Supplementary Files for Safe Inverter-Based Voltage Control in Microgrids with Reachability Constrained Decentralized Reinforcement Learning

I. CONFIGURATIONS OF TEST SYSTEMS

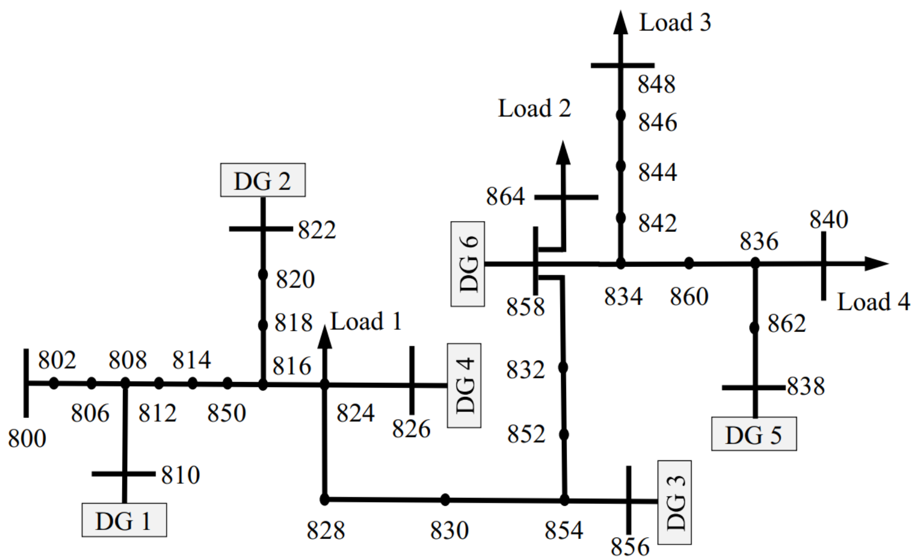

Fig. 1. Topology of 6-inv. system [1].

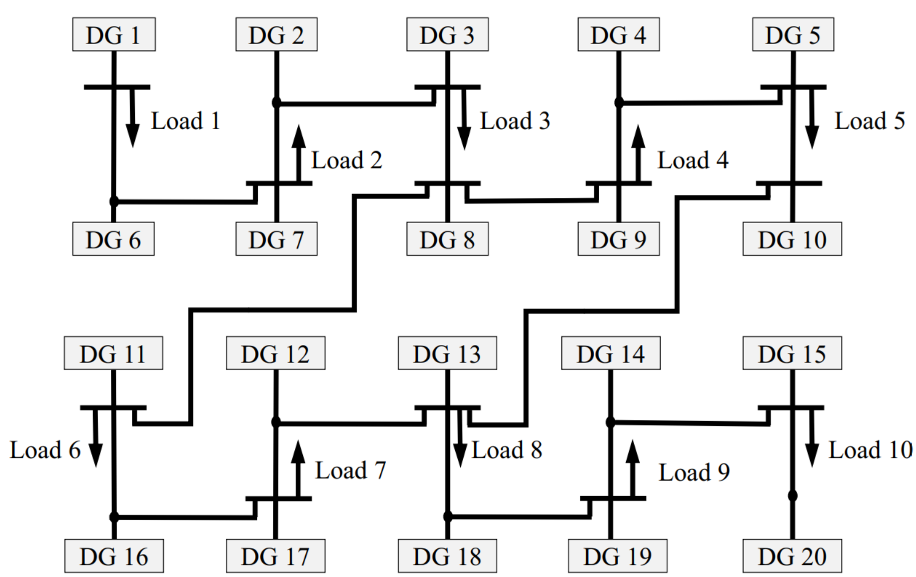

Fig. 2. Topology of 20-inv. system [1].

II. Discussions on the Impact of Several External Factors

A. PV Penetration Rate

The impact of increasing PV penetration rate on system control performance is both highly significant and inherently complex. On the one hand, higher PV penetration inevitably reduces the share of conventional generators, thereby diminishing system inertia. Moreover, the inherent stochasticity and intermittency of PV generation pose additional challenges to voltage and frequency regulation. On the other hand, PV inverters offer superior controllability and fast response capabilities; when equipped with advanced control strategies or coordinated with energy storage, they can even outperform traditional generators in certain control tasks. Consequently, this issue embodies an intrinsic tradeoff, i.e., balancing destabilizing uncertainties against enhanced flexibility. In response to this issue, existing literature presents different perspectives. Some studies argue that renewable energy resources must be integrated with conventional generators to ensure system stability [3], [4]. Others, based on engineering demonstrations, show that 100% PV based control is achievable through advanced control strategies [5]. Additionally, certain scholars have used modeling and data-driven analysis to suggest that as penetration increases, the impact of adverse disturbances (such as extreme weather events) on the system may first decrease and then increase, forming a non-monotonic trend [6]. Therefore, this issue remains a subject of active debate and ongoing investigation within the research community. Given its complexity and the lack of consensus, we cannot draw a definitive conclusion at this stage for our work.

B. Disturbance Magnitude

We set the disturbance magnitude during offline training as 100% and evaluated the control performance of the proposed method MARCSAC under online disturbances of 100% (as in the original tests), 105%, 110%, 120%, 130%, 140%, and 150%. The test results are presented below:

TABLE I
Execution Performance of Proposed Methods Under Different Disturbances

Case	Disturbance	Total reward		Total violation	
		Mean	Std.	Mean	Std.
6-inv. system	100%	-2.24	0.279	0.00	0.00
	105%	-2.50	0.273	0.00	0.00
	110%	-2.70	0.236	1.12e-04	8.41e-04
	120%	-2.99	0.205	4.32e-03	8.50e-03
	130%	-3.22	0.258	2.29e-02	2.94e-02
	140%	-3.47	0.338	6.74e-02	8.90e-02
	150%	-3.76	0.422	0.169	0.218
20-inv. system	100%	-4.75	0.272	0.00	0.00
	105%	-4.94	0.296	2.29e-05	3.49e-04
	110%	-5.17	0.323	2.50e-04	2.55e-03
	120%	-5.76	0.463	4.22e-03	2.11e-02
	130%	-6.57	0.651	3.48e-02	9.10e-02
	140%	-7.60	0.837	0.146	0.251
	150%	-8.75	1.02	0.421	0.522

It can be observed that the control performance is satisfactory when the disturbance magnitude is small or falls within the range encountered during offline training. However, as the disturbance increases, voltage violations begin to occur. For example, voltage violations emerge at 110% disturbance magnitude and become very severe at 130%. This behavior stems from two primary reasons: first, when the disturbance exceeds the microgrid's inherent capacity to absorb it, violations become inevitable no matter what control strategies are executed; second, if the RL agents have not been exposed to such disturbance magnitudes during offline training, its control policy degrades accordingly.

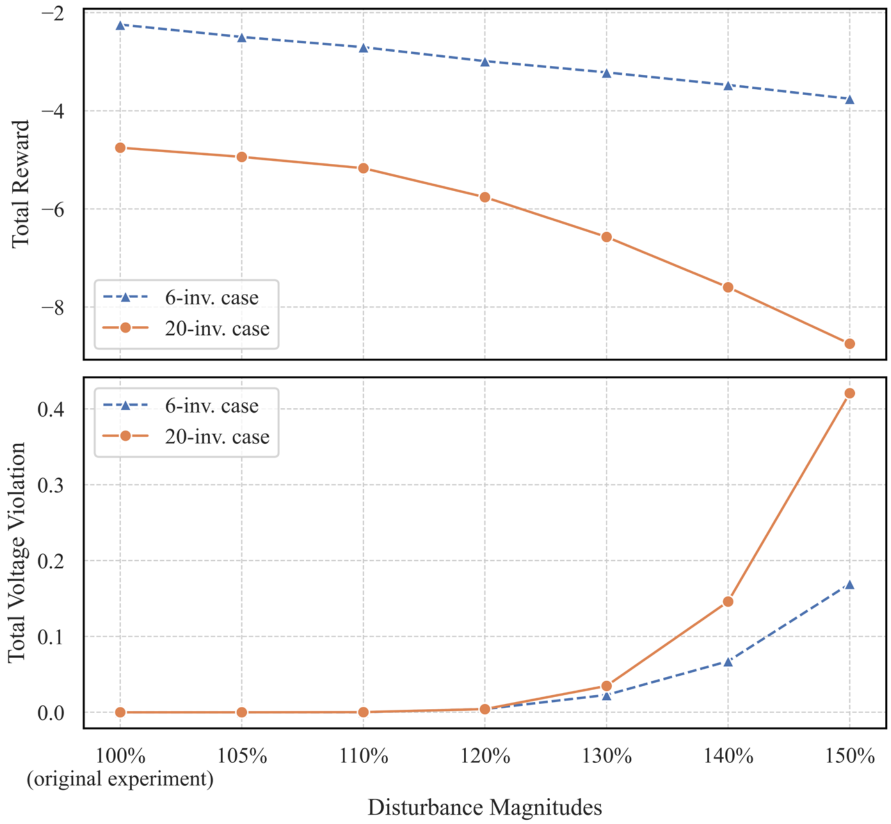

Fig. 3. Execution Performance of Proposed Methods Under Different Disturbances.

REFERENCES

[1] D. Chen, K. Chen, Z. Li *et al.*, "PowerNet: Multi-Agent Deep Reinforcement Learning for Scalable Powergrid Control," *IEEE Transactions on Power Systems*, vol. 37, no. 2, pp. 1007-1017, Mar. 2022.

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