Solving strategies for the optimisation of energy systems

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Key messages

- What is an optimization strategy?
- How can we use a model to state an optimization problem?
 - Define of solving strategy to use an optimization algorithm
- What are the advantages and drawbacks of the solving strategies?



Thermo-economic Model

$$F(X_{state}, \pi) = 0$$
 Model equations

$$S(X_{state}, \pi) = 0$$
 Context specifications

 π Model parameters

$$X_{state}$$
 State variables

DOF: Degree of freedom of the system

DOF of the system = $N_{\text{state variables}} - N_{\text{Model equations}}$

Decision variables

 $N_{\text{Decision variables}} = DOF - N_{\text{Context specifications}}$

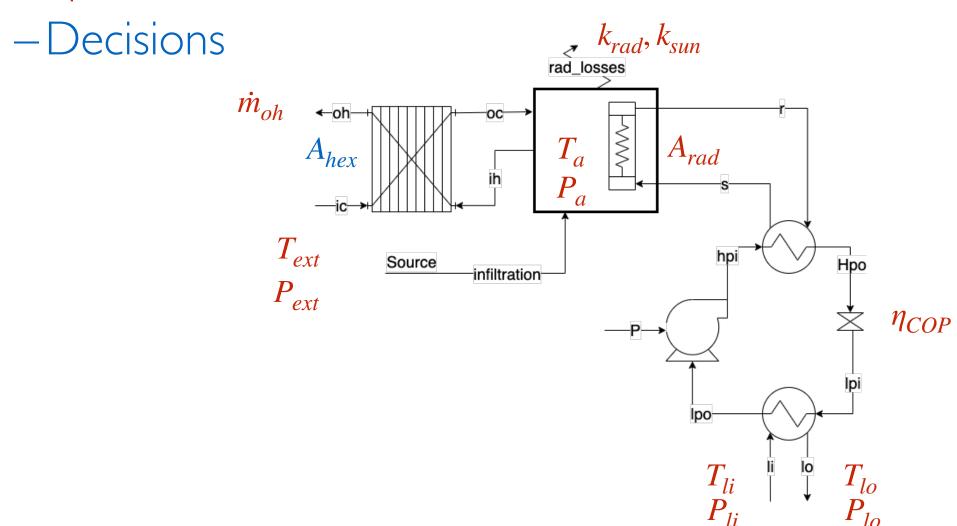
$$X_{d,min} \le X_d \le X_{d,max}$$

- Degree of freedom for which I do not have any rationale to fix the value
- I only know the possible range



Heat recovery by a double flux heat exchanger

- Degrees of freedom?
 - Specifications



Example of objective function

$$TotalCost[CHF/year] = OPEX + CAPEX + Tax$$

$$OPEX = \sum_{p=1}^{n_p} (\sum_{r=1}^{n_r} \dot{m}_{r,p}^+ c_{r,p}^+ + \dot{E}_p^+ c_{e,p}^+ - \dot{E}_p^- c_{e,p}^- + \sum_{u=1}^{n_u} f_{u,p} c m_u) d_p$$

$$CAPEX = \sum_{u=1}^{n_u} \frac{1}{\tau(n_{y,u}, i)} (I1_u y_u + I2_u f_u^{max})$$

$$Tax = CO_2^+ \gamma^{CO_2^+}$$

$$CO_2^+ = \sum_{p=1}^{n_p} (\sum_{r=1}^{n_r} \dot{m}_{r,p}^+ \epsilon_r^{CO_2} + \dot{E}_p^+ \epsilon_{e,p}^{CO_2^+} - \dot{E}_p^- \epsilon_{e,p}^{CO_2^-}) d_p$$

$$Impact = \zeta^{CO_2^+} (CO_2^+ + \sum_{u=1}^{n_u} \frac{1}{n_{y,u}} (\xi_{cu}^{CO_2} + \xi_{du}^{CO_2}) f_u^{max})$$

$$RES = \sum_{p=1}^{n_p} (\sum_{r_{res}=1}^{n_{r_{res}}} \dot{m}_{r_{res},p}^+ + \sum_{u=1}^{n_u} f_{u,p} e_{u,p}^{res^+}) d_p$$

$$\dot{E}_p^+ + \dot{E}_p^- + \sum_{i=1}^{n_u} f_{u,p} (e_{u,p}^{res}^+ - e_{u,p}^-) = 0 \qquad \forall p = 1..n_p$$



Thermo-economic optimisation

Fixing the value of the decision variables

$$X_{d,min} \le X_d \le X_{d,max}$$

- Degree of freedom for which I do not have any rationale to fix the value
- I only know the possible range
- I would like to fix the value of X_d so that it minimise an objective function

 X_d is a subset of X_{state}



Inequality constraints

Constraints limit the search space for the values of X_d

- Operating limits
 - safety, equipment limits,
- Regulation
 - -Emission: environment
- Market limits => products quality
- Technology limits and heuristics
 - -Materials
- Models limits
 - Correlations
 - -Structures and models
- Numerical safety; Two types
 - -Hard : can not be violated otherwise crash
 - E.g. flow inversion
 - try to place the hard constraints on the variables
 - -Soft : may be violated during resolution



Different types of problems

Optimal operation

- Decision : Operation set point
- Objective : Operating cost (CHF/s)

Optimal operation stratgey

- Decision : Set point strategy + start/stop
- Objective : Operating cost (CHF/period)

Scheduling

- Decision : Set points strategy, start/stop, when ?, in which equipment ?
- Objective : Operating cost (CHF/period)



Different types of problems

Optimal sizing

- Decision : operating set points, unit sizes, investment
- Objective : Total cost (CHF, CHF/an)

Optimal design

- Decision : operating set points (Operating strategy),
 unit sizes, investment, configuration
- -Objective: Total cost (CHF, CHF/an)

• Retrofit (reuse of existing equipment/configuration)

- Decision : operating set points (Operating strategy), unit sizes, configuration, reuse, reconfiguration, investments
- Objective : total cost



Black box method

Optimisation : min OBJ(X*_{decision})
Subject to G_{inequality}(X*_{decision}) ≥ 0

X*decision

OBJ(X*_{decision})
G(X*_{decision}) inequality
Status

 $\label{eq:model} \begin{tabular}{ll} Model: Solve \\ F(X_{dependent}, X_{specification}, X_{decision})=0 \\ S(X_{dependent}, X_{specification}, X_{decision})=0 => X(X^*_{decision}) \\ X_{decision} - X^*_{decision}=0 \\ then \ calculate \ OBJ(X(X^*_{decision})) \\ G(X(X^*_{decision})) \\ \end{tabular}$

Black Box strategy



Black Box approach

- + Can be used in any kind of optimisation method Heuristic, direct et indirect (derivatives)
- + Solving method to be defined => problem analysis
- + Selection of X*_{decision} by the user
- + Robustness
- + Non convergence analysis
- + Gives a list of system states
- Flexibility
- Computation time
- Inequality might be a problem when not on decision variables
- Derivative calculation (especially when done in iterative loops)

$$\frac{\partial f}{\partial x_i} = \frac{f(X + \Delta x_i) - f(X)}{\Delta x_i}$$



Numerical noise in derivative calculations

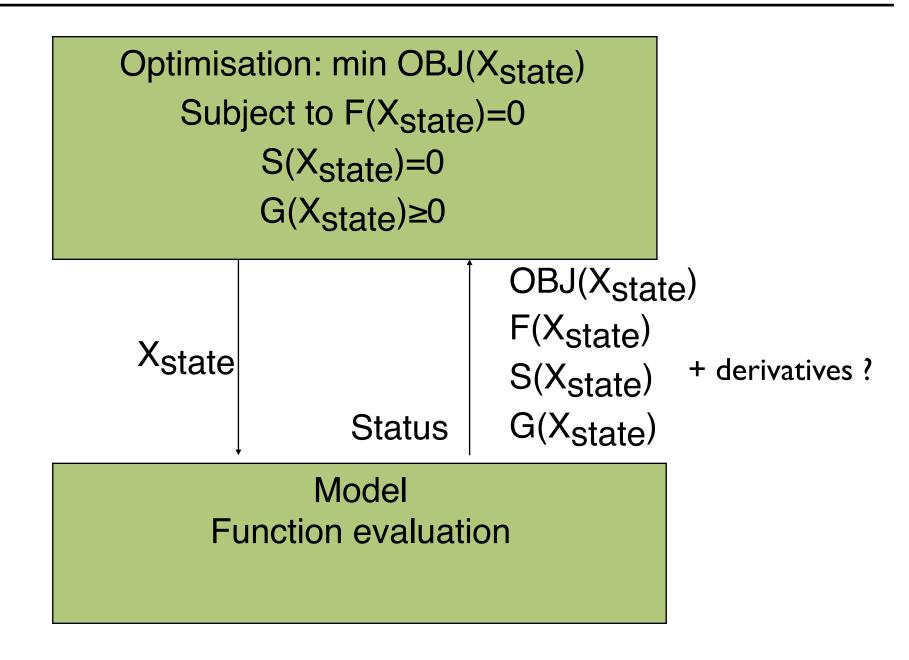
Derivative

$$\frac{\partial f}{\partial x_i} = \frac{f(X + \Delta x_i) - f(X)}{\Delta x_i} \quad \forall i = 1, ..., n_X + 1$$

Noice

$$\Delta f(X) = |F(X)_0 - F(X)_{n_X+1}|$$

Simultaneous method



Simultaneous strategy

$$\min_{X_{state}} TotalCost(X_{state}, \pi)$$

$$s.t. \quad F(X_{state}, \pi) = 0 \Rightarrow \text{equipment model}$$

$$S(X_{state}, \pi) = 0 \Rightarrow \text{Specification equations}$$

$$G(X_{state}, \pi) \leq 0 \quad \text{Inequality constraints}$$

$$X_{state}^{min} \leq X_{state} \leq X_{state}^{max} \quad \text{Bounds}$$

$$where$$

$$X_{state} = \{x_{statevariables}, x_{UnitParameters}, y_{decision} \in \{0, 1\}\}$$

Requires: Non Linear Constrained Optimisation solving method

 X_d is not defined (hidden in X_{state})



Simultaneous approach

- + Optimisation under constraints
 - => indirect method with 2nd derivatives if possible
- + Flexibility: different pbm with the same model (changing specification set and not the model)
- + Efficient and robust for on-line optimisation systems
 Bounds definition!
- + Computing time
- + Automatic DOF analysis and sensitivity analysis
- + Hard and soft inequality constraints
- Initialisation!
- Derivatives calculation (during function evaluation, symbolic?)
- No system state when no convergence
- Scaling!
- No explanations when the problem does not converge!
- Push button system?



Two levels approach

Optimisation:

min OBJ(X*decision, X*specification)
Subject to H(X*decision, X*specification)=0
G(X*decision, X*specification)≥0

Requires a constrained optimisation solver

X*decision,
X*specification

Status

OBJ(X*_{decision}, X*_{specification})

H(X*decision, X*specification)

G(X*decision, X*specification)

+ derivatives ?

Modèle

 $X_{dependent} = \Phi(X^*_{decision}, X^*_{specification})$



Two level strategy

$$\min_{\substack{X_{decision}^*, X_{Specs}^* \\ X_{Specs}^* \\ S.t.}} \quad TotalCost(X_{decision}^*, X_{Specs}^*, X(X_{decision}^*, X_{Specs}^*), \pi) = 0 \quad \text{some equality constraints} \\ G(X_{decision}^*, X_{Specs}^*, X(X_{decision}^*, X_{Specs}^*), \pi) = 0 \quad \text{inequality constraints} \\ Where \quad X_{decision}^*, X_{Specs}^*, X(X_{decision}^*, X_{Specs}^*), \pi) \leq 0 \quad \text{inequality constraints} \\ (X_{decision}^*, X_{specs}^*) \quad Calculated by solving: \\ (N+Ns)x(N+Ns) \quad Calculated by solving: \\ (N+Ns)x(N+Ns) \quad S(X_{state}, \pi) = 0 \Rightarrow \text{system model} \\ S(X_{state}, \pi) = 0 \Rightarrow \text{Specification equations} \\ X_{decision} - X_{decision}^* = 0 \Rightarrow \text{Specification of the value of decision variables} \\ X_{specs} - X_{specs}^* = 0 \Rightarrow \text{Specification of the value of specification variables} \\ Where \quad X_{state} = \{x_{StateVariables}, x_{Unitparameters}, y_{decision} \epsilon\{0, 1\}\}$$



Two levels strategy

- + Best of both world
- +Robustness of unit models (single calculation mode)
- +Code Maintenance
- +Derivative chaining is possible

 Analytical calculation is possible
- + Soft inequality constraints
- + Sensitivity analysis
- Conditional simulation
- Computing time (solving the lower level iteratively)
- Hard bounds (except when they are at the decision variable level).
- Noise in derivatives evaluation Internal iterative calculations

