International Journal of Mathematical Archive-6(3), 2015, 85-94
Available online through www.ijma.info ISSN 2229 – 5046

STATE OF ART HYBRIDIZED ALGORITHM FOR FUZZY SHORTEST PATH PROBLEM – HYBRIDIZED GENETIC ANT (HGA) ALGORITHM

V. Anusuya[1] and R. Kavitha*[2]

[1]P.G. & Research Department of Mathematics,
Seethalakshmi Ramaswami College, Tiruchirappalli-620002, TamilNadu, India.

[2]Department of Mathematics,
Chevalier T.Thomas Elizabeth College for women, Chennai-600011, TamilNadu, India.

(Received On: 12-03-15; Revised & Accepted On: 31-03-15)

ABSTRACT

The evolution of fuzzy shortest path from the shortest path problem overcomes the uncertainty problem in the usage of real numbers as parameters in real time applications. The major difference that has evolved to solve uncertainty problem in real time applications are appears to be in the definition of parameters in which the fuzzy numbers are used. Fuzzy shortest path problem in which finding the least fuzzy measured path from the source vertex to the destination vertex, in the network graph $G = \{V, E\}$ where V represents the number of vertices and E represents the number of edges,is intensively applicable in fields like robotics, communication, transportation, mapping, VLSI design and routing. The higher degree application of fuzzy shortest problem impresses to work on several methods for the best results in the reasonable time. Ant Colony Optimization (ACO) works well on the optimization of the Travelling Salesman Problem (TSP) and interns can be used for shortest path problem. The next generation problem solving influences Genetic Algorithm (GA) with natural selection of heuristic for complex problems. The hybridization of both algorithms is termed by many researchers in order to achieve better results with natural convergence. Our objective is to keep track on each individual genetic operator with the term hybridization and to propose next generation hybridization algorithm that hybrids the characteristics of ants with each conventional operator in which, is a first experiment ever in the history of hybridization with the best of our knowledge. We proposed hybrid model for each individual genetic operator and now comprises to form complete hybridization. The proposed model inherits the healthy (continuous path) individual to next generation and hence reduce the convergence without affecting the natural selection of the algorithm.

Key words: *Genetic algorithm, ant colony, generalized trapezoidal fuzzy number, hybridization, fuzzy distance measure, shortest path problem*

2010 Mathematics Subject Classification: *03B52, 03E72.*

1. INTRODUCTION & BACKGROUND

The shortest path problem has accustomed abundant impression in the literature. While considering a network, the arc length may represent time or cost. Therefore, in real life applications, it can be advised to be a fuzzy set. Fuzzy set theory, proposed by Zadeh [32], is frequently used to accord with uncertainties in a problem. The evolution of fuzzy shortest path from the shortest path problem overcomes the uncertainty problem in the usage of real numbers as parameters in real time applications. The major difference that has evolved to solve uncertainty problem in real time applications are appears to be in the definition of parameters in which the fuzzy numbers are used. Fuzzy shortest path problem in which finding the least fuzzy measured path from the source vertex to the destination vertex, in the network graph $G = \{V, E\}$ where V represents the number of vertices and E represents the number of edges, is intensively applicable in fields like robotics, communication, transportation, mapping, VLSI design and routing. We are concerned with finding a path from the source vertex to destination vertex while optimizing the fuzzy distance measure of the path using the properties of generalized fuzzy numbers. Blue *et al.* [6] give taxonomy of network fuzziness that distinguishes five basic types combining fuzzy or crisp vertex sets with fuzzy or crisp edge sets and fuzzy weights and fuzzy connectivity.

Corresponding Author: R. Kavitha[2], [2]Department of Mathematics,*
Chevalier T.Thomas Elizabeth College for women, Chennai-600011, TamilNadu, India.

The fuzzy shortest path problem was first analysed by Dubois and Prade [12]. They utilized the conventional shortest path algorithms, to treat the fuzzy shortest path problem. Klein [20] proposed a dynamic programming recursion-based fuzzy algorithm. Lin and Chen [23] found the fuzzy shortest path length in a network by means of a fuzzy linear programming approach. Another algorithm for this problem was presented by Okada and Gen [27,28], using a generalization of Djikstra's algorithm. In this algorithm, the weights of the arcs were considered to be interval numbers and defined by a partial order of interval numbers. Fuzzy distance is the distance between two fuzzy numbers and generalized Hamming and Euclidean distances have reviewed [8] and proposed new distance measure based on the similarities of fuzzy numbers. Abbasbandy [1] reviewed various distance measure and characterize each methods along various dimensions and proves it with numerical example. Ebadi [13] proposed the new distance measure of fuzzy numbers based on the centroid points.

In order to make evolve the design of fuzzy systems, several meta-heuristic learning algorithms are projected. One major improvement class uses evolutionary algorithms (EAs) [31]. These algorithms are heuristic and random. The next generation problem solving influences Genetic Algorithm (GA) with natural selection of heuristic for complex problems. They involve populations of individuals with a particular behaviour like a biological development, like crossover or mutation [29]. The most well-known biological process fuzzy systems are the genetic fuzzy systems [9], [14], [18], [19], [24] that design fuzzy systems using Genetic Algorithms (GAs). The view of the Genetic Algorithm (GA) should include concentration over various individual genetic operations. The various selection methods of the genetic algorithms are reviewed in [21], [26] which differ in the selection of individual by two major criteria, one by the probability to the individual and other by the best individual. On the other hand, genetic operator crossover also have various successive methods is explained [16] and also the genetically corrected process of obtaining chromosomes.

The higher degree application of fuzzy shortest problem impresses to work on several methods for the best results in the reasonable time. Ant Colony Optimization (ACO) works well on the optimization of the Travelling Salesman Problem (TSP) and interns can be used for better results of shortest path problem. The ACO technique is impressed by real-ant-colony observations. It is a multiagent approach that was originally projected to resolve troublesome discrete combinatorial- optimization issues, like the traveling salesman problem (TSP) [10], [11]. In some studies, completely different ACO models were applied to FS design problems [17], [25]. In these studies, the antecedent-part parameters of an FS were manually appointed ahead.

The hybridization of both algorithms is termed by many researchers in order to achieve better results with natural convergence. The consequent-part parameters were optimized in discrete space using ACO.ZainudinZukhriet. al. [33] proposed Genetic Ant Colony Optimization (GACO) which hybrids Genetic Algorithm (GA) and Ant Colony Optimization (ACO) uses the random selection of chromosome for first generation and pheromone. The population initialization has been made by both ants and GA and results better convergence than GA.

Cauvery [7] proposed mobile agents in genetic algorithm where ants are used as mobile agents. The population initialization is done with the ants and rest of the algorithm proceeds with genetic algorithm and results in finding the shortest path more effectively and also in load balancing. Shang Gao[30] proposes a novel ant colony genetic algorithm in which genetic and ant colony algorithm is mixed up and different mutation operation is carried out to select the best outcome. The results provide the way of combining both algorithms.

This paper is organized as follows. In section 2, explains the properties of generalized trapezoidal fuzzy numbers and describes the distance measure of generalized trapezoidal fuzzy numbers. Section 3 briefs the network terminology. Section 4 explains the approach of Genetic Algorithm (GA). Section 5describes the proposed hybridized genetic ant (HRA) algorithm which hybridized each individual genetic operators of the Genetic Algorithm (GA). In section 6, numerical example along with the example calculation is given. Section 7 deals with the results and discussion. And paper ends with the conclusion and future enhancement in section 8.

2. BASIC DEFINITIONS

The basic definitions of some of the required concepts are reviewed [22] in this section.

2.1. Fuzzy set

Let X be a universal set of real numbers R, then a fuzzy set is defined as

$$A= \{[x,\mu_{\tilde{A}}(x)], x \in X\}$$

This is characterized by a membership function: $X \rightarrow [0\ 1]$, Where, $\mu_A(x)$ denotes the degree of membership of the element x to the set A.

2.2. Characteristics of generalized fuzzy number

A fuzzy set $\tilde{A}$ which is defined on the universal of discourse R, is known to be generalized fuzzy number if its membership function has the following characteristics

a) $\mu_A : R \to [0,1]\ iscontinuous.$
b) $\mu_A(x) = 0\ forallx \in (-\infty, a] \cup [d, \infty).$
c) $\mu_A(x) isstrictlyincreasingon[a,b]andstrictlydecreasingon[c,d].$
d) $\mu_A(x) = w, forallx \in [b,c], where\ 0 < w \leq 1.$

2.3. Membership function of generalized trapezoidal fuzzy number

A generalized trapezoidal fuzzy number $\tilde{A}$ = (a, b, c, d; w) is known to be a generalized trapezoidal fuzzy number, if its membership function is given by

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{w(x-a)}{(b-a)} & a \leq x \leq b \\ 1 & b \leq x \leq c \\ \frac{w(x-d)}{(c-d)} & c \leq x \leq d \end{cases}$$

Let$\tilde{A} = (a, b, c, d; w)$ be a generalized trapezoidal fuzzy number then
a) $R(\tilde{A}) = \frac{w(a+b+c+d)}{4}$, b) $M(\tilde{A}) = \frac{w(b+c)}{2}$, c) divergence $D(\tilde{A}) = w(d-a)$, d) Left spread $LS(\tilde{A}) = w(b-a)$, e) Right spread $RS(\tilde{A}) = w(d-c)$

2.4. Fitness function

Jahantigh [15] described the relation between generalized trapezoidal fuzzy number (a, b, c, d; w) and trapezoidal fuzzy number (a, b, c, d) that the trapezoidal fuzzy number has value of w=1 whereas generalized trapezoidal fuzzy number has the range $0 < w \leq 1$ and also described the relation between generalized triangular (a, p, q; w) and trapezoidal (a, b, p, q; w) fuzzy numbers in which trapezoidal is equivalent to trapezoidal having a=b.

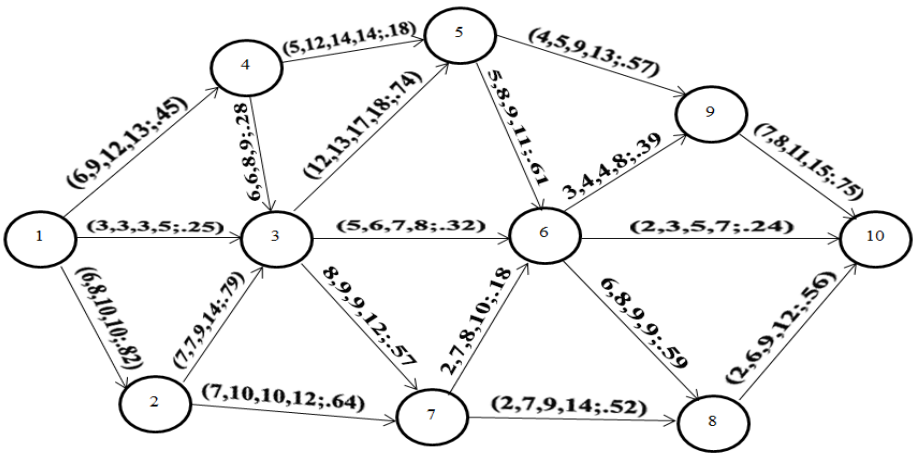
The distance measure between the generalized trapezoidal fuzzy numbers $\tilde{A}$ (a_1,b_1,c_1,d_1;w_1) and $\tilde{B}$ (a_2,b_2,c_2,d_2;w_2) using centroid points (α, β) of $\tilde{A}$ is given by [10]

$$f_d(\tilde{A}, \tilde{B}) = \max\{|\alpha_{\tilde{A}} - \alpha_{\tilde{B}}|, |\beta_{\tilde{A}} - \beta_{\tilde{B}}|, |R(\tilde{A}) - R(\tilde{B})|, |LS(\tilde{A}) - LS(\tilde{B})|, |RS(\tilde{A}) - RS(\tilde{B})|\}$$

where $\alpha = \frac{1}{3}\left[a_1 + a_2 + a_3 + a_4 - \frac{a_4 a_3 - a_1 a_2}{(a_4+a_3)-(a_1+a_2)}\right]$ and $\beta = \frac{1}{3}\left[\frac{a_3 - a_2}{(a_4+a_3)-(a_1+a_2)}\right]$

3. NETWORK TERMINOLOGY

Consider the directed network G (V, E) consisting of a finite set of vertices V= {1, 2……n} and a set of m directed edges $E \subseteq V \times V$. Each edge is denoted by an ordered pair (i,j) where i, j∈ v and i ≠ j. In this network, we specify two vertices namely source vertex and the destination vertex. The term$\widetilde{d_{ij}}$ denotes the generalized trapezoidal fuzzy number associated with the edge (i, j). The fuzzy distance along the path P is given in section 2.4.



4. GENETIC ALGORITHM

Genetic Algorithm (GA) is a type of Evolutionary Algorithm (EA) which is based on the natural selection phenomenon. GA usually has an analogy to the randomness in solving a problem. It is comprised of generations where children are produced by the mating of the parents with genetic operators. Selection and reproduction to produce efficient generation is based on the random procedures, known to be natural selection.

4.1. Representation of an individual (chromosome)

Each chromosome is represented in integer representation and it is also important which represents the solution in the generations. The representation defines the path traversed and indirectly refers the fuzzy fitness of the chromosome. The number of integer used in representing chromosome various between the vertex visited and maximum to the number of vertices in the network graph$G = \{V, E\}$. The vertex visited is represented by its own vertex number and the vertex which is not visited is not represented.

4.2. Population initialization

The initial population is generated randomly in usual GA and each chromosome represents the collection of edges which are represented by generalized trapezoidal fuzzy numbers explained in previous sections. The default population size 20 is used.

4.3. Selection operation

Selection operation is used in initialization process and parent selection for crossover operation. Various selection operations involve Roulette wheel selection, Random selection, Rank selection, Tournament selection and Boltzmann selection [29].

Here we choose distance measure considering rank, divergence, left spread and right spread of generalized trapezoidal fuzzy numbers explained in previous section as the fitness function. As the fuzzy shortest path problem is considered, minimum will survive by the selection the chromosome values.

The distance measure between every two edges is calculated and obtained distance is summed up throughout the path. The chromosome having minimum distance (fitness) will have more priority to be selected in the generation.

4.4. Crossover operation

Crossover operator mates two parent chromosomes and produces children which comprise the essence of two parent chromosome mated. Crossover operation is mainly categorised into two single point and multi point crossover.

The single point crossover has single crossover site whereas multi point crossover has more than single crossover site. There are also some advanced multipoint crossover methods [29].

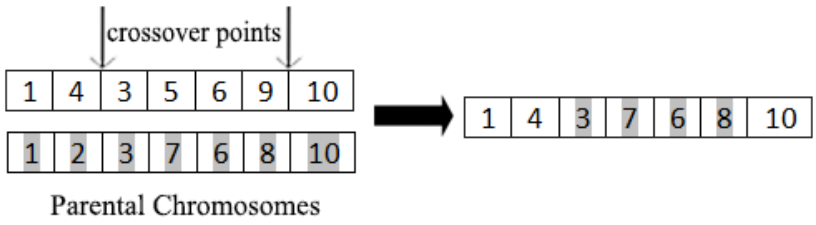


Fig. 4.1: Two – Point Crossover operation

4.5. Mutation operation

The conventional mutation operator performs the minute changes of the reproduced child randomly under a certain rate which undo the degradation of the population due to crossover operation.

There were many mutation operations for real integers. Here we choose integer mutation that may be uniform, insertion, interchanging, boundary, non – uniform and others [2].

© 2015, IJMA. All Rights Reserved

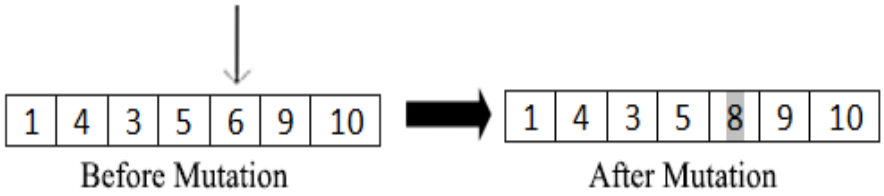


Fig. 4.2: Mutation operation

4.6. Elitism

Elitism in the genetic algorithm helps to obtain quality of the generations. It guaranties the health factor of the chromosomes that should not degrade from one generation to the next generations.

According to elitism, the reproduced individual is checked that its fitness should be less than the individual having maximum fitness in the generation. The reproduces individual which met these criteria will able to proceed to the next generation.

4.7. Termination condition

Termination condition produces the optimal solution through the convergence. Mostly termination condition will be the maximum number of generations. Other conditions are the idealness of the chromosomes in the generation. In order to test the algorithm, maximum number of generations can be used as termination condition which clearly represents the convergence of the algorithm.

Here, idealness of the chromosomes is considered as termination condition because of the usage trapezoidal fuzzy numbers and uncertainty in real numbers. When no change in the optimal fitness (minimal) and the idealness of the chromosomes in generations for at least 5 generations, then the algorithm reaches the termination condition.

5. HYBRIDIZED GENETIC ANT (HGA) ALGORITHM

The objective is to keep track on each individual genetic operator with the term hybridization and to propose next generation hybridization algorithm that hybrids the characteristics of ants with each conventional operator in which, is a first experiment ever in the history of hybridization with the best of our knowledge. The proposed model inherits the healthy (continuous path) individual to next generation and hence reduce the convergence without affecting the natural selection of the algorithm.

5.1. Population initialization using initializing ants (IA)

Genetic Algorithm (GA) possesses random selection of chromosomes in initializing the population, in which chromosomes may uncertain in the existence as solution space. Randomness may also produce discontinuous path as the chromosome in initializing population and leads to unhealthy and unfitted generations. Since initialization of population implicates the convergence rate, the chromosomes should exist, continuous and provide optimal fitness in solution space.

The population initialization is achieved by Initializing Ants (IA) which has the characteristics of ant that chooses different paths randomly from source vertex to the destination vertex. The property of each IA is made to be unique and every IA chooses only the valid vertex as its next visit where valid vertex is the vertex in which there exists a path. The proposed method is elaborately explained in our previous work [3].

Initializing Ant (IA) that has to be used in the algorithm is based on the number of vertices and possible number of edges that is somewhat in the range of $2^{V/2}$. The range of the size of IA is given by $IA_size = \begin{cases} 2^{V/2}, & V > 8 \\ 20, & otherwise \end{cases}$, where n represents the number of vertices.

Once the behavioural paths of IA are noted, the fitness of the paths is compared using fuzzy distance measure. The best (minimal) 20 (population size of GA) path are considered as the initial population. The initial population thus produces in the proposed method has the chromosomes with continuous paths and existed in the network.

© 2015, IJMA. All Rights Reserved

5.2. Roulette ant wheel selection (RAWS)

Roulette Ant Wheel Selection works on the Roulette wheel principle which contributes to the randomness along with the fitness measure in the selection of parents. This algorithm is not only focused on randomness as proposed in Roulette Wheel Selection (RWS)[8,21] but also focused on the criteria of best selection in the population. RAWS consists of Roulette wheel, Inner Cyclic Ant (ICA) and Outer Cyclic Ant (OCA).

Inner cyclic ant (ICA) and outer cyclic ant (OCA)
Inner Cyclic Ants (ICA) present in the inner circle whereas Outer Cyclic Ants (OCA) in the outer circle of the Roulette wheel traverses the chromosomes in clockwise and anti – clockwise direction respectively. The ICAs and OCAs are positioned in random chromosome and the next chromosome they have to be traversed is also made as random. Whenever the chromosome is traversed, the pheromone is shed.

Since the shortest path has the less fitness and proposed pheromone is inversely proportional to the fitness, a chromosome having small fitness value reaches the maximum pheromone in least number of traversal than the chromosomes having the larger fitness. Hence chromosome of small fitness with least number of traversal or chromosome of large fitness with most number of traversal has high pheromone.

When chromosome with equal or above $P_{mone}\ (max)$ value of pheromone is traversed by any of the ICAs, the traversal is temporarily stopped and checks for the OCAs whether any of the chromosomes has pheromone with equal or above $P_{mone}\ (max)$ value. The pair of chromosome with high pheromone is selected, if and only if both ICAs and OCAs met the same condition.

Methodology
Roulette Wheel Ant Selection (RAWS) explained elaborately in our previous work [4] uses random best selection criteria in selection the individuals as the parents of next generation. This algorithm should not spoil the principle 'Natural selection' of Genetic Algorithm (GA) but keep tracks on the selection of best individual. In shortest path algorithm, the least fitness becomes the best solution and the pheromone P_{mone} () is formulated inversely to the fitness, i.e. inversely proportional to the fitness value. Hence chromosome of least fitness is shed by the ants with greater pheromone.

$$P_{mone}\ (P_i) = \frac{1}{\sqrt{(2f_d(i) - low)^2 + f_d(i)^2}}$$

Where P_i represents i^{th}chromosome in the population P and $f_d(i)$ represents the fitness value (fuzzy distance measure) of the ith chromosome in the population P.

$$P_{mone}\ (max) = \frac{\sqrt{(high^2 - low^2)}}{\sqrt{(high^2 + (high + low)^2)}}, high > low > 0.$$

The stopping criteria of the selection $P_{mone}\ (max)$ can be calculated with the help of high and low fitness values in the population in which both should be greater than zero ($high, low > 0$).

5.3. HYBRID CROSSOVER – MUTATION PAIR

Hybrid crossover – mutation pair comprises of Predominant Ant (PA) and Subordinate Ants (Ants) with their unique characteristics. The hybridization works under the criteria that it should not produce unhealthy (discontinuous path) chromosomes without affecting the behavioral principle 'natural selection' of the genetic algorithm.

PA traverses the path that has to be traversed alone to reach the desired destination vertex whereas SAs traverses to find the alternate paths that cannot be reached by the PA. It has to be assumed that both PA and SAs traverse the existing path alone.

Crossover can be obtained by the PA where it chooses one parental chromosomes and traverse along the path till it finds discontinuity or crossover point. When PA finds discontinuity or crossover point, it switches over to chromosome just after the crossover point of next parental chromosomes. As explained in PA and SAs [5], the alternative path can be found and results the continuous path after the crossover.

Hybrid mutation works along PA and SAs with the criteria in producing healthy (continuous path) chromosomes for the next generation. The integer to be mutated is selected by the mutation value M_{vertex} which is given by

$$M_{vertex} = (Tot_{alter} - 1) * ran_{vertex}$$

whereM_{vertex} represents mutation value of a particular vertex, Tot_{alter} represents total number of alternative paths found by SAs from start vertex to end vertex given by PA and ran_{vertex} is existing vertex chosen randomly in the network graph.

PA traverses on the path specified by chromosomes and SAs helps to find the alternative path for the vertex given by PA to calculate M_{vertex} of given vertex. Mutation may or may not be takes place based on the condition that any vertex has $M_{vertex} > 0$.

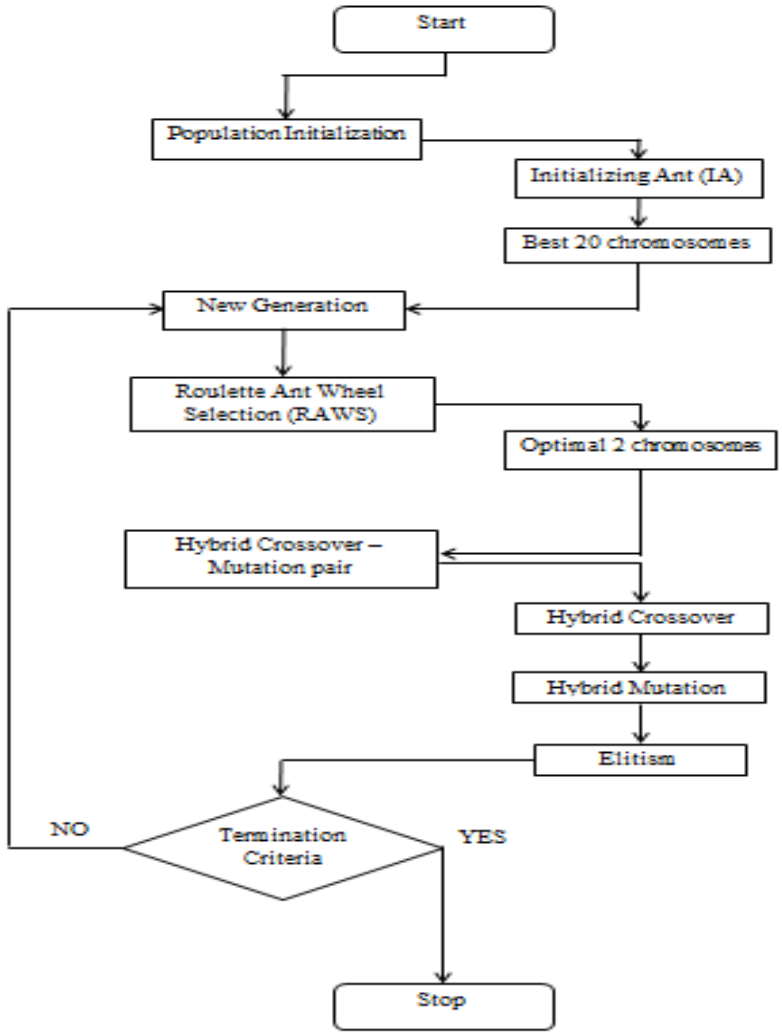


Fig. 5.1: Flow diagram of proposed HRA

6. NUMERICAL EXAMPLE

We Consider the network $G = \{V, E\}$ of co vertices (n=10). Every edge is represented by the generalized trapezoidal fuzzy number. The fitness, distance measure and properties of generalized trapezoidal fuzzy number in which described in previous chapters, are used to calculate.

Let consider two edges A(3,3,3,5;.25) and B(5,6,7,8;.32) and the distance measure given in section 2.4 can be calculated using the centroid points, rank, Left spread and Right spread.

$\alpha_A = 3.67$ $\quad \alpha_B = 6.5$ $\quad \alpha_A - \alpha_B = 2.83$
$\beta_A = 0.33$ $\quad \beta_A = 0.42$ $\quad \beta_A - \beta_A = 0.09$
$R(A) = .88$ $\quad R(B) = 2.08$ $\quad R(A) - R(B) = 1.2$
$LS(A) = 0$ $\quad LS(B) = .32$ $\quad LS(A) - LS(B) = .32$
$RS(A) = .50$ $\quad RS(B) = .32$ $\quad RS(A) - RS(B) = .18$

$$f_d(\tilde{A}, \tilde{B}) = \max\{|\alpha_{\tilde{A}} - \alpha_{\tilde{B}}|, |\beta_{\tilde{A}} - \beta_{\tilde{B}}|, |R(\tilde{A}) - R(\tilde{B})|, |LS(\tilde{A}) - LS(\tilde{B})|, |RS(\tilde{A}) - RS(\tilde{B})|\}$$
$$= \max\{2.83, 0.09, 1.2, .32, .18\} = 2.83$$

Table 7.1: Sample calculation $f_d()$ of path 1-3-6-10 (continuous path)

Path	Next vertex	$f_d(\tilde{A}, \tilde{B})$(section 2.6)
1	3	0
1-3	6	0+2.833=2.833
1-3-6	10	2.833+2.214=5.047

Let consider path P_{16} 1-4-5-9-10 with the fitness value$f_d() = 9.599$. The pheromone can be calculated with $low = 5.047$ and $high = 14.746$ as

$$P_{mone}\ (P_4) = \frac{1}{\sqrt{(2f(i)-low)^2+f(i)^2}} = \frac{1}{\sqrt{200.25}+92.14} = \frac{1}{17.099} = 0.0585$$

$$P_{mone}\ (max) = \frac{\sqrt{(high^2 - low^2)}}{\sqrt{(high^2 + (high + low)^2)}} = \frac{13.86}{24.68} = 0.5616$$

Thus continuous consequent execution of each operations of genetic algorithm leads to the reproduction of chromosomes which evolves with the principle of natural selection. The evaluation of chromosomes leads to the convergence of the result optimizes as 1-3-6-10 as shortest path between the source and the destination vertex.

7. IMPLEMENTATION & RESULTS

The implementation is carried out in Matlab 8.1 (R_{2013a}) 32 bit student version. The assumptions explained before are implemented and the selection of valid path is controlled using adjacency matrix.

The network $G = \{V, E\}$of 30 nodes with the edges of generalized trapezoidal fuzzy number is initialized. The proposed Hybridized Genetic Ant (HGA) is implemented along with conventional Genetic Algorithm (GA) and Ant Colony Optimization (ACO) for the comparative analysis.

The algorithm is implemented as per the given description and demonstrated numerical calculation. 3278 IA is separately generated and individual path of IA obtained is measured. The random function with time constraint is used to implement the IA with unique behaviour. The outcome of IA path is comprised and the centroid points, rank, mode, divergence, left spread and right spread of shortest path is used to measure fuzzy numbers. The best (minimal) 20 IA (population size of GA) paths are initialized to the GA populations.

The same random function which is implemented in population initialization is used to regulate the random moves of both ICA and OCA with unique behaviour. The clockwise traversal is generally achieved for ICA and anticlockwise traversal for OCA is achieved by performing (N-n) clockwise direction moves where N represents population size and n represents the moves that have to be carried out in anti-clockwise directions.

The random function as natural selection moves both PA and SAs with unique behaviour. The random movement and the interactions between the PA and SAs are controlled by the adjacent matrix that describes the existence of the path between the vertices. The idealness of the best solution for more than 5 consecutive generations is taken as termination criteria.

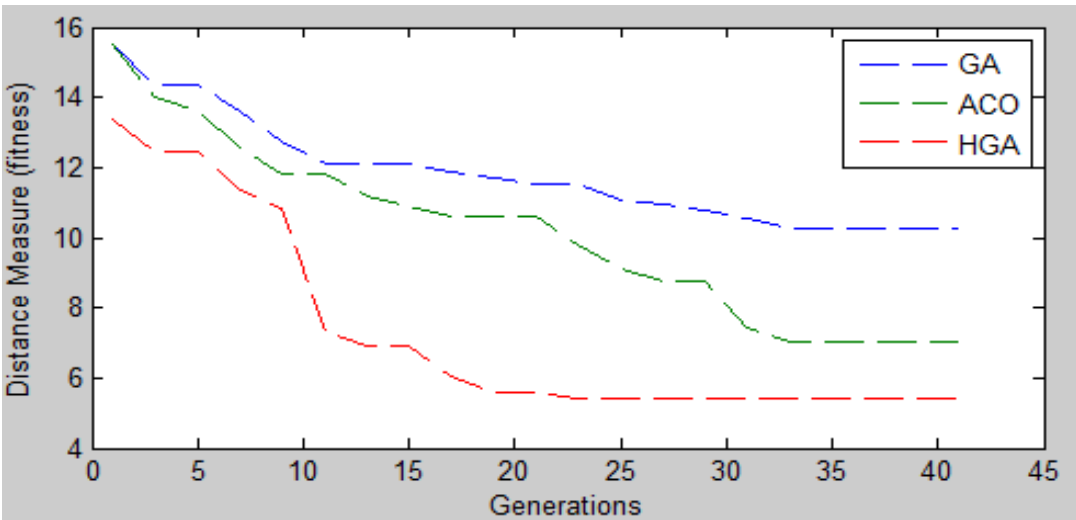


Fig. 7.1: Comparison of GA and ACO with the proposed HRA method in terms of number of generations and optimum result

From the figure 7.1**,** it is clear that the distance methoddepends on the centroid points, rank,mode, divergence, left spread and right spread. The path at which all the components attain equilibrium is considered to be the shortest path. Here, generations around 23-41 for HRA, 33-41 for ACO and 32-41in which chromosomes possess constant fitness andidealness in the generations and the path obtained by that chromosome is considered to be shortest path.

The genetic operations for proposed HRA and conventional GA are commonly implemented along with conventional ACO and the result of number of generations in which the solution obtained is compared along with the various numbers of vertices for both algorithms. This clarifies the advantage and the importance of hybridization in genetic algorithm. The huge difference in the convergence of algorithms presents not only the impression of hybridization and also proves the importance of each genetic operator has its influence in the formation of genetic algorithm.

8. CONCLUSION & FUTURE IMPLICATION

The shortest path problem in many applications is uncertain in parameters (Distance, Range, etc.). Hence, there occurs the necessity of fuzzy numbers for uncertain parameters. Our objective is to keep track on each individual genetic operator with the term hybridization and to propose next generation hybridization algorithm that hybrids the characteristics of ants with each conventional operator in which, is a first experiment ever in the history of hybridization with the best of our knowledge.

Our proposed HRA algorithm provides the selection of best solution through certain conditions and also without affecting the originality of the GA 'natural selection'. According to the proposed algorithm, individual of best outcome can be selected with less number of traversal than the better solution which needs comparatively more number of traversal by ants. Thus the survival of worst solution in next generations cannot be possible. The result clears that the proposed new hybrid Genetic Algorithm (GA) comprises the shortest path with optimal generations using swarm intelligence and all the chromosomes in every generations is continuous and existed in the network. The hybrid crossover – mutation pairs explain the influence of crossover and mutation operators in genetic algorithm and also the effectiveness of the proposed hybridization in the convergence of the algorithm. The proposed hybrid pair is considered as best pair as the conventional crossover – mutation pairs.

The result clears that the proposed HRA comprises the shortest path with optimal generations using swarm intelligence and all the chromosomes in every generations is healthy (continuous path) and existed in the network.

REFERENCES

1. S. Abbasbandy, S. Salahshour., New results on the existing fuzzy distance measures, Iranian Journal of Fuzzy Systems, Vol. 10, No. 3, pp. 115-124, 2013.
2. Aluizio F. R. Araújoet. al., Multicast Routing Using Genetic Algorithm Seen as a Permutation Problem, Proceedings of the 20th International Conference on Advanced Information Networking and Applications, 2006.
3. V.Anusuya and R.Kavitha, Initializing Ant(IA) as an agent in Initializing population of Genetic Algorithm on fuzzy shortest path International Journal of Applied Mathematics & statistical Sciences(IJAMSS), ISSN(online) 2319-3980, vol 4, Issue-I, Jan 2015. pg 17-27.
4. V.Anusuya and R.Kavitha, Roulette Ant Wheel Selection(RAWS) for Genetic Algorithm- Fuzzy shortest path problem International Journal of Mathematics &computer Applications Research, ISSN(online) 2249-6955,E-ISSN 2249-8066, vol 5, Issue 2, Apr 2015pg, 1-14.
5. V.Anusuya and R.Kavitha, 'Hybrid crossover-Mutation pair for Genetic Algorithm in solving Fuzzy shortest path problem- Predominant and subordinate ants, International Journal of Science & Research(IJSR), ISSN(online) 2319-7064,Vol 4, Issue 2, Feb 2015, pg 2074-2081.
6. Blue, M., Bush, B. and Puckett, J., Unified approach to fuzzy graph problems, Fuzzy Sets and Systems 125, 355–368, 2002.
7. F.A Cauvery N K, S.B. Dr K V Viswanatha., Routing Algorithm using mobile agents and Genetic Algorithm, International Journal of Computer and Electrical Engineering, Vol. 1, No. 3, pp. 293-296, 2009.
8. Chetan Chudasama, S. M. Shah and Mahesh Panchal., Comparison of parents selection methods of genetic algorithm for TSP, International Conference on Computer Communication and Networks, pp. 85-87, CSI- COMNET-2011.
9. C. H. Chou, "Genetic algorithm-based optimal fuzzy controller design in the linguistic space," IEEE Trans. Fuzzy Syst., vol. 14, no. 3, pp. 372–385, Jun. 2006.
10. M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: Optimization by a colony of cooperating agents," IEEE Trans. Syst., Man, Cybern. B,Cybern., vol. 26, no. 1, pp. 29–41, Feb. 1996.
11. M. Dorigo and L. M. Gambardella, "Ant colony system: A cooperative learning approach to the traveling salesman problem," IEEE Trans. Evol.Comput., vol. 1, no. 1, pp. 53–66, Apr. 1997.
12. Dubois, D. and Prade, H., Fuzzy Sets and Systems: Theory and Applications, New York, Academic Press, 1980.
13. M. J. Ebadi, M. Suleiman, Fudziah Bt. Ismail, A. Ahmadian, M. R. BaloochShahryari, and S. Salahshour., A new distance measure for trapezoidal fuzzy numbers, Hindawi Publishing Corporation, Mathematical Problems in Engineering, Volume 2013, Article ID 424186, pp. 1-4, 2013.
14. F. Hoffmann, D. Schauten, and S. Holemann, "Incremental evolutionary design of TSK fuzzy controllers," IEEE Trans. Fuzzy Syst., vol. 15, no. 4, pp. 563–577, Aug. 2007.

© 2015, IJMA. All Rights Reserved

15. M. A. Jahantigh, S. Hajighasemi., Ranking of generalized fuzzy numbers using distance measure and similarity measure, Int. J. Industrial Mathematics (ISSN 2008-5621), pp. 405-416, 2012.
16. Jorge Magalhães-Mendes, 'A comparative study of crossover operators for genetic algorithms to solve the job shop scheduling problem,' WSEAS Transactions on computers, pp. 164-173, Volume 12, April 2013.
17. C. F. Juang, C. M. Lu, C. Lo, and C. Y. Wang, "Ant colony optimization algorithm for fuzzy controller design and its FPGA implementation," IEEE Trans. Ind. Electron., vol. 55, no. 3, pp. 1453–1462, Mar. 2008.
18. C. F. Juang, "A TSK-type recurrent fuzzy network for dynamic systems processing by neural network and genetic algorithms," IEEE Trans. Fuzzy Syst., vol. 10, no. 2, pp. 155–170, Apr. 2002.
19. C. F. Juang, "Combination of on-line clustering and Q-value based GA for reinforcement fuzzy system design," IEEE Trans. Fuzzy Syst., vol. 13, no. 3, pp. 289–302, Jun. 2005.
20. Klein, C.M., Fuzzy shortest paths, Fuzzy Sets and Systems 39, 27–41, 1991.
21. Khalid Jebari, Mohammed Madiafi., Selection methods for genetic algorithms, Int. J. Emerg. Sci., 3(4), pp. 333-344, 2013.
22. Kaufmann A., Gupta, MM., Fuzzy mathematical models in engineering and management science. Elsevier Science Publishers, Amsterdam, Netherlands, 1988.
23. Lin, K. and Chen, M., The fuzzy shortest path problem and its most vital arcs, Fuzzy Sets and Systems 58, 343–353, 1994.
24. E. G. Mansoori, M. J. Zolghadri, and S. D. Katebi, "SGERD: A steadystate genetic algorithm for extracting fuzzy classification rules from data," IEEE Trans. Fuzzy Syst., vol. 16, no. 4, pp. 1061–1071, Aug. 2008.
25. M. Mucientes and J.Casillas, "Quick design of fuzzy controllerswith good interpretability in mobile robotics," IEEE Trans. Fuzzy Syst., vol. 15, no. 4, pp. 636–651, Aug. 2007.
26. Noraini MohdRazali, John Geraghty., Genetic algorithm performance with different selection strategies in solving TSP., Proceedings of the World Congress on Engineering 2011 Vol II, pp. 1134-1139, 2011.
27. Okada, S. and Gen, M., Order relation between intervals and its applications to shortest path problem, In: Proc. 15th Annual Conference on Computers and Industrial Engineering 25, 156-167, 1993.
28. Okada, S. and Gen, M., Fuzzy shortest path problem, In: Proc. 16th Ann. Conf. on Computers and Industrial Engineering 27, 1994.
29. Sivanandam S.N. &Deepa S.N. (2008): Introduction to Genetic Algorithms, 2008.
30. Shang Gao, Zaiyue Zhang and Cungen Cao., A novel ant colony genetic hybrid algorithm, Journal of Software, VOL. 5, NO. 11, pp. 1179-1186, 2010.
31. X. Yao, Ed., Evolutionary Computation—Theory and Applications. Singapore: World Scientific, 1999.
32. Zadeh, L.A., Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets and System 1, 3–28, 1978.
33. Zainudin Zukhri and Irving VitraPaputungan., A hybrid optimization algorithm based on genetic algorithm and ant colony optimization, International Journal of Artificial Intelligence & Applications (IJAIA), Vol. 4, No. 5, pp. 63-75, 2013.

Source of support: Nil, Conflict of interest: None Declared

[Copy right © 2015. This is an Open Access article distributed under the terms of the International Journal of Mathematical Archive (IJMA), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.]