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RESEARCH ARTICLE

A Spatial Decision Support System for Prioritizing Repair Interventions on Power Networks

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ABSTRACT The business continuity of services provided by Critical Infrastructures is vital in order to ensure the security, the economy and the public's health of a nation. Delays and bad recovery strategies after disasters or failures can lead to impairing impacts in terms of injury to people, environmental pollution and loss of time, money and resources. In such a context, the adoption of a spatial Decision Support System (DSS) might play a crucial role in order to help operators to adopt the best recovery strategy in the shortest possible time frame. Current approaches do not consider the problem of assigning an intervention location to a maintenance crew and do not account for the effective time needed for emergency intervention. In this paper we develop a novel spatial multi-criteria DSS methodology for prioritizing repair interventions on power networks. The multi criteria strategy is solved by the adoption of Incomplete Analytic Hierarchy Process (AHP) which computes holistic assignment costs as the result of the combination of multiple and possibly conflicting metrics of cost. Then, we use the holistic costs as the basis for a task assignment phase that is based on the Hungarian algorithm. The proposed strategy has been implemented as a module in the Decision Support System, namely Critical Infrastructure Protection Risk Analysis and Forecast (CIPCast), whose outputs are represented on a web-based Geographic Information System (GIS) platform. The effectiveness of the proposed multi-criteria strategy has been validated via a real case study on the Rome City electrical distribution network.

INDEX TERMS Decision support, multi-criteria decision aiding, power networks, repair prioritization, incomplete analytic hierarchy process, assignment problem, Hungarian algorithm, CIPCast.

I. INTRODUCTION

Critical infrastructures (CI) are physical infrastructures essential for the efficiency, security and the correct functioning of a nation [1]. Among CI we ascribe networks for water and energy transmission and distribution, telecommunication networks, asset for mobility and transportation such as roads and railway which, combined, produce higher level services as the health service, financial services etc. Notably, such systems are typically composed of a large set of tightly interdependent and geographically dispersed subsystems such as electrical substations, gas pumping stations or water reservoirs [2]. An efficient management of such infrastructures is vital in order to guarantee the continuity and the quality of the released services. Delays or bad recovery strategies after failures or disasters could lead to serious inefficiencies with unsustainable losses of time, money and resources, and can generate severe consequences on citizens. Under such premises, complex platforms acting as Decision Support System (DSS) might play a crucial role in helping operators

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to adopt the best recovery strategies in the shortest possible time frame. The effectiveness of such DSS has been widely demonstrated by scientific literature. Sharda et al. in [3] examined the effectiveness of DSS-aided decision makers relative to decision makers without a DSS over an eight-week period. Results showed that the group supported by the DSS assumed significantly more effective decisions in a business simulation game than their non-DSS opponents. DSSs are widely used in supporting human decisions for many critical-decision fields such as, for instance, transportation [4], [5] or infrastructure management [6]. Given the spatial dispersion of CI's subsystems, we argue that, in order to be effective, DSSs should take into account the spatial dimension. In particular, over the years, Spatial DSS have proven their effectiveness in a wide variety of scenarios. In [4], authors proposed a GIS-based DSS for planning urban transportation policies on the Greater Athens Area in Greece. In [5], a methodology is developed to evaluate the transportation network performance in disaster situations based on multiple criteria. In [6], the authors applied a DSS to road infrastructure in order to identify the best asset rehabilitation projects based on data regarding the existing condition, risk of its use, life cycle costs and age. In [40] a spatial DSS to contrast Malaria has been developed. In [39] a spatial DSS for multifunctionality landscape assessment was provided. In [7], [8] a web-based Multi-criteria Spatial Decision Support System for land suitability evaluation has been developed.

In [9] a DSS in the context of coastal zone watershed has been developed. In [10] a DSS aiming at protecting natural and cultural heritage has been presented. Moreover, in [11] the authors conduct a comparative review of existing DSS approaches to urban development and land management. Finally, it is worth mentioning that Multi-criteria Decision-Aiding techniques have proven an effective tool for importance assessment and resource prioritization, with several applications such as in the context of ecology [38], infrastructures [43], supply chain [42], [44] or portfolio management [41].

In this paper, we develop a novel methodology, integrated into a DSS called CIPCast, purposely designed and realized for the monitoring and the risk analysis of Critical Infrastructure, for prioritizing repair interventions on distribution power networks [12]. Specifically, the main objectives of the paper are:

- to develop a system that allows to assign repair crews to intervention locations of a power network;
- to consider holistic assignment costs that are the result of the combination of multiple and possibly conflicting metrics of cost.

We consider a scenario problem consisting in the allocation of several technical crews to recover faulted elements, located in different city areas, of an electrical distribution network.

The proposed strategy combines a set of criteria into a more effective multi-criteria strategy for decision making and task assignment. In depth, we first consider several criteria for task assignments, whose effectiveness is measured by a given cost metric that is based on the $k_{\min}$ indicator, which measures the impact of an electric outage in terms of its duration and considering the number of affected consumers. Then, by combining them into a multi-criteria metric, we obtain a new strategy whose effectiveness outperforms that resulting from the fault solution when tackled based on the single criteria. The multi-criteria strategy is the result of a weighted linear combination of the single strategies where combination weights are estimated on the basis of experts opinions through the incomplete Analytic Hierarchy Process (AHP) methodology [13], [14], which does not require the experts to compare all possible pairs of alternatives, but can instead focus on the comparisons they feel comfortable providing. The possibility to consider partial information, as advocated by several works at the state of the art (e.g., see [15], [16], [17] and references therein), reduces the information overload and the burden for the experts; conversely, forcing the respondents to compare all possible pairs of alternatives may be detrimental for the quality of the resulting ranking. Notably, the proposed approach combines the opinion of several experts and decision-makers, seeking a trade-off among them. At the end, crew assignment to faulted cabins and their time sequence is provided by minimizing the holistic cost index using the Hungarian algorithm. The proposed DSS consists of two modules: the CIPCast DSS, a GIS platform that allows network power information and a web server which returns the optimal allocation of repair crews to intervention location. The effectiveness of the proposed approach has been validated via a case study based on fault analysis of the electrical distribution network of the city of Rome.

A. CONTRIBUTION WITH RESPECT TO THE STATE OF THE ART

Several works have addressed maintenance prioritization of power network elements, taking into account multiple, possible conflicting, strategies. In [18], a multi-objective problem is considered with the aim to balance preventive and corrective maintenance in power distribution networks. In [19], [20], the authors introduce an index to prioritize interventions in a power network as a weighted combination of indices (e.g., the frequency and the duration of a fault); the approach in [19] does not discuss how to calculate the weights, while in [20] they are chosen in order to normalize the indices being summed. In [21] a multi-criteria decision approach to prioritizing maintenance is considered where the criticality of different component of a power network are evaluated based on several indices, composed via Fuzzy AHP.

Table 1 provides a comparison of our strategy with respect to the previous DSS solutions. The current approaches focus on predictive maintenance and do not account for the effective time needed for emergency intervention, nor for the problem of assigning an intervention location to a maintenance crew. These issues are, in turn, also considered by the proposed approach, where weights obtained by combining the opinion

TABLE 1. Qualitative comparison of our strategy with respect to previous DSS solutions.

Contributions	Incomplete AHP	Multi-criteria DSS	task assignment problem	power networks	real test case scenario
[4]	X	✓	X	X	✓
[6]	X	✓	X	X	✓
[7], [8]	X	✓	X	X	X
[9]	X	X	X	X	✓
[10]	X	✓	X	X	✓
[15]	✓	✓	X	X	✓
[18]	X	✓	X	✓	✓
[19]	X	✓	X	✓	X
[20]	X	✓	X	✓	X
[21]	X	✓	X	✓	✓
[39]	X	✓	X	X	✓
[40]	X	X	X	X	✓
Our strategy	✓	✓	✓	✓	✓

of several experts, each providing a partial assessment regarding the relative importance of pairs of criteria is considered. Finally, within the proposed approach, the holistic metric of cost of assigning a crew to an intervention location becomes the basis for solving an optimal assignment problem. Thus, the main novel contributions of this paper are as follows:

1) We develop a multi-criteria strategy based spatial DSS for prioritizing repair interventions on a power network by considering the effective time needed for emergency intervention;
2) We evaluate the multi-criteria strategy by adopting the incomplete AHP which does not require the experts to compare all possible pairs of alternatives;
3) We apply the proposed approach on a real test-case scenario consisting of the electrical distribution network of the city of Rome.

B. PAPER OUTLINE

The paper is organized as follows. Section II provides the problem background and the features of the proposed optimization method, while Section III outlines the software architecture of the proposed system. Section IV describes the results obtained in the method validation on a real electrical distribution network of a large city; Section V is then used to draw conclusions and lay ideas for further work.

II. MATERIALS AND METHODS

In this paper, we aim to solve an assignment problem whereby repair crews are assigned to intervention locations. In particular, our aim is to identify assignment costs that take into account several, possibly conflicting, cost metrics. Such heterogeneous and clashing costs are merged via the sparse Analytic Hierarchy Process approach (specifically, by resorting to the Logarithmic Least Squares method), based on pairwise preference data elicited from experts. Using such data, we derive absolute importance values for the different metrics, and the holistic cost used for the assignment essentially amounts to a weighted sum of the different costs. To this end, in this section, we collect the mathematical and methodological building blocks of the proposed approach.

TABLE 2. Notation adopted in this paper.

Meaning	Notation
Vector	$\boldsymbol{x}$ (bold lowercase letter)
Matrix	A (uppercase letter)
i-th entry of a vector $\boldsymbol{x}$	$\boldsymbol{x}_i$
(i, j)-th entry of a matrix A	A_{ij}
Vector with n components, all equal to one	$\mathbf{1}_n$
Vector with n components, all equal to zero	$\mathbf{0}_n$
$1_{n\times m}$ matrix with all entries equal to one	$1_{n\times m}$
$0_{n\times m}$ matrix with all entries equal to zero	$0_{n\times m}$
$n \times n$ identity matrix	I_n
cardinality of a set $\mathcal{S}$	$\mathtt{card}(\mathcal{S})$
Component-wise exponential of $\boldsymbol{x}$	$\exp(\boldsymbol{x})$
Component-wise logarithm of $\boldsymbol{x}$	$\ln(\boldsymbol{x})$

Specifically, we provide in Table 2 the main notation of the paper. Then, we consider the following aspects:

- we briefly review the Kendall's correlation index, which will be used for a sensitivity analysis of the information elicited from the experts (Section II-A);
- we recall some graph-theoretical preliminary notations and definitions, which will be used to characterize the data available within the incomplete AHP problem (Section II-B);
- we recall the Minimum Cost Assignment Problem as a way to solve the task assignment problem (Section II-C);
- we discuss the Incomplete AHP problem as a framework for deriving absolute importance values for a set of alternatives based on pairwise comparisons (Section II-D);
- we provide a synthesis of the above tools by introducing a Minimum Cost Assignment Problem based on multiple criteria (Section II-E).

A. KENDALL'S CORRELATION INDEX

This subsection reviews the Kendall's correlation index, a way to measure the correlation between two rankings from the ordinal point of view. This index will be pivotal for the analysis of the stability of the relevance of the different criteria obtained based on the information elicited from experts. Given two pairs of values (a_i, b_i) and (a_j, b_j), we say they are *concordant* if both $a_i > a_j$ and $b_i > b_j$ or if both $a_i < a_j$

and $b_i < b_j$; similarly the pairs are *discordant* if $a_i > a_j$ and $b_i < b_j$ or if $a_i < a_j$ and $b_i > b_j$. If $a_i = a_j$ or $b_i = b_j$ the pairs are neither concordant nor discordant. Given two vectors $a \in \mathbb{R}^n$ and $b \in \mathbb{R}^n$, the *Kendall's correlation index* [22] τ is defined as

$$\tau = \frac{\mathtt{card}(\mathtt{C}) - \mathtt{card}(\mathtt{P})}{n(n-1)/2}, \tag{1}$$

where $\mathtt{C}$ and $\mathtt{P}$ are the sets of concordant and discordant pairs (a_i, b_i) and (a_j, b_j), respectively.

When b is a permutation of the components of a, the Kendall's tau can be interpreted as a measure of the degree of shuffling of b with respect to a, between minus one and one. In this sense $\tau = 1$ implies $a = b$, while $\tau = -1$ represents the fact b is in reverse order with respect to a. The closer is τ to (minus) one, therefore, the more the two rankings are (anti-) correlated, while the closer is τ to zero the more the two rankings are independent.

B. ELEMENTS OF GRAPH THEORY

Let $G = \{V, E\}$ be a *graph* with n nodes $V = \{v_1, \ldots, v_n\}$ and e edges

$$E \subseteq V \times V \setminus \{(v_i, v_i) \text{ such that } v_i \in V\},$$

where $(v_i, v_j) \in E$ captures the existence of a link from node v_i to node v_j. A graph is said to be *undirected* if $(v_i, v_j) \in E$ whenever $(v_j, v_i) \in E$, and is said to be *directed* otherwise. In the following, when dealing with undirected graphs, we represent edges using unordered pairs $\{v_i, v_j\}$ in place of the two directed edges $(v_i, v_j), (v_j, v_i)$. A graph is *connected* if, for each pair of nodes v_i, v_j, there is a path over G that connects them. Let the neighborhood $\mathcal{N}_i$ of a node v_i in an undirected graph G be the set of nodes v_j that are connected to v_i via an edge $\{v_i, v_j\}$ in E. The *degree* d_i of a node v_i in an undirected graph G is the number of its incoming edges, i.e., $d_i = \mathtt{card}(\mathcal{N}_i)$. The *degree matrix* D of an undirected graph G is the $n \times n$ diagonal matrix such that $D_{ii} = d_i$. The *adjacency matrix* $\mathtt{Adj}$ of a directed or undirected graph $G = \{V, E\}$ with n nodes is the $n \times n$ matrix such that $\mathtt{Adj}_{ij} = 1$ if $(v_i, v_j) \in E$ and $\mathtt{Adj}_{ij} = 0$, otherwise. The *Laplacian matrix* associated to an undirected graph G is the $n \times n$ matrix L, having the following structure.

$$L_{ij} = \begin{cases} -1 & \textit{if } \{v_i, v_j\} \in E, \\ d_i, & \textit{if } i = j, \\ 0, & \textit{otherwise}. \end{cases}$$

It is well known that L has an eigenvalue equal to zero, and that, in the case of undirected graphs, the multiplicity of such an eigenvalue corresponds to the number of connected components of G [23], [24]. Therefore, the eigenvalue zero has multiplicity one if and only if the graph is connected.

Give two disjoint sets of nodes V_s and V_t let $G_{st} = \{V_s \cup V_t, E_{st}\}$ be a complete undirected bipartite graph, where $\mathtt{card}(V_s) = \mathtt{card}(V_t) = n$ and the set E_{st} contains all edges (s_i, t_j) such that $s_i \in V_s$ and $t_j \in V_t$. Let a *matching* over G_{st} be a set of edges $E_m \subseteq E_{st}$ without common vertices, while a *perfect matching* is a matching E_m with exactly n links. A node of the graph G is *covered* by the matching if it is the endpoint of an edge in the matching, and is *free* otherwise.

C. MINIMUM COST ASSIGNMENT PROBLEM

Let us consider two disjoint sets of nodes V_s and V_t, and let $G_{st} = \{V_s \cup V_t, E_{st}\}$ denote an undirected bipartite graph with $\mathtt{card}(V_s) = n$, $\mathtt{card}(V_t) = m$, and let c_{ij} denote the cost associated to an edge $(s_i, t_j) \in E_{st}$. The cost of a matching $\mathcal{M} \subset E_{st}$ is the sum of costs C_{ij} associated to the edges $(s_i, t_j) \in \mathcal{M}$. The assignment problem consists in finding the perfect matching over G_{st} with minimum associated cost. This problem can be optimally solved via the *Hungarian Algorithm* [25], a combinatorial optimization algorithm that accomplishes the task in polynomial time and, specifically, with a computational complexity between $O(\max\{n, m\}^3)$ and $O(\max\{n, m\}^4)$, depending on the particular implementation. The algorithm was originally devised to assign n tasks to m workers while minimizing the total cost of the assignment. The cost of the assignments is represented by the $n \times m$ *cost matrix* C, where c_{ij} is the cost associated to the assignment of the i-th worker to the j-th task.

The main idea of the algorithm is that, if some cost $c_{ij} = 0$, then the assignment of source i to destination j does not augment the cost of the objective function. If we can find a maximum matching involving just edges with $c_{ij} = 0$, we can conclude that the solution is optimal.

The algorithm alternates between a *matching phase*, where a maximum matching involving only links with cost equal to zero is searched and a *zero creation phase*, where the problem is converted into a similar problem where a fixed cost is removed from and added to selected links. During the zero creation phase more $c_{ij} = 0$ entries are generated, simplifying the seek of a perfect matching. If a perfect matching is found with a modified cost matrix, then the solution found is optimal also for the original problem. The procedure is iterated until a perfect matching with zero cost is obtained; the cost of the selected assignment is given by the sum of the costs of the edges according to the original cost matrix.

D. INCOMPLETE ANALYTIC HIERARCHY PROCESS

In this subsection we review the AHP problem when the available information is incomplete.

The aim is to compute an estimate of the unknown utilities, based on information on relative preferences. To this end, consider a set of n alternatives, and suppose that each alternative is characterized by an unknown utility or value $w_i > 0$. In the incomplete information case, we are given a value $\mathcal{A}_{ij} = \epsilon_{ij} w_i / w_j$ for selected pairs of alternatives i, j; such a piece of information corresponds to an estimate of the ratio w_i / w_j, where $\epsilon_{ij} > 0$ is a multiplicative perturbation that represents the estimation error. Moreover, for all the available entries $\mathcal{A}_{ij}$, we assume that $\mathcal{A}_{ji} = \mathcal{A}_{ij}^{-1} = \epsilon_{ij}^{-1} w_j / w_i$, i.e., the available terms $\mathcal{A}_{ij}$ and $\mathcal{A}_{ji}$ are always consistent and satisfy $\mathcal{A}_{ij}\mathcal{A}_{ji} = 1$.

We point out that, while traditional AHP approaches [26], [27], [28] require knowledge on every pair of alternative, in the partial information setting we are able to estimate the vector $w = [w_1, \dots, w_n]^T$ of the utilities, knowing just a subset of the perturbed ratios. Specifically, let us consider a graph $G = \{V, E\}$ with $\mathtt{card}(V) = n$ nodes; in this view, each alternative i is associated to a node $v_i \in V$, while the knowledge of w_{ij} corresponds to an edge $(v_i, v_j) \in E$. Clearly, since we assume to know w_{ji} whenever we know w_{ij}, the graph G is undirected. Let $\mathcal{A}$ be the $n \times n$ matrix collecting the terms $\mathcal{A}_{ij}$, with $\mathcal{A}_{ij} = 0$ if $(v_i, v_j) \notin E$.

Notice that, in the AHP literature, there is no universal consent on how to estimate the utilities in the presence of perturbations (see for instance the debate in [29] and [30] for the original AHP problem). This is true also in the incomplete information case, see, for instance, [31], [32], [33]. While the debate is still open, we point out that the Logarithmic Least Squares (LLS) approach appears particularly appealing, since it focuses on error minimization.

For these reasons, we now review the Incomplete Logarithmic Least Squares (ILLS) Method [31], [33], which represents an extension of the classical LLS Method, developed in [27] and [28] for solving the AHP problem in the complete information case.

1) ILLS APPROACH TO AHP

Within the ILLS algorithm, the aim is to find a logarithmic least-squares approximation w^* to the unknown utility vector w, i.e., to find the vector that solves

$$w^* = \arg\min_{x \in \mathbb{R}^n_+} \left\{ \frac{1}{2} \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} \left(\ln(\mathcal{A}_{ij}) - \ln\left(\frac{x_i}{x_j}\right)\right)^2 \right\}, \quad (2)$$

where we use i to iterate over all alternatives, while for a given i the index j iterates over the alternatives for which a pairwise comparison with the i-th one is available (i.e., over the neighbors $\mathcal{N}_i$ of node i in a graph-theoretical representation). An effective strategy to solve the above optimization problem is to operate the substitution $\boldsymbol{y} = \ln(\boldsymbol{x})$, where $\ln(\cdot)$ is the component-wise logarithm, so that Eq. (2) can be rearranged as

$$w^* = \exp\left(\arg\min_{\boldsymbol{y} \in \mathbb{R}^n} \left\{ \frac{1}{2} \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} \left(\ln(\mathcal{A}_{ij}) - y_i + y_j\right)^2 \right\}\right), \quad (3)$$

where $\exp(\cdot)$ is the component-wise exponential. Let us use $\kappa(\boldsymbol{y})$ to denote the objective function of the above problem i.e.,

$$\kappa(\boldsymbol{y}) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} \left(\ln(\mathcal{A}_{ij}) - y_i + y_j\right)^2;$$

because of the substitution $\boldsymbol{y} = \ln(\boldsymbol{x})$, the problem becomes convex and unconstrained, and its global minimum is in the form $w^* = \exp(\boldsymbol{y}^*)$, where for all $i = 1, \dots, n$, $\boldsymbol{y}^*$ satisfies

$$\left\{ \frac{\partial \kappa(\boldsymbol{y})}{\partial y_i} \right\}_{\boldsymbol{y}=\boldsymbol{y}^*} = \sum_{j \in \mathcal{N}_i} (\ln(\mathcal{A}_{ij}) - y_i^* + y_j^*) = 0,$$

i.e., we seek the argument of the function that nullifies its derivative. Let us consider the $n \times n$ matrix P such that $P_{ij} = \ln(\mathcal{A}_{ij})$ if $\mathcal{A}_{ij} > 0$ and $P_{ij} = 0$, otherwise; we can express the above conditions in a compact form as

$$L\boldsymbol{y}^* = P\boldsymbol{1}_n, \quad (4)$$

where L is the Laplacian matrix associated to the graph G. Notice that, since for hypothesis G is undirected and connected, the Laplacian matrix L has rank $n-1$ [23]. Therefore, a possible way to calculate a vector $\boldsymbol{y}^*$ that satisfies the above equation is to fix one arbitrary component of $\boldsymbol{y}^*$ and then solve a reduced size system by simply inverting the resulting nonsingular $(n-1) \times (n-1)$ matrix [13].

Vector $\boldsymbol{y}^*$ can also be written as the arithmetic mean of vectors calculated from the spanning trees of the graph of comparisons, corresponding to the incomplete additive pairwise comparison matrix $\ln \mathcal{A}$ [13].

2) MERGING MULTIPLE OPINIONS

We now review the way to calculate a ranking for a group of decision makers, each with its own perturbed ratio matrix $\mathcal{A}^{(u)}$ which does not necessarily correspond to a connected graph [14].

To this end, we consider m decision makers and suppose that each decision maker u provides an $n \times n$ possibly perturbed sparse ratio matrix $\mathcal{A}^{(u)}$, which has the same structure as a possibly disconnected graph $G^{(u)} = \{V, E^{(u)}\}$. Denote by

$$\widehat{G} = \left\{ V, \bigcup_{u=1}^{m} E^{(u)} \right\}$$

the graph corresponding to the overall information provided by the m decision makers (i.e., a graph featuring the union of the edges provided by all decision makers, where repeated edges are allowed), and consider the optimization problem

$$\boldsymbol{w}^* = \exp\left(\arg\min_{\boldsymbol{y} \in \mathbb{R}^n} \frac{1}{2} \sum_{u=1}^{m} \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} \left(ln\left(\mathcal{A}_{ij}^{(u)}\right) - y_i + y_j \right)^2 \right), \quad (5)$$

where u iterates over all experts, i iterates over all alternatives, while for a given expert u and a given alternative i, the index j iterates over the alternatives for which a pairwise comparison with the i-th one is provided by the u-th expert. The global optimal solution to the above problem $\boldsymbol{y}^*$ satisfies

$$\sum_{u=1}^{m} L(G^{(u)})\boldsymbol{y}^* = \sum_{u=1}^{m} P^{(u)}\boldsymbol{1}_n, \quad (6)$$

where $L(G^{(u)})$ is the Laplacian matrix associated to $G^{(u)}$ and $P^{(u)}$ is an $n \times n$ matrix collecting the logarithm of the nonzero entries of $\mathcal{A}_{ij}^{(u)}$, while $P_{ij}^{(u)} = 0$ when $\mathcal{A}_{ij}^{(u)} = 0$. Moreover,

$exp(\boldsymbol{y}^*)$ is unique up to a scaling factor if and only if $\widehat{G}$ is connected. More in detail, we observe that the problem is an unconstrained convex minimization problem; therefore, by evaluating the derivative of the Eq. (5) at zero, we have that the optimal solution $\boldsymbol{y}^*$ satisfies Eq. (6).

E. MINIMUM COST ASSIGNMENT PROBLEM BASED ON MULTIPLE CRITERIA

In this subsection we discuss a strategy to solve the minimum cost assignment problem considering, at the same time, several and possibly clashing metrics of cost. In particular, consider n possibly clashing cost metrics and m decision makers and let $\boldsymbol{w}^* \in \mathbb{R}^n$ be the vector collecting the relevance of each criterion, computed as discussed in the above subsection based on the subjective evaluations of the m decision makers. In particular, let us assume that $\boldsymbol{w}^*$ is normalized so that $\mathbf{1}_n^T \boldsymbol{w}^* = 1$.

At this point, consider a scenario featuring ℓ sources and ℓ destination, and for each pair (s_i, t_j), let us assume that a cost $c_{ij}^{[h]}$ is available for the h-th metric of cost. In particular, let us assume that the cost metrics are suitably normalized between zero and one; for instance costs are normalized so that for all $h \in \{1, \dots, n\}$ it holds $c_{ij}^{[h]} \in [0, 1]$ and $\max_{(s_i,t_j)\in E_{st}} c_{ij}^{[h]} = 1$. Based on the vector $\boldsymbol{w}^*$, we define the overall *holistic cost* as

$$c_{ij} = \sum_{h=1}^{n} w_h^* c_{ij}^{[h]}.$$

Cost c_{ij} can be regarded as a holistic cost representing a compromise among the original cost metrics. Based on this holistic cost, by resorting to the Hungarian algorithm, it is possible to solve the assignment problem in a way that reflects the relevance of the different metrics of cost.

III. PROPOSED SYSTEM ARCHITECTURE

The overall architecture consists of two main modules: the *CIPCast* platform, providing GIS information about the power network and the *repair assignment module*, which returns the optimal associations between the intervention locations and the intervention crews.

1) CIPCAST DECISION SUPPORT SYSTEM

CIPCast Decision Support System is a GIS platform providing a real-time and operational (24/7) monitoring and risk analysis of built and natural environments, with special focus on the analysis of interdependent critical infrastructures such as electric power, water, telecommunication, road networks and strategic buildings subjected to natural hazards. The basic geospatial information, the considered assets and the processed maps and scenarios can be selected both graphically and spatially, and are characterized by topologically defined spatial relationships or by specific descriptive attributes. The GIS layers are loaded through the Web Map Service (WMS) standard [34] and listed directly into the left side section of the Web-GIS interface (Figure 1).

CIPCast consists of four main functionalities (F_i):

- F_1 **Real time Hazard assessment**: This service allows the assessment of hazard maps in real time for an on-going event (e.g., earthquakes, meteorological events);
- F_2 **Physical damage scenario assessment**: This service allows the assessment of damage scenarios for CI components (e.g., disruption of an electric substation due to a flood) based on the hazard outputs from the hazard assessment and the vulnerability of exposed objects;
- F_3 **Impact scenario assessment**: This service allows the prediction of the degradation of CI services based on with the predicted physical damage and the dependencies among CI;
- F_4 **Support of Efficient Strategies**: This service allows to support the operator in the decision making process, i.e., to provide multiple strategies to manage crisis scenarios.

The application proposed in this paper falls within the F_4 functionality, as it supports the electric operator in a crisis scenarios which involves the failure of electric substations that requires the allocation of repair crews to be sent in the substation's location to repair the element thus reducing the geographic extent and the time duration of the fault.

2) REPAIR ASSIGNMENT MODULE

The *repair assignment module* is the module in charge of carrying out the assignment of the repair crews to the intervention locations, based on information that is retrieved by CIPCast and based on the travel times, provided by an external provider. In particular, the module is activated by CIPCast, which provides the intervention locations and the current position of the crews, as well as information regarding the relevance of the different locations based on real data on the power infrastructure and the weights to be associated to each criterion. Based on such data, which is complemented with the real-time travel times by resorting to an external provider, the repair assignment module returns to CIPCast the best associations between the repair intervention locations and the intervention crews. As described in Figure 2, the module performs five main tasks:

1) accepting an input JSON file containing all the power network information: source locations, destination locations, criteria and weights;
2) retrieving the travel time between sources and destinations from an external location provider;
3) elaborating the holistic cost based on the criteria, the travel times and the weights;
4) computing the optimal allocation of repair crews to intervention locations based on the holistic cost;
5) returning an output JSON file containing the best associations between sources and destinations.

This module has been implemented on an HTTP web server using the HTTPServer Python library.[1]

[1] https://docs.python.org/3/library/http.server.html

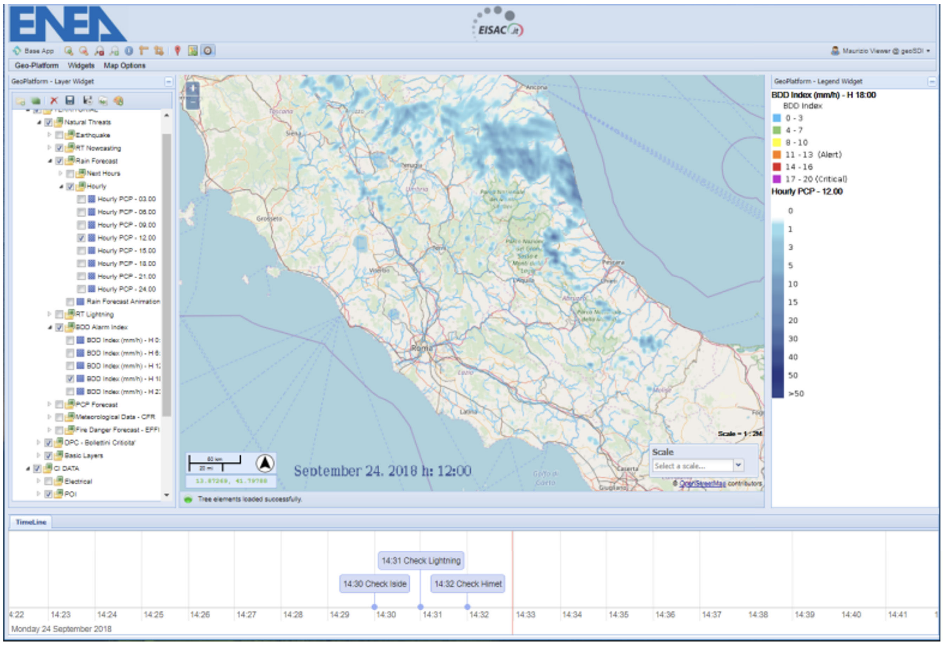

FIGURE 1. **CIPCast Decision Support System Graphical User Interface.**

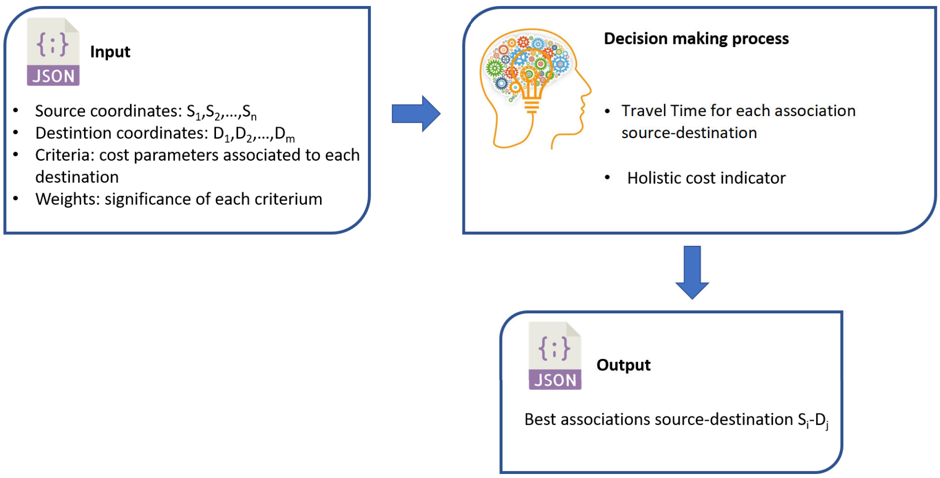

FIGURE 2. **Input-output behavior of the repair assignment module, in a nutshell.**

In particular, when the web server is requested with a POST method, the optimal repair algorithm starts. After retrieving all the network power information from the json input file, the criteria and the weights are normalized in order to anonymize all possible sensitive information like the number of residents and the number of Point of Interest (POI) near the intervention locations. Therefore, the travel times from sources to destinations are requested to an external location provider and then added to the criteria as additional parameters. Thus, the holistic cost index is computed as described in Section II-E and then given as an input to the Hungarian algorithm function. As a result, the best associations are encapsulated in an output json file.

A. USE CASE

Figure 3 summarizes the overall architecture. The CIPCast system requests the best associations between repair intervention locations and intervention crews to the repair assignment module, which is implemented on an HTTP web server. This request includes an input JSON file which reports information in terms of source locations, destination locations, weights and criteria. The web server asks to an external location provider the travel times between each association source-destination. After adding this new parameter to the pre-existing criteria, the holistic cost index is computed and then minimized by the Hungarian algorithm which returns the best associations between sources and destinations. In the last

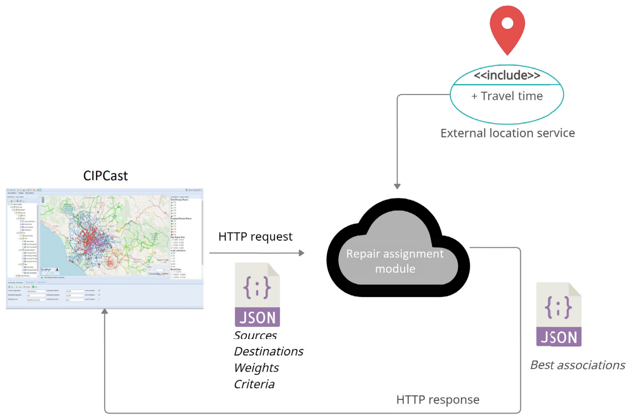

FIGURE 3. Overall architecture of the proposed system.

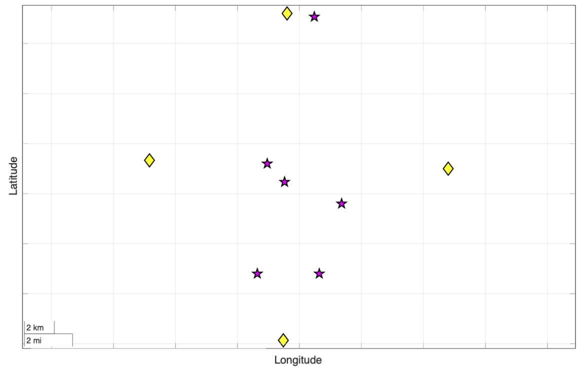

FIGURE 4. Map showing the intervention locations (magenta stars) and the position of the maintenance crews (yellow diamonds). The positions and the basemap are anonymized for security reasons related to the nondisclosure agreement with the Operator. See online version for colors.

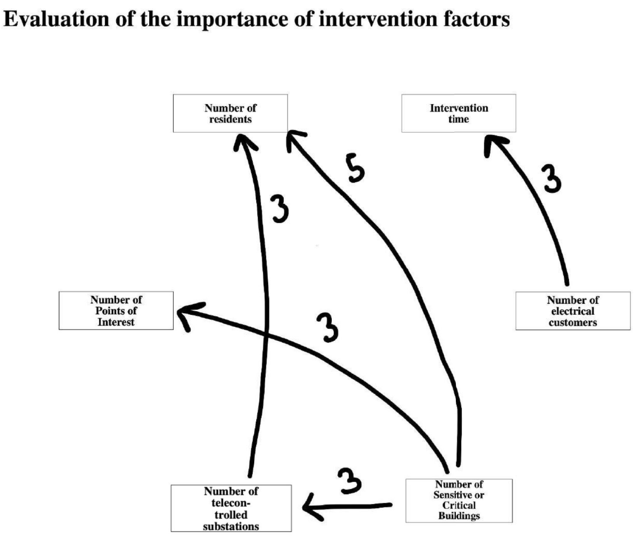

FIGURE 5. Example of pictorial questionnaire filled by an expert.

step, such information is encapsulated in a JSON file and sent back to the CIPCast module.

IV. VALIDATION OF THE PROPOSED APPROACH

In this section we demonstrate the effectiveness of the proposed "multi-objective" strategy by applying it to a case study based on a real scenario, as occurred in the real electrical distribution network of the city of Rome (Italy) and by comparing the solution of the same problem when dealt with by using the single criteria to prioritize crew interventions. In particular, we consider a scenario where, on January 18th, 2022 at 12:00, local time, six different substations of the Rome power distribution network needed to be repaired or undergo to maintenance activities. Moreover, we assume that only four maintenance crews were available, at different locations in the city: the crisis problem consists in the most appropriate assignment of technical crews to the different intervention site and in their order of priority. Tables 3 and 4 summarize the details of the intervention locations and the real-time travel times for the maintenance crews, respectively, while their position on the map is reported in Figure 4. Note that, for confidentiality reasons, we opted to report only normalized values in Table 3, while Figure 4 reports the positions without the underlying detailed map of Rome. In particular, for each criterion h, we distinguish between criteria where larger raw values correspond to larger costs (e.g., larger amount of tele-controlled substations implies that there is less a need to intervene physically) and criteria for which they correspond to a larger utility (larger number of electrical customers implies larger need of intervention). We scale the latter group of raw values by -1, thus obtaining a cost instead of a utility.

Then, we normalize costs $c_{ij}^{[h]}$ for the h-th (possibly scaled) criterion by considering the value via the min-max normalization technique [35] a popular approach for normalizing features in machine learning applications. Specifically, we apply the following normalization

$$\frac{c_{ij}^{[h]} - \min_{i,j}\{c_{ij}^{[h]}\}}{\max_{i,j}\{c_{ij}^{[h]}\} - \min_{i,j}\{c_{ij}^{[h]}\}},$$

and, to avoid inconsistencies, we set the normalized value to zero when $\max_{i,j}\{c_{ij}^{[h]}\} = \min_{i,j}\{c_{ij}^{[h]}\}$.

In order to assign the maintenance crews to the intervention locations, we consider the following six criteria which could be used to drive the problem's solution.

1) **Number of electrical customers:** number of active electrical users in the intervention location. According to this strategy, the assignment priority is proportional to the number of electrical users involved in the fault (lower the number of electrical customers in the area, higher the intervention priority).
2) **Number of Sensitive or Critical Buildings (SCB):** number of strategic buildings such as hospitals, barracks or decisional centers in the intervention location. According to this strategy, the assignment is made in relation only to the target location and is inversely proportional to the number of such buildings or infrastructures (larger the number of SCBs in the area, higher the intervention priority).

TABLE 3. Table summarizing the six intervention locations, along with their costs according to different criteria (normalized for non-disclosure reasons).

	Location #1	Location #2	Location #3	Location #4	Location #5	Location #6
Electrical Customers	0.18	0.68	1	0.99	0.54	0
SCB	0	0	1	1	1	0
POI	1	0	1	1	1	0.91
Residents	0	0.97	1	0.7	0.48	0.43
Telecontrolled substations	0.67	1	0	0.33	0.33	0

TABLE 4. Table summarizing the four maintenance crews with their travel time to reach the six intervention locations.

	Crew #1	Crew #2	Crew #3	Crew #4
Time to location #1 $[s]$	489	1615	884	1005
Time to location #2 $[s]$	2012	1342	1607	1625
Time to location #3 $[s]$	1295	1864	1292	2021
Time to location #4 $[s]$	1886	1495	1934	1586
Time to location #5 $[s]$	1892	832	1246	1299
Time to location #6 $[s]$	1977	1199	1317	1998

TABLE 5. Saaty's Ratio Scale [36].

Intensity of importance	Definition	Symbol
1	Equal importance	=
3	Somewhat more important	>
5	Much more important	>>
7	Very much more important	>>>
9	Absolutely more important	>>>>
2,4,6,8	intermediate values	

3) **Number of Points of Interest (POI):** number of schools, offices, commercial activities, etc. in the intervention location. According to this strategy, the priority for crew assignment is proportional to the number of points of interest (larger the number of POIs in the area, higher the intervention priority).
4) **Number of residents:** number of residents in proximity of the intervention location. According to this metric, the assignment cost depends only on the target location and is proportional to the number of residents.
5) **Number of telecontrolled substations:** the presence of telecontrolled substations facilitates the remote intervention from the control room. According to this metric, the assignment cost depends only on the target location and is proportional to the number of telecontrolled substations.
6) **Intervention time:** the time required for a given maintenance crew to reach a given location, taking into account the real-time traffic situation. According to this metric, the assignment cost depends on both the maintenance crew and the target location and is proportional to the time required for the maintenance crew to reach the intervention location.

A. DATA ANALYSIS AND PROCESSING

In order to construct a holistic cost of the assignment of maintenance crews to intervention locations, we interviewed ten decision-makers, i.e., experts, managers and stakeholders in the context of power distribution networks. With the aim to construct the matrices $\mathcal{A}^{(u)}$ collecting the opinion of each decision maker, we asked the experts to fill the pictorial questionnaire reported in Figure 5. Specifically, a questionnaire was submitted to the experts where the criteria were presented as text boxes, and the decision makers were asked to express their preferences on pairs of alternatives by drawing arrows (the tail box is considered more important than the box at the head of the arrow) and by associating a numerical value to the arrow, according to Saaty's scale (Table 5). For instance, in Figure 5 the number of electrical customers is considered "somewhat more important" (i.e., three times more important) than the intervention time. Notably, the experts were asked to compare only pairs of alternatives they felt comfortable comparing. In the example of Figure 5, the obtained graph is disconnected, and thus the information gathered is insufficient to construct a proper ranking of the cost metrics; however, by combining the opinion of multiple decision makers, we obtain a connected graph and thus a ranking.

Before analyzing the results based on the elicited data, let us fist investigate their consistency. To this end, we construct a matrix $\overline{\mathcal{A}} \in \mathbb{R}^{6\times 6}$ where each entry $\overline{\mathcal{A}}_{ij}$ is the geometric average of the nonzero entries $\mathcal{A}_{ij}$ provided by the decision makers, i.e.,

$$\overline{\mathcal{A}}_{ij} = \left(\prod_{u\in\mathcal{U}_{ij}} \mathcal{A}_{ij}^{(u)}\right)^{\frac{1}{|\mathcal{U}_{ij}|}},$$

where $\mathcal{U}_{ij}$ is the set of decision-makers that provided a pairwise comparison for the i-th and j-th alternative, i.e.,

$$\mathcal{U}_{ij} = \left\{u \in \{1,\ldots,m\} \,|\, \mathcal{A}_{ij}^{(u)} > 0\right\}.$$

As a result, we obtain a matrix $\overline{\mathcal{A}}$ as follows (for simplicity, we express the entries are ratios)

$$\overline{\mathcal{A}} = \begin{bmatrix} 1 & 79/109 & 244/189 & 94/49 & 594/167 & 257/158 \\ 109/79 & 1 & 341/161 & 244/63 & 378/209 & 323/367 \\ 189/244 & 161/341 & 1 & 214/175 & 1 & 553/1475 \\ 49/94 & 63/244 & 175/214 & 1 & 169/218 & 48/127 \\ 79/281 & 47/85 & 1 & 218/169 & 1 & 94/213 \\ 83/135 & 367/323 & 1475/553 & 717/271 & 213/94 & 1 \end{bmatrix},$$

TABLE 6. Weights w^* (normalized so that the sum is equal to one) obtained based on the information provided by all experts and corresponding ranking for the considered criteria.

Criterion	w_i^*	Ranking
Number of electrical customers	0.1066	#5
Number of strategic buildings or infrastructures	0.2383	#1
Number of Points of interest	0.1107	#4
Number of residents	0.0938	#6
Number of telecontrolled substations	0.2331	#2
Intervention time	0.2175	#3

and we note that, for the data at hand, $\overline{\mathcal{A}}$ is complete, i.e., no comparisons are missing. Then, we compute the consistency index [26], [30]

$$CI = \frac{\lambda_{\max}(\overline{\mathcal{A}}) - n}{n-1} = 0.0386$$

and we consider a normalization

$$\overline{CI} = \frac{CI}{RI} = 0.0309,$$

where $RI = 1.2490$ is the so-called *Random Index*, i.e., the consistency associated to a random instance with $n = 6$ alternatives [26], [30]. Notably, in [26] and [30] the index $\overline{CI}$ is deemed acceptable if $\overline{CI} < 0.1$; therefore, we observe that the data at hand, having a value $\overline{CI}$ that is about one third than the acceptability threshold, can be considered quite consistent.

Table 5 reports the numerical value of the weights w_i^* associated to each criterion, along with their ranking; the numerical values were computed using the approach discussed in Section II-D2 and were normalized to their unitary sum. According to the table, the decision makers consider the number of strategic buildings or infrastructures as the most important "single-objective" strategy (i.e., it contributes of about 23.8% to the holistic cost), while the least important strategy is related to the number of residents (it contributes of about 9.4% to the holistic cost).

Let us now assess the level of agreement of the decision makers. Figure 6 reports a matrix whose (i, j)-th entry contains the number of times the i-th strategy was considered by the decision makers to be more important than the j-th one, while Figure 7 reports a matrix whose (i, j)-th entry contains the number of times the i-th strategy was considered by the decision makers to be equally as important as the j-th one. According to Figure 6, although the decision makers agree on some pairwise comparison (e.g., six decision makers consider the intervention time as more important than the number of residents, while just one decision maker has an opposite view; similarly, five decision makers believe the number of telecontrolled substations is more important than the number of points of interest, and no one believes the inverse), in some cases they are not in agreement (e.g., number of electrical customers and number of telecontrolled substations). Notably, while attempting to solve the problem in the case of just one decision maker, the objective function assumes, on average a value equal to 5.2882, while the standard deviation is equal

TABLE 7. Sensitivity analysis of the information elicited from the experts. For each decision-maker we report the Kendall's correlation coefficient between the weight vector and the one obtained ignoring the decision-maker.

Decision-Maker	τ
#1	0.8667
#2	0.8667
#3	0.4667
#4	0.7333
#5	0.7333
#6	0.7333
#7	1.0000
#8	0.8667
#9	0.7333
#10	0.7333
average	0.7733
st.dev	0.1412

to 5.8803. Conversely, the objective function value achieved while considering the information provided by all $m = 10$ decision makers at once is equal to 187.4194 and thus the average contribution of each decision maker to the objective function is 18.7419, well above the single decision-maker case (although with a limited increase). We also observe that, according to Figure 7, overall, the decision makers consider several pairs of strategies as equally important; in particular, 36 pairs (i.e., 42.35% of all comparisons provided) are considered as equally important. Overall, this suggests that the decision makers are only in partial agreement, and thus there is a need to find a weighting vector enabling to realize a nontrivial trade off of their arguments. The proposed approach guarantees that the chosen vector represents the best compromise in a logarithmic least squares sense.

Let us now conduct a sensitivity analysis of the information elicited from the experts. Specifically, Table 7 reports, for each decision-maker, the Kendall's correlation coefficient between the weight vector and the one obtained ignoring the decision-maker. According to the table, the average correlation coefficient is 0.7733 with standard deviation 0.1412 and the coefficient for nine out of ten decision-makers is above 0.7333, while only for one decision-maker the correlation coefficient is smaller, although being equal to 0.4667. Overall, the results of the sensitivity analysis suggest that the decision-makers are quite in accordance in their judgements.

B. EXPERIMENTAL RESULTS

Let us now discuss how the problem at hand is solved based on the above weights. As discussed in the previous section, when there is a need to assign maintenance crews to intervention locations the CIPCast system resorts to the proposed repair assignment module and, specifically, the corresponding webservice is invoked by passing to it a JSON file containing the coordinates of sources and destinations, the numerical values of the associations according to the single cost metrics (save the intervention time) and the weights. Then, the module retrieves the intervention times via a location provider,

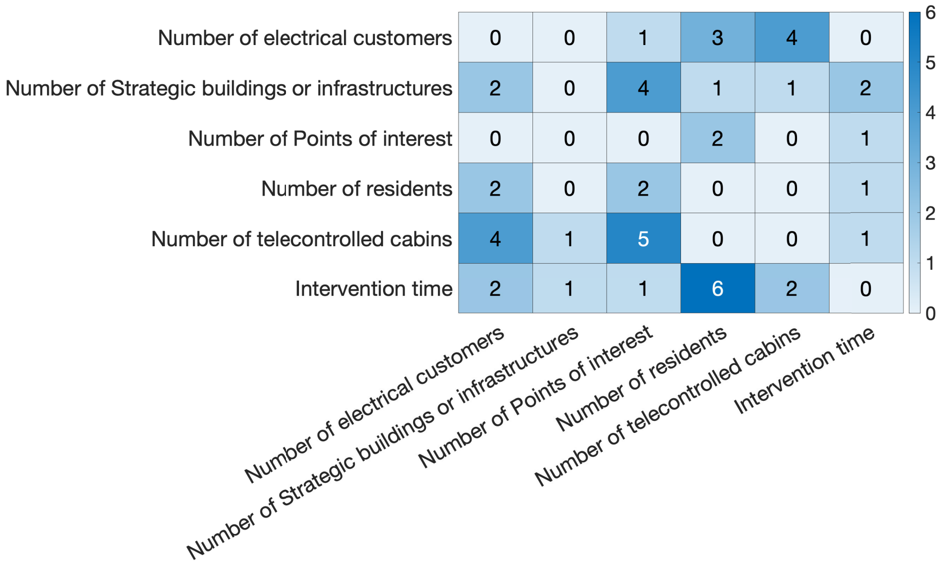

FIGURE 6. Number of times the cost metric on the row was considered by the decision makers to be more important than the one on the column.

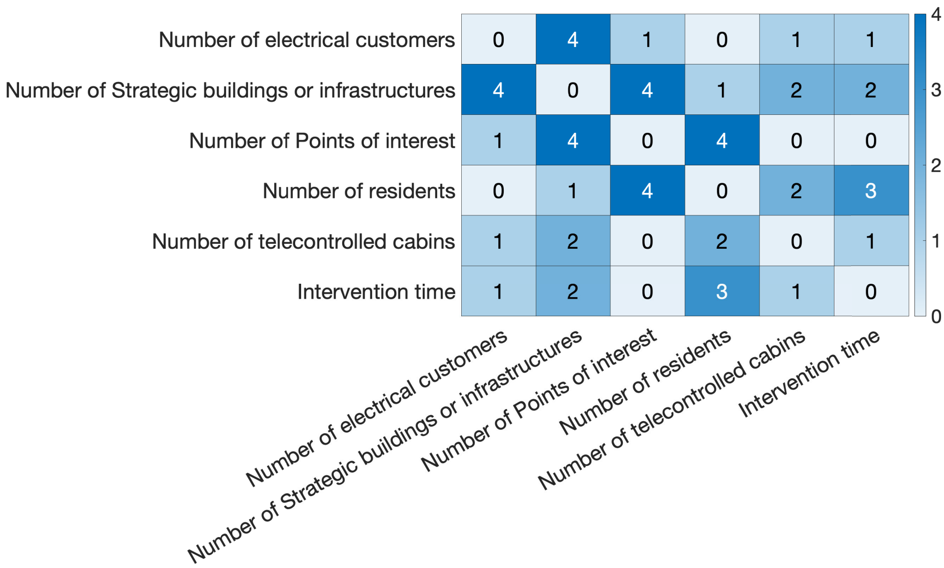

FIGURE 7. Number of times the cost metric on the row was considered by the decision makers to be equally as important as the one on the column.

computes the overall cost of the associations and identifies the optimal association via the Hungarian algorithm.

The holistic costs c_{ij} that are the result of the AHP procedure are as follows:

$$C = \begin{bmatrix} 0.29 & 0.61 & 0.66 & 0.80 & 0.73 & 0.35 \\ 0.45 & 0.52 & 0.74 & 0.74 & 0.58 & 0.24 \\ 0.34 & 0.56 & 0.66 & 0.80 & 0.64 & 0.26 \\ 0.36 & 0.56 & 0.77 & 0.75 & 0.64 & 0.35 \end{bmatrix}.$$

Notably, we observe that such holistic costs, being a tradeoff among the different metrics, are quite different from the mere travel times. For instance, cost c_{25} is larger than c_{21} (i.e., $+6.67\%$), but the travel time for the second repair crew to the first and fifth locations are equal to $1615[s]$ and $832[s]$, respectively (i.e., the first corresponds to an increase of $+94.11\%$); in other words, the ranking of the cost of assigning the first crew to these locations is reversed.

In order to provide a visual understanding of the association, Figure 8 shows the repair crews (yellow diamonds) and intervention locations (magenta stars) connected by blue lines that represent the association. Notice that, when the assignment is done based on just the real-time travel times, the result is the one reported in Figure 9.

By comparing the two assignments, we observe that the holistic cost yields results that are not uniquely driven by

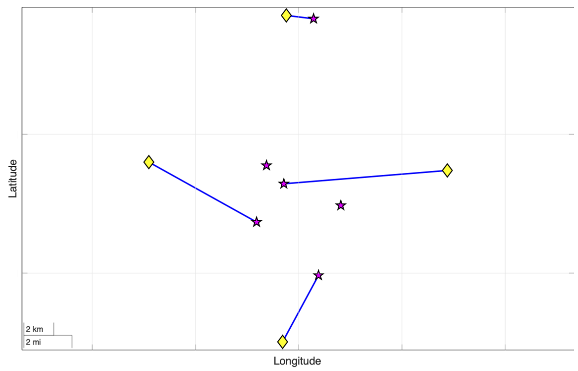

FIGURE 8. Map showing the intervention locations (magenta stars), the position of the maintenance crews (yellow diamonds) and the assignments based on the holistic cost (cyan lines). The positions and the basemap are anonymized for security reasons related to the nondisclosure agreement with the Operator. See online version for colors.

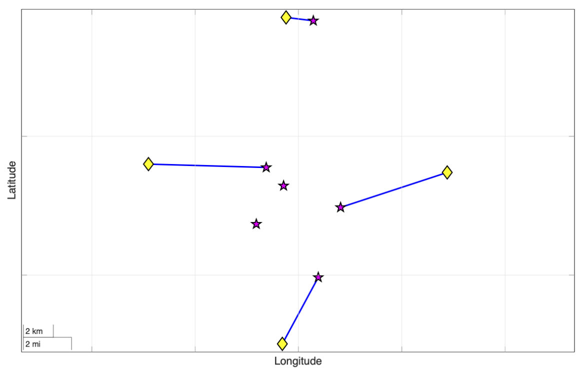

FIGURE 9. Map showing the intervention locations (magenta stars), the position of the maintenance crews (yellow diamonds) and the assignments based on the real-time travel time (cyan lines). The positions and the basemap are anonymized for security reasons related to the nondisclosure agreement with the Operator. See online version for colors.

TABLE 8. Validation of the proposed approach (Multi-criteria strategy) against the single criteria and against a multi-criteria strategy based on just the number of residents and the intervention time (equally important). The metric value $k_{\min}$ is used to estimate the resulting cost of the fault (see [37]) thus allowing to evaluate the effectiveness of the proposed sequence of interventions and scheduling of the work of the technical crews.

Intervention strategy	Overall $k_{\min}$
Proposed multi-criteria strategy	8.83×10^3
Multi-criteria based on #residents and intervention time	9.89×10^3
Criterion #1: Number of residents	1.11×10^4
Criterion #2: Intervention time	1.54×10^4
Criterion #3: Number of strategic buildings	1.64×10^4
Criterion #4: Number of Points of interest	2.20×10^4
Criterion #5: Number of telecontrolled substations	2.34×10^4
Criterion #6: Number of electrical customers	2.36×10^4

distance, in that some crews (e.g., the leftmost and rightmost ones) neglect close destinations and are assigned to more important (but farther) locations.

To conclude this section, we validate the results of the proposed multi-criteria approach against the results obtained by using each of the single criteria and against a multi-criteria strategy based on just the number of residents and the intervention time, assuming the latter objectives to be equally important. Specifically, in Table 8, we report the value of the metric used to estimate the effectiveness of the different strategies $k_{\min}$ that considers for each disconnected user, the total time of its disconnection from the electrical network. [37]. This figure is related to the sequence of interventions produced by the used strategy; in this sense, each strategy will provide a different "crisis impact indicator" ($k_{\min}$) which can be measured by the electrical operator. Lower the $k_{\min}$ value, less severe the crisis. Notably, according to the table, the proposed approach, being a compromise that reflects the experts' opinion, is able to outperform the approaches based on the single criteria. Moreover, we observe that the proposed approach outperforms also the multi-objective strategy based on just the number of residents and the intervention time. This supports the conclusion that our approach, by incorporating the experts' know how, yields a more faceted and nuanced strategy.

V. CONCLUSION AND FUTURE WORK

This work was aimed at presenting a novel methodology for prioritizing repair interventions on an electrical distribution network in a large urban area, which provides an essential service to the citizens. The combination of GIS techniques and multi-criteria strategies is able to provide an effective tool for supporting CI operators and stakeholders in decision making processes, especially in case of calamitous natural events (e.g., earthquakes, floods, extreme weather, etc.) impacting the area of interest. The proposed approach combines task assignment, based on the Hungarian Algorithm, with a holistic assignment cost that represents a tradeoff between several, possibly conflicting, intervention strategies. The proposed approach has been implemented as a software module of the CIPCast DSS, a real-time GIS monitoring and risk analysis platform that, among other geo-referenced data, is able to provide information regarding different measures of relevance of intervention locations in a power network.

In order to experimentally demonstrate the potential of the proposed approach, a realistic case study set in Rome, Italy, has been considered. The case study shows how, as a result of the aggregated preferences of several decision-makers and experts, the association of repair crews to intervention locations can yield solutions where crews neglect nearby locations in order to maximize the overall utility. As a result, the proposed approach yields intervention associations that outperform those based on each single criterion. Notably, the proposed multi-criteria strategy represents a compromise that reflects the preferences of experts; the experimental results suggest that such a strategy is quite successful, thus confirming that the experts' opinions can be condensed in a useful index to drive the assignment of repair crews to intervention locations. In addition, the exploitation of the CIPCast DSS has allowed to obtain enriched geographical information, facilitating the decision-making and supporting an effective urban management.

Future work will focus on four main research directions:

- extend the framework to a real-time setting where, in the event of a major disruption or disaster, crews that have been already assigned to an intervention location can be dynamically re-assigned;
- consider possible re-assignment of the crews based on the real time traffic conditions during the implementation of the assignment;
- extend the framework taking into account scenarios where only some crews have the necessary tools or expertise to intervene at a particular location, thus further constraining the assignment;
- apply the proposed strategy to other applications such as rescue scenarios involving first responders.

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