

## Application of Recurrent Neural Network with Long Short-Term Memory Cells on Partial Discharge Identification

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### ABSTRACT

By introducing Artificial Intelligent (AI) techniques through the design of a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) cells, it is possible to significantly reduce the time and cost of identifying Partial Discharge (PD) pulses. The proposed work is performed solely on PD pulses gathered from in-service cables. Waveforms vary inherently due to attenuation and distortion resulting from reflection and refraction, which makes recognition challenging. Our results show that an accuracy higher than 95% be achieved through the proposed methodology.

### KEYWORDS

Medium-Voltage cables, Partial Discharge, Artificial Intelligence, Recurrent Neural Network, Long Short-Term Memory Cells

### INTRODUCTION

Medium-voltage cables are the backbone of electricity distribution. Major developed cities are laced with complex, underground networks. Underground cables provide protection from natural and man-made damage and adds to the aesthetic quality of the landscape, but is several times more expensive than overhead lines [1]. This high cost comes from the combination of logistics and more expensive extruded power cables. Based on these circumstances, it is apparent that it is in the owner's best interest to have reliable knowledge of the cable conditions within the quickest possible time frame.

During offline cable diagnostic test, multiple waveform snapshots (approximately 30 to 50) of time-resolved partial discharge (TRPD) pulses are taken at various voltage levels. The combination of different voltage levels and phases results in a large total number of data samples. The complexity of the obtained waveforms make evaluation an arduous task. Conventionally, evaluation is performed after testing. This approach has two potential problems. Firstly, if decision is made after evaluation, the delay could result in further undesired downtime of the network. Secondly, if re-energising of the cable is performed before evaluation, there is a probability that a defected cable may be re-connected, which could also lead to further undesired downtime of the network.

The presented work proposes a technique that employs RNN with LSTM cells for PD identification. Application of neural network on PD has existed for nearly 30 years [2]. The results presented in this paper refute the notion that neural networks are less useful for discharge recognition [3]. Recent progress in deep learning techniques, computational capability and storage capacity has shown AI to be the superior approach, largely due to

its ability to continuously improve the quality of results through the combination of historical data and scientific advances in deep learning.

The rest of this paper is organised as follows. We present a brief theoretical introduction on RNN and LSTM. We define the proposed architecture, consisting of hyperparameter, as well as the data used and methods employed in training the network. This is followed by a description of waveforms encountered in field testing. Results, a discussion and future work concludes the paper.

### RNN WITH LSTM

#### Recurrent Neural Network

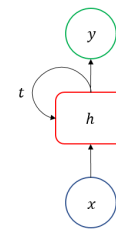


Fig. 1: Basic RNN Cell

The model proposed in this paper is a multilayer Recurrent Neural Network (RNN), which consist of an input layer  $x$ , hidden layer  $h$  and an output layer  $y$ . Similar to the traditional Feedforward Neural Network, the RNN has propagations forward through the network to generate output values. A backward propagation is then performed to retrieve the error. The error calculation for the RNN is slightly different, because the nodes are connected in a cycle  $t$  as show in Fig. 1. In this topology, Backpropagation Through Time (BPTT) is used instead to update weights in the RNN. This loop allows information to persist and influence over time. The purpose of the loop is to ingest information in sequential data [4].

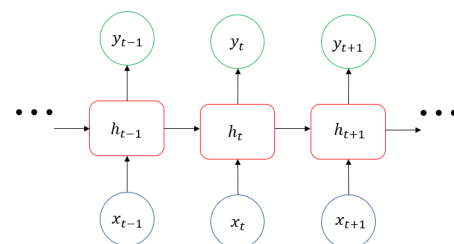


Fig. 2: Unfolded RNN Cell

To gain more insight, the network can be unfolded as shown in Fig. 2. It can be thought of as multiple copies of