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DEEPSO
EVOLUTIONARY SWARMS IN THE OPF CHALLENGE

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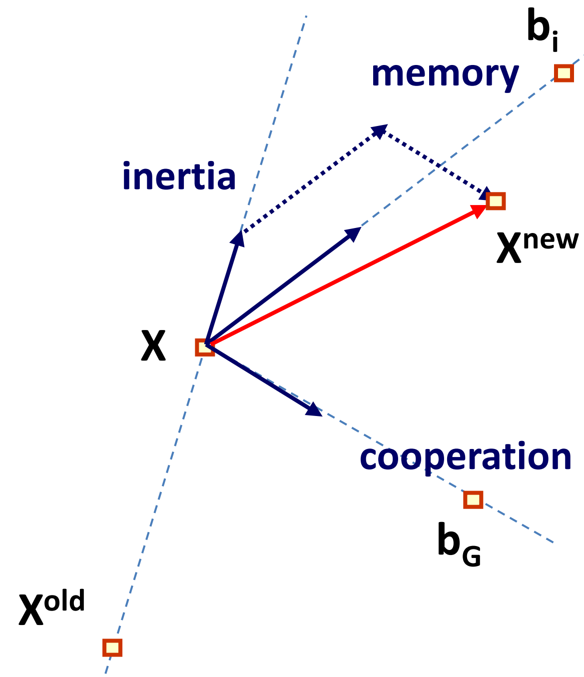
Particle Swarm Optimization (Classic PSO)

A set of particles (solutions) in the search space

movement of a particle:

$$X^{new} = X + V^{new}$$

- **inertia**:
  moving in the same direction
- **memory**:
  attraction by particle past best
- **cooperation**:
  attraction for global best



basic

$$V_i^{new} = w_I V_i + Rnd_1 . w_M (b_i - X_i) + Rnd_2 . w_C (b_G - X_i)$$

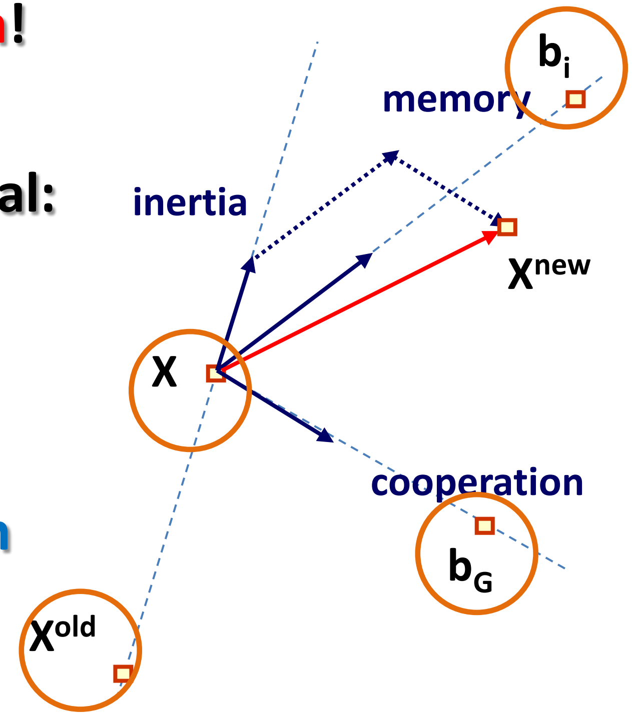
Re-interpretation of the movement rule

What is the PSO movement rule, really?

- **It is a form of intermediary recombination!**

Four ancestors (4) to produce a new individual:

- **A particle**
- **Its direct ancestor**
- **Its best ancestor**
- **The best ancestor found by the swarm**



The sharing proportion is defined by the weights:

$$\mathbf{X}^{new} = (1 + w_I - w_M - w_C)\mathbf{X} - w_I\mathbf{X}^{old} + w_M\mathbf{b}_i + w_C\mathbf{b}_G$$

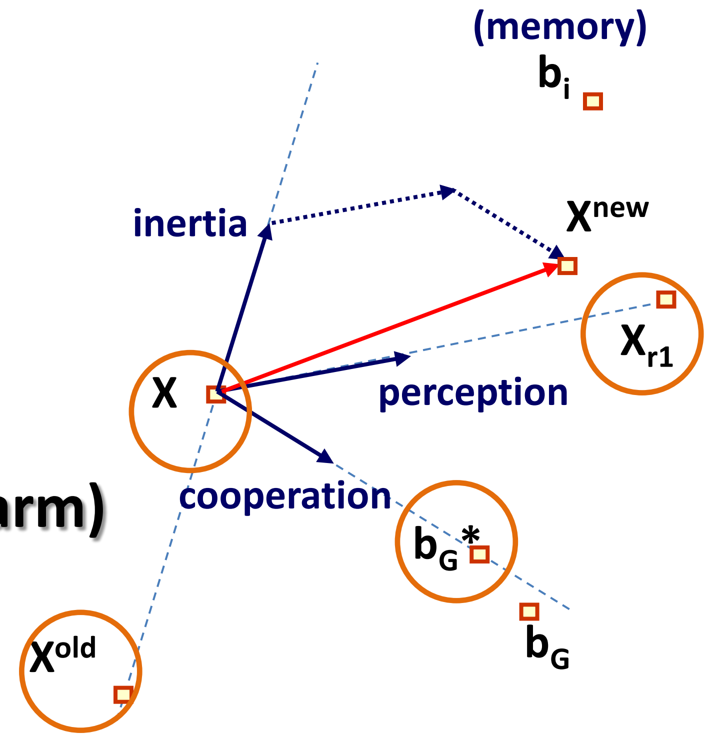
DEEPSO: a flavor of Differential Evolution in EPSO

RECOMBINATION via THE MOVEMENT RULE

movement of a particle:

$$X^{new} = X + V^{new}$$

- **inertia**:
  moving in the same direction
- **perception**:
  sensing a local gradient (by the swarm)
- **cooperation**:
  attraction to the proximity of the global best



$$V^{new} = w_I^* V + w_M^*(X_{r1} - X) + w_C^* \, P \, (b_G^* - X)$$

Towards a self-adaptive recombination process

Each weight is subject to mutations

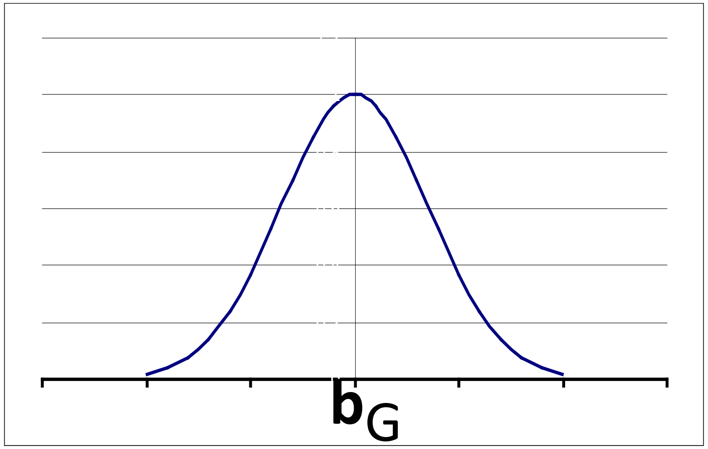
$$w^*_{\{I,M,C\}} = w_{\{I,M,C\}}(1 + \tau N[0,\sigma^2])$$

PLUS - the global best has a "foggy" definition

$$\mathbf{b}^*_G = \mathbf{b}_G(1 + w^*_b N[0,1])$$

Exploration strength

$$w^*_b = w_b(1 + \tau' N[0,\sigma^2])$$



(τ, τ' are constant)

EVOLVING SWARMS – EPSO AND DEEPSO

EPSO – the gradient perception is based on the particle self-memory term

$$\mathbf{V}^{new} = w_I^* \mathbf{V} + w_M^* (\mathbf{b}_i - \mathbf{X}) + w_C^* \, \mathbf{P} \, (\mathbf{b}_G^* - \mathbf{X})$$

DEEPSO – a flavor of Differential Evolution added to EPSO

$$\mathbf{V}^{new} = w_I^* \mathbf{V} + w_M^* (\mathbf{X}_{r1} - \mathbf{X}) + w_C^* \, \mathbf{P} \, (\mathbf{b}_G^* - \mathbf{X})$$

Variants :

$\mathbf{X}_{r1}$:

- **sampled among the current generation : Sg**
- **sampled among the matrix b_i of individual past bests : Pb**
- **as a uniform recombination of the current generation : Sg-rnd**
- **as a uniform recombination within the matrix b_i : Pb-rnd**

for the latter 2:

not taking in account the direction of $(\mathbf{X}_{r1} - \mathbf{X})$: $.^{-}$ ***minus***

taking in acc. the direction of $(\mathbf{X}_{r1} - \mathbf{X})$: $.^{+}$ ***plus***

taking in acc. the direction of $(\mathbf{X}_{r1} - \mathbf{X})$ in each coordinate: $.^{0}$ ***zero***

A SWARM WITH SELF-ADAPTIVE RECOMBINATION

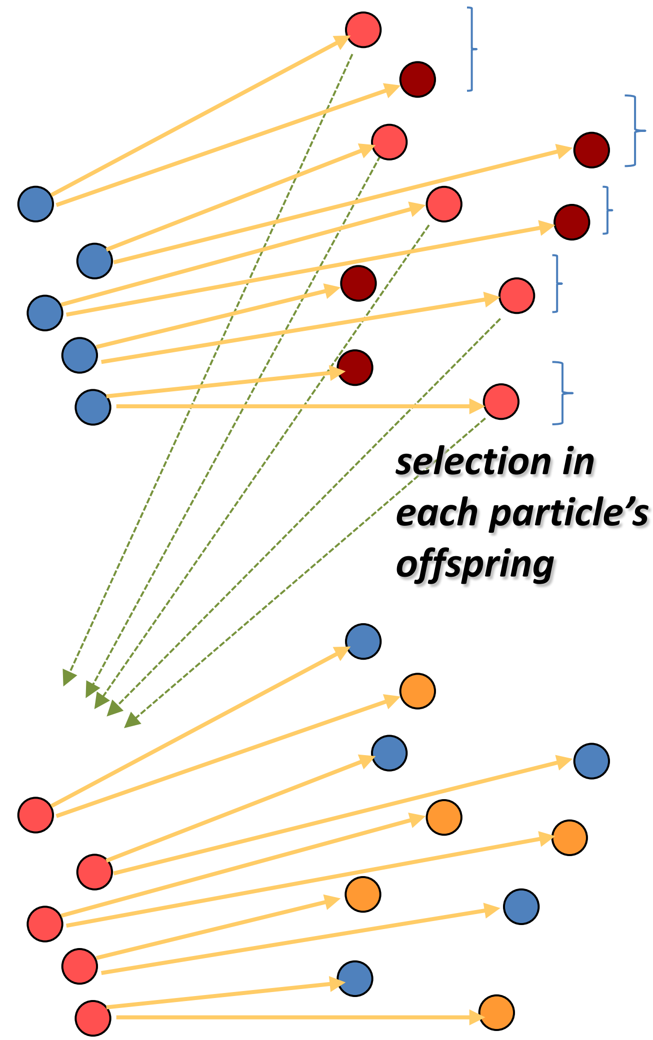
REPLICATION - each particle is replicated **r** times

MUTATION – r-1 clones have their weights **w** **mutated**

RECOMBINATION - each particle generates 1 offspring

EVALUATION - each offspring has its fitness evaluated

SELECTION - by stochastic tournament (or elitism) the best particle in each group of **r** survives to form a new generation



Selection acts separately on the descendents of each particle. The best particles carry with them, to the following generation, their mutated weights.

The recombination proportion is evolving under selection pressure!

Stochastic communication

Stochastic star

There is a communication probability threshold **p** below which communication is allowed – and above which no information about b_G is taken in account. The probability threshold p is applied to each dimension of an individual.

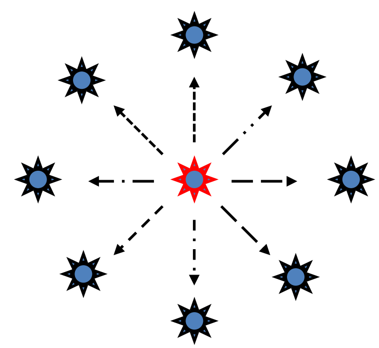
On average, a percentage (1-p)*100 of the (b_G – X) macro-gradient is ignored in each movement.

If $i \neq k$ then $P_{ik} = 0$

r := Rnd()

If r > p then $P_{ii} = 0$ else $P_{ii} = 1$

$$\begin{bmatrix} 1 & & & \\ & 0 & & \\ & & \ddots & \\ & & & 1 \end{bmatrix} \begin{bmatrix} (b_G - X)_1 \\ (b_G - X)_2 \\ \vdots \\ (b_G - X)_n \end{bmatrix}$$



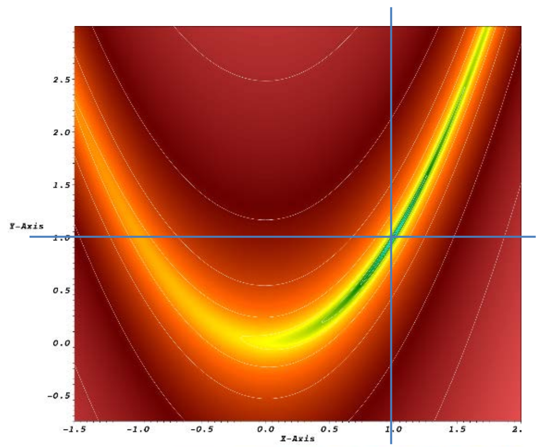
$$\mathbf{V}^{new} = w_I^* \mathbf{V} + w_M^* (\mathbf{X}_{r1} - \mathbf{X}) + w_C^* \, \mathbf{P} \, (\mathbf{b}_G^* - \mathbf{X})$$

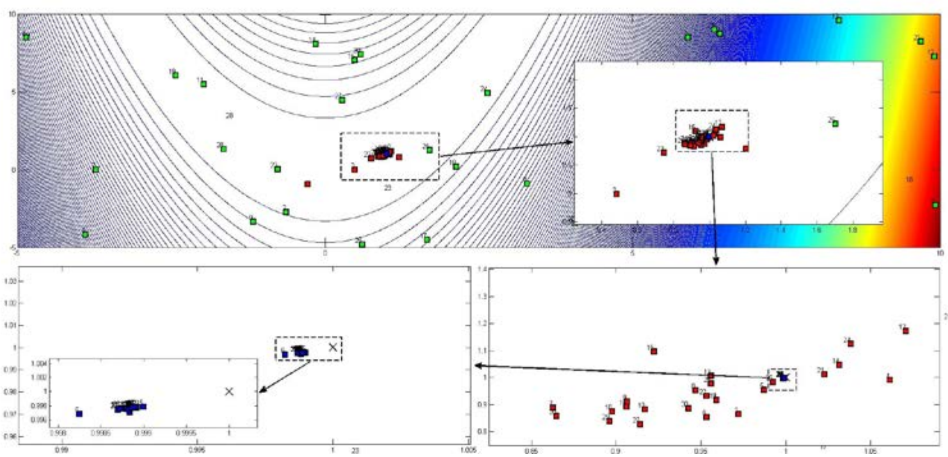
IMPORTANCE OF THE STOCHASTIC STAR TOPOLOGY

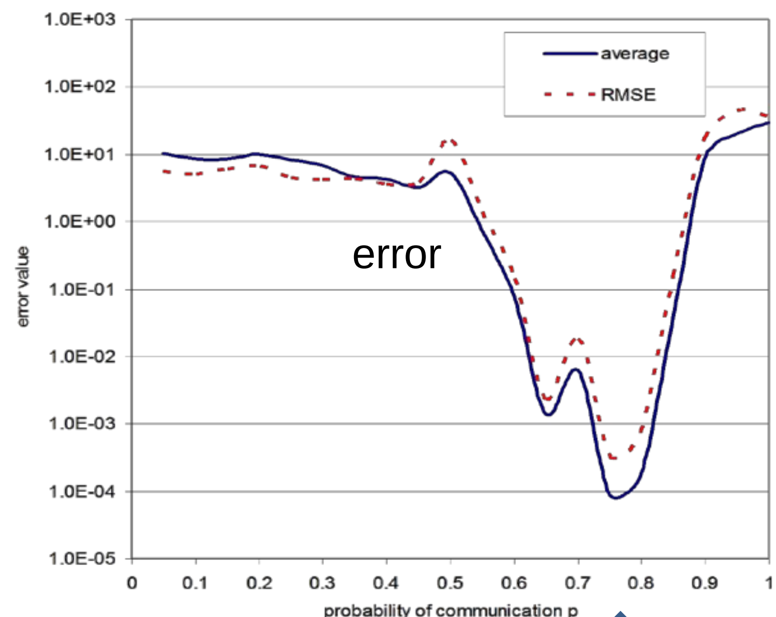
Rosenbrock function, 30 dim

EPSO, 20 runs, 100,000 objective function evaluations

Evolving swarm in the Rosenbrock 2D Landscape







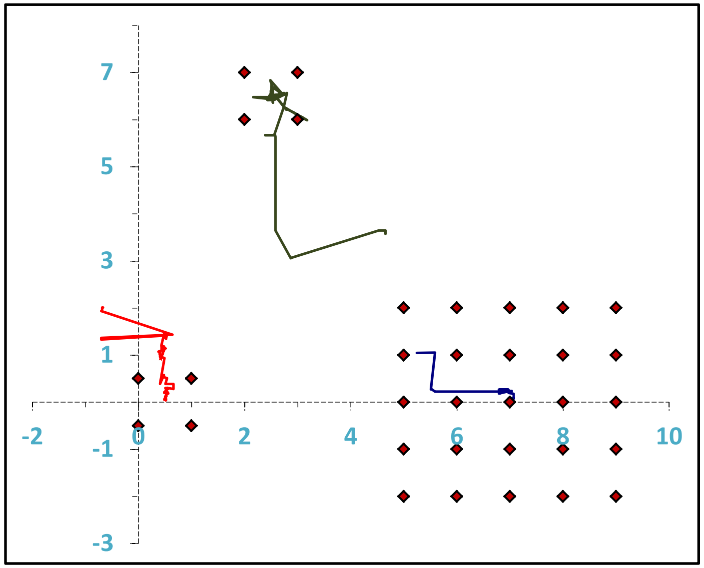
p = 0.75 leads to the most robust results

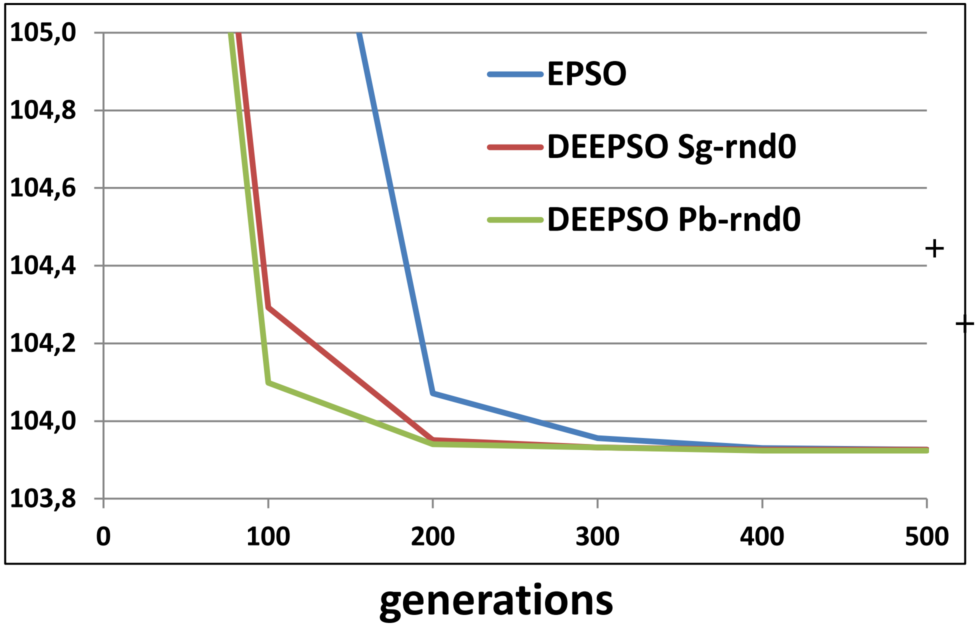
EPSO is sensitive to p

EPSO vs. DEEPSO

A simple fuzzy clustering problema (fuzzy c-means)

EPSO vs. DEEPO (2 variants) – average of 20 runs, 8 particles



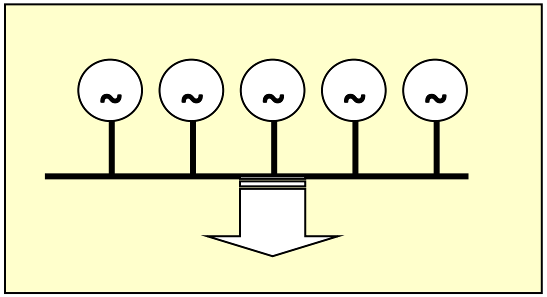


Faster convergence of DEEPSO variants

EPSO vs. DEEPSO

Toy Unit Commitment problem: Load 15 MW

1000 evaluations, 16 particles, 100 runs

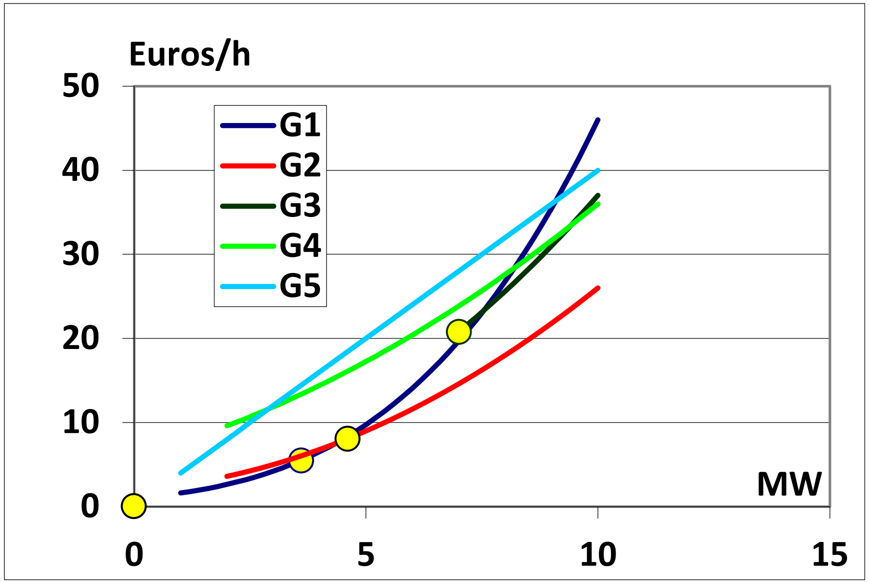


No. of hits on the exact solution:

EPSO	DEEPSO Sg-rnd0	DEEPSO Pb-rnd0
46%	71%	81%

A mixed-integer problem

Difficult because of the deceptive landscape – and a local optimum has almost the same value as the global optimum



EPSO vs. DEEPSO

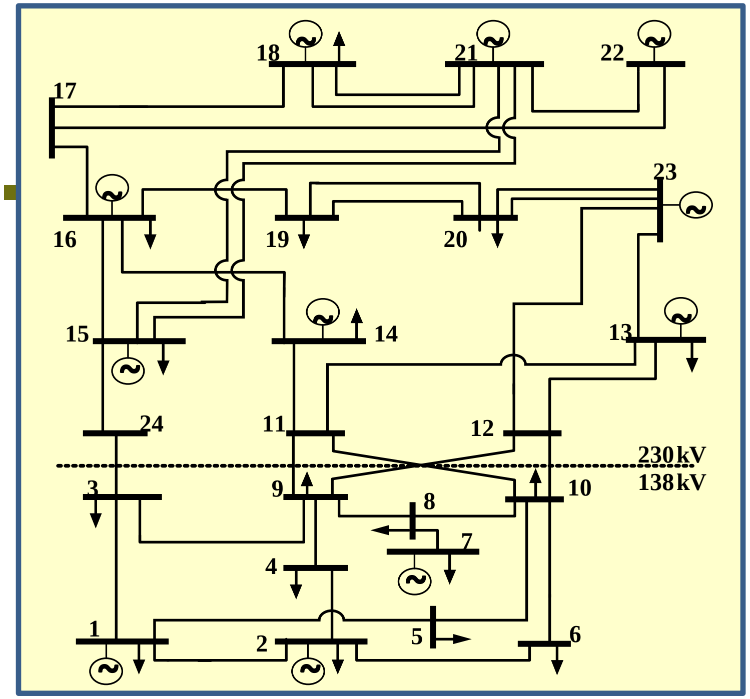
Stochastic planning for PAR/PST location

- k (wind power x load) scenarios

$$\min J = \sum_{k=1}^{S} p_k J_k$$

$$J_k = \sum_{i=1}^{N} u_i (A + B(\alpha_i^{Max})^2) + \text{Penalties}$$

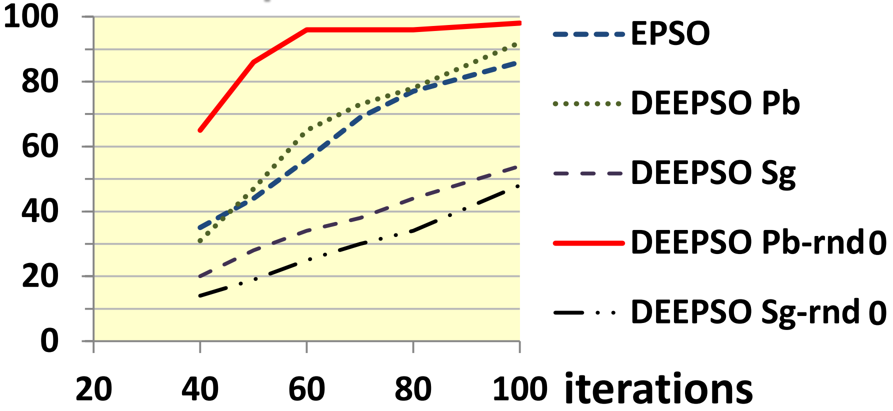
$$\alpha_i^{min} \le \alpha_i \le \alpha_i^{max} \qquad u_i \in \{0,1\}$$



Penalties on spilling wind and load curtailment

Again a mixed-integer problem
Again DEEPSO performs

Hits on the optimum in %



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The application of DEEPSO to OPF challenge

VERSION USED

- DEEPSO Pb-rnd^{-} - sampling X_{r1} from the Matrix of Memories P_i
- Not evaluating X_{r1} , not looking at the sign of $(X_{r1} – X)$

RAW APPLICATION, brute force approach

- No benefits from the mathematical model
- No benefits from clever initialization

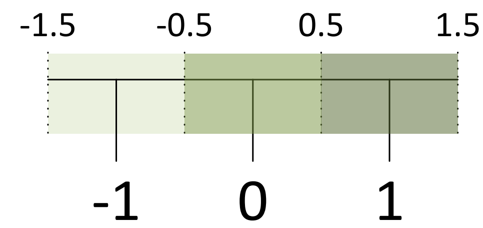
SPECIAL HANDLING OF INTEGER VARIABLES

SPECIAL HANDLING OF THE BALANCE OF CONSTRAINT VIOLATIONS

Handling of integer variables in DEEPSO

1. Deterministic rounding process

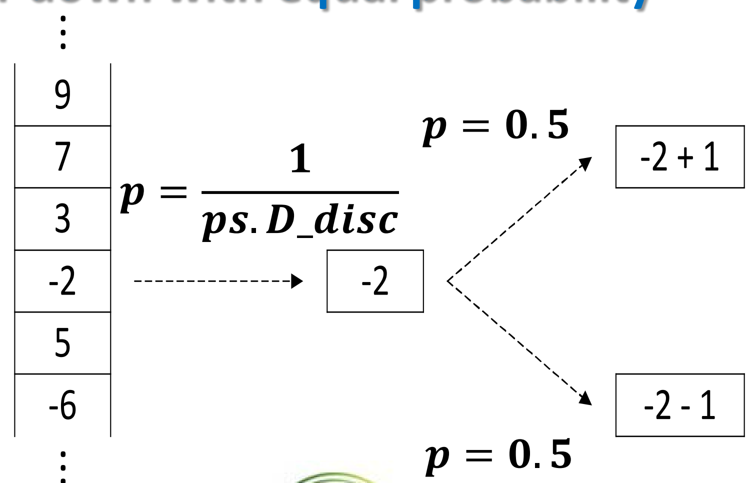
- After every particle move



2. Probabilistic mutation scheme

- Governed by a probability of occurrence pStall, applied to the generation counting - in the OPF challenge, pStall = 0.2
- Then, within the chromosome, the genes for integer values are randomly selected, with a low probability
- If a gene is selected, mutation up or down with equal probability

Gently… not to disturb the learning process of DEEPSO…



Handling of constraint violations in DEEPSO

There are several types of violations with different magnitudes for different scenarios

- Active power generation in REF bus, MW
- Voltage magnitude in PQ busbars, p.u.
- Reactive power generation in PV busbars, MVAR
- Apparent power in transmission lines, MVA

Separate penalties for each type of violation

- ORPD:

$$f = g + \alpha\left[\lambda_1 \sum |\Delta V| + \lambda_2 \sum |\Delta Q| + \lambda_3 \sum |\Delta S|\right]$$

- OARPD:

$$f = g + \alpha\left[\lambda_1 \sum |\Delta P| + \lambda_2 \sum |\Delta V| + \lambda_3 \sum |\Delta Q| + \lambda_4 \sum |\Delta S|\right]$$

α	ORPD	OARPD
41 Bus	1	
IEEE 57 Bus	1	1
IEEE 118 Bus	1	10
IEEE 300 Bus	1	100

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Handling of Constraint Violations in DEEPSO

Basic principle: no preference between different types of violations (*– but… is this good?*)

STRATEGY

The λ weights are adaptively adjusted every iteration according to the average value of the sum of deviations

$$\lambda_1 \sum |\Delta P| \approx \lambda_2 \sum |\Delta V| \approx \lambda_3 \sum |\Delta Q| \approx \lambda_4 \sum |\Delta S|$$

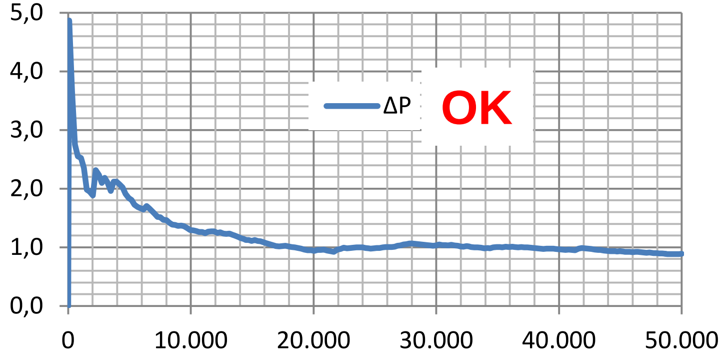
- **Select the maximum of the average sum of deviations at gen. *T***

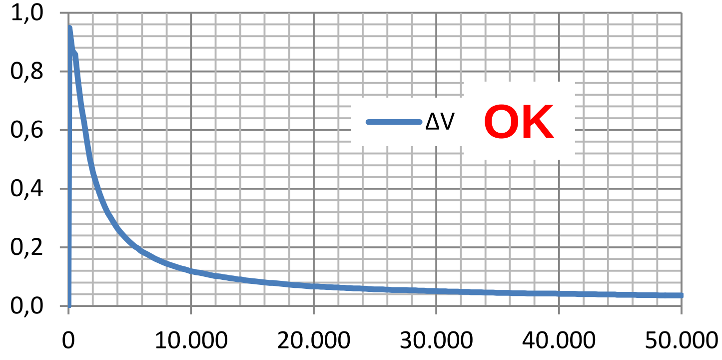
$$max\left(\frac{1}{T-1}\sum_{t=1}^{T-1}\sum|\Delta P_{t-1}|, \frac{1}{T-1}\sum_{t=1}^{T-1}\sum|\Delta V_{t-1}|, \frac{1}{T-1}\sum_{t=1}^{T-1}\sum|\Delta Q_{t-1}|, \frac{1}{T-1}\sum_{t=1}^{T-1}\sum|\Delta S_{t-1}|\right)$$

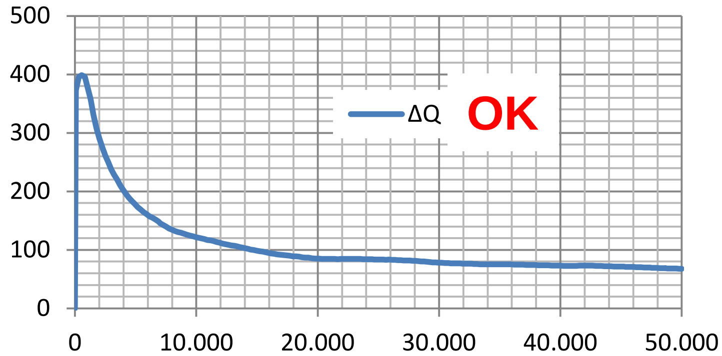
- **The coefficient λ corresponding to the maximum is equal to 1**
- **The remaining coefficients are adjusted so that every term of the fitness function has the same order of magnitude**

IEEE 57 Bus (OARPD)

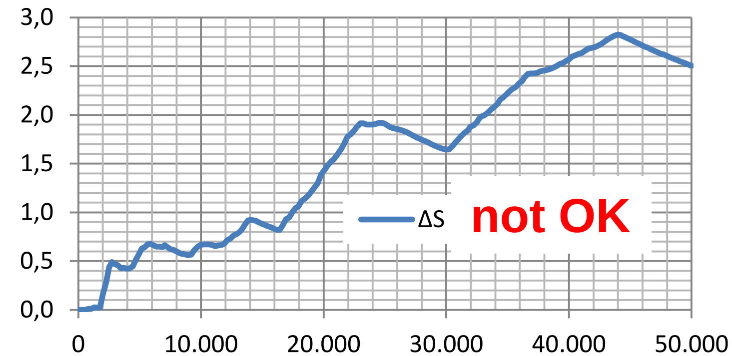
Average (for the swarm) of the Sum of Deviations







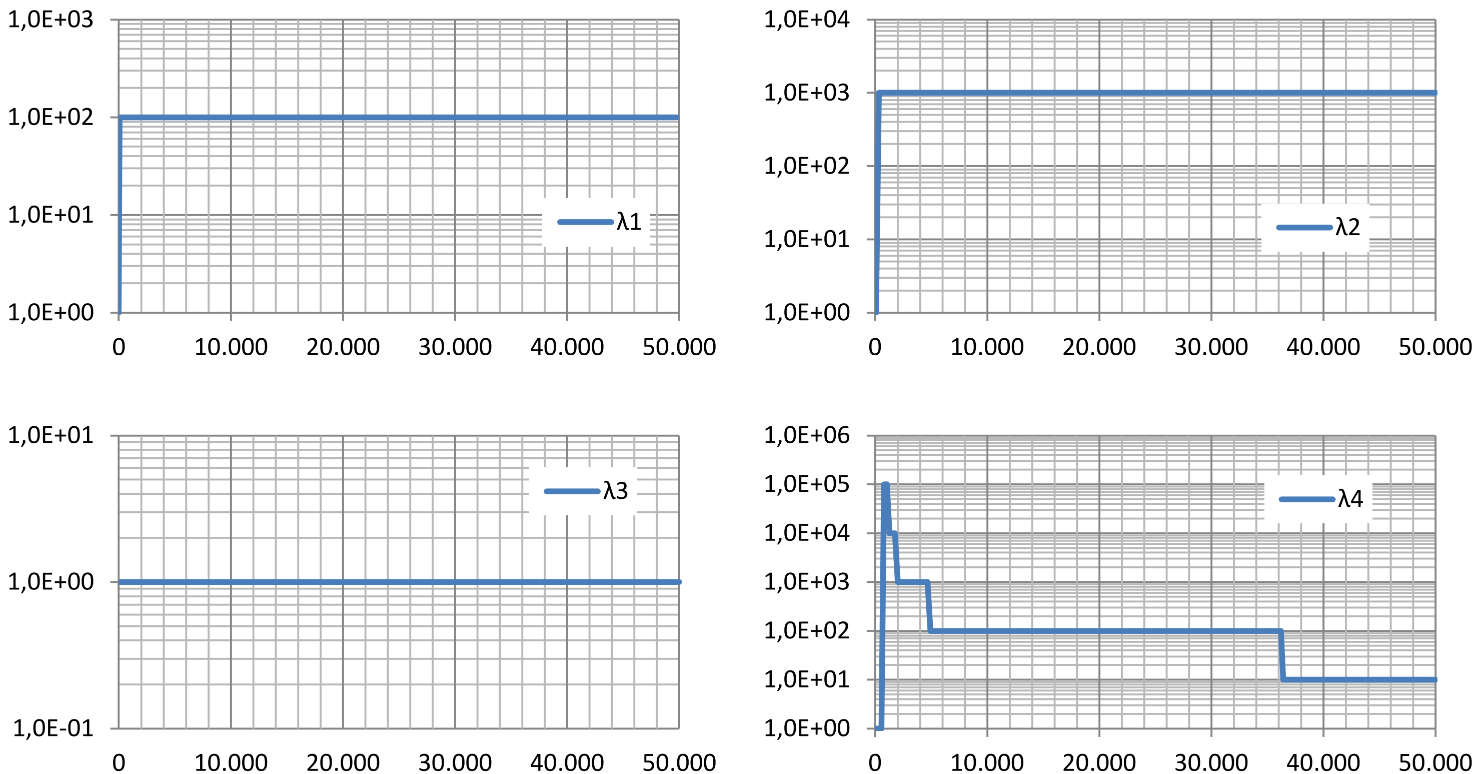
Evidence that the swarm increases in variance in ΔS to reduce the other violations



IEEE 57 Bus (OARPD)

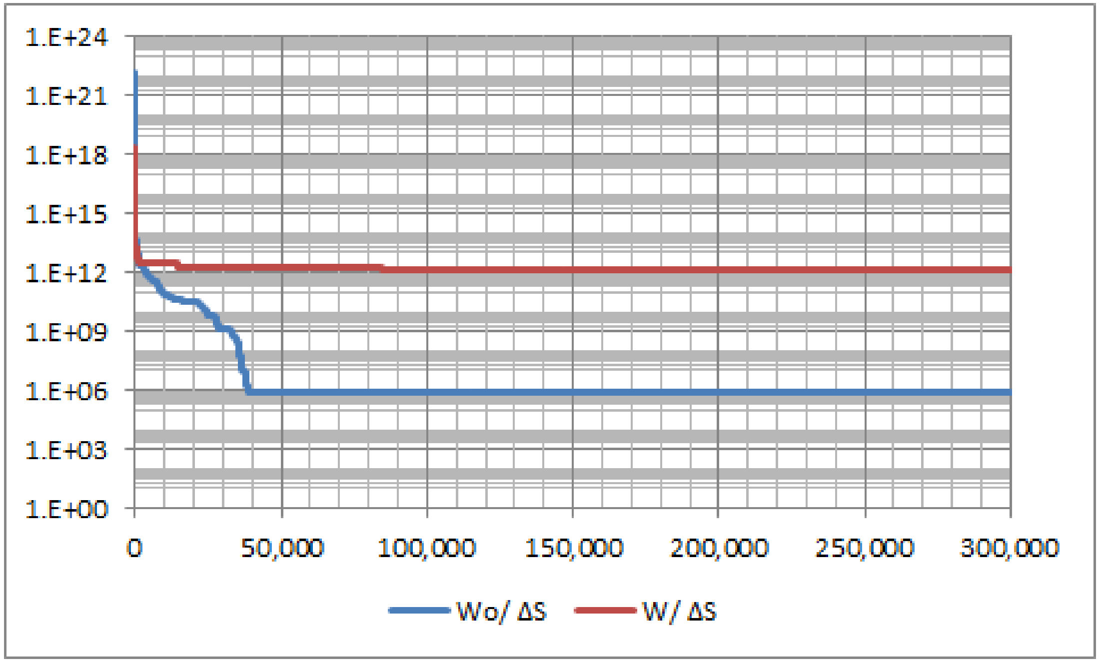
PENALTY COEFFICIENTS

evidence that λ_4 is the most unstable



IEEE 300 Bus (OARPD)

Comparing the evolution of the fitness function of the best solution in both adaptive penalty strategies



Obviously, the sensitivity of the stability of the process to the violation of different constraint types must be taken in account

INSPIRATIONS

IMPROVEMENT AFTER THE COMPETITION

- DEEPSO P_G-rnd0 is more promising
- Mutations also applied to the real variables
  - Evolving to a hybrid of DEEPSO with EP, with a sequence of EPSO moves being followed by a cromosome improvement process
- This process resulted in higher robustness!
  - Reduced variance of the results in 31 runs in all cases!, compared with the submitted results – and even better solutions!

OPRD		
IEEE 300 Bus	Sent	New*
Maximum	562,46	413,08
Minimum	391,44	385,43
Mean (31)	414,62	395,15
Std Deviation	42,04	6,74

OPARD		
IEEE 300 Bus	Sent	New*
Maximum	736.527,31	725.457,95
Minimum	721.377,54	721.166,66
Mean (31)	723.041,13	722.069,70
Std Deviation	2.669,91	818,74

** Results with DEEPSO PG-rnd+*

CONCLUSIONS

DEEPSO has 5 setting parameters

- Population size **N**
- Mutation rate, **τ**
- Communication probability **p**
- Probability of chromosome improvement (mutation) **pStall**
- Scaling coefficient **α** (= max λ)

Future work

- Fully investigating a hybrid of DEEPSO with EP chromosome improvement for real and integer variables
- Improving the adaptive penalty scheme
- Adding the mathematical knowledge to a process that would be more “industry friendly”

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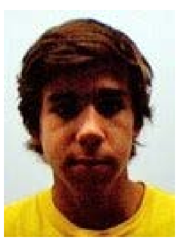

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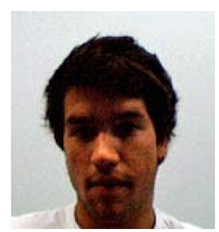

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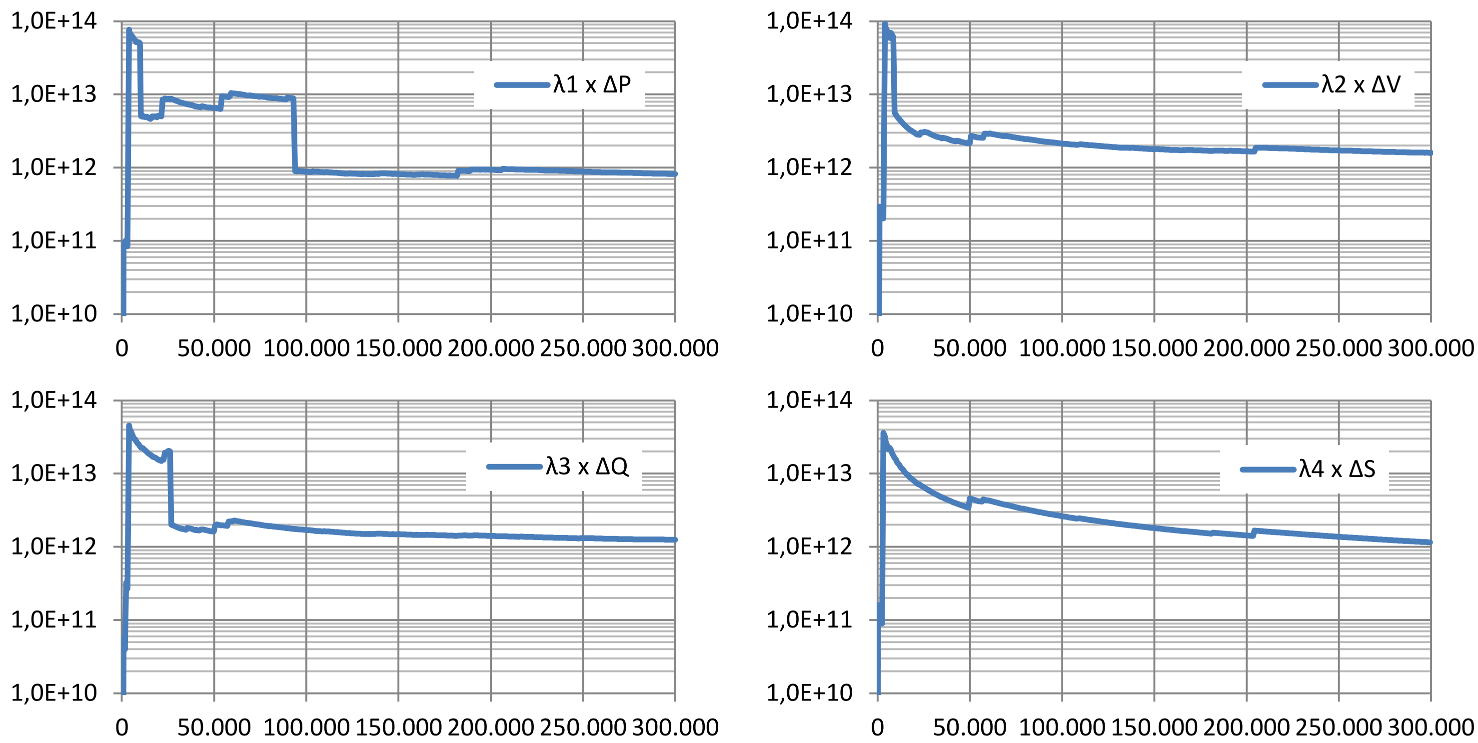
IEEE 300 Bus (OARPD)

CONFIRMATION OF CRITICALITY OF ΔS

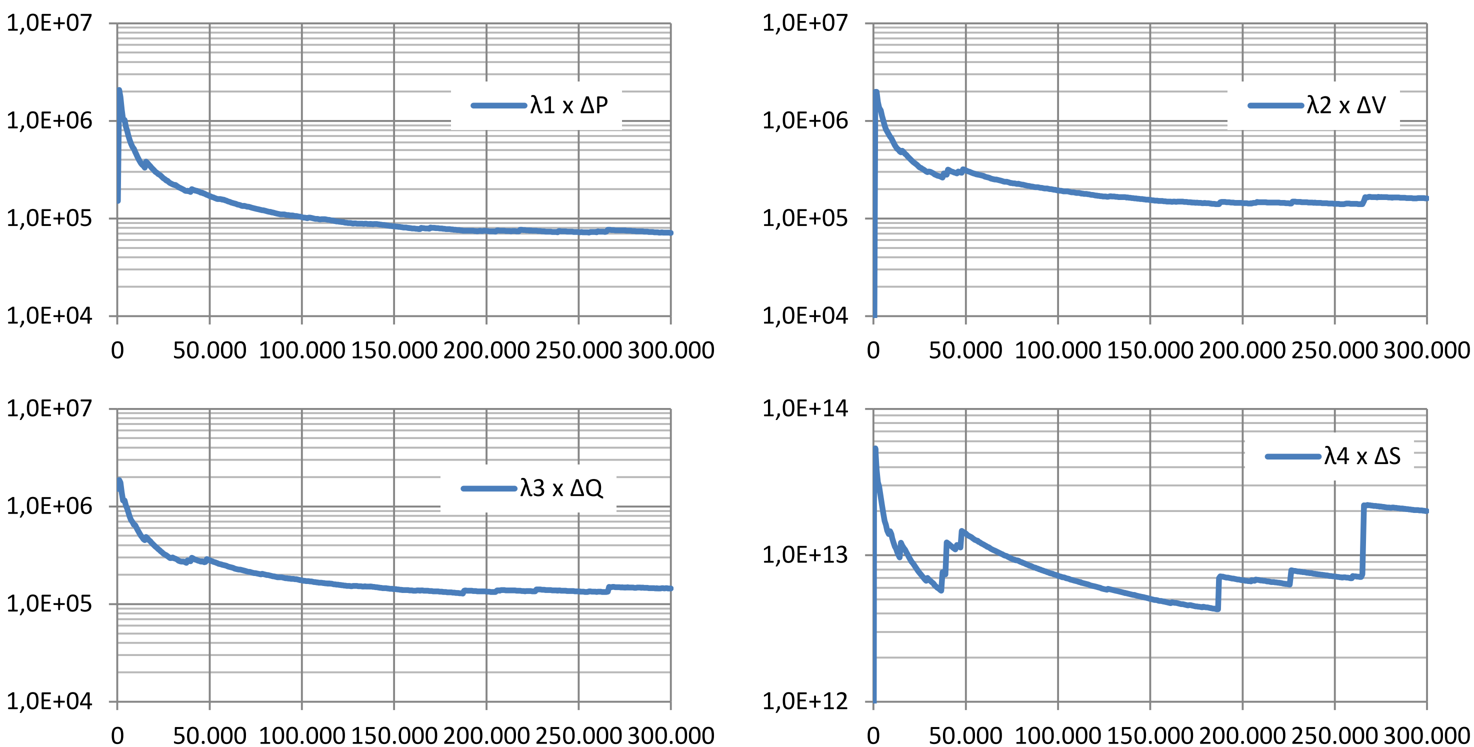
Average (in the swarm!) penalty evolution when including an adaptive ΔS term together with the other terms



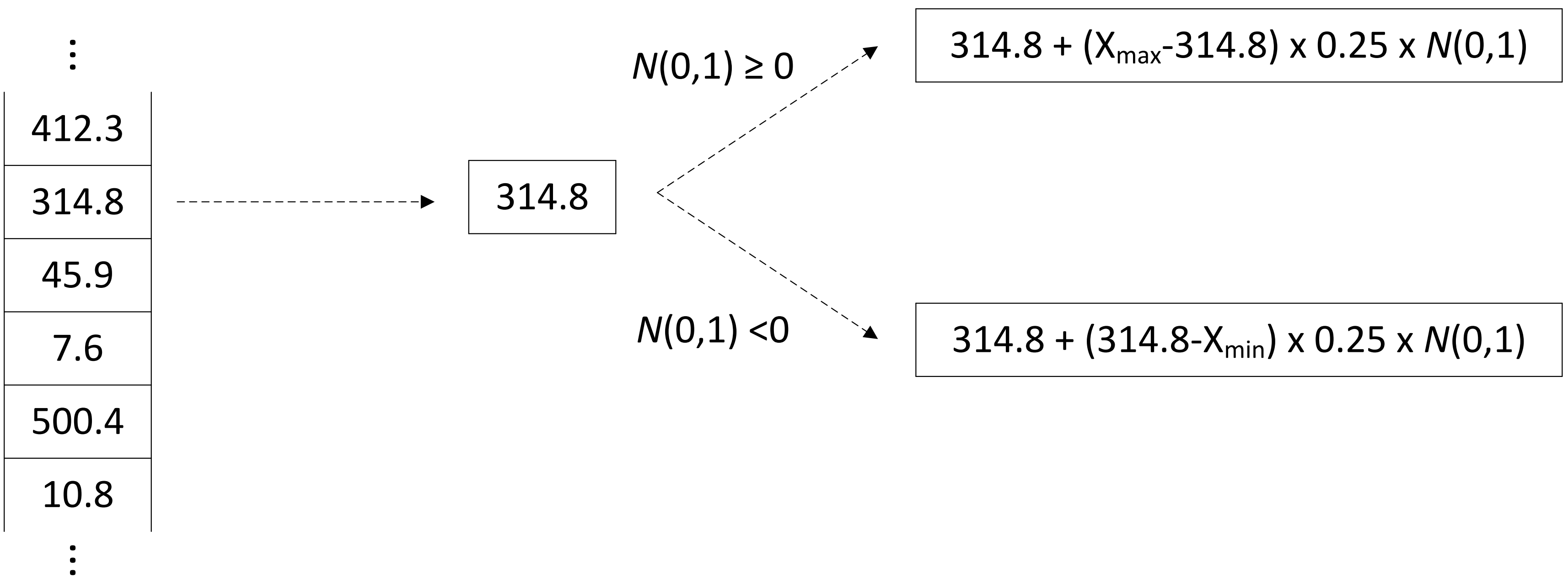
IEEE 300 Bus (OARPD)

CONFIRMATION OF CRITICALITY OF ΔS

Average (in the swarm!) penalty evolution when not including an adaptive ΔS term – fixing λ_4 at a very high level $\rightarrow$ stable results!



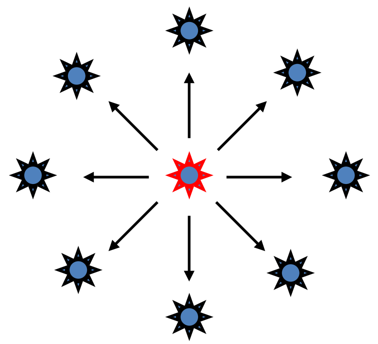
Real Variables Mutation



Communication structure among particles

Classical communication structure: the star

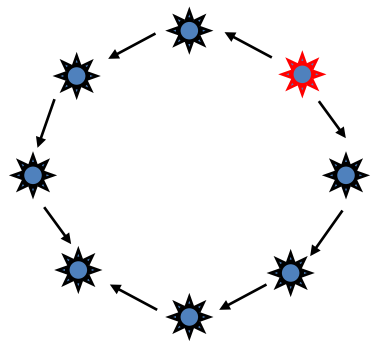
- all individuals share at the same time the knowledge about the location of b_G



Too much communication is against exploration of the search space – may induce premature convergence

Alternative structure: the ring

- each particle only communicates with two neighbours - information about a new b_G takes time until it reaches all individuals



Too little communication risks approaching the process to a set of parallel independent individual searches