Earthquake Early Warning through Terrestrial Optical Networks: A Bi-GRU Attention Model Approach on SOP Data

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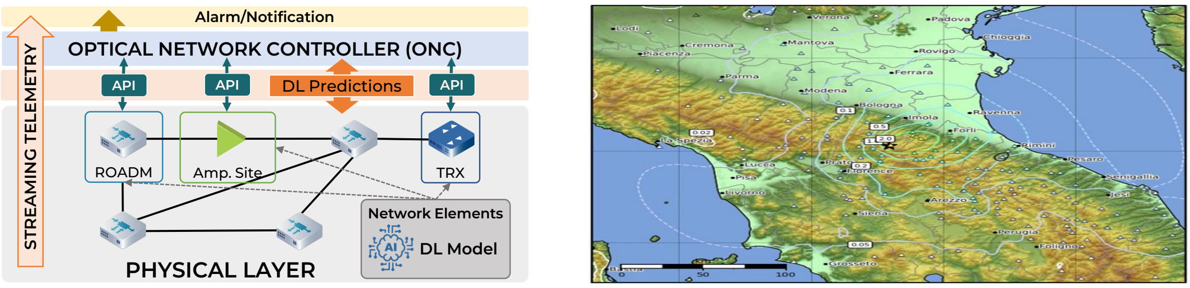
Abstract: We propose a smart grid fiber sensing approach based on a Bi-GRU model with an attention mechanism for earthquake early warnings exploiting terrestrial optical networks. Model training and testing use realistic synthetic earthquake waves.

1. Introduction

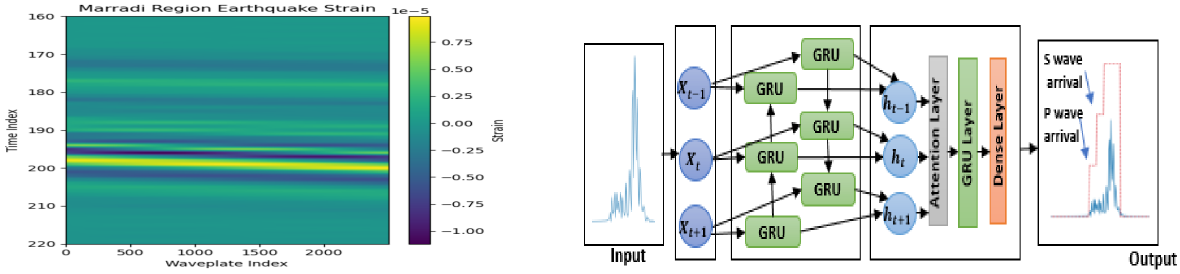
In recent years, wavelength division multiplexing (WDM) based optical transmission infrastructure has revolutionized the telecommunication industry to satisfy the massive needs of the rapidly expanding global internet traffic. As a result, the deployment of optical fiber is growing over the majority of the world, particularly in heavily populated areas. Aside from offering high-capacity data transmission, recently we have witnessed a growing interest in investigating how existing optical fiber networks can be turned on wide fiber sensing network smart grids. This has numerous applications, including monitoring anthropogenic activities [10] and seismic detection [1, 2]. While distributed fiber optic sensing use dedicated and costly hardware to perform accurate event localization and detection with a remarkable accuracy, the usage of telecommunications network here proposed aims at perform sensing using the physical quantities already measured by the network elements (NE) on the data signals, such as changes in the frequency, intensity, phase, and state of polarization (SOP), or integrating them with additional cheap sensors. While this approach has the disadvantage of being less accurate and resoluted in space, using the already deployed telecommunication infrastructure enables the availability of many sensing sources over wide terrestrial areas. Here we focus on the monitoring of SOP changes on the intensity modulated optical channels [3] or on the coherent channels [1] caused by earthquake induced mechanical stress. Although many other works based on phase monitoring have been proposed, one of the compelling concerns remains on how a particular event, such as an earthquake, can be detected on the incoming waveform, independently on the measured quantity. Deep learning (DL) approaches are the best candidates to accomplish this task, as they allow the identification or segmentation of events based on knowledge of the essential traits that identify them. In this work, we propose to integrate a DL model based on a Bidirectional Gated Recurrent Unit (Bi-GRU) with an attention mechanism for environmental sensing services into the already installed optical network infrastructure, particularly for earthquake early warnings. The core idea of our approach is to deploy a fast, accurate and reliable trained DL model in each NE that is constantly monitoring the SOP of data signals traveling through the optical line system (OLS). Thus, this deployment strategy enables the creation of a sensing smart grid that can continuously monitor wide areas and respond with early warning signals for forthcoming earthquakes.

2. Smart grid network based on Bi-GRU model with an attention layer

The architecture of our proposed smart grid optical sensing network is shown in Fig. 1a and exploits the streaming telemetry paradigm available for monitoring of data transmission [11]. The NEs continuously collect the telemetry data for network control and management purposes and communicate with a centralized optical network controller (ONC), via application programming interfaces (API). For example, reconfigurable add/drop multiplexers (ROADM) and inline amplifiers already monitor power evolution or temperature variations. Thus, Some NEs can monitor additional quantities useful for environmental sensing, such as phase (transceivers) or SOP fluctuations to integrate the existing telemetry. For example, SOP evolution may be gathered by tapping a small quantity of optical power to operate an SOP monitoring device [3, 12]. As proposed in [4] the proposed DL model can be implemented into NEs, continuously providing predictions based on the variations of SOPs, leveraging on the edge-computing power of NEs and send timely updates to the ONC, thus creating a smart grid network. For this study, we are considering the real earthquake scenario that occurred on September 18, 2023, at 03:10:14 UTC near Marradi, Florence, Italy. The earthquake had a magnitude of 4.9. Fig.1b shows the peak ground velocity (PGV) of an earthquake, with its epicenter indicated by a black circle. The seismic waves radiate out from the epicenter in all directions, with the strongest waves occurring closest to the epicenter. To mimic this real earthquake, we



(a) Fig. 1: (a) Architecture of sensing network, (b) Real earthquake footprit (b)



(a) Fig. 2: (a) Realistic strain curve, (b) Architecture of proposed DL model (b)

represented the geographical footprint of the earthquake-affected region using the INGV online service. We specifically chose the seismic station at 43.4418 latitude and 12.9973 longitude known as Monte Murano (MMUR). The displacement waveform for that event is then extracted at the station, specifically in the East. We employ the SYNGINE tool [5] to produce displacement waveforms that closely resemble the seismic conditions seen during real earthquakes. SYNGINE is an open-source service that provides customized synthetic seismographs. It was difficult to obtain a perfect waveform match because SYNGINE uses a 1D Earth model while the actual Earth's crust is more accurately described by 3D models. In our simulation setting, we assumed to use a 10-km fiber optic connection simulated by a model with 2500 waveplates. We translate the displacement into a nanostrain value along the fiber using the conventional DAS conversion technique described in [9]. The obtained strain curve is presented in Fig.2a showing a 10-second lag between the p-wave and surface wave arrival times. The time index of the P wave is from 171 to 180 seconds, the S wave is from 181 to 190 seconds and the surface wave is from 191 to 210 seconds. Subsequently, we apply the raw strain matrix generated to our waveplate model [4] to observe the SOP evolution. We generate the dataset by running the simulator numerous times using a different set of orientation angles for the waveplates at each iteration. After obtaining the SOP time evolution, we determine the state of polarization angular speed (SOPAS) [6]. We propose to train a Bi-GRU with an attention mechanism model on obtained SOPAS to sense the forthcoming earthquake. The architecture of our proposed DL model is shown in Fig. 2b. The proposed model has one input layer with 50 neurons, a Bi-GRU layer with 128 neurons in each direction, an attention layer with one neuron, a GRU layer with 32 neurons, and an output layer with 4 neurons for classification of no earthquake, P-Wave, S-Wave and Surface wave. The Bi-GRU layer employed the tanh activation function whereas the attention layer, GRU layer and output layer used the softmax activation function for the prediction. The model is trained over 1000 epochs using an adaptive learning rate optimizer (ADAM) and a categorical cross-entropy loss function. Bi-GRU is the variant of the Recurrent neural network (RNN) which can process the data in the form of sequences in both forward and backward directions. Given an input sequence $X = (x_1, x_2, ..., x_T)$ of length T=20, the forward and backwards hidden states are computed and then passed to the attention layer. The attention layer employs mechanisms that weigh different elements of the input sequence to compute the context vector which selectively concentrates on important temporal aspects in the input sequences. The learned context vector is then passed to the final dense layer for generating class probabilities. The proposed model is trained on the realistic synthetic time-series dataset files with a single feature defined as the norm of SOPAS variation in time. The 60% of the dataset is used for training, 20% for validation and 20% for testing purposes. In order to simulate realistic environmental conditions and assess the robustness of the model, a 20% Gaussian noise was introduced to the original signal based on the variance of the original signal, as in a terrestrial scenario the SOP measurements may be impaired by polarization noise coming from other anthropic activities.

3. Results

We consider the F1 score, recall, precision and accuracy metrics to verify the effectiveness of our model. Fig.3 shows the precision, recall, F1 score and accuracy of our model on the validation dataset during the training against

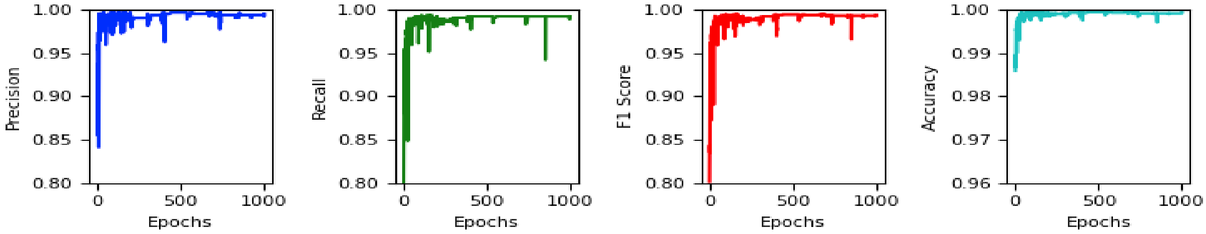
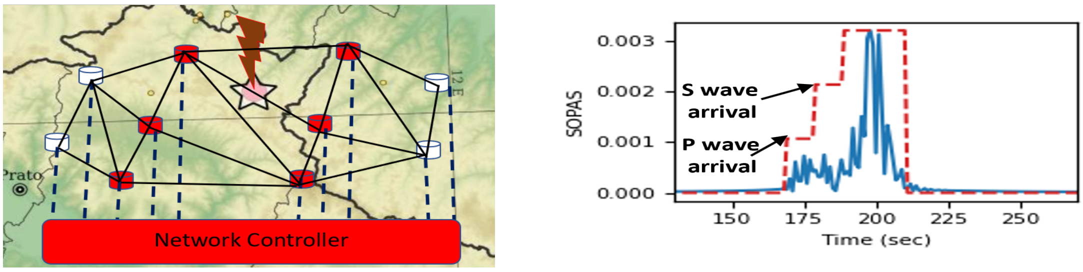


Fig. 3: Precision, Recall, F1 score, and Accuracy during training on validation dataset



(a) (b)

Fig. 4: (a) Considered earthquake scenario , (b) DL predictions

several epochs. It is evident from the results that all the metrics show a consistent and promising performance, reaching nearly 98% accuracy. This indicates that the model is well-trained and performing well on the validation dataset. We consider a realistic scenario for our model as shown in Fig. 4a. In this scenario, we consider that our smart grid network is deployed in Florence city where the earthquake occurred and emergency response measures should be taken by the residents of Florence. As shown in Fig. 4b, our DL model can detect P waves in less than a second. The red dashed line shows our model predictions. In second scenario, we consider that the emergency measures should be taken by the residents of Arrezo city which is approximately 76 km away from our smart grid network. As we know, the time lag between the P wave and Surface wave is 10 seconds. For the first scenario, Florence has approximately 9 seconds to take precautionary measurements. In the second scenario, the distance between our deployed smart grid network and Arezzo is 76 km and the speed of the P wave is 5.8 km/s [8], so the time for the seismic wave to travel is 76 km/5.8 km/s = 13.1 seconds, thus, Arezzo residents have approximately 22 seconds to take precautionary measures. We evaluated our model's performance in detecting P waves by calculating the accuracy using the actual and predicted labels. The obtained accuracy was approximately 97%. In this case, accuracy refers to the proportion of correctly classified instances of P waves out of the total number of predictions made.

4. Conclusions

Our findings show that our proposal of using a deployed terrestrial optical network as smart grid sensing network based on Bi-GRU with an attention mechanism can capture and learn key characteristics of seismic waves, enabling reliable P wave detection promptly. Our suggested approach and results can serve as a first step towards the development of early warning earthquake systems based on SOP measurements. This approach is not limited to detecting earthquakes and can be further evaluated for road traffic detection, and other fiber-sensing applications.

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