Automatic Generation Control for a Two Area Power System Using Deep Reinforcement Learning

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Problem Statement & Aim

An increase in photovoltaic power generation, and battery energy storage systems is causing Australian power system dynamics to become increasingly non-linear, driving a need to explore novel control architectures to improve frequency control. This research aims to investigate the feasibility of controlling power system frequency with a neural network.

Reinforcement Learning

Reinforcement learning is a branch of machine learning concerned with an agent's sequential decision making to maximise cumulative reward [1].

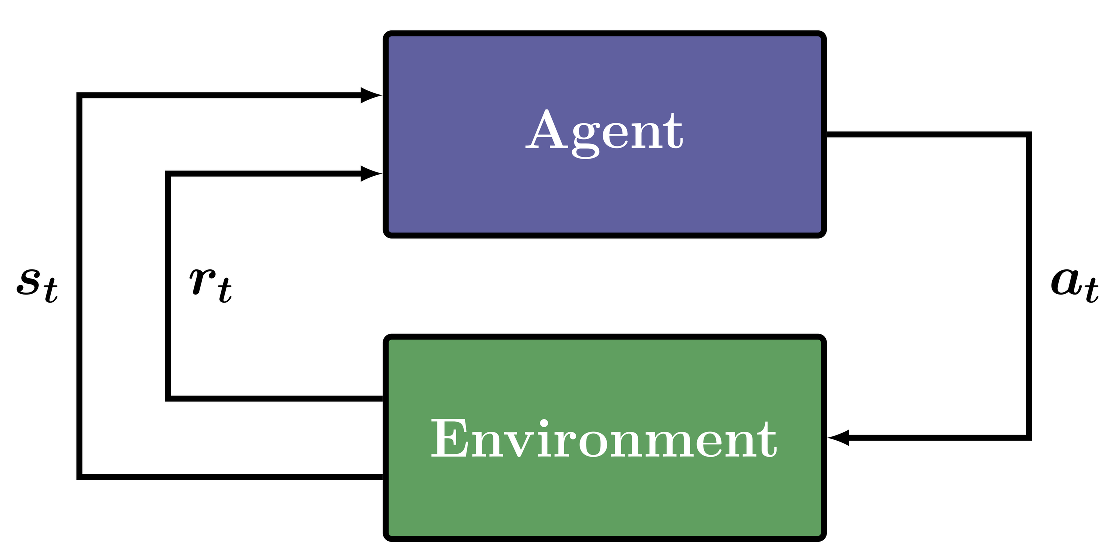

Figure 1: The agent exists in some environment and at each time step observes a state $s_t \in S$; and takes an action $a_t \in A$. Following this, the agent then receives a reward $r_t \in R : S \times A \times S \to [R_{min}, R_{max}]$.

The Environment

The control objective is to maintain inter-area power transfer, whilst regulating the frequency of each area.

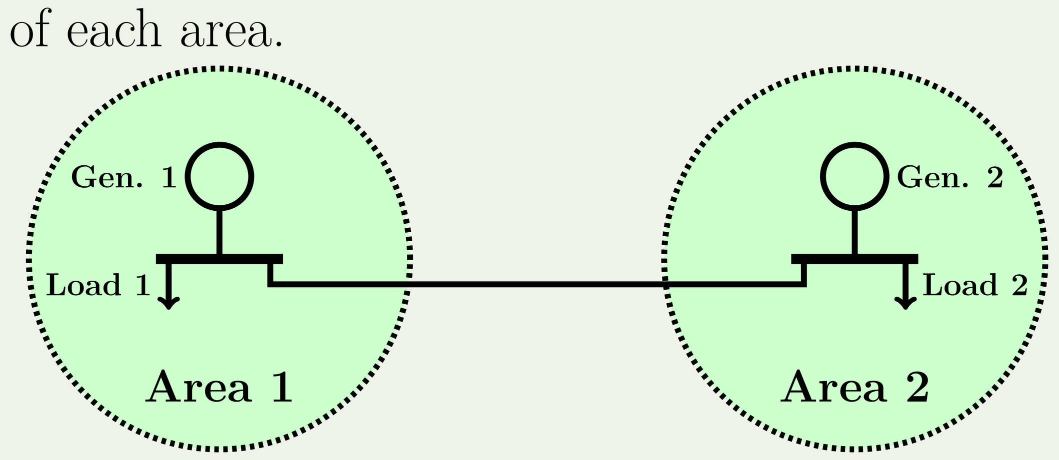

Figure 2: Two power areas connected via a transmission line. Each power area consists of: a governor controlled generator and a stochastic load demand.

The Environment: A More Detailed View

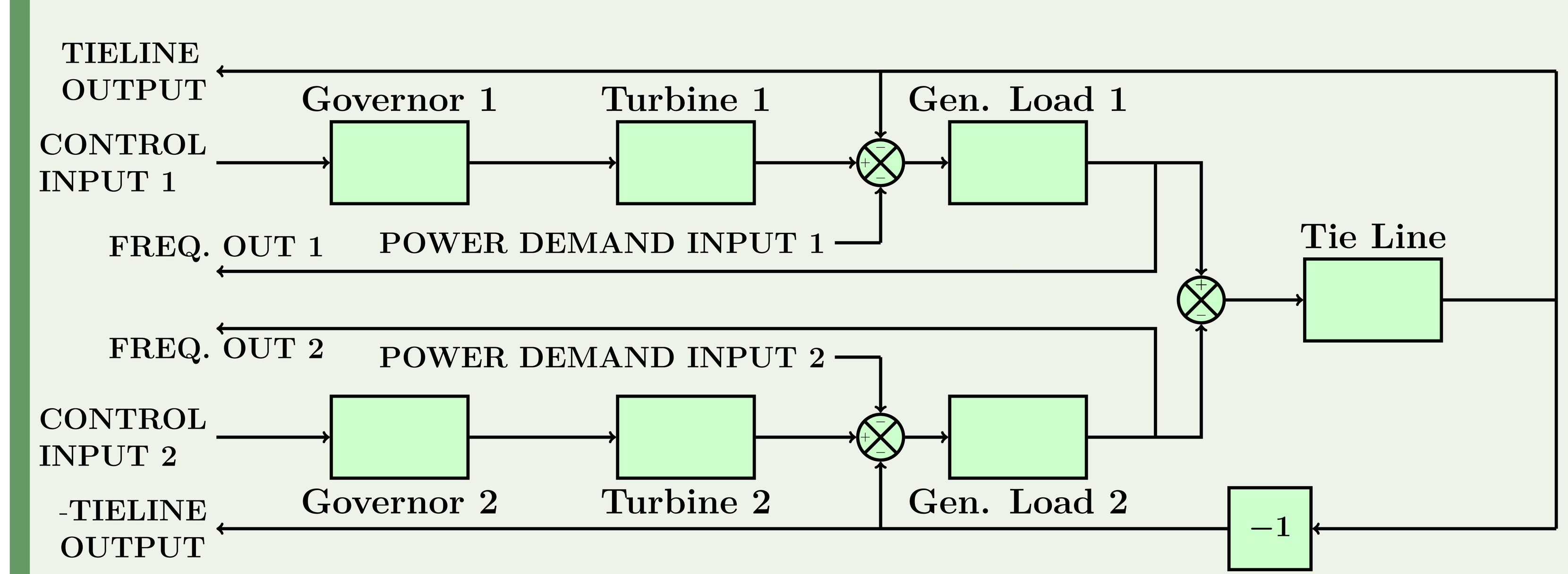

Figure 3: Block diagram of two area power system connected via a tie-line. Generators are modelled using governor and turbine models. Governors, turbines, generator loads, and tie-lines are all modelled using first order linear systems [2]. Simulation is undertaken in the temporal domain.

Results Comparison from Preliminary Experiments

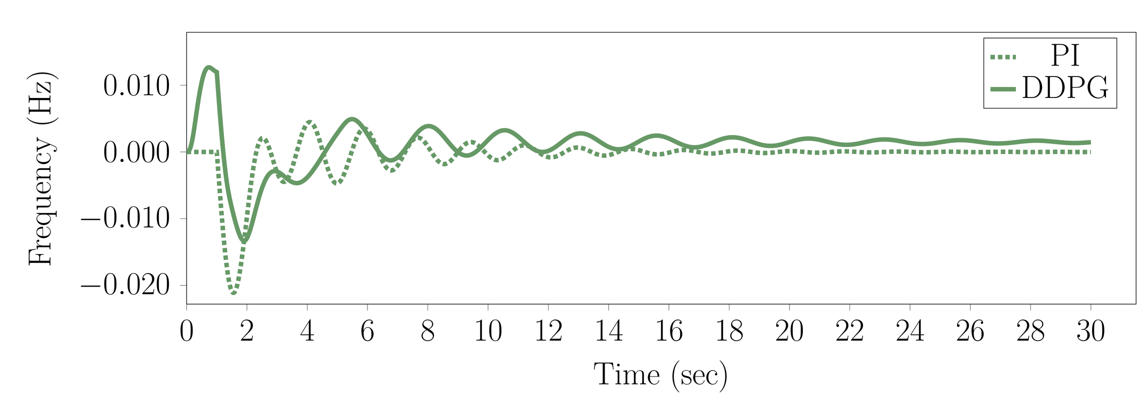

Figure 4: PI vs. DDPG frequency (Hz) for power area one over time (seconds).

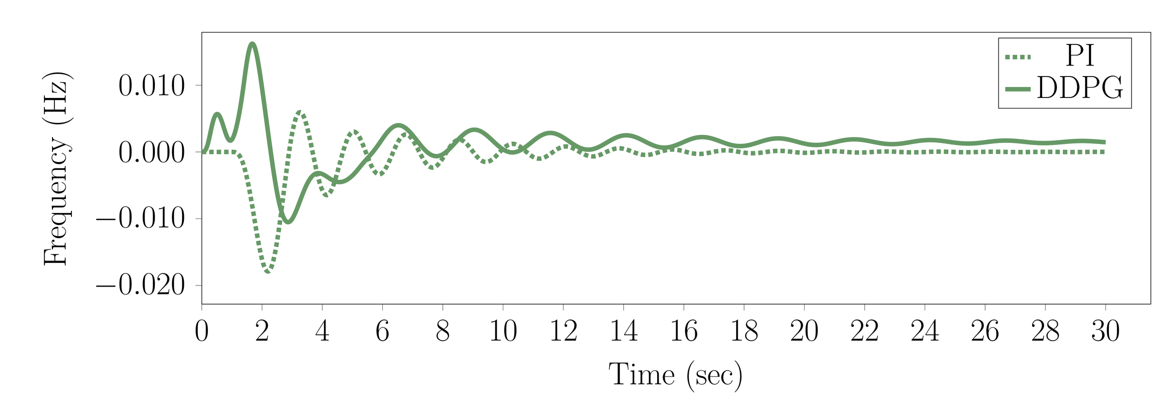

Figure 6: PI vs. DDPG frequency (Hz) for power area two over time (seconds).

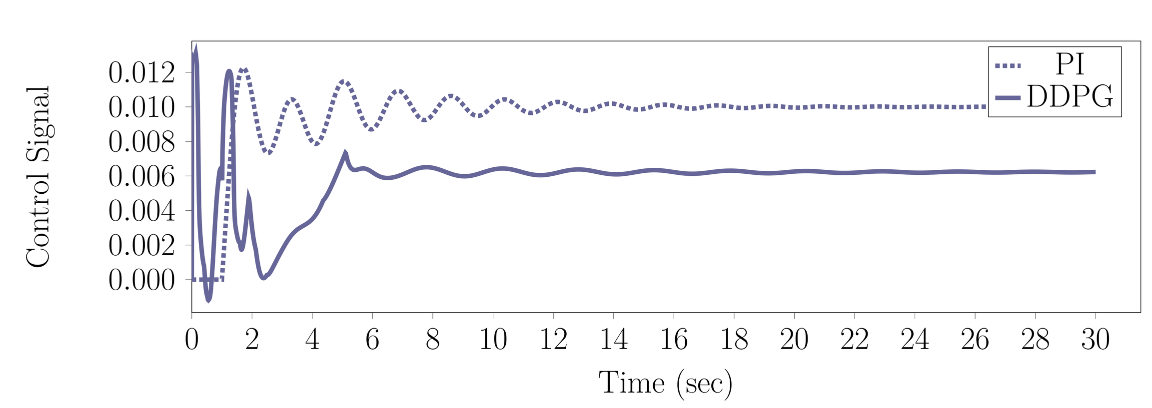

Figure 5: PI vs. DDPG control signal for power area one over time (seconds).

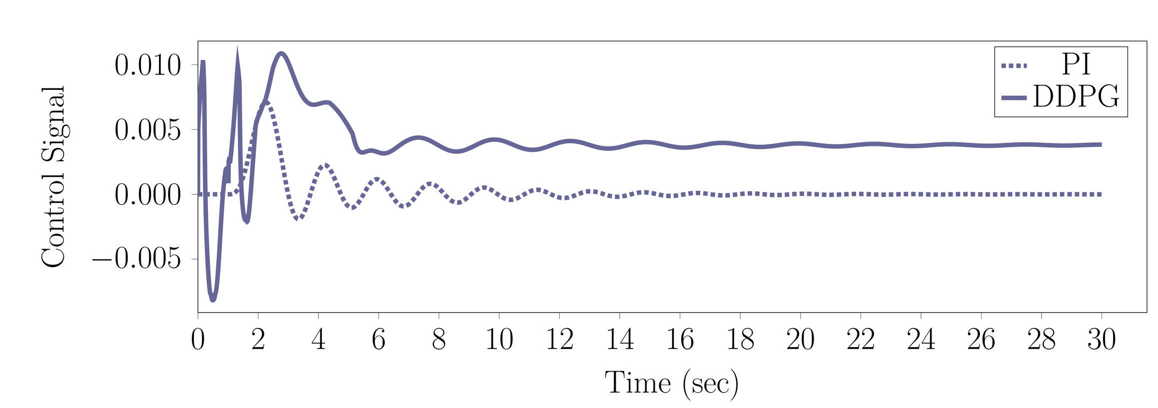

Figure 7: PI vs. DDPG control signal for power area two over time (seconds).

PI Controller

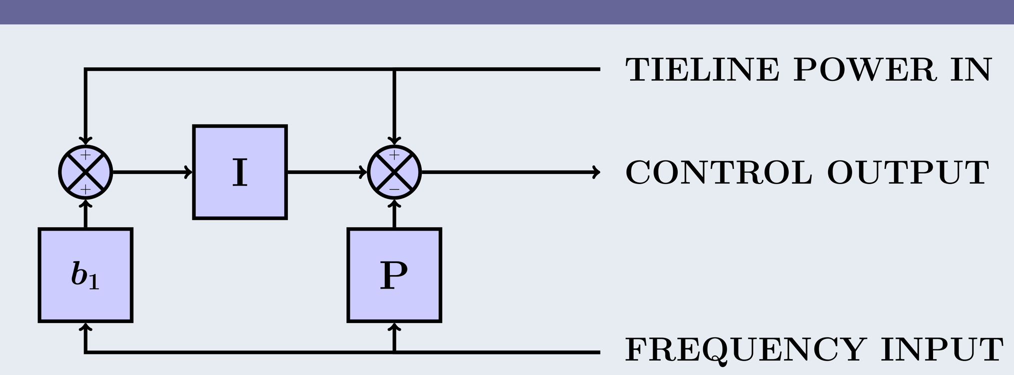

Figure 8: Block diagram of the proportional integral (PI) controllers used to classically control power system frequency. Two feedback loop PI controllers are used to control the frequency and the tie-line power flow.

DDPG Controller

Neural Network Architecture

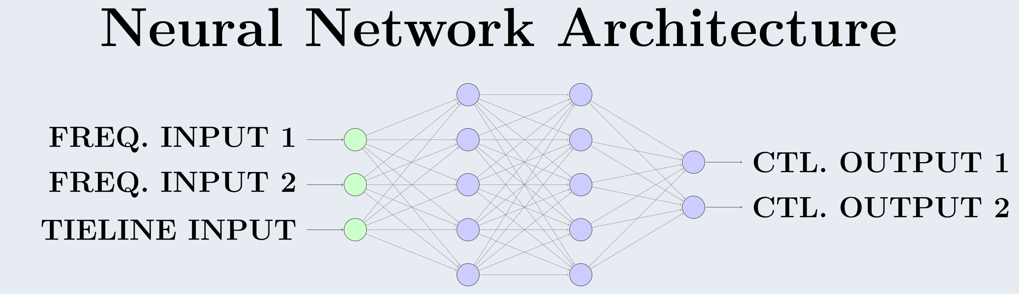

Figure 9: Indicative architecture of a neural network.

Deep deterministic policy gradient (DDPG) trains two neural networks to perform control actions, using an experience replay buffer. An Ornstein–Uhlenbeck process is used to explore [3].

Preliminary Experiment & Results

The environment was configured to experience a load demand step change in area one at the 1 sec mark, and run for a total of 30 sec. The DDPG algorithm was trained for approximately 210 episodes.

PI and DDPG controller performance was evaluated for 3000 time steps of 0.01 sec. At each time step the agent received the reward:

$$\begin{aligned} \texttt{r} = & -8 \times |\texttt{Frequency 1} + \texttt{Frequency 2}| \\ & -4 \times |\texttt{Tieline}| \\ & -5 \times |\texttt{Control 1} + \texttt{Control 2}| \end{aligned}$$

The calculated cumulative rewards for the PI and DDPG controllers are shown in Table 1

Table 1: Cumulative reward for PI and DDPG agents

Agent	Cumulative Reward
PI	-211.15
DDPG	-311.42

Cumulative reward is bound in the region $[0, -\infty)$ providing evidence the DDPG controller's performance is comparable to the PI controller performance. Demonstrable results of the DDPG controller performance compared to PI control is shown in Figure 4 and 6.

Discussion & Conclusion

PI controllers are an industry standard for frequency control of power systems. Preliminary experiments show comparable performance of PI and DDPG controllers and demonstrate that using a DDPG trained neural network to control power system frequency is feasible. Future research will explore DDPG performance under increasingly stochastic load demands.

References

[1] R. S. Sutton and A. G. Barto, *Reinforcement Learning*, M. Press, Ed. 2018.

[2] D. P. Kothari and I. J. Nagrath, *Modern Power System Analysis*, 4th Edition. McGraw Hill India, 2011.

[3] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, *Continuous control with deep reinforcement learning*, 2015. arXiv: 1509.02971 [cs.LG].