The Basic Tasks in the Development of the Smart Protection Device

Stepanova D.A.
Power and electrical engineering department
Chuvash State University
Cheboksary, Russia
https://orcid.org/0000-0001-8726-3521

Antonov V.I., member IEEE
Power and electrical engineering department
Chuvash State University
Cheboksary, Russia
https://orcid.org/0000-0001-5567-4473

Naumov V.A.
Power systems automation department
R&P EKRA Ltd
Cheboksary, Russia
https://orcid.org/0000-0003-1890-4238

Soldatov A.V.
Power systems automation department
R&P EKRA Ltd,
Cheboksary, Russia
https://orcid.org/0000-0002-5652-4730

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***Abstract* —The Smart Protection Devices are intelligent relay protection devices based on machine learning methods. They can delimit complex unconnected parameters areas of various electrical system modes in a multidimensional space. Despite the complexity of the functional load, their implementation does not require an avant-garde computing environment, since all the laborious work on the development of the cognitive abilities of the device's intelligence is carried out even at the development stage. The report notes the importance of thoughtful localization of machine learning methods in relay protection algorithms. It is noted that the solution of the well-known problem of intersection of areas of controlled parameters of various modes of the electrical network is possible if the dimension of the precedent space and the power of the training dataset is sufficient. The success of the Smart Protection Device training largely depends on the appropriate feature engineering, the provision of the necessary capacity and power of the training dataset, and the formation of a compressed training dataset while preserving its information basis. The paper formulates the listed tasks and presents the ways to solve them on the example of the development of the Intelligent Mode Discriminator.**

Keywords—the Smart Protection Device, electrical system modes classification, the Intelligent Mode Discriminator, a power system protection

I. Introduction

Traditionally, the development of the theory of classical relay protection has been aimed at improving trip characteristics. For many years, relay protection devices based on the use of integral characteristics of input signals and the evaluation of virtual measurements have ensured the stability of power systems. The desire to realize the full potential of microprocessor devices has contributed to the development and implementation in practice of relay protection of multifunctional devices called the Intelligent Electronic Device (IED). However, their operation was limited only to the implementation of new functions, while the device's decision was still carried out within the framework of the fixed logic of the trip characteristics on the set plane.

The digitalization of the electric power industry has opened the way for new, more advanced technologies based on artificial intelligence. It became obvious that one of the aspects of the development of relay protection is the development of devices with advanced intellect based on machine learning methods. Such devices were first introduced by the authors in [1] and were called the Smart Protection Devices (SPDs).

The fundamental idea of the Smart relay Protection Devices is the recognition of electrical network modes, which consists in distinguishing between monitored and alternative modes [2]. Traditionally, the problem under consideration is solved at the development stage based on simulation modeling (Fig. 1), playing out the full set of scenarios for the modes of the protected electrical network and training relay protection devices [3].

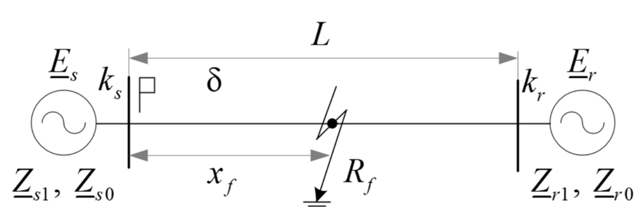

Fig. 1. Simulation model for the preparation of the training dataset

In this respect, the Smart Protection Devices have similarities to classic relay protection devices; therefore, the use of machine learning methods in algorithms for the functioning of new generation devices looks quite reasonable [4] - [9].

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The Smart Protection Device (Fig. 2), just like the classical relay protection device, generates measurements, uses the trip characteristics set by the discriminant functions. The result is the same, the difference is in the richness of the trip characteristics.

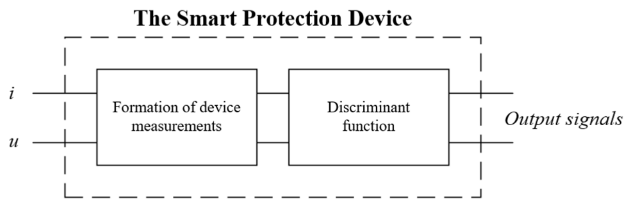

Fig. 2. The Smart Protection Device's architecture

The Smart Protection Devices operating in multidimensional space are capable of classifying the most complex modes of an electrical system. The trip characteristics obtained as a result of training are formed by nonlinear classifiers based on the use of nonlinear kernels. Due to them, the Smart Protection Devices can design intelligent protection relays and select the trip characteristics of various configurations. The selectivity of the new generation of protection is ensured by the appropriate assignment of the data on the mode of the electrical network arriving at the rate of the process to one of the classes defined in the space of parameters controlled by the protection.

II. Used Definitions and Terms

A vector of controlled parameters $\mathbf{x}_j$ arriving at the rate of the process, characterized by a sign of belonging to a certain class $y_j \in \{1,-1\}$, is called a precedent. If the vector of monitored parameters $\mathbf{x}_j$ belongs to the class of monitored modes, then its feature $y_j = 1$; if $\mathbf{x}_j$ belongs to the class of alternative modes, then its feature $y_j = -1$. The Smart Protection Device is trained using a variety of the training dataset precedents:

$$\mathbf{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_j, \ldots, \mathbf{x}_n\},\ \mathbf{y} = \{y_1, \ldots, y_j, \ldots, y_n\}. \quad (1)$$

where $\mathbf{X}$ – the training dataset; $\mathbf{y}$ – the vector of features of the training dataset objects.

In the tasks of delimiting complex unrelated areas of use cases [4] - [7], one of the machine learning methods - the Support Vector Machine (SVM) [10] - [12], has proven itself in the best way. The method offers its elegant solution due to its inherent property of constructing a dividing hypersurface in multidimensional space both in the case of linear (Fig. 3, a) and nonlinear (Fig. 3, b) data separation, allowing the formation of enclaves of one mode in the space of another one.

In addition, the method allows equipping the device with the ability to rebuild the dividing hypersurface in multidimensional space at the rate of the process, adapting it to the characteristics of the protected object. To do this, the operating personnel must add features to each of the incoming objects, turning them into use cases.

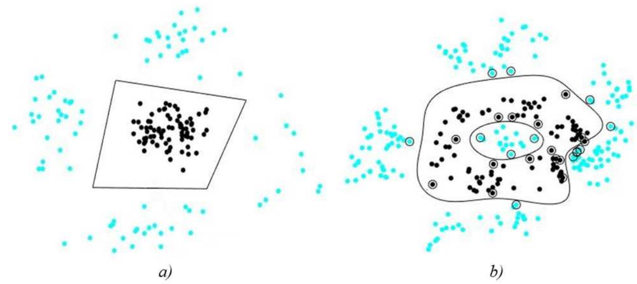

Fig. 3. Characteristics of the Smart Protection Devices using linear (a) and nonlinear (b) classifiers. Dark dots denote precedents of monitored modes (class "+1"), light dots - alternative modes (class "-1"), circles - support vectors

III. Implementation Tasks of the Smart Protection Devices

The capabilities of the Smart Protection Devices are great, but it is important to realize that their perfection fully depends on the thoughtful localization of machine learning methods in relay protection algorithms. The training of the Smart Protection Device, which is carried out at the development stage, includes a sequence of stages of forming the training dataset, choosing reference cases for deep learning of a neural network, and confirming the effectiveness of training. The success of training a device depends on the proper implementation of measures aimed at choosing a feature space and managing the dimension of the training dataset. It is clear that the choice of the elements of the vector of controlled parameters and its dimension requires the developer to have a good knowledge of the research area, and feature engineering for training requires the formulation of a clearly formulated problem.

In the following sections of the work, the tasks arising in the implementation of the Smart Protection Device and the ways of their solution are considered on the example of the development of the Intelligent Mode Discriminator (IMD) [8].

A. A Feature Engineering

The solution to the problem of differentiating the electric network modes based on the trip characteristics formed on the setting planes, which are usual for specialists of relay protection, is often fundamentally impossible. Therefore, the main course in solving this problem is the transition to a multidimensional space. The Smart Protection Device in this respect is not constrained by the dimension of the vector of controlled parameters, it has access to the trip characteristics of any complexity in the space of precedents of any dimension, and the abstractness of the interpretation of the learning result is not alien to it. However, a relay protection specialist has difficulty in interpreting and visualizing the learning result in a multidimensional space. There is a kind of "crisis of confidence" in the training outcomes, overcoming which is usually sought by the projection of the result onto various attribute subspaces, for example, of the third order one.

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For the Intelligent Discriminator of electrical network modes, the feature space should be universal for any phase and not depend on the voltage class of the network. Bringing the characteristics to a unified form is carried out by taking the positive sequence current and voltage as the basic values [8].

These conceptual provisions are illustrated in Fig. 4, which shows the display of the measurements of the discriminator designed to recognize the modes both of single- and double-phase faults to ground, in feature space using the normalized zero-sequence current angle and the normalized negative sequence current angle, measured relative to the base electrical quantity, which in this case is the positive sequence voltage. In the figure, the dark color shows the measurements of the discriminator that recognizes the mode of a single-phase fault to ground, light - the mode of a double-phase fault to ground. The measurement subspaces of the discriminators of the special, lagging, and leading phases designated as ξ, $\xi-1$ and $\xi+1$ respectively. Symbols $\dot{I}_1$, $\dot{I}_2$ and $\dot{I}_0$ denote the currents of positive, negative, and zero sequences.

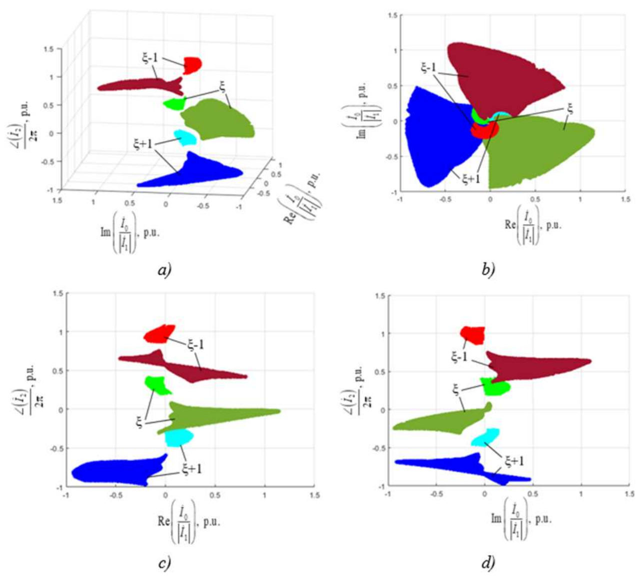

Fig. 4. Display of discriminator measurements in case of single-phase and double-phase fault to ground in feature space (a) and on the plane (b) - (d) in the form of feature space projections

B. A Formation of the Training Dataset

For the Smart Protection Device to function properly, it must be trained. The training of the Smart Protection Device, in particular, the Intelligent Mode Discriminator, is carried out at the development stage based on the training dataset.

The perfection of artificial intelligence depends on the information content of the information provided. An inappropriate approach to the formation of the training dataset can complicate the training of the device, and sometimes make it almost impossible.

The information capacity of the precedent space will be insufficient if the training dataset is represented only by the precedents of a part of the electrical network modes and there are no precedents of important modes for recognition. The training dataset will be in short supply since it is replete with uninformative precedents. A very wide range of grid mode parameters may be required. The informational sufficiency of the training dataset may be ensured only with synchronized measurements of the controlled parameters at different points of the protected electrical system. In this case, the neural network will be able to adapt to the features of the protected object.

Another unpleasant feature of the neural network training procedure is the tendency of the training dataset to explosive growth, known as the "curse of dimensionality". Therefore, one of the most important stages in the formation of the training dataset is to control its size by compression by identifying the training dataset precedents located on the border of the areas of precedents of different classes. In the previous work of the authors [13], approaches to the formation of a lean training dataset based on regular methods of computational geometry are presented. They are based on the construction of shells that enclose the subspaces of the monitored and alternative modes. Their use makes it possible to compress the training dataset of the Smart Protection Device without compromising its information capacity.

One of the methods for finding the best contours of the use case subspaces is the method of alpha shapes [14] - [17]. Let us consider its application in the formation of the training dataset of the Intelligent Mode Discriminator [8], which recognizes the mode of a single-phase fault to the ground.

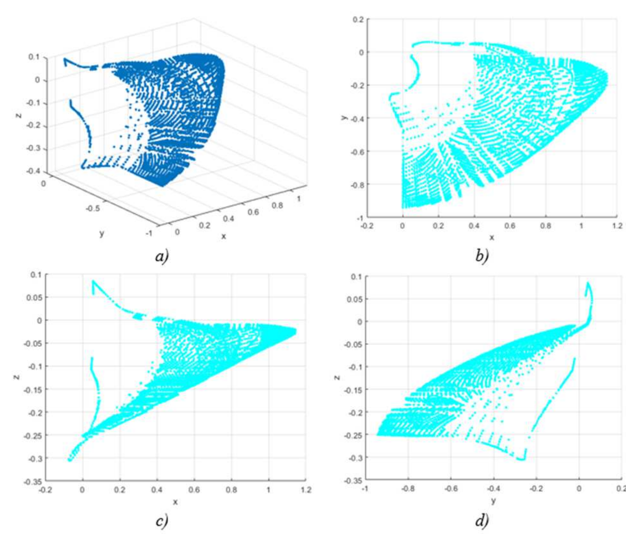

Fig. 5. The boundary points of feature space (a), obtained using the alpha-shapes method. In fig. (b) - (d) are the projections of feature space on the corresponding plane

Fig. 5 shows the precedents of the hull of the subspace of the monitored modes of the special phase ξ of the intellectual discriminator, formed using alpha shape (Fig. 4). The obtained precedents represent a new training dataset with the preservation of the information capacity of the original sample.

The applied approach to the formation of the training dataset provides informational sufficiency of the precedent space.

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Fig. 6 shows the result of training the Intelligent Mode Discriminator, the trip characteristic of the discriminator is built according to the support precedents of the training dataset subjected to compression. The training dataset corresponds to single-phase ground fault modes.

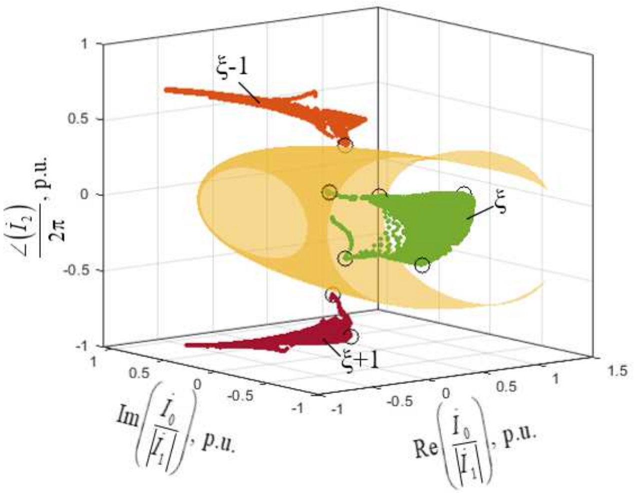

Fig. 6. The Intelligent Discriminator trip characteristic by operating in the mode of a single-phase fault to ground. Designations correspond to designations in Fig. 5.

IV. Conclusions

1. The proposed Smart Protection Devices of the new generation have advanced intellect generated by deep learning neural networks. Neural networks, which are classifiers, equip the device with fundamentally new capabilities, consisting in the construction of characteristics of any complexity in a multidimensional space controlled by the protection of parameters. Thanks to them, the device can adapt to the characteristics of the protected object. The innovations introduced will not require the device to be an avant-garde computing environment, since the devices do not have a branched, rigid logic computing circuit.

2. The procedure for tuning up the Smart Protection Device is carried out at the development stage and includes the formation of the training dataset, the selection of reference cases for deep learning of the neural network, and confirmation of the effectiveness of training. However, training the device is possible only with the preliminary implementation of actions that are based on feature engineering, the formation of the training dataset using simulation scenarios, control of the dimension of the training dataset, as well as the choice of a suitable training method. All of these stages determine the capabilities of the device in operation.

3. The versatility and effectiveness of the Smart Protection Device are provided by a well-thought-out strategy for choosing a feature space and ensuring its information capacity.

4. The training dataset compression step is one of the most important steps in preparing the device for training because it avoids the computational effect known as the "curse of dimensionality". The best performance when compressing the Smart Protection Device training dataset is provided by the alpha-shape method.

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