Assessment of relevant assets for outage coordination

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***Abstract*—The internationalization of the electrical grid augmented the complexity associated with maintaining the transmission network and coordination between the Transmission System Operators (TSOs) pertaining to the same interconnected electrical grid. From the TSOs' perspective, it is vital to understand and quantify the influence that the interruption of an external network element can have on their control area, to manage the impacts of outside interference that may put at risk the service quality and continuity that they are meant to preserve. In this work, we address three specific problems: (i) how to evaluate the relevance of external assets for outage coordination, (ii) how to identify the relevant assets efficiently and within proper execution times, and (iii) how to minimize the influence of data error in the results. To handle problem (i), we developed a robust and scalable algorithm for Portugal's specific context that computes sensitivity values generated by Spanish outages. The results are then compared against threshold values and submitted under inspection to detect outlier features, such as isolation and cross-border distance. For problem (ii), we propose limiting the disconnected Portuguese assets of the studied outage combinations to Critical Network Elements (CNEs), achieving a decrease in execution time of 82.5%. Finally, to answer problem (iii), we introduce an active power filter that can be turned on or off, depending on the impact of error inserted by scenarios with extreme active power values. Thus, allowing the inclusion of such scenarios, guaranteeing a more reliable representation of the grid's year-long behavior.**

***Index Terms*—Outage Planning Coordination, Regional Security Coordinators, Transmission Network, Transmission System Operators**

I. Introduction

The coordination of outages gained traction on November 4, 2006, in Europe, following a severe electrical power disruption that affected 10 countries, which resulted from a poorly performed outage simulation and consequent disconnection of a transmission line. This event pointed out the dangers of fragile coordination between the Transmission System Operators (TSOs) in Central Western Europe and led to the creation of the first Regional Security Coordinators (RSCs) in 2008, with the mission of helping TSOs ensure the security of supply on a European level by identifying and implementing measures while also developing and performing coordination services, such as Outage Planning Coordination (OPC) [1].

In Portugal's context, the coordination of outages is primarily within Portugal and Spain's integrated electrical systems since Portugal only has direct cross-border interconnections with Spain, which expand Spanish outages' influence into Portugal's national network assets.

As the OPC service is to be applied to all interconnected Continental European grid, it cannot test all the possible outages combinations and deliver remedial actions under the time constraints imposed by the type and frequency of the analysis it performs. Having said this, ENTSO-E developed a methodology that allows TSOs to identify relevant external assets to their control area during outage coordination in order to allow the OPC service to obey its intrinsic time constraints.

In this paper, we apply the aforementioned methodology to the Portuguese context and propose an iterative analysis of possible relevant asset lists by testing multiple power flow influence thresholds, complemented by a geographical analysis to exclude outliers. We also address two other problems: (i) how to identify the relevant assets efficiently and within proper execution times and (ii) how to minimize the influence of data error in the results. To handle problem (i), we propose limiting the possible outage combinations in regard to the disconnected Portuguese network elements. For problem (ii), we introduce an active power filter to exclude data errors introduced by scenarios with extreme active power values.

The remainder of this document is organized as follows: Section II introduces the background of the methodology for assessing relevant assets for OPC. In section III, we formalize the algorithm proposal. In section IV, we discuss the implementation of the algorithm and the simulation environment. The results are presented in section V. Finally, in section VI, we sum up the paper's main findings while emphasizing its contributions.

II. Background and related work

The focused methodology for assessing relevant assets is a crucial component of the OPC service that the RSCs provide to their integrating TSOs.

A. Transmission System Operator

European Network of Transmission System Operators for Electricity (ENTSO-E) defines the TSO as "a company that is responsible for operating, maintaining and developing the transmission system for a control area and its interconnections" [2]. In this paper's scope, it is also the TSO's responsibility to assess the relevance that external assets have on its control area and provide a list of relevant assets to its RSC for outage coordination. The Portuguese TSO is Rede Elétrica Nacional (REN); its collaboration was fundamental, as only with it were we able to access exclusive network services that allowed us to simulate the data, using real scenarios of the National Transmission Network (RNT), to create, test, and optimize the developed algorithm.

B. Regional Security Coordinator

As we introduced in section I, the first RSCs were born in 2008, in an effort to improve the coordination between TSOs of the same interconnected network. One of the first RSCs was Coordination of Electricity System Operator (Coreso), located in Brussels, in the heart of the Western European energy sector. Coreso is Portugal's RSC and helps the country dealing with the ever-changing interconnected operating conditions through network planning, system adequacy analysis, and market setups.

In total, Coreso comprises nine TSOs, who are all its shareholders and provides each one five services [3]:

- Individual Grid Model and Common Grid Model;
- Coordinated Security Analysis;
- Coordinated Capacity Calculation;
- Short and Medium Term Adequacy Forecasts;
- Outage Planning Coordination.

C. Outage Planning Coordination

The development of the OPC service was spurred because generation and transmission systems such as overhead lines, transformers, breakers, or measuring devices have a service life. Therefore, regular maintenance work is required to keep the systems healthy. While maintenance work is ongoing, the equipment is unavailable; therefore, the TSOs need to be informed when their counterparts are carrying out work to avoid particularly tense situations on the grid.

This service aims at (a) identifying outage incompatibilities between relevant assets (grid elements, generators, and loads) whose availability status has cross-border impact which limits the outages that can be performed at pan-European level; (b) proposing solutions to relieve these incompatibilities; (c) coordinating findings and Remedial Actions proposals with other adjacent RSCs; and (d) increasing the operational security of Europe's power system by coordinating outage planning on a weekly basis, based on generation and demand forecast provided by all ENTSO-E Member TSOs.

To implement this service, RSCs require common reference scenarios established by the TSOs and corresponding Common Grid Model (CGM), and knowledge of all preliminary planned outages on the main transmission network - AC and DC [4]. Furthermore, RSCs need, from each TSO, a list of relevant assets. These are obtained by applying the methodology established to assess the relevance of assets in accordance with Article 84 of Commission Regulation (EU) 2017/1485 of 2 August 2017 [5].

To the author's knowledge, no studies are proposing an algorithm for the relevance assessment of assets for outage coordination. However, there is some related work focused on the challenges of interconnected power systems and the importance of coordination between neighboring countries. For instance, [6] studies the impacts of cross-border electricity interconnections on the reliability and vulnerability of interconnected power systems. The importance of managing interconnected power systems is also addressed by [7] when studying the opportunity for a different initiative of regional cooperation for the Greece-Italy region power system integration. Lastly, [8] recognizes the newer challenges introduced by the increasing integration of renewable energies in the French electricity network, such as the inadequacy of existing maintenance outage planning methods.

Coreso itself, when mentioning the scope of the OPC service, states that this is still a topic under development and that its definition is subject to evolution depending on the outcomes of the experimentation [4]. This ties into one of the most significant contributions of this paper, which is working on this methodology that is still being actively worked on by REN in collaboration with Coreso and ENTSO-E.

III. Proposed Framework

This paper proposes the application of ACER's approved methodology for assessing the relevance of assets for outage coordination to identify the Spanish outages that arise significant power flow variations in assets that belong to the control area of REN. For the methodology's application, an algorithm encompassing a program written in the high-level programming language PYTHON [9] was developed for Portugal's specific case as a robust and scalable tool.

The algorithm is prepared to analyze two different network conditions:

- N-1, when one asset of the grid is disconnected. The asset can be internal ("N-1 PT") or external ("N-1 ES") to the TSO's control area.
- N-2, when two assets of the grid are disconnected. These can be simultaneously from a control area external to the TSO ("N-2 ES") or one internal to the TSO's control area and the other external ("N-1 PT + N-1 ES").

This N-2 contingency analysis is critical to understand the power system conditions pre-emptively before taking corrective control.

The analysis of "N-2 ES", unfortunately, will not be addressed in the context of this paper results, only in the context of the tool specifications, since due to delays related to the COVID-19 pandemic, we were not able to incorporate the necessary data.

A. Methodology for assessing the relevance of assets

To apply the methodology, each TSO has to identify its Outage Coordination Region (OCR) since this allows to limit the external assets to the pertinent for the analysis being performed. ACER decided the division of regions in accordance with the Commission Regulation (EU) 2015/1222 of 24 July 2015 on CACM Regulation [10], meaning that the OCRs were defined to be the same as the Capacity

Calculation Regions (CCRs) unless the involved TSOs decide to merge their coordination regions into one unique OCR. In the Portuguese context, the CCR includes Spain and France.

The quantification of the relevance of the assets is carried out by applying the influence computation method on a year-ahead CGM developed in accordance to Article 67 of Commission Regulation (EU) 2017/1485 of 2 August 2017 [11]. This application outputs a relative or absolute value of power flow or voltage variation whose result can be compared against defined thresholds.

The computation method measures the power flow influence factor of simultaneous interruptions of network elements connected outside the TSO's control area on network elements inside the TSO's control area. In circumstances where the power flow influence factors are insufficient to identify relevant external network assets that can cause significant voltage variations in the TSO's control area, the TSO can use voltage influence factors to determine its proposal of relevant assets, as long as all the affected TSOs are informed.

The influence factors computed for each external network element are compared to the selected and correspondent threshold values, and if the influence factors are greater than the thresholds, then the network element can be considered a relevant asset.

Network elements can be power generation modules, demand facilities connected to a TSO, transmission power lines, autotransformers, and Significant Grid Users (SGUs).

The relevance of external network elements should be reassessed every three years after the first assessment. Additionally, after obtaining the list of relevant assets, the TSOs shall complement it with the critical network elements identified in accordance with the CACM Regulation [5], [10].

B. *Influence Thresholds*

In Table I, we can see the range of thresholds published by ACER. Each TSO must choose a value for each threshold. If the methodology is applied using power flow, then two values must be chosen – one for the power flow filtering influence threshold and another for the power flow identification influence threshold. If the methodology is applied using voltage, then the TSO needs to choose one value for the voltage threshold.

TABLE I
RANGE OF INFLUENCE THRESHOLDS FOR POWER FLOW AND VOLTAGE. SOURCE: [5]

Power flow identification threshold	**Power flow filtering threshold**	**Voltage threshold**
15 - 25%	3 - 5%	3 - 5%

As previously mentioned, when applying the methodology, the TSO may opt to compute the voltage influence factor instead of the power flow influence factors.

When we compute the voltage influence factor, we are verifying if external assets disconnected outside the TSO's control area can trigger a significant voltage deviation on a node of the TSO's control area. Voltage deviations are related to reactive power generation and consumption. Excessive reactive power in the grid raises the voltage while insufficient reactive power decreases the voltage. In the Portuguese context, the RNT does not suffer heavily from voltage deviations because of voltage support provided by hydroelectric and thermal generators, synchronous compensators, and due to investment in grid components such as shunt reactors, transformer tap-changers, and capacitor banks. Portugal's lack of voltage issues means that the disconnection of Spanish assets would not affect Portugal's voltage control making it impertinent to opt for a voltage analysis during the implementation of the methodology for assessing the relevance of assets. For this reason, we focus solely on an active power flow analysis [12].

Having determined the type of analysis we wish to perform, we will now look into the two power flow influence thresholds.

The power flow filtering influence threshold represents the associated precision of measurement expected of the control system Supervisory Control and Data Acquisition (SCADA), state estimation computations, and the models used to calculate the power flows. If the power flow filtering influence factor is less than or equal to the correspondent threshold, then we know that the power flow measurements used to compute the influence factor are affected by the measuring and transmission systems errors; therefore, they should not be considered relevant assets.

In turn, the power flow identification influence threshold represents the minimum active power flow variation value necessary for the TSO, based on its experience, to identify and deem a change relevant. A change greater than the defined threshold should be seen, independently of the cause, as warning information in need of careful evaluation and monitoring from the dispatcher. When the variations of active power flow are less than or equal to the defined threshold, the external assets should not be identified as relevant for the coordination of outages.

Each TSO chooses a value associated with the power flow filtering influence threshold and another one associated with the power flow identification influence threshold. These two chosen values, which are within the range of values defined by ENTSO-E, are independent of the asset type.

For a network asset connected outside the TSO's control area to be considered relevant for the coordination of outages, the values resulting from the computation of both influence factors must be greater than their correspondent influence threshold values since the two influence factors are interdependent, meaning both must verify the criteria in order to validate the relevance classification.

Choosing the adequate threshold values is an iterative process. When analyzing different combinations of thresholds, to decide which one to use, we have to consider the following criteria: (a) thresholds should be low enough to minimize the risk of not including all relevant grid elements that can threaten the security of neighboring control areas; (b) thresholds should be high enough to avoid overly lengthy relevant asset lists filled with noise, thus leading to an inefficient process, potentially not compatible with time constraints of the outage coordination process.

C. Power Flow Influence Factors

According to the guideline on electricity transmission system operation, influence factor is "the numerical value used to quantify the greatest effect of the outage of a transmission system element located outside of the TSO's control area excluding interconnectors, in terms of a change in power flows or voltage caused by that outage, on any transmission system element. The higher is the value the greater the effect" [11].

For each external asset r, there are two influence factors – the power flow filtering influence factor and the power flow identification influence factor.

To explain these two factors, one needs to introduce the Outage Transfer Distribution Factor (OTDF), a sensitivity measure of how a change in a line's status affects the active power flow on other lines in the system. Each external asset r has as many OTDFs as the total number of combinations of assets t and i ($t \times i$) considered in the analysis.

$$OTDF = \frac{P^t_{s,n-i-r} - P^t_{s,n-i}}{P^r_{s,n-i}} \tag{1}$$

The power flow filtering influence factor, $IF_r^{pf,f}$, is the maximum OTDF of an external element r on any given internal element t, in any scenario s, and taking into account any element i disconnected.

$$IF_r^{pf,f}\,(\%) = MAX_{\forall i \in I, \forall s, \forall t \in T}\,(OTDF \times 100) \tag{2}$$

The power flow identification influence factor, $IF_r^{pf,id}$, is the maximum normalized OTDF of an external element r on any given internal element t, in any scenario s, and taking into account any element i disconnected.

$$OTDF_{norm} = \frac{P^t_{s,n-i-r} - P^t_{s,n-i}}{P^r_{s,n-i}} \times \frac{PATL^{s,r}}{PATL^{s,t}} \tag{3}$$

$$IF_r^{pf,id}\,(\%) = MAX_{\forall i \in I, \forall s, \forall t \in T}\,(OTDF_{norm} \times 100) \tag{4}$$

In equations (1), (2), (3), and (4):

i stands for network element connected either in the TSO's control area or outside TSO's control area considered disconnected from the network when assessing the expression. This network element cannot be the same as element t nor r.

r stands for the network element connected outside TSO's control area whose power flow influence factor is assessed.

t stands for the network element connected inside TSO's control area where the active power difference is observed.

T, I, and R represent the set of their respective lowercase.

$P^t_{s,n-i-r}$ represents the active power flow through the network element t, in scenario s, with network elements r and i disconnected from the network.

$P^t_{s,n-i}$ represents the active power flow through element t, in scenario s, with network element r connected to the network and network element i disconnected from the network.

$P^r_{s,n-i}$ represents the active power flow through the element r, in scenario s, when connected to the network, considering the network element i disconnected from the network.

$PATL^{s,r}$ represents the loading in MVA or MW that can be accepted by network element r, in scenario s, for an unlimited duration.

$PATL^{s,t}$ represents the loading in MVA or MW that can be accepted by network element t, in scenario s, for an unlimited duration.

The difference between the two power flow influence factors is that the power flow filtering influence factor is only an image of the load transfer and is independent of the flow of the assessed element, while the power flow identification influence factor is better at describing the risk of overload since by considering the grid elements PATL values, it is capable of simulating the consequences of occurring an outage in highly loaded network elements.

Looking at equations (2) and (4), we can point out the division of $PATL^{s,r}$ by $PATL^{s,t}$. This division is the numerical representation of the ratio of PATL between the influencing element r and the influenced element t, which has the purpose of normalizing the OTDF value.

PATL is the capacity an asset of the network has of accepting power during an unlimited quantity of time. This parameter describes how loaded an asset can be before it trips out of service. Not all the assets of the network have the same PATL; some have higher values than others. The normalization is crucial when there are high discrepancies in loading between the elements t and r.

Figure 1 illustrates a fictional transmission network to better understand how the OTDF computation is performed.

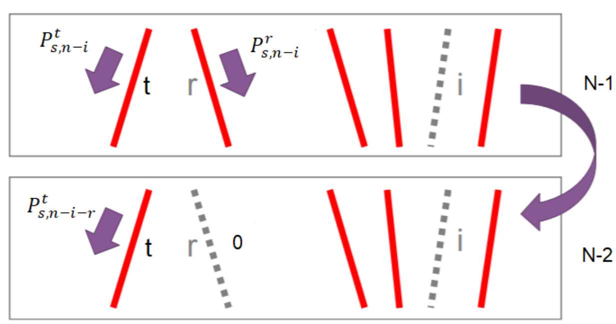

Fig. 1. Computation of the power flow influence factors (adapted from [13])

The example depicted in Figure 1 is repeated hundreds of thousands of times throughout the algorithm with alternating t, r, and i network elements.

D. Algorithm Description

As previously stated, this paper's main contribution is the proposal of an algorithm that will apply the methodology published by ACER for assessing the relevance of assets for outage coordination. The algorithm presented will analyze different combinations of power flow influence thresholds and select the most coherent and reliable relevant assets list for outage planning coordination.

The algorithm encompasses three main steps: (i) data simulation, (ii) power flow influence factors computation, and (iii) threshold selection.

Data simulation: The first step of this algorithm is the data simulation since the computation of power flow influence factors is performed by resorting to data extracted from simulations made with models of the known grids. The algorithm needs multiple scenarios representative of the grid's different states throughout the year to generate meaningful data files.

The second step is to define the type of N-2 contingency analysis intended, "N-2 ES" or "N-1 PT + N-1 ES".

The final and third step is to generate a list of Critical Network Elements (CNEs) identified in accordance with the CACM Regulation [14] for the power flow influence factors computation.

Influence factors computation: This algorithm's most complex and demanding process lies in computing the power flow filtering influence factor and the power flow identification influence factor due to the number of iterations necessary. To overcome this challenge, we developed a PYTHON [9] program envisioned for the specific case of Portugal.

For the program's execution, some assumptions regarding the data organization were necessary, such as the overall data hierarchy, the name structure of folders and files, and the data organization within each file. These assumptions were made based on the manner in which the files were delivered and presented by REN.

To compute the power flow influence factor of each asset r, both filtering ($IF_r^{pf,f}$) and identification ($IF_r^{pf,id}$), the program deconstructs equations (2) and (4) in the following steps:

1) For scenario s, compute the OTDF (equation (1)) and normalized OTDF (equation (3)) of asset r on asset t.
2) Compare the computed values to the thresholds defined in the pre-requisites. If the values are less than or equal to the thresholds, they are rejected, and the program moves on to the next asset t. However, if the values computed are greater than the thresholds defined, the values are stored in the respective dictionary associated with the asset r.
3) Replicate the above steps for every asset t.
4) Replicate the above steps for every asset r.
5) Replicate the above steps for every asset i.
6) Compare all the stored values and keep only the maximum values of the OTDFs and normalized OTDFs of each r.
7) Write both power flow influence factors of each asset r ($IF_r^{pf,f}$ and $IF_r^{pf,id}$), of scenario s, in an EXCEL® file.
8) Replicate the above steps for every scenario s.
9) Lastly, compare all the power flow influence factor values for each asset r and keep only the maximum values, thus creating a final EXCEL® file with a unique and global list of the relevant assets r buses names and respective power flow influence factors.

When developing the program, it was ensured that all the data necessary for the computation of the two elementary factors of influence was organized quickly and with low memory consumption.

Threshold selection: The final phase of the algorithm is a testing phase, where different combinations of power flow influence thresholds – filtering and identification – will be compared to conclude which one produces the most coherent and reliable list of external relevant assets for the coordination of planned outages.

To optimally compare the different combinations of values for both thresholds, we propose that the user computes first the extreme values (lower and upper boundary) from the range published by ACER (see Table I) and then run extra combinations until a satisfactory conclusion is reached. This combinatorial analysis is dependent on the TSO's expert evaluation, and its knowledge of the transmission grid since the lists of relevant assets generated may feature assets that are not actually relevant or ignore network elements that should be considered.

Finally, after comparing the different lists of relevant assets produced by different threshold combinations, we select the most coherent and reliable list of assets for outage coordination, along with the corresponding values for both power flow influence thresholds.

IV. Implementation and Optimization of the Algorithm

In this paper, we used the software PSS/E to define and configure the necessary inputs, namely dates, assets to be disconnected, and networks of interest. The dates were defined to have the desired profiles of consumption and production; the disconnected grid elements were defined to represent the possible outage combinations; the networks of interest were defined to only include impactful neighboring networks (Spain Electrical Grid (REE)'s transmission grid). Regarding the latter, initially, we considered the OCR defined by ACER, as mentioned in subsection III-A, but given the accumulated experience of REN, we knew that France's electrical grid is secluded enough from Portugal that it would not have a significant influence on the power flow values of Portugal's transmission network. After setting the desired conditions, we used PSS/E to export the data in CSV files to be used by the developed algorithm to perform the computations. PSS/E used Coreso's CGM and Coordinated Capacity Calculation (CCC) services to run the power flow simulations.

Being Portugal's TSO, REN operated the processes mentioned above and provided different scenarios representative of the grid's behaviors throughout the year.

A. Proposed Scenarios

When choosing the best scenarios to focus on, we decided the days by analyzing the load profiles of previous years. One of those years was 2018, presented in Figure 2, in which we have four curves representing four characteristic days that illustrate specific and relevant load behaviors.

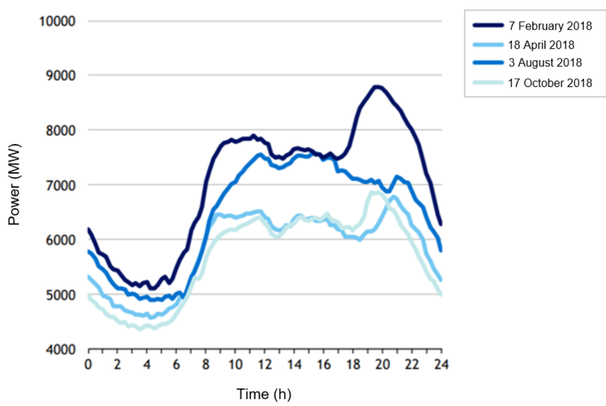

Fig. 2. Load diagram of National Transmission Grid profiling days of 2018 (adapted from [15])

The two curves with the highest power consumption values were on February 7, 2018, and August 3, 2018, while the curves with the lowest power consumption values were on April 18, 2018, and October 17, 2018. We can conclude from these dates that the periods when the transmission grid showcases its most extreme conditions coincide with the different meteorological seasons of the year: winter, summer, spring, and autumn.

For the methodology that we pretend to apply, these extreme conditions are the ones we look for since the grid is in a fragile state, increasing the network elements' sensitivity to external power flow changes. Thus, we chose one scenario for winter and one scenario for summer, both during periods where we noted a peak in consumption since these are the seasons in which consumption is at its highest, but at different times of the day. In addition, we chose two scenarios for spring, the first during a period where consumption was around its peak and the second where the consumption was at its lowest, as this season, much like autumn, displays the lowest peak and off-peak power values. Unfortunately, there is no scenario during autumn, but as we can see in Figure 2, the curves of October 17, 2018, and April 18, 2018, follow a very similar distribution, meaning that conclusions taken from the spring scenario can be extrapolated for the missing autumn scenario.

To find and analyze the grid behaviors described, we used Coreso's services CCC and CGM. Both services work based on grids prepared two days in advance, which means they are an estimate of the state in which the grid will be. We prefer them instead of the real-time grids because the estimated grids have Portugal and Spain's interconnected grid modeled in its totality, which is the best approach for the study this paper proposes to perform, as it permits that we test the effect of disconnecting all the Spanish transmission network elements.

Having set the features and the grid models we wanted to study, we started the iterative process of choosing the best dates. This process's iterative nature came as a consequence of using 2020 scenarios, which are the most relevant and up-to-date scenarios. Something inherent to newer project services is that their availability status is not always positive. On top of that, even when the grid models were available, we also had to guarantee that the power flow values converged during simulations, i.e., the mismatch of active power flow values was low enough to consider the scenario stable. These two traits restricted the pool of options.

For the winter scenario, we wanted high power consumption values, a strong component of hydroelectric and wind energy generation, a weak thermal component, and a positive import balance. The strong component of hydro and wind is due to the fact that these sources of generation are the most prevalent during winter since we observe heavy rain and strong winds. The positive import balance increases the transmission grid's sensitivity to external power flow variations and is usually correlated with a reduction in domestic thermal production. **February 17, 2020**, during the evening **(peak consumption period)**, verified all the above conditions while also having the grid model available and stable power flow computations.

For the spring scenarios, we sought one where we could observe a low value of consumption and another where we could detect a high value of consumption. The other desired conditions were a strong wind and hydroelectric component in the national production that featured a positive import balance for the same reasons stated for the winter scenario. **May 13, 2020**, showcased **off-peak and peak consumption values** in line with the sought-after tendencies. The first during small hours and the latter during the beginning of the afternoon. The grid model of this day was available and also showed stable power flow computations.

In the case of the summer scenario, the specifications we sought were different from the ones mentioned so far. We wanted a weak hydroelectric and wind generation component and a strong thermal production since these are the most representative features of this season. We also wanted a negative import balance since it typically correlates to higher values of thermal production. **July 30, 2020**, during the beginning of the afternoon **(peak consumption period)**, verified all the above conditions, had the grid model available, and stable power flow computations.

B. Algorithm Optimizations

As the first optimization of the algorithm, we looked at how to identify all relevant assets while obeying the execution time constraints. To handle this problem, we propose limiting the possible outage combinations by considering as disconnected Portuguese network elements (i) only the Critical Network Elements.

CNEs are grid assets, such as national very high voltage transmission lines and transformers, that, according to CACM Regulation, restrain the cross-border exchanges through the interconnection lines. In this specific case study, we are talking about the cross-border exchanges between Portugal and Spain. The CNEs limit the interconnection lines' transmission capacity because, during the CACM service development, these network assets were observed as having significant sensitivity to cross-border power flow variations [10]. Due to the sensitivity these network elements present, it becomes crucial to closely monitor them since they affect the security of the RNT and the energy market. What makes for a significant sensitivity was defined by REN through data analysis and experience, and it was concluded that a grid element is considered a CNE if the power flow variation is greater than or equal to 5% when the power flow of the interconnections increases or decreases 100 MW [16].

From Table II, we can infer that by limiting the network element i to CNEs, we obtain results that are equal to the ones contemplated when we consider all the Portuguese contingencies, and we observe a decrease in execution time of 82.5%.

TABLE II
COMPARISON BETWEEN THE RESULTS CONSIDERING AS ELEMENT i ONLY CNES AND ALL PORTUGUESE CONTINGENCIES

Year 2020	# of identified assets		Execution time (min)	
	CNEs	All conting.	CNEs	All conting
February 17	24	24	2	10
May 13 (off-peak)	32	32	1.5	10
May 13 (peak)	125	125	1.5	10
July 30	23	23	2	10
All scenarios	136	136	7	40

Due to the recursive and time-constrained nature of the analysis performed, we conclude that using CNEs is the best approach.

The second optimization performed was developed to increase the robustness of the algorithm through the introduction of a filtering condition that identified when the program was dealing with a network element t that belonged to a tripod node. This filtering condition limits the validation of an asset r if only one of the Portuguese transmission lines that compose the tripod node is significantly sensitive to its outage, as it is improbable that only one of the tripod node transmission lines is critically sensitive to the outage of the said external asset r since they share a common node, as illustrated in Figure 3.

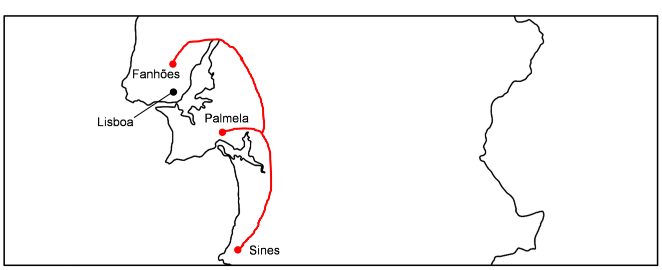

Fig. 3. Tripod node of the 400 kV transmission lines connecting Sines, Palmela and Fanhões substations

The third and final optimization was introduced as a supplementary solution to the power flow filtering influence threshold. Upon compiling and saving the relevant assets list for the first testing iterations, the number of assets included in the output proved to be greater than expected. Some of the identified asset's geographical position would not realistically allow for the values of sensitivity computed. The first approach we took was to tune the threshold values.

When considering the power flow filtering threshold equal to 3% and the power flow identification influence threshold equal to 15%, we identified the network elements distribution throughout Spain, and the number and the location of the assets were respectively high and dispersed. When tuning up the threshold values to their maximum, considering a power flow filtering influence threshold equal to 5% and a power flow identification influence threshold equal to 25%, we observed a decrease of 52.2% in the number of assets identified as relevant. However, the number was still quite elevated, and the assets' dispersion persisted.

For this reason, it was decided to study each scenario separately to locate the source of the problem. We used the developed tool's capability to assess each date independently to look at each scenario's contribution to the final output. As one can see in Table III, it became clear that the contribution of the scenario of May 13, 2020, during the peak consumption period, is vastly more significant than the contribution of the other three scenarios.

TABLE III
RELEVANT ASSETS PER SCENARIO FOR FILTERING THRESHOLD EQUAL TO 3% AND IDENTIFICATION THRESHOLD EQUAL TO 15%

Year 2020	**Number of identified assets**
All scenarios	136
February 17	24
May 13 (off-peak)	32
May 13 (peak)	125
July 30	23
All scenarios minus May 13 peak	38

After consulting with REN, we concluded that the scenario indeed introduced some noise into the results due to the fact that the simulation conditions generated extreme power flow values, which made the influence of errors associated with the criteria of convergence of power flow computation more impactful than desired. Even though the computation did converge with acceptable errors in accordance with the parameter of the power flow tool used by the TSO, the errors introduced noise that could not be filtered solely by the range of thresholds published by ACER. Thus, we developed active power filtering conditions to include this spring scenario.

In Table IV, highlighted in a shade of blue, we point to the total of relevant assets featured in the output list (25) when we consider all the scenarios and the active power filter. When this value is crosschecked to the number of assets present in the output, when the scenario of May 13, 2020 (peak) is excluded, we find that the results are more resemblant than when we consider all the scenarios without the filter.

Although we are missing 13 relevant assets, when we compare the missing relevant assets' geographical position and power flow influence factors, we observe that they are either far from the interconnections lines or have low power flow influence factors, close to the minimum values of the filtering and identification threshold ranges. Such traits make us believe that those assets were validated because of errors present in the inputs, and therefore were correctly expunged.

TABLE IV
ACTIVE POWER FILTER EFFECT IN THE NUMBER OF RELEVANT ASSETS FOR FILTERING THRESHOLD EQUAL TO 3% AND IDENTIFICATION THRESHOLD EQUAL TO 15%

Year 2020	Number of identified assets: Without active power filter	Number of identified assets: With active power filter
February 17	24	16
May 13 (off-peak)	32	15
May 13 (peak)	125	15
July 30	23	13
All scenarios minus May 13 (peak)	38	24
All scenarios	136	25

With a more plausible geographic distribution of the identified relevant assets, we validate the effect of the active power filter and how it enabled us to consider the scenario that otherwise would have to be excluded from the analysis limiting the transmission grid's behavior representation throughout the year.

The active power filter is an optimization that can be turned on and off. It is only necessary when the transmission networks under analysis work mostly with scenarios where the interconnection lines operate at extreme values of active power flow. By implementing this optimization, we provide a solution that minimizes the influence of data error in the results.

V. RESULTS AND DISCUSSION

This section will not present images or tables to accompany the results due to privacy and security reasons.

A. Research Stage 1

As mentioned throughout the paper, one of the objectives of the algorithm is the identification of the most suiting combination of power flow influence thresholds from the range of thresholds published by ACER (see Table I).

The first iteration was performed by defining the minimum threshold values for both the filtering and identification influence thresholds (combination I). In contrast, the second was executed by setting the maximum threshold values for both the power flow influence thresholds (combination II). This strategy allowed us to observe what it meant to use the most permissive definition of thresholds and how the results evolved as more restrictive the algorithm became. The most permissive definition of thresholds would be combination I since the lower the threshold values, the lower are the sensitivities that need to be observed for an external asset to be included in the relevant assets list, meaning that more assets will be included in the output list. On the contrary, the most restrictive combination of thresholds would be combination II as the greater the threshold values, the less external assets will present power flow influence factors that meet the threshold values, therefore restricting the number of network elements included in the algorithm's output.

The results obtained from analyzing the four chosen scenarios for threshold combination I compose a relevant assets list containing 25 assets (twenty-four 400 kV transmission lines and one 220 kV transmission line).

By contrast, the results obtained from analyzing the four chosen scenarios for threshold combination II compose a relevant assets list containing eight 400 kV transmission lines.

When we compared combination I to combination II, we realized that as the threshold values increased, the cluster of transmission lines gravitated to the border between Portugal and Spain, which is expected as what allows different control areas to influence one another in the first place is the interconnections present at the borders. We also noticed that the total number of assets in combination II is 68% lower than in combination I.

B. Research Stage 2

As a complementary analysis, we studied the influence of each power flow threshold separately through two extra combinations. These combinations and the previously mentioned are presented in Table V.

TABLE V
COMBINATION OF THRESHOLDS AND RESPECTIVE QUANTITY OF IDENTIFIED RELEVANT ASSETS

Combination	Power flow influence thresholds: Filtering	Power flow influence thresholds: Identification	# of relevant assets identified
I	3%	15%	25
II	5%	25%	8
III	5%	15%	25
IV	3%	25%	8

On the one hand, as we can see in Table V, the difference between considering the power flow filtering influence threshold equal to 3% or 5% is nonexistent (combination I versus III or II versus IV). This lack of influence does not mean that the range of thresholds published by ACER is inadequate; it is related to the introduction of the active power filter mentioned in section IV-B.

The active power filter was created to solve problems associated with errors introduced during the simulations and power flow computations, and the power flow filtering influence threshold job is to filter power flow filtering influence factors that are less than or equal to the expected sensitivity associated with computation and model errors. By sharing the same purpose of filtering errors from the results, they end up overshadowing each other's influence. In this paper's specific case study, there was a scenario whose simulation conditions and ultimately power flow values were so extreme that the introduction of the active power filter was needed to allow for that specific scenario to be considered. Otherwise, the scenario would have to be excluded from the analysis, limiting the transmission grid's behavior representation throughout the year.

On the other hand, the difference between considering the power flow identification influence threshold equal to 15% or 25% is quite noticeable as from combination I to IV (or II to III), we observe a decrease of 68% in identified relevant assets.

With the results obtained so far, we can analyze and discuss the threshold combination that can produce the most coherent and reliable relevant assets list.

C. Thresholds Selection

The results obtained from combination I (and III) are quite promising as they include a reasonable amount of network elements and demonstrate a coherent geographical position and distribution. However, we can still identify a maverick transmission asset that most likely should be excluded from the end result.

The particular network element that caught our attention was a 400 kV transmission line located in Spain's east coastal area (LC4). This asset's inclusion in the output list is somewhat dubious because of how distant it is from all the other identified assets. For this reason, we looked at its power flow identification influence factor (16.0002%) and power flow filtering influence factor (14.78%). From these two values, we could infer that increasing the power flow filtering influence threshold would not affect this asset's inclusion, but the power flow identification influence threshold would.

Because of that, we increased the power flow identification influence threshold to 16.1% and reran the algorithm to exclude the questionable transmission line from the output. However, two other assets were also excluded as a result of this increase, even though they do not share the same geographic characteristics as the asset we wanted to disregard.

From this point onward, two approaches can be taken. The first is to define the final power flow identification influence threshold equal to 16.1%, while the second is to keep the power flow identification influence threshold equal to 15% and manually remove the problematic transmission line from the output.

To decide which approach fits our objectives best, we need to study the LC4 transmission line and the two assets affected by this decision weighing the value of only excluding the dubious transmission line versus excluding the three network elements.

In this case, the two transmission lines are close to the border between Portugal and Spain and share common nodes with other transmission lines that are also listed in the relevant assets file. Contrarily, the transmission line LC4, as already stated, stands distant and isolated from the border, meaning that it is far from the interconnection lines that allow the asset to influence the Portuguese network elements and that it has no adjacent connections also identified as relevant. The distance parameter is an important characteristic because both the Portuguese and Spanish national transmission grids are quite meshed, which means that there are alternative routes for power to flow in case of outages, making the propagation of congestion to a Portuguese element t significantly less likely the further away the external asset r is from the interconnections.

To further substantiate the argument that LC4 is an outlier and not an odd exception, we look to try to answer the questions: "How many times does this asset r verify the conditions necessary to be considered a relevant asset?" and "In how many of the considered scenario is LC4 classified as relevant?".

To answer the first question, we made the algorithm count how many times the LC4 generated an OTDF and normalized OTDF greater than the defined thresholds. In total, we counted four validations – when most of the relevant assets have 30 to 1500 validations.

To answer the second question, we looked at each scenario's results individually and observed that LC4 was considered relevant in only one scenario – May 13, 2020, during the off-peak consumption period – when most are considered at least in two scenarios.

To summarize, LC4 is distant from the interconnection lines, it does not have any of its adjacent connections considered relevant network elements, its relevancy is only validated four times, and those validations only occur in one of the four considered scenarios. Therefore, we find that the probability of the influence values obtained repeating is low and should not be used as a reference to set the power flow identification influence threshold at the cost of discluding two geographically relevant assets.

Thus, in this paper's scope, we propose to opt for the second approach since it generates the most inclusive result and guarantees that we are not eliminating any asset crucial for the correct application of the OPC service.

Having to exclude a network element from the output list manually does not call into question the contribution that the implemented algorithm provides, as it should be noted that we had data from approximately 1,100 Spanish assets, which was reduced significantly (about 97.7%). Only with this reduction of the assets pool could we make a careful and detailed analysis that would allow an asset to be manually removed from the output list.

In conclusion, we can observe that there is value in allowing space for the TSO to rule out specific assets in cases where increasing the threshold values would harm the overall relevant assets list.

Having set the value for the power flow identification influence threshold, we need to attribute a value to the power flow filtering influence threshold to close the final combination. Although it is true that in the results obtained it was indifferent if the power flow filtering influence threshold was 3% or 5%, we believe that throughout the paper it was proven how crucial it was to decontaminate the results from the noise introduced by the grid models and power flow computations. Therefore, we consider that the best proposal for situations similar to the one studied is to consider the most restrictive value (5%) as a precaution measure.

VI. Conclusions

When implementing the algorithm, different scenarios were considered so that the results are eligible and representative of the transmission grid's year-long behavior. Different optimization studies were performed such as (a) considering only CNEs as disconnected Portuguese network elements effectively cutting the execution time of the algorithm by 82,5% for each run while maintaining the same results as if we did consider all possible Portuguese outages, which was crucial due to the recursive and time-constrained nature of the analysis performed; and (b) implementing a switchable feature for an active power filter as a complementary approach to the power flow filtering influence threshold minimizing the influence of data errors in the results caused by scenarios with extreme power flow values.

Furthermore, to evaluate the relevance of external assets in outage coordination, we propose selecting a power flow filtering threshold equal to 5% and an identification threshold equal to 15% while considering a qualitative assessment to exclude from the final output list assets that are geographical outliers. We chose 5% for the filtering threshold as a precaution measure since with the introduction of the active power filter, the available range for the filtering threshold did not modify the relevant assets list but as we observed throughout the paper it is of upmost importance to guarantee that the results are decontaminated of the influence of data error. Moreover, we chose an identification threshold equal to 15% because we found that the list of relevant assets was already succinct enough that increasing the identification threshold beyond the 15% would eliminate assets that, due to their geographical position and connections, would most likely be crucial during the coordination of outages.

We identified in total twenty-three 400 kV and one 220 kV transmission line as relevant grid assets for outage coordination. The transmission lines concentrate around the border between Portugal and Spain and all of them share nodes with at least one adjacent relevant asset, meaning that there are no single assets dispersed or isolated.

Finally, it can be concluded that the algorithm fulfills the primary objective herein proposed of evaluating the relevance of assets for outage coordination.

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