Safe Reinforcement Learning for Grid Voltage Control

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Abstract

Under voltage load shedding has been considered as a standard approach to recover the voltage stability of the electric power grid under emergency conditions; yet this scheme usually trips a massive amount of load inefficiently. Reinforcement learning (RL) has been adopted as a promising approach to circumvent the issues; however, RL approach usually cannot guarantee the safety of the systems under control. In this paper, we discuss a couple of novel safe RL approaches, namely constrained optimization approach and Barrier function-based approach, that can safely recover voltage under emergency events. This method is general and can be applied to other safety-critical control problems. Numerical simulations on the 39-bus IEEE benchmark are performed to demonstrate the effectiveness of the proposed safe RL emergency control.

1 Introduction

Voltage instability is one of the major causes of power blackouts [Australian Energy Market Operator, 2017]. Rule-based under-voltage load shedding (UVLS) is a standard emergency control to deal with voltage instability [Taylor, 1992]. Though this method is effective and fast, the lack of coordination among substations can lead to unnecessary load shedding [Bai and Ajjarapu, 2011]. Recently, reinforcement learning (RL) approaches [Sutton and Barto, 2018, Mnih et al., 2013, Lillicrap et al., 2016, Schulman et al., 2017, 2015] has been successfully developed for emergency voltage control, while significantly reducing the amount of load shedding [Huang et al., 2020, Zhang et al., 2018, Huang et al., 2020].

Though multiple RL methods were developed in the literature, the safety of the system under RL control is paid relatively less attention. In this paper, we discuss our two recently proposed distinct approaches for safe emergency voltage control, namely the constrained optimization approach [Vu et al., 2020] and Barrier function-based approach [Vu et al., 2021]. In the constrained optimization-based safe RL method, the RL agent searches for the optimal control policy that maximizes the reward function, while obeying the safety constraint. In the Barrier function-based approach, a Barrier function is included into the reward function to guide the searching of the optimal control policy that can render the voltage to avoid safety bounds.

In a related work [Cheng et al., 2019], model-based control Barrier Lyapunov function was used to design a control to compensate for the model-free reinforcement learning control in order to ensure the safety of the system. One limitation of this work lies on the limited scalability of the on-line learning of unknown system dynamics, and thus, this method was only demonstrated in simple...
We use an accelerated Augmented Random Search (ARS) algorithm [Huang et al., 2020] to quickly
consider the RL formulation for the emergency voltage control of power systems with a (partially
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accordingly, the safe RL problem is to design a RL algorithm in which the RL agent learns over the
action space an optimal control policy that maximizes the expected reward function, while obeying
for load bus \( j \). The states during the dynamic events along with reward \( r: \mathbb{R} \times \mathbb{R} \to \mathbb{R} \), and the discount factor \( \gamma \in (0, 1) \).

Safety bounds: In the load shedding problem, the objective is to recover the voltages of the electric
power grid after the faults so that the post-fault voltages will recover according to the standard
recovery profile as shown in the Fig. 1. In particular, the standard requires that, after fault clearance,
voltages should return to at least 0.8, 0.9, and 0.95 p.u. within 0.33s, 0.5s, and 1.5s. The states of
the power grid should obey these time-dependent bounds. Let us denote the safety set \( C_i \subseteq \mathbb{R}^n \) for
the \( i^{th} \) time interval \( t \in T_i \) after faults, then we would require,

\[
s_t \in C_i, \quad t \in T_i.
\]

Observation space: Accessing all the dynamic states of the power system is a difficult task, and
the operators can only measure a limited number of states and outputs. For the voltage control
problem, the bus voltage magnitudes \( V_i(t) \) are easily measurable, and therefore, considered in the the
observation space, along with remaining percentage of loads. Please note that with slight abuse of
notations, we continue to denote partially observable states or the outputs by \( s_t \).

Action space: We consider controllable loads as actuators where load shedding locations are generally
set by the utilities by solving a rule-based optimization problem for secure grid operation. We consider
the operator can shed upto 20\% of the total load at a particular bus at any given time instant. The
action space is continuous with \([-0.2, 0]\) range where \(-0.2\) denotes the 20\% load shedding.

Accordingly, the safe RL problem is to design a RL algorithm in which the RL agent learns over the
action space an optimal control policy that maximizes the expected reward function, while obeying
the safety bounds of power system voltages.

We use an accelerated Augmented Random Search (ARS) algorithm [Huang et al., 2020] to quickly
train the neural network-based control policy in a parallel computing mechanism as our algorithmic
framework even before imposing any safety considerations. The ARS agent performs parameter-space
exploration and estimates the gradient of the expected reward using sampled rollouts to update the
control policy. In the load shedding problem, the objective is to recover the voltages of the electric
power grid after the faults so that the post-fault voltages will recover according to the standard
as shown in Fig. 1. In particular, for the load shedding enabled voltage control problem, the ARS agent’s
objective is to maximize the expected reward, where the reward \( r_t \) at time \( t \) was defined as follows:

\[
r(t) = \begin{cases} 
-1000 & \text{if } \ V_i(t) < 0.95, \quad T_{pf} + 4 < t \\
\phantom{-1000} + c_1 \sum_i \Delta V_i(t) - c_2 \sum_j \Delta P_j(p.u.) - c_3 u_{load}, & \text{otherwise}, 
\end{cases}
\]
invalid action penalty \(u_{\text{valid}}\) 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.

![Figure 1: Safety bounds of voltages due to the transient voltage recovery criterion for transmission system](image)

**3 Safe Reinforcement Learning Approaches**

We discuss two of our recently proposed safe RL approaches for emergency voltage control. The baseline RL algorithm used for both of the methodologies is a parallelized version of augmented random search (ARS) [Mania et al., 2018] developed for power system control [Huang et al., 2020].

### 3.1 Constrained optimization approach

The safety requirement of the power grid can be defined by a constraint on a time-dependent safety function \(f(s_t, a_t, t)\), i.e., the system is safe if \(f(s_t, a_t, t) \geq 0\). For the voltage safety requirement, the following time-dependent safety function can be used:

\[
f(s_t, a_t, t) = \begin{cases} 
0.42 - \max_i(V_i(t) - 1.1)^2 & \text{if } T_{pf} < t < T_{pf} + 0.33, \\
0.35^2 - \max_i(V_i(t) - 1.15)^2 & \text{if } T_{pf} + 0.33 < t < T_{pf} + 0.5, \\
0.32 - \max_i(V_i(t) - 1.2)^2 & \text{if } T_{pf} + 0.5 < t < T_{pf} + 1.5, \\
0.275^2 - \max_i(V_i(t) - 1.225)^2 & \text{if } t > T_{pf} + 1.5.
\end{cases}
\]

where \(V_i(t)\) is the bus voltage magnitude for bus \(i\) in the power grid. The constraint \(f(s_t, a_t, t) \geq 0\) will ensure the voltage will recover as in the criterion (Fig. 1). The goal of a safe ARS agent is to learn the optimal control policy that maximizes the expected 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 [García and Fernández, 2015] is to formulate this problem as the following constrained optimization

\[
\max_{a_t \in A} E[r(s_t, a_t)] \quad \text{s.t.} \quad E[f(s_t, a_t, t)] \geq 0.
\]

which can be approximately solved by putting a high penalty for the safety violation [Kadota et al., 2006].

In this paper, we proposed a different approach in which we consider the Lagrangian function

\[
\mathbf{L}(\pi, \lambda) = E[r(s_t, a_t)] + \lambda E[f(s_t, a_t, t)] = E[r(s_t, a_t)] + \lambda f(s_t, a_t, t)
\]

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 function \(\mathbf{L}(\pi, \lambda)\) is an upper bound for the original optimization problem. As such, we can use the dual gradient descent method to get the optimum value of both \(\mathbf{L}(\pi, \lambda)\) and the safety multiplier \(\lambda\), in which we maximize \(\mathbf{L}(\pi, \lambda)\) when \(\lambda\) is fixed as in the standard ARS algorithm and minimize \(\mathbf{L}(\pi, \lambda)\) 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 \(\pi^*_a(s_t, a_t)\) from a min-max problem on the Lagrangian function

\[
(\pi^*, \lambda^*) = \arg\max_{\pi \in \mathcal{A}} \arg\min_{\lambda > 0} \mathbf{L}(\pi, \lambda)
\]


3.2 Barrier Function-based Safe ARS for Emergency Load Shedding

In the proposed method, the reward function is included with a Barrier function that will go to minus infinity when the system state tends to the safety bounds. Accordingly, the following time-dependent Barrier function can be used:

\[
B(s_t, t) = \begin{cases} 
\sum_i 1/(V_i(t) - 0.7)^2 & \text{if } T_{pf} < t < T_{pf} + 0.33, \\
\sum_i 1/(V_i(t) - 0.8)^2 & \text{if } T_{pf} + 0.33 < t < T_{pf} + 0.5, \\
\sum_i 1/(V_i(t) - 0.9)^2 & \text{if } T_{pf} + 0.5 < t < T_{pf} + 1.5, \\
\sum_i 1/(V_i(t) - 0.95)^2 & \text{if } t > T_{pf} + 1.5.
\end{cases}
\]  

(7)

where \( V_i(t) \) is the bus voltage magnitude for bus \( i \) in the power Now, the reward function we consider in the safe ARS algorithm is as follows:

\[
R(t) = r(t) - c_4 B(s_t, t),
\]  

(8)

where \( r(t) \) is the reward, \( B(s_t, t) \) is defined in (7), and \( c_4 > 0 \) is a weight factor.

Safety Considerations: In this safe ARS algorithm, as the ARS agent learns the optimal control policy that maximizes the reward function, in each iteration it will search over the control policy space and select, among several directions, the best-performance policies where the reward function is highest. Also, when going to the next iteration, the control policy is updated by the surrogate gradient-like method on the reward function. As such, the reward function is increasing in expectation during the update of control policy. Hence, during the exploration and update of the control policy, the reward function cannot tend to minus infinity. As a result, the Barrier function cannot tend to minus infinity during the exploration and update of the control policy. Therefore, the safety bounds of system state are not violated during the searching process of the optimal control policy.

Mathematically, in the ARS-based learning process for the optimum control policy, the expected reward is lower bounded. This means that, along the trajectory of the agent state, there is only a zero-measure set of samples in which the reward function can go to infinity. Hence, the reward function is bounded almost surely, i.e., \( P\{R_t > -\infty, \forall t\} = 1 \). Hence, the Barrier function is also bounded almost surely along the trajectory \( s(t) \). We note that when \( s(t) \) goes through the safety bounds, then the Barrier function will go to minus infinity. Therefore, we can conclude that the voltages will not violate the safety bounds almost surely.

3.3 Algorithmic Description of Safe RL for Voltage Control

Algorithm 1 describes the constrained optimization based approach, and algorithm 2 presents the optimal control design by the Barrier function-based safe ARS method described hereby.

- The safe ARS learner is an actor at the top to delegate tasks and collect returned information, and updates policy weights \( \theta \). For the algorithm 1, it also controls the update of 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 Step 7, the ARS learner combines the results from each worker calculated in Step 5 (which include the average reward of multiple rollouts), sorts the directions according to the reward, selects the best-performing directions.
- Then, in Step 8, for both of the algorithms, the ARS learner updates the policy weights centrally based on the perturbation results from the top performing workers. For Algorithm 1, in Step 10, the safety multiplier \( \lambda \) is centrally updated based on the perturbation results, and checking the safety violations. For simplicity, we proposed a more heuristic approach to find the sub-optimal 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.
- 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 from multiple tasks inferring with the same perturbed policy,
Algorithm 1 Constrained Optimization based Safe ARS:

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: $\theta_{t+1} = \theta_{t-1} + \nu \delta_i$ and $\theta_{t-1} = \theta_{t-1} - \nu \delta_i$.

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., $\bar{R}_{t+1}$ and $\bar{R}_{t-1}$ are

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

   $\bar{R}_{t-1} = \frac{1}{m} R_{p \in T}(\theta_{t-1}, \mu_{t-1}, \Sigma_{t-1})$, \hspace{1cm} (10)

   where the reward function $R$ is defined as the combined reward function in (5), 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 $s_{t,k+1}$

   $s_{t,k} = \frac{s_{t,k} - \mu_{t-1}}{\Sigma_{t-1}}$, \hspace{1cm} (11)

   $a_{t,k} = \pi_{\theta_i}(s_{t,k})$, \hspace{1cm} (12)

   $s_{t,k+1} \leftarrow P(s_{t,k}, a_{t,k})$, \hspace{1cm} (13)

end for

7. Sort the directions based on $\max(\bar{R}_{t+1}, \bar{R}_{t-1})$, select top $b$ directions, calculate their standard deviation $\sigma_b$.

8. Update the policy weight:

   $\theta_{t+1} = \theta_t + \frac{\alpha}{b \sigma_b} \sum_{i=1}^{b} (\bar{R}_{t+1} - \bar{R}_{t-1}) \delta_i$, \hspace{1cm} (14)

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 $\lambda$. 
Algorithm 2 Barrier function-based safe ARS:

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; initialize the running mean of observation states $\mu_0 = 0 \in \mathbb{R}^n$ and the running standard deviation of observation states $\Sigma_0 = I_n \in \mathbb{R}^{n}$, 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 $R_{p \in T}()$ for different tasks $p$ sampled from task set $T$ corresponding to $m$ different faults with the $\pm$ perturbed policy weights. Calculate the average rewards of $m$ rollouts as the rewards for $\pm$ perturbations, i.e., $\bar{R}_{t+}$ and $\bar{R}_{t-}$ are

   $${\bar{R}}_{t+} = \frac{1}{m} R_{p \in T} (\theta_{t+}, \mu_{t-1}, \Sigma_{t-1})$$ \hspace{1cm} (15)

   $${\bar{R}}_{t-} = \frac{1}{m} R_{p \in T} (\theta_{t-}, \mu_{t-1}, \Sigma_{t-1})$$ \hspace{1cm} (16)

   where the reward function $R$ is defined as the combined reward function in [8].

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 $\pi_{\theta_t}$ 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 $s_{t,k+1}$

   $$s_{t,k} = \frac{s_{t,k} - \mu_{t-1}}{\Sigma_{t-1}},$$ \hspace{1cm} (17)

   $$a_{t,k} = \pi_{\theta_t}(s_{t,k}),$$ \hspace{1cm} (18)

   $$s_{t,k+1} \leftarrow P(s_{t,k}, a_{t,k}),$$ \hspace{1cm} (19)

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:

   $$\theta_{t+1} = \theta_t + \frac{\alpha}{b \sigma_b} \sum_{i=1}^{b} (\bar{R}_{t+} - \bar{R}_{t-}) \delta_i$$ \hspace{1cm} (20)

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

end for

return 10. Return $\theta$.

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.

4 Test Results

We perform simulations in the IEEE benchmark 39-bus, 10-generator model as in Fig. 2. The simulations performed in a Linux mainframe with 27 cores. The power system simulator runs using GridPack[2] and the safe deep RL algorithm is implemented in a separate platform using Python. A

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[2]https://www.gridpack.org
software setup has been built such that the grid simulations in the GridPack and the RL iterations in the python can communicate.

The policy generates required optimized load shedding actions at buses 4, 7, and 18 to meet the voltage recovery requirements. Observations included voltage magnitudes at buses 4, 7, 8, and 18 as well as the remaining fractions of loads served by buses 4, 7, and 18. The control action for buses 4, 7, and 18 at each action time step was a continues variable from 0 (no load shedding) to \(-0.2\) (shedding 20\% of the initial total load at the bus). We fix a the task set \(T\) consisting of nine different tasks (fault scenarios) for the training purposes. The fault scenarios began with the flat start in the dynamic simulation. At 1.0 s, we apply short circuit faults at one of the bus 4, 15, or 21 with a fault duration of 0.0 s (no fault), 0.15 s, or 0.28 s and the fault was self-cleared.

When there is no additional feedback control implemented in the system, we can observe voltage recovery profile largely violates the required recovery bounds as in Fig. 3. Fig. 7 shows the performance comparison between standard ARS-based RL scheme and under-voltage load shedding (UVLS ) for a test task with 0.08 s of fault at bus 3, where the voltage with UVLS control (green curve) at bus 4 could not recover while standard-ARS based control (blue curve) could recover to meet the standard. Although standard ARS based RL outperforms the traditional UVLS schemes, it may still encounter safety issues due to the lack of dedicated safety measures. The performances of the standard ARS-based load shedding and safe RL-based emergency control are depicted in Figs. 4-6 for fault at bus 4 with 0.15s duration. These figures show that the safe RL-based load shedding can perform much 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, without any Safety consideration based RL design, the voltages at buses 7, 8, and 18 could not recover to 0.9 p.u. within 0.5s after the fault clearance, 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-based load shedding using both the methods 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 using constrained optimization and Barrier-function based approaches are depicted in Figs. 8-10 substantiating our designs.

5 Conclusions

In this paper, we discussed two safe deep reinforcement learning approaches for power system voltage stability control using load shedding. Remarkably, by incorporating a constrained optimization and a Barrier function into the reward function, the safe ARS algorithm resulted in a control policy that could prevent the system state from violating the safety bounds, and hence, enhance the safety of the electric power grid during the load shedding. Case studies on the IEEE 39-bus demonstrated that safe ARS-based load shedding scheme successfully recovers the voltage stability 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.

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Figure 3: Voltage drops after fault happens at bus 4 without any emergency control measures.

Figure 4: Voltage profile under the standard ARS-based emergency load shedding.

Figure 5: Voltage profile under the constrained optimization emergency load shedding response.

Figure 6: Voltage profile under the Barrier function-based emergency load shedding.

Figure 7: Effectiveness of the ARS-based RL scheme.

Figure 8: Voltage profile under the standard ARS-based emergency load shedding after fault happens at bus 7.

Figure 9: Voltage profile under the constrained optimization emergency load shedding response after fault happens at bus 7.

Figure 10: Voltage profile under the Barrier function-based emergency load shedding after fault happens at bus 7.
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