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An Appraisal of QoS Parameter Achievements in MANET through Learning

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Abstract*— A mobile ad hoc network (MANET) is an autonomous collection of mobile nodes which do not have a fixed infrastructure. Routing in MANET is challenging due to dynamic nature of node and constrained bandwidth. Hence, Reinforcement Learning helps to infer network status information thereby network routing can be enhanced. The information gathered through this learning helps to choose a reliable and stable path by considering the QoS parameters such as minimum power consumption, high energy, bandwidth efficiency, shortest path, throughput, packet loss, End-to-End delay etc. Even though a large number of machine learning algorithms are available, Reinforcement learning helps to achieve an adaptive routing in MANET. Hence, the basic concept of Reinforcement learning and some works related to various aspects of QoS parameters have been discussed.

Keywords*— Machine Learning (ML), Reinforcement Learning (RL), Q-learning, Artificial Intelligence, Quality of Service (QoS), Temporal difference and SARSA.

I. INTRODUCTION

MANET is a collection of independent mobile nodes which can move anywhere in the network and hence the topology changes dynamically. Nodes in MANET have limited bandwidth, battery constraints and no centralized administration. Hence routing in MANET is very challenging. So, a routing should be chosen in such a way that it maximizes delivery ratio and minimizes link or node failures.

Routing can be defined as finding the best path foe a transmitting a packet from the source to the destination. QoS is defined as a set of measurable pre-specified service requirements such as delay, bandwidth, probability of packet loss, and delay variance [1]. QoS for a network is measured in terms of the guaranteed amount of data that is transferred from one place to another during a certain time [2]. The goal of QoS is to achieve a more deterministic network behaviour, so that the information carried out by the network can be better delivered and network resources can be better utilized.

Providing better QoS in MANET is challenging due to the following issues: [3]

- **Node Mobility:** In MANET, the topology is highly dynamic in nature due to the mobility of nodes which results in packet loss and in turn affects the end to end delay.
- **Lack of Central Control:** MANET does not have any pre-existing infrastructure which requires a lot of information, thus increasing the routing overhead.
- **Unreliable Wireless Channel**— Due to interference from other transmissions, thermal noise etc., wireless channel is prone to bit errors. This makes it impossible to provide hard packet delivery ratio or link longevity guarantees.
- **Channel Contention** — In order to discover network topology, nodes in a MANET must communicate on a common channel which introduces the problems of interference and channel contention.
- **Limited Device Resources**—Mobile devices have less computational power, less memory, and a limited (battery) power supply.

The overview of the remaining paper is as follows: Section 2 narrates the outline of Machine Learning, Section 3 briefs about Reinforcement Learning, Section 4 deals with the Review of literature and Section 5 provides Conclusion.

II. MACHINE LEARNING (ML)

Machine Learning is defined as the "Field of study that gives computers the ability to learn without being explicitly programmed". It operates by building a model from example inputs in order to make data-driven predictions or decisions, rather than following strictly static program instructions.

Why increased interest in ML?

- To quickly and automatically produce models that can analyze bigger, more complex data and deliver faster, more accurate results even on a very large scale.
- To guide better decisions and smart actions in real time without human intervention.

Machine Learning methods:

1. Supervised Learning:

The program is "trained" on a pre-defined set of "training examples", which then facilitate its ability to reach an accurate conclusion when given new data. The goal is to learn a general rule that maps inputs to outputs.

- Learning approaches for regression & classification
- Used in applications where historical data predicts likely future events.

2. Unsupervised Learning:

No labels are given to the learning algorithm, leaving it on its own to find structure in its input.

- Learning approaches for dimensionality reduction, density estimation, recoding data based on some principle, etc.
- Used to segment text topics, recommend items and identify data outliers.

3. Semi-supervised learning:

- Uses small amount of labelled data and large amount of unlabeled data for training.
- Helps in identifying a person's face on a web cam.

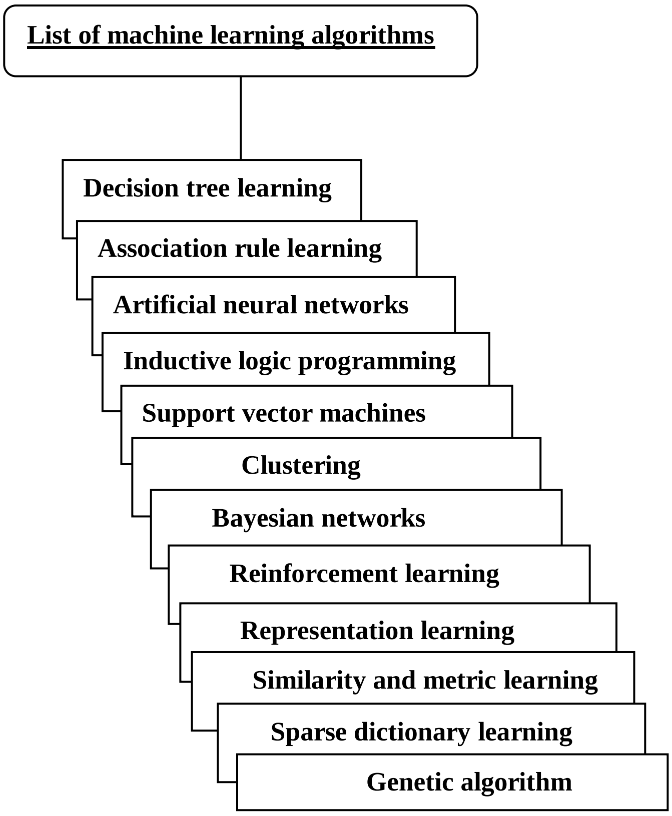

Fig 1: List of Machine Learning Algorithms

III. REINFORCEMENT LEARNING (RL)

The idea of applying reinforcement learning to routing in networks was first introduced by Boyan and Littman [4]. Reinforcement Learning (RL), also called adaptive (or approximate) dynamic programming (ADP), is a powerful tool for solving complex sequential decision-making problems in control theory.

[5] Learn of a behavior strategy (a policy) which maximizes the long term sum of rewards (delayed reward) by a direct interaction (trial-and-error) with an unknown and uncertain environment. Reinforcement learning is defined not by characterizing learning methods, but by characterizing a learning *problem.*

Features of Reinforcement Learning:

Trial-and-error search

Delayed reward

Explicitly considers the *whole* problem as a goal-directed agent.

Challenges:

There is a trade-off between exploration and exploitation. To obtain a lot of reward, a reinforcement learning agent must prefer actions that it has tried in the past and found to be effective in producing reward. But to discover such actions, it has to try actions that it has not selected before. The agent has to *exploit* what it already knows in order to obtain reward, but it also has to *explore* in order to make better action selections in the future.

Objective:

To maximize the total reward it receives in the long run.

Elements of Reinforcement Learning:

The four main sub-elements of a reinforcement learning system: a *policy*, a *reward function*, a *value function* and optionally a *model* of the environment.

1. Policy

- Defines the learning agent's way of behaving at a given time. Called a set of stimulus-response rules or associations.
- Policy may be a simple function or lookup table.
- In general policies may be stochastic.

2. Reward function

- Defines the goal in a reinforcement learning problem, by stating the good and bad events for the agent.
- Maps each perceived state (or state-action pair) of the environment to a single number, a *reward*, indicating the intrinsic desirability of that state.
- In general, reward functions may be stochastic.

3. Value

- Specifies what is good in the long run whereas a reward function indicates what is good in an immediate.
- In fact, the most important component of almost all reinforcement learning algorithms is a method for efficiently estimating values.

Difference between Rewards and Value:

- The *value* of a state is the total amount of reward an agent can expect to accumulate over the future whereas rewards determine the immediate, intrinsic desirability of environmental states.
- Rewards are in a sense primary, whereas values, as predictions of rewards, are secondary.
- Rewards are basically given directly by the environment, but values must be estimated and re-estimated from the sequences of observations an agent makes over its entire lifetime.

4. Model

- Mimics the behavior of the environment. For example, given a state and action, the model might predict the resultant next state and next reward.
- Models are used for *planning*, a way of deciding on a course of action by considering possible future situations before they are actually experienced.

The Agent-Environment Interaction Protocol

Reinforcement Learning is defined as Learning from Interaction. It is said to be a

- Complete agent
- Temporally situated
- Continual learning and planning
- Object is to affect environment
- Environment is stochastic and uncertain

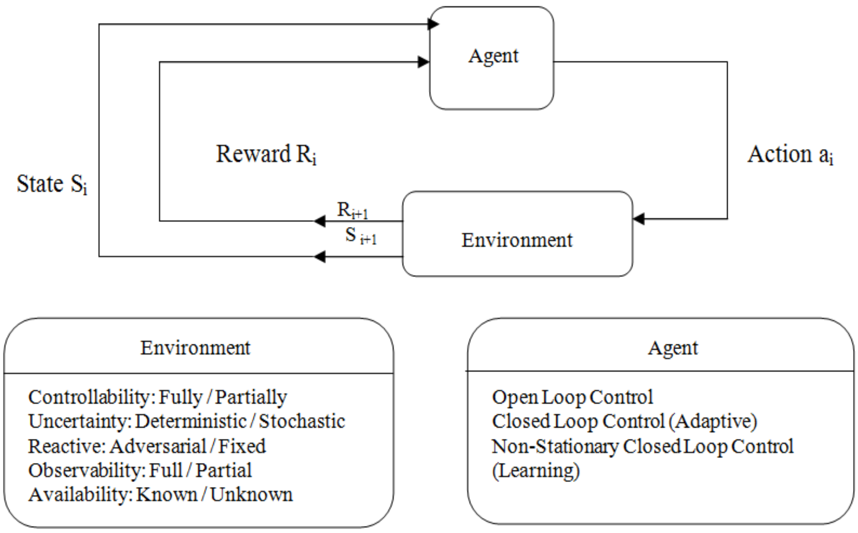

Fig 2: The agent-environment interaction in reinforcement learning

Mathematical Notation of RL: [6]

RL is defined as

s1 a1 r2, s2 a2 r3------- si ai r i+1

Agent's life Unit of experience

Where s_i denotes state, a_i – action, r_i – reward.

1. Agent chooses actions so as to maximize expected cumulative reward over a time horizon. Observations can be vectors or other structures. Agent has partial knowledge about its environment Agent's life Unit of experience
2. Actions can be multi-dimensional.
3. Rewards are scalar & can be arbitrarily uninformative.

Steps:

For t = 1, . . . , n do

The agent perceives state s_t

The agent performs action a_t

The environment evolves to s_{t+1}

The agent receives reward r_t

end for

IV. REVIEW OF LITERATURE

In Wireless Networks, Context awareness and Intelligence are capabilities that enable each host to observe, learn and respond to its complex and dynamic operating environment in an effective manner. These are gaining popularity due to the substantial network wide performance enhancement is needed and here RL is used to achieve context awareness and Intelligence. The RL approach is widely used in routing, resource management and dynamic channel selection in wireless networks. A study on how learning agent is used to improve the outcomes of QoS requirements is presented here.

Table 1: A Survey on the Achievement of Qos Parameters through Learning

Reliability				
Topic	**Author**	**Year**	**Concept**	**Outcome**
Reliability estimation of learning based mobile agent system in MANET [7]	Chandreyee Chowdhury, Sarmistha Neogy	2011	1. Used Mobile Agent Based System (MAS). 2. The agents are intelligent enough to share information and learn (reinforcement learning) about the underlying MANET conditions dynamically	Better performance and improved reliability.
Learning Based Reliable Mobile Agent System for Hostile MANET [8]	Basak, Paramita	2014	1. On-policy Monte Carlo method of Reinforcement Learning. 2. Agents learn about a good policy to choose a mobile node to migrate and also detect malicious nodes present in the network.	Yielded better reliability of mobile agent system in hostile network.
Throughput				
QoS Routing in Mobile Ad-hoc Networks using Agents [9]	V. M. Harnal, V. R. Budyal	2012	1. Used Neuro-Fuzzy System (NF) - to convert uncertain data set to certain data set at the input of the fuzzy logic system, so that the efficiency of the DSR algorithm is improved which provided Quality of service to the user. 2. Optimizes the uncertain weights before QoS prediction using Error Back Propagation (EBP) algorithm, to get acceptable error limit.	Reduced the complexity and improve the flexibility
Q-Decomposition for Reinforcement Learning Agents [10]	Stuart Russell, Andrew L. Zimdars	2003	1. Used Sarsa reinforcement learning algorithm to learn its local Q-function. 2. A complex agent is built from simpler subagents. 3. Each subagent has its own reward function and runs its own reinforcement learning process in which subagent recommends actions.	Eliminated the central arbitrator, making optimality more difficult to achieve.
Self-Organized Routing in Mobile Ad Hoc Networks using SAMPLE [11]	Jim Dowling and Stefan Weber	2006	1. Used collaborative reinforcement learning (CRL). 2. Routing agents collectively learn to exploit stable routing paths in the network environment by providing feedback on the state of routes and network links.	Feedback enables them to self-organize in varying network conditions and properties, resulting in the optimization of network throughput.
Performance	Balram Swami,	2015	1. Used OWL (Ordered Walk Learning Protocol).	OWL performs well

Analysis of DFS based Ordered Walk Learning Routing Protocol in MANET [12]	Ravindar singh,"		2. It is a reactive routing protocol and uses DFS in place of BFS and it does not flood the whole network. 3. OWL can be used efficiently for small scale networks.	with comparable known MANET routing protocols (e.g. AODV and DSDV).
Cooperative Reinforcement Learning Approach for Routing in Ad Hoc Networks [13]	Rahul Desai, B P Patil	2015	1. Used cooperative reinforcement learning – To determine the Optimum path by considering the quality of links within the network on continuous basis instead of discrete time.	Optimized the performance of a network on trial and error basis
A MANET Routing Protocol using Q-Learning Method Integrated with Bayesian Network [14]	Ke Wang ,Wai-Choong Wong and Teck Yoong Chai	2012	1. Used self-learning routing protocol based on Q-learning and Bayesian Network. 2. Estimated neighbouring network congestion level to tune the Q-learning weights. 3. Protocol also sends out probing packets to detect and solve the routing-loop problem.	Better performance in a dense heavy-loaded scenario.
Route Selection				
Real-time routing algorithm for mobile ad hoc networks using reinforcement learning and heuristic algorithms [15]	Ali Ghaffari	2016	1. Reinforcement learning was used. 2. Aimed in predicting the behaviour pattern of the nodes in relation to the target node.	Helped in finding the best choice among the neighbours for transmitting a packet to the destination.
A Proactive Link-Failure Resilient Routing Protocol for MANETs based on Reinforcement Learning [16]	Guido Oddi, Donato Macone, Antonio Pietrabissa and Francesco Liberati	2012	Proactive routing protocol via Reinforcement Learning (RL) was developed.	1. Dynamically choose the most stable path, based on GPS information. 2. Helped to consequently increase resiliency to link failures.
A Mobile Ad hoc Network Q-Routing Algorithm: Self-Aware Approach [17]	Amal Alharbi, Riyadh Abdullah Al-Dhalaan, Riyadh Mznah Al-Rodhaan	2015	1. Combines the self-aware capabilities in CPN with a Q-learning inspired path selection mechanism. 2. Defines a Q-routing reward function as a combination of high stability and low delay path criteria	Discovered a long-lived routes without disrupting the overall delay.
Link Stability				
Unicast Quality of Service Routing in Mobile Ad Hoc Networks Based on Neuro Fuzzy Agents [18]	V.R.Budyal, S.S.Manvi, S.G.Hiremath	2011	Used i) Fuzzy static agent to decide whether each node in the path satisfies QoS requirement for multimedia applications ii) Neuro Fuzzy agents for training and learning to optimize the input and output fuzzy membership functions according to the user requirement iii)Q-Learning (Reinforcement learning) static agent is used for fuzzy inference instead of experts experience.	Tried to establish QoS path whenever there is failure in link or node.
Q-learning based adaptive QoS routing protocol for MANETs [19]	G.Santhi, Dr.Alamelu Nachiappan Mougamadou Zaid Ibrahime	2011	Used Q-Learning to enhance network routing.	Learn about the expiry of links and choose the path with more expiration time and the minimum power consumption.
Mobilized ad-hoc networks: a reinforcement	Chang and Kaelbling	2004	Reinforcement learning methods – were applied to Packet routing and node movement.	Improved the connectivity of the network.

learning approach [20]				
A MANET protocol considering link stability and bandwidth efficiency [21]	Wu, C., Kumekawa K, Kato. T	2009	Q-Learning AODV (QLAODV) uses distributed Q-learning to infer network status information.	Handled network mobility by switching to a better route before the current route fails.
Self-Adaptive Trust Based ABR Protocol for MANETs Using Q-Learning [22]	Anitha Vijaya Kumar & Akilandeswari Jeyapal	2014	1. Used Q-learning to weigh the trust of a particular node over associativity based routing (ABR) protocol.	Secure and stable route was calculated using associativity ticks.
Maintenance of Link for Stability in MANET [23]	Amit Gupta	2015	2. Used Q-learning concept and used most stable routes for data transmission since less energy nodes can also responsible to path break and link failure.	Free from link and node failure.

V. CONCLUSION

MANET consists of mobile nodes which are free to move at any speed in any direction and organize themselves randomly. Nodes in the network can operate as a router or a host. MANET has certain issues like dynamic nature, bandwidth restriction, limited processing and node mobility. Learning helps to handle these challenging nodes more effectively. The survey states that some of the QoS parameters like reliability, link stability, throughput, stable route selection, minimizing end-to-end delay and packet loss have been achieved through learning concept.

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