CGE model calibration using multi-objective evolutionary algorithms

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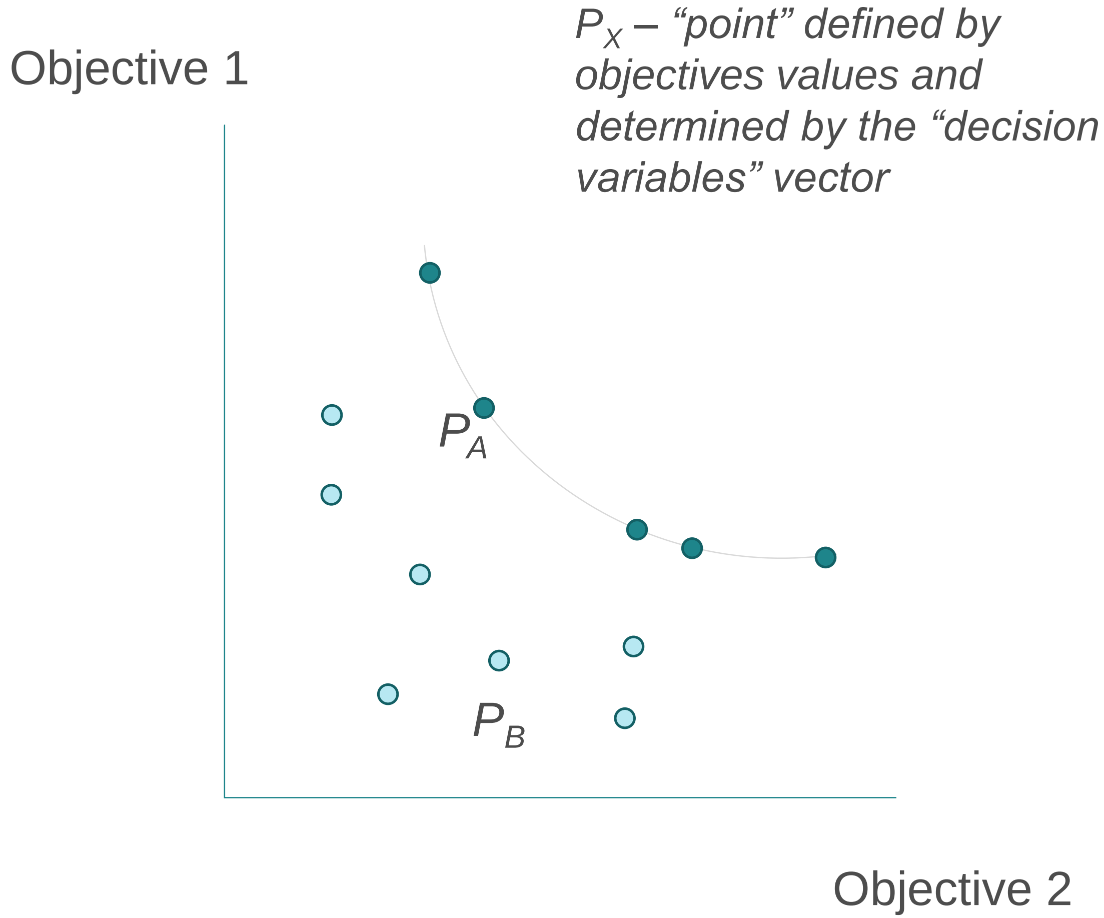
Baseline calibration challenges

- Trade-offs across calibration objectives (multiple model responses) resulting from behavioral parameter changes
  - Single calibration objective in an error minimization problem = single solution
  - No embedded calibration objective – manual iterations with no guaranteed success
- Modifications to the model code through e.g. the Cross Entropy approach (Arndt et al. 2002, Go et al. 2015)
  - The use of time series for observed variables requires the addition of the time dimension to all variables and equations
  - Recursive dynamics are simplified unless intertemporal relationships are introduced – capital accumulation, migration, etc.

Multi-objective Evolutionary Algorithms (MOEA)

- Multi-objective – rely on meta-heuristics to construct an approximation of a Pareto front across a number of conflicting objectives
- A sorting process filters out the sub-optimal "dominated solutions"
- Evolutionary – use the evolutionary operations of "crossover" and "mutation" in the search process to generate populations with new characteristics for the next iteration ("generation")
- Each generation improves the Pareto front until a stopping criteria is reached



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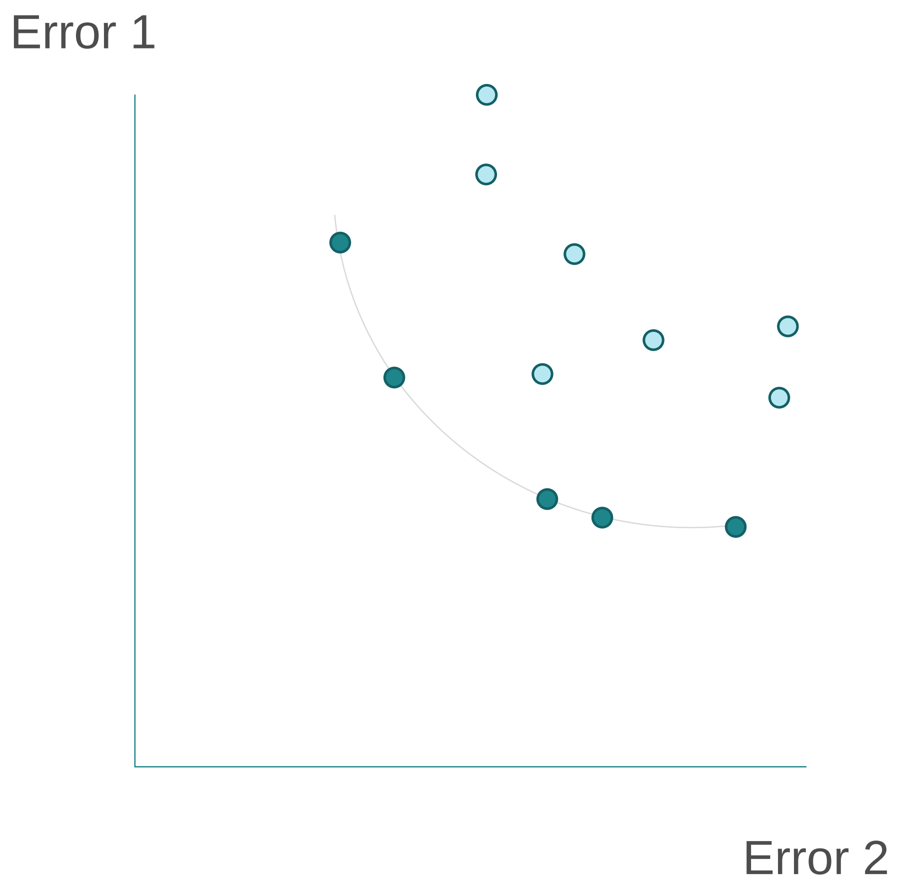
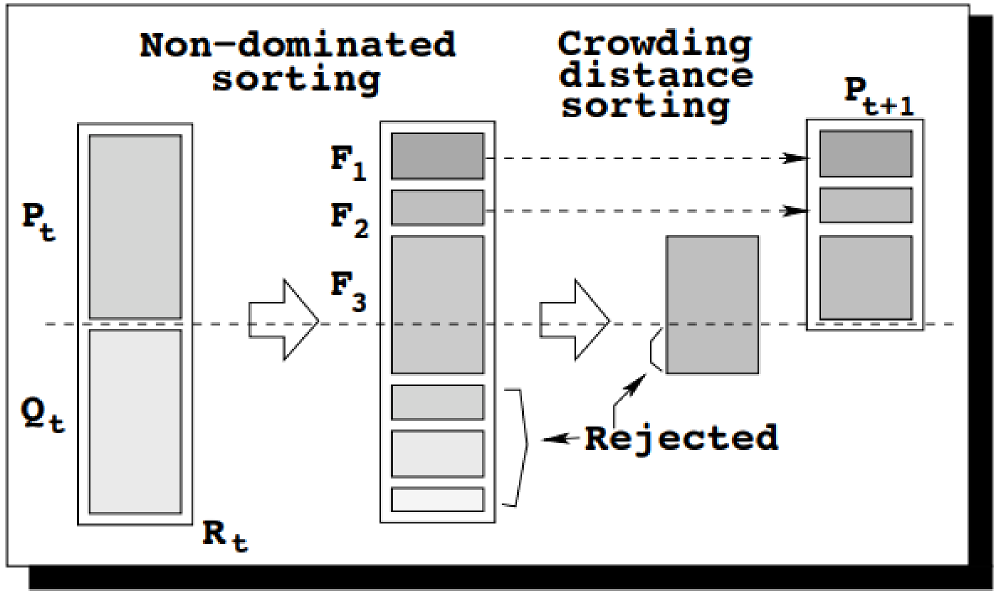


MOEA example: NSGA-II characteristics

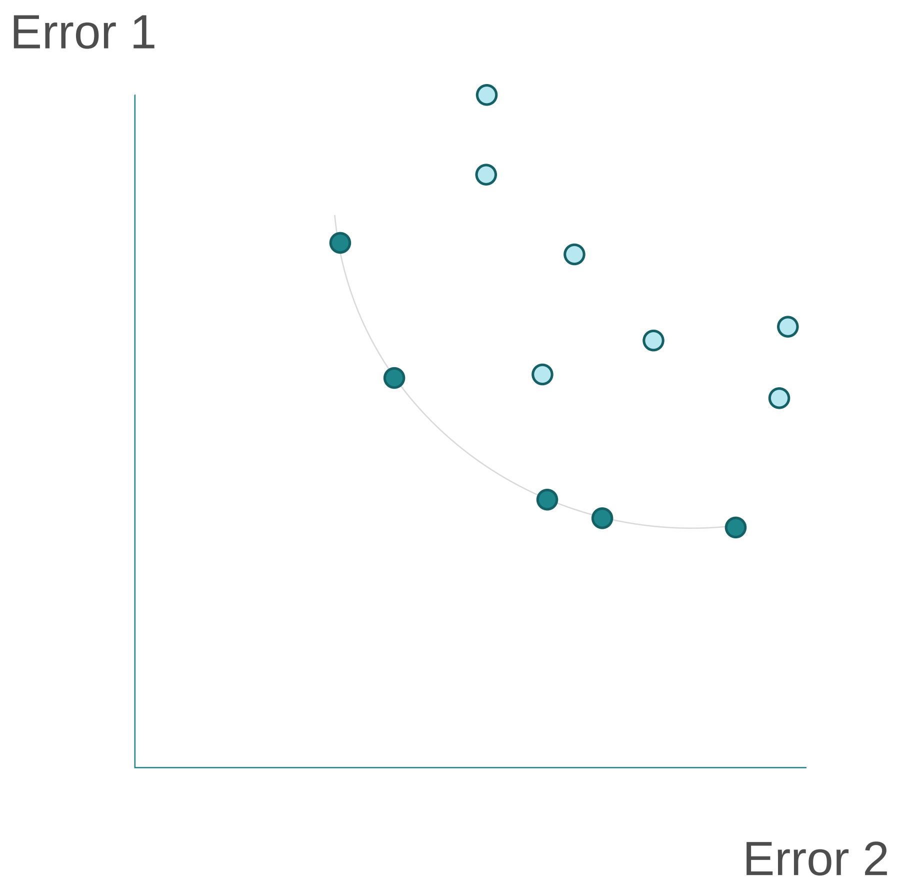
- Elitist principle: combining the parent population (P of card=n) with an offspring population (Q of card=n) => card=2n
- From the 2n points, n parents are selected starting from the top Pareto fronts
- t=generation; NSGA-II runs population sizes of 100



Source: Deb (2011)

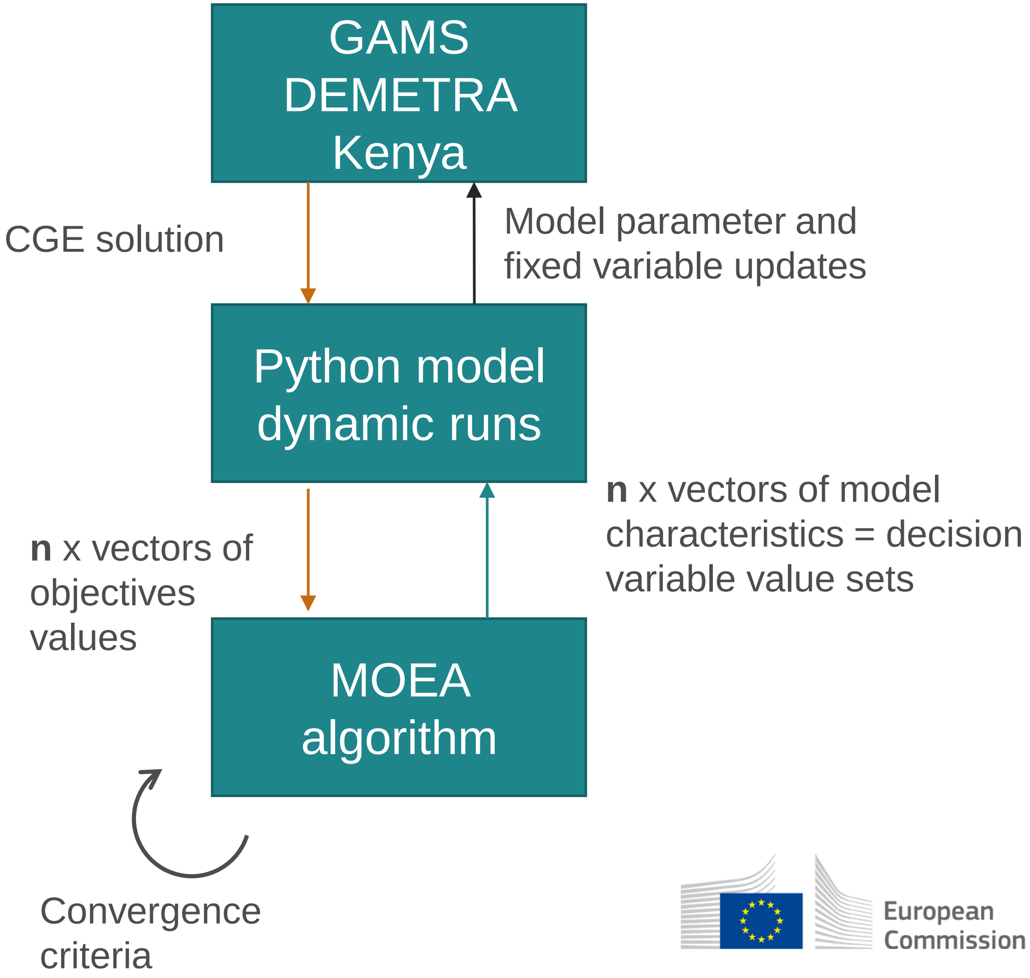
MOEA advantages for CGE calibration

- Relatively easy to implement – algorithms are readily available in Python libraries e.g. platypus
- Beyond the CGE model specification, mathematical formulations are not necessary
- …although the integration with a GAMS-based CGE model implies additional work notably for recursive dynamics
- Makes use of parallel processing
- Flexible – the algorithm is easy to adjust by adding decision variables and objectives; can work with mixed types of variables
- Same CGE model and closure rules can be used for ‘search’ and ‘simulation’ modes
- **Can reveal hidden information about how a model implementation works around objective min/max and beyond**



OPTCGE calibration framework setup (1/2)

- Calibration of a single-country CGE model – JRC DEMETRA (Boulanger et al. 2019) for Kenya
- The model trade baseline is aligned with that of a global model baseline (MAGNET)
- The GAMS model is integrated in a Python-based algorithm using the Python API
- The Python algorithm runs the MOEA search based on alternative GAs



OPTCGE calibration framework setup (2/2)

DEMETRA Kenya model characteristics

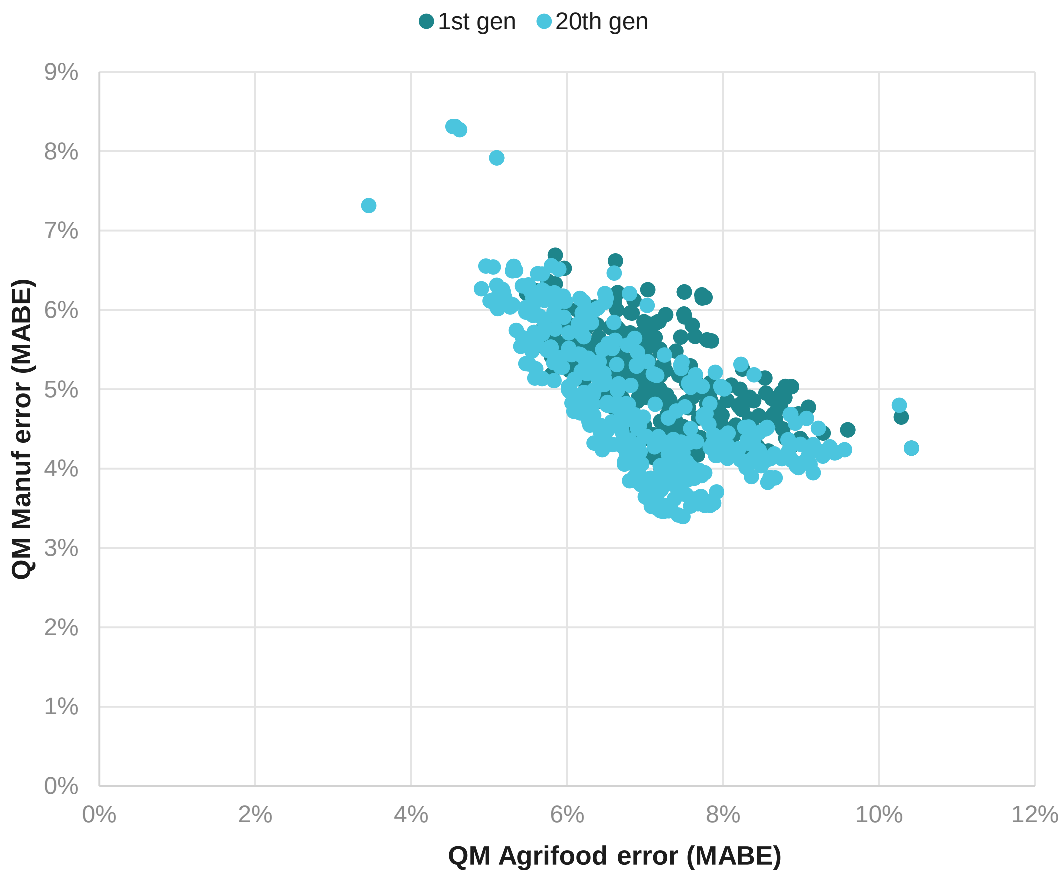
- The DEMETRA model uses a small SAM for Kenya (4 sectors, 1 household)
- 3 commodities are traded: c_agrifood, c_manuf, c_serv
- The process is over the 2020-2025 period with annual timesteps
- Model is run in ‘calibration mode’ = RGDP is fixed with variable TFP
- MAGNET world import and export prices are applied to DEMETRA → quantities are free variables

MOEA search definition

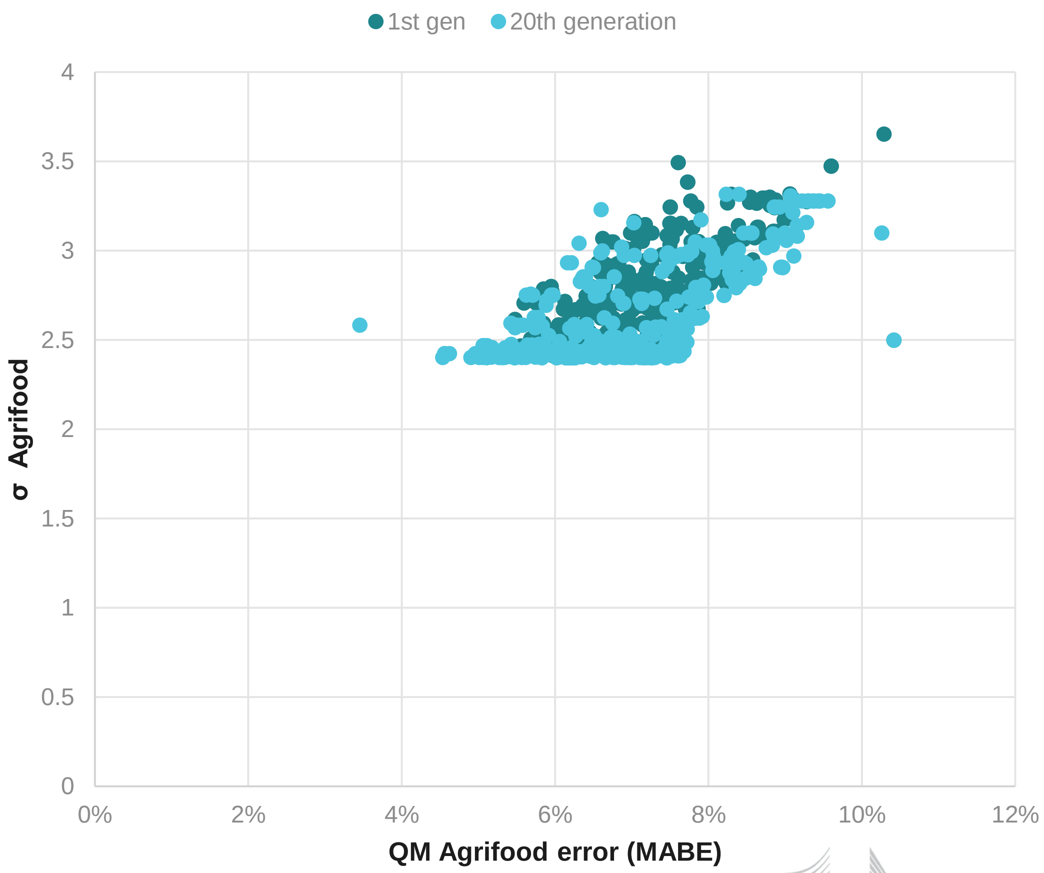
- Armington elasticities (σ) and CET export elasticities (ω) as decision variables
- 4 objectives are minimized
  - Mean Average Bias Error (MABE) for import quantity growth (*qimp*) for each commodity (3 objectives)
  - Cross Entropy in the spirit of Arndt et al. (2002) based on σ prior values and distributions and on *qimp* errors. σ prior values are set to 3 for all commodities
- Search is limited to σ = [2.4; 4.2] *and* ω = [2;8]

Results – Pareto front trade offs

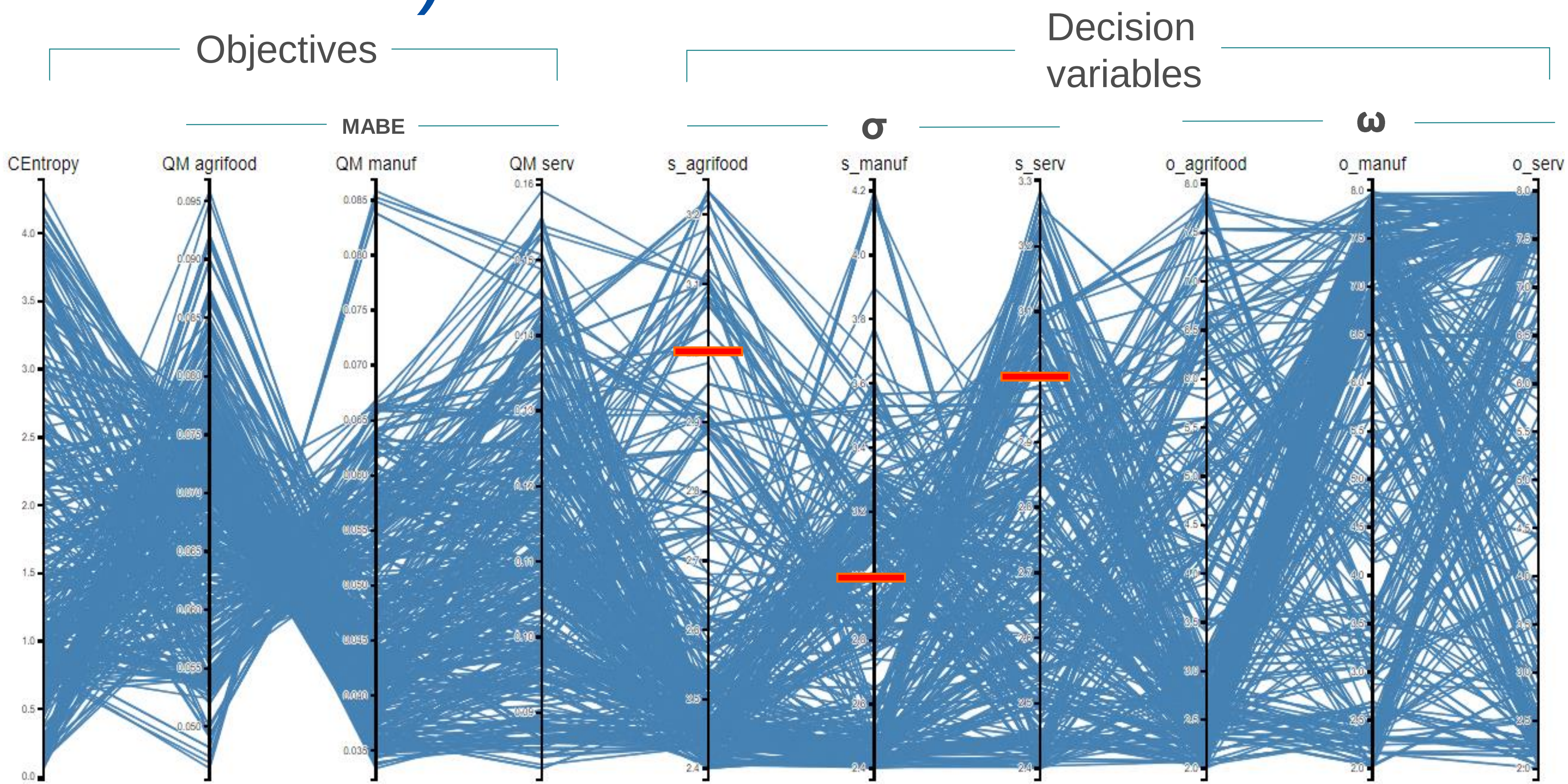
Between calibration objectives



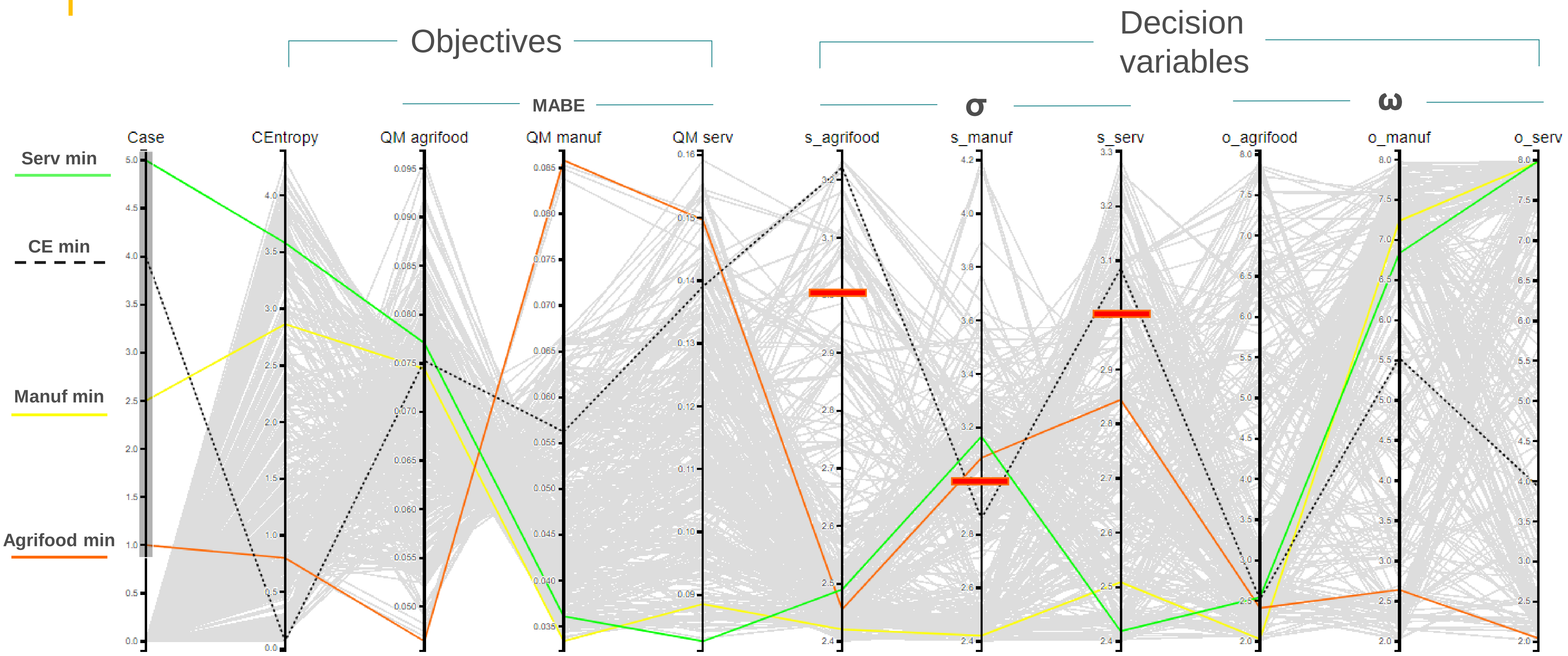
Between objectives and decision variables



Results – objectives and variables (400+ solutions)

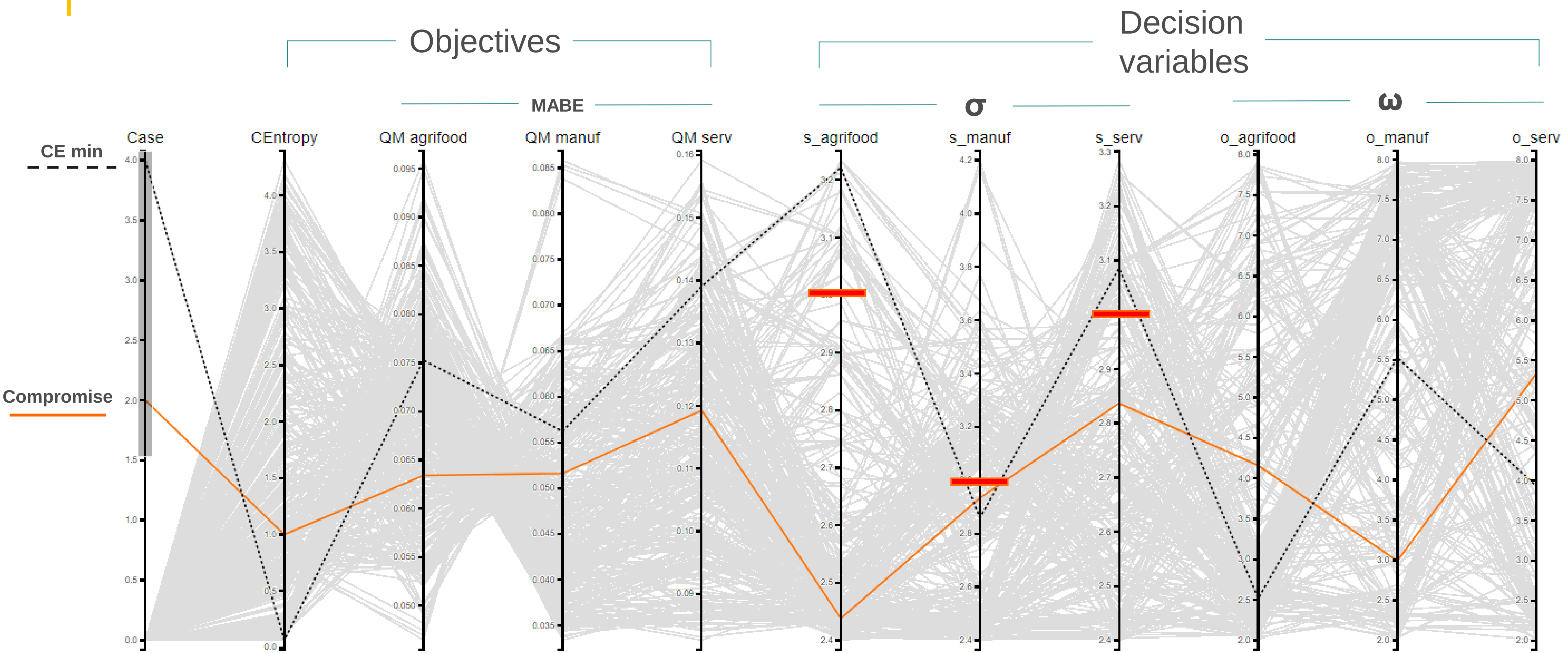


Results



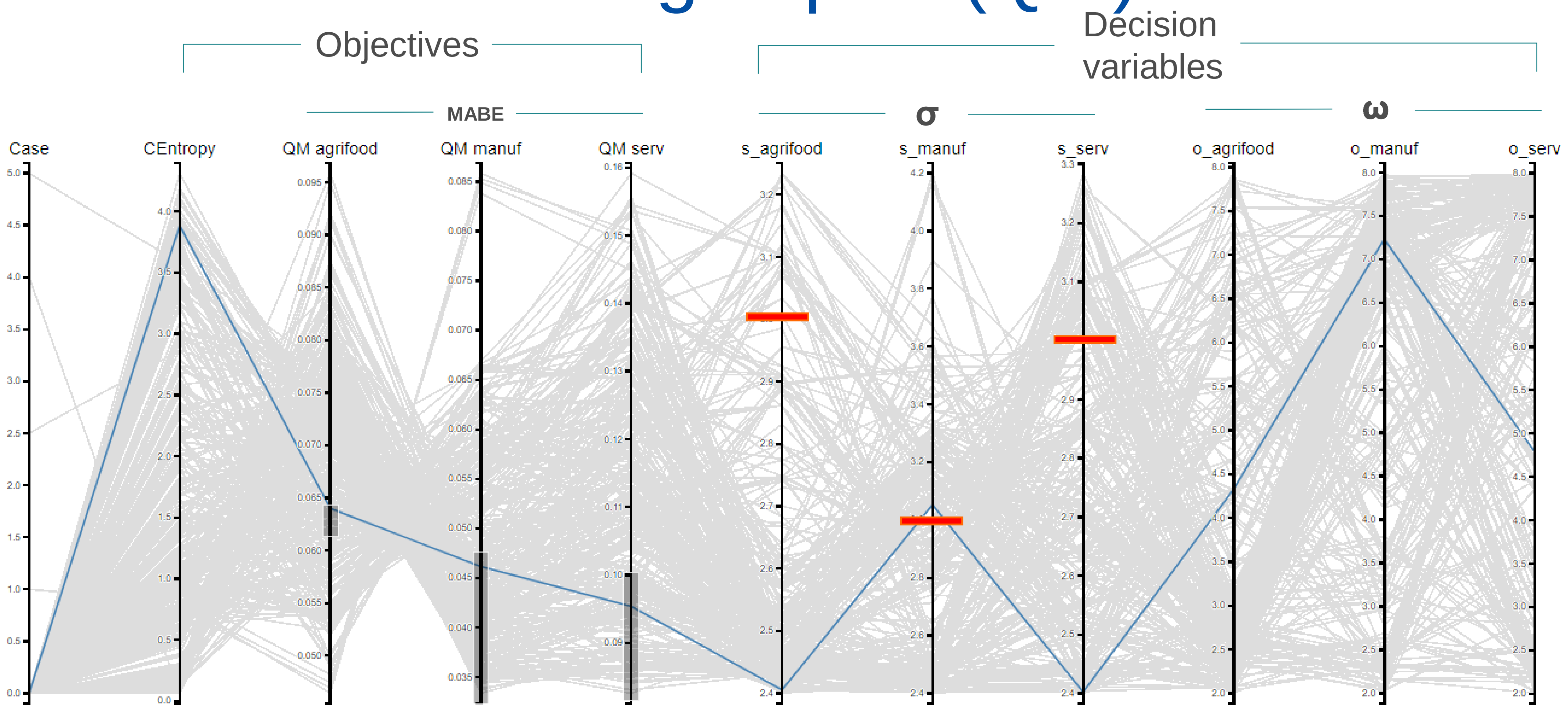
Objectives
Decision variables
MABE
σ
ω
Case
CEntropy
QM agrifood
QM manuf
QM serv
s_agrifood
s_manuf
s_serv
o_agrifood
o_manuf
o_serv
Serv min
CE min
Manuf min
Agrifood min

Results



Objectives
Decision variables
MABE
σ
ω
CE min
Compromise
Case
CEntropy
QM agrifood
QM manuf
QM serv
s_agrifood
s_manuf
s_serv
o_agrifood
o_manuf
o_serv

Results – minimizing import (QM) errors



Preliminary conclusions

- The MOEA provides for a supple way to estimate model parameters by building on previous estimation work from e.g. Arndt et al. (2002), Ferrari and Müeller (2011)
- The solution space allows for an exploration of trade-offs between calibration objectives and estimated parameters
- The use of parallel processing through GAMS Python API can speed up the search process
- Going forward: the use of larger SAMs and the application machine learning techniques to establish individual parameter importance in the baseline construction

Thank you!

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