Multi-stage Transmission Line Flow Control Using Centralized and Decentralized Reinforcement learning Agents

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NEURAL INFORMATION PROCESSING SYSTEMS

Introduction

Planning future operational scenarios of bulk power systems that meet security and economic constraints typically requires intensive labor efforts in performing massive simulations. To augment this process and relieve engineers' burden, a novel multi-stage DRL approach is presented in this work.

- Stage one: centralized soft actor-critic (SAC) agent is trained to control generator active power outputs in a wide area to control transmission line flows against specified security limits.
- Stage two: If line overloading issues remain unresolved, decentralized SAC agents via load throw-over at local substations.

Problem Formulation

To maintain the safety of power grid, **Quasi-Steady-State(QSS)** conditions need to be met at all time under power grid system physics constraints.

The control objective is to minimize the difference between transmission line flow to its physics constraint value at various contingencies.

$$min \sum_{n=1}^{N} \left[P_n - P_{n\_limit} \right]$$

For stage one, **the control action** is to adjusting generators of whole power environment.
For stage two, **the control action** is to adjusting loads power of local area.

The reward function is defined to evaluate the safety of transmission lines in the system, it includes base reward and contingency reward.

$$r = r_{base} + r_{con}$$

$$r_{base} = a \sum_{k=1}^{N} \left[max(|P_{from}|, |P_{to}|) - bP_{limit} \right]$$

$$r_{con} = a \sum_{k=1}^{N} \sum_{l=1}^{N-1} \left[max(|P_{from}|, |P_{to}|) - bP_{limit} \right]$$

Notations: N: total transmission lines, P: transmission line flows, V: voltage magnitude of buses, G: generators active power, D: loads power.

Proposed Approach

We propose a multi-stage DRL control approach to regulate transmission line flow under contingencies. The offline training process is to learn the agent control strategy, while the online using process is to test our system.

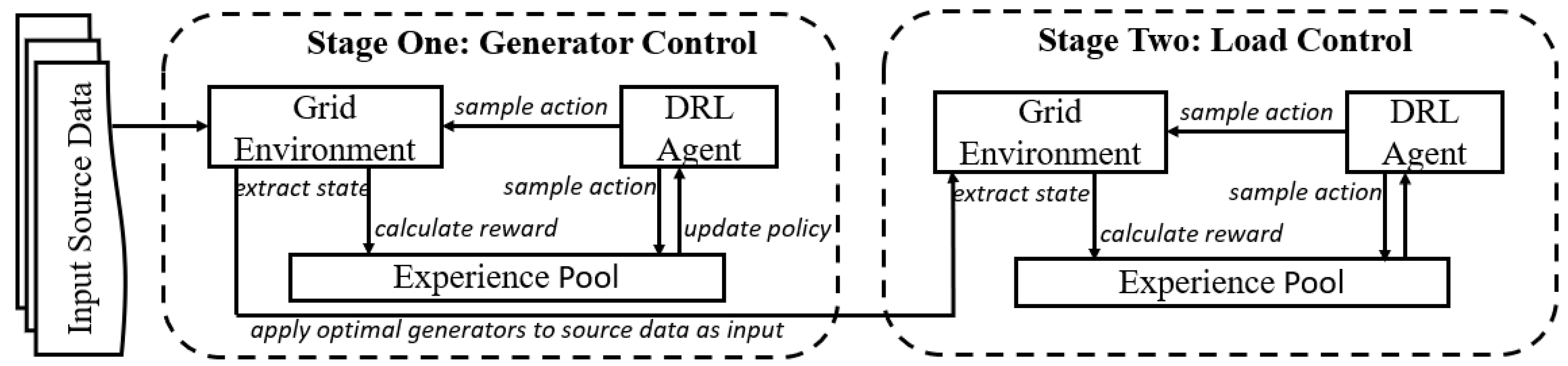

Fig 1: Offline training process

Fig 1 shows the online training process, there are two stages: generator control stage and load control stage.

In generator control stage, the objective is to get an optimal policy to control generator values to keep QSS under contingencies.
The state space $\mathbf{S_g = [P, V, G]}$, the action space $\mathbf{A_g = [G]}$.
If QSS could not reach after stage one, there should be overloading issue exists in local area of the current environment, and stage two is activated.
In load control stage, the objective is to train an optimal policy to redistribute the loads in the local area to keep QSS under contingencies.
The state space $\mathbf{S_d = [P, V, D]}$, the action space $\mathbf{A_d = [D]}$.

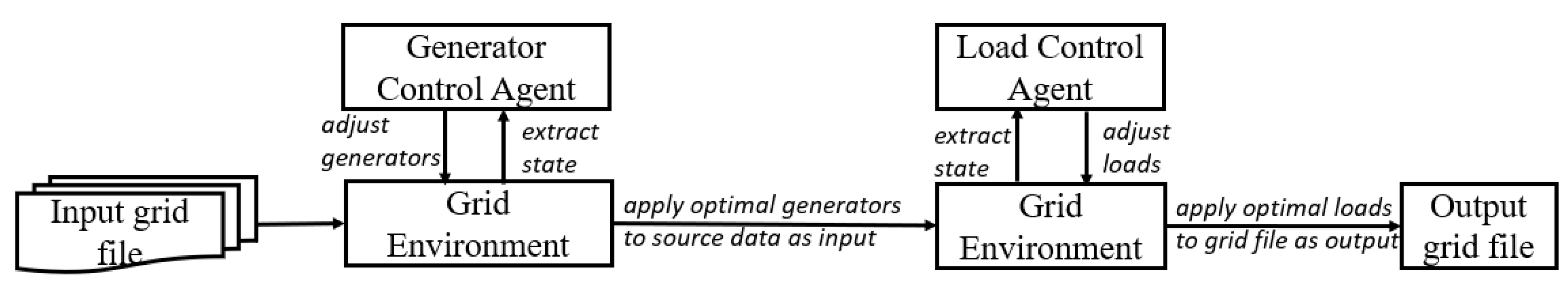

Fig 2: Online using process

Fig2 shows the online using process, the trained policies will be applied to generator control agent and load control agent, respectively.

Agents control process: the input grid file will be updated by generator control agent, if QSS still not reach, the load control agent will redistribute the loads in local unsolved area and output the grid file which could stay secured against contingency.

Experiments and Results

The experiment environment used in our study is power grid planning models, which are generally used for creating future operational scenarios of a real power system.

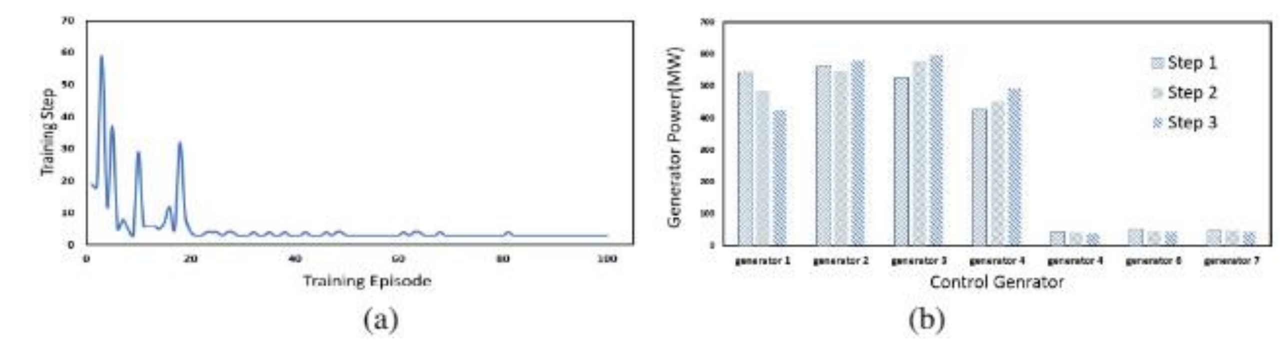

Fig 3: Results of generator control stage in first experiment

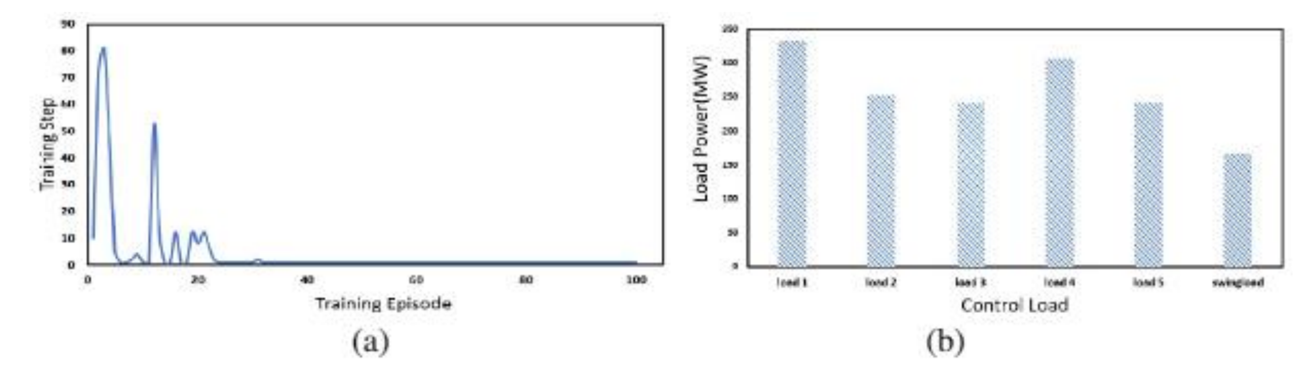

Fig 4: Results of load control stage in second experiment

Results: both experiments show the effectiveness of solving transmission line flow control problem under contingencies with our approach.

For future work: our approach could be further expanded to different local areas using the second stage control.

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