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# Dynamic Programming for Damping Oscillations in Power Systems

*IEEE Transactions on Systems, Man and Cybernetics (2008)*

*Chao Lu, Jennie Si, and Xiaorong Xie*



*Aryan Ritwajeet Jha*

# Motivation

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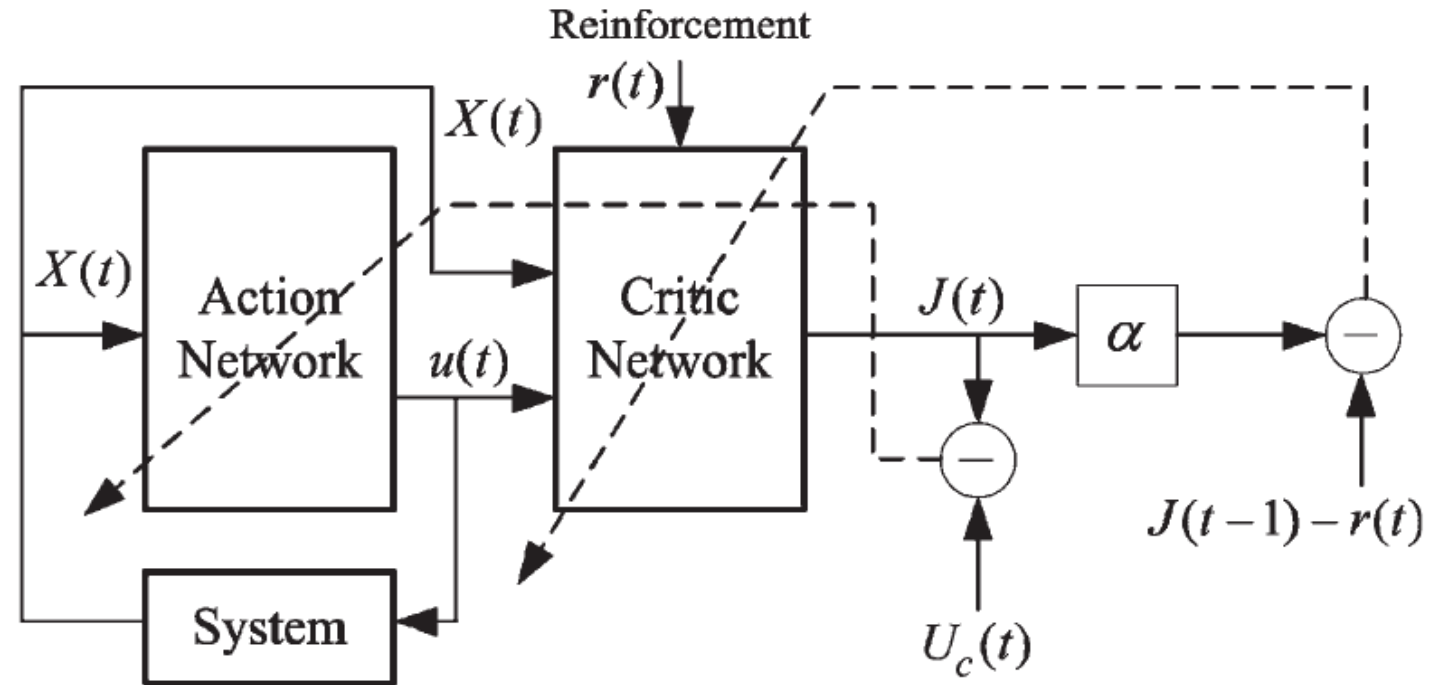
Global stability problems such as low-frequency network oscillation at the network level can be countered using proper coordination of these controllers.

However, most controllers are designed and tuned:

1. Independently of each other.
2. Relying on having accurate system models



# Approximate Dynamic Programming (ADP)



Schematic for implementation of Direct Heuristic Dynamic Programming (HDP).

- Model Independent.
- Complex, Continuous State/Control MIMO Non-Linear System with Uncertainty.
- Good for Low Frequency Oscillation Problem because swing period long enough to provide sufficient time for controller to learn and adapt.





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# Online Learning Control by Association and Reinforcement

*IEEE Transactions on Neural Networks (2001)*

*Jennie Si and Yu-Tsung Wang*

Among the various algorithms of Adaptive Critic Designs, a specific system architecture called **Action Dependent Heuristic Dynamic Programming (ADHDP)** for online learning control is proposed and demonstrated in this paper.

Here onward, all these algorithms will be only called as 'Dynamic Programming'.

# Motivation behind Heuristic Dynamic Programming

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- Domain: A class of learning decision and control **problems** where the **environment/system** that interacts with the 'learner' is NOT known beforehand.

**Problem** = Maintaining Stable Operation in **Environment** = Power Distribution Systems

- Environment: The environment can be **Stochastic**, **Non-Linear** and Subject to **change over time**.

Powerflow is **Non-Linear**. Loads are **Stochastic**, Network could trip leading to **topology changes**, Extreme weather could block your generation.

- Problem Statement: Devise a control learning algorithm which **optimizes** some sort of **figure of merit** over time.

**Merit** could be minimizing deviations from grid frequency and voltage dip.



# Motivation behind Heuristic Dynamic Programming

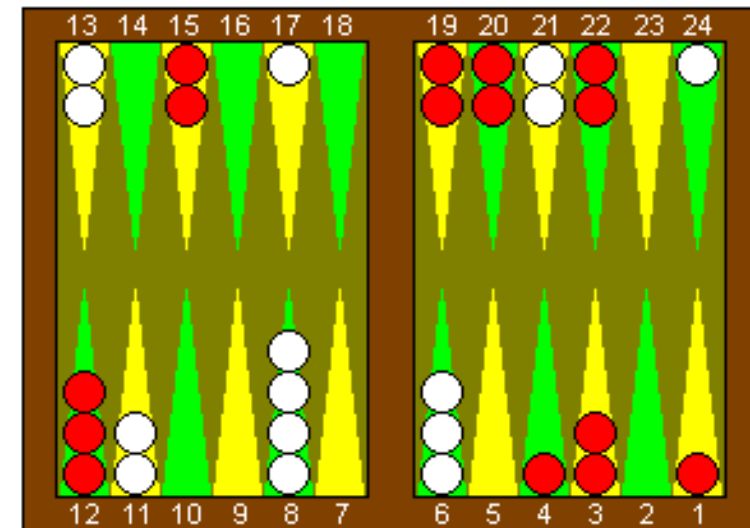
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- Learning Timeline: 'On-the-fly' i.e. Online learning during interaction with the environment itself.
- Learning Outcome: While measurements from the environment are available from one decision and control step to the next, a final outcome of the learning process from a generated sequence of decisions and controls may come as a delayed signal in only an indicative 'win' or 'lose' format.



# Motivation behind Heuristic Dynamic Programming

- Dynamic Programming has garnered great intuitive appeal for solving such class of problems.
- Noteworthy example: TD-Gammon program has learnt to play Backgammon at a grandmaster level.



**Figure 3.** A complex situation where TD-Gammon's positional judgment is apparently superior to traditional expert thinking. White is to play 4-4. The obvious human play is 8-4\*, 8-4, 11-7, 11-7. (The asterisk denotes that an opponent checker has been hit.) However, TD-Gammon's choice is the surprising 8-4\*, 8-4, 21-17, 21-17! TD-Gammon's analysis of the two plays is given in Table 3.



# Motivation behind Heuristic Dynamic Programming

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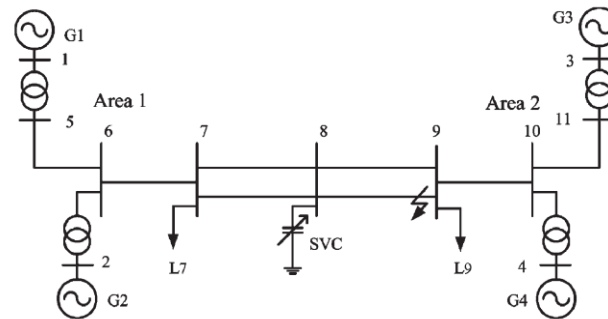
- Dynamic Programming (via Reinforcement Learning) excels in **Markovian Environments** compared to traditional Supervised and Unsupervised Machine Learning Algorithms.
- **Markovian Environment**: An environment where a system's next state is dependent on the current control step as well as the previous  $N$  states of the system.





# Systems Tested

- Kundur 4 Machine  
2 Area (4M2A)  
system.



China Southern  
Power Grid  
(CSG)



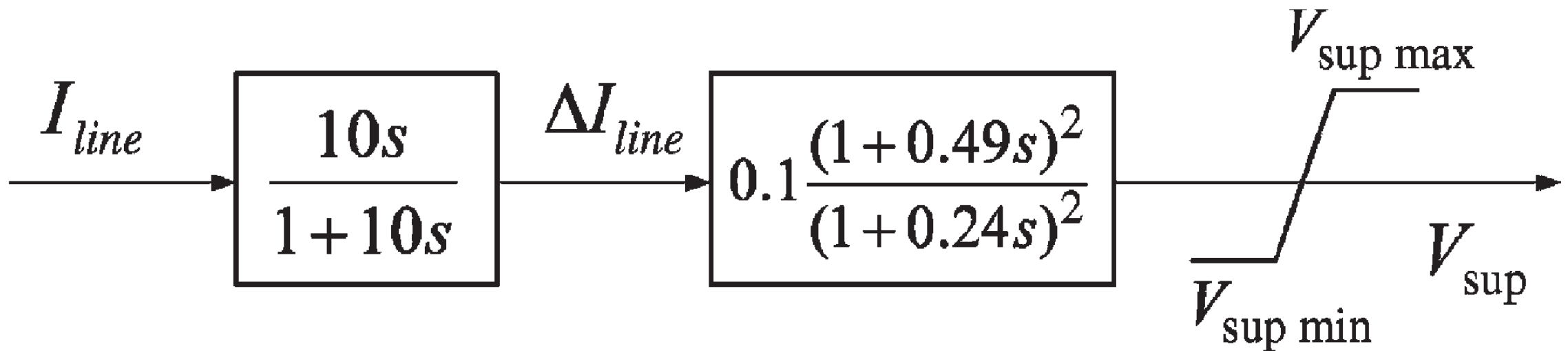
$$\left\{ \begin{array}{l} u_d = x_q i_q - r i_d, \quad u_q = E_q - x_d i_d - r i_d \\ E'_q = E_q - (x_d - x'_d) i_d, \quad M_e = (i_d u_d + i_q u_q) / \omega \\ dE'_q / dt = (E_{fd} - E_q) / T'_{d0} \\ d\Delta\omega / dt = (M_m - M_e - D) / T_J \\ d\delta / dt = \omega_0 (\omega - 1). \end{array} \right. \quad (1)$$

Machine Model Used by the  
Authors

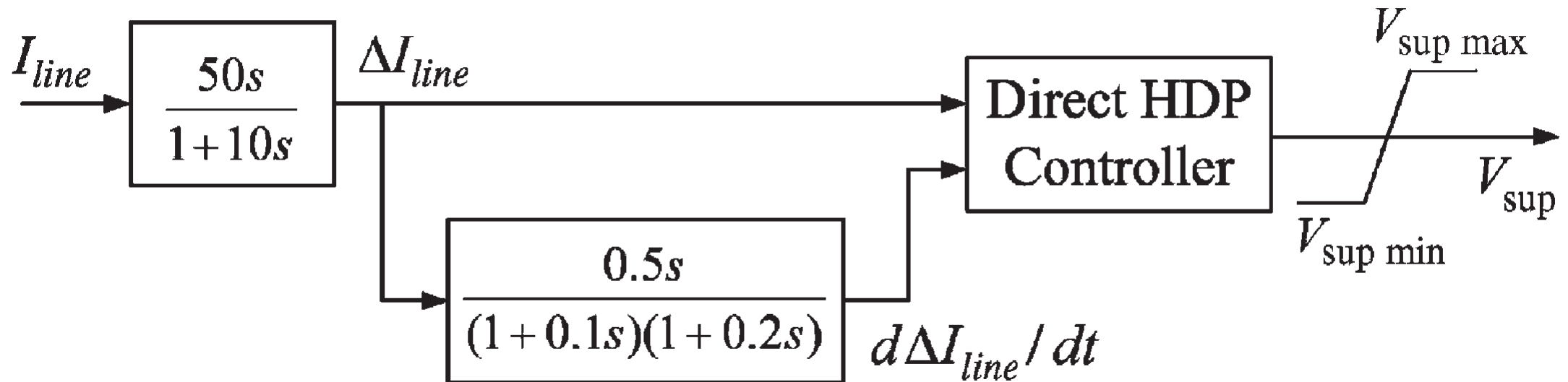
Type 2 and One-Axis Model

## Conventional Supplementary Controller

- Conventional Supplementary Controller uses Inter-area line current as its only input.



# Proposed Supplementary Controller using Dynamic Programming



The action and critic networks are only using a small number of hidden layer neurons. So in order to better suppress the generator inter-area oscillation swings, apart from the inter-area line current, its derivative was also used as an input.



# Online Learning Control by Association and Reinforcement

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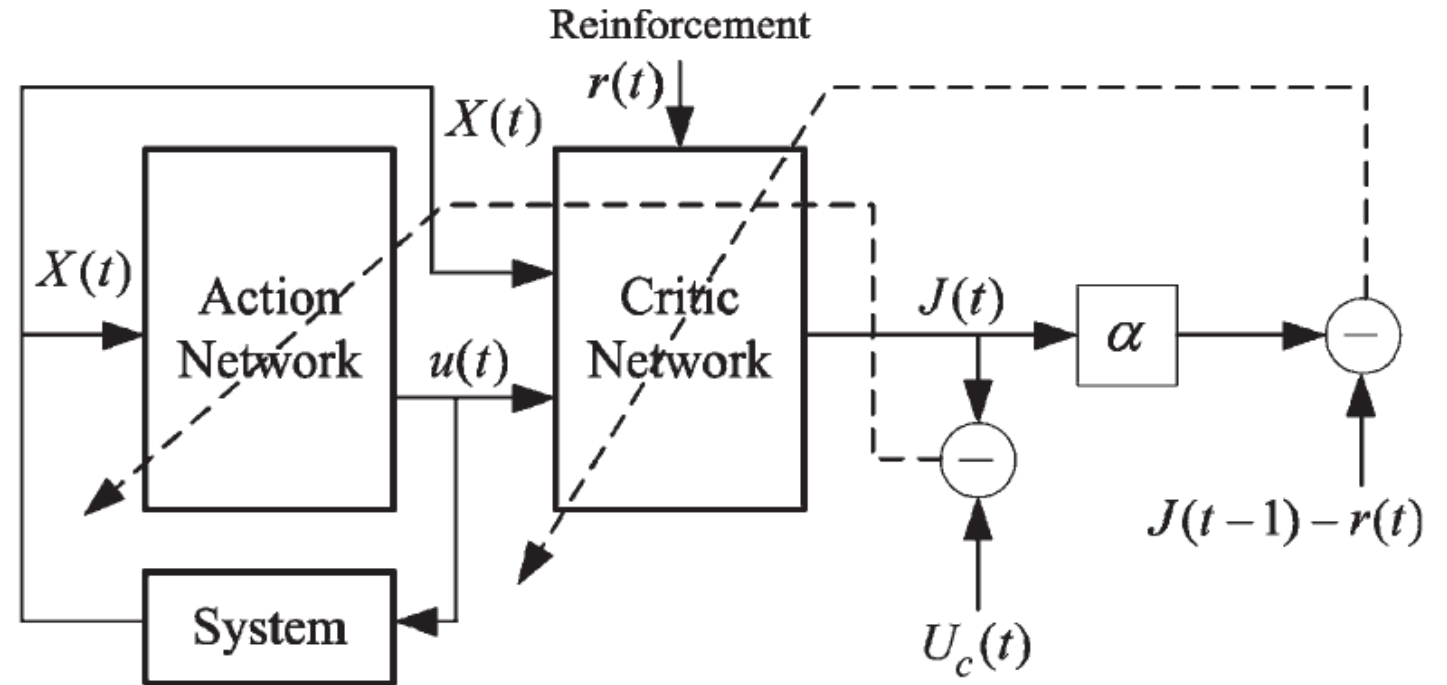
- A Critic network 'critiques' the generated action value in order to optimize a future 'reward-to-go' by propagating a temporal difference between consecutive estimates from the critic/prediction network.

$$J^*(X(t)) = \min_{u(t)} \left\{ J^*(X(t+1)) + g(X(t), X(t+1)) - U_0 \right\}$$

The Bellman Equation



# Approximate Dynamic Programming (ADP)



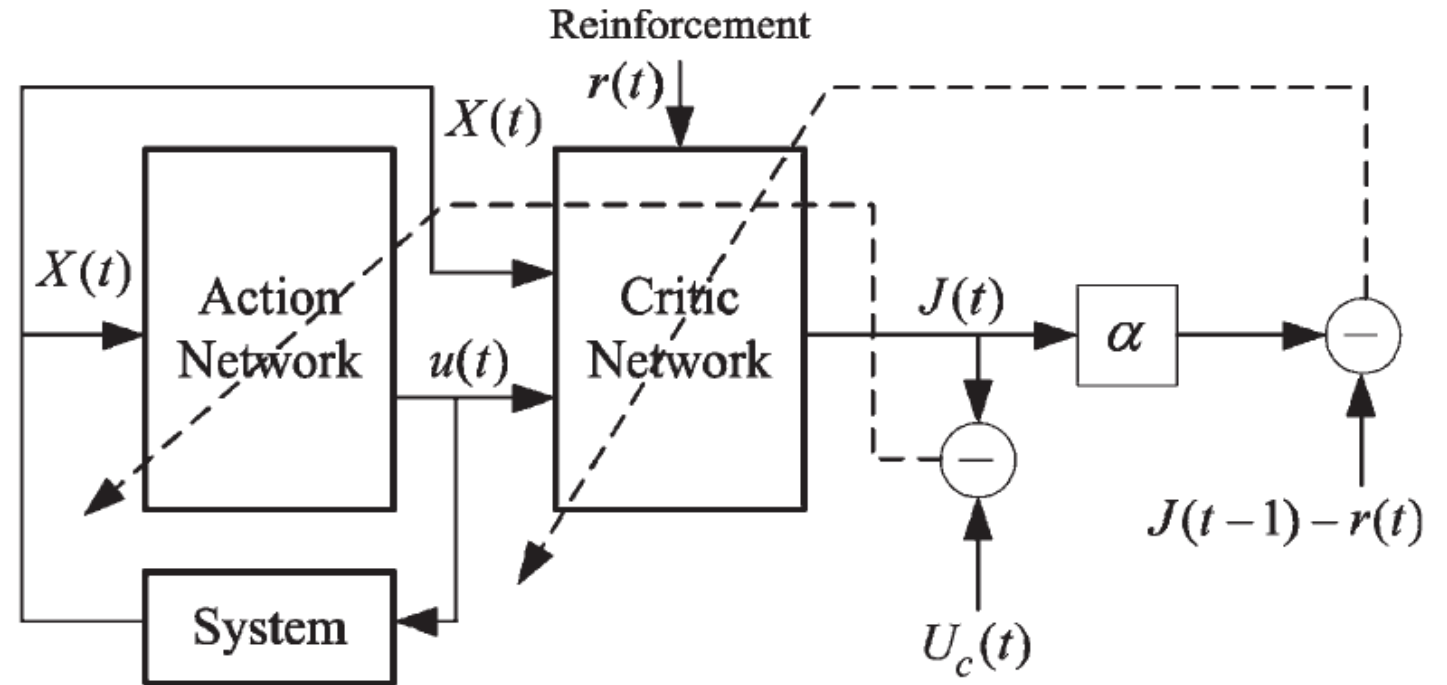
Schematic for implementation of Direct Heuristic Dynamic Programming (HDP).

$$r(t) = - \left( \sum_{i=1}^m b_i \Delta \omega_{\text{inter}-i}^2 + \sum_{j=1}^n b_{m+j} \Delta \omega_{\text{local}-j}^2 \right) \quad (2)$$

The Cost Function is the only feedback to the controller on its performance. All controllers controlled using the same (unified) cost function. The difference in rotor speeds for inter-area oscillations is a sensible choice for reinforcement signal.



# Approximate Dynamic Programming (ADP)



Schematic for implementation of Direct Heuristic Dynamic Programming (HDP).

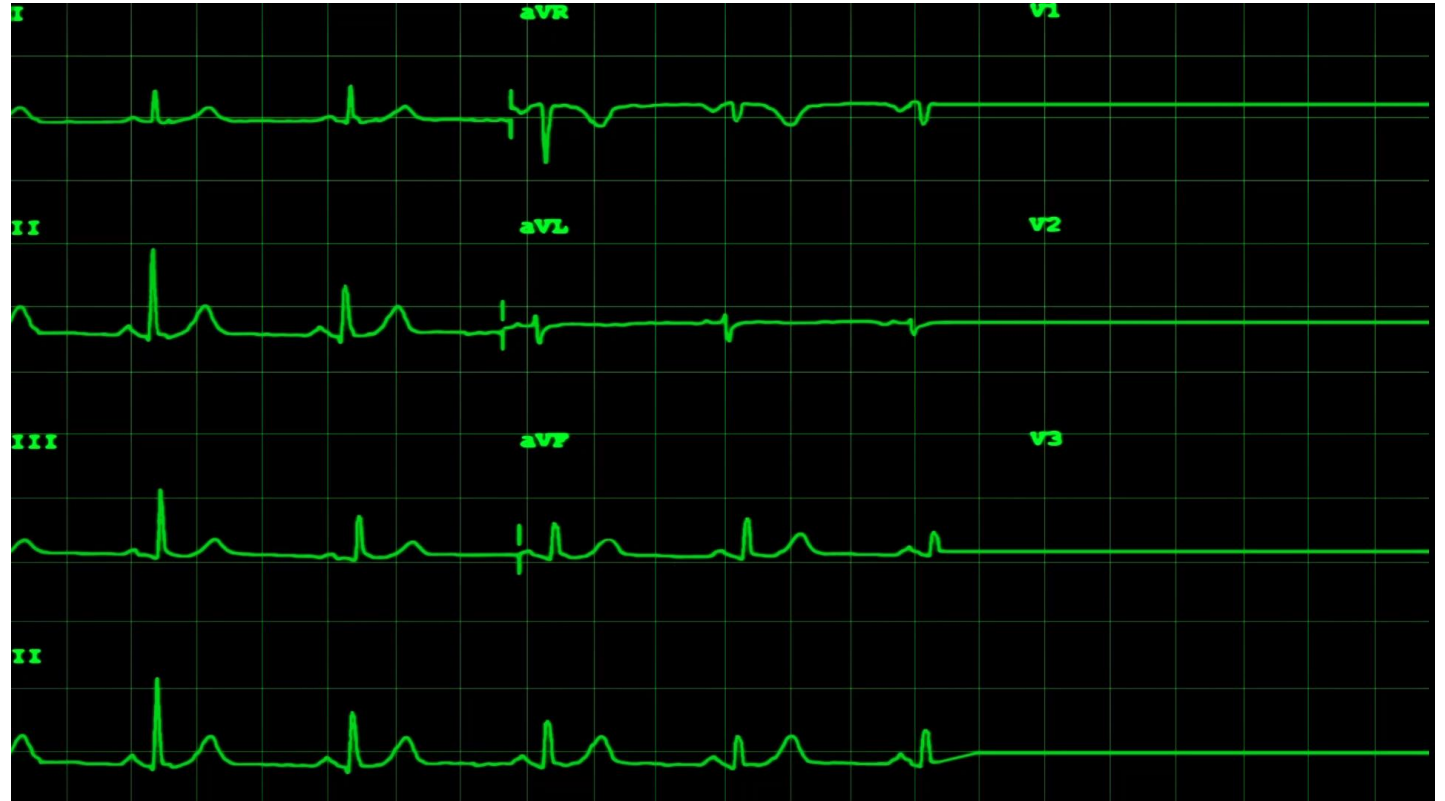
$$r(t) = - (b_1 \Delta \omega_{\text{interarea}}^2 + b_2 \Delta \omega_{\text{local-1}}^2 + b_3 \Delta \omega_{\text{local-2}}^2) \quad (3)$$

Action and Critic Networks are modelled using a single hidden layer Neural Network.

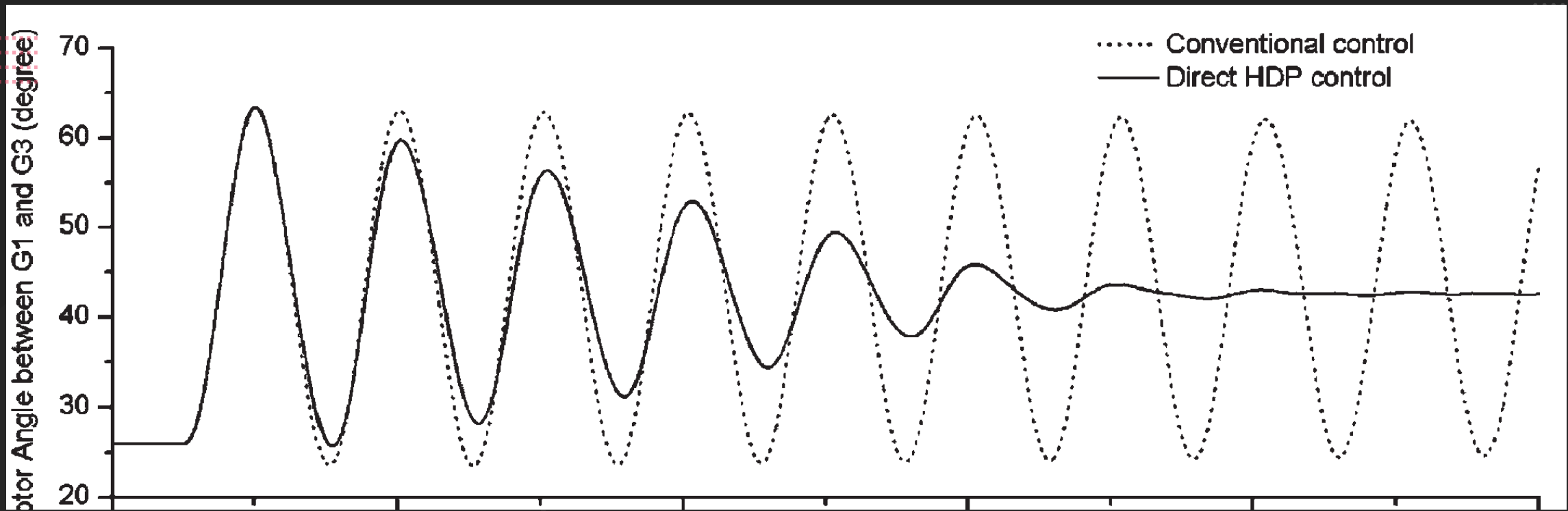




Case Study: Short Circuit  
Fault Occurred on the  
inter-area line between  
buses 7 and 8.  
Fault Cleared after 74 ms.





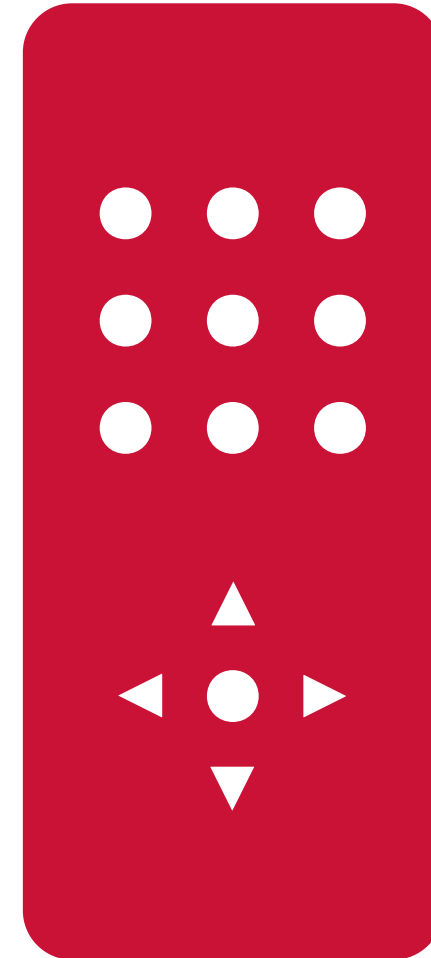


## Simulation Results and Comparison between Dynamic Programming Method and Conventional Method for Damping Inter-area Oscillations

- Rotor Angle difference between Generators 1 (Area 1) and Generator 3 (Area 2) damped after clearing the fault, whereas the conventional supplementary controller couldn't stabilize the network after the fault.
- Similarly, for the CSG, the study conducted on two generators (Qiangxi and SJCG) yielded the same outcome.

# Project Objectives

- Implement both the proposed supplementary controller and the conventional supplementary controller on the inter-area line.
- Perform transient simulation and cross-check the results.
- How are the damping values for small-signal stability affected for different modes and machines?





# References

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Lu, C., Si, J., & Xie, X. (2008). Direct Heuristic Dynamic Programming for Damping Oscillations in a Large Power System. *IEEE Trans. Syst. Man Cybern. Part B Cybern.*, 38(4), 1008–1013. doi: 10.1109/TSMCB.2008.923157

Si, J., & Wang, Y.-T. (2001). Online learning control by association and reinforcement. *IEEE Trans. Neural Networks*, 12(2), 264–276. doi: 10.1109/72.914523