Neural Network Design for Energy Estimation in Surge Arresters

Zohreh Dorrani[1], Hojat Jannat Abadi[2]
1, 2- Department of Electrical Engineering, Payame Noor University (PNU), Tehran, Iran.
Email: dorrnai.z@pnu.ac.ir (Corresponding author)

ABSTRACT:
In power systems, the transmission and distribution networks of electrical energy rely heavily on the performance of various equipment. Any malfunction within these systems can lead to network interruptions, short circuits, and power failures. Arresters are critical devices used to limit transient overvoltages caused by lightning strikes and switching events in transmission and distribution networks. These arresters protect equipment from transient overvoltages while ensuring that they do not react to temporary overloads. Their effectiveness is influenced by environmental conditions, such as humidity and pollution. This research aims to analyze the factors affecting voltage and energy absorption during lightning strikes on power systems. Additionally, we focus on designing an artificial neural network (ANN) to estimate the energy absorbed by the arrester, minimizing the error of this neural network. The results demonstrate that the ANN can effectively estimate the power of the arrester within the power system, providing a valuable tool for enhancing system reliability and performance. This study contributes to the understanding of arrester behavior under transient conditions and offers a novel approach to estimating their energy absorption capabilities using advanced computational techniques.

KEYWORDS: Arresters, Lightning, Neural Network, Power Systems.

1. INTRODUCTION

The lightning strike is a natural phenomenon that has long been the source of many human and financial injuries. This phenomenon is the main reason to cause line tripping and service interruption, the many numbers of accidents in the power system are caused by lightning which has brought a great loss to the national economy [1]. Lightning is an enormous flash resultant from the increase of millions of volts between clouds or between a cloud and the earth [2].

To prevent the destructive effects of lightning, a suitable earth system was proposed [3]. The earth system is to provide the electric earth with low-resister that can protect the equipment against electric shock. The effect of grounding resistance connected to surge arresters [4] was presented and the result shows that the grounding resistance of Surge Arresters can be increased to some extent without decreasing the lightning protection level [5]. Today, the surge arrestor is often used to protect the equipment of the power system against transient overvoltages.

Lightning rod arrester [6] is used to keep the tower and present another tradition for lightning current. This arrester has reduced the potential of tower overhead and the performance of a 500 kV lighting rod arrester is tested, and employed in transmission arrangement. When it is linked to the tower, the top possible of the tower can be limited. Understanding the nature of overvoltages and mobile waves makes it possible for manufacturers to design the appropriate level of insulation to protect the power systems [7]. The back flashover, direct lightning hit to a phase conductor, and lightning-induced voltage are the category of lightning overvoltages. A statistical technique was used to investigating the energy absorption of each surge arrester to take into account the lightning parameter randomness [8]. A probabilistic evaluation of the energy absorption capability of transmission line surge arresters (SAs), based on the Monte-Carlo method was presented.

We propose investigating the factors affecting the voltage and energy absorbed by the arrester when the lightning

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strikes the system power and the design of an artificial neural network [9] to estimate the energy of the arrester. So that the error neural network [10] can be neglected and it is possible to use this neural network to estimate the power of the arrester in the power system.

The energy source estimation using the neural network [11] has not been done before. With this method, the accuracy level. To study the characteristics of power line arrays in high voltage substations and power lines, the EMTP Works software [12] is a very useful tool for simulating the power system. So, using EMTP Works software, we first identified the effective factors on the amount of voltage and energy depleted on the arrester when the lightning strikes into the power system. Then, after identifying the factors affecting the voltage and energy of the arrester, with the help of the MATLAB software, we designed an artificial neural network [13]. The neural network can be neglected and it is possible to estimate the power of the arrester in the power system. The arrester must have sufficient absorption capacity to withstand the thermal shock caused by the shock absorber discharge. A choice of energy capacity for a surge arrester depends on many factors, including practical experience, statistics on network connections, storm statistics with lightning strikes and information about the line drainage class. Choosing the right amount for the energy of an arrester is very difficult, which is possible using the neural network [14] in this paper. This network has an amount of non-critical error to predict the energy of the archer so this network Nervous system as a power surge arrester in the power system.

2. MATERIALS AND METHODS

The ZnO arresters [15] have important dynamic and frequency characteristics for lightning waves and other waves with a rapid wavefront. In the simulation, the arrester is simulated with a nonlinear resistance. The lightning waves have a fast front slope therefore; the dynamic effects are provided for the ZnO arresters. Fig. 1 shows the proposed model for The ZnO arrester. For waves with a slow front, the RL filter shows the small impedance. The value of the impedance of the RL filter is very important in waves with high-speed wavefront [16]. The practical arrester data be given by:

$$L_0 = 0.33\mu H \qquad L_1 = 32\mu H \qquad C = 0.031nH$$
$$R_0 = 170\Omega \qquad R_0 = 105\Omega$$

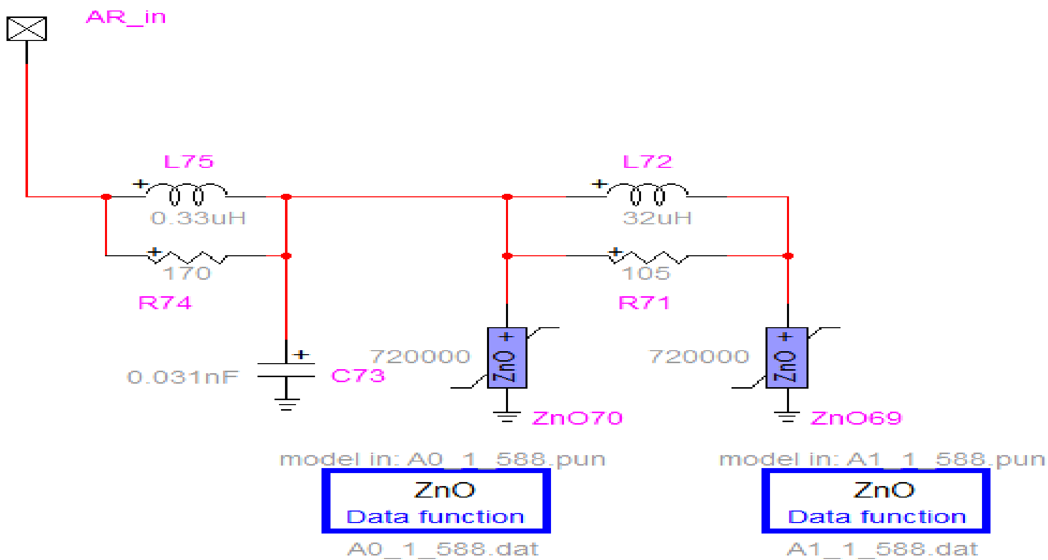

Fig. 1. Frequency model of ZnO arrester.

$$R_0 = \frac{100d}{n}\Omega\,,\,, L_0 = \frac{0.2d}{n}\mu H\,, R_1 = \frac{65d}{n}\Omega \qquad (1)$$
$$L_1 = \frac{15d}{n}\mu H\,, C = \frac{100n}{d} PF [20]$$

Where d is the length of the arrester in meters, n is the number of parallel columns consisting of disks ZnO, L_0 is magnetic inductance due to adjacent fields of arrester or ring inductance including transformer and arrester, R_0 is to stabilize integral calculations and c is a capacitor of the arrester. To calculate the energy of the archer, the power of the arrester is calculated then, the energy of the archer can be achieved following equation:

$$E(t) = \int_0^t P(\tau)d\tau \qquad (2)$$

Where $E(t)$ is the energy and $P(\tau)$ is the power. The archer's energy mainly depends on three factors, the current intensity of the lightning wave, the sequence duration time of the lightning wave behind, and the resistance of the tower foot. The current intensity of the lightning wave and the sequence duration time of the lightning wave behind have a random nature and the resistance of the tower foot has a selective nature. Therefore, by changing the resistance of the tower foot, the stress of the energy entered by the arrester can be changed.

3. RESULTS

When lightning happens, it may collision to phase conductor or wire guard. The simulation operation was performed for the lightning collision to once to the wire guard and once to the phase conductor.

To investigate and compare the affecting factors on the voltage and energy of the arrester, before the simulation, a base state was required. The base state should not be too small or too large. If these parameters are small, the factors affecting the voltage and the energy of the arrester are not possible. If the parameters of the base state are large, we will give the incorrect and unrealistic values of the voltage and energy values of the arrester. These parameters can be achieved with a test and error model. We consider the base state as Table 1.

Table 1. The base state parameters for investigating the voltage and energy of the arrester.

$I_{surg\ (base)}$ (KA)	$t_{f\ (base)}$ (µs)	$t_{h\ (base)}$ (µs)	Span Length$_{(base)}$(m)	$R_{foot\ (base)}$(Ω)
100	8	200	450	200

The simulation results were obtained for measuring the voltage and energy when a lightning strike hit the wire guard and phase conductor. It is estimated that by gathering this information, the amount of network load can be measured to appropriately design and utilize arresters. All energy values in the tables are expressed in joules, and all voltage values are presented in kilovolts.

Table 2. Energy stress of the arrester with change in the intensity of the lightning current.

I(KA)	10	20	35	50	80	100	120	140
E (Guard wire)	2	3	8	642	10915	22253	36845	5401
E (Phase inductor)	314819	1279274	2991618	5079131	9792491	13196658	16811545	20610291

As can be seen from the table above, if the other parameters remain constant, E (Guard wire) initially increases and then decreases. The sharpness of E (Phase inductor) increases.

Table 3. Voltage stress of the arrester with change of the intensity in the lightning current.

I(KA)	10	20	35	50	80	100	120	140
V (Guard wire)	3	11	33	118	281	386	490	582
V(Phase inductor)	834	907	962	1015	1126	1182	1231	1273

Table 3 shows that if the lightning current is variable, the sharpness of E (Guard wire) and E (Phase inductor) increases.

Table 4. Energy stress of the arrester is presented with changes in the duration time of the lightning wave.

th(μs)	20	50	100	150	200	250
E (Guard wire)	3	1999	11390	18723	22253	23763
E (Phase inductor)	928714	3615554	7505276	10521206	13196658	15593095

In this table, with increasing time behind sequence duration time of the lightning wave, (Phase inductor) increases.

Table 5. Voltage stress of the arrester with change behind sequence duration time of the lightning wave.

$t_h(\mu s)$	20	50	100	150	200	250
V (Guard wire)	315	362	379	384	386	387
V(Phase inductor)	1173	1181	1193	1205	1219	1226

Table 5 demonstrates that as the duration time of the lightning wave increases, both V (Guard wire) and V (Phase inductor) increase.

Table 6. Energy stress of the arrester with a change of resistance of the tower foot.

$R_{foot}(\Omega)$	50	100	200	300	400	500
E (Guard wire)	1403	22253	74878	122333	159079	186089
E (Phase inductor)	13206049	13196658	13192783	13188450	13185333	13183057

Table 7. Voltage energy stress of the arrester with change of resistance of the tower foot.

$R_{foot}(\Omega)$	50	100	200	300	400	500
V (Guard wire)	172	386	662	712	742	762
V(Phase inductor)	1183	1174	1150	1139	1128	1114

The effect of tower footing resistance on the voltage and energy of the lightning arrester is illustrated in Tables 6 and 7. It is summarized that when a lightning strike hits a phase inductor, the arrester's energy and voltage decrease as the tower footing resistance increases. An inverse relationship exists between tower footing resistance and the voltage and energy of the lightning arrester. Conversely, when a lightning strike impacts the guard wire, an increase in tower footing resistance leads to a rise in both the energy stress and voltage of the arrester. In this scenario, a direct relationship is observed.

According to the results, the main factors controlling energy absorption have been identified. Currently, neural networks are employed for various pattern-recognition tasks, including line recognition, speech recognition, and image processing. They are also utilized for classification issues such as text or image categorization. An artificial neural network has been designed to estimate the energy absorbed by the arrester, focusing on minimizing the error of this neural network. It is noteworthy that the neural network can effectively estimate the energy of the arrester within power systems.

Although deep learning is a newer approach today, the use of simple neural networks for estimating the energy of surge arresters offers significant advantages. One of these advantages is high prediction accuracy. Neural networks are capable of learning complex patterns and relationships within data, leading to more precise predictions of energy absorption during lightning strikes. Additionally, these networks can be trained on historical data, allowing them to adapt to various environmental conditions and changes in lightning characteristics.

Moreover, efficiency in data processing is another benefit of using neural networks. These networks can process large volumes of data quickly and effectively, enabling real-time analysis and decision-making. Furthermore, by automating the estimation process, the likelihood of human error in calculations and assessments related to surge arresters is reduced. Ultimately, the accuracy in estimating the energy absorbed by surge arresters contributes to enhancing the reliability and stability of electrical systems.

The use of simple neural networks has significant advantages over deep learning methods. One of these advantages is the simplicity and speed of training. Simple neural networks typically have fewer structures and therefore require less computational resources. This results in reduced training time and a faster model development process, especially in projects that require quick implementation [17].

Additionally, the reduced risk of overfitting is another benefit of using simple neural networks. With fewer parameters in these types of networks, the likelihood that the model becomes overly dependent on the training data and fails to generalize well to new data is lower. This characteristic is particularly important in applications where training data is limited or insufficient [18]. Although deep learning and artificial intelligence are suitable methods, they can be utilized in future research.

The number of neurons in the hidden layer was determined using the test and error method. After testing, 10 neurons were selected as the optimal number that produced the best convergence between the generated results and the training data. The neural network consists of three layers: an input layer containing 3 neurons, a hidden layer containing 10 neurons, and an output layer containing 1 neuron (Fig. 2).

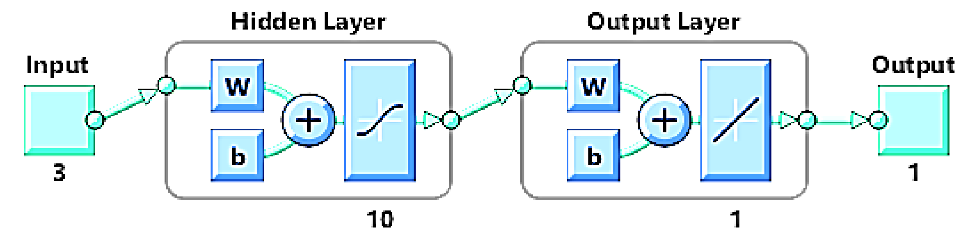

Fig. 2. MLP neural network designed.

Selecting input-output data is very important for network education. This information should include various conditions and conditions that may occur in the actual system so that the neural network [19] experiences different conditions and is resistant to various inputs. The current intensity of the lightning wave, the sequence duration time of the lightning wave behind, and the resistance of the tower foot are inputs and the energy of the arrester is the output factor of the neural network [20] model. (Fig. 3)

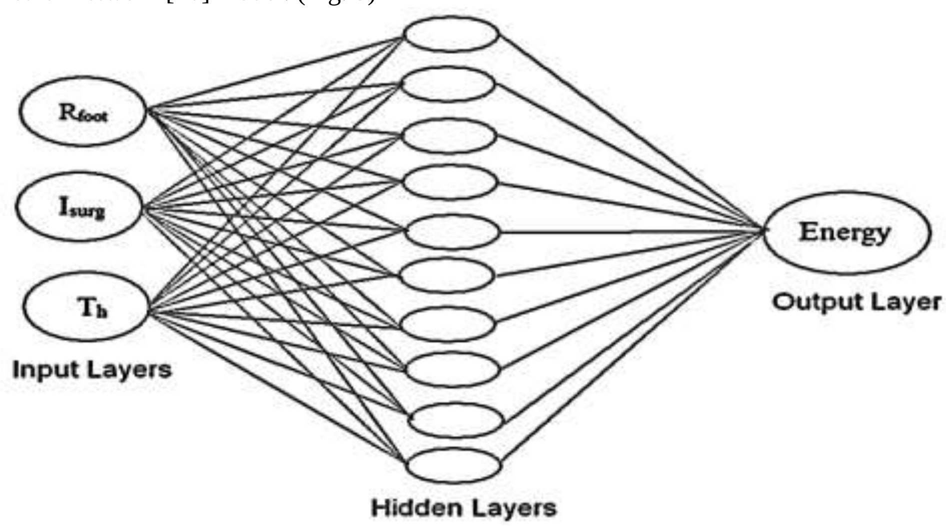

Fig. 3. The general scheme of the MLP neural network.

The amount of the lightning current between 4-140KA, the sequence duration time of the lightning wave behind between 20-250μs, and the R foot value increased by 9 steps and at each step of 50 ohms, ranging from 100 ohms to 500 ohms.

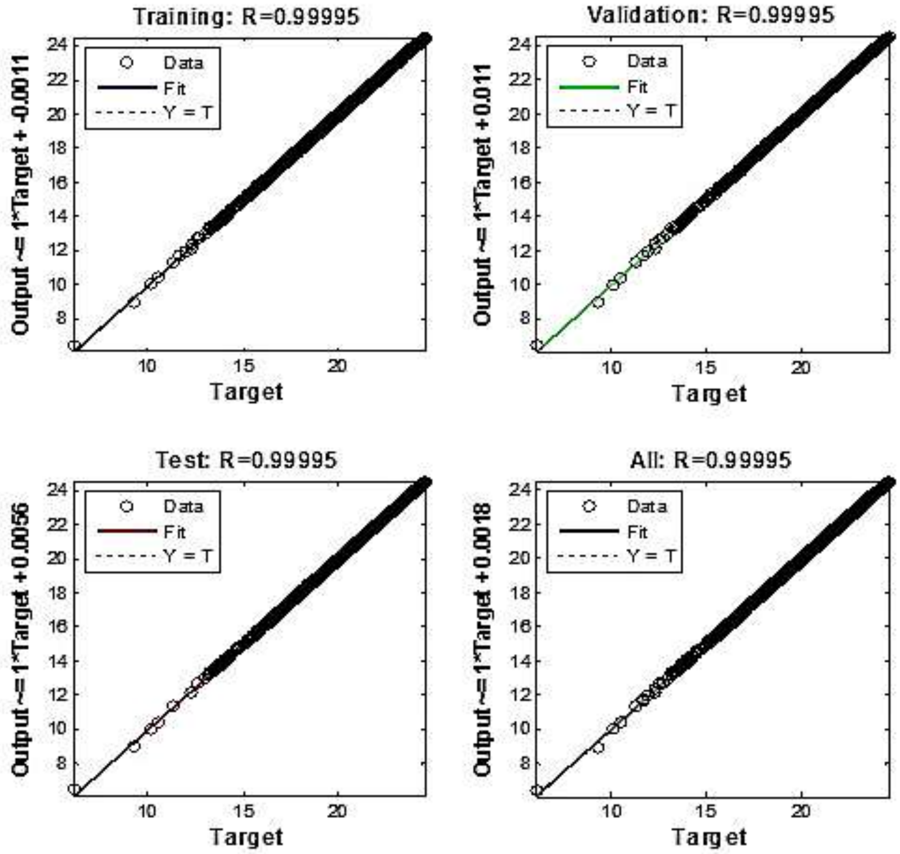

Fig. 4. Regression status of learning, testing, verification, and data allowed data when hit lightning phase conductor.

The energy values of the arrester were obtained in two scenarios: when lightning struck the phase conductor and when it impacted the wire guards. For each scenario (lightning strike on the phase conductor and wire guard), a total of 29,187 input/output samples were considered for network training. To enhance training efficiency and accommodate the energy array sizes, all input-output data were normalized using the non-linear log2X function within the interval (2.24).

After designing the network, simulated results were obtained through the inverse method of normalization. It was noted that normalizing the results caused them to differ from the original values. To retrieve the original results, a reverse normalization process was necessary.

Once the neural estimator was developed and subjected to various inputs while determining appropriate network weights, it could be utilized to estimate the energy absorbed by the arrester in the power grid. In the designed neural network, which aims to predict the energy of the arrester during collisions, the regression status of training, testing, and verification data is illustrated for lightning strikes on the phase conductor in Fig. 4. This graph displays the output in relation to the target. The vertical axis represents the optimal measured value and the maximum coefficient (μ), which indicates the degree of difference that should be reflected in the diagram. The target variable corresponds to impacts with either a guard wire or phase conductor, varying from 0 to 25.

Ideally, when the calculated outputs are almost in line with the target outputs, the graph is in a straight line with a gradient of 45 degrees and can be used to accurately the results. The mean square error (MSE) [21] in the training, test, and confirmation data was illustrated for each repetition in Fig. 4. The vertical axis gives the average output error of the applied 3 data. This figure is the best condition where the error rate is close to real.

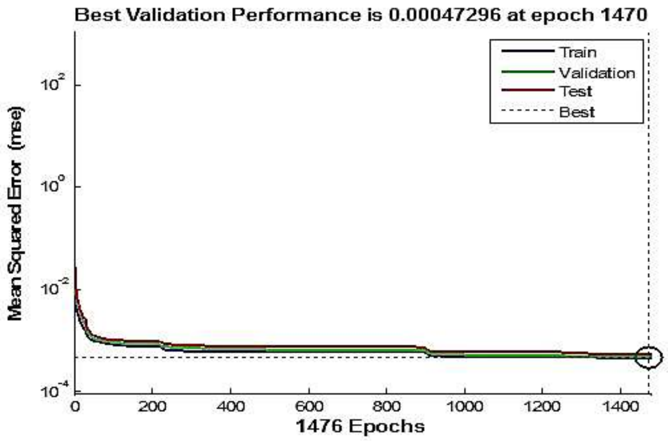

Fig. 5. MSE status in educational, testing, and verification data for each repetition when attacking the lightning to the phase conductor.

In Fig. 5, the average errors of confirmed data, test data, and historical data (real) are represented by the green, red, and blue colors, respectively. The error rate is calculated for each iteration, and the optimal mode, where the error rate closely aligns with reality, is indicated by a circle in the diagram. It is observed that after 1,476 iterations, no further changes occur, and the error stabilizes at that point. This indicates that the network's error is unlikely to decrease further after 1,476 iterations. Therefore, lightning strike data can be effectively integrated into the power network with a good fit.

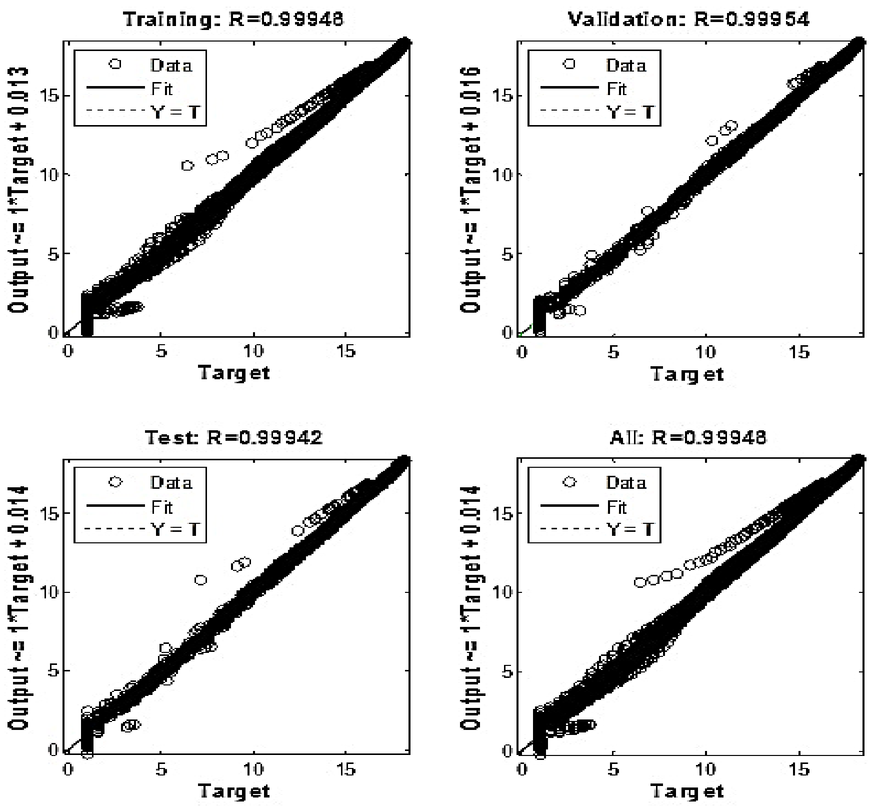

Fig. 6. Regression status of learning, testing, verification and data allowed data when hit lightning to the wire guard.

Figures 6, and 7 show data regression and the mean squared error of output, respectively when the lightning strikes the guard wire.

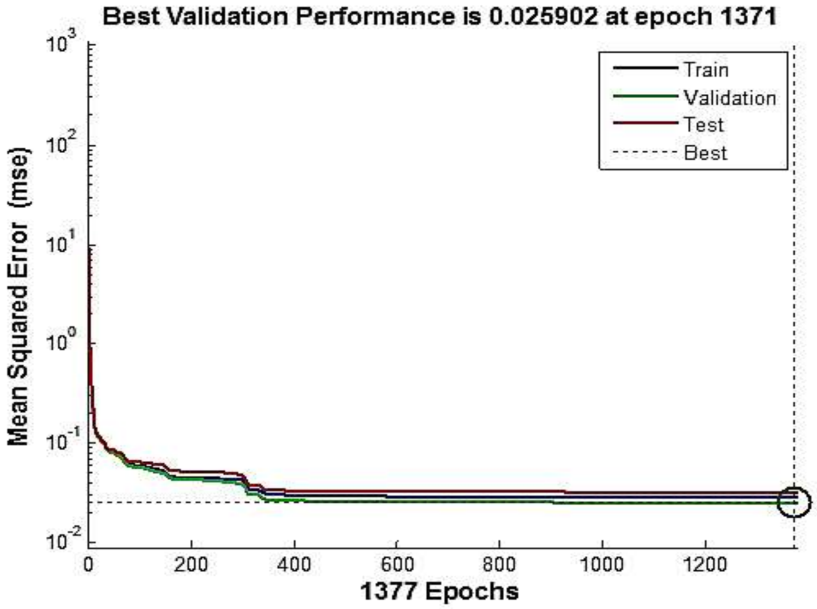

Fig. 7. MSE status in educational, testing, and verification data for each repetition when attacking the lightning to the wire guard.

In this case, the network error after 1371 times, there is no longer the probability of it, and so it is possible to easily load the loaded lightning with a good ratio to the power grid.

4. CONCLUSIONS

The results of this study highlight the critical role of surge arresters in limiting transient overvoltages in power systems. By utilizing EMTP Works software, the transient states within the network were accurately simulated, allowing for a detailed analysis of the voltages and energies absorbed by the arresters during lightning strikes. It was determined that the energy and voltage experienced by the arresters are influenced by three key factors: the intensity of the lightning wave, the duration of the lightning wave, and the resistance at the tower's base.

Through this research, significant insights into the parameters affecting arrester performance were gained. The implementation of a powerful neural network provided a robust tool for estimating energy surges, yielding a low error rate in predictions. This advancement demonstrates that neural networks can effectively model complex behaviors in power systems, ultimately enhancing the reliability and protection offered by surge arresters against transient overvoltages.

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