International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 6 (2015) pp. 15091-15107

http://www.ripublication.com

Hybridization Of Genetic Algorithm (GA) And Ant Colony Optimization (ACO) – A Review On Solving Fuzzy Shortest Path Problem

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

[1] *P.G & Research Department of Mathematics, Seethalakshmi Ramaswami College, Tiruchirappalli-620002,TamilNadu, India*
**E-mail: anusrctry@gmail.com*
[2] *Department of Mathematics, Chevalier T.Thomas Elizabeth College for women, Chennai-600011,TamilNadu, India*
***E-mail: kavi.jash@gmail.com*

Abstract

The uncertainty in the usage of real integer values as the parameters of network graph $G = \{V, E\}$ where V represents the number of vertices and E represents the number of edges in graph G, is resolved in fuzzy shortest path problem. The distance measures between fuzzy numbers in finding the least distance between source vertex and destination vertex can be derived by the characteristics of fuzzy numbers such as centroid points, rank, divergence, mode, left spread and right spread. Fuzzy numbers in the sense, the characteristics of triangular and trapezoidal fuzzy numbers along with their generalized forms are reviewed in this paper. Ant Colony Optimization (ACO) works on the behaviour of the ants and the swarm intelligence suits 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 and the survival of the best individual to next generationfor complex problems. Due to the wide range of applications of fuzzy shortest path problem including robotics, routing, mapping, networking, VLSI design and transportationimpresses researchers to work on hybridization for the best results in the reasonable time. This paper reviews some of the best hybridization and compares each individual genetic operator with our proposed Hybridized Genetic Ant (HGA) algorithm and concludes the best suitable hybridization for fuzzy shortest path problem.

Key words: Genetic algorithm, ant colony, fuzzy numbers, hybridization, fuzzy distance measure, shortest path problem, genetic operators.

2010 Mathematics Subject Classification: 03B52, 03E72

1. Introduction

The shortest path problem has accustomed abundant impression in the literature. While considering a network, the arc length may represent time or cost. The uncertainty in the usage of real integer values as the parameters of network graph $G = \{V, E\}$ where V represents the number of vertices and E represents the number of edges in graph G, is resolved in fuzzy shortest path problem. The distance measures between fuzzy numbers in finding the least distance between source vertex and destination vertex can be derived by the characteristics of fuzzy numbers such as centroid points, rank, divergence, mode, left spread and right spread. It has various applications such as robotics, scheduling, communication, transportation, VLSI design, routing and mapping in which the shortest path problems are applied importantly. So to deal with uncertainty in searching, we feel that non-classical logic that is fuzzy logic will be the appropriate tool. Blue et al. [7] gives 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.

The fuzzy shortest path problem was first analyzed by Dubois and Prade [9]. They utilized the conventional shortest path algorithms, to treat the fuzzy shortest path problem. Klein [16] proposed a dynamic programming recursion-based fuzzy algorithm. Lin and Chen [17] found the fuzzy shortest path length in a network by means of a fuzzy linear programming approach. Fuzzy shortest path problem comprises of fuzzy numbers as parameters. Fuzzy distance is the distance between two fuzzy numbers and generalized Hamming and Euclidean distances have reviewed [13] 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 [12] proposed the new distance measure of fuzzy numbers based on the centroid points. Fuzzy numbers in the sense, the characteristics of triangular and trapezoidal fuzzy numbers along with their generalized forms are reviewed in this paper.

The next generation problem solving influences Genetic Algorithm (GA) with natural selection of heuristic and the survival of the best individual to next generation for complex problems. Genetic Algorithm (GA) is the most powerful among the optimization methods which involves ‘natural selection’ and the survival of the best individual to the next generation. The major operations of the genetic algorithm are population initialization, selection, crossover and mutation. In order to upgrade the optimization, evolutionary optimization is often used and hence Genetic Algorithm (GA) is packed with Ant Colony Optimization (ACO) for the better optimization. The ACO technique is impressed by real-ant-colony observations. It is a multi-agent 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 fuzzy system design problems [14], [18].

Due to the wide range of applications of fuzzy shortest path problem including robotics, routing, mapping, networking, VLSI design and transportation impresses researchers to work on hybridization for the best results in the reasonable time. Rigi et. al. [19] reviewed the shortest path routing algorithms and explores the potential of using genetic algorithm to solve the shortest path problem in wireless sensor network. The energy efficient genetic algorithm routing prolongs the network lifetime Genetic Algorithm is a problem solving method which is based on the concept of natural selection and genetic. The paper gives an overview of shortest path algorithm with genetic algorithm and some existing algorithm. The paper concludes that GA has main two advantages over other traditional algorithms. The first one is that the GA algorithm is insensitive to variations in network topologies with respect to route optimality and convergence speed. The second one is that the real computation time of the proposed GA is shorter than that of traditional algorithms. Malhotra et. al [20] reviews the concepts, design of Genetic Algorithm (GA) in the process control. The paper discusses the concept and design procedure of Genetic Algorithm as an optimization tool. Further, it explores the well-established methodologies of the literature to realize the workability and applicability of genetic algorithms for process control applications. Our objective is this paper is to review some of the best hybridization and compares each individual genetic operator with our proposed Hybridized Genetic Ant (HGA) algorithm and concludes the best suitable hybridization for fuzzy shortest path problem.

This paper is organized as follows. In section 2, some basic definitions and characteristics of fuzzy numbers are reviewed and discussed. Section 3 compares the characteristics and properties definition of triangular and trapezoidal fuzzy numbers along with its generalized forms. Section 4 briefs the network terminology. Section 5 explains the individual genetic operator of various hybridized genetic algorithms. Section 6 describes the proposed Hybridized Genetic Ant (HRA) algorithm which hybrids each individual genetic operators of the Genetic Algorithm (GA) along characteristics of ants. Section 7 deals with the comparison of proposed HGA with the reviewed hybrid genetic algorithms. And paper ends with the conclusion in section 8.

1. Basic fuzzy definitions

The basic definitions of some of the required concepts are reviewed [15] in this section.

2.1 Fuzzy set

Let X be an universal set of real numbers R, then a fuzzy set is defined as
A= {[x,$\mu_{\tilde{A}}$(x)], x ϵ X}

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

2.2 Definition of triangular fuzzy number

A fuzzy set$\tilde{A}$, defined on the universal set of real numbers R, is said to be a triangular fuzzy number if its membership function has the following characteristics:

1. $\mu_{\tilde{A}}$: R → [0,1] is continuous
2. $\mu_{\tilde{A}}(x)$ = 0 for all x∈ (-∞,a]∪[d,∞)
3. $\mu_{\tilde{A}}(x)$is strictly increasing on [a,b] and strictly decreasing on [c]

4. $\mu_{\tilde{A}}(x)$ =1 for all x∈[b,c] , where a < b < c

2.3 Definition of generalized triangular fuzzy number

A fuzzy set $\tilde{A}$, defined on the universal set of real numbers R, is said to be generalized triangular fuzzy number if its membership function has the following characteristics.

1. $\mu_{\tilde{A}}$: R → [0,w] is continuous
2. $\mu_{\tilde{A}}(x)$ = 0 for all x∈ (-∞,a]∪[d,∞)
3. $\mu_{\tilde{A}}(x)$is strictly increasing on [a,b] and strictly decreasing on [c]
4. $\mu_{\tilde{A}}(x)$ =w for all x∈ [b,c] , where 0 < w≤ 1

2.4 Definition of trapezoidal fuzzy number

A fuzzy set$\tilde{A}$, defined on the universal set of real numbers R, is said to be a trapezoidal fuzzy number if its membership function has the following characteristics:

1. $\mu_{\tilde{A}}$: R → [0,1] is continuous
2. $\mu_{\tilde{A}}(x)$ = 0 for all x∈ (-∞,a]∪[d,∞)
3. $\mu_{\tilde{A}}(x)$is strictly increasing on [a,b] and strictly decreasing on [c,d]
4. $\mu_{\tilde{A}}(x)$ =1 for all x∈ [b,c] , where a < b < c < d

2.5 Definition of generalized trapezoidal fuzzy number

A fuzzy set $\tilde{A}$, defined on the universal set of real numbers R, is said to be generalized trapezoidal fuzzy number if its membership function has the following characteristics.

1. $\mu_{\tilde{A}}$: R → [0,w] is continuous
2. $\mu_{\tilde{A}}(x)$ = 0 for all x∈ (-∞,a]∪[d,∞)
3. $\mu_{\tilde{A}}(x)$is strictly increasing on [a,b] and strictly decreasing on [c,d]
4. $\mu_{\tilde{A}}(x)$ =w for all x∈ [b,c] , where 0 < w≤ 1

2.6 Membership function of trapezoidal fuzzy number

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

$$\mu_{\tilde{A}}(\mathrm{x}) = \begin{cases} \frac{(x-a)}{(b-a)} a \le x \le b \\ 1 \qquad b \le x \le c \\ \frac{(x-d)}{(c-d)} c \le x \le d \end{cases}$$

2.7 Membership function of generalized trapezoidal fuzzy number

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

$$\mu_{\tilde{A}}(\mathrm{x}) = \begin{cases} \frac{w(x-a)}{(b-a)} a \le x \le b \\ w \qquad b \le x \le c \\ \frac{w(x-d)}{(c-d)} c \le x \le d \end{cases}$$

2.8 Membership function of triangular fuzzy number

A fuzzy number $\tilde{A} = (\mathrm{a,b,c})$ is known to be a triangular fuzzy number, if its membership function is given by

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

2.9 Membership function of generalized triangular fuzzy number

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

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

3. Comparison of fuzzy numbers

In this chapter, the fuzzy numbers in which the basic definitions are reviewed are compared. Triangular fuzzy numbers, generalized triangular fuzzy numbers, trapezoidal fuzzy numbers and generalized trapezoidal fuzzy numbers are compared in terms of their distance measure. The new form of distance measure of fuzzy numbers is given by [12].

3.1 Characteristics of triangular fuzzy number

Let $\tilde{A} = (a, b, c)$ be a triangular fuzzy number then

Rank $R(\tilde{A}) = \frac{(a+b+c)}{3}$ Mode $(\tilde{A}) = b$

Let centroid points be $(\alpha_A,\ \beta_A)$ and it is given by,

$\alpha_A = \frac{(a+b+c)}{3}$ and $\beta_A = \frac{1}{3}$

The distance measure between the triangular fuzzy numbers $\tilde{A}$ (a_1,b_1,c_1) and $\tilde{B}$ (a_2,b_2,c_2) using centroid points (α, β) of $\tilde{A}$ is given by

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

3.2 Characteristics of generalized triangular fuzzy number

Let$\tilde{A} = (a, b, c)$ be a triangular fuzzy number then

Rank $R(\tilde{A}) = \frac{w(a+b+c)}{3}$ Mode $(\tilde{A}) = wb$

Let centroid points be $(\alpha_A,\ \beta_A)$ and it is given by,

$\alpha_A = \frac{w(a+b+c)}{3}$ and $\beta_A = \frac{w}{3}$

The distance measure between the generalized triangular fuzzy numbers $\tilde{A}$ (a_1,b_1,c1;w_1) and $\tilde{B}$ (a_2,b_2,c_2;w_2) using centroid points (α, β) of $\tilde{A}$ is given by

$f_d(\tilde{A}, \tilde{B}) =$ max $\{|\alpha_{\tilde{A}} - \alpha_{\tilde{B}}|, |\beta_{\tilde{A}} - \beta_{\tilde{B}}|, |R(\tilde{A}) - R(\tilde{B})|, |w_1 - w_2|\}$

3.4 Characteristics of trapezoidal fuzzy number

Let $\tilde{A} = (a, b, c, d)$ be a trapezoidal fuzzy number then

Rank $R(\tilde{A}) = \frac{(a+b+c+d)}{4}$ Mode $(\tilde{A}) = \frac{(b+c)}{2}$

Divergence $D(\tilde{A}) = (d - a)$ Left spread $LS(\tilde{A}) = (b - a)$

Right spread $RS(\tilde{A}) = (d - c)$

Let centroid points be (α_A, β_A) and it is given by,

$\alpha_A = \frac{1}{3}\left[a_1 + a_2 + a_3 + a_4 - \frac{a_4a_3 - a_1a_2}{(a_4+a_3)-(a_1+a_2)}\right]$ and $\beta_A = \frac{1}{3}\left[\frac{a_3 - a_2}{(a_4+a_3)-(a_1+a_2)}\right]$

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

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

3.4 Characteristics of generalized trapezoidal fuzzy number

Let $\tilde{A} = (a, b, c, d; w)$ be a generalized trapezoidal fuzzy number then

Rank $R(\tilde{A}) = \frac{w(a+b+c+d)}{4}$ Mode $(\tilde{A}) = \frac{w(b+c)}{2}$

Divergence $D(\tilde{A}) = w(d - a)$ Left spread $LS(\tilde{A}) = w(b - a)$

Right spread $RS(\tilde{A}) = w(d - c)$

Let centroid points be (α_A, β_A) and it is given by,

$\alpha_A = \frac{1}{3}\left[a_1 + a_2 + a_3 + a_4 - \frac{a_4a_3 - a_1a_2}{(a_4+a_3)-(a_1+a_2)}\right]$ and $\beta_A = \frac{1}{3}\left[\frac{a_3 - a_2}{(a_4+a_3)-(a_1+a_2)}\right]$

The distance measure between the generalized trapezoidal fuzzy numbers $\tilde{A}$ (a_1,b_1,c1,d1;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 [2]

$f_d(\tilde{A}, \tilde{B}) = \max\{|\alpha_{\tilde{A}} - \alpha_{\tilde{B}}|, |\beta_{\tilde{A}} - \beta_{\tilde{B}}|, |R(\tilde{A}) - R(\tilde{B})|, |LS(\tilde{A}) - LS(\tilde{B})|, |RS(\tilde{A}) - RS(\tilde{B})|, |w_1 - w_2|\}$

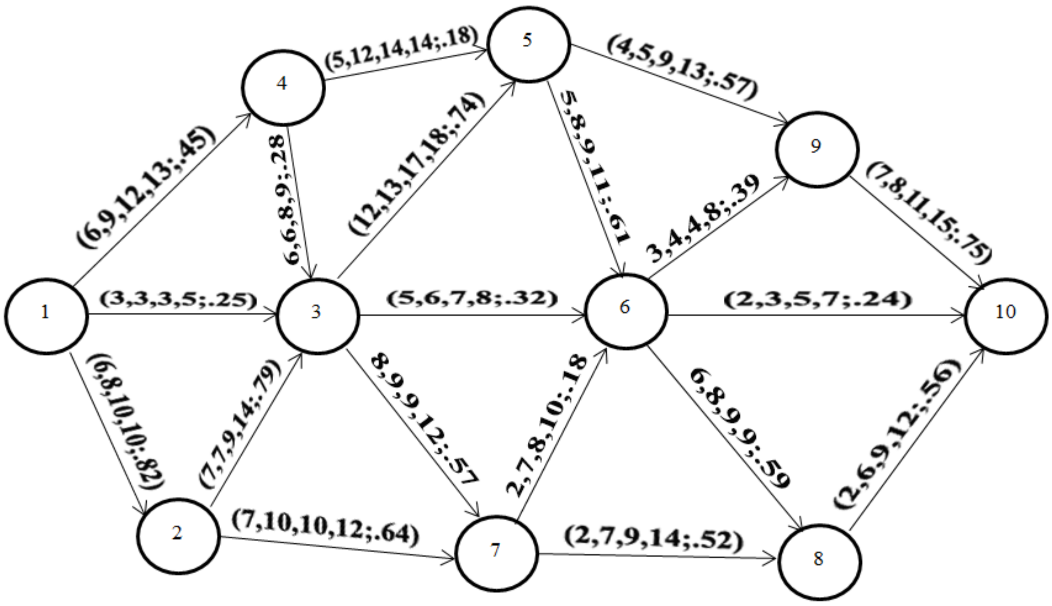
Table 3.1: Comparison of various fuzzy numbers in terms of distance measure

Term	Triangular	Generalized Triangular	Trapezoidal	Generalized Trapezoidal
General form	$\tilde{A} = (a, b, c)$	$\tilde{A} = (a, b, c; w)$	$\tilde{A} = (a, b, c, d)$	$\tilde{A} = (a, b, c, d; w)$
W	1	$0 \leq w \leq 1$	1	$0 \leq w \leq 1$
Centroid Points	Section 3.1	Section 3.2	Section 3.3	Section 3.4
Rank	Section 3.1	Section 3.2	Section 3.3	Section 3.4
Mode	Section 3.1	Section 3.2	Section 3.3	Section 3.4
Divergence	-	-	Section 3.3	Section 3.4
Left Spread	-	-	Section 3.3	Section 3.4
Right Spread	-	-	Section 3.3	Section 3.4
Distance Measure	Section 3.1	Section 3.2	Section 3.3	Section 3.4

The table 3.1 presents the comparison of triangular and trapezoidal fuzzy numbers in terms of the parameters of its distance measure. The comparative results clarifies that trapezoidal fuzzy numbers conveys more information than the triangular fuzzy numbers. In trapezoidal fuzzy number, generalized form comprises $0 \leq w \leq 1$ whereas normal form comprises of$w = 1$. Hence it is concluded that the generalized trapezoidal fuzzy numbers provide more contribution in the calculation of distance measure and it is used as parameters of fuzzy shortest path problem.

4. 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. $\widetilde{d_{ij}}$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.



5. Various hybridization methods

The various hybridization methods, which hybrids Genetic Algorithm (GA) with the Ant Colony Optimization (ACO) are reviewed in concentrating each individual operator in terms of hybridization. Zainudinet. al. [24] proposed Genetic Ant Colony Optimization (GACO) for Travelling Sales Man (TSM) problem. The background behind the hybridization is finding the operators of GA and ACO sharing same or related characteristics. Shenget. al. [21] proposed Pseudo-Parallel Genetic Algorithm – Ant Colony Optimization (PPGA-ACO) for Travelling Sales Man (TSM) problem in which pseudo-parallel represents the divide and conquer of populations into sub-problems. The hybridization involves pipelining of PPGA with ACO where results of PPGA are fed into ACO. Shang Gao et. al. [22] proposed Ant Colony Genetic Hybrid Algorithm (ACGHA) in solving Travelling Sales Man (TSM) problem in which genetic operators are proposed. The hybridization involves pipelining of ACO with GA where results of ACO are fed into GA. Aravindh et. al. [6] proposed a hybridization of Genetic Algorithm (GA) and Ant Colony Optimization (ACO) for solving shortest path problem in wireless mess networks. The hybridization involves pipelining of ACO with GA where results of ACO are fed into GA. Cauvery et. al. [8] proposed a hybridized GA and ACO algorithm for routing in dynamic networks. The hybridization is focused on the population initialization of genetic algorithm with forward and backward ants.

5.1 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$\mathrm{G} = \{\mathrm{V}, \mathrm{E}\}$. The vertex visited is represented by its own vertex number and the vertex which is not visited is not represented.

GACO by Zainudinet. al. [24] uses binary representation of chromosomes with the reason that it is more compatible to compare the proposed with the traditional algorithms.

5.2 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.

GACO by Zainudinet. al. [24] uses ants with the characteristics that it should traverse along the valid paths where valid paths are the paths that exist between the cities. Each at is initiated with the 1st city and next city that has to be traversed is calculated with the formula which comprises from information of visited and unvisited cities along the trials. Paths of each ant is updated when it reaches traverse all the cities.

PPGA-ACO by Shenget. al.[21] uses pseudo-parallel genetic algorithm where populations are divided into sub solutions. The population initialization is randomly initiated to the ants.

ACGHAby Shang Gao et. al. [22] uses Ant Colony Optimization as population initialization. Each ant is initialized with any of the existed city randomly. The next city that has to be traversed is controlled by the pheromone of the ants. The paths are updated when the ant traverses all the cities once.

Aravindhet. al. [6] uses Ant Colony Optimization as population initialization. Each ant is initialized with any of the existed city randomly. The next city that has to be traversed is controlled by the pheromone of the ants. The paths are updated when the ant traverses all the cities once.

Cauveryet. al. [8] proposed population initialization operation with Forward and

Backward ants (FA and BA). Each ant is initialized with the source node and said to be FA. The FAs have characteristics that it should traverse randomly towards existing nodes without forming cycles and update. When FAs reaches destination node or found no link, it produce BA and update the path traversed to it and kill itself. The BAs have characteristics that it should follow the path traversed by FAs. When it reaches source node, updates the information and kill itself. By the combination of FAs and BAs, the population initialization is carried out.

5.3 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 [23].
PPGA-ACO by Shenget. al.[21] uses double selection procedure where the selected sub-population is evolved by crossover-mutation pair and again newly formed sub-population is selected for another evolution.
Aravindhet. al. [6] uses Roulette Wheel Selection (RWS) as the selection operator.
Cauveryet. al. [8] uses Roulette Wheel Selection (RWS) as the selection operator.

5.4 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 [23].

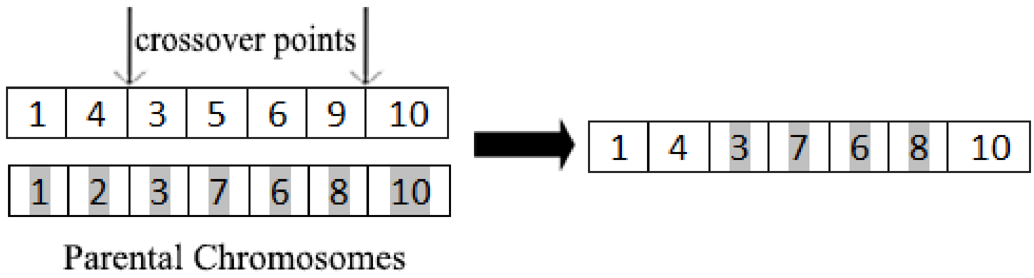


Fig 4.1: Two – Point Crossover operation

GACO by Zainudinet. al. [24] uses uniform random crossover with the rate 0.9.
PPGA-ACO by Shenget. al.[21] uses double crossover operation procedure where already evolved new sub-population is again made to the evolution by crossover-mutation pair.
ACGHAby Shang Gao et. al. [22] proposed ant colony crossover where it uses the paths with least distance between the cities. In the parental chromosome, the path between the cities having least cost is given more priority in reproducing the

offspring. When the connection is not suitable, nearest cities are chosen.
Aravindhet. al. [6] uses single point crossover in which the crossover point is selected randomly and the order of the parental chromosomes is also made to random.
Cauveryet. al. [8] uses single or two point crossover with the rate of 0.6.

5.5 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. The integer mutation may be uniform, insertion, interchanging, boundary, non – uniform and others [2].

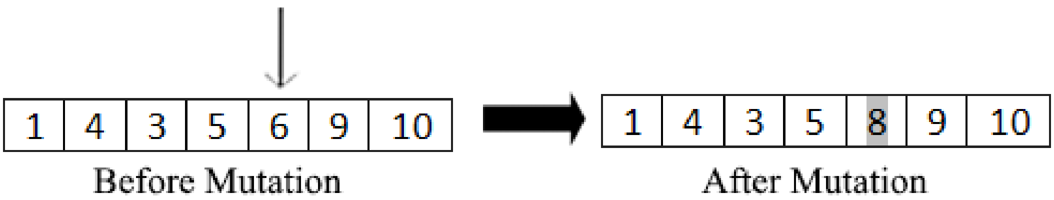


Fig 4.2: Mutation operation

GACO by Zainudinet. al. [24] uses genetic mutation with the rate of 0.1.
PPGA-ACO by Shenget. al.[21] uses double mutation operation procedure where already evolved new sub-population is again made to the evolution by crossover-mutation pair.
ACGHA by Shang Gao et. al. [22] proposed four mutation operations which swaps two integers from the parental chromosome, select a city randomly and swap the city with next city, reverse all cities between the chosen random cities and select two cities randomly and place the 1st city after the 2nd city which are selected randomly.
Aravindhet. al. [6] proposed a new insertion mutation operation where the repeated city in the parental chromosome is replaced with the missed city. The resultant offspring contains all the cities in the network.
Cauveryet. al. [8] uses insertion as mutation operation with the rate of 0.01.

5.6 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.
PPGA-ACO by Shenget. al.[21] uses random initialization by ants in each and every generation. Thus next generation should not depend on the previous generation.
ACGHAby Shang Gao et. al. [22] uses ACO algorithm with the sequence with the

GA in which the elitism is controlled by ants of ACO.
Cauveryet. al. [8] uses dynamic network and every time the forward and backward ants are responsible for elitism. Thus next generation should not depend on the previous generation.

5.7 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.

6. Proposed hybridized genetic ant (HGA) algorithm [3]

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.

6.1 Population initialization using initializing ants (IA)

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 [4].
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.

6.2 Roulette ant wheel selection (RAWS)

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.

6.3 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.

Crossover – mutation 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 evolution.

7. Comparison of hybridized algorithms

The genetic operators of various hybridization algorithms are reviewed in previous sections. The proposed HGA algorithm is also reviewed. These various hybridization algorithms are compared with proposed Hybridized Genetic Ant (HGA) [3] in terms of hybridization. The comparison parameters are availability of genetic operators, hybridization of genetic operators, health factor of chromosome in genetic operators, novelty in genetic operators and the availability of characteristics of ants in genetic operators. The results of the comparison of each term are tabulated.

Table 7.1: Comparison of various hybridized algorithms in terms of availability of each genetic operator

Algorithm	Population Initialization	Selection	Crossover	Mutation	Percentage
GACO [15]	✓	-	✓	✓	75
PPGA-ACO [16]	✓	-	✓	✓	75
ACGHA [17**]**	✓	✓	✓	✓	100
Aravindh et. al. [18]	✓	✓	✓	✓	100
Cauvery et. al. [19]	✓	✓	✓	✓	100
Proposed HGA [22]	✓	✓	✓	✓	100

Table 7.1 shows the existence of genetic operators. Merely all hybridization algorithms use the genetic operators. The other terms are compared as follows.

Table 7.2: Comparison of various hybridized algorithms whether the method is hybridized in each genetic operator

Algorithm	Population Initialization	Selection	Crossover	Mutation	Description	Percentage
GACO [15]	Hybrid	-	-	-	ACO	25
PPGA-ACO [16]	Hybrid	-	-	-	PPGA-ACO	25
ACGHA [17]	Hybrid (ACO)	-	Hybrid (Proposed)	-	ACO and Proposed	50
Aravindh et. al. [18]	Hybrid	-	-	-	ACO	25
Cauvery et. al. [19]	Hybrid	-	-	-	FAs and Bas	25
Proposed HGA [22]	Hybrid (IA)	Hybrid (RAWS)	Hybrid (PAs and SAs)	Hybrid	Proposed	100

Table 7.2 presents whether each genetic operator is hybridized with Genetic Algorithm (GA) and Ant Colony Optimization (ACO) in various hybridized algorithms. Every hybridized algorithm possesses hybridization in population initialization operation. ACGHA [22] possesses hybridization in population initialization and crossover operation. The only hybridized algorithm that possesses hybridization in each individual genetic operator is the proposed HGA [3] algorithm.

Table 7.3: Comparison of various hybridized algorithms in terms of health factor (continuous path) of the chromosome in each genetic operator

Algorithm	Population Initialization	Selection	Crossover	Mutation	Percentage
GACO [15]	Healthy	Healthy	Healthy / Unhealthy	Healthy / Unhealthy	50
PPGA-ACO [16]	Healthy	Healthy	Healthy / Unhealthy	Healthy / Unhealthy	50
ACGHA [17]	Healthy	Healthy	Healthy / Unhealthy	Healthy / Unhealthy	50
Aravindh et. al. [18]	Healthy	Healthy	Healthy / Unhealthy	Healthy / Unhealthy	50
Cauvery et. al. [19]	Healthy	Healthy	Healthy / Unhealthy	Healthy / Unhealthy	50
Proposed HGA [22]	Healthy	Healthy	Healthy	Healthy	100

Table 7.3 demonstrate the health factor of the chromosomes in each genetic operator in various hybridization algorithms. Health factor is nothing but the existence of the path that is described by the chromosomes. The unhealthy path is discontinuous. The health factor can be sustained by nature of the algorithm or the certain criteria that possess the health of the chromosome.
Almost all the hybridized genetic algorithms having population initialization operation and selection operation produces healthy chromosomes. The proposed HGA [3] alone reproduce healthy chromosomes in each and every genetic operator.

Table 7.4: Comparison of various hybridized algorithms whether the methodology is novelfor each genetic operator

Algorithm	Population Initialization	Selection	Crossover	Mutation	Percentage
GACO [24]	Novel	-	-	-	25
PPGA-ACO [21]	-	Novel	Novel	Novel	75
ACGHA [22]	Novel	-	Novel	Novel	75
Aravindh et. al. [6]	Novel	-	-	-	25
Cauvery et. al. [8]	Novel	-	-	-	25
Proposed HGA [3]	Novel	Novel	Novel	Novel	100

Table 7.4 clarifies the introduction of novelty in genetic operators of various hybridized genetic algorithms. Most of the hybridized genetic algorithms introduce a novel population initialization that hybrids both GA and ACO in sequence manner in which results of one algorithm is fed into the other algorithm.
PPGA-ACO [21] introduced novelty in population initialization operation, crossover operation and mutation operation and these novel methods are not always hybridization. The proposed HGA [3] introduced novel and hybrid methodologies for every genetic operator.

Table 7.5: Comparison of various hybridized algorithms whether characteristics of ants is used in each genetic operator

Algorithm	Population Initialization	Selection	Crossover	Mutation	Description	Percentage
GACO [15]	✓	-	-	-	-	25
PPGA-ACO [16]	✓	-	-	-	-	25
ACGHA [17]	✓	-	✓	-	-	50
Aravindh et. al. [18]	✓	-	-	-	-	25
Cauvery et. al. [19]	✓	-	-	-	-	25
Proposed HGA []	✓	✓	✓	✓	✓	100

Table 7.5 explains the availability of characteristics of ants in each genetic operator for various hybridized genetic algorithms. The characteristics of ants indirectly show the availability of hybridization but hybridization can be without the characteristics of ants.

8. Conclusion

Fuzzy shortest path problem that has higher degree of applications which overcomes the uncertainty of real numbers in real time applicationsis hybridized with Genetic Algorithm and Ant Colony Optimization in tracking the algorithm for next generation. The various fuzzy numbers are reviewed and compared in terms of the distance measure. The comparison concludes that generalized trapezoidal is more suitable and possess more information about position in terms distance measure. The hybridization is explained and various hybridized genetic algorithms are reviewed along with the proposed HGA algorithm. The hybridization is achieved in various forms such as sequencing the algorithms, feeding the results of one algorithm to the other and hybrid any of the genetic operators with the characteristics of ants. In case of proposed method, the objective to concentrate each genetic operator and hybrids every individual genetic operator with the characteristics is achieved. The reviewed hybridized genetic algorithms are compared with the proposed HGA in terms of the parameters of hybridization such as availability of genetic operators, hybridization in each genetic operator, health factor of chromosome in each genetic operator, novelty of methodology in each genetic operator and the availability of characteristics of ants in each genetic operator. The comparison results that the proposed method has cent percentage in all the comparative terms. Hence the review results that proposed HGA is not only good at the results [3] but also provide best in the terms of hybridization.

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', International Journal of Applied Mathematics & Statistical Sciences, pp 17-27, January 2015.

[4]. V.Anusuya and R.Kavitha, 'Roulette Ant Wheel Selection (RAWS) for genetic algorithm – fuzzy shortest path problem', International Journal of Mathematics and Computer Applications Research, vol 5,Issue2, April 2015, 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 and Research, pp 2074-2081, Vol 4, Issue2,Feb 2015.

[6]. S.Aravindh, Mr. G. Michael, 'Hybrid of Ant Colony Optimization and Genetic Algorithm for Shortest path in Wireless Mesh Networks' Journal of Global Research in Computer Science, pp. 31-34, Vol. 3, January 2012.

[7]. Blue, M., Bush, B. and Puckett, J., Unified approach to fuzzy graph problems, Fuzzy Sets and Systems 125, pp. 355–368, 2002.

[8]. F.A Cauvery N K, S.B. Dr K V Viswanatha, 'Routing in Dynamic Network using Ants and Genetic Algorithm,' IJCSNS International Journal of Computer Science and Network Security, pp. 194-200 Vol.9, March 2009.

[9]. Dubois, D. and Prade, H., Fuzzy Sets and Systems: Theory and Applications, New York, Academic Press, 1980.

[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]. 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.

[13]. 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.

[14]. 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.

[15]. Kaufmann A., Gupta, MM., Fuzzy mathematical models in engineering andmanagement science. Elsevier Science Publishers, Amsterdam, Netherlands, 1988.
[16]. Klein, C.M., Fuzzy shortest paths, Fuzzy Sets and Systems 39, pp. 27–41, 1991.
[17]. Lin, K. and Chen, M., The fuzzy shortest path problem and its most vital arcs, Fuzzy Sets and Systems 58, pp. 343–353, 1994.
[18]. 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.
[19]. MisRigi C.R, Ms. AncyAntony.C, Ms.ShalinuSaju, Mr.SachinPadikkal, 'Shortest path routing algorithm in wireless sensor network – A Review,' International Journal Of Scientific Research And Education, Vol. 2, pp. 407-413 (2014).
[20]. Rahul Malhotra, Narinder Singh, Yaduvir Singh, 'Genetic Algorithms: Concepts, Design for Optimization of Process Controllers,' Computer and Information Science, Vol. 4, pp. 39-54, March 2011.
[21]. Sheng Li, Huiqin Chen, Zheng Tang, 'Study of Pseudo-Parallel Genetic Algorithm with Ant Colony Optimization to Solve the TSP,' IJCSNS International Journal of Computer Science and Network Security, pp.72-79, VOL.11 No.3, March 2011.
[22]. 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.
[23]. Sivanandam S.N. &Deepa S.N. (2008): Introduction to Genetic Algorithms, 2008.
[24]. ZainudinZukhri 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, Sept. 2013.