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Field Electrical Engineering

PhD THESIS
– ABSTRACT –

Contributions to fault detection and prediction in electrical cables

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INTRODUCTION

Electricity has gradually insinuated itself over time into almost all sectors of daily life. It is hard to imagine a sector in which this has not become an acute necessity. In these new circumstances, continuity in the supply of electricity to consumers has become a permanent concern, ensuring a quality of electricity supply is ultimately an important indicator of the quality of life. On the other hand, any interruption of the electricity supply process leads to economic losses, difficulties in carrying out technological processes, risks in the carrying out of medical procedures and finally to irritation and discomfort in people's lives.

To ensure the continuity and reliability of an electricity distribution system, it is essential that all of its constituent elements operate at the required parameters. If one of the components does not work at normal parameters, it affects the entire system, affecting the quality of electricity and implicitly the equipment powered from it.

Electric cables have a significant weight in any electrical energy transport and distribution system, so their integrity is a constant concern of supply companies [1]–[4]. That is why the need to detect and locate faults in electrical cables has led to the development of a wide variety of methods and with them more and more efficient support equipment [5]–[12].

The use of the Matlab/Simulink platform allowed the development and testing of a reflectometer model, whose interactive interface helps substantially to understand and deepen the method's operating principle, while also allowing the simulation of practical situations in which real-time reflectometry was used in determination of the type of fault and its location.

Continuing the development of innovative aspects, an algorithm for detecting and predicting faults in medium and low voltage electrical cables was designed and tested, an algorithm based on artificial intelligence. Its implementation required the following preliminary stages: the analysis of electrical cables and the types of possible faults, the analysis of methods for detecting and locating faults in electrical cables and, finally, the study of the equipment designed to locate the routes of underground electrical cables and the faults that can appear in these. After going through these stages, it has been modeled and simulated a solution for detecting and locating faults in electric cables, by developing an algorithm for detecting and predicting faults in electric cables, based on artificial intelligence philosophy, in particular on artificial neural networks.

Far from being just a field of topicality, which penetrates almost mystifyingly, sometimes insidiously and sometimes even brutally in some aspects of human life and civilization, for the present thematic based on artificial intelligence, it represents, as will be seen in the thesis chapters, a innovative and at the same time particularly useful technical support, which will obviously lead to the evolution of this field, which it will enrich with new and important future approaches.

Prediction, which represents the key and novelty element in the problem of cable faults, is one of great importance, especially in the current conditions when the approach to the concept of predictive maintenance is increasingly taking place in the concerns of utility companies, considerably improving the continuity of supply and the quality of electricity, being at the same time a generator of material and cost savings.

The work is structured in two large parts: the first part, dedicated to the current state of knowledge, includes five chapters, the following four chapters, representing the second part, which is the author's personal contribution.

Contents of the chapters:

Chapter 1 contains a series of theoretical aspects related to the analysis of electricity transmission lines and their characteristic parameters.

Chapter 2 presents a brief classification of electrical cables and their main characteristics.

Chapter 3 details the main types of faults encountered in electrical cables and their causes, with particular emphasis on short circuits.

Chapter 4 presents four methods for detecting and locating faults that may occur in electrical cables, namely: time-domain reflectometry, impedance-based methods, travelling wave methods, and artificial intelligence-based methods.

Chapter 5 is dedicated to equipment for the detection and location of underground electrical cable routes and equipment for the detection and location of faults in electrical cables.

Chapter 6 presents a practical application of detecting and locating a fault in an underground electrical cable using a Ridgid SeekTech SR-60 locator in conjunction with the Ridgid SeekTech ST-510 transmitter. Thanks to the high accuracy of the locator, the route of the underground electric cable connecting a generator set used for emergency power supply in a commercial space (mall) and its transformer station located inside the building was identified.

Chapter 7 is dedicated to the location of a fault in an electrical cable (presented in chapter 6), made with the help of a Megger TDR 2000/2R reflectometer. Using the principle of real-time reflectometry, led to the location of the fault in the cable and the establishment of the type of defect according to the appearance of the graph displayed on the equipment screen. In order to obtain high accuracy, the theoretical elements presented in chapter 5 were applied.

Chapter 8 presents the modeling and simulation of a solution for detecting and locating faults in electrical cables, based on time-domain reflectometry, modeling and simulation developed with the help of Matlab and Simulink (R2022a) programs. It contains two sections, one in which the modeling of a reflectometer is detailed and one in which the development of an interactive interface of the reflectometer model is presented. Through this modeling and the interactive interface, one can study and deepen the way a reflectometer works.

Chapter 9 details the development of fault location and classification algorithms in electrical cables using artificial neural networks that can be used to predict the location and location and type of a fault in a power distribution system. These algorithms were developed using the Matlab/Simulink (R2022a) platform. In order to develop the algorithms, four steps were followed: modeling an electrical power distribution system, repeatedly running the model simulation, training the algorithms based on artificial intelligence and predicting the location, respectively the location and the type of fault for a new situation. The proposed algorithms overcome the limitations of classical methods of detecting and locating faults in electrical cables, managing to provide viable solutions for complex electrical power distribution systems.

The last two sections are dedicated to the general conclusions, the presentation of the elements of originality and the innovative contributions of the thesis.

CURRENT STAGE OF KNOWLEDGE

1. Theoretical aspects regarding the transmission of electrical energy through cables

An electrical system with lumped parameters is one in which any change in electrical quantities occurring at one point of the system propagates instantaneously to any other point of the system. The hypothesis is only valid for an electrical system called a short electrical system. The concept of short electrical system must be understood in conjunction with the concept of electrical length of the system for a given frequency. The electrical length is a dimensionless quantity defined as the ratio between L, the physical length of the system, and λ, the wavelength corresponding to the frequency of the signal trafficked in the system. Thus: electrical length = L/λ. In general, any system whose electrical length is less than 1/20 can be considered electrically short [13]. Such a system, having lumped parameters, can be modeled by ordinary differential equations.

On the other hand, in a system with distributed parameters, it takes a finite time for a change in an electrical quantity occurring at one point of the system to be transmitted to another point at a given time. Thus, in addition to the time-independent variable, the spatial variable must also be considered, the equations describing systems with distributed parameters becoming equations with partial derivatives dependent on both time and the spatial variable.

Strictly speaking, all systems can be considered to some extent, distributed parameter systems. Power transmission line models are an eloquent example. Each elementary section of a line is characterized by resistance, inductance, shunt conductance and shunt capacitance. For short lines, however, the shunt capacitance and conductance are ignored, while for medium-length transmission lines the approximation with concentrated-parameter T and Π quadrupole models is used, while for long transmission lines the models of lines with distributed parameters [14] – [18].

2. Types of electrical cables

The coverage of the various needs in the operation of electrical systems, required the development of multiple types of electrical cables, being mainly used electrical cables with XLPE and PVC insulation, producing a wide range of sections of conductors for both low and medium voltage [19] – [24].

3. Types of faults in electrical cables

Electric cables represent the component with the largest weight in an electrical system, which requires maintaining them in a good working condition. Any fault in a cable leads to the alteration of the operation of the entire system [25]–[27].

Internal and external conditions to which cables are exposed, such as local heating, corrosion, humidity and mechanical aggressions, increase the possibility of faults. Faults can be divided into two main categories: severe defects (open circuit faults and short-circuit faults) and minor defects (insulation damage, cracks, etc.) [28], [29].

On the other hand, faults in cables can be classified into two other categories: incipient defects and permanent defects. Early defects are usually due to their progressive aging process when local insulation damage occurs. Most of the time, incipient faults can turn into permanent faults due to unfavorable environmental conditions [29]–[31].

Open circuit faults type are characterized by an increase in the value of the voltage and a decrease in the value of the current intensity on the faulty phase. Interruptions can occur both on a single phase of the conductor and on several of its phases.

When short-circuit faults occur, an increase in the value of the current intensity and a decrease in the value of the voltage are recorded. This type of fault is divided into five categories: phase to ground, phase to phase, three phase, phase to phase to ground, three-phase to ground [32] – [33].

Short circuit type faults are the most frequent and severe faults, being caused by the degradation of the insulation between phases or between phases and earth [34].

Faults on a cable can occur individually or in different combinations, for example, it can be an open circuit fault with grounding or a short-circuit fault between two phases, with grounding of another phase [28].

The previously described faults can be further divided into two categories, namely symmetrical and unsymmetrical faults. Symmetrical faults are considered three-phase faults such as three-phase short-circuits or three-phase short-circuits with grounding, and the rest of the faults are considered unsymmetrical. The most common faults are the unsymmetrical ones, especially short circuits of the single-phase to ground type [34].

4. Methods of prediction, detection, and location of faults electrical cables

Fast and accurate detection of faults in an electrical system is essential, requiring increased attention due to their possible negative effects on operational safety and economic losses. As a result, numerous methods of fault detection and localization based on various principles have been developed [35]–[37].

Some of the most common fault location methods will be pointed out, namely time domain reflectometry, impedance-based methods, travelling wave methods and artificial intelligence-based methods. Methods capable of both locating and predicting faults will also be presented.

4.1. Time Domain Reflectometry

The time domain reflectometry (TDR) technique is used to evaluate the characteristics of power lines and to detect their faults [38]–[42].

The operating principle of this method of locating faults is similar to a radar. Thus, when transmitting an electrical signal of a certain frequency along a conductor, it will be partially reflected if there is an impedance difference between the load impedance and the characteristic impedance of the line. Due to the time difference between the incident and the reflected signal (delay time) the fault can be located on the conductor [43]–[51].

4.2. Impedance based methods

The methods of locating faults in electric power distribution networks, based on impedance, are divided into methods using one or two line terminals. The methods that use a single terminal are used when the distance between the two extremities is large, while for the use of the method with two terminals a communication system between them is required [35].

The basic principle of this method is to use the impedance value determined at the measurement point, in order to locate the fault. To calculate the impedance, the voltage and current values are used, it is also necessary to know the parameters of the line and the distance between the two terminals [32], [52].

4.3. Traveling-wave Methods

The wave propagation method is based on the principle of wave propagation in a homogeneous medium. When a fault occurs on a cable, voltage and current waves are initiated from the fault location to both ends of the cable [7], [28], [29], [53].

Methods based on wave propagation are divided according to the mode of operation and model into five categories, type A, B, C, D and E.

Type A uses measurements from one end of the line, so the distance to the fault location is calculated as a function of the incident wave due to the fault and its reflection. This type can impose difficulties if there are several discontinuities along the line route, making it difficult to differentiate the waves [28], [53].

Type B uses measurements from both ends of the line and involves starting a timer when the incident wave due to the fault reaches the end closer to the fault and stopping it when the waves reach the other end of the line. With the help of the delay time, the distance to the defect can be determined [33].

Type C is an active method, which involves measurements from one end of the line through which a signal is transmitted on the line, in order to then record its reflection. This method is known as time domain reflectometry.

Type D uses measurements from both ends of the line, increasing the accuracy of the method, but essential is the synchronization of the time measuring instruments at the two ends (using a GPS system) and a communication system to centralize the data.

Type E is a method that takes measurements at one end of the line and uses the transient waves produced when the line is re-energized by closing switches [28], [53].

4.4. Knowledge Based Methods

In addition to the traditional methods of detecting and locating faults, the development of the concept of predictive maintenance also imposed the need for their prediction for electrical cable systems. The latter led to the finding of innovative methods based on principles of artificial intelligence (AI). The used techniques in AI for fault detection are those based on expert systems, fuzzy logic, and artificial neural networks (ANNs) [7], [28], [54].

4.4.1. Expert Systems

Expert systems are interactive systems that work based on written rules using the syntax "If ... Then ...". They can solve problems in a specific domain using a knowledge base.

In the first phase, it is necessary to acquire knowledge from a certain domain with the help of the human expert and the knowledge engineer. After that, the totality of the knowledge becomes the knowledge base to be accessed by the inference engine, in order to be able to generate a solution in the case of a given situation, in accordance with the knowledge base owned by the system [28], [55].

4.4.2. Fuzzy Logic

The specificity of Fuzzy logic is that it provides a conclusion based on vague, ambiguous and imprecise data. In Fuzzy logic, the belonging of an object to a class is not determined by true or false (1 or 0), but is gradual, having the probability between the two limit values above [28], [55].

There is a similarity between this and the structure of expert systems, sometimes referred to as fuzzy expert systems. The inputs to the inference engine first go through the fuzzification process, assigning their degree of membership, and the fuzzy outputs from it go through the defuzzification process, in order to finally obtain the output data [56], [57].

4.4.3. Artificial Neural Networks

Unlike the expert systems and fuzzy logic presented earlier, artificial neural networks (ANNs) do not need a knowledge base, they require a learning process. The learning process is carried out through numerous concrete cases. ANNs are designed according to the human model and consist of layers of interconnected artificial neurons [7], [58] – [68].

5. Equipment used for locating routes and faults in underground electrical cables

Due to the need for continuity in the supply of electricity to consumers, in the event of a fault in an electric cable, it is essential to locate it in the shortest possible time and with high precision. As technology has evolved, powerful equipment has been developed both for locating electrical cable routes (such as the Ridgid SeekTech SR-60 Locator [69]) and for locating faults in them (such as the Ridgid A-Frame Fault Locator and Transmitter FT-103 [69] or the Megger TDR 2000 Reflectometer [70] – [72]).

PERSONAL CONTRIBUTION

6. Detection and location of underground electrical cables routes

In the event of a fault in an underground electric cable, the precise location of its route is essential before locating the fault. To locate the route, the technical drawings project related to the work can be used, with the mention that there is a possibility that the position of the cable may differ in the work compared to the position provided in the technical project.

Locating devices based on the identification of certain preset frequencies can be used for precise locating of underground cable routes. This technique was used to locate the route of a faulty underground cable, which connected the generating set of a commercial space (mall) to one of the transformer substations inside the building.

The generator set (Fig. 6.1) used for the emergency power supply of that mall had a power of 888 kW, and the connection between it and the building was made by three CYY 3x240+120 type cables. As a result of insulation resistance measurements, it was found that one conductor of a cable was defective.

Fig. 6.1 Connecting the Ridgid SeekTech ST-510 line transmitter to the faulty cable

In order to be able to identify the location of the fault on the conductor, it was first resorted to locating its route with the help of the Ridgid SeekTech SR-60 location equipment (Fig. 6.3) together with the Ridgid SeekTech ST-510 line transmitter (Fig. 6.4).

The Ridgid SeekTech SR-60 locator can be used on a wide range of frequencies to locate cables, but to avoid confusion it can be used in conjunction with the Ridgid SeekTech ST-510 line transmitter. For example, if the locator is set to 50 Hz, it will indicate all live underground cables. Unfortunately, in the vicinity of a building, as there are usually several underground circuits, tracking a single conductor becomes extremely difficult. Using the line transmitter makes it easy to track a conductor, as it can be set to emit a frequency of 33 kHz, which is not naturally found on any of the conductors. After connecting the line transmitter to one of the conductors at a certain frequency, the locator is also set to the same frequency, so that the tracing of the conductor's path can be done with very good precision. By following the route with the help of the locator, the exact position of the conductor was determined and its total length (267.3 m) was measured.

Fig. **Error! No text of specified style in document.**.1 Ridgid SeekTech SR-60 Locator

Fig. **Error! No text of specified style in document.**.2 Ridgid SeekTech ST-510 line transmitter

7. Detection and location of faults in electrical cables

To determine the location of a fault in an electric cable, a reflectometer of the type shown in Fig. 7.1 can be used, this being a Megger TDR 2000/2R equipment. This equipment was used to locate the fault on the cable shown in the previous section, which connects the generator set to the commercial space building.

Fig. **Error! No text of specified style in document.**.3 Connecting the Megger TDR2000/2R reflectometer to the faulty cable

In order to make correct measurements with a reflectometer, it is very important that it is calibrated according to the cable on which the measurements are made. The most effective calibration of the device can be done by means of a cable without defect, of known length and having the same characteristics as the faulty cable to be tested. By repeated measurements, the speed of signal propagation is adjusted until the device displays the same length as the actual length of the cable.

After completing the calibration process of the reflectometer, the value of the signal propagation speed was determined to be the ratio 0.550R (55% of the value of the speed of light), and then the measurements for the faulty conductor were performed.

After carrying out the measurement for the faulty conductor, a change in the appearance of the curve displayed on the reflectometer screen is found at a distance of 134.6 m from the reflectometer. Analyzing the appearance of the graph on the reflectometer display, an area is highlighted where there is a possibility of moisture penetration through the conductor insulation.

The chapter highlights the advantages but also the limitations of the classic real-time reflectometry method used. It is a truism that prevention is much easier than cure, which demonstrates and enforces the necessity and superiority of predictive methods that can lead to a predictive maintenance plan from utility companies. This latter approach is one that involves a much higher degree of supply continuity coupled with significant cost reductions.

8. Modeling a solution for detection and location faults in electric cables

One of the most used methods for detecting and locating a fault in an electric cable is based on time domain reflectometry principle, equipments built on this technique are called reflectometers [73]–[78].

8.1. Modeling a reflectometer using the Matlab/Simulink platform

With the help of the Simulink program, a reflectometer was modeled, the model being shown in Fig. 8.1. With the help of this model, the operating principle of reflectometers can be studied, thus highlighting both the advantages and possible limitations of their use [79]–[88].

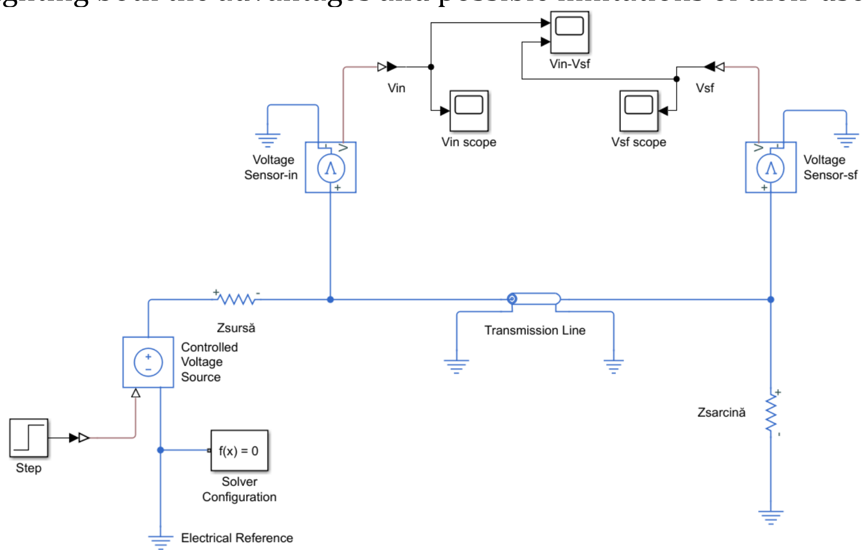

Fig. 8.1 Model of a reflectometer and an electrical cable (Simulink)[81]

For creating the model from Fig. 8.1 were used blocks from both the Simscape electrical library (represented in blue) and from the Simulink library (represented in black), which can be divided into three parts: the signal source, the tested cable and the measuring equipment.

Similar to a real reflectometer, first the operating parameters (signal source parameters and electrical cable parameters) were preset, after which the signal detection process was started by transmitting a signal on the tested cable, finally analyzing the reflected signal pattern.

After setting the parameters of the electrical signal source and the cable, three simulations were performed to verify the correct operation of the model. The situations when the line termination is an open circuit, a short circuit, and a matched impedance termination.

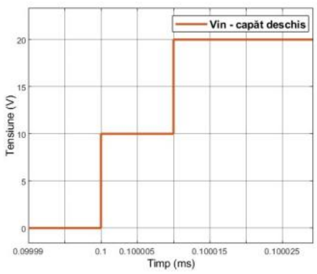

Fig. 8.8 Vin oscilloscope display for an open circuit termination

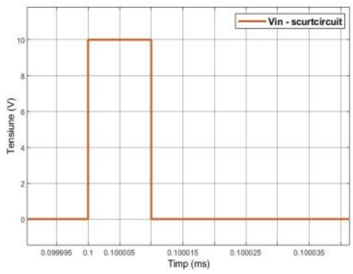

Fig. 8.9 Vin oscilloscope display for an shirt circuit termination

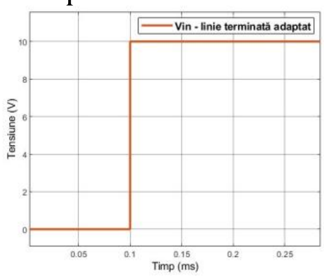

Fig. 8.10 Vin oscilloscope display for a matched impedance termination

After verifying the proper functioning of the model, simulations were performed for situations involving impedance differences along the cable, similar to cable faults. The modeling of an impedance difference on a cable was carried out using two cable segments, between which a resistor (Zd) was inserted, with the help of which several such situations were simulated, assigning different values to Zd. The previously described configuration can be found in Fig. 8.13.

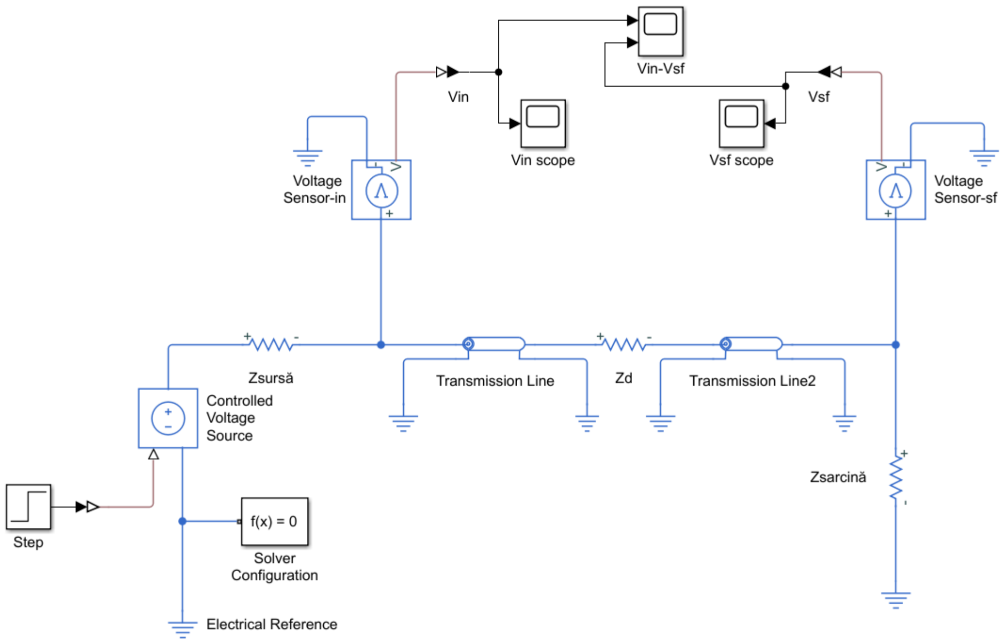

Fig. 8.13 Model of an electrical cable with an impedance difference inserted along its length (Simulink) [81]

In Fig. 8.14 a comparison between two simulations was presented, with the aim of highlighting the influence of introducing the impedance Zd between two identical cable segments. With a broken blue line is represented the reflection of the voltage wave for the case where there is no impedance difference along the length of the cable and the cable has an open circuit termination, and with a continuous red line for the case where an impedance Zd has been inserted in the middle of the cable. Analyzing the graph, it is observed that in the case of the cable without the Zd impedance inserted, the wave change occurs after twice the time duration compared to the case of inserting the Zd impedance in the middle of the cable.

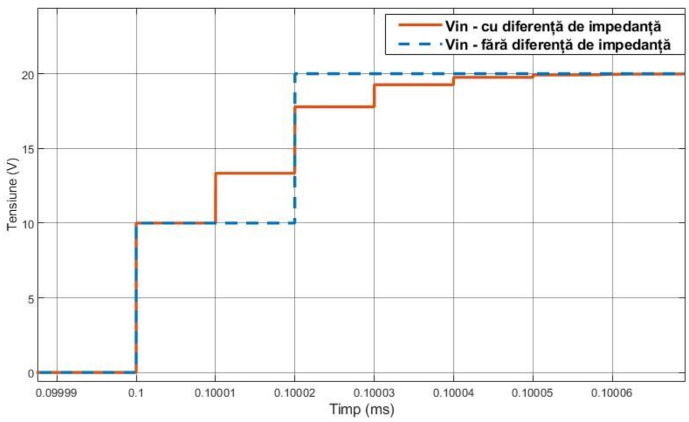

Fig. 8.14 Comparison of Vin oscilloscope displays between a cable with an impedance difference inserted and the same length of cable without an impedance difference

The utility of a TDR-based equipment for detecting and locating faults in a branched cable system was studied. In Fig. 8.17 is exposed a Simulink model containing two cables, named Transmission Line and Transmission Line2 for which several types of termination of the two cables were simulated by means of resistors Zsarcina and Zsarcina2.

For the model from Fig. 8.17 four scenarios were simulated whose graphs are shown in Fig. 8.18 and Fig. 8.19. In Fig. 8.18 are shown two situations with two cables of the same length, which end the same. In the representation with red line both end in open circuit, and in the one with blue line, both in short circuit. It can be seen that at the same moments of time there are changes on the reflected wave captured by the Vin oscilloscopes, but the allure of the graphs is opposite.

In Fig. 8.19, with a red line is highlighted the situation where the two branches have equal lengths, but one end of a cable is an open circuit and one is short-circuited, and with a blue line the two branches have different lengths and their endings are also different.

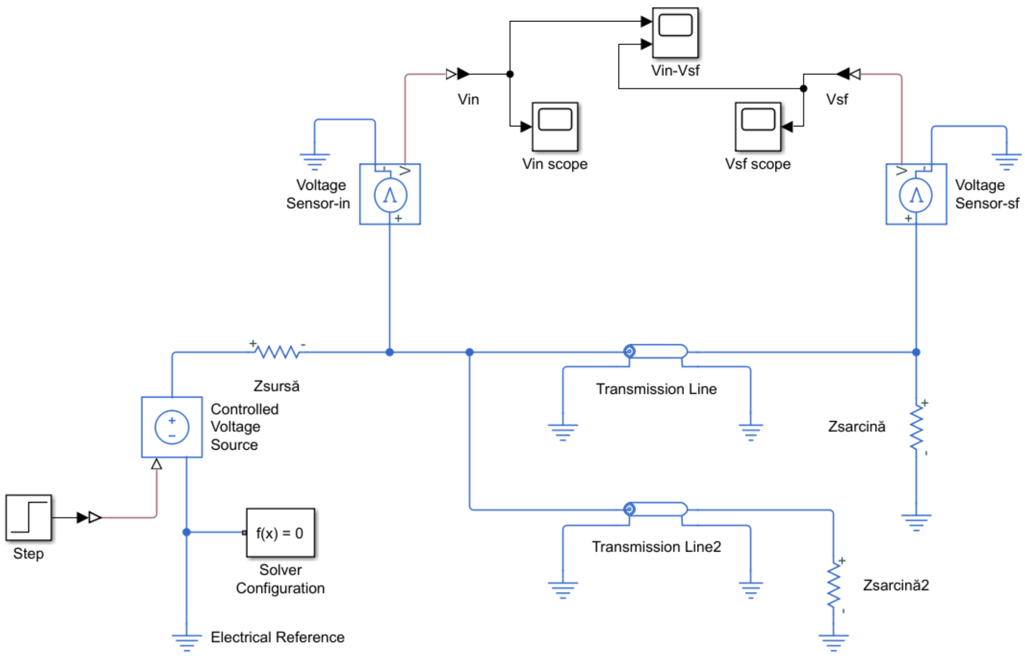

Fig. 8.17 Model of an electrical cable structure having two branches [81]

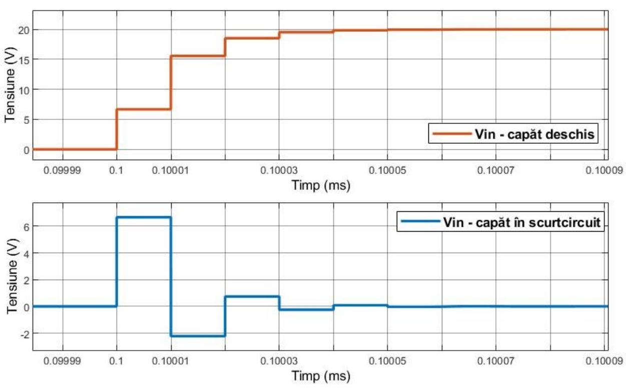

Fig. 8.18 Vin oscilloscope display for the branched structure

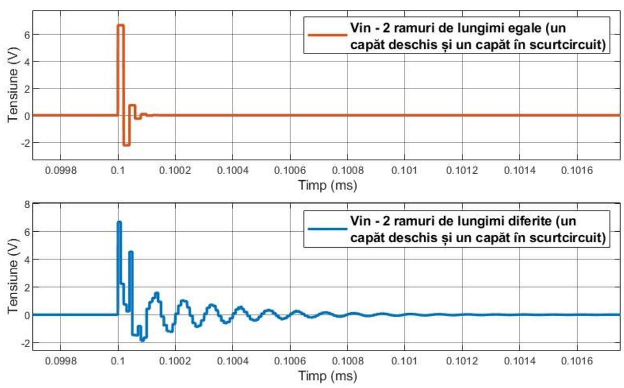

Fig. 8.19 Vin oscilloscope display for the branched structure

After simulating the situations described previously, for a branched model and analyzing the related graphs, it is found that TDR-based equipment is not effective for detecting and locating faults in such a system. In the case of a more complex model, the TDR-based technique is not conclusive, as it is impossible to indicate on which branch the open end is located and on which branch the short-circuited one is located, as it is not possible to locate the impedance differences [9], [81], [89]. Thus, for a branched system, a different approach is needed for locating faults, and one of the proposed solutions is based on artificial intelligence, namely on artificial neural networks [57], [63], [90].

8.2. Development of an interactive interface of the reflectometer model

To facilitate the interaction with the reflectometer model from the Simulink program (Fig. 8.1), an application was created with the help of Matlab App Designer (Fig. 8.20). Through this interface, the model parameters can be modified, and the simulation results can be analyzed.

The application interface is structured in the form of four quadrants: Simulink model, cable and signal source data, signal representation as a function of time, and signal representation as a function of cable length.

In Fig. 8.20 the home screen of the application is shown, noting the four specified quadrants. The image in the quadrant called the Simulink model represents the model of a reflectometer on the basis of which the application operates, and in the "Cable-data" and "Source-data" quadrants are the parameters of the Simulink model that can be modified.

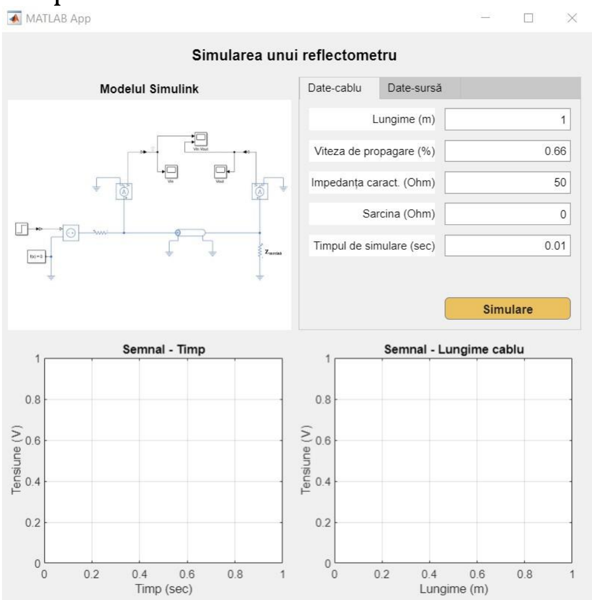

Fig. 8.20 Ecranul de pornire al aplicației – setarea datelor pentru cablu

In the quadrants at the bottom of the interface are two graphs, one for signal versus time and one for signal versus cable length.

By pressing the "Simulate" button, the code starts running, which takes the data from the application interface and enters it into the Simulink model of the reflectometer. Thus, the values set by the user become the parameters of the Simulink model blocks.

The verification of the proper functioning of the application was carried out through three simulations, for the same length of a cable, having the short-circuited termination, the open circuit termination, and the matched impedance termination.

The analysis of the influence of the parameters set using the interactive interface on the reflectometer model was carried out through several simulations by changing the length of the cable, the ratio of the propagation speed or the impedance of the load.

In Fig. 8.25 is exposed the simulation of a cable with a length of 2 m, twice the length compared to the simulation in Fig. 8.22.

Another parameter with a direct influence on the reflected signal is represented by the propagation speed ratio. In the previous examples it was 0.66 (the speed of propagation being 66% of the value of the speed of light). In Fig. 8.28 the situation of a 1 m long cable was simulated, having a propagation speed ratio of 0.55. For this situation, the time required to travel the cable is $0.00012 \cdot 10^{-4}$ sec, compared to $0.0001 \cdot 10^{-4}$ sec for the same length of cable (1 m) but for a velocity ratio of 0,66. It is obvious that with the decrease in the propagation speed there is an increase in the cable travel time. This parameter is essential in the calibration process of real reflectometers, so that the recorded measurements are conclusive.

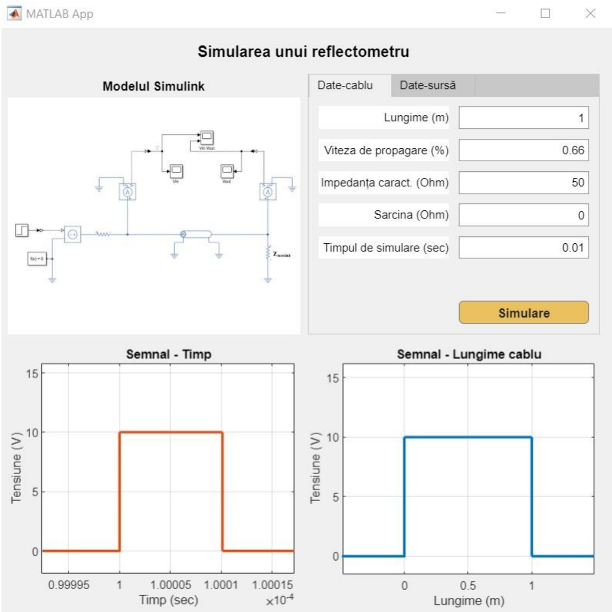

Fig. 8.22 Simulation of testing a 1 m long cable, with short circuit termination

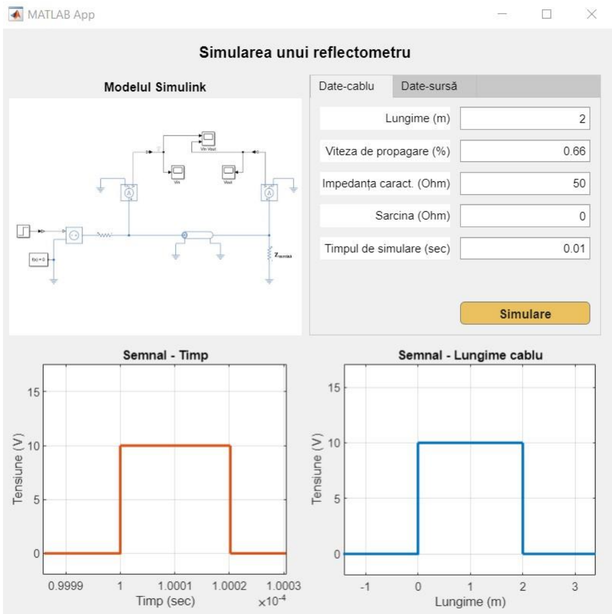

Fig. **Error! No text of specified style in document.**.4 Simulation of testing a 2 m long cable, with short circuit termination

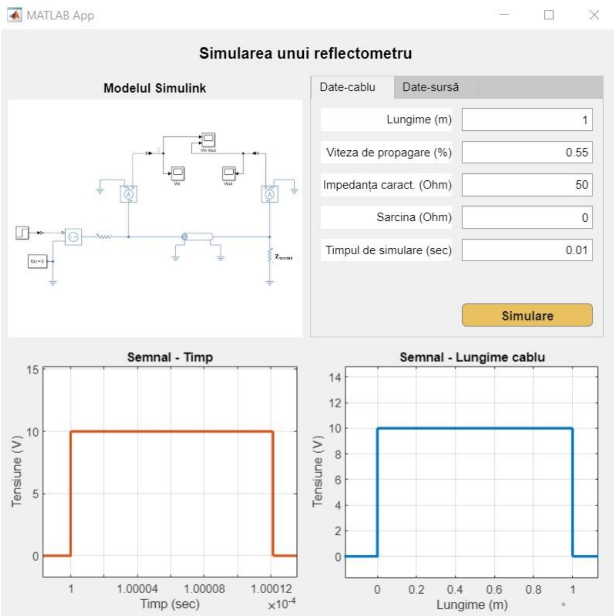

Fig. 8.28 Simulation of testing a 1 m long cable, with short circuit termination and propagation speed ratio of 0.55

The simulation of a faulty cable was realized through an application like the one in Fig. 8.29 based on the Simulink model shown in Fig. 8.13.

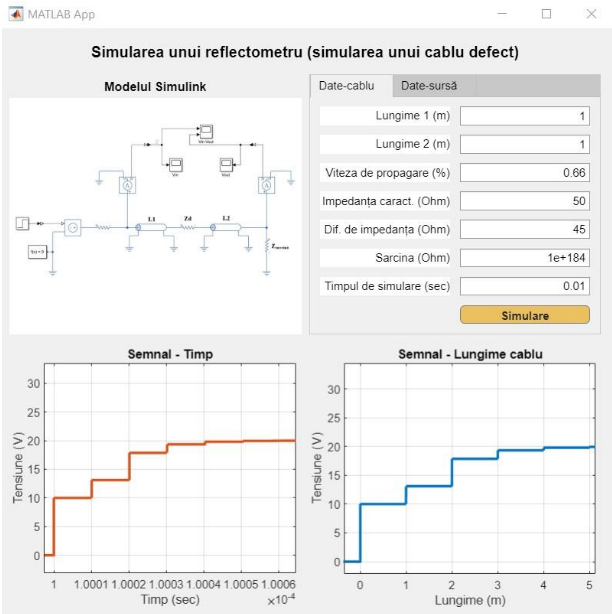

Fig. 8.29 Simulation of testing a 2 m cable with an open circuit termination and an impedance difference of 45 Ω at 1m from the signal source

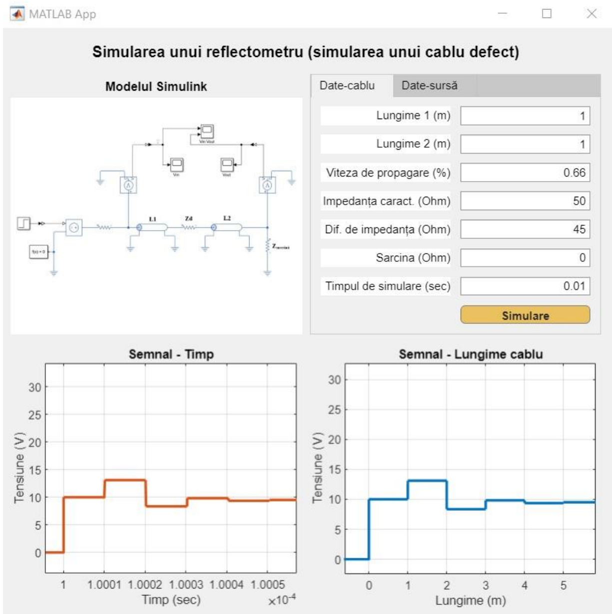

Fig. 8.30 Simulation of testing a 2 m cable with an short circuit termination and an impedance difference of 45 Ω at 1m from the signal source

As presented in the previous section, in order to simulate a faulty cable, a resistor was inserted in the Simulink model that introduces an impedance difference (Zd) between two cable segments. Because of this, the input data required for the application is more in number than for the previous application. In addition to the first application, two cable lengths are required, length 1 (m) for the first cable segment, length 2 (m) for the second cable segment and the impedance difference (Ω), as can be seen in Fig. 8.29.

In Fig. 8.29 and Fig. 8.30 the situation of a cable with a total length of 2 m was simulated, with an impedance difference inserted at a distance of 1 m from the signal source. The two simulations are similar to using real equipment, because for the same cable data, a measurement with the open end (Fig. 8.29) and a measurement with the short-circuited end (Fig. 8.30) are performed.

After analyzing the displayed results, a change in the signal wave is observed after the distance of 1 m, the place where the signal meets the impedance difference, and the difference between the displays of the two cases appears after the distance of 2 m, that is, at the end of the tested cable.

To illustrate that this application also works for longer cable lengths, the simulation in Fig. 8.31, where an impedance difference is introduced at a distance of 1000 m from the signal source, on a cable with a total length of 1500 m. Having a longer cable length required the simulation time of the Simulink model to be set to 0.1 sec versus 0.01 sec value set in previous examples.

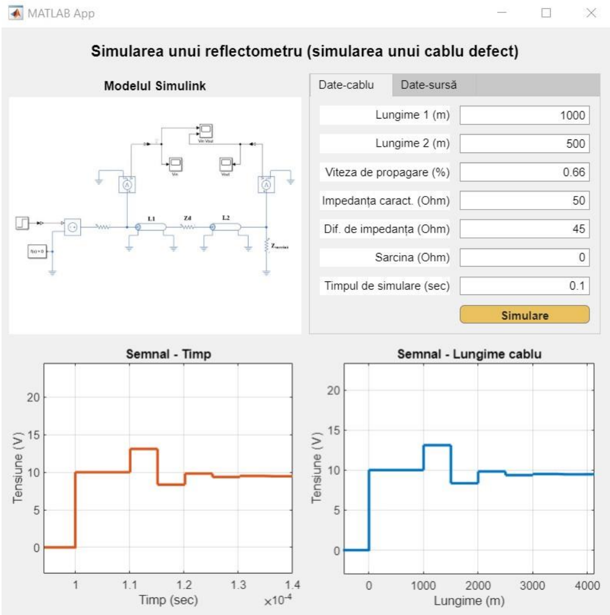

Fig. 8.31 Simulation of testing a 1500 m long cable with a short circuit termination and an impedance difference of 45 Ω at a distance of 1000 m from the signal source

The presented applications represent a useful tool in understanding the working principle of a reflectometer and highlight the importance of calibrating real equipment before starting the actual measurements. Also, the developed model and interactive interface represent useful simulation tools in the analysis of the detection and localization of faults in real situations.

9. Algorithms for detection and prediction of faults in electrical cables using Artificial Neural Networks

The methods of locating and detecting faults in electrical cables exposed previously have the disadvantage of not being effective in the case of a power distribution system, which has many ramifications. A solution to solve this impediment can be implemented with the help of algorithms based on artificial intelligence (AI) [91]–[97], especially with the help of artificial neural networks (ANNs) [98]–[104]. Next, an RNA-based method is detailed, the process diagram of which is shown in Fig. 9.1.

The proposed method combines the advantages of simulating an electricity distribution system using the Simulink program with the versatility of the Classification Learner application within the Matlab program. This method achieves a prediction with increased accuracy of both the fault location and the location and type of fault in an electrical cable. Its implementation involves going through four stages: creating the Simulink model, repeatedly running the Simulink model simulation to create the database needed to train the learning algorithms, classifying the place or place and the type of fault with the help of artificial intelligence within the Classification Learner application, and finally, prediction of fault location and type for further fault cases [68].

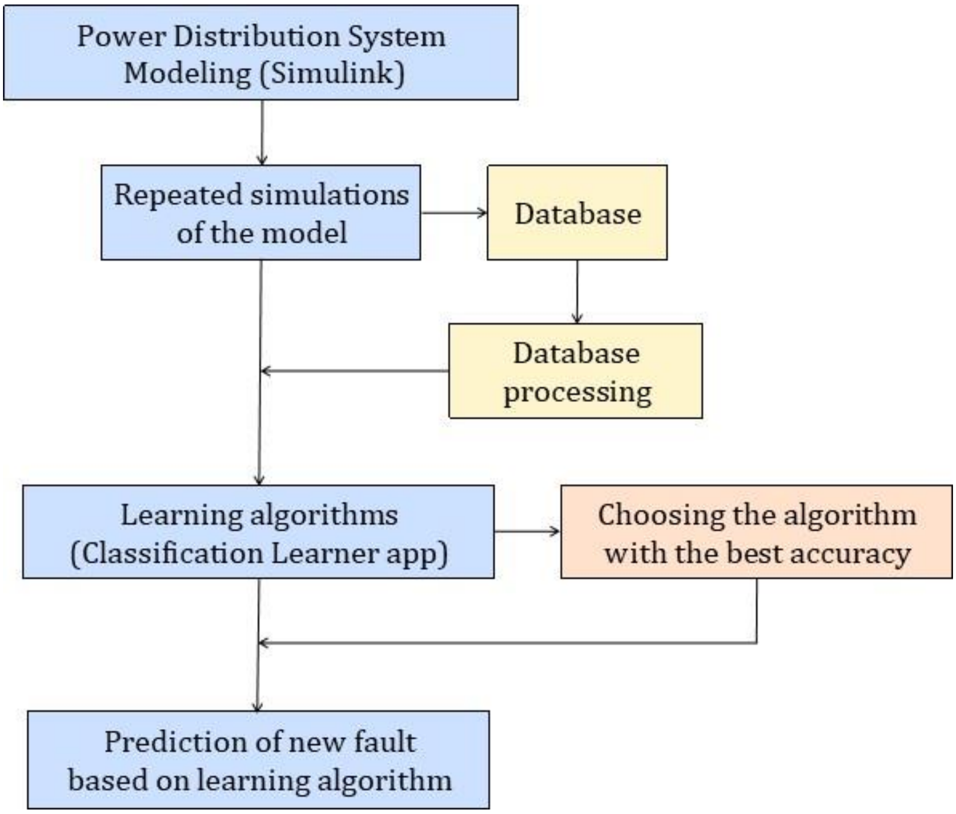

Fig. 9.1 Process diagram of the presented method

9.1. Power distribution system modeling (Simulink model)

In the first stage of the presented method, a model was made in the Simulink program (R2022a) of an electrical energy distribution system, shown in Fig. 9.2, with the help of blocks from the Simscape electrical library, a library dedicated to electrical systems [105], [106]. The concept of this model involves repeatedly simulating it for short-circuit faults in different places and recording the voltage and current values for each situation. The data obtained from numerous simulations were used as a database for the learning algorithms within the Classification Learner application in the Matlab program [68].

The Simulink model, from Fig. 9.2, contains:

- a three-phase source block (depicted in green);
- six subsystems (L1-L6), for six lines (depicted in dark green);
- eight three-phase voltage-intensity measurements blocks (B1 - B8, depicted in blue);
- three-phase load blocks (noncolored);
- a three-phase fault block (bordered in red);
- powergui block.

The modeling of the electrical cables was accomplished by six subsystems (L1 - L6, ex. Fig. 9.4), inside which there are three or four cable simulation blocks with distributed parameters.

The six subsystems represent a total length of 22 km of electrical cables, made up of 1 km long segments. The modeling of electric cables with the help of segments allows the introduction of the three-phase fault block after each separate km, obtaining 22 locations for which fault simulations were done, for each of the locations simulating all possible types of short circuit.

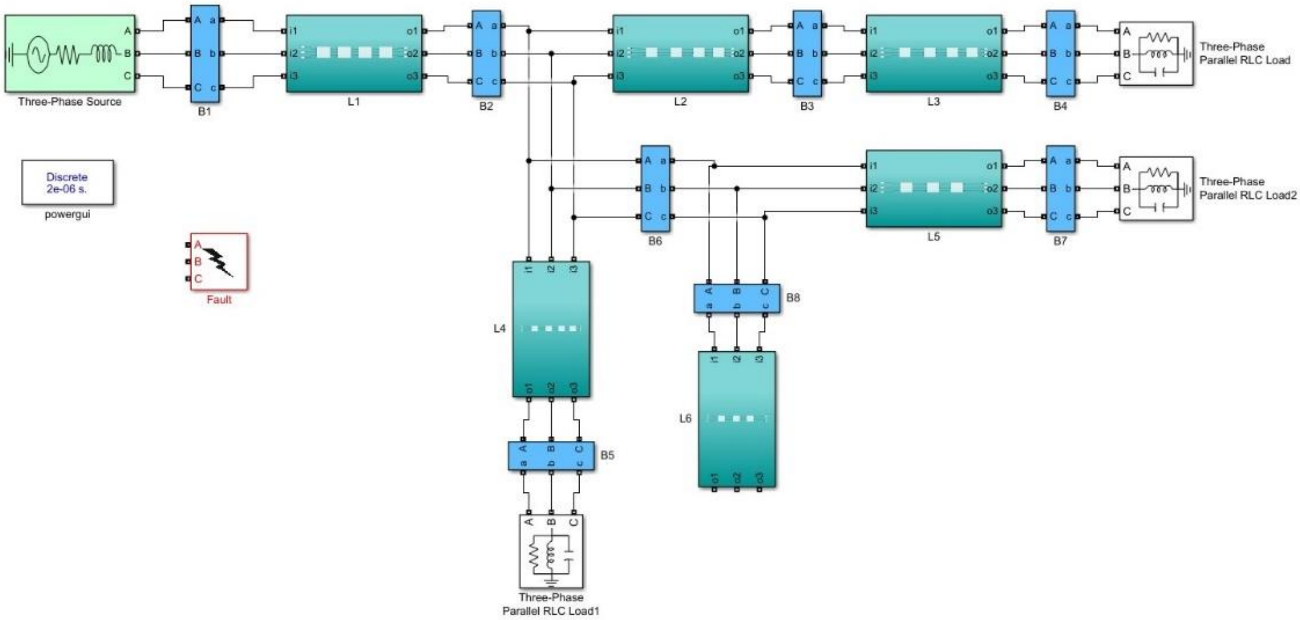

Fig. **Error! No text of specified style in document.**.5 Distribution electrical system – Simulink model [68]

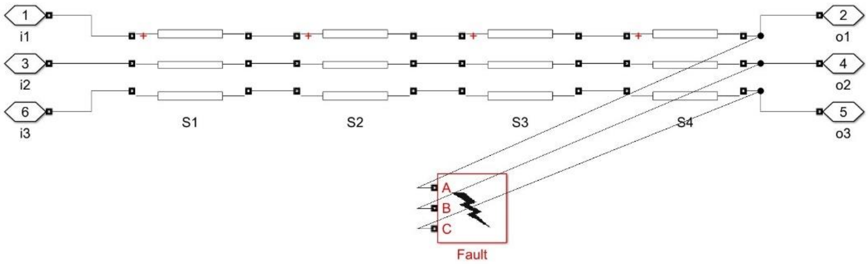

Fig. 9.4 Fault block connected to L1 – Sector 4 [68]

The three-phase fault block was used to simulate short-circuit type faults for electric cables, all 12 possible fault types, shown in Table 9.1, were simulated, and the values for the fault resistance (Ron) and ground resistance (Rg), from Table 9.2 were considered.

Tabel 9.1 Types of faults

Tip defect	ag	bg	cg	ab	bc	ac	abg	bcg	acg	abc	abc	normal

Tabel 9.2 Values for fault resistance (Ron) and ground resistance (Rg)

Ron (Ω)	0,0001	0,0021	0,0447	0,9457	20
Rg (Ω)	0,0001	0,0021	0,0447	0,9457	20

After each simulation, all the values measured by the measurement blocks (B1 - B8) were entered into a database. So that the measurements can be processed later, the data acquisition structure shown in Fig. 9.9, Fig. 9.10 and detailed in Fig. 9.11 was used.

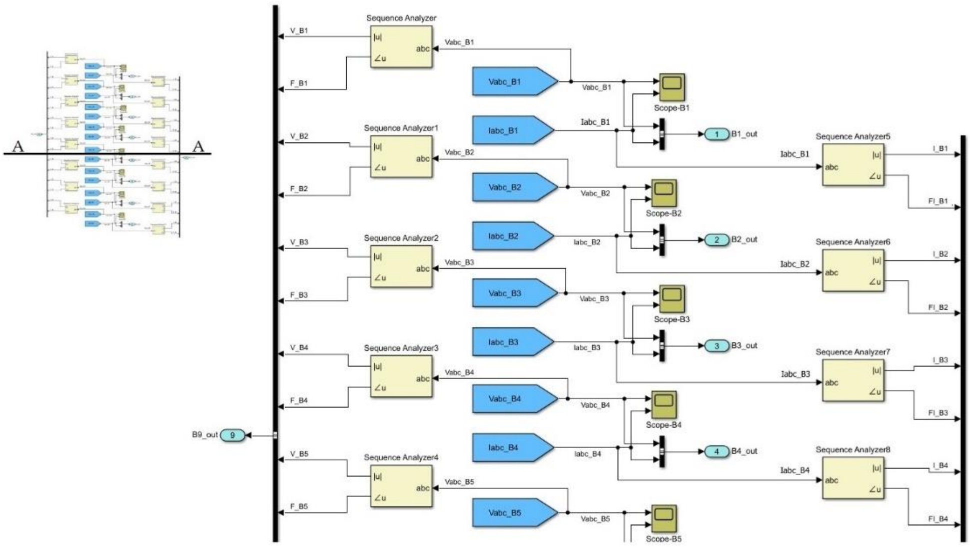

Fig. 9.9 Data acquisition from Simulink model
(first half of the structure A-A) [68]

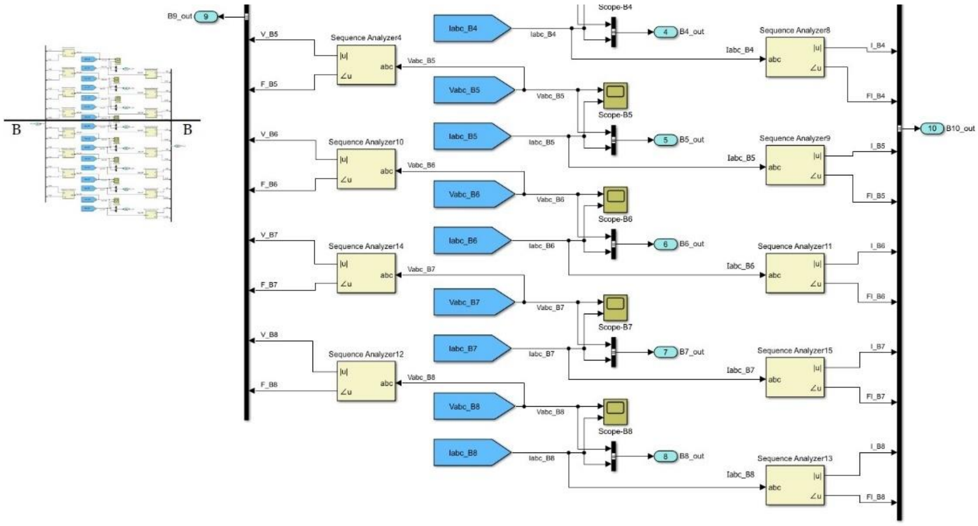

Fig. 9.10 Data acquisition from Simulink model
(second half of the structure B-B) [68]

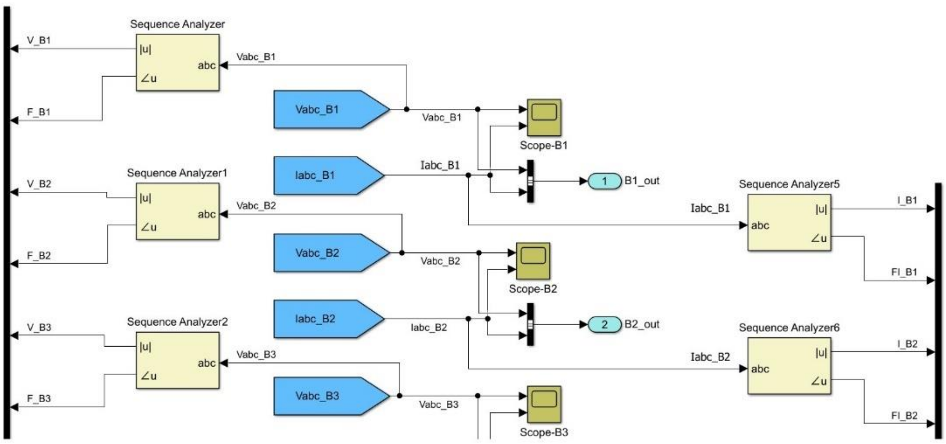

Fig. 9.11 Data acquisition from Simulink model (cropped detail) [68]

The previously presented data acquisition structure makes it possible to create the database necessary for the learning algorithms of the Classification Learner application in Matlab.

9.2. The process of repeatedly running the model simulation

After making the electric power distribution system model in the Simulink program, the process of repeatedly running the simulation began. In this step, the fault block was positioned in various locations, being set for different types of short circuit, and different values were set for the fault resistance and ground resistance [68].

The fault block was moved along the system and positioned after each sector of the six lines, a total of 22 positions. For each position, 25 situations were simulated for different values of fault and ground resistance and for each of the 12 types of short circuit. Performing these simulations involves changing for each individual simulation the location of the fault, the type of fault, or the values for the fault or ground resistance. The time required for such a simulation is approximately two minutes, without taking into account the time required to change the fault parameters. This fact assumes that less than 30 simulations can be performed within an hour. Due to the large number of simulations required and the long duration of time for each simulation, it was necessary to automate the process of repeatedly running the model simulation [68].

The automation process has been achieved by implementing a Matlab program, which runs the Simulink model. For each run of the model automatically is changed either the location of the fault or its parameters. This automation reduced the time of a simulation to approximately 1.5 min/simulation, thus shortening the total time of the simulations. The data obtained during the simulations were saved in a database, which was later used as a database for the learning algorithms of the ANN [68].

After the entire simulation process of the Simulink model was completed, a total of 6150 simulations were obtained, and the voltage and current values were used as input data for the Classification Learner application.

Running the 6150 simulations of 1.5 min each requires a simulation time of almost a week. This time was shortened by using a virtual machine, and the simulations were run using both local and virtual machine hardware resources.

The MathWorks platform offers the possibility of running Matlab and Simulink programs on a virtual machine configured on an Amazon web server (Amazon Web Services – AWS) [61], and the architecture of this service can be seen in Fig. 9.24.

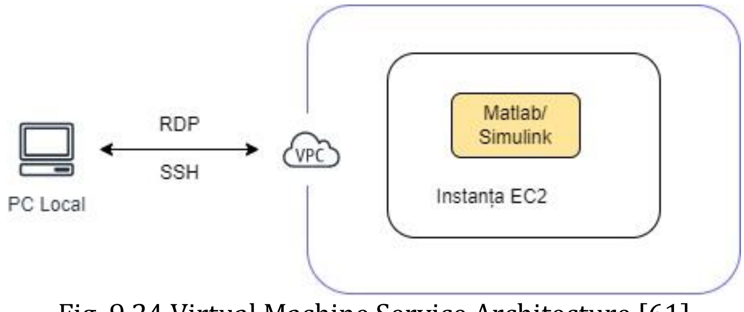

Fig. 9.24 Virtual Machine Service Architecture [61]

The communication between the local hardware resource and the virtual machine was realized through Matlab Drive, transferring both the Simulink model and the code required to automate the simulations. At the end of the simulation process the obtained data were transferred to the local hardware resource and all the obtained data were centralized in a unitary database.

9.3. Classification Learner app

After finishing the entire process of repeatedly running the Simulink model simulation, the obtained data was entered into a database used in the Classification Learner application to train the learning algorithms. This app uses AI-based algorithms and can classify data based on the training data used. For a new situation, different from those contained in the training set, the application will return a single answer [61].

9.3.1. Analysis of the learning algorithm training process for a simplified Simulink model

For a detailed analysis of the operation of the Classification Learner application, its operation was studied on a simplified model of an electricity distribution network, such as the one in Fig. 9.26. The Simulink blocks used in the simplified model were set to the same parameters as the blocks in the model shown in Fig. 9.2. The model in Fig. 9.26 contains a three-phase power supply, two measurement blocks (B1, B2), subsystem L1, inside which there are four cable simulation blocks with distributed parameters, a three-phase load, the fault block and the powergui block. Thus, a 4 km long cable was modeled, and the fault block was inserted after each individual segment.

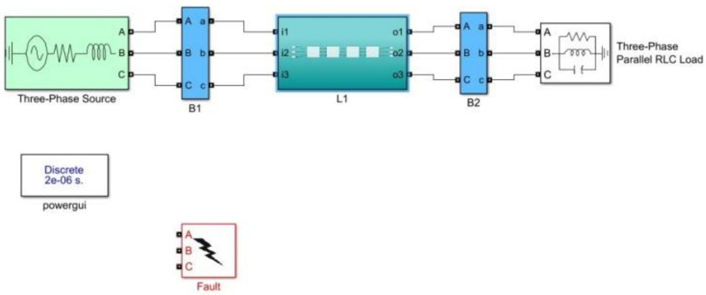

Fig. 9.26 Simplified model of an electrical power distribution system

To carry out the repeated simulations, the same procedure was used as for the entire initial model. The fault block was inserted consecutively after each individual sector, and for each of its positions, 25 situations were simulated for different values of fault and ground resistance, as well as each of the 12 types of short circuit. A total of 1125 simulations resulted. The data obtained from the simulations were entered as input data into the Classification Learner application in Matlab, becoming the training data set for the learning algorithms.

The settings shown in Fig. 9.27 were used when loading the database in the Classification Learner application. The measurements during the 1125 simulations were centralized in the "tabeldateL1" table, imported from the Matlab workspace. The data in this table are divided into two categories: the response (in the case shown in Fig. 9.27 being the location of the fault - "LocDefect", and in the case shown in Fig. 9.28 being the location and type of fault - "TipDefect") and the predictors (represented by the values of the voltage-current pairs measured in each individual simulation). The 5 folds cross-validation scheme was set, after which the training session of the learning algorithms began by pressing its start button ("Start Session"). It can be seen in Fig. 9.27 and Fig. 9.28 the major difference between the number of possible responses associated with the two mentioned situations. If the response is only the place of the fault, there are 5 possible responses, and if the response returned is both the place and the type of fault, the number of possible responses becomes 45.

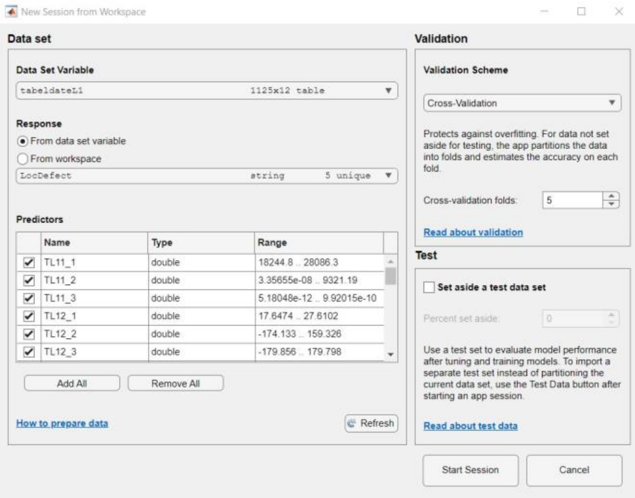

Fig. 9.27 Loading the data for the learning algorithms in the Classification Learner app in Matlab (for predicting the fault location – for the L1 line)

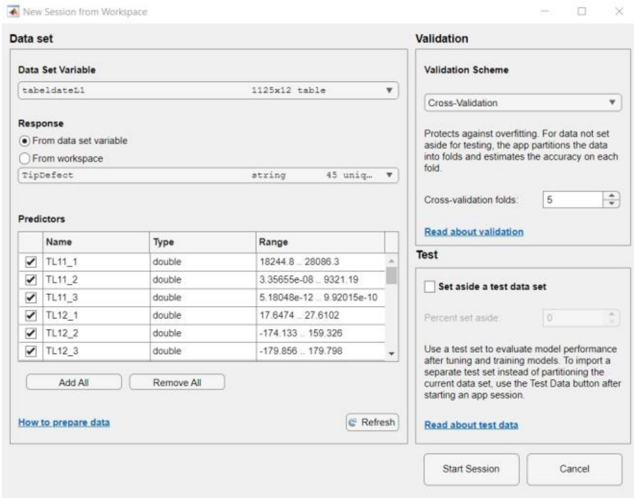

Fig. 9.28 Loading the data for the learning algorithms in the Classification Learner app in Matlab (for predicting the location and type of fault– for the L1 line)

After loading the database into the Classification Learner application, the process of training the AI-based algorithms began. The application offers the possibility of choosing the type of algorithm you want, or you can use the option of training all algorithms in order to obtain the highest accuracy validation. The algorithms offered by this application are divided into the following categories: decision trees, discriminant analysis, naive Bayes classifiers, support vector machines, nearest neighbor classifiers, ensemble classifiers and neural network classifiers.

To choose the algorithm with the highest accuracy validation, the option to train all types of algorithms was used. After the end of the training process, a classification of the algorithms was made according to the value of their accuracy validation. After the completion of the first training process of the algorithms, it was observed that the algorithms with the best accuracy are those in the category of artificial neural networks, the highest accuracy validation value being 98.8%, for the three-layer RNA-based learning algorithm. This accuracy was achieved on the basis of the training data set, which contained the measurements during the 1125 simulations and resulted in the determination of the location of the fault.

Studying the performance of a learning algorithm can be done by tools provided by the Classification Learner application, such as the confusion matrix and the receiver operating characteristic curve (ROC curve).

The confusion matrix is a matrix that contains the predicted classes on the columns and the true classes on the rows. The confusion matrix related to an algorithm with a accuracy validation of 100% contains values only on the principal diagonal. Any value that lies outside the principal diagonal implies the existence of inconsistencies between the predicted and true responses [61].

In Fig. 9.30 is exposed the confusion matrix for the three-layer RNA-based learning algorithm with 98.8% accuracy - for fault location prediction. It can be seen that the only situation predicted 100% correctly is the one in which the system has no fault (the class called "normal"). For the other four classes, the existence of values deviating from the main diagonal is observed. For example, for the situation where the fault is on L1/S1, the algorithm erroneously predicts four situations where it would be found on L1/S2. From this matrix it can be seen that the most erroneous predictions occur for L1/S3. Thus, in three situations the algorithm predicts that it would be on L1/S2 and in 2 situations on L1/S4. The confusion matrix provides an overview of the algorithm's performance, making it possible to identify erroneously predicted classes as well as those with maximum accuracy.

The confusion matrix can be generated to provide the same information under different aspects. This can contain either the number of predicted situations and true situations, as in Fig. 9.30, either the percentage of true positive rates in relation to false negative ones, as in Fig. 9.31. The four erroneously predicted situations for L1/S1 that can be observed in Fig. 9.30, represent the 1.5% false negative prediction rate, observed in Fig. 9.31.

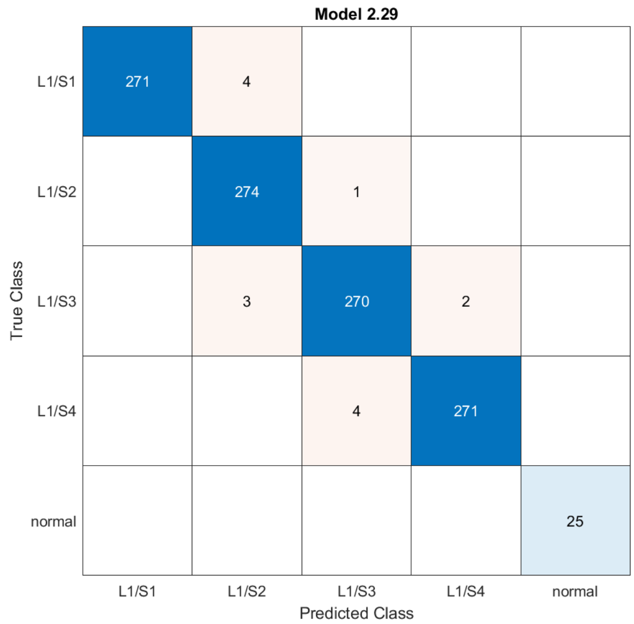

Fig. 9.30 Confusion matrix for three-layer RNA-based learning algorithm (with 98.8% accuracy - for fault location prediction)

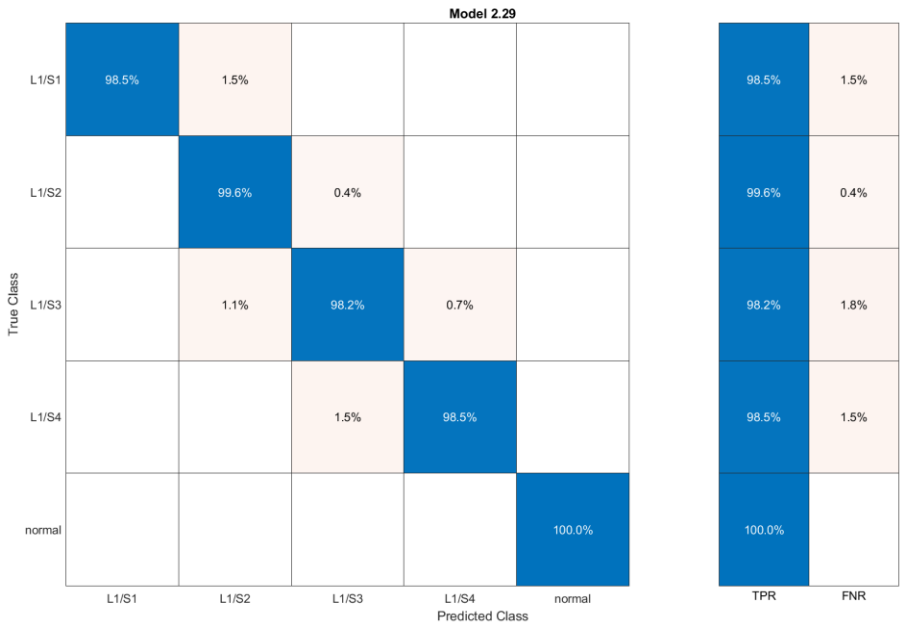

Fig. 9.31 Confusion matrix (showing true positive and false negative rates) for the three-layer RNA-based learning algorithm (with 98.8% accuracy - for fault location prediction)

Another tool used in algorithm performance analysis is the ROC curve. This is a graphical representation illustrating the ratio of the true positive to false positive prediction rate for each individual classifier. Each point on the ROC curve corresponds to a pair of numbers representing the false positive and true positive rates. An ideal classifier is represented by the pair (0,1) which indicates that it identifies all true positive situations and does not indicate any false positive situations. On the other hand, a classifier to which the pair (1,0) corresponds is a classifier that always makes wrong predictions. The ROC curve for an ideal classifier will pass through the points (0,0), (0,1) and (1,1) leading to the area under the ROC curve (AUC) value of 1. The area under the ROC curve corresponds to the integral of the ROC curve and can have values between 0 and 1. The closer the AUC value is to 1, the better the classifier performs [61].

For the studied algorithm, graphs can be generated containing the ROC curve for each of the five classifiers, for each individual fault location. The ROC curve line is highlighted in dark blue, the AUC is represented in light blue, the red dot represents the position of the classifier characterized by the pair of values, the false positive rate and the true positive rate. From the analysis of the five figures, it emerges that only the classifier corresponding to the situation without fault (normal) is an ideal one, having the pair (0.00,1.00), the L1/S1 and L1/S4 classifiers have the same performance (0.00,0.99), and the least performing is the L1/S3 classifier with the pair (0.01,0.98).

By using the two methods of evaluating the performance of an algorithm, the areas with the lowest accuracy in the prediction of a fault and the areas for which the prediction is very good can be highlighted. Analyzing the confusion matrix and the ROC curves side by side, it can be seen that they provide the same information, but in different ways. The best performing classifier (normal) corresponds in the confusion matrix to the true positive rate of 100%, and on the ROC curve the pair (0.00,1.00), and the least performing classifier (L1/S3) corresponds to the true rate in the confusion matrix positive of 98.2%, and on the ROC curve the pair (0.01,0.98) (Fig. 9.34).

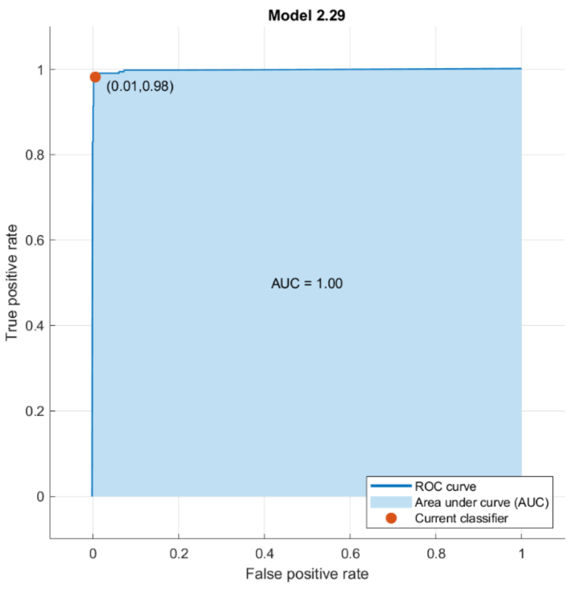

Fig. 9.34 ROC curve for three-layer RNA-based learning algorithm (with 98.8% accuracy) with AUC(ASC)=1.00 for Line 1 – Sector 3

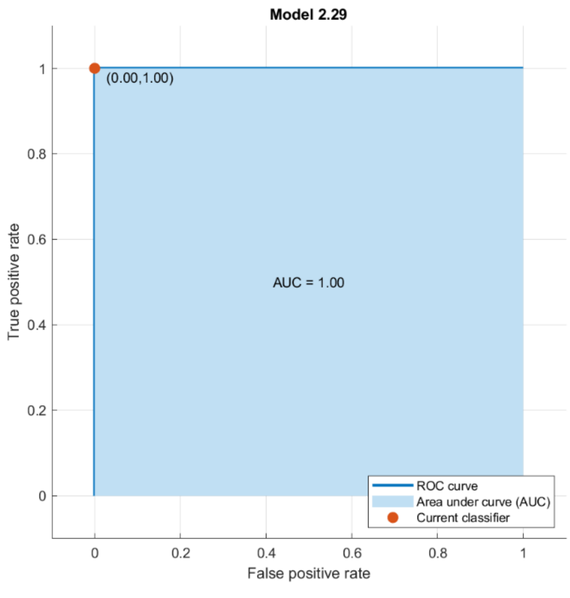

Fig. 9.36 ROC curve for three-layer RNA-based learning algorithm (with 98.8% accuracy) with AUC(ASC)=1.00 for no fault situation (normal)

After training the learning algorithms, it resulted that for the presented study, the algorithms based on ANN have the best accuracy validation. This result led to the next step, namely, to try to optimize these types of algorithms. This optimization was achieved by selecting the Optimizable Neural Network option, available in the Classification Learner application. When selecting this option, the application performs a series of tests by changing the following hyperparameters: the number of neuron layers, the activation function and the regularization coefficient (Lambda). It is also possible to optimize only one of these hyperparameters.

To obtain the best accuracy validation value, the optimization option of all hyperparameters was used first, after which the optimization option was used for each individual activation function.

After completing the training processes of the optimized algorithms, the results were centralized in Table 9.5.

Tabel 9.5 Accuracy validation for learning algorithms after hyperparameter optimization

Optimized hyperparameters	**Accuracy validation**	**The lowest performing classifier**
No. of layers, activation function, regularization coefficient	99,5%	L1/S1 L1/S3
Activation function: ReLu	98,9%	L1/S1
Activation function: Sigmoid	99,8%	L1/S1 L1/S4
Activation function: Hyperbolic Tangent	99,2%	L1/S1
Activation function: Linear	99,7%	L1/S3

After analyzing the matrices, it is found that the algorithms do not have the same classifier with the lowest performance. This situation is due to cross-validation, as the division of the algorithm's training database into five parts is done randomly.

Following the optimization process of the learning algorithms for the simplified model of a power distribution network (Fig. 9.26), the best accuracy validation value of 99.8% was obtained for the learning algorithm based on ANN with option to optimize the hyperparameter of the Sigmoid activation function for fault location prediction.

Accuracy validation of 99.8% was achieved with the five folds cross-validation setting. To highlight the importance of cross-validation, repeated simulations were performed for the same database and for the same types of learning algorithms and for three folds cross-validation with the fault location as the response.

A total of 32 learning algorithms were trained (Table 9.6), with five folds and three folds cross-validation set. It can be seen in Fig. 9.47, that for the same type of algorithm the value of accuracy validation is higher for five folds cross-validation compared to three folds cross-validation.

Tabel 9.6 Types of AI-based algorithms in the Classification Learner application

No.	**Algorithm type**	**No.**	**Algorithm type**	**No.**	**Algorithm type**
1	Fine Tree	12	Medium KNN	23	Wide NN
2	Medium Tree	13	Coarse KNN	24	Bilayered NN
3	Coarse Tree	14	Cosine KNN	25	Trilayered NN
4	Kernel Naïve Bayes	15	Cubic KNN	26	SVM Kernel
5	Linear SVM	16	Weighted KNN	27	Logistic Regression Kernel
6	Quadratic SVM	17	Boosted Trees	28	Optimizable ANN
7	Cubic SVM	18	Bagged Trees	29	Hyperparameter ReLu
8	Fine Gaussian SVM	19	Subspace Discriminant	30	Hyperparameter Tanh
9	Medium Gaussian SVM	20	Subspace KNN	31	Hyperparameter Sigmoid
10	Coarse Gaussian SVM	21	Narrow NN	32	Hyperparameter None
11	Fine KNN	22	Medium NN		

Similar to the process of training learning algorithms with fault location as a response, learning algorithms were trained for both location and type of fault prediction. The same 32 learning algorithms as for fault location prediction were trained and both five folds cross-validation and three folds cross-validation were used. Accuracy validation values are represented in Fig. 9.49, which highlights the fact that in the case of five folds cross-validation the performance of the learning algorithms is higher than in the case of the three folds one. The best performing algorithms are those based on RNA, obtaining the value of 98.7% for the accuracy validation, in the case of optimizing the hyperparameter of the activation function, Sigmoid.

The situation where the prediction of the learning algorithm is both the location and the type of fault corresponds to a total number of 45 possible responses, while for the prediction of the fault location only 5 possible responses resulted. For both situations, the same algorithm training database was used, noting that in the case of increasing the number of possible responses, the accuracy validation value decreases. If for the prediction of the fault location, the accuracy validation of 99.8% was obtained, for the prediction of the location and type of fault, the accuracy of 98.7% was obtained.

The comparison of the accuracy validation values for the previously presented cases was made through the graph in Fig. 9.49. When analyzing this graph, it can be seen that the best performing learning algorithms for fault classification are in all cases those based on RNA, and the accuracy validation value is closely related to the number of possible responses. In order to obtain a higher value of accuracy validation, in the case of increasing the number of responses, it is also necessary to increase the training database of the learning algorithms.

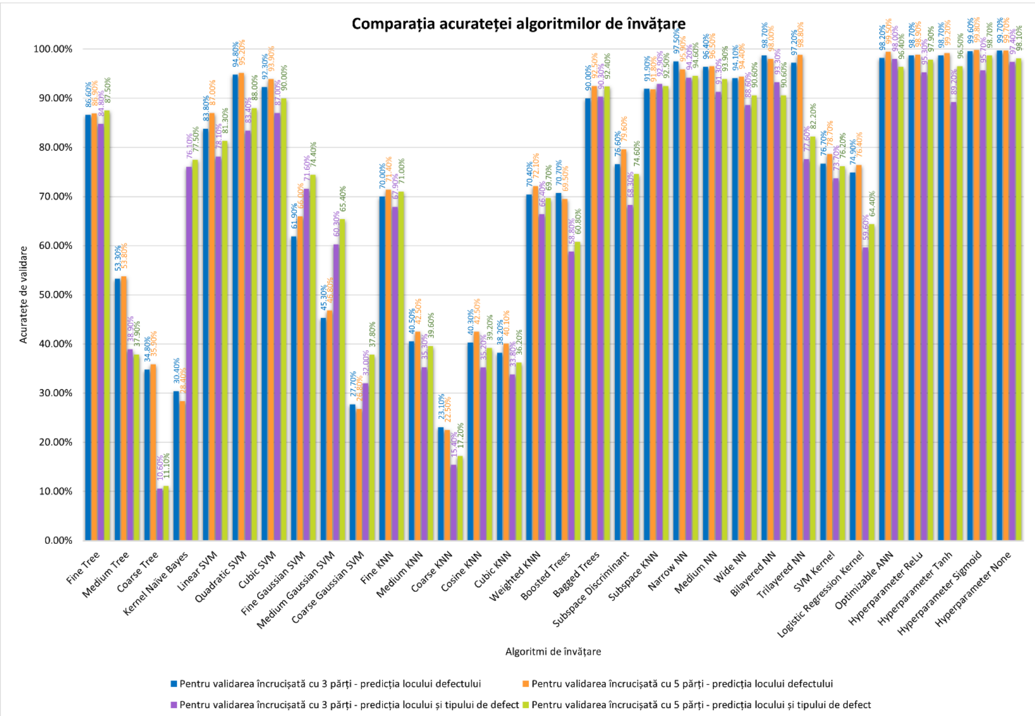

Fig. 9.49 Comparison of the accuracy of learning algorithms

9.3.2. The training process of the learning algorithms for the studied model

After the detailed analysis of the operation of the Classification Learner application for a simplified model of an electrical power distribution system such as the one in Fig. 9.26, the training process of the learning algorithms for the entire model proposed in Fig. 9.2 began. The steps required to implement the learning algorithm training process for the full model are identical to those for the simplified model. The only difference is the size of the training database entered in the Classification Learner app. If for the simplified model a number of 1125 simulations were made to populate the database, for the whole proposed model 6150 simulations were made, and the measurements during the simulations constituted the training database for the learning algorithms [68].

Similar to the training process of the learning algorithms for the simplified model, two situations were studied, one in which was predicted the fault location and one where both the location and type of the fault were predicted. In the case in which the prediction refers to the fault location, a total of 23 possible responses resulted, and in the case in which the prediction contains both the location and type of fault, 243 possible responses resulted.

Knowing the operation mode of the application due to the previous analysis, the five folds cross-validation type was chosen, and the ANN learning algorithms were trained. For each of the two cases, the algorithm with the best accuracy validation value will be presented.

In the first step, the database ("tabledata") containing the values saved during the 6150 simulations was loaded, the fault location ("LocDefect") and the type of 5 folds cross-validation were set as response as possible see in Fig. 9.50.

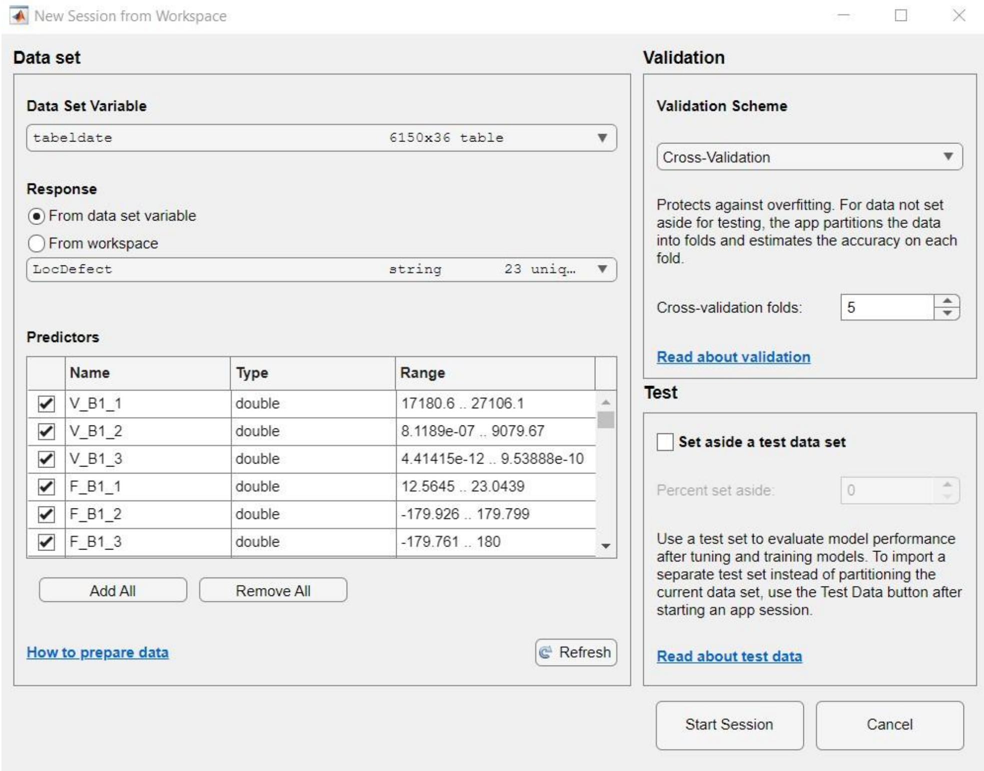

Fig. 9.50 Loading data for learning algorithms into the Classification Learner application in Matlab (for fault location prediction – for the entire model) [68]

After loading the database, the process of training the ANN learning algorithms began and the algorithm optimization option (Optimizable Neural Network) was used. The accuracy validation of the studied algorithms with optimized hyperparameters can be found in Table 9.7.

Table 9.7 Accuracy validation of optimized hyperparameter learning algorithms for fault location prediction

Optimized hyperparameters	Accuracy validation
No. of layers, activation function, regularization coefficient	98,7%

Activation function: ReLu	98,5%
Activation function: Sigmoid	98,4%
Activation function: Hyperbolic Tangent	91,6%
Activation function: Linear	93,5%

After training the learning algorithms, the best accuracy validation value obtained for fault location prediction is 98.7%. This accuracy was obtained by optimizing the hyperparameters, the related confusion matrix being shown in Fig. 9.51, and the minimum error graph in Fig. 9.53.

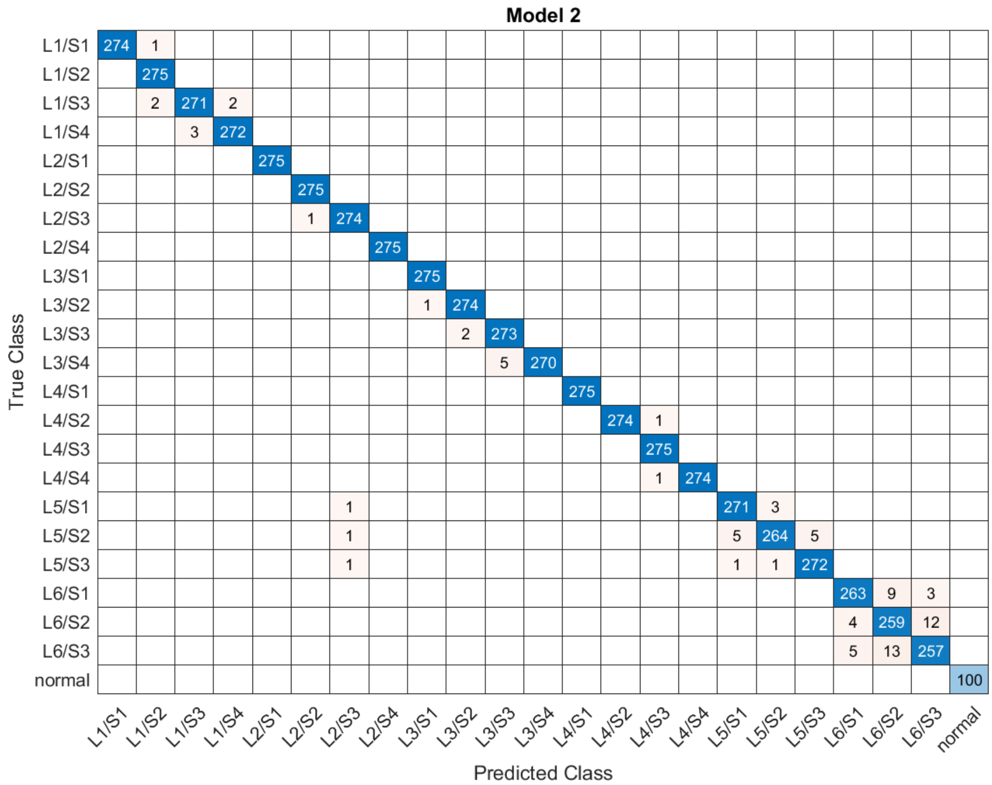

Fig. 9.51 Confusion matrix for the ANN learning algorithm with the option to optimize all parameters (with 98.7% accuracy - for fault location prediction)

After an analysis of the confusion matrix, it can be seen that the line with the most erroneous predictions is line 6, a situation that can also be highlighted by the analysis of the ROC curves, for each individual classifier. The classifier with the lowest value of AUC is L6/S2, having the value of 0.98 (Fig. 9.52).

Using the minimum error graph from Fig. 9.53 the hyperparameters of the learning algorithm can be seen, highlighting the best point of the hyperparameters in the box with its related information. Thus, for the accuracy validation of 98.7%, an algorithm was identified with the Sigmoid activation function, with three layers of neurons and the regularization coefficient (Lambda) of $1.2839 \cdot 10^{-6}$.

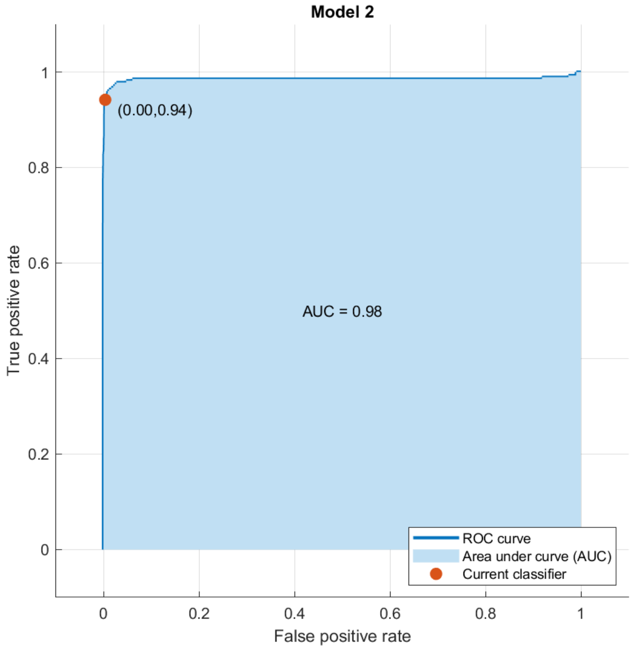

Fig. 9.52 ROC curve for the ANN learning algorithm with the option to optimize all parameters (with 98.7% accuracy - for fault location prediction) with AUC=0.98 for Line 6 – Sector 2

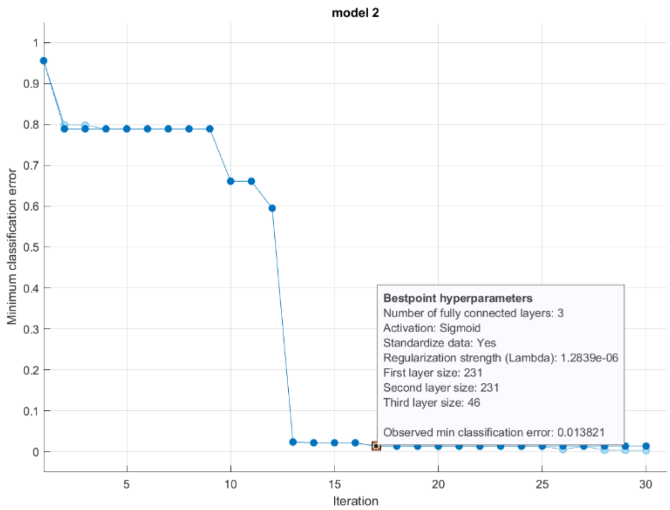

Fig. 9.53 Minimum error graph for the ANN learning algorithm with the option to optimize all parameters (with 98.7% accuracy - for fault location prediction)

For the case where both the location and the type of fault are predicted, the same training database was used, with the data obtained from the 6150 simulations, only that the response of the learning algorithms was both the location and the type of the fault.

Similar to the previous case, after loading the database, the learning algorithms based on ANN were trained, using the algorithm optimization option (Optimizable Neural Network). The accuracy validation of the algorithms trained with optimized hyperparameters is found in Table 9.8.

Table 9.8 Accuracy validation of optimized hyperparameter learning algorithms for location and type of fault prediction

Optimized hyperparameters	Accuracy validation
No. of layers, activation function, regularization coefficient	95,5%
Activation function: ReLu	95,2%
Activation function: Sigmoid	92,9%
Activation function: Hyperbolic Tangent	97,5%
Activation function: Linear	96,3%

For the variant in which both the place and the type of fault are predicted, the best accuracy validation value of 97.5% was obtained. This value was obtained for the ANN learning algorithm with the option to optimize the hyperparameter of the hyperbolic tangent activation function. In Fig. 9.55 the confusion matrix of the algorithm is found, but due to the large number of possible responses of the algorithm (243 possible responses), the confusion matrix is difficult to interpret. However, its principal diagonal can be seen.

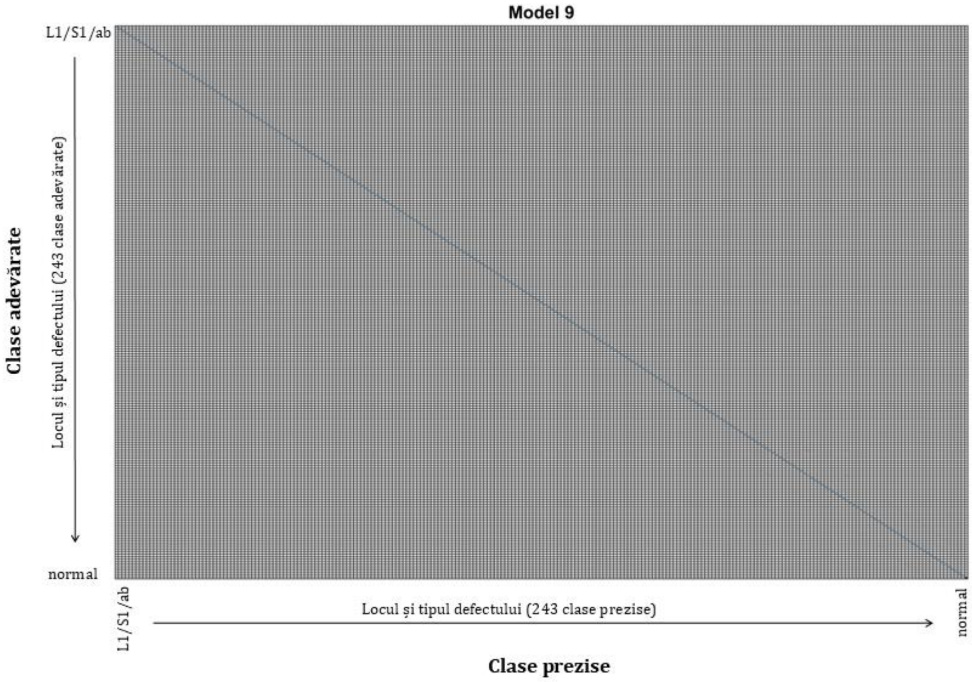

Fig. 9.55 Confusion matrix for ANN learning algorithm with hyperparameter optimization option activation function Hyperbolic tangent (with 97.5% accuracy - for predicting the location and type of fault)

Due to the ambiguity of the confusion matrix, the use of ROC curves is essential to determine the lower performing classifier, which is also found on line 6 – sector 2, for fault type abg.

On the graph of the minimum error in Fig. 9.57 are exposed the characteristics of the learning algorithm for predicting the location and type of fault, with an accuracy of 97.5%. Its activation function is the hyperbolic tangent, with three layers of neurons and the regularization coefficient (Lambda) of $2.5681 \cdot 10^{-7}$.

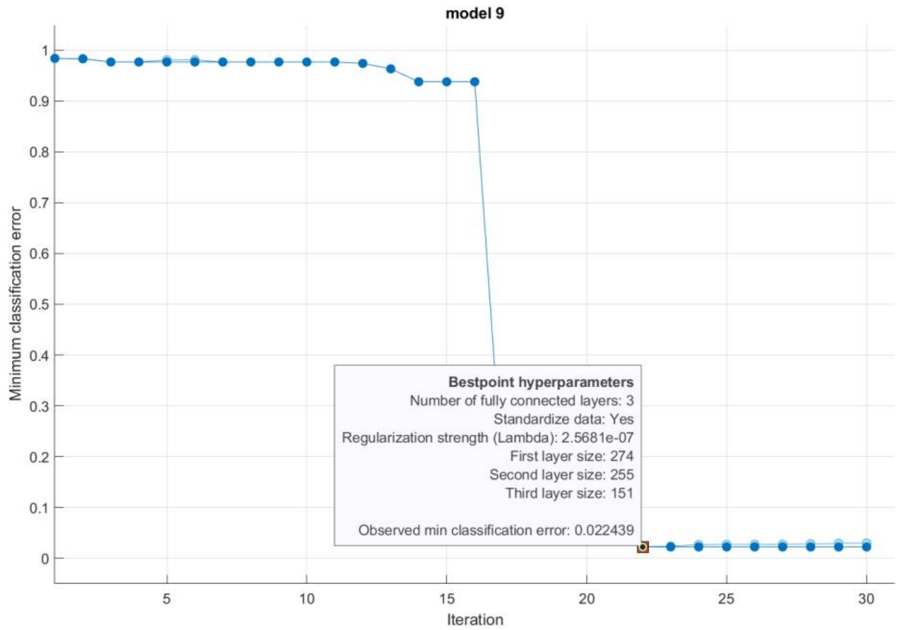

Fig. 9.57 Minimum error graph for ANN learning algorithm with hyperparameter optimization option Hyperbolic tangent activation function (with 97.5% accuracy - for predicting the location and type of fault)

9.4. Prediction of new fault based on learning algorithm

After analyzing several models of learning algorithms, the algorithms with the best accuracy validation were chosen for the two situations studied, respectively the prediction of the fault location and the prediction of location and type of fault.

To predict the location or the location and type of fault for a new situation that may occur within the studied electrical power distribution system, it is necessary to export the learning model from the Classification Learner application to the Matlab workspace.

Exporting the learning models generated variables "predictie_loc_defect" for the learning algorithm with 98.7% accuracy validation and "predictie_loc_si_tip_defect" for the learning algorithm with 97.5% accuracy validation, as can be seen in Fig. 9.58.

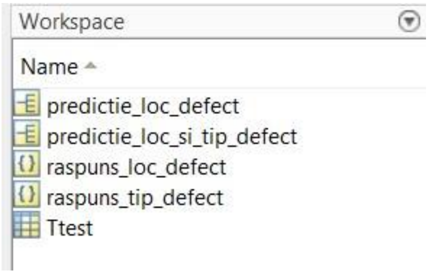

Fig. 9.58 Matlab workspace (the variables for the learning algorithms, their responses and the table of measurements for which the predictions are made)

To verify the learning algorithms, voltage and current measurements were made for the case of new faults with different values of the fault and ground resistances than those provided in the algorithm training database.

The values obtained from the measurements were entered into the "Ttest" variable, which has the same structure as the "tabeldata" table, which constituted the training database for the learning algorithms in the Classification Learner app. To make the prediction, it is necessary to use the prediction function of each learning algorithm separately for the tested variable, as can be seen in Fig. 9.59 and Fig. 9.60.

In Fig. 9.59 is detailed the prediction function call and its result for fault location prediction for the tested examples (for the learning algorithm with 98.7% accuracy validation), and in Fig. 9.60 call and output of the prediction function for predicting the location and type of fault for the tested examples (for the learning algorithm with 97.5% accuracy validation).

It can be seen that after calling the prediction functions, the responses are structured in the form of a column vector, which includes one response for each of the 14 measurements. In both situations, the predictions being made correctly.

From this chapter, the capabilities of artificial intelligence and in the present case of artificial neural networks to address and provide solutions for the proposed theme are evident. It is self-explanatory that as AI methods refine and/or hardware resources increase in speed, working with them will become much easier, results will be obtained much faster and in a much more accessible form.

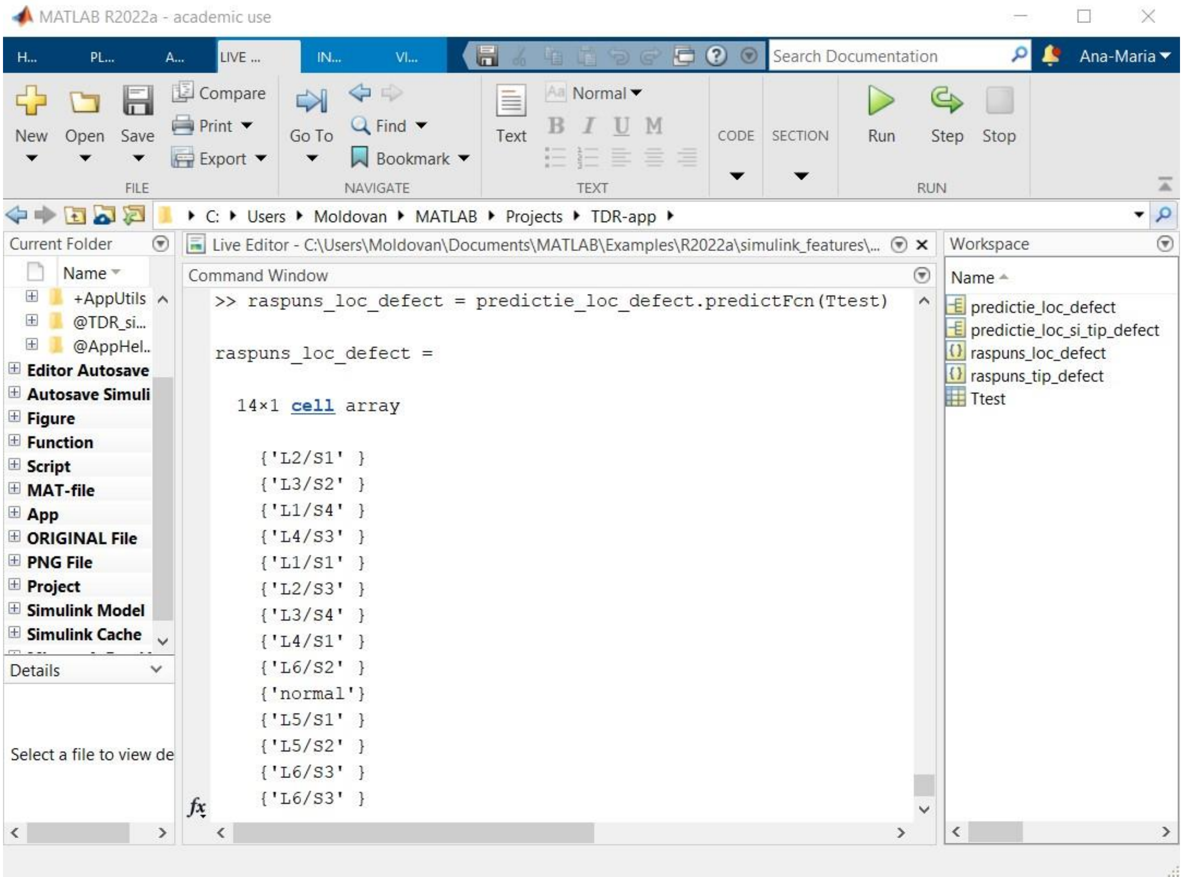

Fig. 9.59 Fault location prediction result for tested examples
(for learning algorithm with 98.7% accuracy validation)

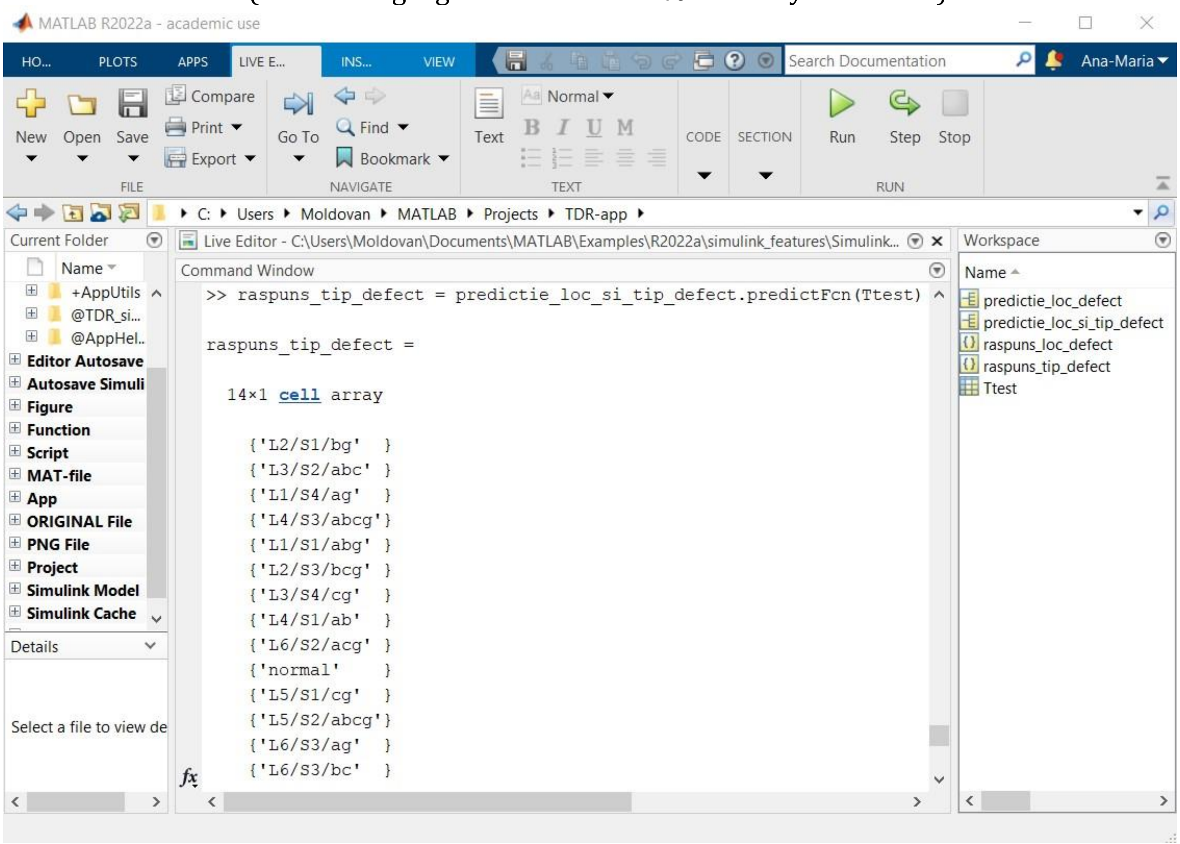

Fig. 9.60 Location and type of fault prediction result for tested examples
(for learning algorithm with 97.5% accuracy validation)

CONCLUSIONS

Although the addressed issue might seem marginal or niche at first glance, this PhD thesis highlights the importance of detecting and locating faults in electrical cables in an electrical power distribution system. It is intended to be an overview of the current state of the methods dedicated to this field, both classical and innovative ones based on artificial intelligence, enriching the topic addressed through a series of personal contributions.

The accuracy and efficiency of the methods of detecting and locating defects in electric cables, which contribute decisively to ensuring the continuity of the supply and not least to ensuring an appropriate quality of electricity, is also influenced by the knowledge of the parameters of the cable in question, which is why the first three chapters of the thesis are dedicated to theoretical aspects regarding electric cables, their classification as well as the causes of defects in cables.

The methods of detecting and locating faults in electrical cables have both advantages and disadvantages, each method used must be chosen according to the type of cable, the possible location of the fault and finally the cost of the detection the fault.

Equipment using time-domain reflectometry has good accuracy but can lead to errors if not properly calibrated and/or the occurrence of possible unwanted impedance differences is ignored.

Traveling waves methods are characterized by high precision and accuracy but involve the need for expensive equipment compared to impedance-based methods.

The use of artificial intelligence in the detection and location of faults in electrical cables generates accurate methods but requires significant prior training.

The underground electrical cable locating equipment (Ridgid SeekTech SR-60) and electrical cable fault detection equipment (Ridgid A-Frame Fault Detector and Megger TDR 2000 Reflectometer) presented in the paper provide an optimal solution for locating a cable fault. Part of this equipment was used in the location of a fault in an underground electric cable connecting the generating set of a commercial space (mall) and one of the transformer stations inside the building.

To locate the cable, the Ridgid SeekTech SR-60 locator was used together with the Ridgid SeekTech ST-510 line transmitter, and to locate the fault in the cable, the Megger TDR 2000/2R reflectometer. The use of the three equipments successively led to the determination of the route of the electric cable as well as the place where the fault was located, highlighting the speed and precision of the detection of the underground electric cable with their help and the importance of the correct calibration of the reflectometer.

The accuracy of fault detection is influenced by the human factor because the calibration of the reflectometer requires knowledge of its operating principle and the characteristics of the tested cable.

To study the working principle of a reflectometer and to highlight its strengths and its possible limitations, such equipment was modeled and simulated with the help of Matlab/Simulink programs (R2022a). The validation of the created model was carried out through specific simulations for terminations of the tested electric cable, open circuit termination, short circuit termination and matched termination.

Matlab App Designer makes it easy to create applications that can help the user interact with a Simulink model through a graphical interface. Such an application was developed for the reflectometer model so that modification of the parameters in the Simulink model can be done through a graphical interface, with the advantage of a much faster and more efficient model run than the default Simulink model run.

For the situation in which there is a branched distribution system of electrical cables, the precariousness of this technique was highlighted, and real-time reflectometry proving ineffective and generating interpretation errors.

Following the observation of the limitations imposed by the method based on time domain reflectometry, the development of algorithms for locating and predicting faults in electric cables was pursued using artificial neural networks, with the aim of detecting and locating faults in a branched system of electrical cables.

The development of the algorithms based on ANN was carried out with the help of Matlab/Simulink programs, going through four stages necessary for the implementation of the algorithms: the modeling of an electrical energy distribution system, the repeated simulations of the model to create a database, the training of the learning and prediction algorithms of the fault location or of the location and type of fault for a new situation.

The efficiency of an ANN depends on the complexity of the database related to the learning process, so the measurements recorded during 6150 simulations within the repeated simulation process led to a high performance of the proposed method.

The time required to generate the database is directly proportional to the hardware and software resources used for the simulations. The use of virtual machines in the AWS cloud helped to reduce the simulation time, as these simulations could be performed in parallel.

At the end of the learning process of algorithms based on artificial intelligence, performed by the Classification Learner application in Matlab, having as input data the previously obtained database, it was found that the highest values of the accuracy validation were obtained by the algorithms based on on ANN.

The implemented ANN algorithm achieved 98.7% accuracy validation for fault location prediction and 97.5% accuracy validation for location and type of fault prediction. In the case of both situations, the same database was used (obtained from the 6150 simulations), but the number of possible responses being different, for the prediction of the fault location there were 23 possible answers, and for the prediction of the location and type of fault, there were 243 possible answers.

By analyzing the presented results, it is highlighted that with the increase in the number of possible responses, the value of the accuracy validation decreases. A large number of possible answers requires a complex database.

The usefulness of the developed method was validated by making correct predictions for new situations, different from those contained in the database related to the learning process of the algorithms, both for the location of the fault and for the location and type of fault.

The proposed method is an efficient and precise method with increased accuracy, but requires a prior preparation of the database used in the learning process of algorithms based on ANN.

The dissemination of the results was achieved through the publication of three articles, one in an ISI indexed journal and two articles presented at international conferences, one article being indexed in ISI Proceedings and one indexed in BDI IEEE:

A. M. Moldovan și M. I. Buzdugan, “Prediction of Faults Location and Type in Electrical Cables Using Artificial Neural Network”, Sustainability (Switzerland), vol. 15, nr. 7, 2023, doi: 10.3390/su15076162. IF: 3,9 Q2

A. M. Moldovan, M. I. Buzdugan, și S. Oltean, “Modeling a Time Domain Reflectometer using Matlab/Simulink for detection of faults in electrical cables”, 2022 IEEE 20th International Power Electronics and Motion Control Conference (PEMC), Brasov, Romania: IEEE, 2022, pp. 281–284. doi: 10.1109/PEMC51159.2022.9962851.

A. M. Moldovan, S. Oltean, și M. I. Buzdugan, “Methods of Faults Detection and Location in Electrical Systems”, 2021 9th International Conference on Modern Power Systems (MPS), 2021, doi: 10.1109/MPS52805.2021.9492549.

ORIGINALITY AND INNOVATIVE CONTRIBUTIONS OF THE THESIS

The originality of the thesis derives from the innovative approach to the problem of faults in electrical cables, through modeling and simulations made in Matlab/Simulink programs.

The modeling of a reflectometer and the simulation application of such equipment, makes a significant contribution to the understanding of the principle of operation and its scope. At the same time, with the help of the developed application, a study can be carried out regarding the behavior of different types of cables during measurements made with a reflectometer. The developed graphical interface facilitates the simulation process with the real-time reflectometer model.

Creating a Simulink model of an electrical power distribution system can be useful if there is a need to modify the existing system. It can be used to simulate the impact of a new structure on the system, as well as to develop possible future improvements to the modeled system.

The method of detecting and locating faults in electric power distribution systems, based on artificial intelligence and in particular on artificial neural networks, can solve complex problems encountered in the case of power lines and branched electric cable systems, difficult situations to manage using the classic methods of detecting and locating faults.

In the perspective of improving this proposed innovative method, future research directions may involve:

- optimization of the repeated simulation process by adding some dynamic changes to the loads;
- transforming the method into a more accessible application, by completing it with a friendly graphical user interface;
- demonstrating the usefulness of this approach, by developing applications that allow the training of algorithms based on ANN with databases obtained from measurements from existing energy distribution systems and their use in the detection and prediction of faults that may appear by utility companies;
- this approach represented pioneering work in the Technical University of Cluj-Napoca, which I hope will be continued in the university and taken to a higher level with the development of the field of artificial intelligence and the increase in the capacity and speed of hardware resources.

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