# Machine Learning Applications in the Routing in Computer Networks

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# MENU

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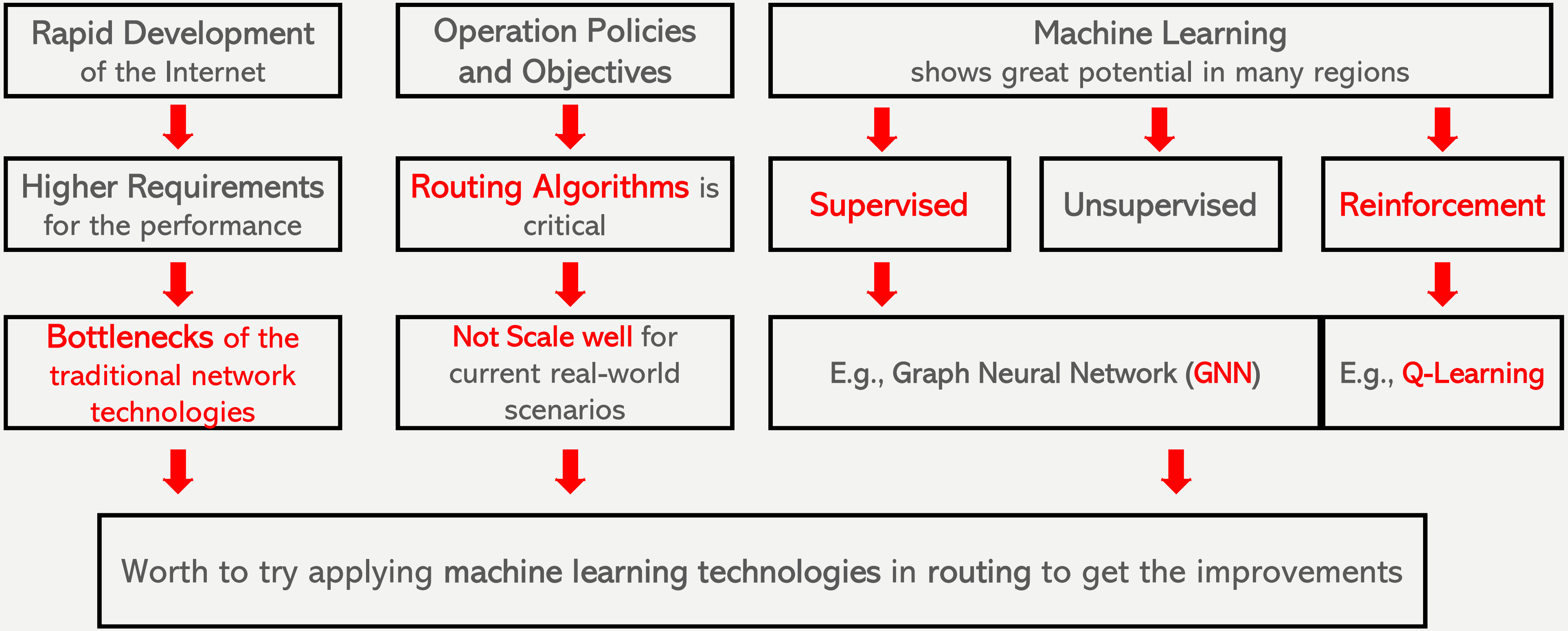
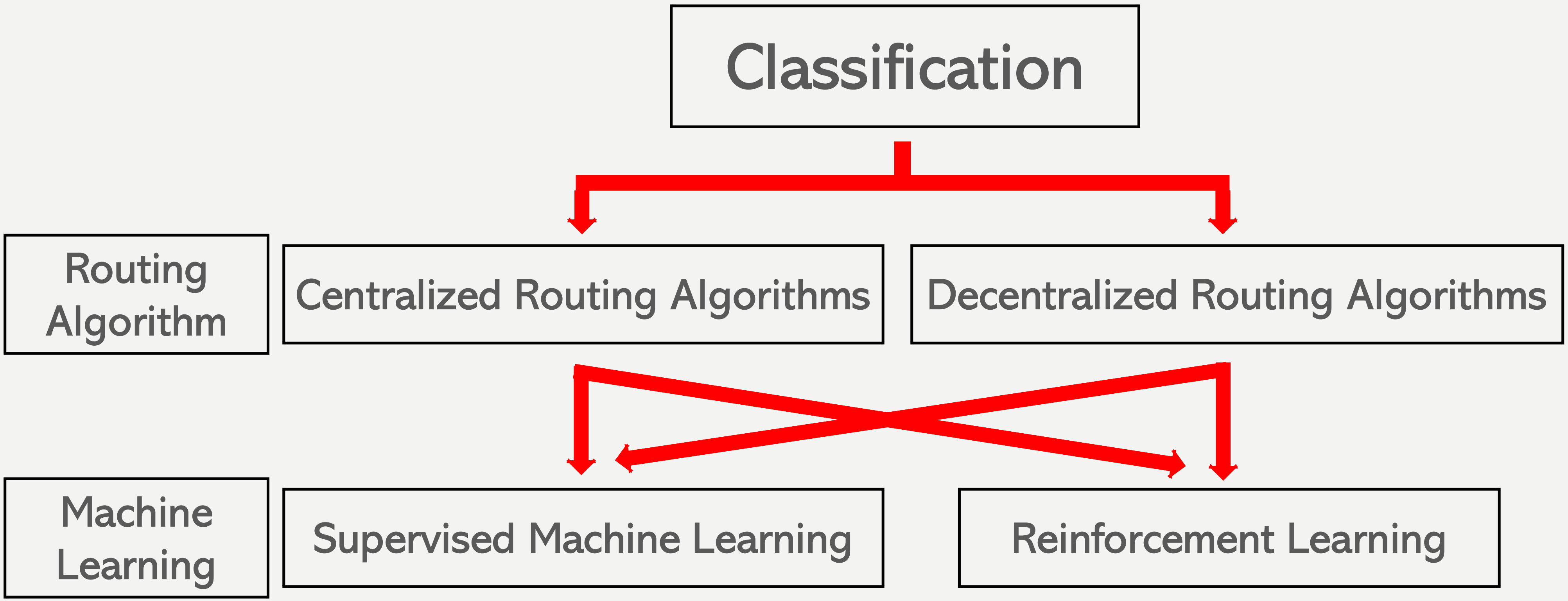
# INTRODUCTION




**Assumption/Scope**:
The routing algorithms combining with the supervised and reinforcement learning.

# CLASSIFICATION (HOW? WHY?)

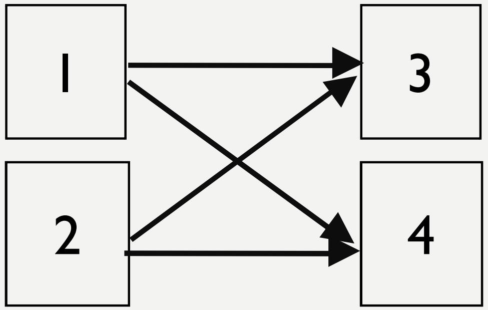


# METHODS OVERVIEW (14 METHODS)

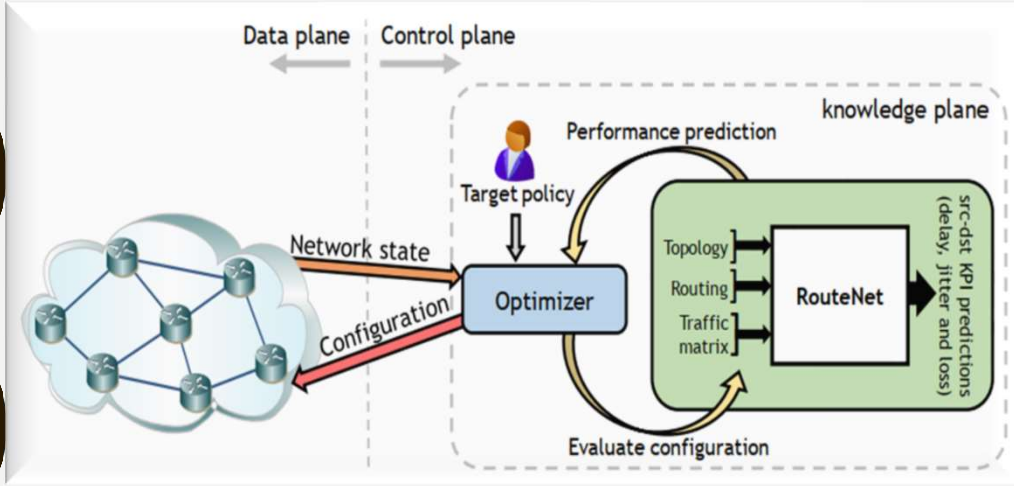
| Method | Type | Machine Learning Technique | Pros | Cons |
|---|---|---|---|---|
| GADL | Centralized Supervised | Graph Neural Networks | Training faster; High accuracy; Reduce average latency | Data hungry |
| ML-assisted LL | Centralized Supervised | Naive Bayes Classifier | Reduce blocking chance | More experiments for circuit-switched network; Data hungry |
| RouteNet | Centralized Supervised | Graph Neural Networks | Minimize the cost for getting performance for different routing policies; Reduce the average delay and packet loss | Complicated preprocess |
| QAR | Centralized Reinforcement Learning | SARSA Reinforcement Learning | Fast convergence; Minimize the signaling delay | Need to improve the scalability |
| DRL-based Cognitive Routing | Centralized Reinforcement Learning | Deep Reinforcement Learning, DDPG framework | Reduce average end-to-end delay | Limited experimental results; Extending to real-world network |
| DL Heterogeneous Traffic Control | Decentralized Supervised | Deep Neural Network | Reduce average delay and increase the throughput | Extend to real-world network |
| DBA Routing | Decentralized Supervised | Deep Belief Architecture | Reduce average delay and increase the throughput | Need to improve the scalability |
| GQNN Routing | Decentralized Supervised | Graph-Query Neural Network. | Generated Models with good delay | Extend to other routing protocols |
| MLProph | Decentralized Supervised | Neural Network, Decision Tree | Reduce average delay and packet loss chance | Simulate with real mobility traces; Test other novel ML models |
| DNN Routing | Decentralized Supervised | Deep NN, MILP | Improved link utilization and reduce the congestion | Data hungry |
| Q-Routing | Decentralized Reinforcement Learning | Q-Learning | Improved performance in high load conditions | Q function table does not scale well to larger networks |
| CQ-Routing | Decentralized Reinforcement Learning | Q-Learning, Confidence Learning | Faster, and sustain higher network load | Extend to real world network |
| NN Q-Routing | Decentralized Reinforcement Learning | Neural Network, Q-Learning | Improved scalability of Q function | Not scale with some network case |
| DRQ Routing | Decentralized Reinforcement Learning | Dual Reinforcement Learning, Q-Learning | Improved delivery time under high load conditions | Extend to real-world network |

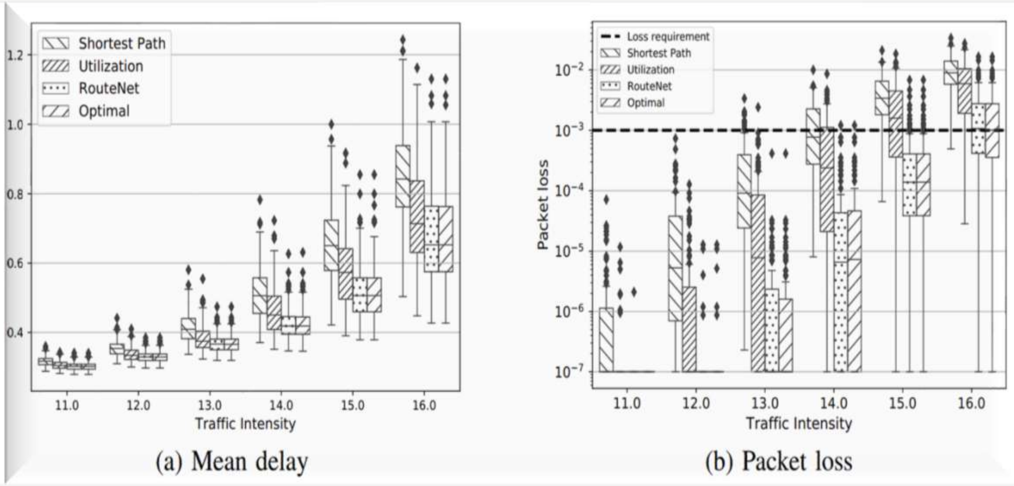
# CLASSIFICATION

| | Classification | Pros | Cons |
|---|---|---|---|
| 1 | **Centralized** | Resources saved, Flexible, etc. | Single point of failure, etc. |
| 2 | **Decentralized** | Adaptive to changing, Scalable, etc. | Need more space, Infinity loop, etc. |
| 3 | **Supervised** | Scalable; Good Performance | Well-constructed Data, and need well constructed the models |
| 4 | **Reinforcement** | Can be easily combined in routing process | Construct Rewards function |

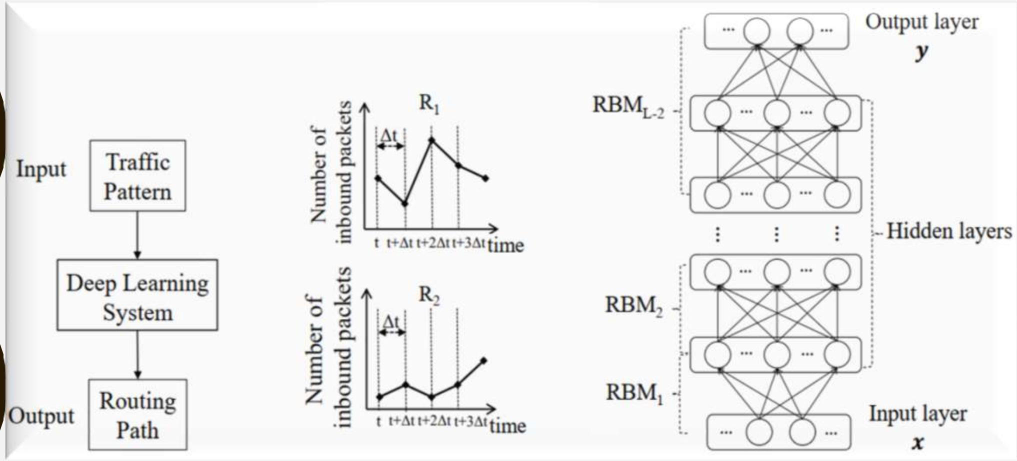


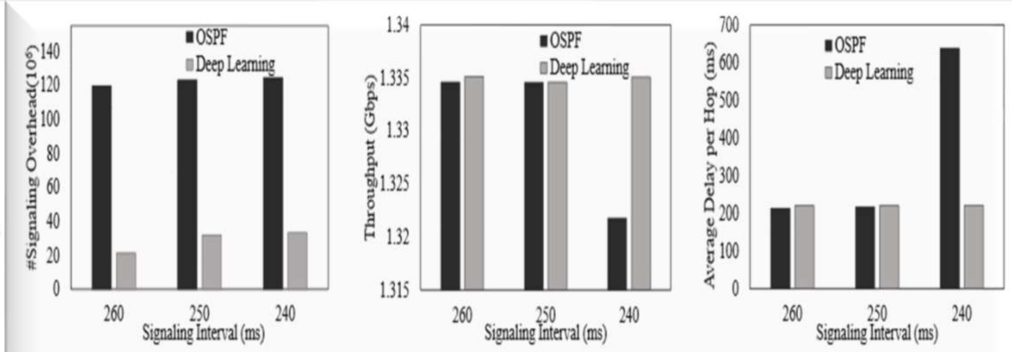
# SELECTED METHOD DETAILS




RouteNet



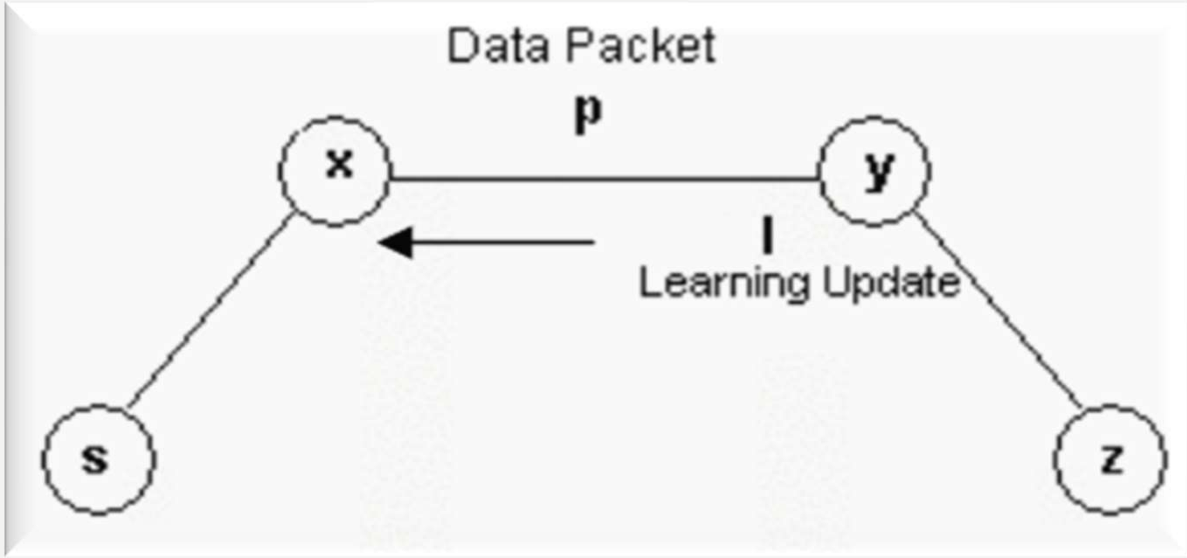

(a) Comparison of signaling overhead for the conventional OSPF and the proposed deep learning system.

(b) Comparison of aggregate throughput for the conventional OSPF and the proposed deep learning system.

(c) Comparison of average delay per hop for the conventional OSPF and the proposed deep learning system.

Deep Belief Architecture Routing

# SELECTED METHOD DETAILS




$$\Delta Q_x(y,d) = \eta\left(min_{Z\in N(y)} Q_y(z,d) + q_x + \delta - Q_x(y,d)\right)$$

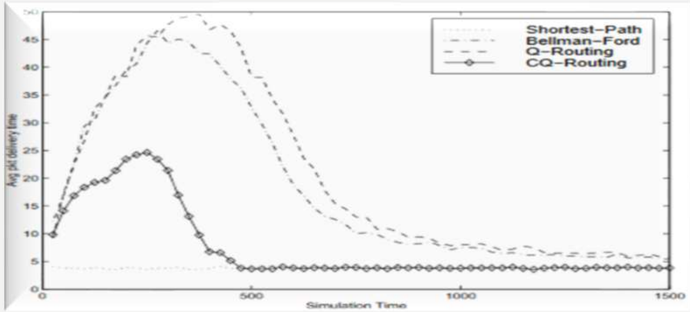
Q-Routing

$$\eta(C_{old}, C_{est}) = max(C_{est}, 1 - C_{old})$$

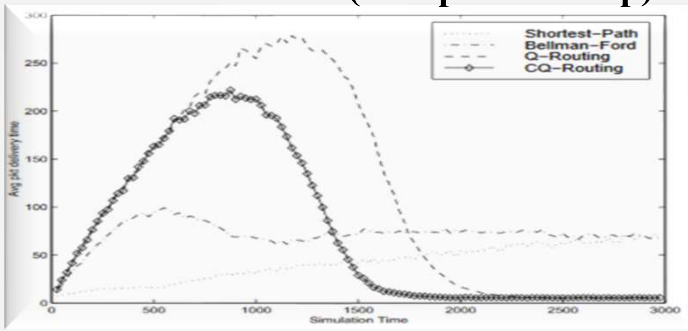
$$C_{new} = \begin{cases} \lambda C_{old} \\ C_{old} + \eta(C_{old}, C_{est})(C_{est} - C_{old}) \end{cases}$$

$$\Delta Q_x(y,d) = \eta(C_{old}, C_{est})\left(min_{Z\in N(y)} Q_y(z,d) + q_x + \delta - Q_x(y,d)\right)$$

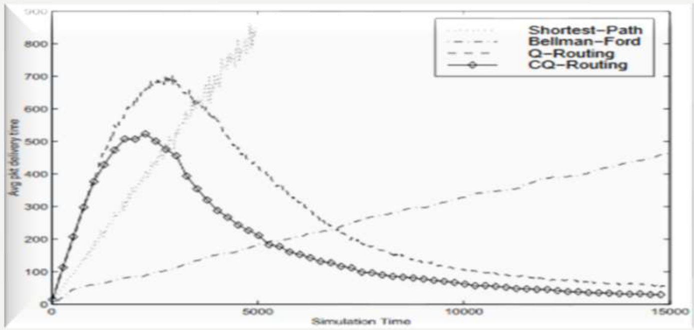
CQ-Routing




**low load levels (1.25 packets/step)**




**medium load levels (2.15 packets/step)**



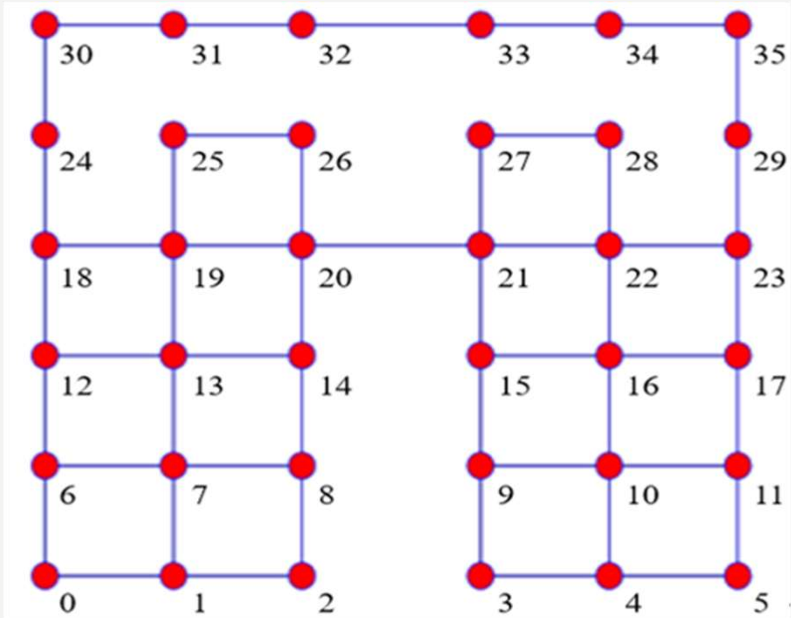

**high load levels (2.75 packets/step)**

# PERFORMANCE COMPARISON (BONUS)

**Comparison on the average delivery time between Q-Routing and CQ-Routing.**

- **Simulation Settings**

- Random nodes will receive the packets with the random destination per simulation step.
- **Network load:** Number of the packets generated per simulation step
- **Delivery time:** The total simulation steps needed for a packet occurs in the source node and disappears in the destination node.
- Unbounded FIFO queue to store.
- Learning rate for Q-Routing: $\eta=0.85$
- Decay constant for CQ-Routing: $\lambda=0.95$




The irregular **6x6 grid** topology

| Medium Load | High Load |
|---|---|
| 2.15 packets/step | 2.75 packets/step |

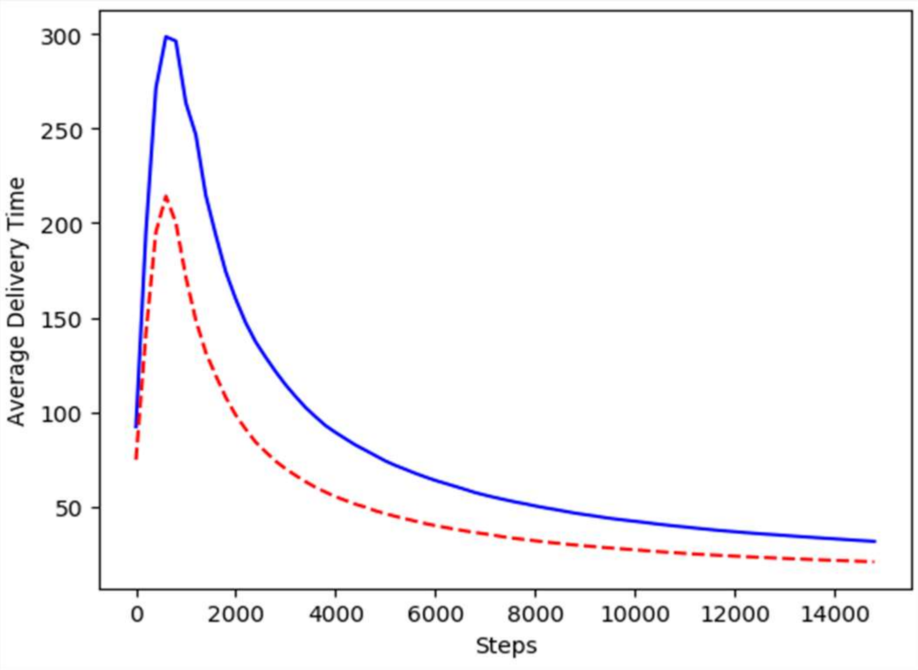
Loads settings

# PERFORMANCE COMPARISON (BONUS)

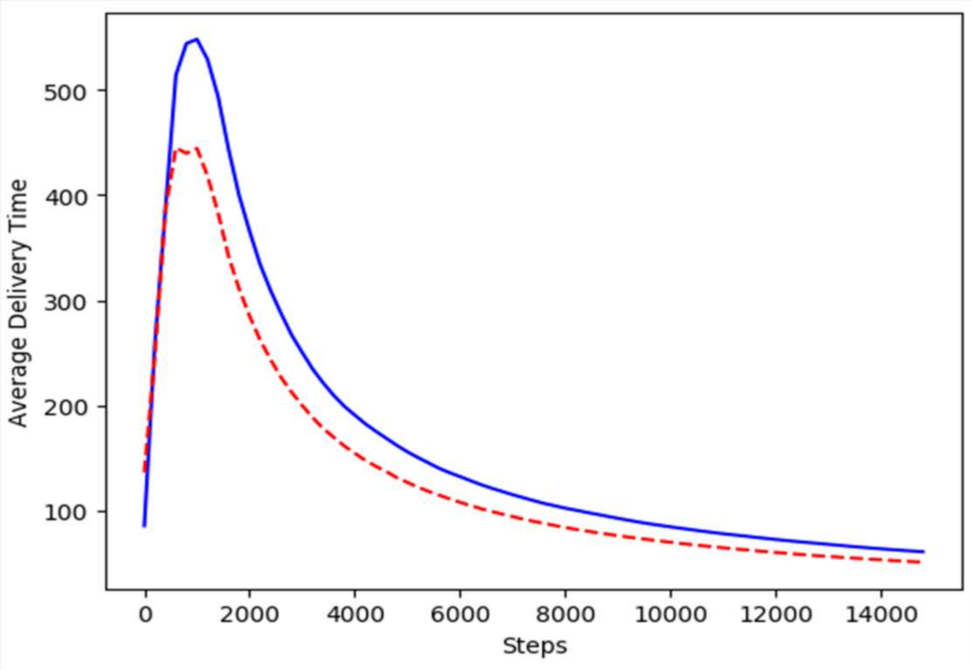
## Simulation Results and Interpretation

**Averages: within 10 test runs**

Red dot line represents the CQ-Routing, and blue line represents the Q-Routing




**medium load levels (2.15 packets/step)**




**high load levels (2.7 packets/step)**

# CONCLUSION

- 1. Need smarter and scalable routing methods
- 2. ML-techniques show promising results for improving routing performance

- Future:
- 1. More research based on realistic network topology environments
- 2. Combination of supervised and reinforcement learning methods
- 3. Need semi-supervised or unsupervised methods

# REFERENCES

[1] James Kurose, Keith Ross - Computer Networking_ A Top-Down Approach (7th Edition)-Pearson, 2016.
[2] R. Boutaba, M.A. Salahuddin, N. Limam, S. Ayoubi, N. Shahriar, F. Estrada-Solano and O. M. Caicedo, “A comprehensive survey on machine learning for networking: evolution, applications and research opportunities,” Journal Internet Service Application vol 9, no.16, https://doi.org/10.1186/s13174-018-0087-2, 2018.
[3] Liu Chenyi, Xu Mingwei, Geng Nan, and Zhang Xiang, “A Survey on Machine Learning Based Routing Algorithms,” Journal of Computer Research and Development, vol. 57,no. 4, pp. 671-687, 2020.
[4] Ian Goodfellow and Yoshua Bengio and Aaron Courville, “Deep Learning,” MIT Press, http://www.deeplearningbook.org, 2016.
[5] N. Kato et al., "The Deep Learning Vision for Heterogeneous Network Traffic Control: Proposal, Challenges, and Future Perspective," in IEEE Wireless Communications, vol. 24, no. 3, pp. 146-153, doi: 10.1109/MWC.2016.1600317WC,2017.
[6] Z. Zhuang, J. Wang, Q. Qi, H. Sun and J. Liao, "Graph-Aware Deep Learning Based Intelligent Routing Strategy," IEEE 43rd Conference on Local Computer Networks (LCN), Chicago, IL, USA, pp. 441-444, doi: 10.1109/LCN.2018.8638099, 2018.
[7]Gangxiang Shen, Longfei Li, Ya Zhang, Wei Chen, Sanjay K. Bose, Moshe Zukerman. “Naïve Bayes Classifier-Assisted Least Loaded Routing for Circuit-Switched Networks,” IEEE. Translations and content mining, vol. 7, pp. 11854-11867, 2018.
[8]Rusek, Krzysztof, Suarez-Varela, Jose, Mestres, Albert, Barlet-Ros, Pere, Cabello, Albert, “Unveiling the potential of Graph Neural Networks for network modeling and optimization in SDN,” SOSR '19: Proceedings of the ACM Symposium on SDN Research. pp. 140-151. 10.1145/3314148.3314357, 2019.
[9] K. Rusek, J. Suárez-Varela, P. Almasan, P. Barlet-Ros and A. Cabellos-Aparicio, "RouteNet: Leveraging Graph Neural Networks for Network Modeling and Optimization in SDN," in IEEE Journal on Selected Areas in Communications, vol. 38, no. 10, pp. 2260-2270, doi: 10.1109/JSAC.2020.3000405, Oct. 2020.
[10] S. Lin, I. F. Akyildiz, P. Wang and M. Luo, "QoS-Aware Adaptive Routing in Multi-layer Hierarchical Software Defined Networks: A Reinforcement Learning Approach," 2016 IEEE International Conference on Services Computing (SCC), San Francisco, CA, pp. 25-33, doi: 10.1109/SCC, 2016.12.
[11]Jiawei Wu, Jianxue Li., Yang Xiao, and Jun Liu, “Towards Cognitive Routing based on Deep Reinforcement Learning,”arXiv:2003.12439, 2020.
[12] B. Mao et al., "Routing or Computing? The Paradigm Shift Towards Intelligent Computer Network Packet Transmission Based on Deep Learning," in IEEE Transactions on Computers, vol. 66, no. 11, pp. 1946-1960, doi: 10.1109/TC.2017.2709742, 2017.
[13] Geyer, Fabien, and G. Carle. “Learning and Generating Distributed Routing Protocols Using Graph-Based Deep Learning,” Big-DAMA '18, 2018.
[14] D. K. Sharma, S. K. Dhurandher, I. Woungang, R. K. Srivastava, A. Mohananey and J. J.P.C. Rodrigues, "A Machine Learning-Based Protocol for Efficient Routing in Opportunistic Networks,"IEEE Systems Journal, vol. 12, no. 3, pp. 2207-2213, doi: 10.1109/JSYST.2016.2 630923,2018.
[15] J. Reis, M. Rocha, T. K. Phan, D. Griffin, F. Le and M. Rio, "Deep Neural Networks for Network Routing," International Joint Conference on Neural Networks (IJCNN), Budapest, Hungary, pp. 1-8, doi: 10.1109/IJCNN.2019.8851733,2019.
[16] B. Fortz and M. Thorup, “Internet Traffic Engineering by Optimizing OSPF Weights,” IEEE International Conference on Computer Com-munications (INFOCOM), 2000
[17] Justin Boyan, Michael Littman. “Packet Routing in Dynamically Changing Networks: A Reinforcement Learning Approach,” NIPS 93: Proceedings of the 6th International Conference on Neural Information Processing Systems November 1993, pp: 671–678
[18] Shailesh KumarRisto Miikkulainen, “Confidence-based q-routing: an online adaptive network routing algorithm,” PROCEEDINGS OF Proceeding Conference on Artificial Neural Networks in Engineering, 1998.
[19]Newton, Will and Wu, Si. “A Neural Network Algorithm for Internetwork Routing,” 2002.
[20] B. Xia, M. H. Wahab, Y. Yang, Z. Fan and M. Sooriyabandara, "Reinforcement learning based spectrum-aware routing in multi-hop cognitive radio networks," 2009 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications, Hannover, pp. 1-5, doi: 10.1109/CROWNCO, 2009.