Decoding Strategies for the 0/1 Multi-objective Unit Commitment Problem

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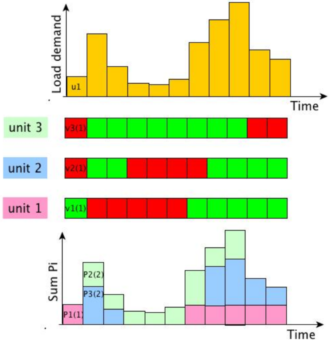
Outline

Unit Commitment Problem



MO-UCP

- The UCP is to give:
  - The on/off scheduling of each production unit ($v_{i,t}$).
  - The exact production of each turned on unit ($p_{i,t}$).
- Such that :
  - The demand is met (u_t).
  - Operational constraints are met.
- Objectives Minimize:
  - the production cost
  - **the emission of SO_2 and CO_2.**

Unit Commitment Problem

Objective functions

- Production cost:
  - Fuel cost : quadratic function of the production.
  - Start up cost : depend on how long a untit have been turned off before being turned of.
- Emission cost : quadratic function of the production.

Unit Commitment Problem

Constraints

- Unit output constraints.
- Spinning reserve constraints.
- Minimum up time limit.
- Minimum down time limit.

Solving method for the mono-objective UCP

2 stages hierarchical problem

- On/off scheduling sub-problem => fix the binary variables
- dispatching sub-problem => fix the continuous variables

Economic dispatching problem

For a given on/off scheduling the dispatching problem is :

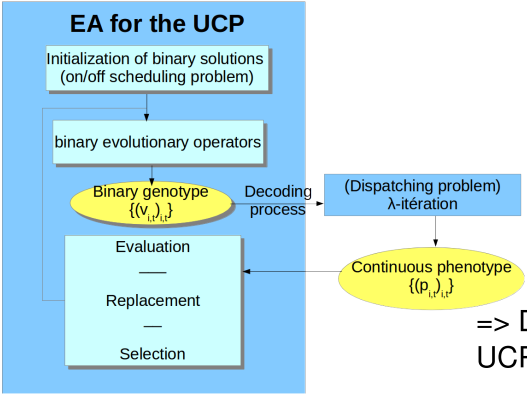
$$\min_{p}\left(\sum_{t}\sum_{i,v_{i,t}=1} a_1 p_{i,t}^2 + a_2 p_{i,t} + a_3\right)$$

such that :

- demand is met : $\sum_{i,v_{i,t}=1} p_{i,t} = u_t \; \forall t.$
- capacity constraints are met : $p_{i,min} \leq p_{i,t} \leq p_{i,max}$ $\forall i, t, v_{i,t} = 1.$

=> Continuous convex problem that can easily be solve exactly with a λ-iteration method.

General framework of EA for the mono-objective UCP



- The state of the art MH for the UCP problem used the following strategy :
  - The metaheuristic focus on the on/off scheduling sub-problem ($v_{i,t}$).
  - Then the economic dispatching problem ($p_{i,t}$) is solved with a λ-iteration method.

=> Difficulties to extend MH for the UCP to MO-UCP.

Decoding Problem for the MO-UCP

Multi-objective dispatching problem

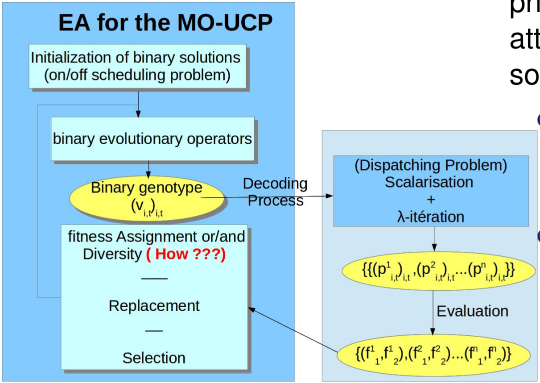
$$\min_{p}\left(\sum_{t}\sum_{i,v_{i,t}=1} a_1 p_{i,t}^2 + a_2 p_{i,t} + a_3; \sum_{t}\sum_{i,v_{i,t}=1} b_1 p_{i,t}^2 + b_2 p_{i,t} + b_3\right)$$

such that :

- demand is met : $\sum_{i,v_{i,t}=1} p_{i,t} = u_t \; \forall t$.
- capacity constraints are met : $p_{i,min} \leq p_{i,t} \leq p_{i,max}$ $\forall i, t, v_{i,t} = 1$.

=> Convex Pareto front => Efficiency of the weighted sum method => interest of decoding

Decoding Problem for the MO-UCP



MO dispatching problem=> Many phenotypic solutions can be attached to one single genotypic solution:

- "How to efficiently attach a single phenotypic solution to each genotypic solution?"
- "How to evaluate the quality of a genotypic solution corresponding to many phenotypic solutions?"

Solving method

Solving method

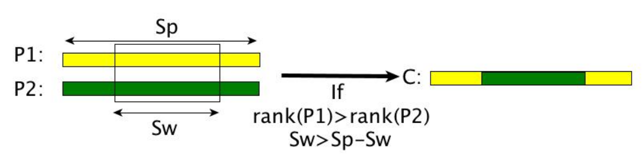
- We propose a simple genetic algorithm that will be applied with 3 decoding strategies:
  - 2 mono-objectives decoders;
  - 1 multi-objective decoder.

Solving method

Genetic algorithm based NSGA-II

- **Representation :** binary vectors :
- **Mutations :** Bit flip and Window mutations.

- **Crossovers:** 1-point crossover and an Intelligent 2-points crossover.



Decoding strategy : Naive Approach

$$\overbrace{\underbrace{010\cdots 1}_{\text{unit 1}}\ \underbrace{010\cdots 0}_{\text{unit 2}}\ \cdots\ \underbrace{110\cdots 0}_{\text{unit N}}}^{\text{v}}$$

$$\Big\Downarrow min_p(\alpha f_1(p) + (1-\alpha) f_2(p))$$

$$p_v\ : \underbrace{0p_{1,2}0\cdots p_{1,T}}_{\text{unit 1}}\underbrace{0p_{2,2}0\cdots 0}_{\text{unit 2}}\cdots\underbrace{p_{N,1}p_{1,2}0\cdots 0}_{\text{unit N}}$$

Naive Approach

A single phenotypic solution p_v is associated with a genotypic solution v. This solution is obtained in solving the aggregated dispatching problem with a fixed weight α.

Decoding strategy : Naive Approach

Drawback of the naive approach

Not all Pareto optimal solutions are reachable

Decoding strategy : Scalarized decoding

$$\overbrace{\underbrace{010\cdots1}_{\text{unit 1}}\ \underbrace{010\cdots0}_{\text{unit 2}}\ \cdots\ \underbrace{110\cdots0}_{\text{unit N}}}^{v}\ \underbrace{101\cdots1}_{\alpha_v}$$

Scalarized decoding

- A weight of scalarization α_v is associated with each solution v.
- This weight is use to attach a single phenotypic solution p_v to v.

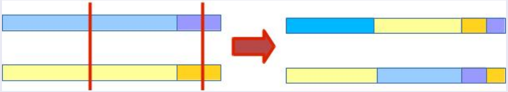
Decoding strategy : Scalarized decoding

Adaptations on the mutations

- 1-bit-flip mutation and the window mutation : applied only on the bit corresonding to v.
- New mutation : replaced α_v by a value chosen randomly between 0 and 1 with a normal distribution centered on its original value.

Adaptation on the Crossover

- A crossover point is add on the α_v vector.



Decoding Strategie : Multi decoding embedded approach

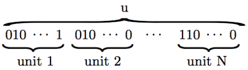
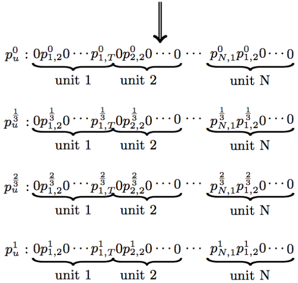


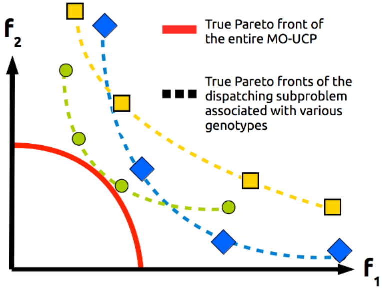
Fig. 3. representation genotypic of a solution u



Multi decoding embedded approach

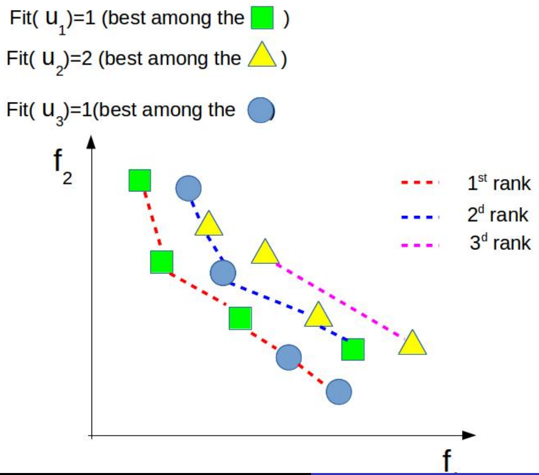
- A Pareto Front of $n_\alpha + 1$ solutions is attached with each genotypic solution.

Decoding Strategie : Multi decoding embedded approach

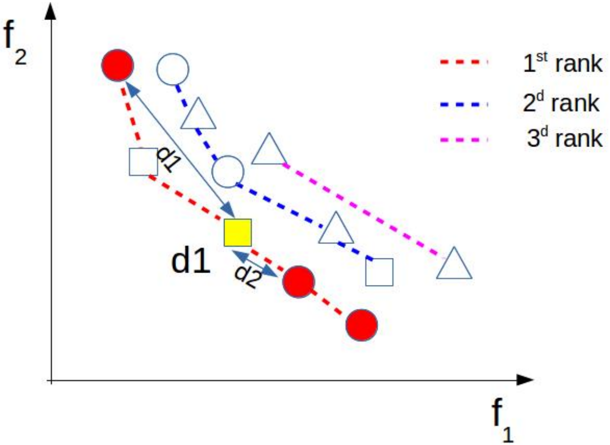


- Decoded-NSGAII :
  - How to adapt the Fitness Assignment strategy ? (rank)
  - How to adapt the Diversity Assignment strategy ? crowding distance

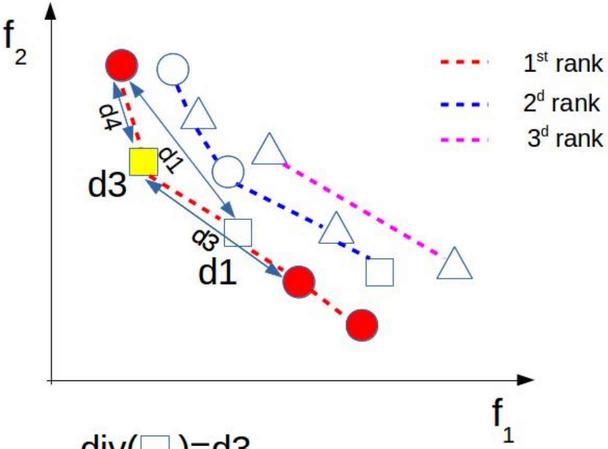
Fitness Assignment



Diversity assignment



Diversity assignment



div(□)=d3

Experimental Protocol

- Instances: 10, 40 and 100-units data.
- Performance Assessment: ϵ-indicator and hypervolume difference indicator.
- Experimental design:
  - Parameter setting: Use of Irace a R package.
  - Population size fixed to 100 individuals.
  - Stopping criterion: convergence time of the algorithms.
  - 20 runs launched for each case and each decoder, results are compared with PISA using Friedman statistical test with a p-value of 0.005.

Results

Cas 10 unités

Decoder	Naive	Scalarized	Multi
Naive	-	$=$	$<$
Scalarized	$=$	-	$<$
Multi	$>$	$>$	-

Indicator	$I^1_{\varepsilon+}$		I^-_H	
Decoder	best	mean	best	mean
Naive	0.736	0.738	0.451	0.455
Scalarized	0.719	0.738	0.433	0.454
Multi	**0.709**	**0.712**	**0.422**	**0.425**

Results

Cas 40 unités

Decoder	Naive	Scalarized	Multi
Naive	-	$<$	$<$
Scalirized	$>$	-	$<$
Multi	$>$	$>$	-

Indicator	$I^1_{\varepsilon+}$		I^-_H	
Decoder	best	mean	best	mean
Naive	0.195	0.333	0.346	0.508
Scalarized	0.181	0.233	0.208	0.377
Multi	**0.00129**	**0.0840**	**0.000880**	**0.100**

Results

Cas 100 unités

Decoder	Naive	Scalarized	Multi
Naive	-	$<$	$<$
Scalirized	$>$	-	$<$
Multi	$>$	$>$	-

Indicator	$I^1_{\varepsilon+}$		I^-_H	
Decoder	best	mean	best	mean
Naive	0.306	0.573	0.549	0.864
Scalarized	0.016	0.404	0.0169	0.636
Multi	**0.00389**	**0.150**	**0.000177**	**0.264**

Conclusion

Contributions

- Extension of the indirect representation in UCP to the MO-UCP.
- Proposition and comparison of 3 decoder systems.
- **Conclusion:** The interest of the Multi decoding embedded approach has been demonstrated.

Perspectives

- Generalized the Multi-decoder strategy to any algorithm.
- Apply this strategy on some others problems.

Merci

Merci pour votre attention