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Original Article

Power Allocation System Using Artificial Neural Network

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***Abstract**: The electric vehicle (EV) and renewable energy generation have achieved considerable development due to the growing energy demand and scarcity in fossil fuels. At the same time, EVs consume a huge amount of electricity when they are clustered in a charging station. In this project we are going to create a Artificial Intelligence based Power Allocation and ev charging system. We are using a deep learning technique called artificial Neural Network and hence we can able to get an accuracy over 90%. We predict the suitable power source for charging the electric vehicles using artificial Neural Network.*

***Keywords**: EV, Power Allocation, Energy, Demand.*

I. INTRODUCTION

A. Prediction

"Prediction" refers to the output of an algorithm after it has been trained on a historical dataset and applied to new data when forecasting the likelihood of a particular outcome, such as whether or not a customer will churn in 30 days. The algorithm will generate probable values for an unknown variable for each record in the new data, allowing the model builder to identify what that value will most likely be.

The word "prediction" can be misleading. In some cases, it really does mean that you are predicting a future outcome, such as when you're using machine learning to determine the next best action in a marketing campaign. Other times, though, the "prediction" has to do with, for example, whether or not a transaction that already occurred was fraudulent. In that case, the transaction already happened, but you're making an educated guess about whether or not it was legitimate, allowing you to take the appropriate action.

B. Electric Vehicles

T HE electric vehicle (EV) and renewable energy generation have achieved considerable development due to the growing energy demand and scarcity in fossil fuels. At the same time, EVs consume a huge amount of electricity when they are clustered in a charging station, which may significantly impact the operation of the grid. Therefore, deploying renewable generation and battery energy storage on the charging station side is regarded as a promising win-win solution. A. Motivation and Incitement By integrating renewable energy and battery, charging stations can greatly reduce the consumed energy from the grid and thus suppress the required grid capacity. Under constantly changing charging power provision, the charging of EVs should also be controlled to avoid undesired overload. These problems pose challenges to the energy management of the charging stations, because the stations must coordinate both the charging power dispatch of EVs and the power allocation among photovoltaic panels (PV), battery and the grid.

II. SYSTEM IMPLEMENTATION

A. Exisiting System

- In the existing system, they used two-stage scheme to solve the power allocation and charging coordination of plugged-in EVs.
- But their system accuracy is very low.

B. Proposed System

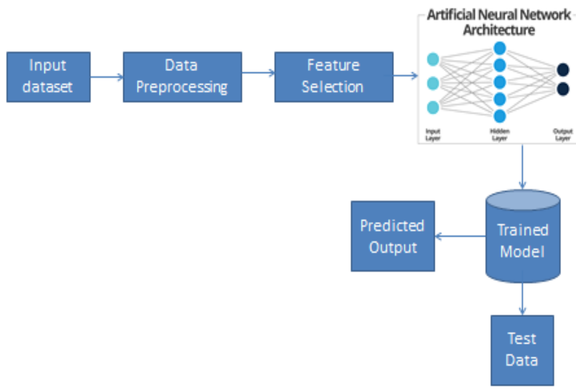
- In the proposed system we used a Deep Learning technique which is called as Artificial Neural Network.
- It will gives accuracy over 95%.
- High Stability
- Low Testing time
- High speed prediction

C. Data Collection

We collected the electric Vehicle power allocation dataset from kaggle website. This dataset contains solar power, wind power, EB power and electric vehicle battery capacity and output label as columns it consists of over 1000 rows

At first the dataset is fetched by using pandas library and then we save the datas inside a pandas dataframe, At first this dataset consists of lots of null values, then we replace all the null values into 0, because our Deep learning model cannot able to process null values

Figure 1 : Proposed System Architecture



a) Module Description

At first the datas are getted from the input dataset by using pandas library. Then we pre-process the data by droping null values, then we make feature selection by selecting input features for feeding it in the Artificial Neural Network module, we design a ANN model with more hidden layers which can able to give high accuracy, the extracted features are inserted in to the ANN model and the machine gets trained. After training we predict power source which is to be feeded for the vehicle to charge is by feeding test datas into the model.

III. DEEP LEARNING

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.

Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolution neural networks have been applied to fields including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

The adjective "deep" in deep learning comes from the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, and then that a network with a nonpolynomial activation function with one hidden layer of unbounded width can on the other hand so be. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

IV. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANNs), usually simply called neural networks (NNs), are computing systems vaguely inspired by the biological neural networks that constitute animal brains.

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called *edges*. Neurons and edges typically have a *weight* that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

A. Training

Neural networks learn (or are trained) by processing examples, each of which contains a known "input" and "result," forming probability-weighted associations between the two, which are stored within the data structure of the net itself. The training of a neural network from a given example is usually conducted by determining the difference between the processed output of the network (often a prediction) and a target output. This is the error. The network then adjusts its weighted associations according to a learning rule and using this error value. Successive adjustments will cause the neural network to produce output which is increasingly similar to the target output. After a sufficient number of these adjustments the training can be terminated based upon certain criteria. This is known as supervised learning.

Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any prior knowledge of cats, for example, that they have fur, tails, whiskers, and cat-like faces. Instead, they automatically generate identifying characteristics from the examples that they process.

Here, each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another

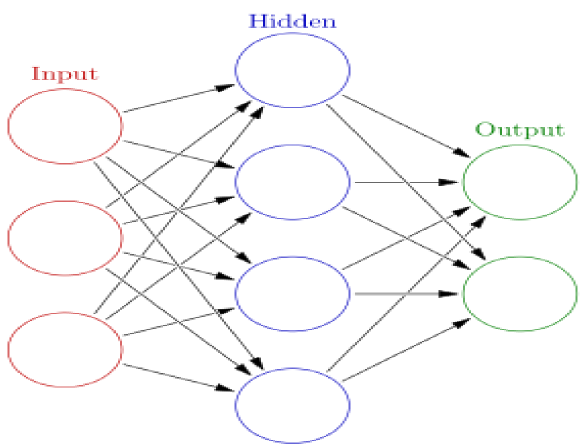


Figure 2 : An Artificial Neural Network is an Interconnected Group of Nodes, Inspired by a Simplification of Neurons in a Brain.

V. MODEL

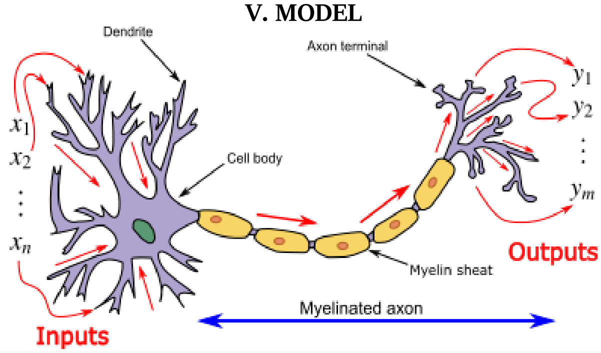


Figure 3 : Neuron and Myelinated Axon, with Signal Flow from Inputs at Dendrites to Outputs at Axon Terminals

ANNs began as an attempt to exploit the architecture of the human brain to perform tasks that conventional algorithms had little success with. They soon reoriented towards improving empirical results, mostly abandoning attempts to remain true to their biological precursors. Neurons are connected to each other in various patterns, to allow the output of some neurons to become the input of others. The network forms a directed, weighted graph.

An artificial neural network consists of a collection of simulated neurons. Each neuron is a node which is connected to other nodes via links that correspond to biological axon-synapse-dendrite connections. Each link has a weight, which determines the strength of one node's influence on another.

VI. RESULTS:

A. Input Dataset

	A	B	C	D	E
1	solar power(w)	wind power(w)	EB power(w)	battery capacity(w)	label
2	5000	3000	6000	4800	solar
3	3000	1000	5000	4800	EB
4	4000	2000	6000	1900	wind
5	5000	3000	4000	3800	EB
6	4500	2000	4000	1500	wind
7	3000	1000	4000	2800	solar
8	1000	3000	4000	2800	wind
9	500	300	4000	3800	EB
10	3000	4000	4000	3800	wind
11	4000	3000	4000	3800	solar
12	1500	2000	3000	1800	wind
13	1000	1200	2000	1800	EB
14	2500	3200	1700	2000	solar
15	1100	2500	4000	2000	wind
16	500	300	2500	2000	EB
17	4000	2500	3000	3800	solar
18	4000	4700	4800	4500	wind
19	3000	3000	5000	4800	EB

Figure 4 : The Input Dataset Consists of Solar Power, Wind Power, EB Power, Battery Capacity and Output Label as Columns it Consists of More Than 1000 Rows.

B. ANN Training

```
*Python 3.7.6 Shell*
File Edit Shell Debug Options Window Help
oss: 6.0172 - accuracy: 0.4097
Epoch 2/1000
 1/31 [..............................] - ETA: 0s - loss: 6.0709 - accuracy: 0.4
062
 5/31 [===>..........................] - ETA: 0s - loss: 5.6236 - accuracy
: 0.4500
 6/31 [====>.........................] - ETA: 0s - loss: 5.9112 - acc
uracy: 0.4219
 7/31 [=====>........................] - ETA: 0s - loss: 5.8883
- accuracy: 0.4241
 8/31 [======>.......................] - ETA: 0s - loss: 5          .
8712 - accuracy: 0.4258
 9/31 [=======>......................] - ETA: 0s - los
s: 5.8579 - accuracy: 0.4271
10/31 [========>.....................] - ETA: 1s
- loss: 5.7514 - accuracy: 0.4375
11/31 [=========>....................] - ETA
: 1s - loss: 5.9257 - accuracy: 0.4205
12/31 [==========>...................]
- ETA: 1s - loss: 5.9378 - accuracy: 0.4193
13/31 [===========>...............
...] - ETA: 1s - loss: 5.8497 - accuracy: 0.4279
14/31 [============>.........
........] - ETA: 1s - loss: 5.8883 - accuracy: 0.4241
15/31 [=============>...
.............] - ETA: 1s - loss: 5.9644 - accuracy: 0.4167
16/31 [============
==>...............] - ETA: 1s - loss: 5.9911 - accuracy: 0.4141
17/31 [=======
========>.............] - ETA: 1s - loss: 5.8830 - accuracy: 0.4246
18/31 [==
==============>............] - ETA: 1s - loss: 5.8757 - accuracy: 0.4253
19/3
1 [================>...........] - ETA: 1s - loss: 5.9364 - accuracy: 0.4194
```

Figure 5 : Training of Artificial Neural Network

The above figure represents the training of artificial neural network. It shows two things one is accuracy during training and another one is loss durin training of each epoch

C. Trained Model

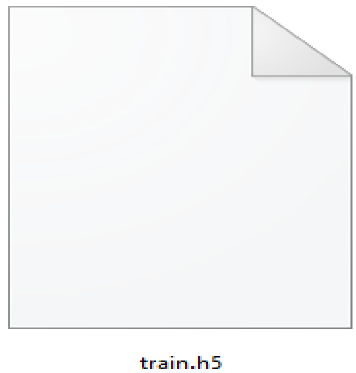
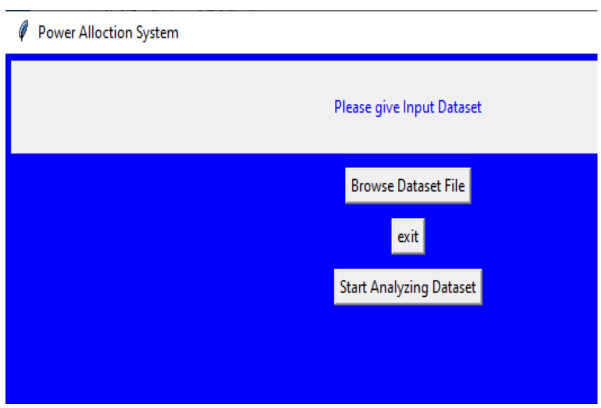


Figure 6 : We Save the Trained Model as Train.H5

D. Testing Application



We use tkinter python module to create this user interface. Through this user interface we can able to upload a test dataset and can get the power source for the ev charging as output.

E. Final Result

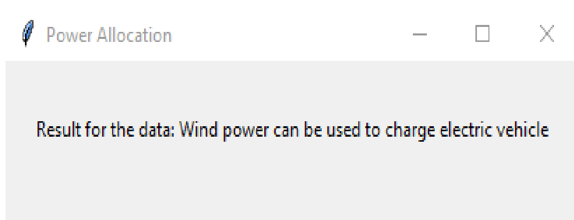


Figure 7 : It Show the Result for the Input Data as Wind Power can be used to Charge the Electric Vehicle.

VII. CONCLUSION

In our project we used Artificial Neural Network for predicting the power source to charge the electric vehicle. It is a one of the deep earning technique which can able to train and predict the power source to charge the electric vehicle based upon input data. We used power source dataset which holds over (1000 datas) for training purpose. After training we predict the power source to charge the electric vehicle by using test data's using ANN. Our Model Archives more than 95% accuracy during testing and training. The predicted results by ANN is accurate and stable, its patterns are also matched with the existing dataset patterns. And hence our model is perfectly trained and it can able to predict the power source to charge the electric vehicle with high stability. Our future work is to improve the accuracy by using hybrid machine learning techniques.

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