

# Multihop Routing Optimization in Communication Networks Using Genetic Algorithms

Shilpa Sirikonda

Department of Electrical Engineering & Computer Science

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Committee

Dr. James P. G. Sterbenz (Chair)

Dr. Alexander M. Wyglinski (Co-Chair)

Dr. Victor Frost

# Outline

- Introduction
- Genetic Algorithms (GA) Overview
- GA Operators
- GA Procedure
- Proposed Approach
- Derivation of Fitness Function
- Simulation Results
- Research Contribution
- Conclusion
- Future Work

# Introduction

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# Introduction

- Challenges faced by multihop networks
  - Finding the best path between end nodes
  - Achieving all the desired metrics simultaneously
- For example, it is difficult to find a path
  - Minimizing both the number of hops and BER
- Earlier GAs were used for single metric optimization
- Proposed approach
  - Multi-objective GA optimization is proposed
  - Simultaneously optimizes five conflicting metrics

# Genetic Algorithms (GA) Overview

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# Genetic Algorithms (GA) Overview

- GA is a random search technique
  - Searches for the best fit based on a 'fitness function'
- Search space
  - Population of binary coded configurations
  - Configurations are also called 'chromosomes' or 'strings'
- Fitness function
  - Evaluated at each individual point in the search space
  - Repeated over several generations
  - A configuration is found that meets the desired objective

# Genetic Algorithms (GA) Overview

- Configurations of next generation
  - Selected through a genetic transformation process
  - Transformation done using genetic operators
- Genetic Operators
  - Reproduction
  - Crossover
  - Mutation

# Genetic Operators

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# Genetic Operators

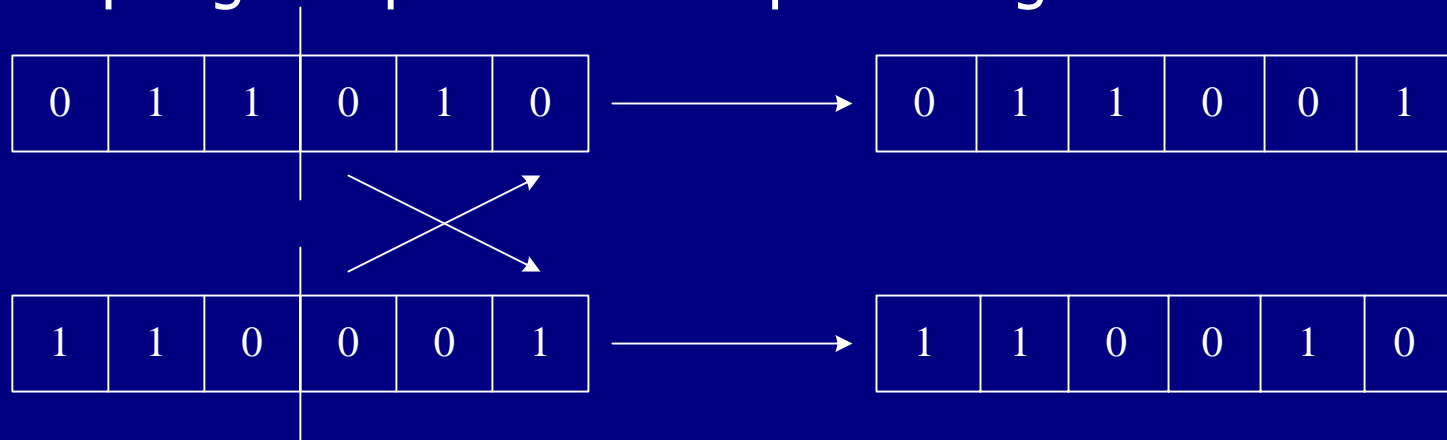
## Reproduction

- Individual configurations
  - Copied directly to the next generation
  - Based on their fitness function values
- Configurations with a higher value of fitness function
  - Have higher probability of contributing
  - Usually one or more off-spring copied to next generation
  - Based on biased roulette wheel selection

# Genetic Operators

## Crossover

- Recombination operator
- Combines subparts of two parent chromosomes
- Offspring has parts of both parents' genetic material



PARENT CHROMOSOMES

NEW OFFSPRING

# Genetic Operators

## Mutation

- Mutation introduces variations into the chromosome
- Randomly alters the value of a string position
- In the string shown below second bit is mutated



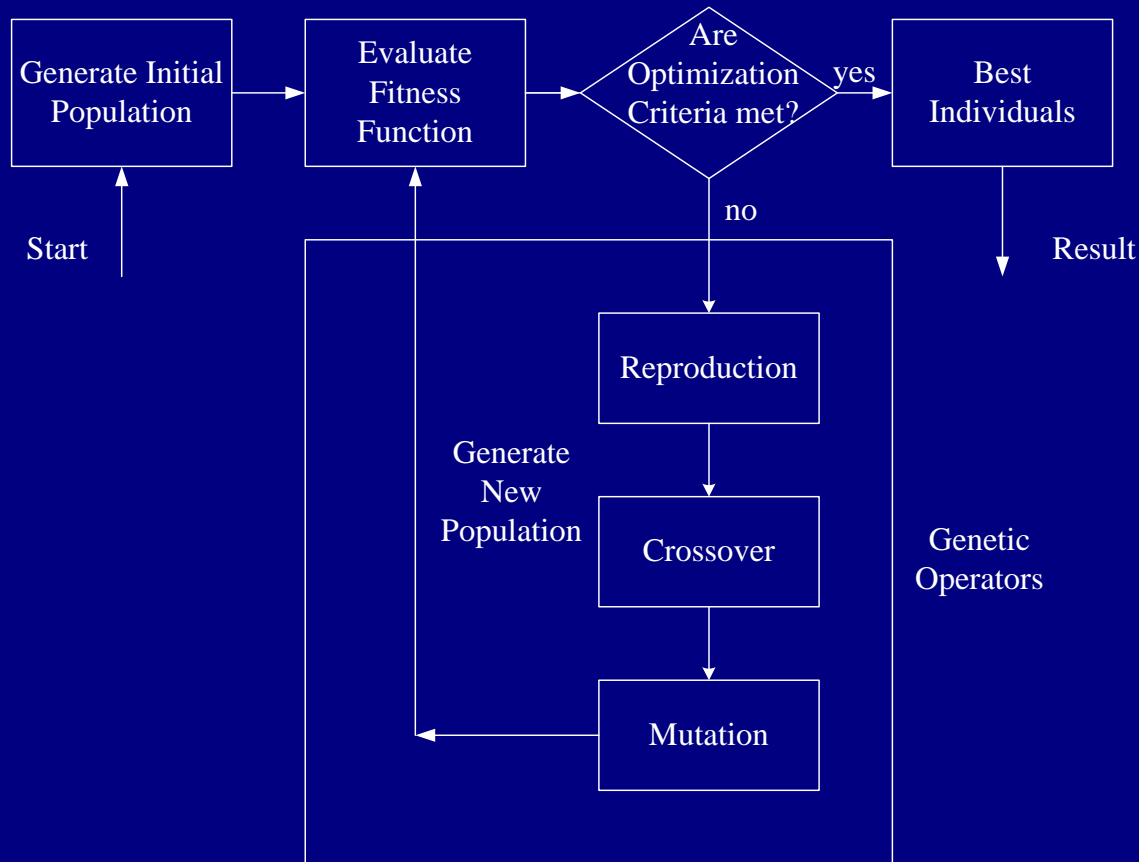
PARENT CHROMOSOME

MUTATED CHROMOSOME

# GA Procedure

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# GA Procedure



# Proposed Approach

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# Proposed Approach

- Objective of the project
  - Devise an optimization algorithm based on GAs
  - Search for best possible path between end nodes
- The metrics used in determining the best path
  - minimum end-to-end distance
  - minimum latency
  - minimum bit error rate (BER)
  - minimum number of hops
  - maximum bandwidth

# Derivation of Fitness Function

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# Derivation of Fitness Function

- Each node is a given binary representation
- Chromosome
  - The path with group of binary represented nodes
  - Ex: 001 | 100 | 101 – Chromosome
- Derivation of fitness function
  - Calculate each metric over a particular path
  - Evaluate overall fitness score
- Final fitness score
  - Weighted sum of the individual metrics
  - Path with maximum fitness score is the best path

# Derivation of Fitness Function

## Example

- Binary representation for 5 node distribution
  - 000, 001, 010, 011, 100 - used for representing 5 nodes
  - 101, 110, 111 - don't care nodes (do not exist in distribution)
  - Don't care nodes keep the chromosome length constant

- Fitness calculation for GA generated example path

Ex:           000 | 001 | 100 | 101 | 010

Source | Hops in between | Destination

- Chromosome is intermediate path without end nodes

001 | 100 | 101

∅

Ex: Here hop count = 3

# Derivation of Fitness Function

## End-to-End Distance (meter)

$D$  is represented as the end-to-end distance for a path

$$D = \sum_{i=0}^{N-1} d_i$$

$d_i$  - Distance between  $i^{th}$  and  $(i + 1)^{th}$  node

$N$  - Number of nodes in the distribution

$$\mathbb{D} = \frac{D}{P}$$

$\mathbb{D}$  - Normalized distance

$P$  - Perimeter of the service area

# Derivation of Fitness Function

## End-to-End Latency

$L$  is represented as end-to-end latency for a path

$$L = \sum_{i=0}^{N-1} \ell_i$$

$\ell_i$  - Latency of  $i^{th}$  node in a path

$N$  - Number of nodes in the distribution

$$\mathbb{L} = \frac{L}{N\ell_{max}}$$

$\mathbb{L}$  - Normalized latency

$\ell_{max}$  - Maximum latency of node distribution

# Derivation of Fitness Function

## Bit Error Rate

$B$  is represented as aggregate BER over a path

$$B = \sum_{i=0}^{N-1} b_i$$

$b_i$  - BER of the link between  $i^{th}$  and  $(i + 1)^{th}$  node

$N$  - Number of nodes in the distribution

$$\mathbb{B} = \frac{B}{\max(B)}$$

$\mathbb{B}$  - Normalized BER

$\max(B)$  - Maximum BER of the node distribution

# Derivation of Fitness Function

## Bit Error Rate

$b_i$  is BER of the link between  $i^{th}$  and  $(i + 1)^{th}$  node

$$b_i = Q(\sqrt{2\gamma})$$

$$\gamma = \frac{C_{pl} \cdot P_t}{N_v} \text{ is signal-to-noise ratio}$$

$C_{pl}$  - Constant of path loss which is proportional to

$$\frac{1}{\text{distance}^2}$$

$P_t$  - Power transmitted

$N_v$  - Noise variance

# Derivation of Fitness Function

## Number of Hops

$H$  is one less than the number of nodes in a path

$$\mathbb{H} = \frac{H}{N-1}$$

$N$  - Total number of nodes in the distribution

$\mathbb{H}$  - Normalized hop count

# Derivation of Fitness Function

## Bandwidth (Rate)

$R$  is minimum link bandwidth over all links in a path

$$R = \min(r_i)$$

$r_i$  - Link bandwidth in a particular path

$$\mathbb{R} = \frac{R}{r_{\max}}$$

$\mathbb{R}$  - Normalized bandwidth

$r_{\max}$  - Maximum bandwidth of the node distribution



# Derivation of Fitness Function

$$S = W_D(1 - \mathbb{D}) + W_L(1 - \mathbb{L}) + W_B(1 - \mathbb{B}) + W_H(1 - \mathbb{H}) + W_R\mathbb{R}$$

$S$  - Fitness score of a particular path

$D$  - Normalized end-to-end distance

$L$  - Normalized latency

$B$  - Normalized bit error rate

$H$  - Normalized number of hops

$R$  - Normalized bandwidth.

$W_D, W_L, W_B, W_H, W_R$  are the weights assigned to each metric

# Simulation Results

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# Simulation Results

- Generated random  $(x, y)$  locations for nodes
- Exhaustive search
  - Generated all possible paths between end nodes
  - Calculated fitness score over all possible paths
  - Path which yields high fitness score is chosen best path
- GA search
  - Calculated fitness score over paths chosen in generation I
  - New paths (chromosomes) generated using GA operators
  - Fitness score is calculated over new paths
  - Repeated over 150 generations to find path with high score
  - Crossover rate = 0.6 Mutation rate = 0.001 Population = 50

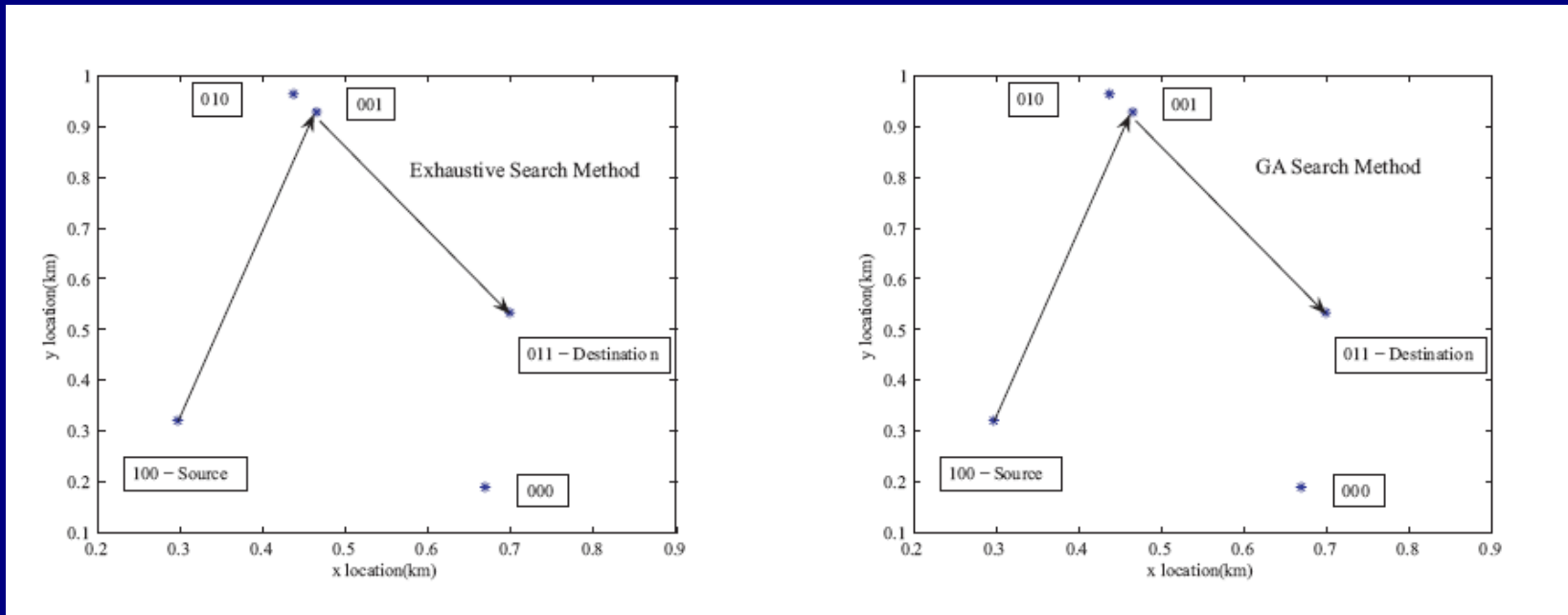
# Simulation Results

## Test Cases

- Testing with various GA weight vectors  
 $(W_D, W_L, W_B, W_H, W_R)$ 
  - $(0.2, 0.2, 0.2, 0.2, 0.2)$  – Equally weighing
  - $(1, 0, 0, 0, 0)$  – Minimizing distance
  - $(0, 1, 0, 0, 0)$  – Minimizing latency
  - $(0, 0, 1, 0, 0)$  – Minimizing BER
  - $(0, 0, 0, 1, 0)$  – Minimizing hop count
  - $(0, 0, 0, 0, 1)$  – Maximizing bandwidth
- Variation of fitness score over generations
- GA over a typical network

# Simulation Results

## Exhaustive Search vs. GA Search

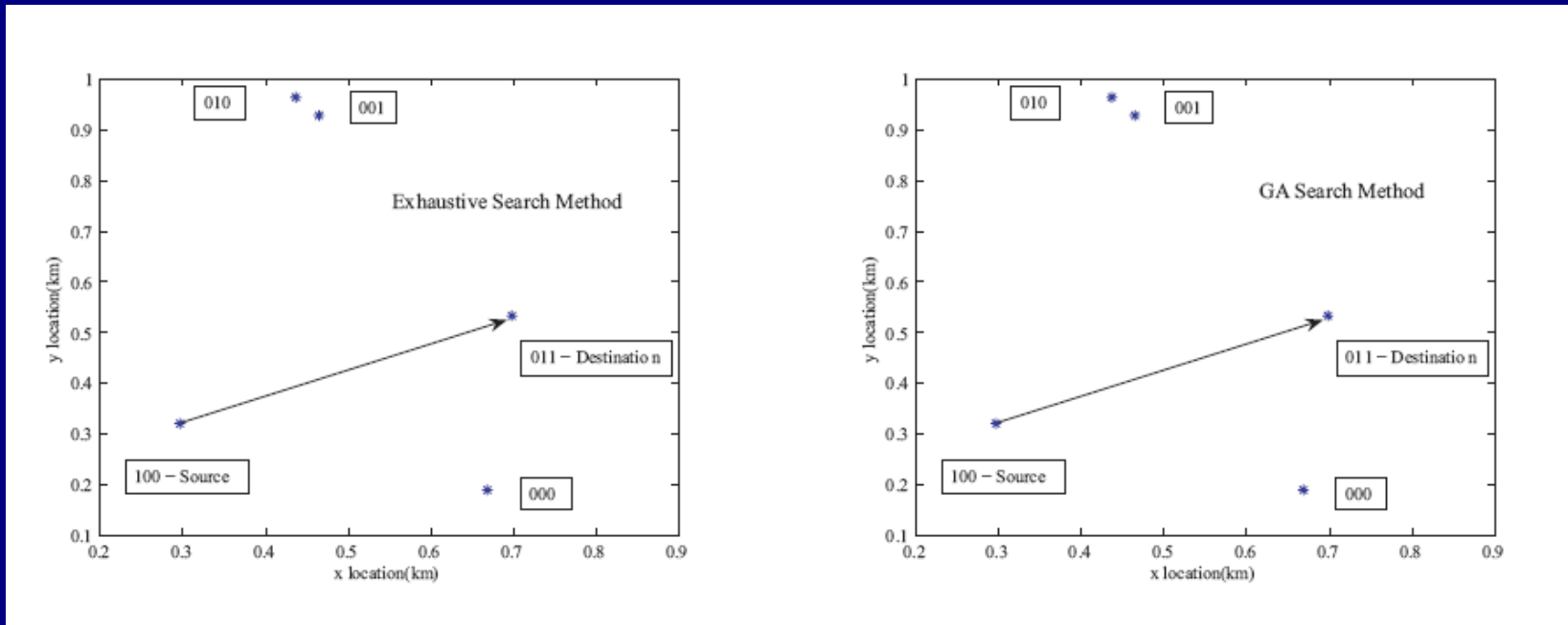


Best Path Equally Weighing Metrics

$$(W_D, W_L, W_B, W_H, W_R) = (0.2, 0.2, 0.2, 0.2, 0.2)$$

# Simulation Results

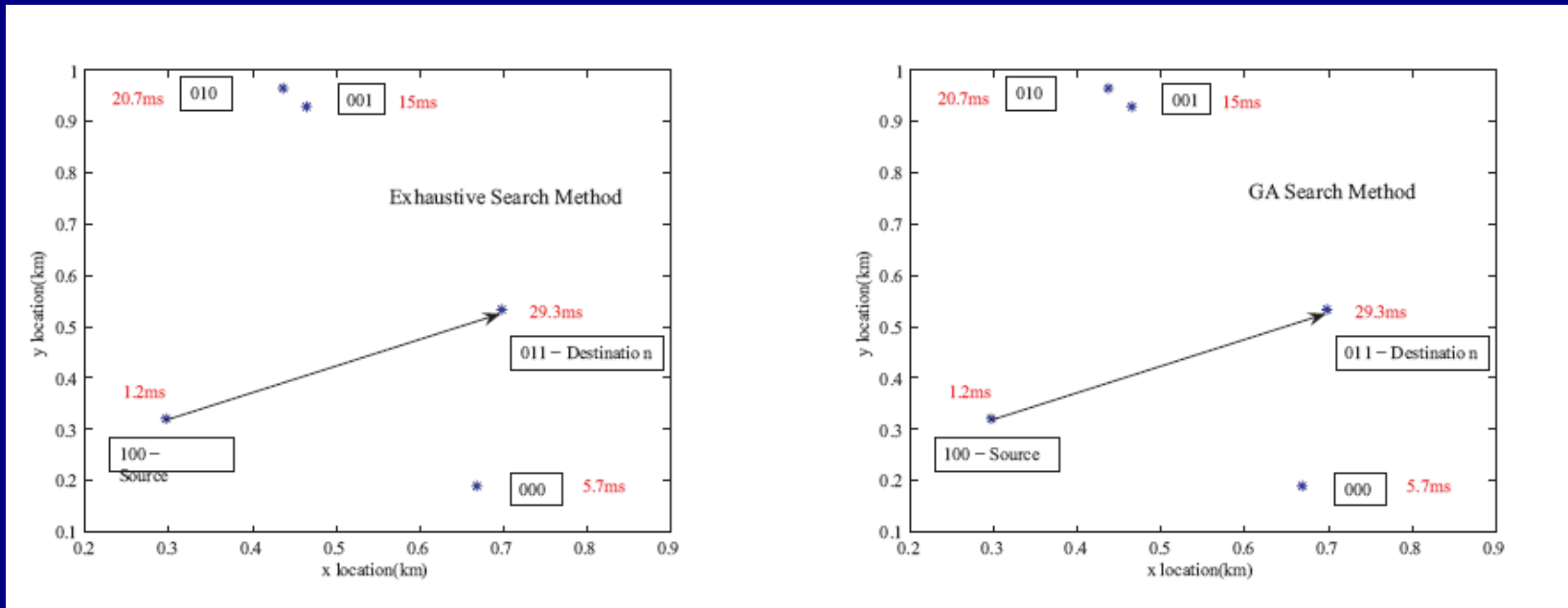
## Exhaustive Search vs. GA Search



Best Path Minimizing the Distance  
 $(W_D, W_L, W_B, W_H, W_R) = (1, 0, 0, 0, 0)$

# Simulation Results

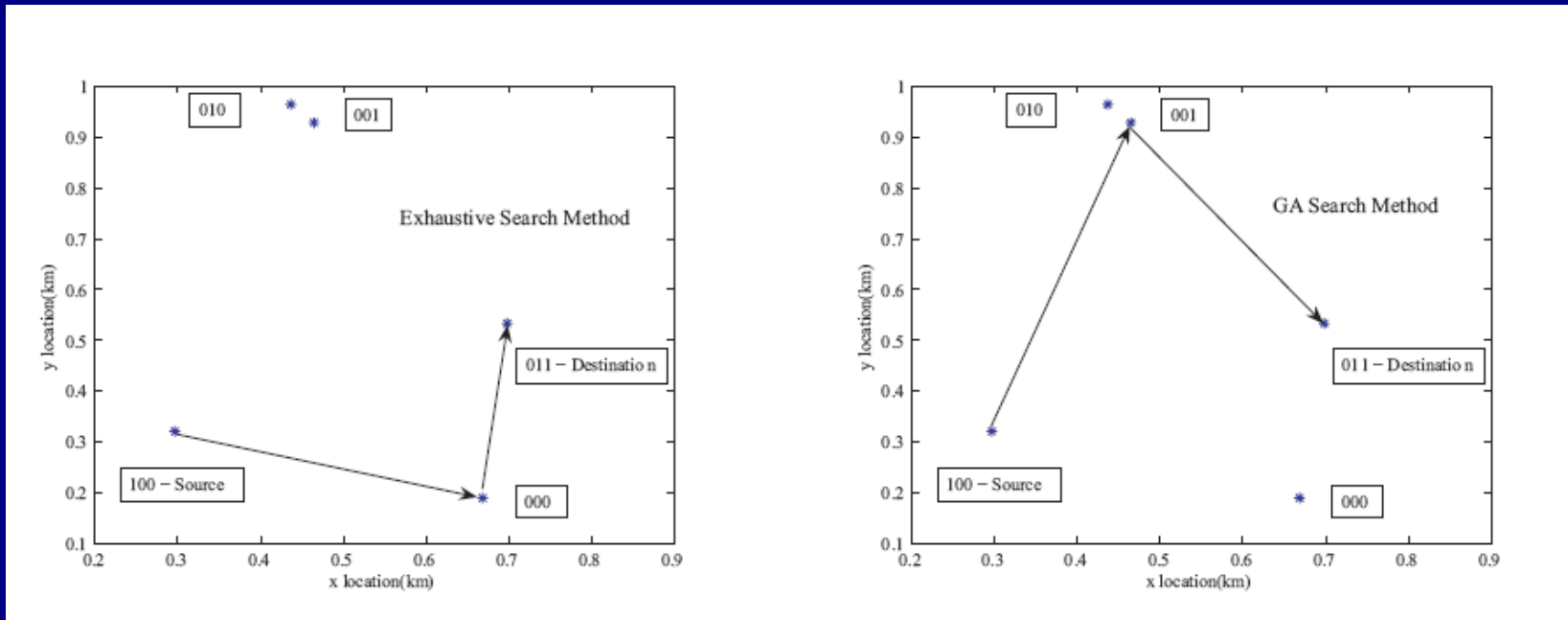
## Exhaustive Search vs. GA Search



Best Path Minimizing Latency  
 $(W_D, W_L, W_B, W_H, W_R) = (0, 1, 0, 0, 0)$

# Simulation Results

## Exhaustive Search vs. GA Search



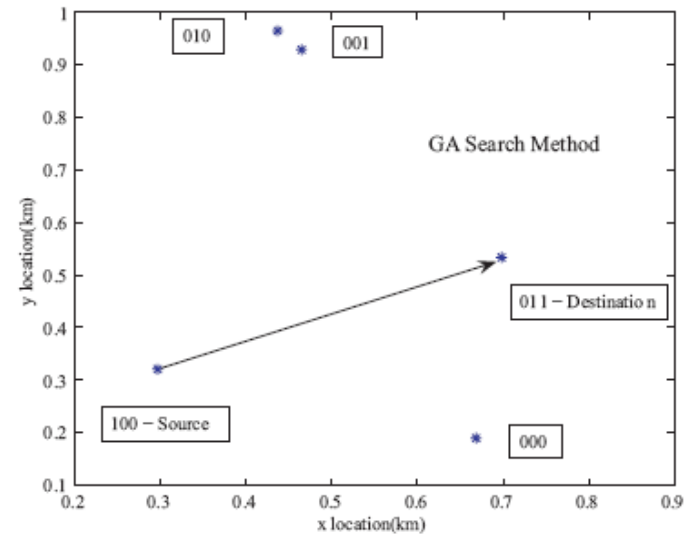
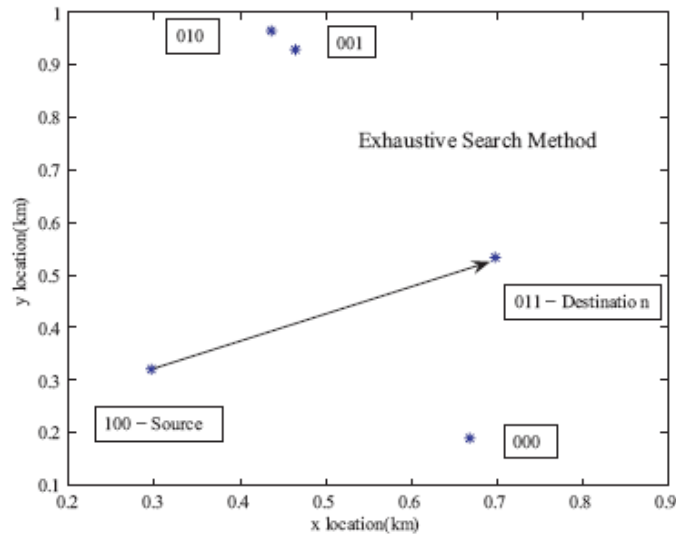
Best Path Minimizing BER

$$(W_D, W_L, W_B, W_H, W_R) = (0, 0, 1, 0, 0)$$



# Simulation Results

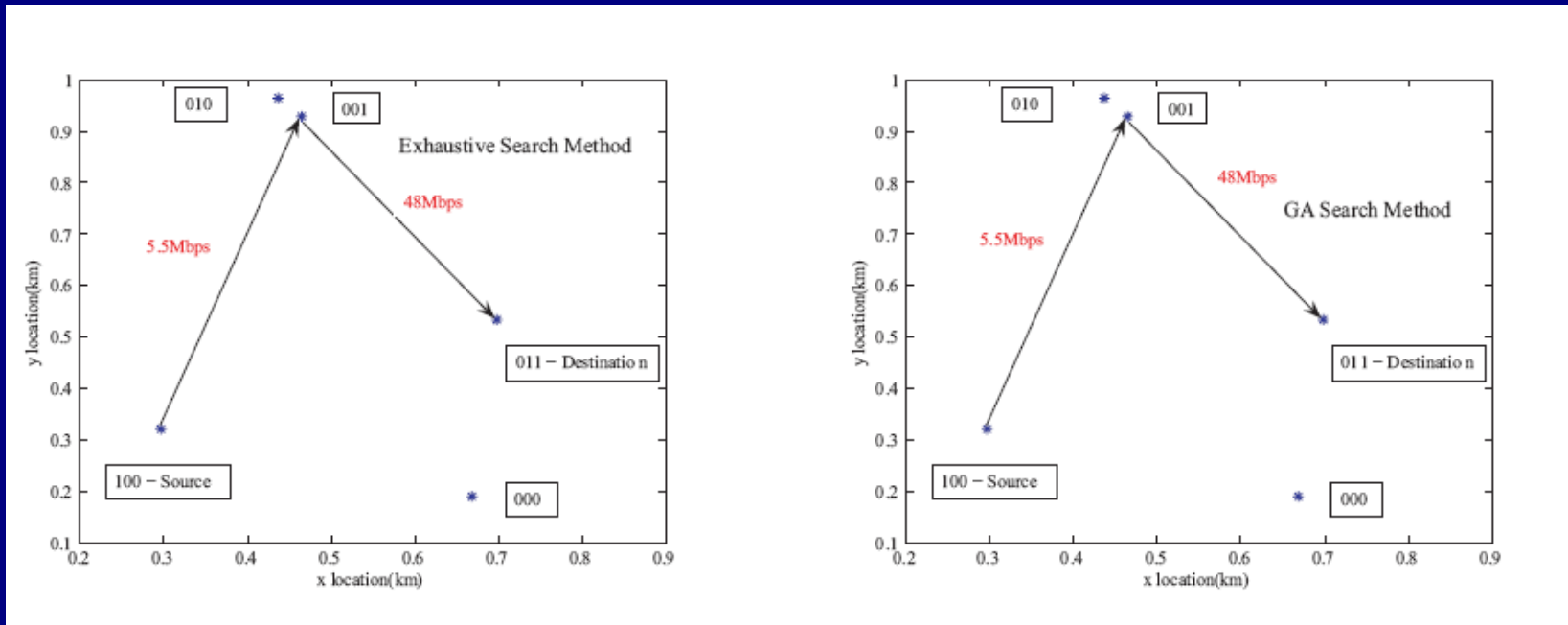
## Exhaustive Search vs. GA Search



Best Path Minimizing Number of Hops  
 $(W_D, W_L, W_B, W_H, W_R) = (0, 0, 0, 1, 0)$

# Simulation Results

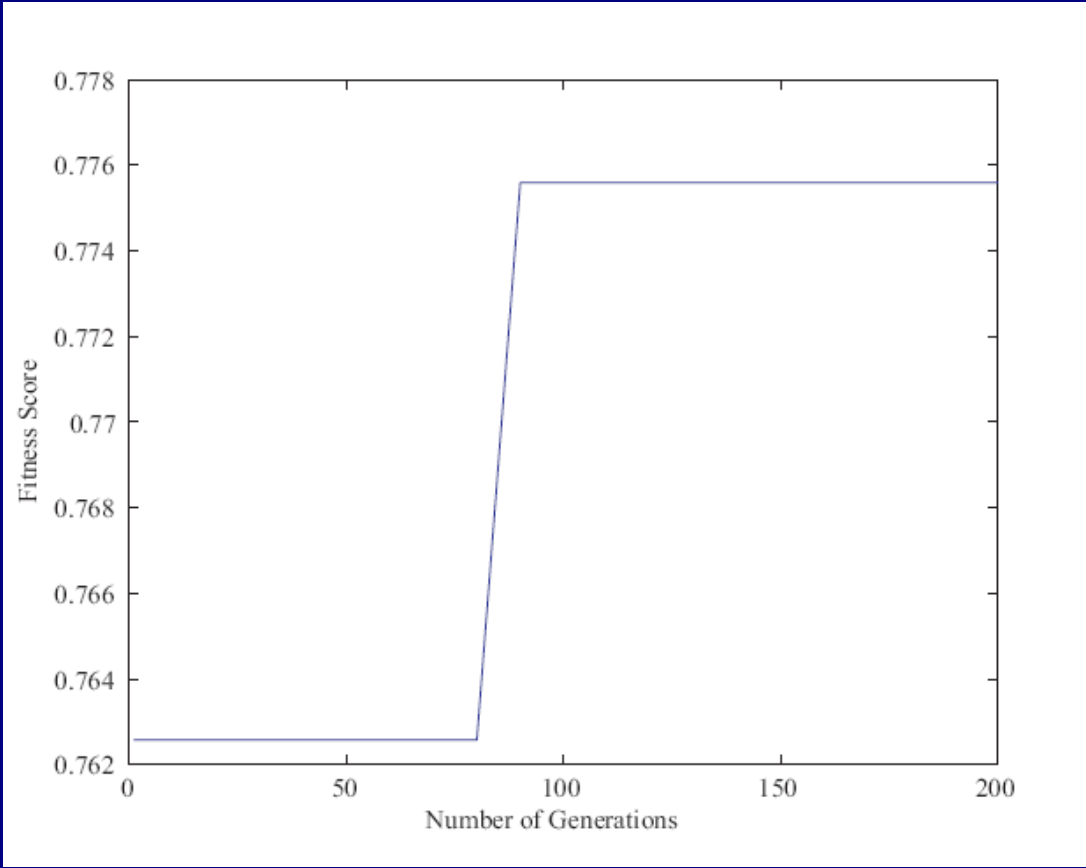
## Exhaustive Search vs. GA Search



Best Path Maximizing Bandwidth  
 $(W_D, W_L, W_B, W_H, W_R) = (0, 0, 0, 0, 1)$

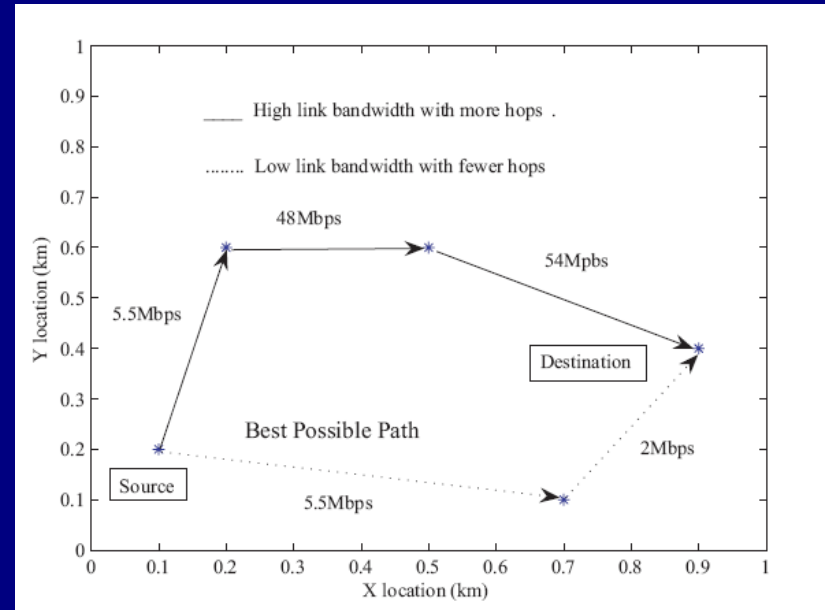
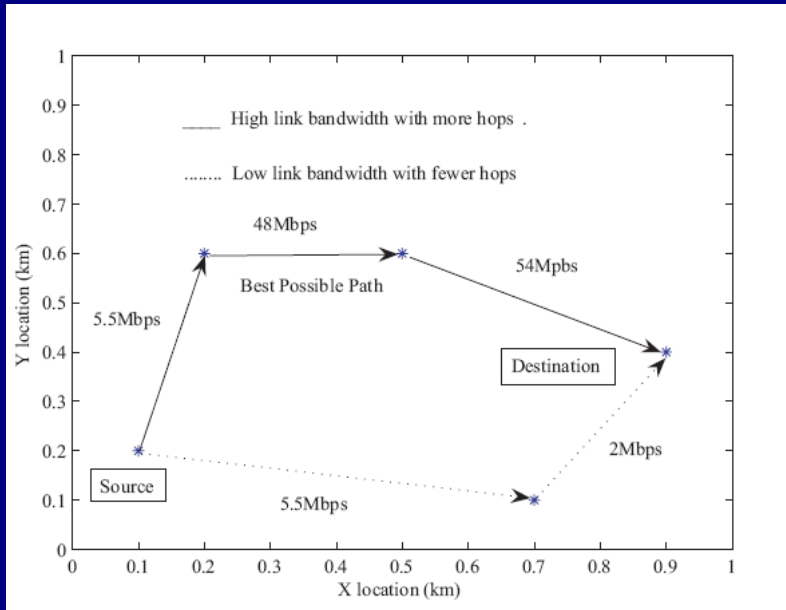
# Simulation Results

## Variation of Fitness Score Over Generations



# Simulation Results

## GA Performance Over a Typical Network



$(0, 0, 0, 0.2, 0.8)$

$(W_D, W_L, W_B, W_H, W_R)$

$(0, 0, 0, 0.5, 0.5)$

$(W_D, W_L, W_B, W_H, W_R)$

# Research Contribution

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# Research Contribution

- Node distribution
  - Generated using 'C' numerical recipes
- Exhaustive search
  - Code written in C
- GA framework has been implemented
  - Sga-c source code available at IlliGAL Institute  
<http://www.illigal.uiuc.edu/web/>
  - Modified to work for the proposed approach
- Fitness function for multi-objective optimization

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# Conclusion

- The proposed framework
  - Useful for multiple metric optimization in routing
  - Weight factors can be adjusted to match user's requirement
- Best path
  - GA results compare favorably with exhaustive search
- Exhaustive search vs. GA search
  - GA takes lesser time compared to exhaustive search
  - GA searches for best path using fewer configurations
  - Exhaustive search evaluates fitness over all configurations



# Future Work

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## Future Work

- Introduce time-variant node metrics
- Unreachable nodes
- More network topologies
- Larger networks
- Multiple source and destination nodes

Thank You

Questions???