Forest Management and Certification

Stand-level management planning - decision analysis in single species even-aged stands

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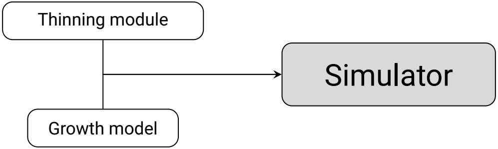
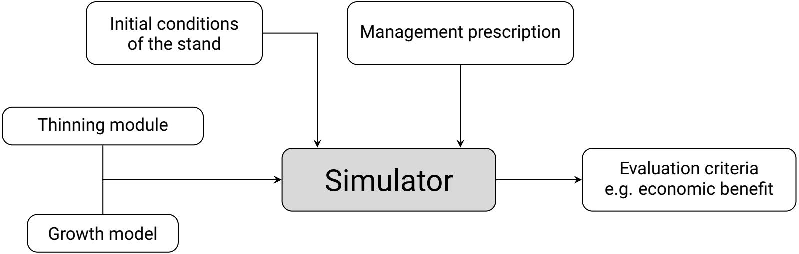
When? 17/10 - 04/11/2016

Reminder!

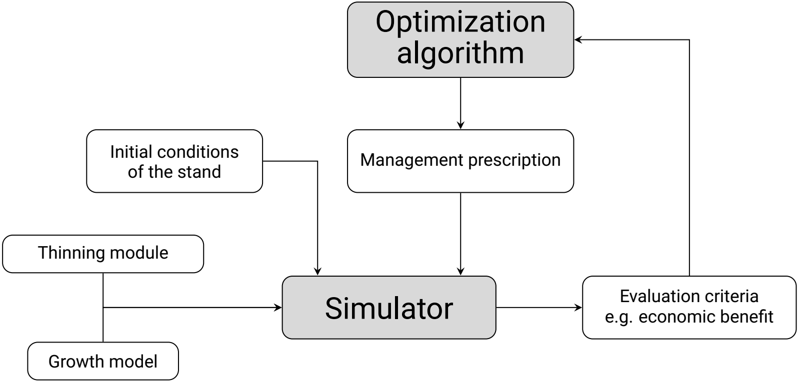
Simulation



Economical evaluation



Optimization



Optimization

Review of some techniques commonly used in optimization

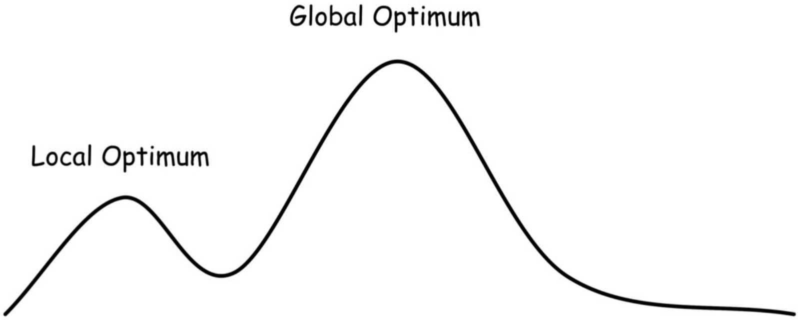
- Depth-first search
- Direct-search methods
  - One solution vector $\rightarrow$ Hooke and Jeeves (1961)
  - Several solution vectors $\rightarrow$ population-based methods
- Non-linear differentiable optimization techniques $\rightarrow$ differentiable objective function

What is a solution vector?

It is a vector where the decision variables are included $\rightarrow$ in stand-level management planning variables that define the management prescription

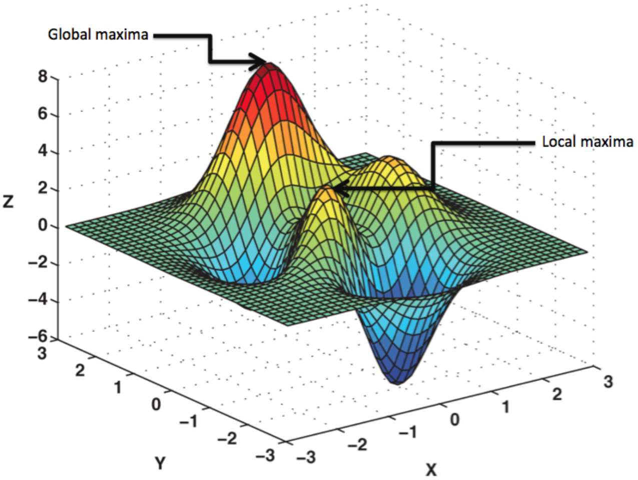
- Thinning type
- Thinning time
- Thinning intensity
- Clearcut age

Local optimum vs. global optimum



Source: `flickr.com`

Local optimum vs. global optimum

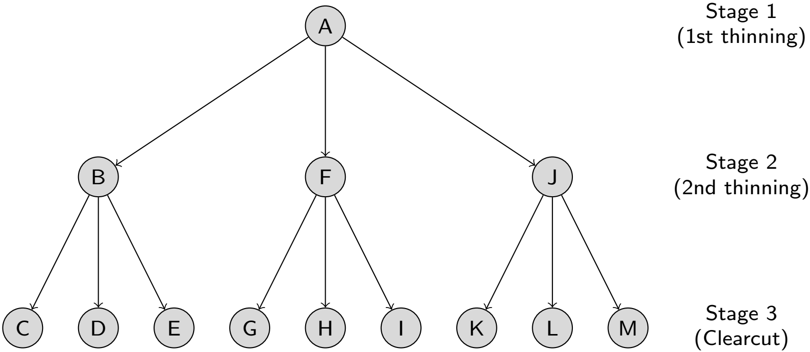


Source: `turingfinance.com`

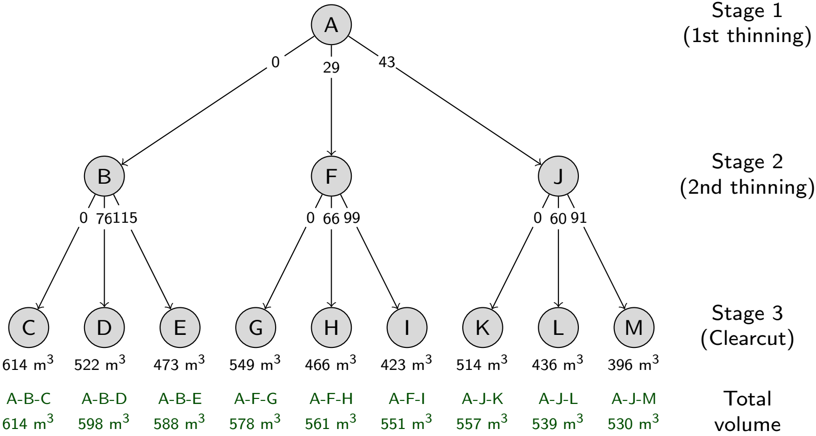
Depth-first search

- Optimization technique that explores trees or graph structures
- Exhaustive search: looks all the possible paths
- It guarantees reaching the global optimum within the defined tree of alternatives
- Decision variables need to be discretized

Tree of alternatives for stand-level management planning



Depth-first search



Depth-first search

Advantages

- It guarantees reaching the global optimum within the tree of alternatives
- It does not need discretization of state variables, in opposite to dynamic programming

Disadvantages

- Discretization of decision variables should be carefully considered
  - Too detailed $\Longrightarrow$ high computation time without a significative improvement in objective function value
  - Too gross $\Longrightarrow$ the optimal found might be far from the 'true' optimal
- Implementation harder than other techniques $\rightarrow$ growth and yield model is implicitly implemented in the optimization algorithm

Direct-search methods

- Let it consider the growth simulator as a **black box** that receives variable values (**decision variable values**) and returns a value (**objective function**)
- **Direct-search methods** iteratively evaluate and modify the solution to optimize the objective function
- **Constraints** $\rightarrow$ interesting to include bounds to some decision variables, e.g. do not allow to apply thinnings that imply removal of more than 45% of the trees, to avoid making the stand too sensitive to wind or snow damage
- Constraints $\rightarrow$ implemented as
  - **penalty function** $\rightarrow$ the objective function value is penalized if any constraint is violated $\implies$ the algorithm keeps searching for better solutions
  - **barrier methods** $\rightarrow$ if a constraint is violated, the solution is discarded

Direct-search methods

Advantages

- They usually provide good solutions in a reasonable amount of time
- The decision variables are continous $\implies$ no discretization

Disadvantages

- They do not guarantee reaching the global optimum
- Some are not deterministic, i.e. do not provide the same results if they are run more than once

Classification

- One solution vector → Hooke and Jeeves (1961) method
- Several solution vectors → population-based methods
  - Differential evolution (DE)
  - Particle swarm optimization (PS)
  - Evolution strategy (ES)
  - Nelder and Mead (1965) method (NM)

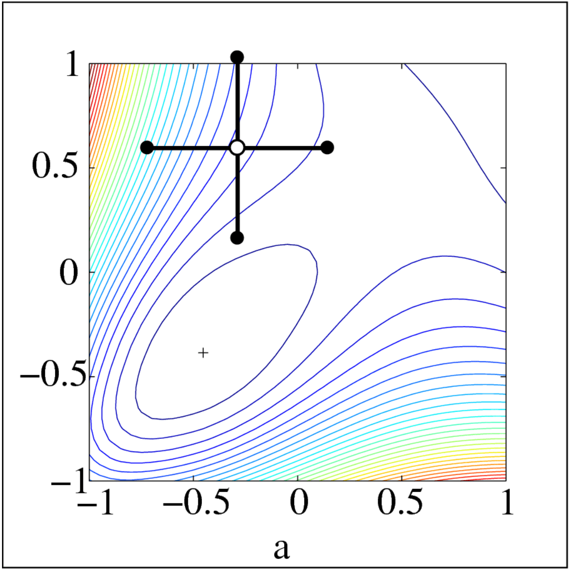
Hooke and Jeeves (1961) method

- An initial solution vector is needed to start the optimization procedure → the best among several solutions randomly generated
- It alternates between two search types
  - **Exploratory search** → a specific step value is summed or substracted to each decision variable value → evaluate whether the objective function value improves or not
  - **Pattern search** → the information provided by exploratory search is used to vary several decision variable values simultaneously

Hooke and Jeeves (1961) method

- If the solution can no longer be improved by exploratory search → **step value** is **halved** and the procedure is repeated until a stopping criteria is met
- This technique has been widely used over the years for stand-level optimization, e.g. Roise (1986), Valsta (1990) or Pukkala et al. (2014)
- The quality solution of the optimal solution found may be dependent on the initial solution used → it may yield a local optima

Hooke and Jeeves (1961) method

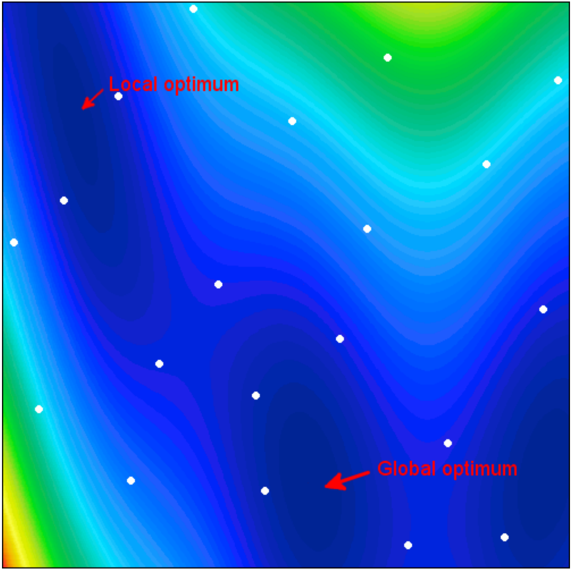


Population-based methods

Population-based methods

- A population of solution vectors is needed to start the optimization procedure
- The solutions are spread all over the solution space to avoid reaching a local optimum → exploration of the whole solution space
- The solutions are combined to form a new solution vector that is compared with the earlier solutions and included in the population if the average quality improves
- Examples of application for stand-level optimization → Pukkala (2009) and Arias-Rodil et al. (2015)
- Further reading → Bazaraa et al. (1993) and Cortez (2014)

Population-based methods



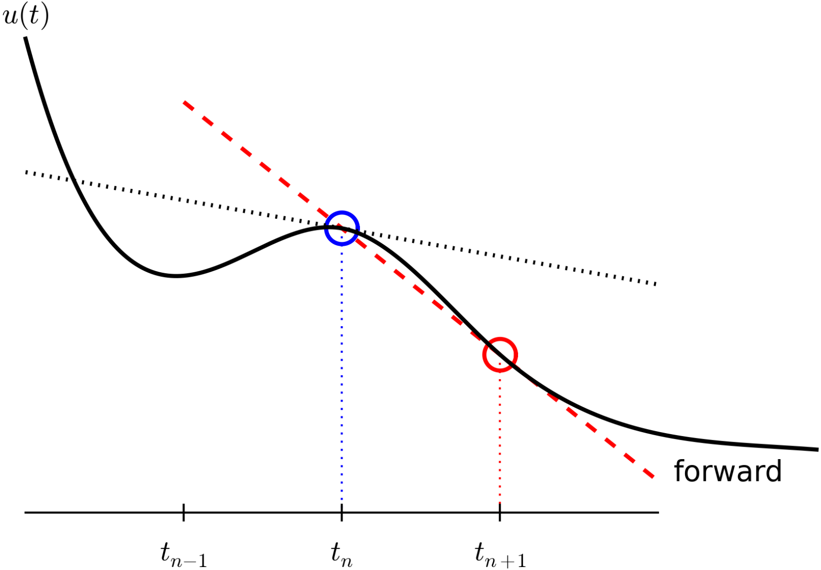
Non-linear differentiable optimization

- If the objective function (e.g. Land Expectation Value) can be expressed as a differentiable function and the set of constraints meet some requirements (to be closed, bounded and convex)
- Non-linear differentiable optimization techniques can be applied $\rightarrow$ for example Sequential Quadratic Programming
- These techniques approximate the objective function gradient

Advantages relative to direct search methods

- The global optimum is commonly reached
- It is much more efficient computationally

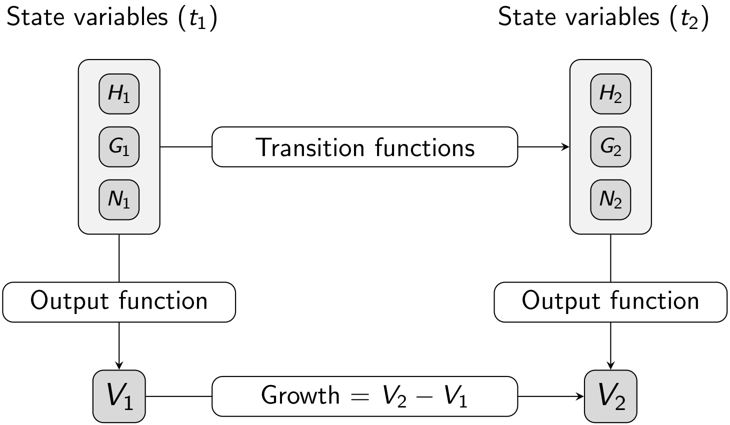
Approximating the gradient



Simulation and optimization example

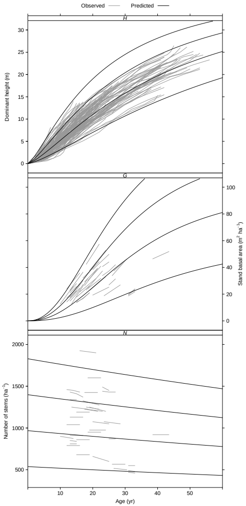
Growth and yield model

State-space approach



Dynamic growth model for even-aged stands

Model developed for *Pinus pinaster* in Asturias (NW Spain)



Simulation and optimization example

Example in spreadsheet

- Dynamic growth model for *Pinus pinaster* in Asturias (Spain)
- Growth simulator → from the simplest to a more complex one
  - Total volume
  - Volume classified by assortments
  - Only incomes
  - Incomes + costs
- Application of an optimization algorithm

Simulation and optimization example

The optimization procedure could be applied for different initial conditions of the stand

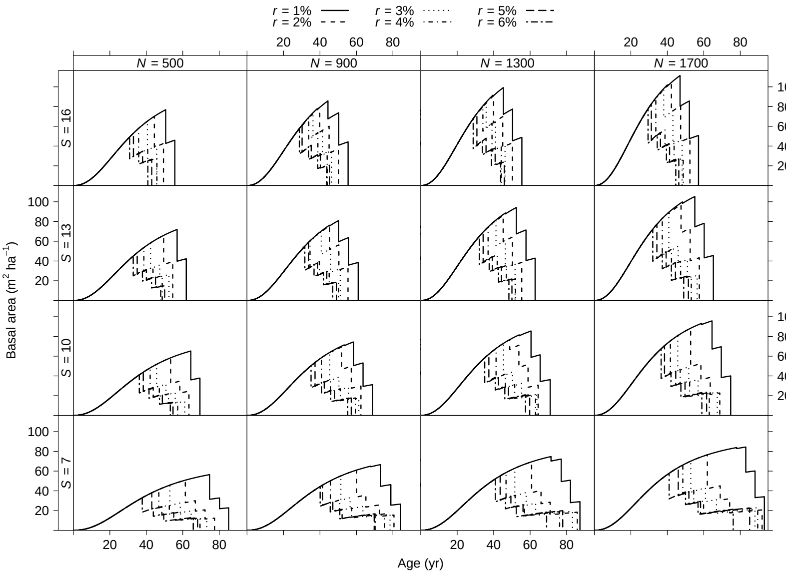
- Number of stems
- Site quality
- Discount rate
- Prices
- Costs
- ...

Simulation and optimization example

The next figure shows the evolution of basal area under the optimal management prescriptions for stands of *Pinus pinaster* in Asturias (Spain), considering different initial conditions

- Number of stems
- Site quality
- Discount rate

Simulation and optimization example



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