Transfer Learning Enhanced Deep Reinforcement Learning for Volt-Var Control in Smart Grids

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Challenges & Motivation

- How do high penetration levels of photovoltaic (PV) systems impact the stability and reliability of distribution grids, particularly in terms of voltage regulation and power quality?
- How can AI agent be utilized to develop adaptive control policies that enhance the integration of high PV penetration into distribution grids?
- How can designing effective strategies for managing and integrating high PV penetration reduce the need for costly grid upgrades and investments, providing a cost-effective approach to modernizing the grid?

Research Objective:

- ➢ Develop a Transfer Learning (TL) with DRL framework to efficiently transfer policy knowledge from one distribution grid to another, enhancing the adaptability and scalability of DRL models.
- ➢ Design and implement a policy reuse classifier to determine the suitability of transferring policy knowledge from the IEEE-123 to the IEEE-13 Bus.
- ➢ Conduct an impact analysis to evaluate the effectiveness of the TL with DRL technique on the IEEE-13, measuring improvements in training time, computational efficiency, and VVC performance.

Proposed TL with DRL Framework Methodology for VVC

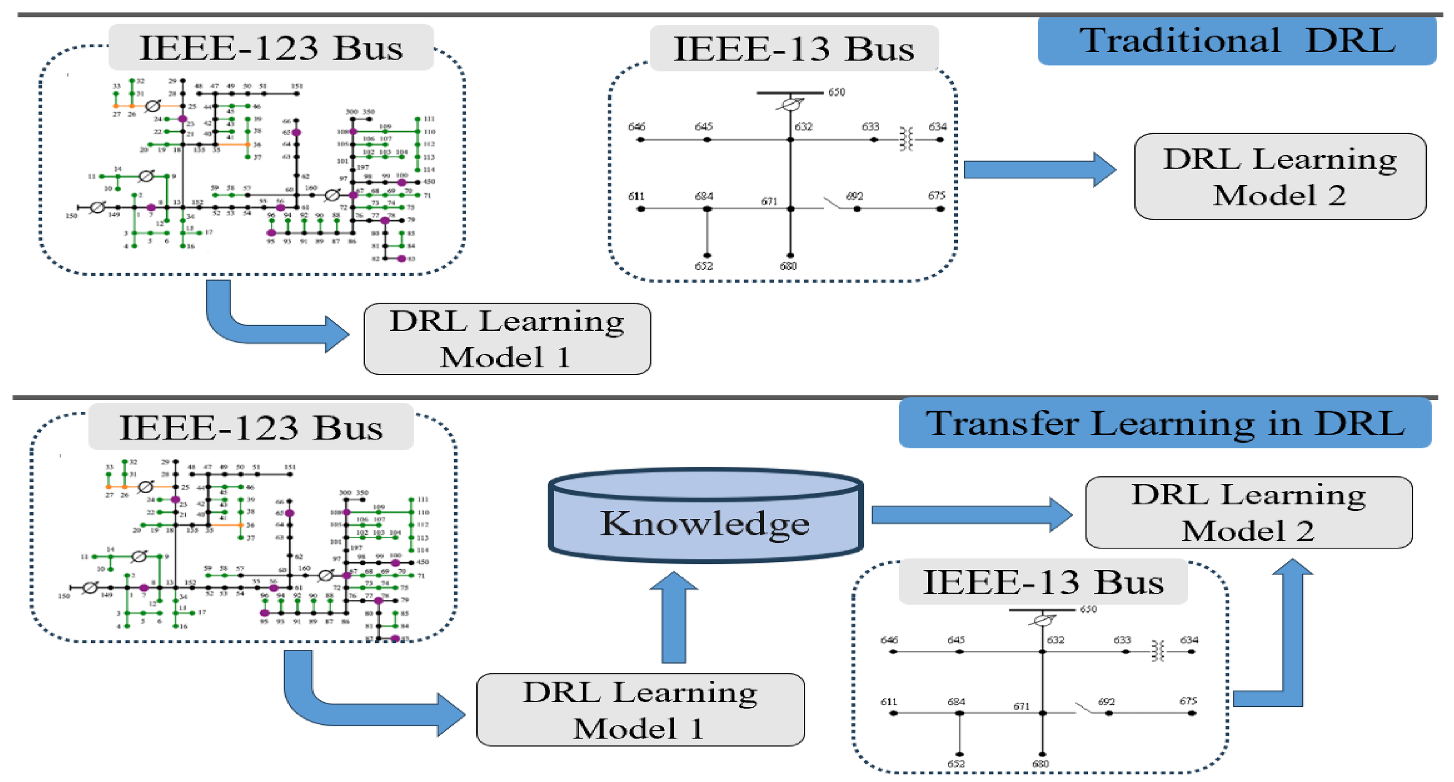


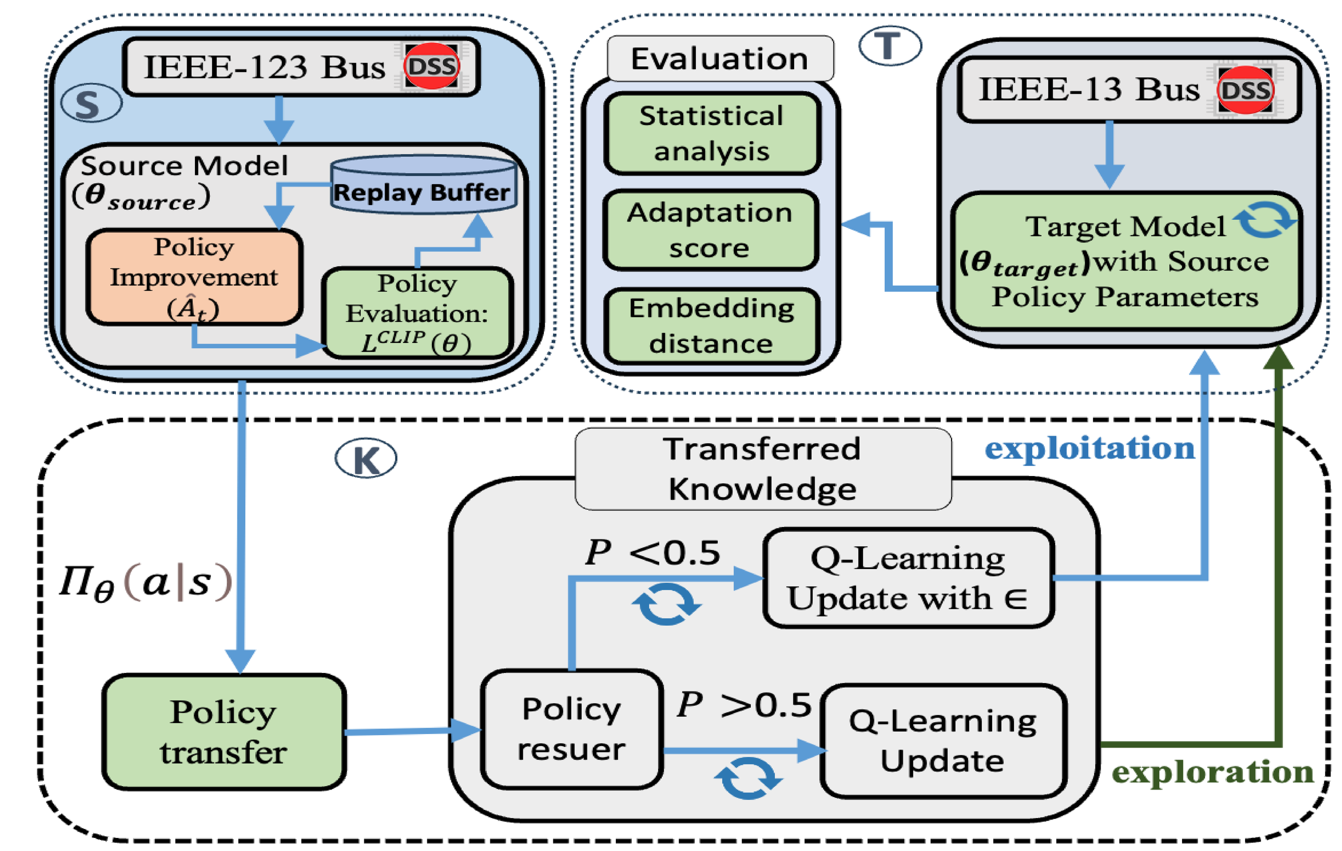
Illustration of Traditional DRL vs TL with DRL

- The reference/source model is trained with the PPO-DRL algorithm for optimal control policies for the IEEE-123 Bus test system.

$$\theta_{\text{source}} = \arg\max_{\theta} \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T}\gamma^t r_t - \beta\,\text{CLIP}(\theta)\right]$$

- The target model uses the policy reuse classifier, which decides the probability of transferring the control policies from the reference to target environment.

$$\theta_{\text{target}} = \begin{cases}\theta_{\text{source}} \text{ if } P(\text{Reuse}|\text{Observation}) > 0.5 \\ \arg\max_{\theta} \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T}\gamma^t r_t\right] & \text{otherwise}\end{cases}$$



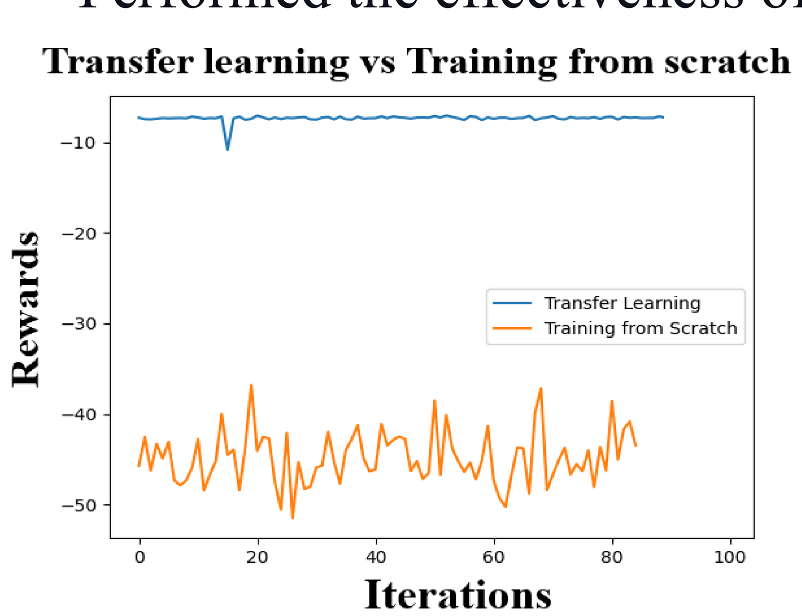
Proposed framework for TL with DRL for VVC

Performance Metric:

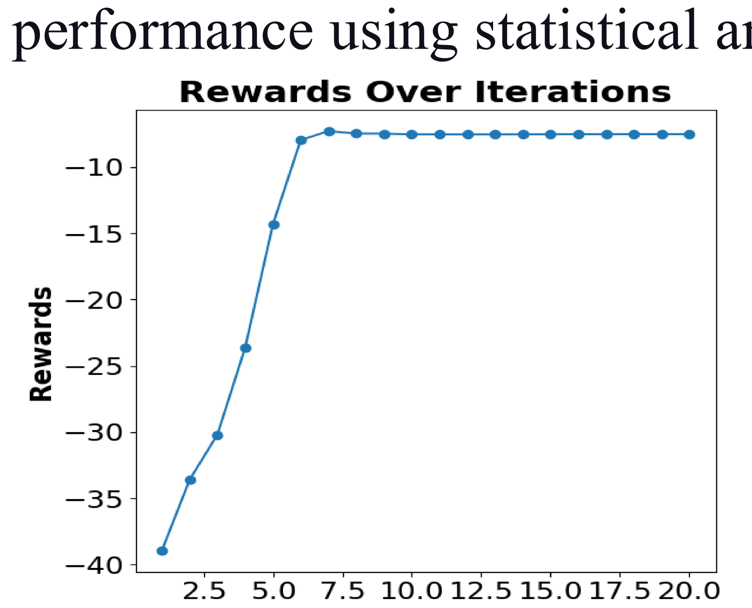
Metric	Transfer learning	Training from Scratch
TAS	72.78	-
ED	31.11	-
T-Statistic	102.93	-
P-Value	6.38	-
Mean Reward	-8.310	-27.256
Training_time	9.62 sec	518.38 sec

Case Study: Transfer Control Policies Knowledge From IEEE-123 to IEEE-13 Bus for VVC

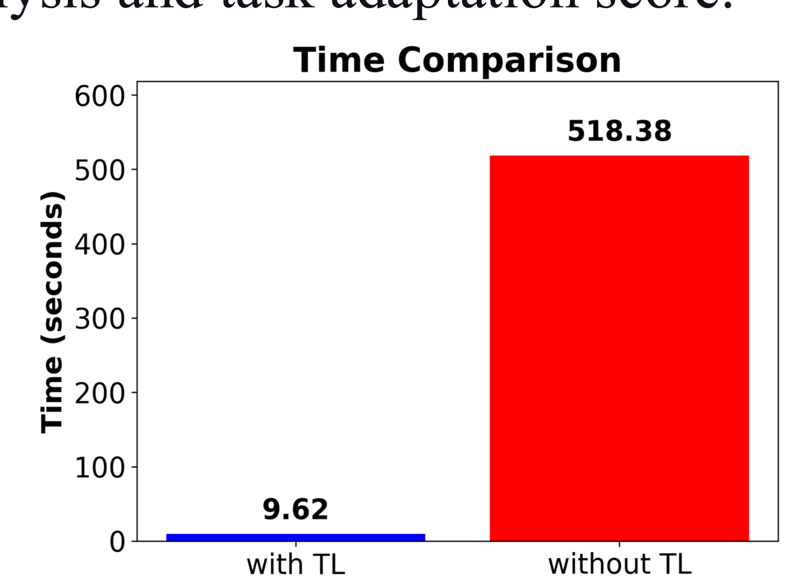
- Transferred the control policies knowledge from IEEE-123 Bus to IEEE-13 Bus test system using policy reuse classifier.
- Performed the effectiveness of the performance using statistical analysis and task adaptation score.



Reward Comparison with and without TL



Total Iterations to adapt in IEEE-13 Bus



Time Comparison for Training

Observations

- ❖ The TL techniques for DRL-based VVC environments improved the training time and resources.
- ❖ The result shows that control policies are transferred well from the IEEE-123 Bus to the IEEE-13 Bus.

Conclusion and Future Work

- The proposed TL with DRL framework addresses challenges of high PV penetration in distribution grids.
- Control policy performance improved by 69.51%.
- Training time reduced by 98.14%.
- Successfully transferred knowledge from the IEEE-123 Bus to the IEEE-13 Bus system which demonstrated the adaptability and scalability of the approach.
- Provided a cost-effective solution for modernizing grids with high renewable energy integration.

Future Work:

- Develop more sophisticated control policies for dynamic grid topologies and enhance the TL with DRL framework to handle real-time grid condition changes.
- Improve the robustness and flexibility of control strategies and further reduce computational resources.

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