

Methodology for Identifying Representative Rates of Change of Frequency (ROCOFs) in an Electric Power System against N-1 Contingencies [†]

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Abstract: An Electric Power System (EPS) is a dynamic system that, due to continuous variations in the load, the presence of disturbances, switching operations, and/or the operation of the protection system, is never in a steady state. A deficit in generation causes a drop in the system's frequency that, if not controlled, could result in the loss of synchronism between generators or areas and, in the worst-case scenario, a total or partial system collapse. This article presents a methodology to identify a subset of representative events that generalizes the N-1 generation contingency space; this subset can later be applied in the development of Under-Frequency Load-Shedding (UFLS) schemes based on the Rate of Change of Frequency (ROCOF).

Keywords: ROCOF; frequency; data mining



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1. Introduction

The stability of an EPS is defined as the property of a power system to remain in a state of operational equilibrium under normal operating conditions and evolve towards an acceptable state of equilibrium after a disturbance [1]. When an EPS operates close to its physical limits it is vulnerable to instability problems, which if left uncontrolled can lead to partial or total system collapse. In general, there are three types of stabilities: (i) angle, (ii) voltage, and (iii) frequency.

Regarding frequency stability, for a safe and reliable operation of the EPS it is necessary to maintain the balance between generation and load. An excess or deficit in power generation produces a change in frequency, possibly resulting in values outside the admissible operating ranges. In order to maintain stability, power-frequency controls are designed, which allow one to maintain the generation–demand balance, achieving frequency values within the admissible operating range [2].

Power-frequency control is organized on three levels: primary, secondary, and tertiary. Each of the levels operates in a specific time range and involves a set of variables: The primary control is the fastest, operating in a time range of 2 and 30 s. The purpose is to limit the frequency deviation after a contingency, recovering the balance between load and generation and placing the system in a new operating point with a frequency value unequal to the nominal value. The primary response comes from the inertia of the generators, the damping of the loads, the speed regulators (governors), and other devices that provide immediate response, such as Battery Energy Storage Systems (BESSs). In the initial instants, after a power unbalance occurs, the ROCOF and the lowest point of the frequency reached

(NADIR) are determined mainly using the magnitude of the power unbalance, the total inertia of the system, and the response of fast-acting devices such as the BESS [3].

The secondary control operates in a time range of 30 s to 10 min. It operates within the control area, considering the frequency and power exchange with neighboring areas, and it is implemented by the Automatic Generation Control (AGC). Finally, the tertiary control operates in a time margin greater than 10 min. It acts in the scope of a large electrical system, seeking optimized load sharing to ensure sufficient energy reserves [3]. During the operation of the EPS, situations may arise in which imbalances between generated power and consumed power are significantly pronounced. In these circumstances, the mechanical valves controlled by the governors may be too slow to react in time before the frequency crosses acceptable operating limits. This may violate safe operating parameters, which could result in damage to the generating units [1,4]. In these cases, remedial strategies consisting of under-frequency load shedding or generation tripping are designed to prevent possible damage to the generating machines and the collapse of the system.

Load-shedding strategies can be classified into three categories: conventional, adaptive, and computational approaches [5]. Within these categories, time-dependent frequency level strategies as well as ROCOF-based strategies are used. Different methodologies have been proposed to implement load-shedding strategies using ROCOF measurements.

In [6], the calculation of the ROCOF is proposed using a local estimation of the center of inertia per generator, which involves detecting inflection points to eliminate local frequency oscillations. For the prediction of ROCOF, equations related to the center of inertia frequency are employed rather than the dynamic response of frequency to various possible events.

In [7], a load-shedding scheme is proposed for electrical systems serving oil platforms. This scheme defines operational scenarios based on generators with the highest probability of going out of operation. Subsequently, a dynamic analysis is conducted to assess the ROCOF behavior of the selected events and the loads that need to be disconnected, with the aid of a priority table. This scheme has a limited number of scenarios, which may not function correctly in scenarios that are not considered.

In [8], a sizing of energy for virtual energy contribution based on the ROCOF is proposed. In this article, the identification of ROCOF measurements is carried out locally, and calculations are performed using center of inertia parameters. This technique is applied to specific areas of the system; however, it does not provide system characterization under different contingencies.

Building on this background, this article introduces a methodology for characterizing a power system through ROCOF measurements, considering multiple operational scenarios in response to N-1 contingencies using Monte Carlo Simulation (MCS). This approach aims to obtain ROCOF values that describe the dynamic frequency behavior, leveraging data mining tools. These adjustments can be applied in a low-frequency load-shedding scheme triggered by the ROCOF.

2. Mathematical Modeling

2.1. System Frequency Response (SFR) Models

The SFR model allows one to calculate the dynamic frequency response when a generation–load imbalance occurs, and it usually consists of a turbine, speed regulator, synchronous generator, and load. More comprehensive models have been proposed that include the effect of the AGC, Under-Frequency Load-Shedding Scheme (UFLS), wind farms, photovoltaic plants, FACTS, and even induction motors. Figure 1 shows the reduced first-order model for N generators, which is applied in this methodology.

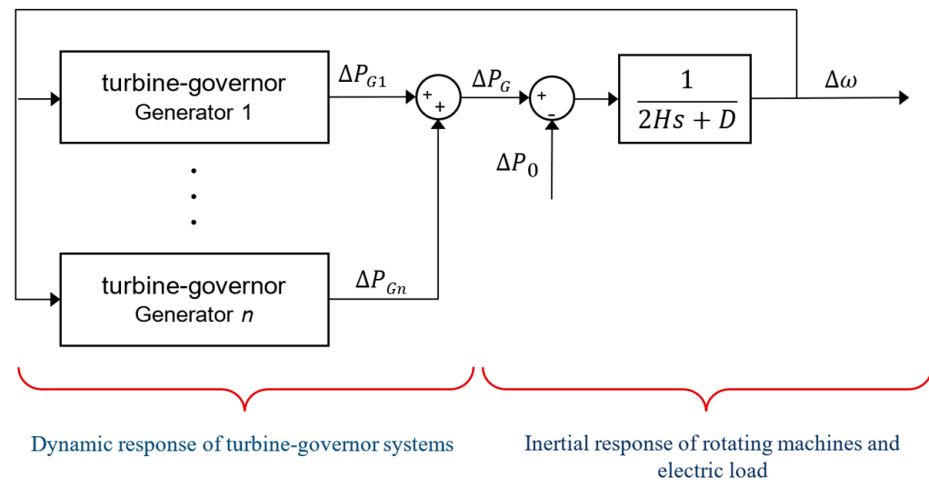


Figure 1. First-order reduced model.

To represent the speed regulator-turbine assembly, a first-order reduced model was proposed in [9], where ΔP_{Gi} , ΔP_o , and $\Delta \omega$, represent electrical power variation, load power variation, and speed variation, respectively, which, when included in the SFR model of the system, yields the average, collective, and coherent response of all generators [10]. This model has a variety of applications, as indicated in [11,12]. However, it has the drawback that all governors of the generators forming the system must be very similar in speed, and, in principle, all generation must be of the steam turbine type [13]. On the other hand, ref. [10] uses a first-order reduced model that accommodates a variety of generation technologies with very different governors. The equivalent SFR model for N generators is shown in Figure 2.

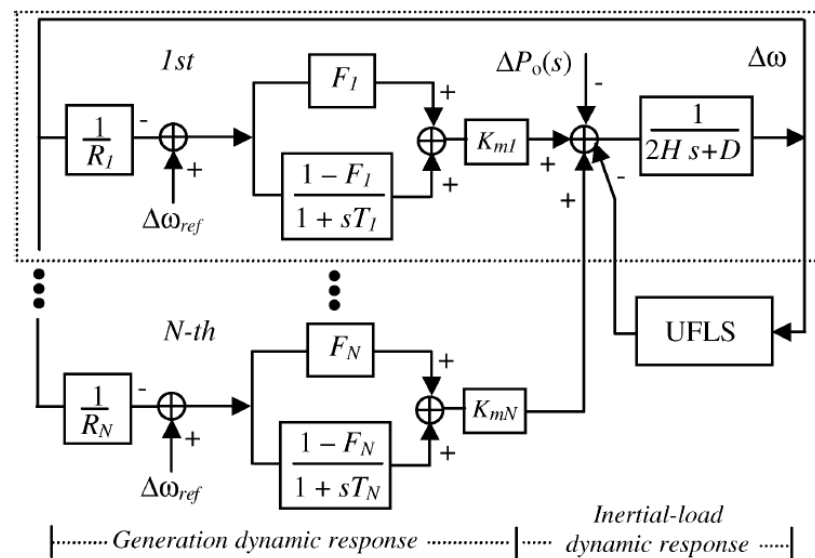


Figure 2. First-order model for dynamic frequency response.

Considering the shown model, the dynamic frequency response $\Delta \omega(s)$ to a generation–load imbalance in the Laplace domain is defined by the following:

$$\frac{\Delta \omega(s)}{\Delta P_o(s)} = \frac{-f_1(s)}{f_2(s)} \quad (1)$$

$$f_1(s) = \prod_{i=1}^N (1 + sT_i) \quad (2)$$

$$f_2(s) = (2sH_{eq} + D) \cdot \prod_{i=1}^N (1 + sT_i) + \sum_{j=1}^N \left[\frac{Km_j}{R_j} (1 + F_j T_j s) \cdot \prod_{i=1, i \neq j}^N (1 + sT_i) \right] \quad (3)$$

where Km_i , F_i , T_i , and R_i are the parameters of the first-order reduced model of the i -th generator and are determined according to the procedure described in Section 3.1, while H_{eq} is the equivalent system inertia, and D represents load damping. The equivalent system inertia is calculated as the sum of the product of inertia H_i by the nominal power S_i of each generator, divided by the system base power S_{sys} , as per the equation

$$H_{eq} = \left(\sum_{i=1}^N H_i \cdot S_i \right) / (S_{sys}) \quad (4)$$

The generation–load imbalance is represented by $\Delta P_o(s)$, mathematically modeled using a unit step function, which, in the Laplace domain, results in $\Delta P_o(s) = \Delta P_o/s$. Solving Equation (1), the dynamic frequency response in the Laplace domain or the time domain is given by the following:

$$\Delta \omega(s) = \Delta P_o \cdot \sum_{i=1}^N \frac{A_i}{p_i} \left(\frac{1}{s} - \frac{1}{s - p_i} \right) \quad (5)$$

where A_i is the real or complex residue and p_i is the real pole or complex conjugate pair of (1) [10].

2.2. Rate of Change of Frequency

The ROCOF allows for characterizing the robustness of an EPS. The dynamic response of this parameter allows one to estimate the power unbalances occurring in the system, which can be calculated with the following equation.

$$ROCOF = \frac{\Delta P}{S} \cdot \frac{f}{2H} \quad (6)$$

where ΔP represents the power unbalance due to an event, f is the nominal frequency of the PES, H is the total inertia constant of the system after the event, and S is the nominal power of the system [14]. The ROCOF calculation for the implementation of the proposed methodology is performed considering a window of 0.5 s as recommended in [15–17].

3. Methodology

Figure 3 shows a diagram of the proposed methodology, which consists of the interaction of three main stages: (1) parametric identification; (2) generation of operational scenarios; and (3) data mining.

The methodology uses MATLAB simulation to perform the parametric identification of the SFR model. On the other hand, the MCS generates the operating scenarios, considering demand uncertainty, generator availability, and N-1 generator contingencies. Then, for each operating scenario generated, the dynamic behavior of the frequency is evaluated, which allows for the generation of a database. This database is a multivariate data matrix that allows for descriptive analysis, correlating variables, and identifying patterns by means of data mining tools.

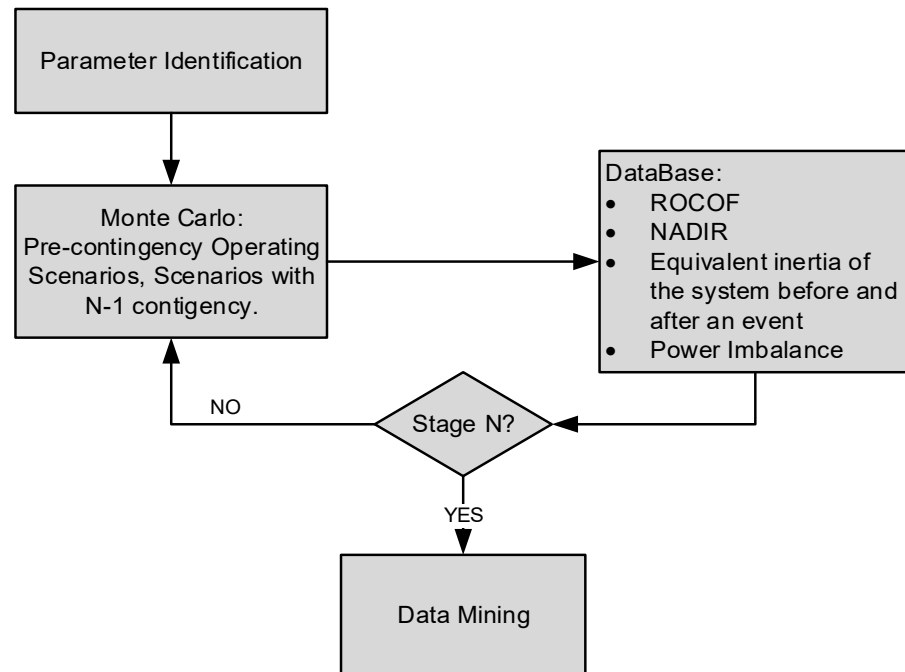


Figure 3. Flowchart of the proposed methodology.

3.1. Parameter Identification

A dynamic equivalent is obtained through a process in which the complexity of a model is reduced while preserving the dynamic response; these equivalents are determined in order to reduce the computational times [18]. At this stage, a validated model of the system behavior is obtained, where a first-order equivalent is implemented that characterizes the dynamic frequency response with the following variables: load unbalance ΔP_o , control system regulation R , and load damping D .

In addition, it is assumed that the dynamic capacity that it can supply is a fraction F of the immediate reserve capacity, the complementary fraction $1-F$ is a first-order phase shift with a time constant T , and K_m is a constant of gain of the spinning reserve of the generators. The proposed model is presented in Figure 2 [10].

In this case, a test system with n generators and complex speed regulators was modeled in the DlgSILENT PowerFactory program to simulate events and emulate real measurements to serve as a reference for the parameter identification of the SFR model. The references extracted from PowerFactory are the mechanical power of each generator and the frequency of the system. Once these measurements are obtained, an optimization tool (lsqcurvefit of Matlab 2022b) is used to identify the constants F , T , and K_m of Equation (2).

$$\Delta W = \frac{-\Delta P_o \prod_{i=1}^N (1 + sT_i)}{(2Hs + D) \prod_{i=1}^N (1 + sT_i) + \sum_{i=1}^N \left(\left(\frac{K_{m_i}}{R_i} \right) (1 + sT_i F_i) \prod_{j=1, j \neq i}^N (1 + sT_j) \right)} \quad (7)$$

The objective function of this problem is to solve the nonlinear curve fitting with the least squares error criterion between the measured signals of the system and the signals obtained through the model. Figure 4 shows the behavior of some generators with the identified parameters. The red line is the signal of the proposed model and the blue is the signal obtained from PowerFactory that simulates the real behavior.

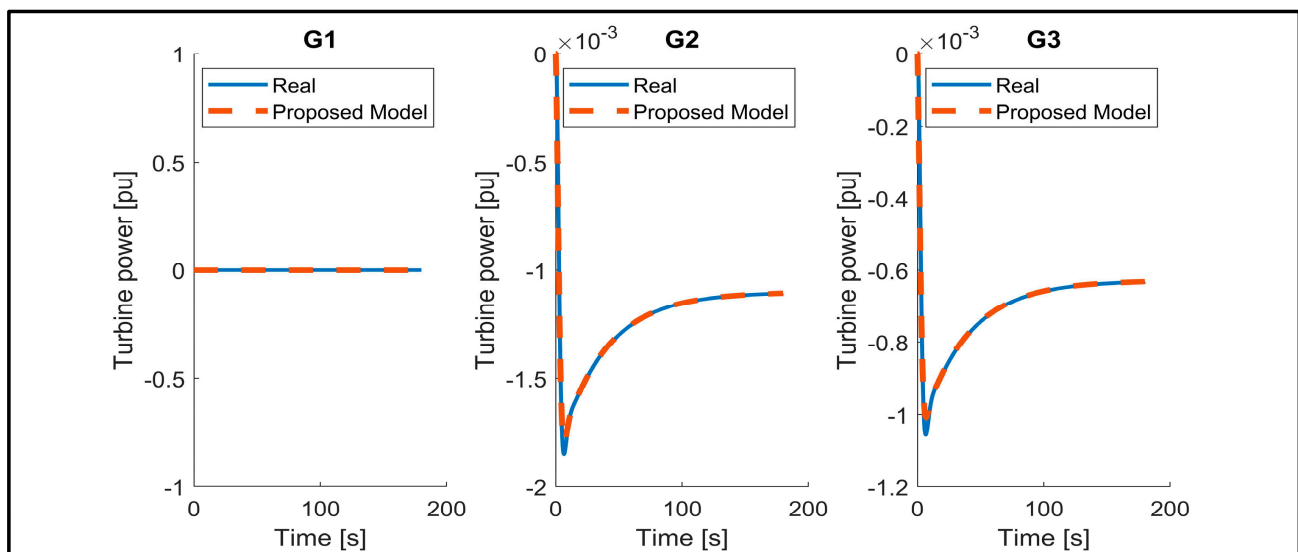


Figure 4. Parameter identification behavior.

3.2. Monte Carlo Simulation

The MCS generates operational scenarios considering uncertainty in demand, generator availability, and N-1 contingencies of the system; then, a dynamic simulation is performed to evaluate the selected variables, which are stored in a database [19].

In the first step, the pre-contingency scenarios are created by using the Matpower tool from Matlab; these scenarios are characterized by operating in a safe region. After obtaining the pre-contingency scenarios under steady-state conditions, the next step involves subjecting each of these scenarios to an N-1 generation contingency. For this stage, it is necessary to create a dynamic model in the Simulink environment with the data acquired through the parametric identification process. For the generation of operating scenarios, the probability distribution functions (PDFs) are used with the data from Table 1.

Table 1. Probability distribution functions.

Component	Variable	PDF	Characteristics
Loads	Active Power	Normal	Mean: [0.5, 0.75, 1] *
	Power Factor	Uniform	Variance = 5% Equal value to base case

* The average of the Normal PDFs is the network condition for a characteristic scenario of the minimum, average, and maximum demand of the system.

3.3. Database

For the elaboration of the database, p numerical variables are identified in a set of n elements that can form a matrix X , of dimension $(n \times p)$, necessary to perform the data analysis and identify the existing patterns [16]. The required database consists of the following variables: ROCOF, equivalent inertia before the event (H_{pre}), equivalent inertia after the contingency (H_{pos}), lost generation power (P_{out}), and the lowest frequency value (NADIR), as shown below.

$$X: \begin{pmatrix} \text{ROCOF}_1 & H_{pre} & H_{pos} & P_{out} & \text{NADIR} \\ \dots & \dots & \dots & \dots & \dots \\ \text{ROCOF}_n & H_{pre_n} & H_{pos_n} & P_{out_n} & \text{NADIR}_n \end{pmatrix}_{n \times p} \quad (8)$$

The ROCOF calculation is performed using a temporal window of 0.5 s. The database must be restructured; this new matrix must discard scenarios where the system recovers to safe levels after a contingency. The decision variable for this selection is the NADIR;

those scenarios where the 59.4 Hz limit has not been exceeded are considered safe and are discarded from the database, and the value of 59.4 Hz is the first step of the under-frequency load shedding recommended in [20].

3.4. Data Mining

In this stage, data analysis is carried out using data mining tools to find anomalies, patterns, and correlations in the large dataset generated using MCS. Data mining or data exploration (it is the analysis stage of “knowledge discovery in databases”, or KDD) is a field of statistics and computer science referring to the process that tries to discover patterns in large volumes of datasets [21]. For data exploration, it is necessary to represent the data resulting from observing several $p > 1$ statistical variables on a sample of n individuals. Each of these p variables is a univariant variable and the set of p variables forms a multivariant variable [22]. Normalization of the data must be performed because the database is formed by variables that have different units; after this result, the desired number of clusters must be selected to apply the “kmeans” algorithm.

4. Application of the Methodology and Analysis of Results

The test system used is an IEEE 39 bus bar system. This system has ten generators, nineteen loads, thirty-five transmission lines, and twelve transformers, whose data can be found in reference [23]. In the present study, a specific modification was made that involves dividing the original generators into eighteen to increase the sensitivity in the analysis of N-1 contingency events.

In the application of the methodology, after performing a selection of data that put the system at risk, three clusters were chosen to represent the frequency dynamics as shown in Figure 5.

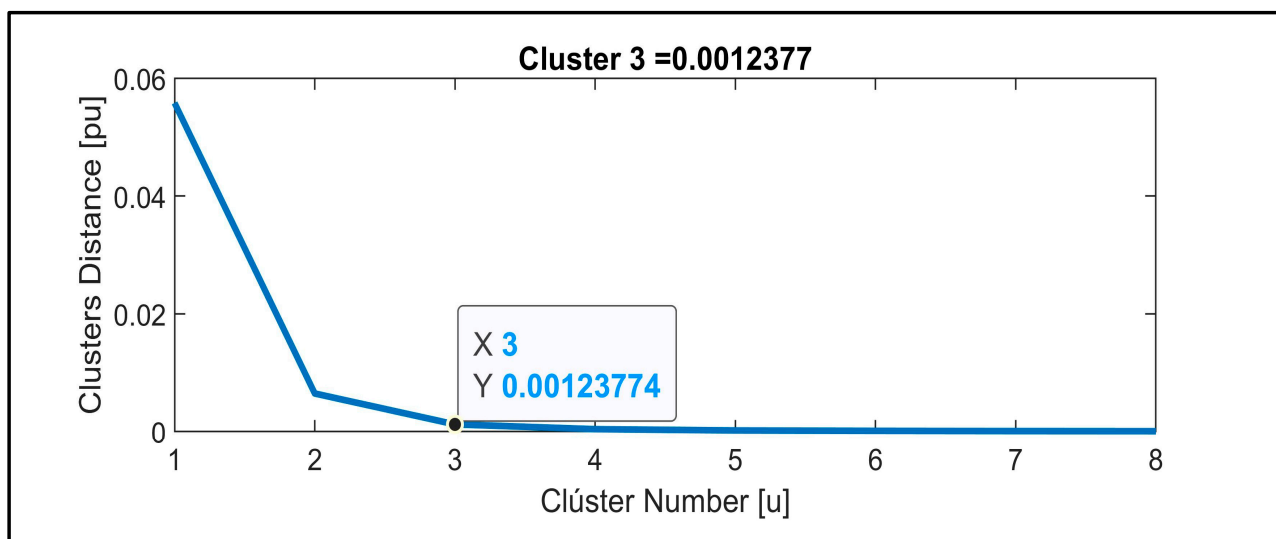


Figure 5. Total cluster distance vs. number of clusters.

For conducting the cluster analysis, the k-means tool from Matlab is used. Figure 6 illustrates the variables displaying strong correlation, showing a linear relationship among them. It can be observed that in cases where an event exhibits substantial strength and the generated output power is higher, it results in increased uncertainty in the NADIR. However, the linear correlation with the ROCOF remains intact. As a result, a UFLS founded on this parameter serves as a reliable predictor of power imbalance magnitude.

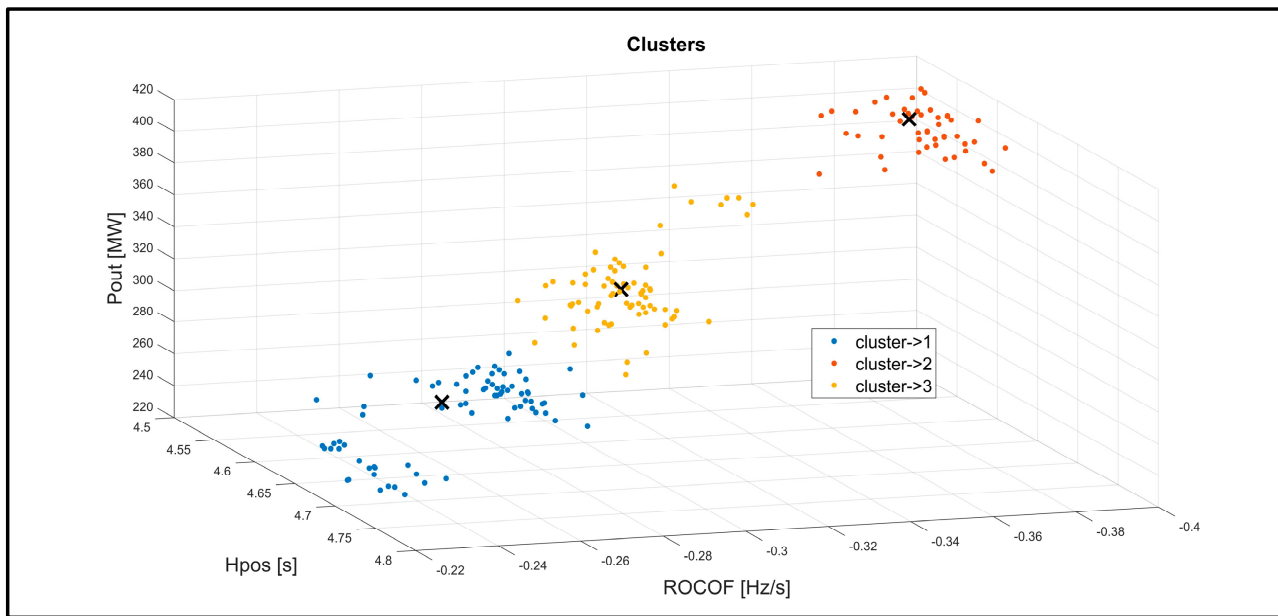


Figure 6. Correlation of variables ROCOF, Hpos, Pout.

Once the groups representing the dynamic frequency response are identified, it is necessary to identify those events which represent the centroid to select them as representative events. Table 2 shows the representative events.

Table 2. Representative events of the contingency space.

Groups	ROCOF [Hz/s]	Hpre	Hpos	Pout	NADIR
Cluster 1	−0.30394497	4.89268039	4.62509346	322.999994	59.0806595
Cluster 2	−0.38361007	4.89527662	4.57441948	403.749999	58.7209959
Cluster 3	−0.25267691	4.88498889	4.66507255	270.696622	59.3051917

5. Discussion of Results

In [6–8], methodologies are presented to obtain a characterization of the ROCOF of an electrical system, of which different strengths and weaknesses can be highlighted as shown in the Table 3.

Table 3. Main advantages and disadvantages of proposed methodologies.

Article	Main Strengths	Main Weaknesses
Underfrequency Load Shedding Using Locally Estimated RoCoF of the Center of Inertia	- Local estimation of the ROCOF in each generator. - Algorithm to eliminate frequency oscillations for ROCOF measurement.	The methodology does not consider the different operational scenarios and contingencies that may occur in the system.
Automatic Load Shedding Scheme for Electrical Systems Serving Oil Extraction Facilities	- System modeling and validation. - Statistical analysis. - Dynamic system simulation.	There are a limited number of contingencies that depend on the designer's experience.
Energy storage sizing for virtual inertia contribution based on ROCOF and local frequency dynamics	Identification of areas of frequency behavior.	A characterization of the system from the ROCOF point of view is not obtained.

The proposed methodology considers several advantages identified in the table above to obtain ROCOF measurements for the system, including the following:

Developing an equivalent model that allows one to obtain the dynamic frequency response, with the flexibility to adapt to any complete or simplified system.

Conducting an MCS to consider a wide range of operational scenarios and contingencies that may arise in the system.

As a result, groups of ROCOF values characterizing the frequency dynamics in a system are obtained. These results can be implemented to determine the minimum amount of load to be shed in a load-shedding scheme. This procedure helps overcome the weaknesses identified in similar proposals.

6. Conclusions and Recommendations

The proposed methodology stands out for its ability to identify and characterize ROCOF groups in the presence of N-1 contingencies and considering a wide range of possible operating scenarios for the system. This characterization allows for the design of an under-frequency load-shedding scheme through the parameterization of frequency relays using the ROCOF. It is recommended to restructure the database according to the needs of the system since this step eliminates scenarios that are considered safe at the frequency level; in this case, 59.4 Hz was chosen, but it can vary according to the needs. The proposed methodology should be used in conjunction with an optimization algorithm to determine the minimum load to be shed. For the nature of the optimization problem, a heuristic solution method should be considered, and thus the necessary adjustments to guarantee the minimum impact when the system needs a UFLS.

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Abbreviations

ROCOF	Rate of Change of Frequency
EPS	Electric Power System
UFLS	Under-Frequency Load Shedding
Governors	Speed Regulators
BESS	Battery Energy Storage System
NADIR	Lowest Point of the Frequency
AGC	Automatic Generation Control
MCS	Monte Carlo Simulation
SFR	System Frequency Response
FDP	Probability Distribution Function
Hpre	Equivalent Inertia before the Contingency
Hpos	Equivalent Inertia after the Contingency
Pout	Lost Generation Power
KDD	Knowledge Discovery in Databases

ΔP_{Gi}	Electrical Power Variation
ΔP_o	Load Power Variation
Δw	Speed Variation
$Km_i, F_i, T_i, \text{ and } R_i$	Meters of the First-Order Reduced Model
H_{eq}	Equivalent System Inertia
D	Load Damping
S_i	Nominal Power of Each Generator
S_{sys}	System Base Power

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