Fundamental Principles of Smart Protection Device

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***Abstract*—The report outlines the general principles of building relay protection devices with their inherently developed intelligence created by deep learning neural networks. It is shown that the functioning of such a smart device in the pace of the emergency process development in the protected electrical system is not constrained by the complexity of solving the problem of training a neural network. The entire computationally complexity procedure for selecting supporting precedents for deep learning of a neural network, developing and playing out a full set of simulation modeling scenarios, and confirming the effectiveness of device training is performed, as before, at the design stage. In contrast to the characteristics of classical relays, which use a limited number of geometric figures (circles, ellipses, polygons, etc.) on a plane to form the tripping characteristics, Smart Protection Devices present their characteristics in the multidimensional space of tracked emergency mode parameters. An important feature of such devices is the absence of a branched rigid logic computing scheme, and its intelligence has access to characteristics of any complexity because the classification of the current mode of the protected electrical system and the decision making by a new generation relay protection device is based on discriminant functions with developed nonlinear cores. It is demonstrated that, despite the use of discriminant functions that are complex in terms of design principles, the functioning of Smart Protection Devices does not require an avantgarde computing environment.**

Keywords: Digital relay protection, smart protection device, artificial intelligence, deep learning, support vector machine method

I. Introduction

Classical relay protection devices have absorbed all the historical wealth of the developers' intellect, concentrating knowledge about normal and emergency modes of the protected electrical system in their response characteristics. Their noble conservatism, focused primarily on the use of integral characteristics of input signals, such as the effective value, and the evaluation of virtual measurements, for example, the resistance at the relay terminals, ensured the stable operation of electric power systems for many years. Changing the paradigm of the formation of the relay protection and automation environment occurred due to the rapid introduction into the relay protection practice of digital systems. Awareness of the limitless possibilities of digital technologies and attempts to realize the full potential of microprocessor devices called to life the distributed monitoring, protection and control systems - WAMPACS. Following the ideology of new technologies, relay protection and automation devices are called Intelligent Electronic Devices (IEDs). However, the change of name did not give the devices new intellectually significant functions, although they managed to overcome the bonds of an outdated ideology of older-generation devices, more and more refusing to copy their algorithms and implementing fundamentally new features. The attempt to apply the information theory of electrical signals in the relay protection algorithms did not improve a situation, since the main function of the device – making decisions in a short time and under strict conditions of the transient process – is still was carried out in the concept of a fixed logic on a tripping characteristics plane. It became clear that the acquisition of control systems, relay protection, and automation of a fundamentally new perfection is possible only when these devices acquire developed intelligence, based on wide use in the algorithms of its functioning machine-learning methods capable of making decisions in multidimensional space parameters.

This report is devoted to the presentation of the general principles of new generation relay protection devices with inherently developed intelligence created by deep learning neural networks. In what follows, such devices will be called intelligent relay protection devices or, more succinctly, Smart Protection Devices (SPDs).

II. Smart Protection Device and Its Features

In relay protection, all network modes are divided into two classes. The first class includes the modes in which the protection should be triggered, and the second - the modes when the actuation is strictly prohibited. In work [1], the first of them was called tracked (observed), and the second - alternative. In the classical theory, the selectivity of relay protection is ensured by an appropriate choice of tripping characteristics, that can be considered as a learning process. The ultimate goal of training protection is to give it the ability to classify the modes of the electrical network, which consists of distinguishing tracked and alternative modes. That is why the use of deep learning methods in modern relay protection devices looks strictly justified [2]– 5].

The fundamental property of artificial intelligence is the acquisition of knowledge through experiment. It plays an important role in the execution of a neural network since it allows them to exclude from it the stage of formal description by a human of the entire spectrum of knowledge about the problem being solved. The teacher participates in training a neural network only as a constructor of a hierarchy of concepts, each of which is based on simpler definitions and opens up opportunities for teaching artificial intelligence to more complex concepts. The hierarchy will contain many levels, so this approach to building a neural network is called deep learning [6], [7].

The neural network forms its knowledge based on the initial data, the idea of which is formed by a human. Therefore, the perfection of artificial intelligence depends entirely on the quality and quantity of information provided about an object or process. This circumstance enhances the importance of thoughtful localization of machine learning methods in relay protection algorithms, rejecting the widespread misconception that artificial intelligence methods by their very presence remove many restrictions and existing uncertainties in the problems of classifying the modes of the protected electrical network.

Hence, it is important to understand that the resolution of the ambiguity of the mode recognition problem caused by the intersection of multidimensional regions of different modes parameters in space is also beyond the control of the neural network if the dimension of the precedent space (tracked parameters, equipped with sign) turns out to be underdetermined, and the power of the training sample is weak. It may require a very wide range of parameters of the electrical network mode, forming separate regions of the modes in the multivariate space of tracked parameters. Perhaps the informational sufficiency of the precedent space for training the SPD will be provided only by synchronized measurements of the tracked parameters at different points of the protected electrical system. In this case, the neural network can be considered as a developed tool for classifying modes in the multidimensional space of parameters tracked by the device, capable of adapting to features of the protected object.

Like before, the entire computationally complexity procedure for configuring the functions of SPD, including the selection of supporting precedents for deep learning of the neural network, the development and playing out of the required set of simulation modeling scenarios and confirmation of device training effectiveness, is performed at the development stage. In this respect, relay protection devices with developed intelligence, forming the boundary surfaces of modes separation in the multidimensional space of tracked parameters at the development stage, retain their similarity with classical relays. However, unlike the latter, smart devices do not form the tripping characteristics that are customary for a relay protection specialist, although after training the neural network of a smart device, it becomes possible to reflect the dividing surface into spaces of lower dimension or on the plane of the usual tripping characteristics. The SPD considers the differentiation of electrical system modes as the task of assigning a multidimensional vector of tracked parameters to one of the mentioned classes – tracked or alternative – based on previously formed boundary surfaces. Therefore, the functioning of SPD in the pace of the emergency process development in the protected electrical system is not constrained by the complexity of solving the problem of training a neural network.

It is clear that SPD fundamentally does not have a branched rigid logic computing scheme, and its intelligence has access to characteristics of any complexity because the classification of the current mode of the protected electrical system and the decision making by a new generation relay protection device is based on discriminant functions with developed nonlinear cores. The main thing is that despite the use of complex – for the design principles – discriminant functions, the functioning of SPD does not require an avantgarde computing environment.

III. Basics of Application of Deep Learning Theory in SPD

Traditionally, the tripping characteristics of relay protection are formed based on the results of calculations of emergency modes of the protected electrical network as an extreme approximation to the boundary lines strictly bordering the regions of tracked modes, the set of tracked parameters vectors of which no case are displayed in the region of alternative modes. Or, in other words, the tripping characteristics of traditional relay protection include only that part of the area of tracked modes on the plane of tracked parameters, which remains after removing from it a part of the area that is common with the area of alternative modes. Therefore, further improvement of relay protection within the framework of established concepts is possible only by expanding the arsenal of used tripping characteristics and increasing the dimension of the vector of tracked parameters, involving in decision making various algorithms for conditional display on the resulting setting plane of the device of the differentiation results of modes on intermediate tripping characteristics, linking various parameters of mode [8]. Unfortunately, despite the relatively high dimension of the vector of the parameters they control, they inherit all the limitations associated with the mapping ambiguity of multidimensional areas of tracked and alternative modes on traditional setting planes (Fig. 1).

Deep learning neural networks are not constrained by the dimension of the vector of tracked parameters and can construct classifiers of electrical system modes with unimaginable complexity of dividing surfaces, not shying away from the dimension of the precedent space itself and the abstractness of its interpretation (Fig. 2) [3], [5]. Like before, the basis for training the neural network of SPD is the results of simulation of normal and emergency modes of the protected electrical network. In this case, the training sample of the tracked and alternative modes is a set of multidimensional vectors, the elements of which are the parameters of the electrical network mode tracked by a smart device. Each training sample vector belongs to a class of either tracked or alternative modes. Belonging to a particular class is determined

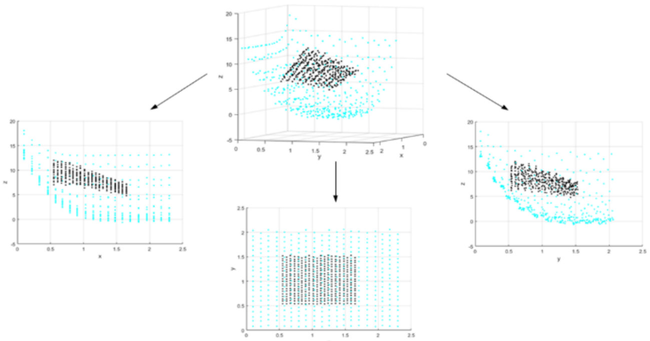
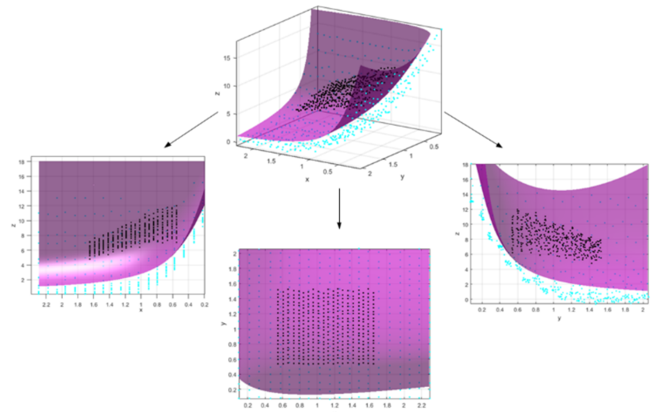


Fig. 1. An illustration of the insolubility of the problem of differentiating modes into classes in the paradigm of classical relay protection, although the fundamental recognizability of modes in the space of tracked parameters is provided. The projections of the features space on the setting planes leads to the imposition of the projections of mode precedents of one class on the projection area of precedents of another class

by the vector of features $\mathbf{y}$ of the objects of the training sample $\mathbf{X}$. The object (vector of tracked parameters) $\mathbf{x}_j$, equipped with the appropriate feature $y_j \in \{1,-1\}$, is called a precedent. It is assumed that the feature is $y_j = 1$ if the object $\mathbf{x}_j$ is assigned to the tracked mode and $y_j = -1$ if it is assigned to alternative mode. Thus, the training of SPD is carried out on a set of training data set $(\mathbf{X};\mathbf{y})$:

$$\mathbf{X} = \left\{\mathbf{x}_1, \ldots, \mathbf{x}_j, \ldots, \mathbf{x}_n\right\},\ \mathbf{y} = \left\{y_1, \ldots, y_j, \ldots, y_n\right\}.$$

One of the methods for training neural networks-classifiers, which has developed tools for constructing various – both linear and non-linear – classifiers, is the Support Vector Machine (SVM). The method formulates the nonlinear problem of delimiting complex unrelated domains of precedents in terms of constrained quadratic programming in the tradition of the Karush – Kuhn – Tucker theorem [7]. The main idea of the method is to construct an optimal dividing hypersurface in a multidimensional space of tracked parameters or a dividing curve (line) on a plane based on a finite number of support vectors of the features set of the training sample of different classes (in our case, classes of the tracked and alternative modes). This important property of the method allows the SPD to function stably under conditions of mutual penetration of the spaces of the tracked (areas of internal short circuits) and alternative (areas of normal mode and external short circuits) modes, allowing the formation of enclaves of one mode in the space of another. At the same time, the SVM method gracefully transforms the data of the electrical network mode tracked by the SPD, which was not included in the training sample, into new precedents, rebuilding the separating hypersurface in the multidimensional space of tracked parameters and continuing to adapt it to the features of the protected object. True, the reconfiguration of the neural network, and in this case, will have to be initiated by a human, who first verified the signs of additional precedents (confirming or refuting the classification results) assigned by the smart protection device to the vector of tracked parameters during the analysis of the emergency mode.



The separating surface of an intelligent protection device in a multidimensional space of features when solving the problem of recognition of modes, formulated in Fig. 1. A Smart Protection Device gracefully solves the problem of differentiating the precedents of the electrical network modes of various classes: the projection of the precedent space on the reference planes confirms that the separating surface reliably masks the light points, located below the dark points

IV. Extreme Possibilities of Smart Protection Devices

The capabilities of the neural network are great, and the tasks of classifying the most complex modes of the electrical system are available to it. They use nonlinear classifiers, the main feature of which is the use of special kernels that can map the feature space into a straightened space, in which classes will be linearly separable [3]. However, it is important to be aware that a neural network is only a mathematical tool for solving the problem of recognizing the electrical system modes and its capabilities are directly dependent on the size of the tracked parameters vector and the power of training data set. If the dimension of feature space is insufficient or deficient (the vector of tracked parameters is devoid of informative parameters or contains uninformative parameters of mode) and a training data set is replete with peripheral precedents (vectors of parameters that lie within the class and do not affect the decision-making), then the training set does not meet the requirement of observability and recognizability modes of the electrical system. Correctly chosen dimension of the precedent space and the power of the training sample guarantees the unambiguity of solving the problem of classifying the electrical system modes, bringing the intelligence of SPD to its limit boundaries. The power of the training sample depends little on its capacity; moreover, an ill-conceived strategy for forming a training data set will only lead to increasing in computational costs when training a neural network, known as the "curse of dimension". Therefore, like before, the choice of well-considered simulation scenarios is an important task when training a smart protection device. In this regard, the rules for identifying the boundary precedents of the training sample, which make it possible to avoid the ballast of peripheral precedents, acquire a special relevance. This task has similar features with the task of creating a prototype of boundary modes in teaching relay protection using conditional mapping methods [8], [9].

Choosing the vector elements of the tracked parameters and the dimension of the vector itself will require the developer to have good knowledge of the subject area. But part of the burden associated with the complexity choice of mode parameters can be borne by the neural network itself, each time showing its assessment of the value of a new element of the tracked parameters vector in the reaction of its discriminant function. If the expansion of the vector of tracked parameters does not lead to a noticeable decrease in the errors of the neural network, then the new element should be rejected with suspicion of linear dependence on other elements or low information value.

V. APPLICATIONS OF THE SMART PROTECTION DEVICE

The use of smart protection devices to implement the functions of simple relays with a vector of tracked parameters $\mathbf{x}_j$ of low dimension does not give tangible advantages over traditional protection devices, since the discriminant functions of their classifiers, with few exceptions, will repeat the usual tripping characteristics [4], [5]. The patrimony of smart devices is multidimensional protections, the dimension of the training sample $(\mathbf{X};\mathbf{y})$ (the order of the tracked parameters vector) of which is so large that the separating surface and the mode classifier do not allow the usual graphical interpretation. Rather, smart protection devices are designed to be part of a distributed monitoring, control and protection system – WAMPACS, the training sample of which includes many multidimensional vectors of distributed measurement of the protected network parameters. The potential of SPD is expected to be higher when used in the preparation of the feature space of the training sample based on advanced methods of processing input signals that take into account the specifics of processes and observed signals, for example, methods of Adaptive Structural Analysis of Signals [10], Discrete Wavelet Transform [11], Principal Component Analysis [12], Independent Component Analysis[13]. It is assumed that the developed relay protection devices with advanced intelligence will find special application in electrical networks with distributed generation, concentrating in themselves both the functions of ensuring the stability of the energy district and the functions of high-speed relay protection and automation. Perhaps that SPD will multiply the benefits of multi-agent systems by offering advanced decision-making intelligence. In local problems of relay protection, they can become the basis for solving various multi-parameter problems, for example, in the development of a universal device for phase selection in the discriminator of faulted phases.

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