

Article

Methodology for Small-Signal Stability Emergency Control in Low-Inertia Power Systems Using Phasor Measurements and Machine Learning Algorithms: A Data-Driven Approach

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Abstract

In the process of decarbonizing electricity generation, renewable energy sources are actively being integrated into traditional power systems. As a result, the inertia of the energy system is reduced, and the speed of transition processes is accelerated. This can lead to instability under small disturbances. This necessitates changing traditional approaches to implementing algorithms for emergency control automation. The paper proposes a methodology to solve the problem of small-signal stability analysis in low-inertia energy systems. The task of the small-signal stability analysis problem is reduced to multi-class classification problems. The proposed methodology can be divided into two main parts: selecting the most informative input features and classifying control actions. The IEEE24 mathematical model of the power system serves as a data source. Measurements from this model are received via phasor measurement units. Among the feature selection algorithms considered, the Random Forest algorithm proved to be the most effective. In terms of efficiency in solving the control action selection problem, the LightGBM algorithm proved dominant. Its accuracy in noise-free data was 98%. With 20 dB of data noise, the algorithm's accuracy decreased slightly: 97%. The algorithm's time delay was only 0.07 ms.

Keywords: power system; small signal stability; emergency control; machine learning; low inertia; renewable energy sources

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1. Introduction

The operation of modern electric power systems (EPS) relies on the integrated use of automated and automatic control means aiming to ensure both reliability and economic efficiency. To synthesize control laws for normal and transitional processes in traditional EPSs, deterministic methods are employed. Their procedure includes solving differential-algebraic equation systems describing energy conversion and transient

processes under fault [1]. These principles for selecting optimal control actions (CA) work effectively in traditional EPSs dominated by fossil fuel-based generators providing sufficient inertial components.

Small-signal stability (SSS) of EPS is the ability of a system to maintain stability under small disturbances. Typically, such phenomena do not lead to changes in the power system topology. Such disturbances include load fluctuations, minor generation changes, switching of small loads, etc. The SSS in traditional EPSs is achieved due to the presence of large rotating masses.

It is worth noting that in traditional EPSs the participation rate of power-electronics-based control devices, energy storage systems [2] and renewable energy sources (RES) is minimal [3,4].

However, in the decarbonization process of electricity generation, a transformation of traditional EPSs is currently taking place. It includes adoption of RES, power-electronic-based control devices, flexible alternating current transmission systems, and energy storage systems coupled with the decommissioning of fossil fuel plants. These changes lead to decreased inertial components and increased oscillatory behavior and transient process velocity. The stochastic nature of the electricity generation process is also amplified. The combination of these factors negatively affects the stability of the EPS to SSS. To solve this problem, deterministic approaches may not be effective due to the increased requirements for speed and additivity. Subsequently, enhancing the adaptivity and responsiveness of emergency control (EC) systems [5] capable of solving the CA problem in conditions of low inertia and faster transient processes is important [6].

Machine learning (ML) algorithms are one of the promising areas for improving adaptability and speed of action when solving the CA selection problem [7]. These algorithms are able to identify hidden correlations in previously accumulated data. The procedure for these algorithms involves training a model based on a set of datasets. The trained model does not require multiple operations, as in traditional EC algorithms. By using a set of decision rules, these algorithms provide high performance.

Supervisory control and data acquisition [8,9] or phasor data concentrator systems [10] are used as a source of data for training ML algorithms.

In terms of ML algorithm synthesis of the Emergency Control Law for EPS, it can be reduced to a multiclass classification problem with multidimensional feature spaces. In this formulation of the problem, the electrical regime parameters will be input features with CA selection as the target variable. The following types of CA can be applied as classes: load scheduling (LS) and generator tripping (GT). Both types of CA are aimed at maintaining stability along the dangerous power lines identified after the EP. To enhance responsiveness of data, the procedure of selecting highly informative features based on ML algorithms can be applied as well.

The purpose of this article is to develop a method for selecting CA for preserving SSS based on ML algorithms. In Section 2 the literature review is given. Section 3 describes the basis for the proposed methodology. Section 4 gives the description of performed numerical experiments and presents more suitable ML algorithms for selecting informative features and CA selection. Section 5 describes the problem of small-signal stability. In the Conclusion, final points and directions for future research are described.

2. Current State of the Problem

Currently, ML-based methods for solution of the SSS estimation and CA selection problem are receiving increasingly broader theoretical development [11–28]. The most common of them are methods operating in real time. In [11–28] the following ML-based SSS estimation and CA selection algorithms are used:

- eXtreme Gradient Boosting;
- Convolutional neural network;
- Graph neural network;
- K-nearest neighbors;
- Support vector machine;
- Naive Bayes classifier;
- Decision trees.

In [11] a methodology for assessing SSS and selecting CA based on the eXtreme Gradient Boosting is proposed. The problem is reduced to a classification problem. Further it will be denoted as M1. The following are used as input features: measurements of active and reactive powers of synchronous generators (SG), active and reactive loads of nodes, flows of active and reactive powers along the branches of the protected EPS model, the damping coefficient of oscillations of the electrical mode parameters. The CA selection was used as the target variable. The methodology was tested during a numerical experiment using the EPS IEEE39 model. To train the M1-based model, a dataset consisting of 6300 electrical modes was used. The dataset was generated using the method of randomly changing loads maintaining the state of the branches and SG of the calculation model. The average error of t M1 was 7.56%.

In [12] a method for real-time correction of the settings of power system stabilizer (PSS) devices using the classification of loss or preservation of SSS based on the CNN algorithm is applied. In the future the method will be denoted as M2. On the basis of the IEEE68 model the 30,000 transient processes were simulated. The resulting accuracy of M2 was 99.99%.

A method of the EPS SSS estimation was proposed in [13]. The base of the method in the CNN algorithm is laid out. The problem is reduced to a classification problem. Hereinafter, it will be referred to as M3. The instantaneous voltage signals in the nodes with SG were used as input data. The dataset generation consisting of 1805 transient process calculations using the IEEE9 model was performed. The classification accuracy of M3 is 99.00%. An average classification delay of M3 for one mode is 0.234 ms. The disadvantages of the study include insufficient testing volume due to the use of the simplest EPS model.

In [14] the EPS SSS estimation method using graph neural network algorithm is proposed. The method allows us to take into account the EPS topology and consider the influence of single outages on the SSS reserve. The problem is reduced to a regression problem. Further it will be considered as M4. The following are used as input features: EPS topology in the form of an adjacency matrix, amplitude and phase of voltages in the nodes, the active and reactive powers of the SG and loads in the EPS nodes. The frequency and damping ratio of oscillations of the signal are used as the target variables. For dataset generation the mathematical model of EPS IEEE39 is used. Based on this model 5250 modes using the method of randomly changing the loads in the EPS nodes with a simultaneous single outage of the SG are generated. The average error of M4 is 6%.

In [15], an artificial neural network with two hidden layers was used to perform EPS SSS estimation. Hereinafter, it will be referred to as M5. The imaginary and real parts of the eigenvalues of the IEEE14 mathematical model are used as input data. The total volume of the generated dataset was 20,000 modes. The authors compare the accuracy and time delay of M5 with KNN, SVM, NBC and DT methods. The M5 algorithm has the lowest computational delay.

The SSS EPS estimation using the convolutional neural network was used in [16]. The problem is reduced to the binary class classification problem. Further it will be denoted as M6. For training M6 the NESTA162 model was involved. The values of active and reactive power flows, as well as voltage levels in the nodes of the EPS mathematical model were

used as input data. The safe/unsafe state is used as a target variable. The total volume of the dataset was 1,000,000 modes. When a dataset generating single outages of the electric network elements with a simultaneous change in loads and generations of the model nodes was considered, the following structure of M6 in [16] was applied: convolutional layer, max pooling layer, equalization layer, and the fully connected layer. The accuracy of M6 on the test sample is 98.54% with a delay of 86 ms.

In [17] a universal convolutional neural network-based technique for solving SSS EPS estimation and transient stability (TS) estimation problems is proposed. According to [17] the technique operates in real time. The same technique for TS estimation is proposed in [18]. The problem is reduced to the classification problem. Further the technique will be referred to as M7. The input data are the voltage measurements in the EPS nodes, the analysis of which is performed on a calculation window of 0.2 s. The IEEE39, IEEE50 and IEEE68 mathematical models were used to test the methodology. During the testing, the classification accuracy values from 98.4% to 100.0% were obtained. The authors point out the difficulty in overtraining the M7, and the accuracy values of 98.0% may indirectly indicate possible overtraining.

The SSS EPS estimation problem in [19] is solved by using a convolutional neural network. Further it will be denoted as M8. Dataset generation is performed based on mathematical modeling using the WSCC9 model. This algorithm was chosen based on the accuracy and time delay defined after comparison with an artificial neural network and support vector machine. As a result, an accuracy of 98.7% was obtained for M8.

Table 1 provides a comparison of the methods proposed in [11–19]. The sign «+» in columns 3 and 4 of Table 1 indicates the possibility of the method for solving SSS assessment and CA selection, respectively. From column 4 of Table 1 it follows that in the considered studies, insufficient elaboration of the problem of CA selection to ensure SSS is highlighted. Furthermore, in most studies, the selection of ML algorithms is performed based on expert assessment. Also, the problem of preliminary processing of the dataset to identify informative features is considered in a limited form in [11–19]. The solution to selecting the informative feature problem can be formulated as an objective function:

$$F(AC, T) = \alpha_1 \cdot AC + \alpha_2 \cdot \frac{1}{T} \rightarrow \max, \quad (1)$$

where AC and T are the accuracy and the time delay of CA selection, respectively, α_1 and α_2 are weighting coefficients reflecting the degree of importance of AC or T in solving the classification problem.

Table 1. Comparative table of SSS estimation and CA selection methods.

Ref.	Method	SSS	CA	Accuracy, %
[11]	M1	+	+	92.44
[12]	M2	+	+	99.99
[13]	M3	+	—	99.00
[14]	M4	+	—	94.00
[15]	M5	+	—	98.53
[16]	M6	+	—	95.54
[17,18]	M7	+	—	98.40
[19]	M8	+	—	98.75

Some of the fastest algorithms for selecting informative features belong to the group of determining statistical relationships based on calculating the correlation coefficient [20], Mahalanobis distance [21] and cause-and-effect analysis [22].

In [20] a methodology of EPS TS estimation based on the eXtreme Gradient Boosting algorithm is presented. Further it will be referred to as M9. This method considers the electrical network topology. To select informative features, the parameters of electrical mode with a correlation coefficient $> 10\%$ in relation to the class were used.

A method for solving the CA selection problem to perform EPS TS estimation based on the mixed-integer linear programming algorithm is proposed in [21]. To reduce the dimensionality of the problem, the Mahalanobis distance is used, which has the property of invariance to the scale of features. Hereinafter, it will be referred to as M10.

In [22] an algorithm for analyzing cause-and-effect relationships to determine informative features is used. Further it will be denoted as M11. Testing M11 is performed based on synthetic data obtained by using the IEEE68 mathematical model.

An alternative to the algorithms for selecting informative features based on M9–M11 can be the following: reducing the dimensionality of a multidimensional space based on the principal component analysis [23] and a diffusion map [24].

The authors of [23] proposed a technique for estimating EPS TS by using a probabilistic artificial neural network and selecting informative features using principal component analysis. Further it will be denoted as M12. In this technique a threshold value of 0.5% was chosen to select informative features. Testing M12 is performed using synthetic data obtained from the IEEE39 mathematical model.

The disadvantage of M12 is identifying linear dependencies of features in relation to a class. To overcome it, in [24] a nonlinear diffusion maps method for reducing the dimensionality of space is proposed. Hereinafter it will be referred to as M13. The use of dimensionality reduction algorithms allows classification in three-dimensional space of the synchronous generator number and two diffusion coordinates. In the generated three-dimensional space, a dividing surface can be determined with high accuracy, ensuring the classification of EPS TS.

For feature selection based on various ML algorithms, the following can be distinguished: the model-independent local interpretation algorithm [25], Random Forest (RF) [26], semi-supervised feature selection method [27] and mutual information calculation in combination with the binary particle swarm method [28]. These methods are used to solve the problem of synthesizing the EPS EC law and estimating TS.

The paper [25] proposed a method based on the eXtreme Gradient Boosting algorithm in combination with a method for selecting informative features based on the model-independent local interpretation algorithm. Further it will be denoted as M14. To test M14, IEEE39 models and a fragment of the North Carolina electrical grid were used.

The paper [26] applied an iterative principle of selecting informative features using the Random Forest algorithm. Hereinafter it will be denoted as M15.

To improve the adaptability of M15, a method for using labeled and unlabeled data is proposed in [27]. Further, it will be denoted as M16.

The study [28] presented a two-stage procedure for selecting informative features. In the first stage, the coefficients of mutual informativeness of the feature in relation to the class are calculated; in the second stage, the binary particle swarm method is applied. In the future, it will be referred to as M17. The numerical experiment of M17 was performed using the NPCC140 mathematical model.

The application of the methods M9–M17 for determining informative features allows us to identify the minimum necessary set of data that ensures the maximization of the objective function (1). The characteristics of these methods are presented in Table 2.

Table 2. Analysis of the informative feature selection methods.

Ref.	Method	Problem	Description
[20]	M9	EPS TS estimation	(√) high speed of the informative feature evaluation (×) unable to provide an estimate of hidden correlations
[21]	M10	CA selection	(√) invariance to feature scale (×) can only be used for ellipsoidally located points
[22]	M11	EPS TS estimation	(√) interpretability, invariance to the system change (×) computational and algorithmic complexity
[23]	M12	EPS TS estimation	(√) efficient data compression (×) able to detect complex, only linear structures
[24]	M13	EPS TS estimation	(√) able to detect complex, nonlinear structures (×) computational and algorithmic complexity
[25]	M14	CA selection	(√) interpretability of each individual feature (×) instability of the algorithm, difficulty of use in a multidimensional feature space
[26]	M15	CA selection	(√) robustness to noises and outliers in data (×) relatively high demands on computing resources
[27]	M16	CA selection	(√) efficiency for normally distributed data (×) computational complexity due to unlabeled data
[28]	M17	CA selection	(√) considering nonlinear dependencies (×) high demands on computing resources

The studies considered in Table 2 are aimed at solving the problems of synthesizing the EPS EC law or evaluating the EPS TS [29] based on ML algorithms. For selecting informative feature algorithms based on the application of the theory of descriptive statistics, the following is true: low computational bottlenecks and high speed in case of absence of analyzing hidden and implicit relationships in the data. Using dimensionality reduction algorithms leads to a decrease in the speed of selecting informative features. Despite this, applying special ML algorithms for selecting features contributes to developing adaptive tools. As a result, the dimensionality reduction problem in the synthesis of the EPS EC law or evaluating the EPS TS, ensuring the necessary speed and considering the features and relationships of the parameters of the electrical mode of the protected EPS [30], can be solved.

To overcome the problems identified in [11–28], this paper proposes a universal method for selecting informative features and CA selection problem. The proposed method is designed for solving the SSS maintenance problem in the post-accident mode of operation of the RES [31]. The detailed description of the proposed method is given in the following section.

The scientific novelty of the method lies in the following provisions:

- A methodology allows to implement the formation of training data, data preparation, training and testing of ML algorithms for solving the EPS EC problem;
- A methodology for selecting informative features for selecting CA in order to ensure SSS in the post-accident operating mode of EPS with a reduced value of constant inertia due to a significant share of RES has been determined;
- A methodology for selecting optimal CA for maintaining SSS in the post-emergency EPS operating mode has been formulated;
- Analysis of computational delays [32] of CA selection for maintaining SSS in post-emergency EPS operation mode has been performed.

3. Methodology of Informative Feature Selection and CA Selection for EPS SSS Estimation

The methodology of selecting informative features and CA selection for maintaining SSS EPS is based on the sequential procedure expressed in processing and converting data. This procedure is shown in Figure 1. In more detail, the procedure of the proposed methodology shown in Figure 1 includes the following steps: data preparation; feature selection; cluster analysis; training models; evaluation of model classification.

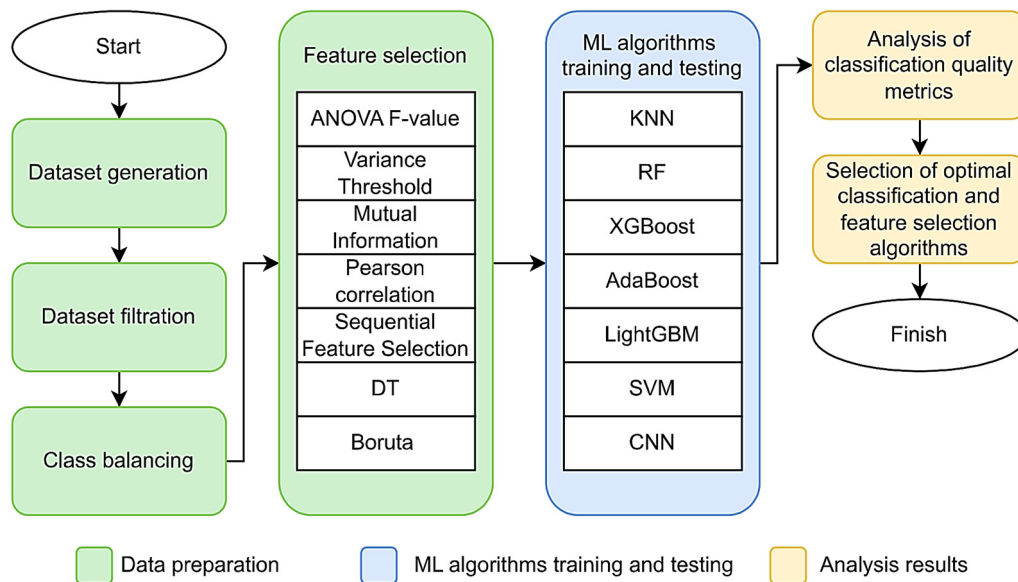


Figure 1. The proposed method for selecting CA to ensure EPS SSS and feature selection.

Data preparation. A dataset describing EPS EC is used as the initial data. The dataset is obtained using deterministic algorithms of CA selection [33]. It contains a set of features and a class describing the place in EPS and the type of CA implementation. The following were used as input features in the dataset:

$$\chi = \{P^{(G)}, Q^{(G)}, P^{(L)}, Q^{(L)}, P^{(ij)}, Q^{(ij)}, \Delta P^{(G)}, V, V_g, I^{(L)}\}, \quad (2)$$

where $P^{(G)}$ and $Q^{(G)}$ are active and reactive powers of generating equipment, respectively; $P^{(L)}$ and $Q^{(L)}$ represent active and reactive powers of loads in EPS nodes, respectively; $P^{(ij)}$ and $Q^{(ij)}$ are flows of active and reactive powers from node i to node j , respectively; V and V_g are voltage modules and angles of EPS nodes; $I^{(L)}$ denotes current load of network equipment; $\Delta P^{(G)}$ is the amount of active power imbalance.

The target variable vector Y contains seven classes, each corresponding to an element of the EPS. Their description is given in Section.

It is worth noting that the data from the model is read by using the PMUs, after forming a dataset filtered to remove gaps, noise and outliers in the original data. Specialized high-speed filters designed for processing data obtained from PMUs [34] can be used to solve this problem. To ensure data homogeneity, a class balancing procedure is used based on the synthetic minority oversampling technique algorithm [35].

Feature selection. The next stage of the methodology is the selection of informative features. As a rule, this stage is performed based on specialized algorithms [36]. To determine informative features to ensure maximization of the objective function (1) the

set of algorithms proposed in [37–43] is used. The first of them, proposed in [37], is a well-known statistical ANOVA method:

$$F\text{-value} = \frac{(SSB/(\xi - 1))}{(SSW/(n - \xi))}, \quad (3)$$

where ξ and n denote the number of groups and the total number of observations, respectively; and SSB and SSW denote sum of squares between and within, respectively.

The higher the F-value in expression (2), the more important the features of the group.

The next feature selection algorithm used in this paper is a Variance Threshold method [38] that can be represented as follows:

$$\sigma^2 = \frac{\sum_i^m (x_i - \mu)^2}{m}, \quad (4)$$

where x_i and μ represent the value of the i -th element of the feature and the mean of x ; and m is the number of observations of the feature.

It is worth noting that the feature selection procedure based on (3) is performed by comparison the σ^2 with a predefined threshold d . In this work the value of this threshold is $d = 0$ meaning that all features with $\sigma^2 = 0$ will be excluded from the DATASET.

The third informative feature selection algorithm is a Mutual Information method [39]. Its essence lies in the relationship between the features and the target variable, and it can be represented as

$$MI(X, Y) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log \frac{p(x, y)}{p(x)p(y)}, \quad (5)$$

where MI is Mutual Information; $p(x, y)$ is the joint probability of x and y ; $p(x)$ and $p(y)$ are the marginal probabilities of x and y , respectively.

$MI(X, Y) = 0$ means that the input feature is not correlated with the target variable.

The essence of the next algorithm is a Pearson correlation [40]:

$$r = \frac{\sum (x_i - \mu_x)(y_i - \mu_y)}{\sqrt{\sum (x_i - \mu_x)^2 \sum (y_i - \mu_y)^2}}, \quad (6)$$

where x_i and μ_x —values of input features and their average; y_i and μ_y —values of the target variable and their average.

The procedure of Sequential Feature Selection algorithms proposed in [41] includes the following methods: ANOVA, Variance Threshold, Recursive Feature Elimination with Random Forest and Least Absolute Shrinkage and Selection Operator. The first two are presented in expressions (2) and (3), respectively. The Recursive Feature Elimination method with Random Forest can be expressed as follows:

$$Importance_j = \sum \left(\text{Decrease in impurity using feature}_j \right)^2, \quad (7)$$

where T_j —the set of nodes in trees where feature j is used.

The Least Absolute Shrinkage (LAS) and Selection Operator method are expressed as follows:

$$LAS = \sum (y_i - y'_i)^2 + \lambda \sum |\beta_j|, \quad (8)$$

where y_i —the true value of the target variable for the i -th observation, y'_i is the predicted value of the target variable for the i -th observation, β_j is the coefficient corresponding to the j -th feature, and γ is the regularization parameter that controls the degree of reduction in the coefficients.

The informative future algorithm based on DT is reduced to the frequency of using an attribute to define objects in classes:

$$AU = \frac{N_{fi}}{N_{total}} 100, \quad (9)$$

where N_{fi} is the objects' numbers defined based on the i -th feature f ; and N_{total} are the total object numbers.

The base of the Boruta feature selection method proposed in [43] is the Random Forest algorithm that is reduced to the following:

$$I_i = \frac{1}{T} \sum_{t=1}^T G_i^{(t)}, \quad (10)$$

where I_i is the importance score of the i -th feature f ; $G_i^{(t)}$ is the Gini importance of the i -th feature f in the t -th tree of the Random Forest; and T is the total number of trees in the forest.

Thus, using the algorithms proposed in [37–43], which are based on Formulas (3)–(10), the most informative features from the DATASET are selected. Their brief description and computational load are presented in Table 3. In the last column of Table 3, the following notations are applied: n and p are the number of observations and features, respectively, k is the size of the future set, t is the number of trees, and $O(\dots)$ is the Big-O notation operator [44].

Table 3. Analysis of the used feature selection algorithms.

Ref.	Algorithm	Description	Computational Effort
[37]	ANOVA F-value	Calculates the significance of differences between groups of features using one-way analysis of variance	$O(n)$
[38]	Variance Threshold	Selects features with variation above a given threshold	$O(p)$
[39]	Mutual Information	Measures the relationship between features and the target variable, identifying nonlinear relationships.	$O(n \cdot p)$
[40]	Pearson correlation	Calculates the linear correlation between each feature and the target value.	$O(n \cdot p)$
[41]	Sequential Feature Selection	Sequentially adds/removes features to optimize the quality of the model	$O(k^p)$
[42]	DT	Builds a decision tree to select the most informative features.	$O(n \cdot p \cdot \log(p))$
[43]	Boruta	Uses Random Forests to estimate feature importance and compare them with noise features.	$O(n \cdot t)$

As can be seen from the last column of Table 3, the simple F-value ANOVA method has a linear complexity of $O(n)$, which ensures fast preliminary removal of insignificant features. The Mutual Information and Pearson Correlation methods are characterized by a complexity of $O(n \cdot p)$, demonstrating efficiency in estimating linear and nonlinear relationships, but are limited by scalability on large datasets. The Sequential Feature Selection method has a moderate complexity of $O(k^p)$, depending on the number of iterations. Decision trees achieve a trade-off between accuracy and performance, having a complexity

of $O(n \cdot p \cdot \log(p))$. The Boruta algorithm, with a complexity of $O(n \cdot t)$, has a high potential for detecting significant features, but requires significant computational resources with a large number of iterations.

Cluster analysis. After completing the stage of selecting informative features, cluster analysis begins. This analysis is produced based on the t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm [45]. The Mean Shift-based algorithm cluster analysis allows to determine the presence of concentrated areas of classes in the data and to identify the possibility of using classification algorithms. The choice of the Mean Shift [46] clustering algorithm is justified by its following abilities: automatic determination of the optimal number of clusters, robustness to the noise and anomalies in the data, and adaptivity to various forms of data distributions in the feature space. To evaluate the quality of the clustering result, the following metrics were used: Silhouette coefficient, Davies–Bouldin index, Calinski–Harabasz index, Adjusted Rand index, Homogeneity score and V-measure score [47].

Training models. After the cluster analysis stage, the procedure of training ML algorithms used for CA classification begins. The choice of ML algorithms is justified by a combination of factors: accuracy; computational complexity; and adaptability.

The list of selected ML algorithms used in this study is presented in Table 4. In the last column of Table 4, the following symbols are used: m is the number of samples; d and p are feature dimensionality and the number of features, respectively, N is the size of the training dataset; M is the number of trees; and i is the number of iterations.

Table 4. Analysis of the used ML algorithms.

Ref.	Algorithm	Description	Computational Complexity
[48]	A1	Classifies based on the majority vote of its neighbors.	$O(m \cdot d)$
[49]	A2	Ensemble method using multiple decision trees.	$O(p \cdot \log(p) + k \cdot N \cdot M)$
[50]	A3	Uses gradient boosted decision trees with regularization.	$O(m \cdot p \cdot i)$
[51]	A4	Iteratively adjusts weights to focus on hard-to-classify instances.	Similar to other ensemble methods but depends on weak learners' performance
[52]	A5	Faster implementation of RF algorithm focusing on leaf-wise splits rather than level-wise splitting.	Typically faster than traditional A2 algorithm due to optimized histogram-based algorithm.
[53]	A6	Maximizes margin between classes by finding optimal separating hyperplane.	Varies from quadratic to cubic in number of training examples depending on kernel type.
[54]	A7	Deep learning architecture suited for image data processing.	Highly dependent on network architecture including layers, filters, pooling operations etc.

A1. The K-nearest neighbors algorithm is easy to implement and widely universal, but its performance significantly deteriorates as the volume and dimensionality of data grow.

A2. The Random Forest algorithm is characterized by stability and reliability, allowing it to effectively process heterogeneous features.

A3. The eXtreme Gradient Boosting algorithm helps improve classification accuracy by regularly growing weak models, but an increase in the number of iterations and the depth of the trees leads to an increase in computational complexity.

A4. AdaBoost is aimed at improving base classifiers, focusing on poorly classified instances, but its performance significantly depends on the quality of the initial models.

A5. Light Gradient-Boosting Machine implements an optimized tree construction procedure, achieving greater efficiency compared to the traditional Random Forest.

A6. Support vector machine aims to maximize the inter-class distance by finding the optimal separating hyperplane. The level of computational complexity of the algorithm increases up to the cubic order with an increase in the number of instances and the choice of special kernel functions. In addition to this, the efficiency of the algorithm is inversely proportional to the growth of the dataset size.

A7. Neural networks with convolutional architectures are the most suitable algorithm for analyzing spatial structures characteristic of visual data, but their use is accompanied by high demands on computational resources.

Since the control action selection problem is reduced to multi-class classification problems, the training result of the machine learning algorithms A1–A7 is $f: \chi \subseteq \mathbb{R}^j \rightarrow Y = \{1, 2, \dots, K\}$, where $\mathbb{R}$ is the feature space of dimension j ; and χ and Y are the sets of input features and class labels, respectively. In this paper, the number of class labels was set to $K = 7$.

Evaluation of model classification. After the procedure of training models, the classification evaluation metrics [55] are calculated: accuracy, precision, recall, F1 and the time delay of classification execution CA. Calculating the value of the objective function (1), the procedure for constructing the variation matrix can be performed, in which the classification algorithms are located on the abscissa axis, and the feature selection algorithms are located on the ordinate axis, and the values of the function (1) are in the variation matrix cells. The best combination of the classification algorithm and the feature selection algorithm gives the maximum value of the function (1).

Figure 2 shows a conceptual illustration of the algorithm variation matrix. It allows us to clearly demonstrate the change in the objective function (1) depending on the selected classification algorithm and feature selection. The values in Figure 2 are indicated without reference to the specific data used in this study. Once the optimal feature selection and CA classification algorithms have been determined, they can be integrated into the existing EPS EC system structure.

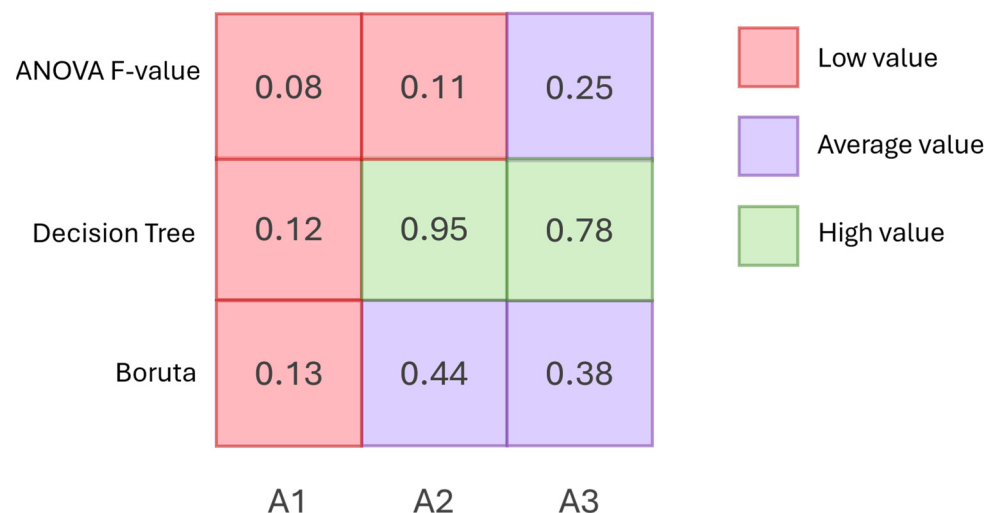


Figure 2. A simplified example of an algorithm variation matrix.

4. Case Study

For the numerical experiment, a modified mathematical model of EPS IEEE24 [56] was used. This model is shown in Figure 3. As can be seen from this figure, in addition to the traditional synchronous generators (SG), the model includes wind generators (WG). To simulate the power change in WG, the output power graphs from work [56] were used.

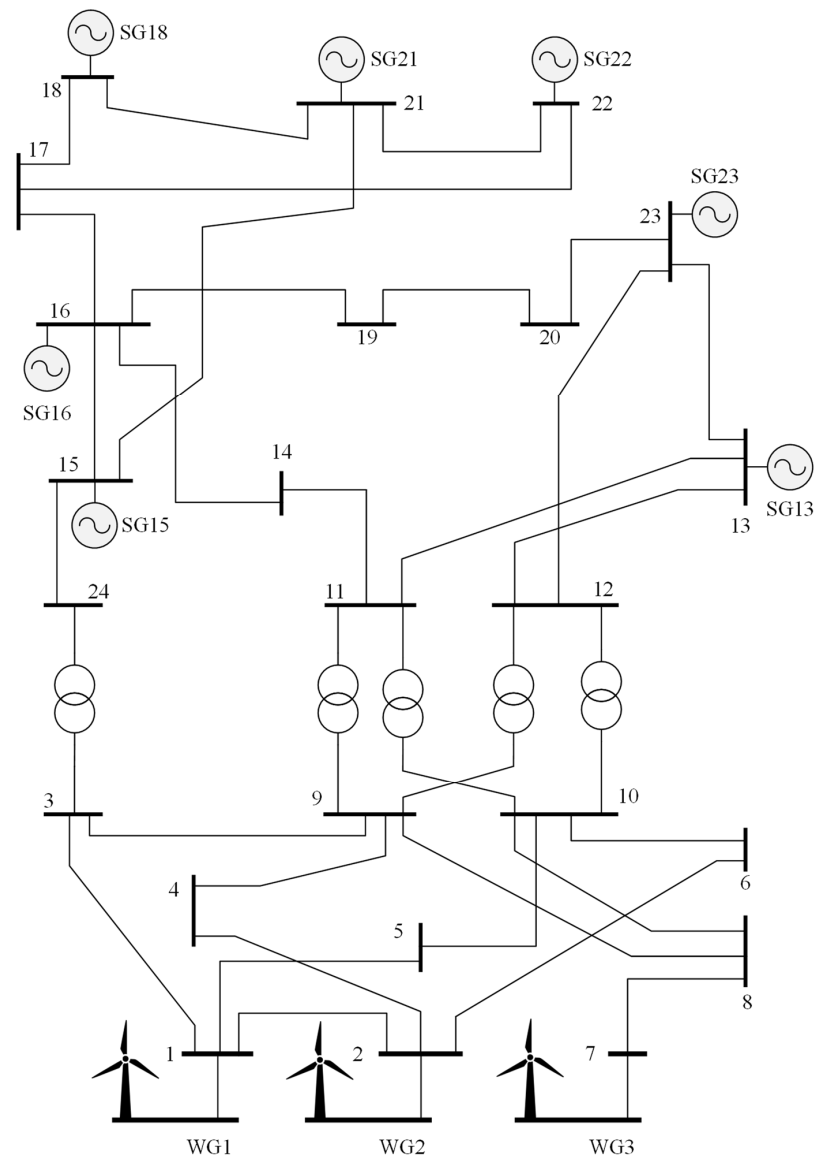


Figure 3. Modified IEEE24 mathematical model.

Table 5 presents the parameters of node loads. In this table the following designations are applied: P and Q are active and reactive power of loads, respectively; V_{max} , and V_{min} are maximum and minimum loads voltage, respectively; and LS is a sign of participation in EPS EC due to the implementation of the CA of the load scheduling type.

Table 5. Parameters of IEEE24 model nodes.

Bus Number	P , MW	Q , MVar	V_{max} , p.u.	V_{min} , p.u.	LS
1	108.0	22.0	1.05	0.95	✓
2	97.0	20.0	1.05	0.95	
4	74.0	15.0	1.05	0.95	✓
5	71.0	14.0	1.05	0.95	✓
6	136.0	28.0	1.05	0.95	✓
9	175.0	36.0	1.05	0.95	
13	265.0	54.0	1.05	0.95	
15	317.0	64.0	1.05	0.95	
16	100.0	20.0	1.05	0.95	
18	333.0	68.0	1.05	0.95	
20	528.0	126.0	1.05	0.95	✓

It is worth noting that in the EPS model shown in Figure 3, bus numbers 3, 7 and 8, 10–12, 14 and 17 have no load. Subsequently, they are absent from Table 5.

Table 6 presents the parameters of synchronous generators (SG) of the EPS model shown in Figure 3. The following designations are used in this table: P_{ref} , P_{max} and P_{min} are rated, maximum and minimum active power of the SG, respectively; Q_{max} and Q_{min} are the maximum and minimum reactive power of the SG, respectively; and GT is a sign of participation in EPS EC due to the implementation of the CA of the generator tripping type.

Table 6. SG and WG parameters.

Generator	P_{ref} , MW	P_{max} , MW	P_{min} , MW	Q_{max} , MW	Q_{min} , MW	GT
WG1	150	152	30	192	−50	✓
WG2	150	152	30	192	−50	✓
WG7	300	350	75	300	0	✓
SG13	600	591	206	591	0	
SG15	200	215	66	215	−100	
SG16	150	155	54	155	−50	
SG18	400	400	100	400	−50	✓
SG21	400	400	100	400	−50	✓
SG22	300	300	0	300	−60	✓
SG23	300	300	10	310	−125	✓

The dataset was formed using the procedure described in the study [57]. The load values were varied by adding a random variable in 20% which had normal distribution relative to the reference values of the base nodes listed in Table 5. According to these changes the load of generators was corrected simultaneously. It is required to maintain active and reactive power balance in EPS. The procedure of changing EPS power flow was automated.

The modified algorithm presented in the study [33] was used as a deterministic algorithm for selecting CA to ensure EPS SSS. As a result, the dataset with 3500 electrical modes was obtained. Then it was divided into training and testing parts in a ratio of 80/20. The class number of the dataset and the description of the classes are given in Table 7.

Table 7. Description of CA classes.

Class Number	GT	LS
0	WG1	4, 5
1	SG18, SG21	4, 5, 6
2	SG22	5
3	SG23	4
4	WG1, WG2, WG3	20
5	WG1, WG2	20
6	No	No

Figure 4 shows the distribution graphs of the normalized values of seven features of the dataset, for the designation of which the following notations are used: F1—active power flow between nodes 14 and 11, F2—active power flow between nodes 19 and 20, F3—active power flow between nodes 5 and 10, F4—reactive power flow between nodes 12 and 23, F5—reactive power flow between nodes 21 and 15, F6—reactive power flow between nodes 19 and 16, and F7—reactive power flow between nodes 12 and 10.

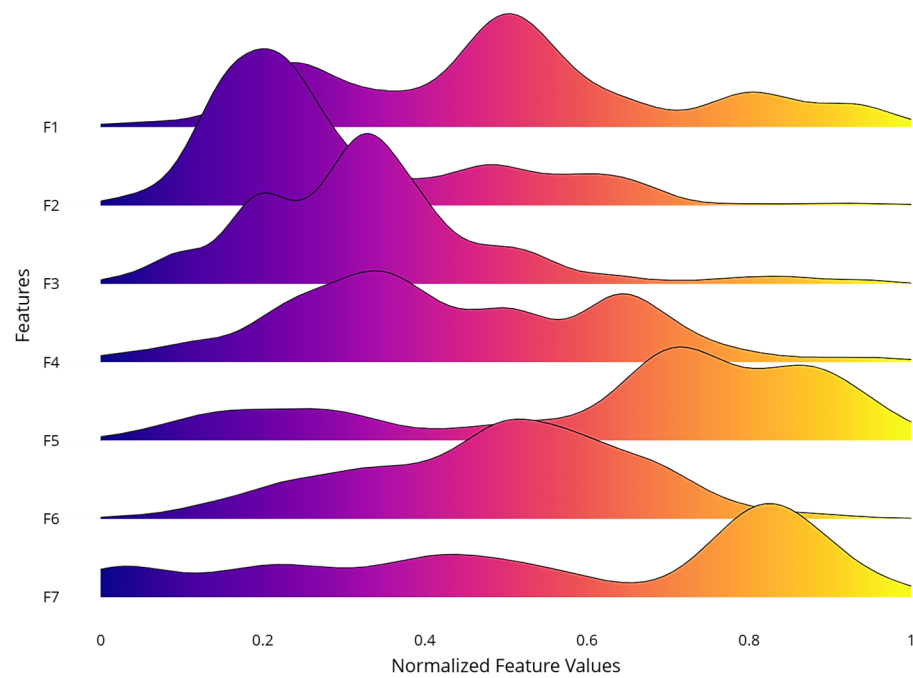


Figure 4. Distributions of normalized features of the formed synthetic data sample.

To visualize the generated synthetic dataset in three-dimensional space, the t-SNE [58] algorithm was used, the results of which are shown in Figure 5.

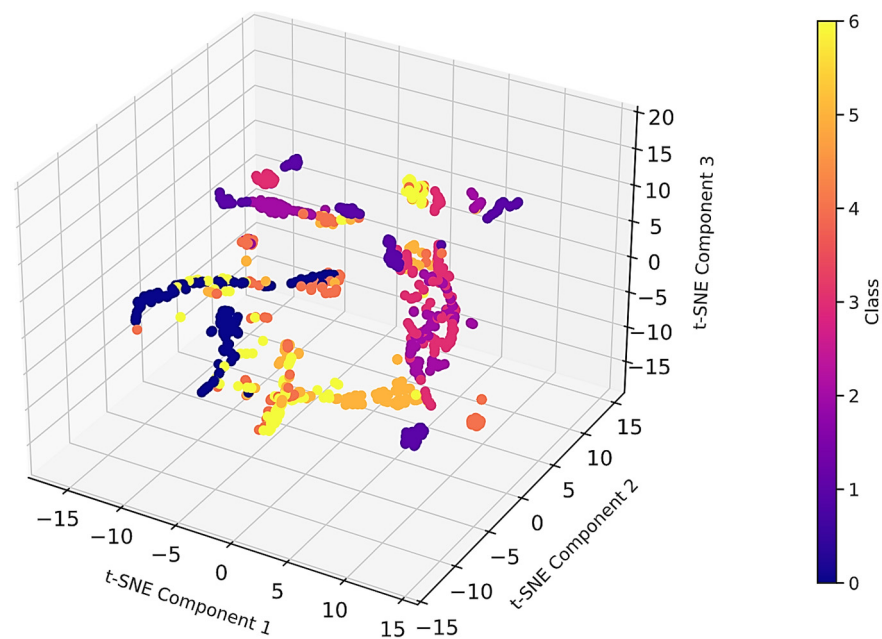


Figure 5. Image of a data sample in three-dimensional space of t-SNE components.

The analysis of the possibility of using classification algorithms was performed using the calculation of data clustering quality metrics through the use of the Mean Shift [59] algorithm. Table 8 shows the results of calculating the clustering quality metrics.

Table 8. Classification of quality metrics.

Metrics	Value
Silhouette coefficient	0.4210
Davies–Bouldin index	0.6211
Calinski–Harabasz index	1147.16
Adjusted Rand index	0.4328
Homogeneity score	0.6104
V-measure score	0.4835

Clustering quality metrics demonstrate a moderate level of quality of applying the Mean Shift algorithm to the dataset used. The Silhouette coefficient indicates weak internal separation of objects within clusters, while the Davies–Bouldin index, remaining below one, confirms the presence of noticeable space for improving the clarity of boundaries between clusters. The Calinski–Harabasz index has a large positive value, indicating a relatively good ratio of internal cohesion and external separability. The Adjusted Rand index Homogeneity score and V-measure score confirm the partial correlation of the formed clusters with the reference classes.

To obtain the optimal hyperparameters of the ML algorithms used, the grid search algorithm [60] was applied. The optimal hyperparameters of the algorithms are given in Table 9.

Table 9. Results of determining ML algorithm hyperparameter values.

Hyperparameters	KNN	RF	XGBoost	AdaBoost	LightGBM	SVM	CNN
Number of neighbors	5	---	---	---	---	---	---
Number of trees	---	100	100	200	100	---	---
Maximum depth of trees	---	10	15	---	---	---	---
Number of features for best split	---	$\sqrt{n}$	---	---	---	---	---
Minimum samples at a leaf node	---	0.02	---	---	---	---	---
Minimum samples to split	---	0.005	---	---	---	---	---
Learning rate	---	---	0.1	0.5	0.1	---	0.001
Base score	---	---	0.7	---	---	---	---
Num leaves	---	---	---	---	31	---	---
Regularization parameter, C	---	---	---	---	---	0.1	---
Number of iterations	---	---	---	---	---	---	30

For the CNN algorithm, the input data was transformed into a matrix form. Figure 6 shows this transformed CNN input data. The following structure was used for the CNN: input layer, hidden layers (convolutional layer, pooling layer, convolutional layer, pooling layer, and alignment), and output layer.

Conductivity matrix of pre-emergency operating mode of the EPS.	Vector of electrical mode parameters
Conductivity matrix of the post-emergency operating mode of the EPS.	Zero matrix.

Figure 6. Representation of input data as an image for the CNN algorithm.

Table 10 presents the parameters of informative future algorithms. In Table 10, the following parameter notations are used: k is the number of selected features, d is the dispersion threshold, $n_neighbors$ is the number of neighbors of the KNN algorithm, max_depth is the maximum depth of the decision tree, and $n_estimators$ is the number of trees in the Random Forest.

Table 10. Parameters of feature selection algorithms used.

Feature Selection Algorithm	Parameters
ANOVA F-value	$k = 20$
Variance Threshold	$d = 0$
Mutual Information	$k = 20$
Pearson correlation	$k = 20$
Sequential Feature Selection	$n_neighbors = 5$
DT	$max_depth = 15$
Boruta	$n_estimators = 30$

Figures 7–9 show the results of evaluating the accuracy, computational delay and objective function (1) for the considered feature selection algorithms and classification algorithms.

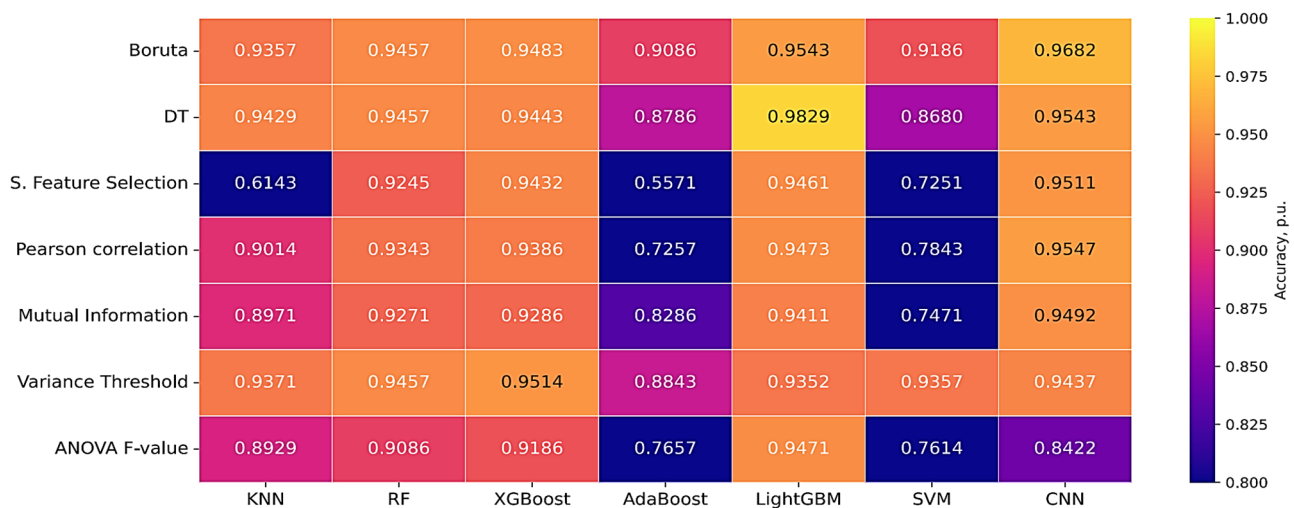


Figure 7. Results of classification accuracy assessment.

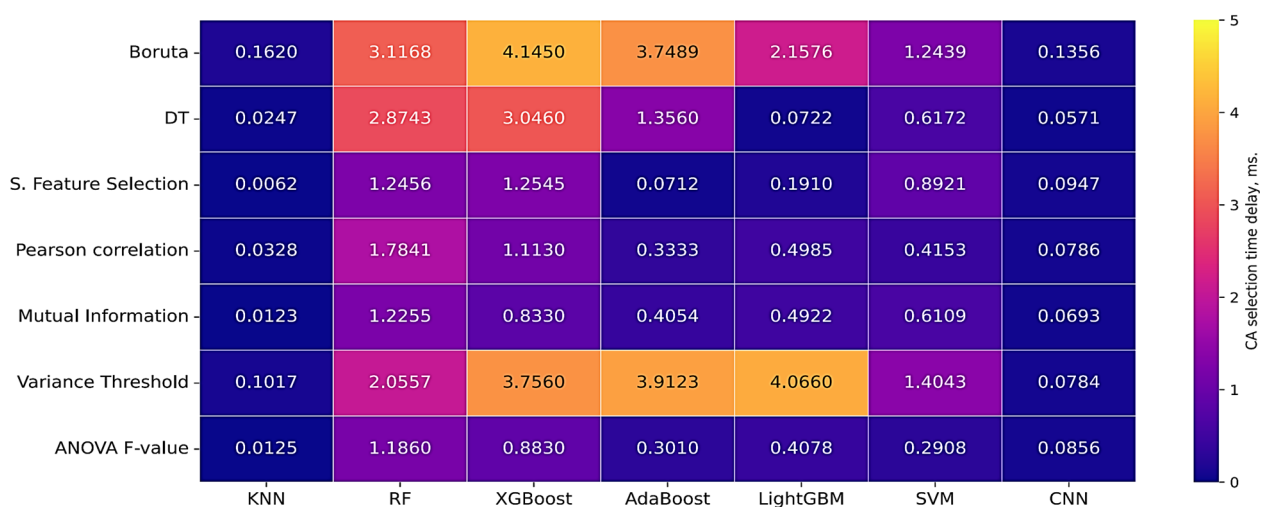


Figure 8. Results of evaluation of computational delay of classification algorithms.

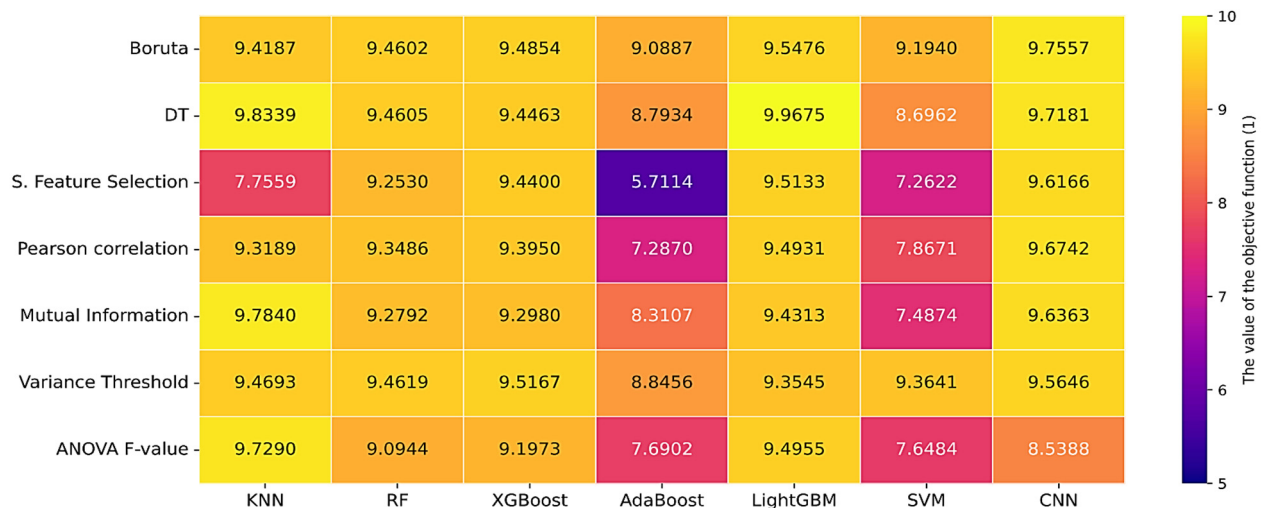


Figure 9. Results of calculating the values of the objective function (1).

To calculate the objective function (1), the following values of the weighting coefficients were used: $\alpha_1 = 10$ and $\alpha_2 = 0.01$. Based on the analysis of the obtained values of accuracy, computational delay and the value of the objective function (1), the optimal algorithms for selecting CA in order to ensure EPS SSS are LightGBM and DT.

To demonstrate the results of training the LightGBM algorithm using the informative features determined by the DT algorithm in the used IEEE24 model, EP was simulated with the disconnection of line 14–11, leading to the violation of EPS SSS; then, CA were selected that ensure the preservation of EPS SSS (CA class 4).

Figure 10 shows the analysis of the eigenvalues of the Jacobian matrix [61], a positive value of the real part of the eigenvalue indicates non-storage of EPS SSS. The implementation of CA leads to a negative value of the eigenvalue and preservation of EPS SSS.

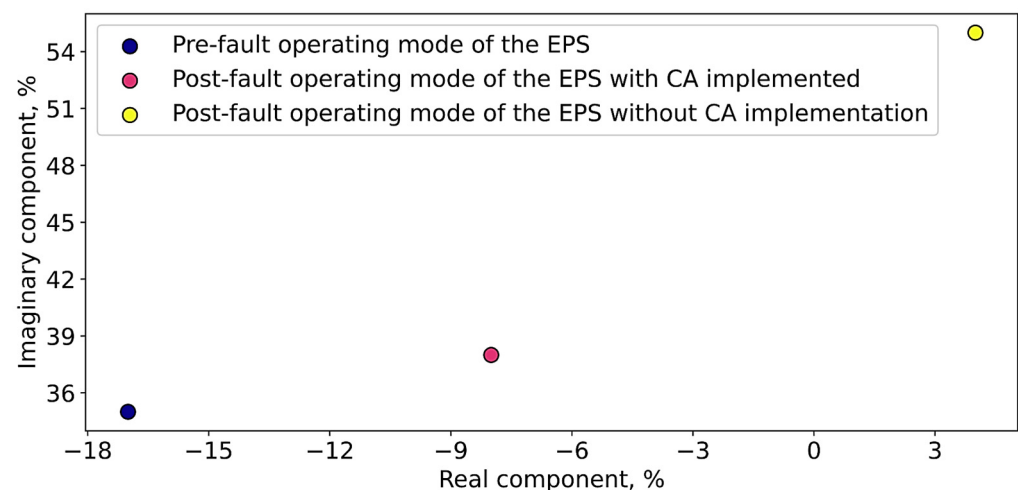


Figure 10. Change in the eigenvalues of the Jacobian matrix taking into account the implementation of CA according to the criterion of ensuring EPS.

The sensitivity to noise in the source data for the LightGBM classification algorithm and the DT feature selection algorithm was assessed. For this, a series of calculations with the addition of a noise level of 0 to 20 dB to the source data was used. The results of changing the classification accuracy in noise conditions in the source data are shown in Table 11. The last column of Table 11 indicates the difference between algorithm accuracy obtained in conditions of a clean, noise-free signal and accuracies obtained in noisy signal conditions.

Table 11. CA classification results when adding noise to informative features.

Noise Level, dB	Accuracy, p.u.	Difference, p.u.
0	0.9829	0
5	0.9811	0.0018
10	0.9795	0.0034
15	0.9782	0.0047
20	0.9711	0.0118

As can be seen from the last column of Table 11, the presence of noise in the source data has minor negative effects. Adding noise to the original data in 20 dB results in an insignificant decrease in accuracy by 0.0118 p.u. Thus, LightGBM algorithm is the robustness to noise in the original data.

5. Discussion

SSS is a phenomenon in which small disturbances lead to loss of EPS stability. When an EP occurs, accompanied by the disconnection of generating or grid equipment, the maximum value of active power transmitted through the elements of the electric grid is reduced. To ensure SSS in post-emergency mode, CAs are used to minimize the flow of active power through the elements of the electric grid. The traditional method for selecting optimal CAs that ensure minimal load and generation shedding is the use of deterministic optimization algorithms. The disadvantage of this class of algorithms is their high computational complexity and the inability to consider the entire list of possible EPSs. Machine learning algorithms allow for the selection of CAs with high speed and adaptability, ensuring the control of modern low-inertia EPSs. However, the use of ML is also associated with a number of difficulties. One of the key issues is the need to collect large volumes of high-quality data for model training. Since many events are rare or even unique, collecting representative data becomes a significant challenge. Furthermore, prediction accuracy depends on numerous factors, including the quality of the source data, the choice of features, and the model's hyperparameters.

Another important issue is the interpretation of results obtained using ML. Many modern models are “black boxes,” whose internal mechanisms remain unclear to users. This creates problems with trust and decision-making based on ML model recommendations. The need to develop interpretable models remains a priority research area in the field of intelligent energy management.

Furthermore, it is important to note that the effectiveness of selected intelligent energy management systems should be assessed not only in terms of preventing instability but also in terms of economic consequences. For example, excessive reduction in transmission power can lead to an unjustified increase in network operating costs. Therefore, the optimal solution must balance technical and economic factors.

It is also necessary to consider the limitations of existing standards and regulations. Some countermeasures may violate existing grid operating regulations, requiring careful verification of each solution before implementation. This increases the complexity of the decision-making process and reduces the potential benefits of implementing new technologies.

It is important to emphasize that developing effective SSS management methods requires an interdisciplinary approach, incorporating knowledge from electrical engineering, mathematics, computer science, and economics. Only an integrated approach will enable the creation of reliable and cost-effective solutions to ensure the stable operation of modern electrical grids.

6. Conclusions

Modern EPS are characterized by significant changes in terms of increasing the speed of transient processes and increasing the requirements for EPS EC adaptability. The study has proposed a structure of the centralized EPS EC system to ensure SSS and CA selection based on ML algorithms. It can be considered as a high-speed backup stage operating during a cascade accident.

An analysis of existing methods for SSS assessment, CA selection, and informative future selection based on machine learning algorithms has been conducted. Their strengths and weaknesses are identified. It is found that most of the existing methods reviewed lack an assessment of time efficiency.

A methodology for selecting CA to ensure EPS SSS based on ML algorithms has been proposed. This methodology allows step-by-step data processing: data preparation; feature selection; cluster analysis; training models; and evaluation of model classification. Based on the numerical evaluation, the most suitable combination of the algorithm for selecting informative features with the CA selection algorithm for solving the SSS assessment problem is shown.

To test the methodology, a synthetic dataset obtained based on the modified IEEE24 power system model was used. This mathematical model has a complex closed structure with two voltage classes, which allows representing the full scope of possible transient processes. The total dataset size after processing was 3500.

The numerical evaluation results show that the DT algorithm provides the maximum value of the objective function (1) for solving the informative feature selection problem. The LightGBM algorithm proved to be the most effective for solving the classification problem of CA selection. The combined latency of the DT and LightGBM algorithms was 0.07 ms. The accuracy of the LightGBM algorithm in noise-free data was 98%. With data noise in the range of 0 to 20 dB, the algorithm's accuracy ranged from 98 to 97%, respectively.

These results demonstrate the effectiveness of the proposed methodology in enhancing the adaptability and responsiveness of EPS EC algorithms.

Future Research Directions

- Application of the method to larger and more complex power system models.
- Use of real PMU measurement data for training and validation.
- Real-time implementation in digital simulators or pilot EPSs.
- Extension to multi-agent or decentralized CA selection for large-scale networks.
- Exploration of hybrid or reinforcement learning approaches for adaptive emergency control under variable operating conditions.

In summary, the study demonstrates that ML-enhanced CA selection provides a significant improvement in centralized EPS EC performance, ensuring SSS with minimal computational delay, high accuracy, and robustness under challenging post-emergency conditions. This approach lays the foundation for next-generation intelligent power system control frameworks that combine deterministic and data-driven methodologies.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Accuracy
AdaBoost	Adaptive Boosting
ANN	Artificial Neural Network
Boruta	Boruta Feature Selection Algorithm
CA	Control Action
CAT	Control Action Table
CNN	Convolutional neural network
DRL	Deep reinforcement learning
DT	Decision tree
EC	Emergency Control
EP	Emergency Process
EP+	Most Hazardous Emergency Process
EPS	Electric Power System
GNN	Graph Neural Network
GT	Generator Tripping
KNN	K-Nearest Neighbors
LightGBM	Light Gradient Boosting Machine
LS	Load Scheduling
ML	Machine Learning
m	Number of Samples
n	Number of Observations/Neighbors
NBC	Naive Bayes Classifier
N	Training Set Size
O(...)	Big-O Notation (Computational Complexity)
P	Active Power
p	Number of Features
PCA	Principal Component Analysis
PMU	Phasor Measurement Unit
RF	Random Forest
RES	Renewable Energy Sources
SG	Synchronous Generator
SSS	Small-Signal Stability
SVM	Support Vector Machine
t	Number of Trees in Iteration
t-SNE	t-distributed Stochastic Neighbor Embedding
TS	Transient Stability
$V_{\max}/V_{\min}$	Maximum/Minimum Node Voltage
WG	Wind Generator

XGBoost	eXtreme Gradient Boosting
α_1, α_2	Weighting Coefficients in Objective Function
CA Class	Control Action Classification Groups
F1–F7	Normalized Feature Values of Active/Reactive Power Flows
$P_{\max}/P_{\min}$	Maximum/Minimum Active Power of Generator
$Q_{\max}/Q_{\min}$	Maximum/Minimum Reactive Power of Generator

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