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Improving distribution network resilience through automation, distributed energy resources, and undergrounding

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ABSTRACT

In recent years, natural disasters such as hurricanes Katrina and Sandy, or deliberate attacks on the power system, have highlighted the importance of a resilient power distribution system that can maximize the energy supply even in the most stressful situations. However, reinforcing the distribution power grid is very costly, and investment decisions must be adequately justified.

This paper proposes a single-stage multi-criteria optimization model to maximize the resilience of a distribution system through a series of investments while minimizing the total cost incurred. The assets to be invested in under this model are the installation of Remotely Controlled Switches (RCSs), Distributed Energy Resources (DERs) such as storage and photovoltaic units, and the undergrounding of overhead lines. The optimization method is based on a customized genetic algorithm that can be successfully applied to solve large-scale networks. To exemplify the application of the proposed optimization method, an actual distribution network is simulated under extreme weather conditions. The results obtained show how the different type of investments are prioritized and the importance of including managerial and logistic training in distribution companies to deal with extreme weather events.

1. Introduction

In 2005, hurricane Katrina hit the east coast of the United States, leaving 1,836 people dead and costing approximately 81 billion dollars [1]. Just seven years later, hurricane Sandy hit the same area with dozens of lives lost and a cost close to 50 billion dollars [2]. Since then, several public and private institutions have joined efforts to maximize the resilience of the system [3]. The term resilience can be defined as the ability of a system to withstand an extreme event and return to its previous functioning while minimizing the consequences.[1]

In many cases, the consequences produced by this type of event do not affect a single system, but rather the numerous connections between sectors [7] can lead to a series of multiple failures between different systems [8]. According to the study conducted by Luiifj [9], energy infrastructures such as the power grid have the most significant impact on other sectors due to their high level of dependence, with the most affected sectors being industry, water services, and telecommunications.

According to the literature, resilience deals with three main types of events: deliberate attacks, natural disasters, and accidents [9]. Deliberate attacks are actions executed by an adversary seeking to inflict specific damage [10] such as cyber-attacks [11] or terrorist acts. Natural disasters are meteorological events with a high destructive capacity [12], such as hurricanes, tornadoes, or floods [13]. Finally, accidents are very similar to deliberate attacks; however, they are unintentional [14], and are usually due to a defect in event prediction [15]. Sometimes, several types of events can coincide, as was the case of the Fukushima nuclear power plant accident in 2011 [16]. This paper focuses mainly on meteorological events, although some concepts could also be applied to other types of events.

An essential factor to consider is the difference between reliability and resilience in the distribution network [17,18]. Commonly, the electrical system's reliability has been optimized to minimize the impact of high probability and low impact events that frequently occur at a specific point of the network and are usually managed through fault detection and service restoration. On the other hand, resilience deals with the study of High Impact Low Probability (HILP) extreme events, which require long restoration times due to structural damage to the system.

Since the nature of the problem addressed differs from that used in

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[1] The above definition is based on the common framework provided by the formalization proposed by institutions such as the Institute of Electrical and Electronics Engineers [4], the Joint Research Center of the European Commission [5] and the Power Systems Engineering Research Center [6].

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Nomenclature

Acronyms

DER Distributed Energy Resources
RCS Remote-Controlled Switches
ENS Energy Not supplied
MG Micro-grid
NS Network Solution
HILP High Impact Low Probability
HWIF High Weather Intensity Factors

Sets

C Set of scenarios
N Set of network nodes
B Set of network branches
F Set of branches affected by an event $F \subseteq B$
O Set of overhead branches.$O \subseteq B$
T Set of branches with an already existing RCS $T \subseteq B$
U Set of initial underground branches.$U \subseteq B$
S Set of NSs
G_s Set of MGs included in the NS s

Indexes

n Index of network nodes,$n \in N$
b Index of network branches, where the index represents the node located downstream of the branch,$b \in B$
c Index of the scenarios,$c \in C$
f Index of the branches affected by an event,$f \in F$
o Index of overhead branches,$o \in O$
t Index of branches with an already existing RCS,$t \in T$
u Index of initial underground branches,$u \in U$
s Index of network solutions,$s \in S$
g_s Index of MGs included in the NS s,$g_s \in G_s$

Variables

$a_{o,c}$ Binary, 1 if overhead line o is affected by the event in scenario c, 0 if not
$rcs_{b,s}$ Binary, 1 if branch b in the NS s includes an RCS, 0 if not
$und_{b,s}$ Binary, 1 if branch b in the NS s is underground, 0 if not
$ens_{b,s}$ ENS in the MG containing branch b in the NS s
$gp_{g,s}$ Sum of the peak power of consumers located in the MG g_s
$dt_{g,s}$ Annual downtime of the MG g_s
$ensg_{g,s}$ ENS of MG g_s
$enss_s$ ENS in the NS s
$aa_{s,c}$ Affectation array of NS s, and scenario c
k_s Number of MGs in NS s
$aibat_s$ Annualized investment in batteries in NS s
$aipv_s$ Annualized investment in PV systems in NS s
$acbat_s$ Sum of the annualized cost of the batteries installed in NS s
$acpv_s$ Sum of the annualized cost of the PV systems installed in NS s
$ombat_s$ Sum of the O&M cost of the batteries installed in NS s
$ompv_s$ Sum of the O&M cost of the PV systems installed in NS s
pf_o^L Failure probability of the overhead branch o, and length L due to an extreme weather event
sf Severity factor
$taibat_s$ Total annual investment in batteries in NS s
$taipv_s$ Total annual investment in PV systems in NS s
$taiders_s$ Total annual investment in DERs in NS s
$taircs_s$ Total annual investment in RCSs in NS s
$taiund_s$ Total annual investment in underground lines in NS s
tai_s Total annual investment in NS s
wif Weather intensity factor

Parameters

D Average length of a power line between to electrical towers
L_b Length of branch b
P_n Peak power of the consumers located at the node n
RT_f Repair time of a failure in branch f per unit length
$VoLL$ Value of Lost Load

network reliability improvement, the evaluation metrics must be different. In this case, some of the metrics used in the state of the art to assess system resilience are: the probability of a potentially damaging event, the robustness and the recomposition capacity of the system and the impact of the consequences caused by the event [19].

To improve network resilience, two strategies must be employed that are not mutually exclusive and must necessarily go hand in hand. The first requires a system operation based on contingency plans specially designed for this type of events. The second strategy consists of planning the distribution network to obtain a solid and versatile infrastructure capable of overcoming extreme situations. Given the low probability and high impact of these types of events, the planning of the distribution network cannot follow the traditional deterministic approach since it would result in very high costs. According to several studies [20,21], a stochastic perspective is more appropriate and better covers the characteristics of resilient planning. The factors that have been determined [22,23] as decisive for an improvement in resilience are: the degree of undergrounding of the grid, the level of automation through remotely-controlled switching elements (RCS), and the availability of distributed energy resources (DERs) to form micro-grids (MGs) and thus ensure supply to consumers in case of a system failure.

Although most of the publications focused on improving the resilience of the power grid analyze the transmission system [24–26], more and more publications are dealing with the distribution grid, as it is the capillary and indispensable system for supplying the end consumer [27]. This is mainly due to its mostly radial structure in which a contingency[2] can trigger the loss of supply to all consumers located downstream.

Table 1 presents different planning options and categories of investments that have been proposed in the literature to improve system resilience. Commonly, the methodologies proposed in the literature consider one single type of investment to improve system resilience, either the installation of RCSs [28,29], the integration of DG/DERs [30,31], or the power line undergrounding/hardening [32,33]. When there is only one type of investment, the optimization process can usually be solved with a single-stage optimization algorithm; however, as the investment categories increase, the optimization algorithm is divided into consecutive optimization stages due to the difficulty involved [34–37]. Unlike other papers, this paper proposes, for the first time, a methodology that provides for optimizing these three types of investments at the same time (single-stage), avoiding optimizations over multiple stages resulting in sub-optimal solution. The proposed optimization allows us to understand and quantify how these very different

[2] In this paper, the term "contingency" is used to represent a single event damaging the distribution network, while the term "event" is used to represent the reason or cause of the contingencies. Thus, an atmospheric event such as a hurricane can cause several contingencies in a distribution network.

Table 1
Resilience improvement studies comparison.

Reference	Optimization: Single-stage	Investment: RCS	Investment: DG/DERs	Investment: Underground/ Hardening
[28]	x			x
[29]	x			x
[30]	x		x	
[31]	x		x	
[32]	x	x		
[33]	x	x		
[34]	x		x	x
[35]		x	x	x
[36]			x	x
[37]	x[1]		x	x
Our proposal	x	x	x	x

[1]It uses a single-stage optimization but through a three-level decomposition of the problem.

categories of investment compete with and complement each other.

A common drawback is the limitation of the size of the network that can be modelled. Given the complexity of the planning problem due to its combinatorial and nonlinear nature, solving it applying an exhaustive search requires a large computational burden that is currently unattainable in large-scale networks [38]. In this paper, metaheuristic algorithms are proposed to solve this issue. Metaheuristic algorithms propose methodologies applicable to a wide range of situations to find quasi-optimal solutions in problems where the exhaustive search or traditional mathematical programming optimization is not feasible. Examples of metaheuristics include genetic-based algorithms, tabu search, simulated annealing, ant colony, and particle swarming [39]. However, as the literature indicates, the most widely used metaheuristics in distribution network optimization are those based on genetic algorithms given their versatility [40,41].

This research paper contributes to the state of the art by proposing a new stochastic model capable of performing a multi-criteria optimization through metaheuristic algorithms in which network resilience is maximized while minimizing the cost of the investments required. In contrast to previous works, this paper presents, for the first time, a methodology that simultaneously optimizes three very different categories of network investments, allowing us to identify how they compete with and complement each other. The three categories of investments are: i) the undergrounding of overhead lines, ii) the location of RCSs, and iii) the location and sizing of DERs (photovoltaic panels and batteries) at specific and optimal selected nodes in the grid. Previous work was mainly focused on only one or two of those categories. Because this type of events commonly affects large regions, the solution method has also been developed to allow work on large-scale grids. Previous work was mainly demonstrated in small scale test systems.

Section 2 defines the nomenclature used in this paper; Section 3 presents the problem to be solved; The methodology and the formulation used in the design of the planning algorithm is described in detail in Section 4; Section 5 applies the proposed planning methodology in a case study and, finally, Section 6 presents the main conclusions drawn.

2. Problem statement

In the introduction of the paper, it was pointed out how a contingency in the distribution network can lead to the loss of supply to all customers located downstream from the fault. This is mainly due to the radial topology of the network, the limited meshing, and the reduced number of remote-controlled switching devices. These assumptions are commonly considered for reliability assessment; however, they fall short in the face of a HILP event such as a hurricane. A HILP event can cause the loss of several sections of the network simultaneously, and their repair cannot be solved in a short period of several hours. For this reason, this paper proposes a new planning model capable of obtaining new network solutions based on creating MGs that maximize system resilience while minimizing additional investment in network undergrounding, RCSs, and DERs. In addition to the planning model, a preprocessing to characterize HILP events that vary in impact and severity has been developed.

For illustration purposes, an example network is used to facilitate the description of the problem statement. Fig. 1 (left) shows the selected base network. In this network, a contingency in branch $b = 3$ would imply the opening of the RCS located at branch $b = 2$ and the loss of supply to all customers located downstream, leaving only customers connected to nodes $n = 0$ (substation) and $n = 1$ with service.

The solutions proposed by the planning model consist of undergrounding certain feeder sections to limit their exposure to weather events, and the installation of RCSs and DERs at specific nodes in such a way that the automation of the grid and self-sufficiency of consumers under isolated MGs are increased. To facilitate the analysis of the different design alternatives within the space of possible solutions, the concept of network solution is defined. A network solution (NS) consists of a set of planning actions, including the undergrounding of selected branches, the installation of a set of RCSs at specific branches, and the location and sizing of a set of DERs at specific nodes. The methodology developed for the selection of optimal NSs is described in Section 4.

Fig. 1 (right) shows a NS for the example network. It can be seen how branches $b = 3$ and $b = 5$ have been undergrounded, one RCS has been installed at branch $b = 4$,[3] and DERs have been installed at nodes $n = 2$ and $n = 4$. The undergrounding of these branches seeks to improve the network's resilience, for example by ensuring atmospheric events such as hurricanes do not cause failures in power lines. The network division, generated when the newly added RCS opens, allows the reconfiguration of the grid into three MGs in case of a contingency. For example, a failure in branch $b = 3$ would imply opening the RCSs located at branches $b = 2$ and $b = 4$ and the islanding operation of MG $g = 3$, while $g = 1$ will continue to be supplied from the substation connected to $n = 0$, and the consumers located in $g = 2$ would lose the supply. It should be noted that MGs will only be operated in isolation mode in the event of contingencies, and if they cannot be supplied from the upstream substation. Another example would be the loss of all overhead power lines in the event of a hurricane. In this case, customers located at $g = 2$ could continue to be supplied from DERs located at node $n = 2$.

3. Methodology

As indicated in Section 3, this research aims to propose a planning methodology to generate NSs based on MGs to increase the system's resilience while minimizing the total investment. This type of NS

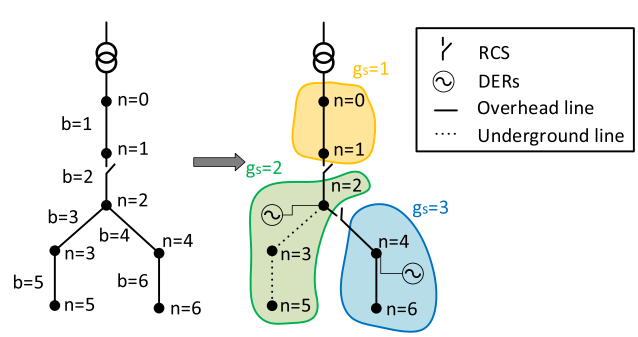

Fig. 1. Example network. Left: Original network. Right: Network solution (NS).

[3] It is assumed that when an RCS is installed at a branch, no intermediate node is added, and the failure probability of the branch remains unchanged.

involves three fundamental actions, the integration of DER installations (in this case, photovoltaic panels and batteries), increasing grid undergrounding, and improving grid automation through the installation of RCSs. In this way, in the event, the damaged network elements will be isolated, and all those customers that can no longer be supplied from the upstream substations will be fed with DERs through isolated MGs obtained by network reconfiguration, if they exist.

Using a multi-criteria optimization algorithm, different NSs are generated and compared in terms of the achieved level of resilience and required investment. It is worth noting the need for joint optimization of the three considered planning actions: network undergrounding, network automation, and DER installations, since, as indicated above, these actions are used simultaneously to improve the network's resilience. The RCSs define and reconfigure the topology of the network after the event, the underground power lines minimize the number of branches affected by atmospheric events such as hurricanes, and the DERs are responsible for supplying those customers that cannot be supplied from the upper voltage level sources, usually the upper primary substation. For this reason, all three elements dependently affect the system's resilience and cannot be considered independently of one another.

This section provides a comprehensive and detailed description of the proposed methodology. Section 4.1 presents a general overview of the complete methodology, with the processes detailed on a step-by-step basis. Then, Section 4.2 describes the details of the optimization algorithm, focusing on the implementation of the genetic algorithm (Section 4.2.1) and the formulation of the objective function (Sections 4.2.2 and 4.2.3 respectively). The optimization algorithm described in Section 4.2 is part of the general methodology presented in Section 4.1; however, due to its innovation and importance, it is described in full in a dedicated section.

3.1. General formulation

A general outline of the proposed planning algorithm is shown in Fig. 2. In the following subsections the different building blocks are described.

3.2. Inputs

As shown in Fig. 2, the algorithm starts from a set of input data that serves as the basis for obtaining the NSs. These inputs are presented below:.

- **Existing distribution network**: The peak power of the consumers, network topology, the position of the switches, underground power lines, and existing loops are specified.
- **Catalog**: List of DER candidates used in the network planning process, detailing the rated power for PV generation and batteries, rated energy (in the case of batteries) and annualized investment cost, annual operation and maintenance costs. It also includes the cost to install a new RCS on an existing line, and the average cost to underground an existing overhead line.

3.3. Event generation

A module is also proposed to generate different types of extreme weather events and, in this way, test the resilience of the distribution network. This module has the versatility of being able to model different types of events according to the needs and risks to which the analyzed network is exposed [27].

The weather intensity factor (*wif*) determines the probability of failure of overhead power lines under an extreme weather event [42]. For example, the East coast of the United States is more exposed to hurricanes [36], while states located east of the Rocky Mountains are more prone to tornadoes [43]. In both cases, the weather intensity factor is wind speed. However, depending on the event, different factors may define the probability of failure of overhead lines, such as the peak ground acceleration in the case of earthquakes [44], or even a mixture of several as in the case of wildfires whereby solar radiation and wind speed are the weather intensity factors [45]. The probability of failure of each overhead line section of length *D,* between two electrical towers can be obtained as a function of the weather intensity factor, as shown in Fig. 3.

Fig. 3 function is defined by equation (1). For weather intensity factors lower than $wif_{critical}$, the probability of failure is zero, while for weather intensity factors greater than $wif_{collapse}$, the probability is equal to 1. For intermediate values, the probability of failure increases as the weather intensity factor increases.

$$pf_o^D(wif) = \begin{cases} 0 & wif < wif_{critical} \\ pf_{o-HWIF}^D(wif) & wif_{critical} \leq wif < wif_{critical} \\ 1 & wif \geq wif_{collapse} \end{cases} \tag{1}$$

The proposed model can be used on large-scale networks covering all the feeders of a primary substation, i.e., tens of square kilometers. However, according to the literature [46], the weather intensity factor determining the probability of a line's failure will be very similar within the considered distribution system. This is especially visible in the case of hurricanes, where hundreds of km are affected by similar wind speeds. Therefore, it can be assumed that the weather intensity factor will be constant in the simulations of critical events in the considered distribution systems. Additionally, in distribution networks, the line section length between two electrical towers is very similar since it is mainly determined by the height of the towers. As previously mentioned in this paper, this line section length is called *D*. Thus, it can be stated that the probability of failure of an overhead line with total length L_o will be determined by the equation (2). This expression assumes that the failure probability of the line section between two towers is constant for the entire overhead line and that the possible failures are independent of each other.

$$pf_o^L(wif) = 1 - \left(1 - pf_o^D(wif)\right)^{\frac{L_o}{D}} \forall o \tag{2}$$

Another relevant aspect in characterizing the considered extreme event is the required service restoration time. This indicator is computed from the instant that the event that causes the failure takes place until the service restoration is complete. It is highly dependent on many factors, among others the resources and capabilities of maintenance crews of the distribution utility, the terrain orography, and the destructive capability of the event itself [47]. For this reason, the duration of the service restoration time is highly variable and dependent on each case, highlighting the need for a sensitivity analysis. This paper defines the parameter that sets the time required to repair 1 km of an overhead line affected by the event since the event causes the failure as the severity factor (*sf*).

Therefore, the two parameters that define the modeling of an event are the weather intensity factor (equivalent to the failure probability of an overhead line section of length *D*), and the severity factor (time required to repair one kilometer of an overhead line affected by the event).

3.4. Scenario generation

In order to simulate the random nature of extreme weather events, the proposed methodology uses a Monte Carlo simulation in which a large number of scenarios are generated to simulate each event. Each scenario *c* maintains the weather intensity factor, but the affected lines may change according to the random numbers in equation (3). This equation seeks to identify whether or not an overhead line *o* is affected by the event in scenario *c*. If an overhead line is affected by the event, the variable $a_{o,c}$ will be equal to 1; if not, it will be equal to 0. Line

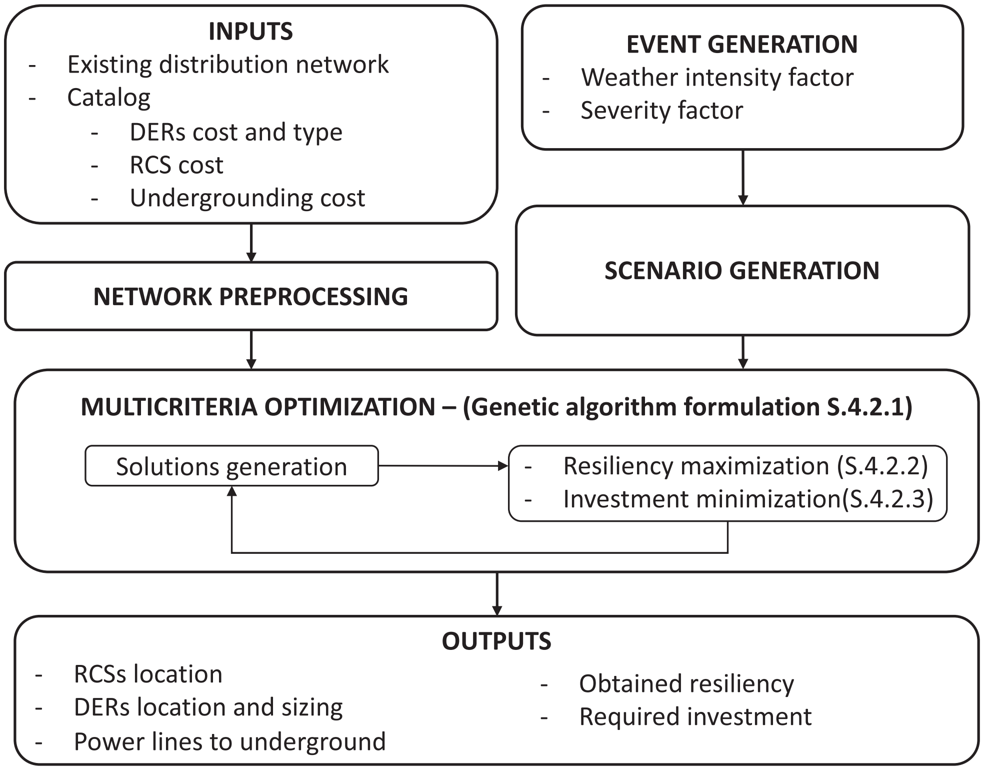

Fig. 2. Methodology flow diagram.

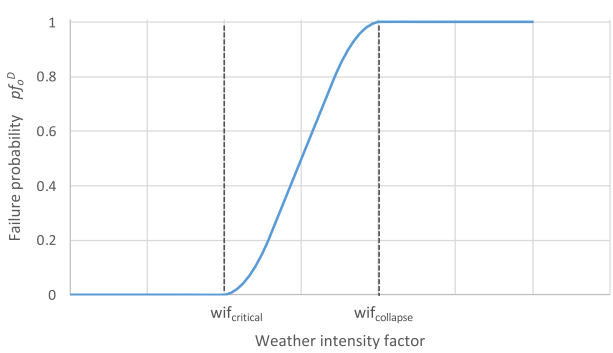

Fig. 3. Overhead line failure probability.

affectation is calculated by comparing the failure probability of each line with random numbers between 0 and 1. If the probability of failure is greater than the random number, the considered line is affected by the event. Each scenario is generated with a different seed so that the failed lines may vary.

$$a_{o,c} = \begin{cases} a_{o,c} = 1 & pf_o^L(wif) > rand(0,1) \\ a_{o,c} = 0 & pf_o^L(wif) \leq rand(0,1) \end{cases} \quad \forall o,c \tag{3}$$

It is assumed that underground lines are never affected by this kind of event.

4. Network pre-processing

Initially, the analyzed network is pre-processed and interpreted as a directed graph to employ complex network theory in the optimization algorithm. Complex network theory allows, among other advantages, the manipulation of an electrical network as a mathematical variable and extracting helpful information quickly and efficiently through its numerous properties [48].

4.1. Multi-criteria optimization

Optimization is then carried out to maximize network resilience while minimizing investment. Classical optimization based on mathematical programming in large-scale networks can currently be computationally infeasible due to multiple nonlinearities. This fact highlights the need for optimization methods such as metaheuristic algorithms to overcome these nonlinearities. In this case, a multi-criteria genetic optimization algorithm is used, which, as previously indicated, maximizes network resilience and minimizes investment employing a multi-attribute objective function. Section 4.2 details this optimization algorithm, emphasizing the formulation (Section 4.2.1) and objective functions (Sections 4.2.2 and 4.2.3 respectively).

One of the fundamental requirements for using genetic algorithms is the high speed in the evaluation of the objective function for the proposed solutions [49], in which a set of initial solutions are evaluated and, according to their optimality, modified to obtain new solutions, as shown in Fig. 2. This process is repeated as many times as solutions are evaluated; therefore, the speed in evaluating the objective function is a critical factor in the model's design. For this reason, the hybridization of complex network theory and genetic algorithms is applied, providing substantial synergies for solving this type of problem and making it computationally feasible.

4.2. Outputs

Finally, the outputs obtained from the optimization model include a set of optimal NSs (non-dominated in the Pareto space). Each of these NSs is characterized by three elements, which are the decision variables of the problem:

- **Location of new RCSs**: Indicating the network branches where they are installed.
- **Location of new underground power lines**: Indicating the network branches to be undergrounded.

- **Location and sizing of DERs**: Indicating the connection node, the rated power (in the case of PV systems and batteries), and, additionally, the rated energy (in the case of batteries).

Therefore, each of the NSs, is defined by a topology, with several MGs, an associated investment in RCSs, undergrounding, and DERs, and a resulting value of energy not supplied in the case of the simulated extreme events that indicates the level of resilience of that NS.

In the following (Section 4.2), the optimization problem is further described, exploring its formulation and the calculation of the resilience and investment attributes.

4.3. Proposed optimization

4.3.1. Formulation

The proposed optimization model seeks to obtain a set of NS S that maximizes resilience while minimizing the investment, selecting different configurations depending on the needs of the analyzed network. As previously indicated, it is necessary to use an optimization that goes beyond traditional methods due to the complexity introduced by the nonlinearity of the problem. For this reason, optimization methods based on metaheuristic algorithms such as genetic algorithms are used.

The formulation of the objective functions for resilience maximization and investment minimization is complex and is detailed in Sections 4.2.2 and 4.2.3, respectively. These functions are evaluated for each of the analyzed NSs independently, obtaining a pair of results for each of them.

An optimization based on genetic algorithms seeks to obtain the value of the genes (decision variables in the optimization) of the chromosomes (set of optimization variables) that obtain the best score in evaluating the objective function, subject to certain constraints. These chromosomes are evaluated in terms of both objective functions, and those with the best solution serve as the basis for creating new generations of chromosomes. These new generations are created performing the operations of mutation (variations in the value of genes) and crossover (exchange of parts of different chromosomes) [49].

In this problem, each of the NSs proposed by the genetic algorithm are modeled with a chromosome, while the genes that compose it are the decision variables of the optimization. Creating new NS is the only common point in which the different NSs interact. The different types of optimization variables are defined below:

- $rcs_{b,s}$: Binary variable that takes a value of 1 when an RCS is installed in branch b, existing as many $rcs_{b,s}$ variables as branches the network has. In case that branch b does not include an RCS, it will take 0 as a value. Fig. 4 shows an example with this notation.
- $ens_{b,s}$: Continuous variable between 0 and 1 that represents, in per unit value, the energy not supplied (ENS) in an MG. The MG this variable refers to is the one to which node $n = b$ belongs. The number of $ens_{b,s}$ variables is equal to the number of branches in the network. It should be noted here that in order to obtain a single value of energy not supplied per MG, only one set of DERs per MG is allowed. Regarding the DERs location, it is worth mentioning that in order to optimize the network's resilience, the most important factor is to determine the MGs where DERs would be located; however, the node in which the DERs are located inside of the selected MGs is not relevant in terms of resilience, because the definition of MG made in the paper assumes that there are not more switching devices that would allow network reconfiguration within the MG. For this reason, it is proposed to locate DERs at the upstream node of the MG, mimicking a radial operation of the network, preventing overloads during the MG-islanded operation and eliminating the need for running power flows. Thus, this set of DERs is located at the upstream node of the MG, in this case, node $n = b$ (lower node of the RCS as shown in Fig. 4). When $ens_{b,s}$ is equal to 1, there are no DERs in that MG. On the contrary, when $ens_{b,s}$ is equal to 0, it implies that the DERs can supply all the power and energy demanded by the MG. Whereas, if $ens_{b,s}$ takes a value between 0 and 1, the installed DERs can increase the autonomy time of the MG but cannot avoid a partial loss of supply. At a later stage, this variable allows us to obtain the set of DERs that meets the indicated energy not supplied while minimizing the investment.
- $und_{b,s}$: Binary variable that takes a value of 1 when the line in branch b is underground, and 0 when it is overhead, therefore, there are as many $rcs_{b,s}$ variables as branches in the network. Fig. 4 shows an example with this notation.

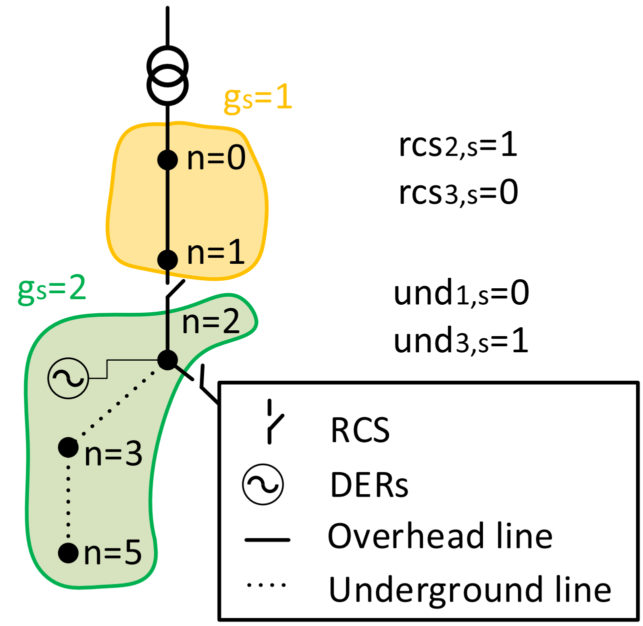

Fig. 4. Network division in MGs and DERs position.

The decision variables of the optimization are composed by $rcs_{b,s}$, $ens_{b,s}$, and $und_{b,s}$ since the union of both of them defines a NS in its totality. As a summary, $rcs_{b,s}$ defines the network division in MGs, $ens_{b,s}$ sets the energy not supplied of each MG that will lead to a set of optimal DERs in a later stage, and finally $und_{b,s}$ indicates the underground lines that serve to improve the resilience of the system. Fig. 5 shows an example of the chromosome coding that is used for the example network used above.

The existing RCSs and underground power lines in the base network are specified as an input to the optimization problem by setting their associated decision variables to 1:.

- The position of the already existing RCSs is indicated according to equation (4):

$$rcs_{b,s} = 1 \forall b \in T \tag{4}$$

- The position of the already existing underground power lines is indicated according to equation (5):

$$und_{b,s} = 1 \forall b \in U \tag{5}$$

The bounds for the variables $rcs_{b,s}$, $ens_{b,s}$, and $und_{b,s}$ are set according to (6), (7), and (8).

$$0 \le rcs_{b,s} \le 1 \forall b, s \tag{6}$$

$$0 \le ens_{b,s} \le 1 \forall b, s \tag{7}$$

$$0 \le und_{b,s} \le 1 \forall b, s \tag{8}$$

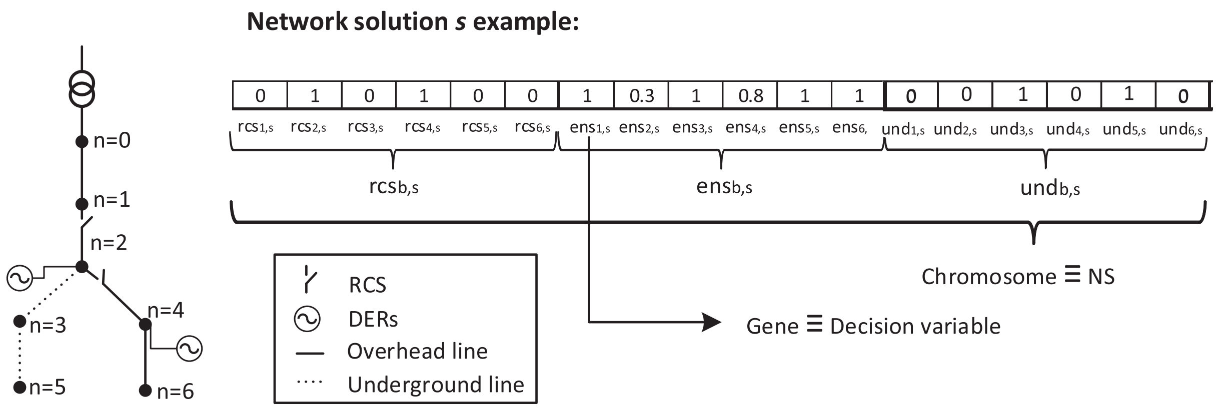

Fig. 5. Example of genetic algorithm coding.

One of the advantages of the proposed optimization is that it has only with one constraint, and it is linear. This constraint indicates that, for all the branches of the network, at most, only one set of DERs per MG can be installed, and that it is located at the upstream node of the MG. This is achieved through the equation (9), in which when $rcs_{b,s}$ is equal to 0 (there is no RCS in branch b), it is forced that no DERs can be installed, where the ENS is equal to 1.

$$rcs_{b,s} + ens_{b,s} \geq 1 \forall b, s \tag{9}$$

For implementation purposes, equations (4), (5) and (9) are not defined as constraints in the problem but as a post-processing of the chromosome when evaluating the objective function. This stems from the difficulty in obtaining random initial solutions that comply with the constraints imposed. In addition, it can be observed that as the generations proposed by the genetic algorithm progress, the algorithm learns, and the chromosomes obtained only include decisions that improve resilience. For example, solutions such as installing an RCS on a line where one RCS was already installed, or DERs in a zone where they already existed, are not proposed since they would not improve resilience and would be detrimental to the investment. With the post-processing step, this is solved because at each evaluation of the objective function, the chromosomes become feasible so that the algorithm can continue discarding them depending only on how optimal they are.

The calculation of the resilience (4.2.2) and investment (4.2.3) of each NS proposed by the genetic optimization algorithm is detailed below. Once the investment and resilience of the analyzed NS are obtained, we can check which solutions minimize the investment and maximize the resilience simultaneously. These solutions are the ones that constitute the Pareto front.

4.3.2. Resilience calculation

The calculation of the resilience metric determines, for a given NS, a representative value to allow a fair comparison of different design options. In this case, after the previously comprehensive literature review, it is decided that the network resilience is calculated as the energy not supplied in case of the simulated extreme events. Fig. 6 shows a flowchart detailing the proposed process for the computation of the network resilience for each NS.

Following the process shown in Fig. 6, the first step is to divide the network into MGs according to the position of the RCSs. Then, the installed power, the annual time out of service, and the energy not supplied of each MG are all computed to form a reduced network topology. The last step is to calculate the resilience of the whole network through the previously calculated parameters and the reduced network topology. These steps are further detailed hereafter.

Initially, for each NS, the network is divided into MGs according to the position of the RCSs defined by $rcs_{b,s.}$ This process allows obtaining all the MGs available to face the consequences of a specified event, and the network elements that belong to each of the MGs. The total number of MGs in a NSs is given by k_s, calculated according to equation (10).

$$k_s = 1 + \sum_b rcs_b \forall b \tag{10}$$

For each of the MGs belonging to a NS, the parameters required for calculating the resilience of the NS are determined:.

- **Peak power in a MG ($gp_{g,s}$):** Calculated as the sum of the peak power of the consumers within the MG as shown in Equation (11).

$$gp_{g,s} = \sum_n P_n \forall n \in g_s \tag{11}$$

- **Time out of service ($dt_{g,s}$):** Period during which the MG g_s is out of service. This parameter is calculated as shown in (12), being RT_f and L_f, the restoration time, and the line length of every affected branch that belongs to the analyzed MG g_s. It should be noted that the RT_f parameter depends on the severity of the event, determined by the event features and network characteristics such as accessibility or construction features, while L_f depends on the affectation of the event, as stated in 4.1.

$$dt_{g,s} = \sum_f RT_f {}^* L_f \forall f \in g_s \tag{12}$$

- **MG energy not supplied ($ensg_{g,s}$):** Energy not supplied during the studied period indicated by the optimization variable $ens_{b,s}$. A factor to be taken into account is the presence of loops that allow the network reconfiguration during a contingency. If in any node of the MG g_s analyzed there is a loop, understood as an external supply point able of feeding the installed power of the MG g_s, the $ens_{b,s}$ will take a value of 0. The presence of loops is especially relevant in urban networks where demand density is higher since they provide greater supply reliability. In this paper, it is assumed that there are no congestions that prevent such supply in the case of such external supply.

The network division process allows us to obtain a reduced network composed only of the head node and the nodes located downstream of the RCSs ($n = b$ when $rcs_{b,s} = 1$). This reduction is shown in Fig. 7 and allows moving from large-scale networks with thousands of nodes to one in which each MG is defined by a single node that collects all the relevant information, preserving the topological characteristics required for the study of resilience.

Table 2 shows the parameters needed to calculate the resilience of the example network (Fig. 7) as a reduction of the network applying the abovementioned methodology.

In order to calculate the resilience metric of an NS, it is necessary to analyze which MGs are affected by the event, and to what extent. At this

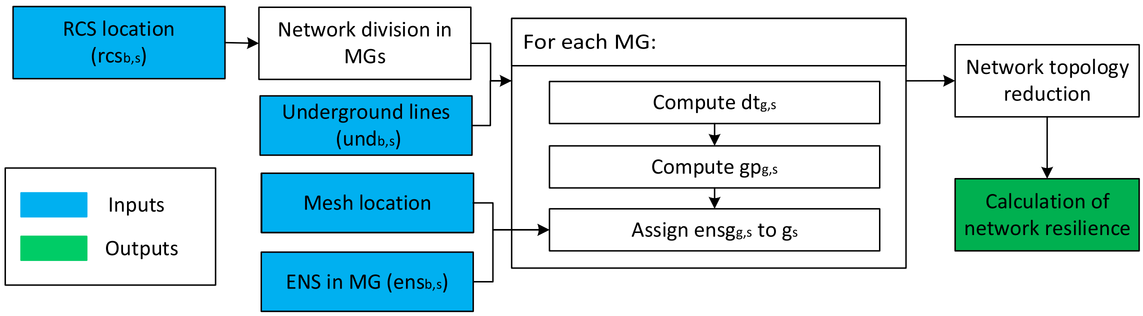

Fig. 6. Resilience calculation flowchart.

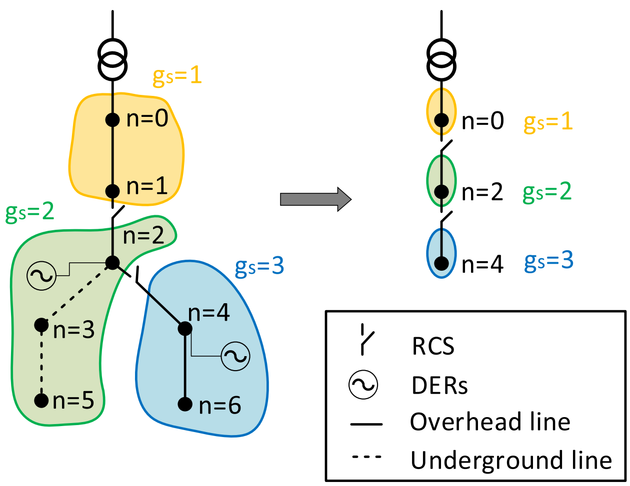

Fig. 7. Example of the NS division and its simplified network.

Table 2
Calculation of the MGs parameters of the example network.

	$gp_{g,s}$	$dt_{g,s}$	$ensg_{g,s}$
$g_s = 1$	$P_0 + P_1$	$RT_1{*}L_1$	$ens_{1,s}$
$g_s = 2$	$P_2 + P_3 + P_5$	$RT_2{*}L_2 + FR_3{*}RT_3{*}L_3 + RT_5{*}L_5$	$ens_{2,s}$
$g_s = 3$	$P_4 + P_6$	$RT_4{*}L_4 + RT_6{*}L_6$	$ens_{4,s}$

point, it is essential to note that several zones may be affected at the same time by the event in the same scenario and, therefore, the network topology determines which MGs can be supplied from the upper substation and which cannot. For this reason, for each NS *s*, and scenario *c*, an affectation array ($aa_{s,c}$) is created automatically, with as many elements as MGs exist. Each of the elements of the $aa_{s,c}$ array can take the following values:.

- 0: If the MG is not affected by the event and can be supplied from the substation.
- 1: If the MG is affected by the event or without being affected, it does not have generation facilities to provide an alternative supply, and the network topology prevents it from being supplied from the upper substation due to an intermediate contingency.
- $ens_{g,s}$: If none of the power lines that comprise the MG are affected, and it has lost the capacity to be supplied from the upper substation due to an intermediate contingency, but it can still be supplied from the generation facilities or the meshes located in the MG.

Finally, the network's resilience is calculated, measured as the average ENS of the scenarios, as shown in equation (13) for a generic NS *s*. In this expression, the ENS of each of the MGs of the analyzed NS is added as the product of the power of each MG ($gp_{g,s}$), the annual time out of service ($dt_{g,s}$), and the affectation array ($aa_{s,c}$).

$$enss_s = \frac{\sum_c \sum_g gp_{g,s} {*} dt_{g,s} {*} aa_{s,c}}{\max(c)} \forall g_S \tag{13}$$

4.3.3. *Investment calculation and DERs sizing*

In order to evaluate the total investment of each evaluated NS, the flow chart shown in Fig. 8 is followed. As observed, we start from the variables $rcsb_{,s}$, $ens_{b,s}$, and $und_{b,s}$, provided by the optimization algorithm. Next, the network is divided into MGs according to the position of the RCS, and the peak power in each of them is calculated in the same way as shown in equation (11). This partitioning together with the ENS (defined by $ens_{b,s}$), allows us to determine which set of DERs minimizes the investment. Then, the investment in DERs is computed and added to the investment in RCSs and network undergrounding to obtain a total value of the investment. This process is further described below.

4.4. *Ders sizing*

The choice of the optimal set of DERs for each MG is made as a selection in a pre-calculated lookup table in which the input parameters are the ENS in the MG ($ens_{b,s}$) and its installed power. This lookup table is obtained at a stage prior to the optimization process and only once. This allows for a reduction of execution times since, as previously mentioned, the speed in the evaluation of the objective function is a fundamental factor for the correct operation of genetic algorithms. To this end, we start from the demand profile of the network consumers and obtain, for different power and ENS levels, those combinations of DERs that minimize the investment. In short, the ENS can be calculated as the ratio of the repair time that DERs can supply customers until the contingency is solved. Those DERs that, for a given power, minimize the ENS and the investment will be selected to be part of the lookup table. This process is further explained in [38].

4.5. *Investment calculation*

The investment calculation is performed by aggregating the investment, and the operation and maintenance costs on an annualized basis for each of the DERs. The annualization process is necessary to compare the optimality of DERs with different lifetimes. In this case, the total investment computation is performed as presented in equations (14), (15), and (16) for batteries and PV systems, however, this process can be replicated for one or several DERs. It should be remarked that the costs of the DERs may vary according to the technology, power, and capacity (in the case of batteries).

$$aibat_s = acbat_s + ombat_s \tag{14}$$

$$aipv_s = acpv_s + ompv_s \tag{15}$$

$$taiders_s = aibat_s + aipv_s \tag{16}$$

Once the investments in DERs for all of the MGs of the NS are

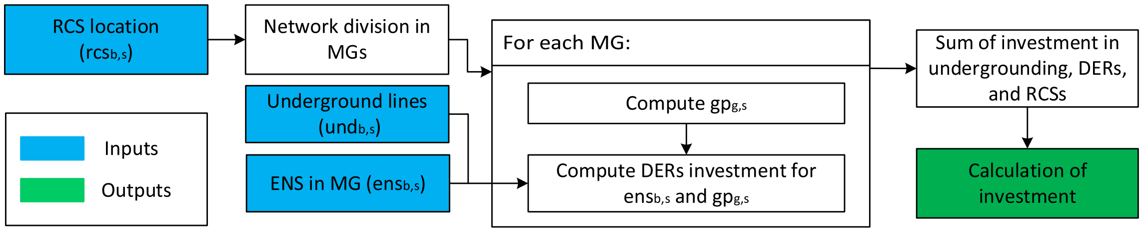

Fig. 8. Investment calculation flowchart.

calculated, the annualized investment of the installed RCSs and the cost of network undergrounding are added to obtain a total value of the investment as shown in equation (17).

$$tai_s = taiders_s + taircs_s + taiund_s \tag{17}$$

5. Case study

5.1. Description

The proposed methodology is applied to a real distribution network affected by extreme weather events. This network has already been used in the study presented in [38], where the problems to obtain the necessary permits to build new support lines due to its location was pointed out. This network has a peak power of 2,742 kW, three RCS, and 74 medium voltage lines, of which 3.08 km are underground, and 36.5 km are overhead. The network structure is shown in Fig. 9.

The decision was taken to select a hurricane as an extreme weather event since, according to the literature, they affect a greater number of consumers [27]. Regarding the base case, a wind speed of 68 m/s is assumed (*wif*), and a repair time equal to 5 h/km (*sf*). According to the literature, a wind speed of 68 m/s on the Florida coast could correspond to a failure probability of 10%[4] [42], where the distribution networks are prepared to withstand a wind speed limit close to 65 m/s [50]. Moreover, 1000 different scenarios are used in the Monte Carlo simulation.

Table 3 shows the costs used for the investments and the annual operation and maintenance (O&M) costs. Manufacturer values have been taken for RCSs [51], while public sources have been used to value the undergrounding of overhead lines [52]. The battery costs have been obtained from [53], while PV system costs have been taken from [54]. The costs have been annualized to be compared with each other since the installation useful lives are different. The annual discount rate used is 7.5%. On the other hand, the useful life is 40 years for RCSs and underground lines, while 15 years has been considered for DERs.

5.2. Results

Fig. 10 shows the Pareto front of the NSs obtained by applying the proposed methodology to the case study, focusing only on NSs with a moderate investment. This figure compares the annualized investment needed to obtain the associated resilience, showing how the initial resilience of the system improves as the investments are increased. Initially, when no investment is made, the ENS of the system due to an event is equal to 43,957 kWh; however, as the investment increases, the ENS is reduced up to 1,300 kWh when the total annuity of investments is 351 k€ (out of scale in Fig. 10). In addition, it can be observed that the most balanced resilience versus investment solutions of the Pareto front are close to 10,000 kWh of ENS and 50 k€ of investment.

Fig. 11 and Table 4 show a breakdown of the investments associated with the results presented in Fig. 10. As can be seen, reductions of close to 80% of the ENS can be obtained by installing RCSs. For higher levels of resilience, other technologies such as line undergrounding would need to be implemented, and only when higher levels of resilience are aimed would it be justified to use DERs for this sole purpose. The following section presents the implications of these results for the profitability of the investments and a sensitivity analysis to the weather intensity and severity factors.

5.3. Discussion and sensitivity analysis

As discussed above, the results show that significant reductions in ENS can be obtained by installing only RCSs. However, if further reductions in ENS are desired, the results indicate that it is appropriate to start undergrounding lines and install DERs. In this context, using DERs for resilience improvement can be seen as an additional network service to those already provided during normal system operation, implying an extra remuneration. However, it can be more debatable the installation of DERs with the only purpose to increase the system's resilience.

It should be remarked that the superiority of simultaneous optimization in comparison to sequential optimization of the different categories of investments (as have been proposed in previous publications) is very clear. Sequential optimization usually is biased to invest in one type of installation over others, depending on the order in which the stages are executed and the stop constraints to go from one stage to the next one [55].

In order to explore the economic implications of the obtained solutions, an assessment of the profitability of the investments, as a post-processing of the obtained results is illustrated below. It is assumed that improvements of the ENS are valued through the VoLL (Value of Lost Load), i.e. the value of a unit of energy not supplied. Therefore, for a given VoLL, for instance, 20 €/kWh [56], it is possible to calculate the minimum frequency of the considered event at which the selected investments would become profitable.

Fig. 12 shows, for the same NS indicated in Table 3, which NSs are profitable (have positive profits, i.e. incomes due to avoided energy not supplied are higher than investment costs) depending on the frequency of the event. As observed, if the considered event has a frequency of occurrence once per year, all the selected investments would become profitable at the set VoLL; however, as expected, as the frequency decreases, the profitability of the investments decrease. They would become unprofitable for frequencies of one event every ten years or more.

Finally, a sensitivity analysis to variations of the weather intensity and severity factors is performed. Fig. 13 shows the results obtained by changing the weather intensity factor in which, setting the severity factor to 5 h, the wind speed varies from 68 m/s to 92 m/s, and, therefore, the probability of failure of the lines from 10 to 90%. As observed, although the initial ENS is very different for the analyzed cases, the most balanced solutions of the Pareto front are in a common range. Investment annuities between 50 and 100 k€ imply resilience levels between 15,000 and 20,000 kWh of ENS. On the other hand, Fig. 14 shows the obtained results with severity factor variations in which, by setting the weather intensity factor to 68 m/s, the time

[4] A critical speed of 65 m/s, and a collapse speed of 95 m/s have been taken according to the indicated literature, assuming an increment of 30 m/s between a zero probability of failure, and a total probability.

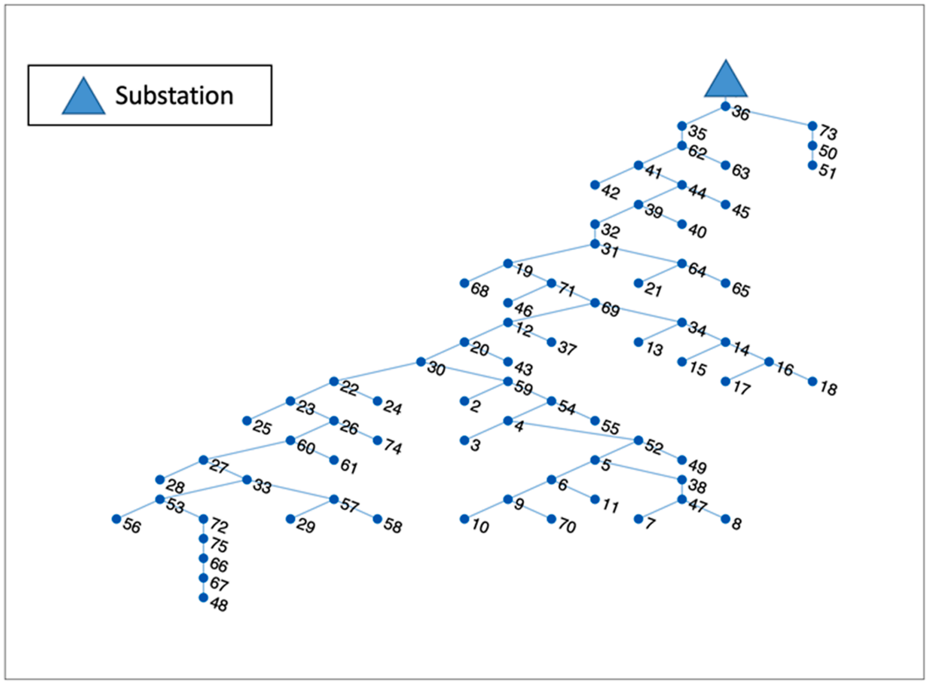

Fig. 9. Distribution network scheme.

Table 3
Investment and O&M costs of network and DER technologies.

Investment	Investment cost	Inv. Annuity	O&M cost
RCS	14,520 €/ud	1,152 €/ud	435 €/ud[1]
Line undergrounding (TI-18VY)	170,751 €/km	13,557€/km	1,772 €/km
DER - Battery systems	156 €/kWh	18 €/kWh	5 €/kWh
DER - PV systems	1,081 €/kW	81 €/kW	32 €/kW

[1]To calculate the operation and maintenance cost of RCSs and DERs, 3% of the investment cost has been assumed.

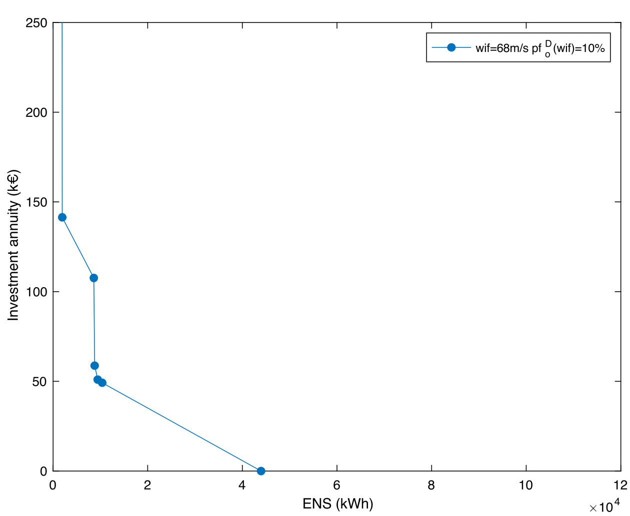

Fig. 10. Network solutions obtained for the case study.

required to repair one kilometer of overhead lines affected by the event varies from 5 to 25 h. The results show that, without any investment, the initial ENS rises proportionally to the increase of the severity factor. Furthermore, the most balanced solutions of the Pareto front are found in a similar region that the ones obtained previously for the weather intensity factor sensitivity.

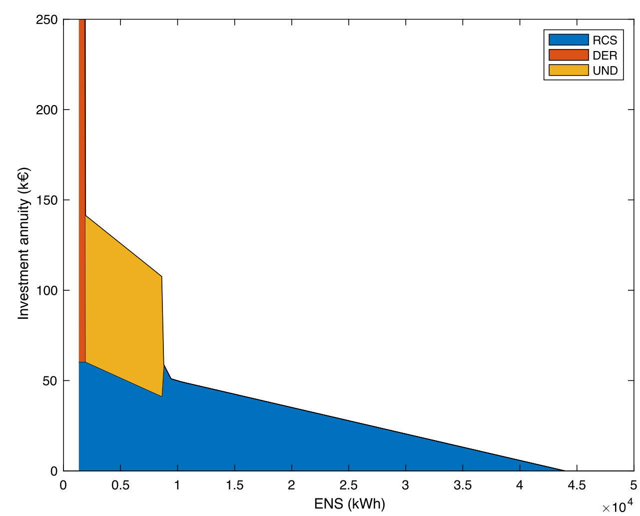

Fig. 11. Unbundled investment for the case study network solutions.

A relevant conclusion of this sensitivity analysis is the impact of the severity factor on the results. Unlike the weather intensity factor that depends on exogenous weather conditions, distribution utilities' managerial and logistic training practices can dramatically improve the severity factor. The impact of this factor is clearly observed in the initial network situation before investments were carried out, where the ENS grows proportionally to it. It should be noted that the NSs obtained with $pf_o^D(wif) = 90\%$ and $sf = 5$ h, present lower ENS values than the solutions obtained with $pf_o^D(wif) = 10\%$ and $sf = 15$ h. This result demonstrates the importance of the severity factor and proposes an improvement in the utility logistics as a complementary alternative to the considered network investments.

6. Conclusions

This paper presents a methodology to maximize the resilience of

Table 4
Unbundled network solutions for the case study.

Network Solution	Investment (k€)	ENS (kWh)	RCS (ud)	Line undergrounding (Km)	Batteries (kWh)	PV (kW)
0	–	43,957	–	–	–	–
1	49,22	10,380	31	–	–	–
2	50,81	9,431	32	–	–	–
3	58,75	8,790	37	–	–	–
4	107,62	8,607	26	4.3	–	–
5	141,42	1,937	38	5.3	–	–
6	351,63	1,342	38	6.0	4,190	931

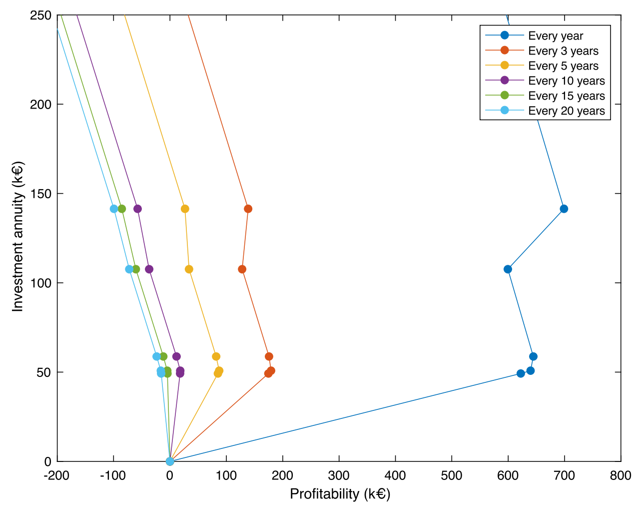

Fig. 12. Network solutions profitability according to the incidence of the event.

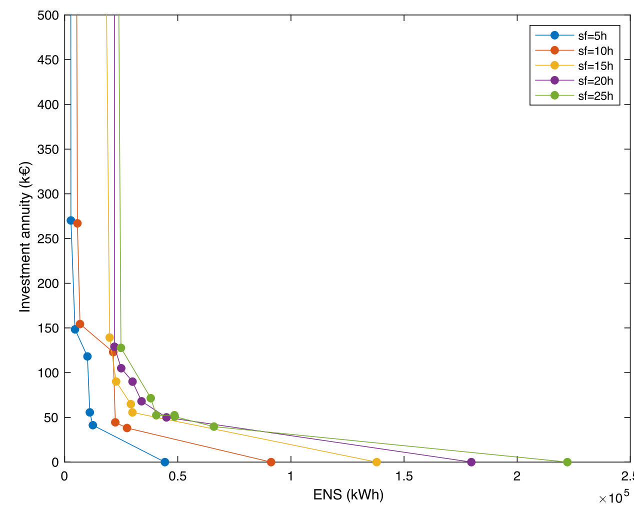

Fig. 14. Network solutions obtained for the case study using different severity factors.

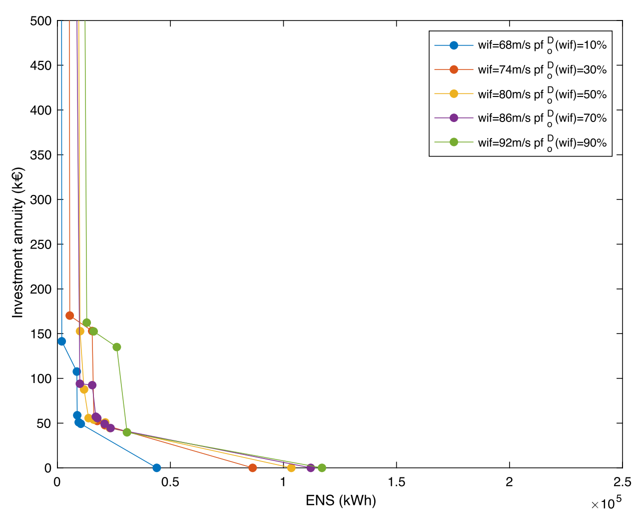

Fig. 13. Network solutions obtained for the case study using different weather intensity factors (wind speeds).

distribution networks while minimizing network and DER investment through single-stage optimization. Three alternatives are presented to improve the resilience of the distribution network, the installation of RCSs, DERs, and the undergrounding of overhead lines. One of the proposed objectives is that the algorithm could be applied to large-scale distribution networks; for this purpose, genetic algorithms are used since they allow dealing with large, highly nonlinear problems with integers and continuous variables such as the one we are studying.

The major scientific contribution of this paper is the integral methodology developed to simultaneously optimize the three very different categories of investments, RCS, DER, and power line undergrounding while maximizing distribution network resilience. Opposed to the methodologies proposed in previous publications, the approach allows us to discover how these alternatives compete with and complement each other. The results obtained demonstrate how priorities in investment decisions are established, and the benefits derived in terms on increasing resilience are quantified. It has proven to be critical in the functioning of the optimization algorithm to introduce some constraints as a post-processing step in the evaluation of the objective function, rather than using mathematical constraints of the problem. This strategy solves convergence problems that would otherwise emerge in the solutions obtained by the genetic algorithm, avoiding local solutions to a problem with a small feasible region.

The results obtained for the realistic case study show how the installation of RCSs can significantly reduce the ENS of the system with moderate investment. The installation of RCSs is followed by overhead line undergrounding, and finally, for the installation of DERs operated as islanded microgrids in case of extreme weather events. Thus, installing DERs for the sole purpose of improving network resilience is less attractive than if they are also used for providing other services during normal system operation. In this case, the total investment would be shared by the different services provided. This is an exciting area for future research.

An important conclusion of the sensitivity analysis conducted is the impact of the severity factor on the results. Unlike the weather intensity factor, which depends on exogenous weather conditions, distribution utilities' managerial and logistic training practices can dramatically improve the severity factor. The impact of this factor is clearly observed in the initial network situation before investments were carried out, where the ENS grows proportionally to it.

The presented results demonstrate the effectiveness of the proposed optimization algorithm, showing how significant improvements in the system's resilience can be obtained through the suggested methodology.

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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.

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