

A Genetic Algorithm for the Biconnectivity Augmentation Problem

Ivana D. Ljubic
Institute of Computer Graphics
Vienna University of Technology
Karlsplatz 13/1861
1040 Vienna, Austria
ljubic@apm.tuwien.ac.at

Jozef J. Kratica
Mathematical Institute
Serbian Academy of Sciences
Kneza Mihajla 35/I
11000 Belgrade, Serbia
jkratica@matf.bg.ac.yu

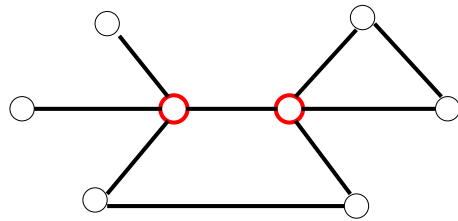
July 2000

IEEE Congress on Evolutionary Computation

Overview

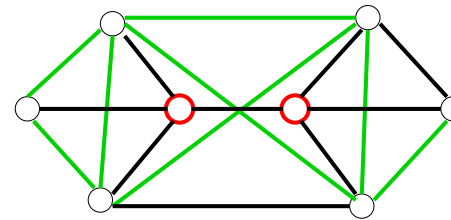
1. The Vertex-Biconnectivity Augmentation Problem
2. Straight-forward GA approach with caching
3. Hybridization with a greedy problem-dependent heuristic
4. Experimental comparisons
5. Conclusions

1. The Vertex Biconnectivity Augmentation Problem

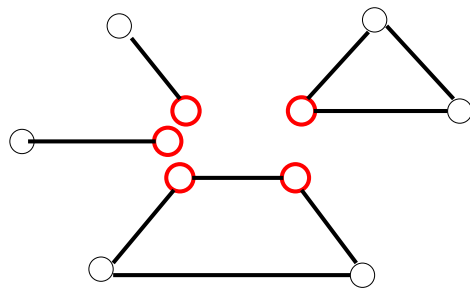


Currently existing network

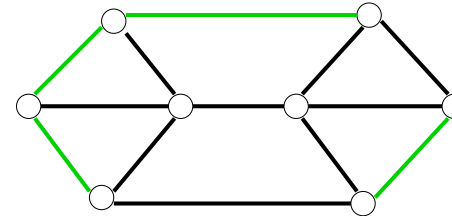
○ Cut points



— Feasible edges



Biconnected components - blocks



Possible biconnectivity augmentation

→ Applications: VLSI design, World Wide Web, telecommunication networks...

Mathematical Definition

- Given: undirected, 2(node)-connected weighted graph $G(V, E)$, and $E_0 \subset E$ set of fixed edges, $w : E \mapsto R^+$.
- Goal: Find the set of augmenting edges $AUG \subset E \setminus E_0$ such that
 1. Graph $G_{AUG}(V, E_0 \cup AUG)$ is node-biconnected, and
 2. The set AUG is of minimal weight, i.e.

$$\text{minimize} \quad \text{obj}(G_{AUG}) = \sum_{e \in AUG} w(e).$$

→ The problem is NP-hard (Eswaran, Tarjan, 1972).

→ The problem stays NP-hard even when $G(V, E_0)$ is connected (Frederickson, Jájá, 1981).

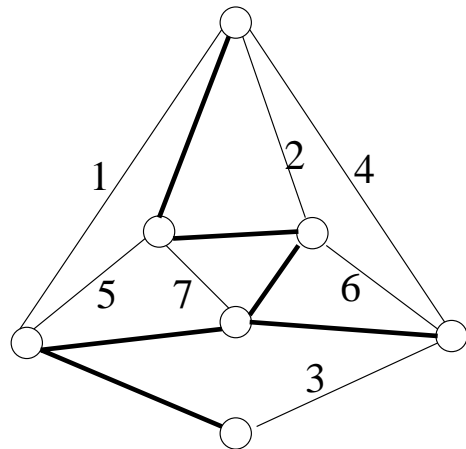
2. Straight-forward GA approach with caching

- Apply a **direct encoding**: $\vec{x} = (x_1, x_2, \dots, x_l)^T$, $x_i \in \{0, 1\}$, ($i = 1, \dots, l$), such that:

$$e_i \in AUG \Leftrightarrow x_i = 1.$$

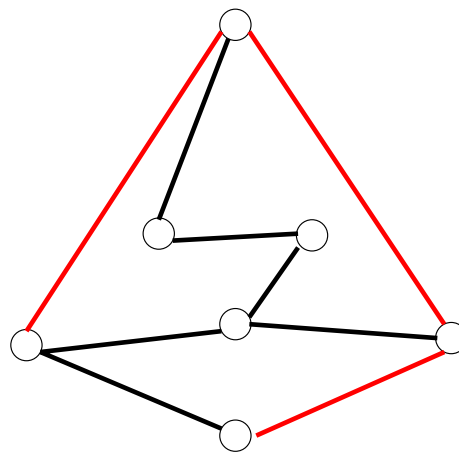
- Every individual represents a graph - potential solution of the problem.
- GANP implementation (Kratika, 2000).

Example of encoding



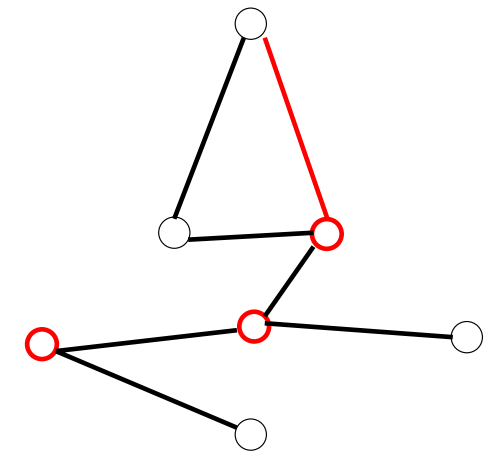
Original graph

- Fixed edges
- Feasible edges



Order the edges: 1 2 3 4 5 6 7 8

Genetic code: 1 0 1 1 0 0 0 0



Genetic code: 0 1 0 0 0 0 0 0

- Augmented edges
- Cut points

Main GA properties

- **Objective value:** Tarjan's (1972) algorithm for checking biconnectivity is applied. Time complexity $O(|E_0 \cup AUG|)$.
- **Discarding infeasible solutions:** Once, when we determine that an individual is not biconnected, we eliminate it from the mating process.
- **Caching:**
 - No influence on the GA's results - only to improve the run-time performance.
 - Avoid the GA's attempt to compute the same objective values repeatedly. Instead of it, remember and reuse objective values.

- **Selection:** Tournament selection (tournament size: 3,5,7).
- **Crossover:** Uniform crossover.
- **Mutation:** Changed during the GA execution, according to the formula:

$$p_m = p_s + (p_e - p_s)2^{-\frac{i}{c}}.$$

- **Initialization** Each gene is randomly initialized with setting each bit to 0 with probability 1/8.

→ Main weakness of this approach: too many infeasible solutions could lead to slow or premature convergence.

→ Penalization or repair of infeasible solutions is necessary.

3. Hybridization with a greedy problem-dependent heuristic

- Each generated infeasible solution is repaired by a greedy heuristic.
- Based on:
 1. Tarjan's (1972) algorithm for checking biconnectivity of connected graphs (in $O(|E|)$ time), and
 2. Kruskal's (1956) greedy algorithm for creating minimum spanning trees (in $O(|E| \log |E|)$ time).
- **Preprocessing:** Sort all edges in $E \setminus E_0$ according to increasing weight, i. e. $E \setminus E_0 = \{e_1, e_2, \dots, e_l\}$, with

$$i < j \Leftrightarrow w(e_i) \leq w(e_j), \quad l = |E \setminus E_0|.$$

A greedy, problem-dependent heuristic

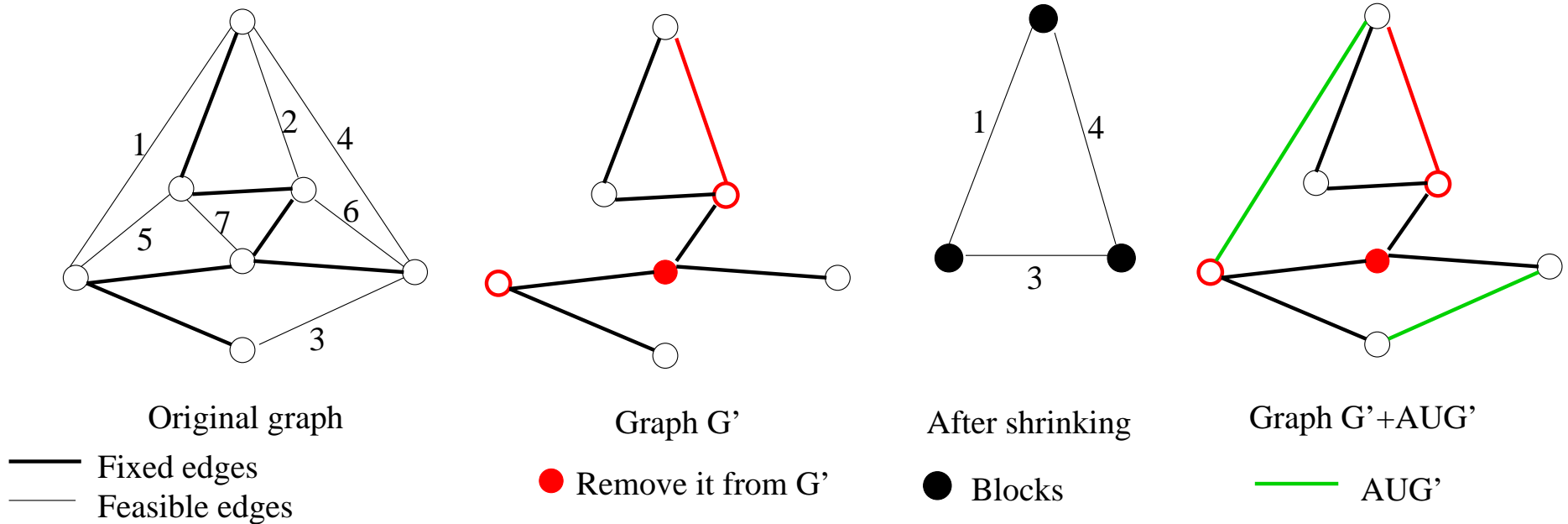
- $AUG' = \emptyset; E'_0 = E_0 \cup AUG$,
- While there are cut points in $G' = G(V, E'_0)$:
 - Randomly choose a cut point a and remove it from G' .
 - Make shrunked graph G_s : shrink connected components of $G' - \{a\}$, and consider only the minimum weight edges connecting two different components.
 - Apply Kruskal's Minimum Spanning Tree algorithm on G_s to find AUG_s .
 - Determine original edges from AUG_s and add them to AUG' .

→ The worst-time complexity: $O(|V||E| \log |V|)$.

→ Max number of iterations is the number of cut points.

→ In practice, algorithm performs faster (cut points are often eliminated simultaneously).

One loop inside the heuristic



4. Experimental Comparisons

Population size - 150

Generation replacement policy

- overlapping populations with elitist strategy,
- only 1/3 of population is generated anew,
- the worst solutions are replaced,
- duplicate phenotypes are discarded
- fitness of the elitist individual is temporarily decreased by the average fitness of the population

Recombination uniform crossover with $p_{unif} = 0.3$ and $p_{cross} = 0.85$

Mutation starting value: $\begin{cases} p_s = 1/2l, & \text{if } 1/2l \geq 0.01 \\ 0.01, & \text{otherwise} \end{cases}$
end value $p_e = 0.01$

Termination best known solution obtained, or
maximal number of generations reached

Number of generations from 100 - 30000 (in PGA case)
from 50 - 2000 (in HGA case)

The test examples

→ All initial graphs are the spanning trees.

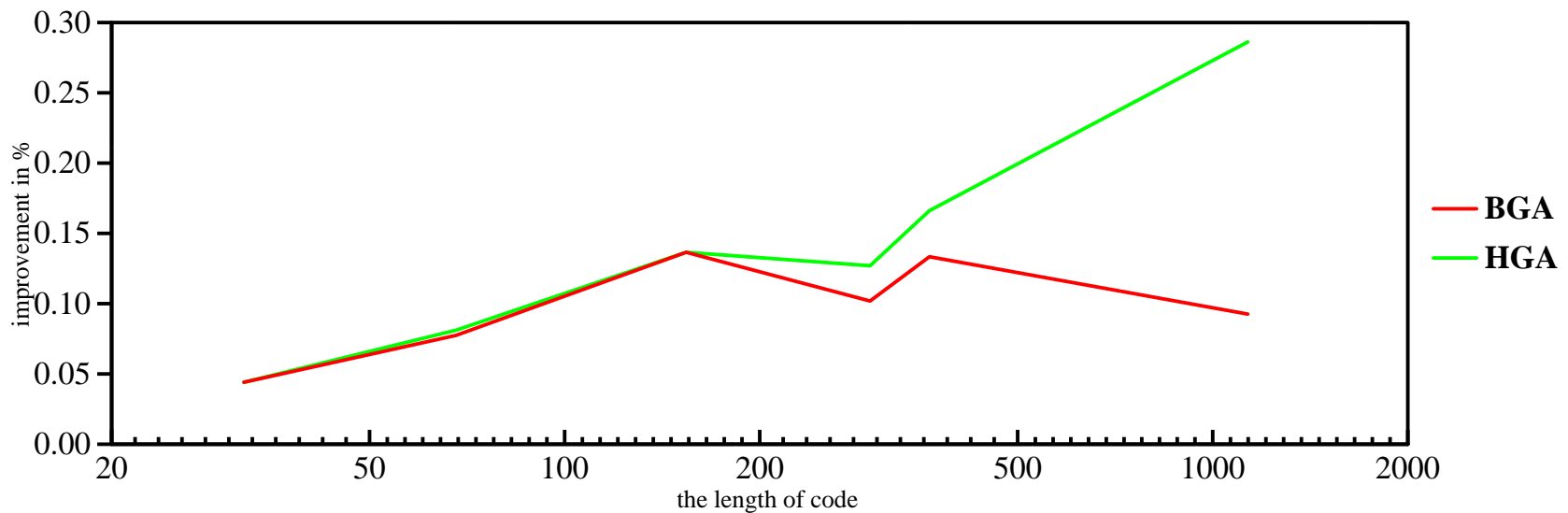
→ Graphs are made by Zhu's (1999) generator.

Category	size	n	m	l	$w(e)$
A	5	[20, 40]	[43, 79]	[24, 40]	$[1, n(n-1)/2]$
B	5	[20, 70]	[81, 150]	[55, 81]	$[1, n(n-1)/2]$
C	4	[20, 100]	[205, 248]	[126, 182]	$[1, n(n-1)/2]$
D	5	[40, 100]	[384, 497]	[315, 398]	$[1, n(n-1)/2]$
M	3	[70, 90]	[312, 438]	[243, 349]	[10, 1000]
N	2	[100, 110]	[1203, 1270]	[1104, 1161]	[10, 50]

(properties of the problem instances)

Category	Greedy	BGA			HGA			Impr. %
	$w(AUG)$	$w(AUG)$	$t[s]$	gen	$w(AUG)$	$t[s]$	gen	
A	2994	2862	0.7	25	2862	0.5	8	6.4
B	9270	8552	3.8	107	8518	2.6	22	7.6
C	35049	30263	16.4	970	30263	35.6	128	13.0
D	12873	11156	556.3	11977	10734	549.3	513	14.5
M	4780	4293	614.3	10639	4173	67.7	128	13.0
N	594	539	1520.62	21221	424	1312.69	1176	28.2

(the best values from 10 consecutive executions of GA's)



Improvements of Greedy algorithm

5. Conclusions

- Both BGA and HGA gives significantly better results then the greedy heuristic alone.
- The straight-forward approach works well for small problem instances.
- HGA is better concerning:
 - quality of the final solution,
 - needed number of generations,
 - corresponding execution times.

Future work

- The same GA approach could be easily adapted to other graph connectivity problems (Ljubic, Raidl, Kratica 2000).
- Examination of other heuristics.
- Preprocessing: shrink biconnected components of $G(V, E_0)$ and reduce the size of $|E \setminus E_0|$.
- Examination of problem-dependent GA operators.