

# Research Progress Report

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# 1 Reading and Research Activities

## 1.1 Reading Summary

With the growth of network nodes and the expansion of application environment of WSNs, it needs to have the ability to handle huge network traffic and more flexibility. So, here are some main problems that need to be solved by Machine Learning.

- 1) Because of the changing rapidly of WSNs environments over time, it need to be adapted to these environments.
- 2) For complicated network environments, a good mathematical model is needed to describe network behavior, which can reduce the complexity of WSNs problems.
- 3) Relationship among network features, such as packet size, delay, error and path, are difficult to extract and describe.
- 4) How to prolong the lifetime of WSNs by choosing the optimal path?

Why machine learning is a good choice to solve these problems? Here is an example for routing search. Figure 1(a) shows the original graph and Figure 1(b) is the traditional spanning tree routing. However, the routing problem can be divided into sub-problems by employing machine learning, shown in Figure 1(c). Each node only needs to consider neighboring nodes' information for deciding the optimal next node.

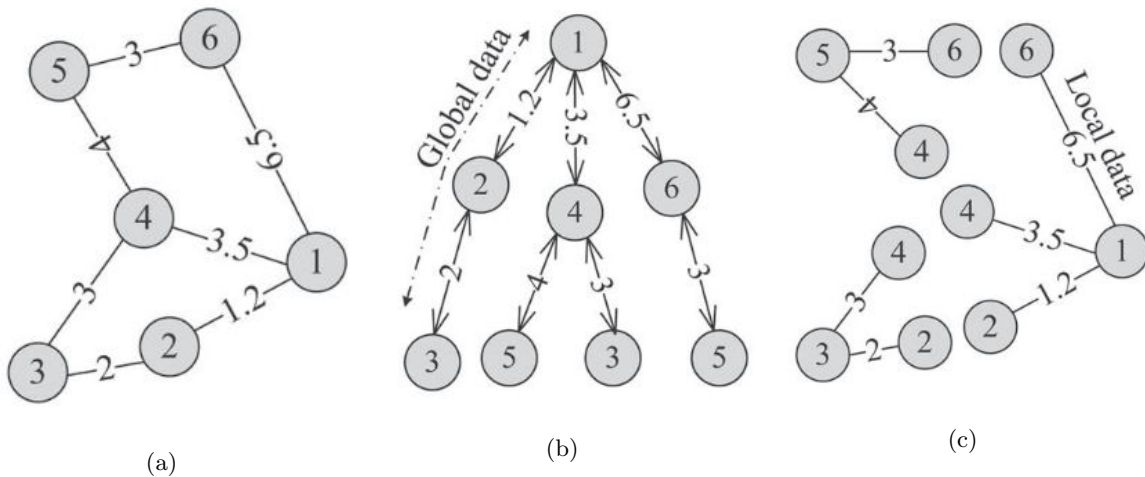


Figure 1: Example of routing problem

For the machine learning-based network topology, there are two main ideas: centralized model and distributed model. With regard to the centralized model, the advantage is that it uses the base stations with huge computation power to train machine learning model while the disadvantage is that the common network nodes are difficult to find the base stations in some cases, like the limitation of geography. However, in the distributed model, each node or edge router needs to train several machine learning models according to previous history network traffic for deciding next node. So, the main problems is each node needs to have the abilities of huge computation and storage. Specially, reinforcement learning and neural networks are the most commonly machine learning-based algorithms used in the distributed WSNs. Here is a brief summary and Table 1 gives a detailed investigation.

### 1) Key steps of applying Neural Network in wireless networks

There are several steps that we need to consider for applying Neural network in wireless network.

Table 1: Investigation of machine learning-based routing search

| Ref.    | Network Simulation Tool | ML Tool        | Dataset Input   | Dataset Output   | Evaluation Index  |
|---------|-------------------------|----------------|---|--|---|
| [1]     | Mininet [2]             | TensorFlow [3] | Network states + traffic matrix   | optimal path   | accuracy  |
| [4]     | NS2                     | NS2            | location and energy of node and its neighbor  | next node  | packets sent, delivery ratio, average delay, network lifetime         |
| [5]     | Aqua-sim(NS2)           | Aqua-sim(NS2)  | states set<br>actions set   | next node  | average latency<br>residual energy<br>transmission errors<br>lifetime |
| [6] [7] | C++                     | WILL [8]       | traffic pattern   | next node  | total throughput<br>average per<br>-hop delay                         |
| [9]     | Qualnet 5.0             | word2vec       | node vector<br>message  | node degree  | packet delivery rate<br>route discovery time                          |
| [10]    | OMNeT++                 | not mentioned  | traffic matrix<br>link weight   | mean of delay  | transmission delay  |
| [11]    | Not mentioned           | CPLEX          | traffic pattern   | next node  | average congestion ratio  |
| [12]    | NS2                     | Not mentioned  | distance between each node and heads  | position of cluster head   | energy dissipation  |
| [13]    | NS2                     | NS2            | energy consumption<br>transmit cost<br>receive cost<br>data packet size<br>sensing radius | network lifetime<br>packet delivery<br>packet delay<br>network balance |   |

Table 2: The comparison of literatures

| ML Techniques          | Ref.                        |
|------------------------|-----------------------------|
| Neural Network         | [6] [7] [14] [15] [16]      |
| Reinforcement Learning | [4] [5] [10] [13] [17] [18] |

- The extraction of traffic features matrix or vector

The input vectors is very important in training neural network. Because of the self-similarity of network traffic, we can use the previous network traffic characteristics to represent the later network traffic. How to choose the appropriate parameters to represent the relationship of network traffics is a very important issue. [9] creates a collection of 20-dimension vectors that can express a single feature in the node vector.

| Device type | Signal strength | Hop number | Distance | Coverage area | Neighbor number | Energy degree | Delay | Communication mode | Move speed | Additional BS |
|-------------|-----------------|------------|----------|---------------|-----------------|---------------|-------|--------------------|------------|---------------|
|-------------|-----------------|------------|----------|---------------|-----------------|---------------|-------|--------------------|------------|---------------|

Figure 2:

- The design of neural network architecture

There are different neural network models and it is important to choose which one. Normally, any neural networks comprise an input layer, multiple hidden layers and an output layer, shown in Figure 3. The input layer has  $N$  units which can be defined as the total number of nodes in the network. In the hidden layers, each layer can compute a non-linear transformation of the previous layer. The output of neural network is the routing path indicating the next router along the path from the source router to the destination. A  $N$ -dimensional vector can represent the output and each of its elements has a binary value. Only the position with value of 1 indicates the next node.

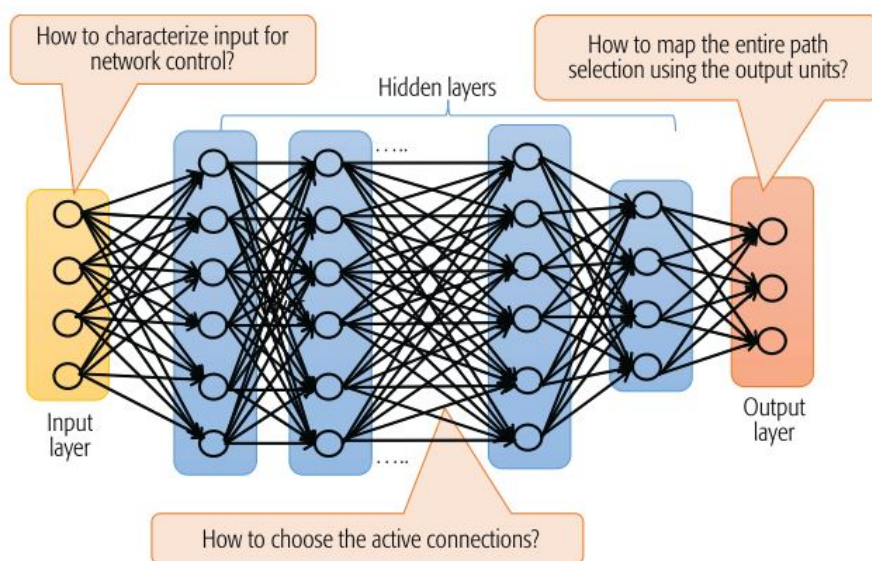


Figure 3: Neural network architecture

- Routing search

Assume there are 10 routers in the network, the source node is  $n_1$ , and the destination node is  $n_{10}$ . The first step of the running phase is to find the optimal router to the source. The NN model  $NN_{1,10}$  is run by  $n_1$ . The input of  $NN_{1,10}$  is vector  $A = [\alpha_1, \alpha_2, \dots, \alpha_{10}]$ , where  $\alpha_i$  is the traffic pattern of router  $i$ . At the output side, one out of 10 routers is chosen which is  $n_3$ .

in the figure 4. Following that, node  $n_1$  runs model  $NN_{3,10}$  to find the second hop node. This operation is repeated until the destination node is reached.

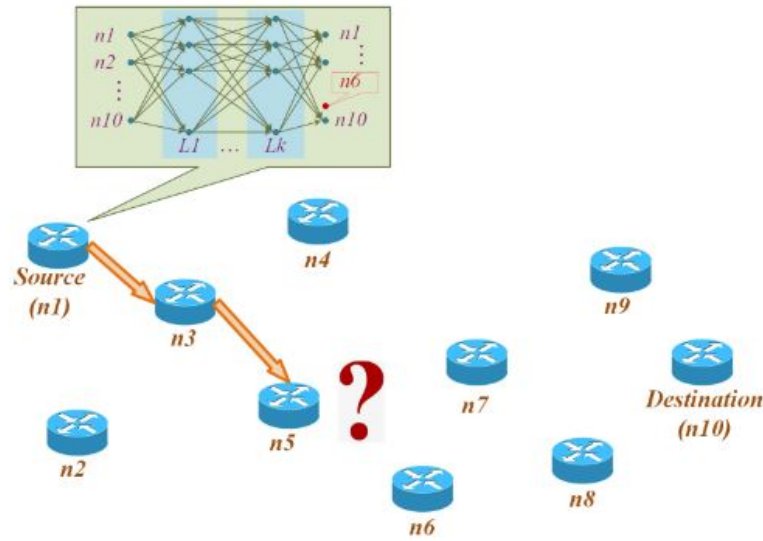


Figure 4: Routing search

In addition to the summary of the important parts above, there are other steps in the process of using neural network, such as initial phase, data collection and NN weight matrix update, etc. Here is a simple flow chart. For the detailed introduction of applying neural network into the field of routing search, please see ref. [6].

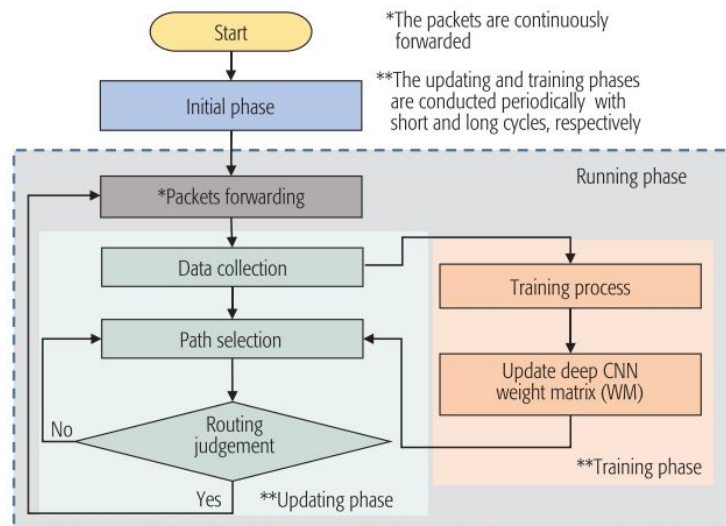


Figure 5: The flow chart of neural network based routing search method

## 2) Reinforcement learning in wireless networks

Reinforcement learning is a branch of machine learning, which is good at controlling an individual

who can act independently in a certain environment, and constantly improve its behavior through interaction with the environment. Reinforcement learning problems include how to do it, how to map the environment into action and how to get the greatest reward. In reinforcement learning, learners are decision-making agents. They try to run repeatedly to find the behavior that can get the greatest reward. Generally speaking, actions will not only affect the current incentives, but also the environment at the next time point and all subsequent incentives.

Reinforcement learning mainly solves continuous decision making problem, which is very similar to routing search. In reinforcement learning, the routing problem can be consider as a Markov decision process, the agent decides at each state which action to take based on its experiences. After taking an action, the agent gets a reward or cost from the environment. The agent uses the reward to update its policy. The advantage of reinforcement learning based routing is that each node does not need global network information, but can still approximate global optimality. Some research has been done in this area, shown in the table 2. Please see ref. [17] for detailed introduction.

By reading some literatures, only Professor N. Kato has done a lot of work in using neural network in the field of routing search. But his work assumes each node in the networks has the ability to train the neural network, which requires that each node has enough energy, storage capacity and computing capacity. At the same time, the neural network is supervised learning, how to obtain labeled data is also a big problem.

Reinforcement learning seems to be a good way to solve routing problems, because it has decision making ability, but has no way to solve perceptual problems. Neural network has strong perception ability, but lacks certain decision making ability. Therefore, deep reinforcement learning, combining deep learning with reinforcement learning, provides a solution for the routing search. The next stage will focus on this point.

## 1.2 Course Summary

Studied chapter 4 of Neural Networks and Deep Learning and chapter 1 of Improving Deep Neural Networks, **Coursera**, <https://www.deeplearning.ai/deep-learning-specialization/>

## 2 Objectives for the Next 2 Weeks

### 2.1 Reading

Reading papers focused on Deep Reinforcement Learning-based routing.

### 2.2 Course

Study chapter 2, 3, 4 of Improving Deep Neural Networks, **Coursera**, <https://www.deeplearning.ai/deep-learning-specialization/>

## 3 Advisor's Comments

# Bibliography

- [1] A. Azzouni, R. Boutaba, and G. Pujolle, “Neuroute: Predictive dynamic routing for software-defined networks,” *CoRR*, vol. abs/1709.06002, 2017. [Online]. Available: <http://arxiv.org/abs/1709.06002>
- [2] “Mininet,” <http://mininet.org/>.
- [3] “Google tensorflow,” <https://www.tensorflow.org/>.
- [4] S. Dong, P. Agrawal, and K. Sivalingam, “Reinforcement learning based geographic routing protocol for uwb wireless sensor network,” in *IEEE GLOBECOM 2007 - IEEE Global Telecommunications Conference*, Nov 2007, pp. 652–656.
- [5] T. Hu and Y. Fei, “Qelar: A machine-learning-based adaptive routing protocol for energy-efficient and lifetime-extended underwater sensor networks,” *IEEE Transactions on Mobile Computing*, vol. 9, no. 6, pp. 796–809, June 2010.
- [6] N. Kato, Z. M. Fadlullah, B. Mao, F. Tang, O. Akashi, T. Inoue, and K. Mizutani, “The deep learning vision for heterogeneous network traffic control: Proposal, challenges, and future perspective,” *IEEE Wireless Communications*, vol. 24, no. 3, pp. 146–153, June 2017.
- [7] B. Mao, Z. M. Fadlullah, F. Tang, N. Kato, O. Akashi, T. Inoue, and K. Mizutani, “Routing or computing? the paradigm shift towards intelligent computer network packet transmission based on deep learning,” *IEEE Transactions on Computers*, vol. 66, no. 11, pp. 1946–1960, Nov 2017.
- [8] “Will,” <https://scarsty.gitbooks.io/will/content>.
- [9] Y. Lee, “Classification of node degree based on deep learning and routing method applied for virtual route assignment,” *Ad Hoc Networks*, vol. 58, pp. 70–85, April 2017.
- [10] G. Stampa, M. Arias, D. Sanchez-Charles, V. Muntés-Mulero, and A. Cabellos, “A deep-reinforcement learning approach for software-defined networking routing optimization,” *CoRR*, vol. abs/1709.07080, 2017. [Online]. Available: <http://arxiv.org/abs/1709.07080>
- [11] A. Valadarsky, M. Schapira, D. Shahaf, and A. Tamar, “A machine learning approach to routing,” *CoRR*, vol. abs/1708.03074, 2017. [Online]. Available: <http://arxiv.org/abs/1708.03074>
- [12] F. Khan, S. Memon, and S. H. Jokhio, “Support vector machine based energy aware routing in wireless sensor networks,” in *2016 2nd International Conference on Robotics and Artificial Intelligence (ICRAI)*, Nov 2016, pp. 1–4.
- [13] F. Kiani, E. Amiri, M. Zamani, T. Khodadadi, and A. A. Manaf, “Efficient intelligent energy routing protocol in wireless sensor networks,” *International Journal of Distributed Sensor Networks*, vol. 11, no. 3, p. 618072, 2015. [Online]. Available: <https://doi.org/10.1155/2015/618072>

- [14] F. Tang, B. Mao, Z. M. Fadlullah, N. Kato, O. Akashi, T. Inoue, and K. Mizutani, "On removing routing protocol from future wireless networks: A real-time deep learning approach for intelligent traffic control," *IEEE Wireless Communications*, vol. 25, no. 1, pp. 154–160, February 2018.
- [15] Z. M. Fadlullah, F. Tang, B. Mao, J. Liu, and N. Kato, "On intelligent traffic control for large-scale heterogeneous networks: A value matrix-based deep learning approach," *IEEE Communications Letters*, vol. 22, no. 12, pp. 2479–2482, Dec 2018.
- [16] Z. M. Fadlullah, B. Mao, F. Tang, and N. Kato, "Value iteration architecture based deep learning for intelligent routing exploiting heterogeneous computing platforms," *IEEE Transactions on Computers*, pp. 1–1, 2018.
- [17] Z. Lin and M. van der Schaar, "Autonomic and distributed joint routing and power control for delay-sensitive applications in multi-hop wireless networks," *IEEE Transactions on Wireless Communications*, vol. 10, no. 1, pp. 102–113, January 2011.
- [18] F. Kiani, "Reinforcement learning based routing protocol for wireless body sensor networks," in *2017 IEEE 7th International Symposium on Cloud and Service Computing (SC2)*, Nov 2017, pp. 71–78.