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Predictive Energy Efficient and Reliable Multicast Routing In MANET

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Abstract: In Mobile Adhoc Networks (MANETs), multicast routing is favorable to minimize the cost of transmission as it routes data to a group of destinations simultaneously. However, the main aim of multicast routing is to maintain energy efficiency, ensure minimum delay and stability of paths. In this study we propose to develop a Predictive Energy efficient and Reliable Multicast Routing using Particle Swarm Optimization (PSO) in MANET. The technique uses PSO algorithm to construct energy efficient and reliable multicast tree. The fitness function of PSO algorithm is designed considering path delay, expected path energy and path stability. The proposed algorithm is simulated in NS-2. The simulation results proved that the proposed algorithm offers energy efficient and reliable multicast routing with low overhead.

Keywords: Mobile Adhoc Networks (MANETs), multicast routing, PSO algorithm

INTRODUCTION

A group of wireless mobile nodes that dynamically transmits data among themselves without requiring any wireless backbone or fixed base station is referred as Mobile Adhoc Networks (MANETs). These mobile nodes are characterized by their dynamic mobility, limited power, processing and memory resources. Mobile nodes communicate with others through multihop communication as they possess limited transmission range. Therefore, the routing problem becomes a significant factor in MANET.

MANET stands as a unique network from others as it does not require any pre-established infrastructure for connecting mobile nodes. Thus, it can be described as a decentralized and self organizing network (Olagbegi and Meghanathan, 2010; Latha and Ramachandran, 2009; Sabari and Duraiswamy, 2009; Singh *et al*., 2010).

Multicast routing in MANETs: The transmission of data to a set of hosts that are recognized by a single destination address is defined as multicasting. In other words, multicasting is the routing of data to a group of destinations at the same time. The main objective of energy efficient multicast routing is to connect multicast source and receivers with maximum longevity and less energy consumption. In communication network, Multicast Routing Problem (MRP) is one of the most demanding problems as it necessitates the source and a set of destinations to be connected with less cost function. Handling, maximum longevity and cost function simultaneously is a demanding process (Cheng *et al*., 2006; Badarneh and Kadoch, 2009; Baburaj and Vasudevan, 2008).

However, owing to increased utilization of the network, multicast routing has attained many applications such as on-demand video, radio and TV transmission, teleconferences, etc., (Pinto and Barán, 2005).

Issues of multicast routing in a mobile ad hoc network: The basic problem in multicast routing is to discover suitable multicast group members in order to transmit data between multicast source and destinations. A dynamic multicast routing problem has to consider load balancing and network resources utilization along with other QoS parameters. Most of the multicast approaches assume to store the detail of multicast group members in routers. However, this resulted in high delay and these approaches were not able to support mobility of nodes. Multicast service in MANET should offer seamless and integrated operation regardless of nodes mobility (Pinto and Barán, 2005; Obraczka and Tsudik, 1998).

LITERATURE REVIEW

Hwang and Pang (2007) have proposed an energy efficient clustering technique for multicast routing protocol, known as EECT. In their technique, every node uses weight cost function, which is computed based on the transmission power level, residual power and node speed to form cluster in the neighboring area. The node with the minimum weight value is selected as the cluster head. Their EECT can improve the energy consumption by adjusting appropriate power level between cluster head and member. The main benefit of

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EECT is it improves the system performance in terms of total energy consumption for different multicast group size and mobility.

An energy-efficient genetic mechanism is proposed in Yen *et al*. (2008). The authors have modeled a source-tree-based routing algorithm. They have constructed the shortest-path multicast tree to lessen delay by means of a small population size in the genetic algorithm. In their mechanism, a few nodes are employed in the route computation process. They have also improved the genetic sequence and topology encoding and prolong the lifetime of mobile nodes that measure the residual battery energy of all nodes in a multicast tree.

Manvi and Kakkasageri (2008) have introduced an Agent Based Multicast Routing Scheme in MANETs, referred as ABMRS. They have utilized a set of static and mobile agents to perform various processes in the network. The proposed agents are divided into five categories as Route manager static agent, Network initiation mobile agent, Network management static agent, Multicast initiation mobile agent and Multicast management static agent. These agents are initialized in the network to recognize and connect reliable nodes, to model a backbone for multicast routing and group member management.

Vennila and Duraisamy (2012) have put forwarded a QoS based clustering technique for multicast security in MANET. Their technique selects the node with highest available bandwidth and residual energy as cluster head and they in turn operates as multicast group leaders. Trust value is evaluated by cluster heads to perform a successful data transmission. Based on computed trust value, multicast group is constructed. The multicast source makes use of secret key based packet forwarding technique. The advantage of their approach is that they have addressed the security of multicast MANET.

The Predictive Energy-efficient Multicast Algorithm (PEMA) has been introduced by Kao and Marculescu (2008). Their algorithm has utilized the statistical properties of the network. The running time of PEMA depends on the multicast group size, not network size; this makes PEMA fast enough even for MANETs consisting of 1000 or more nodes. The advantage of this approach is that it saves energy and also attains good packet delivery ratio in mobile environments.

Motivation and objectives: Nasab *et al*. (2012), an energy-efficient multicast routing based on Particle Swarm Optimization (PSO) has been proposed to prolong the lifetime of mobile nodes of the network. It considers only delay and residual energy values in the fitness function to construct the multicast tree. Since MANET nodes involve high mobility, the link quality or stability should be taken into account while forming the multicast tree. Hence the main objective of this research work is to increase the energy efficiency and ensure reliability for multicast routing in MANET.

In this study, we propose to design a predictive energy efficient and reliable multicast routing using Particle Swarm Optimization (PSO) algorithm.

MATERIALS AND METHODS

Overview: In this study we propose a Predictive Energy efficient and Reliable Multicast Routing using PSO Algorithm in MANET. After deployment of nodes in the network, particles are distributed randomly in the network. Each particle is assigned with a randomized velocity and is iteratively moved in the search space. The fitness function of PSO algorithm is designed considering path delay, expected path energy and path stability. Initially, particles are moved to the random destinations in the search space and the global and individual best positions are set by means of fitness value. After a interval, the fitness value is evaluated and then compared with individual best position and again with Global best position. During the comparison the individual and global best positions are replaced when the evaluated fitness value is greater than those values. This process is iterated until the energy efficient and reliable multicast tree is constructed.

Network architecture: Consider a Mobile Adhoc Network (MANET) with a group of mobile nodes. Assume that the nodes in the network are distributed arbitrarily in a manner corresponding to a planar Poisson distribution with an average density ∂. Specifically, nodes that are positioned within the network area N_A is described as a Poisson random variable with mean of ∂N_A. We presuppose that the number of nodes positioned in a random area is self-reliant of the number of nodes in any disjoint area.

Metrics assessment:

Estimation of residual energy: The source node and hops (intermediate nodes) obtained by broadcasting energy (E_{tx}) for each packet from Eq. (1) in each node can be updated from remaining energy and own Position (GPS):

$$E_{tx} = (Packet_{size} \times P_{tx})/bw \quad (1)$$

where, P_{tx} is the necessary power for broadcasting a packet and *bw* is the single hop bandwidth between two nodes. The shortest path needs minimum energy from source to destination:

$$\text{Similarly, } E_{rx} = (Packet_{size} \times P_{rx})/bw \quad (2)$$

The minimum total energy required for each node can be calculated from Eq. (2) for data transmission:

$$E_{tot} = n * (E_{tx} + E_{rx}) \quad (3)$$

where, 'n' denotes the total data packets for sending and E_{rx} is the essential energy for receiving data packets, if $E_{tx}<E_{rx}$ (Rajendran and Srivatsa, 2012).
Hence residual energy is given by:

$$E_{PE} = E_{ini} - E_{tot} \quad (4)$$

where, E_{ini} is the initial energy.

Delay estimation: In general, the multicast routing problem is defined by means of a directed graph $G = (V, E)$. In this graph model, V is the set of nodes and E is the set of links. V contains a source node (*sn*), a set of destination nodes (*dn*) $dn \subseteq V - \{sn\}$ and a set of intermediate nodes. The *sn* transmits data packets to the *dn's* nodes through a set of intermediate nodes. The paths that connect source and destinations are termed as multicast groups. The group size defined in terms of number of destination nodes (|*dn*|) (Qu *et al*., 2013).

Every link $L_{i,j} \in E$ in G has a delay related with it, which is a positive real value. Consider node *a* and *b* as two nodes and P (*a*, *b*) as the path that connects node *a* and *b*. The delay of a path is the sum of all link delays along the path. It can symbolized as:

$$Delay(Path(a,b)) = \sum_{(L_{i,j} \in Path(a,b))} Delay(L_{i,j}) \quad (5)$$

Link expiration time: The expiration time between two mobile nodes can be found by the rule that two neighbors in movement will be able to predict proposed disconnection time. Using the motion parameters of two nodes, the duration of time for which these two nodes remain connected can be calculated. The parameters included speed, direction and radio range obtained from GPS. It is assumed that nodes n1 and n2 have equal transmission radius r and that they are initially within hearing. Let (x_i, y_i) and (x_j, y_j) denote the x-y position for node n1 and n2 respectively. Let V_i and V_j indicate their speeds along the directions Θ_i and Θ_j, respectively.

The duration of time between n1 and n2 is given by the following equation:

$$PLET = (- (ab + cd) + \sqrt{} (a^2 + c^2) \; r^2 - (ab - bc)^2) / (a^2 + c^2) \quad (6)$$

where,
$a = V_i \text{ Cos } \Theta_i - V_j \text{ Cos } \Theta_j$
$b = x_i - x_j$
$c = V_i \text{ Sin } \Theta_i - V_j \text{ Sin } \Theta_j$
$d = y_i - y_j$

The output of the network topology at the time of 't' is calculated when a source and destination route is required. A weighted graph of the network topology with the nodes as vertices and links as edges takes shape. The power of link (i, j) is the predicted link expiration time PLET. The residual expiration time of a source and destination path, PLET is the minimum of the predicted expiration time of its links. The path stability PS is then obtained from Eq. (5), (Rajendran and Srivatsa, 2012):

$$PS = Min \{PLET_{si}\} \quad (7)$$

Particle swarm optimization: A parallel evolutionary computation technique put forwarded by Kennedy and Eberhart (1995) is referred as the Particle Swarm Optimization (PSO). This optimization technique is rooted on the social behavior metaphor (Trelea, 2003). PSO is also described as a stochastic global optimization method (Parsopoulos and Vrahatis, 2002).

In PSO algorithm, a population of random candidate solutions are initialized in the network, these are syntactically referred as particles called swarm. Every particle is allocated with a random velocity and it is permitted to move in the problem space. The moving particles are attracted towards the best fitness location achieved by itself and the best fitness location accomplished by the entire population. PSO is simpler to implement and every particle has effective memory capability (Valle *et al*., 2008).

Let us consider S as the search space and the i[th] particle of the swarm is characterized in terms of S-dimensional vector as Qu *et al*. (2013):

$$X_i = (x_{i1}, x_{i2}, x_{i3}, \cdots, x_{iS}) \quad (8)$$

Typically, the particle with lowest function value is defined as the best particle of the swarm and it is symbolized as *b*. The previous position of the best position of i[th] particle is recorded and signified as:

$$B_P(i) = (B_P(i1), B_P(i2), B_P(i3), \cdots, B_P(iS)) \quad (9)$$

The position of particle i is changed according to the velocity (V_i) and it is characterized as:

$$V_i = (v_{i1}, v_{i2}, v_{i3}, \cdots, v_{iS}) \quad (10)$$

Every particle moves in the search space S. The particle modifies its position after iteration depending on its own best solution and other best solution recognized by other particles in the swarm. The particles are controlled and updated as per the following equations:

$$V_i^{c+1} = \Psi\left(\vartheta V_i^c + g1R_{i1}^c\left(B_{Pi}^{\ c} - X_i^{\ c}\right) + g2R_{i2}^c\left(B_{Pb}^{\ c} - X_i^{\ c}\right)\right) \quad (11)$$

$$X_i^{c+1} = X_i^c + V_i^{c+1} \quad (12)$$

In the above Eq. (9) and (10), Ψ represents a constrain factor, it is used to regulate and restrict velocities. ϑ symbolizes the inertia weight. g1 and g2 are cognitive and social parameter respectively, they both take positive values. R_{i1} and R_{i2} are randomly generated numbers and that are distributed uniformly within the range (0, 1). In overall, the value i = 1, 2, 3, …, P, where P is the size of the population.

Equation (9) is derived to find out the new velocity of particle i after iteration and Eq. (10) gives the new position of i^{th} particle by summing up new velocity and current position. The inertia weight (ϑ) is proposed to regulate the effect of the prior history of velocities on the current velocities. In simple, the value ϑ controls the ability of tradeoff among the global discovery and the local discovery of the swarm.

In both Eq. (9) and (10), the *c* represents constant value and measured as:

$$c = \frac{2}{\left|2 - \kappa - \sqrt{\kappa^2 - 4\kappa}\right|} \quad (13)$$

Here, $\kappa = g1 + g2$, $\kappa > 4$. Practically, κ is set to 4.1 and the value c as 0.729. It regulates the convergence behavior of the PSO algorithm.

The performance of every particle is calculated depending on its fitness function. The fitness function is an objective function and it is independent of application. In this study, the fitness function is evaluated considering three parameters namely, expected path energy, path delay and path stability. The fitness function is measured as:

$$Fitness\ Function\,(M(sn,dn)) = F_1 E_{PE}(M(sn,dn)) + F_2 \frac{1}{Delay(M(sn,dn))} + F_3 PS(M(sn,dn)) \quad (14)$$

In the above equation, F_1, F_2 and F_3 are normalizing parameters of expected path energy, path delay and path stability respectively.

From Fig. 1, there are three possible paths:

Top path: 1-2-3-4
Middle path: 1-5-6-4
Bottom path: 1-7-8-4

Assume F_1 = 0.5, F_2 = 0.2, F_3 = 0.8 for top path, middle path and bottom path, respectively.

Fitness function for top path is calculated as:

$$f(0) = (0.5 * 8) + (0.2 * \frac{1}{11}) + (0.8 * 8) = 10.42$$

Similarly, $f(1)$ = 12.91, $f(2)$ = 24.11

Hence, the bottom path with highest fitness function is chosen as the best path.

Initially, particles are deployed in the search space S. Every particle upholds its position, candidate solution, estimated fitness function and its velocity. Additionally, it takes into account of best fitness value that it came across thus far and the candidate solution

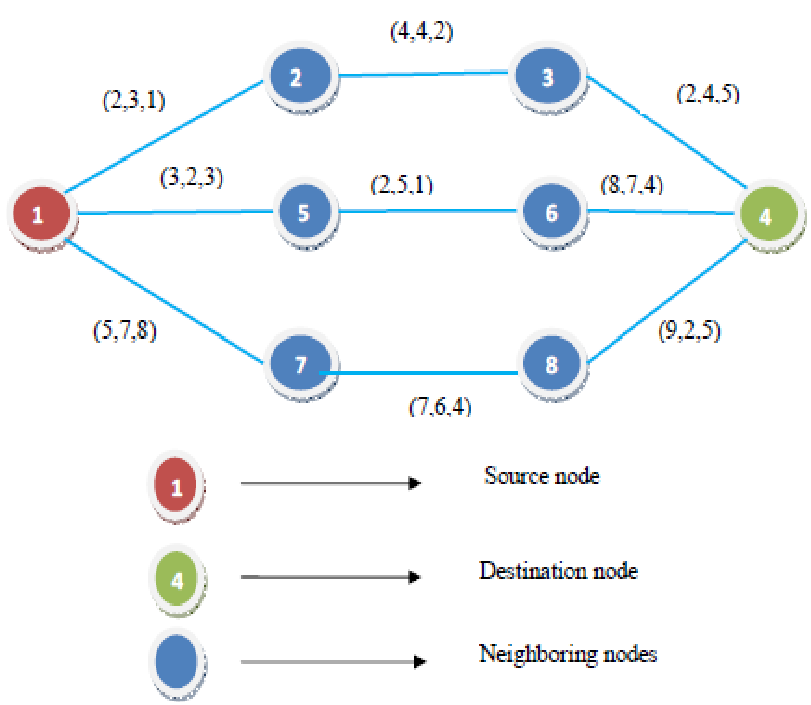

Fig. 1: Example for calculating fitness function

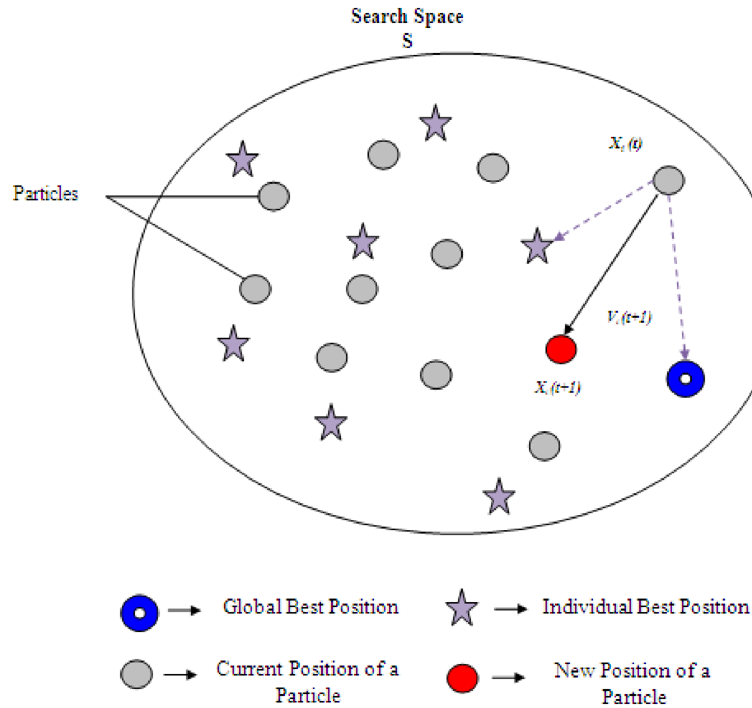

Fig. 2: Particle swam optimization

that accomplished the best fitness value. This value is termed as individual best position. Further, the particle also stores the global fitness value, which is attained by all particles in the swarm. The candidate solution that accomplished the global fitness value is termed as global best position (Fig. 2).
The PSO algorithm involves three phases as:

- Computation of fitness value of each node
- Renew positions, individual and global fitness value
- Renewing of velocity and position of every particle

In this study, in order to implement PSO for discovering reliable and energy efficient multicast routing tree, we take advantage of extended sequence and topology encoding (Huang and Chiang, 2003). This encoding technique encodes the multicast tree. According to this, the multicast tree is characterized by means of two arrays of length L. The first array is used to store the index of nodes in the tree and this array is termed as I_n. The second array (I_p) is used to maintain the index of parent node of each node.

As a first step of encoding, a spanning tree is constructed through prime algorithm; the constructed spanning tree takes in all nodes of the network. After the construction of spanning tree, each node is given a sequence number (i.e.,) index of a node by using preorder traversal algorithm. These indexes of nodes are indexed in array I_n.

After every iteration of PSO algorithm, the particle updates its velocity and then measures its new position in S. Once the particle did update its position, it computes its fitness value using the fitness function given in (22). The individual and global best positions are renewed by matching up the newly generated fitness values with the previously estimated individual and with global best position values. If the estimated fitness value is greater than individual best position then the individual best position is replaced with estimated fitness value. In the same way, if the estimated fitness value of a particle is greater than global best position then it is replaced with estimated fitness value. According to new values, velocity and position of a particle is also updated. Renewing of these values improve the performance of PSO algorithm. Particle encoding scheme is shown in Table 1.

For particle encoding coding algorithm, we first go through the degree array d to find an index. It is clear that the index of 2 the minimum value for the first time in our example as shown in Table 1a. Hence, the edge (1, 2) is deleted so that the degree value changes. The parent node of 2 is 1, which becomes the particle code (1) as shown in Table 1b. Then, the node with first minimum degree is selected i.e., 3. So, the edge (2, 3) is removed and the code becomes (1, 2). Similarly, all the edges are removed. Finally, particle code becomes (1, 2, 1, 5, 1, 7, 3, 0) as shown in Table 1c to e.

The predictive energy efficient and reliable multicast routing using PSO algorithm is given below in algorithm-1.

Table 1: Particle encoding coding

1(a) initial stage								
Index of nodes i	1	2	3	4	5	6	7	8
Parent array	0	1	2	3	1	5	1	7
Degree d [i]	3	2	2	3	2	2	2	2
		Index						
1(b) after deleting (1, 2) edge, code: (1)								
Index of nodes i	1	[2]	3	4	5	6	7	8
Parent array	0	1	2	3	1	5	1	7
Degree d [i]	2	1	2	3	2	2	2	2
1(c) after deleting edges (2, 3), (4, 6) and (1, 5), code: (1, 2, 1, 5)								
Index of nodes i	1	[2]	[3]	4	[5]	[6]	7	8
Parent array	0	1	2	3	1	5	1	7
Degree d [i]	2	1	1	3	1	1	2	2
1(d) after deleting edges (1, 7) and (7, 8), code: (1, 2, 1, 5, 1, 7)								
Index of nodes i	1	[2]	[3]	4	[5]	[6]	[7]	[8]
Parent array	0	1	2	3	1	5	1	7
Degree d [i]	1	1	1	3	1	1	1	1
1(e) after deleting edges (3, 6), (6, 4) and (8, 4), code: (1, 2, 1, 5, 1, 7, 3, 0)								
Index of nodes i	1	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Parent array	0	1	2	3	1	5	1	7
Degree d [i]	1	1	1	1	1	1	1	1

Algorithm-1:

1. Let S be the search space
2. Let X_i be the set that denotes the position of particle in S
3. Consider V_i as the set that contains the velocity of nodes
4. Let E_{PE} be the path energy and PS_i be the stability of path
5. Let t_{FF} be the time interval between two consecutive fitness function comparison of a particle
6. Swarm particles are initialized in S at position x_i\
7. Each particle estimates E_{PE}, PS_i and Delay of the path
8. Every particle computes Fitness Function as per the formula given in Eq. (22)
9. After t_{FF}, Fitness function of each particle is compared with individual best position
10. If (Fitness function $_{xi1}(t_{FF}1)$ >individual best position (x_{i1})) then
11. Individual best position (x_{i1}) = Fitness function $_{xi1}(t_{FF}1)$
12. Else
13. Individual best position (x_{i1}) is not modified
14. After t_{FF}, Fitness function of each particle is compared with global best position
15. If (Fitness function $_{xi1}(t_{FF}1)$ >global best position (x_{i1})) then
16. Global best position (x_{i1}) = Fitness function $_{xi1}(t_{FF}1)$
17. Else
18. Global best position (x_{i1}) is not modified
19. End if
20. The velocity of the particle is renewed as per Eq. (19)
21. The position of the particle is renewed as per Eq. (20)
22. Move the particle to a new position
23. Repeat steps (7) to (17) until the completion of the tree

Merits of our proposed algorithm:

- The proposed predictive energy efficient and reliable multicast routing using PSO algorithm provides reliability and energy efficiency at hand.
- The algorithm prolongs the life time of nodes as the fitness function considers expected path energy.
- This solution guarantees the stability of path between source and destination.

RESULTS AND DISCUSSION

Simulation profile: We evaluate our Predictive Energy Efficient and Reliable Multicast Routing (PEERMR) through NS-2 (Network Simulator: http:///www.isi.edu/ nsnam/ns). We use a bounded region of 1500×300 m^2, in which we place nodes using a uniform distribution. The number of nodes is 50. We assign the power levels of the nodes such that the transmissions range as 250 m. In our simulation, the channel capacity of mobile hosts is set to the same value: 11 Mbps. We use the Distributed Coordination Function (DCF) of IEEE 802.11b for wireless LANs as the MAC layer protocol. The simulated traffic is Constant Bit Rate (CBR).

The following Table 2 summarizes the simulation parameters used.

Performance metrics: We compare the performance of our proposed PEERMR approach with EMR (Nasab *et al*., 2012) protocol. We evaluate mainly the performance according to the following metrics.

Average packet delivery ratio: It is the ratio of the number of packets received successfully and the total number of packets transmitted.

Table 2: Simulation parameters

No. of nodes	50
Area size	1500×300
Mac	802.11 b
Simulation time	50 sec
Traffic source	CBR
Packet size	512
Transmit power	0.660 w
Receiving power	0.395 w
Idle power	0.035 w
Initial energy	10.1 J
Transmission range	250 m
Routing protocol	PEERMR
Rate	250 Kb
Speed	10 and 30 m/sec
Number of senders	1 and 2
Members	10, 20, 30 and 40

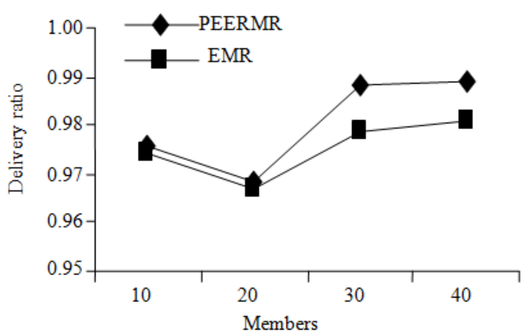

Fig. 3: Members vs. delivery ratio

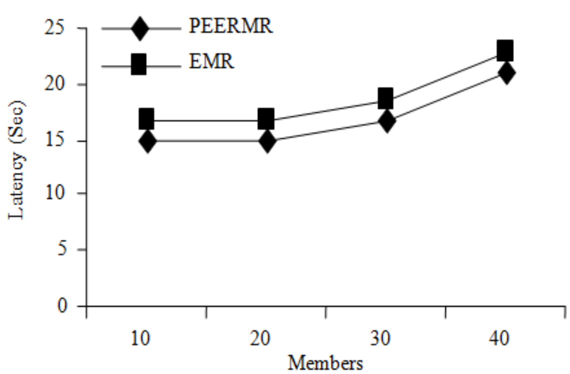

Fig. 4: Members vs. latency

Latency: It is the amount of time taken by the packet to reach the destination.

Residual energy: The average remaining energy of the nodes.

Packets received: It is the total number of packets received during the transmission.

The simulation results are presented in the next section.

Simulation results:

Case -1 (sender-1): Figure 3 shows the packet delivery ratio of PEERMR and EMR protocols when the number

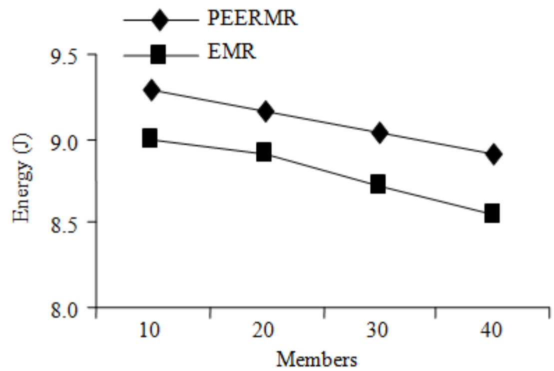

Fig. 5: Members vs. residual energy

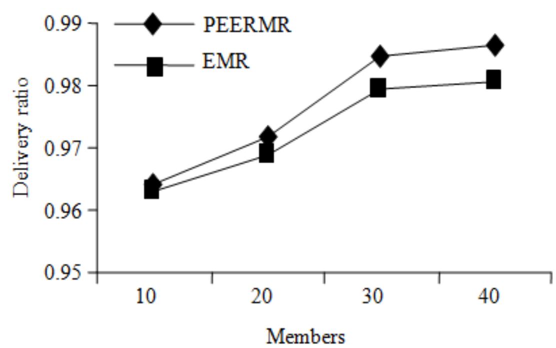

Fig. 6: Members vs. delivery ratio

of receivers is increased from 10 to 40. It can be seen from the figure that when the group size is increased beyond 20, the delivery ratio is also increased. The delivery ratio is same for both the protocols upto 20 receivers and beyond that, delivery ratio of PEERMR is improved by 1% compared to EMR. This is due to the fact that PEERMR uses the link stability in the route selection process.

Figure 4 shows the latency occurred for PEERMR and EMR protocols when the number of receivers is increased from 10 to 40. It is trivial that the latency increase linearly when the receivers are increased, since the route computation time will be more. However, the latency of PEERMR is 10% less than EMR, since PEERMR chooses error free routes by checking the link stability.

Figure 5 shows the residual energy measured for PEERMR and EMR protocols when the number of receivers is increased from 10 to 40. Since the computations involved in PSO will be more in large group size, the residual energy tends to reduce, as shown in figure. But residual energy of PEERMR is 3% higher than EMR, since it estimated predicted path energy.

Case-2 (sender-2): Figure 6 shows the packet delivery ratio of PEERMR and EMR protocols when the number of receivers is increased from 10 to 40 for two senders.

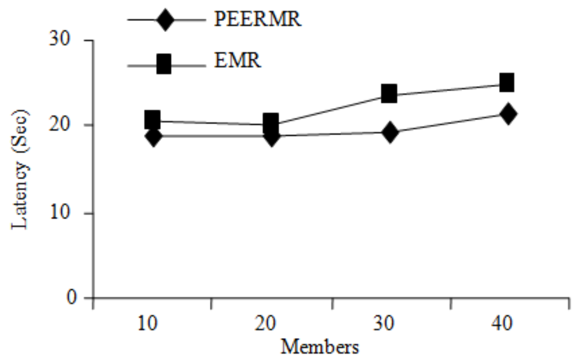

Fig. 7: Members vs. latency

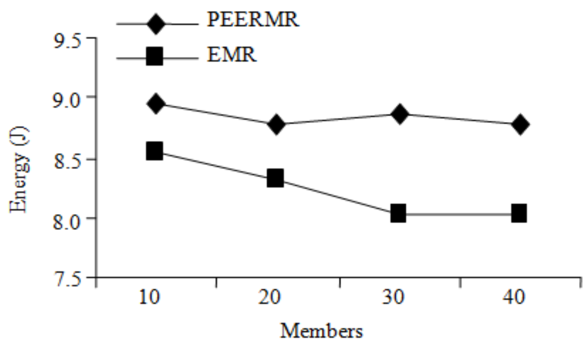

Fig. 8: Members vs. residual energy

It can be seen from the figure, when the group size is increased, the delivery ratio is also increased, since the possibility of receiving the packets will be more in case of two senders. The delivery ratio is almost same for both the protocols upto 20 receivers and beyond that, delivery ratio of PEERMR is improved by 0.7% compared to EMR. This is due to the fact that PEERMR uses the link stability in the route selection process.

Figure 7 shows the latency occurred for PEERMR and EMR protocols when the number of receivers is increased from 10 to 40 for two senders. It is trivial that the latency increase linearly when the receivers are increased, since the route computation time will be more. However, the latency of PEERMR is 12% less than EMR, since PEERMR chooses error free routes by checking the link stability.

Figure 8 shows the residual energy measured for PEERMR and EMR protocols when the number of receivers is increased from 10 to 40 for two senders. Since the computations involved in PSO will be more in large group size, the residual energy tends to reduce, as shown in figure. Bu the residual energy of PEERMR is 7% higher than EMR, since it uses predicted path energy.

CONCLUSION

In this study we have proposed a Predictive Energy efficient and Reliable Multicast Routing using PSO Algorithm in MANET. The technique uses PSO algorithm to construct energy efficient and reliable multicast tree. In PSO, each particle is assigned with a randomized velocity and is iteratively moved in the search space. The fitness function of PSO algorithm is designed considering path delay, expected path energy and path stability. Initially, particles are moved to the random destinations in the search space and the global and individual best positions are set by means of fitness value. The proposed algorithm is simulated in NS-2. The simulation results have proved that the proposed algorithm offers energy efficient and reliable multicast routing with low overhead.

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