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Effective Prediction of Solar Power Using Neural Network

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ABSTRACT

With climate change driving an increasingly secure influence over governments and municipalities, sustainable development, and renewable energy are gaining traction across the globe. In this sense, a tool that aids predicting the energy output of sustainable sources across the year for a particular location can aid greatly in making sustainable energy share more. Energy forecasting can be used to reduce some of the challenges that arise from the uncertainty in the resource. Solar power forecasting is observe a growing attention from the research community. The project presents an artificial neural network model to produce solar power forecasts. Sensitivity analysis of several input variables for best selection, and comparison of the model performance with multiple linear regression and resolve models are also shown.

I. INTRODUCTION

Solar energy is an main origin of renewable energy. It is clean, abundant and easily accessible. Solar energy can be easily gather by using Photo Voltaic (PV) panels, either small-scale roof-top installations or large-scale solar farms. The solar energy can be changed into electricity and used to supply the electricity in the building or integrated into the electricity grid. In recent years, the PV technology has developed rapidly and is now one of the most promising technologies for manufacture solar power. The increased efficiency and lossnessof PV solar panels has led to the rapid growth of installed PV solar panels around the world, both stand-alone and grid-connected.

environmentally-friendly Since solar power is, many governments are encouraging its use by as long as incentives. Due to all these basis, solar power is expected to contribute significantly to the future global energy supply. For example, it is predicted that the next four years would witness a triple rise in the capacity of the installed PV power systems worldwide, reaching 540GW [1], and that by 2050, about 30% of Australian energy supply will come from PV systems [2].

II. RELATED WORKS:

Wang Buwei et al aimed to improving the accuracy of short-term PV power predictions. Firstly, regular power data, satellite-based data and numerical weather prediction data are utilized. The data sets of these origin are preprocessed and stuck with machine learning techniques to get the sequence feature information.

Isha M. Shirbhate et al suggest a photovoltaic management systems is essential to increase the efficiency of solar system. The proposed system implemented in two phases, first is a panel level monitoring system and second is a solar power prediction system.

Fatih Serttas et al introduced a novel methodology called Mycielski-Markov is utilized to forecast solar power generation for short term period. This novel hybrid method is developed based on two dissimilar techniques; Mycielski signal processing technique and probabilistic Markov chain.

Denis A. Snegirev et al considers the problem of day-ahead solar power plant output forecasting, based on the meteorological data. The raise of solar power plant output prediction will significantly simplify power system operation mode planning taking into market procedures and active power generation reserves allocation. Xiyun Yang et al proposed a solar radiation prediction method based on support vector machine (SVM) with similar data. Similar data was extracted from historical data by using pattern recollection with Euclidean distance to create the training samples.

Devangi Solanki et al presents a solar energy prediction model consisting of a mathematical model which enables to compute the amount of solar energy generation for next seven days (including present day) by considering weather data and plant statement

Yan Zhongping et al proposed a novel integrated wind and solar power forecasting. Different with previous systems, the moved system can predict the power of wind and solar electric farms by fusion of the high-resolution predictions of their generating equipments, such as wind turbines and photovoltaic panels

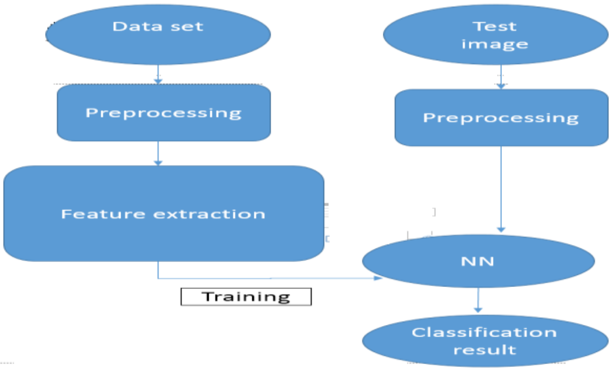
Martin Kroon; et al reports the techniques used to accurately predict the solar array power during various phases of the mission. The power instance insert a hot-case prediction at Closest Sun Approach (0.64 AU) and Low-Intensity, Low-Temperature (LILT) predictions at Jupiter Orbit Insertion (5.42 AU) and End-of-Life (EOL) (5.03 AUSabo Mahmoud Lurwan et al presented a MATLAB/SIMULINK simulation based model for predicting hourly solar radiation using modified Hottel's radiation model . The proposed modified Hottel's model makes it possible to predict solar radiation on hourly basis using current values of day type and geography of the location.

Nian Zhang et al propose an Elman style based regular neural network to predict solar radiation from the past solar radiation and solar energy in this research. A hybrid learning algorithm incorporating particle swarm accessand evolutional algorithm was presented, which takes the parallel advantages of the two global optimization algorithms.

Jingrong Guo et al proposed a systemic technical strategy to the current renewable energy consumption problem, focusing on demand-side response and time-of-use electricity price based on neural network prediction.

III. PROPOSED METHODOLOGY:

In this work , for the classification of solar power , multilayer feed forward network with back propagation algorithm is proposed .The main goal is to classify data in terms of higher accuracy

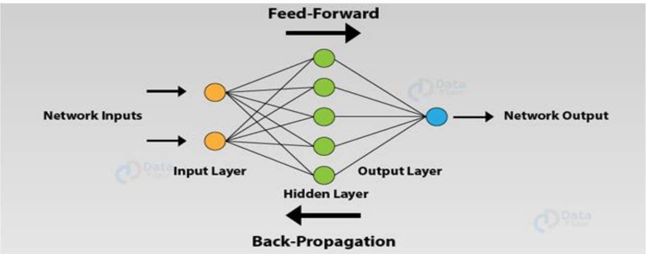


Modules

- Data Preparation
- Feature extraction
- ANN model building
- Performance analysis

ANN

Artificial Neural Networks are the most accepted machine learning algorithms today. The invention of these Neural Networks took place in the 1970 but they have attain huge popularity due to the recent raise in computation power because of which they are now virtually everywhere. In each and every approach that you utilize, Neural Networks applied the intelligent interface that keeps you occupied.



What is ANN?

Artificial Neural Networks are a specific type of appliance learning algorithms that are modeled after the human brain. That is, just for instance how the neurons in our nervous structure are learn from the past data, similarly, the ANN is able to absorb from the data and provide reaction in the form of predictions or classifications.

artificial Neural networks are irregular statistical artificial which display a complex association between the inputs and outputs to discover a new representation. A variation of piece of work such as figure recognition, speech recognition, machine transfer as well as medical diagnosis makes use of these artificial neural networks.

An major advantage of artificial neural networks is the fact that it learns from the example data sets. Most commonly usage of artificial neural networks is that of a random function estimate. With these types of tools, one can have a cost-effective method of arriving at the solutions that define the issues.Artificial neural networks is also capable of taking sample data rather than the entire data banks to provide the output result. With artificial neural networks, one can increase existing facts analysis techniques owing to their advanced predictive capabilities.

Artificial Neural Networks Architecture

The functioning of the Artificial Neural Networks is similar to the method neurons work in our nervous structure. The Neural Networks go back to the prompt 1970 when Warren and Walter Pitts coined this term. In order to understand the workings of artificial neural networks , let us first accept how it is structured. In a neural network, there are trio essential layers –

Input Layers

The input layer is the initial layer of an artificial neural networks that collect the input information in the form of various texts, numbers, audio files, image pixels, etc.

Hidden Layers

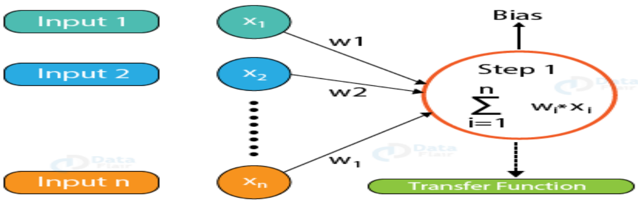
In the central of the artificial neural networks model are the invisible layers. There can be a single invisible layer, as in the case of a perception or multiple invisible layers. These invisible layers carry out various types of mathematical computation on the input data and recognize the patterns that are part of.

Output Layer

In the output layer, we acquire the result that we obtain through rigorous computations performed by the central layer.

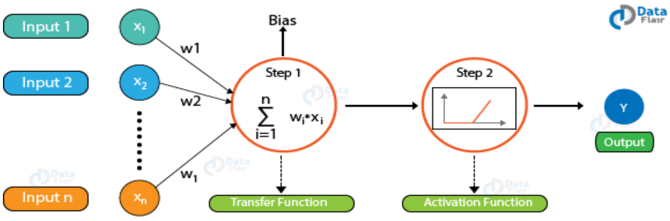
In a neural network, there are many parameters and hyper variable that affect the performance of the model. The output of artificial neural networks is mostly dependent on these variable. Some of these parameters are weights, biases, learning charge, batch size etc. Each node in the ANN has some pressure.

Each node in the lattice has some pressure assigned to it. A shift function is used for calculating the pressured sum of the inputs and the bias



After the shift function has calculated the sum, the operate function obtains the reaction. Based on the output collect, the operate functions fire the appropriate result from the node. For example, if the output received is above 0.5, the operate function fires a 1 otherwise it remains 0.

Some of the popular activation functions used in Artificial Neural Networks are Sigmoid , RELU, Softmax, tanh etc.



Based on the use that the intersection has fired, we obtain the end of the output. Then, using the error functions, we calculate the discrepancies between the forecast output and resulting output and adjust the weights of the neural network through a process known as back propagation.

Artificial Neural Networks are share of an emerging zone in Machine Learning known as Deep Learning. Many people are confused in the middle of the Deep Learning and Machine Learning. Are you among one of them? Check this easy to recognize article on Deep Learning vs Machine Learning.

Back Propagation in Artificial Neural Networks

In sequence to edify a neural network, we give it with examples of input-output mappings. Ultimately, when the neural network completes the training, we trial the neural network where we do not provide it with these mappings. The neural network forecast the output and we evaluate how correct the output is using the various error functions. Ultimately, based on the result, the model adjusts the pressures of the neural networks to correct the network following gradient descent through the chain rule.

Types of Artificial Neural Networks

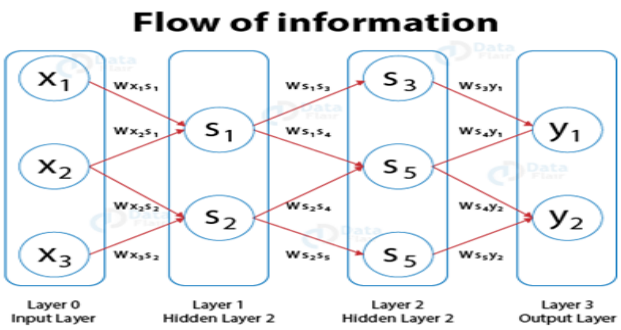
There are pair important types of Artificial Neural Networks –

Feed Forward Neural Network

Feed Back Neural Network

Feed Forward Artificial Neural Networks

In the feed forward Artificial Neural Networks, the flow of information takes place only in one direction. That is, the move of details is from the input layer to the hidden layer and finally to the output. There are not at all feedback loops here in this neural network. These kind of neural networks are mostly used in supervised learning for occurrence such as classification, image recognition etc. We use them in instance where the facts is not subsequent in nature.



Feedback Artificial Neural Networks

In the feedback Artificial Neural Networks, the feedback loops are a part of it. Such kind of neural networks are mostly for memory retention such as in the case of recurrent neural networks. These kind of networks are most suited for areas where the data is sequential or time-dependent.

	A	B	C	D
1	DATE_TIM	DC_POWE	MODULE_	data
2	15-05-202	34.875	22.35346	0
3	15-05-202	278	22.89328	0
4	15-05-202	614.875	24.44244	0
5	15-05-202	1166.857	27.18565	0
6	15-05-202	1661.5	28.88848	0
7	15-05-202	1856.375	29.60564	0
8	15-05-202	1842.286	29.54711	0
9	15-05-202	1877.875	31.41254	0
10	15-05-202	3246	35.52871	0
11	15-05-202	3917.5	40.31806	0
12	15-05-202	4322	39.08195	1
13	15-05-202	4257.125	45.00923	1
14	15-05-202	5706.714	46.61771	1
15	15-05-202	4015.5	39.13633	0
16	15-05-202	3219.286	40.93058	0
17	15-05-202	6454.429	52.54774	1
18	15-05-202	5286.5	47.63374	1
19	15-05-202	6008.375	49.24972	1
20	15-05-202	6637.286	44.04833	1
21	15-05-202	4399.75	47.68545	1
22	15-05-202	5388.375	50.00699	1
23	15-05-202	6829.5	49.84136	1
24	15-05-202	8617.5	47.83638	1
25	15-05-202	6226.125	49.18358	1
26	[illegible]	[illegible]	[illegible]	[illegible]

IV. CONCLUSION

The artificial neural networks model outperforms the multiple linear regression analysis MLR model and the persistence model. The performance of the ANN depends on how well it is trained and on the quality of the data that is used. The feed-forward ANN with 14 weather variables and with hourly step size for forecasts performed better than the recursive neural networks. The normalized input data doesn't improve the performance, but removing the night hours slightly improves the model performance. Plotting the data, investigating the correlation and sensitivity analysis between the variables, as well as data cleansing of outliers are essential data preparation steps before building the forecasting model. In the clear sky hours, the model produces more accurate forecasts than cloudy hours. The more accurate weather forecasts we use, the more accurate solar power forecasts will be produced. Using the classification variables and the interactions between the variables enhances the performance of the MLR model significantly but this is not the case for the ANN model. With additional historical data, the model performance will improve in future.

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