International Journal of Engineering Research and Technology. ISSN 0974-3154, Volume 12, Number 3 (2019), pp. 311-320

Machine Learning and Deep Learning Techniques on Wireless Networks

Pushpender Sarao

Professor, Hyderabad Institute of Technology and Management, Hyderabad, Telangana, India

Abstract

In this paper, we address the several issues and challenges for applying machine learning and deep learning techniques in wireless networks. Designing the machine learning base routing algorithm in heterogeneous networks is a big challenge. This article firstly introduces the basic concepts of machine learning and deep learning in wireless networks. Due to the dynamic behaviour of network scenarios in several ad-hoc networks (like vehicular ad-hoc networks and wireless sensor networks), it is very difficult task to prepare a data sets and training of that data. This paper also overviews several works that applied machine learning techniques and deep learning techniques on diverse research areas including networking, communications and lossy environment. The main aim of this survey work is to identify the possible issues and challenging tasks for applying the different deep learning and machine learning algorithms and strategies in wireless networks and find out a proper research direction aiming the realization of a system that detects, predicts and recovers from abnormal situations on wireless networks.

Keywords—Routing algorithm, Q-Learning, deep learning, machine learning, wireless sensor networks;

I. INTRODUCTION

Machine Learning algorithms are able to learn and adapt to a changing environment in wireless networks. As a promising machine learning tool to handle the accurate pattern recognition from complex raw data, deep learning (DL) is becoming a powerful method to add intelligence to wireless networks with large-scale topology and complex radio conditions. Deep learning uses many neural network layers to achieve a brain-like acute feature extraction from high-dimensional raw data. It can be used to find the network dynamics (such as hotspots, interference distribution, congestion points, traffic bottlenecks, spectrum availability, etc.) based on the analysis of a large amount of network parameters (such as delay, loss rate, link signal-to-noise ratio, etc.). Therefore, deep learning can analyse extremely complex wireless networks with many nodes and dynamic link quality.

Machine Learning Techniques used in Wireless Networks:

- Reinforcement Learning
- Deep Reinforcement Learning (DRL)
- KNN
- Bayesian Net/HMM
- K-Means
- Decision Tree
- Ant based Routing
- Particle Swarming Routing
- Deep Q-Learning
- Q-Learning
- Q-Routing

✓ For packet routing and mobility of nodes in wireless networks, reinforcement learning techniques are most appropriate learning techniques.

✓ Q-Routing protocol works on Q-Learning algorithm.

✓ Q-Routing is suitable for packet routing in wireless networks.

✓ Machine Learning (ML) can be categorized into :

  a. Supervised learning
  b. Unsupervised learning
  c. Semi-supervised learning

✓ Data acquisition and knowledge discovery, network planning, and network operation and management are the main issues in AI-enabled wireless networks.

II. MACHINE LEARNING TECHNIQUES IN WIRELESS MESH NETWORKS

To resolve various management and design issues, machine learning techniques may be used based on the appropriateness of particular technique and network issue.

Mostly, reinforcement learning (RL) is applicable to resolve the design optimization problems in wireless mesh network.

Machine learning approaches used in wireless mesh networks can be classified into three types of learnings: a.) supervised Learning b.) Unsupervised Learning c.) Reinforcement Learning

Further supervised learning can be sub-classified into five categories: SVM (support vector machines), DT (decision tree), ANN (artificial neural networks), perception, Bayesian, unsupervised learning can be classified into: k-means and PCA (principal component analysis). Reinforcement learning can be classified into: Q-Learning, LA (Learning Automata), and MDP (Markov Decision Process).

For solving the channel assignment problem in wireless mesh networks, K-Means, LA (learning automata) techniques may be used.

To resolve the routing issues in wireless mesh networks, LA, MDP, ANN machine learning techniques are suitable.

MDP, Q-Learning have been used to improve the fairness in WMNs.

For rate adaption problem, Q-Learning, LA, Bayesian technique is applicable.

For fault detection problem, K-Means approach has been used in literature.

A. **Routing:**
Q-Learning: in Q-Learning, there is a Q-value Q(s, a) associated with performance action ‘a’ at a state‘s’ that is updated each time that action is performed.
Learning Automata (LA): for route optimization, learning automata based mechanisms have been used. The algorithms like LAMR(Learning Automata based Multicast Routing), DLAMRA(Distributed Learning Automata based Multicast Routing Algorithm), and SCDS(Steiner Connected Dominating Set) uses the learning automata concept to make a optional path from source to destination. There are possibility the some issues like channel allocation, delays in routing decisions, and link congestion. The problem may be resolved only by giving the single common reward for batch of actions; but not individual.
ANN (Artificial Neural Networks): ANN is a most useful technique in routing decision and path finding purposes. CMAC (Cerebellar Model Articulation Controller) algorithm is used to predict the link failure and route possibility.

B. **Channel Allocation**

In literature, learning Automata based distributed algorithms have been used for channel allocation.

Bayesian Learning: Bayesian Learning tries to calculate the posterior probability distribution of the target features of a testing object conditional on its input features and the entire training data set.

K-Means clustering: K-Means clustering algorithm has been used for channel allocation in literature. In this algorithm, rule-based procedures cluster nodes have been used.

C. **Network Deployment**

In network deployment, mesh gateways (MGs) and mesh routers (MRs) have to be located at an appropriate location for ensuring desired performance of the network. Q-Learning and LA (Learning Automata) techniques may be helpful for deploying the MGs (Mesh Gateways) and MRs (Mesh Routers) in wireless mesh networks.

D. **Rate Adaption:** rate adaption problem has been resolved by SARA (Stochastic Automatic Rate Adaptation Algorithm). SARA algorithm uses stochastic learning automata based mechanism. It manages the rate based on probability vector corresponding to each rate.

E. **Joint Approaches:**
Markov Decision Process (MDP): based on status and action, agent receives a reward. To achieve a policy to maximize some function of the sequence of rewards. In literature, Semi Markov Decision Process (SMDP) has been applied to develop a linear programming-based algorithm. Here, actions processes based on the sessions of each class of network traffic.

Role of machine learning for managing the network in wireless mesh networks:

A. **Anomaly/Intrusion Detection**

Decision Tree (DT): in decision tree, leaf nodes in the network represent the class while internal nodes indicate the conditions for decision making. Some IDS (Intrusion Detection System) have been developed using classier like C4.5 and SVM for problem learning. These IDS were developed for cross-layer functionalities.

Perception: some distributed IDSs have been developed using supervised learning like perception in wireless mesh networks.

B. **Integrity and Fault Detection**

Principal component Analysis (PCA): Principal Component Analysis (PCA) has been applied for fault detection purpose in the wireless mesh network for analysing the number of packets transmitted. Here, PCA will be responsible to reduce the number of false alarms.

Layer-wise functionality of deep learning in wireless networks:

1. Physical layer
   a. Anti-jamming
   b. Error correction
   c. Interference alignment management
   d. Modulation classification
   e. Signal detection
2. Data link layer
   a. Channel resource allocation
   b. Traffic prediction
   c. Link evaluation
3. Network layer
   a. Routing establishment
   b. Routing optimization
4. Session layer, presentation layer and application layer
   a. Session scheduling
   b. Quantized compressed sensing
   c. Operating system management
5. Network security
   a. Flow identification
      i. Traffic identification
      ii. Application identification

b. Intrusion detection
    i. Real world data detection
    ii. NSL-KDD data detection

Deep learning algorithms in Wireless networks:

Algorithms:

- RL-LSTM
- DEEP Q-LEARNING
- DNN
- DEEP BELIEF NET
- DEEP Q-NETWORK LSTN
- HYBRID DEP LEARNING (AUTO-ONCODER & LSTM)

III. ISSUES AND CHALLENGES WITH DEEP LEARNING IN WIRELESS NETWORKS:

1. Deep learning for transport layer optimizations
    - Detecting the multi-queue evolution pattern
    - Deciding the queue size for RED zone
    - Combining the congestion control scheme with another schemes and protocols
    - Congestion control for entire path from source to destination
2. Deep learning for facilitating big data transmissions
    - Big data transmissions is a challenging task using deep learning
    - To develop a thick routing pipe having capacity to transmit huge amount of packets per second.
    - Identifying the link failure at each hop
    - Deciding MAC parameters for ensuring the quality of service delivery
3. Deep learning-based network swarming
    - To guide node's mobility for getting desired swarming shape and good communication architecture
    - Cluster forming and nodes management in swarming networks
4. Pairing deep learning with software-defined networks
    - Network profile formation
    - Types of parameter to be collected from design patterns
    - Selection of big data architecture
    - Suitability of deep learning for specific purposes in wireless networks
    - Coordination between different CP controllers
5. Distributed deep learning implementation in wireless nodes
    - Applying the specific part of deep learning algorithm for a specific distributed task
    - Managing the wireless nodes for exchanging the input parameters and output data using MAC protocols
6. Deep learning-based cross layer design
    - To achieve cross layer optimization
7. Deep learning base application layer
    - To define a low-complexity deep learning model based on application layer performance goal
8. Deep learning based Dew-Fog cloud computing security
9. From Deep learning to DRL
    - Applications for cognitive radio network control
10. Efficient DL/DRL implementations in practical wireless platforms
    - Difficulty to collect network parameters for deep learning input layers
    - The presence limits of the wireless devices
    - Incomplete training sample collections
11. Deep learning for transport layer optimizations
    - Detecting the multi-queue evolution pattern
    - Deciding the queue size for RED zone
    - Combining the congestion control scheme with another schemes and protocols
    - Congestion control for entire path from source to destination
12. Deep learning for facilitating big data transmissions
    - Big data transmissions is a challenging task using deep learning
    - To develop a thick routing pipe having capacity to transmit huge amount of packets per second.
    - Identifying the link failure at each hop
    - Deciding MAC parameters for ensuring the quality of service delivery
13. Deep learning-based network swarming
    - To guide node's mobility for getting desired swarming shape and good communication architecture
    - Cluster forming and nodes management in swarming networks
14. Pairing deep learning with software-defined networks
    - Network profile formation
    - Types of parameter to be collected from design patterns
    - Selection of big data architecture
    - Suitability of deep learning for specific purposes in wireless networks
    - Coordination between different CP controllers
15. Distributed deep learning implementation in wireless nodes
    - Applying the specific part of deep learning algorithm for a specific distributed task
    - Managing the wireless nodes for exchanging the input parameters and output data using MAC protocols
16. Deep learning-based cross layer design
    - To achieve cross layer optimization
17. Deep learning base application layer
    - To define a low-complexity deep learning model based on application layer performance goal

18. Deep learning based Dew-Fog cloud computing security
19. From Deep learning to DRL
    - Applications for cognitive radio network control
20. Efficient DL/DRL implementations in practical wireless platforms
    - Difficulty to collect network parameters for deep learning input layers
    - The presence limits of the wireless devices
    - Incomplete training sample collections
21. Deep learning for transport layer optimizations
    - Detecting the multi-queue evolution pattern
    - Deciding the queue size for RED zone
    - Combining the congestion control scheme with another schemes and protocols
    - Congestion control for entire path from source to destination
22. Deep learning for facilitating big data transmissions
    - Big data transmissions is a challenging task using deep learning
    - To develop a thick routing pipe having capacity to transmit huge amount of packets per second.
    - Identifying the link failure at each hop
    - Deciding MAC parameters for ensuring the quality of service delivery
23. Deep learning-based network swarming
    - To guide node's mobility for getting desired swarming shape and good communication architecture
    - Cluster forming and nodes management in swarming networks
24. Pairing deep learning with software-defined networks
    - Network profile formation
    - Types of parameter to be collected from design patterns
    - Selection of big data architecture
    - Suitability of deep learning for specific purposes in wireless networks
    - Coordination between different CP controllers
25. Distributed deep learning implementation in wireless nodes
    - Applying the specific part of deep learning algorithm for a specific distributed task
    - Managing the wireless nodes for exchanging the input parameters and output data using MAC protocols
26. Deep learning-based cross layer design
    - To achieve cross layer optimization
27. Deep learning base application layer
    - To define a low-complexity deep learning model based on application layer performance goal
28. Deep learning based Dew-Fog cloud computing security
29. From Deep learning to DRL
    - Applications for cognitive radio network control
30. Efficient DL/DRL implementations in practical wireless platforms
    - Difficulty to collect network parameters for deep learning input layers
    - The presence limits of the wireless devices
    - Incomplete training sample collections
31. Deep learning for transport layer optimizations
    - Detecting the multi-queue evolution pattern
    - Deciding the queue size for RED zone
    - Combining the congestion control scheme with another schemes and protocols
    - Congestion control for entire path from source to destination
32. Deep learning for facilitating big data transmissions
    - Big data transmissions is a challenging task using deep learning
    - To develop a thick routing pipe having capacity to transmit huge amount of packets per second.
    - Identifying the link failure at each hop
    - Deciding MAC parameters for ensuring the quality of service delivery
33. Deep learning-based network swarming
    - To guide node's mobility for getting desired swarming shape and good communication architecture
    - Cluster forming and nodes management in swarming networks
34. Pairing deep learning with software-defined networks
    - Network profile formation
    - Types of parameter to be collected from design patterns
    - Selection of big data architecture
    - Suitability of deep learning for specific purposes in wireless networks
    - Coordination between different CP controllers
35. Distributed deep learning implementation in wireless nodes
    - Applying the specific part of deep learning algorithm for a specific distributed task
    - Managing the wireless nodes for exchanging the input parameters and output data using MAC protocols
36. Deep learning-based cross layer design
    - To achieve cross layer optimization
37. Deep learning base application layer
    - To define a low-complexity deep learning model based on application layer performance goal
38. Deep learning based Dew-Fog cloud computing security
39. From Deep learning to DRL
    - Applications for cognitive radio network control

40. Efficient DL/DRL implementations in practical wireless platforms
    - Difficulty to collect network parameters for deep learning input layers
    - The presence limits of the wireless devices
    - Incomplete training sample collections
41. Deep learning for transport layer optimizations
    - Detecting the multi-queue evolution pattern
    - Deciding the queue size for RED zone
    - Combining the congestion control scheme with another schemes and protocols
    - Congestion control for entire path from source to destination
42. Deep learning for facilitating big data transmissions
    - Big data transmissions is a challenging task using deep learning
    - To develop a thick routing pipe having capacity to transmit huge amount of packets per second.
    - Identifying the link failure at each hop
    - Deciding MAC parameters for ensuring the quality of service delivery
43. Deep learning-based network swarming
    - To guide node's mobility for getting desired swarming shape and good communication architecture
    - Cluster forming and nodes management in swarming networks
44. Pairing deep learning with software-defined networks
    - Network profile formation
    - Types of parameter to be collected from design patterns
    - Selection of big data architecture
    - Suitability of deep learning for specific purposes in wireless networks
    - Coordination between different CP controllers
45. Distributed deep learning implementation in wireless nodes
    - Applying the specific part of deep learning algorithm for a specific distributed task
    - Managing the wireless nodes for exchanging the input parameters and output data using MAC protocols
46. Deep learning-based cross layer design
    - To achieve cross layer optimization
47. Deep learning base application layer
    - To define a low-complexity deep learning model based on application layer performance goal
48. Deep learning based Dew-Fog cloud computing security
49. From Deep learning to DRL
    - Applications for cognitive radio network control
50. Efficient DL/DRL implementations in practical wireless platforms
    - Difficulty to collect network parameters for deep learning input layers
    - The presence limits of the wireless devices
    - Incomplete training sample collections

IV. DIFFERENT MACHINE LEARNING METHODS FOR PACKET ROUTING

Q-ROUTING

Q-Learning is a reinforcement learning algorithm that is able to learn an optimal sequence of actions in an environment which maximizes rewards received from the environment. Q-Routing is an adaptation from Q-Learning that is able to distributive route packets in a network.

ANT-BASED ROUTING

Ant-Based Routing is a novel variation of reinforcement learning that is based on simple biological "ants". These "ants" explore the network and rapidly learn optimal routes inspired by the stigmergy model of communication observed in ant colonies. This algorithm is more resilient than traditional routing algorithms, in the sense that random corruption of routes has limited effect on the computation of the packet routes.

PARTICLE SWARM ROUTING

Particle swarm optimization is a population based stochastic optimization technique developed by Dr. Russ Eberhart and Dr. James Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. Particle Swarm Routing is initialized with a group of random solutions and then searches for optima by updating generations [3].

- Reinforcement learning methods can be used to control both packet routing decisions and node mobility, dramatically improving the connectivity of the network
- Modern routing protocols developed for wireless networks are basically categorized into four types: routing-table-based proactive protocols, on-demand reactive protocols, geographical protocols, and ML/DL-based routing protocols. DL-based routing protocols have been extensively studied in the past several years due to its superior performance for complex networks.
- For link quality improvement, a new strategy called "RL-Probe" proposed in [1]. To increase the capacity/features of RPL (Routing Protocol for low power and Lossy Networks), RL-Probe played a great role. Based on reinforcement learning model, RL-Probe strategy is implemented to reduce the overhead.
- RL-Probe:
- Both synchronous and asynchronous LQE techniques are compatible with RL-Probe framework. During

the RPL route maintenance and route recovery procedure, clustering decisions are taken place based on the importance of each node.

- To measure the RSSI and ETX, asynchronous probing technique is proposed. Decision-making process is performed using a MAB model. To estimate the trends in link quality variations, reward function has been used by RL-Probe strategy. Three performance evaluation matrices were used to evaluate RL-Probe: PLR (Packet loss rate), packet overhead, normalized energy consumption. At different scenarios and topology, evaluation work was carried out. The RL-Probe strategy worked effectively at different link qualities and topologies.

V. CHALLENGES IN ADOPTING MACHINE LEARNING ON WIRELESS NETWORKS

Recently, machine learning techniques are widely adopted on various areas including image, voice, video, public safety, medical, etc. With the evolution of more sophisticated computer-related techniques, we have a plethora of data stored at a large number of data centres and these are analysed at a speed of real-time. Machine learning techniques can realize the implementation of human-like prediction or decision making process. Ideally, by using machine learning techniques, the whole world can be managed autonomously in safe way by the system. For example, the system collects all the information produced by each human being and learns everything in the world by itself. One of the strongest advantages of adopting machine learning techniques is that it can learn from data continuously over time. Even during the operation of the system, it can be continuously updated by using newly observed or produced data. As a result, with one machine learning algorithm, different logics are produced with different training data. It means that it can learn continuously from the experience and the system is flexible on its decision making process. Back to the example, when the system detects any dangerous or abnormal situation from the world of human beings, it can ring the alarm bell or take any action that may be deemed wise and helpful.

The reality, however, is that this ideal system is hard to construct. The first problem comes from the difficulty in collecting good training data that is including various scenarios. Even though we have good machine learning algorithms that can build strong logic and analyze the large data set in real-time training the system continuously, if we do not have effective data set, we cannot build any prediction or decision model.

Regarding researches on communications or networking, many researchers have tried to adopt machine learning techniques for decision making process in connection with channel error diagnostics, fault detection in wireless sensor networks, routing in wireless sensor networks, network attack, etc. When the environment surrounding the model is stable and persistent except some factors that are closely related to the output of the model, it is not challenging to train the model and make reliable decision. However, if the environment surrounding the model is dynamically changing, the algorithm cannot build reliable model that outputs correct decision from input data. This is because with varying condition, it is difficult to find consistent patterns from various input data to output decision. Consequently, it is hard to build reliable model. Moreover, in this dynamic environment, the system should secure data set for training that is including various scenarios. However, even collecting data set for training is difficult due to the lack consistent pattern from the data set.

In recent years, researchers and industries have been paying attention on Internet of Things. With this trend, plenty of research groups have been made accelerating a growth of relevant techniques. Due to the limited characteristics of constrained devices and low-power communication techniques, which are different from that of conventional sensor networks, networking and communication techniques especially for low power and lossy networks have been received especially huge attention compared to that of the other networks.

To enhance the reliability of communication on low power and lossy networks constructed with constrained devices, routing protocol such as RPL (Routing Protocol for Low Power and Lossy Network) [1] and special mac protocol such as TSCH (Time Slotted Channel Hopping) have been proposed and widely used as standard protocols currently. To summarize briefly, RPL constructs routing paths in simple way and prevents routing loops by constructing DODAG structure. Moreover, topology created for the route management evolves continuously over time considering various network conditions and metrics. With TSCH, various channels can be used and problems caused by interference can be overcome. However, these protocols are operated on the basis of local information obtained at each node. Consequently, the problems that are not immediately captured and fixed by the protocols that are based on local information still exist.

With a global view on a network state, various information can be used for analyse the current state and the problems that can seriously damage the network performance can be detected in advance. In sensor network, there are several abnormal situations that should be detected before they happen. For example, on an application layer, broken sensors might send wrong sensed values to a connected server continuously. If we do not aware of this, we cannot detect the situation where the accident actually happens. On a network layer, though RPL captures the network problem and the topology is continuously updated considering network conditions, each node has simple decision making process on the basis of local information. As a result, if network traffic is concentrated on a specific node, it might not be detected before the problem becomes bigger. In this case, the node with freakishly unbalanced and heavy work load will quickly consume its energy and finally it will be powered off. On a link layer, wireless network interface might break down. In this case, with the global view on the network, all of these situations can be detected before the serious accident happens. The global view can be obtained by information collection and traffic monitoring from the high-powered root node or the server.

Following is the list of examples of faults that should be detected on a low power and lossy networks. We aim to construct reliable system that manages the network automatically or autonomously.

- No energy in a node

- Breakdown on wireless network interface in a node

- Interference on certain channel

- Overloaded CPU usage on a node

- Full memory or buffer on a node

- Abnormal sensed value

- Wrong execution of a command for network management

- Link layer problem falsified data

- Traffic overload due to attack (e.g. DDoS)

- Energy consumption due to unbalanced traffic load

We know that one of the benefits from using machine learning algorithm is that the system can learn various scenarios including unexperienced one over time since the decision making logic is not on the basis of predefined static rules. Accordingly, when we devise techniques for detecting abnormal situation described above on low power and lossy network, it seems good to have an approach by utilizing machine learning algorithms.

However, collecting data set for training the model is challenging. Moreover, the network environment on a low power lossy network is highly dynamic compared to the other networks. As a result, obtaining good data set that is including various scenarios is virtually impossible.

Though there are many researches on networking or communications on the basis of machine learning techniques, only part of that can be applied to real systems or devices. As described above, if the environment surrounding the model is huge and changes dynamically, it becomes harder and harder in training the model. Moreover, though several methods detecting fault scenarios on a sensor network by using machine learning have been proposed, they trained the model with too small data set which were made in artificial way or the data set has not including various possible scenarios. Moreover, the evaluation and the test scenario were done on rigorously restricted environment so it is uncertain whether the constructed model will work properly even with the similar but different scenarios.

In the following sections, we will introduce several works that are adopting machine learning techniques on various networks environments including wireless sensor networks. Though adopting machine learning on wireless network environment is difficult due to dynamicity and unpredictability of wireless network environment, these works are valuable and have shown notable performance improvement through their evaluation.

VI. MACHINE LEARNING IN NETWORKING AND COMMUNICATIONS

We introduce several works that are applying machine learning techniques regarding networking or communications. These methods have strong contribution in terms of utilizing machine learning to overcome challenging problems caused by fluctuating and unpredictable wireless channel state. Though these works have shown notable performance improvement on their evaluation, some works just concentrate on trace-driven simulation or testing using the same data set used for training rather than natural real-world experiment. Nevertheless, these works are valuable in that they paved the way for utilizing various information to construct reliable models to overcome the difficulty in predicting the future state of wireless channel.

A. Signal classification

To implement reliable wireless communication, the signal sent by a sender should be correctly recognized at a receiver side. The authors of [1] are focusing on the impact of interference from modulated signals and the influence of realistic wireless channel conditions on classification performance. They propose machine learning approach can be used for classifying the signal on realistic wireless environment. We regards that this work is similar to pattern recognition since it classifies the signal which has been modified passing through a wireless channel.

B. Data collection and traffic classification for network management

The authors of [2] emphasize the importance of understanding the type of data that can be collected in SDNs and the process of learning information from that data. As a first step toward machine learning based network control, this work presents a simple architecture deployed in an enterprise network that gathers traffic data using the OpenFlow protocol. However, this work just concentrates on studying monitoring and classification of traffic using data obtained with the OpenFlow protocol without proposing sophisticated ML-based system or network management. Nevertheless, this work have paved the way for the use of ML-based network management and shown simple examples applying ML techniques.

C. Network attack prediction

The work [3] have proposed the method defining security rules on the SDN controller on the basis of machine learning technique. Machine learning algorithms are used to predict potential target host that can be attacked and the security rules on the SDN controller are defined to restrict the access of potential attackers by blocking the entire subnetwork. For the evaluation of the proposed method, the same datasets were split for training and testing purpose.

D. Wireless adaptive streaming

Network conditions fluctuate over time and vary significantly across environments. With this reason, predicting future network condition is difficult. Though many rate adaptation algorithm for high QoE video streaming have been proposed, it is not sufficient and there are much room for further improvement. Several works have proposed by adopting machine learning techniques for the video streaming services. [4] Proposed the system that is implemented on server-side, learns critical features and make the best decision on bitrate and CDN for the streaming user to optimize QoE. [5] Also adopted reinforcement learning to generate the best ABR algorithm automatically by considering bandwidth, buffer level and video rate.

E. Mobile cloud offloading

The work [6] introduces the use of cloud computing for mobile device computation offloading and proposes ML-based dynamic algorithm. It monitors device resources and network parameters and makes a decision to offload computation to the cloud. In this work, machine learning technique is used to make a decision on cloud computing and network information such as available bandwidth is only one of various input values. Other input values are user input, device energy level and CPU usage level and these are definite and stable compared to the values influenced by dynamic and unpredictable wireless network. Since the environment surrounding the model is stable compared to other works introduced in this document, we regards that this model is on better condition in terms of a given environment.

VII. MACHINE LEARNING IN WIRELESS SENSOR NETWORKS

In this section, we introduce several works that applied machine learning techniques on sensor networks. These methods also have strong contribution in terms of utilizing machine learning to overcome challenging problems caused by lossy channels and constrained devices. These works are also valuable in that they paved the way for utilizing various information to construct reliable models to overcome the difficulty in predicting the future state of lossy channels.

A. Channel error diagnostics

ISM band is shared by several protocols such as 802.11, 802.15.4, 802.15.1, etc. Here, different systems interfere with each other degrading communication performance. Authors of [7] conducted extensive experiments to study the error patterns in IEEE 802.15.4 and found that there are different patterns for major wireless scenarios. Based on this finding, they designed a machine learning mechanism to classify the wireless channel errors into different categories and proposed the system that diagnoses different troubles in IoT networks.

B. Spectrum decision

The work [8] also points out the pollution of the ISM band and the power constraints in sensor nodes. To overcome this poor environment, it proposes machine learning solution for channel selection. By using ML technique, the system predicts a number of expected transmission attempts. It uses the following attributes as input data: RSSI, number of transmission attempts, reasons of each failed attempt, performance data such as RSSI and LQI from the last received packet. From the output, it selects the best channel and a channel with low number of expected transmission attempts is considered as better one.

C. Outlier detection

Since wireless sensor network composed of constrained nodes is vulnerable to interference, unstable channel or cyber-intrusion, the system performance is degraded and fake data might be provided to higher management levels in a system. This might cause critical problems on sensor network systems for public safety or industry automation. Authors of [9] have pointed out that the existing works for outlier detection require large memory, high computation, high energy consumption, communication overhead and does not support heavy online data streaming. To solve the problem, they proposed online outliers detection by using a machine learning technique as a multi-agent framework.

D. Indoor localization

Generally, GPS is one of the well-known examples regarding object localization. However, inside a building, it is difficult to estimate the correct location of an object due to low received GPS signal strength. With this reason, other approaches are used. For example, several nodes are used as anchor points and this information is used to estimate a relative location of a target object. Devising an accurate indoor localization system is important since the system can be used to increase the safety in underground mines or caves. However, there still exists interference on wireless channel which decreases estimation accuracy. To overcome the problem, the work [10] has used seven different machine learning techniques on two different architectures to find the algorithm that shows the lowest errors and compared the performance. On testbed, the person had a wearable sensor to locate himself within the wireless sensor network.

E. Event detection

Wireless sensor networks are used for various purposes. The work [11] concentrates on detecting pipeline leakage on oil/gas and water transportation system. It uses a pattern recognition algorithm and trains the sensor network to detect and classify new traces of events like leakages. Here, distributed sensor nodes cooperate to identify the leakage event and its size. Though this work includes wireless sensor network, difficulties that comes from using unpredictable and vulnerable wireless channel were scarcely considered.

F. Fault detection

Various problems caused by vulnerable and fluctuating wireless channel together with cheap sensors make collected data from the sink node to be faulty. Fault data should be detected and the cause of the event should be identified to quickly react and manage the system. The work [12] developed a statistical approach to detect and identify faults in a wireless sensor network on the basis of machine learning technique. It classified fault types into two categories: data fault and system fault. Faults caused by degraded or malfunctioning sensor are classified as data fault and the other fault types caused by low battery, calibration, communication, connection failures are classified as system fault. Authors of [13] also studied fault detection on similar environment by using machine learning technique. Here, they classified fault types into four categories: offset fault, gain fault, stuck-at fault and out of bounds.

G. Routing

By adopting machine learning technique, multi-hop routing protocol can be more energy efficient. The work [14] proposed ML-based clustering protocol to assign the sensor nodes to the nearest cluster in energy efficient way. The work [15] also used ML technique on routing method in wireless sensor network. The purpose of proposed routing scheme is to increase network lifetime and transmit information packages in shortest possible time. These works [16][17] insist that applying ML techniques on WSN is beneficial in terms of resource management.

VIII. CONCLUSION

In this survey, we have identified several algorithms and protocols that are useful for optimizing the network and communication operations in wireless networks. From literature, we analysed several issues and challenges for using the deep learning and machine learning algorithms for enhancing the networking processes in several aspects. Deep learning algorithms and machine learning algorithms work very well for network management, network optimization, signal management, channel assignment, network security, route deciding etc. Deep reinforcement learning and deep q-routing are main learning techniques, which are most useful for network operations. However, it is difficult to obtain training data that includes various scenarios. Due to dynamic behaviour of wireless networks, it is difficult to create the data sets for training. Moreover, due to dynamicity and unpredictability of wireless multi hop network, it is hard to find any regular pattern from previously experienced data. Besides, even if we have decision model, it is uncertain whether it will work properly or not in the future where the network environment continuously changing dynamically.

REFERENCES

[1] Emilio Ancillotti, Curlo Vallati, Raffaele Bruno, Enzo Mingozzi, "A reinforcement learning-based link quality estimation strategy for RPL and its impact on topology management", Computer Communications (ELSEVIER) 112(20171-13.

[2] Samurdhi Karunaratne and Haris Gacanin, "An overview of Machine Learning Approaches in Wireless Mesh Networks", Nokia Bell Labs, Antwerp, Belgium

[3] Simi S, Sruthi Ann Varghese, " Enhance QoS by Learning Data flow rates in Wireless Networks using Hierarchical Docition", 4th International Conference on Eco-friendly Computing and Communication Systems, ICECCS 2015, Procedia Computer Science 70 (2015) 708 – 714, Elsevier.

[4] Siddhi Sharma, Deepak Sethi, P. P. Bhattacharya, "Artificial Neural Network based Cluster Head Selection in Wireless Sensor Network", International Journal of Computer Applications (0975 – 8887) Volume 119 – No.4, June 2015. Pp. 34-41.

[5] Chaoyun Zhang, Paul Patras, and Hamed Haddadi, "Deep Learning in Mobile and Wireless Networking: A Survey", IEEE COMMUNICATIONS SURVEYS & TUTORIALS, arXiv:1803.04311v2 [cs.NI] 17 Sep 2018, pp/ 1-53.

[6] Rahul Desai,B P Patil, "Maximizing Throughput using Adaptive Routing Based on Reinforcement Learning" , Int. J. Advanced Networking and Applications Volume: 09 Issue: 02 Pages: 3391-3395 (2017) ISSN: 0975-0290.

[7] Wei Kuang Lai, Mei-Tso Lin, and Yu-Hsuan Yang, "A Machine Learning System for Routing Decision-Making in Urban Vehicular Ad Hoc Networks", International Journal of Distributed Sensor Networks Volume 2015, Article ID 374391, 13 pages http://dx.doi.org/10.1155/2015/374391

[8] Zhenyu Na , Zheng Pan,1 Xin Liu , Zhian Deng , Zihe Gao,and Qing Guo , "Distributed Routing Strategy Based on Machine Learning for LEO Satellite Network", Wireless Communications and Mobile Computing, Volume 2018, Article ID 3026405, 10 pages https://doi.org/10.1155/2018/3026405

[9] T. Alyas, N. Tabassum, S. Naseem, F. Ahmed, Qura-Tul-Ein, "Learning-Based Routing in Cognitive Networks", IARS International Research Journal, Vol. 4 No. 2 2014, pp. 1-8.

[10] Ki-Seong Lee, Sun-Ro Lee, Youngmin Kim and Chan-Gun Lee, "Deep learning–based real-time query processing for wireless sensor network", International Journal of Distributed Sensor Networks 2017, Vol. 13(5), pp. 1-10, DOI: 10.1177/1550147717707896.

[11] Sungwook Kim, "A better-performing Q-learning game-theoretic distributed routing for underwater wireless sensor networks", International Journal of Distributed Sensor Networks 2018, Vol. 14(1) , pp. 1-12, DOI: 10.1177/1550147718754728.

[12] Asaf Valadarsky, Michael Schapira,Dafna Shahaf, Aviv Tamar, "A Machine Learning Approach to Routing", arXiv:1708.03074v2 [cs.NI] 11 Nov 2017, pp. 1-8.
[13] Chaoyun Zhang, Paul Patras, and Hamed Haddadi, "Deep Learning in Mobile and Wireless Networking: A Survey", IEEE COMMUNICATIONS SURVEYS & TUTORIALS, arXiv:1803.04311v2 [cs.NI] 17 Sep 2018, pp. 1-53.
[14] Qian Mao, Fei Hu, and Qi Hao, "Deep Learning for Intelligent Wireless Networks: A Comprehensive Survey", IEEE COMMUNICATIONS SURVEYS & TUTORIALS, VOL. 20, NO. 4, FOURTH QUARTER 2018, pp. 2595-2621.
[15] Giorgio Stampa, Marta Arias, David Sánchez-Charles, Victor Muntés-Mulero,Albert Cabellos, "A Deep-Reinforcement Learning Approach for Software-Defined Networking Routing Optimization", arXiv:1709.07080v1 [cs.NI] 20 Sep 2017, pp. 1-3.
[16] Qimin You1, Yonghui Li1, Zhuo Chen and Md Shahriar Rahman, "A simple near-optimal path selection scheme for multi-hop wireless relay networks based on Viterbi algorithm", TRANSACTIONS ON EMERGING TELECOMMUNICATIONS TECHNOLOGIES Trans. Emerging Tel. Tech. (2014). June 2014, pp. 1-14, DOI: 10.1002/ett.2849.
[17] Pushpender, Sohan Garg , "An Optimization Technique For Wireless Mesh Networks", International Journal of Advanced Research in Computer and Communication Engineering, Vol. 3, Issue 6, pp. 6838-6843, June 2014.