

Large-Scale Cascading Failure Mitigation in Power Systems via Typed-Graphlets Partitioning

Rachad Atat*, Muhammad Ismail†, Katherine R. Davis‡, and Erchin Serpedin‡

* Department of Electrical and Computer Engineering, Texas A&M University at Qatar, Doha, Qatar

†Department of Computer Science, Tennessee Technological University, Cookeville, TN, USA

‡Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX, USA

Abstract—Large-scale cascading power failures impact nations economically and socially. Current literature is lacking effective methods and tools to prevent failures from globally propagating in the system. In this paper, we bridge this gap by proposing a partitioning method that exploits the heterogeneity of the power system by identifying the most vulnerable typed-graphlets. We formulate the partitioning problem as a large-scale mixed integer program, which we solve using Benders’ method. We show through simulations that i) when typed-graphlets are used, a much larger number of failing power nodes is required to reach a complete power blackout compared to the case without typed-graphlets, and ii) the overall damage can be reduced by an average of 61% compared to the case without partitioning.

Index Terms—Power grid, typed-graphlets, constrained clustering, Benders decomposition, and cascading failures.

I. INTRODUCTION

Power blackouts present high economic and social impact. Recent large-scale cascading failures events have motivated authorities to invest in action plans to mitigate power failures and reduce the overall damage impact. However, current results are still lagging behind in offering effective robust solutions to limit the failures impact. One recent blackout example is the Texas blackout from February 2021 due to a winter storm, which left 4.5 million customers without electricity with an estimated loss of over \$195 billion [1]. Thus, this paper focuses on methods to stop the cascading failure propagation, and especially on limiting the failure spread via graph partitioning.

Whenever a failure occurs, the system needs to be immediately configured in such a way to prevent the failure from propagating globally in the system. Such configuration can be achieved by switching off certain transmission lines, which leads to many partitions. These partitions help to contain the failures and prevent them from crossing the tie lines. The power system can be modeled as a heterogeneous graph consisting of multiple node and edge types. The power nodes (PNs) can be categorized as load PNs or generator PNs, while the edges can be classified as transmission lines connecting two PNs of the same voltage, or transformer lines connecting two PNs of different voltage levels [2]. Therefore, it becomes essential to use heterogeneous partitioning tools in order to

capture not only the most vulnerable nodes and edges, but also the higher-order patterns in nodes and connectivity types. Such tools should be scalable with the power grid size and fast enough for real-time emergency control.

Unfortunately, only a limited number of existing works, as summarized in Section I-A, have investigated the power grid partitioning approach for failure containment. These works did not exploit the most vulnerable nodes and edges based on the heterogeneity of the power grid. Herein paper, we employ heterogeneous clustering tools such as the constrained spectral clustering approach based on typed-graphlets. Compared to other clustering methods, the graph spectral clustering does not confine the partitions to specific fixed shapes or patterns, since nodes that are distant from each other may belong to the same partition. This means that spectral clustering is an effective tool for power systems that present varying node connections and sizes. The typed-graphlets are induced subgraphs consisting of different node and edge types. If we identify the most vulnerable typed-graphlets, then the power system can be partitioned such that the failure impact is limited inside the target partition. The critical timeliness and the low complexity of the proposed method are highlighted in this paper.

A. Related Work

So far, very few technical solutions have been proposed to confine the impact of large-scale cascading failures. E.g., [3] shows that switching off a negligible number of transmission lines makes the power grid significantly less vulnerable to outages. In [4], transmission systems are partitioned into several control areas to contain failures. The block decomposition method is used in [5] to identify line failures patterns in transmission systems via topological graph structures. In [6], the failures are stopped from propagating globally by allowing the power system to assume a connected tree structure with minimal load shedding. In [7], the power system islands that minimized the load shedding were obtained in the regions where failures were initiated as well as in their topological complements. The power grid resilience to random failures and intentional attacks was also analyzed in [8].

The current literature does not exploit the heterogeneity of the power grid graph to capture high-order partitions to limit the global failure propagation. Thus, this paper mainly focuses on the higher-order partitioning problem by exploiting the most vulnerable typed-graphlets.

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B. Contributions and Organization

The contributions of this paper are summarized as follows:

First: To control and mitigate outages, this paper proposes partitioning the power grid by exploiting its heterogeneous structure. Using the Analytical Hierarchical Process (AHP), the most vulnerable typed-graphlets are identified which are subsequently used in the constrained graph spectral clustering.

Second: The higher-order partitioning problem is formulated as a large-scale optimization problem, with the objective of minimizing the overall load shedding cost subject to: i) power flow convergence, ii) partition connectivity, iii) frequency/voltage stability, and iv) high quality partitions.

Third: The NP-hard problem is solved using Benders' decomposition, which splits the problem into a master problem consisting of the constrained spectral clustering and a linear optimization of the load shedding cost.

We apply the higher-order partitioning on the IEEE 118-bus system. Our investigations reveal that i) the proposed partitioning method requires a much larger number of failing PNs to reach a complete blackout compared to the method that does not exploit typed-graphlets, and ii) the typed-graphlets partitioning method reduces the impact of large-scale cascading failures by 61% compared to the case without partitioning.

The remainder of this paper is organized as follows. Section II describes the different topological and electrical metrics that are used in the AHP to obtain the most vulnerable PNs. Section III defines the vulnerable typed-graphlets using AHP. Section IV formulates the optimization problem, while Section V presents the solution approach. Simulation results and discussions are provided in Section VI. Finally, the paper concludes with Section VII.

II. FAILURE CRITICALITY ASSESSMENT

The power grid is modeled as a heterogeneous graph of ordered tuples $\mathcal{T} = (\psi, \xi)$ [9], where ψ and ξ are the node-type and edge-type mappings, i.e., $\psi \rightarrow V_P$ and $\xi \rightarrow E_P$, and $V_P = \{1, 2, \dots, N_P\}$, N_P and E_P stand for the nodes set, total number of nodes and edge set, respectively. Matrix \mathbf{A}_P denotes the binary adjacency matrix of graph \mathcal{T} whose entry a_{bv}^u is the $(b, v)^{\text{th}}$ entry of $\mathbf{A}_u \in \{0, 1\}^{N_P \times N_P}$.

Next, we perform failure criticality assessment for each PN in order to identify the set of the most vulnerable nodes to be later used in the optimal partitioning.

A. Topological Metrics

- Connectivity impact (CI) indicates the number of PNs that remain connected after a failure.
- Connectivity loss (C^{loss}) indicates the average decrease in the number of generators after a failure event.
- Geodesic vulnerability (\bar{v}) measures the extent to which the power system remains operational after a node fails.
- Efficiency (EF) indicates the effectiveness when sending data between any pair of nodes.
- Topological damage (Dam) is computed as the normalized efficiency loss after a failure event.

B. Electrical Metrics

We define the following power flow distribution metrics:

- Effective graph resistance (R_G) captures the total cost to transfer power flow between a pair of nodes.
- Load shedding (LS) measures the total apparent power after a node failure.
- Percentage of drop in net-ability (PoDN) measures how well the power grid can supply power.

To assign vulnerability score for each PN, we use AHP, which allows to determine the weight of each metric with respect to how much it is contributing to the overall system vulnerability, with the most critical metric being assigned the largest weight. For this purpose, pairwise comparisons between the different metrics are carried out in order to determine the relative importance of each with respect to the other.

The failure criticality set is $\mathcal{F} = (V_P | R_{\text{vuln}, P, i} > \iota_P)$, where $R_{\text{vuln}, P, i}$ denotes the overall vulnerability score of PN i [10], and ι_P is the vulnerability threshold of the power system.

III. MOST VULNERABLE TYPED-GRAHLETS

Now that we have obtained the most vulnerable PNs, we shall use them to identify the most vulnerable typed-graphlets, which are later used to optimally partition the system.

The typed-graphlets allow to capture the node/edge types that constitute the power system. They are induced subgraphs that retain all of the edges between its different nodes that are present in the large graph.

Definition 1 (Vulnerable Typed-Graphlets). *The vulnerable typed-graphlet of the power graph, \mathcal{T} , is a connected induced subgraph $\mathcal{H} = (\mathcal{T}_{\mathcal{H}}, \psi_{\mathcal{H}}, E_{\mathcal{H}})$ with the following properties:*

- $\mathcal{T}_{\mathcal{H}} = (\psi_{\mathcal{H}}, E_{\mathcal{H}})$ is the subgraph of \mathcal{T} induced by extracting the most vulnerable vertices and their corresponding 2-hop neighbors $|\mathcal{Y}_u|$, $u \in \mathcal{F}$, while retaining all the edges between them. The extraction of the 2-hop neighbors allows to infer unique graphlets structures.
- The vertices set is $\psi_{\mathcal{H}} \subset (\mathcal{F}, \mathcal{Y}_u | u \in \mathcal{F})$, while the edges set is obtained by extracting all the edges between $\psi_{\mathcal{H}}$.

To construct the typed-graphlet adjacency matrix, $\mathbf{A}_{\mathcal{T}_{\mathcal{H}}}$, we count the number of unique instances of \mathcal{H} that contain an edge between the corresponding nodes in the typed-graphlets instances. Finally, to assess the partition quality, we refer to the conductance score. A low conductance score implies a high partition quality, since the partition would have fewer edges to the vertices outside, thereby preserving the most vulnerable typed-graphlets instances. This leads to a sparse and balanced cut. Thus, the objective becomes to minimize the conductance score across all the partitions in order to minimize the number of typed-graphlets that need to be cut.

IV. PARTITIONING FOR FAILURE MITIGATION

In this section, we aim to obtain the most vulnerable K partitions that limit the failure impact. In case of failures, these partitions are enabled by activating the tie switches.

Each partition $I_k \in \mathcal{I}$, where \mathcal{I} is the set of K graph partitions, contains all the unique typed-graphlets instances.

Denote by $I_k^{\mathcal{H}}$ the weighted subgraph partition represented by the submatrix $\mathbf{A}_{\mathcal{H}}$ on that partition. We aim to obtain K partitions that minimize the overall load shedding cost subject to i) the Alternating Current Optimal Power Flow (AC-OPF) feasibility, ii) power connectivity, iii) power stability, and iv) a high partition quality. The K partitions are obtained by solving the mixed-integer program (MIP)

$$\min_{P_G, Q_G, P_{ij}, Q_{ij}, P_{LS}, \theta, e_{ij,k}, v, f_{ij,k}, x_{ik}, z} \sum_{k \in \mathcal{I}} \sum_{i \in I_k} J_{LS_i} P_{LS_i} \quad (1a)$$

$$\left. \begin{array}{l} P_{ij} = (-v_i - 1)G_{ij} + (v_j + \cos \theta_{ij} - 2)G_{ij}) z_{ij} \\ \quad + \theta_{ij} B_{ij} z_{ij}, \forall (i, j) \in L_k, k \in \mathcal{I} \\ Q_{ij} = ((v_i - 1)B_{ij} - (v_j + \cos \theta_{ij} - 2)B_{ij}) z_{ij} \\ \quad + \theta_{ij} G_{ij} z_{ij}, \forall (i, j) \in L_k, k \in \mathcal{I} \\ -P_{ij,\max} \leq P_{ij} \leq P_{ij,\max} \forall (i, j) \in L_k, k \in \mathcal{I} \\ -Q_{ij,\max} \leq Q_{ij} \leq Q_{ij,\max} \forall (i, j) \in L_k, k \in \mathcal{I} \\ P_{G_i} + \sum_{j < i} P_{ji} = P_{D_i} - P_{LS_i} + \sum_{j > i} P_{ij} \\ \quad + \sum_j G_{ij} (2v_i - 1), \forall i \in V_k \\ Q_{G_i} + \sum_{j < i} Q_{ji} = Q_{D_i} - Q_{LS_i} + \sum_{j > i} Q_{ij} \\ \quad - \sum_j B_{ij} (2v_i - 1), \forall i \in V_k \\ 0 \leq P_{G_i} \leq P_{G_{i,\max}}, \forall i \in V_k, k \in \mathcal{I} \\ -\sqrt{v_i^2 I_{a,\max}^2 - P_{G_i}^2} \leq Q_{G_i} \leq \sqrt{v_i^2 I_{a,\max}^2 - P_{G_i}^2}, \\ \quad \forall i \in V_k, k \in \mathcal{I} \\ 0 \leq P_{LS_i} \leq P_{D_i} \quad \forall i \in V_k, \\ Q_{LS_i} = P_{LS_i} \tan \phi_i \quad \forall i \in V_k, \\ \sum_{i=1}^{N_{d,k}} P_{D_i} < \sum_{i=1}^{N_{g,k}} P_{G_i}, \quad \forall k \in \mathcal{I} \\ \sum_{i=1}^{N_{d,k}} Q_{D_i} < \sum_{i=1}^{N_{g,k}} Q_{G_i}, \quad \forall k \in \mathcal{I} \end{array} \right\} \quad (1b)$$

$$\left. \begin{array}{l} \sum_{i \in V_k} \mathbb{1}_i^g x_{ik} \geq 1, \quad \forall k \in \mathcal{I} \\ \sum_{i \in V_k} \mathbb{1}_i^d x_{ik} \geq 1, \quad \forall k \in \mathcal{I} \end{array} \right\} \quad (1c)$$

$$\left. \begin{array}{l} \sum_{(i,j) \in L_k} f_{ij,k} = \sum_{i \in V_k} x_{ik} - 1, \quad \forall k \in \mathcal{I}, \\ \sum_{(i,j) \in L_k} f_{ij,k} + x_{ik} = \sum_{(j,i) \in L_k} f_{ji,k}, \quad \forall i \in V_k^{(p)} \setminus i_k \\ 0 \leq f_{ij,k} \leq x_{ik} \sum_{i \in V_k} x_{ik}, \quad \forall (i, j) \in L_k, k \in \mathcal{I} \\ 0 \leq f_{ij,k} \leq x_{jk} \sum_{i \in V_k} x_{ik}, \quad \forall (i, j) \in L_k, k \in \mathcal{I} \\ x_{ik} \in \{0, 1\}, \quad \forall i \in V_k, k \in \mathcal{I} \end{array} \right\} \quad (1d)$$

$$-\Delta f_{\%} \leq \Delta \omega_k \leq \Delta f_{\%}, \quad \forall k \in \mathcal{I} \quad (1e)$$

$$1 \leq LVSI_{ij} \leq 2, \quad \forall (i, j) \in L_k, k \in \mathcal{I} \quad (1f)$$

$$|V_k| \geq \varsigma, \quad \forall k \in \mathcal{I} \quad (1g)$$

$$\frac{\lambda_2}{2|E_{\mathcal{H}}|} \leq \phi^{\mathcal{H}}(I_k) \leq \sqrt{2\lambda_2}, \quad \forall k \in \mathcal{I}, \quad (1h)$$

where

- P_{ij}, Q_{ij} are the active/reactive power flow on line (i, j) .
- $P_{ij,\max}, Q_{ij,\max}$ are the active/reactive transmission capacity for line (i, j) .
- P_{G_i}, Q_{G_i} are the active/reactive power at generator i .
- $P_{G_{i,\max}}, Q_{G_{i,\max}}$ are the active/reactive generation capacity at PN i .
- P_{LS_i}, Q_{LS_i} are the active/reactive load shed at PN i .

- B_{ij} is the susceptance of line (i, j) .
- G_{ij} is the shunt conductance of line (i, j) .
- v_i is the voltage magnitude at PN i .
- θ_{ij} is the voltage angle difference between PNs i and j .
- ϕ_i is the power factor angle at PN i .
- $I_{a,\max}$ is the maximum allowable armature current.
- J_{LS_i} is the load shedding penalty cost at PN i .
- V_k is the set of power vertices in partition k .
- L_k is the set of transmission lines in partition k .
- $\mathbb{1}_i^g$ and $\mathbb{1}_i^d$ are indicator functions equal to 1 if i is a generator or a load, respectively.
- f_{ij} is the flow unit on transmission line (i, j) .
- x_{ik} is a decision variable denoting if i is in partition k .
- z_{ij} is a decision variable equal to 0 when PNs i and j belong to different partitions, and 1 otherwise.
- $\Delta \omega_k$ is the steady-state frequency deviation in partition k .

Eq. (1b) guarantees the feasibility of piece-wise linear approximation of AC power flow. Eq. (1c) ensures that every partition contains at least one generator and one demand load. Eq. (1d) ensures partition connectivity using the single-commodity flow constraints. To guarantee power system stability in terms of frequency and voltage, Eq. (1e) imposes a deviation limit of $\pm \Delta f_{\%}$ from the nominal frequency in partition k , while Eq. (1f) ensures the line voltage stability index (LVSI) for each transmission line in each partition falls between 1 and 2 to avoid voltage collapse [11]. Eq. (1g) sets a minimum partition size ς in order to eliminate small partitions with little value in practice. Finally, Eq. (1h) imposes a high quality partition by verifying that the conductance score falls within the specified near-optimal bounds [9], where λ_2 is the second smallest eigenvalue of the graph Laplacian matrix. Such bounds allow to preserve the typed-graphlets and their isomorphic instances. The defined optimization problem is NP-hard, and the search for optimal partitions is computationally infeasible for large systems. In the next section, we propose to use Benders' decomposition method to solve the large scale MIP. The authors in [7] found that the running time to solve the optimal partitioning of the IEEE 30-bus system using CPLEX software was 3.5 hours. On the other hand, Benders' method eliminates the computational bottleneck when solving the problem as a whole by exploiting the structure of the problem. In Section V, we justify the low computational complexity of the method, and in Section VI, we show that the iteration process is quite fast in finding an optimal solution.

V. SOLUTION APPROACH

We propose to solve the MIP using Benders' decomposition method in two stages. The first stage, a.k.a. the master problem, consists of obtaining the partitions that minimize the typed-graphlet conductance score, while the second stage, a.k.a. the linear subproblem (LP subproblem) consists of minimizing the overall load shedding cost subject to power flow convergence and power stability. If the LP subproblem solution is infeasible, feasibility cuts are added to the master problem, which is then re-solved. The master problem solution provides a lower

bound, while the LP subproblem solution provides an upper bound. The iterative procedure between the master and LP subproblems should guarantee that the gap between the upper and lower bounds falls within a specified gap tolerance ϵ_{tol} .

Minimizing the typed-graphlet conductance score is NP-hard. A relaxation solution is the constrained graph spectral partitioning. Therefore, the relaxed master problem would consist of incorporating a constraint matrix $\mathbf{Q}_k^{|V_p| \times |V_p|}$ for partition $I_k \in \mathcal{I}$, whose elements are defined as follows

$$q_{ij,k} = q_{ji,k} = \begin{cases} +1, & \text{if } i \text{ and } j \text{ must link in } I_k \in \mathcal{I}. \\ -1, & \text{if } i \text{ and } j \text{ must not link in } I_k \in \mathcal{I}. \\ 0, & \text{no side information available.} \end{cases} \quad (2)$$

Then, the constraints of (1c) can be incorporated in \mathbf{Q}_k as

$$\mathbf{Q}_k = \left\{ \{q_{ij,k}\} \middle| \sum_{i \in N_{g,k}} q_{ij,k} \geq 1; \sum_{i \in N_{d,k}} q_{ij,k} \geq 1 \right\},$$

The solution of the relaxed master problem is provided by [12, Algorithm 2].

The LP subproblem is formulated as

LP Subproblem:

$$\min J(x), \quad x \in I_k, \quad \forall k \in \mathcal{I},$$

$$J(x) = \min_{P_{G_i}, Q_{G_i}, P_{ij}, Q_{ij}, P_{LS_i}, v, \theta} \sum_{\substack{i \in I_k \\ k \in \mathcal{I}}} J_{LS_i} P_{LS_i}$$

$$\text{s.t.} \quad \text{Eqs. 1b, 1e - 1g.}$$

Note that the first constraint in Eq. (1b) contains the quadratic term $z_{ij} = \sum_k x_{ik} x_{jk}$, with $(i, j) \in L_k$ and $k \in \mathcal{I}$. To linearize z_{ij} , we introduce the auxiliary variable $w_{ij,kk'} = x_{ik} x_{jk'}$ as the product of two binary variables. Then, $w_{ij,kk'}$ can be linearized as [13] $w_{ij,kk'} \leq x_{ik}; w_{ij,kk'} \leq x_{jk'}; w_{ij,kk'} \geq x_{ik} + x_{jk'} - 1; w_{ij,kk'} \geq 0$.

If the LP subproblem solution is infeasible, then the obtained partitions are added to \mathbf{Q} in the relaxed master problem as

$$\mathbf{Q} = \left\{ \{q_{ij}\} \middle| \sum_{i,j \in I_k} q_{ij,k} = - \sum_{i \in I_k} x_{ik}; \forall k \in \mathcal{I} \right\}. \quad (10)$$

The computational complexity of the relaxed master problem is $O(nN_p)$, where n denotes the number of eigenpairs that need to be computed to obtain $K-1$ feasible eigenvectors on which the K -means clustering is performed to obtain the final K partitions [12]. If B_{iter} denotes Benders' number of iterations for convergence, then the computation time of the overall solution scales linearly with the number of PNs as $O(nB_{\text{iter}}N_p)$. This highlights the scalability and the low-complexity of the proposed solution with the total number of PNs in the system.

VI. SIMULATIONS RESULTS AND DISCUSSIONS

The proposed partitioning solution is implemented in MATLAB on the IEEE 118-bus system.

We start by performing AHP analysis on the topological and electrical metrics defined in Section II. The AHP of the

topological metrics are: Dam : 0.41152; \bar{v} : 0.22847; and CI : 0.36002. The AHP output of the electrical metrics are: LS : 0.40111; PoDN : 0.26059; and R_G : 0.3383.

The AHP weights are then used to obtain the criticality score of each node. As an illustrative example, we select 30% of PNs to be the most critical nodes by first sorting the nodes from those with the highest criticality scores to the lowest, and then selecting the top 30% of them. If this percentage becomes larger, more typed-graphlets structures that are less vulnerable will be exploited, which in turn can lead to larger partition sizes, and thereby larger damage impact. Using the definition of the vulnerable typed graphlets, we plot in Fig. 1 the resulting non-isomorphic typed-graphlets, which are then used to construct the typed-graphlet adjacency matrix. To obtain the

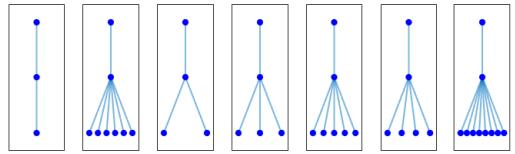


Fig. 1. Non-isomorphic vulnerable typed-graphlets.

minimum partition size ς and the number of partitions K for the case when the most vulnerable typed-graphlets are used, we plot in Fig. 2(a) the average load shedding cost for different values of K and partition sizes. From Fig. 2(a), we select $\varsigma = 7$ for $K = 2$ and $K = 3$; and $\varsigma = 4$ for the remaining values of K since the shedding cost increases thereafter. Moreover, given ς , we plot in Fig. 2(b) the average shedding cost for different values of K . While $K = 2$ achieves the lowest shedding cost, we select $K = 4$ to maximize the advantages of the proposed partitioning method. Similarly, we obtain $\varsigma = 4$ and $K = 8$ for the case without typed-graphlets.

The resulting partitions with and without typed-graphlets are depicted in Fig. 3. The partitions for the case of typed-graphlets were obtained in 27 iterations with a running time of 9.75 seconds, while those for the case without typed-graphlets were also obtained in 21 iterations but with a running time of 9.81 seconds. As for Benders' convergence, the final gap between the upper and lower bounds is 0.01694 and 0.04125 for the partitioning with and without typed-graphlets, respectively. Based on Section V, the computational complexity of the 118-bus system is linear and scales with the number of eigenpairs that need to be computed to obtain the K partitions.

Whenever a failure occurs, the intentional partitioning should be activated within 30 seconds [14]. Within 30 seconds to 15 minutes after a failure event, the system frequency should be restored back to its nominal value to avoid tripping generators and loads. Since the partitions were obtained under 10 seconds, we can confidently say that both of the partitioning methods are efficient for real-time emergency control.

To highlight the advantages of using the most vulnerable typed-graphlets in the partitioning method, we plot in Fig. 4(a) the average accumulated overall percentage of damage that corresponds to different nodes failing randomly for the case

with and without typed graphlets using MATLAB MATCASC toolbox, which simulates the cascading failure of a target line by identifying the overloaded lines and those power islands that are free from any generation source. The overall damage is assessed as a weighted measure of PoDN, CI, and Dam metrics. Fig. 4 shows an average decrease of 11.93% in the overall damage when typed-graphlets are used compared to the case without using typed-graphlets. However, the main advantage of the typed-graphlets is that a complete power blackout is reached with 56 failing PNs versus 22 failing PNs for the case without typed-graphlets, even though the latter one is heavily partitioned. In addition, we compare in Fig. 4(b) the overall damage over the entire power grid when partitioning with typed-graphlets versus without any partitioning. We found an average of 60.67% decrease in the overall damage for the typed-graphlets-based partitioning method compared to the case without any partitioning.

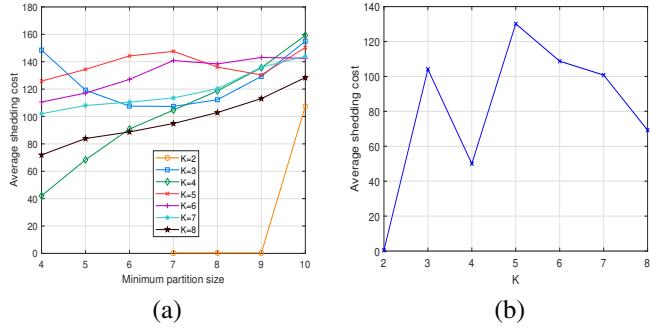


Fig. 2. The relation between (a) load shedding cost and the partition size, and (b) load shedding cost and K for the case when the most vulnerable typed-graphlets are used.

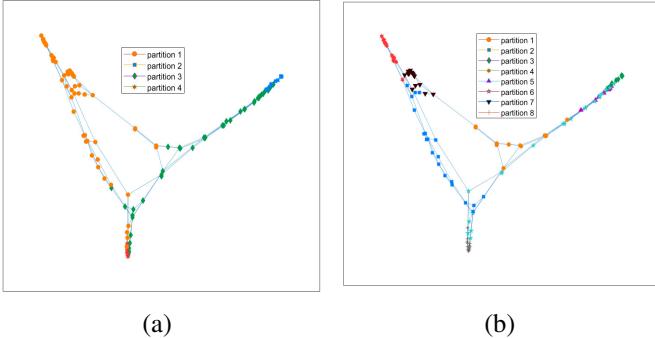


Fig. 3. Power partitions (a) using typed-graphlets, and (b) without using typed-graphlets.

VII. CONCLUSIONS

In this paper, we have proposed a partitioning method for the power system using the most vulnerable typed-graphlets in order to limit the failure impact of large-scale cascading failures. The proposed partitioning method was 61% better in reducing the overall damage compared to the case without any partitioning. As the proposed partitioning method was shown

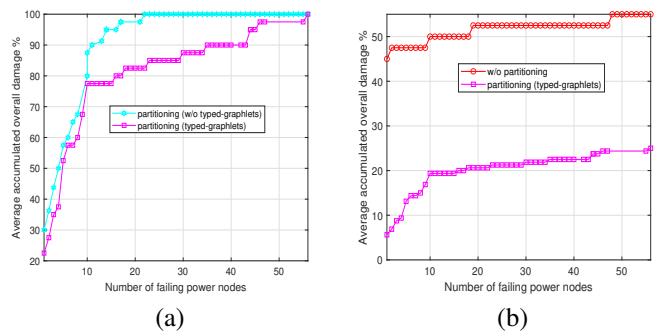


Fig. 4. Comparison of the average overall percentage of damage in the case of a) partitioning with typed-graphlets and without typed-graphlets, and b) partitioning with typed-graphlets and without any partitioning.

to be fast enough for emergency control, it can be used by the system operators to stop the cascading failure propagation, and thus, to avoid a complete blackout. An important problem open for future study is to depict the relationship between the selection of the most critical nodes and the overall damage.

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