

Introduction

Mobility
Management

GPSO

HNN+BD

Experiments

Conclusions

New Research in Nature Inspired Algorithms for Mobility Management in GSM Networks



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Introduction

Mobility Management

GPSO

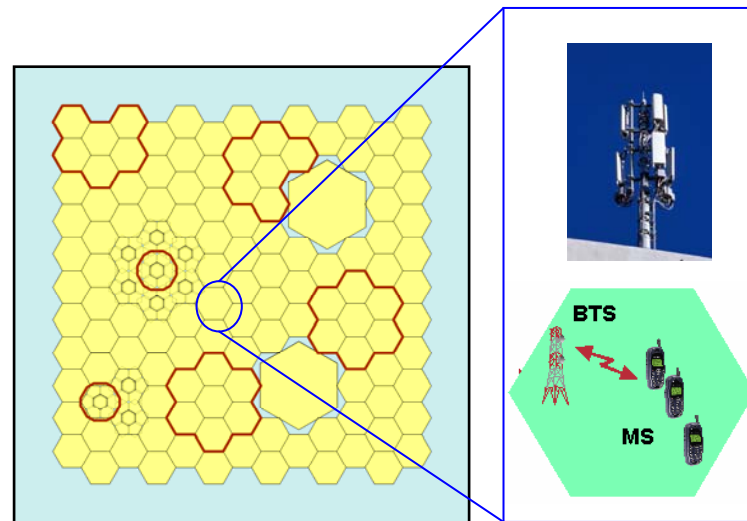
HNN+BD

Experiments

Conclusions

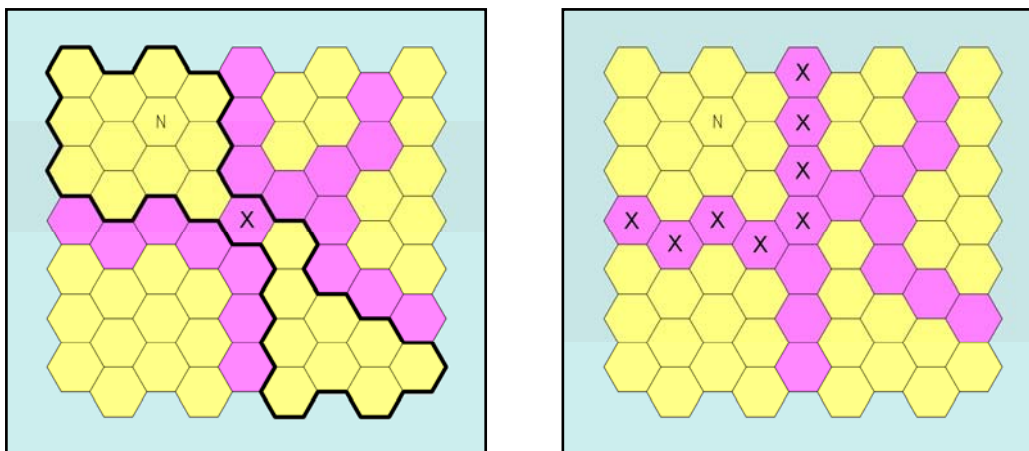
Introduction

- **Mobility Management becomes a crucial issue when designing infrastructure for wireless mobile GSM networks**
- **The network must keep track of the location of each mobile terminal in order to route incoming calls**
- **Hundreds (even thousands) of communication transactions each minute in each cellular node which must be managed:**
 - **support a huge number of users**
 - **bandwidth requirements**
 - **quality of signal**
- **Techniques for optimizing the network management are required:**
 - **Design scheme optimization**
 - **Location of manager devices**
 - **Updating cost and paging cost**



The Mobility Management Problem

- Point of view:
 - Location Area (LA) scheme \longrightarrow Reporting Cells (RC) strategy
- Main Goal: reducing the total cost of managing a mobile cellular network
 - Updating cost
 - Paging cost
- Only an optimal set of cells must be RCs



- When a call arrives, the search is confined to the RC the user last reported and the neighboring bounded
- Vicinity factor : maximum number of neighbors for each cell that must page the user in case of incoming calls

Introduction

Mobility Management

GPSO

HNN+BD

Experiments

Conclusions

The Mobility Management Problem

Introduction

Mobility Management

GPSO

HNN+BD

Experiments

Conclusions

- Total Cost function:

$$Cost = \beta \times \sum_{i \in S} N_{LU}(i) + \sum_{i=0}^N N_P(i) \times V(i)$$

Number of location updates

Number of arrived calls

Vicinity

N: Total number of cells in the network

S: Set of cells defined as RCs

β : Constant, cost ratio of a LU to a P transaction ($\beta = 10$)

- P.R.L Gondim: finding an optimal set of reporting cells is NP-Complete
- Efficient optimization techniques are needed to solve it; bioinspired algorithms (GPSO & HNN)

Geometric Particle Swarm Optimization

Introduction

Mobility Management

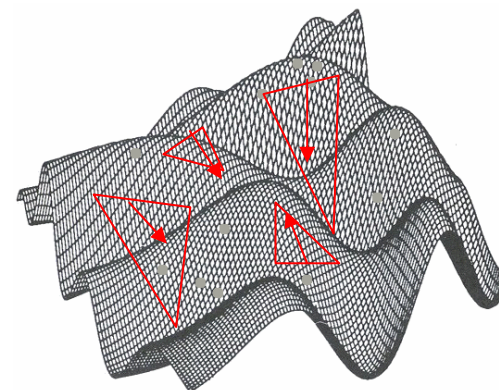
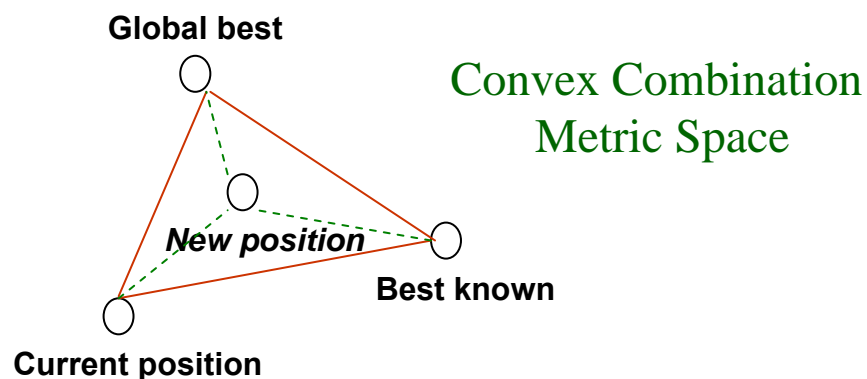
GPSO

HNN+BD

Experiments

Conclusions

- Poli & Moraglio 2006; GPSO allows to generalize PSO virtually **any solution representation** (for us, **binary representation**), extending the search to richer spaces such as Euclidean, Manhattan and **Hamming**
- **Key issue: multi-parental recombination of particles** which leads
 - generalization of a mask-based crossover
 - being convex combination in **Hamming spaces**
- **Operators:**
 - **Movement** (updating velocity and position of particles) by means of **three parent mask-based crossover**
 - **3 parents: global best, current position, historical best known**
 - **Mutation** (bit-flip)



Geometric Particle Swarm Optimization

- GPSO Pseudocode

```

1:  $S \leftarrow SwarmInitialization()$ 
2: while not stop condition do
3:   for each particle  $x_i$  of the swarm  $S$  do
4:     evaluate( $x_i$ )
5:     if  $fitness(x_i)$  is better than  $fitness(h_i)$  then
6:        $h_i \leftarrow x_i$ 
7:     end if
8:     if  $fitness(h_i)$  is better than  $fitness(g_i)$  then
9:        $g_i \leftarrow h_i$ 
10:    end if
11:  end for
12:  for each particle  $x_i$  of the swarm  $S$  do
13:     $x_i \leftarrow 3PMBCX((x_i, w_a), (g_i, w_b), (h_i, w_c))$ 
14:    mutate( $x_i$ )
15:  end for
16: end while
17: Output: best solution found
  
```

Canonical PSO

Weight values

Movement operators:
three parent mask-based crossover

- **Solution encoding:** binary vector representing RC network configuration
 - for each position (cell) '1' is RC and '0' is non-RC

Introduction

Mobility
Management

GPSO

HNN+BD

Experiments

Conclusions

Introduction

Mobility
Management

GPSO

HNN+BD

Experiments

Conclusions

Hopfield Neural Networks with Ball Dropping

- The Ball Dropping technique is used as backbone of the algorithms that employs Hopfield Neural Network as optimizer
- Inspired in the behavior of dropped balls onto a plate with troughs and crest
 - random positions of balls representing RCs
- Periodical drops increase the energy and the HNN tries to reduce it

-
- 1: Drop a predefined number of balls onto random positions
 - 2: **repeat**
 - 3: Shake the plate
 - 4: Remove unnecessary balls
 - 5: **until** location of balls does not lead to any better configuration
 - 6: **Output:** best solution found
-

HNN optimization process

- HNN: the state vector considers two different components for location updates and call arrivals (being 'N' the total number of cells)

$$X = [x_0 \ x_1 \ \wedge \ x_{N-1} \ x_N \ x_{N+1} \ \wedge \ x_{2N-1}]^T$$

LU
NP (call arrivals)

Experiments

Introduction

Mobility
Management

GPSO

HNN+BD

Experiments

Conclusions

- GSM Network Instances
 - 12 square instances with different dimension: 4x4,6x6,8x8 and 10x10
 - Generated according to realistic models (call arrivals and location updates)
 - Available in URL <http://oplink.lcc.uma.es/problems/mmp.html>
- Parameter Setting

Instance	HNN+BD		GPSO			
Dimension	N.DropBalls	N.Trials	N.Particles	Pcross	Pmut	wa+wb+wc
(4x4)	7	3	20	0.9	0.1	0.33+0.33+0.33
(6x6)	10	5	50			
(8x8)	15	5	100			
(10x10)	15	5	120			

- For each algorithm and for each instance: 10 independent runs

Experiments

Introduction

Mobility Management

GPSO

HNN+BD

Experiments

Conclusions

• Results

- GPSO obtains better results in terms of optimal and average cost
- However, the differences are not significant
- Robustness: GPSO obtains similar solutions in all executions (generally, std. dev. < 0.3)

Instances	HNN+BD			GPSO		
	Best	Aver.	Std. Dev.	Best	Aver.	Std. Dev.
1 (4x4)	98,535	98,627	0.09%	98,535	98,535	0.00%
2 (4x4)	97,156	97,655	0.51%	97,156	97,156	0.00%
3 (4x4)	95,038	95,751	0.75%	95,038	95,038	0.00%
4 (6x6)	173,701	174,690	0.56%	173,701	174,090	0.22%
5 (6x6)	182,331	182,430	0.05%	182,331	182,331	0.00%
6 (6x6)	174,519	176,050	0.87%	174,519	175,080	0.32%
7 (8x8)	308,929	311,351	0.78%	308,401	310,062	0.53%
8 (8x8)	287,149	287,149	0.00%	287,149	287,805	0.22%
9 (8x8)	264,204	264,695	0.18%	264,204	264,475	0.10%
10 (10x10)	386,351	387,820	0.38%	385,972	387,825	0.48%
11 (10x10)	358,167	359,036	0.24%	359,191	359,928	0.20%
12 (10x10)	370,868	374,205	0.89%	370,868	373,722	0.76%

Introduction

Mobility Management

GPSO

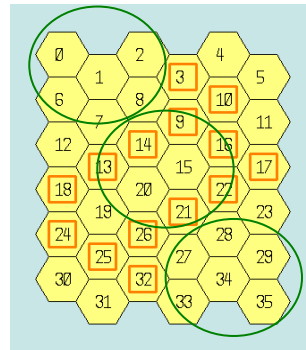
HNN+BD

Experiments

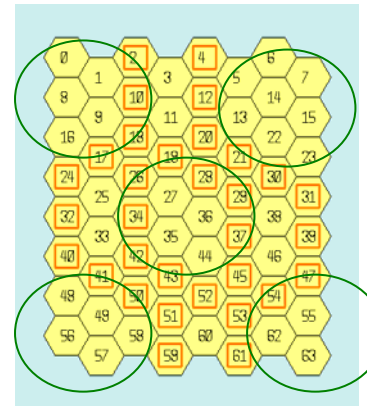
Conclusions

• Results

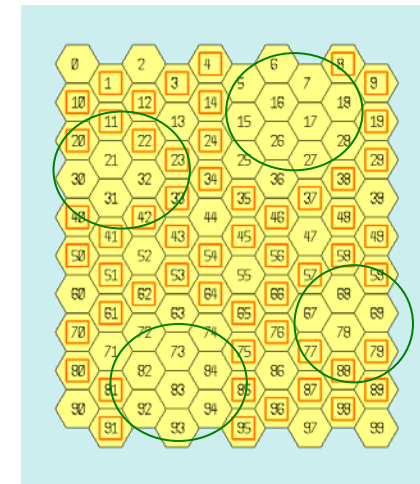
- Cluster organization of reporting cells constituting neighborhoods
- Examples (6x6, 8x8 and 10x10)



Test Network 6
Best Cost: 174,519
Alg: HNN+BD & GPSO



Test Network 8
Best Cost: 287,149
Alg: HNN+BD & GPSO

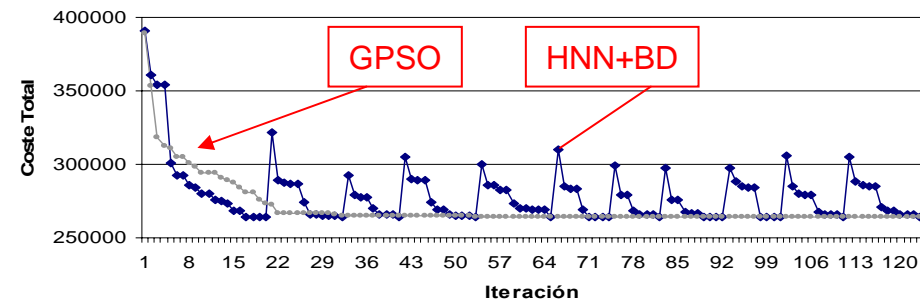


Test Network 12
Best Cost: 370,868
Alg: HNN+BD & GPSO

• Different behavior

- Dropping effects vs. effects vs.
- Monotonous decreasing

Test-Network-9



Introduction

Mobility
Management

GPSO

HNN+BD

Experiments

Conclusions

- Comparison with other optimizers

- Genetic Algorithm (Subatra & Zomaya 2003)

- Parameters:

Population m	100
Best cloned σ	5
Tournament selection p_s	0.8
Two-point crossover p_c	0.8
Gene mutation p_m	0.001
Max stale period T_{stale}	20
Escape mutation p_{mm}	0.2

- Instance: 6x6 square dimension

- Results

<i>Algorithm</i>	<i>Total Cost</i>	<i>Number of RCs</i>
GA	229,556	26
GPSO	214,313	23
HNN+BD	211,278	24

- Both algorithms beat the GA
- Different possibilities concerning the making decision process

Conclusions

Introduction

Mobility Management

GPSO

HNN+BD

Experiments

Conclusions

- We solved the Mobility Management using two new nature inspired techniques: GPSO and HNN+BD
- Twelve new realistic instances were used in experiments
- Simulation results show that the proposed algorithms outperform existing methods in the literature
- Comparisons reveal that GPSO performs more robust. However, final results are quite similar in both algorithms
- In addition, GPSO can be more easily adapted to other GSM network schemes and configurations (different to RCs)
- We are interested in evaluating new instances under different conditions of topology and larger dimensions
- Further work will involved new techniques and comparisons