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Hybrid Evolutionary Game Theory in QoS Routing of Wireless Mesh Networks

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***Abstract*– Wireless mesh networks are a powerful and reliable solution to create and access wireless broadband services for Internet service providers, network construction, military applications and other end users are considered. These networks have features such as high reliability, low installation cost, wide coverage area and connect to the network automatically. The QoS routing service is a primary problem for wireless mesh networks. Evolutionary game theory by which agents can play optimal strategies in the absence of rationality. Through the process of Darwinian selection, a population of agents can evolve to an Evolutionary Stable Strategy. In this article we have tried to solve this problem by using evolutionary game theory as a hybrid genetic algorithm to optimize the parameters by simulated anneling at lower cost than traditional routing arrived. The results of the simulation and compare it with other optimization algorithms confirms that the evolutionary game parameters can be optimized by the evolutionary algorithms and achieve better results.**

***Index Terms*– Wireless Mesh Networks, QoS Routing, Genetic Algorithm, Game Theory and Simulated Anneling**

I. INTRODUCTION

A wireless mesh network is a communications network made up of radio nodes organized in a mesh topology. Wireless mesh networks often consist of mesh clients, mesh routers and gateways. The mesh clients are often laptops, cell phones and other wireless devices while the mesh routers forward traffic to and from the gateways which may, but need not, connect to the Internet. The coverage area of the radio nodes working as a single network is sometimes called a mesh cloud. Access to this mesh cloud is dependent on the radio nodes working in harmony with each other to create a radio network. A mesh network is reliable and offers redundancy. When one node can no longer operate, the rest of the nodes can still communicate with each other, directly or through one or more intermediate nodes.

We can classify wireless networking architecture to point-to-multipoint infrastructure-aided approach like wireless single hop networks (e.g., IEEE 802.11 wireless LAN) and peer-to-peer multihop approach e.g., mobile ad hoc networks (MANETs) [6].

The difference between mesh networks and conventional infrastructure wireless LANs is the fact that mesh networks result in a multihop topology which requires decentralized coordination. The difference between mesh networks and the mobile ad hoc networks resides in the existence of the infrastructure connection. The access points deployed can act both as a peer of the internal wireless ad hoc network and the bridge to the wired network. To provide sufficient infrastructure access bandwidth, multiple access points can be deployed within the network. Traffic balancing can be achieved by the underlying mesh routing protocol. The mesh network features presented above lend themselves to easy scalability [9], [10].

Wireless mesh networks seamlessly integrate these two network architectures. This integration is obtained by the proposed WMR protocol, implemented in each wireless node. The connectivity to the wired backbone is provided by the wireless infrastructure access points.

Each node in the network is both a service provider and a service consumer, i.e., each node has forwarding ability similar to the nodes' functionality in MANETs.

In the wireless Mesh network, if you want to add a new device, simply plug in the power on it, it can automatically configure itself, and determine the best multi-hop transmission path [1]. Add or mobile device, the network

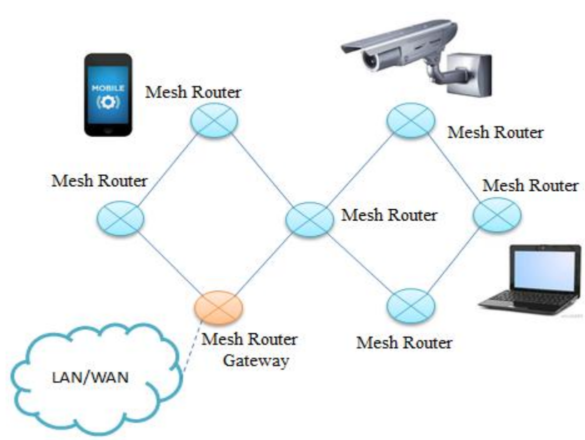

Fig. 1: Intelligent Mesh Networking

topology changes can automatically find and automatically adjust the traffic routing in order to obtain the most efficient transmission path. A typical Wireless mesh network can be described like Fig. 1.

Wireless mesh network's business is usually gathered in the Mesh Router or Gateway, easily lead to local network congestion, making it difficult to maintain network globally optimal routing. Thus routing protocols must be able to adapt to this situation so as to provide better QoS for the users. So, the research of wireless mesh network routing protocol is of great significance.

Game theory is used to model strategic interaction among rational players. It cannot be used to model irrational misbehavior of faulty nodes. Nevertheless, it is adequate to mitigate selfishness and malicious behaviors. In ad hoc network, the players are the nodes. Each node wants to maximize its own utility (payoff). That means sending the most possible packets while forwarding the least packets and saving energy and bandwidth. The best objective in a network is to converge to a Pareto efficient Nash equilibrium [25]. However, the main challenge is that the allocations in the Nash equilibrium are not always Pareto efficient. The following are some of the approaches using game theory.

The another algorithm that we used for QoS routing problem is the coevolutionary algorithm. This method can be made using a game matrix, and as an optimal solution of the game, the equilibrium state of this coevolutionary algorithm can be found. As well, our aim is to combine the coevolutionary algorithm with evolutionary game theory and confirm that this Game theory based Coevolutionary Algorithm (GCEA) can be used in optimization [3].

In a model of the co-evolutionary algorithm studied this phenomenon from the evolutionary game theory point of view. Kauffman [27] introduced co-evolution based on the NK class of statistical models. He indicated how readily coevolving ecosystems achieve Nash equilibria and how stable to perturbations such equilibria are. In his paper, he described a new class of models with which to investigate the coevolutionary problems. The class of models was related to ESS introduced by Maynard Smith and Price [26].

Genetic algorithm is a generalized search and optimization technique. It works with populations or chromosomes of "individuals", each representing a possible solution to a given problem. Each individual is evaluated to give some measure of its fitness to the problem from the objective functions. Three basic operations namely: reproduction, crossover, and mutation are adopted in the evolution to generate new offspring [2].

Simulated annealing algorithm (SA) is a general purpose optimization technique and has been applied to many combinatorial optimization problems. The main idea behind SA is an analogy with the way in which liquids freeze and crystallize.

When liquids are at a high temperature their molecules can move freely in relation to each other.

Rahbari and Toosizadeh introduced Combination methods of genetic algorithm and simulated annealing are based on this idea that diversity rate and convergence to goal in genetic algorithm caused to general optimization. Simulated annealing have a key parameter called temperature that if it is low then algorithm would be close to goal. Heuristic function for the combination this two algorithms is use of coordination in decreasing of temperature and mutation rate while reach to optimal goal [2]. We will show how use new combination methods as following.

II. EVOLUTIONARY GAME THEORY

Non-cooperative game theory is the decision-making in a distributed environment, the analysis of individual utility maximization Player for the optimal policy choice. Evolutionary game, non-cooperative game, a branch of a game strategy for further analysis of game populations in a long-term stability. Evolution of the Nash equilibrium (all Player of the optimal strategy) with groups of stability, which is executed when the other Player balanced strategy, any Player cannot be balanced by a unilateral departure from the strategy for more effective; Meanwhile, the implementation of a balanced strategy can reveal the individual proportion of total population [7], [8].

As the novel achievement in the research field of non-cooperative game theory, the research on evolutionary game theory attracts great attentions in not only academy but also industry field. Integration of evolutionary game theory, economics and evolutionary biology of rational thought, no longer human model into the game super-rational side, that the human is usually achieved through trial and error method of game balance, and biological evolution is common[19], the choice The balance is the balancing process to achieve a balanced function, and thus the historical, institutional factors and the balancing process are some of the details of the game will affect the choice of multiple equilibria.

Set the evolution game located in an N-node MANET, any node with M, that except the node i other than the collection. N_i denotes the data packets generated by source node I which is called i's group. Data between source and destination nodes transmit a complete data service is called a session; the node mobility will lead to changes in network topology, the completion of a session requires multiple routing paths to create different groups[11].

Table 1: The game Matrix between labor nodes in WNN

*	failure	successful
The packet reachs node N_j	(B , C)	(0 , C)
The packet not reachs node N_j	(B , 0)	(0 , 0)

As far as the author is aware of, Hillis [4] was the first to propose the computational use of predator-prey coevolution. He tested coevolving sorting network architectures and sets of lists of numbers on the sorting networks. The computational study of coevolution initiated by Hillis gave birth to competitive coevolutionary algorithms. In 1994, Paredis introduced Coevolutionary Genetic Algorithms (CGAs). In contrast with the typical all-atonce fitness evaluation of Genetic Algorithms (GAs), CGAs employ a partial but continuous fitness evaluation. Furthermore, the power of CGAs was demonstrated on various applications such as classification, process control and constraint satisfaction. In addition to this, a number of symbiotic applications have been developed [1], [20].

The use of multiple interacting subpopulations has also been explored as an alternate mechanism for coevolving niches using the so-called island model. In the island model a fixed number of subpopulations evolve competing rather than cooperating solutions. In addition, individuals occasionally migrate from one subpopulation to another, resulting in a mixing of genetic material. The previous work that has looked at cooperating rather than competing subpopulations has involved a user specified decomposition of the problem into species.

Potter and De Jong have also explored the use of multiple cooperative interaction subpopulations as an alternate mechanism for representing the coevolution of species. The previous work that has looked at coevolving multiple cooperative species in separate subpopulations involved a user-specified decomposition of the problem into species. In this coevolutionary approach, multiple instances of GAs are run in parallel, each instance of which evolves a species of individuals, which are good at particular tasks. This is accomplished by selecting a representative from each of the GA populations and combining them into a single composite agent, which is capable of evaluating the top level goal. These composite agents were called collaborations. Credit from evaluating the composite agent flows back to the individual subcomponents reflecting how well they collaborate with the other subcomponents to achieve the top level goal. This credit is then used by the GA instances to evolve better subcomponents. Such systems are called Cooperative Coevolutionary Genetic Algorithm.

As previously stated, from a mathematical point of view, coevolution has both game theoretical properties and dynamics [22], [23], [24]. For that reason coevolution finally reaches the stable equilibrium state and this state is thought of as an optimal solution because of the dominance property of the game. From these properties, we assume that the coevolutionary algorithm can be made using a game matrix, and as an optimal solution of the game, the equilibrium state of this coevolutionary algorithm can be found. As well, our aim is to combine the coevolutionary algorithm with evolutionary game theory and confirm that this Game theory based Coevolutionary Algorithm (GCEA) can be used in optimization. Although, in particular, we suppose that the population dynamics of evolutionary game theory can be used to most advantageously control the ratio of agents having diverse strategy according to the change of environment[21]. As such, firstly we apply this algorithm to Multiobjective Optimization Problems (MOPs) for an optimization performance evaluation.

Most of the real-world problems encountered by engineers involve simultaneous optimization of several competitive objective functions. The traditional optimization problems attempt to simultaneously minimize cost and maximize fiscal return. In searching solutions for these problems [13], we discover that there is not a single optimal solution but rather a set of solutions. These solutions are optimal in the wider sense that no other solutions in the search space are superior to them when all objectives are considered. They are generally known as Paretooptimal solutions.

Table 2: The game matrix for population 1

*	V'1	V'2	…	V'n
V1	P1(V1, V'1)	P1(V1, V'2)	…	P1(V1, V'n)
V2	P1(V1, V'1)	P1(V1, V'2)	…	P1(V1, V'n)
…	…	…	…	…
Vn	P1(V1, V'1)	P1(V1, V'2)	…	P1(V1, V'n)

Table 3: The game matrix for population 2

*	V'1	V'2	…	V'n
V1	P2(V1, V'1)	P2(V1, V'2)	…	P2(V1, V'n)
V2	P2(V1, V'1)	P2(V1, V'2)	…	P2(V1, V'n)
…	…	…	…	…
Vn	P2(V1, V'1)	P2(V1, V'2)	…	P2(V1, V'n)

From these establishments, GCEA is as follows:

Step 1: Two populations are randomly generated.

Step 2: The Player selected in the first population plays with that from the second population and then he is paid off using Table 1 and (2).

Step 3: The Player in the second population is paid off using Table 1 and (2).

Step 4: The fitness of each player Fn and F 'n is updated using (4).

Step 5: The process from Step 2 to Step 3 is executed for all individuals of each population one by one.

Step 6: Each population is regenerated separately using genetic algorithms.

Step 7: The process from Step 2 to Step 6 is executed.

III. QUALITY OF SERVICE (QOS)

The route break can not be detected easily. The common approach used in most of existing ad hoc routing protocols is by waiting for a neighbor timeout, i.e., the hello message from a neighbor does not arrive to the node on time. When neighbor timeout is discovered, a route error message is sent to the source notifying about the break. However this kind of route break detection method normally takes several seconds, which is not desirable to time sensitive QoS flows[12]. We utilize the bandwidth reservation timeout at the destination to signal possible route breaks. If the destination fails to receive data packets of an active flow 21 before its reservation timeout, route recovery will be triggered at the destination. Using this method, we can detect both types of QoS violations at the same time and handle them identically. The neighbor lost detection will also be used in case the destination that initiated instant recovery can not reach the source because of network partition or packet loss. When a node detects that the downlink node of a reserved route is lost, it will send a route error packet, with its current route sequence number, to the corresponding uplink node. The route error packet is then forwarded upwards to the source to indicate the occurrence of the route break. As a consequence, the reserved bandwidth of the flow will be released at the forwarding nodes [14].

To provide instant route adaptivity, we use destination initiated route recovery. After the QoS violations are detected, the destination will increase its route sequence number and broadcast an unsolicited route reply packet, also called route update packet, back to the source.

The route update packet is treated in the same manner as a route request packet with admission control and loop prevention mechanism, but in the reverse direction from destination to source. Upon receiving the first in time route update packet with appropriate sequence number, the source switches the flow in question to the reverse route on which the update arrives [17], [18].

On the other hand, a late route update packet or a route error packet, with the valid route sequence, signals the occurrence of QoS violation and the failure of route recovery. In such case, the application can either decide to continue transmitting the flow with the absence of QoS guarantee or suspend the flow and try later.

IV. GENETIC ALGORITHM

Genetic algorithm is a generalized search and optimization technique. It works with populations (chromosomes) of “individuals”, each representing a possible solution to a given problem. Each individual is evaluated to give some measure of its fitness to the problem from the objective functions. Three basic operations namely: reproduction, crossover, and mutation are adopted in the evolution to generate new offspring.

To optimization of multi paths to destinations will construct one routing table that shows all finding paths in network. In this problem, each path assumed as a chromosome that first gene is source node and last gene is destination node and each row of table show multi path to destinations [2].

The coevolutionary algorithm with evolutionary game theory and confirm that this Game theory based Coevolutionary Algorithm (GCEA) can be used in optimization.

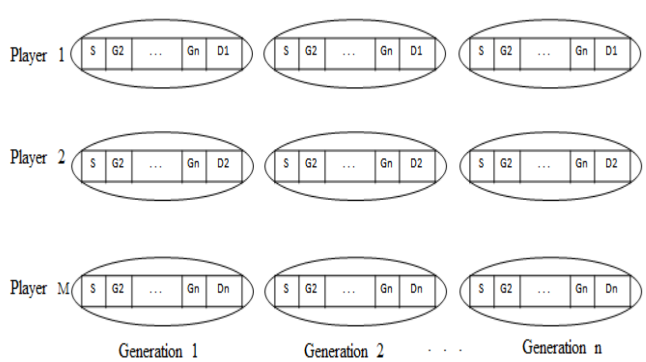

Fig. 2: Chromosome structure

A) Chromosome structure

The chromosome length in this problem is equal size of logical longest path that is include 39 genes (2*column or row – 1 = 39).

In grid environment, data packet will moved of current position to eight next positions that have shown in Fig. 2 [15], [16]. So the paths to destinations are chromosome include sequence of digits that is sample in Fig. 3:

(S) 4 2 7 3 3 3 . . . 3 4 5 6 6 1 (Destination 1)
(S) 4 3 4 5 5 6 . . . 6 7 7 8 1 1 (Destination 2)
. . .
(S) 1 2 2 2 2 5 . . . 4 4 4 7 7 5 (Destination N)

Fig. 3: Sample of paths of a source to destination

B) Population

The population in this problem is routing table that explained its structure in section 2 as each row show the multi paths of one source to multi destinations that will optimize in duration of generations. In initialization steps the population size (PS) of chromosomes assigned by 100. The repeated chromosomes are removed in the initialization phase (all chromosomes are different from each other). This work decrease search space at different places (randomly) which increases the convergence rate.

C) Fitness or Payoff function

The High Fitness value demonstrator optimal chromosome, so used of cost inverse until path cost have decreasing rate.

In this section, we design a Game theory based Coevolutionary Algorithm to solve MOPs. Through the evolutionary game, players try to optimize their own objective function and all individuals of the Population are regenerated after players have been rewarded. The reward value is determined from the game matrix. For example, in the case of minimization MOPs, which have two variables x , y and objective functions f1(x, y) , f2 (x, y) , the architecture of populations for GCEA is designed as follows. Fitness Fi is determined from the game matrix where i = 0,1,..,n . The game matrix is defined in the previous tables and two populations coevolve with each other through the game. Payoff of the game for each population, Gi , is calculated from the differences between two objective functions [3].

$$\begin{aligned} \mathrm{P1}(v_i, v'_i) &= \mathrm{P1}((x_i, y_i), (x'_i, y'_i)) \\ &= f_1(x_i, y_i) - f_2(x'_i, y'_i), \\ \mathrm{P2}(v_i, v'_i) &= \mathrm{P2}((x_i, y_i), (x'_i, y'_i)) \\ &= f_2(x'_i, y'_i) - f_1(x_i, y_i). \end{aligned} \tag{1}$$

From these payoffs, the fitness of each player is calculated:

$$F_i = 100 \times \frac{\text{P1}\,((x_i, y_i), (x'_i, y'_i))}{\alpha},$$
$$F'_i = 100 \times \frac{\text{P2}\,((x_i, y_i), (x'_i, y'_i))}{\alpha}, \qquad (2)$$

where α is constant to normalize the fitness of Fi or F 'i so that α must be max|$G_k((x_i, y_i)$, $G_k((x'_i, y'_i)$.

D) Crossover

Crossover is used to cross breed the individuals, Using crossover operator, information between two chromosomes are exchanged which mimic the mating process. This operator exchanges half of two parent chromosomes and generates two childs with by condition that paths to destination not miss. For the exchange each of gene checked before and after genes in parent chromosome that not cause missing of paths. Fig. 5 show the crossover operator on two parents.

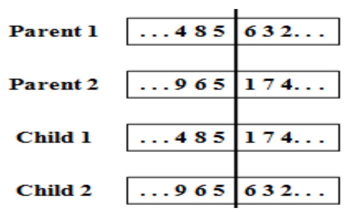

Fig. 4: Crossover operator

We would like maintenance population diversity in preliminary generations and increase the convergence in end generations, at result assume crossover rate in first half generations equal 5.0% and in the second half generations equal 44.0%.

E) Mutation

Mutation operator changes 1 to 0 and vice versa with small probability Pm. The mutation operator introduces new genetic structures in the population by randomly modifying some of the genes, helping the search algorithm to escape from local loop. The values of gene is digit between one to eight and mutate gene had been different with pervious gene also had select that not miss path to destination.

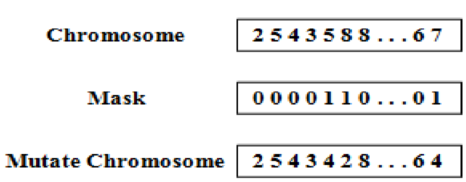

Fig. 5: Mutation Operator

Mutation operator maintenance the diversity in population so in the start of generations maintenance high diversity and in the end generations decrease this rate, at result this rate on the first half generation is equal 54% and on the second half is equal 15%.

V. SIMULATED ANNEALING ALGORITHM

Simulated annealing algorithm (SA) is a general-purpose optimization technique and has been applied to many combinatorial optimization problems. The main idea behind SA is an analogy with the way in which liquids freeze and crystallize. When liquids are at a high temperature their molecules can move freely in relation to each other. As the liquid's temperature is lowered, this freedom of movement is lost and the liquid begins to solidify. If the liquid is cooled slowly enough, the molecules may become arranged in a crystallize structure. The molecules making up the crystallize structure will be in a minimum energy state. If the liquid is cooled very rapidly it does not form such a crystallize structure, but instead forms a solid whose molecules will not be in a minimum energy state. The fundamental idea of SA is therefore that the moves made by an iterative improvement algorithm are like the re-arrangement of the molecules in a liquid that occur as it is cooled and that the energy of those molecules corresponds to the cost function which is being optimized by the iterative improvement algorithm. Thus, the SA aims to achieve a global optimum by slowly convergence to a final solution, making downwards moves with occasional upwards moves and thus hopefully ending up in a global optimum [3].

SA algorithm is the following steps:

1. Create the decrease list of temperature with value in range [0,1]. (Annealing Cooling schedule)

2. Initializing population called by Path0 and assignment maximum value to path0. (Objective function)

3. Change in the population and create Path.

4. If fitness of path is great than maximum fitness then goes to 5 else go to 6.

5. New Path equal Path0 and maximum fitness is for Path.

6. If T[i] > Random (0,1) then (Acceptance function)

Path0 = Path.

7. If end of generation go to 3 else go to 8.

8. End

Simulated annealing algorithm is useful method than genetic algorithm because of cause scape of local optimum goal. Also runtime of this algorithm is very lower of genetic algorithm.

VI. HYBRID GENETIC AND SIMULATED ANNEALING ALGORITHM

Each of the above approaches to hybridize GA and SA described in Section II.A has its own strengths, because some good characteristics of GA and SA are maintained when combining GA and SA together. In this paper, a new GA and SA hybrid, GSA, is presented.

After crossover and mutation for a couple of individuals, there are four chromosomes: two parents and two offspring. In conventional GA, two parents are replaced by their offspring. But in GSA, two chromosomes are chosen to form the next generation from these four individuals. The selection criterion is based on the fitness values of these four individuals.

Individuals with higher fitness values have a greater probability of surviving into the next generation. Those with less fitness values are not necessarily discarded. Instead, a local selection strategy of SA is applied to select them with a probability related to the current temperature (as in simulated annealing). In this selection process, a Markov chain is executed, which is composed of two offspring. Four parameters (fbest, fworst, Tt, fi) are involved to describe this selection process:

fbest — the best fitness value of two parents;

fworst — the worst fitness value of two parents;

fi — the fitness value of one offspring (i= 1, 2);

Tt — control temperature;

During the course of the Markov chain at temperature Tt, the fitness value fi (i =1, 2) of the trial chromosome is compared with fworst. Chromosome i is accepted to replace the worst individual, if the following requirement is met:

$$\min\{1, e^{\frac{f1-f_{worst}}{T_t}}\} \quad (3)$$

Where r is a randomly generated number between 0 and 1. If chromosome i is accepted, the worst chromosome and the best one are updated and then the course of the Markov chain continues until completion. After the implementation of the Markov chain, the best and the worst individuals are survived into the next generation.

In SGA, mutation simply changes the value for a particular gene with a certain probability. It helps to maintain the vast diversity of the population and also prevents the population from stagnating. However, at later stages, it increases the probability that good solutions will be destroyed. Normally, the mutation rate is set to a low value (e.g., 0.01) so that accumulated good candidates will not be destroyed. This negative effect of mutation has been eliminated for GSA, because the local selection of SA is applied after mutation, such that at the later stage, only better solutions are retained after mutation. Therefore, the initial value of mutation probability can be larger than the recommended values in [5].

In this study, the mutation probability pm of GSA is initially set to a higher value, and a simple annealing process is then used to adjust pm. After every certain generations, the mutation probability pm is updated with (pm×α) until it reaches to a certain value, where α is the cooling rate of SA. Thus, at the initial stage, when manipulating the cooling schedule of SA properly, the initial higher temperature can ensure that parents will be replaced by their offspring after crossover and mutation whether they are much fitter or not. More importantly, the initial higher mutation probability is capable of improving population diversity greatly, which can eliminate the premature convergence problem of conventional GA. On the contrary, at the later stage the mutation probability and the temperature become lower, and the chances for the fitter parents to be replaced decrease greatly. In this way, the current best individuals may continue to remain in the next generation. Thus, the possibility of removing potentially useful individuals in the last generation because of the mutation operation can be reduced. The pseudo-code of GSA is illustrated in following, where P(t) is the population of individuals at generation t, and n is the string length of chromosome.

Combination algorithm (GSA):

```
t = 0
initialize P(t) and temperature Tt
evaluate P(t)
while not termination-condition do
  t = t + 1
  select P(t) from P(t-1)
  select individuals for reproduction from P(t)
  repeat
    select two unused individuals P1, P2
   crossover & mutation; generate two children C1, C2
    evaluate C1, C2
    for all i = 1 to 2 do
      if min{1, exp((fi-fworst)/Tt)}> random[0,1) then
      accept Ci and replace the corresponding parent
       update the new best and worst points
    end if
    end for
    until all selected parents finish reproduction
    Tt+1 = Tt × α; 0 <α < 1
    if the modulus of t divided by 10 == 0&& pm > 1/n then
       pm = pm×α
    end if
end while
```

T: temperature parameter, α: decrease temperature coefficient and mutation rate, Pm: mutation rate.

The Combination of GSA and Evolutionary Game Theory is based on optimization of EGT parameters by GSA. In fact each of the players wants to reach best fitness value. GSA algorithm is suitable solution for scape of local optimum obtain best fitness value that in result. We call combination of two algorithms by GSA-EGT and compare results to gather.

VII. SIMULATION AND RESULT

For the test of algorithm performance designed a dynamic environment by 20 columns and rows that each cell is a node in network, each node maybe destroy and disconnect the

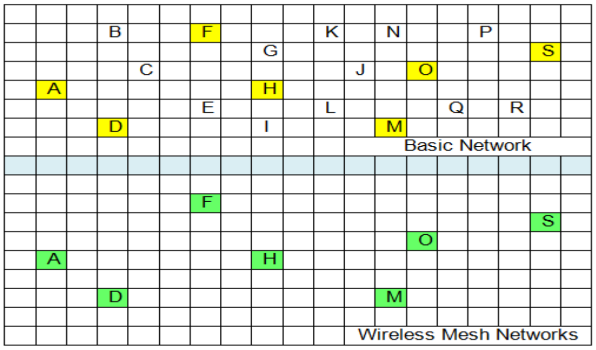

Fig. 6: Environment of Simulation

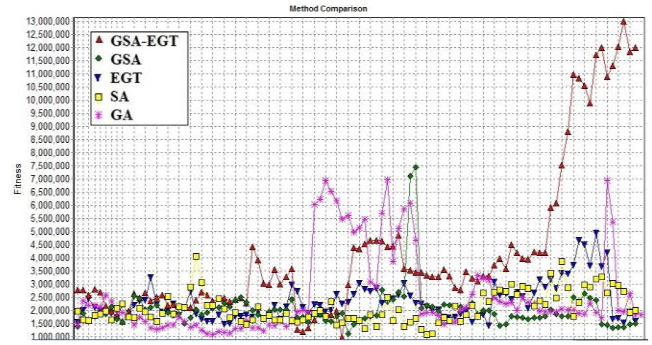

Fig. 7: Comparison of best fitness value then of 30 times of execution

relation between nodes. For the implementation of another dynamic in this work, bandwidth, delay and cost values randomly changes between defined values.

Also destination nodes move and destroy and or add to dynamic network. To create a dynamic environment executes a synchronic procedure with presented algorithms that changes above items in the Network.

Algorithm parameters are the following: Population size is 100, number of generations is 100, chromosome length is 40 and destination count is 6.

The Selection of genetic operations with suitable rate has most efficacies in maintenance of diversity and convergence speed. In this work have tested different values for mutation and crossover rate that after study of simulation results outcome best rates.

α: temperature decrease coefficient and mutation rate for the combination of genetic and simulated annealing algorithm is 0.85.

By use of done simulation and based on explained assumes we studied performance of used methods of many aspects that is the following:

- Fitness value in duration generations
- Maximum of fitness value
- Execution Time
- Result comparison by change of algorithms parameters
- Average of fitness value in duration of generation

Fig. 7, Fig. 8 and Fig. 9 are based on progress of generations on horizontal pilot and on vertical plot also Fig. 7 is fitness values, Fig. 8 is delay values and Fig. 9 is bandwidth values for whole algorithms used in this paper.

By 30 times of simulation execution of the best of fitness average is for combination of GSA and EGT method and lower fitness is for SA method. The Selection of genetic operations with suitable rate has most efficacies in maintenance of diversity and convergence speed. In this work have tested different values for mutation and crossover rate that after study of simulation results outcome best rates.

Fig. 7 shows the fitness for GSA-EGT hybrid algorithm, but this procedure will result in delay in routing.

As fitness levels, bandwidth values given in Fig. 8 shows that the new algorithm is the best in this parameter.

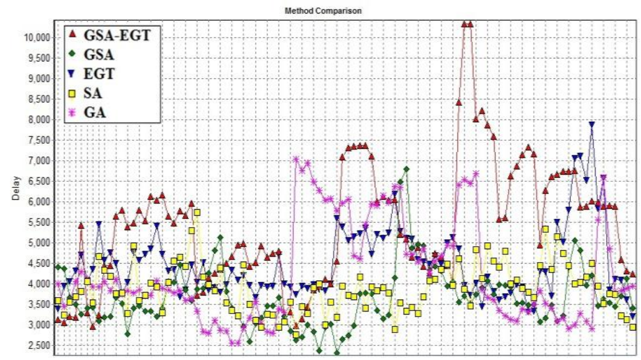

Fig. 8: Comparison of Delay value then of 30 times of execution

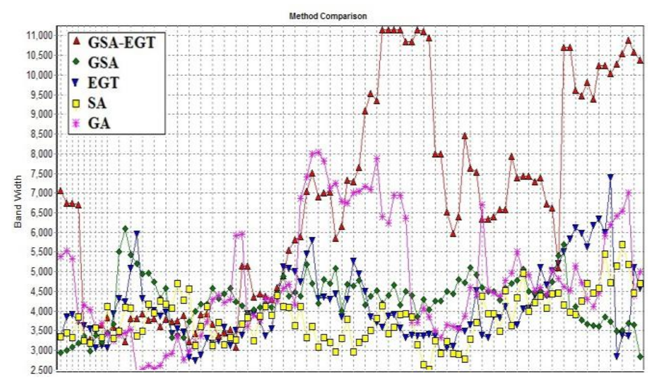

Fig. 9: Comparison of best Band Width value then of 30 times of execution

Fig. 10: Average of Run Time then of 30 times of execution

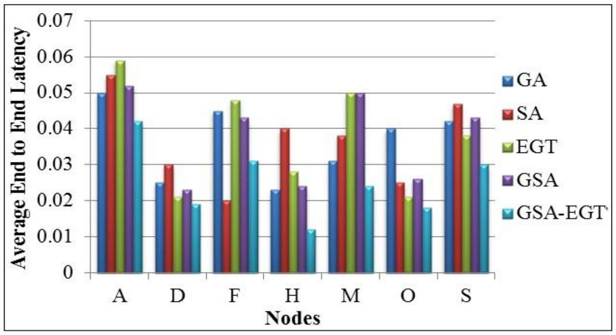

Fig. 11: Average End to End Latency

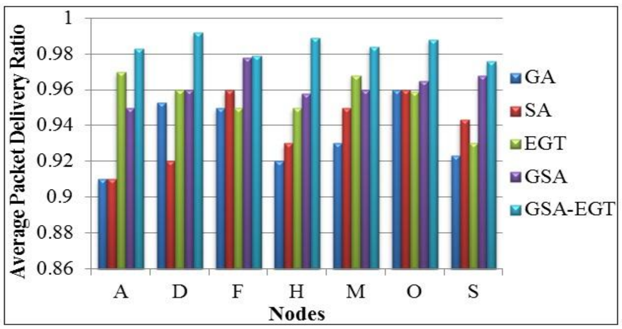

Fig. 12: Average Packet Delivery Rat

The suitable combination of GSA algorithm is caused optimal run time. Also the used algorithm is not completing sequential and this is a good value at whole solution.

Fig. 11 shows the average end to end latency of the different flows. It is worth noting that among the five different protocols only GSA-EGT satisfies the average end to end latency for all the flows. This shows that selective routing combined with stable path selections result in much better QoS behavior.

Fig. 2 shows that maximum number of packet delivery is relation to GSA-EGT algorithm, this result is because of optimized QoS routing by evolutionary methods.

VIII. CONCLUSION

Mesh based wireless LANs are a promising approach to wireless Internet connectivity for mobile users. The mesh wireless LAN architecture provides the advantages of Internet connectivity provided by the Access Points at relatively high speeds, and ad hoc wireless networks which provide a relatively large geographical span without the deployment of a large number of APs.

In this paper, we discussed a new method to show that optimized Parameters by evolutionary game theory by evolutionary genetics and conditioning techniques to bring elegance and performance Quality of service routing problem in wireless mesh networks is relevant. The coevolutionary algorithm with evolutionary game theory and confirm that this Game theory based Coevolutionary Algorithm (GCEA) can be used in optimization.

Simulated annealing algorithm used in this work cause scape of genetic algorithm of local optimum, for hybrid this two algorithm use of coordination temperature and mutation is good selection better that another methods.

The suitable combination of GSA algorithm is caused optimal run time. Also the used algorithms are not completing sequential and this is a good value at whole solution.

In forms of achieved results, the raw fitness function values are calculated on the basis of yet. Therefore provide an appropriate percentage of the correct implementation of the algorithm, the thirty run time and average cases represent them as a result.

Achieve 98% efficiency compared to other methods can be considered as a new approach to the problem of routing. We hope that this method is a good alternative to the wireless network QoS routing.

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