Multi-Objective Reinforcement Learning-based Deep Neural Networks for Cognitive Space Communications

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Paulo Ferreira – *Worcester Polytechnic Institute*

Randy Paffenroth – *Worcester Polytechnic Institute*

Alexander M. Wyglinski – *Worcester Polytechnic Institute*

Timothy Hackett – *The Pennsylvania State University*

Sven Bilén – *The Pennsylvania State University*

Richard Reinhart – *NASA John H. Glenn Research Center*

Dale Mortensen – *NASA John H. Glenn Research Center*

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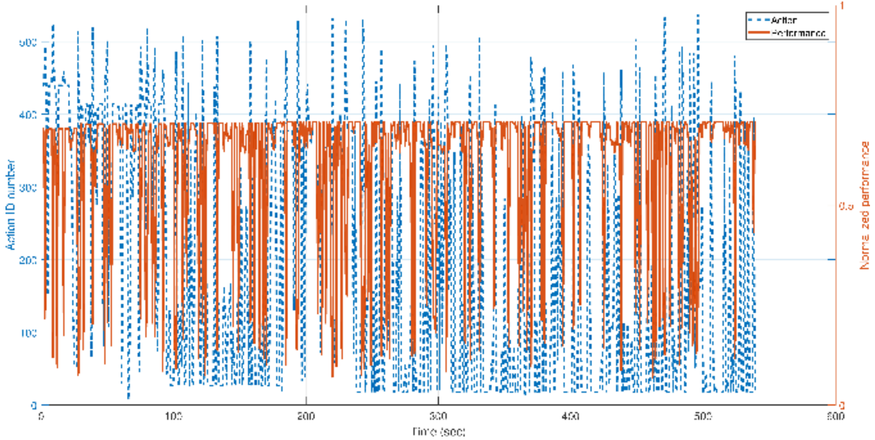
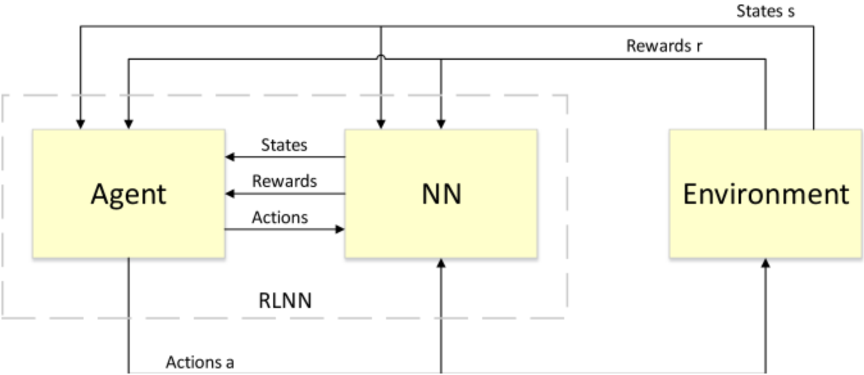
Motivation



P. V. R. Ferreira, R. Paffenroth, A. M. Wyglinski, T. M. Hackett, S. Bilén, R. Reinhart, and D. Mortensen, "Multi-Objective Reinforcement Learning for Cognitive Radio-Based Satellite Communications," in 34th AIAA International Communications Satellite Systems Conference, October 2016.

Proposed Solution

RLNN: a neural network-based reinforcement learning method



Proposed Solution

Reinforcement learning Q–function equations:

- State-Action-Reward-State-Action (SARSA)

$$Q_{k+1}(s_k, a_k) = Q_k(s_k, a_k) + \alpha[r + \gamma Q(s_{k+1}, a_{k+1}) - Q(s_k, a_k)] \quad (1)$$

- Time-Difference

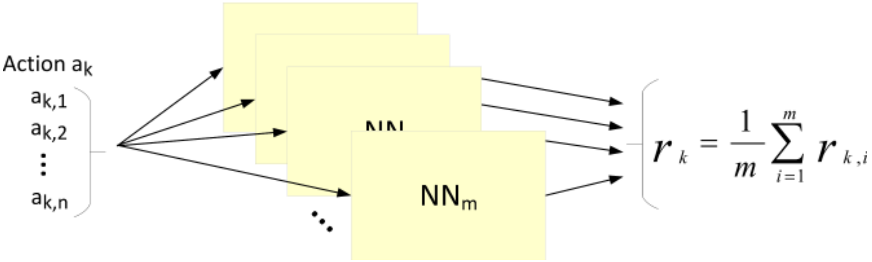
$$Q_{k+1}(s_k, a_k) = Q_k(s_k, a_k) + \alpha[r + \gamma \max_a Q_k(s_{k+1}, a) - Q_k(s_k, a_k)] \quad (2)$$

- Proposed equation for SATCOM

$$Q_{k+1}(s_k, a_k) = Q_k(s_k, a_k) + \alpha[r_k - Q_k(s_k, a_k)] \quad (3)$$

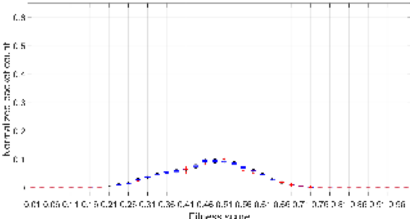
Proposed Solution

Ensemble of deep neural networks

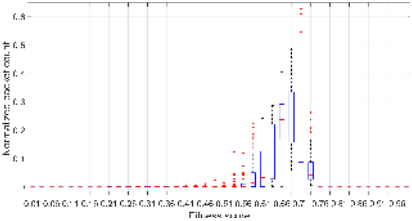


Simulation results

Exploration probability $\epsilon = 0.5$, $w_i = 1/6$



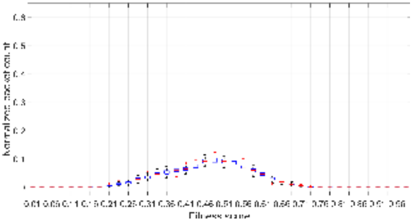
(a) Exploration OFF



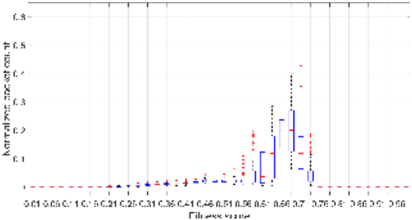
(b) Exploration ON

Simulation results

Exploration probability $\epsilon = 1/k$, $w_i = 1/6$



(a) Exploration OFF



(b) Exploration ON

Conclusions

- Hybrid ML-based multi-objective radio resource allocation – RLNN
  - Virtual exploration enables control over:
    - Performance levels while exploring actions
    - Time spent exploring very “bad” actions
- RLNN is independent of exploration probability function
- Improvements of up to $3.9\times$ on packets experiencing performance values higher than 0.55

Thank you!

Alexander Wyglinski: alexw@wpi.edu

Paulo Ferreira: paulovrf@hotmail.com

Backup

- Performance threshold
  - 95% of current maximum performance predicted by NN
- Rejection probability $= 1$

Backup

$$f_{obs}(x) = w_1 f_{\text{Thrp}} + w_2 f_{\text{BER}} + w_3 f_{\text{BW}} + w_4 f_{\text{Spc\_eff}} + w_5 f_{\text{Pwr\_eff}} + w_6 f_{\text{Pwr\_con}} \tag{4}$$

Throughput

$$f_{Thrp} = R_s * k * c \tag{5}$$

Bandwidth

$$f_{BW} = R_s * (1 + \beta) \tag{6}$$

Spectral efficiency

$$f_{Spc\_eff} = k * c/(1 + \beta) \tag{7}$$

Power efficiency

$$f_{Pwr\_eff} = (k * c)/((10^{(E_s/N_0)/10)}) * R_s) \tag{8}$$

Additional consumed power

$$f_{Pwr\_con} = E_s * R_s \tag{9}$$

Backup

Table 1: Adaptable parameters

Parameter	Variable	Value range
Modulation order	$\bar{M}$	$[4, 8, 16, 32]$
Bits per symbol	$\bar{k}$	$[2, 3, 4, 5]$
Encoding rate[1]	$\bar{c}$	$[1/4 - 9/10]$
Roll-off factor	$\bar{\beta}$	$[0.2, 0.3, 0.35]$
Bandwidth	$B\bar{W}$	$[0.5 - 5]$ MHz
Symbol rate	$\bar{R}_s$	$[0.41 : 0.1 : 3.7]$ MSamples/sec
Additional Tx E_s/N_0	$\bar{E}_s$	$[0 : 1 : 10]$ dB

[1]Different modulation schemes use different encoding rate sets