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Compression of the Training Sample of the Smart Protection Device without Compromising its Information Capacity

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***Abstract*—In the algorithms of their functioning, Smart Protection Devices use machine learning methods that provide them with the ability to make decisions in the multidimensional space of parameters controlled by the device. To make the Smart Protection Device capable of classifying monitored and alternate modes of the electrical network, it must be trained. Learning is carried out at the development stage, and its effectiveness depends on the training sample. Correctly chosen dimensionality of the precedent space and the power of the training sample guarantee the unambiguity of the solution to the problem of classifying the modes of the electrical system since shortcomings in the strategy for forming the training sample can lead to an explosive increase in computational costs during training. This effect is called the "curse of dimension". The purpose of this work is to describe the methods of compression of the training sample, based on the identification of boundary precedents of the training sample and getting rid of the ballast of internal precedents that do not take part in decision making. The paper discusses various approaches to managing the size of the training sample. It is shown that the method of constructing a hull, bordering the feature space of the Smart Protection Device, based on the use of alpha forms, allows compressing the training sample without compromising its information capacity. The application of the compression of the training sample of the Intelligent Discriminator of the modes of ground short circuits in the recognition of a single-phase short circuit to ground is demonstrated. The training results confirm that the training set retained its effectiveness even after compression.**

Keywords—learning of the Smart relay Protection Device, classification of electrical system modes, training sample, the curse of dimension, information compression

I. Introduction

Smart relay Protection Devices (Smart Protection Device – SPD) [1] to recognize the modes of the electrical network use classifiers that allow them to classify various network modes as monitored (in which relay protection should operate) and alternative (in which operation is strictly prohibited) modes [2–4]. To give the devices the ability to classify modes, it is necessary to train them [1], [5–6]. Usually, learning takes place at the development stage and includes the formation of the training sample based on playing out the full set of simulation modeling scenarios for the protected electrical network, the choice of support precedents for deep learning of the neural network, as well as confirmation of the effectiveness of learning.

The perfection of new generation protections depends on the correctly chosen dimension of the precedent space and the power of the training sample. A well-thought-out strategy for the formation of the training sample eliminates the explosive growth of computational costs when training a neural network, known as the "curse of dimension".

This report is devoted to the presentation of the authors' approach to managing the size of the training sample of the Smart Protection Device without compromising its information capacity and power through the use of various strategies for transforming its data, excluding from the sample uninformative internal objects that do not affect decision making.

II. Task Definition

By compression of the training sample of the Smart Protection Device, the authors understand the identification of training set precedents located on the border of the areas of use cases of different classes.

There are several approaches to identifying the boundary precedents. Let us consider their capabilities on the example of forming the training sample of the Intelligent Mode Discriminator [6], working in the recognition of a single-phase short circuit to ground.

To realize the full potential of the Intelligent Mode Discriminator, it is necessary to conduct its training, the ultimate goal of which is to give the Intelligent Discriminator the ability to recognize the modes of the electrical system. To achieve this goal, simulation modeling of various modes of operation of the electrical network is used. The training sample must have the necessary capacity. Usually, the information capacity of the training sample is provided by a large amount of simulation modeling. This often leads to an explosive increase in computational costs, known as the "curse of dimension" effect. This complicates the training of the discriminator and sometimes makes it almost impossible. Therefore, the main goal of this report is to formulate a strategy for eliminating uninformative precedents by identifying the boundary precedents of the training sample. Thus, the task of the strategy will be to find a hull that borders the discriminator's feature space.

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III. Controlling the Size of the Training Sample

Consider approaches to identifying the boundary precedents of the training sample using the example of the subspace of measurements of the discriminator of the special phase ξ, obtained as a result of simulation (Fig. 1). Let us use regular methods of computational geometry, in particular, the methods for constructing the hull enclosing the feature space of the discriminator.

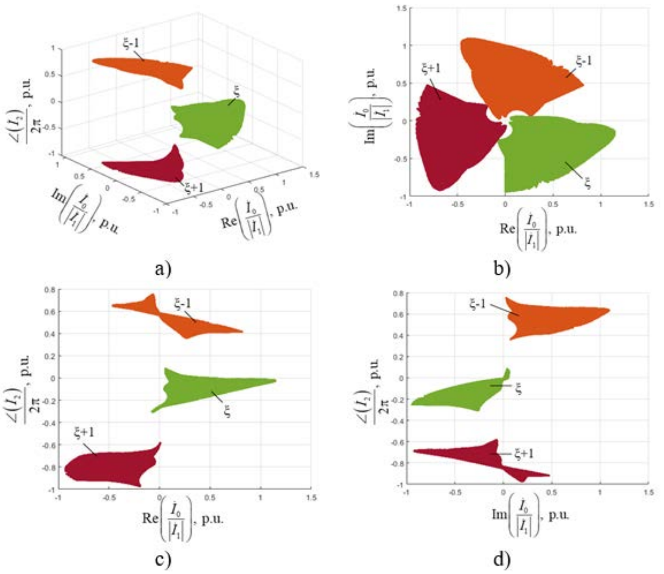

Fig. 1. Display of measurements of the discriminator with a single-phase short circuit in the feature space (a) and in projections (b) - (d) on the plane, where $\dot{I}_1$, $\dot{I}_2$, $\dot{I}_0$ - currents of direct, reverse and zero sequences. The measurement subspaces of the discriminators of the special, lagging and leading phases are designated as ξ, $\xi-1$ and $\xi+1$ respectively

The simplest algorithm for constructing the hull is to use **a convex shape** [7–8] (Fig. 2).

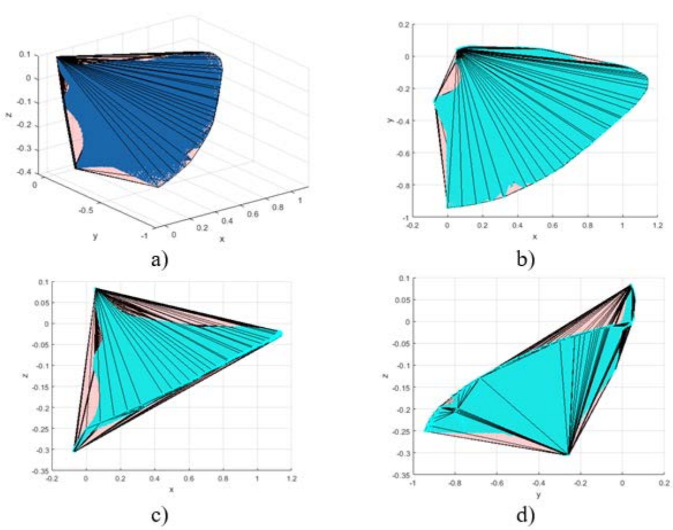

Fig. 2. The hull of the subspace of the monitored modes, formed using a convex shape (a), and its projection (b) - (d) on the plane

The considered approach makes it possible to form a convex hull with a minimum volume. Fig. 2, a) demonstrates the main disadvantage of the applied approach, which consists in the overestimation of the region – the presence of empty places in the internal bends of the shell (the regions marked with a light background). For this reason, this compression method significantly reduces the information capacity of the compressed subspace of the monitored modes (Fig. 3).

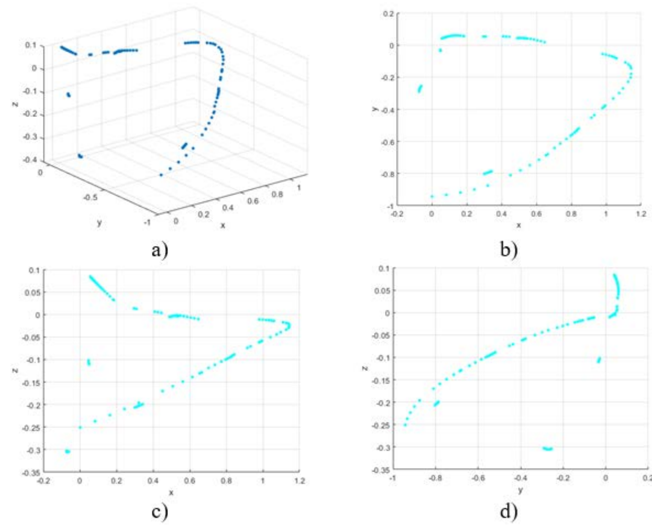

Fig. 3. Boundary points of the convex hull (a) of the subspace of the monitored modes (Fig. 2, a) and their projections (b) - (d) on the plane

The best results are achieved by an improved version of the method using **concave shapes** (Fig. 4) [7].

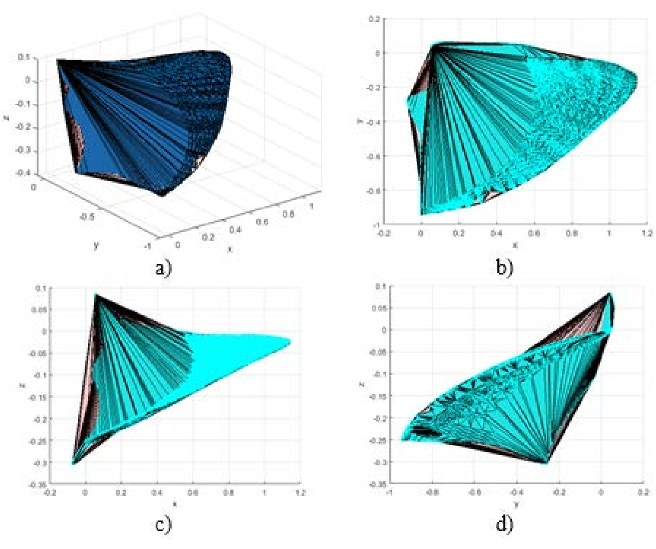

Fig. 4. The hull of the subspace of the monitored modes, formed using a concave shape (a), and its projection (b) - (d) on the plane

Fig. 5 demonstrates that when using concave shapes, the resulting hull takes into account the internal bends of the monitored mode precedent region better.

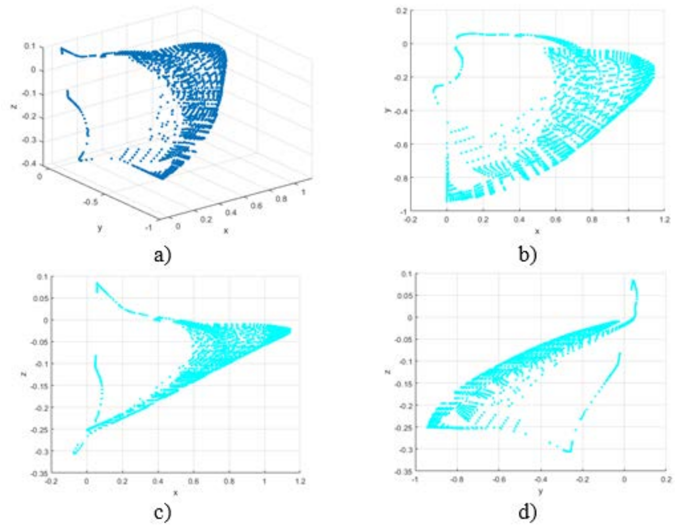

Fig. 5. Boundary points of the concave hull (a) of the subspace of the monitored modes (Fig. 4, a) and their projections (b) - (d) on the plane

However, the method under consideration is also not free from drawbacks, since it can give both overestimation and underestimation of the precedents space of the monitored mode. This is due to the multiplicity of solutions inherent in the method: several variations of concave hulls are possible for the same point cloud.

The most advanced method of adjusting the degree of concavity to achieve the best contour is the method of **alpha shapes** [9–12].

Alpha shape (Fig. 6) filters the convex hull obtained by Delaunay triangulation. The final result of the Delaunay triangulation is its convex hull, containing various triangles in the two-dimensional point cloud representation or tetrahedrons in the three-dimensional version. The boundaries of the triangles have a certain length. The idea of alpha shapes is to remove some of the boundaries that form empty regions of the hull enveloping the original point cloud.

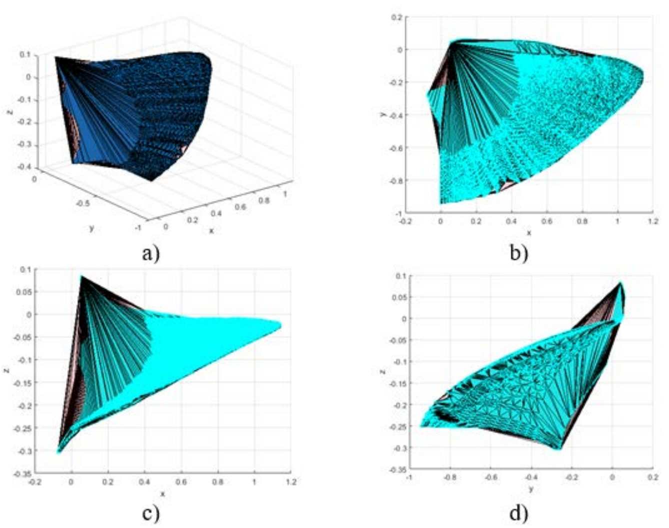

Fig. 6. The hull of the subspace of the monitored modes, formed using a alpha shape (a), and its projection (b) - (d) on the plane

Comparison of the hulls obtained by the considered methods (Fig. 3, 5, 7) shows that the hull of the alpha-form has a more flexible contour, taking into account the entire volume of the cloud of initial points.

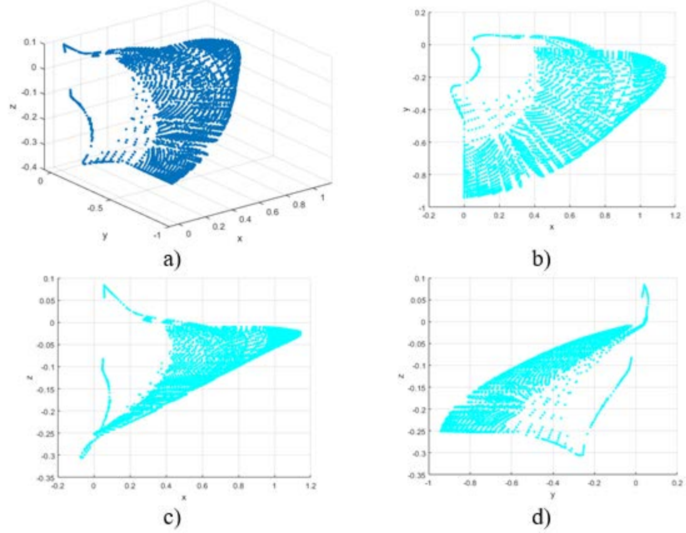

Fig. 7. Boundary points of the alpha form (a) of the subspace of the monitored modes (Fig. 6, a) and their projections (b) - (d) on the plane

The adopted approach to the formation of the training sample allows us to ensure the preservation of the information capacity of the training sample of the Smart Protection Device.

IV. A Tuning of the Intelligent Mode Discriminator

A. The Intelligent Mode Discriminator Learning Method

To ensure the proper functioning of the new generation Smart Protection Device, it must be trained in advance. Simulation scenarios and the stages of managing the dimension of the training sample are important, but only preparatory measures for training the device. The choice of a suitable teaching method is also important, since it is he who determines the capabilities of the device in operation.

The best method that has proven itself in solving problems like ours is the Support Vector Machine (SVM) [13–15]. The peculiarities of using SVM in the tasks of relay protection are described in the works [16–20].

The basis of deep learning of the Intelligent Discriminator is a nonlinear SVM classifier containing nonlinear kernels

$$\mathbf{K}\left(\mathbf{x}_i, \mathbf{x}_j\right) = \left\langle \varphi\left(\mathbf{x}_i\right), \varphi\left(\mathbf{x}_j\right) \right\rangle$$

designed to map cases into a new straightening space, in which the cases will subsequently be linearly separable.

A feature of the algorithms of the Smart Protection Devices is the ability to select trip characteristics of various configurations.

The trip characteristic of the discriminator in the general case will be as follows:

$$\mathbf{y} = \operatorname{sign}\left(\sum_{j=1}^{s} \lambda_j y_j \mathbf{K}\left(\mathbf{x}_j, \mathbf{x}\right) + w_0\right),$$

where $\mathbf{x}_j$ is the support vector, λ_j is the multiplier of the Lagrange function, y_j is the attribute of the support vector $\mathbf{x}_j$ to a certain class, w_0 is the displacement of the dividing hypersurface in feature space of precedents, s is the number of support vectors, $\mathbf{x}$ and $\mathbf{y}$ is the vector of modes recognized by the discriminator and the corresponding vector of attributes of belonging to the tracked or alternative modes.

The richness of the trip characteristics forms is provided by the use of the radial-basis function of the kernel

$$\mathbf{K}\left(\mathbf{x}_i, \mathbf{x}_j\right) = e^{-\left\|\mathbf{x}_j - \mathbf{x}_i\right\|^2}. \tag{1}$$

It has high efficiency in the implementation of various trip characteristics and the ability to form characteristics with enclaves of monitored modes in the field of alternative modes [5].

Fig. 8 illustrates the operation of a nonlinear SVM classifier with a radial-basis kernel function (1). The figure confirms the effectiveness of the choice of the function under consideration when learning the Intelligent Discriminator of electrical network modes.

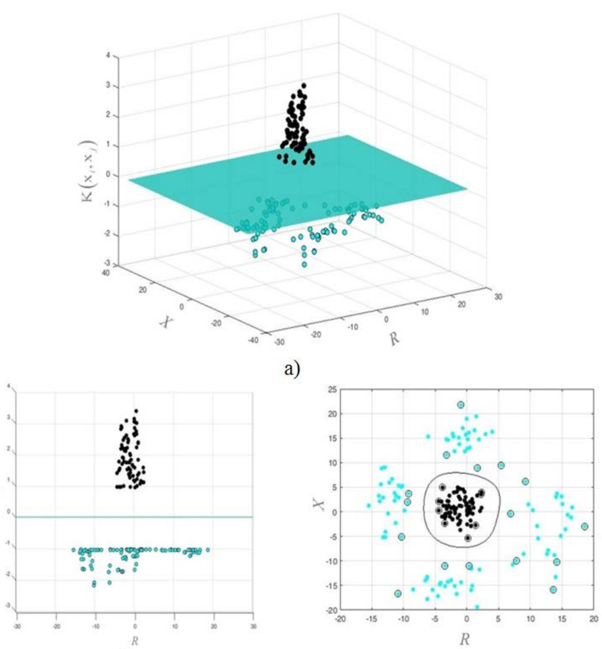

Fig. 8. Straightening space found by nonlinear SVM classifier with radial-basis kernel function. The precedents from the original space (c) are displayed using the kernel function $\mathbf{K}\left(\mathbf{x}_j, \mathbf{x}\right)$ in the new straightening space (a), in which they subsequently become linearly separable (b). Fig. 8 b demonstrates the projection of the straightening space on the plane (R, X). Dark points denote precedents of monitored modes, light points denote alternative modes, circles denote support vectors

B. A Learning of the Intelligent Mode Discriminator

The versatility and efficiency of the Intelligent Mode Discriminator is also guaranteed due to the proper choice of the size and type of feature space. A description of the strategy for choosing a feature space is presented in the previous work of the authors [6].

The result of the compression of the training sample in the feature space of the Intelligent Discriminator and the formation of the optimal separating hypersurface for the single-phase ground fault mode is shown in Fig. 9. The trip characteristic of the discriminator is based on the support precedents of the training sample subjected to compression

The parameters of the trip characteristic

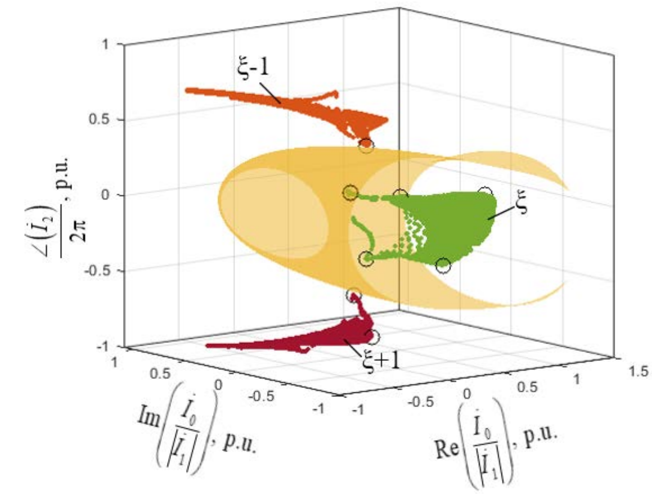

Fig. 9. The Intelligent Discriminator tuning in single-phase earth fault mode. The notations correspond to those of Fig. 1. In Fig. circles indicate the support precedents involved in determining the optimal separating hypersurface

$$\mathbf{y} = \operatorname{sign}\left(\sum_{j=1}^{s} \lambda_j y_j e^{-\left\|\mathbf{x}_j - \mathbf{x}\right\|^2} + w_0\right)$$

are summarized in Table 1.

V. Conclusions

1. Methods of compression of the training sample, based on the use of hulls, separately bordering the subspaces of the monitored and alternative modes, preserves its information capacity and avoids the computational effect known as the "curse of dimension".

2. The alpha-forms method provides the best performance when compressing the training sample of the Smart Protection Device.

TABLE I. PARAMETERS OF THE TRIP CHARACTERISTIC OF THE INTELLIGENT MODE DISCRIMINATOR

Support Vector Number (*j*)	**Support Vector coordinates** $(\mathbf{x}_j)$			**Attribute of Support Vector** (y_j)	**Lagrange Coefficient for Support Vector** (λ_j)	**Scalar** (w_0)
	$\mathrm{Re}\left(\frac{\dot{I}_0}{\dot{I}_1}\right)$	$\mathrm{Im}\left(\frac{\dot{I}_0}{\dot{I}_1}\right)$	$\frac{\angle(\dot{I}_2)}{2\pi}$			
1	0,0866	0,0516	0,0710	1	8,0723	-1,3309
2	0,0815	0,0501	0,0732		9,2346	
3	-0,0672	-0,2656	-0,3053		4,4625	
4	0,0015	-0,9423	-0,2507		1,1166	
5	0,5317	0,0441	-0,0014		4,8161	
6	1,1386	-0,1315	-0,0202		1,5576	
7	0,2511	0,0755	0,3626	-1	17,9220	
8	-0,5774	-0,8594	-0,6794		0,1291	
9	0,0066	-0,0694	-0,5827		11,2066	

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