A Methodology for Resilience-oriented Planning in the Italian Transmission System

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***Abstract*— The increasing frequency and extension of extreme weather events in the last few years require transmission grid planning and operation approaches able to cope with these challenges, thus increasing system resilience. In this regard, initiatives have been launched by transmission and distribution system operators worldwide, often to comply with specific requirements set by regulators. This paper describes a risk-based resilience assessment methodology jointly developed by the Italian TSO and RSE aimed to capture the benefits for system resilience against extreme weather events, brought by grid hardening interventions, with a focus on the two most impacting threats for the Italian transmission system, namely wet snow and wind. The final objective is to support cost-benefit analyses in resilience-boosting plans, as required by the Italian energy regulating entity to all electric utilities. An important target is to include climate change modelling in grid planning, together with the typical planning drivers i.e. security of supply, market efficiency and renewable integration. The case study, focused on a portion of the grid, demonstrates the good matching between the outage return periods calculated for the overhead lines and the actual failure rates derived from historical datasets, as well as the effectiveness of the cost benefit analysis in prioritizing the hardening interventions in case of the two analysed threats.**

Keywords— Resilience, overhead lines, wet snow, wind.

I. Introduction

Extreme weather events, which affect power systems more and more frequently, urge Transmission System Operators (TSOs) to attain two important targets: (a) to assess the risk of multiple dependent outages, and (b) to elaborate preventive or corrective countermeasures aimed to absorb the effects of disruptive events and to recover fast, i.e. to increase system resilience [1]. Research has focused on power system resilience for some years [1][2]. In the regulatory context, the National Regulatory Authority for Energy, Networks and Environment (ARERA) in Italy has recently defined a resilience indicator and established "Guidelines for the presentation of Resilience Plans for the increase of resilience of Power System" [3]. Thus, the TSO and DSOs must prepare resilience plans against extreme weather events and assess the measures therein proposed by suitable cost-benefit analyses (CBA) [4].

On its side, the Italian TSO Terna has been working since 2018 to find the most suitable methodology aimed at assessing the resilience of its system.

The present paper introduces the systemic methodology jointly developed by Terna and RSE for resilience assessment. The methodology was used to define criteria and priorities for the implementation of interventions to enhance resilience with respect to events of strong wind and wet snow in the Italian Transmission Network.

The paper is organised as follows: Section II describes the proposed risk-based methodology. Section III focuses on the developed analytical models for line vulnerability to strong wind and wet snow events, and on the computation and validation of the return periods (RP) of line outages. Section IV presents the procedure to efficiently enumerate the multiple contingencies to be studied based on the spatial extent of historical events, and the simulator of the power system response to contingencies. Section V discusses the results of the validation tests and the application of the methodology to a case study. In Section VI some conclusions are drawn.

II. The Proposed Methodology

This section describes the proposed risk-based resilience assessment methodology developed in a joint collaboration between Terna and RSE.

A. An overview

Fig. 1 shows the architecture of the methodology for resilience assessment.

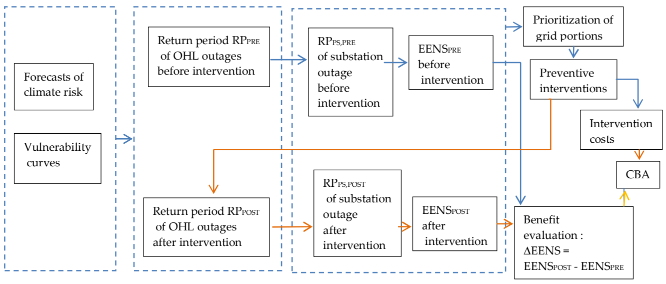

Fig. 1. Architecture of the resilience assessment methodology.

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The methodology is composed by seven main steps:

1. Calculating the probability of occurrence of meteorological phenomena in the future as a function of predefined intensity thresholds, by an ensemble of state-of-the-art climatological models.
2. Quantifying the vulnerability of grid components as a function of the intensity of the considered meteorological event, by developing vulnerability curves applied to a georeferenced grid model.
3. Combining the probabilistic model of the weather event (from step 1) with the vulnerability curve (from step 2) of the grid components, specifically lines, which leads to the return period of outages of the components in the "pre-intervention phase" (RP_{PRE}) i.e. in the initial conditions.
4. Determining the return period ($RP_{PS,PRE}$) of the Primary Substations (PS) and the corresponding value of Expected Energy Not Served (EENS) by applying a cascading outage simulator.
5. Identifying possible interventions aimed at increasing resilience, based on the analysed meteorological events and the characteristics of the reference area and its relevant lines, with reference to the critical primary substations in terms of return period and damage extent.
6. Evaluating the impact of the interventions identified in step 5, expressed in terms of increase of the Return Period of the line (RP_{POST}). This is achieved by running the cascading outage simulator, assuming that the interventions have been implemented, and determining the new return period of the primary substations.
7. Calculating the resilience benefit associated with each identified intervention and the relevant economic evaluation.

Even if the methodology is general and can be applied to any kind of threat, the present paper will focus on its application to the events of wet snow and strong wind, which most affect areas in the national transmission grid. Thus, the analysis will focus on the vulnerability models for the components which are most exposed to these threats i.e. overhead lines (OHLs). The Cost Benefit Analysis of interventions is based on the economic valorisation of the EENS which is used to quantify the benefit of a specific intervention on the grid.

B. Evaluating the RPs of OHL outages

The evaluation of the return periods of HV/MV substation outages starts from the assessment of the failure return periods of the lines which directly or indirectly connect the substation to the rest of the grid.

In Std. CEI EN 50341-1 [5], the line design target is to withstand wind loads and ice / wet snow sleeve loads ("threat actions") with a return period of 50 years. The relevant load values are provided in the national normative addendum [6] to the same standard, according to a suitable classification of the Italian territory: more refined evaluations can be made using meteorological reanalysis [7]. The existing transmission lines, however, were designed based on previous standards. For some of them, the failure return times recalculated in the light of the load values contained in [6] may be less than 50 years, as confirmed by operational experience.

The return periods of the overhead line outages are evaluated starting from the map of extreme values of the stress variables (snow loads and wind speeds) over different time horizons provided by climatological models [8][9] as well as from the vulnerability models of the OHLs.

The general formulation of the OHL vulnerability model includes both the direct effects of simultaneous actions of wet snow and strong wind (increased loadings and mechanical tensions of the line components) and their indirect effects (fall of trees especially on HV lines). Moreover, the flexibility of the modelling approach allows to separately consider the effects of wind and wet snow, thus computing two separate RPs.

C. Evaluating the RPs of substation outages

Customer interruption in distribution grids may directly result from disruption events in the (sub)transmission systems, in case of high voltage / medium voltage (HV/MV) substations (primary substation) outages.

A HV/MV substation may result disconnected due to (a) the simultaneous outage of all of the HV lines directly connected to it, or (b) the simultaneous outage of any other set of lines in the neighbouring of the network (in particular, within the same subtransmission "island"), also resulting from a cascading, that causes the lack of supply to the HV/MV substation itself. These events, called contingencies henceforth, determine the loss of supply for the customers fed by the substation. Hence, the return period of substation outage depends on the failure return period of the lines that directly or indirectly supply the substation.

The risk of energy not served ($EENS_{PSj}$) to the j-th substation can be written as (1):

$$EENS_{PSj} = \sum_{h=1}^{Nctg,j} t_{recovery} \times Load_{j,h} \times prob_{ctg,h} \quad (1)$$

where $N_{ctg,j}$ is the number of contingencies causing a partial or total loss of supply at the j-th substation, $Load_{j,h}$ is the unserved load at the j-th substation and the h-th contingency, $prob_{ctg,h}$ is the annual probability of occurrence of the h-th contingency which determines the loss of load at the j-th substation while $t_{recovery}$ is a conventional recovery time set to 16 hours.

Term $prob_{ctg,h}$ is given by the product of two terms:

- the annual probability of the weather event provoking the line outages, given by the inverse of the maximum RP of the lines tripped in the h-th contingency,
- the conditional probability $prob\_cond_{ctg,h}$ of the h-th contingency (identified by a specific combination of trippings and not trippings), given the occurrence of the weather event. Probability terms $prob\_cond_{ctg,h}$ are computed by exploiting the copula theory [10] taking into account the typical geographical extension of the weather phenomenon in the area.

The copula theory is applied to the average hourly probabilities of the contingencies (i.e. combinations of trippings and not trippings). Over such a limited time interval the assumption of mutual exclusivity among contingencies holds valid, thus the hourly probability of substation outage is given by the sum of the hourly probability of occurrence of all the contingencies (s = 1 … N_{NSPSj}) which directly or indirectly cause the complete loss of supply of the same substation PS_j: it's worth noting these contingencies are a subset of the $Nctg,j$ contingencies causing any loss of load and mentioned in equation (1). The passage from average hourly probabilities to annual probabilities $prob_{ctg,h}$ as used in (1) is performed assuming an exponential distribution for the failure events, a typical hypothesis in reliability analyses [11].

Moreover, distribution grid operators may carry out reconfiguration actions to resupply customers from another substation that is still energised. In this case, the loss of a substation would not necessarily imply the permanent loss of load. However, multiple simultaneous substation outages may occur, leading to the impossibility to counterfeed the load.

The individual terms which allow to calculate the equivalent return period of a HV/MV substation are described in the following sections.

III. Line vulnerability: modelling and validation

This section presents the probabilistic analytical models for the OHL vulnerability to both direct and indirect effects of wet snow and strong wind, as well as the RPs of OHL outages.

A. Vulnerability models against direct effects of wind and snow

As far as direct effects of wind and snow on the OHL are concerned, it's worth noting that the relevant vulnerability of the overhead line individual subcomponents to the threats under study (snow and wind) is quantified via analytical vulnerability models obtained considering the design criteria established in [5], in unified guidelines by Terna, and in previous standards (in particular CEI 11.4:1998-09). The return period of a line for direct effects depends on its weakest subcomponent.

As a matter of fact, vulnerability evolves over time due to degradation processes, aging, etc. So far, the analytical model doesn't catch these aspects: however, suitable probabilistic models can be integrated to analytically describe such complex and uncertain degradation phenomena. In this respect, analytical vulnerability curves of the different line subcomponents, namely phase conductors, cross-arms, insulators, shield wires, tower body and foundations [12][13] can be used.

Vulnerability is represented by probabilistic models, which express the probability of failure for a given intensity of the stress (conditional probability of failure). As the stress increases, the probability of failure increases [12][13].

Vulnerability depends on quantities such as the parameters and configuration of the conductors, the distance between consecutive towers, the conductor sag, the mechanical characteristics of the subcomponents, etc. Vulnerability analyses must therefore be conducted, accounting for the specific parameters of the line under consideration.

The vulnerability model of the single span of a line considers the vulnerability curves in terms of mechanical fragility of phase conductors, shield wire, tower body, cross-arms and foundations, each represented by a lognormal distribution [12][13]. In particular, the parameters characterising the vulnerability of tower, cross-arms and foundations are computed starting from the mechanical utilization curves available for standardised supports.

Each vulnerability curve corresponds to a specific mechanical stress variable, namely (i) the tension (in kN) on the individual phase conductor, (ii) the tension (in kN) on the individual shield wire, and (iii) the resultant (in kN) of the forces acting on the support, in particular the resultant of the vertical loads (conductor weight and snow load) and the horizontal ones (wind action on the conductors) and longitudinal ones (due to load imbalance on adjacent spans).

The probability of failure of each line span due to direct effects of wind and snow is calculated by assuming that a line span failure occurs if just one of the subcomponents fails. More details can be found in [12][13].

B. Vulnerability models against indirect effects of wind and snow

The contact with trees is a frequent cause of failures in MV and HV grids, due to strong wind or snow. The analytical probabilistic vulnerability model used to describe the interactions between the line and the interfering vegetation in presence of wind and snow [12][14] accounts for:

- vertical contact due to trees unexpectedly grown in the Right-Of-Way ROW (very unlikely events due to the prescriptions of Italian Std. CEI 11-4),
- lateral contact due to fall of trees from outside the ROW,
- lateral contact between the line catenary (inclined with respect to the vertical axis) and the trees at the ROW boundaries (unlikely event, due to the strict prescriptions of the Italian Std. CEI 11-4).

The main factors considered are:

- tree linear coverage density (no. of trees per km),
- clearance distance (horizontal distance between tree line and the closest phase conductor),
- tree species (trunk height, coniferous or broad leaf, maximum breaking strength, root-soil system characteristics),
- orography (terrain slope),
- weather conditions (wind, snow, ice etc.),

The tree characteristics (mechanical properties e.g. the Young's modulus, the modulus of rupture, etc.) and the weather conditions affecting line sag (solar irradiation, wind speed) are treated as stochastic variables.

Moreover, the developed model takes into account the following effects of wet snow loads: (1) increased line sag, (2) increased vertical component of the resulting force on the tree, (3) reduced streamlining of wind among tree branches, which means an increase of the area exposed to the wind force, (4) increased water content inside the soil-root mass, in case of snow melting, due to the infiltration of a part of the melted snow inside the terrain. Water content strongly affects the mechanical performance of the root soil system as it reduces the hinge length of the soil root plate and above all the maximum overturning moment. Suitable derating factors are applied to model these effects. More details are in [13].

C. Evaluating the RP of the overall OHL

The combination of the vulnerability curves of each OHL span against both direct and indirect effects of wind and snow with the known return periods for specific values of the threat actions (e.g. wind and snow loads) allows to compute the return period of the outage of each OHL span due to direct and indirect effects of snow and wind.

After that, given the indications of Std. IEC 60826 [15] about the extension of the weather events, the line is divided into groups of N spans which are assumed to be simultaneously struck by the threat. The RP of each group is the minimum RP of the spans composing the group, while the RP of the line is obtained by computing the probability of the "OR" of the failure probabilities of each group.

D. Validating the models

The validation process is carried out on two models: (1) the climatological models, (2) the outage return periods of the OHLs, considering the two threats (wet snow and wind). The former validation consists in comparing the climatic values of some quantities recorded in the past (20-30 years), e.g. sleeve thickness, with the values of the same quantities evaluated in the scenarios developed by climatological models. Climatological models are affected by significant uncertainties [16], but in the analysis above the degree of matching between the quantities reconstructed by a climatological model and the corresponding values recorded in the past can help to identify the most reliable models for future climate projections. After all, modeling the future climate trends is essential for decision making in long term planning. Moreover, the expected increase of spatial and time granularity in these models will lead to higher accuracies in case of locally complex meteo-orographic conditions.

The latter validation consists in comparing the return periods of line outages computed by the methodology with the actual outages recorded in the last years. The validation process is a complex task due to the limited number of past events available for statistical analyses, and the wide feature heterogeneity of the lines under study. This process is not in the scope of the paper.

IV. Efficient Enumeration of Multiple Contingencies and Power System Response Simulation

This section describes an efficient contingency screening algorithm, which combines clusterization and copula theory. It also briefly presents the methodology for power system response simulation.

A. Efficient enumeration of multiple contingencies

In order to be applied to a model of the national transmission grid, the methodology aimed at calculating the probabilities of the combinations of trippings and not trippings needs to fulfil the following requirements:

- ensuring scalability and computational efficiency for high numbers of lines to be analysed,
- verifying the condition that the sum of the average hourly probabilities of the contingencies involving the tripping of a generic line j is equal to P_j, being P the vector of the average hourly probability of line failures discussed in section III, given the validity of the mutual exclusivity assumption on an hourly basis,
- accounting for the correlation between faults due to the fact that the same weather event (strong wind or snow) can affect several lines in the same time span e.g. 1 hour.

Accordingly, the proposed methodology includes the following logical steps:

- Calculating the correlation matrix of the continuous Gaussian copula that best quantifies the simultaneity of the same weather event on different lines (step 1),
- Clustering the lines based on the correlation matrix of line trippings (step 2),
- Calculating the probability of the logical AND of trippings for the lines of any set with dimension ranging from 1 to the cluster cardinality by using matrix M of the weather events and the RPs discussed in section III, and retaining the combinations of trippings and non-trippings (i.e. the contingencies), with a non-negligible probability of the AND of trippings (step 3),
- Calculating the probability of the combinations of trippings and non-trippings by applying a continuous copula to the clusters of lines (step 4).

1) Calculation of correlation matrix

The method starts from an $[N_{events} \times N_{lines}]$ event matrix M evaluated as in (2), where N_{events} is the number of weather events when a specific intensity threshold has been overcome at least on one line of the set, N_{lines} is the total number of lines considered in the analysis.

$$M(i,j)=\begin{cases}0 & if \quad i-th\ event\ does\ not\ strike\ j-th\ line \\ 1 & if \quad i-th\ event\ strikes\ j-th\ line\end{cases} \quad (2)$$

Matrix M allows to compute the event tables which reports the number of weather events when the intensity threshold has been overcome on the lines, see example referring to lines L1 and L2 in Table I.

Table I. Event table for lines L1 and L2

	L2	not L2	Totals
L1	n_{11}	n_{10}	n_{1*}
not L1	n_{01}	n_{00}	n_{0*}
Totals	n_{*1}	n_{*0}	

where:

- n_{11} is the number of severe events for which both lines L1 and L2 are affected by a weather variable exceeding a threshold Th (in m/s for wind and kg/m for wet snow);
- n_{10} is the number of severe events for which line L1 is affected while line L2 is not affected by a weather variable exceeding a threshold Th;
- n_{00} is the number of severe events for which neither line is struck by a weather variable exceeding a threshold Th;
- n_{01} is the number of severe events for which line L2 is affected while line L1 is not affected by a weather variable exceeding a threshold Th.

Linear correlation coefficient φ_{12} between line L1 and L2 is given in (3).

$$\varphi_{12} = \frac{n_{11} \cdot n_{00} - n_{10} \cdot n_{01}}{\sqrt{n_{*1} \cdot n_{*0} \cdot n_{1*} \cdot n_{0*}}} \quad (3)$$

Repeating the computation in (3) for any pair of lines, the algorithm builds the line correlation matrix R for the whole set of lines.

2) Line clustering

Clusterization consists in grouping the lines into sets with specific features (cardinality, etc.) based on the correlation matrix R. The adopted clusterization algorithm for the pre-intervention scenario:

1. identifies the correlation threshold value for which the maximum cluster size is k_{max},
2. identifies clusters of lines on the basis of the correlation threshold itself,

3. Optionally it allows to re-aggregate singleton clusters considering lower correlation thresholds with respect to the one identified in step 1.

In the post-intervention analysis, the steps of the re-clusterization with N_{pi} partially buried lines and N_{green} greenfield lines are shown below:

1. consider the clusters C_h $h = 1 \dots NC$ identified in the pre-intervention analysis
2. modify matrix M in the columns of the partially buried lines $i = 1 \dots N_{pi}$
3. The partially buried lines that are part of singleton clusters in the pre-intervention analysis remain in the singleton cluster
4. Increase the number of matrix M columns by adding the columns of greenfield lines $i = 1 \dots N_{green}$ (on the basis of the hypothetical layout of the greenfield lines, the events of exceeding the threshold on the greenfield lines are counted considering the same events of the pre-intervention analysis)
5. Calculate the correlation coefficients R_{qj} between each partially buried line $q = 1 \dots N_{pi}$ not belonging to singleton clusters and the other lines j
6. Calculate the correlation coefficients R_{ij} between the greenfield line $i = 1 \dots N_{green}$ and the other lines j
7. Greenfield line i is attributed to cluster h^* which has the highest median value calculated on the absolute values of the coefficients R_{is} with $s \in C_h$, i.e. $\max_{h=1 \dots Nc} \left[median\left(\left| R_{is} \right| \right) \right] \quad with \quad s \in C_h$
8. Steps 6 and 7 are repeated for all greenfield lines
9. New combinations involving greenfield lines and existing lines are not subject to minimum probability threshold ε, while combinations involving partially buried lines are subject to minimum probability threshold ε

3) Screening of contingencies

This contingency screening method exploits the theorem of the total probability [10]. In particular it efficiently evaluates the probabilities of an exhaustive set of combinations (logic AND) of trippings and descards the combinations for which the probability is lower than a given probability threshold. As the j-th contingency consists in a combination of ns_j trippings and nns_j not trippings, its probability is always lower than the probability of the AND of the ns_j trippings thanks to the total probability theorem. Thus, the contingencies which include any of the descarded AND combinations are also descarded by the algorithm.

4) Copula based calculation of contingency probabilities

The probability of a certain combination of trippings (set S) and non-trippings (NS) is then calculated using the CDF of the Gaussian copula. This copula type has been chosen because it proved to be a good tradeoff between accuracy and applicability. Each line is associated with a binary variable X such that $X = 0$ when the line is in service and $X = 1$ when the line is faulty. The variable follows a Bernoulli probability mass function such that:

$$\begin{aligned} P\left(X_j = 0\right) &= 1 - P\left(F_j\right) \\ P\left(X_j = 1\right) &= P\left(F_j\right) \end{aligned} \tag{4}$$

where $P\left(F_j\right)$ is the probability of failure of the j-th line.

For Sklar's theorem [10] applied to discrete variables (in particular binary) the probability mass function for a combination of trippings and non-trippings, i.e. P($S \cap NS$), can be written as an algebraic sum of the cumulative probability distribution of the copula (copula CDF) evaluated at appropriate points according to the general formula in (5).

$$P\left(\overline{X}\right) = \sum sign\left(\overline{s}\right) \cdot C\left[F_1\left(s_1\right) \dots F_n\left(s_n\right)\right] \tag{5}$$

where $\overline{X} = \left(X_1 = x_1, \dots, X_n = x_n\right)$ and $\overline{s}$ is a vector of n components $s_1 \dots s_n$ which can be set to x_i or x_i-1.

$$sign\left(\overline{s}\right) = \begin{cases} 1 \quad if \quad s_j = x_j - 1 \; for \; an \; even \; number \; of \; positions \; j \\ 0 \quad if \quad s_j = x_j - 1 \; for \; an \; odd \; number \; of \; positions \; j \end{cases} \tag{6}$$

B. Power system response simulation

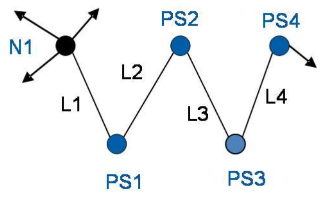
The response of power system to contingencies is simulated via a quasi-steady state cascading outage simulator developed ad hoc for resilience analysis. In fact, line outages may be caused not only by physical damages due to the threat, but also by protection trippings within the context of stressed operating situations associated to grid disruption. Therefore, in order to assess the outage of a substation the methodology also evaluates line cascading outages due to overloads (overload protections are not actually present in Italy but they can be considered a proxy e.g. when it is impossible to re-dispatch and restore operational security conditions quickly). The adopted cascading simulator also models the generation redispatching and load/generation shedding actions, in coherence with the way how such phenomena are evaluated by the Italian TSO to perform power grid studies [17].

V. Case Study

This section presents a simple case study to demonstrate the effectiveness of the resilience-oriented cost benefit analysis carried out by the methodology to prioritize the hardening interventions on the grid.

A. Test system

In order to demonstrate the effectiveness of the methodology in evaluating the benefit of hardening interventions in the grid, the case study refers to a portion of the transmission system which is critical for wind induced faults, see Fig. 2a). Fig. 2b) reports the linear correlation coefficients among the lines under study.



	L1	L2	L3	L4	…
L1	1	0,987	0,995	0,107	
L2	-	1	0,999	0,106	
L3	-	-	1	0,107	
L4	-	-	-	1	
…	-	-	-	-	1

(a) (b)

Fig. 2. (a) one line diagram of the portion of the grid vulnerable to wind events, (b) the correlation submatrix corresponding to the set of lines {L1, L2, L3, L4}. The black arrows represent the connections to the rest of the HV grid.

The RPs of L1, L2 and L3, calculated by combining climatological models with OHL vulnerability models. are equal to 3, 13 and 13 years, while L4 is found to be resilient for the wind threat (RP = Inf). The analysis focuses on wind and considers both its direct and indirect effects on the OHLs.

B. Evaluation of the EENS in the pre-intervention phase

In the pre-intervention phase, the contingency analysis module analyses the contingencies reported in TABLE II for increasing values of RP (RP*), where probabilities are computed according to the formulation in subsection IV.A.4).

TABLE II. LIST OF ANALYSED CONTINGENCIES FOR INCREASING RP VALUES

RP*	Ctg ID	Outaged lines			Prob(ctg_h) [p.u./year]
		L1	L2	L3	
3	A	1	0	0	0.209877
13	B	0	1	0	0.000465
	C	1	1	0	0.018467
	D	0	0	1	0.000463
	E	1	0	1	0.018469
	F	0	1	1	0.000057
	G	1	1	1	0.055354

The methodology evaluates the response of the system to the abovementioned contingencies, assuming a conventional restoration time of 16 hours. Table III reports the amount of unsupplied load, the yearly contingency probability and the risk indicator of unsupplied energy for the three contingencies that cause the disconnection of PS1 substation. The total EENS is equal to 44.3 MWh/year and the RP of CP1 substation outage is 11 years. It is worth noticing that the response of the system to multiple contingencies is simulated considering the model of the whole transmission system in the cascading outage simulator.

TABLE III. CONTRIBUTIONS OF CONTINGENCIES TO ANNUAL EENS

RP*	Ctg ID	Unsupplied substation	Unsupplied load [MW]	Prob(ctg_h) [p.u./year]	$EENS_h$ [MWh/year]
13	C	PS1	30	0.018467	8.9
	E	PS1	30	0.018469	8.9
	G	PS1	30	0.055354	26.6

C. Evaluation of the EENS in the post-intervention phase and quantification of the benefit for CBA

Lines L2 and L3 present few spans with relatively low RP due to interfering vegetation. In this specific case under study a possible solution could be the partial undergrounding of the lines which avoids the line exposition to the trees. This intervention makes lines L2 and L3 resilient to wind threat. The application of the methodology confirms that the post intervention EENS for the specific threat is null. In the end, the relevant benefit in the CBA in terms of EENS variation is given by $\Delta EENS = EENS_{POST} - EENS_{PRE} = -44.3$ MWh/year. Substation PS1 becomes completely resilient to wind threat.

VI. CONCLUSIONS

This paper has proposed a methodology jointly developed by RSE and Terna to evaluate a long-term resilience indicator with the final aim to prioritize the grid hardening actions presented in the annual resilience plan.

This methodology, currently focused on wet snow and strong wind events i.e. the major causes of failures in the Italian EHV and HV grid, is based on a probabilistic approach where the climatological distributions of extreme values of the stress variables (snow loads and wind speeds) for different time horizons (up to 2050) are combined with the probabilistic analytical models of the OHL vulnerability against the direct and indirect effects of wet snow and wind. An efficient enumeration algorithm combining line clusterization with copula theory finds a set of representative multiple contingencies, which makes the methodology suitable for applications to large power systems. System response to contingencies is simulated via a cascading outage simulator. The resilience assessment outcomes are the annual expected energy not served and the outage return periods of primary substations and, more in general, of all power withdrawal plants. The tool, applied in the paper on a portion of the grid particularly subject to wind threat, computes the outage return periods of the HV lines, and identifies the set of contingencies causing the lack of supply to the primary substations, evaluating the indicators of interest, i.e. EENS and substation outage RP, both before and after the application of a specific measures, thus demonstrates the capability of the methodology in quantifying the economic benefit of the grid interventions in terms of variation of such indicators. Future works consist in extending the methodology to further threats other than wet snow and wind.

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