chargers in the UK nearly doubled from 2021 to 2022 and then more than doubled again from 2022 to 2023, despite the fact that the rapid charging infrastructure could not keep up with the higher ownership rates. In the same time as the number of electric vehicles increased by a "mere" 150%, the number of ultra-rapid chargers quadrupled in just two years.

From a situation in 2021 when there was a possibility of significant queuing during the busiest times, we are currently in a far better position, and the most crucial metric for home chargers is the availability of rapid chargers on main routes. While this is encouraging, it in no way ensures that the infrastructure will be sufficient to handle the expected further growth in demand. The infrastructure is still lacking in both physical availability and price models to accommodate the 25-30% of automobile owners without access to off-street parking and charging. Public charging fees are comparable to those of an efficient gas-powered vehicle, and there are huge swaths of the nation where this is the case. A lot of people will be turned off by either of those things, and they're both serious issues. Number of charging point across

USA can be depicted in the figure 1 to get the glimpse of importance of the EV charging stations in power redistribution phenomenon.

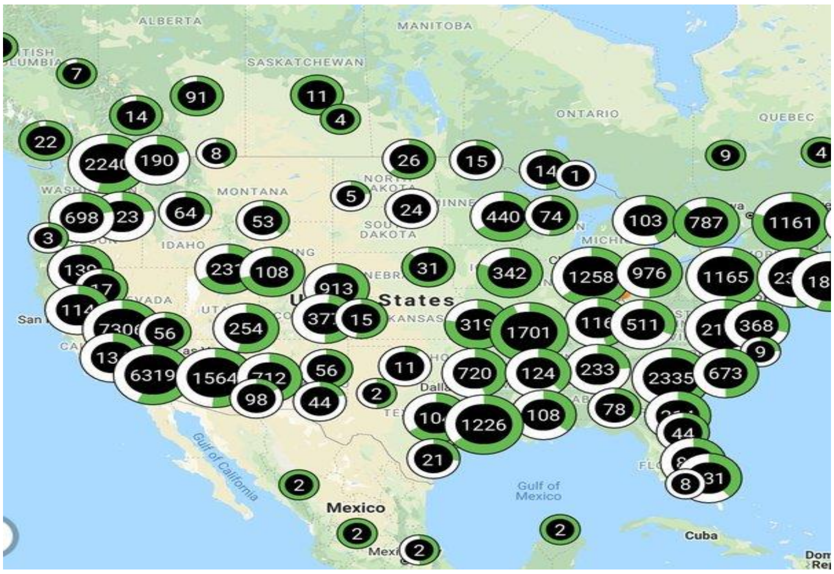

Figure 1: Number of charging station across USA

The growing incorporation of renewable energy sources into the power grid has created new, complicated problems, this is narrated by [1] Iacovos I. Ioannou et al. be addressed by implementing a Distributed AI (DAI) architecture. The improved smart features of power consuming devices and the unpredictable nature of renewable energy sources pose a significant challenge to the stability, quality, and balance of the power grid. Several power control strategies are theoretically developed and implemented within the suggested framework to protect the power system from generator and load variability. To illustrate the framework's utility, an example of a Nano-Grid is used, which includes the possible use of battery sources in extreme scenarios.

In author's performance evaluation, it is demonstrated that combining BDIx agents with the Particle Swarm Optimization (PSO) algorithm creates a strong solution for managing resources in a dynamic power network. This is supported by author's novel architecture. The author has various ideas for potential future research directions. Research into, and development of, DAI methods to improve the algorithms' scalability and efficiency is crucial, particularly for power grid systems that are bigger and more complicated than the Nano-Grid that was studied. Creating more advanced AI models with the ability to learn and adjust to shifting power consumption patterns and renewable energy outputs could be one way to achieve this.

[2] In order to quickly assess voltage stability for distribution networks, Huimin Gao et al. describe a new HEM-based method for computing sensitivity information, including topological-sensitivity and partial-sensitivity. This method overcomes known issues in the field. Equations for calculating voltage sensitivity are given in detail. An attractive alternative to progressively straining system loads for voltage stability assessment, the suggested method relies solely on topological information.

The small-scale electric power systems that [3] Arqum Shahid et al. suggested have played a crucial role in making energy more resilient and sustainable. By enabling local generation, storage, and distribution, these systems provide a more efficient and adaptable approach to energy management, which in turn reduces the difficulties of integrating renewables. This review paper provides a comprehensive analysis of AI applications in these systems, showcasing the revolutionizing impact of AI on different parts of energy production, storage, and consumption. It offers a fresh viewpoint on how AI will improve the efficiency and dependability of small-scale electric power systems in the future. To start, the history of small-scale electric power systems is quickly reviewed. Their critical role in making modern energy distribution more resilient and efficient is then examined in the review. An extensive examination of AI in power systems is offered, spanning multiple domains such as smart load management, predictive maintenance, real-time anomaly detection, and optimizing energy usage and demand response through dynamic pricing. At this point in time, everyone is agreeing on the AAPIs framework as the best way to evaluate artificial intelligence (AI) in micro- and small-scale power grids.

In order to rebalance the power consumption of individual charging ports at a charging station for electric vehicles, this study developed a model method. In order to maximize energy utilization and reduce user waiting time, this has been done based on the current demand and battery state-of-charge. To accomplish this, we draw on a large dataset that includes information on the charging ports at stations and the current battery charge level for each instance. In order to redistribute dynamic power among the charging ports in electric vehicle charging stations, this dataset is first thoroughly examined to preprocess the attributes according to their needs. We eliminate unnecessary columns, assign labels to them, and construct relationships using the Pearson correlation matrix during the preparation phase. We want to fully charge the vehicle's battery by designing the proposed system to redistribute electricity to the charging port. The K-nearest neighbor technique is employed by the designed model to determine which fast charging port has the least amount of remaining battery. Our deep belief neural network model, which relies on historical data, allows us to locate these ports and do additional redistribution tasks. Using the decision tree technique, we maximize the redistribution prediction values produced by the DBN model and make an instantaneous choice about how to divide the power across the charging ports in the electric vehicle charging station.

The second section of this research paper is based on earlier works. Section 3 explains the designed model under the 'Related Works' title 'Designed Model.' Section 4 tabulates and plots the obtained results under the title 'Results and Discussion'. We conclude this paper with suggestions for future enhancements.

2. Related Works

One practical solution to pollution caused by transportation is the electric vehicles discussed in Mohd Bilal et al. [4]. While EVCSs are a direct outcome of the growing popularity of electric vehicles, it is impossible to ignore the detrimental impact that a large number of charging stations has on the power grid. This paper uses a direct method load flow analysis to show how EVCS will affect the IEEE standard system. Consequently, DG should be used to compensate for the power losses caused by EVCS. To compensate for the power loss in the system, this work makes use of Type 2 DG. In addition, a hybrid algorithm known as HGWOPSO has been used to find the best node to insert EVCS and DG in order to minimize losses.

The increasing penetration of distributed energy resources (DERs), electric vehicles, heat pumps, and other new demands were brought to the attention of Muhammad Adnan Khan et al. [5] and pose new challenges to electrical networks. To avoid costly upgrades to the electrical network or investments in a large amount of costly backup generation, grid operators can maintain electrical grid balance by investing little in DR schemes. DR is thus a cost-effective solution to these problems. Despite DR programs' original intent of serving a small subset of large industrial and heavy commercial users, there is a great emphasis on expanding the portfolio to include residential and business clients. As part of this change, you'll need to decide which end users are responsible for a given consumption hour, as well as plan their usage, manage DR units, and establish incentive and punishment systems. More than 150 papers, 35+ businesses and commercial initiatives, and 20 major projects were combed through by the writers in this study to discover and examine the tendencies for AI methods in the energy DR sector.

Renewable energies are becoming more popular globally due to the pressing need to mitigate the effects of climate change and global warming, according to Andreea Claudia Őerban et al. [6]. When considering the current economic climate in light of resource depletion and the critical need to safeguard the environment, renewable energy (RE) stands out as both an essential R&D industry and a viable alternative. Better outcomes in terms of efficiency and accessibility to RE are being produced by the sector's growing integration of AI. Artificial intelligence aids in the management of energy production and consumption within a dynamic market and environmental context. As the percentage of energy produced by renewable sources (RES) continues to rise, one of the biggest problems facing this industry is the unpredictability of these sources. Microeconomic integration of AI is the way to go for mitigating the risk of RE source variability through predictive analysis, pattern recognition, reduced storage cost, improved grid-user connectivity, and ultimately, grid stability, reliability, and sustainability. As a consequence of the fast advancement of AI-based technologies, it will offer improved process insights through smart linkages between critical components and speed forecasts.

In power distribution in Sub-Saharan Africa, staff actions substantially contribute to non-transient losses (NTL), according to Obumneme Nwafor et al. [7]. Previous studies have mostly focused on customer activities. The study's innovative holistic ranking and SHAP algorithm both show that staff-related features account for four of the top six most influential features in the predictive models. This adds to the growing body of evidence suggesting that employees of power distribution corporations are also significant sources of NTL. The purpose of this study was to compare five ensemble learning strategies with a deep learning architecture that could predict NTL utilizing 12 input features. According to the research, the suggested NTLCONVNET outperforms all the ensemble techniques in every assessment metric that was tested at a significant level ($p < 0.05$). This study lays the groundwork for future studies that will investigate the links between staff activities and NTL in electricity distribution and quantify the impact of these actions. Additional staff-related features and machine learning methods can be utilized to further enhance this topic's research. Research in the future can evaluate the efficacy of combining various deep learning architectures and then compare the results to the author's suggested approach.

In order to make power distribution systems more resilient, Yuzhou Chen et al. [8] suggested a new graph learning model that uses Hodge-Laplacian analytics to extend the convolutional operation to simplicial complexes on the distribution network and makes use of persistent homology on graphs. Hodge-Laplacian analytics take into consideration complicated interactions among the higher-order substructures of the distribution grid, and by including persistent homology into learning distribution networks, we are able to extract the most distinctive topological descriptors of the grid. The new HOT-Nets model outperforms the state-of-the-art learning approaches in power distribution network resilience research. It predicts the network's outage status under different operating scenarios.

[9] A technique for controlling power distribution in communication-free MIMO wireless power transfer (WPT) by estimating load impedance and mutual inductance is presented by Jun Heo et al. This method's strength is that it can estimate these parameters using values derived from primary side measurements alone, without the requirement for wireless connection. A MIMO-WPT system consisting of two receiving (Rx) coils and four transmitting (Tx) coils was established in order to assess the efficacy of this approach. The load impedance and mutual inductance were measured in experiments with either one or two Rx coils.

In their study, Amr Khaled Khamees et al. [10] compared two new AI algorithms to four popular numerical approaches for estimating Weibull parameters. According to the results of the error analysis, the two AI systems performed the best. Once that is done, the MA approach is used to minimize fuel expense, power loss, VSI, and emissions while addressing the single-objective and multi-objective OPF problems. Using benchmarked IEEE-30 bus systems, we compared the proposed method's performance to that of other optimization methodologies previously published in the literature. The results proved that the MA approach was the most effective, legitimate, and accurate option. Additionally, on a modified IEEE-30 bus system with two wind farms, the MA approach is used to solve single-objective and multi-objective SCOPF. In a number of cases, the outcomes indicated the optimal wind schedule. Weibull parameter determination and solving of single and multi-objective OPF problems with wind energy penetration were both handled more efficiently by the Mayfly algorithm (MA) method compared to other numerical and meta heuristic approaches. The optimal wind schedule for the SCOPF was also more easily obtained using it.

An intelligent grid-wide maintenance support system was proposed by Ralf Gitzel et al. [11] in an interdisciplinary and all-encompassing manner. In their thorough analysis, the authors have covered all the necessary technologies to bring the author's notion to life, and they have also shown how important it is in relation to other ongoing scientific endeavors. The author has performed empirical research to identify the present challenges faced by electrical grid operators. In response to these concerns, the author proposes a multi-tiered system that can diagnose problems, evaluate risks, and convey this information to service workers in an approachable and educational manner. A wide variety of mechanical and electrical fault types can be handled by the algorithms and sensors. To prove that author's concept is feasible, author will keep improving algorithms, digital twins, and sensors based on initial prototypes and the pilot installation at WWN.

The multi-objective reactive power optimization model developed by Yongle AI et al. [12] is built and solved using NSGA-III. The model aims to minimize system active power losses, reduce PVs, and CLs. The updated IEEE123-bus distribution system validates the simulation. These two points are the meat and potatoes of this paper's findings. 1. When optimizing reactive power for many objectives at once, NSGA-III performs better because its Pareto distribution is more uniform. 2. As a result, when PVs supply reactive power, system operation improves and active power losses are mitigated.

In order to improve PEDG's transient responsiveness and resilience, Mohsen Hosseinzadehtaher et al. [13] suggest rethinking the function of GFLIs at the grid edge using an AI-PRC method. As a result of the BRA learning a two-layer feedforward ANN, the AI-PRC module is able to forecast the system frequency trajectory and supply the necessary amount of correction power to GFLIs in the event that the grid experiences disturbances. An accurate data mining approach was developed for the purpose of training the ANN after detailed analysis of the GFLI and GFMI dynamic. Compared to the state-of-the-art frequency restoration technique, several simulation and experimental case studies show a considerable improvement in resilience and transient responsiveness.

In order to incorporate averaged models of switched subsystems like power converters, Hannes Gernandt et al. [14] suggested averaged pH systems as a modeling framework. Several kinds of proportional and PI controllers for averaged pH systems, especially for EV charging stations, are derived by the author using the pH modeling framework. Since the controllers' design relies just on the averaged models' system equations, they may be easily modified to accommodate various EV charging station types or bigger networks of interconnected charging stations by adjusting the two scalar parameters of the pH PI controller. The designed controllers were successfully tested in simulations using a specific EV charging station's switched model. The benefits over a standard cascaded PI controller are detailed. Moving forward, the author intends to think about optimized pH control designs since there is still a lot of room to play with when choosing control design matrices.

According to the story told by Pengkun Quan et al. [15], an automated charging scene for electric vehicles was equipped with a comprehensive detection system for fast charging ports. The identification procedure acquired the charging port's location data by combining the Hough circle and Hough line. By merging the original and gradient photos, more accurate contour information may be extracted, leading to better recognition accuracy.

A stochastic expansion planning model for a coordinated natural gas and electricity network, which incorporates gas-fired generators, power-to-gas (P2G) facilities, and renewable power sources, was been forward by [16] Patrick Sunday Onen et al. Researchers looked at the pros and cons of two common approaches to network planning: integrated natural gas and electricity networks and the more conventional method of designing each network independently. Optimal infrastructure type, location, and size were determined by the final planning solution to achieve the best operation strategy while minimizing overall expenses throughout the planning horizon.

3. DESIGNED MODEL

This paper develops a redistribution model for the power in electric vehicle charging stations based on the state of the charge and battery parameters of the vehicle to speed up the process of charging. Figure 2 depicts the designed model, while a detailed explanation of the steps involved in this process follows.

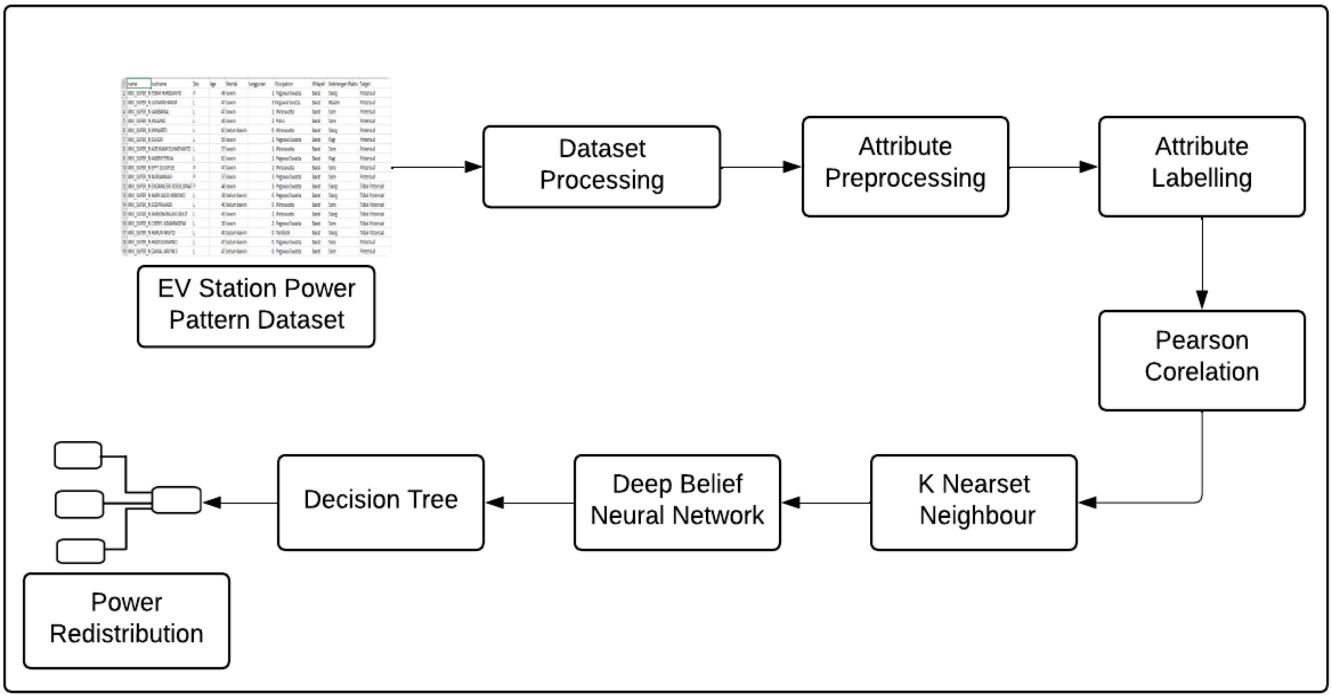

Figure 2: Designed model overview

3.1 Dataset processing

A model for electric vehicle charging stations that redistributes power based on the charge state and battery parameters of the vehicle in order to speed up the charging process is achieved by obtaining the dataset from the URL: https://www.kaggle.com/datasets/valakhorasani/electric-vehicle-charging-patterns . This dataset offers a thorough examination of charging patterns and user behaviour related to electric vehicles (EVs). Energy consumption, charging duration, and vehicle details are just a few of the metrics included in the 1,320 samples of charging session data. Insightful analysis and predictive modelling are made possible by each entry's recording of several characteristics of EV usage.

This dataset contains many attributes such as "User ID," which stands for "user-specific identifier," 'car Model': specifies the specific model of the electric car that is being charged, such as a Tesla Model 3 or a Nissan Leaf. 'Battery Capacity (kWh)': shows the total amount of energy that the vehicle's batteries can store in kilowatt-hours. A distinct identifier for the specific charging station that was utilized, as shown by the "Charging Station ID" Location of the charging station (e.g., New York City or Los Angeles) is shown by "Charging Station Location." A timestamp denoting the start of the charging session is shown by "Charging Start Time." A timestamp marking the end of the charging session is displayed by "Charging End Time." Amount of energy used when charging in kilowatt-hours, as shown by "Energy Consumption (kWh)" The "Charging Duration" field displays the overall amount of time required to charge the vehicle, expressed in hours. "Charging Rate (kW)" shows the average kilowatt-hour power delivery rate throughout the charging session. The "Charging Cost (USD)" field shows the overall cost of the charging session in US dollars. 'Time of Day' describes the time of day when the charging took place (e.g., morning or afternoon), 'Day of Week' describes the day of the week (e.g., Monday or Tuesday), and 'State of Charge (Start %)' describes the percentage of battery charge when the charging session began. "Distance Driven" (since last charge) (km): This metric measures the distance driven in kilometres since the last charging session, and "State of Charge (End %)" shows the percentage of the battery charge at the end of the charging session. The second field, "Temperature (°C)," specifies the Celsius temperature of the surrounding air while the charging is taking place., The "Vehicle Age" field, which is expressed in years, shows how old the electric car is. The 'Charger Type' field specifies the kind of charger that was used, such as a Level 1 or Level 2 DC Fast Charger. The 'User Type' field categorizes the user according to their driving habits, such as Commuter or Long-Distance Traveller.

3.2 Dataset Pre-processing

The obtained dataset from the mentioned The previous step stores the URL in a comma-separated value format, also known as.csv. The Python programming language assigns this dataset path to the pandas library object. When working with datasets, the Python package known as Pandas is a useful tool to have at our disposal. Through its assistance, it is possible to do tasks such as data analysis, cleansing, exploration, and modification. Pandas initially reads the dataset as an object and then uses it to describe the dataset attributes in detail. While detailing the same, initially the mean of the attribute and standard deviation is shown along with the 25%, 50%, and 75% of the max column attributes, and then the total count of the rows is also visualized. We import the Seaborn library in Python to display the heatmap of the attributes, aiding in understanding the data quality and distribution factors. Python Users can create statistical visuals with the help of Seaborn, which is a library. It interacts tightly with pandas data structures and builds on top of matplotlib as its structural foundation. Our data can be explored and understood with the assistance of Seaborn. Its charting functions operate on dataframes and arrays that include entire datasets, and they carry out the necessary semantic mapping and statistical aggregation on their own to generate charts that are informative. Its declarative application programming interface (API) is focused on datasets, which allows you to concentrate on the meanings of the many components of your plots rather than the specifics of how to show them. After the heat map visualization the attribute types are obtained to understand the different data type formats such as object, float and integer etc.

After this process, some unnecessary columns, like ‘ driver_type’, ‘charging Station ID’ and ‘Charging Station Location’ not really wanted for the next process of the redistribution process. Hence, these parameters are dropped from the dataset object, and the rest of them are converted into a double-dimension list.

3.3 Data labelling and Correlation

This step involves using the dataset in the double dimension list to access each of the column data types. The numerical values of each column undergo evaluation. If any column type is a string, then the unique values of the column are extracted, and then these unique values are enumerated with the integer values to label them and set them back in the dataset object in a double dimension list.

For the purpose of determining which attributes have the least amount of correlation, the Pearson Correlation values are utilized. To determine whether or not there is a connection between the attributes , the Pearson correlation is utilized. As a consequence of this, a correlation matrix is generated, which might be of assistance in identifying the most suitable combination regarding attributes. As a result of this finding, the right attributes that have a lower correlation are discarded, and new correlation values are generated. Equation 1, which is presented below, is utilized in the process of calculating the Pearson correlation.

$$\frac{\sum(x_i-\bar{y})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \text{ ------- } (1)$$

Where,

x_i=values of x (independent) variable ,y_i= values of y (Dependent) variable,$\bar{x}$= mean of x variable values and $\bar{y}$= mean of y variable values

3.4 K- nearest Neighbour

The pre-processed list that was obtained in the stage before this one is used as an input in this step of the operation. This is done in order to categorize the data in relation to the charging completion charging port that is closest to what is being charged. Following the steps that are outlined below is how this operation is carried out.

3.4.1 Distance Evaluation – Evaluation of the distance between the dataset characteristics and the instance charging slot input is being measured using the Euclidean Distance equation, as shown in equation 2 below. Input to this stage of the process is a list containing the dataset. The information contained in each row of this list is utilized to determine the distance from the instance charging slot input; this calculated distance is then placed as the row distance at the list's end. After each item in the list, this is repeated until the list is clear.

$$ED = \sqrt{\sum(ATi - ATj)^2} \text{ \_\_\_\_\_\_\_\_ } (2)$$

Where,

ED=Euclidian Distance

A_{Ti}=Attribute at index i

A_{Tj}= Attribute at index j

3.4.2 Centroid Estimation –This phase takes as input the data list and row distances computed in the previous step. After random data point selection, the list is sorted ascending by Row distance. K data points have been chosen for this analysis, and they all reach the centroid. With these numbers, we can calculate the row distance of the chosen index. In order to determine the neighbors' boundaries, the calculated row distance is then utilized. The total list's average row distance is derived from the previously attained row distances. In the next cluster construction technique, the average row distances and the extracted centroid row distance are utilized to ascertain the cluster borders.

3.4.3 Nearest neighbour estimation –

During the previous stage, the average row distance and centroids were used to inform the neighbour estimation process. After that, the maximum and minimum values for the average row distance and centroid row distance are obtained by adding and subtracting, respectively, in order to determine the neighbour borders. Next, the data is used to create the neighbours that will eventually make up a cluster list by applying these boundaries. The following phase is fed this sorted neighbour list in descending order, along with the top cluster.

3.5 Deep belief neural network and Decision Tree

Pre-training and fine-tuning are the two primary stages of a DBN's operation. Prior to training, the network learns to construct a layer-by-layer representation of the incoming data. The network is able to learn complicated data representations fast since each layer is trained independently as an RBM. Here, the network learns the inputs' probability distribution, which gives it insight into the data's structure. The DBN fine-tunes its parameters throughout the training phase so that it can perform a certain task, such as classification or regression. A common method for this is back propagation, which includes testing the network's capabilities on a given job and then adjusting its parameters based on the results. Supervised learning, in which the network is taught using tagged data, is commonly used during this stage.

At the beginning of building a deep belief neural network, the necessary Python libraries, such as keras, tensorflow, scikit-learn, and others, are imported. The train_test_split function divides the dataset into two parts: one for training and one for testing. Next, the data is normalized by scaling it using StandardScaler. This usually improves neural network performance. The initialization of a Restricted Boltzmann Machine (RBM) is done with a predetermined learning rate and number of components. By recreating the inputs, RBMs—unsupervised neural networks—are able to discover patterns in data. Equation 3 illustrates the RBM based model.

$$\mathrm{E(v,h)} = \sum_i \mathrm{ai\ vi} - \sum_j \mathrm{bj\ hj} - \sum_{ij} vjhjwij \_\_\_\_(3)$$

Where ,

E- Energy function

V- Visible units

h- Hidden units

Here, ai and bj are bias terms, and wij represents the weights between units.

The last layer of prediction uses a logistic regression classifier. When it comes to classification tasks, logistic regression is a straightforward linear model that works well. A pipeline connects the RBM with the logistic regression model. Because of this, the RBM can be used for feature extraction first, and then logistic regression can be used for classification. The DBN's pipeline is taught using the X_train_scaled preprocessed training data. The logistic regression model uses the features learned by the RBM to categorize the power redistribution factor, which is derived from equation 4.

$$P(v,h)=Ze-E(v,h) \_\_\_\_(4)$$

Here, the normalizing factor Z, which is the total of all possible pairs of visible and hidden units, is computed as part of the partition function.

Contrastive Divergence (CD) is the standard method for training RBMs. In order to adjust the weights wij and biases ai,bj to optimize the likelihood of the training data under the model, this method approximates the gradient of the log-likelihood.

Every one of these RBMs is stacked in a DBN. What you see as the visible layer of one RBM becomes the hidden layer of another. Using supervised approaches such as back propagation, the network can be fine-tuned after this unsupervised layer-wise training by reducing the discrepancy between the training data's actual label and the anticipated output. While training the model test size of 0.2 is selected with random state of 42. N component of 256 is used with learning rate of 0.01 by setting epochs with 50. For logistic regression max iteration value of 1000 is adjusted to obtain the desired predicted values. The architecture of the Deep belief neural network and Boltzmann machine is depicted in the figure 3.

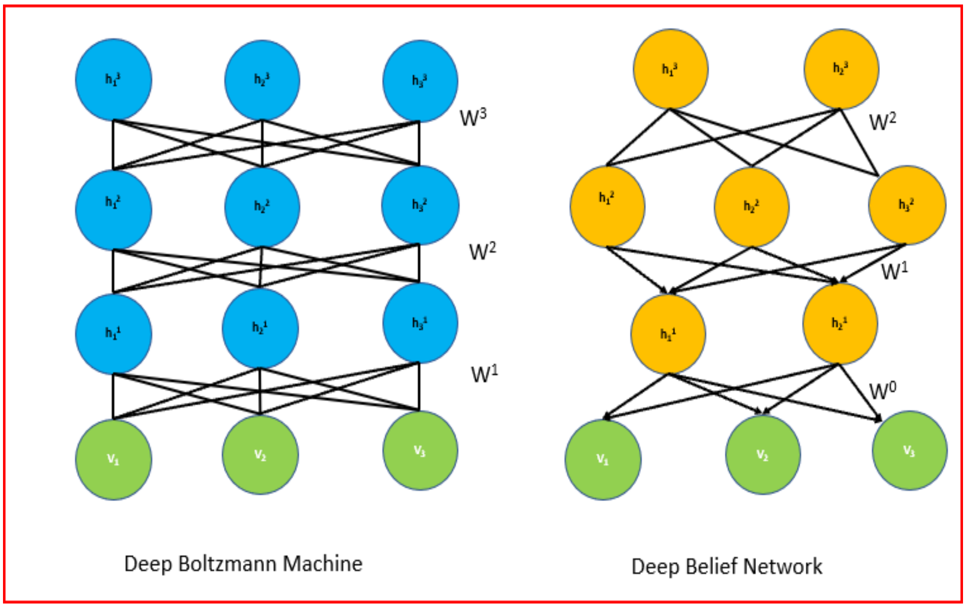

Figure 3: Architecture of Deep belief neural network

To make the right decision on power redistribution, the prediction scores that were collected are fed into a decision tree. A decision tree is a graphical representation of a series of choices and the outcomes that could result from them. The decision-making process is depicted by the tree's nodes, and the decisions' outcomes are shown by the branches. The conclusions or forecasts are symbolized by the tree's leaves. The process of iteratively subdividing data into smaller and smaller subsets is used to generate decision trees. Splitting the data in a way that maximizes information gain is done at each partition, and the data is split depending on a given attribute.

The scores are input into a decision-starting node, and from there, data is divided up according to the attributes using internal branch nodes that stand in for the decision points. Next, as indicated in equation 5, the terminal nodes, which are the leaf nodes, contribute to the formation of the decision rules that control the data splitting at each branch node according to the Gini index. The obtained rules actually feed the software define network model to redistribute the power for the slots within the Electric vehicle charging station to obtain the optimal solution in charging process.

$$\text{Gini Index} = 1 - \sum j j2 \qquad (5)$$

The Gini Index is a statistic for gauging the likelihood of an incorrect identification of a randomly selected element.

4. RESULTS AND DISCUSSION

Python is used to include the model that was designed and put into use for dynamically redistributing power among charging ports within a station based on current demand and battery state-of-charge (SoC). The Anaconda repository is used to install and launch the IDEs, like Jupyter and Spyder, along with the Conda console command prompt for the installation of the libraries. The model is deployed on a Core i7 machine with 16 GB of primary memory and 1 TB of secondary memory. The deployed model utilizes the dataset in CSV format to find the power redistribution factors among charging ports within the electric vehicle charging station. The obtained Deep belief neural network accuracy while training the model is depicted in figure 4 and 5 Respectively for 40 epochs.

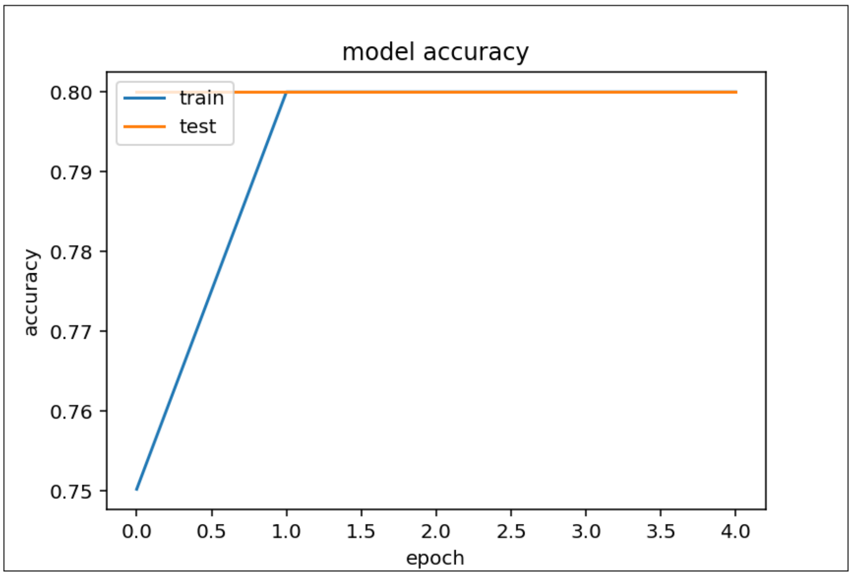

Figure 4: Deep belief neural network accuracy

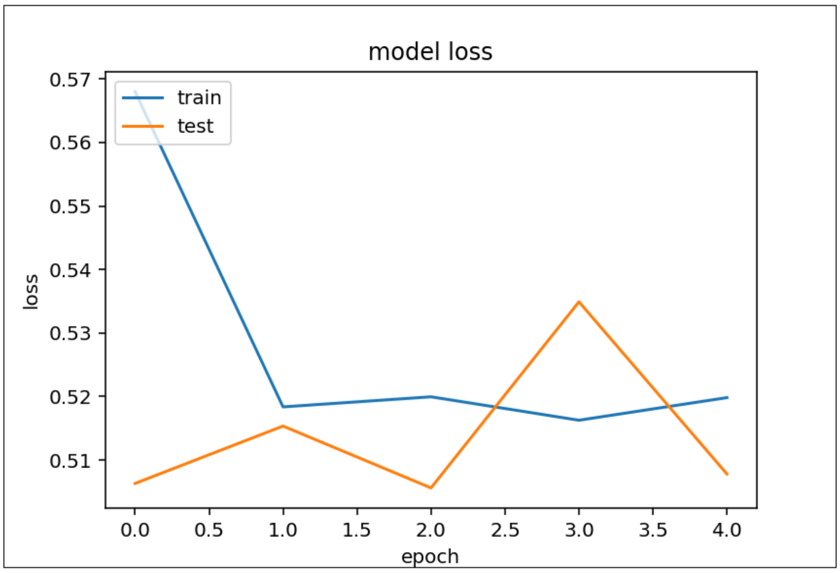

Figure 5: Deep belief neural network Loss

Observing figures 4 and 5, we come to the conclusion that the deep belief neural network model yields almost 80% flat accuracy for 40 epochs, which is an ideal result for the first time deployment of the model.

In order to determine whether or not the method is successful, we must first determine the degree of precision with which the electricity is distributed within the charging station. A strategy that has a reduced rate of errors is indicative of a more exact approach. The root-mean-squared error measure is a reliable tool that can be utilized for error identification and analysis.

When comparing the level of accuracy between two sets of linked continuous variables, the root mean squared error (RMSE) is one of the most effective performance metrics that can be utilized. The effectiveness of the proposed approach will be evaluated based on two metrics: the percentage of power redistribution that is correct and the percentage of redistribution that is erroneous. In order to calculate the root-mean-square error, the following equation 6 is supplied for your convenience.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_{1,i} - x_{2,i})^2}{n}} \quad \_\_\_\_\_\_(6)$$

Where,

∑ - Summation

(x1 – x2)2 – Disparities Squared for the total of the differences

N - The Count of Trails

The observed and predicted distribution factors can be seen in the figure 6 for 25 trails.

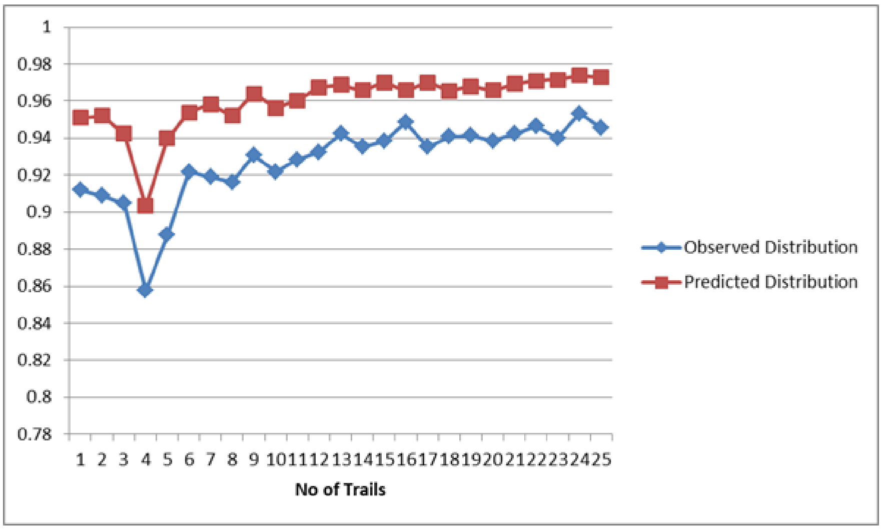

Figure 6: Observed and Predicted distribution

After evaluating the RMSE for the observed data and predicted scores of power distribution, we obtain an RMSE of 0.894. This RMSE is too low and shows a satisfactory error rate in redistributing power among charging ports within a station based on current demand and battery state-of-charge (SoC), which minimizes wait times for users and maximizes energy use in this case.

5. CONCLUSION AND FUTURE SCOPE

This research article designed a model approach to redistribute the power among the charging ports within an electric vehicle charging station. This has been done based on the current demand and battery state-of-charge to minimize user waiting time and maximize the energy utilization in the given charging instance. To achieve the stated goal, we use an extensive dataset that contains the station charging port data for any given instance along with the battery state-of-charge. Initially this dataset is scrutinized well to preprocess the attributes based on their requirements in the process of redistribution of dynamic power among the charging ports within the electric vehicle charging stations. During the preprocessing phase, we remove unwanted columns, label them, and use the Pearson correlation matrix to establish correlations. We design the proposed system to redistribute power to the charging port, which has the potential to fully charge the vehicle's battery. Designed model uses the K nearest neighbor algorithm to identify the fast charging port with the lowest battery percentage remaining. Using the deep belief neural network model, which is based on data that has already been recorded, we find these ports and do more redistribution work.The redistribution prediction values yielded by the DBN model is then optimized by using the decision tree algorithm to make instant decision to redistribute the power among the charging ports within the electric vehicle charging station. While maximizing energy efficiency and minimizing user wait times, the deployed model achieves an RMSE of 0.894—too low—and demonstrates a tolerable error rate when dispersing power among charging ports inside a station based on current demand and battery state-of-charge (SoC).

As future work the designed model can enhance to use real-time data periodically from a large number of charging stations to train the model using the transformers, thereby updating the model in all the charging stations. We can use an advanced software-defined network to redistribute power, utilizing the best hardware modules.

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