Surrogate assisted optimization

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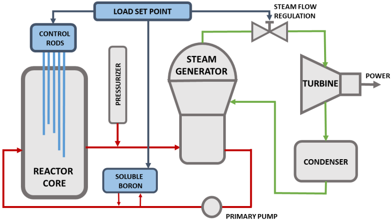
Context

Mobility system

Nuclear energy system



A priori, each domain is very different
But, share :

- Design problems for new perspectives,
- Inaccessible (cost) quantities, scales, etc.

Solving design problems, etc.

Solving optimization problems (mono- or multi-objective)

- Using the cognitive, and social abilities of humans :
  expert knowledges, evaluation of risk, uncertainties, divide into sub-problems, complex reasoning, etc.
- Using the computational, and memorization abilities of machines :
  automatic, data, formal language, speed, multi-scale, etc.

Main AI approaches for automatic solving

- Algebraic approach : algebraic, or formel model
- Digital twin approach :
  numerical model, and numerical simulation

Comparaison of approaches

Algebraic approach

- Formal model
- Aggregated variables, noice (demand, incertainties), contraints,...
- Artificial or real-like problem instances
- Offline

Tools :
cplex, gurobi, constr. prog., local search, ea, etc.

Digital twin approach

- Low level model
- Complex interactions
- Flow of data : sensor, etc.
- Offline, Online

Tools :
simcore, simio, matsim, devs,...

$$\max \sum_{t\in T}(pf_t) - \sum_{t\in T}\sum_{o\in O}(g_{t,o}u_{t,o} + 5s_{t,o})$$

$$s_{t-1,o} + b_{t,o} = u_{t,o} + s_{t,o} \quad \forall t \in T \setminus t_0,\ \forall o \in O$$

$$i + b_{t_0,o} = u_{t_0,o} + s_{t_0,o} \quad \forall o \in O$$

$$s_{t_e,o} = i \quad \forall o \in O$$

$$\sum_{o\in V} u_{t,o} \leq 200 \quad \forall t \in T$$

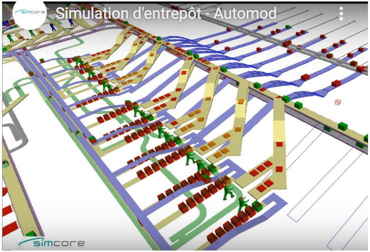
$$\sum_{o\in N} u_{t,o} \leq 250 \quad \forall t \in T$$

$$3f_t \leq \sum_{o\in V} h_o u_{t,o} \leq 6f_t \quad \forall t \in T$$

$$\sum_{o\in V} u_{t,o} = f_t \quad \forall t \in T$$

$$b_{t,o}, u_{t,o}, s_{t,o} \geq 0 \quad \forall t \in T,\ \forall o \in O$$

$$f_t \geq 0 \quad \forall t \in T$$



Consequences for automatic solving

$$\max \sum_{t\in T}(pf_t) - \sum_{t\in T}\sum_{o\in O}(g_{t,o}u_{t,o} + 5s_{t,o})$$

$$s_{t-1,o} + b_{t,o} = u_{t,o} + s_{t,o} \quad \forall t \in T \setminus t_0,\ \forall o \in O$$

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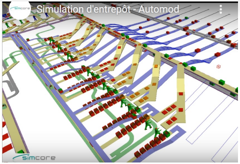


Algebraic approach

Pros :

- Exploitation of the algebraic properties (fast to compute)
- Explicit, and synthetic model

Difficulties :

- Design of the model :
  creation of languages, etc.

Digital twin approach

Pros :

- Low level description
- Tests, visualization

Difficulties :

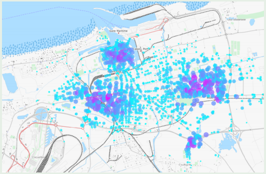
- $\approx$ Black-box : $(x, f(x))$
- Costly simulation
  (time, energy)

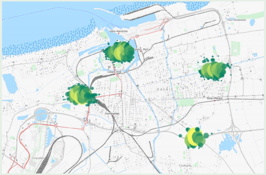
Indeed, not only "solving", but also support of decision making : before, during, and after the optimization process

Digital twin for mobility system

F. Leprêtre, V. Marion, C. Fonlupt, S. Verel (LISIC) - thesis 2017 - 2020.
H. Aguirre, R. Armas, K. Tanaka (Shinshu Univ., Nagano, jp)
Partner : Calais City, Marie Capon, (expertise, and funding)

SIALAC benchmark of mobility





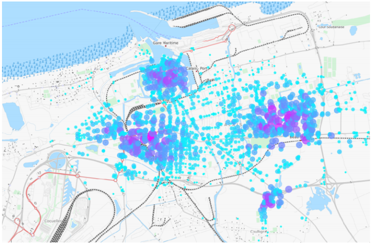
Different and, futur scenario : home, agents, activity

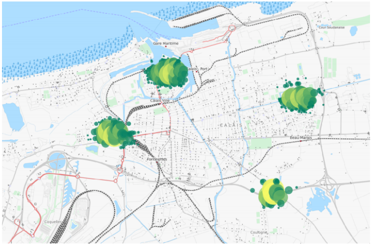
Two problems

- Tuning of traffic light
- Bus stop position

SIALAC benchmark of mobility

Leprêtre, F., et al. Applied Soft Computing, 2019 [12]





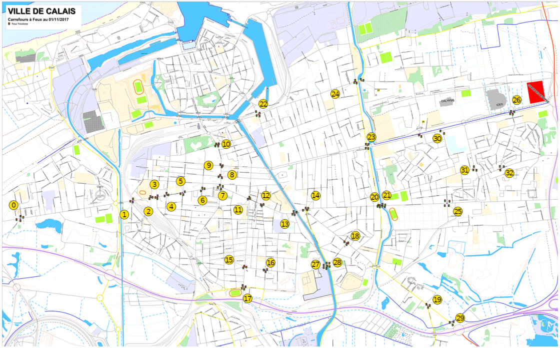
Number of agents	$\{5, 10, 15, 20\} \times 10^3$
Home	$\{1 \text{ cluster}, 4 \text{ clusters}, \text{ uniform}\}$
Activity	$\{1 \text{ cluster}, 4 \text{ clusters}\}$
Signals systems	$\{50\%, 75\%, 100\%\}$

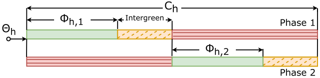
72 scenario using MatSim (Multi-Agent Transport Simulation)

Goal

- Show to the partner what it is possible with such tools
- Design **robust** optimization algorithms for mobility problems

Traffic light problem for Calais, and Quito cities





- Space : 33 (Calais, France), 70 (Quito, Equator) intersections
  search space dim. $\times 4$ integer variables
- Criteria : minimize average travel time (black-box problem)
- Computational time per simulation $\approx$ 1 minute

Gradient free optimization algorithms

Stochastic Hill Climber

$x \leftarrow$ initialize random solution
repeat

$x' \leftarrow$ mutate x
$x \leftarrow x'$ **if** $f(x') < f(x)$
until stopping criterion met

Evolutionary Algorithm

$P = \{x_1, \ldots, x_\mu\} \leftarrow$ rnd. init.
repeat
$P_{genitor} \leftarrow$ selection from P
$P_{children} \leftarrow$ breed $P_{genitor}$
$P \leftarrow$ replace $P \cup P_{children}$
until stopping criterion met

- `mutate` : random variation of candidate solution
- Tradeoff exploration / exploitation : `mutate` / `selection`

How to tune the mutation operator ?
i.e. Where to explore ?

Surrogate, and model-based approaches

According to the context, the search strategy can be different.

When the evaluation time of a single candidate solution is :

- short : try, and test strategy (local search, EA, etc.)
  a test is fast, so multiple tests are possible.
  Memory "less" strategy.
  ex. : re-computation of a solution
- long : model based strategy
  spend more time to design a new candidate solution,
  aggregation of information on the problem (model), and test
  ex. : 200 evaluations available on problem of dimension 100

Structure of real-world problems

Intuitively

Real-world problem instances are often "structured" :

- Local sub-problems are not random,
- Interdependency between sub-problems are not random.

Importance of variables

Consequence : some variables are more impactful than others.

Examples

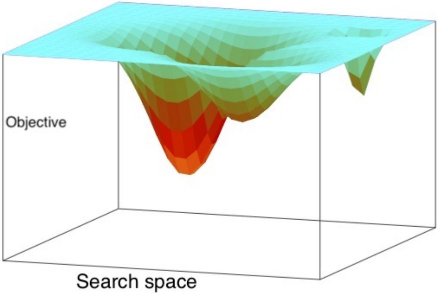
Isolated traffic lights are less impact on travel time
than central traffic lights

How to detect important variable to design a model of problem ?
Expert knowledge, or more automatically....

Fitness landscape : a model of the search space

Fitness landscape (Wright 1920)

- $\mathcal{S}$: set of candidate solutions, search space
- $f : \mathcal{S} \rightarrow \mathbb{R}$: objective function
- $\mathcal{N} : \mathcal{S} \rightarrow 2^{\mathcal{S}}$, neighborhood relation between solutions



- Geometry of the fitness landscape :
  Features/metrics
  are correlated to
  algorithm performance

$\Rightarrow$ Toward automatic design (tuning/control) of algorithms

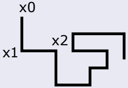
Offline model of problem

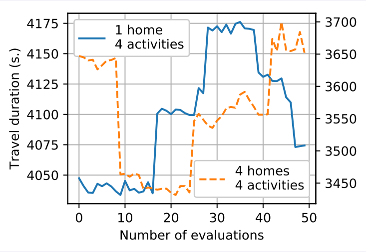
Importance degree of variable i

$$\delta_i = |f(mutate_i(x)) - f(x)|$$

Estimation : Random walk on fitness landscape

Sequence of neighboring solutions : $(x_0, x_1, x_2, \ldots)$

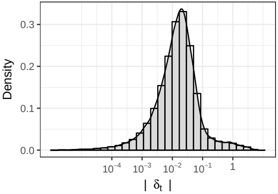


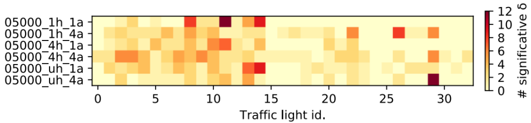


Offline model, before running the algorithm (expert knowledge ?) :

Importance δ_i associated to each var. i

Add explainable model to optimization





⇒ Explainable model (cf. XAI) defined with "score",
Improve the communication with the partners

Adaptive algorithm based on offline model

Backbone in combinatorial problems :
"good" solutions have some specific variables value

Design of mutation operator

- **Hypothesis** : modify in priority important variables
- **Goal** : automatic learning of expert knowledge

Method

- Divide the set of variables into 3 groups according to importance
- Use reinforcement machine learning technique to select the group to mutate.

Adaptive bandit descent

Multi-armed bandit problem (reinforcement learning)

UCB strategy to select to relevant arm :

$$\hat{r}_i + C\sqrt{\frac{S}{s_i}}$$

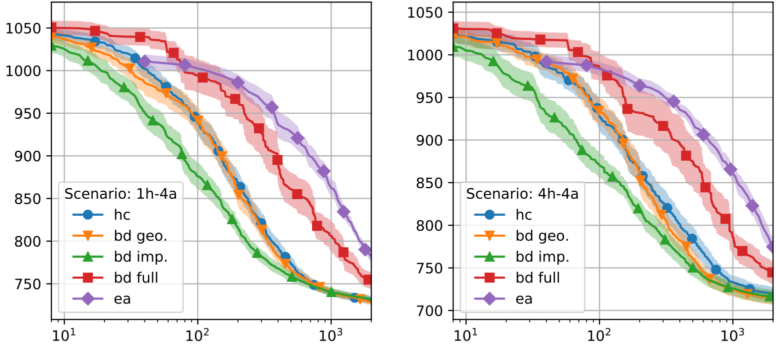
$\hat{r}_i$: reward, s_i : nb. of selection of arm i, and S : total nb. of selection, C : tradeoff parameter

Adaptive algorithm

$G \leftarrow$ split var. into groups
$x \leftarrow$ initialize random solution
repeat
  $g \leftarrow$ select group in G using UCB rule
  $x' \leftarrow$ mutate a variable from g of x
  $x \leftarrow x'$ **if** $f(x') < f(x)$
  Update rewards
until stopping criterion met

Some results

Quality *vs.* number of evaluations :



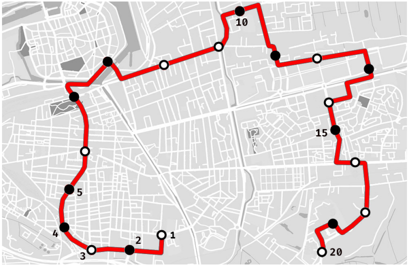
- Speed up the convergence
- Better than "hand made" groups,
  or previous Evolutionary Algorithm
- Robust on different scenario (also for Quito city)

Optimisation with time expensive simulation

- Parallel computation : distribute computation on machines
- **Surrogate model** : online substitution of the original function with an (approximated) function fast to compute

Surrogate model

- A lot of works on numerical optimization :
  $f : \mathbb{R}^d \to \mathbb{R}$
- Few works on discrete/combinatorial optimization :
  $f : \{0,1\}^d \to \mathbb{R}$, or $f : \mathcal{S}_n \to \mathbb{R}$



Bus stop position problem

- Space : $\{0,1\}^d$ open or close possible stops
- Criterium : min. travel time

Surrogate-assisted opt. of pseudo-boolean problems

Florain Leprêtre, Virginie Marion, Cyril Fonlupt (LISIC),
K. Tanaka, H. Aguirre (Univ. Shinshu), A. Liefooghe, B. Derbel (univ. Lille)

Surrogate-Assisted Optimization

$X \leftarrow$ initial sample
repeat
  $M \leftarrow$ Build model of f from X
  $x^\star \leftarrow$ Optimize *w.r.t.* an acquisition function based on M
  $y^\star \leftarrow f(x^\star)$ using the numerical simulation
  $X \leftarrow X \cup \{(x^\star, y^\star)\}$
until time limit

In numerical optimization [18] :

- Models :
  Gaussian Process, polynomial chaos, NN, RBF, RF, deep$*$, etc.
- Acquisition function :
  M, Expected improvement, probability impr., UCB, etc.

In discrete optimization [2] :

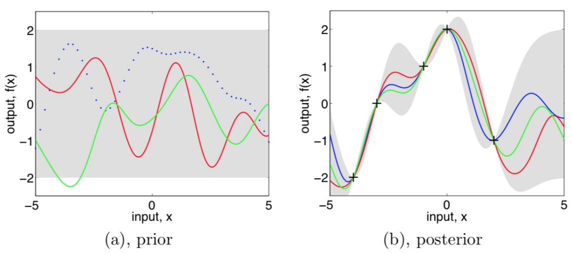
- Use discrete distance, or numerical variable

Example : Efficient Global Optimizer [9] [20]

- Model : Gaussian Process $M(x) \approx \mathcal{N}(m(x), K(x, x'))$
- Acquisition function : Expected Improvement

GP : Random variables which have joint Gaussian distribution.

mean : $m(y(x)) = \mu$; covariance : $cov(y(x), y(x')) = exp(-\theta \text{ dist}(x, x')^p)$



from : Rasmussen, Williams, GP for ML, MIT Press, 2006.

pros : estimation of incertainty (expected improvement etc.)
cons : estimation is costly, and distance in high distance is not informative

Polynomial regression model

Polynomial chaos regression (PRC)

Model

A basis of functions $\{\varphi_j : j \in \{1, \ldots, p\}\}$

$$M(x) = \sum_{j=1}^{p} \beta_j \varphi_j(x)$$

Regression using least square method, or bayesian approach

Example : second-order polynomial

$$M_2(x) = \beta_0 + \sum_{i=1}^{d} \beta_i \; x_i + \sum_{i=1}^{d-1} \sum_{j=i+1}^{d} \beta_{ij} \; x_i x_j$$

Pros :

Easy interpretation (XAI), fast to compute, polynomial regression

Cons :

Use a relevant basis of functions (Fourier transform, etc.)

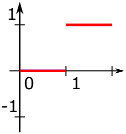
Number of terms increases exponentially with order (sparse methods)

Pseudo-boolean surrogate : Walsh functions

- Space pseudo-boolean function is a vector space
- Basis : multi-linear functions, $x_{k_1} \dots x_{k_\ell}$ [Baptista, Poloczek, BOCS, ICML 2018][1]

Multi-linear :

$d = 1$, $\psi_1(x) = x$

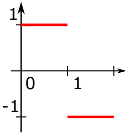


Orthogonal : No

x	ψ_0	ψ_1
0	1	0
1	1	1

Walsh :

$d = 1$, $\varphi_1(x) = (-1)^x$



Orthogonal : Yes

x	φ_0	φ_1
0	1	1
1	1	-1

Extension to dimension d using tensorial product :

$$\psi_{k_1 \dots k_\ell}(x) = x_{k_1} \dots x_{k_\ell}$$

$$\varphi_{k_1 \dots k_\ell}(x) = (-1)^{x_{k_1}} \dots (-1)^{x_{k_\ell}}$$

Surrogate model for pseudo-boolean functions

Walsh functions

$$\forall x \in \{0,1\}^d, \quad \varphi_k(x) = (-1)^{\sum_{j=0}^{d-1} k_j x_j}$$

Normal, and orthogonal basis

Any function can be written as :

$$f(x) = \sum_{k=0}^{2^d-1} \beta_k . \varphi_k(x)$$

with : $\beta_k = \frac{1}{2^d} \sum_{x \in \{0,1\}^d} f(x) . \varphi_k(x)$

Example with order 2, model limited to quadratic interactions :

$$f(x) = \beta_0 + \sum_{i=1}^{d} \beta_i . \sigma_i + \sum_{i<j=1}^{d} \beta_{ij} . \sigma_i \sigma_j \text{ with } \sigma_i = (-1)^{x_i}$$

Why Walsh functions ?

$$f(x) = \beta_0 + \sum_{i=1}^{d} \beta_i.\sigma_i + \sum_{i<j} \beta_{ij}.\sigma_i\sigma_j \text{ with } \sigma_i = (-1)^{x_i}$$

- Explicit algebraic model (not black-box) : easy to interpret
  Interaction between variables, intensity of interaction $|\beta_{i,j}|$
- Efficient algorithms to optimize such problems
- Model of function used in quantum computing
  Also know as Spin-Glasses, or QUBO / UBQP problems [8]

Surrogate model based on Walsh fonctions

Expansion to order ℓ (cf. polynomial chaos, sparse grid, etc.)

$$M(x) = \sum_{k \ : \ \text{ord}(\varphi_k) \leqslant \ell} \widehat{\beta}_k . \varphi_k(x)$$

- Pros :
  See previous slides
- Cons :
  model dimension (quadratic, cubic, etc.)
  No uncertainty estimation

Estimation of coefficients :
linear regression using sparse techniques : LARS/LASSO, etc.
LASSO : $\hat{\beta} = \text{argmin}((M(x_i) - y_i)^2 + \alpha||\beta||_1\ )$

Walsh Surrogate-assisted Optimizer (WSaO)

Surrogate-Assisted Optimization

$X \leftarrow$ initial sample
repeat
  $M \leftarrow$ Build Walsh model of f from X
  $x^\star \leftarrow$ Optimize M using Eff. Hill-Climber
  $y^\star \leftarrow f(x^\star)$ using the numerical simulation
  $X \leftarrow X \cup \{(x^\star, y^\star)\}$
until time limit

Efficient optimization algorithm for Walsh functions

using the additive property :

$$\delta_i(x) = M(x \bigoplus i) - M(x) = -2 \sum_{k \supset i} \beta_k \varphi_k(x)$$
$$\delta_{ij}(x) = \delta_i(x \bigoplus j) - \delta_i(x) = 4 \sum_{k \supset i \& k \supset j} \beta_k \varphi_k(x)$$

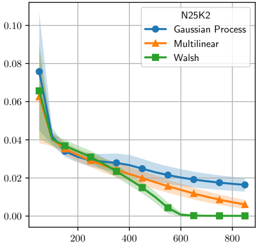
Find best improving move in $O(\ell)$ at each step of the search.
Partition crossover to combine 2 solutions

Chicano, Whitley, Ochoa, and Tinós. "Optimizing one million variable NK landscapes by hybridizing deterministic recombination and local search." In Genetic and Evolutionary Computation Conference, 2017. [3]

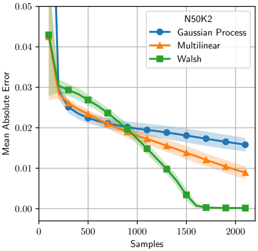
Quality of Walsh regression on academic benchmarks

Mean abs. error on NK-landscapes benchmark

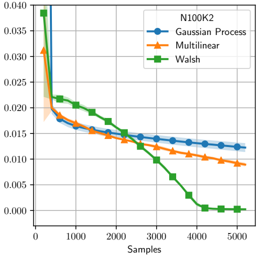
$d = 10$



$d = 25$

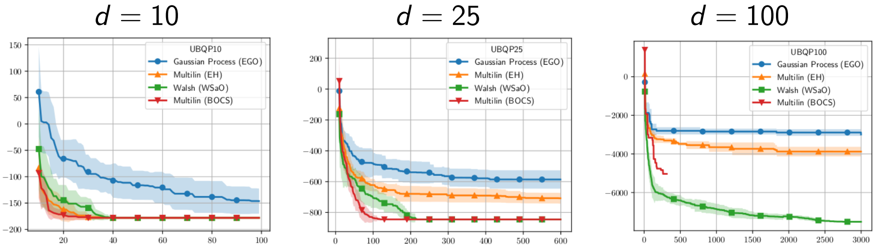


$d = 100$



Walsh Surrogate-assisted Optimizer (WSaO)

Performance on UBQP benchmark

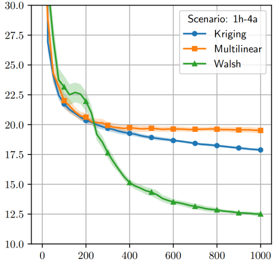


- Krigging : information of distance decreases with dimension
- BOCS : bayesian estimation of multilinear basis, SA opt. alg. (very expensive to compute)

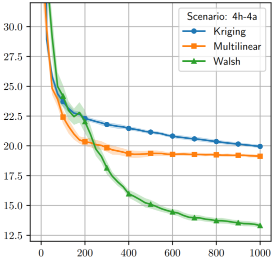
Preliminary results on bus stop problem

Mean abs. error on instances with $d = 20$, 4 activity centers

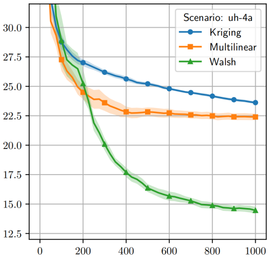
1 home



4 home

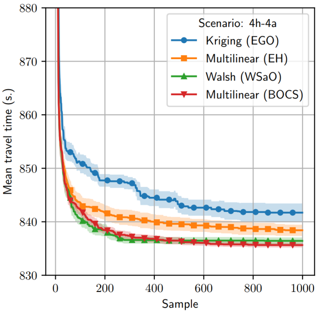


uniform



WSaO on bus stop problem

Preliminary results for small dimension $d = 20$ problem



The work is progressing on real data :
Valentin Vendi, PhD student, 2021-2024, "Design of decision-making tools for sustainable mobility in the Hauts-De-France region", co-direction with C. Fonlupt.

Others master student positions, and possible PhD position coming soon, please contact me.

Comments with surrogate models

- Result with surrogate assisted optimization :
  Near optimal solution, and an explicit model of your problem
  Use non black-box machine learning model are useful !
- Open issues :
  Tradeoff between quality of the model (uncertainty),
  and optimization effort
- Perspectives :
  multi-objective optimization, uncertainty,
  permutation space, numerical & discret, large scale, etc.

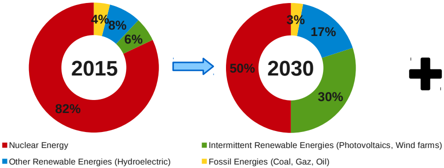
Context

Joined work

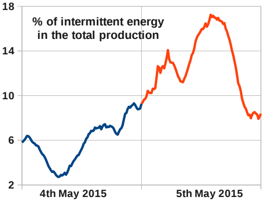
Jean-Michel Do, Jean-Charles Le Pallec, Cheikh Diop, CEA Saclay,
PhD : Mathieu Muniglia (2014 - 2017), Valentin Drouet (2017 - 2020), Baptiste Gasse (2020 - 2023)

Multi-objective optimization of nuclear power plant control for load following in the context of energy transition using evolutionary algorithms

Context



(Source : ADEME)



(Source : RTE eco2mix)

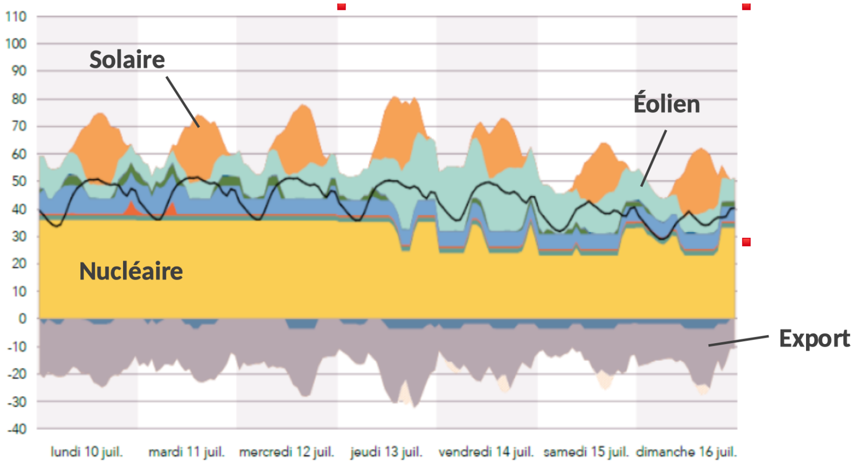
Large scale deployment of **intermittent renewable energies** in France

Highly fluctuating production rate (up to 3 times the average)

Possible solutions of intermittency :

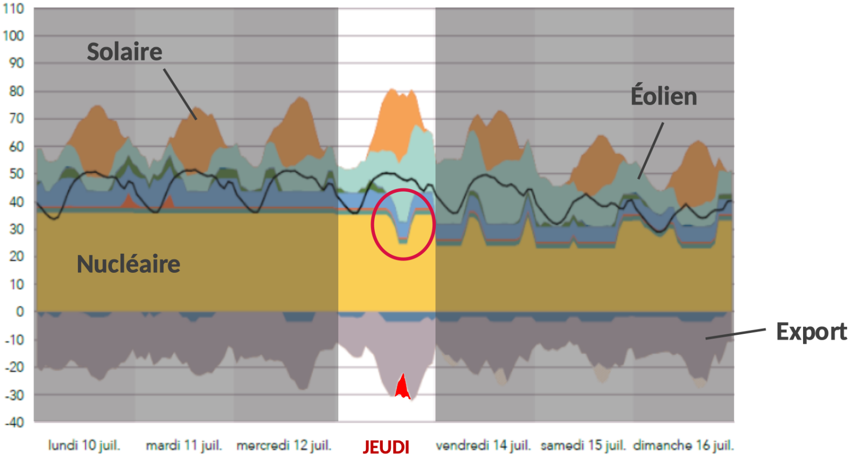
- Flexibility (on demand)
- Smart grid
- Storage
- Manageability of Pressurized Water Reactors

Scenario of energetic transition in France



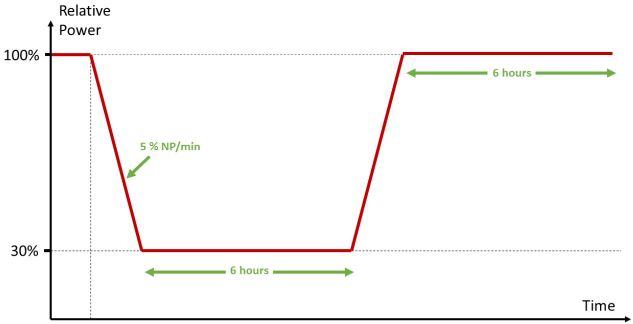
RTE (french electricity transport compagny) prediction for a typical week in 2035 (VOLT scenario)

Scenario of energetic transition in France



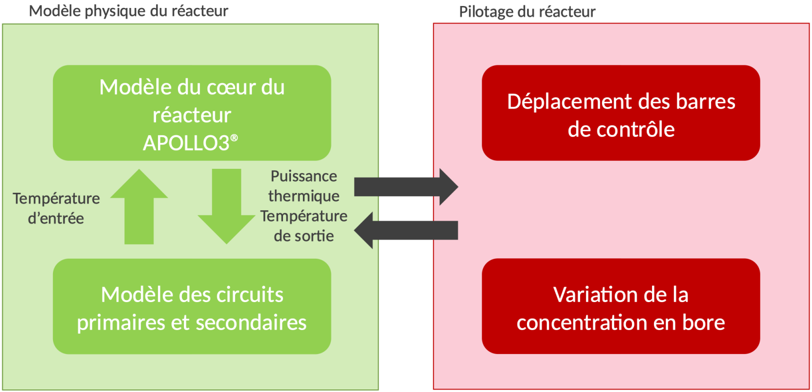
RTE (french electricity transport compagny) prediction for a typical week in 2035 (VOLT scenario)

Target production transient



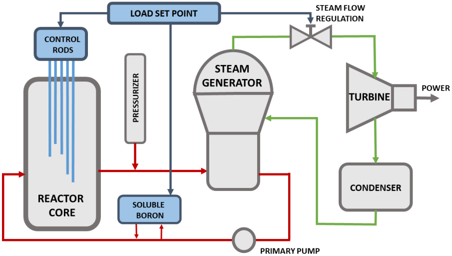
24h of production : most penalizing possible transient

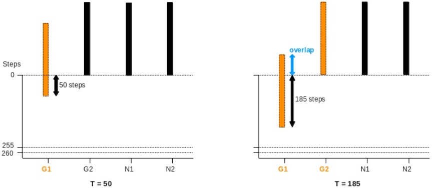
Multi-physic simulator



Around 10 minutes for the simulation of one transient
(Now in 2022, 4 reactors, and potentially 40 min of simulation...)

Optimization problem





Possible criteria

More than 7 criteria can be used :

related to cost, safety, and stability

Available control parameters

- Power Shimming Rods :
  - Overlap (x3)
  - Speed control (x4)
- Temperature Regulation Rods :
  - maneuvering band (x1)

Search space size $\approx 10^{12}$

Fitness landscape analysis : offline model

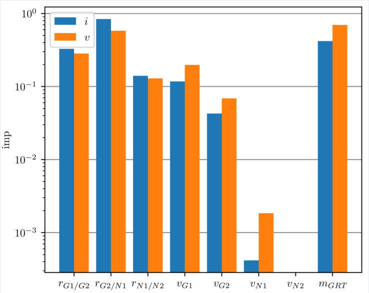
Using random walk sampling

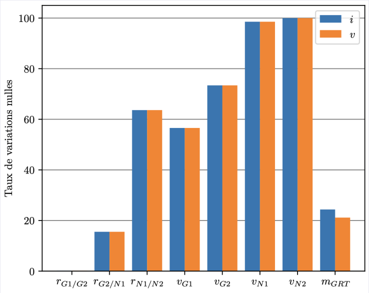
Objective correlation

	v	N_R	C_{IPG}	ΔT	f_T	i	F_v
v	1.0	-0.75	-0.91	-0.14	0.12	-0.06	-0.01
N_R	-0.75	1.0	0.7	0.68	0.17	0.14	0.4
C_{IPG}	-0.91	0.7	1.0	0.12	-0.17	-0.02	-0.1
ΔT	-0.14	0.68	0.12	1.0	0.7	0.51	0.79
f_T	0.12	0.17	-0.17	0.7	1.0	0.83	0.72
i	-0.06	0.14	-0.02	0.51	0.83	1.0	0.58
F_v	-0.01	0.4	-0.1	0.79	0.72	0.58	1.0

2 groups are highly correlated

Variable importance

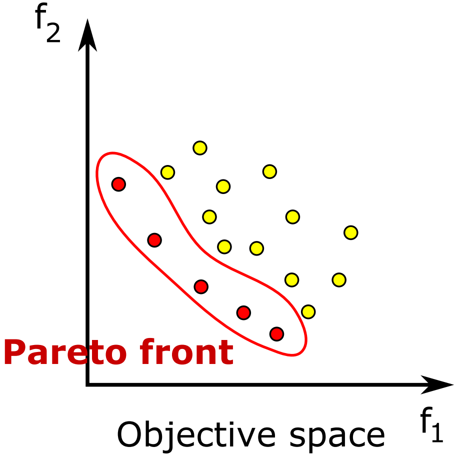




Reduce the dimension to 6, and better understanding of the system

Allow to tune the mutation parameters

Multiobjective optimization

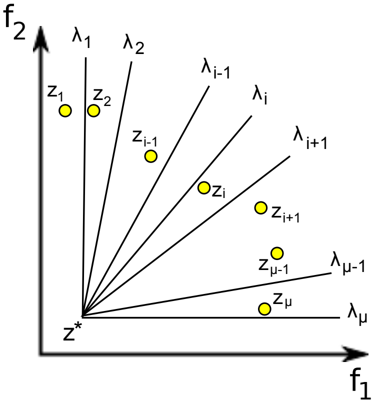


Goal

No a priori on the order/importance of the objectives,
Decision a posteriori based on the optimal Pareto solutions.

MOEA/D : Multi-Obj. Evo. Algo. based on Decomposition

A lot of MO algo. :
Pareto based (NSGAII,...), indicator based (IBEA,...), and



Population at iteration t

- One solution x_i for each sub pb. i of direction λ_i
- Scalar function g :
  Weighted Tchebycheff
- Representation of solutions in objective space : $z_i = g(x_i | \lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Neighborhood size $\sharp B(i) = T = 3$

MOEA/D : Multi-Obj. Evo. Algo. based on Decomposition

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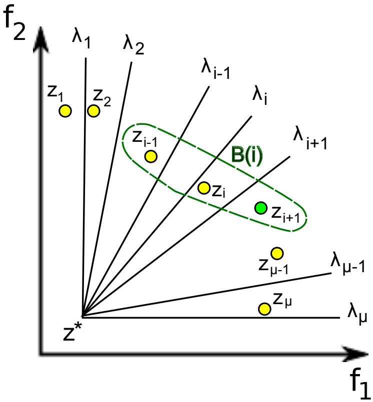

From the neigh. $B(i)$ of sub-pb. i, x_{i+1} is selected

- One solution x_i for each sub pb. i of direction λ_i
- Scalar function g :
  Weighted Tchebycheff
- Representation of solutions in objective space : $z_i = g(x_i | \lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
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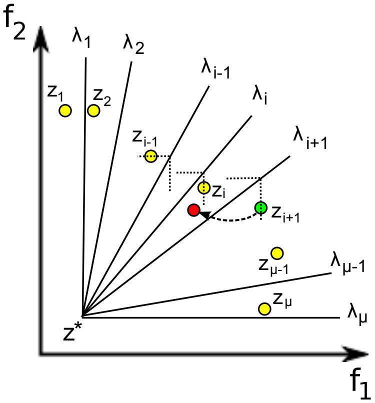

The mutated solution y is created

- One solution x_i for each sub pb. i of direction λ_i
- Scalar function g :
  Weighted Tchebycheff
- Representation of solutions in objective space : $z_i = g(x_i|\lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Neighborhood size $\sharp B(i) = T = 3$

MOEA/D : Multi-Obj. Evo. Algo. based on Decomposition

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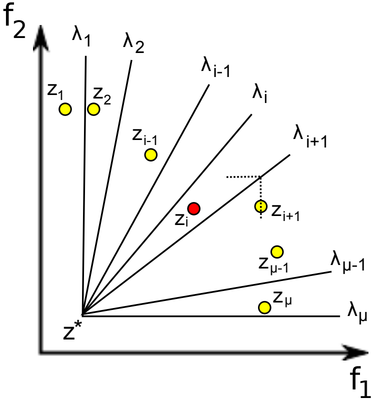
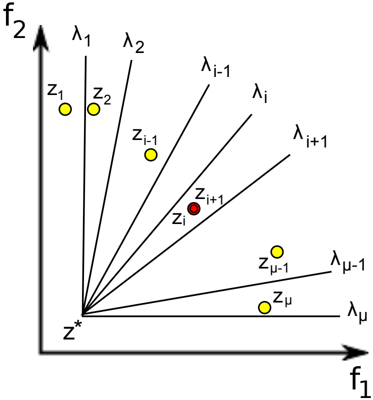


According to scalar fonction,
y is worst than x_{i-1},
y is better than x_i and replaces it.

- One solution x_i for each sub pb. i of direction λ_i
- Scalar function g :
  Weighted Tchebycheff
- Representation of solutions in objective space : $z_i = g(x_i|\lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Neighborhood size $\sharp B(i) = T = 3$

MOEA/D : Multi-Obj. Evo. Algo. based on Decomposition

A lot of MO algo. :
Pareto based (NSGAII,...), indicator based (IBEA,...), and



According to scalar fonction,
y is also better than x_{i+1}
and replaces it for the next iteration.

- One solution x_i for each sub pb. i of direction λ_i
- Scalar function g :
  Weighted Tchebycheff
- Representation of solutions in objective space : $z_i = g(x_i | \lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Neighborhood size $\sharp B(i) = T = 3$

Massively parallel algorithm

Optimization of problems based on expensive simulation

- Relevant tuning of parameters of the algorithm
- Surrogate model
- Parallel computing

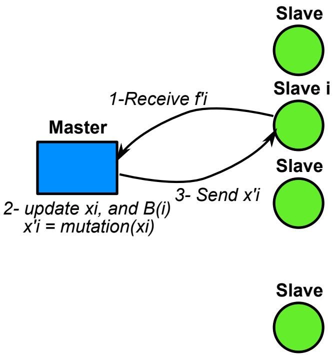
Here,
Simulation for one burnup : 10 min
Simulation of 4 burnups (life cycle) : 40min

Massive parallel system (HPC)

Algorithms for the TGCC (GENCI Projet)
2 500 000 hours of available computation
1008 cores for 24h of computation.

Asynchronous MOEA/D

Master-slaves architecture



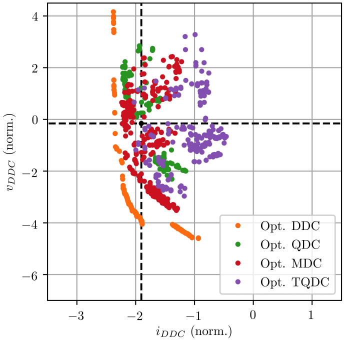
Algorithm on Master

$\{x_1, \ldots, x_\lambda\} \leftarrow$ **Initialization**()
for $i = 1..\lambda$ **do**
  Send (Non-blocking) x_i to slave S_i
end for
repeat
  if there is a pending mess. from S_i **then**
    Receive fitness f_i' of x_i' from S_i
    Update x_i, and $x_j \in B(i)$ with (x_i', f_i')
    $x_i' \leftarrow \texttt{mutation}(x_i)$
    Send (Non-blocking) x_i' to slave S_i
  end if
until time limit

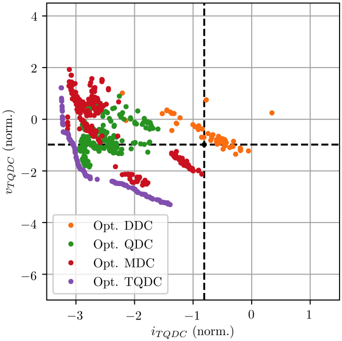
V. Drouet, S. Verel, and J-M. Do. "Surrogate-assisted asynchronous multiobjective algorithm for nuclear power plant operations.", Gecco 2020. [4]

Results at different burnups

At the beginning of exploitation



At the end of exploitation



Optimization on the whole cycle is necessary

Asynchronous MOEA/D with surrogate model

Algorithm on Master

$\{x_1, \dots, x_\lambda\} \leftarrow$ **Initialization**()
for $i = 1..\lambda$ **do**
  Send (Non-blocking) x_i to slave S_i
end for
repeat
  if there is a pending mess. from S_i **then**
    Receive fitness f_i' of x_i' from S_i
    Add (x_i', f_i') to sample S
    Update x_i, and $x_j \in B(i)$ with (x_i', f_i')
    Train model M with Sample S
    if $|S| < N_{start}$ **then**
      $x_i' \leftarrow \texttt{mutation}(x_i)$
    else
      Select x_i' using model M
    end if
    Send (Non-blocking) x_i' to slave S_i
  end if
until time limit

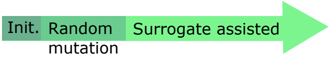
Surrogate model

Random forest

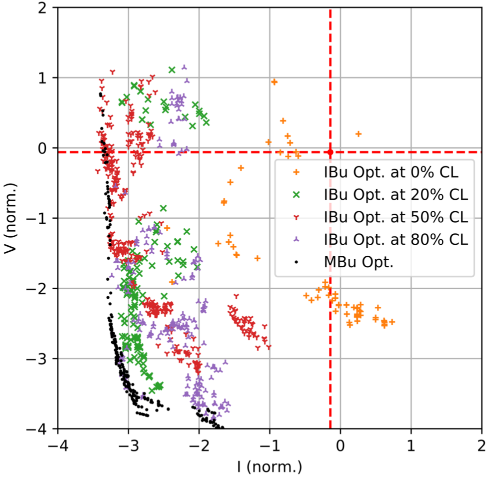
Offline tuning using data

Acceleration of convergence :
Double the prob. of improv.

Surrogate model can be misleading
(poor accuracy at the begin.) :

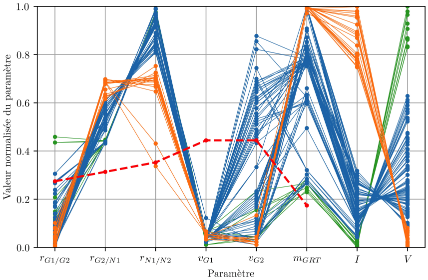


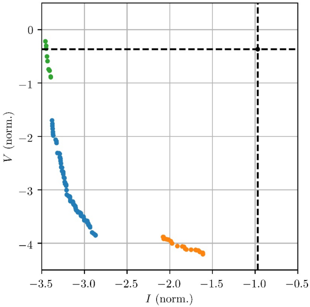
Results on whole exploitation cycle



Reduce Volume of effluent, and Instability (axial offset) from current setting

Analysis of decision variables





A posterio interpretation of the candidate solutions on Pareto front

Conclusion

Optimization, machine learning techniques to solve design problems with digital twins

- Main tools :
  Analysis fitness landscape to understand pb., and tune algo.
  Use surrogate models, to accelerate the search, and bring an algebraic model
  Parallel, and distributed computation
- A good algorithm is a tradeoff between :
  Final decision making
  Search space dimension, and its properties
  Computation time, and power.
- Digital twins, and AI offers a lot of perspectives
  How to combine different methods ?
  How to better understand systems ? ...

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