Optimising Small-World Properties in VANETs with a Parallel Multi-Objective Coevolutionary Algorithm

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High-Performance Computing - LATAM

Outline

1. Introduction
2. Asynchronous Parallel CCNSGA-II
3. Injection Network Problem
4. Experimental Setup
5. Numerical Results
6. Conclusion and Perspectives

Outline

Introduction

Motivation

- Real-world (RW) problems are typically multi-objective
- MOEAs show limitations on such large-scale problems
- Cooperative coevolutionary MOEAs are one promising option, but few works:
  - applied them on RW problems,
  - exploit their parallelization capabilities.

Objectives

- Apply for the first time a parallel asynchronous cooperative coevolutionary MOEA
- Optimize a topology control problem in VANETs
- Analyze its performance (speedup, quality)

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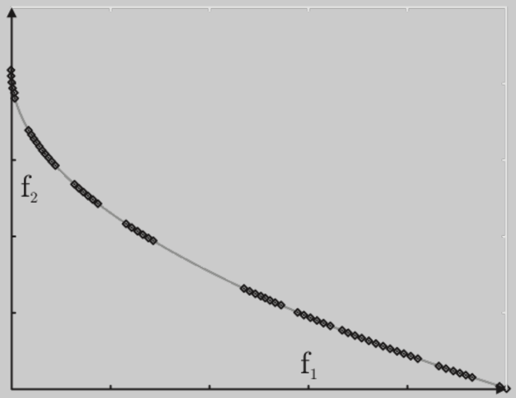
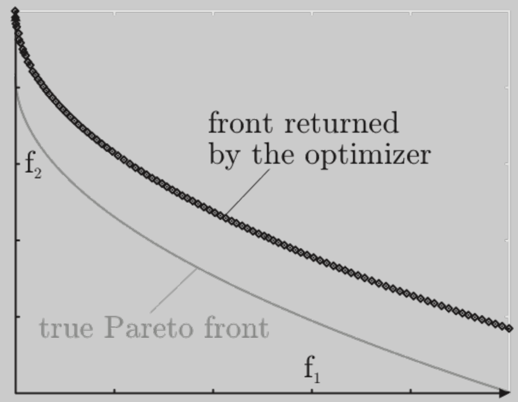
Multi-Objective Optimization

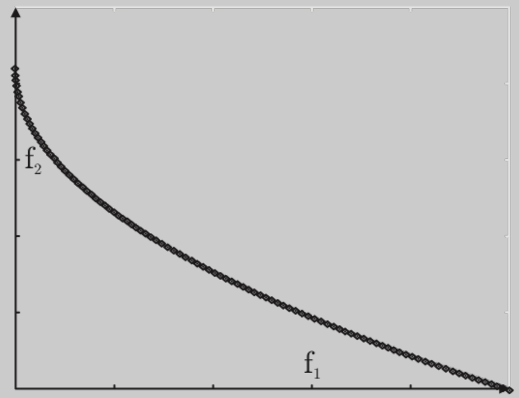
- Optimize more than one objective at the same time
  - Objectives are usually conflicting
  - Improving one means worsening the others
- Results in a set of non-dominated solutions
  - Pareto front
- Performance of approximate techniques
  - Convergence
  - Diversity



Bad diversity



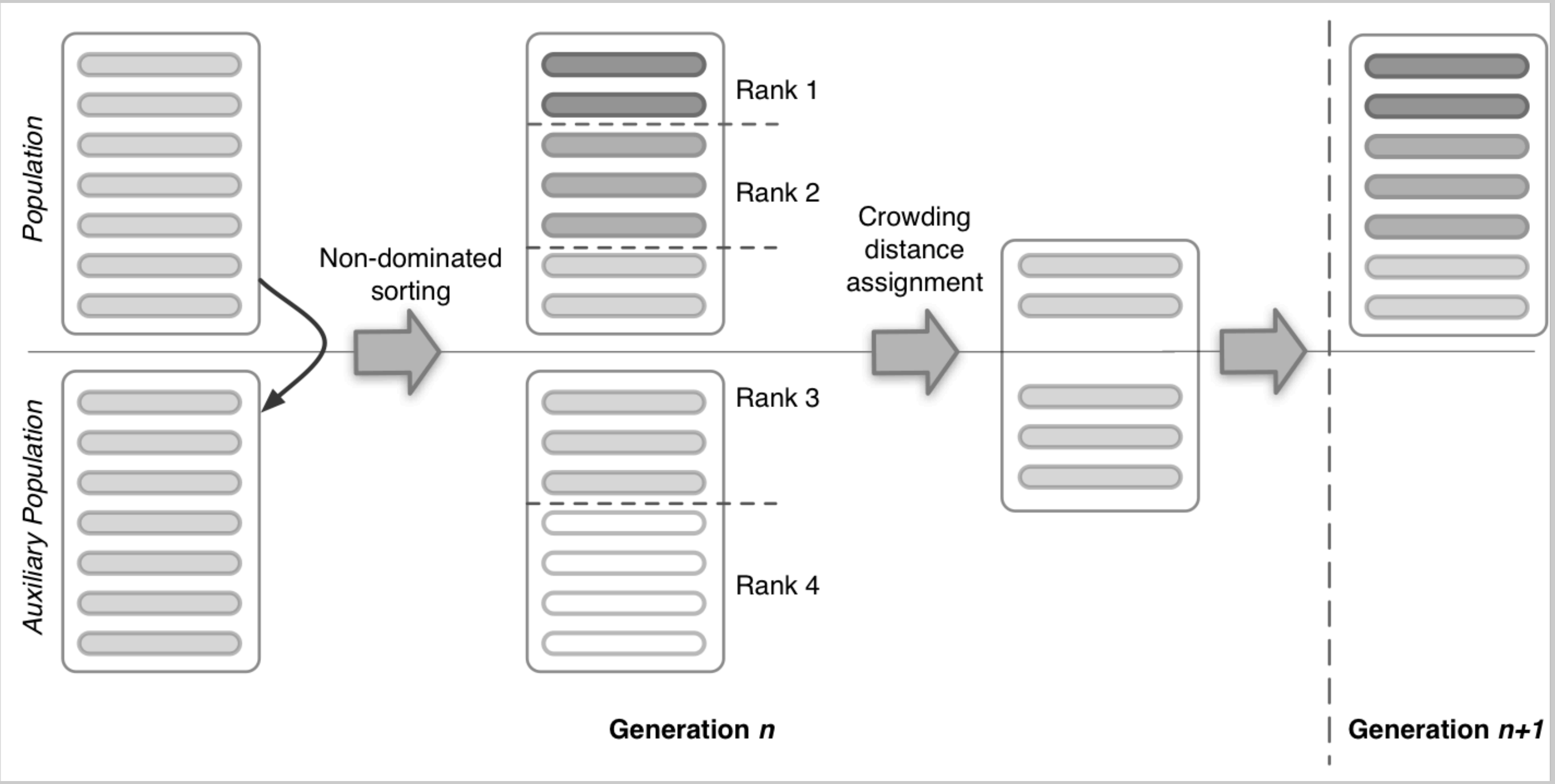
Bad convergence



Ideal case

NSGA-II

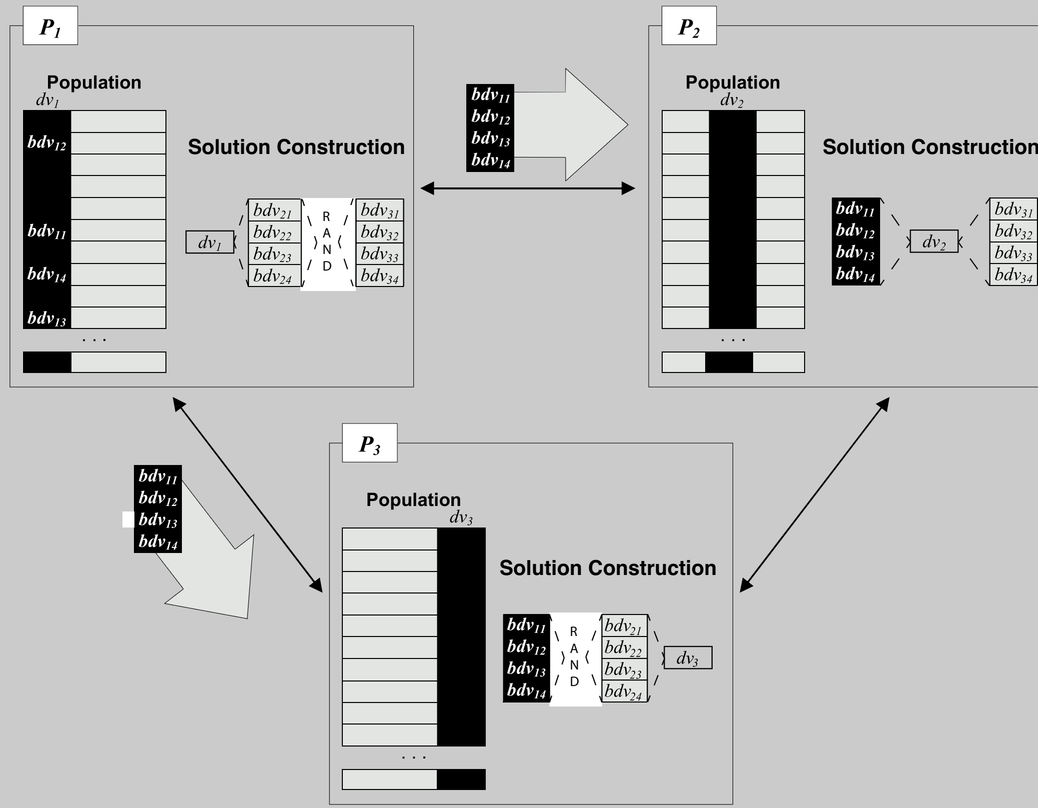
- Non-dominated Sorting Genetic Algorithm [1]
- Most popular metaheuristic for multi-objective optimization



[1] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. Evolutionary Computation, IEEE Transactions on, 6(2):182{197, 2002.

CCNSGA-II

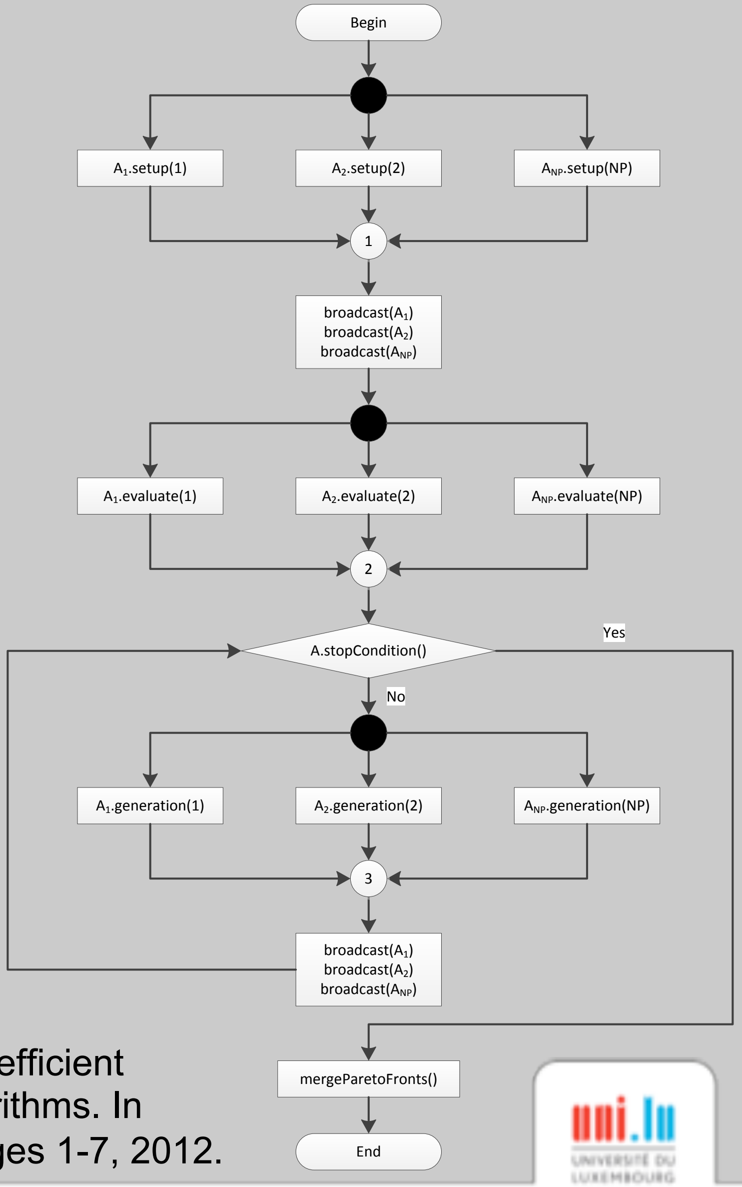
- Based on Potter Cooperative Coevolutionary EA [2]
- Subpopulations evaluate part of global solution vector
- Cooperate by exchanging local representatives



[2] M.A. Potter and K. De Jong. A cooperative coevolutionary approach to function optimization. In Parallel Problem Solving from Nature (PPSN III), pages 249-257. Springer, 1994

Parallel Asynchronous CCNSGA-II

- Good parallelization capabilities
  - Subpopulations evolve in parallel
- Asynchronous CCNSGA-II
  - Proposed in [3]
  - Only applied on MO test functions



[3] S. Nielsen, B. Dorronsoro, G. Danoy, and P. Bouvry. Novel efficient asynchronous cooperative co-evolutionary multi-objective algorithms. In Evolutionary Computation (CEC), 2012 IEEE Congress on, pages 1-7, 2012.

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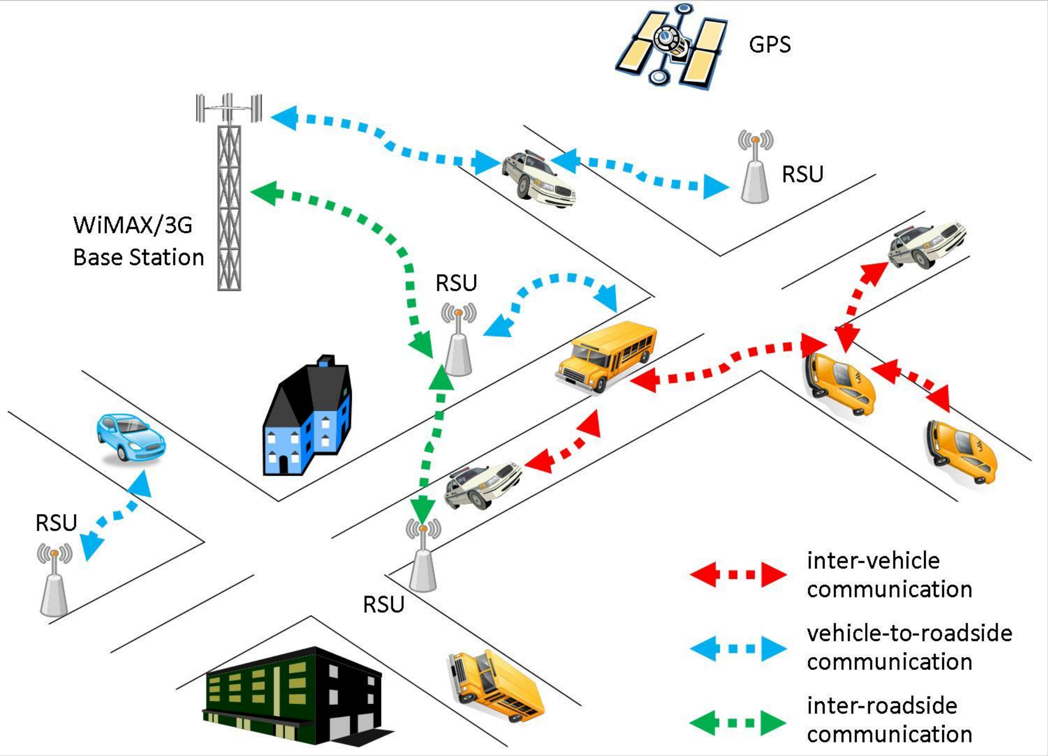
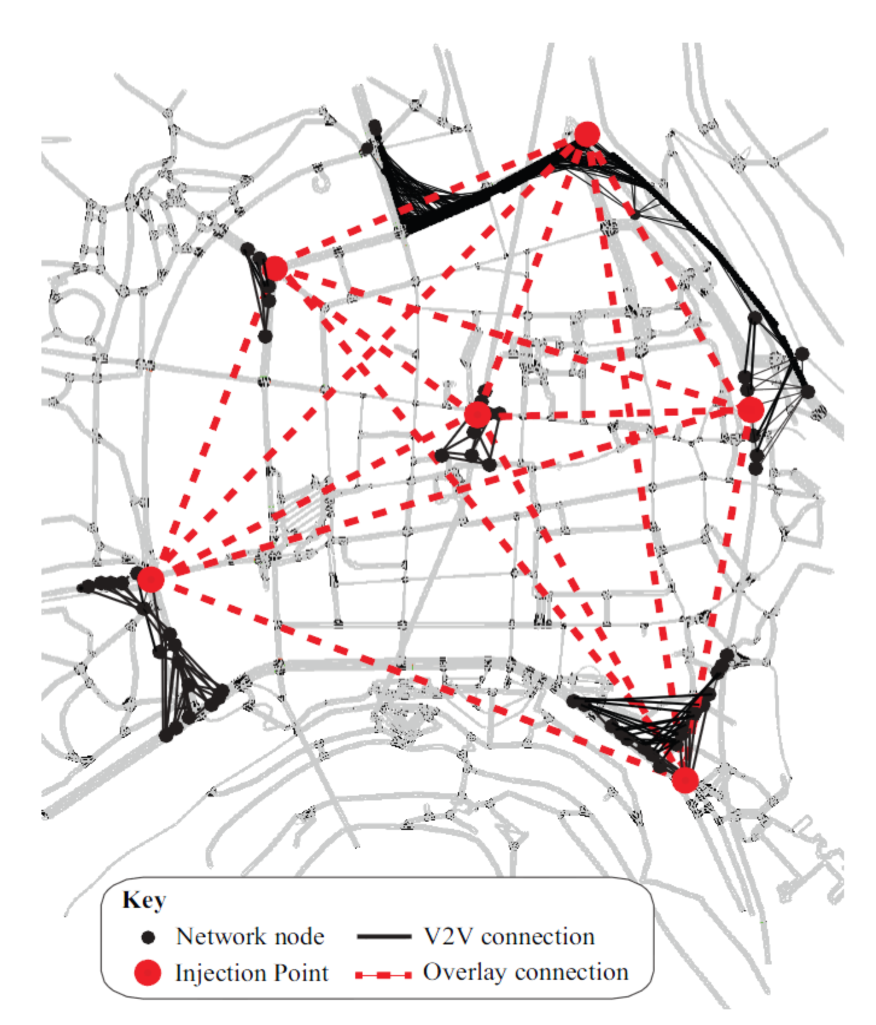
Vehicular Ad hoc Networks (VANETs)

- Wireless ad hoc network
  - No central entity
  - Nodes act as routers
- Mobility induces topological changes
- Partitioning problem



Injection Network

- Hybrid VANETs
  - Vehicle-to-Vehicle and vehicle-to-Infrastructure
- Injection points
  - Nodes connected to infrastructure
  - Form fully-connected overlay network
- Rely on small-world properties
  - High CC: better broadcasting efficiency
  - Low APL: faster and easier to maintain routing



[4] J. Schleich, G. Danoy, B. Dorronsoro, and P. Bouvry. An overlay approach for optimising small-world properties in VANETs. In Applications of Evolutionary Computation, volume 7835 of Lecture Notes in Computer Science, pages 32-41. Springer Berlin Heidelberg, 2013.

Multi-objective Optimization Problem

$$f(s) = \begin{cases} min\,\{inj\} \\ max\,\{cc\}\ ; \\ min\,\{apl_{diff}\} \end{cases} \quad \text{s. t. } component = 1$$

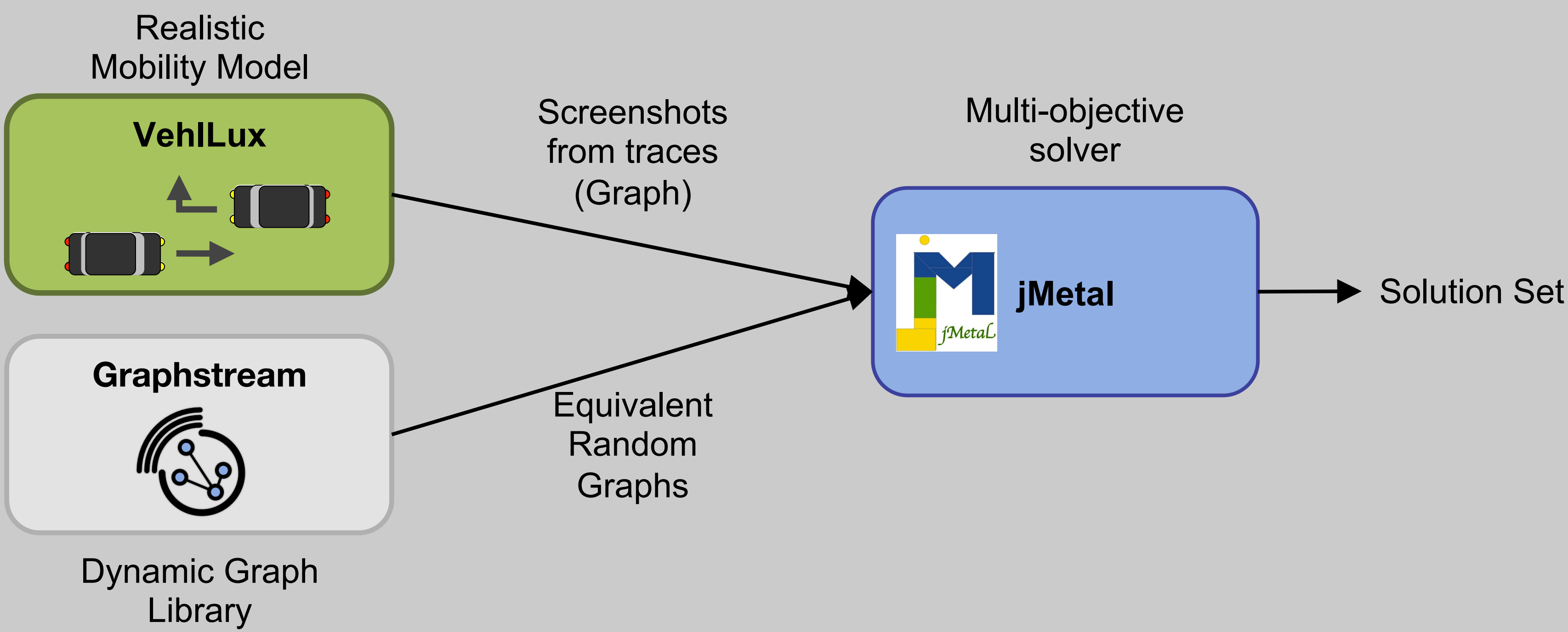
With $apl_{diff} = |apl - apl_{random}|$

- Equivalent random graph
  - same number of nodes and average density
  - averaged over 30 different instances
- Generated using Watts rewiring process [5]
  - with randomness, i.e. p = 1

[5] **Collective dynamics of small-world networks**, *D. J. Watts and S. H. Strogatz,* Nature vol 393, 1998, pp 440-442

Outline

Experimental Setup



Experimental Setup - Algorithms configuration

- Configuration is the one originally suggested by the authors in [2]

- Solution encoding: binary array
  - 1 for injection point
  - 0 for normal node
  - length: number of devices (cars)

Numb. of subpop.*	4
Cores used	4 (1 for NSGA-II)
Number of threads	1 per subpopulation
Population size	100
Final archive size	100, from all subpops.
Migration policy *	20 random
Max. evaluations	$50,000$
Pop. initialisation	Random
Selection	Binary tournament
Recombination	DPX
Probability	0.9
Mutation	Bit Flip
Probability	$\frac{1}{number\_of\_variables}$
Independent runs	30

* Not applicable for NSGA-II

[2] **A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II**, *K. Deb and A. Pratap and S. Agarwal and T. Meyarivan,* IEEE Trans. on Evol. Comp. vol 6 (2), 2002, pp 182-197

Experimental Setup - Network instances

- VehILux mobility model [3]
  - Realistic road network topology (OpenStreetMaps)
  - Real traffic counting data from the Luxembourg Ministry of Transport

	Surface	$0.6\ km^2$		
	Coverage radius	100 m		
6 a.m.	Network Number	21900	22200	22500
	Number of Nodes	40	62	60
	Partitions	10	8	6
	Solution space size	1^{12}	4.61^{18}	1.15^{18}
7 a.m.	Network Number	25500	25800	26099
	Number of Nodes	223	248	301
	Partitions	10	6	7
	Solution space size	1.34^{67}	4.52^{74}	4.07^{90}

[3] **A vehicular mobility model based on real traffic counting data**, *Y. Pigné and G. Danoy and P. Bouvry,* ACM Int. Conf. on Communication Technologies for Vehicles, 2011, pp 131-142

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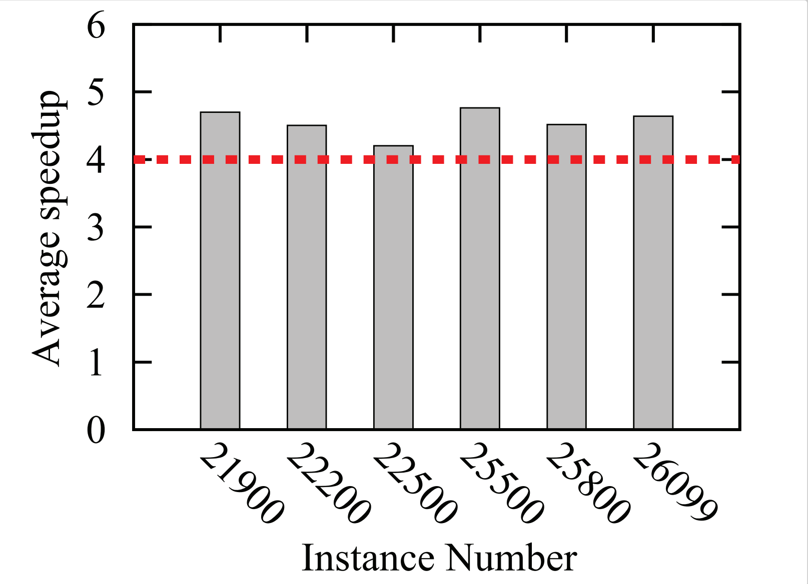
Speedup

- HPC facility of the UL
  - Nodes HP Proliant
  - 2 Intel L5640 CPUs having 6 cores each at 2.26 GHz.
- Computation times
  - Increase drastically with the problem size
- Super-linear speedup
  - For all instances
  - Average: 4.55

Instance	NSGA-II	CCNSGA-II	Speedup
21900	569.62	121.18	4.70
22200	2159.40	479.35	4.50
22500	1892.97	450.23	4.20
25500	141387.52	29676.34	4.76
25800	192580.75	42622.23	4.52
26099	386924.15	83420.32	4.64



Solution quality

	SPREAD			EPSILON		
Instance	NSGA-II	CCNSGA-II	Conf.	NSGA-II	CCNSGA-II	Conf.
21900	$6.55e-01_{4.5e-02}$	$7.32e-01_{7.9e-02}$	▲	$7.00e+00_{0.0e+00}$	$1.67e+00_{2.1e-08}$	▽
22200	$6.85e-01_{4.6e-02}$	$7.70e-01_{4.7e-02}$	▲	$3.00e+00_{0.0e+00}$	$1.40e+00_{7.0e-02}$	▽
22500	$7.25e-01_{3.8e-02}$	$7.44e-01_{6.7e-02}$	–	$4.00e+00_{0.0e+00}$	$1.90e+00_{2.9e-02}$	▽
25500	$8.56e-01_{1.1e-01}$	$7.41e-01_{4.1e-02}$	▽	$1.57e+01_{4.3e+00}$	$2.93e+00_{9.0e-01}$	▽
25800	$8.36e-01_{7.2e-02}$	$7.49e-01_{7.0e-02}$	▽	$8.87e+00_{4.1e+00}$	$3.14e+00_{1.2e+00}$	▽
26099	$7.31e-01_{1.1e-01}$	$7.86e-01_{5.2e-02}$	▲	$1.56e+01_{6.7e+00}$	$4.00e+00_{1.4e+00}$	▽

- SPREAD - Diversity of solutions
  - NSGA-II better on half of the instances
- EPSILON - Convergence
  - CCNSGA-II better on all instances

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Conclusions and Perspectives

- Conclusions
  - First application of asynchronous parallel CCNSGA-II on RW problem
    - Injection Netwok in VANETs
  - Analyzed performance of CCNSGA-II on realistic instances
    - Super linear speedup
    - Better convergence

- Perspectives
  - Analyze scalability of the parallel CCNSGA-II
  - Develop decentralised heuristics
  - Use CCMOEA empirical bounds to assess the heuristics performance

Thank you for your attention

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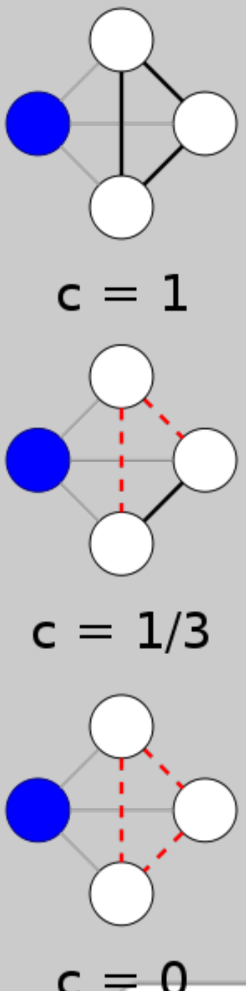
Small world Properties

- Small Average Path Length (APL)

$$APL = \frac{1}{n(n-1)} \sum_{i,j} d(v_i, v_j)$$

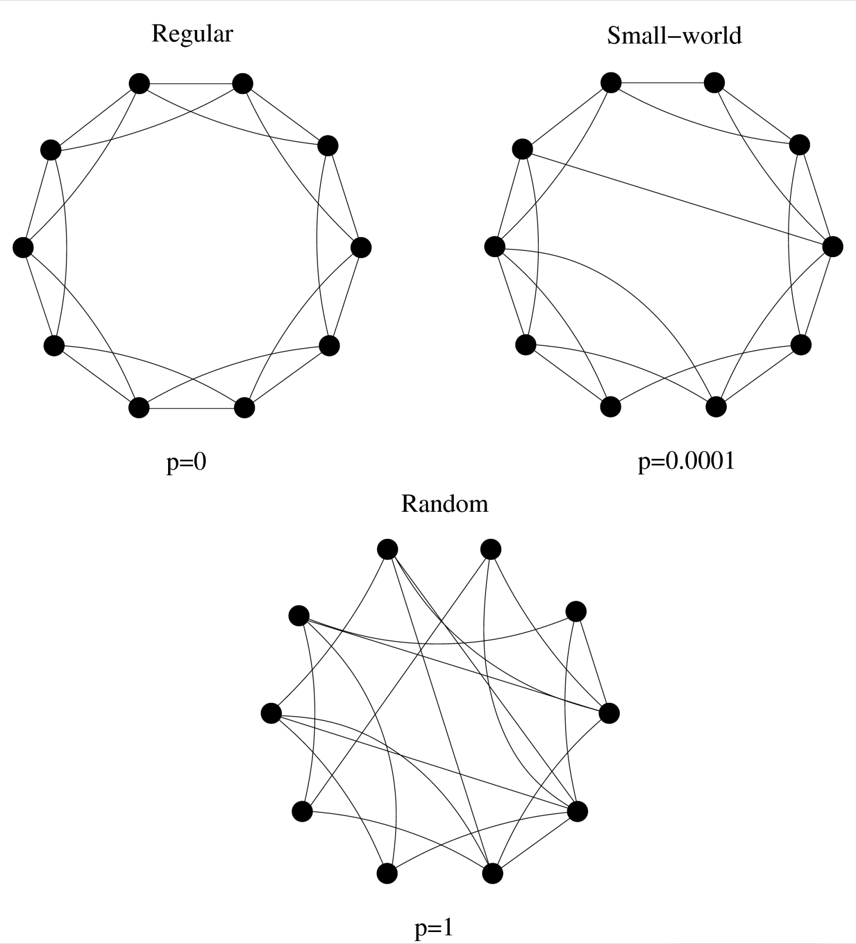
- High Clustering Coefficient (CC)
  - Local
$$CC_v = \frac{|E(\Gamma_v)|}{k_v(k_v - 1)}$$
  - Global
$$CC = \frac{1}{n} \sum_{v} CC_v$$



Small world Properties

- Definition of Watts [1]

$$APL \approx APL_{random}$$
$$CC \gg CC_{random}$$



[1] **Collective dynamics of small-world networks**, *D. J. Watts and S. H. Strogatz,* Nature vol 393, 1998, pp 440-442

Vehicular Ad hoc Networks (VANETs)

Problem 1: the network can be partitioned

- There exists no path between some pair of nodes

Solution 1: injection points

- A subset of nodes use an additional network interface
- This subset of nodes forms a fully connected overlay network

Vehicular Ad hoc Networks (VANETs)

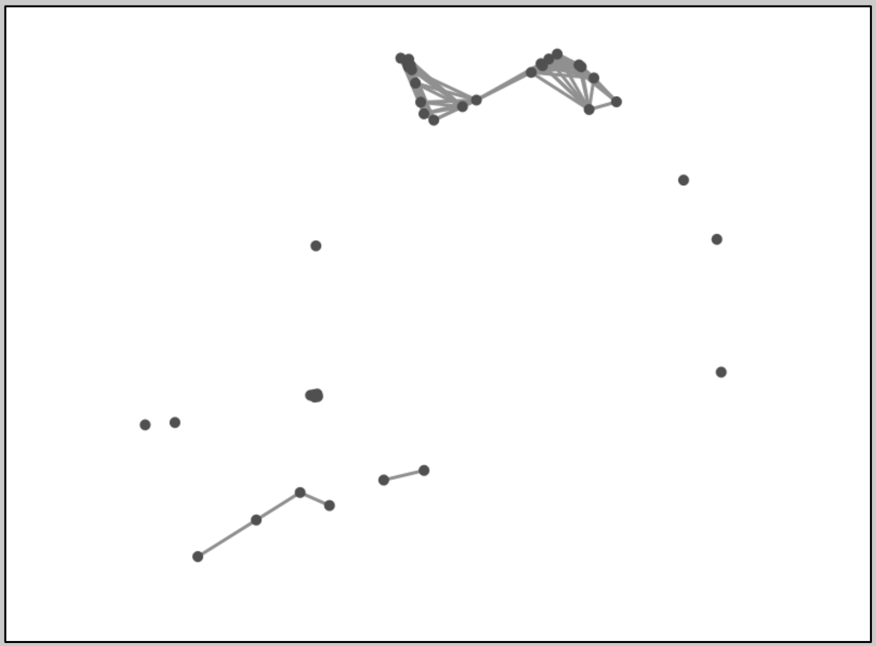
Problem 2: the topological properties are not optimal

Solution 2: select injection points in order to obtain better small world properties

- High CC: better broadcasting efficiency
- Low APL: faster and easier to maintain routing

Network Instances

Instance 21900



Instance 25800