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To cite this article: Liang Feng et al 2018 IOP Conf. Ser.: Earth Environ. Sci. 192 012032

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Deep Learning Algorithm for Preliminary Siting of Substations Considering Various Features in Distribution Network Planning

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Abstract. Substation siting and sizing planning is one of the important contents of distribution network planning, which directly affects the results of subsequent distribution network planning, and affects the quality of power supply and the economy of power grid operation. Given this background, a deep learning algorithm for preliminary siting of substations in distribution network planning is proposed in this work. Features related to the principle of siting of substations are extracted and multichannel data characterization are utilized. Then, the features are integrated into a convolutional neural network (CNN), which is one of deep learning algorithms, based on actual geographical relationships. Next, the preliminary siting of substations for the subsequent planning process is completed. Finally, the validity of the proposed algorithm considering different input features is demonstrated on a distribution network of one certain province in China by case studies and comparisons. The simulation results show that the proposed deep learning algorithm for preliminary siting of substations is more accurate with more input features, and is better than shallow learning algorithms, thus can be employed to preliminary siting of substations in distribution network planning.

1. Introduction
The planning of the substations and grids is one of complex issues of distribution network planning [1], [2]. Further, substation siting and sizing planning are important contents of distribution network planning, which directly affects the results of subsequent distribution network planning, and affects the quality of power supply and the economy of power grid operation.

The specificity of actual geographical conditions should be taken into consideration in substation siting. Thus, research on the siting of substations has been conducted by some experts and scholars. There are studies to plan the number, capacity, and power supply range of substations, and the substation load capacity is taken as the main constraints of the planning model [3], [4]. The more complex principle of substation siting selection has been considered in some studies, and the corresponding characteristic indexes are extracted. Then, an index system is established, and the candidate areas are evaluated according to the index system and the substation site is selected [5], [6]. In [7]-[9], the heuristic algorithm such as genetic algorithm and particle swarm algorithm are utilized to solve the siting optimization model, and the analytic hierarchy process (AHP) and other evaluation methods are used to modify the siting results. So far, there are mainly three type of planning methods...
in the practical application and research: 1) Subjective determination based on the experience of power system planners; 2) Extract general principles of substation siting as characteristic indexes, establish the index system, and evaluate and screen the candidate sites; 3) Plan the substation siting with the number, capacity and power supply scope of the substations considered, and determine whether the substation siting results in the distribution network planning are feasible. If it is not feasible, further adjustments should be made for the substation siting.

In the planning process of substation siting, human judgment is required based on planners’ experience in the aforementioned methods. Deep learning is a subfield of machine learning that has evolved from shallow learning. For shallow learning, when it comes to the representation of complex functional relationships, the learning volume is large, the generalization ability is weak, and it is easy to over fit. The data is abstracted by deep learning model through a series of multilayer nonlinear transformations and fewer learning units are used to realize the approximation of more complex functions [10]. The hidden layer increased by deep learning to form a deep network [11] to overcome the problem of gradient dispersion caused by network deepening. The common models [12]-[15] of deep learning include Auto Encoder (AE), Convolutional Neural Network (CNN), Recurrent Neural Networks (RNN), Restricted Boltzmann Machine (RBM), etc.

Given this background, a deep learning algorithm for preliminary siting of substations in distribution network planning is proposed in this paper. Features related to the principle of siting of substations are extracted and multichannel data characterization are utilized. Then, the features are integrated into a convolutional neural network (CNN), which is one of deep learning algorithms, based on actual geographical relationships. Next, the preliminary siting of substations for the subsequent planning process is completed. Finally, the validity of the proposed algorithm considering different input features is demonstrated on a distribution network of one certain province in China by case studies and comparisons.

2. Deep learning algorithm for preliminary siting of substation

Substation siting and sizing planning is one of the important contents of distribution network planning, which directly affects the results of subsequent distribution network planning, and affects the quality of power supply and the economy of power grid operation [16]. To determine the optimal siting of the substations, the principle to be followed includes the terrain and geology where the substations locate; the convenience of transportation, and urban and rural planning are also should be considered [17]. Some terrains (e.g. rivers and roads) do not have the conditions for the construction of substations, and areas with high population densities (e.g. commercial areas) are not suitable for the construction of substations. On the one hand, different properties of land use have different impacts on the preliminary siting and daily operation and maintenance of substations; on the other hand, substation construction has different effects on users of different land properties. Therefore, it is complex to choose the substation site.

In the planning process, the location of the substation is usually assessed by the planners based on the substation siting principle or the established index system, which has high requirements for the planners’ experience and is time-consuming and laborious [18], [19]. If an appropriate algorithm is used for preliminary screening through the features related to the planning area and the planning principles, the workload of distribution network planners and their dependence on their experience can be reduced. Because the area involved in the substation siting is relatively large, there are many features related to siting. Therefore, data-intensive problems will be caused and it is difficult for the traditional mode of shallow learning of pattern recognition to handle such high-dimensional features. Therefore, deep learning method is adopted in this paper to extract and learn the characteristics related to the principle of substation siting, and determine whether or not the blocks in the planned area are suitable for substations, so as to perform preliminary siting of substations. Thus, the selection process is based on a large number of proven planning schemes, and the reliance on the planner's experience is reduced. Besides, preliminary siting results can be substituted into the distribution network planning model for further planning calculations.

The basic unit of the convolutional neural network includes a convolutional layer and a downsampling layer [20]. A convolution kernel is used for each feature to be learned in the convolution layer, and neurons are connected to the input of the layer to perform feature extraction using a convolution
operation. The downsampling layer is also called the Pooling Layer. By calculating the average and maximum of a feature in an area of an image, the summary features of the image are obtained and sent to the next convolutional layer. This operation can effectively reduce the dimension of the feature and reduce the probability of over fitting the model. After several convolution and downsampling layers, the extracted features are gradually transformed from low-level to high-level. Finally, all local features are integrated through a fully connected layer, and a classifier or a regression device is added at the top of the network to implement classification or prediction functions [21].

At the convolution layer, multiple features of the image can be learned using multiple convolution kernels, and each feature can be compared to each channel of the image. The network reduces the number of training parameters through sparse connection [22] and weight sharing [23]. The sparse connection means that each neuron is connected with only part of the feature map of the previous layer through the convolution kernel, so that only partial images are perceived. Weight sharing means different neurons learn the same feature using the same set of weight parameters. In addition, in order to prevent over fitting, the dropout technique can also be adopted by convolutional neural network so that some hidden neuron output values are zero, and thus do not participate in the forward and backward propagation process. The complexity of adaptation between neurons is reduced and the over fitting is prevented [24].

A typical convolutional neural network structure (i.e., LeNet5) [25] is shown in Figure 1. There are eight layers of LeNet5: input layer, convolutional layer C1, pooling layer S2, convolutional layer C3, pooling layer S4, convolutional layer C5, fully connected layer F6, and output layer; where sparse connections are applied only in layers C1 and C3 [25], and the number and size of feature maps for each layer are also indicated in Figure 1.

![Figure 1. The network structure of LeNet5 [25]](image)

The algorithm for preliminary siting of substations based on CNN is as follows.

1. Extract the features of land type, terrain, neighbouring substations, etc. The type of land use is represented by the sketch map, and different types are denoted by different colors. Most of the land use planning maps are drawn according to the reference color standard. For the same land type, the land is represented by the same color, and the color of the schematic at a certain pixel can be used to represent the corresponding type of the site. Besides, the terrain can be derived from the GIS system elevation data. If there is no corresponding data, the data can be directly scaled according to the steepness of the terrain, such as 2, 1 and 0 for the definitions of mountains, hills and plains (i.e., plateau, flatland).

2. Mark the non-image features of the training data and the data to be predicted on the geographic coordinates and align them with the pixels of the image. The training data and the data to be predicted are organized according to the geographic coordinates of the input data vector and the channels (3 to 4 channels for land use type, 1 channel for terrain, and 1 channel to the neighbouring substation), and represent the ground for the input vector in the training data. If substations are contained, the output of the training data is set to 1; otherwise, it is set to zero.

3. Input the training data and the data to be predicted into the convolutional neural network and set the parameters for prediction.

The flowchart of the method of preliminary siting of the substations based on convolutional neural network (CNN) is shown in Figure 2.
3. Case Studies

In order to demonstrate the effectiveness of the proposed algorithm, a distribution network of one certain province in China is taken as an example. The sketch map of the land use plan and the distribution of the substations in the area is extracted from the distribution network planning reports. Then, the topographic data from Google Earth is extracted to form 2,100 5-channel training data. The size of each training data is 10×10, including land type (3 channels), terrain (1 channel), and distance from the nearest substation outside the supply area (1 channel). k-fold cross-validation is performed and the training data is randomly divided into 21 clusters (i.e., 21-fold cross-validation). One cluster is used as a test set at a time and the remaining 20 clusters are used as training set. Take the training data size and characteristics into consideration, the structure of the established CNN network is as follows.

(1) Input layer: the number of input data channels is 5;
(2) Convolution layer: convolution kernel is with 5 × 5, and the number of feature maps (number of channels) is 4;
(3) Pooling layer: pooling area is with 1 × 1, and the number of feature maps (channels) is 4;
(4) Convolution layer: convolution kernel is with 5 × 5, and the number of feature maps (number of channels) is 4;
(5) Pooling layer: pooling area is with 2 × 2, and the number of feature maps (channels) is 4;
(6) Output layer: it is fully connected, the number of output data channels is 1, and the activation function is Sigmoid function.

3.1. Preliminary siting results based on deep learning algorithm

After inputting the above data into the CNN network, a total of 2043 data correctly judge whether there is a substation in the concerned area, and the accuracy rate is equal to 97.29%. The correctness of each cluster as a test set is shown in Figure 3, and the number of data clusters for each accuracy rate interval is shown in Figure 4. The results show that it has a high accuracy rate of the judgment that using the CNN of deep learning algorithm for the distribution of existing substations and regional characteristics of learning.

![Figure 3. The accuracy rate of each cluster as a test set for deep learning algorithm](image1)

![Figure 4. The number of data clusters for each accuracy rate interval for deep learning algorithm](image2)
In order to analyse the impact of input features on the accuracy rate of the judgment, the circumstances of lacking in terrain data, lacking in neighbouring substations, and features that contain only the type of land are input to the network, and the results are analysed.

(1) Judgment results in the absence of terrain data
A total of 2019 data correctly judge whether there is a substation in the area, and the accuracy rate is equal to 96.14%. The accuracy rate of judgment for each cluster as a test set is shown in Figure 5, and the number of data clusters for each accuracy rate interval is shown in Figure 6.

(2) Judgment results in the absence of neighboring substations information
A total of 1996 data correctly judge whether there is a substation in the area, and the accuracy rate is equal to 95.05%. The accuracy rate of judgment for each cluster as a test set is shown in Figure 7, and the number of data clusters for each accuracy rate interval is shown in Figure 8.

(3) Judgment result considering the land type only
A total of 1932 data correctly judge whether there is a substation in the area, and the accuracy rate is equal to 92.00%. The accuracy rate of judgment for each cluster as a test set is shown in Figure 9, and the number of data clusters for each accuracy rate interval is shown in Figure 10. The results show that the accuracy rate is the lowest when input features only include the type of land (that is, the lack of terrain and neighbouring substation data). The accuracy of some clusters is lower than 90% or even 80%, and the stability is relatively low. When the terrain or neighbouring substation data are added, the accuracy rate of judgment will be improved. The accuracy rate of judgment of each cluster is above 90%, but both are lower than the input data including the terrain and neighbouring substation data simultaneously. It shows that adding terrain features and neighbouring substation features will help improve the accuracy rate of the CNN-based substation pre-siting model in preliminary siting of substations.
3.2. Comparisons of preliminary siting results with shallow learning algorithms

To demonstrate the superiority of the preliminary siting method based on the convolutional neural network, two commonly used shallow learning models, i.e., Back Propagation (BP) neural network and Radial Basis Function (RBF) neural network, are selected. The input features were input into the above model for preliminary siting of substations. The above 2100 training data are still used and the k-fold cross validation method is used. The training data is randomly divided into 21 clusters (i.e., 21-fold cross-validation). One cluster is used as a test set at a time and the remaining 20 clusters are used as training set. The results are as follows.

(1) Judgment results based on BP neural network

A total of 1625 data correctly judge whether there is a substation in the area, and the accuracy rate is equal to 77.38%. The accuracy rate of judgment for each cluster as a test set is shown in Figure 11, and the number of data clusters for each accuracy rate interval is shown in Figure 12.

(2) Judgment results based on RBF neural network

A total of 1719 data correctly judge whether there is a substation in the area, and the accuracy rate is equal to 81.86%. The accuracy rate of judgment for each cluster as a test set is shown in Figure 13, and the number of data clusters for each accuracy rate interval is shown in Figure 14.

The results show that the accuracy rate of the preliminary siting based on BP neural network and RBF neural network is significantly lower than that based on CNN. It indicates that the preliminary siting of the substation based on CNN is superior to the preliminary siting based on shallow learning algorithms such as BP neural network and RBF neural network.
4. Conclusion
This paper proposes a deep learning algorithm for preliminary siting of substations in distribution network planning. By extracting features related to the principle of substations siting and using multichannel data characterization methods which are analogous to pictures, the features based on actual geographical relationships are integrated into a convolutional neural network for preliminary siting method of substations. The preliminary siting of substations for the subsequent planning process is completed. Finally, the validity of the proposed algorithm considering different input features is demonstrated on a distribution network of one certain province in China by case studies and comparisons. The simulation results show that the proposed deep learning algorithm for preliminary siting of substations is more accurate with more input features, and is better than shallow learning algorithms, thus can be employed to preliminary siting of substations in distribution network planning.

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