Thermal Monitoring of Underground Medium Voltage Cables Based on Machine Learning Techniques

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Abstract. In this paper a monitoring system for Medium Voltage (MV) cables is presented and simulated. It consists of a classification tool capable of identifying the working temperature of several sections of underground cables starting from the Frequency Response Analysis (FRA). This means that the monitoring procedure can be applied during normal network operation with a low intrusive level and allows the localization of the cable section in the worst working conditions. Starting from this information it is possible to organize the maintenance operations and avoid the occurrence of catastrophic failures. The monitoring method shown in this paper focuses on the relationship between cable temperature and conductor resistance. The online classification of the working temperature is carried out through two different machine learning techniques: Support Vector Machine (SVM) and Complex Neural Network (CNN). Both the single-fault hypothesis and the multiple-fault hypothesis are studied; in the first case the classification results are always higher than 95%, while in the more complex situation the classification rate decreases slightly. To make the simulation procedure as general as possible, Simulink-Simscape blocks, called “Three-phase AC power cable”, are used in this paper.

1. Introduction

Monitoring of underground cables is one of the most important activities for guaranteeing the continuity of the electricity distribution service. Unlike high voltage lines, which are realized through overhead infrastructures, medium voltage networks are usually buried and used near urban centres. For this reason, the development of a monitoring system capable of identifying the health state of the grid without the extraction of the cables plays a fundamental role in the organization of maintenance operations [1]. The development of smart grids in fact requires the introduction of numerous diagnostic systems applied to electrical power devices [2], in order to extend their useful life and prevent the occurrence of catastrophic failures [3].

There are several techniques that can detect damage in MV cables, but they cannot be used online during normal network operation [4]. A procedure based on measurements of dielectric losses is shown in [5] and, in this case, a parameter called tan δ is used to identify the degradation level of the insulation material. This information is certainly useful for knowing the residual life of the electrical infrastructure, but the measurement methodology includes numerous steps to be performed in the laboratory [6]. Other methods, based on the reflection of the measurement signals, can be used to detect the conductor point characterized by an impedance value different from the nominal one [7]. This technique, usually called Time Domain Reflectometry (TDR), does not require the extraction of the cables, but presents some problems when used during normal network operation. Moreover, the TDR method focuses on the impedance discontinuity and, therefore, it does not detect the insulation
problems. The main objective of the monitoring system presented in this paper is the prevention of catastrophic failures by analysing the working temperature of successive cable sections. There are several factors that can increase the temperature of the cable, such as the value of the phase current, the ambient temperature, and the presence of insulation problems [8-9]. If the phase current and the ambient temperature are not different from those considered when dimensioning the line, the cause of an increase in the cable temperature is the presence of a malfunction. In this case, the localization of the cable section characterized by a higher temperature allows to focus the maintenance operation in a specific area. Even if the overheating of the cable is caused by a current overload or an unusual increase in the ambient temperature, it is very important to immediately identify this situation and monitor its duration. The permanence of this condition, in fact, could introduce an anomalous degradation of the cable insulation [10]. This work presents a monitoring method based on FRA, which is able to classify the working temperature of the cable using machine learning techniques. The procedure describes an intrusive low-level analysis method, which can be implemented through devices commonly used for Power Line Communication (PLC) in MV lines. Therefore, no substantial changes to the network configuration are required and the signals used for the measurements do not represent disturbances to the phase voltage and current. The simulations presented are developed through Simulink software and allow a generalization of the method for any other electrical transmission line scheme.

The paper is organized as follows: the second section shows the theory of the monitoring method, the third section presents the simulation procedure carried out using Matlab and Simulink, and the last section contains the evaluation of the classification results.

2. Theoretical concepts

The first purpose of the monitoring system presented in this paper is to verify the thermal behaviour of underground MV cables starting from the online analysis of the network frequency response. This means that the development of the intelligent classifier capable of evaluating measurements of the line equivalent admittance is the main part of the theoretical procedure.

2.1. Monitoring system

Two different machine learning technics are used in this work: Support Vector Machine and Complex Neural Network. In both cases, the inputs of the classifier are pairs of magnitude and phase of the line admittance, evaluated for different frequencies and extracted at the end of the network branch taken into consideration. The number of pairs corresponds to the number of frequencies used for the measurements and the output of the classifier allows the identification of the cable temperature. If, during the learning phase, the classifier is trained by dividing the network branch into several sections, the output allows the detection of the cable section in the worst condition. Three cable sections are considered in this work and both the single-fault hypothesis and the multiple-fault hypothesis are studied.

In the hypothesis of single fault, it is assumed that overheating can affect one cable section at a time. This means that four classes of failure are considered; the first of them, called “class 0”, describes the normal working condition of each cable section. The other n classes are used to describe the abnormal working temperature of each cable section (n = 1, 2, 3). Therefore, two different conditions are used to describe the health state of the cable sections: the nominal condition corresponds to a working temperature lower than or equal to that obtained with the nominal current, while the fault condition indicates a higher temperature.

In the hypothesis of multiple failure, more than one cable section can be overheated at the same time. In order to check the performance of the classifiers in a very complicated situation, three different conditions are used to describe the health state of the cable sections: the nominal condition corresponds to a working temperature lower than or equal to that obtained with the nominal current (70°C), the soft fault condition represents the temperature range between 70°C and the maximum limit shown in the datasheet of the cable (105 °C) and, finally, the hard fault condition indicates a temperature higher than 105 °C. In this case there are 27 fault classes.
The main theoretical concept on which the operation of the classifier is based is the relationship between cable temperature and cable resistance. In fact, as the working temperature increases, the resistance of the conductor also increases. Equation (1) shows the relationship between the resistivity of the conductor material and its temperature:

$$\rho_\tau = \rho_{20} \left[ 1 + (\tau - 20) \alpha \right]$$

where $\rho_\tau$ is the resistivity of the material at the working temperature $\tau$ expressed in °C, $\rho_{20}$ is the resistivity at 20°C, and $\alpha$ is the thermal coefficient of the conductor material. Starting from this value it is possible to calculate the resistance of the cable referred to the unit of length and the same rule can be used for the sheath material. Equation (2) allows the calculation of the resistance with respect to the size of the cable:

$$R_\tau = \frac{\rho_\tau}{S}$$

where the term $S$ represents the surface of the material considered. Formula (2) can be used for the conductor and the sheath, obtaining $R_{\tau c}$ and $R_{\tau s}$ respectively. As shown in [13], the variation in resistance introduces a corresponding change in the frequency response of the network. Therefore, the line admittance measurements contain the cable temperature information, and the primary purpose of the classifier is to extract this information.

In order to train the intelligent classifiers, it is necessary to create a specific dataset containing several samples of each possible fault class. Since the machine learning techniques used in this work require a supervised learning algorithm, the dataset must contain examples of line admittance measurements with the corresponding fault class index. To obtain this information, a Simulink-Simscape scheme managed by a Matlab script is used and the three sections of the cable taken into consideration are simulated using the block called “Three-phase AC power cable”. Before looking at the simulation procedure in detail, it is necessary to evaluate the Testability of the electrical circuit and define the main characteristics of the coupling system used to simulate the measurements.

2.2. Testability assessment

Testability assessment represents a fundamental step for any diagnostic system based on FRA in the field of analog circuits [14]. In general, more than one electrical component can be faulty when a malfunction occurs and, therefore, the detection of the faulty component depends on the corresponding variation of the frequency response. The Testability assessment can be obtained as shown in [15] starting from the symbolic form of the circuit transfer function. When Testability is maximum, it corresponds to the total number of potentially faulty components. In this case, each electrical parameter introduces a different variation in the frequency response, and it can be detected in the event of fault. In this work, the Testability analysis is performed as shown in [16] considering the cascade connection of three pi-models. In fact, the previously mentioned Simulink-Simscape block is based on a pi-structure in which the user can choose the value of the resistance per unit of length. This means that during the testability study the three resistances of the equivalent circuit must be considered as variable terms. Therefore, if the testability is equal to three, each resistance introduces a different variation in the line admittance and four classes of failure are distinguishable. The symbolic procedure confirms the maximum Testability value and, consequently, it is possible to detect the overheating of each cable section.

2.3. Coupling circuit

As mentioned before, line admittance measurements are used for FRA. This means that a low voltage signal must be injected at the end of the line and the ratio between current and voltage is considered to train the classifiers. Several signals with different frequencies are used in this work and the bandwidth taken into consideration is the CENELEC band, normally used for PLC in Europe [17-18]. The frequency range is (35 - 148) kHz, and a high pass filter is used to exclude the fundamental component (50 Hz) from the measurements. A matching transformer is used to adapt the transmitter impedance and the line impedance respecting the scattering parameters reported in [19] and the attenuation level.
shown in [20]. The Simulink-Simscape scheme is completed by introducing “line traps” as described in [21].

3. Simulation procedure
The simulation procedure presented in this paper is organized in three main steps: creation of the Simulink-Simscape electrical circuit, dataset generation and training of the machine learning techniques.

3.1. Electrical circuit
The first step in the simulation procedure is the creation of the equivalent circuit using the Simulink software and the elementary blocks belonging to the Simscape library. The main parts of the diagram are the blocks called “Three-phase AC power cable”, which allow the simulation of the line starting from the cable size and laying characteristics. The use of these blocks allows the simulation of the cable behaviour in a very realistic way, and it is not necessary to calculate all the effects on the pi-model caused by the phase current, the positioning of the conductors and the configuration of the MV network. In this way the prognostic method can be easily adapted to other types of network and the analytical procedure for the creation of the dataset is simplified. Three of these blocks are used in cascade connection as shown in figure 1 and the “Expanded three phase ports” configuration is selected to analyse each phase conductor separately. The user interface of these blocks requires the geometrical characteristics of the cable, the relative position of the phases and the values of conductor and sheath resistance. Table 1 summarizes the main information of the underground cable considered. It should be noted that the cable length shown in table 1 refers to a single cable section.

| Table 1. Cable Characteristics |
|-------------------------------|
| Cable length (km) | Conductor radius (mm) | Sheath radius (mm) | Outer cable radius (mm) | Line-line spacing (mm) | Line formation | Insulation relative permittivity |
|------------------|----------------------|--------------------|------------------------|-----------------------|----------------|-------------------------------|
| 0.3              | 7                    | 17                 | 23.2                   | 46.4                  | Flat           | 2.4                           |

It is necessary to highlight that the resistance values required from the blocks are referred to unit of length and represent the variable terms used to describe the working temperature of the cable. They are set at the start of each simulation to create different working conditions. In order to inject the signals used for measurements, a fourth order high pass filter is used. It is built with common analog components from the Simscape library and designed using the Butterworth approximation. The equivalent model of the network is completed by the introduction of a line trap for each phase, which is constituted by a double resonant circuit designed as shown in [21]. Figure 1 shows the Simulink-Simscape diagram used for the simulation procedure.

![Figure 1. Simulink-Simscape diagram.](image-url)
3.2. Dataset generation

The generation of the dataset is performed using a MatLab script in which the user can set the characteristics of the cable shown in Table 1 and calculate the resistance values by (1) and (2). As previously mentioned, the dataset must contain the measurements of the line admittance at multiple frequencies and the corresponding fault class. The cable used in this work is extracted from [2] and presents a maximum working temperature of 105 °C. Assuming that the phase current is approximately equal to the maximum current rating of the cable, and that the ambient temperature is equal to 25°C, the working temperature of the cable is about 70°C. The heat balance equation shown in [11] is used to obtain this value.

3.2.1 Dataset generation in the single fault hypothesis. In this case two possible working conditions are considered for each cable section: when the cable temperature is lower than 70°C, it is assumed that it works in nominal condition; if, on the contrary, the temperature exceeds 70°C, the cable is considered overheated. Consequently, the meaning of the four classes of failure can be summarized as follows.

- Class 0: the working temperature of each cable section is lower than 70°C.
- Class 1: the working temperature of the first cable section is higher than 70°C.
- Class 2: the working temperature of the second cable section is higher than 70°C.
- Class 3: the working temperature of the third cable section is higher than 70°C.

The lowest working temperature is assumed equal to 30°C and represents the condition of minimum load. The maximum working temperature is 135 °C and indicates that there is a problem. In order to create the dataset, 200 samples for each fault class are generated by randomly choosing the temperature of each cable section in the range (30-70) °C and (70-135) °C. These temperatures are converted into resistance values using (1) and (2) and then implemented in the cable models. The measurements of the line admittance (magnitude and phase) are extracted from Simulink and saved in a specific matrix with the corresponding class number in the last column. Equation (3) represents the structure of the matrix used as a dataset.

\[
\begin{bmatrix}
|M_1|_{f_1} & |\Phi_1|_{f_1} & L & |\Phi_1|_{f_0} & 0 \\
|M_2|_{f_0} & |\Phi_1|_{f_0} & L & |\Phi_1|_{f_m} & 0 \\
M & M & O & M & M \\
|M_{100}|_{f_1} & |\Phi_{100}|_{f_1} & \ldots & |\Phi_{100}|_{f_m} & 3
\end{bmatrix}
\]  

where, for example, $|\Phi_{100}|_{f_1}$ represents the second measure of magnitude corresponding to the class 0 made at the frequency $f_1$ and $|\phi_{100}|_{f_1}$ represents the second measure of phase corresponding to the class 0 made at the frequency $f_1$. It is necessary to observe that all measurements are repeated for each test frequency. In this paper 100 frequencies are selected in the CENELEC band, dividing the range (35-148) kHz in 100 equal parts [23].

3.2.2 Dataset generation in the multiple fault hypothesis. In the hypothesis of multiple failure, it is necessary to adapt the dataset described in (3) to the number of fault classes. Since there are three possible conditions for each cable section, the dataset matrix is changed as shown in (4). The last three columns represent all possible combinations of the three cable sections: the number 0 is used to describe the nominal condition (30-70) °C, the number 1 represents the soft fault condition (70-105) °C and the number 2 is used to describe the hard fault condition (105-135) °C. In this case are used 45 samples for each fault class and 10 frequencies which equally divide the CENELEC band.

\[
\begin{bmatrix}
|M_1|_{f_1} & |\Phi_1|_{f_1} & L & |\Phi_1|_{f_0} & 0 & 0 & 0 \\
|M_2|_{f_1} & |\Phi_1|_{f_1} & L & |\Phi_1|_{f_m} & 0 & 0 & 0 \\
M & M & O & M & M & M & M \\
|M_{1215}|_{f_1} & |\Phi_{1215}|_{f_1} & L & |\Phi_{1215}|_{f_m} & 2 & 2 & 2
\end{bmatrix}
\]
3.3. Machine learning techniques

The main purpose of this work is the development of a monitoring system able to recognize the working condition of the cable sections by analysing the admittance measurements. To achieve this goal, two different machine learning techniques are used: Support Vector Machine and Complex Neural Network. The procedure is organized in two steps: training phase and testing phase. During the training phase, a part of the dataset is used to calculate the classification error and modify the weights of the structure. In the test phase, however, the performance of the classifiers is checked without correction.

3.3.1 Complex Neural Network in the single fault hypothesis. The theoretical basis of the Complex Neural Network is described in [24] and some applications of this tool in diagnostic problems are shown in [13, 16, 25]. In this paper, the discrete activation function (5) is used, and one output neuron is considered for each cable section.

\[ P(z) = e^{\frac{2\pi j}{k}} \text{ if } \frac{2\pi j}{k} \leq \arg(z) \leq \frac{2\pi (j+1)}{k} \]

In equation (4), \( k \) is the total number of the sectors into which the neurons divide the complex plane, \( j \) represents one of the possible sectors and \( \arg(z) \) represents the argument of the weighted sum \( z = W'_{1}X_{1} + \cdots + W'_{n}X_{n} \). Therefore, the complex neural network has three outputs and a variable number of neurons in the hidden layer. This number is set by a heuristic approach during the learning phase. It should be noted that each output neuron is binary and can assume the values 0 or 1. In fact, each output neuron divides the complex plane into two sectors: the first corresponds to the upper half plane \([0, \pi]\) and is identified by the value 0; the second sector corresponds to the phase interval \([\pi, 2\pi]\) and is encoded by the number 1. In the single fault hypothesis, when the first output neuron is “high” the first fault class is identified. Similarly, the high level on the second or third neuron corresponds to the second or third class respectively. When all outputs are “low”, class 0 is the result of the classification procedure. The “winner takes all” rule is used to get a single high-level output. The inputs of the network are the complex numbers corresponding to the line admittance measurements. Initially the complex weights are randomly chosen and then, by applying a backpropagation procedure, their values are modified to minimize the classification error [24]. Equation (6) represents the standard rule used for weight correction,

\[ \Delta W_{i}^{k,m} = \frac{\alpha_{k,m}}{(n_{m+1}+1)}|z_{i,m}^{s}| \delta_{i,m}^{s} \bar{Y}_{c,m-1} \]

where \( \Delta W_{i}^{k,m} \) is the correction for the \( i \)-th weight of the \( k \)-th neuron belonging to the layer \( m \), \( \alpha_{k,m} \) is the corresponding learning rate, \( n_{m+1} \) is the number of the inputs equal to the number of the outputs of the previous layer, \( |z_{i,m}^{s}| \) is the magnitude of the weighted sum calculated for the \( s \)-th sample, \( \delta_{i,m}^{s} \) represents the corresponding output error obtained through the backpropagation method and \( \bar{Y}_{c,m-1}^{s} \) is the conjugate-transposed of the input. In this work, the correction rule is optimized by applying a linear least square (LLS) method as shown in [26].

3.3.2 Complex Neural Network in the multiple fault hypothesis. Even in the hypothesis of multiple failure, the discrete activation function shown in (5) and the learning rule described in (6) are used. Furthermore, the binary nature of neurons is maintained, but the structure of the output layer is changed. In this case two output neurons are used for each cable section: the first of them is used to distinguish the nominal condition from the soft fault condition, while the second neuron identifies the presence of a hard failure. In fact, when both neurons are “low”, the nominal condition is identified. If, on the other hand, both neurons are “high”, a hard fault is presumed. Finally, the situation with the first neuron “high” and the second “low” is used to describe the soft fault condition. This means that the output layer of the complex neural network has six neurons, two for each cable section.

3.3.3 Support Vector Machine. The training of the Support Vector Machine algorithm is performed through a MatLab toolbox called “Classification Learner”. In this case, the classifier processes
magnitude and phase separately without forming the corresponding complex number. This type of algorithm focuses on finding the best hyperplane that separates data points of one class from those of the others. Since in this case there are more than two classes, the learning method used is called “One-vs-One”. This means that the training procedure is done six times, once for each pairs of classes. Therefore, six binary classifiers are trained, and, at the end of the procedure, the most probable class is chosen for each element of the dataset. In this paper a quadratic learner function is used.

4. Results and conclusion
The main index used to evaluate the performance of the machine learning techniques is called Classification Rate (CR). It corresponds to the ratio between the number of correctly classified samples and the total number of samples. The first simulation presented in this paper concerns the single-fault hypothesis. In this case, hold-out validation is used, and this means that 80% of the data is processed during the training phase and 20% during the testing phase. Therefore, at the end of each training phase, the classification results are verified by using unused samples for weights adjustment. For the complex neural network, a specific MatLab application developed by the authors is used, and the trend of the CR in the two phases can be graphically checked as shown in figure 2. Table 2 shows the classification results obtained during the testing phase for both machine learning techniques. Finally, a further verification of the results is achieved by applying the classifiers on measurements extracted directly from the Simulink model. Figure 3 shows these classification results.

Figure 2. Classification rate obtained during the training phase (red line) and testing phase (blue line) for the Complex Neural Network in the hypothesis of single fault.

Figure 3. Performance of the classifiers obtained on new data directly extracted from the Simulink diagram in the case of single fault.

Table 2. Classification Results

|                | CNN       | SVM       |
|----------------|-----------|-----------|
| Classification Rate | 96.528%   | 95.8%     |

It can be stated that the performance is excellent for both techniques and the results obtained during the training phase are confirmed. As for the simulation in the hypothesis of multiple failure, the overall accuracy level of the monitoring system decreases due to the high complexity of the problem (27 fault classes). However, the complex neural network-based classifier has a classification rate higher than that of the SVM technique by 10%. Furthermore, by analysing the performance of each output neuron, it is possible to make some considerations: first, it can be seen that the classification rate of the first
four neurons is greater than 90% and this means that the monitoring system can accurately identify the health status of the first two cable sections. As shown in figure 4, the neurons used to classify the health conditions of the third cable section have a classification rate of approximately 80%.

![Classification Rate](image)

**Figure 4.** Classification Rate.

This result, although good individually, causes a decrease in overall performance compared to the case of a single failure and will be studied in detail in future works to further improve the proposed monitoring system. Therefore, as shown in table 3, the proposed classifier allows the accurate identification of the working temperature of each single cable section, while further development will be necessary to classify all the possible combinations of three and more cable sections. Currently, the main limitation of the prognostic method consists in the low number of cable sections that can be analysed simultaneously while maintaining high reliability. As regards the practical application of this analysis, it should be noted that the PLC coupling system must be slightly modified with respect to the normal setup to inject the measurement signals, and, in addition, not all the lines are equipped for power line communications. In this sense, one of the most important future developments will be the adaptation of the monitoring system to MV networks with multiple branches and the study of how the load and closure conditions of the line can modify the performance.

| Neuron   | Classification Rate | Cable Section |
|----------|---------------------|---------------|
| Neuron 1 | 96.71%              | 1             |
| Neuron 2 | 95.06%              |               |
| Neuron 3 | 97.53%              | 2             |
| Neuron 4 | 93.00%              |               |
| Neuron 5 | 78.19%              | 3             |
| Neuron 6 | 80.25%              |               |

**Table 3.** Classification results for each neuron in the multiple fault hypothesis

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