

Fuse Melting Curve Fitting and Implementation in a Time-Domain Simulation Environment

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ABSTRACT

Over the last few years, intelligent protection schemes have been proposed for distribution networks to address the effects of distributed generation insertion. Nonetheless, most distribution protection systems still employ fuse links, whose operations are not affected by these methods. Since the actions of digital and analog protective devices must be coordinated, the intelligent equipment must account for the operation of fuse links. However, the fuse melting curves' equations are not known. Thus, alternative methods to determine their operation time must be adopted. In this paper, we propose using artificial neural networks to represent the melting curves of the 15 type T fuse links, as they can be used to fit nonlinear equations. Furthermore, we implement the resulting equations in the ATP-EMTP environment and provide the resulting simulation blocks, which can be integrated with more complex distribution protection systems.

KEYWORDS. Artificial Neural Networks, Distribution Protection System, Fuse Melting Curves, Curve Fitting, ATP-EMTP.

Paper topics: SIM - Simulation, IC - Computational Intelligence, EN&PG – Energy, Oil and Gas.

1. Introduction

The Distribution Systems (DSs) have undergone severe modifications over the last few years, especially due to the insertion of Distributed Generators (DGs), which compromised the historical passive characteristic observed in these networks [Pereira et al., 2018]. Simultaneously, most electricity regulatory agencies in the world have stiffened the rules and guidelines for power quality, service continuity, and reliability. In this context, some researchers propose that the Distribution Companies (DISCOs) should address the new technical and regulatory demands through the application of intelligent tools for the DSs planning [Guarda et al., 2017; Izadi et al., 2019] and operation stages [Kumar, 2018; Jain et al., 2019].

The DSs are critical structures that are subjected to many types of faults and are responsible for more than half of the interruption time considering the entire power system structure [Teng e Liu, 2003]. The protection system planning and operation affect the impact of the faults in a DS and have been studied for decades [Izadi et al., 2019; Alam et al., 2020; Soudi e Tomsovic, 1998]. In this sense, the proposal of adaptive protection systems is an example of intelligent methods applied for the DS to attain a more secure, more reliable, and less susceptible to interruptions operation [Momesso et al., 2019]. The variables considered by each adaptive protection proposal are different; however, these methods can only be applied to digital micro-processed devices. In the DS context, these elements are relays and automatic reclosers. It is fundamental to stress that most distribution protection systems are also composed of fuses that must operate in coordination with digital protective devices. In this sense, the adaptive protection approaches must somehow estimate, in many cases in real-time, a fuse's melting time for a fault situation [Momesso et al., 2022].

Although the manufacturers provide graphs demonstrating the fuses' melting behavior, a fuse's melting curve mathematical equation is not known, as opposed to the digital protective devices'. Hence, the fuse's acting time cannot be calculated, only estimated. Two methods are commonly adopted for this end: (1) mathematical interpolation [Pereira et al., 2018; Peñuela e Roberto Sanches Mantovani, 2013] and (2) predicting the fuse's melting curve equation via curve fitting [da Costa et al., 2019a, 2018]. From a practical standpoint, the first method's employment depends on storing the curve's known values, which must be consulted to estimate the melting time for an ongoing fault. Alternatively, the melting time is easily calculated from an equation once the curve fitting process is complete. In this sense, curve fitting reduces the computational burden on the protection devices, an essential feature for online applications such as adaptive protection.

The curve fitting process can be perceived as an optimization problem that aims to minimize the Mean Square Error (MSE) by controlling an equation's parameters. Some approaches for fuse melting curve fitting found in the literature optimize the parameters of polynomial functions to minimize the MSE [da Costa et al., 2018, 2017]. However, it should be mentioned that the melting curves of every fuse can hardly be properly described by the same polynomial degree. Additionally, recent researches indicate the superiority of using Artificial Neural Networks (ANNs) compared to the polynomial function [da Costa et al., 2019b].

In this paper, we employ ANNs to obtain equations that describe the fuse links' minimum melting and maximum clearing times. These equations can be applied in adaptive protection schemes for fuse melting time estimation with low computational costs. We train the ANNs using three training methods and compare the curve fitting quality for each technique. Moreover, we implement the fuse links' operating characteristics in the Alternative Transient Program version of the Electromagnetic Transients Program (ATP-EMTP) via MODELS and provide the codes aiming to ease the simulation of fuse links and for future integration with more complex protection systems in a simulation environment. Finally, we provide all the ANNs data in an open platform for reproducibility and replicability purposes.

2. Fuse Melting Curve Fitting

The fuses' characteristic operating curves are similar to exponential, hence continuous and non-linear. In this sense, a Multilayer Perceptron (MLP) with a single hidden layer is theoretically enough to represent the fuses' melting curve exact equation [Kolmogorov, 1957], as long as there are enough neurons in the hidden layer. This number must be empirically determined by comparing the curve fitting quality and generalization capacity of each ANN topology. Furthermore, it should be highlighted that besides determining the number of neurons one must calibrate the ANN's synaptic weights, which are the result of the training process.

The MLP's training process can be seen as an optimization model that aims to determine the best set of synaptic weights to minimize the MSE between the ANN's output and the actual fuse melting curve. There are many training methods, and picking one depends on the problem one tries to solve as there is no indisputable better method. One of the most adopted training methods is the Backpropagation (BP) [Rumelhart et al., 1986]; however, there are many other methods that may replace this routine. In this paper we focus on the deterministic method Adam [Kingma e Ba, 2015] and the metaheuristic (stochastic) Differential Evolution (DE) [Storn e Prince, 1997]. Previous research has investigated the efficiency of using the DE algorithm for training ANNs and the results show that the metaheuristic's performance is similar to BP-based algorithms, such as Levenberg-Marquardt and quasi-Newton [Ilonen et al., 2003]. The Adam optimizer is based on gradient descent and combines features of two other optimization tools, namely AdaGrad [Duchi et al., 2011] and RMSProp [Hinton et al., 2012]. The method considers adaptive rates for the gradient moment, which allows escaping from local minima and, consequently, better performance than other deterministic methods [Kingma e Ba, 2015].

2.1. Backpropagation Algorithm

The BP algorithm is the training method originally proposed for MLP. The BP is based on the delta rule and, therefore, is a deterministic algorithm [Rumelhart et al., 1986]. It should be mentioned that optimality is not guaranteed for the set of synaptic weights found by this method, as the search may reach a local optimum depending on the problem it is trying to solve and the initial set of values. In this paper, the stop criterion is the MSE value.

2.2. Adam Optimizer

The BP algorithm is a straightforward method that considers a single learning rate which may lead to convergence problems. There is a gamma of newer gradient-based approaches that consider adaptive learning rates, amongst which one can highlight the Adam optimizer. This optimizer was designed to be easy to implement, computationally efficient, and require little tuning. According to the authors, the same set of hyper-parameters can be used to solve multiple non-convex optimization problems [Kingma e Ba, 2015]. In this paper, the stop criterion is the MSE value.

2.3. Differential Evolution Algorithm

Determining the MLP's synaptic weights is a nonlinear nonconvex optimization problem. In this sense, adopting metaheuristics is a valid approach, as not even the mathematical models can guarantee optimality. The DE is a non-bioinspired evolutionary algorithm originally proposed in [Storn e Prince, 1997] that combines mathematical and heuristic knowledge to disturb its current solution as a means to escape local optima. The method was designed for continuous optimization problems, which reaffirms the adoption of this algorithm. In this paper, the stop criterion is the iteration limit.

3. Experiment Design

In this section, we present the details regarding the data preparation, the parametrization of the optimization tools, and the methods for evaluating and comparing the results.

3.1. Data Preparation

The fuse melting curve's exponential behavior causes the range of variables (melting time and short-circuit currents) to be very broad. Considering a 6T fuse, for instance, the Short-Circuit Currents (SCCs) magnitudes available in the melting time behavior provided by the manufacturer range from 12 A to 380 A, while the operating time ranges from 0,01 s to 298 s. The ANN's activation function does not cover this range; therefore, the input data (SCC magnitudes) must be treated to be expressed in a narrow range that depends on the adopted activation function. In this paper, we applied the natural logarithm function followed by a normalization process to prepare the input data, as done in other approaches for this problem [da Costa et al., 2018, 2017, 2019b].

In this approach, the sigmoid activation function shown in (1) was applied to every neuron in the MLP. We adopted $\beta = 5$ as the ANN is trained for curve fitting and not classification. A graphic representation for the proposed MLP with n neurons in the hidden layer is presented in Fig. 1.

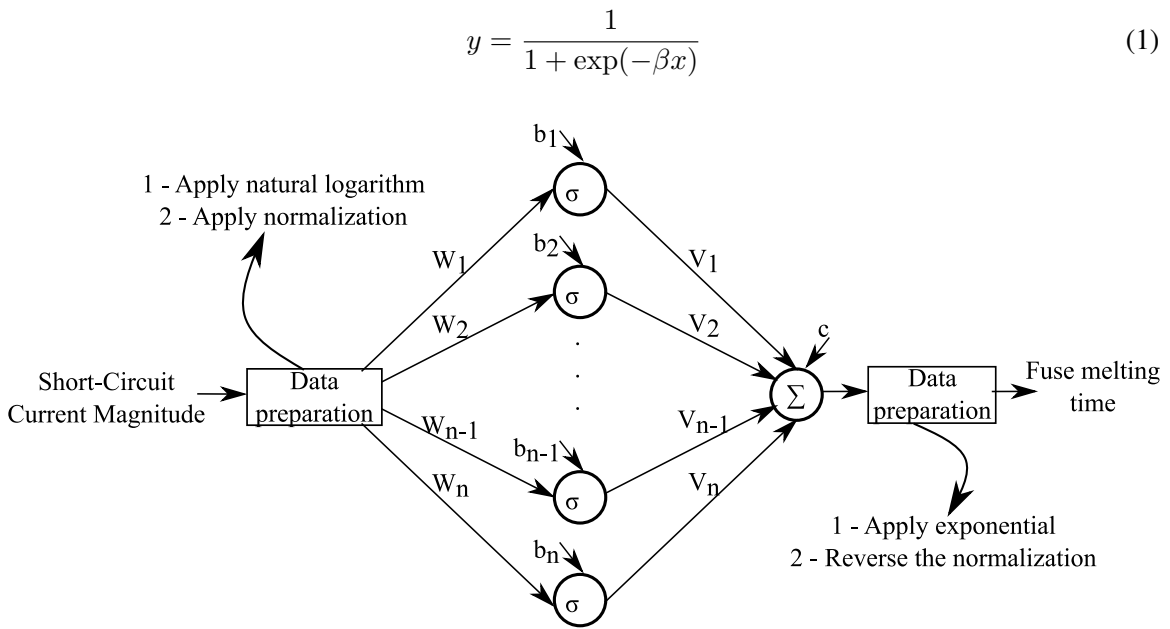


Figure 1: Illustration of the Proposed Method

3.2. Optimization Tools' Parametrization

According to the universal approximation theorem, a continuous function can be represented by a MLP with a single hidden layer [Kolmogorov, 1957]. Additionally, since the MLP must provide only the estimated melting time as output, the number of synaptic weights to be optimized can be defined as $3N + 1$, being N the number of neurons in the hidden layer. Thus, both Adam and DE algorithms are encoded as arrays composed of $3N + 1$ real values; $2N$ of those values represent the synaptic weights while the other codifies the biases. The Adam and DE algorithms were implemented as originally proposed in [Kingma e Ba, 2015] and [Storn e Prince, 1997], respectively.

The MSE tolerance adopted as the stop criterion for BP and Adam algorithms was set as 10^{-8} . Additionally, a training epoch limit was adopted as a second stop criterion; the maximum values for the BP and Adam were 10,000 and 5,000, respectively. The Adam algorithm hyperparameters were set as proposed in [Kingma e Ba, 2015] and the BP learning rate was set as 0.1. Finally, the DE hyperparameters were: a population composed of 50 individuals and 1,000 generations as the stop criterion.

3.3. Evaluation Method

The BP and Adam algorithms are deterministic, which means the set of optimal weights found by each method will be the same as long as the initial weights do not change. Thus, it is important to execute these methods considering different starting points as a means to explore different regions in the search space. In this approach, both algorithms were executed 30 times, considering different sets of initial weights for each run. The initial sets of weights were shared between the two algorithms. As for the DE, a stochastic method, it is important to evaluate its capacity to always converge to the same results. In this sense, we carried out 30 executions of this algorithm considering the same initial population.

The holdout validation was adopted considering 60% of the data for training, 20% for validation, and 20% for testing. Statistic metrics (average, median, and standard deviation of the MSE) were adopted to compare the training methods' performance. The ANNs with lower MSE were implemented and simulated in ATP-EMTP environment, and the results were compared with the data provided by the manufacturer.

4. Results

In this section, we present the comparison between the training methods and the ANNs' implementation in ATP-EMTP environment to simulate the operation of the fuse links.

4.1. Training Methods' Evaluation

Every training method adopted in this approach was capable of calibrating the MLP considering the data treatment procedure presented in Section 3.1. The MSE obtained by each training method for each fuse link considering a MLP with 5 neurons in the hidden layer are presented in Table 1. It can be observed that the BP-based training yields the worse MSE. Additionally, the DE-trained MLP presents the best results for most of the fuse links. It should be mentioned that the employment of the Adam algorithm prompts results similar to the ones observed for the DE. As for evaluating the methods' capacity of finding the best weights considering different start points for the search, note that the DE also presents most of the lowest standard deviations, followed by the Adam algorithm.

An illustration of the ANNs' curve fit for the 12T fuse link is presented in Fig. 2. Observe that, even though every MLP has its error in comparison to the real melting curve, the DE- and Adam-trained networks yield better approximation than the BP-trained. This significant performance difference can also be noticed in Table 1, wherein the best result obtained with a BP-trained MLP (65T) is approximately 5 times worse than the same Adam-trained and DE-trained networks. The discrepancy is even greater when comparing the best results found by each training method: Adam's best result (80T) is 7 times better than the BP's and the DE's best fit (30T) is 21 times better than the BP's.

4.2. Fuse Link Simulation in ATP-EMTP Environment

The results presented in the previous subsection attest to the MLP's efficiency in representing the fuses' melting behavior. Nonetheless, it is important to implement these ANNs models in a time-domain power system simulation environment wherein more complex protection schemes can be integrated. Once the weight, biases and normalization parameters illustrated in Fig. 1 are known, one can easily write the ANNs' output as nonlinear equations, as shown in (2)–(5), which can be implemented in ATP-EMTP environment via MODELS. There are two characteristic curves for each fuse link, namely minimum melting time and maximum clearing time. Each curve is described by an ANN and the average operation time can be expressed as the mean between the two outputs. The ANN weights and the normalization parameters needed to represent each fuse link acting curve are available in [Faria et al., 2022].

Table 1: Curve Fitting Evaluation for Each Training Method

Fuse Link	Training Method	Mean ¹	Median ²	Standard Deviation ³	Best Result
6T	BP	2.58E-03	4.92E-04	6.32E-03	4.04E-04
6T	Adam	6.59E-04	6.30E-05	1.54E-03	2.20E-05
6T	DE	7.90E-05	1.50E-04	1.54E-04	5.80E-05
8T	BP	5.29E-04	5.16E-04	1.97E-04	3.04E-04
8T	Adam	4.45E-04	9.40E-05	1.07E-03	2.10E-05
8T	DE	1.27E-04	1.94E-04	2.29E-04	1.40E-05
10T	BP	3.39E-03	8.92E-04	4.71E-03	4.46E-04
10T	Adam	7.60E-04	4.10E-05	1.73E-03	1.70E-05
10T	DE	1.32E-04	1.27E-04	6.65E-05	3.40E-05
12T	BP	9.90E-04	3.93E-04	2.19E-03	2.61E-04
12T	Adam	1.10E-03	1.36E-04	1.84E-03	4.00E-05
12T	DE	4.20E-05	4.94E-05	2.25E-05	1.70E-05
15T	BP	1.69E-03	5.35E-04	3.05E-03	3.49E-04
15T	Adam	9.79E-04	6.30E-05	1.79E-03	3.30E-05
15T	DE	1.05E-04	3.16E-04	5.58E-04	1.70E-05
20T	BP	2.65E-03	3.26E-04	3.89E-03	2.23E-04
20T	Adam	3.85E-04	7.50E-05	1.05E-03	2.30E-05
20T	DE	5.60E-05	5.83E-05	3.22E-05	1.40E-05
25T	BP	8.88E-04	2.63E-04	2.27E-03	1.45E-04
25T	Adam	7.54E-04	6.60E-05	1.75E-03	2.40E-05
25T	DE	5.50E-05	2.24E-04	3.44E-04	7.00E-06
30T	BP	2.19E-03	2.95E-04	3.29E-03	1.12E-04
30T	Adam	8.82E-04	1.37E-04	1.54E-03	4.00E-05
30T	DE	3.20E-05	1.32E-04	2.91E-04	5.00E-06
40T	BP	8.92E-04	2.87E-04	2.02E-03	1.11E-04
40T	Adam	1.33E-03	1.84E-04	2.07E-03	1.80E-05
40T	DE	4.10E-05	1.57E-04	3.20E-04	8.00E-06
50T	BP	1.84E-03	2.64E-04	3.14E-03	1.08E-04
50T	Adam	3.98E-04	5.90E-05	1.05E-03	1.70E-05
50T	DE	3.20E-05	1.07E-04	2.10E-04	9.00E-06
65T	BP	2.70E-03	2.27E-04	5.59E-03	1.05E-04
65T	Adam	4.23E-04	7.70E-05	1.25E-03	2.30E-05
65T	DE	4.20E-05	9.95E-05	1.38E-04	1.90E-05
80T	BP	7.79E-04	2.06E-04	2.09E-03	1.48E-04
80T	Adam	5.66E-04	6.00E-05	1.24E-03	1.50E-05
80T	DE	3.70E-05	6.04E-05	7.80E-05	1.30E-05
100T	BP	2.49E-03	4.58E-04	3.59E-03	9.70E-05
100T	Adam	1.46E-04	1.08E-04	1.15E-04	2.70E-05
100T	DE	2.60E-05	1.32E-04	3.91E-04	6.00E-06
140T	BP	7.53E-04	3.97E-04	9.74E-04	2.89E-04
140T	Adam	4.81E-04	3.91E-04	3.86E-04	2.67E-04
140T	DE	1.29E-04	2.06E-04	1.87E-04	1.40E-05
200T	BP	4.37E-04	4.11E-04	1.06E-04	3.40E-04
200T	Adam	5.42E-04	2.22E-04	6.42E-04	1.02E-04
200T	DE	6.70E-05	1.76E-04	2.52E-04	1.20E-05

¹ Average MSE in 30 runs.

² Average median of the MSE in 30 runs.

³ Average standard deviation of the MSE in 30 runs.

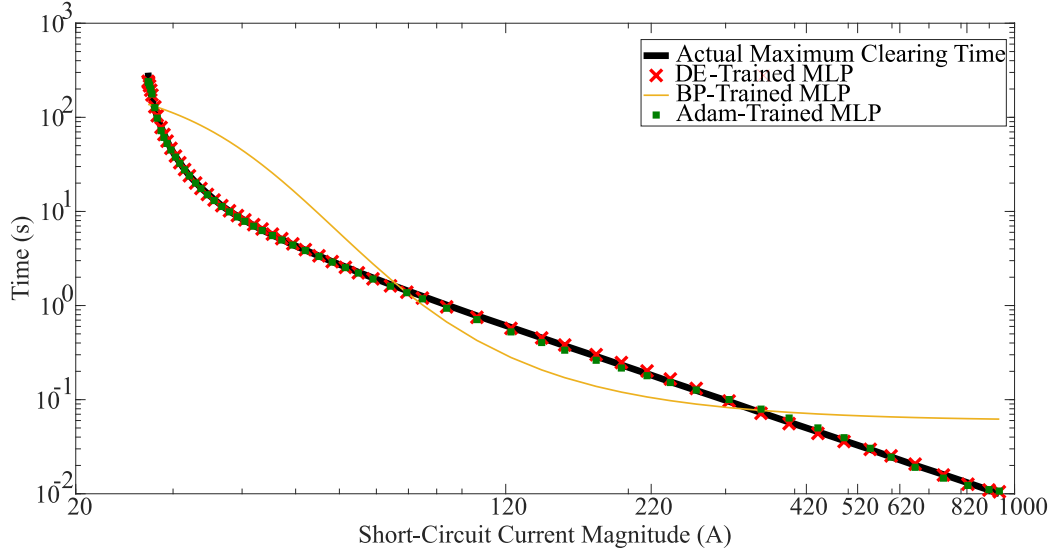


Figure 2: Fuse Link 12T Melting Curve Fit Results Obtained by Each Training Method

$$A = (\ln(I) - \bar{I}) \cdot \Delta_I + \underline{I} \quad (2)$$

$$O_{1,i} = \frac{2}{1 + e^{-2 \cdot (A \cdot W_i + b_i)}} - 1 \quad (3)$$

$$O_2 = \sum_i^N O_{1,i} \cdot V_i \quad (4)$$

$$O_3 = e^{\frac{O_2 \cdot c - \bar{t}}{\Delta_t}} + \bar{t} \quad (5)$$

wherein A is the treated input data I , *i.e.*, after the natural logarithm and normalization are applied to the input data. The normalization process depends on the fuse link curve's maximum and minimum SCCs ($\bar{I}$ and $\underline{I}$), and normalization slope (Δ_I). $O_{1,i}$ represents the output of neuron i , which is in the hidden layer, and O_2 is the input of the neuron in the output layer. Finally, O_3 is the ANN's output after another treatment process, which consists of applying the exponential function and reversing the normalization. The de-normalization depends on the fuse link curve's maximum and minimum action time ($\bar{t}$ and $\underline{t}$), and the de-normalization slope (Δ_t).

The result yielded by (5) is the estimated action time of a fuse link for a given current. Nonetheless, it should be highlighted that in the simulation or real-life environment, the SCC changes throughout time, which affects the fuse's melting time. More importantly, even when exposed to a constant SCC, the remaining time for a fuse to melt decreases with time. In this sense, to successfully simulate the fuse link, one must not only estimate the melting time but also account for how long has passed since the fault incipience. A way to simultaneously consider the two mentioned issues is by modeling the energy dissipated by the fuse link, as shown in (6).

$$E = \int_0^t I(t)^2 dt \quad (6)$$

wherein $I(t)$ is the instantaneous SCC through the fuse link. Noteworthy, the accumulated energy E is calculated only when $I(t)$ is greater than 1.5 times the fuse link's rated current. Additionally,

if the overcurrent scenario extinguishes before the fuse melts, the accumulated energy decreases. Once the accumulated energy crosses a threshold, the fuse melts. The pseudo-code designed in ATP-EMTP to simulate this behavior is presented in Algorithm 1, and the complete source code is available in [Faria et al., 2022].

Algorithm 1 Fuse Link Behavior Pseudo-code

Input: ANN weights, Normalization data

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1: Calculate instantaneous RMS current ( $I$ )
2: if ( $I \leq 1.5 \cdot I_{nom}$ ) then
3:    $E(t) = E(t-1) - k \cdot \Delta_t$ 
4: end if
5: if ( $I > 1.5 \cdot I_{nom}$ ) then
6:    $E(t) = E(t-1) + I^2 \cdot \Delta_t$ 
7:   Calculate  $O_3$  according to (2)–(5)
8:    $E^{max} = I^2 \cdot O_3$ 
9: end if
10: if ( $E^{max} \leq E(t)$ ) then
11:   Trip Signal = 1
12: end if
13: return Trip Signal
  
```

Next, we present the response of a 50T fuse link simulated in ATP-EMTP according to the proposed pseudo-code. We have considered three fault resistances: 0.001Ω , 10Ω and 40Ω . Fig. 3 illustrates the scenario wherein the system is subjected to a fault with resistance 0.001Ω at $t = 1$ s. Note that the accumulated energy and energy threshold curves cross at $t \approx 1.80$ s, which indicates the fuse link has melted. Simultaneously, a new energy threshold is defined and is much greater than the previous one. This happens because the instantaneous current becomes zero when the fuse melts. Hence, the fuse's maximum exposure time to the new current ($I = 0$ A) is infinite.

The same behavior is observed for the other two fault scenarios, illustrated in Figs. 4 and 5. The main differences between the three fault scenarios are the SCCs magnitude, which affects the energy threshold calculation ($E^{max} \approx 185,000$ for the first scenario, $186,000$ for the second and $200,000$ for the third) and, consequently, the fuse melting time, as expected for faults with different contact resistance. Finally, a comparison between the fuse melting times obtained in the ATP-EMTP environment and the values provided by the manufacturer for each fault scenario is displayed in Table 2. As can be noticed, the simulation results, which are the result of the MLP implementation, are similar to the ones provided by the manufacturer.

Table 2: Comparison Between Simulation and Manufacturer Data

Fault Resistance	SCC	Data Source	Melting Time
0.001Ω	470–490A	Simulation	0.8086 s
		Manufacturer	0.8–1 s
10Ω	430–450A	Simulation	0.9745 s
		Manufacturer	1.00084–1.18274 s
40Ω	284–297A	Simulation	2.3799 s
		Manufacturer	2.351–2.72329 s

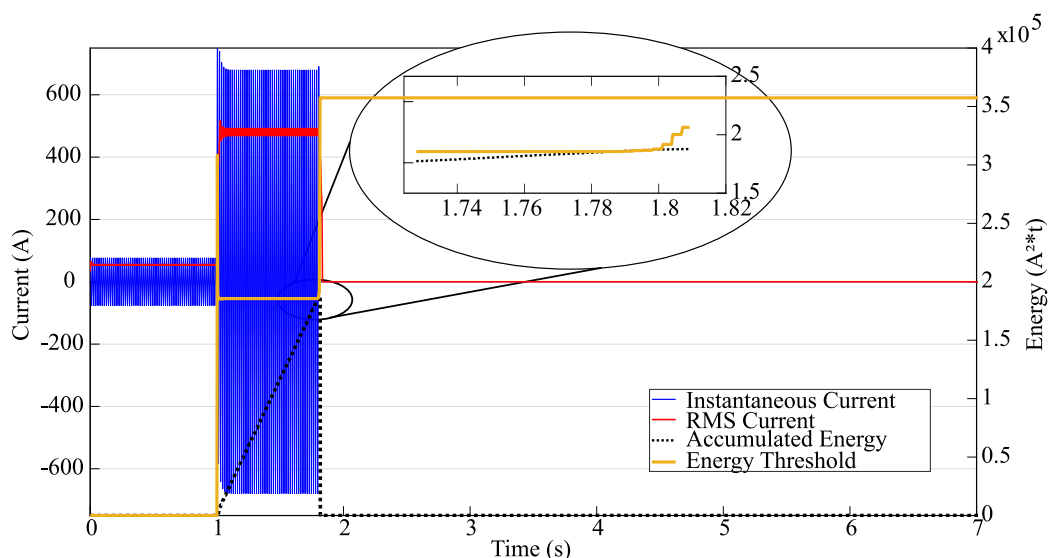


Figure 3: Simulated 50T Fuse Link Exposed to a 0.001 Ω Fault

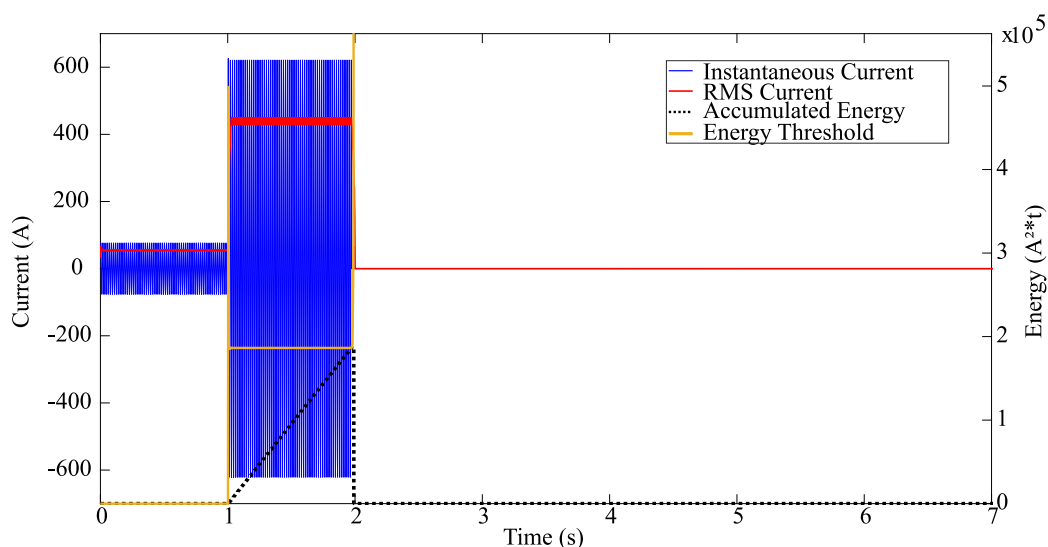


Figure 4: Simulated 50T Fuse Link Exposed to a 10 Ω Fault

5. Conclusion

In this paper, three training algorithms are employed to determine the weights of ANN that fit the type T fuses' melting curves. The BP, Adam, and DE algorithms were implemented without altering their original formulations. They were executed 30 times to verify which is superior for this problem and find the best result each algorithm could provide. The results show that the DE-trained ANNs present the lower MSEs, closely followed by the Adam-trained networks.

Finally, the ANNs with the lowest MSEs were implemented in the ATP-EMTP environment via MODELS to simulate the type T fuses' operation. The fuse link model was tested for different short-circuit cases and the resulting behavior was compared with the fuse melting curve provided by the manufacturer. The simulation block has proven to be well-suited to emulate the fuse operation. The data necessary to replicate the experiment, as well as the actual ATP-EMTP source codes, were made public in an open platform aiming to facilitate the integration of fuse links

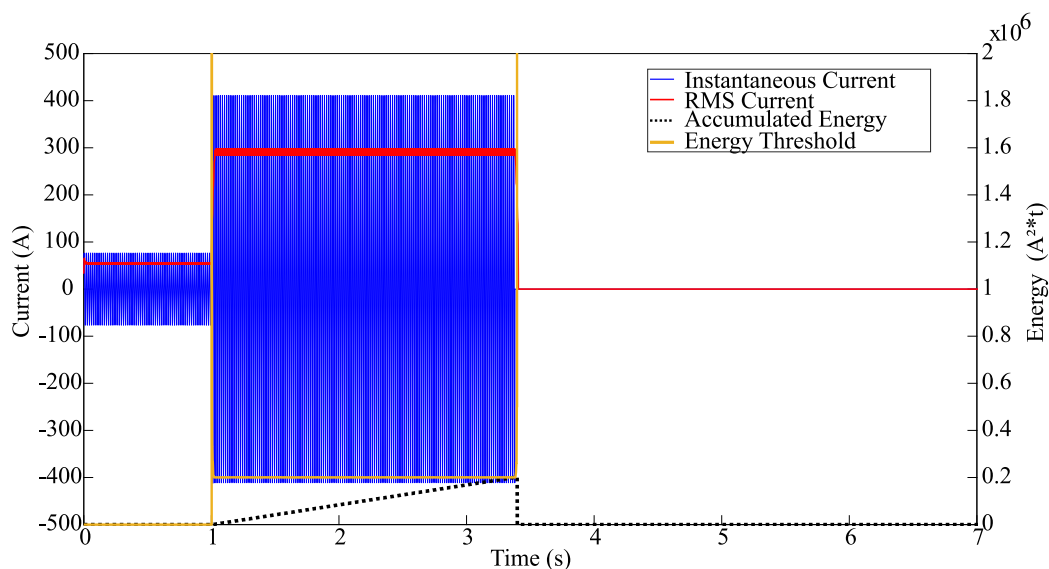


Figure 5: Simulated 50T Fuse Link Exposed to a 40 Ω Fault

and more complex protective schemes in future distribution protection system works involving time domain simulation.

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