# MOSA Monitoring Technique Based on Analysis of Total Leakage Current

George R. S. Lira, *Member, IEEE*, and Edson G. Costa, *Member, IEEE*

***Abstract*—Currently, the majority of metal–oxide surge arrester (MOSA) monitoring techniques are based on total leakage current decomposition of their capacitive and resistive components. However, these techniques are subject to some financial, technical, and practical limitations, which can hamper their usage on the field. In this paper, a new monitoring technique for the zinc–oxide surge arrester is proposed. The technique is based on the feature extraction of measured total current signals and on the analysis of these characteristics by artificial neural networks. The measured total currents were obtained from station class surge arresters submitted to their maximum continuous operating voltage. In the lab tests, six different kinds of failures were simulated on the tested MOSA with the purpose of evaluating the capacity of the technique to distinguish different operating conditions of surge arresters. Hit ratios greater than 98% were obtained in the identification of the operating conditions. The results show the viability of the technique on MOSA monitoring procedures.**

***Index Terms*—Arresters, feature extraction, leakage currents, monitoring, neural networks.**

## I. Introduction

METAL-OXIDE surge arresters (MOSA) are equipment applied to power systems for protection against switching and lightning surges. Thus, they decisively contribute to the increase of the reliability, economy, and continuity of the system operation, since failures on surge arresters can yield nonprogrammed power-supply interruption, damage to other substation equipment, and risks to technical personnel. Hence, several monitoring techniques or procedures have been proposed in the literature [1]–[5] with the purpose of monitoring and evaluating the risk of MOSA failure.

A class of techniques normally applied to the monitoring and diagnosis of MOSA is based on the measurement and decomposition of total leakage current (the current and total current terms may be used as synonyms, except in specific situations) of the zinc–oxide (ZnO) arrester on steady-state operation. The resistive component of the leakage current is obtained from the decomposition process. This component and its third-order harmonic have meaningful variations in their magnitudes and waveshapes proportional to the surge arrester degradation level. The identification and analysis of these variations are the aim of most MOSA monitoring and diagnosis techniques [3], [6].

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The methods based on total leakage current decomposition often require the measurement of the applied voltage in the MOSA to perform the decomposition of the current in its resistive and capacitive components [6]. Normally, this is an important limitation for this type of technique, because on the field, measuring high voltages (HVs) is a hard task, since there are practical and safety restrictions which complicate the access and connection of voltage meters in the secondary side of HV measurement devices, such as capacitive voltage transformers. In [2], it is not necessary to measure the applied voltage; however, it is necessary to measure the induced current on a field probe. The resistive third harmonic current is obtained from empirical relationships between the total current, the probe current, and the electric-field pattern around the arrester. This method requires previous knowledge about the manufacturer data to perform comparative analysis; it is subject to operator errors on the field probe placement, and it can be influenced by the neighboring transmission lines.

So the need to develop monitoring and diagnosis methods to overcome the limitations of the current methods is evident, to guarantee the reliability and accuracy of the yielded results, and to aid the technical substation personnel in predictive and preventive maintenance activities. Thus, with this goal in mind, a new MOSA monitoring technique is proposed. The technique is based on the analysis of features extracted from only the total leakage current. In such case, the measurement arrangement is simplified, since it is only necessary to measure the total current signal from the surge arrester. Good results have been achieved with the new technique.

## II. Proposed Technique

The harmonic distortion level and the total current magnitude (especially its resistive component) are important indicators of the MOSA degradation level [3], [6]. Thus, a classification system with the ability to identify the operating conditions of surge arresters, based on features extracted from the total current, can be designed. Thereby, the harmonic components are extracted from the total current and used to identify the operating conditions of MOSA. At first, the proposed technique differs from that which is normally employed in ZnO arresters monitoring, since there is no need to measure the voltage on the surge arrester, because it is not necessary to perform the decomposition of the total current in the resistive and capacitive components as is usual procedure in common methodologies. Thus, several problems due to the total current decomposition process in its capacitive and resistive components are avoided.

The proposed technique (just like the existing ones) must be used on the power system steady-state operation, because

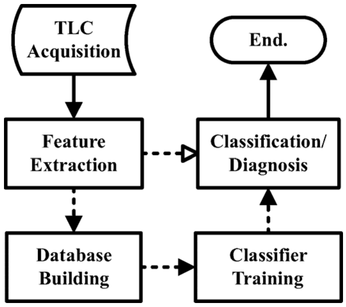


Fig. 1. Proposed technique overview.

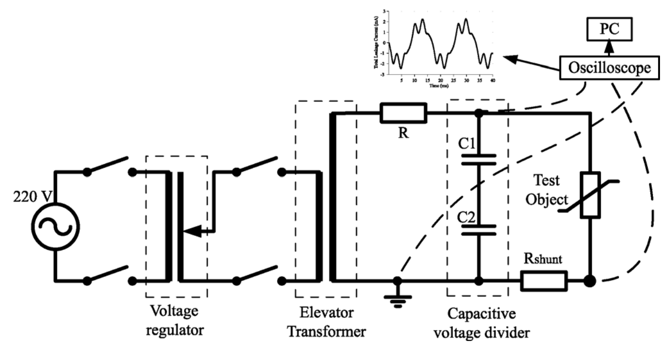


Fig. 2. Experimental arrangement diagram.

during transient phenomena, the arrester behavior can change temporarily or permanently (i.e., the total current can increase significantly by a few periods or definitively). So during the transient phenomena, erroneous conclusions can be obtained. However, after the transient, the arrester operation condition can be determined reliably. The power system steady-state operation can be verified by the electrical utility oscillography network.

In Fig. 1, an overview of the proposed technique is presented. The technique can be divided into two different phases. In phase 1, called the training phase, the total current signal is obtained from a surge arrester installed on the field or tested in laboratory. Next, the feature extraction (harmonic components) of the MOSA current signals is performed. From the extracted harmonic components, a feature database is built, which relates the components to the arrester operating conditions. Finally, the database is used in the training of a condition operating classification system, based on artificial neural networks. The second phase, denominated testing phase, consists in directly submitting the measured current signal to the classification system which was previously trained, with the objective of determining the MOSA condition. The training phase is necessary when the technique is being implanted, while the testing phase can be used in the routine tests by maintenance personnel.

## III. Total Leakage Current Measurements

During the development and testing of the technique, tests of MCOV were carried out in the laboratory. From these tests, it was possible to obtain the MOSA total leakage current. In Fig. 2, the experimental arrangement used in the tests is shown.

The experimental arrangement was composed by a sinusoidal adjustable voltage source (voltage between 0 and 220 V), a voltage elevator transformer (voltage between 0 and 100 kV), a protection resistance against short-circuit (R) in series with the test object (evaluated MOSA), a capacitive voltage divider (just to monitor the applied voltage), and a shunt resistance ($R_{\rm shunt}$). The current signals were obtained from $R_{\rm shunt}$ along with a data-acquisition system composed by a voltage probe and a digital oscilloscope. The measured current signals were stored in a PC for postprocessing.

The HV source used in laboratory tests had harmonics levels limited according to the established power-quality rules of international (such as IEEE 519) and local (Brazilian) standards for transmission systems. The harmonics levels were changed during the tests, with the purpose of evaluating the capacity of the proposed technique to carry out the MOSA diagnosis in the presence of harmonics on system voltage.

### A. Tested Samples

The testing of MCOV application and current measurement was carried out in some station class surges arresters with rated voltage and an MCOV of 92 kV and 76 kV, respectively. These pieces of equipment had different levels of conservation. The evaluated surge arresters had their levels and types of degradation changed during the tests, by inserting failures produced artificially in the laboratory. Altogether, 07 different types of MOSA operating conditions were evaluated in the tested samples. The conditions corresponded to the good condition and typical failures found in surge arresters [3]–[5], [7], [8]: sealing loss, superficial pollution, varistors degradation, internal humidity, displacement along the active column, and nonuniform voltage distribution.

The purpose of testing different surge arresters samples with several distinct operating conditions was to evaluate the capability of the proposed technique to detect these conditions by analyzing only the total current (i.e., proving that it is possible to perform the MOSA monitoring and the identification of different operating conditions from the total leakage current measurement and analysis), without obtaining the resistive component of the current or employing complex measurement arrangements.

The evaluated MOSA operating conditions are described as follows.

### B. Evaluated MOSA Operating Conditions

The first condition considered in the testing of the MOSA was the good condition. In this case, the tested surge arresters presented characteristics and behaviors similar to the nominal ones. Then, typical failures found in ZnO surge arresters were artificially inserted in the evaluated samples. The faulty conditions are described as follows.

- **Sealing loss:** characterized by the loss of physical isolation between the environment and the interior of the surge arrester, enabling the exchange of gases. The loss of sealing was created artificially in the laboratory by opening communication channels between the environment and the interior of the arrester, allowing the exchange of heat and gas.
- **Internal humidity:** can occur in surge arresters due to failures in the manufacturing process at the moment of the sealing, or by sealing loss caused by the natural aging

process of the equipment. To simulate this defect, the arresters were opened and water was aspersed in the varistor column. Then, the arrester was closed.

- **Superficial pollution:** occurs due to the presence of pollution on the surge arrester housing. To simulate this defect, a salt suspension was aspersed on the entire porcelain of the surge arrester.
- **Varistor degradation:** can occur due to natural or precocious varistor aging. To simulate this failure in the laboratory, damaged varistors were inserted in the arrester active column. The varistors were damaged by the electrical stress produced by the application of current impulses and overvoltages.
- **Displacement along the active column:** generally occurs due to inadequate transportation or storage of the surge arresters. However, this kind of problem may be caused by the manufacturing process due to assembly errors. In the simulation, displacements in the active column were performed.
- **Nonuniform voltage distribution:** occurs due to failures in the arrester project or superficial pollution on the arresters. In the simulation of this kind of failure, several assemblies were used with internal short-circuited varistors, therefore, modifying the electrical-field distribution along the arrester.

## IV. Total Current Feature Extraction

The next step in the methodology consisted of extracting relevant features of current signal to enable the creation of rules to distinguish the surge arrester operating conditions. The distortion level and the magnitude of the current in MOSA are important indicators of the surge arrester degradation level [1]–[3], [6]. So it is reasonable to think that the harmonic components of the current signal constitute a set of features for the effect of monitoring and diagnosing MOSA.

A traditional way of extracting the harmonic content of a signal is by applying the fast Fourier transform (FFT). However, there is a series of known pitfalls in the FFT technique [9], [10], such as: leakage, picket-fence, and aliasing effects. These effects may result in a distorted version of the real signal spectrum, due to poor estimation of harmonic components.

Here, the extraction of the harmonic components of the current signal was performed by an adapted version of the parametric identification technique proposed in [11], which consists of automatically determining the parameters of the equation (mathematical model) that represents the behavior of MOSA in a low-current region. To determine the best model that self-adapts well to the measured current signals, several tests and adjustments on the model were made. After this, it was found that the model which best represented the measured data was (1), which consists in the sum of the first five odd harmonic components of the signal

$$s(t) = \sum_{i=1}^{5} A_i \cos[(2i-1)\omega t + \theta_i]. \tag{1}$$

The identification parameter technique is based on the nonlinear least squares method associated with the Levenberg–Marquardt optimization algorithm. The technique is used to estimate the parameters (magnitude and phase angles) of (1), in order to minimize the error between the signal reconstructed from the model with identified parameters and the measured signal, that is, to minimize the following equation (objective function):

$$f(\mathbf{x}) = \frac{1}{2}\sum_{j=1}^{m}[r_j(\mathbf{x})]^2 = \frac{1}{2}\|\mathbf{r}(\mathbf{x})\|^2 = \frac{1}{2}\mathbf{r}(\mathbf{x})^{\mathrm{T}}\mathbf{r}(\mathbf{x}) \tag{2}$$

where the $\mathbf{r}(\mathbf{x})$ function ($\mathbf{r}(\mathbf{x})^{\mathrm{T}}$ is the transpose of $\mathbf{r}(\mathbf{x})$) is called residual and is defined by

$$\mathbf{r}(\mathbf{x}) = \mathbf{i}_m - \mathbf{i}_c \tag{3}$$

where

$\mathbf{x}$ — $n$-dimensional (10 in this case) parametric vector ($\mathbf{x} = \{A_1, \theta_1, A_2, \theta_2, A_3, \theta_3, A_4, \theta_4\, A_5, \theta_5\}$);

$k$ — number of samples in the total current signal;

$\mathbf{i}_m$ — $k$-dimensional vector corresponding to the measured and digitalized current signal;

$\mathbf{i}_c$ — $k$-dimensional vector corresponding to justify reconstructed signal obtained from the application of $\mathbf{x}$ in (1).

To obtain a vector $\mathbf{x}$ that minimizes (2), the updates given by (4) must be performed, until a pre-established stopping criteria (invariance on (2), for example) of the iterative procedure is satisfied

$$\mathbf{x} = \mathbf{x}_0 + \mathbf{d} \tag{4}$$

where $\mathbf{x}_0$ corresponds to an initial guess of the parameters to be determined (magnitudes and phase angles of harmonic components) and $\mathbf{d}$ (search direction) is the update given to parametric vector $\mathbf{x}$ on each iteration of the Levenberg–Marquardt method, with the purpose of minimizing (2).

The search direction $\mathbf{d}$ is obtained by the resolution of the following system of equations:

$$\mathbf{H} \cdot \mathbf{d} = -\mathbf{g} \tag{5}$$

where $\mathbf{H}$ and $\mathbf{g}$ correspond to the Hessian matrix with the update of the Levenberg–Marquardt method, and to the gradient of the objective function (2), respectively.

The gradient and the Hessian matrix can be obtained in terms of the Jacobian matrix of $\mathbf{r}(\mathbf{x}_0)$ as shown in (6) and (7), respectively. The damping factor $\mu$ in (7) is a strategy of the optimization method to guarantee that the Hessian is positive definite and the search direction always conducts to the local minimizer of (2). $\mathbf{I}$ is the identity matrix

$$\mathbf{g} = \mathbf{J}(\mathbf{x}_0)^{\mathrm{T}}\mathbf{r}(\mathbf{x}_0)\,, \tag{6}$$

$$\mathbf{H} = \mathbf{J}(\mathbf{x}_0)^{\mathrm{T}}\mathbf{J}(\mathbf{x}_0) + \mu\mathbf{I} \tag{7}$$

TABLE I
MOSA CONDITION CLASSIFICATION CODES

| MOSA condition | Coding Vector |
|---|---|
| Good | 0 0 0 0 0 0 |
| Sealing loss | 1 0 0 0 0 0 |
| Superficial pollution | 0 1 0 0 0 0 |
| Varistor degradation | 0 0 1 0 0 0 |
| Internal humidity | 0 0 0 1 0 0 |
| Displacement along the active column | 0 0 0 0 1 0 |
| Non-uniform voltage distribution | 0 0 0 0 0 1 |

TABLE II
DATABASE GENERAL FORMAT

| Inputs | Outputs |
|---|---|
| $A_2/A_1$ $A_3/A_1$ $A_4/A_1$ $A_5/A_1$ | S1 S2 S3 S4 S5 S6 |

where the Jacobian matrix is given by

$$\mathbf{J}(\mathbf{x}_0) = \left[\frac{\partial r_i}{\partial x_j}\right]_{\substack{i=1,2,\ldots,k \\ j=1,2,\ldots,n}}. \quad (8)$$

## V. DATABASE BUILDING

Since the total current features (harmonic components) have been extracted, it is possible to build a feature database of all of the measured signals. This database is utilized in the training and testing of the MOSA operating condition classifier.

The set of model parameters returned by the feature extraction method $\mathbf{x} = \{A_1, \theta_1, A_2, \theta_2, A_3, \theta_3, A_4, \theta_4\, A_5, \theta_5\}$ corresponds to the amplitudes and phase angles of the evaluated harmonic components of the signal. After some analysis, it was observed that the phase angles did not provide good correlation of the signal and the MOSA condition, since there is not any phase angle of reference. So the phase angles are discarded in the construction of the database. Another important preprocessing phase in database building was the normalization of the harmonic amplitudes in relation to the fundamental component. After this, the fundamental component can be omitted from the final database.

With these preprocessing phases, the dimensionality of the problem is reduced to only four input variables, the normalized amplitudes of the remaining harmonic components. Finally, since each signal is related to a kind of MOSA condition (defective or not), each element in the database is composed by the grouping of the remaining identified parameters plus an identification code corresponding to the surge arrester condition.

In the MOSA operating codification condition, a vector of six elements was chosen. Each active element in the coding vector corresponds to a different surge arrester condition. Only one element can be activated at a time. In Table I, the codification vectors related to each surge arrester condition are shown.

In Table II, the general format of each element in the feature database is shown. The *Inputs* section is related to current model identified parameters (i.e., to the normalized amplitudes of the current harmonic components). The *Outputs* section corresponds to the code of the MOSA operating condition as shown in Table I.

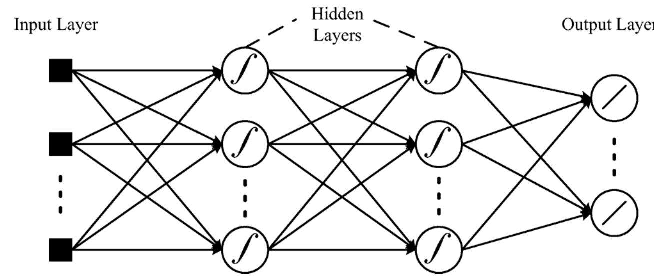

Fig. 3. MLP network typical architecture.

All current signals obtained in the laboratory were processed and grouped according to the format shown in Table II. Thus, the feature database with 480 current records (obtained in laboratory tests) and 10 parameters (input plus output parameters) was obtained, to be employed in the training and testing process of the MOSA condition operating classifier.

## VI. OPERATING CONDITION CLASSIFIER

The identification of the surge arrester operating condition was treated as a pattern-recognition task, where the patterns to be recognized are the harmonic components of the MOSA total current when submitted to the operation voltage on industrial frequency. Here, an arrester operating condition classifier based on neural networks was chosen, more specifically, one called multilayer perceptron (MLP), since this class of neural networks is greatly consolidated on pattern-recognitions tasks, due to the good performances presented in several kinds of practical problems [12].

The MLP network is based on a network architecture called *feedforward*, where the synapses between the artificial neurons occur only in one direction. In Fig. 3, an MLP network typical architecture is shown. The first neuron layer is called the input layer. The data to be processed are provided in this layer. The intermediate layers are named hidden layers. They have the function of separating the input patterns in several classes, arranging and adjusting the data so that on processing ends, it is possible to obtain some useful information. The last layer is the output layer. In this layer, the results of the pattern recognition (MOSA operating condition, in this case) are presented. The linkages between the neurons of each layer are performed by synaptic linkages (or weighting), always observing that the linkages are made layer by layer without feedback, so that there are not feedback connections between neurons from the same or previous layers.

For an MLP network to work properly, it is necessary to perform its training from examples of situations to be analyzed/idenfied automatically, in the future, by the network. Here, the network was trained to identify the MOSA operating condition from samples of the harmonic components of the total current signals obtained in the laboratory tests. Thus, the trained network can detect the correlation between nonevaluated signals and the surge arrester condition, and provide a diagnosis of the evaluated surge arrester. If the training database is built with samples from different types of surge arresters, the classification system will be able to diagnose the condition of different arresters. This is a special capability of the used system, which

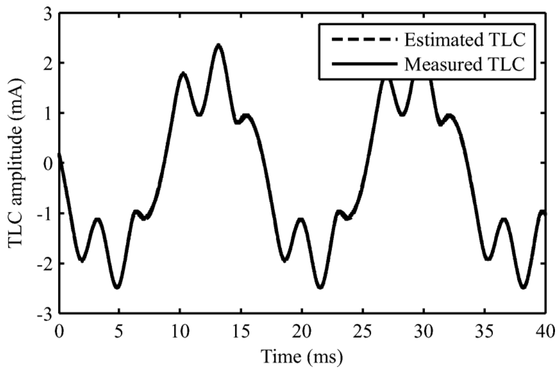


Fig. 4. Measured and estimated TLC signals.

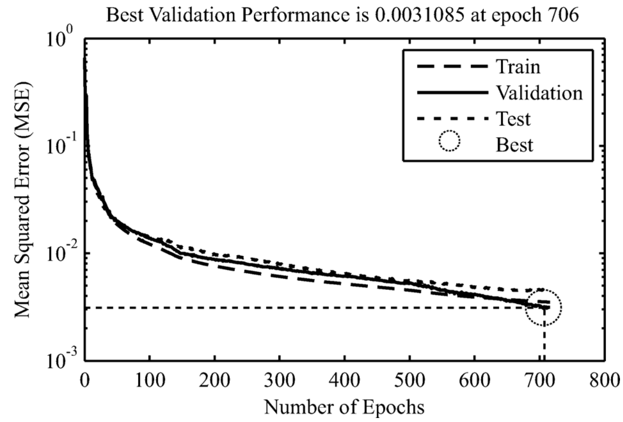


Fig. 5. Classifier performance for the original database.

can construct complex rules of separation of classes (situations or conditions) in a database.

In the training process of the adopted network, the resilient propagation (RPROP) training algorithm [13] was used to adjust the network synaptic weights with the purpose of providing the network with the capability of analyzing the current signals. The RPROP was chosen because of its good performance in practical applications, and it has been faster, more accurate, and more robust than its predecessors; and, furthermore, it is easily implementable and only slightly susceptible to numerical troubles [14].

## VII. Results

Initially, the performance of the feature extraction technique was evaluated in obtaining the harmonic components of the measured total current signal. The reconstructed (estimated with full set of parameters) signals were compared one by one with the measured ones by the $R^2$ statistics value, which will be defined. The $R^2$ statistics numerically shows the goodness of the estimation. If $R^2$ is close to 1, the quality of the signal estimation is the highest. In Fig. 4, typical measured and estimated current signals are plotted. Both are superimposed. The $R^2$ is 0.9994, which is very close to 1, evidence of the quality of the total current estimation by the proposed technique. The mean value of the $R^2$ statistics was 0.9982 for all 480 current records corresponding to signals of surge arresters in good condition and simulated failures

$$R^2 = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}} \tag{9}$$

where

$$\mathrm{SSE} = \sum_{j=1}^{k} \left[\mathbf{i}_{m_j} - \mathbf{i}_{c_j}\right]^2 \text{ and } \mathrm{SST} = \sum_{j=1}^{k} \left[\mathbf{i}_{m_j} - \bar{\mathbf{i}}_m\right]^2$$

where $\mathbf{i}_m$ and $\mathbf{i}_c$ are the measured and estimated current vectors, respectively; $k$ is the number of samples; $\bar{\mathbf{i}}_m$ is the average of the measured current; SSE is the sum of squares of the residuals; and SST is the sum of squares about the mean.

To use the feature database in training, testing, and validation of the artificial neural network, the database was randomly divided into three subsets composed by 60%, 20%, and 20% of the original database records. The greater one (60%) was utilized in the MLP training, while the others were used in testing and validation. This procedure is commonly used to avoid the neural network of memorizing all situations, so in some moments, the network will be forced to treat unknown situations. If the network presented high hit ratios for unknown situations, it was said that the classifier worked properly and could be tested in real cases.

The classifier that was used consisted of an MLP network with four neurons on the input layer (corresponding to the normalized amplitudes of the harmonic components); two hidden layers with 12 and 14 hidden neurons on each one; and one output layer with six outputs corresponding to the MOSA condition code. The activation functions are sigmoid-like.

To evaluate the average hit ratio ($h_r$) of the classifier, the test database (20% of the original database randomly chosen) and the following equation were used:

$$h_r = \frac{1}{N} \sum_{i=1}^{N} \frac{na_i}{np} \cdot 100\% \tag{10}$$

where $N$ is the number of times that distinct test patterns were evaluated by the network, $na_i$ is the number of the classifier hits for the $i$th dataset, that is, the number of times where the network output coincided with desired output (known in advance), and $np$ is the total number of evaluated patterns.

In Fig. 5, a typical evolution of the mean square error (MSE) between the desired outputs and that provided by the classifier along the epochs of training is shown for training, testing, and validation datasets. The errors decreased at the same rate for all training epochs. The training process was finished when the *Best* (see dotted lines and circle in Fig. 5) training epoch was achieved. This moment occurred when the training algorithm noticed that the MSE for the validation dataset had a tendency to increase in relation to the other errors (training and testing) or achieved a plateau region, where no significant variations are detected along the training epochs. So the training process does not extend indefinitely, avoiding wasted time and memorization of the patterns (overfitting) by the network.

The classifier mean hit ratio was 98.02%, after 100 consecutive runs of the training process. Thus, the classifier identified the MOSA operating condition correctly in more than 98% of the evaluated situations, so it is possible to identify the surge

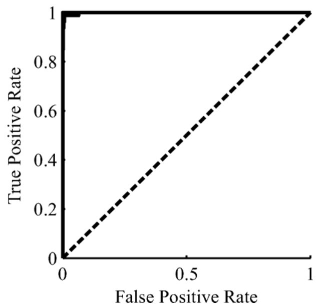


Fig. 6. Classifier performance for the original database.

arrester condition with high precision, taking into account only a few harmonic components of the total leakage current.

In the evaluation of the classifier performance, the true positive and false positive rates were computed. In Fig. 6, a typical plot of the receiving operating characteristics obtained during the training process for the MOSA simulated operating conditions is shown. The rates for all surge arrester conditions are above the dotted line and close to the maximum value in the $Y$-axis, therefore indicating that the true positive rate is closer to maximum for all cases (i.e., there were practically no false positives in the evaluated situations). This is very important for a classifier, since this shows the reliability of the classification process.

## VIII. Conclusion

In this paper, a new technique for MOSA monitoring and diagnosis is presented. The technique is based on the analysis of only the surge arrester total leakage current. This represents a paradigm break in relation to most of the ZnO surge arrester monitoring and diagnosis methodologies based on the analysis of the leakage current, since HV measurements, the decomposition of the total current in their capacitive and resistive components, the employment of empirical equations or approach, and the previous knowledge about the surge arrester characteristics are unnecessary. With the proposed technique, it is sufficient to measure the current signal, extracting its relevant features (harmonic components), and from these features the MOSA operating condition is evaluated by a condition classifier (a monitoring system).

To evaluate the performance of the monitoring system, a database of harmonic components of total current signals was created in the laboratory, obtained from station class surge arresters with seven different operating conditions, which include good conditions and several kinds of failures found on the field, such as sealing loss, internal humidity, superficial pollution, varistor degradation, displacement along the active column, and nonuniform voltage distribution.

The utilized surge arrester condition classifier was based on artificial neural networks. The developed classifier could correctly identify the MOSA operating condition 98% of the time (i.e., it could distinguish the seven evaluated surge arrester conditions from only the analysis of the current, with high hit ratios).

The results show that it is possible to perform the MOSA monitoring and diagnosis from only the total leakage current. Moreover, it can be concluded that the diagnosis is performed with high accuracy and hit ratios.

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