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Multi-Step Controlled Islanding of Transmission Power Systems Using Constrained Spectral Clustering and Deep Learning Assistance

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Abstract - This paper presents a multi-step controlled islanding (CI) approach for transmission power systems, utilizing spectral clustering techniques enhanced by deep learning assistance. The methodology aims to proactively divide the power grid into stable islands in response to severe faults, thereby preventing widespread outages. The approach commences with monitoring the power system based on voltage and frequency data, adhering to North American Electric Reliability Corporation (NERC) standards to detect critical system instability. Upon detecting a severe system state, coherency analysis is performed to identify coherent generator groups, which then is used in a constrained spectral clustering (CSC) algorithm to generate initial islanding solutions. To expand further potential solutions, a boundary space expansion (BSE) technique is applied. For each generated split option, relevant islanding indicators, including rate of change of frequency (ROCOF), normalized directed power imbalance (NDPI), inter-cluster voltage angle indicator (ICVAI), and root mean square error (RMSE) indicators, are calculated. A deep learning model, trained on historical simulations and the relationship between these indicators and an overall system stability score, is then employed to predict the optimal cut set, facilitating informed decision-making by system operators. The proposed approach has been validated through RMS simulations on the IEEE 9-Bus and IEEE 39-Bus systems, demonstrating its capability to accurately detect system instability, identify coherent generator groups, and effectively rank potential islanding solutions. The generic nature of the trained deep learning model suggests its potential applicability to diverse power system models.

***Keywords*:** 4 - 8 Spectral Clustering, Coherency Analysis, NERC-Standard, Deep Learning

AI	Artificial Intelligence
CI	Controlled Islanding
FRT	Fault Ride Through
ICVAI	Inter-Cluster Voltage Angle Indicator
KHMC	K-Harmonic Means Clustering
MSE	
NDPI	Normalized Directed Power Imbalance
NERC	North American Electric Reliability Corporation
PMU	Phasor Measurement Units
RMSE	Root Mean Square Error
ROCOF	Rate of Change of Frequency
SC	Spectral Clustering

1. Introduction

Transmission power systems have increasingly interconnected over wide areas, enhancing stability while delivering economic, political, and social benefits. This development aligns with the decentralization of energy resources. ENTSO-E exemplifies this balance in Europe, showcasing the advantages of interconnection alongside operational complexity. However, severe faults that are not promptly cleared can lead to uncontrolled islanding, spreading disturbances and causing extensive outages with substantial socioeconomic impacts [1].

To address these risks, CI strategies proactively divide the grid into stable, self-sustaining islands. Research focuses on minimizing power imbalance and flow disruption, though these objectives often involve NP-hard optimization problems that lack efficient exact solutions for large grids. Spectral clustering provides computationally efficient graph partitioning but often neglects dynamic generator coherency—a critical factor for maintaining island stability [2]. Real-time coherency assessment is crucial, as offline analyses may fail to capture current system states [3]. Online coherency identification has been proposed using a correlation index applied to generator oscillations [4]. k-harmonic means clustering (KHMC) has also been utilized for online clustering of coherent generator groups based on rotor angle or speed data [3]. To integrate online coherency identification into spectral clustering efficiently, researchers have modified the graph Laplacian subspaces [5] or incorporated constraint matrices into the generalized eigenvalue problem [6]. Recent advancements in artificial intelligence (AI) have further enhanced CI strategies. For instance, Mixed Integer Linear Programming (MILP) combined with Artificial Neural Networks (ANN) has been used to monitor power line criticality and prevent transient instability [7]. Structural deep clustering networks (SDCN) have introduced entropy loss to ensure generator coherency within islands [8].

Given the necessity for time-efficient solutions considering the flexibility needs of system operators, we propose a multi-step controlled islanding approach. This method solves the islanding problem in polynomial time using spectral clustering techniques while respecting generator coherency and operational constraints. It also provides multiple ranked solutions for easier decision-making, supported by deep learning assistance. By relying on state estimation data, this approach offers flexibility in selecting suitable solutions beyond a globally optimal one. Furthermore, it addresses both key islanding questions: determining "when" to initiate islanding without jeopardizing the system and solving "how" to implement it effectively.

Our paper is structured as follows: Section 2 outlines our methodology for tackling the islanding problem, including monitoring and fault detection, mathematical representations of constrained spectral clustering (CSC), and the use of islanding indicators to train a deep learning model. Section 3 details the modeling of deep learning and its evaluation on test and validation data before application to new case scenarios. Simulation results focus primarily on the IEEE-39 Bus System to maintain scope while also being validated on the IEEE-9 Bus System. Finally, Section 4 concludes with results and recommendations.

2. Methodology

A multi-step approach is defined to handle the islanding problem. First, we need to detect the adequate timing for system severity, which justifies triggering of controlled islanding signal as a severe countermeasure. Second, coherency analysis is applied to obtain coherent generator groups in the system. If such groups are detected, this side information flows into the input parameters of a subsequent CSC algorithm, and by lacking clear coherency groups, this information is neglected in the CSC algorithm.

If and only if a critical system state according to NERC standard is detected, the following steps apply to solve the islanding problem, otherwise the system remains in monitoring state with no further actions required. Considering the boundary nodes in the initial solution of CSC, a Boundary Space Expansion is applied in the next step to increase the number of solutions incorporating the boundary space. For each of the established combinations, various islanding indicators are calculated, including consideration of Power Imbalance and Power Flow Disruption for each split option. Finally, a deep learning model, which is trained on previous simulations, is used to predict the optimal cutset out of split options suggested out of the CSC-BSE steps [1].

2.1 Monitoring and Islanding Time Detection

The power system is monitored based on voltage and frequency data. We rely on RMS-Simulation to mimic the lacking synchronized voltage and frequency measurements provided in practice phasor measurement units (PMU) devices. NERC standard is considered in this research as we use power system models based on modelling of parts of the U.S. power grid.

[1] The following description of our methodology is kept short and we refer the reader to our publication in [9] and [10] for more details.

The NERC standard provides information about generator protection settings and the allowed times for Fault Ride Through (FRT) curves of voltages and frequencies [11].

In our approach, we run a simulation and wait until a sliding window is filled, separately for voltage and frequency data. The dimension of the corresponding matrix is given by $n \times m$, where n stands for number of samples or rows, and m for number of bus bars or columns. We consider a sliding window of 40 samples in this work, which can be expressed in a time-period of 400 ms for a simulation step size of 10 ms.

With continued simulation, the sliding window is updated every s steps and monitoring according to the NERC limits is applied. In each update, the data corresponding to the recent s samples is added and those corresponding to the oldest s samples are withdrawn, so that the window size remains unchanged as illustrated in Fig. 1.

NERC limits are checked based on corresponding timers of the various voltage and frequency violations. With each increment, the voltage and frequency data is calculated and compared to the various NERC ranges. The timers corresponding to those ranges are updated by either increasing or resetting, which occurs at the discrete times: $T, T+s, T+2s, \cdots$. Once one or more ranges are violated, the corresponding violation (voltage or frequency) is recorded, and an islanding signal is triggered. Note that we consider a threshold of 10 % to avoid islanding decisions based on single or short-term faults. As an example, consider the voltage range 0.45 p.u. – 0.60 p.u., if at the evaluation time at least 10% of the bus bars show voltage levels within this range, the timer is increased by corresponding time to the number of steps s. For $s = 5$ steps and 10 ms step size, the timer is increased by 50 ms; otherwise, it is reset to zero.

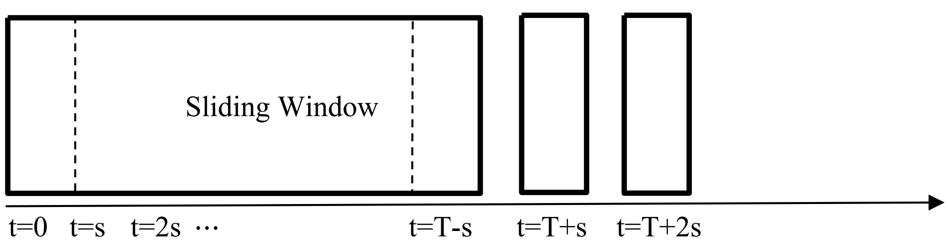

Fig. 1: Sliding window of voltage and frequency, updated every s steps.

2.2 Constrained Spectral Clustering and Boundary Space Expansion

Spectral Clustering is a widely used technique in controlled islanding due to its time efficiency and strong mathematical foundation. It leverages the graph Laplacian, typically in normalized forms such as random walk (L_{rw}) or symmetrical forms (L_{sym}) for result's stability. In power systems, SC models the system as an undirected weighted graph where nodes represent bus bars, edges represent transmission lines, and weights correspond to average active power flows. Clustering involves solving eigenvalue problems on the normalized Laplacian matrix and applying algorithms like k-means to group data into clusters [12].

Generator coherency as nodal information is however a main constraint in power system clustering [13] and hence we need a way to incorporate this information in the clustering process. We apply KHMC algorithm to detect coherent generator groups, which is reflected in a constraints matrix Q that is normalized similarly to the Laplacian matrix and which incorporates Must-Link (+1) and Cannot-Link (-1) constraints. The clustering objective is modified to include these constraints, ensuring coherence while minimizing inter-cluster connections. The form used to solve the CSC problem is given by:

$$\underset{v \in R^N}{\arg\min}\; v^T L_N v,\ s.t.\ v^T Q_N \geq \beta,\ v^t v = vol,\ v \neq D^{\frac{1}{2}} 1 \tag{1}$$

Where v maps the solution eigenvectors, $Q_N \in R^{n \times n}$ the normalized constraint matrix, β a user-defined control parameter, D the degree matrix and vol its volume. The initial solution is expanded by reassigning boundary nodes among clusters to generate additional potential split options using our approach of BSE. The total number of splits is determined by the number of boundary nodes (n_b), calculated as $n_s = 2^{n_b}$. Validation rules ensure that all generated solutions are feasible by preventing node isolation, maintaining the connection between generator nodes and their corresponding transformer nodes, and preserving connectivity within each cluster after reassignment. This process ensures that only valid split options are considered for further evaluation and optimization.

2.3 Islanding Indicators

For each split option, the following indicators are calculated per cluster (potential island), which are considered either as main or as complementary indicators:

- rate of change of frequency: ROCOF
- normalized directed power imbalance: NDPI
- inter-cluster voltage angle indicator: ICVAI
- root mean square error: RMSE

ROCOF and NDPI are used as main indicators in the research in different variations [14, 15] and hence are used in this approach. Additionally, we introduce further potential indicators, ICVAI and RMSE to investigate them in later feature analysis, prepared for a deep learning prediction algorithm. We obtain ROCOF for an island based on the ratio of frequency weighted by the active generation-load imbalance ΔP to the total island's inertias H_{sys} according to Eqs. (2), where H_{gen} and S_{gen} stand for generator's inertia and apparent power, respectively. NDPI is calculated for an island based on the sum of directed (signed) active power flow among cutset lines ψ_c, related to the total island's apparent power

$$\mathrm{ROCOF}_c = \frac{\Delta P \cdot f_n}{2\ H_{sys}} = \frac{P_{gen} - P_{load}}{2 \sum_{i=1}^{I} H_{gen},i \cdot S_{gen},i} \tag{2}$$

$$\mathrm{NDPI}_c = \frac{\sum P\left(l_{i,j}\right), (i,j) \in \psi_c}{S_{sys},c} \tag{3}$$

The indicator ICVAI is obtained as the sinusoidal summation of the voltage angle differences among cutset lines ψ_c, related to the number of those lines $|\psi_c|$. Finally, RMSE is calculated as the deviation from reference values for both voltage (1 p.u.) and frequency (60 Hz) as given in Eqs. (4) – (5).

$$\mathrm{ICVAI_c} = \frac{\sum \left| \sin\left(\Delta\phi_{i,j}\right) \right|, (i,j) \in \psi_c}{|\psi_c|} \tag{4}$$

$$\mathrm{RMSE_c} = \sqrt{\frac{1}{N}\sum_{1}^{N} (X_c(i) - X_c(i,ref))^2} \tag{5}$$

Note that all parameters are calculated at a potential islanding time and system state is considered critical.

2.4 Data Modelling

To model the data in our deep learning algorithm, we need first to select the relevant input features including their form e.g. in terms of aggregation among the islands, and the target variable or output. As we target a generic solution that is independent of the system or the number of islands considered, we describe the modelling challenge as a multi-input, single-output problem. That is given by multiple islanding indicators as input and a score for the output that is globally calculated between 0 and 1, which is composed of the aggregated islands contribution to the score. The contribution of certain features might also be weighted to strengthen the contribution of more relevant compared to less relevant features, as demonstrated in Eqs. (6) for sample features X_i:

$$\hat{y} = \alpha X_1 + \beta X_2 + \gamma X_3 + \cdots + f \cdot X_n \tag{6}$$

$$y = 1 - \hat{y}_N \tag{7}$$

Where $\hat{y}$ is the initial form of the output, which describes the power system state based on the aggregated "instabilities" defined by the islanding indicators. To represent the output as a stability score, we normalize $\hat{y}$ by applying a min-max scaler within the range [0,1] resulting in $\hat{y}_N$. Its complement is then taken to derive y, as described in Eqs. (7).

After preparing the relevant set of input features and the corresponding output variable, the dataset can be partitioned for model training and evaluation. Once trained, the model can then be applied to make predictions on new data.

3. Modeling, Simulations and Results

In this chapter, we fine-tune and use the deep learning model for CI problems and apply our methodology on two test systems: IEEE 9-Bus System and IEEE 39-Bus system. To evaluate the approach, we conduct RMS simulations on both test systems and evaluate the training and evaluation results, while detailed results are focused on the larger, 39-Bus System due to its larger size and higher relevance for the research.

3.1 Feature Analysis and Model Evaluation

We defined islanding indicators for training the deep learning model. Before training, relevant features are selected and aggregated. Simulations on both test systems yield 250 split options, followed by augmentation to 1000, which are analyzed to study input-output relationships with a focus on per-island features. The correlation results are listed in Table 1.

Table 1: Single features and their correlation coefficients.

Feature/Variable	**$ROCOF_1$**	**$ROCOF_2$**	**$NDPI_1$**	**$NDPI_2$**	**$VRMSE_1$**
Correlation to output	0.62	0.68	0.64	0.68	0.13
Feature/Variable	**$VRMSE_2$**	**$FRMSE_1$**	**$FRMSE_2$**	**ICVAI**	**Output**
Correlation to output	-0.19	0.25	0.63	0.47	1

We observe that ROCOF and NDPI show the highest correlation with the output, while VRMSE remains low and FRMSE varies notably across islands. ICVAI, as a global feature, shows moderate relevance with a correlation of 0.47. Aggregating features improves correlation further—ROCOF and NDPI exceed 0.8, and ICVAI increases to 0.63, as shown in Table 2. The strong correlation between ROCOF and NDPI highlights their complementary role as islanding indicators. The output (y) is computed per Eqs. (7) using individual or aggregated features, with equal weighting for comparability.

The prediction model is a feedforward neural network with ReLU activation, dropout regularization, and a sigmoid output layer, trained using MSE loss and Adam optimizer.

Table 2: Correlation results of aggregated features

	ROCOF	**NDPI**	**ICVAI**	**Output**
ROCOF	1.00	0.88	0.15	0.84

NDPI	0.88	1.00	0.18	0.85
ICVAI	0.15	0.18	1.00	0.63
Output	0.84	0.85	0.63	1.00

In the next step, we apply grid search to find optimal model configuration with the lowest validation MSE, which is highlighted in the results shown in Table 3, with a layer size of 64 neurons for input and 32 neurons for the hidden layer, 0.001 learning rate, unchanging dropout rate of 0.25 and a total number of 200 epochs. Using an 80/20 train-test split, the data is first scaled with a min-max scaler, and the model is trained using the highlighted parameters. The resulting predictions are then evaluated and compared against the actual values. As seen in Fig. 2, the model was able to detect the test data with minor deviation.

Table 3: Parameter grid and grid search (optimal parameters highlighted in blue).

Parameter	**Layer size**	**Learning rate**	**Dropout**	**Batch size**	**Epochs**
Value	[64, 32], [128, 64, 32], [256, 128, 64]	[0.001, 0.005, 0.01]	0.25	[8, 16, 32, 64]	[100, 200, 300]

Fig. 2: Model evaluation on test data.

3.2 Study Cases

We use the IEEE 39-Bus System and initiate a three-phase short circuit on bus bar 7 at the time t = 0.5 s and clear it at t = 0.75 s. As a result of the fault, the NERC limits are violated due to voltage violation of the voltage range: 0.0 p.u. − 0.45 p.u. with a duration larger than the maximum threshold of 0.15 s. Applying the KHMC algorithm results in the coherent generator groups at the corresponding bus bars: $g_1 = \{30, 31, 32, 37, 39\}$ and $g_2 = \{33, 34, 35, 36, 38\}$, which reflects the coherency constraint used in the CSC approach to cluster the power grid.

The islanding indicators of the initial CSC output as well as the new generated split options via the BSE approach are calculated and listed in Table 4, with a total of six valid split options and where the fourth split option being the initial or the reference. With the input features of Table 4, the model evaluates the output prediction. As shown in Fig. 3, the model assigns the highest stability score to option 6.

Table 4: Splitting options and islanding indicators as clustering result with BSE.

Split Option	**Cutset Lines**	**ROCOF Island 1**	**Island 2**	**NDPI Island 1**	**Island 2**	**ICVAI**
1	15-16, 17-18, 25-26	−0.016	0.790	0.014	0.056	0.211
2	03-18, 15-16, 25-26	−0.013	0.777	0.012	0.051	0.192
3	14-15, 17-18, 25-26	−0.010	0.765	0.012	0.050	0.174
4	03-18, 14-15, 25-26	−0.007	0.752	0.010	0.045	0.155

5	04-14, 13-14, 17-18, 25-26	−0.010	0.765	0.011	0.046	0.090
6	03-18, 04-14, 13-14, 25-26	−0.007	0.752	0.009	0.041	0.076

Simulations of the corresponding cutsets demonstrate strong alignment between the model's predictions and the RMS-based simulations of voltage and frequency behavior across the resulting islands, as illustrated in Fig. 4. for a 20-second simulation period. The lower-ranked split option exhibits an initial voltage rise in one island and increasing frequency deviations in both, indicating instability. In contrast, the proposed optimal split maintains voltage and frequency within acceptable operational limits in both islands throughout the simulation. While the performance of the optimal split is only marginally better than the reference split (split option 4), it significantly outperforms other alternatives (split options 1, 2, 3, and 5) in terms of voltage and frequency stability. Overall, the simulation results validate the ranking produced by the deep learning model.

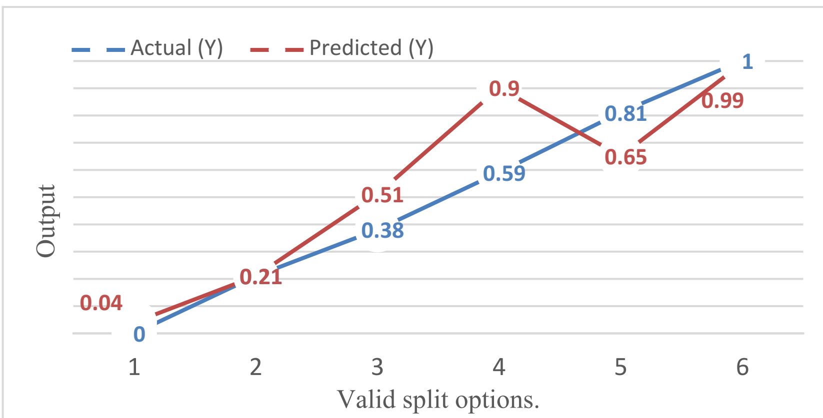

Fig. 3: Split options in the use case of IEEE-39 Bus System.

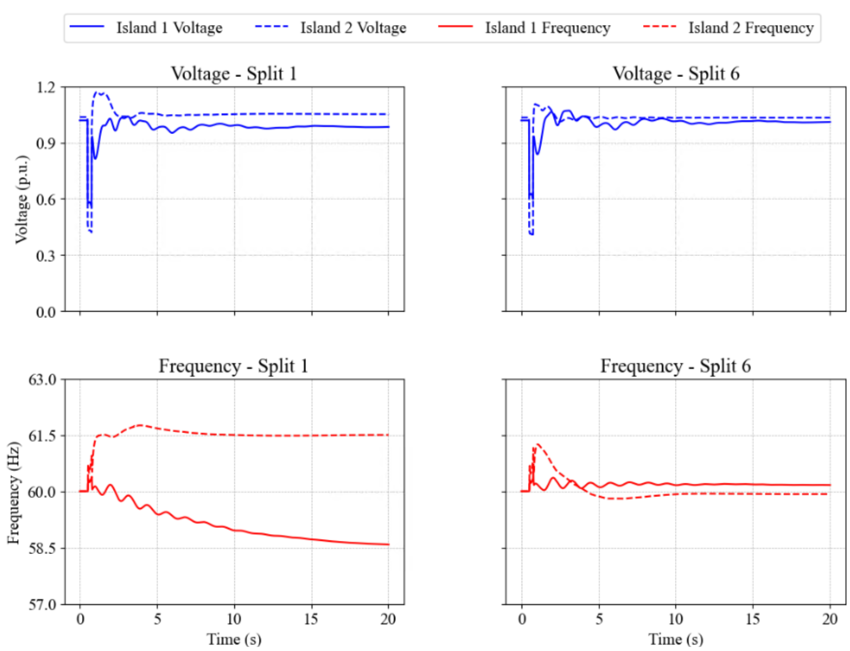

Fig. 4: Comparison of split options in the study case of IEEE 39-Bus System.

4. Conclusion

In this research, we introduced a multi-step controlled islanding approach in endangered transmission power systems using a modified form of spectral clustering under deep learning model assistance, capable of handling nodal side-information and suggestion of optimized islanding solution. It starts by data evaluation according to the NERC standard to determine instability in the system. Once detected, coherency analysis and subsequent constrained spectral clustering are performed to solve the initial islanding problem. Expansion of the solution space is achieved in a reassignment process at the boundary region, at which pre-defined islanding indicators are calculated for valid, potential splits. Finally, a deep learning model is trained and used to assist system operators in their decision-making by favoring potential cut set solutions.

The proposed approach has been validated on the IEEE 9-Bus and IEEE 39-Bus systems, with results primarily illustrated on the latter due to its greater complexity and relevance. The case studies demonstrate that the method effectively detects system instability resulting from voltage or frequency violations, identifies coherent generator groups, and reliably ranks split options using the feedforward deep learning model. By training the model on stability-based input-output relationships in a system-agnostic manner, the approach offers flexibility for system operators to evaluate multiple islanding scenarios without relying on a fixed system topology.

This generalization has been confirmed across two distinct dynamic power system models. However, to further address potential issues such as overfitting and to enhance robustness, future work will focus on extending the approach to larger, more complex systems, including those with integrated renewable energy resources. Line loading indicators, which were outside the scope of this study, are also planned for inclusion—particularly in the context of protection schemes and cascading failure modeling. Additionally, the integration of emerging AI technologies, including agent-based models, is expected to further enhance decision support in high-dimensional, real-time environments.

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