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Optimization of Energy Policies

Using Direct Value Search

Jeremie Decock

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Olivier Teytaud

Inria, Artelys

May 12, 2014



Introduction

- ▶ Optimization of Energy Policies
- ▶ with *Direct Value Search* (DVS)
 - ▶ Linear Programming
 - ▶ Direct Policy Search

Overview

Power Systems Problems

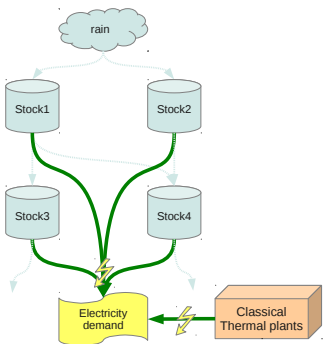
Direct Value Search

Experiments

Conclusion

Power systems problems we try to solve...

Unit commitment



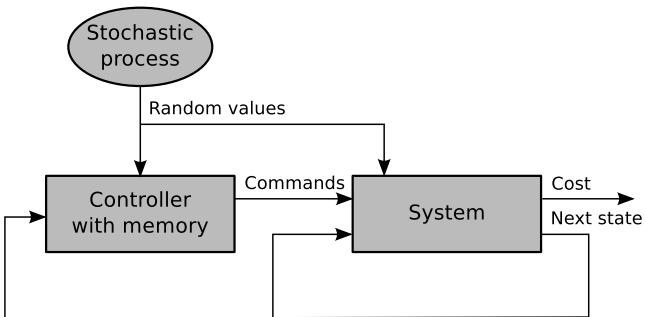
A short reminder

- ▶ A multi-stage problem
- ▶ Energy demand (forecast)
- ▶ Energy production:
 - ▶ Hydroelectricity (N water *stocks*)
 - ▶ Thermal plants
- ▶ Water flow through stock links

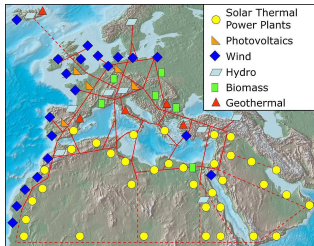
Problem

Which production unit should be used at time t to satisfy the demand with the lowest possible cost ?

Stochastic Control



POST (ADEME)



High scale investment studies
(e.g. Europe + North Africa)

- ▶ Long term (2030 - 2050)
- ▶ Huge (non-stochastic) uncertainties
 - ▶ Future technologies
 - ▶ Future laws
 - ▶ ...
- ▶ Investment problem
 - ▶ Interconnections
 - ▶ Storage
 - ▶ Smart grids
 - ▶ Power plants
 - ▶ ...

Issues and methods

Issues

- ▶ Limited forecast (e.g. demand, weather, ...)
- ▶ Renewable energies increase production variability
- ▶ Transportation introduces constraints

Methods

- ▶ Can't assume Markovian process
 - ▶ Weather (influences production and demand)
 - ▶ ...
- ▶ Avoid simplified models to avoid model errors
 - ▶ Convex value function
 - ▶ Linear transition function
 - ▶ ...

Most classical solutions

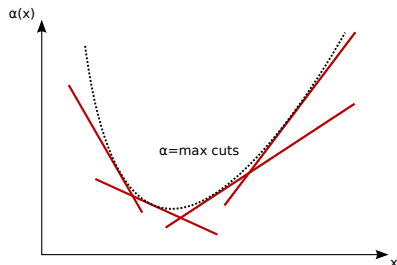
Stochastic Dual Dynamic Programming

Decompose the problem in instant cost + future cost as:

$$\min_x \underbrace{\text{cost}(x)}_{\text{instant cost}} + \underbrace{\alpha(x)}_{\text{Bellman Value}}$$

Approximate $\alpha(\cdot)$ with Bender cuts.

Problems: It needs convexity of $\alpha(\cdot)$, a markovian process and not too many state variables.



Direct Value Search

Direct Policy Search

Goal

Finds “good” parameters for a given parametric policy

$\pi_{\theta} : \text{states} \rightarrow \text{controls}$.

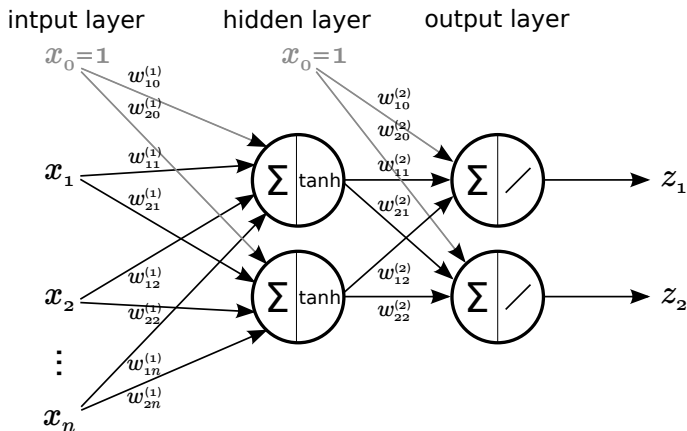
Requires a parametric controller (e.g. neural network)

Principle

Optimize the parameters on simulations (Noisy Black-Box Optimization).

Parametric policies π_θ

Neural Networks: $\theta = \left(w_{10}^{(1)}, \dots, w_{mn}^{(1)}, w_{10}^{(2)}, \dots, w_{km}^{(2)} \right)^T$



Summary

	Pros	Cons
S(D)DP	large constrained \mathcal{U} polynomial time decision making asymptotically find the optimum	not anytime convex problems only (SDDP) small \mathcal{S} markovian random process
DPS	anytime large \mathcal{S} works with non linear functions no random process constraint	slow on large \mathcal{U} hardly handles decision constraints

Direct Value Search

Merge both approaches

Direct Value Search

An overview

Like Bellman decomposition: present cost and futur state valorization

$$\begin{aligned} \Pi(\mathbf{s}_t) &= \arg \min_{\mathbf{u}_t} \text{cost}(\mathbf{u}_t) + V(\mathbf{s}_{t+1}) \\ V(\mathbf{s}_{t+1}) &= \underbrace{\alpha_t \cdot \mathbf{s}_{t+1}}_{\text{LP}} \\ \alpha_t &= \underbrace{\pi_{\theta}(\mathbf{s}_t)}_{\text{not LP}} \end{aligned}$$

- ▶ Given θ , decision making solved as a LP
- ▶ Non-linear mapping for choosing the parameters of the LP from the current state

Requires the optimization of θ (noisy black-box optimization problem)

Direct Value Search

Assumptions

We assume we know $\iota_{t\dots k}$ the random realizations from current stage to tactical horizon.

Direct Value Search

Step 1 (offline): compute $\pi_{\theta}(\cdot)$

Build parametric policy π_{θ}

Require:

- a parametric policy $\pi_{\theta}(\cdot)$ where π_{θ} is a mapping from \mathcal{S} to \mathcal{U} ,
- a Stochastic Decision Process SDP,
- an initial state s

Ensure:

- a parameter $\hat{\theta}$ leading to a policy $\pi_{\hat{\theta}}(\cdot)$

Find a parameter $\hat{\theta}$ minimizing the expectation of the following fitness function

$\theta \mapsto \text{Simulate}(s, \text{SDP}, \pi_{\theta})$

with a given non-linear noisy optimization algorithm (e.g. SA-ES, CMA-ES, ...)

return $\hat{\theta}$

Direct Value Search

Step 1 (offline): compute $\pi_\theta(\cdot)$

Simulate($s_0, \text{SDP}, \pi_\theta$)

```

c ← 0
for t ← t0, t0 + h, t0 + 2h, ..., T do
    ut...k ← get_random_realizations(.)

    if t + k - 1 < T then
        α ← πθ(st+)
        ut...k ← arg minu cost(ut...k, lt...k, st) - αsT · st+k-1
    else
        ut...k ← arg minu cost(ut...k, lt...k, st)
    end if

    c ← c + SDP_cost(st, ut...h, lt...h)
    st+h ← SDP_transition(st, ut...h, lt...h)
end for

return c

```

Direct Value Search

Step 2 (online): use $\pi_\theta(\cdot)$ to solve the actual problem

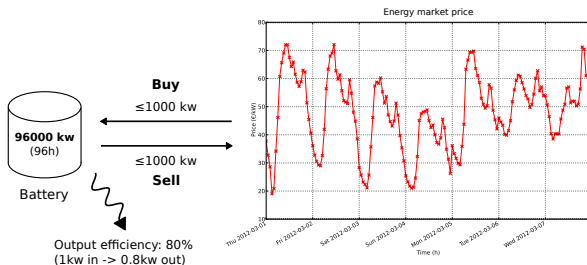
The offline optimisation of π_θ can be stopped at any time.

Then

- ▶ we have π_θ , an approximation of state's marginal value
- ▶ we can use it to solve the actual problem, the same manner as in *Simulate*

Experimental results

A simple test case



Goal: find a policy which maximise gains

Buy (and stock) when the market price is low, sell when the market price is high.

- ▶ The market price is stochastic.
- ▶ 10 constrained batteries.

A simple test case

- ▶ The state vector \mathbf{s}^+ is the stock level of the 10 batteries and additional information (4 handcrafted time-dependent auxiliary inputs);
- ▶ 10 decision variables have to be made at each time step (i.e. the quantity of energy to buy or sell for each batteries);
- ▶ we work in maximization, costs are replaced by rewards.

Baselines used for comparison

Recourse planning without final valorization

Bellman values are considered to be null ($\alpha = \mathbf{0}$)

$$u(x, t) = \arg \min_{u_t} \min_{u_{t+1}, \dots, u_{t+k-1}} \mathbb{E}c_t + \dots + c_{t+k-1}$$

Recourse planning with constant marginal valorization

This is a linear approximation of Bellman values. Bellman values are considered to be independent of the current state (α is constant)

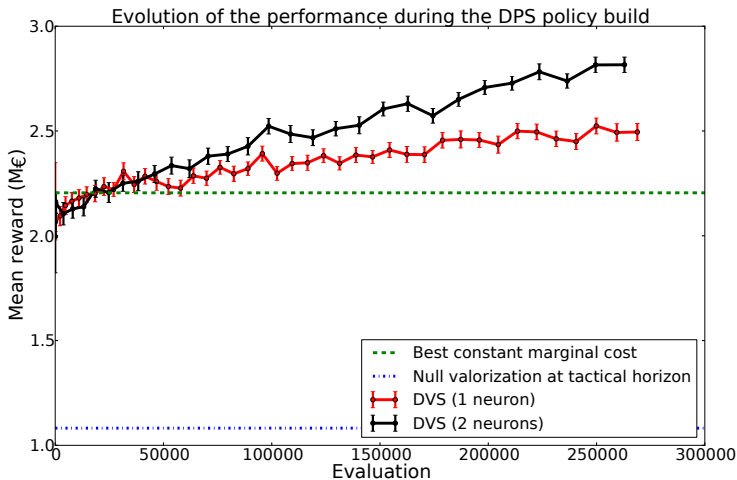
$$u(x, t) = \arg \min_{u_t} \min_{u_{t+1}, \dots, u_{t+k-1}} \mathbb{E}c_t + \dots + c_{t+k-1} + \alpha \cdot x_{t+k-1}$$

We look for the best constant marginal valorization α .

DVS setup

- ▶ Parametric policy π_{θ} = a neural network with N neurons in a single hidden layer and weights vector θ ;
- ▶ θ is optimized by maximizing $\theta \mapsto \text{Simulate}(\theta)$ with a Self-Adaptive Evolution Strategy (SA-ES).

Results



Conclusion

Conclusion

Still rather preliminary (a little tested) but promising

- ▶ forecasts naturally included in optimization
- ▶ anytime algorithm (users immediately get approximate results)
- ▶ no convexity constraints
- ▶ room for detailed simulations (e.g. with very small time scale, for volatility)
- ▶ no random process constraints (not Markov)
- ▶ can handle large state spaces (as DPS)
- ▶ can handle large action spaces (as SDP)

Can work on the “real” problem, without “cast”

Future work

- ▶ add relevant information in the state vector
 - ▶ e.g. moving average or regression analysis on the price
- ▶ optimize parametric policies with something else than SAES
 - ▶ Fabian
 - ▶ Newton
 - ▶ ...
- ▶ test DVS on a more challenging problem
 - ▶ more decision variables
 - ▶ more timesteps
 - ▶ non-convex Bellman values
 - ▶ ...
- ▶ parallelization





Bibliography

- ▶ *NEWAVE versus ODIN: comparison of stochastic and deterministic models for the long term hydropower scheduling of the interconnected brazilian system.* M. Zambelli et al., 2011.
- ▶ *Dynamic Programming and Suboptimal Control: A Survey from ADP to MPC.* D. Bertsekas, 2005. (MPC = deterministic forecasts)
- ▶ Astrom 1965
- ▶ *Renewable energy forecasts ought to be probabilistic!* P. Pinson, 2013 (WIPFOR talk)
- ▶ *Training a neural network with a financial criterion rather than a prediction criterion* Y. Bengio, 1997 (quite practical application of direct policy search, convincing experiments)





Thank you for your attention

Questions ?




References I

-  S. Astete-Morales, J. Liu, and O. Teytaud, *log-log convergence for noisy optimization*, Proceedings of EA 2013, LLNCS, Springer, 2013, p. accepted.
-  alexander shapiro, *Analysis of stochastic dual dynamic programming method*, European Journal of Operational Research **209** (2011), no. 1, 63–72.
-  R. Bellman, *Dynamic programming*, Princeton Univ. Press, 1957.
-  Yoshua Bengio, *Using a financial training criterion rather than a prediction criterion*, CIRANO Working Papers 98s-21, CIRANO, 1998.

References II

-  Dimitri P. Bertsekas, *Dynamic programming and suboptimal control: A survey from ADP to MPC*, Eur. J. Control **11** (2005), no. 4-5, 310–334.
-  H.-G. Beyer, *The theory of evolutions strategies*, Springer, Heidelberg, 2001.
-  D.P. Bertsekas and J.N. Tsitsiklis, *Neuro-dynamic programming*, Athena Scientific, 1996.
-  Zhihao Cen, J. Frederic Bonnans, and Thibault Christel, *Energy contracts management by stochastic programming techniques*, Annals of Operations Research **200** (2011), no. 1, 199–222 (Anglais), RR-7289 RR-7289.

References III

-  Gérard Cornuéjols, *Revival of the gomory cuts in the 1990's*, Annals OR **149** (2007), no. 1, 63–66.
-  Z. L. Chen and W. B. Powell, *Convergent cutting-plane and partial-sampling algorithm for multistage stochastic linear programs with recourse*, J. Optim. Theory Appl. **102** (1999), no. 3, 497–524.
-  Christopher J. Donohue and John R. Birge, *The abridged nested decomposition method for multistage stochastic linear programs with relatively complete recourse*, Algorithmic Operations Research **1** (2006), no. 1.

References IV






Vaclav Fabian, *Stochastic approximation of minima with improved asymptotic speed*, Ann. Math. Statist. **38** (1967), no. 1, 191–200.







S. Hong, P.O. Malaterre, G. Belaud, and C. Dejean, *Optimization of irrigation scheduling for complex water distribution using mixed integer quadratic programming (MIQP)*, HIC 2012 – 10th International Conference on Hydroinformatics (Hamburg, Allemagne), IAHR, 2012, pp. p. – p. (Anglais).





References V

-  Verena Heidrich-Meisner and Christian Igel, *Hoeffding and Bernstein races for selecting policies in evolutionary direct policy search*, ICML '09: Proceedings of the 26th Annual International Conference on Machine Learning (New York, NY, USA), ACM, 2009, pp. 401–408.
-  Nikolaus Hansen, Sibylle D Müller, and Petros Koumoutsakos, *Reducing the time complexity of the derandomized evolution strategy with covariance matrix adaptation (cma-es)*, *Evolutionary Computation* **11** (2003), no. 1, 1–18.
-  Holger Heitsch and Werner Römisch, *Scenario tree reduction for multistage stochastic programs*, *Computational Management Science* **6** (2009), no. 2, 117–133.

References VI

-  L. G. Khachiyan, *A polynomial algorithm in linear programming*, Doklady Akademii Nauk SSSR **244** (1979), 1093–1096.
-  K. Linowsky and A. B. Philpott, *On the convergence of sampling-based decomposition algorithms for multistage stochastic programs*, J. Optim. Theory Appl. **125** (2005), no. 2, 349–366.
-  A.B. Philpott and Z. Guan, *On the convergence of stochastic dual dynamic programming and related methods*, Operations Research Letters **36** (2008), no. 4, 450 – 455.
-  P. Pinson, *Renewable energy forecasts ought to be probabilistic*, 2013, WIPFOR seminar, EDF.

References VII

-  W.-B. Powell, *Approximate dynamic programming*, Wiley, 2007.
-  M. V. F. Pereira and L. M. V. G. Pinto, *Multi-stage stochastic optimization applied to energy planning*, Math. Program. **52** (1991), no. 2, 359–375.
-  A. Ruszczyński, vol. 10, ch. Decomposition methods, North-Holland Publishing Company, Amsterdam, 2003.
-  S. Uryasev and R.T. Rockafellar, *Optimization of conditional value-at-risk*, Research report (University of Florida. Dept. of Industrial & Systems Engineering), Department of Industrial & Systems Engineering, University of Florida, 1999.

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Simulate(s_0 , **SDP**, π_θ)

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c ← 0
for t ← t0, t0 + h, t0 + 2h, ..., T do
   $\mathbf{u}_{t\dots k} \leftarrow \text{get\_random\_realizations}(\cdot)$ 

  if t + k - 1 < T then
     $\boldsymbol{\alpha} \leftarrow \pi_\theta(\mathbf{s}_t^+)$ 
     $\boldsymbol{\alpha}_s \leftarrow \text{scale}(\boldsymbol{\alpha}, \mathbf{n}_f)$ 
     $\mathbf{u}_{t\dots k} \leftarrow \arg \min_{\mathbf{u}} \text{cost}(\mathbf{u}_{t\dots k}, \mathbf{u}_{t\dots k}, \mathbf{s}_t) - \boldsymbol{\alpha}_s^\top \cdot \mathbf{s}_{t+k-1}$ 
  else
     $\mathbf{u}_{t\dots k} \leftarrow \arg \min_{\mathbf{u}} \text{cost}(\mathbf{u}_{t\dots k}, \mathbf{u}_{t\dots k}, \mathbf{s}_t)$ 
  end if

  c ← c + SDP_cost( $\mathbf{s}_t$ ,  $\mathbf{u}_{t\dots h}$ ,  $\mathbf{u}_{t\dots h}$ )
   $\mathbf{s}_{t+h} \leftarrow \text{SDP\_transition}(\mathbf{s}_t, \mathbf{u}_{t\dots h}, \mathbf{u}_{t\dots h})$ 
end for

return c

```


Direct Value Search

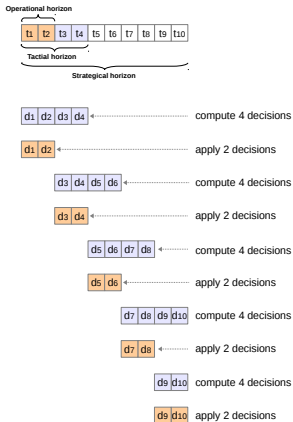
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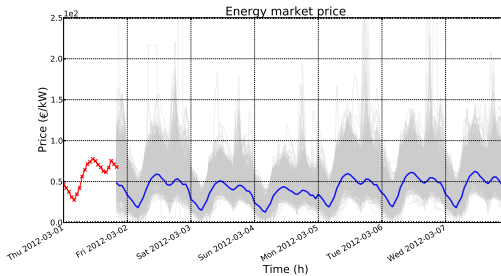
Recourse planning (closed loop)



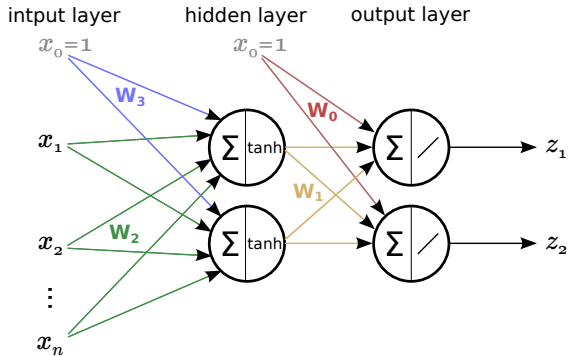
Recourse planning:

- ▶ Decisions $u_1, u_2, \dots, u_{\tau_t}$ are optimized (tactical horizon)
- ▶ Only $u_1, u_2, \dots, u_{\tau_o}$ are applied (operational horizon)
- ▶ The system is now in a new state at stage τ_o
- ▶ Decisions $u_{\tau_o}, u_{\tau_o+1}, \dots, u_{\tau_o+\tau_t}$ are optimized (tactical horizon)
- ▶ Only $u_{\tau_o}, u_{\tau_o+1}, \dots, u_{\tau_o+\tau_o}$ are applied (operational horizon)
- ▶ ...

MPC example



Parametric policies



$$\mathbf{z} = \mathbf{W}_0 + \mathbf{W}_1 \tanh(\mathbf{W}_2 \mathbf{x} + \mathbf{W}_3)$$

Parametric policies

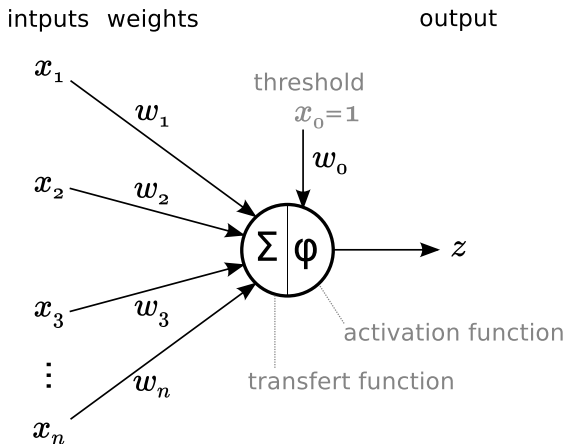
$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \quad \mathbf{z} = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \end{pmatrix}, \quad \mathbf{W}_3 = \begin{pmatrix} w_{10}^{(1)} \\ w_{20}^{(1)} \\ \vdots \\ w_{m0}^{(1)} \end{pmatrix}, \quad \mathbf{W}_0 = \begin{pmatrix} w_{10}^{(2)} \\ w_{20}^{(2)} \\ \vdots \\ w_{k0}^{(2)} \end{pmatrix},$$

$$\mathbf{W}_2 = \begin{pmatrix} w_{11}^{(1)} & w_{12}^{(1)} & \cdots & w_{1n}^{(1)} \\ w_{21}^{(1)} & w_{22}^{(1)} & \cdots & w_{2n}^{(1)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1}^{(1)} & w_{m2}^{(1)} & \cdots & w_{mn}^{(1)} \end{pmatrix}, \quad \mathbf{W}_1 = \begin{pmatrix} w_{11}^{(2)} & w_{12}^{(2)} & \cdots & w_{1m}^{(2)} \\ w_{21}^{(2)} & w_{22}^{(2)} & \cdots & w_{2m}^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k1}^{(2)} & w_{k2}^{(2)} & \cdots & w_{km}^{(2)} \end{pmatrix}.$$

$$\mathbf{z} = \mathbf{W}_0 + \mathbf{W}_1 \tanh(\mathbf{W}_2 \mathbf{x} + \mathbf{W}_3)$$

Artificial Neurons

Artificial neuron



Self-adaptive Evolution Strategy (SA-ES) with revaluations

Require:

$K > 0$, $\lambda > \mu > 0$, a dimension $d > 0$, τ (usually $\tau = \frac{1}{\sqrt{2d}}$).

Initialize parent population $P_\mu = \{(\mathbf{x}_1, \sigma_1), (\mathbf{x}_2, \sigma_2), \dots, (\mathbf{x}_\mu, \sigma_\mu)\}$
with $\forall i \in \{1, \dots, \mu\}$, $\mathbf{x}_i \in \mathbb{R}^d$ and $\sigma_i = 1$.

while stop condition do

Generate the offspring population $P_\lambda = \{(\mathbf{x}'_1, \sigma'_1), (\mathbf{x}'_2, \sigma'_2), \dots, (\mathbf{x}'_\lambda, \sigma'_\lambda)\}$
where each individual is generated by:

1. *Select* (randomly) ρ parents from P_μ .
2. *Recombine* the ρ selected parents to form a recombinant individual (\mathbf{x}', σ') .
3. *Mutate* the strategy parameter: $\sigma' \leftarrow \sigma' e^{\tau \mathcal{N}(0,1)}$.
4. *Mutate* the objective parameter: $\mathbf{x}' \leftarrow \mathbf{x}' + \sigma' \mathcal{N}(\mathbf{0}, \mathbf{1})$.

Select the new parent population P_μ taking the μ best form $P_\lambda \cup P_\mu$.

end while

Fabian

- 1: Input: an initial $x_1 = 0 \in \mathbb{R}^d$, $\frac{1}{2} > \gamma > 0$, $a > 0$, $c > 0$, $m \in \mathbb{N}$, weights $w_1 > \dots > w_m$ summing to 1, scales $1 \geq u_1 > \dots > u_m > 0$.
- 2: $n \leftarrow 1$
- 3: **while** (true) **do**
- 4: Compute $\sigma_n = c/n^\gamma$.
- 5: Evaluate the gradient g at x_n by finite differences, averaging over $2m$ samples per axis:

$$\forall i, j \in \{1, \dots, d\} \times \{1 \dots m\}, x_n^{(i,j)+} = x_n + u_j e_i,$$

$$\forall i, j \in \{1, \dots, d\} \times \{1 \dots m\}, x_n^{(i,j)-} = x_n - u_j e_i,$$

$$\forall i \in \{1, \dots, d\}, g^{(i)} = \frac{1}{2\sigma_n} \sum_{j=1}^m w_j \left(f(x_n^{(i,j)+}) - f(x_n^{(i,j)-}) \right).$$

- 6: Apply $x_{n+1} \leftarrow x_n - \frac{a}{n} g$
- 7: $n \leftarrow n + 1$
- 8: **end while**

Fabian's stochastic gradient algorithm with finite differences. Several variants have been defined, in particular versions in which only one point (or a constant number of points, independently of the dimension) is evaluated at each iteration.