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Planification d'Expansion du Réseau Distribution Avec Programmation Linéaire Binaire

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RESUME - Dans cet article, des prévisions des congestions thermiques et des problèmes de tension (durée et intensité) dans un réseau de distribution électrique sont utilisées pour déterminer une liste de candidats potentiels pour mettre à jour l'infrastructure. Un espace de recherche réduit permet de décider entre la mise à jour des lignes/câbles, l'installation de régulateurs de tension et de systèmes de stockage d'énergie. Cela est complété par un algorithme utilisant la programmation linéaire binaire pour identifier les candidats à coût minimal dans cet espace de recherche restreint, qui résolvent tous les événements de violation des contraintes. Cette méthode est appliquée dans le réseau IEEE 33-bus à travers de nombreuses simulations de haute résolution. Les résultats initiaux montrent que la méthodologie proposée est un outil polyvalent pour les concepteurs, les planificateurs et les régulateurs. Il est démontré, à l'aide de travaux de simulation, que le plan d'investissement sélectionné résout tous les événements de violation de contraintes prévus.

ABSTRACT - In this article, forecasted duration and intensity of thermal congestion and voltage problems in an electrical distribution network are used to determine a pool of potential candidates for infrastructure upgrade. A reduced search space allows for decisions between updating lines/cables, installing voltage regulators, and energy storage systems. This is complemented by an algorithm aiming to obtain the list of minimal-cost candidates in this restricted search space, thus solving all constraint violation events using binary linear programming. This is tested on the IEEE 33-bus network through numerous high-resolution quasi-static time series simulations. Initial results show that the proposed methodology is a versatile tool for designers, planners, and regulators. It is demonstrated, through simulation work, that the selected investment plan solves all forecasted constraint violation events.

MOTS-CLES - stockage d'énergie, planification d'expansion du réseau de distribution, flexibilité, lignes de distribution.

1. Introduction

There is growing attention from industry and the research community around the evolution of electricity distribution networks. Industrial and residential growth, inclusion of new loads resulting from the electrification of heat and transport systems, and inclusion of distributed energy resources (DER) [1] represent challenges for the planning of future grids. Distribution network planning is shifting away from a traditionally passive approach (i.e., waiting for issues to manifest, and reacting with infrastructure upgrades (IU) and voltage regulators (VR) to solve them) [2]. Other forms of flexibility like energy storage systems (ESS) are proposed as non-wire alternatives (NWA) to address these challenges.

In this context, this manuscript takes the perspective of the system operator planning its grids to prevent future congestion and voltage issues resulting from increasing load and generation connections. Traditionally, system operators carry out demand projection studies that help them design grid expansion plans consisting of IUs (i.e., conductor resizing, adding parallel branches, etc.) and VRs [3]. This way, the grid capacity increases, as well as the potential to connect additional load and generation resources. Alternatively, grid-scale flexibility resources (e.g., ESS) can act as flexible loads or generators that allow the grid to cope with excess demand or supply in certain operational moments - reducing the occurrence of constraint violation events [4].

The calculation, quantification and definition of the set of investments that prepare the grid for the future are also known as distribution network expansion planning (DNEP). The large body of works on DNEP focuses on finding mathematical approximations to a complex and intractable problem (non-linear and stochastic). An inherently mixed-integer non-linear programming (MINLP) problem is usually reformulated as mixed-integer linear programming (MILP) like [5], or second order cone programming (SOCP) as [6]. Existing approaches for the DNEP problem in the literature involve the definition of one or multiple objective functions (e.g., minimising investments, emissions, etc.), a set of constraints (e.g., network constraints, reliability, etc.), a temporal model (e.g., dynamic, static, or pseudo-dynamic), a network model, and a solution algorithm (e.g., mathematical, evolutionary, hybrid, artificial intelligent, etc.) [7]. While these approaches can consider stochastic or deterministic parameters, integer or continuous variables, they always result in a non-convex problem that is hard to solve exactly in reasonable time [8]. These approaches must decide from a very large set of potential candidates (search space), requiring relaxations and scenario reduction approaches that can potentially misrepresent the complexity of distribution network applications.

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This paper proposes an approach that can overcome such computational drawbacks, relying on forecasts of future congestion and voltage issues. The information on the constraint violation events is leveraged to design a binary linear programming (BLP) problem which accounts for the remote influence that the different candidate installations present on such events. Using this tool, grid operators, policymakers and designers can extract a list of investment candidates that together address future technical issues of a distribution network at the minimum cost. Furthermore, this method allows the evaluation of multiple pools of candidates in short computational time, making it a practical tool to complement other planning methods. Ultimately, to understand the potential trade-offs between the proposed approach and the common industry practices, they are compared from a technical and economic point of view through extensive simulation work.

The main contribution of this work is presenting a novel methodology for the location and sizing of IU, VR, and ESS candidates applicable to radial distribution networks effectively reducing the search space. This is based on the duration and intensity of forecasted constraint violation events and the physics of electricity networks. These candidates are then used to build a BLP tool for system operators, policy-makers, and designers to decide from a technical point of view, and to translate them into a minimum-cost investment plan (i.e., a DNEP). A comparison with the literature showing the benefits of the proposed method in terms of computational intensity is ultimately followed by a discussion on the opportunities, challenges, scalability, and applicability of the proposed approach.

2. Methodology

This section presents the proposed numerical approach to select the minimum-cost plan, and to validate if the future topology solves forecasted events.

2.1 Preliminary identification of constraint violation events

Forecasted consumption and generation patterns in distribution networks can show which portions of the grid require reinforcement through IU or VR, or can benefit from grid-scale ESS. The first step requires identifying and prioritising the constraint violation events: this gives an idea of the relative urgency of certain upgrades/installations over others, as well as clues on their location and size. If consumption and generation patterns are appropriately forecasted for future scenarios, it is possible through simulation work to determine which portions of the network may present congestion and voltage issues.

An AC power flow (ACPF) simulation is proposed to determine voltage profiles and power flows for the studied network. Values resulting from the ACPF can be normalised as a percentage of a limit being breached: for the case of voltage, the tolerable voltage drop/increase given by the local regulation authority (often $\pm 2\%$, $\pm 5\%$ or $\pm 10\%$ voltage deviations for MV networks). Similarly, power flows are normalised as a percentage of the line loading rating of the existing line to represent thermal limits. Given a grid with a set of lines L and a set of nodes N connected, voltage deviation $\Delta V_{n,t}$ in node n can be expressed as a percentage $\Delta V_{n,t}^{\%}$ of the predefined limit ΔV_n^{LIM} for each time step t of the examined time window \mathcal{T} , using (1). Similarly, power flow $S_{l,t}$ for all time steps t in each line l can be expressed as a percentage $S_{l,t}^{\%}$ of the thermal rating of the conductor S_l^{LIM} using (2). Following this notation, we define constraint violation event as any timestep t in which either a thermal or voltage limit is exceeded anywhere in the network (i.e., $S_{l,t}^{\%}$ or $\Delta V_{n,t}^{\%}$ are larger than 100%).

$$\Delta V_{n,t}^{\%} = (\Delta V_{n,t} / \Delta V_n^{LIM}) \times 100 ; \forall t \in \mathcal{T}, n \in N \quad (1)$$

$$S_{l,t}^{\%} = (S_{l,t} / S_l^{LIM}) \times 100 ; \forall t \in \mathcal{T}, l \in L \quad (2)$$

It is important to differentiate violation events in terms of origin. Thus, a candidate's (i.e., IU, VR or ESS) influence on these events will depend on its origin: ESS for example reduces congestion towards the head of the feeder when charged with excess generation from the end of the feeder. Any congestion or voltage issue is assumed to be different if they respond to an excess in demand or generation. In line with this, it is useful to define congestion as demand-caused $S_{l,t}^{dem}$ or generation-caused $S_{l,t}^{gen}$.

2.2 Numerical approach

It is possible to use the duration and intensity of events to size, locate and prioritise candidate solutions. Ultimately, having a defined list of candidates, it will be possible to calculate each candidate's local and remote influence for voltage and congestion. The proposed method complements existing decision support tools used by modern system operators, including transmission-like methods, other DNEP approaches, network reconfiguration studies, etc. Moreover, it is a practical mechanism that incorporates traditional design practices, and ultimately represents a straightforward implementation that is expected to be of great interest for industry.

2.2.1 Locating and sizing candidates

Defining which combination of IUs solves the congestion issues is a trivial calculation. The new current-carrying capacity (i.e., new limit) $S_{l,new}^{LIM}$ of a line l part of the subset of problematic lines L_p should be above the maximum violation identified previously, this can be calculated using (3).

$$S_{l,new}^{LIM} = \max_{\forall t \in \mathcal{T}} \{S_{l,t}^{\%}\} * S_l^{LIM}; \forall l \in L_p \quad (3)$$

This can be complemented by locating VRs in one or more nodes, part of the subset N_q with voltage violation events. VRs can alleviate voltage events up to the range of the regulation equipment (typically $\pm 10\%$ of the nominal voltage) on the subset of nodes N^v part of its area of influence. Together, these IU and VR represent the candidates for the traditional expansion plan calculated by system operators, responding to forecasted issues.

Alternatively, local congestion issues can be solved by installing an ESS in nodes next to congested lines. The capacity and charge/discharge rating of the ESS is proposed to be determined using the intensity and duration of the associated congestion events. Consider a node n connected to one or more congested lines (the latter represented by the subset L_n). The maximum charge/discharge rating $CH_{n,ESS}^{rate}$ necessary to solve local congestions of the subset of lines can be calculated as the maximum difference between new conductor ratings and original conductor ratings using (4).

$$CH_{n,ESS}^{rate} = \max_{\forall l \in L_n} \{S_{l,new}^{LIM} - S_l^{LIM}\} \quad (4)$$

To calculate ESS capacity it is important first to define the nodal loading that comes from excess demand $S_{n,t}^{dem}$ or generation $S_{n,t}^{gen}$, as the maximum power flow in any congested line l connected to n , at any given time step t . The nodal limit coming from connected lines S_n^{LIM} is represented by the minimum thermal limit in any of them.

$$S_{n,t}^{dem} = \max_{\forall t \in \mathcal{T}, l \in L_n} \{S_{l,t}^{dem}\} \quad (5)$$

$$S_{n,t}^{gen} = \max_{\forall t \in \mathcal{T}, l \in L_n} \{S_{l,t}^{gen}\} \quad (6)$$

$$S_n^{LIM} = \min_{\forall l \in L_n} \{S_l^{LIM}\} \quad (7)$$

The capacity of the ESS $E_{n,ESS}$ is then calculated by finding the maximum energy that would be required to solve all congestion events in any day, either from demand or generation excess. This is given by the maximum between daily-aggregated demand-caused and generation-caused congestion issues using (8). This approach accounts for two or more subsequent congestion events without enough time for the ESS to charge/discharge back into levels that could address the second congestion. This will be tested with a daily cycle, where any charge or discharge occurs on a day.

$$E_{n,ESS} = \max \left\{ \sum_{t \in day} [(S_{n,t}^{gen} - S_n^{LIM}) \times t] \quad \sum_{t \in day} [(S_{n,t}^{dem} - S_n^{LIM}) \times t] \right\} \quad (8)$$

2.2.2 Addressing local and remote violation events

Some candidates can solve congestion and voltage issues in local remote locations. This paper proposes estimating this based on the physical relationships between technologies, congestion and voltage drop, analogue to the critical sensitivity indices in [9]. Voltage drop δV over a line is calculated using (9), where I is the transported current, Λ is the length of the conductor with a cross-section A_{cond} . The influence of temperature, the material (e.g., copper or aluminium) and the configuration of the installation (e.g., three-phase or single-phase) is represented by the constant k . Voltage drops can be added for different sections that have various values of current, length and cross-sections. For this study, Λ is assumed constant because lines are only upgraded, not rerouted.

$$\delta V = (k \times I \times \Lambda) / A_{cond} \quad (9)$$

The candidates dimensioned above can have direct and/or indirect influences over congestion and voltage drop/rise: IU and ESS have a direct influence on congestion, and an indirect influence on voltage via the increased conductor cross-section and reduced line loading, respectively. VR have a direct influence on remote voltages and a negligible influence on congestion.

- IUs only affect congestion locally, therefore its remote influence on congestion CIS_{IU,l_b}^{remote} in a remote line l_b is assumed to be zero. In contrast, A remote influence on voltage will be considered from IUs for each node n part of the subset N^* that has voltage issues and is part of the direct path of the current that goes through the upgrade. The remote voltage influence score $VIS_{IU,n}^{remote}$ of upgrading line l in voltage-problematic node n is calculated using the proportion between the change in voltage drop across the line l (i.e., from the old line and the line after the IU), and the maximum voltage event seen by n . Voltage drops across non-upgraded sections also remain unchanged. We assume that k remains constant and that the change in current due to conductor resizing is negligible.
- VRs have zero influence in remote congestion. In contrast, a VR installed in node n with bandwidth $\Delta V_{n,VR}^{range}$ alleviates voltages in nodes $n_b \in N^v$ that see the regulator as head of the feeder.

- A remote influence on congestion will be considered from ESS installations for the subset of lines L^ν that are part of the direct path of the current that goes through the element. This influence depends on the origin of the congestion. As discussed before, demand-caused and generation-caused congestions are treated differently. Assuming that the ESS responds to a congestion signal, any charge with magnitude $CH_{n,ESS}^{rate}$ in congested moments is the power that is not going to flow through the grid and as such alleviates congestion in remote sections. We assume that the ESS does not cause problems when charging/discharging back in moments without constraint violation events.

Since voltage drop is directly proportional to the current flowing through a conductor, an ESS reducing congestion, also has a positive impact on voltage issues across the network. A similar approach to that of the voltage influence score for IUs can be used. The difference here is that instead of the current being constant, the cross-section remains constant. Therefore, given a constant k , we find the remote voltage influence score using $I_{l_a}^{old}$ (the maximum current in any congestion event) and $I_{l_a}^{new}$ (the reduced current in a congestion event) when the ESS alleviates congestion in line l_a , the line connected to the node n where the candidate ESS is proposed - looking towards n_b . While reducing the current flowing through the lines between n and n_b reduces voltage drop in all of them, it is proposed to calculate only the voltage influence score for the node n_b - this simplifies the problem and makes it a conservative approach: the candidate is assigned a smaller influence than it has in reality. We used the same base voltage to work with power flows instead of currents.

The relations described above are defined when it comes to remote addressing of congestion and voltage issues, and a summary is presented in Table I.

Tableau I
SUMMARY OF CANDIDATE INFLUENCES ON LOCAL AND REMOTE VIOLATION EVENTS

Type of event	Influence	IU	VR	ESS
Congestion	local	1	0	1
	remote	0	0	$\frac{CH_{n,ESS}^{rate}}{\max_{\forall t \in \mathcal{T}} \{S_{l,t}\} - S_l^{LTM}} ; \forall l \in L^\nu$
Voltage	local	0	$\frac{\Delta V_{range}^{VR}}{\max_{\forall t \in \mathcal{T}} \{\Delta V_{n,t}\} - \Delta V_n^{LTM}}$	0
	remote	$\frac{1 - (A_t^{old} / A_t^{new})}{\Delta V_n^{MAX}}$	$\frac{\Delta V_{range}^{VR}}{\max_{\forall t \in \mathcal{T}} \{\Delta V_{n_b,t}\} - \Delta V_{n_b}^{LTM}}$	$\frac{CH_{n,ESS}^{rate}}{\max_{\forall t \in \mathcal{T}} \{S_{l_a,t}\} \times \max_{\forall t \in \mathcal{T}} \{\Delta V_{n_b,t}\}}$

2.2.3 Finding the minimum cost investment

Since it is not expected that one candidate is able to solve all issues, the last step is defining which combination of candidates does it at a minimum cost. Let us define p , q and r as the number of IU, VR, and ESS candidates, respectively. The binary vector \mathbf{x} containing the decision variables x_i to install or not each candidate i out of all options is defined in (10). This vector has size $p + q + r$. Similarly, the costs c_i associated with each candidate i are contained in the vector \mathbf{c} (11).

$$\mathbf{x} = [x_{IU_1}, \dots, x_{IU_p}, x_{VR_1}, \dots, x_{VR_q}, x_{ESS_1}, \dots, x_{ESS_r}] \quad (10)$$

$$x_i \in \{1, 0\}; \forall i$$

$$\mathbf{c} = [c_{IU_1}, \dots, c_{IU_p}, c_{VR_1}, \dots, c_{VR_q}, c_{ESS_1}, \dots, c_{ESS_r}] \quad (11)$$

Finding the minimum-cost list of candidates that solve all events can be cast as a BLP problem. The premise of this method is that the influences of different candidates are independent from each other, and are cumulative. This might result in a more conservative solution compared to regular DNEP approaches. The BLP is defined in (12), where \mathbf{b} is a unitary vector with the size of the problematic elements.

$$\begin{aligned} & \text{minimise} && \mathbf{c}^T \mathbf{x} \\ & \text{subject to} && \mathbf{A} \mathbf{x} \geq \mathbf{b} \end{aligned} \quad (12)$$

Where \mathbf{A} is a matrix of influence scores that includes all the local and remote influence scores on congestion and voltage issues. Each candidate has an associated score between 0 and 1 in all the p congested lines and q voltage-problematic nodes, therefore \mathbf{A} has a size of $[p + q] \times [p + q + r]$ (i.e., number of problematic elements \times number of candidates). The inequality in (12) guarantees that the addition of influence scores VIS and CIS (represented in \mathbf{A}) from selected candidates (represented by \mathbf{x}), solve the issues in all problematic elements (represented by unitary vector \mathbf{b}). The global optimal is found with conventional solvers.

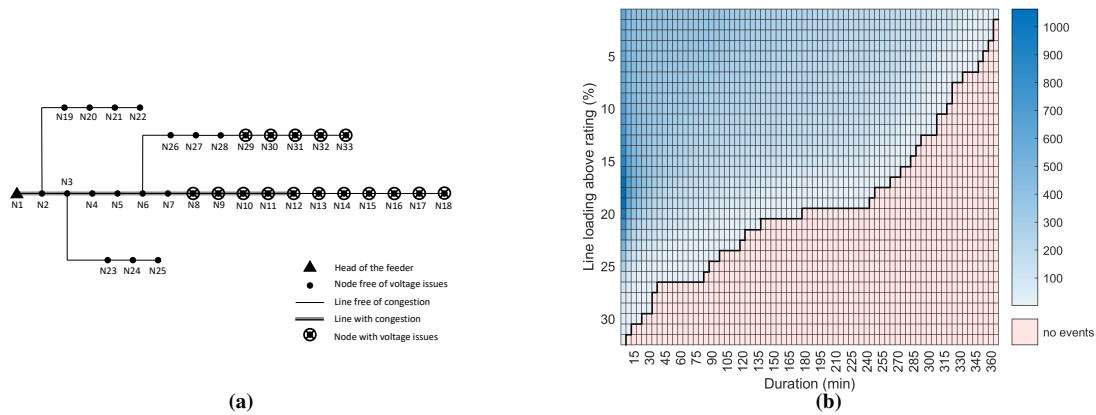


Figure 1: Results of the preliminary analysis for the IEEE 33-bus network. (a) Topology highlighting voltage and line loading violation locations. (b) Heatmap with the numerical occurrence of line loading events at the most congested line L1 between N1 and N2.

3. Results and Validation

We tested this method using the modified IEEE 33-bus distribution grid, common in distribution network studies. The technical data paired with peak loads can be found in [10]. The point of connection is modelled as the point of supply by the system operator, and the 32 remaining nodes represent aggregated low-voltage customers connected to the node through a distribution transformer. The forecasted scenario selected for demand is given by a 250% increase for the target year, using the historical peak load reported in the documentation as a reference. This information is complemented using the CREST demand model [11] to generate synthetic profiles for demand and photovoltaic (PV) production throughout the year. An expected growth of 250% in the installed generation capacity allocated in previous work by the authors in [12] was used as a reference.

A full ACPF simulation of the networks with forecasted demand and generation profiles was performed using OpenDSS. This results in networks with line congestion and voltage issues: 11 lines present congestion issues and 16 nodes present voltage issues for the IEEE 33-bus network (see Fig. 1a). Based on the topology and these preliminary results of congestion and voltage issues for the IEEE 33-bus network, it is possible to determine the existence of 11 candidates for IU, 16 candidates for VR and 12 candidates for ESS. The event heatmap at a critical location is shown in Fig. 1b.

The duration and intensity of events is used to size candidates. As an example, using the information on the congested line L1 available in Fig. 1b it is possible to size a candidate for IU and for ESS. The maximum intensity registered in the figure is 34.4% above the rating of L1 - which is 5,064 kVA. Therefore, the new rating of the upgraded conductor (ID 1) must be at least 6,805 kVA. Similarly, the charge or discharge rate from ESS that would solve the congestion issue in L1 corresponds to the difference between the new rating and the old one (i.e., 1,741 kVA charge/discharge rate). The maximum value obtained for the energy requirements for charge or discharge on a single day was 11.45 MWh. This can also be translated into an ESS duration of 6.6 hours. This process is repeated for all potential candidates considered for the IEEE 33-bus network.

A technology-specific assessment of candidates is not the purpose of this study: this paper will not extend to the technical and economic constraints for particular IU, VR and ESS technologies. Instead, for the purpose of this work and following current trends, VR will be modelled as OLTC with a $\pm 10\%$ bandwidth, and ESS as Li-Ion battery with a minimum state of charge of 20%. The costs of installing, operating and maintaining each candidate in the planning timescale can be calculated and brought to present value considering local economic constraints.

3.1 BLP solution

After defining and characterising candidates, their local and remote influences on congestion and voltage are calculated using the information in Table I. The minimum-cost list that solve all violation events of the network can be found through the BLP problem formulation in (12). The **intlinprog** functionality of Matlab was used to find a solution, and the algorithm was run using a desktop PC equipped with an Intel Core i7, CPU at 2.3 GHz, and physical system memory of 16 GB. Table II presents the results of simulation work.

Using different cost projections for ESS does not result in radically different solutions, the same candidates are selected even if the total costs of the installation vary. These results suggest that the proposed method is not highly sensitive to inputs and requires a small computational time. The advantages of the proposed method are highlighted when comparing these results with those reported by other authors as shown in Table II. Without considering pre-processing times for any, the proposed method finds a solution many orders of magnitude faster.

The method used as comparison in Table II has power flow calculations embedded. In contrast, the BLP method proposed runs power flows at the pre-processing stage. The comparison is not complete without including such pre-processing computational burden. The ACPF and influence score calculations run time for the 33-bus networks studied is 18,925.7, this is the same order of magnitude as their reported solution. The usefulness of the BLP approach is

Tableau II
COMPARISON WITH OTHER METHODS IN THE LITERATURE

Ref.	Case study	Data (timestep)	Selected candidates	Solving time* [s]
BLP	33-bus	1y (1m)	6 IU, 3 ESS	0.013
[13]	25-bus	8d (15m)	2 IU, 1 ESS	66,996
	55-bus	8d (15m)	2 IU, 1 ESS	70,812
	69-bus	8d (15m)	2 IU, 1 ESS	307,008
	123-bus	8d (15m)	2 IU, 1 ESS	299,016

* Not including scenario reduction or data pre-processing run time

highlighted because of two reasons. First, when noting that the data set in this study is many times larger and has a considerably higher temporal resolution. Second, when considering that this computationally-heavy pre-processing stage must be conducted only once for our method: after one run the BLP outperforms others.

As a final check, a year-long quasi-static time-series simulation of the selected “future topology” was performed. IUs replaced old conductors (impedances and thermal limits from cable sizing were assumed continuous and were adjusted according to the IU), VRs were installed when selected, and Li-Ion ESS candidates configured for peak-shaving were connected. The results of this simulation confirm that the application of the selected candidates resolved all congestion and voltage issues previously reported.

4. Conclusion

This work presents a numerical method to define a list of minimum-cost candidates (i.e., IU, VR and ESS), reducing the search space for the DNEP problem, this is based on forecasted constraint violation events. The proposed methodology presents reduced computational time, has low sensitivity to inputs and has been validated through extensive simulation work. The results suggest that applying the BLP solution solves 100% of forecasted violation events. This study is particularly useful for system operators, planners and designers because it makes it possible to run multiple simulations in little time. Numerous candidate pools can be tested, including customised installations and different technologies.

The authors foresee the addition of two layers of complexity to the method in future work. First, it is possible to replace manufacturer’s line ratings to include weather-dependent dynamic line ratings. Secondly, this work can be further developed if it is cast for multiple planning steps. If the forecasted demand and generation information is available for different discrete moments over a planning horizon, each discrete value provides an answer on which candidates have priority in the short and medium term. The candidates selected in a discrete-time step can become part of the “current topology” for subsequent time steps.

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