Detection of Secondary Arc Extinction and Auto-reclosing in Compensated AC Transmission Lines Based on Machine Learning

Abraham D. Arefaynie, Muhammad Saad, Chul-Hwan Kim

***Abstract*— Detecting and recognizing the secondary arc extinction is considered as a backbone of the single pole auto reclosing schemes. This paper proposes a multi-channel convolutional network to detect the secondary arc extinction during in a long AC power transmission line arc fault. In contrast to the conventional methods, the proposed Machin learning-based method can automatically learn the features from the raw data given as input. Multivariate time series data of phase voltage, current and neutral reactor signals were used as the input to the proposed model. The features are extracted in the convolution layer instead of using hand-crafted feature extraction like most of the existing research. The softmax classifier is used to detect the fault and secondary arc extinction. Matlab Simulink is used to simulate the test system and collect the dataset to evaluate the proposed neural network model. To verify the generalizability of the proposed architecture datasets were collected at different locations and different phase lines. The proposed algorithm was able to detect the secondary arc extinction with 98.26% accuracy and able to give signal for auto-recloser logic with the maximum window length of three cycle. The result shows that the proposed neural network architecture is accurate and robust to detect the secondary arc extinction further can be used as a signal for a single pole adaptive auto recloser scheme.**

***Keywords*: Arc Fault, Fault Detection, Multi-channel Convolutional Neural Network (MC-CNN), Secondary Arc Extinction, Single-pole Auto reclosing, Machine learning.**

I. Introduction

FAULT extinction detection and clearing time are the main aspects of power transmission line reclosing algorithms. Many researchers have worked for many years to achieve fast and accurate adaptive single phase reclosing scheme using various methods to protect the power system from transient faults. When a single phase to ground fault detected by protective relay, faulted phase will be isolated to protect the line from the primary arc fault. However, a voltage called secondary voltage is induced in the faulted phase due to electromagnetic and electrostatic coupling between the faulted and healthy phases after the primary arc extinguished by the action of line's circuit breaker and protective relays. The secondary arc current and voltage characteristics are the most crucial information providing the state of the arc fault [1] and its presence of that secondary arc will jeopardize the operation and will ultimately cause failure of single phase auto reclosing system (SPAR). The secondary arc must be extinguished to prevent it from re-igniting while reclosing the faulted line circuit breakers (CBs).

Many scholars proposed a number of secondary arc extinction detection methods. Voltage and current signals were used intensively to study the characteristics of arc extinction using different time and frequency domain signal analysis techniques [2]. Author [3] proposed arc extinction based on the derivative of faulted phase voltage magnitude and phase angle used to detect the arc extinction improved by the phase angle of faulted phase. However, several false arc extinction signal has been observed slightly earlier than the actual arc extinction using this technique. Author [4] also proposed arc extinction characteristics by comparing the faulted phase voltage measured phasor with phasor calculated under fault condition. [5] also proposed neutral-frequency voltage to detect arc extinction such that the neutral-frequency voltage of a recovery voltage will be greater than zero. [6] proposed arc extinction criteria by comparing inner product between faulty phase current with neutral point current of reactor and derivative of faulted phase current with neutral point current of a reactor. Author [14] used the content of 3^{rd}, 5^{th} and 7^{th} harmonic characteristics caused by the non-linear arc to detect the arc extinction in the system. All researcher mention used some sort of signal analysis to detect extinction which most of them would be computationally expensive.

Author [8] proposed adaptive single phase reclosing algorithm using coefficient of recovery voltage as a feature for SVM based classifier to detect the arc extinction time. Author [9] used two stage fault detection method. The first stage is unsupervised feature learning via feature mapping and pooling while the second stage is softmax classifier to classify the fault type. Most of aforementioned papers approach need

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independent mathematical or unsupervised feature extraction stage which make the computation expensive.

Most recently, Yao Wong etl [10], proposed series AC arc fault detection method based on raw current data and convolutional neural network. They develop 1D-CNN based model to monitor the load current in different scenario and detect a series AC arc fault due to lose of connection and failure of the insulation.

In this paper, Multi-channel Deep convolutional neural network (MC-DCNN) base secondary arc extinction detection algorithm has been proposed. The phase voltage and current, and neutral point current of a reactor data has been used to train the proposed model ad multivariate time series data to detect secondary arc extinction criterion. Parallel transmission line with shunt reactor were used to collect required voltage and current data. The main contribution of this paper is development of a neural network architecture that can automatically learn features from raw data and accurately detect arc extinction, allowing for triggering of auto reclosing in compensated AC transmission lines.

The remainder of the paper is structured as follows. Section II goes into detail about system modeling data collection. Section III presents the proposed model. Section IV explains about experimental setup. While section V analysis the result achieved and section VI give a conclusion to the paper.

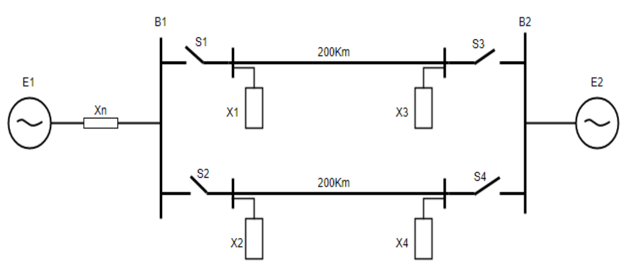


Fig 1. Test system under study

II. Test System and Data Collection

A. Test system Modelling

Fig. 1 depicts a system that is being studied. The simulation studies are conducted on a test system developed by G. Sybille (Hydro-Quebec) [7]. The test system consists of two parallel 735kv transmission lines that are 200 km long and transmit 3000MW of power from a generation plant (12x350MVA) to an equivalent network with a short circuit level of 20 GVA.

The transmission lines in the system are modeled as distributed parameter lines. They are assumed to be transposed, and their parameters (R, L, C per km) are specified in the positive and zero-sequence components. Each transmission line is shunt compensated by two shunt reactor of 200MVARs each, connected at the line ends. The use of neutral inductances for the shunt reactors of line 2 allows for single-pole reclosing at the 735kV voltage level. Without these neutral inductances, the secondary arc current induced into the fault would be too high to allow arc extinction after the opening of the line breakers on the faulted phase. Table I summarize the line parameters of the system being studied.

TABLE I
System Parameters for Dataset Generation

Time	[Positive Zero]
Resistance (ohms/km)	[0.01165 0.2676]
Inductance (H/km)	[0.8679e-3 3.008e-3]
Capacitance(F/km)	[13.41e-9 8.57e-9]

B. Arc Modelling

In this model [7], the arc is modeled as a non-liner resistance that changes based on the RMS current value of the arc. The mean arc resistance increases as the rms current decreases, which shortens the time it takes for the arc current to decay below the threshold value. The arc extinguishes when the rms current falls below a threshold value, typically 50A.

In this model, the mean arc resistance is programmed as an exponential function of rms current. For example, at a current of 1kA the mean arc resistance is 0.1 ohms, while at current of 100A the mean arc resistance is 30ohms.

When the fault is applied at t cycles, the opening command is sent to both breakers after 1=4cycles (3cycles detection + opening time). The two breakers are then reclosed at 34 cycles after a dead time of 30 cycles, during which the arc should extinguish.

Figure 2 shows the simulation output for the arc fault, including the current, voltage and reactor neutral current waveform during the arc fault. The fault current is measured in amperes and reaches 22kA during the first cycle. It then stops to a very small value after 3 cycles when the line breakers open. As the rms value of current is below 50A, the arc extinguishes at the first current zero crossing.

TABLE II
System Parameters for Dataset Generation

Time	Values
Fault Distance(km)	20, 40, 60, 80, 100, 120, 140, 160, 180
Fault Phases	Phase A, Phase B, Phase C
Fault inception angles(degrees)	0, 30, 60, 90, 120, 150, 180, 210, 240, 270, 300, 330,

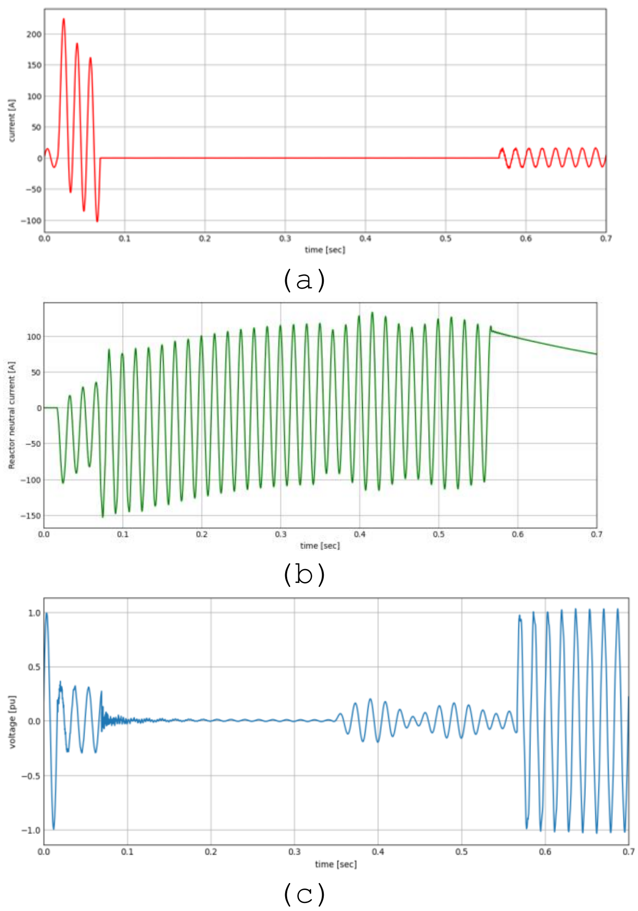


Fig. 2. Voltage and current waveforms simulated during arc fault (a) arc current (b) reactor neutral current (c) voltage current.

C. Dataset

The Data set for proposed neural network were collected by running test model on MatLab Simulink by varying different tunable system parameters such as fault location, faulted phase and fault inception angle. System parameters used for generating the data set are presented on Table II. Each data is collected as univariate time series $X = [x_1, x_2, \ldots, xT]$ where T is length of time series data and combined together to form multivariate time series data such that $Z = [X^1, X^2, \ldots, X^M]$ where M is the number of univariate data. Dataset, $D = \{(X_1,Y_1), (X_2,Y_2), \ldots, (X_N,Y_N)\}$, is a collection of pairs of multi-variate time series with its corresponding one-hot label vector label. A total of 1402 data samples window has 1200 samples for single channel are collected in the dataset and used to train the model for purpose of detecting the arc extinction.

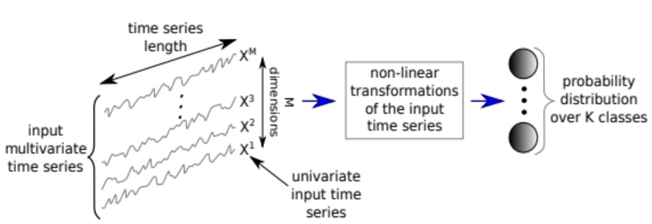


Fig 3. General DL framework for time series classification [2]

Our dataset is composed of seven univariate data that were collected from matLab Simulink and combined to create the data set. Six of them are phase current and voltage while the last univariate signal used was neutral current of a transmission reactor. Sample of a collected dataset is presented on table III.

TABLE III
SAMPLES OF DATASET COLLECTED AND USED

time	V1	V2	V3	I1	I2	I3	iN
0.00000	0.181326	-0.929879	0.748553	3.192504	14.254821	11.062317	3.150000e-10
0.00005	0.190425	-0.940595	0.750170	3.273268	-14.437824	11.164556	3.150000E-10
0.00010	0.206158	-0.941975	0.735817	3.494987	-14.424628	10.929641	3.150000e-10
0.00015	0.229934	-0.948709	0.718775	3.888012	-14.526897	10.638885	3.140000e-10
…	…	…	…	…	…	…	…

III. PROPOSED NEURAL NETWORK

Fig3., depicts the general set up of deep learning framework for time series classification. The modified convolutional network is proposed to detect the secondary arc voltage pattern and used as criteria of arc extinction in the AC arc fault of transmission line. The input of the proposed network are multivariate time series data of phase voltage and current with neutral current of compensator reactor. In contrast to image data time series data are 1D sequences. Each phase current and voltage data are given to the network as univariate time series data in each channel. Our multi-channel convolutional network architecture has seven (7) channels 3 for phase currents, 3 for phase voltages and 1 channel for neutral reactor neutral current. Fig 4 depicts the proposed Multi-channel convolutional neural network architecture. Multi-channel convolutional neural network was suggested for time series classifier on [11,13,12] and many other literatures in different application area. The proposed architecture doesn't require feature extraction stages since the network itself has a feature extractor through filter and activation layers. Finally, the feature extracted in the feature extraction stage is used to for feature mapping and classifying the secondary arc pattern in order to detect the arc extinction event.

The loss function of the proposed model can be formulated as a multi-class classification problem. Therefore, categorical cross entropy for multi-class classification problem can be written as follow:

$$L = -\sum_t \sum_k y_k^*(t) \log\big(y_k(t)\big) \qquad (1)$$

where $y_k^*(t)$ and $y_k(t)$ are the target and predicted value of t-th training sample at k-th class. Simple back pass of gradient of a loss is used to optimize the parameters of the proposed model using stochastic gradient decent. Forward pass is series of computation to predict the value given as follows;

$$z_j^l = pooling\Big(sigmoid\Big(\sum_i x_i^{l-1} * w_{ij}^l + b_j^l\Big)\Big) \qquad (2)$$

Where pooling(.) is pooling stage, sigmoid(.) activation and the inner summation term represents single neural node. While the backward pass is used to propagate the gradient of the loss function on each parameter of each layer to tune and train the model. The backward pass can be given as flow using chain rule;

$$\Delta w_{ij}^{l} = sigmoid'(z_j^l) \cdot rev - pool\left(\frac{\partial E}{\partial pooling(z_j^l)}\right) * reverse(x_i^{l-1}) \quad (3)$$

Where the rev-pool(.) is up sampling and reverse(.) function reverse the corresponding feature map and perform elementwise multiplication with rev-pool function.

After the gradient of the parameter is found, learning is possible by updating the parameters of the weights and biases of each layer and each neural node as follows;

$$w_{ij}^{l} = w_{ij}^{l} + \alpha \Delta w_{ij}^{l} \quad (4)$$

Where w_{ij}^{l} is ij-th weight, α is learning rate and Δw_{ij}^{l} is gradient of loss function with respect to weight w_{ij}^{l}.

During a training each normalized time series signal feed to a single channel as univariate time series by using a sliding window size of 1 cycle to 3cycle and sliding step of single cycle.

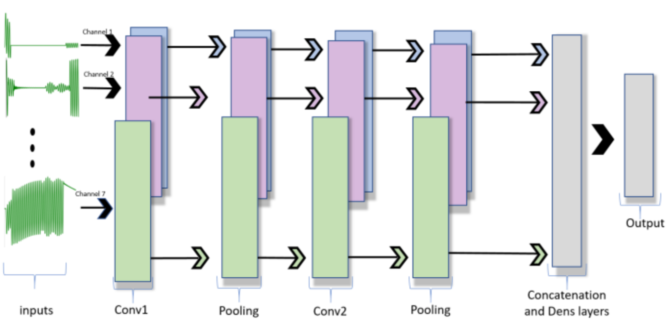


Fig 4. proposed architecture

IV. AUTO RECLOSING IMPLEMENTATION COMBINED WITH SIMPLE LOGIC

The one of the application of the proposed algorithm is auto reclosing. By using simple delay logic, it can be used to send a reclosing signal after the secondary arc extinction is detected. The developed model trained to detect the arc fault and arc extinction.

Our arc extinction detection logic is based on two input conditions: '*arc_is_detected*' and '*recovery_is_detected*'. These conditions are generated by a multi-channel neural network, which is trained to recognize the characteristics of the arc fault in AC power transmission line. The control logic initializes four control variables: '*arc*', '*recovery*', '*timer*' and '*deadtime*'. '*arc*' is used to track whether an arc fault has been detected. '*recovery*' is used to track whether a recovery voltage has been detected. 'timer' is used to track the duration of the arc fault, and '*deadtime*' is a predefined threshold that determines the minimum allowable duration for an arc fault to exist before concluding the fault as permanent fault.

When '*arc_is_detected*' is true, the control logic sets '*arc*' to 1 and starts the '*timer*'. If '*recovery_is_detected*' is true, the control logic checks whether the '*arc*' is 1. Which makes sure that the arc fault has happened before the recovery voltage has happened. If the '*arc*' is 1, the control logic checks whether the value of '*timer*' is less than 'deadtime'. If 'timer is less than 'deadtime', the control logic sets, '*arc*', '*recovery*', and '*timer*' to 0 for next time fault detection and returns the 'arc extinction signal to the circuit breaker. This indicates that the arc fault has been extinguished within the allowable time period.

If '*timer*' is greater than or equal to '*deadtime*', the control logic returns permanent fault signal as the arc fault has been persisted for longer than the allowable time period, and is therefore considered as a permanent fault.

In summary, our logic is able to detect and respond to that arc fault, by tracking the presence and duration of th arc fault and comparing them to predefined deadtime to make sure that the logic provides proper signal within a certain period of time. Pseudocode presented in table IV summarizes the auto reclosing logic.

TABLE IV
SINGLE-POLE RECLOSING ALGORITHM

Algorithm 1 Single-Pole recloser based on MC-CNN

```
arc = 0;
recovery = 0;
deadtime = 300ms
while Power network is operating do
    if arc is detected then
        arc = 1
        Starttimer
    else
    end if
    if Secondary arc is detected then
        if timer ≤ deadtime then
            arc = 0;
            recovery = 0;
            timer = 0;
            return arc extinction detected;
        else
            return arc is not extinction within the time limit
        end if
    else if arc = 1 then
        if timer ≥ deadtime then
            return permanent fault detected
        else
        end if
    end if
end while
```

V. RESULT AND ANALYSIS

A. Experiment Settings

Three phase voltage and current signal and reactor normal current, 7D time series data, were collected in different conditions and carefully labeled the class. Each phase signal counted as univariate time signal and normalized by using StandardScalar technique. Labels are converted in to one-hot code. Also in this paper, we use the sliding window algorithm to extract subsequences from 7D (seven channel) input time series data with sliding widows. We train our network by varying our window size from 400 samples (1 cycle data) to 1200 samples per window (3 cycles) and with the size of 256 to 400 sliding window. Window of data that composed of more than one class is assigned by comparing the frequency of occurrence of each label with fixed threshold. To validate the performance of the proposed model we use leave-one-out cross validation technique. In this technique; we use single fault condition, for example fault distance 80km, fault inception angle 30 degree as a test data and the rest of fault scenario are used as training data. This allows us to train and evaluate the network efficiently.

B. Experimental Results and Discussion

In this paper, we proposed a Multi-Channel Deep Convolutional Neural Network model for arc fault extinction detection. To verify the proposed model, we developed Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) models and compare the performance of proposed model with them.

We demonstrate the performance of our proposed MC-DCNN models on the dataset collected using MatLab Simulink, and compared them with SVM and LSTM model. In comparison, the accuracy of SVM was 90.8% and LSTM achieved 96.26% accuracy. While our model achieved 98.26% accuracy. The evaluation results are summarized on table V.

TABLE V
F1 SCORE OF EACH MODEL

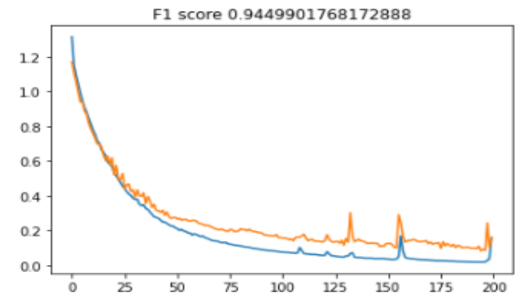
Model	F1 Score
MC-DCNN	**98.26%**
LSTM	96.26%
SVM	90.8%

Our experiment showed that the proposed MC_CNN model out preformed the SVM and LSTM models in terms of accuracy and F1-score. We found that MC-CNN models were able to capture feature of time series data and were efficient in handling Multi-Variate time series data using multiple channels.

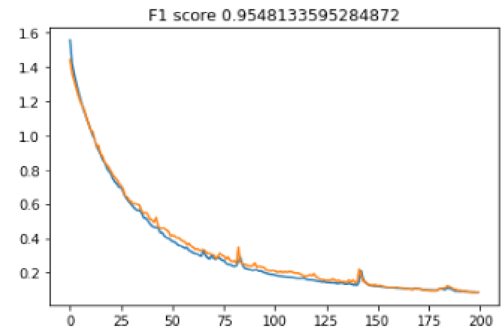
Effect of window size: Since window size is assumed to be determinant factor for response time it was studied in more depth. In our study we observed that the performance of the proposed model highly affected by the window size, which concedes with the fact that when the input data window is smaller the performance of the CNN models to extract relevant features may be reduced. To overcome this limitations, we experiment with different window size that will not affect the response time and improve the performance. Window size 1200 and stepping size of 800 achieved the maximum accuracy.

However, we also approach using L2 regularization to overcome this limitation so that we can achieve high performer model within small window size of data. However, it didn't improve the performance that much other than stabilizing the model performance as shown figure 5.

Another aspect that makes our proposed model better option among others that MC-CNN can be trained on large datasets and then fine-tuned on smaller datasets with similar domain of application in power system. Additionally, this models can be easily scaled to handle larger and more complex datasets, making them a good choice for real-world application. In contrast both LSTM and SVM models may require more training data, feature engineering and computational resources to achieve similar levels of performance.



(a)

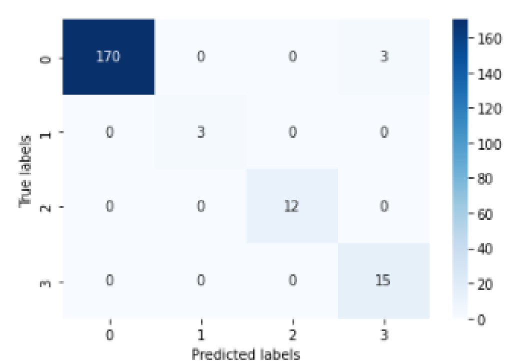


(b)

Fig. 5. Training and Testing accuracy of a proposed model (a) without L2 regularization (b) with L2 regularization

The following confusion matrix shows that the result of our MC_CNN model that was trained by our own dataset. The data were label as normal labeled as '0', arc fault labeled as '1', secondary voltage labeled as '2' and recovery voltage labeled as '3'.

TABLE VI
CONFUSION MATRIX OF A PROPOSED MODEL



From the matrix, we can see that the model correctly classifies 170 instance of windowed data and correctly classified all 3 windows of arc fault. However, the model predicted 3 windows of normal operation condition as a recovery mod. Overall, the model seems performing well.

Even though our ultimate goal was to detected only fault clearance of case we trained our model in four labels to overcome the data imbalance to some extent. If we labeled the dataset into only two classes, the data will be highly imbalance and hard to fit the model to it. By labelling the dataset into four classes, we are providing the model with more information and enabling it to learn more about different types of data points that it may encounter which make our model robust.

VI. Conclusions

In this paper, we propose a multi-channel convolutional neural network for detecting the extinction of secondary arcs in compensated transmission lines. This approach allows for fast signaling of reclosing within an acceptable time range, and does not require a mathematical model or hand-crafted features for detecting arc extinction. Instead, the proposed mode is able to learn and extract the features of the recovery voltage during an arcing fault, and uses these indicative characteristics to accurately detect the arc extinction.

Experimental results show that the proposed model performs well in detecting arc extinction, and is able to extract the relevant features form the input voltage and current time series data. By using a multi-channel convolutional neural network, the feature extraction and detection are performed within a single model, which simplifies the overall process and improve the performance of the system.

VII. References

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