Available online at www.sciencedirect.com
ScienceDirect
December 2017, 24(6): 67–73
www.sciencedirect.com/science/journal/10058885
The Journal of China Universities of Posts and Telecommunications
http://jcupt.bupt.edu.cn

Anomaly detection in smart grid based on encoder-decoder framework with recurrent neural network

Zheng Fengming[1,2] (✉), Li Shufang[1,2], Guo Zhimin[3], Wu Bo[3], Tian Shiming[4], Pan Mingming[4]

1.Beijing Laboratory of Advanced Information Networks, Beijing University of Posts and Telecommunications, Beijing 100876, China
2. Beijing Key Laboratory of Network System Architecture and Convergence, Beijing University of Posts and Telecommunications, Beijing 100876, China
3. State Grid Henan Electric Power Research Institute, Zhengzhou 450052, China
4. China Electric Power Research Institute, Beijing 100192, China

Abstract

Anomaly detection in smart grid is critical to enhance the reliability of power systems. Excessive manpower has to be involved in analyzing the measurement data collected from intelligent motoring devices while performance of anomaly detection is still not satisfactory. This is mainly because the inherent spatio-temporality and multi-dimensionality of the measurement data cannot be easily captured. In this paper, we propose an anomaly detection model based on encoder-decoder framework with recurrent neural network (RNN). In the model, an input time series is reconstructed and an anomaly can be detected by an unexpected high reconstruction error. Both Manhattan distance and the edit distance are used to evaluate the difference between an input time series and its reconstructed one. Finally, we validate the proposed model by using power demand data from University of California, Riverside (UCR) time series classification archive and IEEE 39 bus system simulation data. Results from the analysis demonstrate that the proposed encoder-decoder framework is able to successfully capture anomalies with a precision higher than 95%.

Keywords smart grid, encoder-decoder framework, anomaly detection, time series mining

1 Introduction

Over the past decade, social economy has experienced unprecedentedly rapid and continuous development. Production of human society (especially information-related technologies) is increasingly dependent on stable electricity supply, which has been an indispensable support. In order to prevent power system instability and even accidental large-scale power outage (e.g., unexpected blackout) from happening, anomaly detection in smart grid has attracted much importance and plays a significant role. Conventionally, anomaly detection in smart grid has to involve specific expertise as well as non-negligible manpower in the costly while powerless computing due to the drastically increasing measurement data volume.

To address such issues, techniques related to machine learning and data mining have been extensively used for intelligent data analysis in detecting anomalies. A spatial-temporal correlation based anomalous behavior model was proposed in Ref. [1] to capture the characteristics of anomaly in smart grid. The authors in Ref. [2] focused on the security of energy management system (EMS) modules by detecting anomalies in an electric network database. They proposed a graph comparison-based approach for identifying anomalies in an electric network database. In Ref. [3], in order to analyze stochastic processes over graphs associated with smart grid systems, a novel learning and estimation framework was proposed which induced an underlying sparse structure enabling dimension reduction. The authors in Ref. [4] used artificial neural networks to report energy fraud. A generic and scalable framework for automated anomaly detection on large scale time-series data was

Received date: 28-04-2017
Corresponding author: Zheng Fengming, E-mail: zfm@bupt.edu.cn
DOI: 10.1016/S1005-8885(17)60243-7

introduced in Ref. [5]. The authors in Ref. [6] introduced a new similarity function for heterogeneous graphs that compares two graphs based on their relative frequency of local substructures, which was the most important module in their proposed anomaly detection approach. In Ref. [7], the authors proposed a prediction-based contextual anomaly detection method for complex time series that was not described through deterministic models.

In the paper, we propose an anomaly detection model for electric power system based on encoder-decoder framework with RNN. To be more specific, an input time series is reconstructed and an anomaly can be detected by an unexpected high reconstruction error. We also come up with a novel approach to estimate the probability of an anomaly, which employs both Manhattan distance and the edit distance to evaluate the difference between an input time series and its reconstructed one.

The proposed encoder-decoder framework has a number of inherent advantages to identify anomalies in smart grid system:

First, a large number of records are being collected from intelligent monitoring devices in smart grid, only a tiny fraction of them are anomalous. The proposed model is suitable for the case where distribution of positive and negative samples is unbalanced. Only normal data is needed for training the proposed model. In contrast, conventional methods for anomaly detection based on machine learning usually require that the numbers of the two types of samples are approximately equal with each other. Oversampling or undersampling of the samples is necessary to balance the data, which however, could result in either exaggerating insignificant features or overlooking important information.

Second, conventional methods for detecting anomaly in smart grid rely to a large extent on expertise in electric power field in order to make judgement according to operation curves in smart grid. In contrast, the proposed method ignores the expertise in electric power field and delivers the work of anomaly detection completely to machines such that human workload can be significantly reduced. Moreover, the proposed model is also one of the most typical examples which combine advanced deep learning techniques with traditional electric power.

Third, the proposed method is applicable to anomaly detection for both univariate and multi-dimensional time series. However, conventional methods such as support vector machine (SVM) [8] usually fails to detect anomalies for multi-dimensional time series, because SVM requires that the train data be a point on a high continuous dimensional space but it is difficult to contain spatio-temporality at the same time.

The remaining of this paper is organized as follows. In Sect. 2, we introduce the encoder-decoder framework with RNN as well as similarity evaluation in details. In Sect. 3, we provide an overview of data set for anomaly detection in electric power system and demonstrate experimental results. Finally, we summarize our work and conclude the paper in Sect. 4.

2 System framework

2.1 Encoder-decoder reconstruction model

RNN is a kind of artificial neural network, which imposes the connection edge of adjacent time nodes and introduces the concept of time into the model. It makes RNN suitable for processing time series. The encoder-decoder reconstruction model [9] consists of two RNNs called encoder and decoder, respectively. The encoder learns a fixed dimensional vector representation of an input time series and the decoder converts the output vector of the encoder into an output time series.

Consider a time series $\boldsymbol{X} = \left[x^{(1)}, x^{(2)}, \dots, x^{(L)} \right]$ with length L as the input of the model, where element at time t_i is a m-dimensional vector (m can be one), representing the data collected from m different devices at time t_i. The input time series is reconstructed by a reconstruction model based on encoder-decoder framework with RNN and anomalies can be detected by unexpected high reconstruction errors.

As an extension of the feed forward neural network, the RNN reflects the connection between the current and past information by adding an edge between two hidden states adjacent over time, which is referred to as a loop edge. At time t_i, current state value of hidden layer is affected not only by the current input vector $x^{(i)}$, but also by the previous state value $h^{(i-1)}$ of hidden layer.

In addition to the classical activation functions (e.g., hyperbolic tangent function (tanh), sigmoid, rectified linear unit (relu)), there are two special structures in hidden layer: long short-term memory (LSTM) and gated recurrent unit (GRU), introducing a memory cell, a unit of computation that replaces the traditional nodes in the