2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)

Enabling Online, Dynamic Remedial Action Schemes by Reducing the Corrective Control Search Space

Shamina Hossain-McKenzie
Cyber Resilience R&D
Sandia National Laboratories
shossai@sandia.gov

Eric Vugrin
Cyber Resilience R&D
Sandia National Laboratories
edvugri@sandia.gov

Katherine Davis
ECEN Department
Texas A&M University
katedavis@tamu.edu

***Abstract*—To combat dynamic, cyber-physical disturbances in the electric grid, online and adaptive remedial action schemes (RASs) are needed to achieve fast and effective response. However, a major challenge lies in reducing the computational burden of analyses needed to inform selection of appropriate controls. This paper proposes the use of a role and interaction discovery (RID) algorithm that leverages control sensitivities to gain insight into the controller roles and support groups. Using these results, a procedure is developed to reduce the control search space to reduce computation time while achieving effective control response. A case study is presented that considers corrective line switching to mitigate geomagnetically induced current (GIC) -saturated reactive power losses in a 20-bus test system. Results demonstrated both significant reduction of both the control search space and reactive power losses using the RID approach.**

***Keywords*–cyber-physical system, energy management systems, remedial action schemes, sensitivities, distributed control**

I. Introduction

Energy management systems (EMSs) are used by grid operators to monitor, control, and optimize the performance of the power system; typically, EMSs focus on physical data obtained from the grid, including supervisory control and data acquisition (SCADA) and/or distributed phasor measurement unit (PMU) data. Due to communication advancements, renewable energy integration, and various modernization efforts, the electric grid is transitioning from a predominantly physical infrastructure into a highly cyber-physical system. Diverse smart grid technologies and advancements improve grid operation but also produce new access interfaces, third-party software, and other intricacies. These factors can introduce new vulnerabilities and broaden the threat landscape for adversaries to exploit. Reliance on physical data for situational awareness is no longer adequate for EMSs. EMSs must evolve and incorporate deep understanding of cyber-physical interactions to improve operations, mitigate disturbances, and achieve resilient and safe operations.

The ongoing Department of Energy (DOE) Cybersecurity for Energy Delivery Systems (CEDS) project "Deep Cyber-Physical Situational Awareness for Energy Systems: A Secure Foundation for Next-Generation Energy Management" is developing a next-generation EMS that fuses cyber and physical data and controls to deploy online and automated control actions. Specifically, adaptive remedial action schemes (RASs) are proposed to achieve fast and accurate response to cyber-physical disturbances. That effort has identified the computational burden required to select and deploy effective controls as a significant challenge to online, automated response. For example, when performing corrective line switching to mitigate system losses, an exhaustive search may be needed to determine the set of lines that achieve the highest reduction of losses while converging to a power flow solution. The computational burden of these calculations scales significantly as system size increases.

Previous work in the online RAS domain has researched methods to quicken transient stability analyses. Shrestha et al. sought a dynamic, online RAS that is able to update response control actions according to real-time system operation and topology. They proposed an approach using single machine equivalents and wide-area measurements to compute stability margins for credible contingencies in real-time [1]. Atighechi et al. proposed fast loading RASs using generation patterns of local wind farms by leveraging wide-area monitoring [2]. Their method determined shedding candidates based on load types and their impact on voltage profiles and transient performance. Both approaches focus on online transient stability analyses and the ability to leverage wide-area measurements.

In this work, we propose an alternative method to reduce the computational burden for identifying effective control strategies. This approach processes control sensitivities to compute controller roles and support groups that can be obtained *a-priori*. The resultant controller characterization can augment fast transient stability analysis approaches to help realize a fully online, dynamic RAS.

The structure of this paper is as follows. Section II provides background on RASs and the role and interaction discovery (RID) method developed in [3]. Section III describes how

Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525; This material is based upon work supported by the U.S. Department of Energys Cybersecurity for Electric Delivery Systems (CEDS) project under DE-OE0000895; SAND2020-9402 C; 978-1-7281-6127-3/20/$31.00 ©2020 IEEE.

978-1-7281-6127-3/20/$31.00 ©2020 IEEE

the RID method could be used for automated, corrective line switching responses, and Section IV demonstrates the implementation for a 20-bus system. Section V analyzes this initial application to inform integration into an overall online, cyber-physical RAS.

II. Background

A. Remedial Action Schemes

Presently, RASs are used by utilities to provide automatic mitigations to grid performance violations without operator intervention. Unlike typical protection schemes that focus on system faults, RASs encompass various disturbances including single- and multiple-contingency events [4]. RAS actions include changes to demand, generation, and system topology.

Automated RAS actions are taken only for pre-determined disturbances for which the resultant system conditions are already known or studied and can be automatically sensed. The triggering conditions are unique to the grid system and require careful analysis and high familiarity of system behavior. Similarly, the pre-designed response actions for those sensed conditions/events are developed for the specific system and types of events. The playbook manner deployment of RAS performs well for typical grid disturbances such as component failures, significant faults, and/or sudden generation/load changes. Yet this approach is only suitable for known, pre-determined events with predictable system conditions.

Grid modernization efforts are introducing new access interfaces, third-party software, automation, and new communication functions. These changes are advancing grid capabilities and performance, but also increasing the grid attack surface and introducing new vulnerabilities. Ideally, RAS approaches must extend their focus from typical power system contingencies to disturbances such as cyber attacks and automated grid-support function failure or compromise. Pre-determination and planning in advance for these new disruptions will be extremely difficult, if not impossible, due to the unpredictable nature of these disturbances and the vast number of possible events, which could also included extreme weather events such as severe storms and geomagnetic disturbances that can cause dangerous geomagnetically induced currents (GICs) and require fast, effective response.

B. Role and Interaction Discovery Algorithm

The distributed controller RID algorithm, presented in [3] and summarized in Fig. 1, identifies essential, critical, and redundant controllers for controllability of a system and identifies control support groups. An example of the assigned roles and control support groups for a set of 10 distributed controllers is illustrated in Fig. 2.

- *Essential controllers* are the minimal set of devices required to maintain system controllability; all devices that occur in a minimal-cut set for system controllability are considered essential controllers.
- *Critical controllers* are essential controllers that are irreplaceable and mandatory for system controllability; that is, critical controllers are essential controllers that occur in every minimal-cut controllability set of the system.
- *Redundant controllers* are the devices that reinforce the control capability of essential controllers and can be removed without affecting system controllability.
- *Control support groups* contain devices that are highly coupled in terms of impact on the control objective and with each other.

This section and the following describe the RID approach and how it can be extended to the application of corrective line switching for integration into an online RAS. The challenge for online, automated response is reacting to real-time disturbances while still reducing computational burden such that fast and accurate response is achieved. The RID algorithm aims to help hasten computation by leveraging the discovered roles and control support groups to reduce the line switching solution search space.

The RID algorithm identifies these roles and groups through a 3-step process summarized below. (See [3], [5], [6] for comprehensive details of the algorithm applications to mitigate distributed controller compromise and other case-studies.)

1) Obtaining Sensitivity Matrix $\mathbf{A}''$*:* The RID algorithm determines the roles and groups by processing the target system's control sensitivity matrix, labeled $\mathbf{A}''$ in Fig. 1. The sensitivity matrix must reflect the relationship between the controlled quantity and the control parameter. For example, when assessing generator redispatch, the controlled quantity is the real power flow and the control parameter is the generator setpoint [6]. For the line switching application in this paper, described in Section IV, the line outage distribution factor (LODF) sensitivity matrix is processed using the RID approach.

2) Finding Controllability-Equivalence Sets: The *control support groups* are found by clustering the sensitivity matrix rows to reveal how controls within a set are affected by each other. Cosine similarity between row vectors $\mathbf{v_i}$ and $\mathbf{v_j}$ of $\mathbf{A}''$ or coupling index $\mathbf{CI}$ (1) is used to find coupled sets of lines as clusters that are approximately orthogonal to each other [7].

$$\mathbf{CI} = \mathbf{cos}(\theta_{\mathbf{v_i}\mathbf{v_j}}) = \frac{\mathbf{v_i} \cdot \mathbf{v_j}}{\|\mathbf{v_i}\|\|\mathbf{v_j}\|} \tag{1}$$

These controllability-equivalence sets, or control support groups, are determined through clustering using the coupling index. Hierarchical agglomerative clustering is chosen as it groups data by creating a cluster tree or dendogram; however, any suitable clustering method may be used [3]. A well-known challenge for clustering algorithms (e.g., k-means or k-medoids) is the selection of the number of clusters k [8], [9]. An approach developed by Gavish and Donoho that leverages singular value decomposition to compute an intial estimate of number of clusters is applied to the sensitivity matrix [10]. When considering lines as controls, the line flows within a cluster are decoupled from flows in other clusters. Flows within a cluster are coupled and mutually dependent.

3) Finding Critical, Essential, and Redundant Sets: The *critical*, *essential*, or *redundant* status of a controller is determined by coupling the columns of $\mathbf{A}^{''}$ (rows of $[\mathbf{A}^{''}]^{\mathbf{T}}$). Essential controllers are linearly independent and have the best control range/influence to meet the objective. While some essential controllers are exchangeable with redundant controllers, other essential controllers are critical controllers that lack redundancy. Particularly, Chen et al. [11] defined a critical measurement as a measurement whose elimination from the measurement set results in an unobservable system. A similar approach is applied to identify critical controllers. LU factorization is applied on $[\mathbf{A}^{''}]^{\mathbf{T}}$ to obtain the change of basis, decomposing the transposed sensitivity matrix to lower and upper triangular factors [12]. The following decomposition of $[\mathbf{A}^{''}]^{\mathbf{T}}$ is obtained:

$$[\mathbf{A}^{''}]^{\mathbf{T}} = \mathbf{P}^{-1}\mathbf{L_F}\mathbf{U_b} \tag{2}$$

$$\mathbf{L_F} = \begin{bmatrix} \mathbf{L_b} \\ \mathbf{M} \end{bmatrix} \tag{3}$$

Using Peters-Wilkinson method [12], $[\mathbf{A}^{''}]^{\mathbf{T}}$ is decomposed (Eqn. 2); $\mathbf{P}$ is the permutation matrix and $\mathbf{L_b}$ and $\mathbf{U_b}$ are the lower and upper triangular factors of dimension n, respectively. $\mathbf{M}$ is a sparse, rectangular matrix with rows corresponding to redundant controllers. The new basis has the structure:

$$\mathbf{L_{CER}} = \mathbf{L}_{\beta}{}^{\mathbf{T}} = \mathbf{L_F}\mathbf{L_b^{-1}} = \begin{bmatrix} \mathbf{I_n} \\ \mathbf{R} \end{bmatrix} \tag{4}$$

The new basis, shown in (4), must be full rank for a controllable system and this requires the $m \times (n-1)$ matrix to have a column rank of $(n-1)$ to be a controllable n-bus system with m-measurements. Since $\mathbf{L_b}$ and $\mathbf{U_b}$ will be nonsingular for a controllable system, the rank of $[\mathbf{A}^{''}]^{\mathbf{T}}$ can be confirmed by checking the rank of the transformed factor $\mathbf{L_F}^{\mathbf{T}}$. Also, $\mathbf{L_b}$ has full rank and with (4) multiplied by $\mathbf{L_b^{-1}}$ from the right, the row identities will be preserved in the transformed matrix $\mathbf{L_F}^{\mathbf{T}}$. Each row of the matrix will, therefore, correspond to the respective controllers [11].

Rows of $\mathbf{I_n}$ correspond to essential controls that are sufficient to assure independent controllability of the equivalent line flows. Non-zero entries in the rows of $\mathbf{R}$ correspond to redundant controls. Columns correspond to the equivalent flows which can easily be mapped back to the original flows using the permutation matrix $\mathbf{P}$ obtained from the LU decomposition step.

III. Automating Response using the RID Algorithm

The RID algorithm provides insight into controller roles and interaction groups by leveraging control sensitivities. The control support groups provide information on which controllers work best together in achieving a particular control objective and the controller roles provide information on which controllers require added redundancy and which controllers can provide that redundancy (when available).

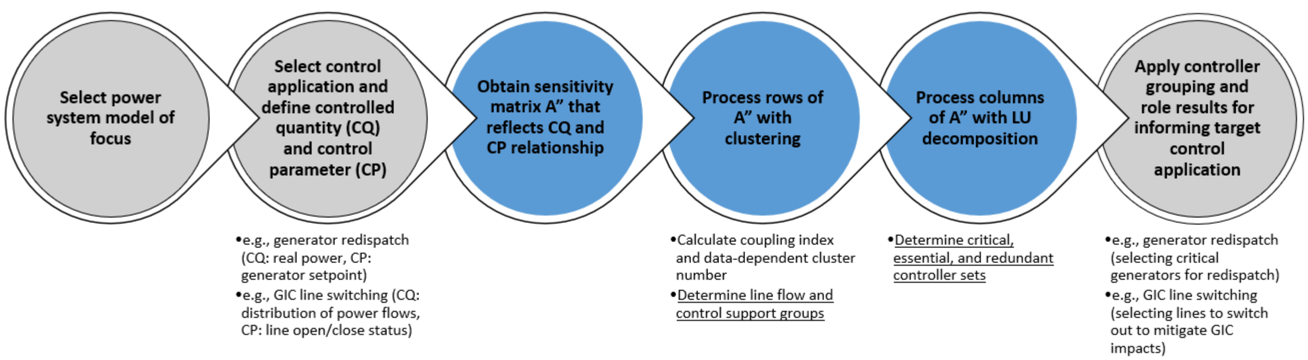

Fig. 1: Controller role and interaction discovery (RID) method applies clustering and factorization to process controller sensitivities (highlighted in blue); the RID algorithm is general to any control application, main requirement is the ability to derive suitable sensitivity matrices.

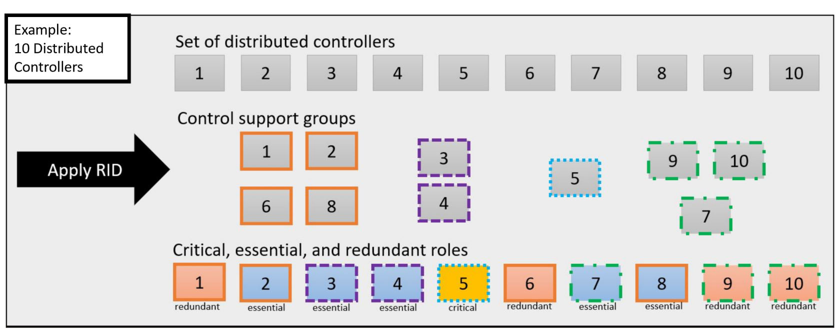

Fig. 2: Example set of 10 distributed controllers for which RID algorithm is applied; control support groups and controller roles are assigned for each controller.

In fact, the controllers can be ranked using the $\mathbf{R}$ matrix obtained in (4) to determine which controllers provide better redundancy/control within the control support group.

Candidate controllers for RID application encompass various distributed controllers such as distributed flexible AC transmission system devices (D-FACTS) and static VAr compensators (SVCs), as well as grid components such as generators, transformer taps, and lines. The RID algorithm's only requirement is a sensitivity matrix that reflects the quantity to be controlled and the control parameter. Thus, grid components such as lines for corrective line switching strategies can be considered where the parameter is whether the line is open or closed and the controlled quantity are the resultant LODFs. This will be expanded upon in later sections.

Demonstration of how the RID algorithm can be used to help automate response to cyber-physical grid disturbances within a next-generation EMS is best explained in the context of a case study. Consider the 20-bus system studied by Kazerooni et al. [13] and shown in Fig. 3. Kazerooni et al. considered corrective line switching as a remedial action for mitigating GICs in power systems. The aim was to reduce GIC-saturated reactive power loss by leveraging linear sensitivity analysis to determine the line switching strategy. Specifically, the transformer line outage distribution factors (TLODFs) were computed and column sums were ranked to determine critical lines. The first C (a user-defined parameter) critical lines, calculated from the initial TLODFs, were utilized in the line selection strategy analysis to reduce the computational complexity.

Kazerooni et al. effectively demonstrated that corrective line switching can be utilized to mitigate GICs in power systems. Their approach to minimize computational burden by selecting the first C critical lines also indicated faster performance than finding a line switching solution from an exhaustive search considering all the lines. Results for the 20-bus system using the critical line approach are shown in Table I. The line names are formatted as $a-b(c)$ where a is the from bus, b is the to bus, and c is the circuit number. However, Kazerooni et al. noted in their paper that their critical line heuristic approach can be naive and ignore corner case solutions that may provide better reactive power loss reduction.

The RID algorithm is specifically designed to not miss these corner cases. Furthermore, the RID algorithm can provide computational efficiencies, especially if control roles and support groups are calculated in advance from the initial LODF sensitivities. With the RID algorithm results calculated *a-priori*, only the power flow solution and GIC-saturated reactive power loss computation need to be iterated to ensure the line switching solution reduces the reactive power loss and the power flow solution converges (as demonstrated in Kazerooni et al.'s paper [13]). The following section describes application of the RID algorithm to the 20-bus system for mitigating GICs.

IV. Case Study: Mitigating GIC-Saturated Reactive Power Losses

Consider the 20-bus system studied by by Kazerooni et al. (Fig. 3) in which an electric field with the magnitude of 8 V/km and the orientation of 124° N is applied to produce the largest GICs for the system. The GIC-saturated reactive power losses resulting from this electric field are 2039.5 MVAr (20.395 pu). This test system was designed specifically for GIC case studies and details of its construction can be found in [14]. This section describes how the RID algorithm can be used to inform automated line switching RASs. Specifically, to understand the relationship between different lines and their coordinated impact on line flows, we will apply the RID algorithm to the LODF matrix of the 20-bus system to determine controller roles and support groups.

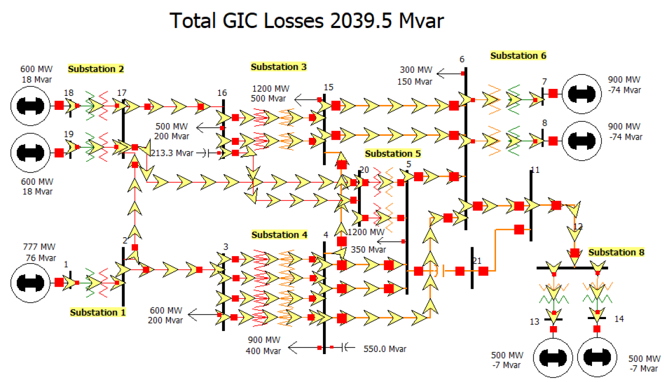

Fig. 3: 20-bus test system designed for GIC analysis [14].

A. Sensitivity Matrix Derivation

Line outage distribution factors (LODFs) are sensitivities that provide a measure of how a change in a line's status (open/close) affects flows on other lines. Specifically, for an energized line, LODFs provide the percentage of present line flow that will appear on other lines after the outage of the line [15]. A LODF matrix was constructed using only viable lines for line switching; thus, no lines with transformers or connections to generators were included.

B. Controller Support Group and Role Derivation

With the LODF sensitivity matrix shown in Table II, the RID algorithm was applied to compute the controller roles and control support groups. First, the suitable number of clusters is computed using the optimal hard threshold method; for the 20-bus system, the threshold was computed to be

TABLE I: GIC-Saturated Reactive Power Loss Reduction Results for 20-Bus System using Kazerooni et al. [13] method.

Lines Out	Lines (Kazerooni et al.)	Q Loss	PF Soln. ?
1	4-5(1)	18.16 pu	Yes
2	4-5(1), 4-5(2)	15.24 pu	Yes
3	4-5(1), 4-5(2), 4-6	12.34 pu	Yes

TABLE II: LODF sensitivity matrix for 20-bus system.

Line	2-3(1)	17-2(1)	4-5(1)	4-5(2)	4-6(1)	15-4(1)	5-6(1)	5-21(1)	6-11(1)	15-6(1)	15-6(2)	21-11(1)	16-17(1)	16-20(1)	17-20(1)
2-3(1)	-100	-100	-24.71	-24.71	-12.72	37.87	-0.53	-0.43	0.43	6.84	6.84	-0.43	-56.71	5.16	43.29
17-2(1)	-100	-100	-24.71	-24.71	-12.72	37.87	-0.53	-0.43	0.43	6.84	6.84	-0.43	-56.71	5.16	43.29
4-5(1)	-5.75	-5.75	-100	53.85	16.25	-24.14	-18.67	-14.93	14.93	8.67	8.67	-14.93	-0.59	7.39	5.16
4-5(2)	-5.75	-5.75	53.85	-100	16.25	-24.14	-18.67	-14.93	14.93	8.67	8.67	-14.93	-0.59	7.39	5.16
4-6(1)	-5.05	-5.05	27.69	27.69	-100	-39.57	30.74	24.59	-24.59	22.34	22.34	24.59	-3.54	-1.55	1.5
15-4(1)	10.98	10.98	-30.06	-30.06	-28.91	-100	-23.86	-19.09	19.09	35.93	35.93	-19.09	12.37	15.76	1.4
5-6(1)	-0.14	-0.14	-21.66	-21.66	20.94	-22.25	-100	43.98	-43.98	17.54	17.54	43.98	-3.57	-9.27	-3.43
5-21(1)	-0.13	-0.13	-19.52	-19.52	18.86	-20.04	49.53	-100	100	15.81	15.81	-100	-3.22	-8.35	-3.09
6-11(1)	0.13	0.13	19.52	19.52	-18.86	20.04	-49.53	100	-100	-15.81	-15.81	100	3.22	8.35	3.09
15-6(1)	1.94	1.94	10.57	10.57	15.97	35.18	18.42	14.74	-14.74	-100	50.87	14.74	4.65	9.31	2.7
15-6(2)	1.94	1.94	10.57	10.57	15.97	35.18	18.42	14.74	-14.74	50.87	-100	14.74	4.65	9.31	2.7
21-11(1)	-0.13	-0.13	-19.52	-19.52	18.86	-20.04	49.53	-100	100	15.81	15.81	-100	-3.22	-8.35	-3.09
16-17(1)	-45.35	-45.35	-2.03	-2.03	-7.14	34.14	-10.58	-8.46	8.46	13.09	13.09	-8.46	-100	39.68	-54.65
16-20(1)	3.04	3.04	18.7	18.7	-2.31	32.05	-20.22	-16.17	16.17	19.35	19.35	-16.17	29.25	-100	26.21
17-20(1)	38.78	38.78	19.85	19.85	3.39	4.32	-11.37	-9.1	9.1	8.54	8.54	-9.1	-61.22	39.83	-100

TABLE III: Control support group results for 20-bus system.

Cluster	Line	R Col. Sum	Critical?
1	15-6(1)	0.4288	No
1	15-6(2)	0.4288	No
1	4-5(1)	0.4907	No
1	4-5(2)	0.4907	No
1	4-6	0.9545	No
1	15-4	1.2886	No
2	17-2	1.5686	No
2	17-20	2.3573	No
2	2-3	2.9388	No
2	16-17	4.2743	No
3	16-20	3.8831	No
4	6-11	0	Yes
4	5-6	0.6383	No
4	5-21	2.4291	No
4	21-11	5.1656	No

TABLE IV: GIC-Saturated Reactive Power Loss Reduction Results for Ranked Cluster Lines for 20-Bus System using RID algorithm.

Cluster	Ranked Line	R Col. Sum	Q Loss	PF Soln. ?
1	15-6(1)	0.4288	17.513 pu	Yes
2	17-2	1.5686	20.424 pu	Yes
3	16-20	3.8831	20.015 pu	Yes
4	6-11	0	20.078 pu	Yes

4. Next, k-means clustering was applied using the cosine distances of the LODF matrix and $k = 4$.

The resulting clusters are provided in Table III: the cluster assignment for each line is shown as well as that line's $\mathbf{R}$ column sum (R Col. Sum) derived from (2). The column sums of $\mathbf{R}$ indicate the level of redundancy for each line. Lines with lower $\mathbf{R}$ column sum values are better able to provide the target control than those with higher column sum values. This information is used to rank the order to switch out lines within a cluster, ensuring that the most effective lines to reduce the GIC-saturated reactive power loss are utilized first. Further details on using the $\mathbf{R}$ column sums for ranking can be found in [5].

Next, the resulting clusters' silhouette values are shown in Fig. 4. Silhouette values help measure an element's similarity to other members of its cluster, and its difference from members of other clusters. Higher, positive values indicate suitable cluster membership (range is [-1,1]); the plot shown in Fig. 4 indicates similar, positive silhouette values for most of the elements (i.e., lines). Lastly, the roles are calculated by applying the LU decomposition approach to the transposed LODF sensitivity matrix. Table III also lists whether or not a line was found to be critical; for the 20-bus system, only line 6-11 was found to be critical.

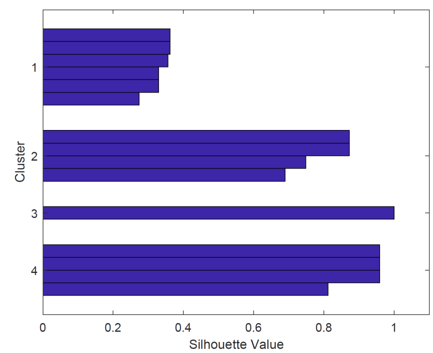

Fig. 4: Silhouette values for control support group clusters.

C. Loss Reduction Results

With the control support groups and roles calculated for the lines in the 20-bus system using the LODF sensitivity matrix, insight into the relationships between different lines is obtained. This can aid selection of which lines to switch out and in what order for line switching strategies, reducing computational burden. The following approach was developed to utilize the RID algorithm results for line switching:

1) Select the lowest $\mathbf{R}$ column sum line from each cluster and compute the GIC-saturated reactive power loss reduction and power flow solution (check convergence).
2) Select the cluster whose lowest $\mathbf{R}$ column sum line produced the highest loss reduction to be initial line switching strategy search space.
3) Iterate through cluster members, ranked from lowest to highest $\mathbf{R}$ column sums, and compute loss reduction and check power flow convergence.
4) If power flow solution converges and loss continues to be reduced, add ranked lines from cluster with second lowest $\mathbf{R}$ column sum from 1) and continue.
5) If power flow no longer converges, select set of lines that produced largest loss reduction and deploy as response to GIC disturbance.

Table IV displays the initial cluster selection step where the the lowest $\mathbf{R}$ column sum line from each cluster was chosen and the loss was computed. Line 15-6(1) produced the highest loss reduction and, thus, Cluster 1 was chosen as the initial line switching strategy search space.

TABLE V: GIC-Saturated Reactive Power Loss Reduction Results for 20-Bus System using RID algorithm.

Lines Out	Lines (RID Alg.)	Q Loss	PF Soln. ?
1	15-6(1)	17.513 pu	Yes
2	15-6(1), 15-6(2)	13.754 pu	Yes
3	15-6(1), 15-6(2), 4-5(1)	12.361 pu	Yes
4	15-6(1), 15-6(2), 4-5(1), 4-5(2)	9.71 pu	Yes
5	15-6(1), 15-6(2), 4-5(1), 4-5(2) , 4-6	-	No
5	15-6(1), 15-6(2), 4-5(1), 4-5(2), 15-4	-	No

Next, the ranked lines within Cluster 1 were iterated through and the loss reduction and power flow solution were computed as lines were added, as shown in Table V. The power flow solution converged up to a total of 4 lines outaged and thus the highest, feasible reduction was found to be with lines 15-6(1), 15-6(2), 4-5(1), and 4-5(2).

Compared to the critical line heuristic approach by Kazerooni et al. (Table I), the RID algorithm approach achieved greater loss reduction for one and two lines outaged (18.16 pu vs. 17.513 pu and 15.24 pu vs. 13.754 pu, respectively). Three lines outaged produced similar results (12.34 pu vs. 12.361 pu). These results indicate that by considering all the lines initially and only downselecting using the RID insight into control support groups, corner cases with better loss reduction were not ignored. Furthermore, as the RID roles and control support groups were calculated *a-priori* (not during the GIC contingency), the downselection could be computed in advance. Kazerooni et al.'s entire algorithm (including line switching set search iterations and power flow solution calculation) took about 0.41 seconds with a critical line set of 16 lines. The RID computation, which can be performed online or offline, took about 0.075 seconds and considered 15 lines. These computations were both performed on a Microsoft Surface Book system with Intel Core i7-6600U, 16GB RAM. These results indicate that the RID computation combined with the iterative power flow calculation would have similar, if not less, computation time with greater loss reduction.

V. Conclusions

Knowledge of controller roles and support groups can aid informing response quickly and effectively and ultimately help reduce the computational burden of online RAS methods. In this paper, a case study for corrective line switching strategies was explored to mitigate GIC-saturated reactive power losses. Compared to heuristic-based approaches, the RID algorithm demonstrated superior performance for reducing the line search space and obtaining greater loss reduction.

For online RAS approaches that consider actions other than line switching, the RID algorithm approach can aid reducing control search space by leveraging the controllability analysis based role and control support group results. In future work, case studies that leverage the controller roles ($critical$ vs. $essential$ vs. $redundant$) precisely will be explored as well as different controls.

Specifically, the combination of different controls (e.g., line switching and load shedding) will be investigated. With a range of different controls and insight into their roles and control support groups, the RID algorithm can aid faster, effective computation of response to facilitate online RASs. Online, dynamic RASs would aid the development of a next-generation EMS that is able to operate an increasingly cyber-physical system and combat both predictable and unpredictable disturbances.

Acknowledgments

The authors would like to acknowledge the valuable help provided by Dr. Maryam Kazerooni for understanding the heuristic critical line approach presented in [13] and the indispensable support from Dr. Thomas Overbye for conducting GIC analyses.

References

[1] A. Shrestha, V. Cecchi, and R. W. Cox, "Dynamic remedial action scheme using online transient stability analysis," in *2014 North American Power Symposium (NAPS)*, 2014, pp. 1–6.

[2] "An effective load shedding remedial action scheme considering wind farms generation," *International Journal of Electrical Power and Energy Systems*, vol. 95, pp. 353 – 363, 2018.

[3] S. Hossain-McKenzie, K. Davis, M. Kazerooni, S. Etigowni, and S. Zonouz, "Distributed controller role and interaction discovery," in *2017 19th International Conference on Intelligent System Application to Power Systems (ISAP)*, Sept 2017, pp. 1–6.

[4] "WECC Remedial Action Scheme Design Guide," White Paper, WECC, 2016.

[5] S. S. Hossain-McKenzie, "Protecting the power grid: strategies against distributed controller compromise," Ph.D. dissertation, University of Illinois at Urbana-Champaign, 2017.

[6] M. Kazerooni, S. Hossain-McKenzie, S. Etigowni, S. Zonouz, and K. Davis, "Fast generation redispatch techniques for automated remedial action schemes," *IEEE IEEE Transactions on Smart (Under Review)*, 2017.

[7] K. Rogers, R. Klump, H. Khurana, and T. Overbye, "Smart-grid - enabled load and distributed generation as a reactive resource," in *Innovative Smart Grid Technologies (ISGT), 2010*, Jan. 2010, pp. 1–8.

[8] J. A. Hartigan and M. A. Wong, "Algorithm as 136: A k-means clustering algorithm," *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, vol. 28, no. 1, pp. 100–108, 1979.

[9] H.-S. Park and C.-H. Jun, "A simple and fast algorithm for k-medoids clustering," *Expert Systems with Applications*, vol. 36, no. 2, pp. 3336–3341, 2009.

[10] M. Gavish and D. Donoho, "The optimal hard threshold for singular values is $\frac{4}{\sqrt{3}}$," *IEEE Transactions on Information Theory*, vol. 60, no. 8, pp. 5040–5053, Aug. 2014.

[11] J. Chen and A. Abur, "Placement of PMUs to enable bad data detection in state estimation," *Power Systems, IEEE Transactions on*, vol. 21, no. 4, pp. 1608–1615, Nov. 2006.

[12] G. Peters and J. H. Wilkinson, "The least squares problem and pseudo-inverses," *The Computer Journal*, vol. 13, no. 3, pp. 309–316, 1970.

[13] M. Kazerooni, H. Zhu, and T. J. Overbye, "Mitigation of geomagnetically induced currents using corrective line switching," *IEEE Transactions on Power Systems*, vol. 33, no. 3, pp. 2563–2571, 2018.

[14] R. Horton, D. Boteler, T. J. Overbye, R. Pirjola, and R. C. Dugan, "A test case for the calculation of geomagnetically induced currents," *IEEE Transactions on Power Delivery*, vol. 27, no. 4, pp. 2368–2373, 2012.

[15] J. D. Glover, M. S. Sarma, and T. Overbye, *Power system analysis & design, SI version*. Cengage Learning, 2012.