Machine Learning and Adaptation in Long-term Operating Underwater Acoustic Communication Networks

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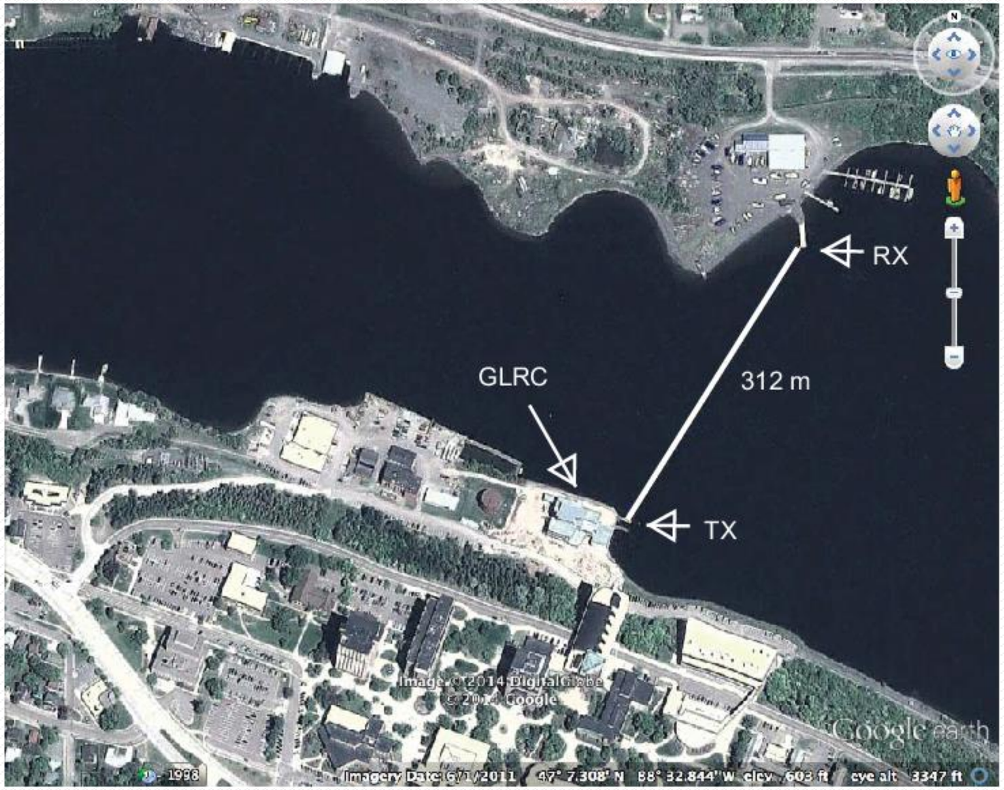
Outline

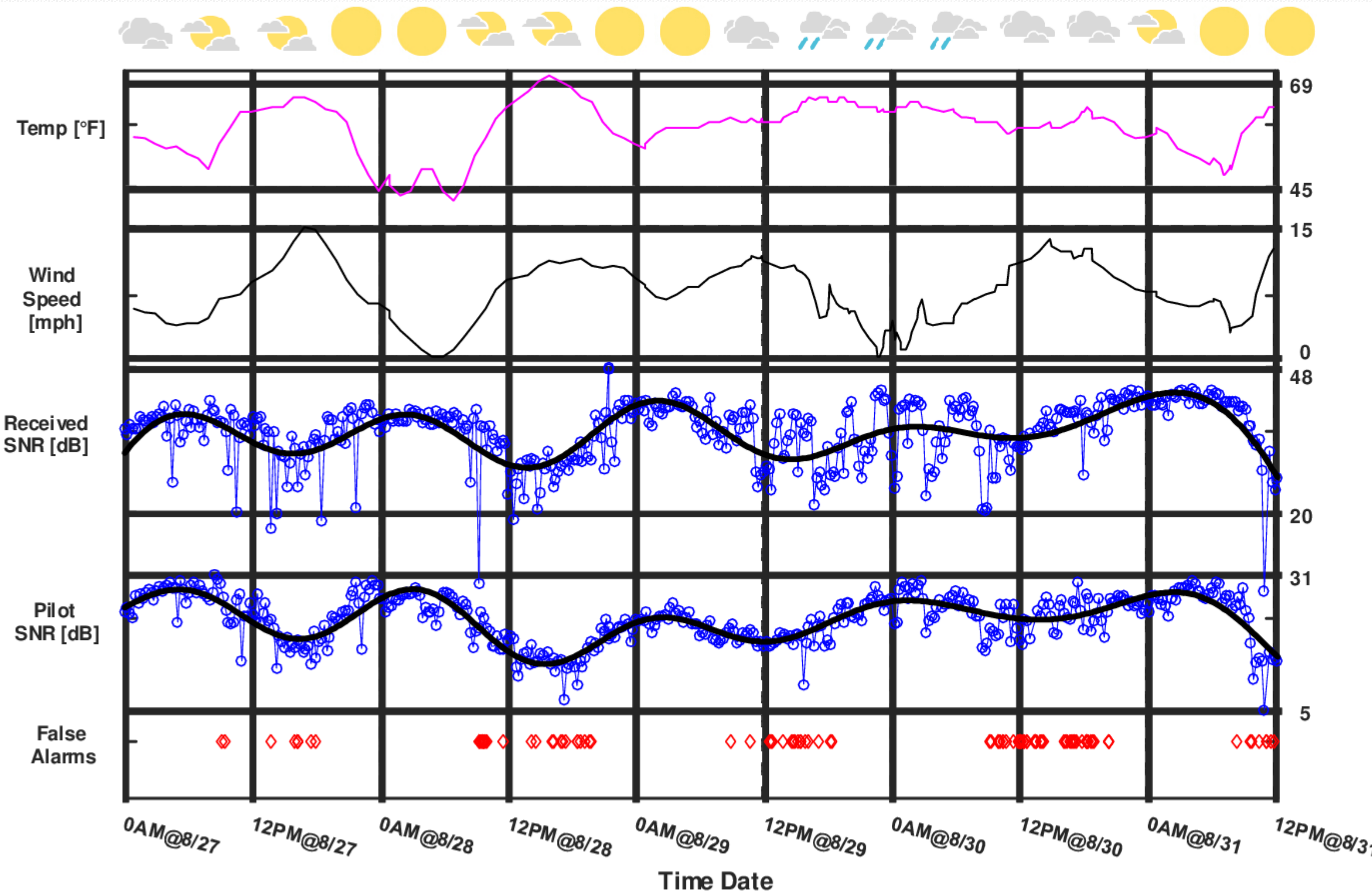
- Experimental observations of UWA channel dynamics
- Machine learning-based underwater wireless networking framework
- A case study: Learning-based adaptive transmissions
- Conclusions

Field Experiments



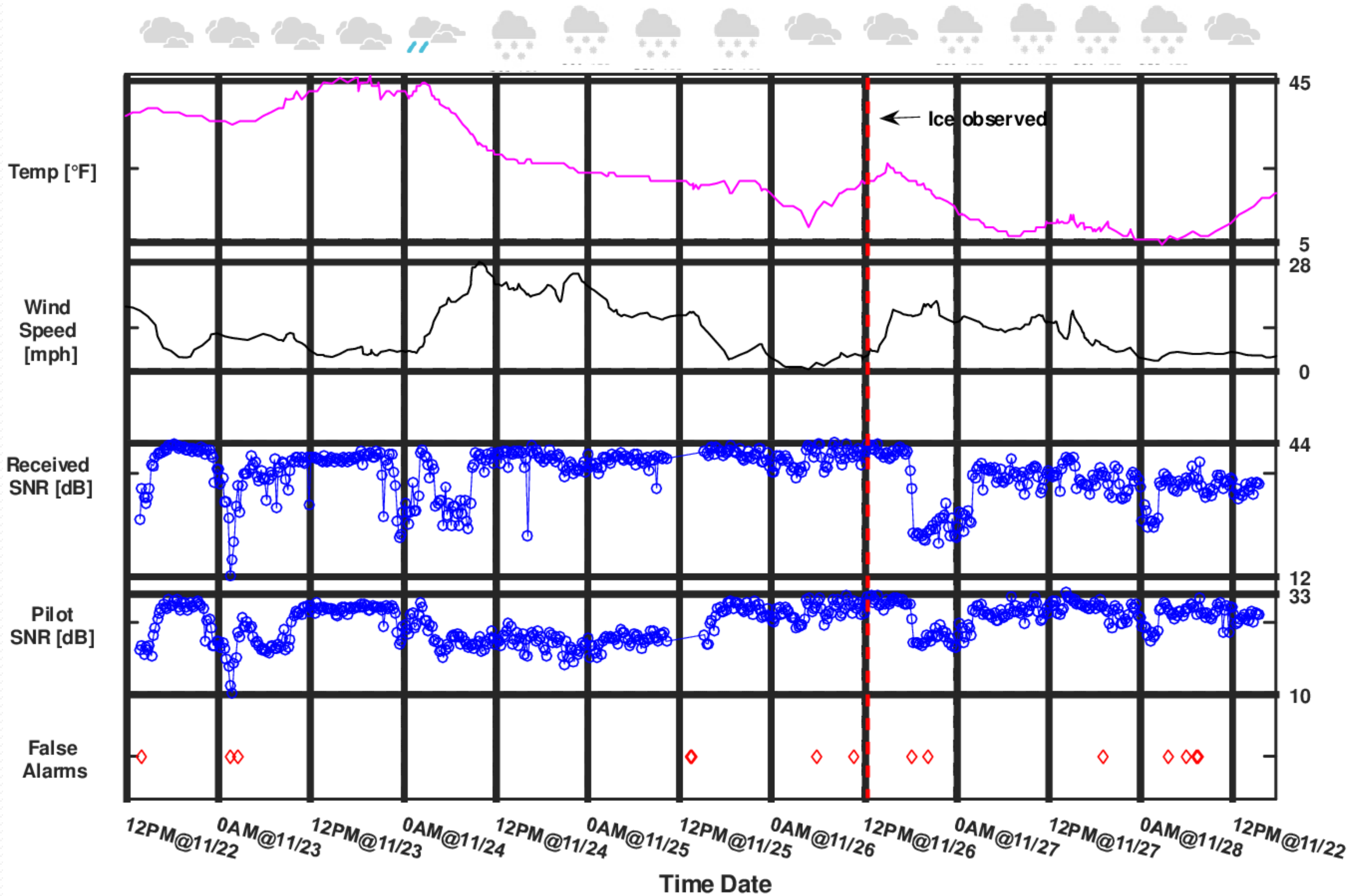
- Date: Aug. 2014, Nov. 2014, Jan. 2015, and May 2015
- Modulation: OFDM
- Trans. duration: 8.8 secs
- Repetition period: 15 mins
- # of hydrophones: 4
- Fixed transmission power

Field observation on Channel Long-term Evolution (Aug, 2014)



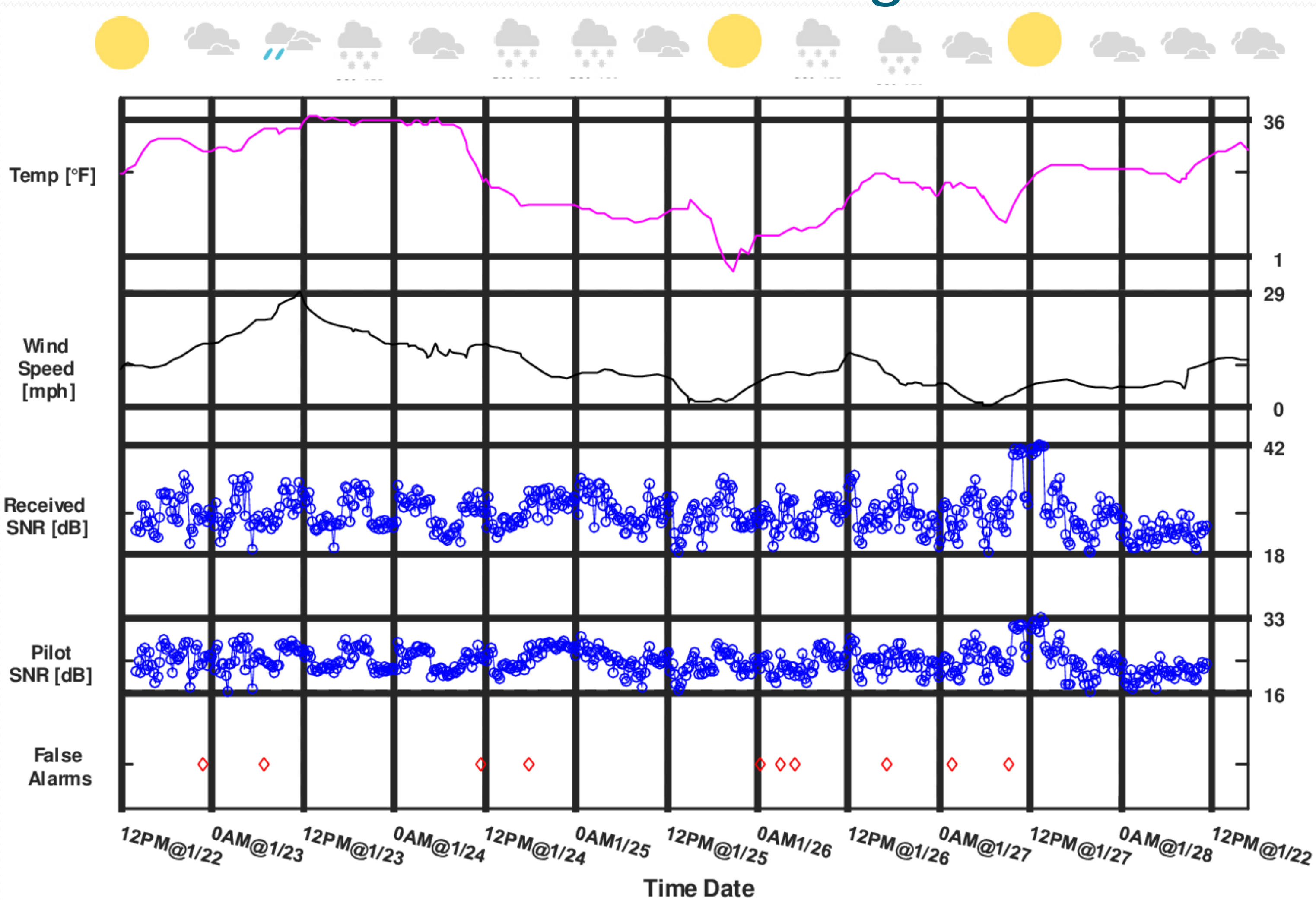
open water;
a diurnal pattern
observed

Field observation on Channel Long-term Evolution (Nov, 2014)



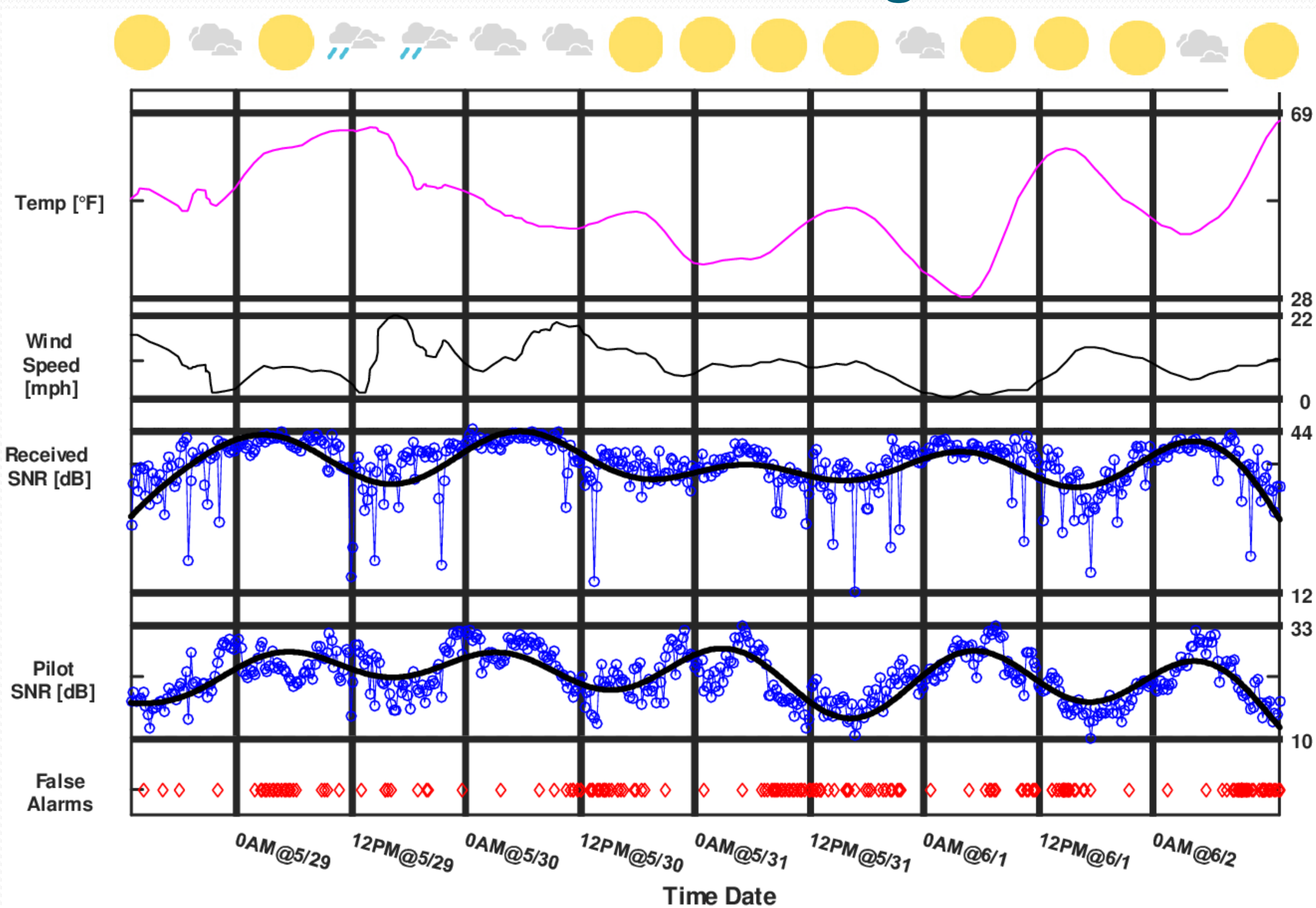
relatively constant SNR; a very thin layer of ice observed in the second half of the experiment

Field observation on Channel Long-term Evolution (Jan, 2015)



under-ice;
the SNR changes in sync with the on-off of a nearby de-icing agitator

Field observation on Channel Long-term Evolution (May, 2015)



open water;
the diurnal pattern is back!

Field Observations and Insights

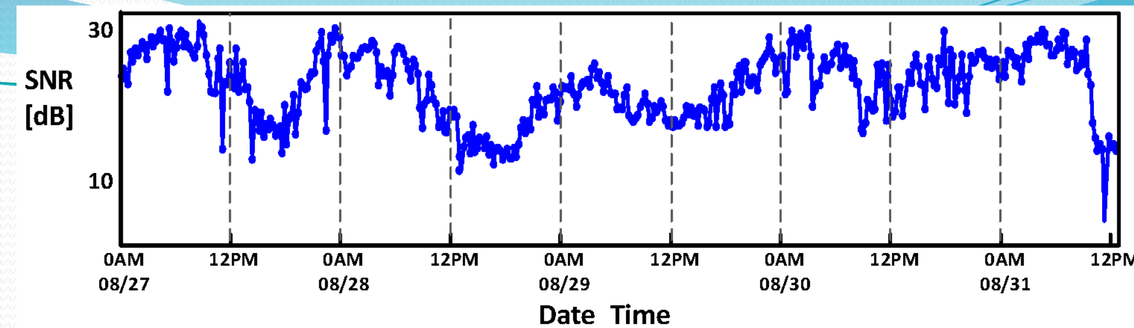
- UWA channels have spatial-temporal dynamics in a long term
  - Propagation loss
  - Multipath structure
  - Doppler effect
  - Interference characteristics
- There is no one size fits all!
  - Transmission parameters: e.g., power, modulation size, coding rate
  - Modulation techniques: e.g., SC, OFDM, spread spectrum
  - Networking protocols: e.g., UW-Aloha, slotted FAMA, DBR, …
  - Interference mitigation: e.g., impulsive noise, narrowband interference
- Q: how to intelligently adapt to the unknown and dynamically changing environments/situations to optimize the long-term performance?

Learning-based Underwater Comm Networks

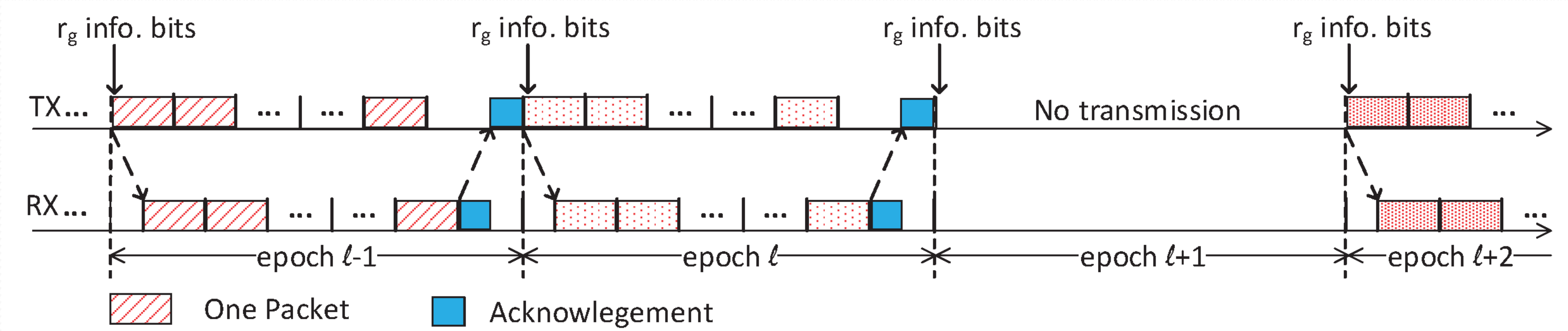
- To intelligently tackle uncertain and dynamically changing environments
- We propose a machine learning-based framework for long-term adaptation
  - Domain-specific techniques + machine learning techniques

- Domain-specific techniques (> three decades of research)
  - OFDM, single-carrier, spread spectrum, MIMO, …
  - Pre-processing techniques, channel estimation, equalization, symbol detection …
  - MAC protocols, routing protocols, …
- Machine learning techniques
  - Learning for self-awareness and environment-awareness through improving models of the system and the underwater environment that are incomplete or inaccurate
  - Adapting the communication/networking strategies based on past experiences, observations, and interaction with other underwater systems

Adaptive Transmission



- Point-to-point transmission on epoch-by-epoch basis



- For each epoch, TX decides the transmission action (power, modulation size, and coding rate) based on the previous RX feedbacks (channel info. and decoding results)
- Goal: To minimize a long-term cost based on energy consumption & TX queue length

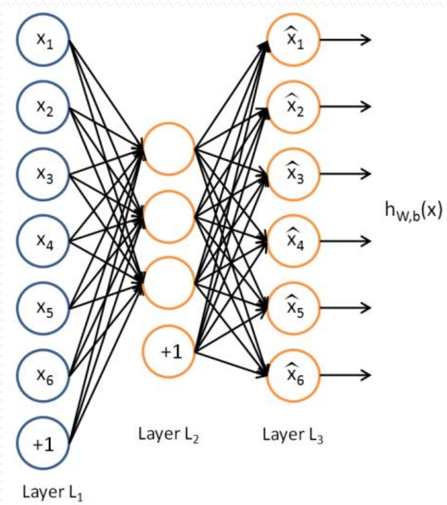
C. Wang, Z. Wang, W. Sun, and D. R. Fuhrmann, "Reinforcement learning-based adaptive transmission in time-varying underwater acoustic channels," IEEE Access, vol. 6, pp. 2541-2558, 2018.

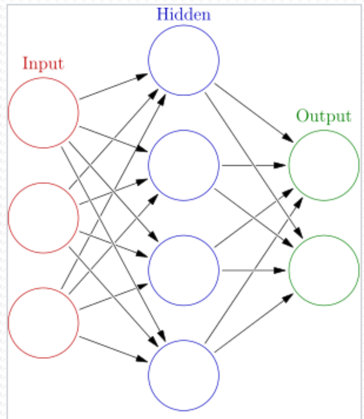
Learning for Adaptive Transmission

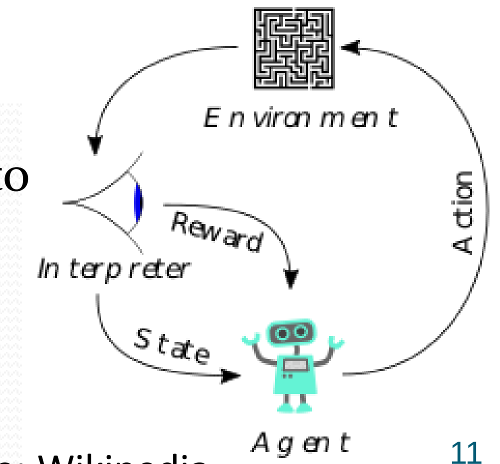
- Unsupervised learning (representation learning)
  - To capture hidden features (channel states) based on various channel-related variables
  - Channel modeling and prediction

- Supervised learning
  - To map the channel hidden features to PER for a specific transmission strategy

- Reinforcement learning
  - how the agent ought to take actions in such an environment so as to maximize (minimize) a long-term reward (cost).
  - it strikes a balance between exploration of the unknown environment and exploitation of current knowledge.







Source: Wikipedia

Problem Formulation

- Transmission action: $\boldsymbol{a}(\ell) \coloneqq [P, M, r_c]$ (tx power, modulation size, and coding rate)
- System state: $\boldsymbol{s}(\ell) \coloneqq \{\boldsymbol{s}_{\mathrm{ch}}(\ell), q(\ell)\}$
- The transmitter data queue length: $q(\ell) = q(\ell-1) - r(\ell-1)N_{\mathrm{s}}(\ell-1) + r_{\mathrm{g}}$
  - $r(\ell-1)$: the amount of info. bits in each packet according to $\boldsymbol{a}(\ell-1)$
  - # of successfully delivered packets $N_{\mathrm{s}} \sim \mathfrak{B}(N, 1-\mathrm{PER}(\boldsymbol{s}_{\mathrm{ch}}, \boldsymbol{a}))$
- Cost function: $\mathrm{C}\big(\boldsymbol{s}(\ell), \boldsymbol{a}(\ell)\big) = f_{\mathrm{p}}\big(P(\ell)\big) + f_{\mathrm{q}}\big(q(\ell)\big)$
- Goal: Decide transmission actions to minimize the long-term expected total discounted cost:

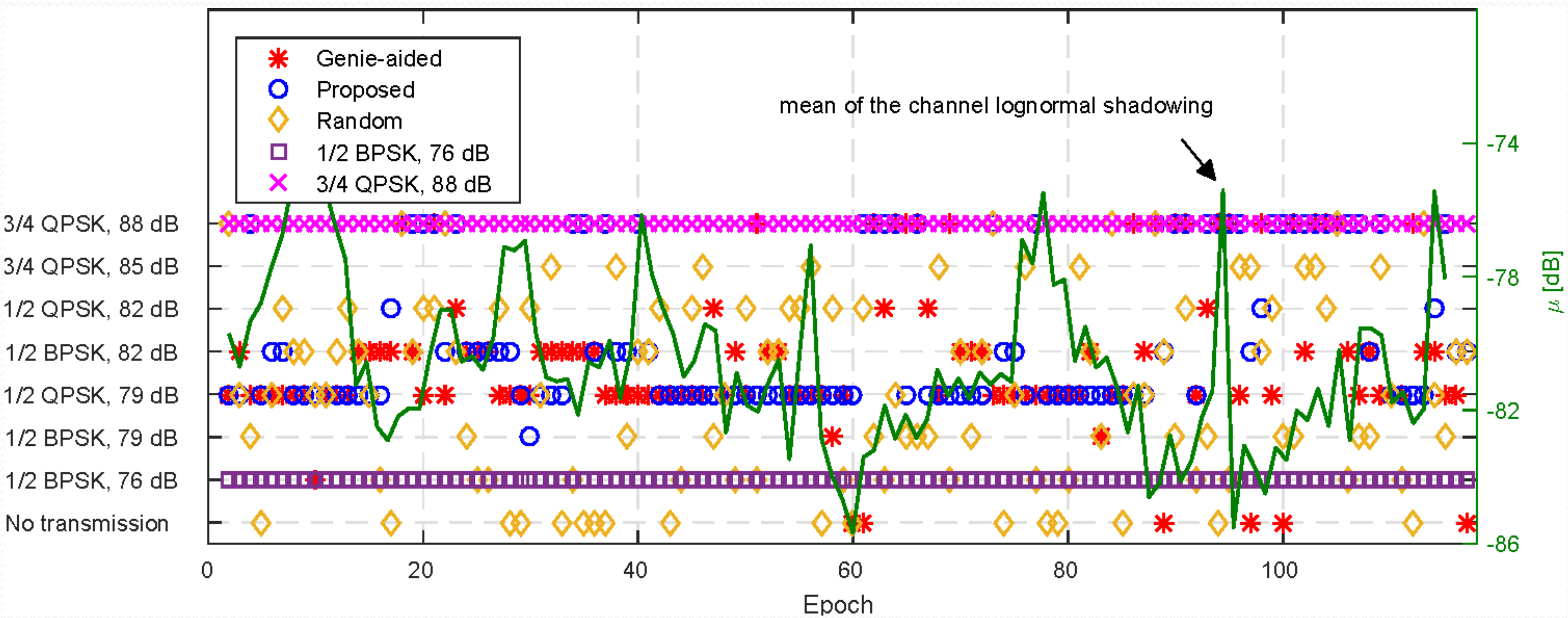
$$\min_{\{\boldsymbol{a}(\ell)\}_{\ell=0}^{\infty}} \mathbb{E}\left\{\sum_{\ell=0}^{\infty} \gamma^{\ell} \mathrm{C}\big(\boldsymbol{s}(\ell), \boldsymbol{a}(\ell)\big)\right\}$$

- The optimization problem can be reformulated into the Bellman optimality equation.
- A near-optimal solution can be found via searching over a Monte Carlo planning tree, augmented by the temporal difference learning.

SPACE08 Data Set

- # of info. bits from the application layer: r_g = 20 kilobits/epoch

TX method	Aver. Q length [kb]	Aver. TX power [dB]	Aver. cost
Clairvoyant	10.9	76.2	0.47
Proposed	13.1	81.1	0.58
Random	254.8	81.3	4.48
½ BPSK, 76 dB	949.6	76.0	15.79
¾ QPSK, 88 dB	7.1	84.4	0.65



Building Blocks of An Intelligent Underwater Wireless Network Architecture

- Components for machine learning-based underwater wireless networking
  - Unsupervised learning to capture hidden features of complex multidimensional environmental/system signals that cannot be replicated by mathematical or simulation models, e.g., spatial-temporal UWA channel representation
  - Supervised learning to map hidden features to the network task specific performance metrics, e.g., PER at the PHY layer, end-to-end latency/loss rate
  - Reinforcement learning to decide actions (comm/networking strategies and parameters) via an action-reward feedback loop to strike a balance between exploration and exploitation, thereby maximizing a long-term system reward
  - Learning at both the node level and the network level
- Implementation
  - Software defined communication modems
  - Software defined wireless networking: Control plane + Data plane

Conclusions

- Machine learning offers tools to tackle the dynamics and uncertainty in underwater wireless networks
- An intelligent underwater wireless networking architecture
  - Algorithm/protocol-wise: machine learning + domain knowledge
  - Implementation-wise: software-defined modems and networking
- A direction with rich research challenges and opportunities