Fuzzy Cost Enabled Multipath Routing With Rough Set Approach in Mobile Ad Hoc Network

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***Abstract*— In this article, we propose on selecting the effective routing paths in Mobile Ad Hoc Network (MANET) with fuzzy cost using rough set theory. MANET is a collection of wireless mobile nodes that can dynamically form a network. Many routing protocols have been existed to find the shortest path using various resources. Fuzzy and Rough set theory is one of the approach for choosing the best path with minimal number of resources. The problems with existing methods are frequent route change with respect to change in topology, congestion as result of traffic and battery limitations since it's an infrastructure less network. So overcome these problems an optimal path management approach called path vector calculation based on fuzzy and rough set theory addressed. Focus of this research activity is to justify simpler rules and removes irrelevant resources for evaluating the best path. An example is also given to illustrate the efficiency of our proposed method.**

Keywords: MANET, path vector, Multipath, Fuzzy cost, Fuzzy and Rough set theory, Membership function, Information gain

I. INTRODUCTION

In this Age of Globalization and Network System, movable ad hoc network takes much importance and in communication satisfying the technological urge and need especially exchange merge. In this Age of Computer, mobile also takes an indispensable role. However, a MANET is nothing but an independent collection of mobile nodes linked by wireless unfixed infrastructure. In a MANET all mobile hosts cooperate with another host and share their sources to achieve goals. In the consideration of either security cost or quality, the wireless can be set in any available existing infrastructure which rarely meets application requirements. The network topology called MANET has fast changes owing to the high moment of nodes and it was much difficult to identify the routes which have message packets to use. As a matter of fact, this is kept under constrained bandwidth, limited power and difficulty. It throws challenges upon the architect of a routing strategy in wireless network. In this dynamic connectivity, to build and maintain multihop route adds in MANET. In fact there are a large number of routing paths available from source to destination node [1]. The path can be selected using any one of the algorithm such as On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR), Destination Sequence Distance Vector (DSDV) and WRP(Wireless Routing Protocol).is a table driven routing scheme, is purely set for mobile ad hoc networks of mobile nodes. DSDV guarantees. But DSDV can rarely suitable for highly network. It never controls traffic and region of the network without change in topology [2]. AODV is helpful to handle unicast and multicast routing and it dynamically maintains loop-free routes. Simultaneously AODV creates a disadvantage that leads to unnecessary bandwidth consumption[3].WRP protocol bring into light above mechanism which not only reduces route loop but also ensures re message exchange. Also it requires abundant memory storage and resources for the purpose of keeping its table as a result of high mobility the control overhead updates table entries. Since it suffers from limited scalability, the protocol does not appear to be suitable and ideal for the large mobile ad hocnetworks.DSR makes use of source routing which depends upon the routing table at a frequency of each intermediate device. In respect of routing algorithm mentioned above, routes will fail. A new route is with evaluation from source to destination node.

In this paper, we concentrate on selecting the effective routing paths based on with fuzzy cost using rough set theory. Hence it generates simpler rules and removes irrelevant attributes (resources) for evaluating the best path [4].

II. LITERATURE SURVEY

2.1. Fuzzy cost routing algorithm

Each vector is assigned to calculate fuzzy cost as displayed in Table 1. One agrees with the technical view fuzzy cost based routing protocol takes the routing decision by considering the predefined fuzzy cost threshold value. To utilize cluster algorithm and to construct hierarchical topology requires an ideal method because any problem can be at easy stroke, solved. When an Adapted mobile cluster algorithm sustains the mobility and maintains stability. The clustering management activates tract deployment of network and dynamic reconstruction after topology transformation in order to extend support of the multihop and mobile feature of ad hoc network [5].

2.2 Fuzzy set theory

Fuzzy set theory was first proposed by Zadeh (1965). The main objective of this theory is to develop a methodology for the formulation and solution of problems that are too complex or ill-defined to be suitable for analysis by conventional Boolean techniques. A fuzzy set can be defined as a set of ordered pair A = {x, μA(x)/x ∈ U}. The function μA(x) is called the membership function for A, mapping each element of the universe U to a membership degree in the range [0, 1]. An element x ∈ U is said to be in a fuzzy set if and only if μA(x) > 0 and to be a full member if and only if μA(x) = 1. Membership functions can either be chosen by the user arbitrarily, based on the user experience or they can be designed by using optimization procedures.

2.3. Rough Set Theory

Rough set theory (RST) is an extension of conventional set theory that supports approximations in decision making. A rough set is itself the approximation of a vague concept (set) by a pair of precise concepts, called lower and upper approximations, which are a classification of the domain of interest into disjoint categories. The lower approximation is a description of the domain objects which are known with certainty to belong to the subset of interest, whereas the upper approximation is a description of the objects which possibly belong to the subset. It provides useful information about the role of particular attributes and their subsets, and prepares the ground for representation of knowledge hidden in the data by means of "*if ..., then ...*" decision rules [6].

2.4. Information System

An information system can be viewed as a table of data, consisting of objects (rows in the table) and attributes (columns). An information system may be extended by the inclusion of decision attributes. Such a system is termed as decision system. Suppose we are given two finite and non empty sets U and A where U is called the universe and A, a set of attributes. With attribute $a \in A$, we associate a set V_a (value set) called the domain of a[7].

2.5. Lower and upper approximation

Let us consider $B \subseteq A$ and $X \subseteq U$. We can approximate X by using only the information contained in B by constructing lower approximation (2) and upper approximation (3) of x in the following way Eq. 2 and 3

$$B_*(x) = \{x \in U: B(x) \subseteq x\} \quad (2)$$

And

$$B^*(x) = \{x \in U: B(x) \cap X \neq \phi\} \quad (3)$$

Equivalence classes contained within X belongs to the lower approximation whereas equivalence classes within X and along its border form the upper approximation [8]. Let P and Q be set of attributes including equivalence relation over U, then the positive region is defined as Eq. 4:

$$POS_P(Q) = \bigcup_{x \in U/Q} P_*X \quad (4)$$

Where, $POS_P(Q)$ compromises all objects of U that can be classified to classes U/Q using the information contained within attributes P.

III. ILLUSTRATIVE EXAMPLE

A data set of resources allotted to five paths is given in Table 1 to select efficient path.

TABLE 1

THE DATA SET OF RESOURCES ALLOTTED TO FIVE PATHS

Path	Band Width	Comp Effici-ency	Power Cons	Traffic load	no of Inter Nodes	Total vector cost
1	0.82	0.889	0.29	1	0	3.017
2	0.570	0.776	0.41	0.24	0.3	2.515
3	0.41	0.443	0.22	0.7	1	2.576
4	0.29	1	0	0.73	0.76	2.7
5	1	0.232	0.17	0	0.168	1.526

3.1 Fuzzifying the dataset

From Table I, we consider five condition attributes: Band width, Computer efficiency, Power consumption, Traffic load and Number of internodes and a decision attribute: Total vector cost to represent minimum cost for the selection of best path.

Initially, in order to represent a continuous fuzzy set, we need to express it as a function which maps each real number to a membership degree. A very common parametric function is the triangular membership function which can be derived through automatic adjustments. Each attribute have three fuzzy regions (Low, Medium and High) described as follows:-

Band width : Low (0, 0.3, 0.5) Medium (0.4, 0.6, 0.8) High (0.7, 0.9, 1.0)

Computer efficiency : Low (0, 0.3, 0.5) Medium (0.4, 0.6, 0.8) High (0.7, 0.9, 1.0)

Power consumption : Low (0, 0.2, 0.3) Medium (0.16, 0.26, 0.35) High (0.4, 0.5, 0.6)

Traffic load : Low (0, 0.3, 0.5) Medium (0.4, 0.6, 0.8) High (0.7, 0.9, 1.0)

Number of internodes : Low (0, 0.3, 0.5) Medium (0.4, 0.6, 0.8) High (0.7, 0.9, 1.0)

Thus three Fuzzy membership values are produced for each path according to the predefined membership functions. The fuzzified result is shown in Table II.

TABLE II

ALOTTED MEMBERSHIP FUNCTION

Path	Band Width	Comp Effici-ency	Power Cons	Traffic load	no of Inter Nodes	Total vector cost
1	H	H	H	H	L	3.018
2	H	H	H	M	M	2.518
3	L	L	L	M	H	2.574
4	M	H	L	H	H	2.8
5	H	L	H	L	L	1.528

3.2 Information Gain

ID-3 uses an information theoretic approach aimed at minimizing the expected number of tests to classify an object. Using (5) and (6) we calculate each attributes information gain. We get Gain (Band width) = 0:25, Gain (Computer efficiency) = 0: 43, Gain (Power consumption) = 0:45, Gain (Traffic load) = 0:95, and Gain (Number of internodes) = 0:55. Since, traffic load and number of internodes has the highest information gain among the five attributes, band width, computer efficiency and power consumption may be excluded due to their less importance. The data set is shown in Table III.

TABLE III

DATA SET AFTER THE CALCULATION OF INFORMATION GAIN

Path	Traffic load	No of Inter Nodes	Total vector cost
1	H	L	P
2	M	M	G
3	M	H	G
4	H	H	P
5	L	L	G

The decision attribute (Total vector cost) have two values: Good and Poor. Each value may be classified into its partition. For example path 2, 3 and 5 belong to partition X_G and path 1, 4 belong to partition X_P. $X_G = \{3, 4, 6\}$, $X_P = \{2, 5\}$. For each partition, identifying the C- lower approximation of X_Y and $X_{N,}$ we identify that $CX_G = \{0\}$ and $CX_P = \{0\}$. Next, build the positive region by combining the C-lower approximations of the two partitions:

POS_C (D) = {1, 2, 3, 4, 5}. From POS_C (D), C-equivalence classes in the positive region are constructed as in Table IV.

TABLE IV

THE C-EQUIVALENCE CLASSES IN THE POSITIVE REGION

Path	Traffic load	No of Inter Nodes	Total vector cost	Class
1	H	L	P	Equiv 1
2	M	M	G	Equiv 2
3	M	H	G	Equiv 3
4	H	H	P	Equiv 4
5	L	L	G	Equiv 5

Then build the discerning matrix .Discern = $(dis_{ij})_{5x5}$ where $dis_{ij} = \{r/r \in C, r\ (Equiv_i) \neq r\ (Equiv_j)\}$ .The calculated result is shown in Table V.

TABLE V

DISCERNING MATRIX

	E1	E2	E3	E4	E5	Ri
E1	-	a v b	a v b	b	a	R1
E2	a v b	-	b	a v b	a v b	R2
E3	a v b	b	-	a	a v b	R3
E4	b	a v b	a	-	a v b	R4
E5	a	a v b	a v b	a v b	-	R5

Reduct í of an equivalence class should be able to distinguish Equiv í from all other equivalence classes. Reduct í should be the joint of the entries in the íth row of the discerning matrix. Using Boolean operation, we get

Reduct 1 = $(a \vee b) \wedge (a \vee b) \wedge (b) \wedge (a) = (a \vee b) \wedge b \wedge a = b \wedge a$

Reduct 2 = $(a \vee b) \wedge (b) \wedge (a \vee b) \wedge (a \vee b) = (b) \wedge (a \vee b) \wedge (a \vee b) = b$

Reduct 3 = $(a \vee b) \wedge b \wedge (a) \wedge (a \vee b) = b \wedge a \wedge (a \vee b) = b \wedge a$

Reduct 4 = $(b) \wedge (a \vee b) \wedge a \wedge (a \vee b) = b \wedge a$

Reduct 5 = $a \wedge (a \vee b) \wedge (a \vee b) \wedge (a \vee b) = a$

Finally, the decision table can be built to extract the rules.

TABLE VI

DECISION TABLE FOR RULE EXTRACTION REGION

Path	Traffic load	No of Inter Nodes	Total vector cost	Class
1	H	L	P	E 1
2	-	M	G	E 2
3	M	H	G	E 3
4	H	H	P	E 4
5	L	-	G	E 5

From the above table, we can extract decision rules in IF-THEN form. Here the condition attribute values (traffic load = high, No. of internodes = low) are used as the rule antecedent and class label attribute (Total vector cost = Poor) as the rule consequent. Hence, we can extract the following decision rules:

If traffic load = high, No. of internodes = low, then Total vector cost = Poor.

If No. of internodes = medium, then Total vector cost = Good

If traffic load = medium, No. of internodes = high, then Total vector cost = Good

If traffic load = high, No. of internodes = high, then Total vector cost = Poor

If traffic load = low,
then Total vector cost = Good

Hence, path2, 3 and 5 are considered as the best path.

3.3 Information Gain

ID-3 uses an information theoretic approach aimed at minimizing the expected number of tests to classify an object. Using (5) and (6) we calculate each attributes information gain. We get Gain (Band width) = 0:24, Gain (Computer efficiency) = 0: 42, Gain (Power consumption) = 0:44, Gain (Traffic load) = 0:94, and Gain (Number of internodes) = 0:54. Since, traffic load and number of internodes has the highest information gain among the five attributes, band width, computer efficiency and power consumption may be excluded due to their less importance .The data set is shown in Table III.

TABLE VII

DATA SET AFTER THE CALCULATION OF INFORMATION GAIN

Path	Traffic load	No of Inter Nodes	Total vector cost
1	H	L	P
2	M	M	G
3	M	H	G
4	H	H	P
5	L	L	G

The decision attribute (Total vector cost) have two values: Good and Poor. Each value may be classified into its partition. For example path 2, 3 and 5 belong to partition X_G and path 1, 4 belong to partition X_P. $X_G = \{2, 3, 5\}$, $X_P = \{1, 4\}$. For each partition, identifying the C- lower approximation of X_Y and $X_{N,}$ we identify that $CX_G = \{0\}$ and $CX_P = \{0\}$. Next, build the positive region by combining the C-lower approximations of the two partitions:

POS_C (D) = {1, 2, 3, 4, 5}. From POS_C (D), C-equivalence classes in the positive region are constructed as in Table VIII.

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3	M	H	G	Equiv 3
4	H	H	P	Equiv 4
5	L	L	G	Equiv 5

Then build the discerning matrix .Discern = $(dis_{ij})_{5x5}$ where $dis_{ij} = \{r/r \in C, r(Equiv_i) \neq r(Equiv_j)\}$ .The calculated result is shown in Table IX.

TABLE IX

DISCERNING MATRIX

	E1	E2	E3	E4	E5	Ri
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E2	a v b	-	b	a v b	a v b	R2
E3	a v b	b	-	a	a v b	R3
E4	b	a v b	a	-	a v b	R4
E5	a	a v b	a v b	a v b	-	R5

Reduct ί of an equivalence class should be able to distinguish Equiv ί from all other equivalence classes. Reduct ί should be the joint of the entries in the ίth row of the discerning matrix. Using Boolean operation, we get

Reduct 1 = $(a \vee b) \wedge (a \vee b) \wedge (b) \wedge (a) = (a \vee b) \wedge b \wedge a = b \wedge a$

Reduct 2 = $(a \vee b) \wedge (b) \wedge (a \vee b) \wedge (a \vee b) = (b) \wedge (a \vee b) \wedge (a \vee b) = b$

Reduct 3 = $(a \vee b) \wedge b \wedge (a) \wedge (a \vee b) = b \wedge a \wedge (a \vee b) = b \wedge a$

Reduct 4 = $(b) \wedge (a \vee b) \wedge a \wedge (a \vee b) = b \wedge a$

Reduct 5 = $a \wedge (a \vee b) \wedge (a \vee b) \wedge (a \vee b) = a$

Finally, the decision table can be built to extract the rules.

TABLE X

DECISION TABLE FOR RULE EXTRACTION

Path	Traffic load	No of Inter Nodes	Total vector cost	Class
1	H	L	P	E 1
2	-	M	G	E 2
3	M	H	G	E 3
4	H	H	P	E 4
5	L	-	G	E 5

From the above table, we can extract decision rules in IF-THEN form. Here the condition attribute values (traffic load = high, No. of internodes = low) are used as the rule antecedent and class label attribute (Total vector cost = Poor) as the rule consequent. Hence, we can extract the following decision rules:

If traffic load = high, No. of internodes = low, then Total vector cost = Poor.

If No. of internodes = medium, then Total vector cost = Good

If traffic load = medium, No. of internodes = high, then Total vector cost = Good

If traffic load = high, No. of internodes = high, then Total vector cost = Poor

If traffic load = low, then Total vector cost = Good

Hence, path2, 3 and 5 are considered as the best path.

IV. MATERIALS AND METHODS

This model is implemented with NS2 simulator with radio propagation rate 2mbps. In our proposed protocol 100 mobile nodes are placed randomly in a region of 1500m´500m with a maximum and minimum speed from 5ms to 10ms.The transmission range is 250 meters for all nodes. The execution time is 900 seconds for each simulation.

V. RESULTS

Fig 1 shows the result about number of routing discovery phases against the mobility. The frequency of routing invention and identification for the multipath routing FCMR and CBMR is almost the same and is not more than that for the unipath routing approach.FCECR plays an important role in minimizing the cost in route discovery and deleting broken routes. Fig 2 it is states that there are results about average end-to-end delay, which causes for the queue delay in every host and the propagation delay from the source to the destination. So multipath routing FCECR results in reduction of the queue delay by reason of which traffic is distributed through various tracks. If not, it naturally increases the propagation delay because a few data packets are forwarded along the sub-optimal paths. From Fig 3, is not that the unipath routing have higher average point-to-point delay in compensation with multipath routing and the average point-to-point delay of FCECR is higher than that of CBMR and FCMR. From the demonstration it is understood that the multipath routing control distributes the traffic and improve the end-to-end delay and the improvement in limited below pause time of 300 seconds. The network topology changes more frequently at smaller pause time and hence the average end-to-end delay for the both multipath routing and unipath routing decreases. Thus queuing delay of the data packets in the source node increases which leads the increase of the average end -to-end delay.

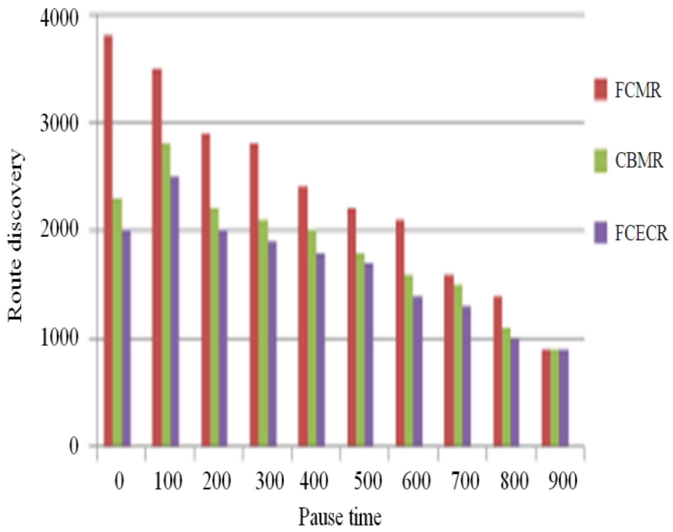

Fig. 1: Route discovery

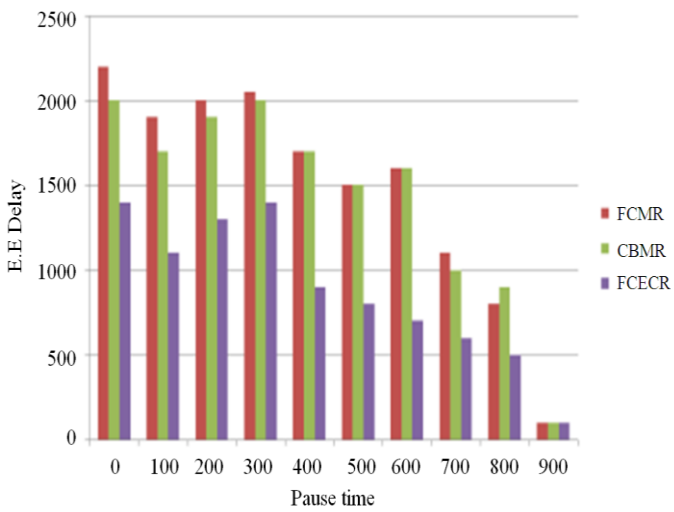

Fig.2: End-End delay

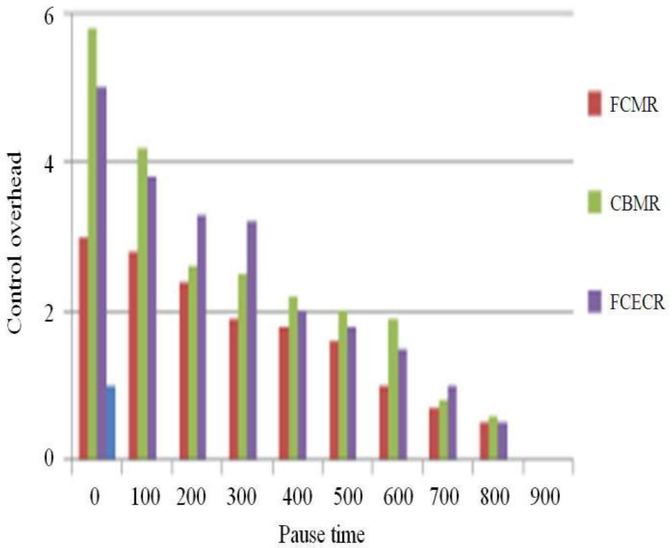

Fig. 3: End-End delay

VI. CONCLUSION

In this paper we have proposed Fuzzy and Rough set approach for the selection of best path from existing multipath. When the number of resources in the MANET is very large, the total vector cost will be increased. Hence, we introduce Fuzzy and Rough set theory and proved all the reductions can be obtained by using the method of indiscernibility matrix. Next IF- THEN decision rules provides an alternative for evaluating the selection of best path with minimum number of resources and total vector cost.

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