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Improving supply quality in distribution power networks: A game-theoretic planning approach

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ABSTRACT

Electric companies need to plan carefully the updates in their distribution power networks, assessing not only the expected impact on supply quality indicators, but also the cost of the different possibilities considered. To this end, we propose a planning method to improve the quality of supply in distribution power networks by upgrading devices so that they can be remotely operated. In the first place, our method identifies the lines with the lowest performance in an area of interest. Then, in each of these lines, the set of devices that can be upgraded is used to define the set of players of a cooperative game whose characteristic function provides a measure of the expected performance and economic impact of the updates in the infrastructure. Finally, the best locations to install remote control devices are determined by computing the Shapley value of this cooperative game, which, in addition, offers very valuable insight regarding each location considered. A case study based on a real substation in Spain is used to illustrate our approach and compare its performance with respect to the greedy-based method.

1. Introduction

An effective reliability assessment is essential in the design and planning of distribution power networks so that they can operate in an economical manner with minimal interruption times for customer loads [1,2]. For example, recent approaches study reliability under cyber attacks [3] and consider time-of-use strategies [4]. In general, the notion of reliability is directly associated with the concept of *electricity supply quality*, which in turn comprises: (i) *supply continuity*, related to the number and duration of interruptions; (ii) *power quality*, which studies voltage and frequency deviations from its reference; and (iii) *service quality*, which deals with the interaction between the supplier and the customer [5].

Focusing on the continuity of supply, there are several *reliability indices* utilized worldwide, e.g., the *System Average Interruption Frequency Index* (SAIFI), which measures how often the average customer experiences a sustained interruption; the *System Average Interruption Duration Index* (SAIDI), which computes the average time that customers' service is interrupted; the *Customer Average Interruption Duration Index* (CAIDI), which provides the average time required to restore the service to the average customer per sustained interruption; and the *Average Service Availability Index* (ASAI), which is given by the fraction of time that a customer receives power during a certain interval. Further information is given in [6,7], where several indices can be found, e.g., based on load rather than customers, or including only customers who actually experience an interruption. Other alternative performance indicators are the *Total Power Quality Index* (TPQI) [8], which is calculated using neural networks, and the *Interruption Time Equivalent to the Installed Capacity*, known by its Spanish acronym *TIEPI* [9], which will be considered in this article because it is the load-based legal reliability index used in Spain for distribution power lines. In particular, *TIEPI* measures the time of supply interruptions in terms of interrupted power.

Power interruptions are mainly caused by *scheduled works* to improve the electric infrastructure, which are planned to minimize the number of affected customers, and *power failures* or *faults*, which are unpredictable shortages of supply due to, e.g., material degradation, electric storms, wind, birds, and vandalism. When a fault affects a distribution line, the *recloser* located at its beginning isolates the electric facility, and a process starts to find its location. In particular, sections of the power line are sequentially energized to locate the fault, which will be isolated to be repaired. Several fault detection methods can be found in the literature, dealing, e.g., with transmission lines and distribution systems [10], pipeline faults [11], commercial buildings [12], and photovoltaic systems [13]. Regardless of the method used, different devices are required to control, protect, and isolate electrical equipment during fault location/repair in a power line. Depending on whether human intervention is required at the device location, these can be

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classified either as *local devices* (LDs) or *remote control devices* (RCDs). While the former are more economic, they need to be operated by human maintenance teams, which is time-inefficient. On the contrary, a fully remotely controlled line is expensive for the company, but it allows for a fast isolation of faulty sections. Therefore, a balance between LDs and RCDs should be attained.

In this context, it is clear that companies need to plan the updates in their power infrastructure, evaluating how they affect the previously mentioned supply quality indicators, but also the economic impact of the different options considered. In the literature there can be found some recent works in this line. For example, reclosers are allocated in radial nonreturn lines in [14], where cross-entropy methods [15] are used to reduce the occurrence of voltage sags. Also, [16] places load switches and reclosers in theoretical bus test systems to reduce non-supply energy, by using mixed integer programming (MIP) techniques. A similar mathematical approach is followed in [17], where fault indicators (FIs), reclosers and switch-disconnectors are inserted/relocated based on devices and crew costs; [18], which seeks to reduce the isolation times of faults by placing switch-disconnectors and FIs in strategic locations; and [19], which focuses on installing FIs with the aim of balancing costs due to customer interruptions and updates on the power lines. Likewise, a metaheuristic approach based on multi-objective particle swarm optimization is employed in [20,21] to minimize power outages and company costs by finding the number and optimal placement of switch-disconnectors and reclosers/sectionalizers, respectively, in electric distribution feeders. In [22], the set of switch-disconnectors to be upgraded is determined by formulating a weighted set cover problem considering both functional and economic requirements. Furthermore, in [23] an algorithm is provided to determine the optimal number of load switches assuming that all outage sections can be restored by supplying power from other feeders.

In general, the previously mentioned articles lead to optimization problems that can provide an allocation for the new or upgraded resources to be included in the power network. However, these approaches may suffer from the curse of dimensionality in large-scale networks and do not provide as much insight regarding *all* the existing elements in the network. To cover this gap, we address the same problem from a different perspective. In particular, we propose a planning method to improve supply quality in distribution power networks based on the *replacement* of LDs by RCDs without reconfiguring the network, which is less costly for the company. To this end, we consider a *TIEPI*-based index to find which distribution lines have more potential to increase performance. Then, we enhance the preliminary results of [24] by setting a cooperative game in which players are LDs that can be upgraded to RCDs. Note that transformation and distribution centers will also be considered as LDs, generalizing previous approaches that only use overhead devices in their analysis.

Our proposal leverages cooperative game theory to define a *coalitional game* where every possible subset of upgraded elements is assessed by a weighted measure of expected performance and economic impact [25–27]. In this way, it is possible to evaluate the benefit/cost of upgrading each of the LDs considered using tools such as the Shapley value [28], which allows us to rank the LDs according to their average impact, providing a means to find the best locations to install RCDs, hence reducing the non-supply intervals in a cost-efficient manner. Unlike many of the previously reported works, the proposed method does not imply solving an MIP problem. Instead, it averages the marginal contribution of the players for each possible coalition they can form and can be approximated in polynomial time [29].

Therefore, the major contribution of our work is to provide a game-theoretic method that assesses and ranks *every* element in the power network according to its average impact on a multi-criteria function, providing a superior insight regarding the different alternatives available. The benefits of this method are illustrated with a case study based on a real Spanish substation. Indeed, other related fields have already approaches making use of tools from game theory, e.g., electrical and power applications in the context of solar energy [30,31], cellular networks [32], renewable energy communities [33,34], circuit theory [35], microgrids [36,37], and energy trading [38–40].

The rest of the article is organized as follows. In Section 2, the formulation of the problem is stated and some common devices are described. In Section 3, a reliability index based on the Spanish indicator *TIEPI* is presented to classify the distribution lines by their performance. Section 4 presents the methodology employed in this work, introducing a cooperative game based on supply quality and economic indicators, and computing its Shapley value to find the most appropriate LDs to be upgraded to RCDs. Next, in Section 5, a scheme representing a Spanish electrical substation is considered as a case study to test the feasibility of the proposed approach. Finally, conclusions and lines of future research are given in Section 6. A list with the key abbreviations employed along the text is detailed in Table 1.

Table 1
List of abbreviations.

LD	Local device
RCD	Remote control device
Ψ	Set of lines in the area under study
$\mathcal{N}$	Set of players (LDs) in a given line l
$\mathcal{S}$	Coalition of players or topology
$\mathcal{T}$	Set of topologies
$t_{\mathrm{o}}(\mathcal{S})$	Overall time spent in restoring normal service
$t_{\mathrm{a}}(\mathcal{S})$	Actuation time spent in locating the fault
t_{r}	Repair time
n	Number of stages
$t_j(\mathcal{S})$	Duration of stage j
t_{REM}	Average time spent in remote maneuvers
t^1_{MAN} (t_{MAN})	Average time spent in the first (the rest of) manual maneuvers
t_{REC}	Average reclosing time
P_l	Power capacity of line l
TIEPI - γ_l	Interruption time equivalent to the installed capacity of line l
NIEPI - σ_l	Number of interruptions equivalent to the installed capacity of line l
δ_l	Relative *TIEPI* of line l with respect to set Ψ
α_l	Overhead section length of line l
β_l	Underground section length of line l
C_l	Number of transformation and distribution centers in line l
ρ_l	Expected performance index of line l
η_l	Distribution network performance index of line l
c_{ins}	RCD installation average cost
c_{man}	RCD yearly maintenance average cost
c_{ene}	Energy cost per kVA
r	Annual average rate of faults per km
T_{c}	Amortization horizon
T_{p}	Investment cycle
$J_{\mathrm{ins}}(\mathcal{S})$	Installation cost of topology $\mathcal{S}$
$J_{\mathrm{man}}(\mathcal{S})$	Maintenance cost of topology $\mathcal{S}$
$E_{\mathrm{loc}}(\mathcal{S})$	Amount of non-supply energy during fault location of topology $\mathcal{S}$
$J_{\mathrm{loc}}(\mathcal{S})$	Average power failure location cost of topology $\mathcal{S}$
E_{rep}	Amount of non-supply energy during power failure repair
J_{rep}	Average power failure repair cost
$J(\mathcal{S})$	Full cost of topology $\mathcal{S}$
$(\mathcal{N}, \boldsymbol{J})$	Cooperative game
$\phi_i(\mathcal{N}, \boldsymbol{J})$	Shapley value of player $i \in \mathcal{N}$ for game $(\mathcal{N}, \boldsymbol{J})$
$\mathbf{M}_N = [m_{i\mathcal{S}}]$	Shapley standard matrix for a game with N players
L	Number of samples in probability distributions
μ_{ϕ_i}	Mean value of the Shapley value of player i

2. Problem statement

We focus on distribution power networks, which are composed of electrical substations from where distribution power lines supply energy to end-users. Our goal is to improve the performance – in terms of continuity of supply – of the lines in an area under study, e.g., substations, geographical territories, etc. To this end, let us represent the different distribution lines of the area by the set

$$\Psi = \{l_1, l_2, \dots, l_h\}. \tag{1}$$

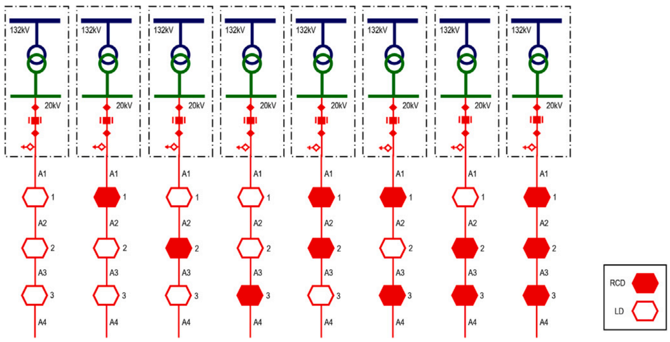

Fig. 1. Distribution line $l \in \Psi$ with an initial configuration of $N = 3$ LDs, represented by hexagons, which leads to a set $\mathcal{T} = \{\mathcal{S}_0, \mathcal{S}_1, \ldots, \mathcal{S}_7\}$ composed of $2^3 = 8$ topologies.

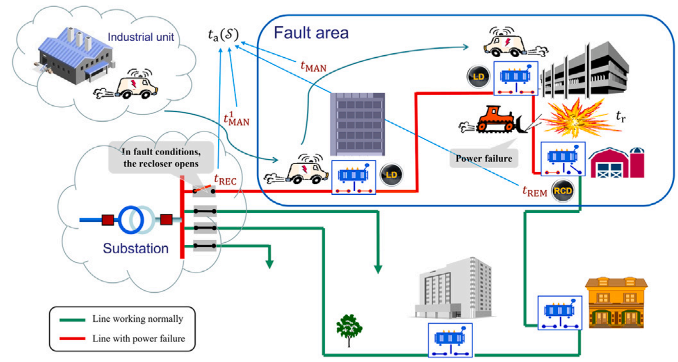

Fig. 2. Actuation and repair time parameters involved in presence of a power failure.

In general, each line $l \in \Psi$ is composed by sections of overhead/underground cables that connect a set of *switchgear*, which can be manipulated either remotely or manually to locate, isolate, and repair a power failure. Although an exhaustive analysis of switchgear properties is beyond the scope of this article,[1] a brief description of common devices is presented below:

- *Disconnectors* guarantee an isolation distance between electrical equipment (LD).
- *Load switches* make/break currents under nominal load, and also break temporary fault currents **(LD/RCD)**.
- *Switch-disconnectors* combine the two previously mentioned features **(LD/RCD)**.
- *Cut-outs* blow in fault conditions and must be replaced after the power failure is repaired (LD).
- *Fault Indicators (FIs)* identify the path followed by the fault current (LD).
- *Reclosers* detect and interrupt fault currents and have the ability to automatically restore power in temporary fault situations **(LD/RCD)**.
- *Sectionalizers* automatically isolate a faulted section after a preselected number of operations of an interrupting device that feeds the circuit, such as a recloser, have happened. It must be closed manually after the fault is repaired (LD).
- *Distribution centers* are installations that share power between several branches **(LD/RCD)**.
- *Transformation centers* reduce the distribution lines' voltage to supply the end-users **(LD/RCD)**.

Devices such as disconnectors, cut-outs, FIs, and sectionalizers cannot be normally remotely controlled in distribution lines, whereas the rest can be controlled, either locally or remotely. The elements in the latter set, highlighted in bold font in the above list, will be associated with the players in this work. Hence, let us introduce set $\mathcal{N} = \{1, 2, \ldots, N\}$, which denotes all LDs in a distribution line $l \in \Psi$ that can be upgraded to RCDs. Therefore, there are 2^N different scenarios or *topologies* depending on the specific subset $\mathcal{S} \subseteq \mathcal{N}$ of LDs proposed to be replaced by RCDs. The full set of topologies is symbolized here by $\mathcal{T} = \{\mathcal{S}_0, \mathcal{S}_1, \ldots, \mathcal{S}_{2^N-1}\}$, where $\mathcal{S}_0 = \emptyset$ and $\mathcal{S}_{2^N-1} = \mathcal{N}$ correspond, respectively, to the configurations of no and full upgrade. The cardinality of $\mathcal{S}$, symbolized by $S = |\mathcal{S}|$, gives us the number of new RCDs. For instance, for a line with three LDs, the eight different topologies and their corresponding elements are depicted in Fig. 1.

The *overall time* t_o that takes place since the fault occurs until service is restored can be divided into the *actuation time* t_a, i.e., the time spent by remote operators at the control center and the local maintenance crew to locate the fault, and the *repair time* t_r, or time to repair damages caused by the fault

$$t_o(\mathcal{S}) = t_a(\mathcal{S}) + t_r. \tag{2}$$

Note that the actuation time depends on topology $\mathcal{S} \subseteq \mathcal{N}$, for it establishes the number and position of LDs/RCDs in the line object of study. In particular, it can be defined as

$$t_a(\mathcal{S}) = \sum_{j=1}^{n-1} t_j(\mathcal{S}), \tag{3}$$

where n refers to the number of *stages*, i.e., time periods where the number of customers affected by the power outage remains constant. Once the fault has been located, the last stage, say t_n, corresponds to the *repair time* t_r, i.e., $t_n = t_r$.

Several time parameters come into play in the computation of $t_a(\mathcal{S})$. In particular, we will distinguish between the time consumed in *remote* maneuvers executed in the control center, denoted by t_{REM}, the time used by the maintenance team in performing the first *manual* maneuver, which includes the time spent to move from the industrial unit to the fault area, and it is symbolized by t^1_{MAN}, and the time utilized in manual maneuvers (except the first one) denoted by t_{MAN}. Finally, a time t_{REC} will be included to consider the *reclosing time*, i.e., the recloser opening/closing cycle at the beginning of the fault location process. Note that the aforementioned times strongly depend on the line length, its location, e.g., urban/city areas, the time when the fault occurs for it affects the number of people available, unexpected events as storms, traffic jams or car breakdowns, etc. These aspects make the duration of these times unpredictable. For this reason, we have averaged them considering the opinion of many network operation experts. An scheme that illustrates these concepts is depicted in Fig. 2. Finally, we consider the following assumptions:

Assumption 1. The RCDs installed on a given line $l \in \Psi$ always work correctly and require a maintenance cost per year.

Assumption 2. The assessment of the lines in Ψ and the decision to install new RCDs are performed cyclically by the company in *investment cycles*. Energy, installation, and maintenance costs will remain constant along each cycle. An average consumer price index (CPI) will be used to adjust these costs at the end of the cycle as a function of the expected inflation.

Assumption 3. A standard sequence of maneuvers, which depend on the exact location of the power failure and the expertise of the remote network operators, will be considered to isolate the affected section, independently of the number and position of LDs/RCDs.

[1] The interested reader can find several specialized references in the literature, e.g., [41,42].

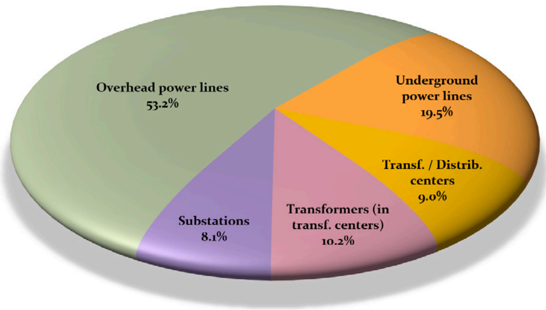

Fig. 3. Historical data for faults origin in distribution power networks in the South of Spain. Power failures can be due to: *overhead power lines*, which include overhead devices, *underground power lines*, small *transformers* inside transformation centers, *distribution* and *transformation centers* not including transformers, and *substations*.

3. Supply quality indicators for distribution power networks

The notion of *supply quality* consists in the distribution of electricity maintaining its voltage and frequency values under desirable limits, while minimizing the *number* and *duration* of electric interruptions, and without neglecting the interaction between supplier and customer. In particular, the most critical aspect from the consumer' viewpoint is the supply *continuity*. In this regard, the Spanish law defines two reliability indices to measure the impact of a power failure in a distribution line $l \in \Psi$, which are known by their Spanish acronyms as *TIEPI* (γ_l) and *NIEPI* (σ_l), and respectively refer to the *Interruption Time* and the *Number of Interruptions Equivalent to the Installed Capacity* [9]. These indices are respectively defined as

$$\gamma_l = \frac{\sum_{j=1}^{n} \left(P_j \times t_j(S) \right)}{P_l}, \tag{4}$$

$$\sigma_l = \frac{\sum_{j=1}^{n} P_j}{P_l}, \tag{5}$$

where P_l is the full power capacity of line l in kVA and n refers to the number of *stages* in the fault location/repair as commented before. Finally, terms P_j and $t_j(S)$, with $P_j \leq P_l$, denote respectively the non-supply power capacity in kVA during stage j and its duration in hours, which will be computed for each fault and topology as a function of the average times introduced in the previous section. Note that index γ_l is measured in hours while σ_l is dimensionless. Indeed, *TIEPI* is more restrictive from a legal perspective, given that it averages the power affected by periods of supply disruption. On the contrary, the duration of power interruptions is not considered in *NIEPI*. For this reason, the results provided in this work will focus on the former indicator.[2] Note that both definitions (4) and (5) can be easily extended to a set of faults involved in the chosen line in any time interval, typically a year, simply by aggregating the individual indices due to each fault. Also, the indices related to a full area, e.g., a substation, can be obtained by summing the individual indices of its lines and transformers.

3.1. A refined supply quality indicator

We are interested in improving the performance of the distribution power lines in Ψ. To this end, the first step is to detect which of those lines need more improvement from a supply-continuity viewpoint. Since γ_l does not consider the *relative* power capacity of line l with respect to Ψ, we define the following weighted measure of all *TIEPI* indices in an area of interest regarding their power capacity:

$$\delta_l[\%] = 100 \times \frac{\gamma_l}{\sum_{s \in \Psi} \gamma_s} \times \frac{P_l}{\sum_{s \in \Psi} P_s}, \tag{6}$$

where P_l is the power capacity of line l in kVA and γ_l is given by (4). Hence, by index δ_l, we give more relevance to lines with higher contracted power, normally related to a large number of customers.

Lines $l \in \Psi$ can be classified regarding their *current* performance using (6), but it is also interesting to consider their *expected* performance. To this end, historical average fault data in distribution power lines obtained from a Spanish electric company will be used (see Fig. 3). Considering this information, it is possible to compute the expected performance index for each line l as the following weighted summation over Ψ:

$$\rho_l[\%] = \frac{53.2\ \alpha_l}{\sum_{s \in \Psi} \alpha_s} + \frac{19.5\ \beta_l}{\sum_{s \in \Psi} \beta_s} + \frac{9.0\ C_l}{\sum_{s \in \Psi} C_s} + \frac{10.2\ P_l}{\sum_{s \in \Psi} P_s} + \frac{8.1}{|\Psi|}, \tag{7}$$

where α_l and β_l respectively correspond to the overhead and underground section lengths in km, C_l is the number of transformation and distribution centers, P_l gives the power capacity in kVA, and $|\Psi| = h$ represents the cardinality of Ψ.

Finally, with the aim of ranking lines $l \in \Psi$ regarding the relation between their current and expected performance, the *distribution network performance index* is introduced as

$$\eta_l = \frac{\rho_l}{\delta_l}. \tag{8}$$

Eq. (8) considers not only the continuity of supply, but also the relative power capacity inside the area of interest and the physical and electrical features of the lines involved. This index connects the *TIEPI* impact of a distribution line relative to a reference scope with its expected *TIEPI* based on historical data. The larger η_l is, the better the continuity of supply of line l, achieving a value of 1 if both the current and expected performance coincide. For this reason, index (8) can be used to perform an efficient ranking of power lines inside Ψ.

Example 1. Let the area under study be described by the scheme shown in Fig. 4, where set Ψ is composed of $h = 3$ distribution power lines that have experienced one power failure each during a year, with information per stage detailed in Table 2. Note the short actuation times in the first stage of the fault in line 2 due to the RCD installed on the line, symbolized in this work by a double edge. The aggregated values for γ_l are given in Table 3, achieving a full area *TIEPI* index of $\gamma = \gamma_1 + \gamma_2 + \gamma_3 = 174.11$ min. The parameters α_l, β_l, C_l, P_l, which allow computing indices δ_l, ρ_l and hence η_l, following (6), (7) and (8), respectively, are also shown in Table 3. When analyzing the results, note that line 2, with the lowest *TIEPI*, is, however, the one with the worst performance regarding η_l. Similarly, it is remarkable the high performance index of line 3 independently of its *TIEPI*. Indeed, the relative power capacity with respect to area Ψ penalizes line 2 and fosters line 3 in terms of performance. Also, the length of the latter line contributes to its high performance index. Summing up, by exploring η_l, it can be concluded that first line 2, and secondly line 1, should be improved, while line 3 presents satisfactory results.

4. Improving distribution lines performance by game theory

Sections 2 and 3 have respectively introduced the problem statement and some performance metrics. Here, we present the methodology employed to determine the upgrades of devices in the power network. In particular, we leverage the cooperative game theory framework to model the impact of the upgrades through the characteristic function

[2] Power failures whose cause is external to the company, e.g., due to private facilities or extreme weather conditions, are not legally considered for the computation of *TIEPI* and *NIEPI*. Also, there are some legally established annual upper bounds for these indices, which depend on the line configuration: urban, rural, etc. If exceeded, they may result in a penalty for the company.

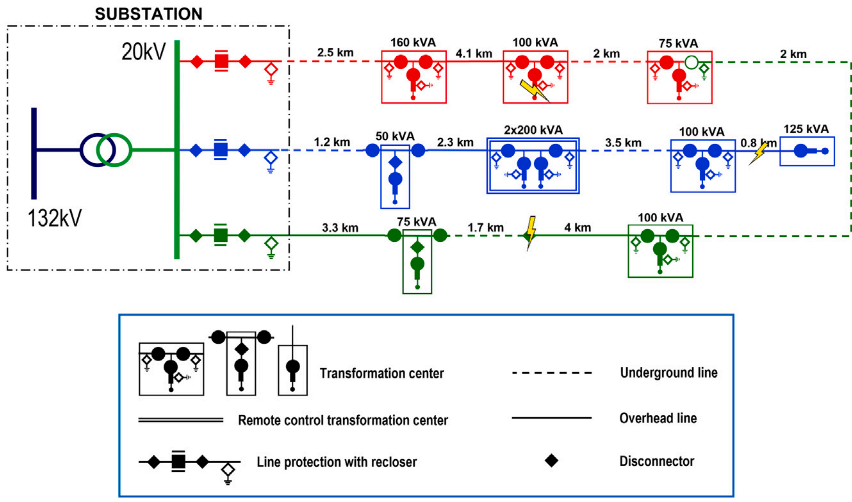

Fig. 4. Power network diagram of Example 1.

Table 2
TIEPI index γ_l for lines in Example 1.

Stages/fault	Line 1 $P_1 = 335$			Line 2 $P_2 = 675$			Line 3 $P_3 = 175$	
	1	2	3	1	2	3	1	2
P_j [kVA]	335	260	100	675	225	125	175	100
$t_j(\mathcal{S})$ [min]	39	12	71	6	27	183	38	31

Table 3
Line parameters needed to compute index η_l in Example 1.

	α_l	β_l	C_l	P_l	γ_l [min]	ρ_l	δ_l	η_l
Line 1	4.1	4.5	3	335	69.51	30.43	35.26	0.86
Line 2	3.1	4.7	4	675	48.89	30.99	49.97	0.62
Line 3	7.3	3.7	2	175	55.71	38.58	14.76	2.61

of the game, which is a weighted measure of the expected performance given by the *TIEPI* index (recall Eq. (4)) and other relevant dimensions for the company such as economic viability and sustainability over time. By finding the Shapley value [28] of the cooperative game, it is possible to rank the alternatives considered according to their average impact, therefore providing a means to select which parts of the network should be upgraded.

4.1. Measuring expected performance and impact

While replacing all LDs by RCDs provides the best results for the customer, it also generates the highest costs for the company. Therefore, given a line $l \in \Psi$, the best locations for new RCDs should be determined balancing their both needs. In particular, given a topology $\mathcal{S}$, the company investment will depend on *installation* and *maintenance costs*

$$J_{\text{ins}}(\mathcal{S}) = c_{\text{ins}}\, S, \qquad J_{\text{man}}(\mathcal{S}) = c_{\text{man}}\, S\,(T_{\text{c}} - 1), \tag{9}$$

where c_{ins} and c_{man} are respectively the average costs of installation and yearly maintenance of RCDs, and T_{c} corresponds to a reasonable *amortization horizon*. In contrast, customer satisfaction is related to *location* and *repair costs* of the average power failure, which can be expressed as

$$J_{\text{loc}}(\mathcal{S}) = c_{\text{ene}}\, r\,(\alpha_l + \beta_l)\, T_{\text{c}}\, E_{\text{loc}}(\mathcal{S}), \qquad J_{\text{rep}} = c_{\text{ene}}\, r\,(\alpha_l + \beta_l)\, T_{\text{c}}\, E_{\text{rep}}, \tag{10}$$

where c_{ene} is the energy cost per kVA×h, r measures the annual average rate of faults per km, and the overhead and underground lengths are given respectively by α_l and β_l, as seen in Section 3. The amount of non-supply energy in kVA during the power failure location and repair can be calculated as

$$E_{\text{loc}}(\mathcal{S}) = \sum_{j=1}^{n-1} \left(P_j \times t_j(\mathcal{S})\right), \qquad E_{\text{rep}} = P_n \times t_{\text{r}}, \tag{11}$$

where n is the number of stages, P_j provides the non-supply power in kVA during stage j, and $t_j(\mathcal{S})$ measures the duration in hours of stage j, which depends on topology $\mathcal{S}$. Note that this term is closely related to the time spent in completing the fault location and repair maneuvers, as commented in Section 2. Finally, t_{r} is the average time to repair the fault during last stage n.

To evaluate the different possibilities for LDs to be upgraded to RCDs, i.e., the topologies $\mathcal{S} \subseteq \mathcal{N}$, we define the following cost function:

$$J(\mathcal{S}) = J_{\text{ins}}(\mathcal{S}) + J_{\text{man}}(\mathcal{S}) + J_{\text{loc}}(\mathcal{S}) + J_{\text{rep}}. \tag{12}$$

Eq. (12) goes beyond the affected power capacity and the duration of interruptions included in *TIEPI*, for it considers installation, maintenance, and operating costs as well. Therefore, it can be used to balance the customers' and electric company's goals. A cooperative game based on (12) is introduced below.

4.2. Cooperative game theory tools applied to power networks

A cooperative game is defined by pair $(\mathcal{N}, \boldsymbol{J})$, where $\mathcal{N}$ is the set of players containing the possible locations for new RCDs in a given distribution line, and vector $\boldsymbol{J} = [J(\mathcal{S}_0), J(\mathcal{S}_1), \dots, J(\mathcal{S}_{2^N-1})]^{\mathrm{T}}$ evaluates (12) for every topology. In other words, $\boldsymbol{J}$ provides us with the cost of each of the 2^N possible configurations as a function of the upgraded locations in the line of study. In order to find the average contribution of the N players in this large amount of information, we will consider the Shapley value [28], the most used payoff rule in cooperative game theory. This value assigns to game $(\mathcal{N}, \boldsymbol{J})$ payoff vector $\boldsymbol{\phi}(\mathcal{N}, \boldsymbol{J})$, defined for all $i \in \mathcal{N}$ as

$$\phi_i(\mathcal{N}, \boldsymbol{J}) = \sum_{\mathcal{S} \subseteq \mathcal{N} : i \notin \mathcal{S}} \frac{S!(N - S - 1)!}{N!} \left[J(\mathcal{S} \cup \{i\}) - J(\mathcal{S})\right], \tag{13}$$

that is, the marginal contribution of each player in $\mathcal{N}$ is averaged for all the possible permutations it can be part of, with weights depending on the size of each coalition $\mathcal{S}$ by term $\frac{S!(N-S-1)!}{N!}$. In our context, the Shapley value of a location corresponds to the average impact of its upgrade from LD to RCD. Therefore, the best locations to become RCDs will be associated with the lowest payoffs. Since we deal with the *cost* game given by (12), *negative* Shapley values will be related to locations that are *beneficial* to be remotely controlled, both from the viewpoint of the company and the customers. From an axiomatic perspective, the

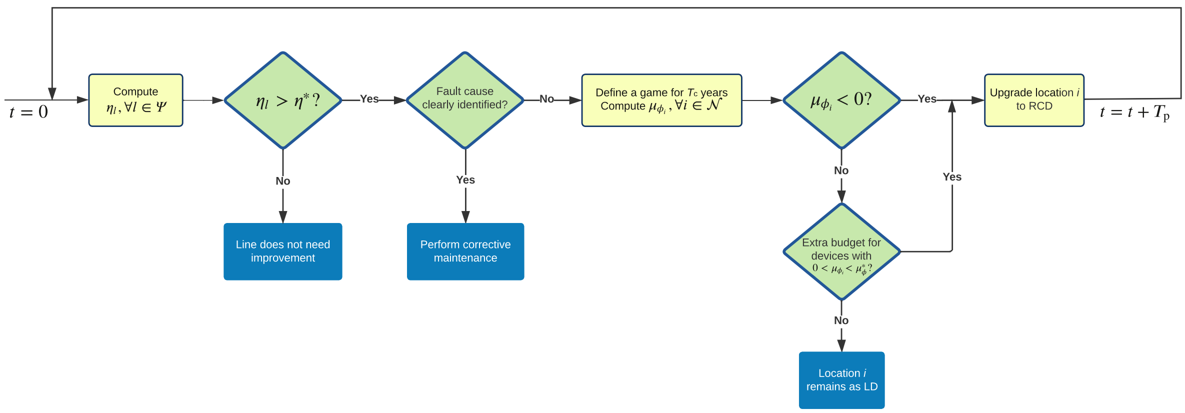

Fig. 5. Game-theoretic planning method overview.

Shapley value is formally characterized by the properties of *linearity*, *efficiency*, *dummy player*, and *symmetric players* [28]. In particular, the *efficiency* property states that the value of full set $\mathcal{N}$ is totally distributed among the players

$$\sum_i \phi_i(\mathcal{N}, \boldsymbol{J}) = J(\mathcal{N}). \tag{14}$$

We will consider an alternative matrix formulation of the Shapley value that allows for a fast and simple computation. Following [43], it is possible to rewrite (13) as

$$\boldsymbol{\phi}(\mathcal{N}, \boldsymbol{J}) = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_N \end{bmatrix} = \mathbf{M}_N \begin{bmatrix} J(\mathcal{S}_0) \\ J(\mathcal{S}_1) \\ J(\mathcal{S}_2) \\ \vdots \\ J(\mathcal{S}_{2^N-1}) \end{bmatrix} = \mathbf{M}_N \boldsymbol{J}, \tag{15}$$

where $\mathbf{M}_N \in \mathbb{R}^{N \times 2^N}$ is known as the Shapley standard matrix [43], with its rows corresponding to players $i \in \mathcal{N}$, and its columns to the different topologies $\mathcal{S} \subseteq \mathcal{N}$. Each element of this matrix is defined as

$$m_{i\mathcal{S}} = \begin{cases} \frac{(S-1)!(N-S)!}{N!}, & i \in \mathcal{S}, \\ -\frac{S!(N-S-1)!}{N!}, & i \notin \mathcal{S}. \end{cases} \tag{16}$$

For instance, for a game with three players, as that of Fig. 1, the Shapley standard matrix becomes

$$\mathbf{M}_3 = \begin{bmatrix} -\frac{1}{3} & \frac{1}{3} & -\frac{1}{6} & -\frac{1}{6} & \frac{1}{6} & \frac{1}{6} & -\frac{1}{3} & \frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{6} & \frac{1}{3} & -\frac{1}{6} & \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} & \frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{6} & -\frac{1}{6} & \frac{1}{3} & -\frac{1}{3} & \frac{1}{6} & \frac{1}{6} & \frac{1}{3} \end{bmatrix}. \tag{17}$$

Remark 1. To formally consider pair $(\mathcal{N}, \boldsymbol{J})$ as a cooperative game, the cost of the empty set should be zero, that is, $J(\emptyset) = 0$. This fact can be achieved by considering a new game $(\mathcal{N}, \boldsymbol{J}')$ that corresponds to a simple redefinition of cost function (12) by

$$J'(\mathcal{S}) = J(\mathcal{S}) - J(\emptyset). \tag{18}$$

The Shapley value remains unchanged because both games only differ in a constant term, i.e., $\boldsymbol{\phi}(\mathcal{N}, \boldsymbol{J}) = \boldsymbol{\phi}(\mathcal{N}, \boldsymbol{J}')$.

4.3. Probability distributions to manage varying parameters

When evaluating (12), parameters are assumed *fixed* so that the characteristic function only depends on topology $\mathcal{S}$. Nevertheless, parameters can vary to generalize the results. To this end, we will consider here that both the average rate of faults r and the energy cost c_{ene} can change in a prespecified interval. Therefore, the characteristic function would be re-formulated as $J(\mathcal{S}, r, c_{\text{ene}})$, and the Shapley value could be computed by averaging a large number L of these parameters' samples. Following a Monte Carlo approach [44], discrete probability distributions for the Shapley value can be obtained, with their respective mean values

$$\mu_{\phi_i} = \frac{1}{L} \sum_{p=1}^{L} \phi_i^p(\mathcal{N}, \boldsymbol{J}), \tag{19}$$

representing a measure of each location's performance.

4.4. Optimization procedure

To conclude this section, we summarize the steps to apply the full game-theoretic planning method to improve the quality of the supply of distribution power networks:

1. Rank the lines inside Ψ using the distribution network performance index η_l presented in Section 3.1, which measures their continuity of supply, and choose those below a considered threshold η^*.
2. Take the lines resulting from step 1 and perform a qualitative analysis to discard those whose faults can be solved by simple maintenance works (e.g., faults generated by trees touching power lines, high salinity concentration, and cables in bad conditions).
3. For each remaining line, consider the LDs to form the set of players $\mathcal{N}$ of a cooperative game.
4. To define the characteristic function of the game, choose an amortization cost T_c, and evaluate Eq. (12) for every possible subset of players (and a statistically relevant sample size L of parameter values in case the parameters are not fixed).
5. Compute $\boldsymbol{\phi}(\mathcal{N}, \boldsymbol{J})$ and upgrade those LDs that verify $\phi_i(\mathcal{N}, \boldsymbol{J}) < 0$ ($\mu_{\phi_i} < 0$ in case the parameters are not fixed).
6. Rank the remaining LDs in increasing order with respect to the Shapley values and evaluate one by one performing a cost–benefit analysis regarding the possible upgrade.
7. The procedure stops once the cost–benefit analysis reveals that one LD should not be upgraded.

In a nutshell, the method seeks distribution lines where RCDs can substantially reduce supply shortage, which could be particularly interesting in lines that require *large actuation times* for manual maneuvers, e.g., those in areas that are hard to access. All LDs with a negative Shapley value will be proposed to be replaced by RCDs because this upgrade implies a net benefit for both the company and the customers. Additionally, extra LDs can be promoted to RCDs depending on the *company's investment budget* for the next T_p years. Note that this analysis can be repeated cyclically to deal with the customers' evolving needs, and hence the installed infrastructure can change dynamically. A full diagram that illustrates the proposed method is given in Fig. 5.

Remark 2. In the first step of the method, a search of low-performance lines is performed inside Ψ, which is not computationally expensive because it scales linearly with the number of lines h. Later, a game over a set of N players is defined for some of the selected lines. The computational complexity related to the evaluation of $J(S)$ for every topology $S \subseteq \mathcal{N}$ grows exponentially with 2^N, which limits the applicability of our method as it is to medium-scale lines with around 15–20 LDs. Nevertheless, *randomized methods* such as those proposed in [29,45] can be implemented to mitigate this issue. Basically, a number q of random orderings from the full set of permutations are taken for estimating the Shapley value of each player, with the estimation error being bounded as a function of q. Some large-scale network applications of this method are given in [46], which deals with the *PageRank* computation, and [47], which partitions a drinking water network. Therefore, it could be possible to use the proposed method in larger networks. Also, as the method is implemented offline for each investment cycle, there are no critical time restrictions to compute the solution. For example, it is acceptable if it is found after several days of computation.

5. Case study

To evaluate the method introduced in the previous section, we consider the electric scheme for the substation and the distribution lines depicted in Fig. 7, which is based on the *orthogonal scheme* of a real substation in the South of Spain. More specifically, three-phase circuits are represented by a single-line diagram for ease of display, and different line sections are not to scale. In particular, the substation – detailed in Fig. 6 – consists of two 66/20 kV, 20 MVA power transformers, which feed five distribution lines each, through their corresponding *busbars* B1 and B2. Other elements inside the substation are the *coupling*, which provides an alternative feeder for the customers when their transformer is unavailable; the *capacitor banks*, which mainly regulate the reactive power; and the *ancillary services*, which give energy to control, measurement, protection, and supervision equipment. Focusing on distribution lines, we can broadly distinguish between urban, rural, mixed, and private lines, which in this particular case correspond to photovoltaic facilities. Regarding the network configuration, each line may have an alternative feeder coming from another line (in the same or other substation) or even from the same line.

Two iterations of the procedure in Section 4.4 have been performed considering an investment cycle of $T_\mathrm{p} = 3$ years and a performance threshold of $\eta^* = 0.9$. The simulations were implemented using the `numpy` [48,49] package of Python®, Microsoft Excel®, and the tool `Crystal Ball` [50] by Oracle® in a 3.2 GHz Intel® Core™ i3-6100T/8 GB RAM computer.

5.1. Performance index

The first step is to compute the performance indices η_l for every line in the substation. For this computation, the private photovoltaic lines are not taken into account because their management does not correspond to the electric company. The resulting values for the indices are given in Table 4, iteration 1, where fault events in a full year have been taken into account. It can be seen that lines *UTRERA*, *ROQUETAS* and *J.S.TOMAS* should be improved, as they verify $\eta_l < \eta^*$. Nevertheless, it is detected that rural line *UTRERA* has many recurrent faults related to several cypress trees touching lines, which can be solved by tree pruning tasks, while urban line *J.S.TOMAS* has most of its faults located in a very damaged cable, which should be replaced. By contrast, the faults in line *ROQUETAS* are very diverse. Also, large actuation times for manual maneuvers are required in this line due to its length. Hence, it is an interesting option to upgrade to RCDs some of its LDs.

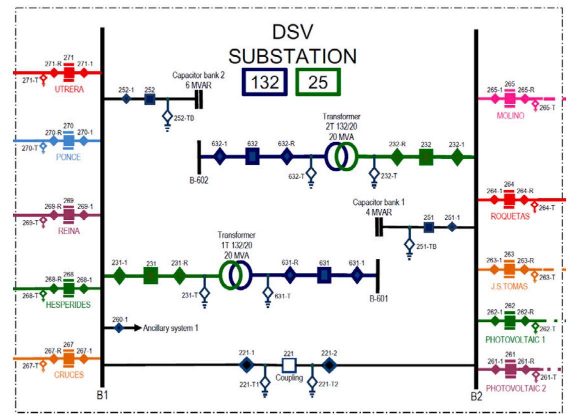

Fig. 6. Detail of the electrical substation from the full scheme depicted in Fig. 7.

5.2. Ranking devices by the Shapley value

To define a cooperative game in line *ROQUETAS*, whose initial configuration is represented in Fig. 8a, we consider an amortization horizon of $T_\mathrm{c} = 15$ years, with $c_\mathrm{ins} = 14200$ € and $c_\mathrm{man} = 500$ € being the RCDs installation and yearly maintenance average costs, respectively. Also, a fault repair is assumed to be done in $t_\mathrm{r} = 175$ min. Regarding actuation time t_a, different scenarios depending on topology S have been considered for the computation of $t_j(S)$, assuming $t_\mathrm{REM} = 1$ min, $t^1_\mathrm{MAN} = 37.5$ min, $t_\mathrm{MAN} = 14.5$ min, and $t_\mathrm{REC} = 2.8$ min. These values were obtained averaging the estimates given by more than 50 network operation experts. Also, unlike [24], note that faults in the devices – and not only in the cables – are also considered in this work. To implement the Monte Carlo method commented in Section 4.3, we assume that both the annual average rate of faults r and the energy cost c_ene are normally distributed, with mean 0.19 and standard deviation 0.003 in the former case and mean 0.83 €/kVA×h and standard deviation 0.0005 €/kVA×h for the latter. Taking this information into account, which was estimated based on data from a Spanish electric company, a game in line *ROQUETAS* has been considered, with its 10 LDs acting as the players, which correspond to the seven transformation centers indicated in Table 4 and three switch-disconnectors. Therefore, cost function $J(S, r, c_\mathrm{ene})$ for the 2^{10} topologies has been evaluated by (12) for $L = 10^5$ samples, and the average results considering all the fault locations scenarios have been used in the computation of the fault location and repair costs. Terms $J_\mathrm{ins}(S) + J_\mathrm{man}(S)$, concerning the company, and $J_\mathrm{loc}(S) + J_\mathrm{rep}$, related to the customers, have been represented for every topology in Fig. 9a. As expected, the former increases with cardinality S. By contrast, the latter strongly depends on the sequence of fault location maneuvers and the location of RCDs, being reduced when relevant locations – indeed those with lowest Shapley values – are remotely controlled.

At this point, the Shapley standard matrix $\mathbf{M}_{10}$ has been utilized to compute (15), obtaining for a sample size L of parameters r and c_ene the probability distributions of the Shapley values, which are drawn in terms of standard deviation bands in Fig. 10a. Their mean values have been calculated by (19), achieving the following results:

$$\boldsymbol{\mu}_\phi = 10^3 \times [19.15 \;\; 18.45 \;\; -92.35 \;\; 21.70 \;\; 2.47 \;\; 15.02 \;\; -16.51 \;\; 16.88 \;\; 20.26 \;\; 21.70]^\mathrm{T}, \tag{20}$$

where the values corresponding to LD_3 and LD_7 are negative. Therefore, it is economically interesting for the company and also beneficial for the customer to install RCDs in these locations, reaching the configuration shown in Fig. 8b. This upgrade makes sense from a topological viewpoint, for these locations are respectively situated in the line bifurcation point and in the urban center alternative feeder. Finally, at the end of this investment cycle, no more LDs are considered to be upgraded by the company.

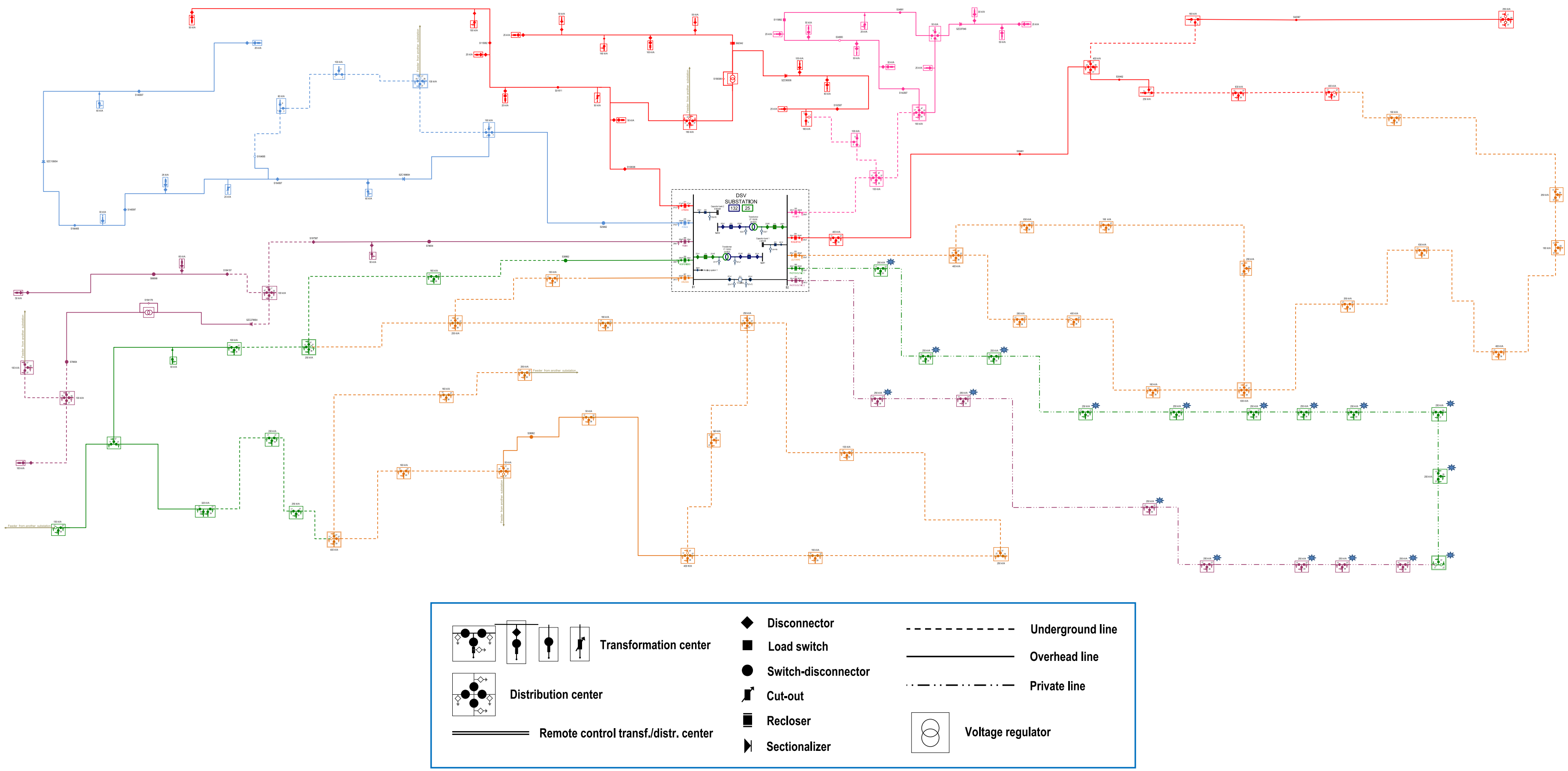

Fig. 7. Electrical substation and their distribution lines analyzed in the case study.

Table 4
Computation of index η_l for lines in the substation under study. Indices that verify $\eta_l < \eta^*$ are highlighted in bold font, meaning that these lines should be improved. From this set, those with $\eta_l \geq \eta^*$ in iteration 2 are underlined.

	Busbar	Line	Faults/yr	α_l	β_l	C_l	P_l	γ_l [min]	ρ_l	δ_l	η_l
Iteration 1	B1	UTRERA	4	22.9	0	16	1180	44.84	11.69	18.38	**0.64**
		PONCE	9	35.8	5.6	10	585	68.65	16.70	13.95	1.20
		REINA	7	43.7	4.3	7	560	72.31	18.92	14.07	1.34
		HESPERIDES	3	12.6	5	9	1480	15.87	8.70	8.16	1.07
		CRUCES	1	2.1	22.5	15	2900	8.12	10.77	8.18	1.32
	B2	MOLINO	4	14.3	4	13	660	16.40	8.90	3.76	2.37
		ROQUETAS	3	16	18.3	7	2490	23.72	13.68	20.52	**0.67**
		J.S.TOMAS	3	0	20.3	14	4730	7.89	10.65	12.97	**0.82**
Iteration 2	B1	UTRERA	2	26.3	0	17	1230	22.95	12.54	13.27	0.95
		PONCE	7	35.8	10.1	11	685	57.27	16.95	18.44	0.92
		REINA	8	43.7	8.4	8	585	69.10	18.95	19.00	1.00
		HESPERIDES	6	12.6	5.9	9	1480	18.03	8.50	12.54	**0.68**
		CRUCES	2	3.4	22.5	15	2900	6.42	10.43	8.75	1.19
	B2	MOLINO	5	14.3	7.2	14	710	14.94	9.28	4.99	1.86
		ROQUETAS	2	19.1	18.3	7	2490	13.80	13.87	16.15	**0.86**
		J.S.TOMAS	1	0	20.3	13	4100	3.56	9.48	6.86	1.38

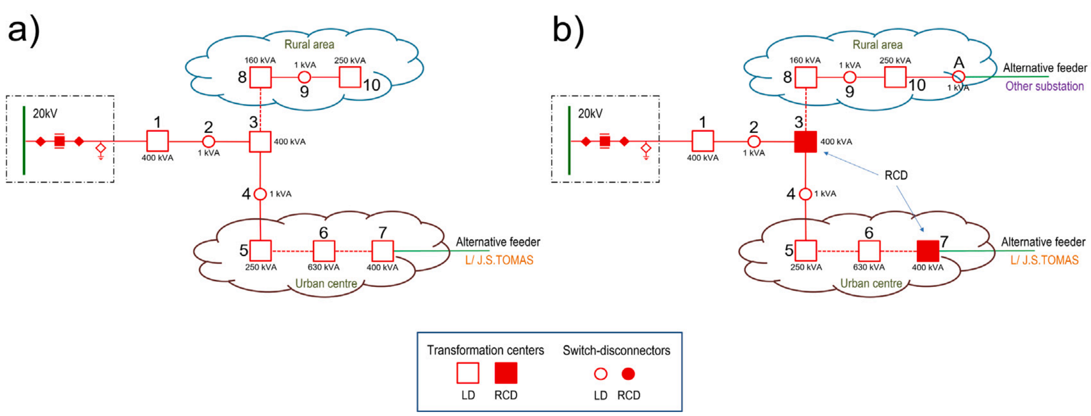

Fig. 8. Configuration of line *ROQUETAS* at the beginning of first (left) and second (right) iteration. Note that a symbolic power capacity of 1 kVA has been considered in switch-disconnectors to model their driving motors and ancillary services.

5.3. Second iteration

As commented, it is expected that lines experiment changes through the investment cycle of $T_p = 3$ years. Consequently, these changes will alter the needs of the distribution network, which in turn will modify the sorted list of LDs to be upgraded to RCDs. The new specifications and the corresponding performance indices for iteration 2 are also detailed in Table 4, where it can be seen that with the exception of line *HESPERIDES*, the *TIEPI* indices for every line have been reduced. It is usual that this index gradually decreases over the years due to the more efficient power network management. Note also that the three lines that were improved in the first iteration have accordingly increased their performance index η_l. Nevertheless, as can be seen, the improvement of line *ROQUETAS* is unsatisfactory considering threshold η^*, and hence a new cooperative game will be defined in this line. Also, line *HESPERIDES* does not satisfy our requirements, but most of their faults are condensed in a near-the-sea area, whose *isolators* require immediate cleaning and/or replacement. Hence, a corrective maintenance is the best choice for improving this line.

The new game implemented in line *ROQUETAS* contains nine players corresponding to the eight LDs that were not remotely controlled in the first iteration and a new switch-disconnector LD_A that has been inserted in the line, providing an alternative feeder, as can be seen in Fig. 8b. That is, actuation times in RCD_3 and RCD_7, which are no longer players, correspond to $t_{REM} = 1$ min for every topology, which in turn will consequently reduce the costs and hence, in general, the

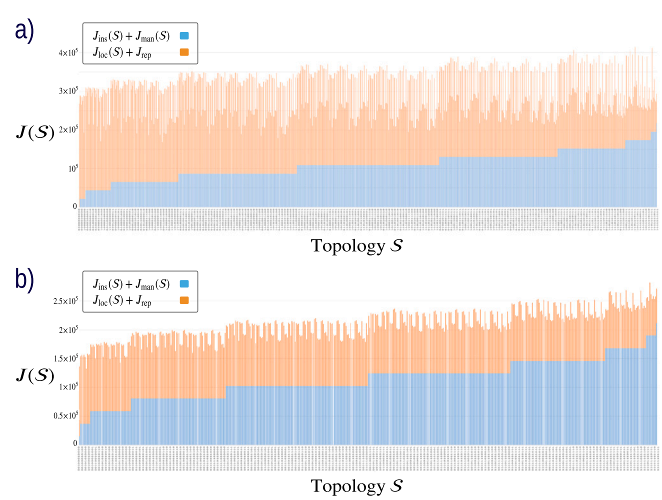

Fig. 9. Cost function terms due to company and customers: Evolution with topology $\mathcal{S}$.

mean values obtained, as shown below. The same parameters used in the first iteration are considered, but with a 3% CPI 3-years increment in the costs, i.e., $c_{ins} = 14626$ €, $c_{man} = 515$ € and $c_{ene} = 0.8549$ €/kVA×h. The new cost function $J(\mathcal{S}, r, c_{ene})$ computed for each topology is shown

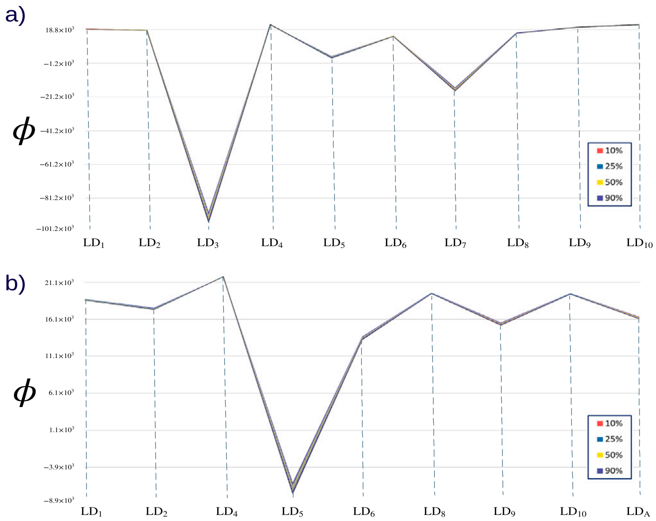

Fig. 10. Shapley values distributions corresponding to first (top) and second (bottom) iterations. Standard deviation bands of 10%, 25%, 50% and 90% have been considered.

in Fig. 9b. Finally, matrix $\mathbf{M}_9$ is considered to calculate the Shapley values distributions represented in Fig. 10b, whose mean values are given by

$$\mu_\phi = 10^3 \times [18.76 \;\; 17.53 \;\; 21.83 \;\; -6.70 \;\; 13.55 \;\; 19.63 \;\; 15.46 \;\; 19.56 \;\; 16.28]^{\mathrm{T}}, \tag{21}$$

where LD_5, the only location with negative Shapley value, should be upgraded to RCD. Notice that locations situated in the urban center (LD_5, LD_6) have lower Shapley values than some in the rural area (LD_9, LD_A), which at first sight can present a more strategic location. The rationale of this fact is the high difference of installed capacity in both areas – 1280 kVA vs. 410 kVA – which outperforms the LDs topological situation. Also, note that feeder LD_A is only considered for faults in the rural area, since for the rest of the line the new RCD_7 is used as alternative feeder.

It is also interesting that, in both iterations, the lower the Shapley value, the higher the dispersion of the data set, as can be appreciated in Fig. 10. This fact can be explained by considering that LDs with the lowest Shapley values have more impact on the improvement of the distribution line. Hence, they are more sensitive to changes in energy cost and fault rate. Notice also that the aggregate of all Shapley values coincides with $J(\mathcal{N})-J(\emptyset)$, as can be extracted from (14) and Remark 1.

To test its applicability, the results of the proposed method have been contrasted with those obtained by using a *greedy algorithm*, which in essence consists of ranking the players, successively selecting the one with the best marginal costs with respect to the previous list. As shown in Table 5, the greedy-based method is slightly faster than our method. Also, similar results to the proposed method are obtained when upgrading few devices to RCDs in this manner. Nevertheless, some differences are detected when the number of updated devices grows. In particular, our method gives more relevance to LD_1 and LD_2 over LD_8, LD_9 and LD_{10}, which has sense from an electrical viewpoint given that a failure in the former devices – and not in the latter – implies an *overload* of an alternative feeder line. Indeed, the proposed method is more *robust* to faults because it averages information regarding all possible topologies, while the greedy-based method assumes the previous devices promoted to RCDs operative, i.e., it only explores a very limited set of topologies. Therefore, the approach presented here is more comprehensive than the solution provided by the greedy algorithm, at the cost of a small increase in computational burden (5.11%). Finally, note that the analysis performed in this case study has been

Table 5
Comparison of the proposed method with the greedy algorithm for the LDs upgrade in line *ROQUETAS*.

Iter.	Method	Time [s]	LDs ranking by μ_{ϕ_i}									
1st	ϕ-based	145.13	3	7	5	6	8	**2**	**1**	9	4	10
	Greedy	138.90	3	7	5	6	8	9	**2**	**1**	4	10
2nd	ϕ-based	101.89	5	6	9	A	**2**	**1**	10	8	4	–
	Greedy	95.85	5	6	9	A	10	8	**2**	**1**	4	–

limited to two method iterations for the sake of simplicity, but it can be easily extended in time. Moreover, note that the performance indices globally approach to theoretical value 1 when improving the installations, as can be checked in Table 4. Indeed, each η_l depends on *every* line $l \in \Psi$, hence promoting a cooperative improvement of the full area under study.

6. Conclusions

In this article, a planning method for improving the quality of supply in distribution power networks has been presented. A performance index that ranks the lines in a certain area considering reliability indices, power capacity, and physical features has been defined. Once the most damaged lines are detected, either corrective maintenance measures or the installation of remote control devices (RCDs) are proposed depending on the cause of the fault and the actuation times. In the latter case, a cooperative game in which the players are the locations that can be upgraded is defined, with a cost function that considers both the needs of the company and the customers. Then, the Shapley value is utilized to decide the most adequate locations to install new RCDs. This analysis can be repeated to consider the network reconfiguration every time the electric company starts a new investment cycle. Therefore, the presented methodology can be used in practice to complement/verify the current company strategy to decide the RCDs location, based on qualitative/heuristic methods and experts opinions. To the best of our knowledge, the proposed method is novel and provides a more insightful view regarding the possible upgrades in the network than methods based on integer optimization problems. Our approach also includes some steps that require the assessment of the experts at the power company, which is another significant difference with other methods in the literature. To validate the proposed strategy, an electric scheme based on a real substation in the South of Spain has been considered as a case study, achieving satisfactory results.

Future work should include the extension of this method to more complex power systems, where randomized methods to estimate the Shapley value could be implemented in the line of Remark 2. Also, alternative mechanisms for establishing the sequence of fault location maneuvers could be considered. Moreover, human-in-the-loop techniques to manage the maneuvers performed by human teams could be explored. Finally, the use of other cooperative game theory tools to perform rankings, as the Banzhaf value [51], could be object of further research.

CRediT authorship contribution statement

Francisco Javier Muros: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Daniel Saracho:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation. **José María Maestre:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All necessary data to reproduce the presented results are included along the manuscript.

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