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Improved Routing Protocol WRP using Machine Learning Algorithms

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Abstract- In a mobile ad hoc network, all nodes are moving and dynamically establish communication with a customized approach. All nodes in this network act as a router and help to other nodes involved in route discovery and maintenance, so knowing the node mobility model is very important in evaluating its performance. Considering that in the real world,node mobility model is not always available or network mobility model may change in time, but the mobility model can be estimated by using of some algorithms and these estimates will be used in routing. In this paper, WRP protocol was described and then was improved by usingthe Q-learning algorithms.

Keywords- *Mobile Ad Hoc Networks, Routing Protocols, Machine Learning Algorithms, Q-Learning Algorithm.*

I. INTRODUCTION

Ad Hoc mobile networks (MANET's) are a group of wireless computers, forming a communication network, which has no predetermined structure. Configuration and management of this network is not dependent on any particular user. In other word, specific networking allows formation of an autonomous complex. There are numerous scenarios that a network with a fixed structure and configuration cannot meet their needs and then networks like special networks are needed for military mission, emergency operations, commercial projects, training courses and etc. therefore, in recent years, special attention is paid to these networks. There are many problems in a specific network such as open network architecture, shared wireless media and transport [1].

Although these networks were originally composed for a small group of cooperating nodes, but now large groups on a broad geographical regions use these networks well. So scalable is another difficulty in creating this kind of network. Thus, mobile computing devices are suitable to grow case networks in terms of networks transportation ability and forms of networks [1,2].

One of the basic problems of such networks is routing in them and due to the mobility of nodes, ad hoc network protocols cannot be used. Routing protocols in such networks are divided in to two categories: On-Demand and Table-Driven that their main differences are in saved data and also in transmitting this data. Many parameters influence on the performance of routing protocols and one of the most effective parameters is mobility network model. This model contains information such as speed, acceleration and direction of each node at any moment of time.

The purpose of this paper is improvement of WRP protocol [3]by using Q-learning algorithm [4] and we call this improved protocol as QLWRP.WRP and QLWRP protocols both are routing protocols for ad hoc networks, but WRP are used in normal machine and QLWRP are used in machines with learning ability. NS2 is used for this purpose and this software includes implementation of standard for WRP protocol based on which the QLWRP protocol has been implemented.

New version of QLWRP allows the source node to estimate the path of the destination node and sends routing information to some nodes. Totally, several works have been improved in this new protocol resulting to improving WRP protocol.

The structure of the paper is: Section 2 deals with the study WRP protocol, sections 3 and 4 respectively overview the mobility models and machine learning algorithms. The proposed method described in section 5 and simulation results are discussed in section 6.

II. WIRELESS ROUTING PROTOCOL (WRP)

WRP uses an enhanced version of the distance-vector routing protocol, which uses the Bellman-Ford algorithm to calculate paths. Because of the mobile nature of the nodes within the MANET, the protocol introduces mechanisms which reduce route loops and ensure reliable message exchange [1,2]. Each node implementing WRP keeps a table of routes and distances and link costs. It also maintains a 'message retransmission list (MRL).

Routing table entries contain distance to a destination node, the previous and next nodes along the route and are tagged to identify the route's state: whether it is a simple path, loop or

invalid route. (Storing the previous and successive nodes assists in detecting loops and avoiding the counting-to-infinity problem - a shortcoming of Distance Vector Routing). The link cost table maintains the cost of the link to its nearest neighbors (nodes within direct transmission range), and the number of timeouts since successfully receiving a message from the neighbor. Nodes periodically exchange routing tables with their neighbors via update messages, or whenever the link state table changes. The MRL maintains a list of which neighbors are yet to acknowledge an update message, so they can be retransmitted if necessary. Where no change in the routing table, a node is required to transmit a 'hello' message to affirm its connectivity. When an update message is received, a node updates its distance table and reassesses the best route paths. It also carries out a consistency check with its neighbors, to help eliminate loops and speed up convergence.

A unique characteristic of this algorithm is that it checks adaptation of all neighboring nodes when a change occurs in transplant of any of the neighbors. Compatibility checking of this method will help a lot to eliminate the loop and to accelerate the converging paths.

III. AN OVERVIEW OF THE MOBILITY MODELS

Mobility models are divided into two categories independent mobility models and group mobility models [3]. In independent ones, moving of a node is independent of the other nodes. Random walk mobility models, RWP, Gauss - Markov and others are in this category. In contrast, in group mobility models, moving of a node depends to the moving of one or more nodes in the network. The most important models existing this group are dynamic models Highway, Manhattan, RPGM, Column noted, etc. In this section, we examine 3 types of movement models that are used in most simulations.

- *RWP model:* at any moment, a node randomly selects a destination and moves toward it with a random speed and without acceleration with uniform distribution [5] which is selected of the interval [0, Vmax].
- *RPGM model:* Nodes make one or some groups in which a node is selected as a leader. Initially, the group members are uniformly in leader neighborhood. Then at each moment, each node chooses its speed and direction with a random deviation from the leader [2].
- *Highway mobility model:* The main application of this method is tracking cars on a highway. Naturally, there are main differences between this method and previous ones which are derived from the laws governing highways [6].

IV. A REVIEW OF MACHINE LEARNING TECHNIQUES

First of all a precise definition of learning must be provided. In general, if a test shown as E, all things that a computer program can do are shown as S and program performance and evaluation criteria as P, then learning is defined as follows:

Definition: If performance of a computer program (P) while running something of the set S by using of test E is improved then we call that a program of learning. In other words, machine learning is how to write programs that will learn through experience and improve their performance. Learning may cause changes in the structure of programs or data.

The main goal of machine learning algorithms (ML) is automatic learning of environment characteristics and behaviors as quick and easy to environmental factors. Some characteristics of mobile ad hoc networks are: memory, computational constraints, communication costs and remaining energy. On the other hand, there are many machine learning techniques that are useful for networks and a suitable ML method can be selected by using different characteristics of mobile ad hoc networks. From these characteristics we can name non-static nature, topology changes and mobility, energy constraints and the physical distribution. In the following sections an overview of some of widely used ML techniques is provides [4,7,8].

A. *Decision Trees*

Decision trees are one of the most powerful and popular tools. A decision tree is a data structure thatcan be used to divide a large collection of records into smaller sets of records. Decision tree does it with a series of questions and very simple decision-making rules. With each successful division, members which are in a set become more similar to each one. As an overview of a decision tree, it can be considered as a hierarchical structure in which intermediate nodes are used for testing a feature. Branches show test output and leaves show class label or class label distribution procedures [8].

B. *Neural Networks*

An Artificial Neural Network (ANN) is an idea inspired by biological neural system for processing information such as the brain deals with information processing. The key elements of this idea are new structure of data processing system. This system consists of many interconnected processing elements (neurons) that acts together to solve a problem. ANNs learn by example like humans. ANN is set for a specific task such as pattern recognition and data classification through a learning process [8].

C. *Computational Learning*

Computational Logic is a part of the logic that deals with review of different ways of verification of provisions in different logical systems. This field is deeply linked with computer science and it is real growth began when computer computing power was developed and complex calculations by computers and with low cost were possible. Computational Logic generally sees the logic from computational point of view, that is, in a logical device, doing a calculation (for example, checking the correctness of a proposition) is possible or not and if it is possible, how much does it cost. Because scientific facts have a deep bond with logic, sousing logical language to investigate the facts is one of the best possible ways. A general method for understanding a sentence correctly is beginning with assumptions and at every stage concludes a

new sentence based on former sentences and by use of rules. This procedure will be continued until they get to the question or conflicting.

D. Evolutionary Computation (genetic algorithms)

In brief, Genetic Algorithm (or GA) is a programming technique which uses genetic evolution as a model of problem solving. The problem that must be solved is input and the solutions are encoded as a model and metric-fitness function-evaluates each candidate solutions, most of which are randomly selected. In general, the algorithms consist of fitness functions, selection, handling, and mutations.

E. Reinforcement Learning

When we speak about learning, the most common method that comes into mind is learning by interacting with the environment. So it seems natural that learning by interacting with the environment is one of the fundamental ideas of machine learning and artificial intelligence. Reinforcement learning is one of the machines learning method in which its problem is learning and it learns a behavior through trial and error and interaction with a dynamic environment. There are some reinforcement learning methods amongst which time difference is more famous [4,7,8].

Algorithms that are used for reinforcement learning are generally known as Markov decision process. The output of this algorithm examines each activity is each position only according that activity in that position (that is without making it dependent on previous activities and situation). Among the issues that algorithms can cover are most of nodal control robots, automated factories and time different issues.

Q-Learning is one of the reinforcement learning in which it learns an evaluation function based on the operation and position. Accurately, it can be said that the evaluation function Q (s, a) is defined as function obtaining maximum expected response that the agent could achieve by performing action in situation S. Q-Learning algorithm has this advantage that it can be used even if the agent has no previous knowledge about the impact of action on the environment.

V. THE PROPOSED METHOD

This section describes the proposed method to estimate mobility model and to improve the WRP protocol in mobile ad hoc networks. Learning algorithms for this purpose is called Q-Learning algorithm. In this method it is assumed that the mobile network mobility model is RWP model and each node in the network acts as a learner; the algorithm has no previous knowledge based on relationship between mobility models and parameters received from the mobile ad hoc networks simulation. There are two important criteria in analysis of mobility models in mobile ad hoc networks: degree of spatial dependence, and relative speed. Degree of spatial dependence shows the degree of similarity between the velocity vectors of two different nodes, which are not so far apart and relative speed of two nodes is defined in a specific moment [9].

The procedure is that for each node in the mobile network the following information, in addition to the information in section 2, will be added:

- *Location table:* includes the physical location of the destination node which is a point in Cartesian coordinates.
- *The relative speed table:* is the relative speed of the destination node in relation to source node.
- *Q -Table:* includes Q-values of Q (d, x) which are described below.

When a source node needs to communicate with a destination node, it first checks whether there is a path in its routing table or not. If it does not find a path, it will use common routing WRP methods to find a path to destination.

The Q-value Q(s,a) in Q-learning is an estimate of the value of future rewards if the agent takes a particular action a when in a particular states. By exploring the environment, the agents build a table of Q-values for each environment state and each possible action. Expect when making an exploratory move, the agents select the action with the highest Q-value. The learning rate and the discount factor are important parameters of the Q-learning algorithm. The learning rate parameter limits how quickly learning can occur. It governs how quickly the Q-values can change with each state/action change. The discount factor controls the value placed on future rewards. If the value is low, immediate rewards are optimized, while higher values of the discount factor cause the learning algorithm to count future rewards more strongly [10,11].

As previously mentioned, every node maintains a Q-Table which consists of Q-values Q(d,x) whose values range from 0 to 1, where d is the destination node and x is the next hop to the destination. We use a dynamic Q-Table, such that the size of the Q-Table of a node is determined by the number of destination nodes and neighbor nodes. The Q-Table and learning tasks are distributed among the different nodes (states)[11]. When sending a packet is successfully done from node x, the value is 1 otherwise the value is 0.

In the exchange of information between the source node x with the destination node y, if y starts to move, x agent using a Q-learning algorithm and the relative speed of the destination node estimates y`s mobility model by location table and Q-Table and finds the approximate optimal path to the estimated point based on information in its routing table. This makes when finding a new route, routing information will not be sent to all nodes and information will be sent only through nodes in the approximate direction. Original optimal path will be calculated after receiving destination node location information. Because keeping adapted information of all tables of nodes is one of the main conditions of WRP protocol, the information will be sent to all neighboring nodes. The neighboring nodes with respect to changes in direction update the information and continue the process.

VI. SIMULATION

The ultimate goal of this simulation is implementing the QLWRP protocol and comparison with WRP protocol. Simulation was done by 50 mobile nodes in an area of

300*1500 m^2 and time of 900 seconds. The simulator accepts a file for each scenario in which the motion of each node and the packets generated by each node is shown and they are different in the differences in the changes that occur in these parameters. For this purpose, 210 different scenario files with changes in movement pattern and traffic load were created and then all of them were run for all seven protocols [2].

A. Movement Model

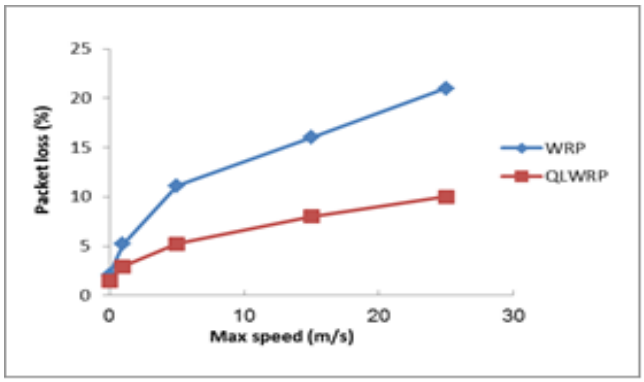
The NS2 simulator is used for simulation which nodes move according to random waypoint model that the movement scenarios include time stop characteristics [2]. A random destination in an area of 1500*300m^2 is chosen toward which a node moves with non-uniform speed between zero and its maximum velocity. When the node reaches to its destination, it stops there (in seconds) then chooses another destination and continues this manner during total simulation time. Each simulation is run in 900 seconds and stop times considered for the simulation are 0, 30, 60, 120, 130, 600 and 900 seconds. Zero stop time means a continuous movement and 900 seconds stop time shows a static network. Since protocol efficiency is very dependent on nodes movement model, so we have considered 70 different movement models for nodes. 10 different runs has been done for each time stop and 2 different values for the maximum speed of node have been considered. In next section, the simulation results with maximum speed 20m/s and average speed 10m/s and maximum speed 1m/s are shown.

B. Communication Model

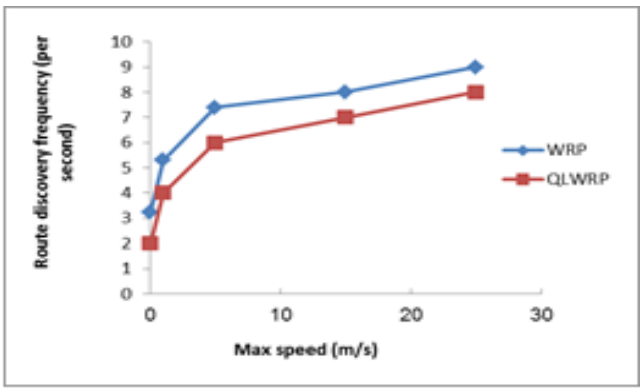
For mentions simulations, we considered a constant bit rate traffic source (CBR), transfer rate of 1, 4 and 8 packets per second, and 10, 20 and 30 sources and 64- byte and 1024-byte packets [2]. Change of total CBR source is very similar to the change of transfer rate. Thus, we considered the transfer rate as constant as 4 packages per seconds and 3 different patterns of CBR source with 10, 20 and 30 source. When we used 1024-byte packages a heavy congestion appeared because of lack of diversity of space and this problem exists for all protocols, one node or two nodes must destroy the received packages to solve the problem. If none of the nodes does not participate in load balancing then topology must be changed and size of the sent packages must be minimized to 64 bytes. All of the communication models are peer to peer and initial connections are distributed uniformly between 0 and 180 seconds [2]. Three communication models (10, 20 and 30 sources) are combined with 70 movement patterns and create 210 different scenarios for each nodes maximum of speed (1m/s and 20 m/s)[6].

C. Simulation Results

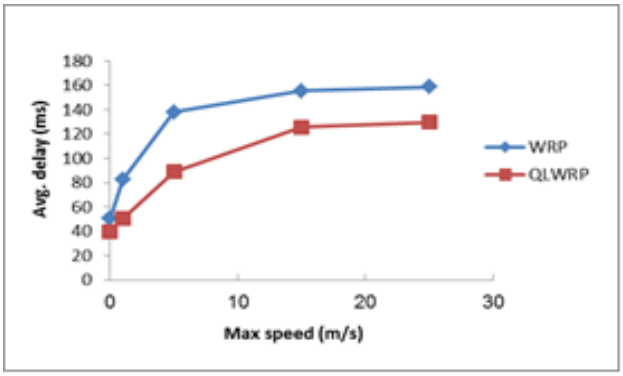
Figure 1 (a-h) depicts results of the simulation of WRP and QLWRP protocols.



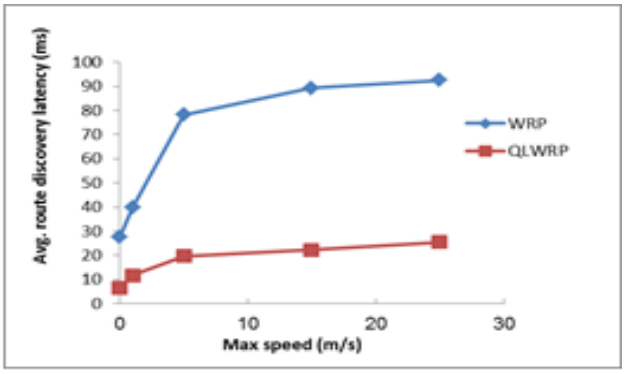
(a)



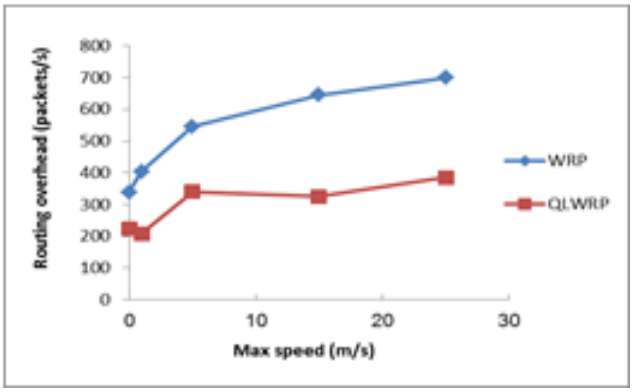
(b)



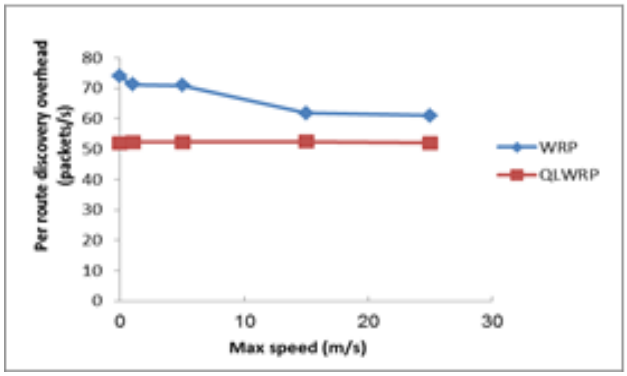
(c)



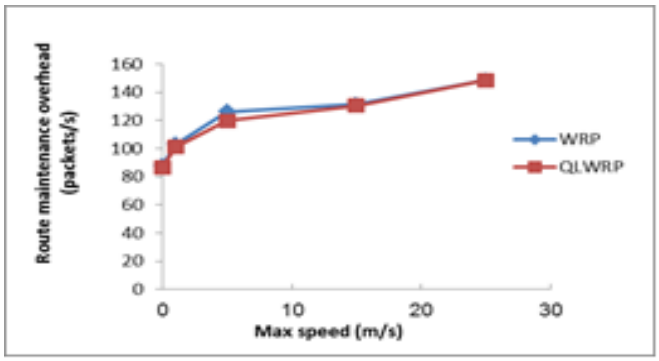
(d)



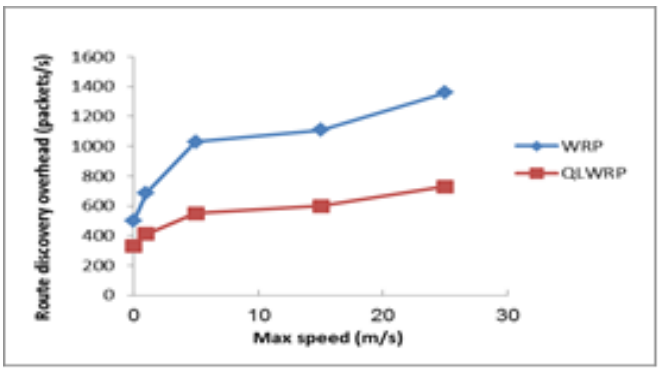
(e)



(f)



(g)



(h)

Figure 1. (a-h)Results of the simulation WRP and QLWRP protocols

VII. CONCLUSION

Mobile ad hoc networks which are being expanded and also their users are growing every day need to the concept of mobility model for better performance and more accurate assessment. Because the mobility model of a mobile network is not previously known or is likely to change over time, thus a new problem – estimate of mobility model of mobile ad hoc networks- appears. In this paper, we used Q-learning algorithm and estimate of mobility model to improve the efficiency of routing protocol WRP and significantly reduced the routing overhead.

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