Bayesian Optimization for Deep Reinforcement Learning (DRL) for Robust Volt-VAR Control

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Motivation & Research Objective

- The high penetration of renewable energy into the power grid introduces complexity to the operation and optimization of energy.
- The objective is to enhance the performance and robustness of VVC using Bayesian optimization (BO) within the DRL framework.
- It accelerates the DRL model training process and BO within DRL is also resource intensive.

Research Objective:

- ➢ Develop a Bayesian-optimized DRL framework for VVC for optimal policies.
- ➢ Proposed hyperparameters optimization, specifying the bounds and constraints of search space and utilizing Expected Improvement (EI) acquisition function to effectively balance exploration and exploitation during optimization.
- ➢ Performed an impact analysis to determine the effectiveness of the DRL performance on the IEEE-13 and IEEE-123 bus systems.

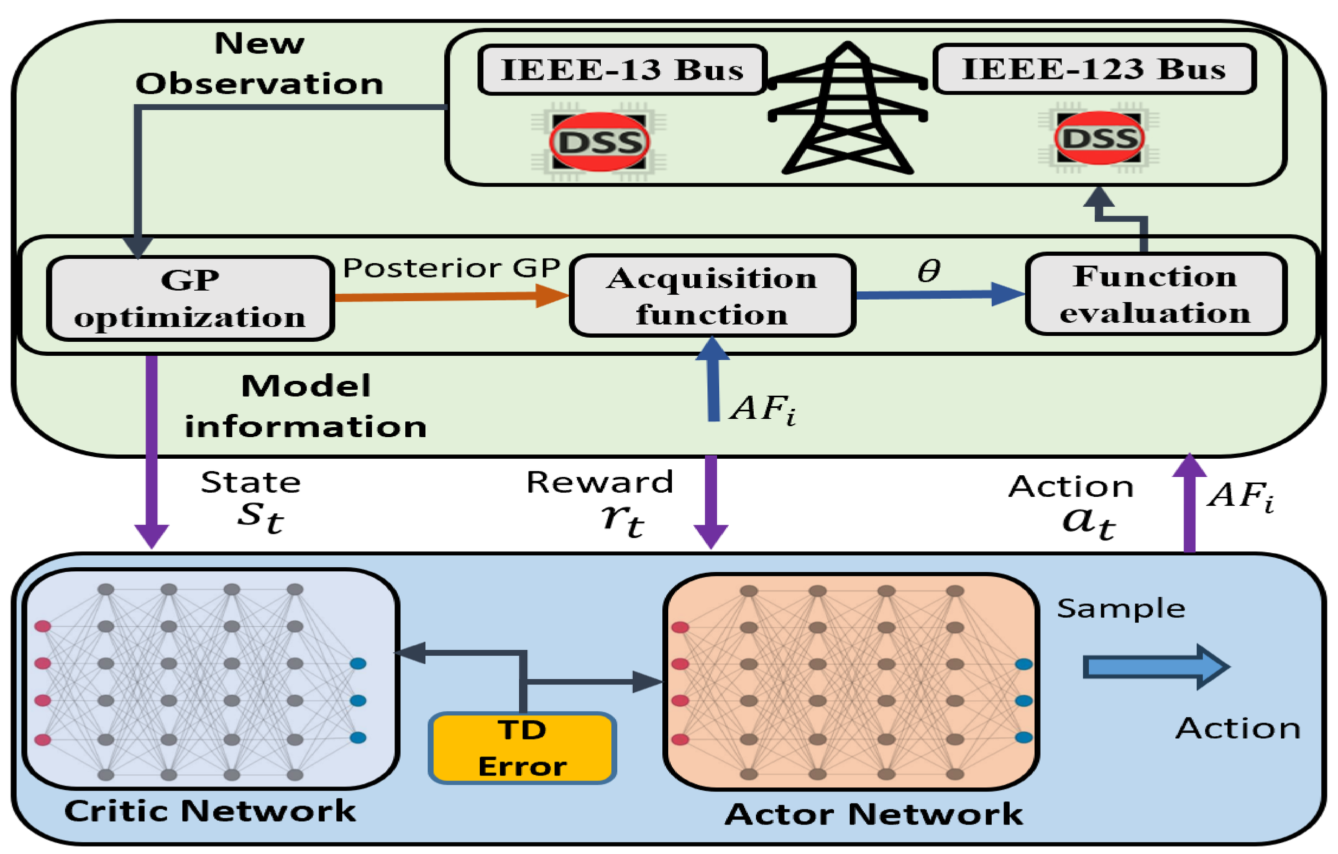
Proposed Bayesian Optimized Deep Reinforcement Learning Methodology for VVC

- IEEE-13 and IEEE-123 Bus are simulated and created a sequential decision process using Markov Decision Process.
- The Reward function is the sum of control error, voltage violation, and power loss.

$$R = -f_{volt} - f_{ctrl} - f_{power}$$

- The objective of DRL-based VVC agents is to optimize the control policies.

$$\bar{J}(\theta) = E_{t\sim\pi_\theta}[R(t)]$$



Proposed Bayesian Optimization DRL-based VVC Framework

- Gaussian process to estimate the performance of DRL agent with parameters $\theta = (\alpha, \beta, y)$.

$$f(\theta) \sim GP\big(m(\theta), k(\theta, \theta')\big)$$

- The acquisition function EI, EP and LCB evaluated the objective function at the point θ during the GP.

$$\theta_{next} = \arg max_\theta \{\alpha(\theta)|D_{t-1}\}$$

- For EI, maximizes the expected cumulative reward.

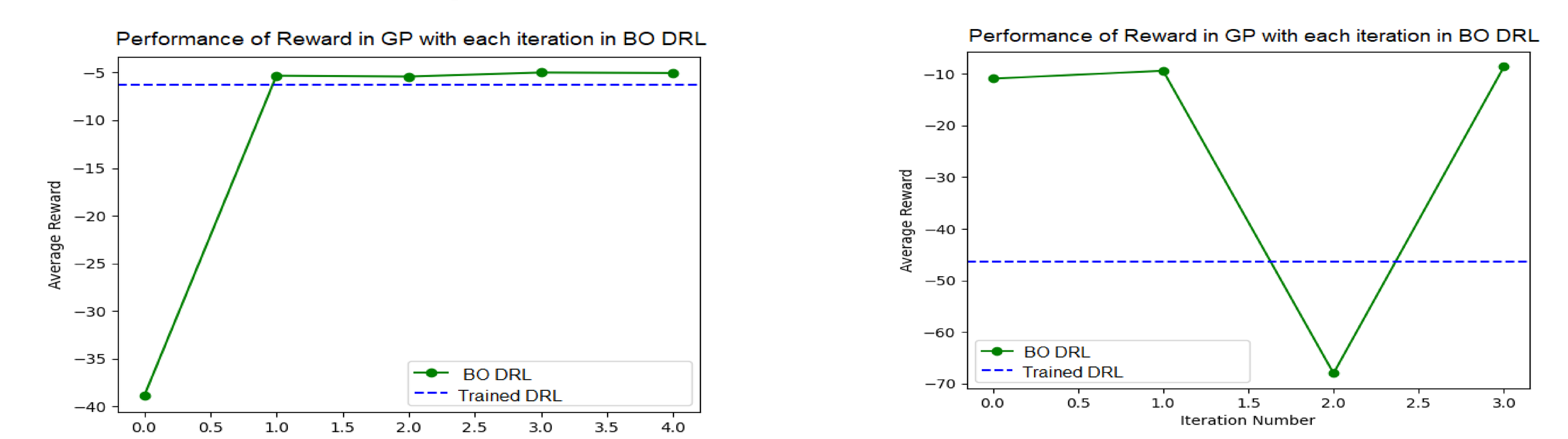
$$EI(\theta\,|D_{t-1}) = E_{y\sim p(y|\theta, D_{t-1})}[max\,(0, y - \hat{y}_{best})]$$

- Optimization of GP to reduce uncertainty and model's accuracy.

$$D_{new} = D \cup \big(\theta_{next}, f(\theta_{next})\big)$$

- Select the best GP model for the best parameters.

$$\theta_{optimal} = \arg max_\theta \{f(\theta)|\theta \in D\}$$

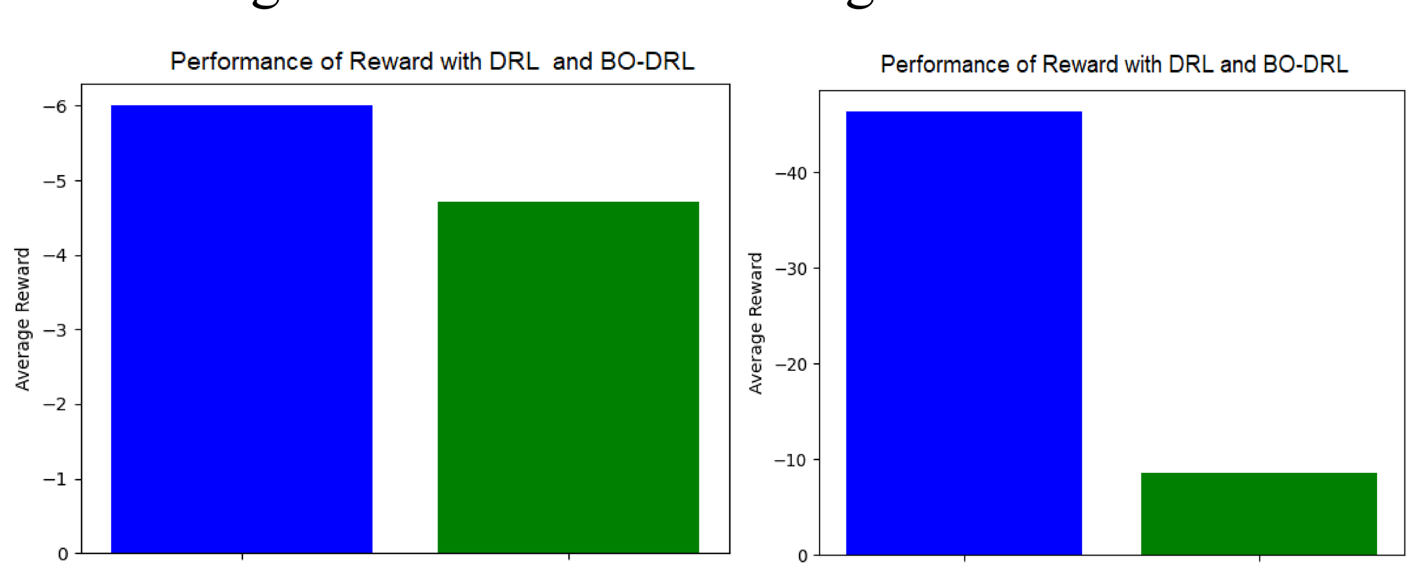


IEEE-13 Bus IEEE-123 Bus

Comparison of reward with each iteration of GP in BO with DRL

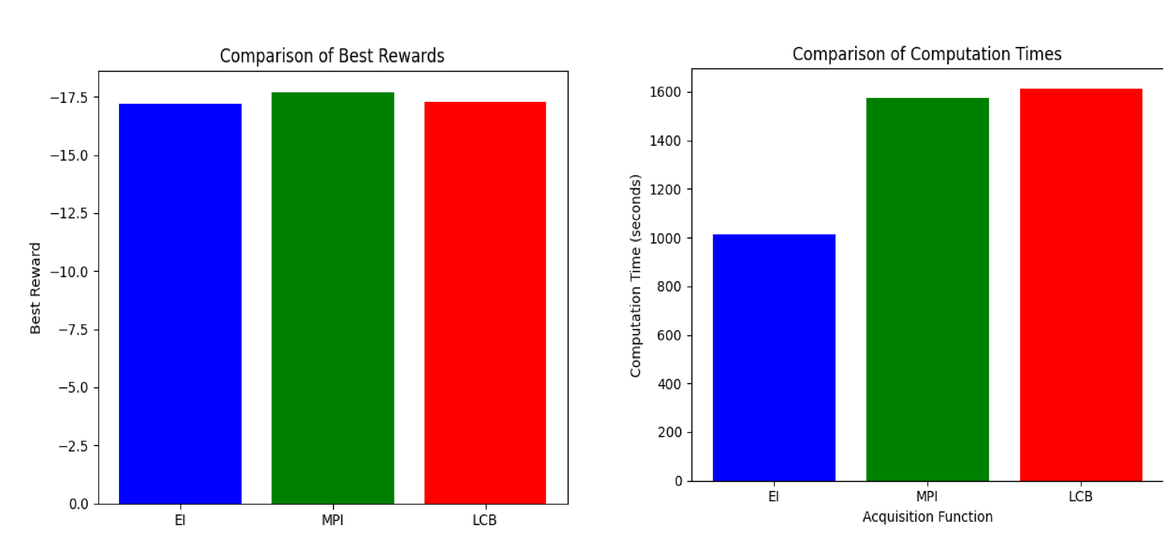
Case Study: BO with DRL Control Policies Performance for VVC

- Performed the control policies effectiveness of BO with DRL on IEEE –13 Bus and IEEE – 123 Bus distribution grid.
- Compared the different acquisition functions to validate the best performance and robustness of the DRL agents on the distribution grid.



IEEE-13 Bus IEEE-123 Bus

Reward Comparison



IEEE-13 Bus IEEE-123 Bus

Acquisition Function Comparison

Observations

- ❖ BO optimized DRL performed better than DRL actor-critic Network.
- ❖ Control policies have improved and reduced voltage violations in both distribution grids.
- ❖ Model Training time is improved significantly in both IEEE-13 bus and IEEE-123 bus.

Conclusion and Future Work

- The proposed BO with the DRL model enhances the VVC performance by fine-tuning the actor-critic network.
- Experimental results demonstrated that the decision-making process is improved by 21.11% for IEEE-13 Bus and 81.81% for 123 Bus.

Future Work:

- Developing an interpretable DRL and human-in-loop model for enhanced and verified of control actions.

References

[1] K. Kumar and G. Ravikumar, "Deep RL-based Volt-VAR Control and Attack Resiliency for DER-integrated Distribution Grids," 2024 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 2024, pp. 1-5, doi: 10.1109/ISGT59692.2024.10454163.

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