SIMULATION OPTIMIZATION OF GRAZING MANAGEMENT STRATEGIES

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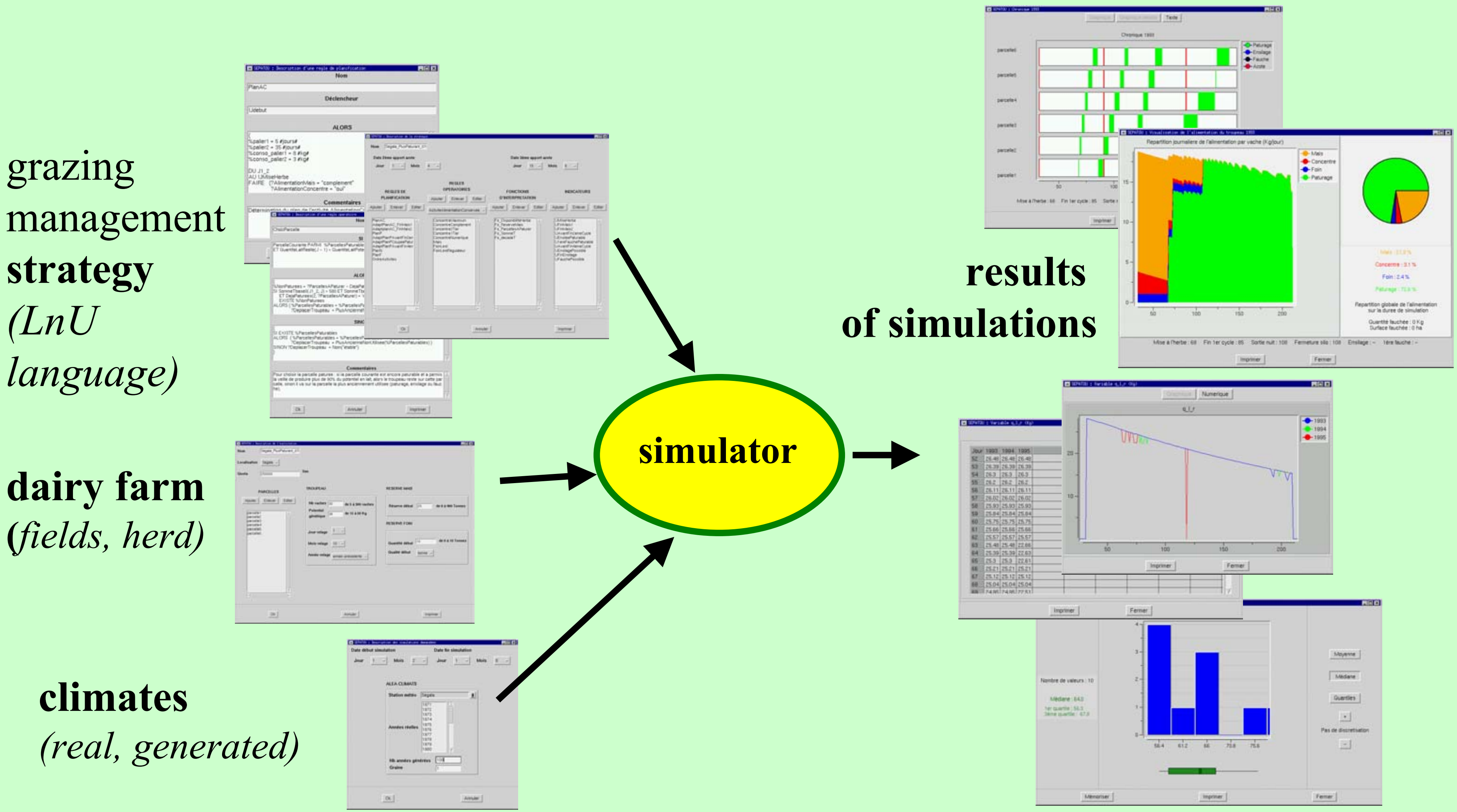
THE SEPATOU SIMULATOR

Reproduces daily dynamics induced by a given strategy of a dairy cows system
considering various climates
from February to July

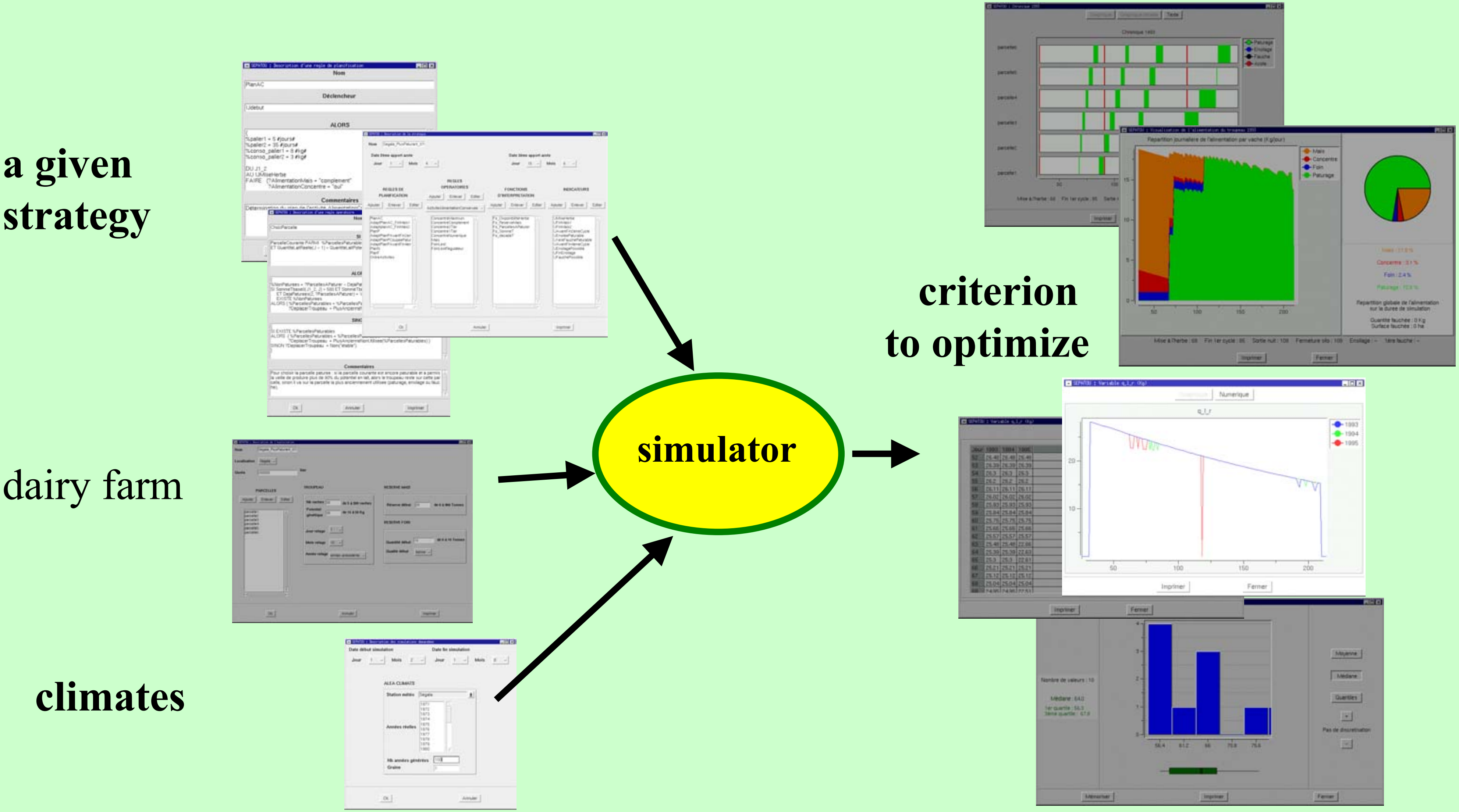
> To evaluate typical strategies

Decided actions concern feeding of cows (essentially grazing), cutting and fertilization of fields

THE SEPATOU SIMULATOR



THE OPTIMIZATION PROBLEM



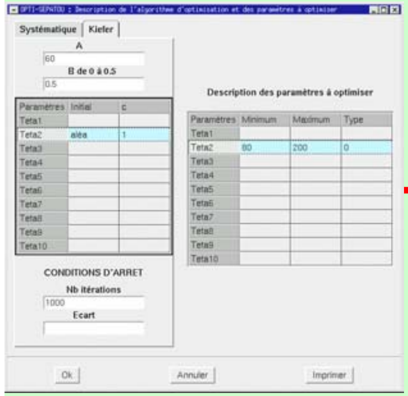
OPTIMIZATION FRAMEWORK

- parameterization of the strategy (*organization rules, operational rules, state indicators, information gathering procedures)* with up to 10 continuous parameters (vector θ)

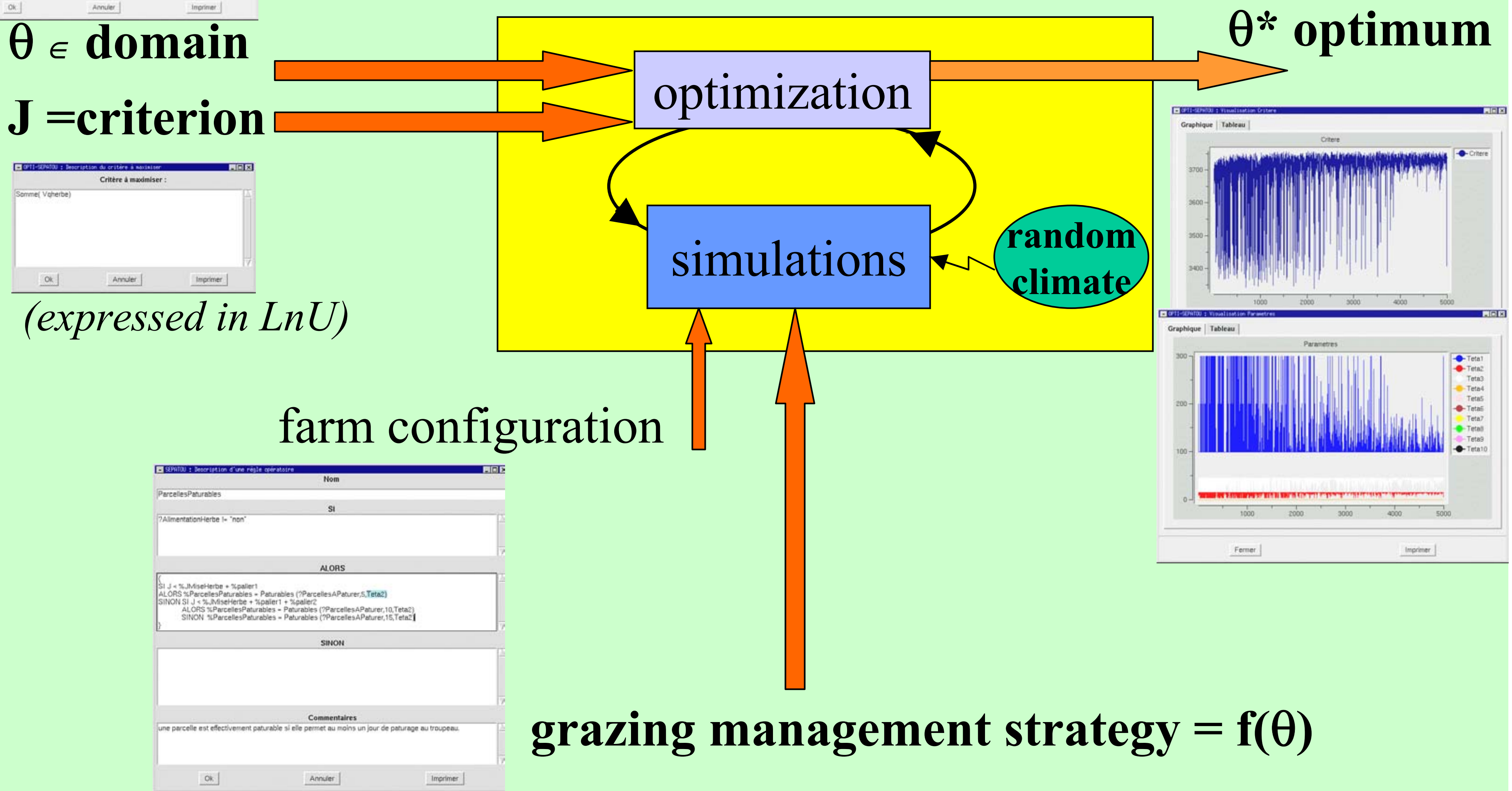
Example : *Definition of the characteristic of turn out indicator*
AvailableGrass(?FieldsToGraze) > **Teta1** #days#

- expression of a numerical criterion J to optimize

- research of a good value for θ
  that optimizes the expected value of J



THE OPTI-SEPATOU OPTIMIZATION TOOL



MATHEMATICAL FORMULATION

The criterion J is a stochastic function *(due to climate)* evaluated by computer simulations

number of parameters

$$J : \theta \rightarrow J(\theta),\ \Theta \subset R^p \rightarrow R$$

feasible domain of θ

Optimization problem

Find the optimum value $\theta\,*$ that optimizes the expected value of the criterion

$$\theta^* = \underset{\theta \in \Theta}{\arg opt}\ E(J(\theta))$$

OPTIMIZATION METHODS

Continuous input parameters

Gradient approaches
- stochastic approximation method
- response surface methodology
- stochastic counterpart

Non-gradient approaches
- Nelder-Mead (simplex) method
- Hooke and Jeeves method
- sample path method

Choice of stochastic approximation, the most popular and widely used optimization algorithm

STOCHASTIC APPROXIMATION

Exploration of the feasible domain
using estimations of the stochastic gradient
(adaptation of the steepest descent algorithm)

$$\theta_{n+1} = \pi_{\Theta}\left(\theta_n + a_n . \hat{\nabla} \mathrm{J}(\theta_n) \right)$$

Robbins-Monro, 1951

- θ_{n+1}: new parameters values
- π_{Θ}: projection on the feasible domain
- θ_n: current parameters values
- a_n: gain
- $\hat{\nabla} \mathrm{J}(\theta_n)$: estimated gradient

Generally will only converge to a local optimum solution

GRADIENT ESTIMATION METHODS

Different methods exist to estimate the stochastic gradient : finite differences (forward, central), perturbation analysis, score functions, harmonic analysis

Choice of central finite differences

$$\hat{\nabla}\, J(\theta^i) = \frac{J^m(\theta^i + c) - J^m(\theta^i - c)}{2c}$$

(+) easy to use (no requirement of knowledge of the structure of the stochastic system)

(-) requires several simulation runs (*2pm* simulations)

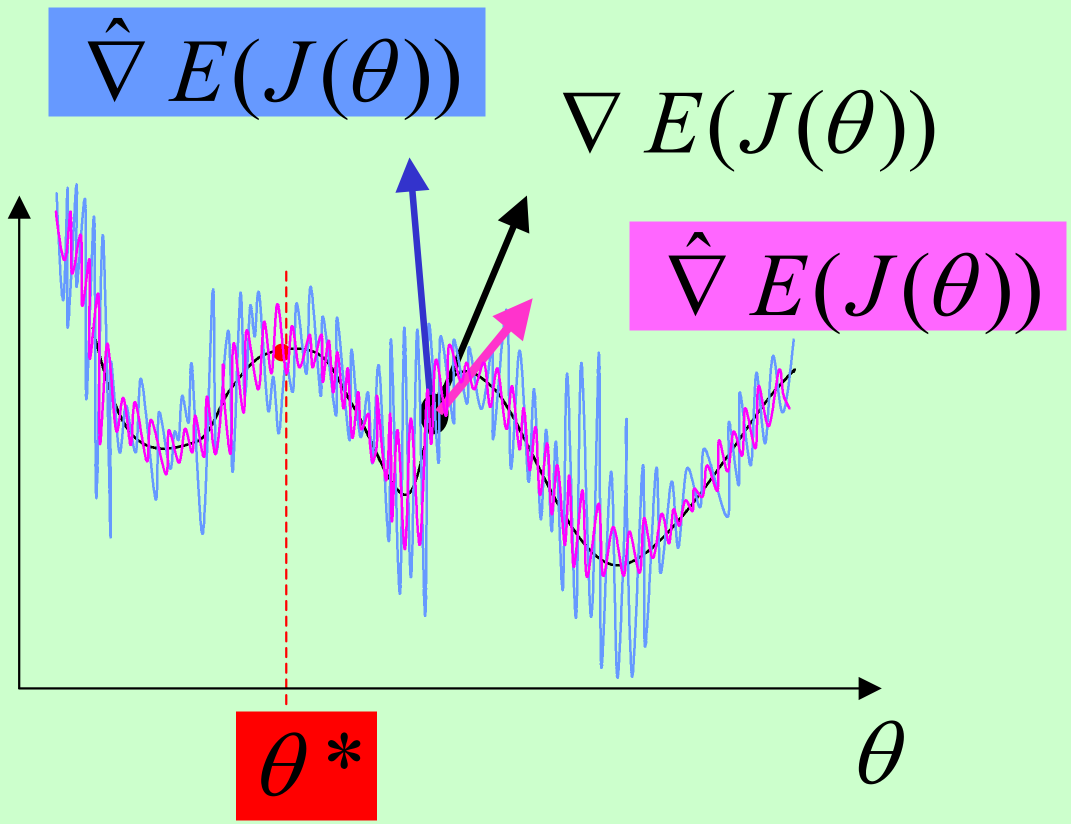
number of parameters ↗ ↖ number of simulation

IMPROVEMENT IN ESTIMATING THE GRADIENT

$J(\theta)$

$E(J(\theta))$

$$J^m(\theta) = \frac{1}{m}\sum_m J(\theta)$$



J^m : a little improvement on the estimation of the gradient may quite improve the convergence

THE KIEFER AND WOLFOWITZ ALGORITHM

$$\theta_{n+1}^{i} = \pi_{\Theta}\left(\theta_{n}^{i} + a_{n}.\frac{J^{m}(\theta_{n} + c_{n}.e^{i}) - J^{m}(\theta_{n} - c_{n}.e^{i})}{2c_{n}}\right)$$

$$\forall i = 1, \ldots p$$

Kiefer and Wolfowitz, 1952

Values chosen for the series: $a_n = \frac{a}{n}$ and $c_n = \frac{c}{n^b}$ a>0, c>0, b∈]0;0.5[

Normalization of interval domains in [0;1]
and projection of values in the feasible domain Θ

EXPERIMENTS

CASE STUDIES in Aveyron *(south-west of France)*

3 typical cases considered

Case C: *30 are/cow :6 fields of 1.5 ha each and 30 cows,*
25 t of maize silage, high nitrogen supply,
stop of use of conserved feed in spring

9 parameters considered *(one by one, by cluster of 3, all together)*

BG: *required available grass in number of days per cow to decide turnout; in [3; 15] days*

DMleft: *dry matter quantity to be left on the field when living it; in [100; 300] g/m2*

d2*: the number of days of the second stage of reduction of maize silage complementation; in [5; 10] days*

several criteria :

total quantity of milk per cow

EXPERIMENTS

ALGORITHM PARAMETRIZATION $a_n = \frac{a}{n}$ and $c_n = \frac{c}{n^b}$

a influences the distance between θ_{n+1} and θ_n

b influences the speed of decrease of the interval size used to estimate the stochastic gradient

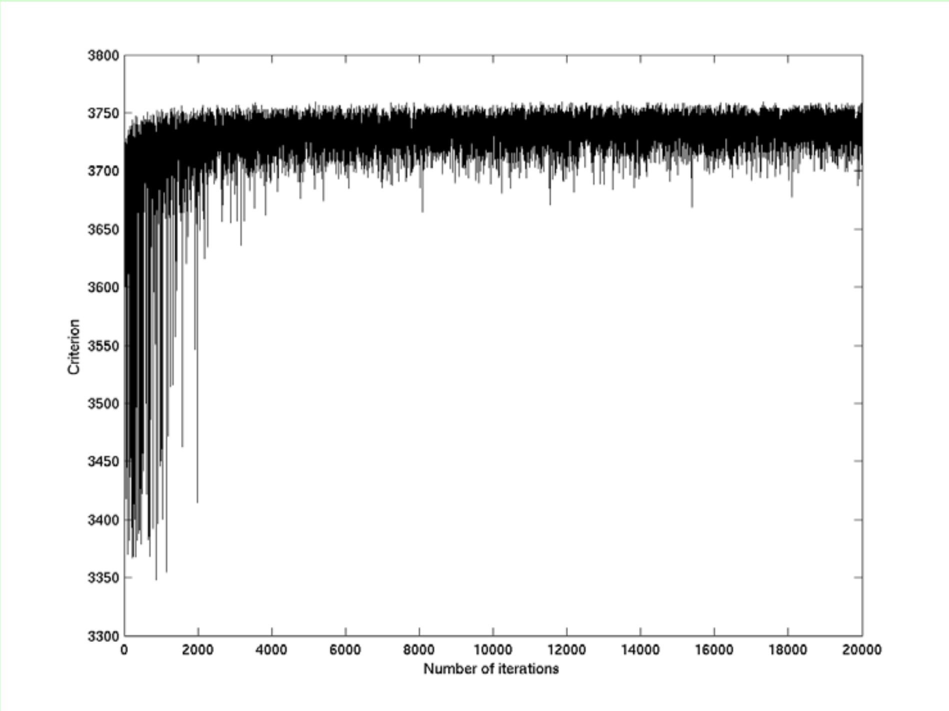
c determines the initial size of the considered interval to estimate the stochastic gradient

m influences the quality of estimation of the gradient

__a__ = 5 __b__ = 0.1 __c__ = 1 m = 5 were often empirically found to be good values

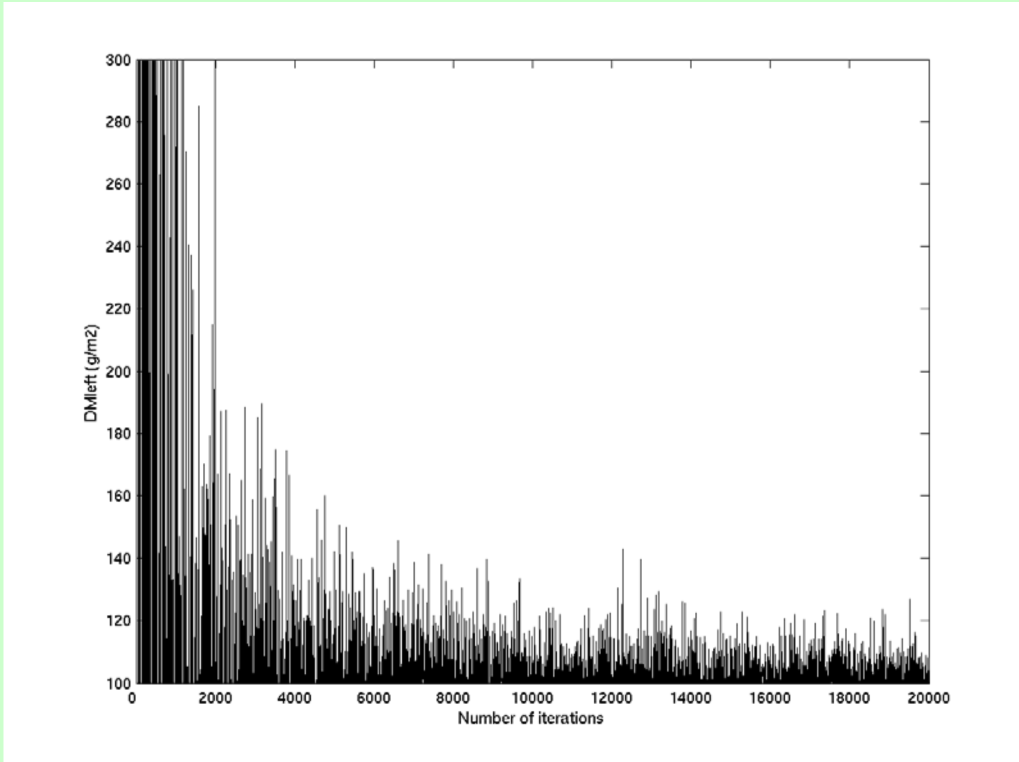
EXAMPLE OF RESULTS

Strategy: **Case *C*,**
Parameters to optimize ***: BG, DMleft and d2***
Criterion: ***total quantity of milk per cow***



Evolution of the criterion
versus the number of iterations

Evolution of the parameter DMleft
versus the number of iterations



RESULTS AND DISCUSSION

• As expected, despite noisy observations, the algorithm approached optimum values *(except if the algorithm was really badly parameterized)*. This was evaluated with a descriptive-enumerative algorithm and confirmed by experts
==> reliable for this application

• Sometimes it was difficult to evaluate if the algorithm had converged
==> it can be long

• Requires a delicate parameterization, specific to each application
==> a training period is necessary

Remark : optimization of discrete parameters is not efficient

DISCUSSION

The following limitations have been identified :

- criterion expression (*multi-objective, qualitative, ...*)
- risk consideration (*avoiding to go below or above a threshold, limiting the variance, ...*)
- no information on the neighborhood of the optimum

Others methods should be explore to identify good regions.
The challenge is then to intelligently
present results in synthetic and intelligible ways.