Safe Reinforcement Learning for Emergency Load Shedding of Power Systems

Thanh Long Vu, Member, IEEE, Sayak Mukherjee, Member, IEEE, Tim Yin, Renke Huang, Member, IEEE, Jie Tan, and Qiuhua Huang, Member, IEEE

Abstract—The paradigm shift in the electric power grid necessitates a revisit of existing control methods to ensure the grid's security and resilience. In particular, the increased uncertainties and rapidly changing operational conditions in power systems have revealed outstanding issues in terms of either speed, adaptiveness, or scalability of the existing control methods for power systems. On the other hand, the availability of massive real-time data can provide a clearer picture of what is happening in the grid. Recently, deep reinforcement learning (RL) has been regarded and adopted as a promising approach leveraging massive data for fast and adaptive grid control. However, like most existing machine learning (ML)-based control techniques, RL control usually cannot guarantee the safety of the systems under control. In this paper, we introduce a novel method for safe RL-based load shedding of power systems that can enhance the safe voltage recovery of the electric power grid after experiencing faults. Numerical simulations on the 39-bus IEEE benchmark is performed to demonstrate the effectiveness of the proposed safe RL emergency control, as well as its adaptive capability to faults not seen in the training.

Index Terms—Emergency voltage control, learning-based load shedding, safe reinforcement learning, safety-constrained augmented random search.

I. INTRODUCTION

The electric power grid, the largest man-made system, has been experiencing a transformation to an even more complicated system with an increased number of distributed energy sources and more active and less predictable load endpoints. At the same time, intermittent renewable generation introduces high uncertainty into system operation and may compromise power system stability and security. The existing control operations and modeling approaches, which are largely developed several decades ago for the much more predictable operation of a vertically integrated utility with no uncertainty, have revealed outstanding issues in terms of either speed, adaptiveness, or scalability. Load shedding is well known, and hopefully stabilize the system. These emergency control measures historically make the electrical power grid reasonably stable to disturbances. However, with the increased uncertainties and rapidly changing operational conditions in power systems, the existing emergency control methods have exposed outstanding issues in terms of either speed, adaptiveness, or scalability. Load shedding is well known, among the measures of emergency voltage control, as an effective countermeasure against voltage instability [5]. It has been widely adopted in the industry, mostly in the form of rule-based undervoltage load shedding (UVLS). The UVLS relays are usually employed to shed load demands at substations in a step-wise manner if the monitored bus voltages fall below the predefined voltage thresholds. ULVS relays have a fast response, but do not have communication or coordination among substations, leading to unnecessary load shedding [6] at affected substations.

Recently, data-driven approaches have been getting investigated to tackle the voltage instability phenomenon in ways less dependent on the model and more adaptive to contingencies. [7] proposed a decision tree based approach for preventive and corrective control actions. For load shedding against fault-induced delayed voltage recovery (FIDVR) events, [8] developed a hierarchical extreme-learning machine based algorithm. Reinforcement learning (RL) based approaches are also applied to voltage control problem in works such as [9]–[11]. In this approach, the machine agent interacts with the system/environment, observes the resulting system state and the corresponding reward, and updates the control actions in a way to maximize the reward which is defined to encourage the voltage stability constraint [9].

Over the last decade, a variety of RL algorithms have been developed, which mainly use the Markov decision process (MDP) based framework. In our previous work, we have designed a deep Q learning based RL control [9] for emergency load shedding in response to voltage stability issues of the electric power grid. Subsequently, we developed an accelerated Augmented Random Search (ARS) algorithm in [11] to quickly train the neural network-based control policy in a parallel computing mechanism. This approach, sketched in Section III, is implemented on a high-performance computing platform in a novel nested parallel architecture using the Ray framework. This architecture allowed parallelizing power grid dynamic simulations in the ARS training and helped exploring the parameter space of the control policy efficiently and adapting ARS to multiple tasks.
quickly train the neural network-based control policy in a parallel computing mechanism. The common root of these two works is the reinforcement learning (RL), which was extensively developed last some decades using the Markov decision process (MDP) based framework.

In the general RL framework, an RL agent interacts with the system/ environment, observes the resulting system state and the corresponding reward, and updates the control actions in a way to maximize the reward. Mathematically, we define a policy search problem in a (partially observable) MDP defined by a tuple $(S,A,P,r,\gamma)$ [12]. The state space $S$ and action space $A$ could be continuous or discrete. In this paper, both of them are continuous. The environment transition function $P : S \times A \rightarrow S$ is the probability density of the next state $s_{t+1} \in S$ given the current state $s_t \in S$ and action $a_t \in A$. At each interaction step, the environment returns a real reward $r : S \times A \rightarrow R$. $\gamma \in (0,1)$ is the discount factor. The standard RL objective is to maximize the expected sum of discounted rewards. Many RL algorithms have been developed in the literature such as value iteration based algorithms like deep Q learning policy gradient based algorithms like deep deterministic policy gradient (DDPG) optimization influenced algorithms such as trust region policy optimization (TRPO) actor-critic methods such as soft actor-critic (SAC), etc.

In the ARS algorithm, that we used in [11], the ARS agent performs parameter-space exploration and estimates the gradient of the expected reward using sampled rollouts to update the control policy. In particular, for the above load shedding problem, the ARS agent’s objective is to maximize the expected reward, where the reward $r_i$ at time $t$ was defined as follows:

$$r(t) = \begin{cases} -1000 & \text{if } V_i(t) < 0.95, \ T_{pf} + 4 < t \\ c_1 \sum_j \Delta V_j(t) - c_2 \sum_j \Delta P_j(p.u.) - c_3 u_{ivld}, & \text{otherwise,} \end{cases}$$

(1)

where,

$$\Delta V_i(t) = \begin{cases} \min(V_i(t) - 0.7, 0), & \text{if } t \in (T_{pf}, T_{pf} + 0.33) \\ \min(V_i(t) - 0.8, 0), & \text{if } t \in (T_{pf} + 0.33, T_{pf} + 0.5) \\ \min(V_i(t) - 0.9, 0), & \text{if } t \in (T_{pf} + 0.5, T_{pf} + 1.5) \\ \min(V_i(t) - 0.95, 0), & \text{if } t > T_{pf} + 1.5. \end{cases}$$

In the reward function (1), $T_{pf}$ is the time instant of fault clearance; $V_i(t)$ is the voltage magnitude for bus $i$ in the power grid; $\Delta P_j(t)$ is the load shedding amount in p.u. at time step $t$ for load bus $j$; invalid action penalty $u_{ivld}$ if the DRL agent still provides load shedding action when the load at a specific bus has already been shed to zero at the previous time step when the system is within normal operation. $c_1$, $c_2$, and $c_3$ are the weight factors for the above three parts.

Furthermore, to scale up the ARS algorithm and reduce the training time, we accelerated it by leveraging its inherent parallelism and implementing it on a high-performance computing platform in a novel nested parallel architecture using the Ray framework. This architecture allowed parallelizing power grid dynamic simulations in the ARS training and
which we will check the safety conditions in each iteration.

Ldescent method to get the optimum value of both optimization problem. As such, we can use the dual gradient dual function
\[ L \]
for the safety violation [14]. which can be approximately solved by putting a high penalty reward, and at the same time, satisfies the safety requirement defined by \( f(s_t, a_t, t) \geq 0 \). A natural approach that was extensively used in the literature [13] is to formulate this problem as the following constrained optimization
\[
\max_{a_t \in A} E[r(s_t, a_t)] \\
\text{s.t. } E[f(s_t, a_t, t)] \geq 0.
\]
which can be approximately solved by putting a high penalty for the safety violation [14].

In this paper, we proposed a different approach in which we consider the Lagrangian function
\[
L(\pi, \lambda) = E[r(s_t, a_t)] + \lambda E[f(s_t, a_t, t)] = E[r(s_t, a_t)] + \lambda f(s_t, a_t, t)
\]
where \( \lambda > 0 \) is the safety multiplier. Since in the original optimization we have the constraint \( f(s_t, a_t, t) \geq 0 \), the dual gradient descent method to get the optimum value of both \( L(\pi, \lambda) \) and the safety multiplier \( \lambda \), in which we maximize \( L(\pi, \lambda) \) when \( \lambda \) is fixed as in the standard ARS algorithm and minimize \( L(\pi, \lambda) \) by using gradient method to find the optimal value of \( \lambda \). In other words, the objective of the safe ARS agent is to learn an optimal policy \( \pi^*(s_t, a_t) \) from a min-max problem on the Lagrangian function
\[
(\pi^*, \lambda^*) = \arg\max_{\pi \in \Pi} \arg\min_{\lambda > 0} L(\pi, \lambda)
\]
For simplicity, we also proposed a more heuristic approach to find the suboptimal value of the safety multiplier \( \lambda \), in which we will check the safety conditions in each iteration.

If the safety constraint is not violated in the iteration, we reduce the value of \( \lambda \) two times. Otherwise, we increase the value of \( \lambda \) two times. Algorithm 1 presents the steps to compute the optimal control policy and safety multiplier.

Similar to the standard ARS algorithm [11], the safe ARS learner is an actor at the top to delegate tasks and collect returned information, and controls the update of policy weights \( \theta \) and the safety multiplier \( \lambda \). The learner communicates with subordinate workers and each of these workers is responsible for one or more perturbations (random search) of the policy weights as in Step 4. In Steps 7, the ARS learner combines the results from each worker calculated in Step 5 (which include the average reward of multiple rollouts and safety violation check), sorts the directions according to the reward, selects the best-performing directions. Then, in Step 8, the ARS learner updates the policy weights and the safety multiplier \( \lambda \) centrally based on the perturbation results from the top performing workers. The workers do not execute environment rollout tasks by themselves. They spawn a number of actors and assign these tasks to these subordinate actors. Note that each worker needs to collect the rollout results (which include the reward function, safety function, and safety violation check) from multiple tasks inferring with the same perturbed policy, and each actor is only responsible for one environment rollout with the specified task and perturbed policy sent by its up-level worker. For the environment rollouts, power system dynamic simulations are performed in parallel.

### IV. Test Results

We consider the IEEE benchmark 39-bus, 10-generator model, showed in Fig. 2. The simulations were performed in the Linux mainframe with 27 cores. The power system simulator was implemented in the GridPack and the safe deep RL algorithm was implemented in the python platform. We built a software setup such that the grid simulations in the GridPack and the RL iterations in the python can coordinate.

We tested the performance of our safe ARS algorithm on the IEEE 39-bus system to learn a closed-loop control

1 https://www.gridpack.org
Algorithm 1 Safe ARS (sARS) for Load Shedding

1. **Hyperparameters:** Step size $\alpha$, number of policy perturbation directions per iteration $N$, standard deviation of the exploration noise $\nu$, number of top-performing perturbed directions selected for updating weights $b$, number of rollouts per perturbation direction $m$. Decay rate $\epsilon$.

2. **Initialize:** Policy weights $\theta_0$ with small random numbers; initial safety multiplier in the reward function $\lambda_0$, the running mean of observation states $\mu_0 = 0 \in \mathbb{R}^n$ and the running standard deviation of observation states $\Sigma_0 = I_n \in \mathbb{R}^{n \times n}$, where $n$ is the dimension of observation states, the total iteration number $H$.

   for iteration $t \leq H$ do

   3. Sample $N$ number of random directions $\delta_1, \ldots, \delta_N \in \mathbb{R}^n$ with the same dimension as policy weights $\theta$.

   for each $\delta_i, i = 1, \ldots, N$ do

   4. Add perturbations to policy weights: $\theta_{t+} = \theta_{t-1} + \nu \delta_i$ and $\theta_{t-} = \theta_{t-1} - \nu \delta_i$.

   5. Do total $2m$ rollouts (episodes) denoted by $R_{p \in T}(\cdot)$ for different tasks $p$ sampled from task set $T$ corresponding to $m$ different faults with the $\pm$ perturbed policy weights. Calculate safety functions for all $\pm$ perturbations and calculate the average rewards of $m$ rollouts as the rewards for $\pm$ perturbations, i.e., $\bar{R}_{t+}$ and $\bar{R}_{t-}$ are

   $\quad \bar{R}_{t+} = \frac{1}{m} R_{p \in T}(\theta_{t+}, \mu_{t-1}, \Sigma_{t-1}), \quad (8)$

   $\quad \bar{R}_{t-} = \frac{1}{m} R_{p \in T}(\theta_{t-}, \mu_{t-1}, \Sigma_{t-1}) \quad (9)$

   where the reward function $R$ is defined as the combined reward function in (4), i.e., $R(\cdot) = r(s_t, a_t) + \lambda_t f(s_t, a_t, t)$.

   6. During each rollout, states $s_{t,k}$ at time step $k$ are first normalized and then used as the input for inference with policy $\pi_{\theta_i}$ to obtain the action $a_{t,k}$, which is applied to the environment and new states $s_{t,k+1}$ is returned, as shown in (3). The running mean $\mu_t$ and standard deviation $\Sigma_t$ are updated with $s_{t,k+1}$

   $\quad s_{t,k} = \frac{s_{t,k} - \mu_{t-1}}{\Sigma_{t-1}}, \quad (10)$

   $\quad a_{t,k} = \pi_{\theta_i}(s_{t,k}), \quad (11)$

   $\quad s_{t,k+1} \leftarrow \mathcal{P}(s_{t,k}, a_{t,k}), \quad (12)$

   end for

   7. Sort the directions based on $\max (\bar{R}_{t+}, \bar{R}_{t-})$, select top $b$ directions, calculate their standard deviation $\sigma_b$.

   8. Update the policy weight:

   $\quad \theta_{t+1} = \theta_t + \frac{\alpha}{b \sigma_b} \sum_{i=1}^{b} (\bar{R}_{t+} - \bar{R}_{t-}) \delta_i \quad (13)$

   9. Step size $\alpha$ and standard deviation of the exploration noise $\nu$ decay with rate $\epsilon$: $\alpha \leftarrow \epsilon \alpha$, $\nu \leftarrow \epsilon \nu$.

   10. Update of the safety multiplier: Check the safety violation for all the rollouts. If there is any safety violation: $\lambda_{t+1} \leftarrow 2 \lambda_t$. Otherwise: $\lambda_{t+1} \leftarrow \lambda_t/2$.

   end for

return 11. Return $\theta$, and $\lambda$. 

Fig. 3. Standard ARS-based emergency load shedding response to the fault that happens at bus 4.

Fig. 4. Safe ARS-based emergency load shedding response to the fault that happens at bus 4.
For comparison with the standard ARS-based emergency control, we also train it with the same set of faults and deploy it to react the same fault at bus 4. The performances of standard ARS-based load shedding and safe ARS-based load shedding are depicted in Figs. 3 and 4. From these figures, we can observe that the safe ARS-based load shedding is better than the standard ARS-based load shedding in meeting the safety requirement described by the transient voltage recovery criterion depicted in Fig. 1. In particular, with the normal ARS-based load shedding, the voltages at buses 7, 8, and 18 do not recover to 0.9 p.u. within 0.5s after the fault-cleared time, and the voltages at buses 8 and 18 do not recover to 0.95 p.u. within 1.5s after the fault-cleared time. Yet, the safe-ARS load shedding makes the voltages at all buses 4, 7, 8, 18 recover well as required.

To test the adaptation of the safe ARS, we consider a fault not encountered during the training, in which short-circuit fault happens at bus 7 at 1.0s with a fault duration of 0.15s and then the fault self-cleared. The performances of standard ARS-based load shedding and safe ARS-based load shedding are depicted in Figs. 5 and 6. From these figures, we can observe that the safe ARS-based load shedding is better than the standard ARS-based load shedding not only in meeting the safety requirement described by the transient voltage recovery criterion, but also in adapting to a fault not encountered during the training.

V. CONCLUSIONS

In this paper, we presented a highly scalable and safe deep reinforcement learning algorithm for power system voltage stability control using load shedding. This algorithm inherits the parallelism of the ARS algorithm and thereby achieve high scalability and applicability for power system stability control applications. Furthermore, by incorporating the safety function into the reward function, the safe ARS algorithm resulted in a control policy that could enhance the safety of the electric power grid during the load shedding. A small number of hyper-parameters makes this algorithm easy to tune to achieve good performance. Case studies on the IEEE 39-bus demonstrated that safe ARS-based load shedding successfully recovers the voltage of power systems even in events it did not see during the training. In addition, in comparison to the standard ARS-based load shedding, it showed advantages in both safety level and fault adaptability.

REFERENCES

[1] E. F. Camacho, T. Samad, M. Garcia-Sanz, and I. Hiskens, “Control for renewable energy and smart grids,” The Impact of Control Technology, Control Systems Society, pp. 69–88, 2011.
[2] D. Chen, S. Liu, and X. Ma, “Modeling, nonlinear dynamical analysis of a novel power system with random wind power and it’s control,” Energy, vol. 53, pp. 139–146, 2013.
[3] A. J. Wood and B. F. Wollenberg, Power Generation Operation and Control (2nd Edition). John Wiley & Sons, 1996, vol. 37, no. 3.
[4] V. Vittal, Emergency Control and Special Protection Systems In Large Electric Power Systems. Boston, MA: Birkhäuser Boston, 2003, pp. 293–314.
[5] C. W. Taylor, “Concepts of undervoltage load shedding for voltage stability,” IEEE Transactions on Power Delivery, vol. 7, no. 2, pp. 480–488, 1992.
[6] H. Bai and V. Ajjarapu, “A novel online load shedding strategy for mitigating fault-induced delayed voltage recovery,” IEEE Transactions on Power Systems, vol. 26, no. 1, pp. 294–304, 2011.
[7] I. Genc, R. Diao, V. Vittal, S. Kolluri, and S. Mandal, “Decision tree-based preventive and corrective control applications for dynamic security enhancement in power systems,” IEEE Transactions on Power Systems, vol. 25, no. 3, pp. 1611–1619, 2010.
[8] Q. Li, Y. Xu, and C. Ren, “A hierarchical data-driven method for event-based load shedding against fault-induced delayed voltage recovery in power systems,” IEEE Transactions on Industrial Informatics, vol. 17, no. 1, pp. 699–709, 2020.
[9] Q. Huang, R. Huang, W. Hao, J. Tan, R. Fan, and Z. Huang, “Adaptive power system emergency control using deep reinforcement learning,” IEEE Transactions on Smart Grid, vol. 11, no. 2, pp. 1171–1182, 2020.
[10] J. Zhang, C. Lu, C. Fang, X. Ling, and Y. Zhang, “Load shedding scheme with deep reinforcement learning to improve short-term voltage stability,” in 2018 IEEE Innovative Smart Grid Technologies Asia (ISGT Asia). IEEE, 2018, pp. 13–18.
[11] R. Huang, Y. Chen, T. Yin, X. Li, A. Li, J. Tan, and Q. Huang, “Accelerated deep reinforcement learning based load shedding for emergency voltage control,” arXiv 2006.12667, 2020.
[12] R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction. Cambridge, MA, USA: A Bradford Book, 2018.
[13] J. García and F. Fernández, “A comprehensive survey on safe reinforcement learning,” Journal of Machine Learning Research, vol. 16, no. 42, pp. 1437–1480, 2015. [Online]. Available: [http://jmlr.org/papers/v16/garcia15a.html](http://jmlr.org/papers/v16/garcia15a.html)
[14] Y. Kadota, M. Kurano, and M. Yasuda, “Discounted markov decision processes with utility constraints,” *Computers and Mathematics with Applications*, vol. 51, no. 2, pp. 279 – 284, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0898122105004657