Application of Deep Spatiotemporal Prediction Model in Power System

Hu Feihu
School of electrical engineering, xi'an jiaotong university

Abstract

The deep spatiotemporal prediction model has been widely used in the fields of traffic flow, product price, information dissemination, weather forecast, ecological environment monitoring, etc. It also has some applications in the fields of new energy power generation, unified power market marginal price, charging load distribution, etc. The typical deep spatiotemporal prediction model combines CNN model representing spatial characteristics with LSTM representing temporal characteristics. This paper will introduce the application of several new deep spatiotemporal prediction models in power system.

Application 1: Deep Spatiotemporal Electricity Price Forecasting Model based on GAT-GRU

GAT-GRU (graph attention network and gated cyclic unit network) is a deep spatiotemporal prediction model based on graph neural network and cyclic neural network. Firstly, a graph model describing the regional distribution and power grid structure of the power market is established, and then the graph neural network inputs the information extracted from the time series based graph into the cyclic neural network to predict the power price in the spot market. Finally, the data of Nord pool is taken as an example for analysis, The results are compared with those of other typical models.

Application 2: Deep Spatiotemporal Electricity Price Forecasting Model based on GAN

The background of the problem is the same as that of application 1. The prediction method is replaced by GAN(Generative Adversarial Networks).

Application 3: Wind Speed Prediction of Wind Farm based on Residual Network

A deep spatiotemporal residual network is proposed to predict the wind speed data of each wind turbine in the wind farm. The residual neural network framework is used to model the wind farm data. For each attribute, a residual convolution unit branch is designed, and each branch simulates the spatial attribute of the wind power data. The spatiotemporal residual network dynamically aggregates the outputs of three residual neural networks according to the data, and assigns different weights to different branches and regions. Finally, combined with the wind direction, temperature, air pressure and other external factors, the wind speed of each fan is predicted. Using the data provided by American Nerl, the experiment results show that this method is superior to the traditional method.

Application 4: Wind Speed Prediction of Wind Farms based on Interpretable Features in High-dimensional Data Scenarios

In order to improve the prediction accuracy, researchers try to add more input data to the prediction model, including wind power time series (power), meteorological space-

time series (wind speed, wind direction, air pressure, air temperature, humidity, etc. of different longitudes, latitudes and elevations) and three-dimensional spatial information of the wind farm (site layout, fan characteristics, etc.). The complex coupling relationship between high-dimensional data makes the fusion of different deep learning models more and more difficult. The automatic extraction effect of spatial-temporal information data features by deep learning models becomes worse. More and more super parameters of different deep learning models need to be adjusted manually before or during training, and the training of models becomes more and more difficult due to the influence of super parameter adjustment of other deep learning models. A method of extracting interpretable features from high-dimensional data using deep learning model is proposed, and then wind speed prediction of wind farm is carried out based on the features. Using the data provided by American Nerl, the experiment has achieved amazing results.