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Qos based energy efficient routing in adhoc networks using genetic algorithm

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ABSTRACT

Multicast routing optimization problem is addressed by considering parameters like cost, battery power, delay and bandwidth. The objectives proposed in this work are minimizing the cost and maximizing the battery power subject to the constraints delay and bandwidth. To find the optimal route with the above objectives, binary coded genetic algorithm (GA) technique has been chosen. In this work, an avoidance strategy is included to avoid the illegal chromosome creation during genetic operation. The simulations are done with the test system which consists of standard graphs with different size. Performances of the given networks are compared with existing approach in terms of fitness values, probabilities of genetic operators, network life and generation of convergence.

Introduction

An adhoc network is a collection of wireless mobile hosts forming a temporary network which exist without a fixed infrastructure and can work in an autonomous manner without the aid of any centralized administration. Mobile adhoc network (MANET) is a self-configuring network of mobile routers (and associated hosts) connected by wireless links. Routing is done at the nodes itself. Each device is free to move in any direction and changes its link to other devices. The primary challenge in building a MANET is equip each device to do routing properly. In adhoc network every communication terminal communicates with its partner to perform peer to peer communication. If the required node is not a neighbor to the initiated call node then the intermediate nodes are used to perform communication. MANETs have numerous applications such as sensor networks, disaster relief, military operations, business and home applications.

MANETs have numerous applications such as sensor networks, disaster relief, military operations, business and home applications. Every mobile device has a maximum transmission power which determines the maximum transmission range of the device.

As nodes are mobile, the link connection between two devices can break depending on the spatial orientation of the nodes. Two mobile wireless devices out of communication range can use other devices within their communication range to relay packets. As adhoc networks may not require any fixed infrastructure, it makes them very flexible to deploy in different scenarios. The adhoc network is independence from central network administration and it is self-configuring and self-healing in which nodes is act as routers. Since the network is infrastructure less any number of nodes are added or removed. Each node is free to move among the networks while communicating with others. The path between different users may have multiple links which makes communication easier. Since the nodes are portable and the network is wireless, any node can access internet from anywhere. A MANET is an autonomous collection of mobile nodes forming a dynamic network and communicating over wireless links. Users are allowed to communicate with each other in a temporary manner with no centralized administration and in a dynamic topology that changes frequently. Mobile adhoc networks have applications in a wide range of areas including disaster relief and military. Most of these scenarios need one to many or many to many communications. This makes multicasting a very important feature in such networks. In multicast communication, messages are concurrently send to multiple destinations. One of the core issues that providing such mechanisms is multicast routing [1, 2, 4].

Supporting point to multipoint connections for multimedia applications requires the development of efficient multicast routing algorithms. Multicast employs a tree structure of the network to efficiently deliver the same data stream to a group of receivers. In multicast routing, one or more constraints must be applied to the entire tree. The main goal in developing multicast routing algorithm is to minimize the communication resources used by the multicast routing. This is achieved by minimizing the cost of the multicast tree, which is the sum of the costs of the edges in the multicast tree. The least cost tree is known as the minimum Steiner tree. The Steiner tree problem tries to find the least-cost tree, i.e. the tree covering a group of destinations with the minimum total cost over all the links. This problem also includes delay and bandwidth problem, which belongs to the class of tree-optimization problems. During routing energy utilized in the nodes must also be minimized or the residual battery power in each node must be increased. To implement this we have chosen genetic algorithm which will include all the objectives and constraints in the fitness function and gives the optimal solution for the given multicast tree [8].

Genetic algorithm is an evolutionary algorithm used for solving optimization problems using techniques inspired by natural evaluation such as inheritance, crossover, mutation and selection. The genetic coding of an individual is called a genotype and the corresponding physical appearance of an individual is called a phenotype. A gene in a chromosome is characterized by two factors: locus, the position of the gene within the structure of chromosome, and allele, the value the gene takes. Genetic algorithm requires a genetic representation

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of domain and fitness function to evaluate the domain. Initial population is generally represented in the form of binary string 0 and 1 but based on coding scheme it may vary. The population is usually randomly generated individuals. In each generation the fitness of every individual in the population are evaluated. Multiple individuals are selected from current population based on their fitness value. Crossover and mutation are applied for the selected individuals. This will form a new population which will be used for next iteration of the algorithm. The algorithm terminates when either a maximum number of generation has been produced or a satisfactory fitness value has been reached. Genetic algorithm finds its application in bioinformatics, computational science, engineering, mathematics, physics, economics, etc. A standard coding scheme is used to solve the objectives which should possess some properties [3, 5, 16].

In this paper, the initial population is done randomly. The length of each chromosome is n (n-1)/2. The population is represented in binary strings 0 and 1. The fitness function formulation will include the objectives cost and energy subjected to the constraints delay and bandwidth for a particular multicast tree of source and destinations. The coding scheme here is connectivity matrix of edges (CME) which has n x n matrix in which top triangle matrix binary strings 0 and 1 which will be the chromosome. To convert the matrix into one dimensional chromosome , n(n-1)/2 elements on the top triangle of matrix starting from first row and from left to right then the 0 and 1 are transferred to the one dimensional array. This scheme follows the properties like non-redundancy, legality, completeness, causality, easy encoding/decoding, short, low order schemata, Lamarckian property, and unbiased representation of trees [11]. The selection schema followed is roulette wheel selection which selects the chromosome randomly based on the selection probability and its cumulative. A random number is generated which breaks the cumulative will select the population corresponding to the cumulative value. Single point crossover will be applied for the selected populations. A random point is selected which has a range of n (n-1)/2. In the selected parents, swapping is done from the selected random point. Binary string from beginning of chromosome to the crossover point is copied from one parent and the rest is copied from the second parent. Mutation is done by selecting the random point and the value in that point is inverted which is called bit inversion. The result after applying genetic operator may have valid or invalid population. Since the good traits only have to be inherited to the next generations, if the chromosome does not have good traits then it has not to be inherited to next generation. So avoidance strategy will avoid such chromosome. The iteration of GA will be stopped when a constant linear graph of fitness value is obtained. The resultant fitness value and chromosome gives the best optimal solution for the given problem [6].

Problem Formulation

Consider the graph G = (N, L), where N is nodes and L is links between nodes. Let n is number of nodes, l is number of links. The link l (u, v) implies the connection between nodes u and v, where u and v belongs to the set N. l (u, v) is the link in the set L. Three values are associated with each link: cost – C (l), delay – D (l) and bandwidth – B (l). The objective energy is associated with each node as E (n). Fig.1 shows the sample network. Consider the multicast tree T(s, M) where s is the source node and M is destination group having multiple destination d1, d2, etc.

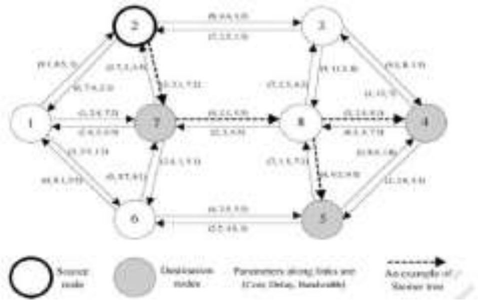

Fig.1. Sample network

The total cost of the tree T(s, M) is defined as the sum of the cost of all links in that tree and can be given by,

$$C(T(s,M)) = \sum_{\ell \in T(s,M)} C(\ell)$$

The total delay of the path $P_T(s, d)$ is simply the sum of the delay of all links along $P_T(s, d)$,

$$D(P_T(s,d)) = \sum_{\ell \in P_T(s,d)} D(\ell)$$

The bandwidth of the path $P_T(s, d)$ is defined as the minimum available residual bandwidth at any link along the path:

$$B(P_T(s,d)) = \min\{B(\ell),\ \ell \in P_T(s,d)\}$$

Let Δ_d be the delay constraint and B_d be the bandwidth constraint, then

$$\begin{cases} D(P_T(s,d)) \le \Delta_d, & \forall d \in M \\ B(P_T(s,d)) \ge B_d, & \forall d \in M \end{cases}$$

The total energy in a path between sources to destination is calculated by adding all the energy of nodes involved between source to destinations is given by:

$$\mathsf{E}(P_T(s,d)) = \sum_{\mathsf{v} \in P_T(s,d)} \mathsf{E}(\mathsf{v})$$

Genetic Algorithm

GA is an evolutionary algorithm used for solving optimization problems using techniques inspired by natural evaluation such as inheritance, crossover, mutation and selection. The genetic coding of an individual is called a genotype and the corresponding physical appearance of an individual is called a phenotype. A gene in a chromosome is characterized by two factors: locus, the position of the gene within the structure of chromosome, and allele, the value the gene takes. Genetic algorithm requires a genetic representation of domain and fitness function to evaluate the domain [12]. The processes involved in GA are:

1. Initial population generation
2. Fitness function evaluation
3. Selection
4. Crossover and Mutation
5. Avoidance and Convergence.

CME Coding Scheme

Let us define the CME, Y n x n; such that the value of each element Y[i, j] € {0,1} tells whether or not a specific edge connects the pair of nodes (i, j). The fig 3.1 shows the example for connectivity matrix of edges for the graph shown in the Fig.2. For converting the connectivity matrix Y into a one-dimensional chromosome x; which consists of n (n-1)/2 elements, we should transfer the elements on the top triangle of matrix Y; starting from the first row and from left to right into the chromosome x. we consider that the network is asymmetric, it is not necessary to use all elements of the connectivity matrix of edges to represent the Steiner tree. In other words, the top triangle of the connectivity matrix of edges is sufficient to represent the Steiner tree [11].

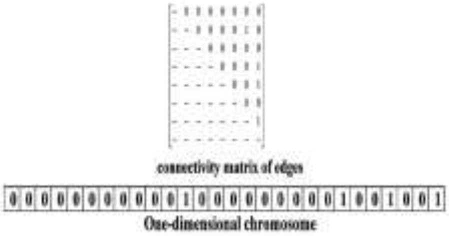

Fig.2. CME coding

Initial Population

The creation of the initial population in this study is based on random individual creation. In this algorithm, an array is constructed from the source node s to one of the destination nodes. Then, the algorithm continues from one of the unvisited destinations and at each node the next unvisited node is randomly selected until one of the nodes in the previous sub-tree (the tree that is constructed in the previous step) is visited. The algorithm terminates when all of the destination nodes have been mounted to the tree. This procedure must be called pop-size times, to create the total of initial population. Here initial population will have length n (n-1)/2. So the generated path will be converted to connectivity matrix of edges from which the chromosome of length n (n-1)/2 is obtained.

Fitness Function

Fitness function will include all the constraints by which the objective will be minimized. Let F(T(s, M)) be the fitness function then it will include Cost C(e) Delay D(e) Bandwidth B(e) and Energy E(n) for the nodes and edges involved in the given graph. Through connectivity matrix of edges we can identify the edges involved in graph. Fitness function is given by,

$$F(T(s,M)) = \frac{\alpha}{\sum_{\ell \in T(s,M)} C(\ell)} \prod_{d \in M} \phi(D(P(s,d)) - \Delta_d) \prod_{d \in M} \times \phi(B(P(s,d)) - B_d) \,X\, E(P_T(s,d)) = \sum_{n \in P_T(s,d)} E(n)$$

$$\phi(z) = \begin{cases} 1 & z \le 0 \\ \gamma & z > 0 \end{cases}$$

Where α is a positive real coefficient.
γ is the degree of penalty.
F (T(s, M)) is the fitness function.
T(s, M) is the multicast tree.
C (l) is the cost for each link.
E (n) is the energy of each node.
P_T (s, d) is the path between source to destination.
D (P_T (s, d)) is the delay in the path P_T (s, d).
B (P_T (s, d)) is the bandwidth in the path P_T (s, d).
E (P_T (s, d)) is the energy of each node in the path P_T (s, d).

The best result was achieved by setting γ equal to 0.5. However, it is better to use an adaptive penalty function that produces a low penalty value in the earlier generations to widen the search space, and increases the penalty value in later generations to lead to faster convergence.

Selection

The selection process is based upon roulette wheel selection. In Roulette wheel selection, selection probability is calculated by dividing individual fitness function to sum of all fitness function. Cumulative value is calculated for all selection probability. Now last column will have the value 1. A random number is created which will have value less than 1. Two chromosomes in the population are selected in such a way that cumulative value will break the generated random value [14]. The formula for selection probability is given by,

$$p_i = \frac{F(T_i)}{\sum_{j=1}^{pop\text{-}size} F(T_j)}$$

Where F(T_i) is the fitness of the T_i individual.

Genetic Operators

The crossover scheme implemented is one point crossover. From selection population p1, p2 are selected. On the 2 populations crossover is applied. Crossover is applied based on random number generation. If generated random number has value less than pc (crossover probability) then not applicable else crossover is applied by, Generating a random number less than or equal to length of chromosome which is the cross over point. Binary string from beginning of chromosome to the crossover point is copied from one parent and the rest is copied from the second parent [12, 14].

For example, the two selected parents are a and b with crossover point as 5. Then the chromosome becomes c and d respectively, which is shown in the Fig.3.

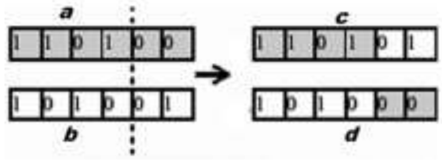

Fig.3. Simple crossover example

Mutation applied here is random point bit inversion mutation. There will be a probability for mutation pm<1. A random number is created if it is less than pm then mutation is done otherwise not done. Mutation is done by selection a point randomly among the length of chromosome. The selected point will have either 0 or 1. No operation is done over the point selected [12, 14]. For example, mutation takes place in the chromosome a and the mutation point is 5, and then the chromosome becomes b, which is shown in the Fig.4.

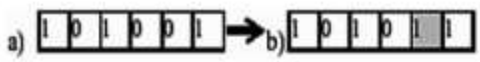

Fig.4 Simple Mutation example

Avoidance Strategy

After doing crossover and mutation, the corresponding parent values are replaced by its offsprings. While replacing convergence graph may get varied because if good chromosome on crossover becomes invalid to avoid this we use repair function. Also crossover and mutation is done to take good traits to next generation. Avoidance Strategy is implemented when; the chromosomes after crossover and mutation must be valid or should have less invalid entries in it. If the parent population has better values than offsprings then parents are not replaced. Valuation between parent and child is done by fitness value and validity of chromosome. After avoidance done, minimization done until all chromosomes becomes valid [10, 13].

Simulation Results

The existing scheme has minimized the cost of the multicast routing subjected to constraints delay and bandwidth which are included in the fitness function and minimized. The Fig.5 shows the convergence of fitness value to iteration for various numbers of nodes. The proposed scheme minimizes cost of multicast route and also minimizes the residual battery power. This is shown in the Fig.6. The various crossover probabilities like 0.6, 0.7, 0.8, and 0.9 are given as input and fitness value is calculated for convergence. The Fig.7 shows that for probability 0.7 the graph has converged better. The various mutation probabilities like 0.6, 0.7, 0.8, and 0.9 are given as input and fitness value is calculated for convergence. The Fig.8 shows that for probability 0.7 the graph has converged better. The minimum fitness values for various iterations for various nodes are compared and the Fig.9 shows that proposed and existing has only little difference in the iteration of convergence. It also says that the graph which includes energy takes minimum energy to reach the destination in the last iteration than in the first iteration. The minimum fitness value for different number of nodes is compared between proposed and existing technique shows fitness value of proposed takes maximum value than existing because of the objective energy added to it but routing to destination is done efficiently. This is shown in the Fig.10.

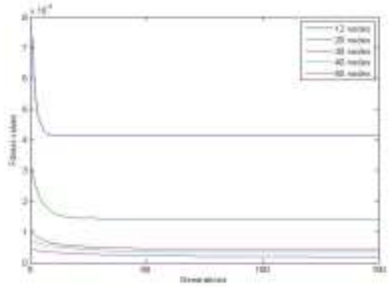

Fig.5 Fitness values Vs Generations for Existing scheme

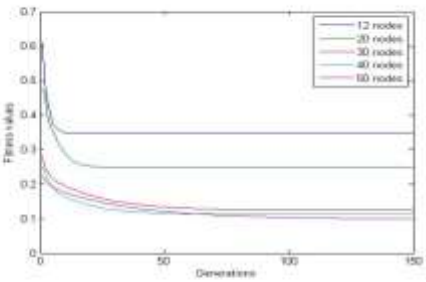

Fig.6 Fitness values Vs Generations for Proposed scheme

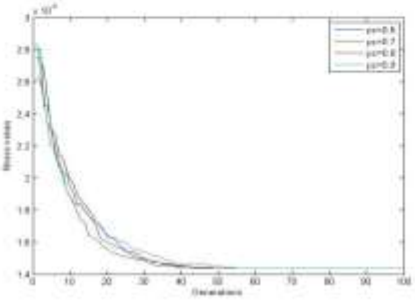

Fig.7 Comparison of crossover probability

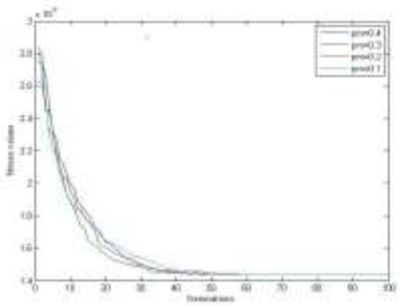

Fig.8 Comparison of Mutation Probability

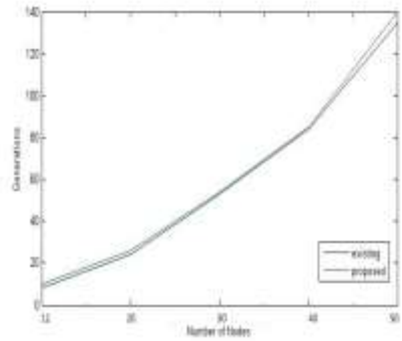

Fig.9 Comparison of fitness values for various number of nodes

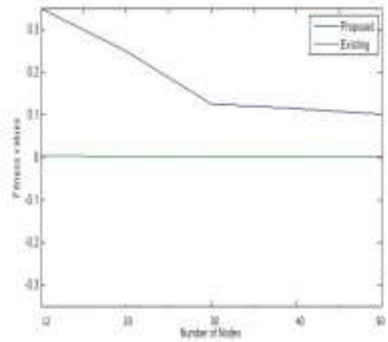

Fig.10 Comparison of minimum fitness value with number of nodes

Conclusion

Using binary coded genetic algorithm technique the multicast routing scheme for adhoc networks has been implemented. In this work, the traditional one point crossover and bit inversion mutation strategies are used to form the offsprings. To avoid the creation of illegal chromosomes, an avoidance strategy has been implemented in the genetic operators. The optimal solution for the given graphs is identified through simulation. Using the standard input, the simulation code has tested and compared with the existing schemes with respect to the various multicast routing measures like fitness value, probability of genetic operators, network life and generation of convergence.

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