Applying Stopping Criteria in Evolutionary Multi-Objective Optimization

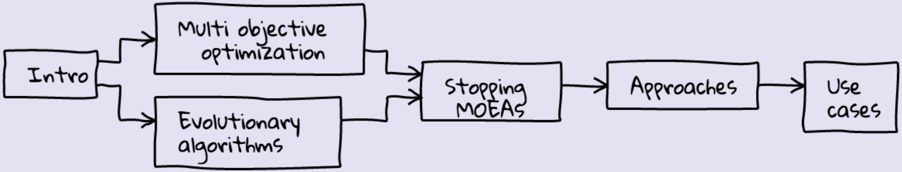
Nayat Sanchez-Pi[1] Luis Martí[2]

Group of Research on Intelligence and Optimization (RIO Group)

1. Institute of Mathematics and Statistics, State University of Rio de Janeiro
2. Institute of Computing, Universidade Federal Fluminense

2017 IEEE Congress on Evolutionary Computation
Donostia/San Sebastián, Spain. June 5–9, 2017.

Talk outline



Do you know them?

Rudolph Diesel

Internal combustion ‘diesel’ engine

Fred Duesenberg

Hydraulic brakes

It seems that stopping things does not make you famous.

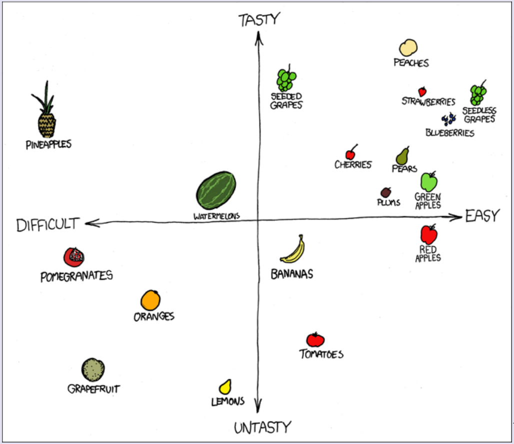
What does “until end condition is met” really means?

Multi-objective optimization

Most *-if not all-* optimization problems involve more than one objective function to be optimized simultaneously.

- For example: optimize a given feature of an object while keeping under control the resources needed to elaborate that object.
- Sometimes those other objectives are converted to constraints or fixed to default values, but they are still there.
- Multi-objective optimization is also known as *multi-objective programming*, *vector optimization*, *multicriteria optimization*, *multiattribute optimization* or *Pareto optimization* (and probably by other names, depending on the field).

The multi-objective ‘fruit selection problem’



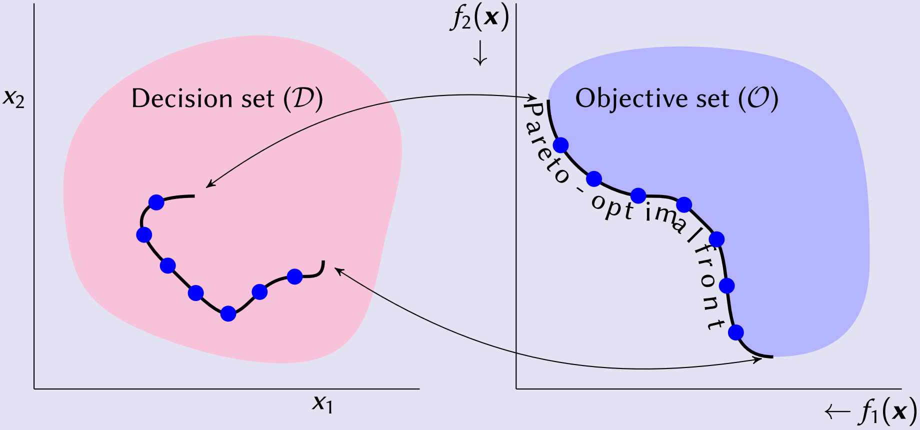
[1]

We do it all the time!

[1] from http://xkcd.com/388

Two-dimensional example

$$\text{minimize } \boldsymbol{F}(\boldsymbol{x}) = \langle f_1(\boldsymbol{x}), f_2(\boldsymbol{x}) \rangle\,,$$
$$\text{with } \boldsymbol{x} \in \mathcal{D} \subseteq \mathbb{R}^2\,.$$



Multi-objective optimization problem

$$\begin{gathered}\text{minimize}\ \ \boldsymbol{F}(\boldsymbol{x}) = \langle f_1(\boldsymbol{x}), \ldots, f_M(\boldsymbol{x}) \rangle\,, \\ \text{with}\ \boldsymbol{x} \in \mathcal{D}\,.\end{gathered}$$

- $\mathcal{D}$: feasible set — can be defined as constraints;
- $\mathcal{O}$: objective set;
- optimality — *Pareto dominance*;
- $\mathcal{D}^*$: Pareto-optimal set;
- $\mathcal{O}^*$: Pareto-optimal front, and;
- $\mathcal{P}^*$: optimizer solution.

A decision maker selects elements of $\mathcal{P}^*_t$.

Pareto dominance relation

Usually, there is not a unique solution that minimizes all objective functions simultaneously, but, instead, a set of equally good *trade-off* solutions.

- Optimality can be defined in terms of the Pareto dominance relation.
- That is, having $\boldsymbol{x}, \boldsymbol{y} \in \mathcal{D}$, **$\boldsymbol{x}$ is said to dominate $\boldsymbol{y}$** (expressed as $\boldsymbol{x} \prec \boldsymbol{y}$) iff $\forall f_j$, $f_j(\boldsymbol{x}) \leq f_j(\boldsymbol{y})$ and $\exists f_i$ such that $f_i(\boldsymbol{x}) < f_i(\boldsymbol{y})$.
- Having the set $\mathcal{A}$. $\mathcal{A}^*$, the *non-dominated subset* of $\mathcal{A}$, is defined as

$$\mathcal{A}^* = \left\{ \boldsymbol{x} \in \mathcal{A} \,\middle|\, \nexists \boldsymbol{y} \in \mathcal{A} : \boldsymbol{y} \prec \boldsymbol{x} \right\}.$$

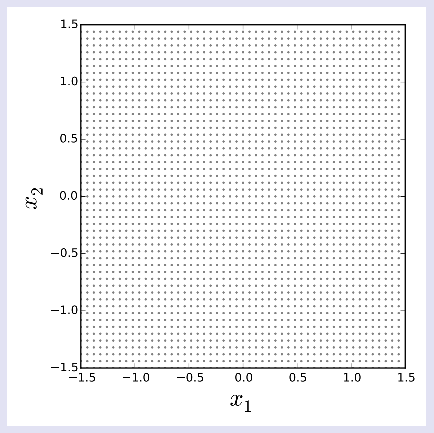
- The *Pareto-optimal set*, $\mathcal{D}^*$, is the solution of the MOP. It is the subset of non-dominated elements of $\mathcal{D}$.
- Its image in objective set is called the *Pareto-optimal front*, $\mathcal{O}^*$.

Example: Dent problem

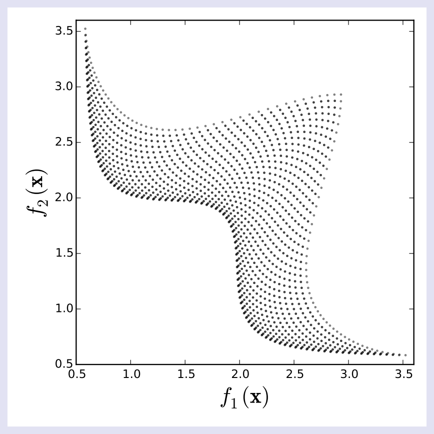
$$
\begin{aligned}
\text{minimize} \quad & f_1(\boldsymbol{x}), f_2(\boldsymbol{x}) \\
\text{such that} \quad & f_1(\boldsymbol{x}) = \tfrac{1}{2}\left(\sqrt{1+(x_1+x_2)^2}\sqrt{1+(x_1-x_2)^2} + x_1 - x_2\right) + d, \\
& f_2(\boldsymbol{x}) = \tfrac{1}{2}\left(\sqrt{1+(x_1+x_2)^2}\sqrt{1+(x_1-x_2)^2} - x_1 - x_2\right) + d, \\
\text{with} \quad & d = \lambda e^{-(x_1-x_2)^2}. \\
& \text{generally } \lambda = 0.85 \text{ and } \boldsymbol{x} \in [-1.5, 1.5]^2.
\end{aligned}
$$

Example: Dent problem — Plots

Decision set

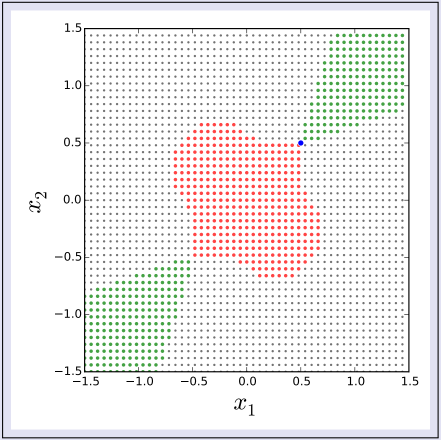


Objective set

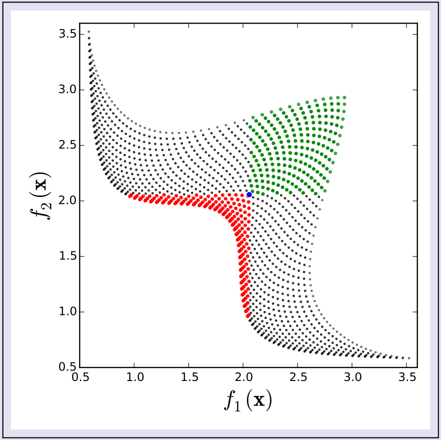


Example: Dent problem — the dominance relation

Decision set

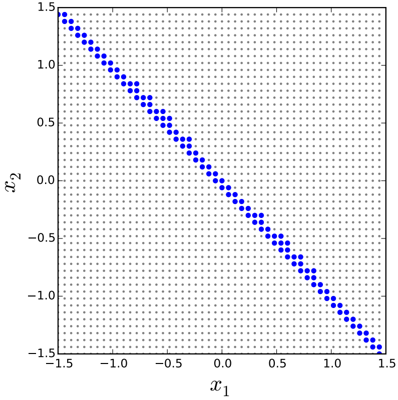


Objective set

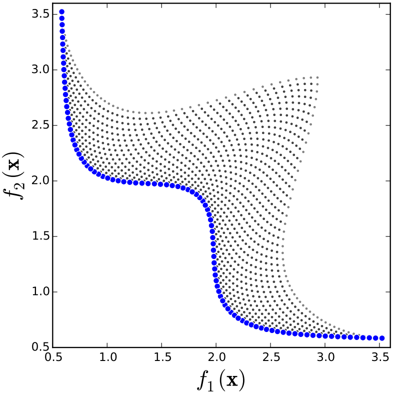


Example: Dent problem — non-dominated front

Decision set



Objective set

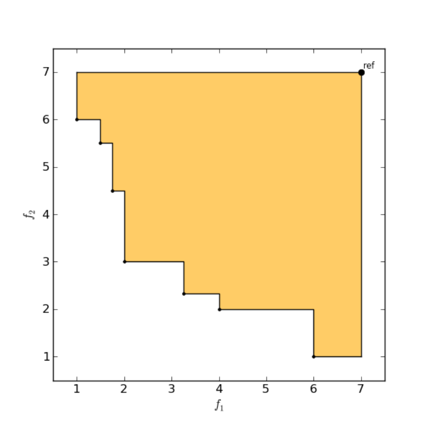


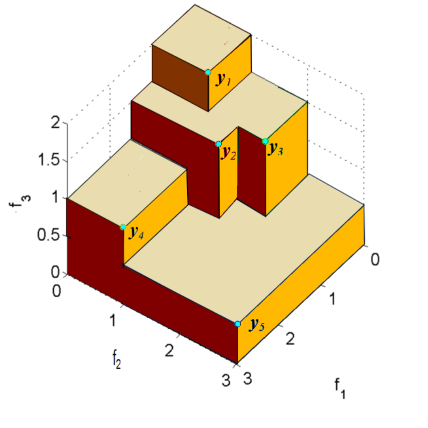
Performance indicators

How can we compare different (sets of) solutions?

- Hypervolume indicator;
- additive/multiplicative epsilon indicator;
- R1/R2 indicators;
- inverted generational distance, etc.

The hypervolume indicator





[2]

[2] From Günter Rudolph's site:
`https://ls11-www.cs.uni-dortmund.de/rudolph/hypervolume/start`.

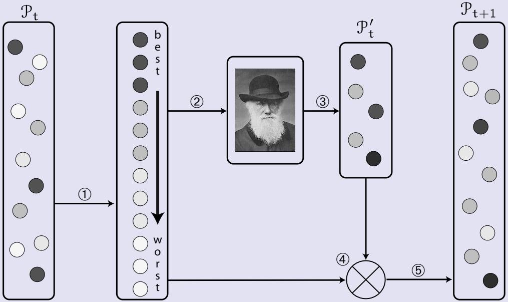
Formalization of the hypervolume

For a set of solutions $\mathcal{A}$,

$$I_{\text{hyp}}(\mathcal{A}) = \text{volume}\left(\bigcup_{\forall \boldsymbol{a} \in \mathcal{A}} \text{hypercube}(\boldsymbol{a}, \boldsymbol{r})\right).$$

- We need a *reference point*, $\boldsymbol{r}$.
- Hypervolume is Pareto compliant (Fleischer, 2003): for sets $\mathcal{A}$ and $\mathcal{B}$, $\mathcal{A} \prec \mathcal{B} \implies I_{\text{hyp}}(A) > I_{\text{hyp}}(B)$.
- Calculating hypervolume is **NP**-hard.

Evolutionary algorithms



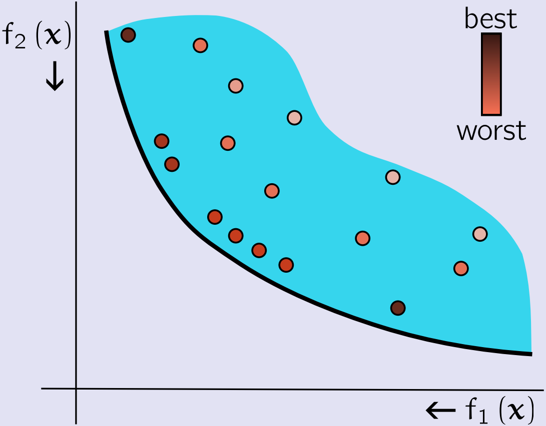
- A **population** of **individuals**;
- individuals are ranked using a **fitness assignment function**;
- **evolution-inspired** operators are applied;
- fittest individuals have a more active role.

Multi-objective evolutionary algorithms (MOEAs)

- One of the hottest topics in EA research.
- MOPs put EAs "to the limit".
- Succeeded in yielding relevant results.
- Do not makes any assumptions about the problem.
- Parallel nature of the search process produces sets of solutions.

Cornerstone issue: fitness assignment.

Ranking a multi-objective population



- Objective aggregation.
- Pareto-based ranking.
- Performance indicator-based ranking.

Many-objective problems

Problems with four or more objectives.

Challenges

- Visualization.
- Poor understanding of convergence and progress $\rightarrow$ stopping criteria.
- Scalability.

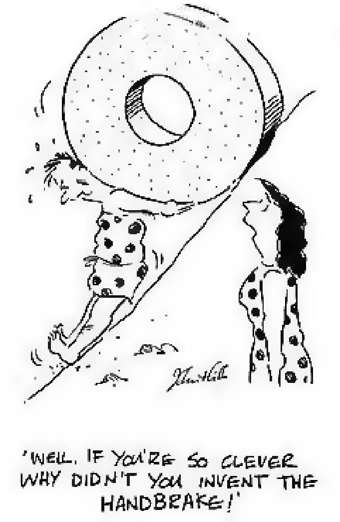
Scalability

- Exponential relation between the number of objectives and the amount of resources.
- Large populations are needed.

Stopping a multi-objective optimization

Stopping criteria

- Detect when there is no sense in proceeding with the search;
- they are usually a heuristic.
- This matter have been overlooked in the EMO context, but;
- complex and real-world applications demand them.



[3]

[3] from https://www.cartoonstock.com/cartoonview.asp?catref=jhin64.

Stopping criteria in general

A stopping criterion is invoked at the end of an iteration of the algorithm being controlled.

Scenarios

1. the solution obtained so far is satisfactory;
2. we have a feasible solution that is not satisfactory in terms of optimality, but a better one is unlikely to be produced;
3. the method is unable to converge to any solution, or;
4. the amount of computation performed so far is *sufficient*.

In brief…

A stopping criterion should detect “**success**” and “**failure**” scenarios.

A multi-objective optimization stopping criteria

- Judging the advance of the optimization can become as complex as the optimization itself;
- unlike other problems there is no “axis” to be used as reference;
- therefore any assessment must be carried out in a relative fashion, but;
- current performance indicators have a high computational cost.

Desirable properties

- An execution-wise criterion is required because of the nature of the problem;
- Resource requirements should be kept as low as possible, in particular;
- the criterion should be embedded in other processes.
- As few parameters as possible!

Karush-Kuhn-Tucker (KKT) optimality

If we encounter problems, where the feasible set is given implicitly by constraints,

$$\mathcal{S} = \{\boldsymbol{x} \in \mathbb{R}^n; (c_1(\boldsymbol{x}), \dots, c_C(\boldsymbol{x})) \leq \boldsymbol{0}\} ,$$

and $f_1, \dots, f_M$ and constraint functions $c_1, \dots, c_C$ are continuously differentiable.

Definition (Karush-Kuhn-Tucker proper optimality condition[4][5])

A solution $\boldsymbol{x} \in \mathcal{S}$ is said to be properly Pareto-optimal if it holds the Pareto-optimality condition and $\nexists \boldsymbol{b} \in \mathbb{R}^n$ such that

$$\forall i = 1, \dots, M : \quad \nabla f_i(\boldsymbol{x})^{\mathrm{T}} \boldsymbol{b} \leq \boldsymbol{0} ; \tag{1}$$

$$\exists j = 1, \dots, M \text{ such that} : \quad \nabla f_j(\boldsymbol{x})^{\mathrm{T}} \boldsymbol{b} < \boldsymbol{0} ; \tag{2}$$

$$\forall c_c(\boldsymbol{x}) = 0 : \quad \nabla c_c(\boldsymbol{x})^{\mathrm{T}} \boldsymbol{b} \leq \boldsymbol{0} . \tag{3}$$

[4] Karush, W. (1939). Minima of functions of several variables with inequalities as side constraints. Master's thesis, Department of Mathematics, University of Chicago, Chicago, IL, USA

[5] Kuhn, H. W. and Tucker, A. W. (1951). Nonlinear programming. In Neyman, J., editor, *Proceedings of Second Berkeley Symposium on Mathematical Statistics and Probability*, pages 481–492, Berkeley, LA, USA. University of California Press

…from multi-criteria decision making?

1. Initialize: calculate ideal and approximated nadir objective vectors and show them to the decision maker.
2. Generate a Pareto optimal starting point (by using e.g. some no-preference method or solution given by the decision maker).
3. Ask for preference information from the decision maker (e.g. aspiration levels or number of new solutions to be generated).
4. Generate new Pareto optimal solution(s) according to the preferences and show it/them and possibly some other information about the problem to the decision maker.
5. If several solutions were generated, ask the decision maker to select the best solution so far.
6. Stop, if the decision maker wants to; otherwise, go to step 3).

They even have a name for that: **psychological convergence**[6]

[6] Stewart, T. J. (1997). Convergence and validation of interactive methods in mcdm: simulation studies. In *Essays in Decision Making*, pages 7–18. Springer

Where can we look for ideas?

"Classical" multi–criteria decision making

- We have proper definitions of optimality, like the Kuhn–Tucker condition, but;
- perhaps they are more relevant from a theoretical point of view.
- *Ideal solution.*

Single–objective EAs

- Search space exploration[7]: all states visited with a certain probability;
- objective convergence[8];
- population convergence — population diversity.

[7] Aytug, H. and Koehler, G. J. (2000). New stopping criterion for genetic algorithms. *European Journal of Operational Research*, 126(3):662–674

[8] Jain, B. J., Pohlheim, H., and Wegener, J. (2001). On termination criteria of evolutionary algorithms. In Spector, L., Goodman, E. D., Wu, A., Langdon, W., Voigt, H.-M., Gen, M., Sen, S., Dorigo, M., Pezeshk, S., Garzon, M. H., and Burke, E., editors, *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO 2001)*, page 768, San Francisco, California, USA. Morgan Kaufmann

Guidelines

Desirable properties

- An execution–wise criterion is required because of the nature of the problem;
- resource requirements should be kept as low as possible, in particular;
- the criterion should be embedded in (and profit from) other processes, and;
- to have as few parameters as possible!

At least two components

- A local **progress indicator**, and;
- An **evidence gathering process** that combines the local measurements.

Situation

- There has been few theoretical works[9] that deal with EMO convergence, and;
- there has been even more sparse attempts to deal with the stopping issue.

The importance of this matter has not been correctly underscored until recently.[10]

[9] Rudolph, G. and Agapie, A. (2000). Convergence properties of some multi–objective evolutionary algorithms. In *2000 IEEE Congress on Evolutionary Computation (CEC 2000)*, volume 2, pages 1010–1016, Piscataway, New Jersey. IEEE Press

[10] Fonseca, C., Gandibleux, X., Korhonen, P., Martí, L., Naujoks, B., Thiele, L., Wallenius, J., and Zitzler, E. (2009). Working group on EMO for interactive multiobjective optimization (1st round). In Deb, K., Greco, S., Miettinen, K., and Zitzler, E., editors, *Hybrid and Robust Approaches to Multiobjective Optimization*, number 09041 in Dagstuhl Seminar Proceedings, Dagstuhl, Germany. Schloss Dagstuhl — Leibniz–Zentrum fuer Informatik

Approaches in chronological order

Deb and Jain: Running Metrics[11]

- Deb and Jain were the first authors who proposed the investigation of performance metrics over the run of MOEAs.
- They used two metrics, one for evaluating the convergence and one for measuring the diversity of the Pareto front.
- Convergence metric (CM) calculates the average of the smallest normalized euclidean distance from each individual in the Pareto front to a precomputed reference set.
- For the diversity metric (DVM), all objective value vectors of the Pareto front are projected onto a $m-1$–dimensional hyperplane which is then uniformly divided into discrete grid cells.
- The DVM tracks the number of attained grid cells and also evaluates the distribution by assigning different scores for predefined neighborhood patterns.

[11] Deb, K., Jain, S.: Running performance metrics for evolutionary multi-objective optimization. In: Simulated Evolution and Learning (SEAL), pp. 13–20 (2002) — 2002

Approaches in chronological order

Rudenko and Schoenauer[12] — 2004

- A stopping criterion to be used in conjunction with the NSGA–II algorithm.
- Measure the mean of the spread of the non–dominated individuals.
- Compute an average across iterations of the measurements.

Stoooooop! We found a leitmotiv!

To stop when the "indicator" is **zero** and has a **flat** tendency.

[12] Rudenko, O. and Schoenauer, M. (2004). A steady performance stopping criterion for pareto–based evolutionary algorithms. In *The 6th International Multi–Objective Programming and Goal Programming Conference*, Hammamet, Tunisia

Approaches in chronological order (II)

Martí, García, Berlanga and Molina (MGBM)[13][14] — 2007, 2009

- Iteration-wise measurements with the *mutual domination rate* (MDR) indicator, and;
- a simplified Kalman filter tracks the measurements in an *evidence gathering process*.
- It detects when MDR is close to zero and flat.

- The KF helps to pay less attention to measurements at beginning.
- MDR can be embedded in the EMO supervised (if it relies on Pareto dominance).
- Shown to detect "failure" situations.

[13] Martí, L., García, J., Berlanga, A., and Molina, J. M. (2007). A cumulative evidential stopping criterion for multiobjective optimization evolutionary algorithms. In Thierens, D., Deb, K., Pelikan, M., Beyer, H.-G., Doerr, B., Poli, R., and Bittari, M., editors, *GECCO'07: Proceedings of the 2007 GECCO Conference Companion on Genetic and Evolutionary Computation*, page 911, New York. ACM Press

[14] Martí, L., García, J., Berlanga, A., and Molina, J. M. (2009). An approach to stopping criteria for multi–objective optimization evolutionary algorithms: The MGBM criterion. In *2009 IEEE Conference on Evolutionary Computation (CEC 2009)*, pages 1263–1270, Piscataway, New Jersey. IEEE Press

Mutual domination rate

Having…

- Non-dominated individuals of consecutive iterations: $\mathcal{P}_t^*$ and $\mathcal{P}_{t-1}^*$;
- $\Delta\left(\mathcal{A},\mathcal{B}\right)$: elements of $\mathcal{A}$ that are dominated by at least one element of $\mathcal{B}$;

Mutual domination rate indicator

- Contrasts how many non-dominated individuals of iteration t dominate the non-dominated individuals of the previous one $(t-1)$ and vice versa.
- Formally,

$$I_{\mathrm{mdr}}\left(\mathcal{P}_t^*,\mathcal{P}_{t-1}^*\right)=\frac{\left|\Delta\left(\mathcal{P}_{t-1}^*,\mathcal{P}_t^*\right)\right|}{\left|\mathcal{P}_{t-1}^*\right|}-\frac{\left|\Delta\left(\mathcal{P}_t^*,\mathcal{P}_{t-1}^*\right)\right|}{\left|\mathcal{P}_t^*\right|};$$

It is easy to embed MDR in Pareto-based fitness assignment computations.

Accumulating evidence via Kalman filters

Kalman filter

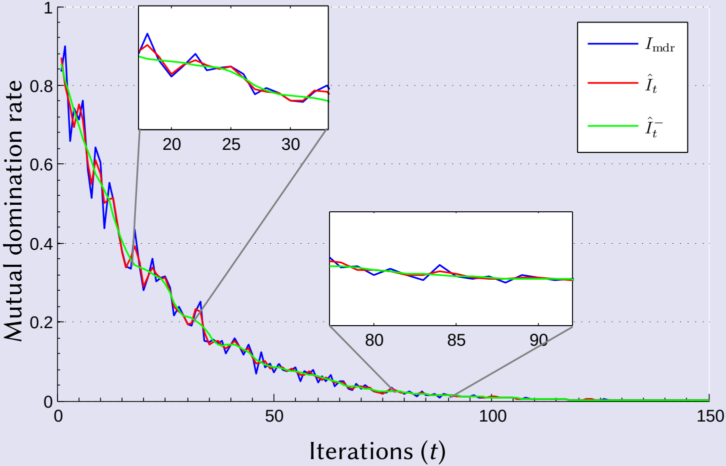
- Estimates the state of a discrete-time controlled process that is ruled by a *linear* stochastic difference equation;
- an efficient computational means to estimate the state of a dynamic system from a series of incomplete and noisy measurements.

For the stopping purpose...

- It is tracked the MDR indicator at iteration t, $I_{\mathrm{mdr}}(t)$.
- The filter is set to predict that the indicator will remain the constant.
- The filter status is updated with the measurements of the indicator.

Stop when estimation and confidence interval bellow threshold.

MGBM at work



Evolution of the MDR indicator, $I_{\text{mdr}}\left(\mathcal{P}_t^*, \mathcal{P}_{t-1}^*\right)$, and the *a priori* and *a posteriori* estimations $\hat{I}_t^-$ and $\hat{I}_t$ across iterations. Here the NSGA–II algorithm is supervised as it successfully solves the DTLZ3 problem.

Approaches in chronological order (III)

Offline convergence detection (Trautmann et al.[15]) — 2008

- A series of statistical hypothesis tests performed on concurrent algorithm executions.
- generational distance, hypervolume, and spread performance indicators are computed.
- This is information is used to decide when the best solutions of the algorithm was obtained.
- Applies Kolmogorov–Smirnov statistical test;
- Sound and robust, but;
- heavy parameterized and very resource demanding.

---

[15] Trautmann, H., Ligges, U., Mehnen, J., and Preuss, M. (2008). A convergence criterion for multiobjective evolutionary algorithms based on systematic statistical testing. In *Parallel Problem Solving from Nature — PPSN X*, pages 825–836. Springer, Heidelberg

Approaches in (...) order (IV): The 2009 boom

Online convergence detection (Wagner et al.[16]) — 2009

- Also tracks a number of progress indicators;
- stops when the variance is below a threshold ($\Xi^2 2$ test), and;
- passes a linear trend statistical test — *t*-test.
- Less resource demanding than the previous one.

Dominance–based stability measure — Bui et al., 2009[17]

- Dominance–based quality indicator.
- Determines how many solutions in a given radius dominate current solutions.
- Only local measurements.
- The radius is hard to set a priori.

[16] Wagner, T., Trautmann, H., and Naujoks, B. (2009). OCD: Online convergence detection for evolutionary multi–objective algorithms based on statistical testing. In Ehrgott, M., Fonseca, C. M., Gandibleux, X., Hao, J.-K., and Sevaux, M., editors, *5th International Conference on Evolutionary Multi–Criterion Optimization (EMO 2009)*, volume 5467 of *Lecture Notes in Computer Science*, pages 198–215. Springer

[17] Bui, L. T., Wesolkowski, S., Bender, A., Abbass, H., and Barlow, M. (2009). A dominance–based stability measure for multi–objective evolutionary algorithms. In *2009 IEEE Congress on Evolutionary Computation (CEC '09)*, pages 749–756, Piscataway, New Jersey. IEEE Press

Approaches in (...) order (V): The 2009 boom

Guerrero et al., 2009[18]

- Improved formulation of filters by adding adaptation;
- combines information from progress indicators, and;
- voting is used to decide when to stop.
- More robust than MGBM.

[18] Guerrero, J. L., García, J., Martí, L., Molina, J. M., and Berlanga, A. (2009). A stopping criterion based on Kalman estimation techniques with several progress indicators. In Raidl, G., Alba, E., Bacardit, J., Bates Congdon, C., Beyer, H.-G., Birattari, M., Blum, C., Bosman, P. A. N., Corne, D., Cotta, C., Di Penta, M., Doerr, B., Drechsler, R., Ebner, M., Grahl, J., Jansen, T., Knowles, J., Lenaerts, T., Middendorf, M., Miller, J. F., O'Neill, M., Poli, R., Squillero, G., Stanley, K., Stützle, T., and van Hemert, J., editors, *GECCO'09: 11th Annual Conference on Genetic and Evolutionary Computation*, pages 587–594, New York, NY, USA. ACM Press

More recent developments

Goel and Stander, 2010[19]

- An indicator that measures how stable are solutions in an archive that contains the best solutions obtained.
- Tied to an specific version of NSGA–II.
- Track the growth of an archive of non-dominated solutions over a few generations.
- Determine the *consolidation ratio* (CR): the ratio of the number of members in a preceding archive that are retained in the current archive, to the size of the current archive (archive inter-spacing is user defined).
- CR represents the proportion of converged solutions in the current archive.
- Terminates when the improvement of CR falls below a threshold.

[19] Goel, T. and Stander, N. (2010). A non-dominance-based online stopping criterion for multi–objective evolutionary algorithms. *International Journal for Numerical Methods in Engineering*

More recent developments

Least square stopping criterion (LSSC) — Guerrero et al., 2010[20]

- Test if a sample of the indicator value can be modelled by a linear regression.
- Instead of using the variance (as in OCD) the slope is used.
- The value of the slope is independent of the scale of the indicators.

[20] Guerrero, J. L., Martí, L., García, J., Berlanga, A., and Molina, J. M. (2010). Introducing a robust and efficient stopping criterion for MOEAs. In *2010 IEEE Conference on Evolutionary Computation (CEC), part of 2010 IEEE World Congress on Computational Intelligence (WCCI 2010)*, Piscataway, New Jersey. IEEE Press

More recent developments (II)

Approximate KKT — Deb, Abouhawwash and Dutta (2015)[21][22]

- Approximate KKT points as a measure of proximity to the Pareto-optimal front.

Population entropy-based — Saxena et al. (2016)[23]

- Entropy-based dissimilarity measure.
- Identifies when the algorithm stabilizes.
- Relies on the relative entropy:
    - the two distributions compared correspond to objective values of non-dominated subset of populations in two successive iterations.

[21] Dutta, J., Deb, K., Tulshyan, R., and Arora, R. (2013). Approximate KKT points and a proximity measure for termination. *Journal of Global Optimization*, 56(4):1463–1499

[22] Deb, K., Abouhawwash, M., and Dutta, J. (2015). *Evolutionary Multi-Criterion Optimization: 8th International Conference, EMO 2015, Guimarães, Portugal, March 29 –April 1, 2015. Proceedings, Part II*, chapter An Optimality Theory Based Proximity Measure for Evolutionary Multi-Objective and Many-Objective Optimization, pages 18–33. Springer International Publishing, Cham

[23] Saxena, D. K., Sinha, A., Duro, J. A., and Zhang, Q. (2016). Entropy-based termination criterion for multiobjective evolutionary algorithms. *IEEE Transactions on Evolutionary Computation*, 20(4):485–498

Summary

Custom indicators:

- mutual domination rate;
- dominance–based quality indicator;
- indicator-based progress indicator;
- consolidation ratio;
- approximate KKT, and;
- population entropy-based.

Evidence gathering:

- online convergence detection;
- Kalman filters;
- combination of filters, and;
- least squares stopping criterion.

Salient issues: Local progress

Are performance indicators suitable?

- Applying them measure the improvement of the solutions, but;
- in “plateau” situations when evolution could be progressing at a slow pace?
- Dominance–based methods are not suitable for the recent indicator–based EMOs.

What are the characteristics of stagnated EMOs?

What if we analyze the “health” of the evolutionary process?

Fitness homogeneity

- It has been shown that a balance between dominated and non–dominated solutions is needed.
- If most of the population is non–dominated the search process becomes stagnated.

We have been working in this matter[24]

- Simple approach that computes the deviation of the fitness values;
- needs a transformation scheme, but;
- can be used with indicator–based EMOs.

[24] Martí, L., García, J., Berlanga, A., and Molina, J. M. (2010). A progress indicator for detecting success and failure in evolutionary multi–objective optimization. In *2010 IEEE Conference on Evolutionary Computation (CEC), part of 2010 IEEE World Congress on Computational Intelligence (WCCI 2010)*, Piscataway, New Jersey. IEEE Press

Using stopping criteria in other contexts:
Population Restarting

Detecting stagnation and population restart

- What if we detect non-progress situations to act upon them.
- …for example for doing a population restart and improve diversity.

Population restart in multi-objective estimation of distribution algorithms (MEDAs)

- Diversity loss has been well documented in MEDAs.
- This hampers their results, in particular in many-objective problems.
- There are different approaches can be used with indicator–based EMOs.

The importance of restarting

- Most successful algorithms in major competitions were restart-enhanced variants of the evolutionary algorithms.
- A restarted version of the Covariance Matrix Adaptation Evolution Strategy (CMA-ES)[25] with increasing population size outperforms the original versions of CMA-ES.
- In the Adapted Maximum-Likelihood Gaussian Model Iterated Density-Estimation Algorithm (AMaLGaM)[26] a specific restart scheme increases the number of solutions upon each restart by alternating between two approaches: a single run with a larger population and more parallel runs.

[25] Loshchilov, I. (2013). CMA-ES with restarts for solving CEC 2013 benchmark problems. In *IEEE Congress on Evolutionary Computation (CEC)*, pages 369–376. IEEE

[26] Bosman, P. A. N., Grahl, J., and Thierens, D. (2013). Benchmarking parameter-free amalgam on functions with and without noise. *Evolutionary Computation*, 21(3):445–469

EDA based on the multivariate estimation of copulas (EDA-MEC)[27]

Composed of the following 4 steps:

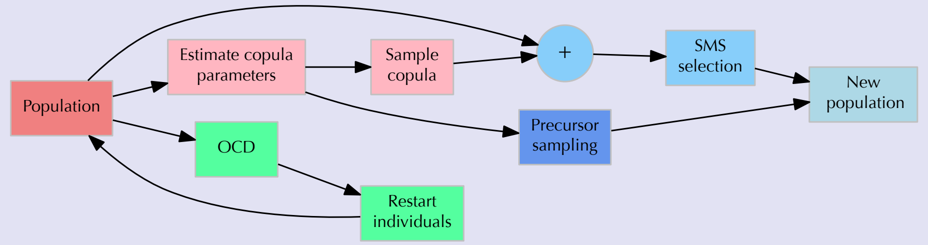
1. Selection or construction of the copula;
2. Estimation of the copula parameter(s);
3. Estimation of the marginal distributions; and
4. Sampling the copula and generating the new individuals.

Complemented by two processes:

- Transforming the probabilistic distribution to generate novel individuals, and
- a strategy for population restarting.

[27] Dias de Mello Jr, H., Martí, L., Abs da Cruz, A. V., and Rebuzzi Vellasco, M. M. B. (2016). Evolutionary algorithms and elliptical copulas applied to continuous optimization problems. *Information Sciences*, 369:419–440

The $\mathcal{S}$-Metric Selection EDA-MEC (SMS-EDA-MEC)[28]



Question:

How to do the restarting in a multi-objectively friendly way?

[28] Martí, L., Dias de Mello Jr, H., Sanchez-Pi, N., and Rebuzzi Vellasco, M. M. B. (2016a). SMS-EDA-MEC: Extending copula-based EDAs to multi-objective optimization. In *Proceedings of the 2016 IEEE Congress on Evolutionary Computation (IEEE CEC 2016) part of the 2016 IEEE World Congress on Computational Intelligence (IEEE WCCI 2016)*, pages 3726–3733. IEEE Press

SMS-EDA-MEC restarting

- We need to detect stagnation $\rightarrow$ stopping criteria;
- We have to restart a limited part of the (dominated?) population.

- We apply online convergence detection (OCD) (Wagner et al., 2009) configured in a 'loose' way.
- Two restart groups: local and global.

SMS-EDA-MEC restart

$\mathcal{P}_{\text{local}}^{\text{restarted}}$ is created by sampling a uniform distribution on the interval of the feature set currently occupied by the population $\mathcal{P}$ as,

$$\mathcal{P}_{\text{local}}^{\text{restarted}} = \left\{ x \sim U(\boldsymbol{\ell}^{\text{lower}}, \boldsymbol{\ell}^{\text{upper}}) \right\},$$

where $\ell_i^{\text{lower}} = \min_{\boldsymbol{x}\in\mathcal{P}}(x_i)$ and $\ell_i^{\text{lower}} = \max_{\boldsymbol{x}\in\mathcal{P}}(x_i)$ for $i = 1, \ldots, n$.

It should be noted that in practical applications it is convenient to disable restarting in the last part of the optimization.

Using stopping criteria in other contexts:

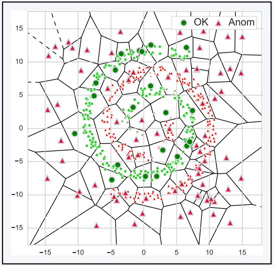
Progressively Adding Objectives

Evolving Voronoi diagrams for anomaly detection

VorEAI[29,30] evolves Voronoi diagrams that encode which areas correspond to '*normal*' or '*anomalous*' data.

- Multi-objective:
  - Classification metrics, like accuracy and recall.
  - Volume-based objectives for compact representation of data.
- An individual represents a Voronoi diagram as a set of sites, $\mathcal{I} = \{\boldsymbol{S}_i\}$, where each site has an associated label, $\boldsymbol{S}.\ell \in \{\text{OK}, \text{Anom}\}$.

$$\text{clsfy}(\mathcal{I}, \boldsymbol{x}) = \boldsymbol{S}^*.\ell; \boldsymbol{S}^* = \arg\min_{\boldsymbol{S}_i \in \mathcal{I}} \|\boldsymbol{x} - \boldsymbol{S}_i\|$$



[29] Martí, L., Fansi-Tchango, A., Navarro, L., and Schoenauer, M. (2016c). VorAIS: A multi-objective Voronoi diagram-based artificial immune system. In *Proceedings of the 2016 Annual Conference on Genetic and Evolutionary Computation (GECCO'16)*, pages 11–12, New York, NY, USA. ACM Press

[30] Martí, L., Fansi-Tchango, A., Navarro, L., and Schoenauer, M. (2016b). Anomaly detection with the Voronoi diagram evolutionary algorithm. In Handl, J., Hart, E., Lewis, R. P., López-Ibáñez, M., Ochoa, G., and Paechter, B., editors, *Proceedings of the 14th International Conference Parallel Problem Solving from Nature (PPSN XIV)*, pages 697–706. Springer International Publishing

In the multi-objective Animal Farm

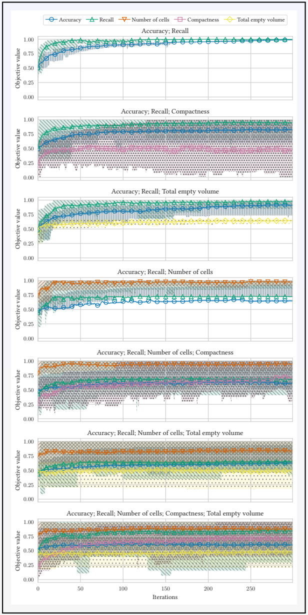
Some objectives are important but some objectives are more important than others!

- Some objectives are more important than others.
- Some objectives are easier to attain than others.
- Some objectives are 'disruptive' and cause that individuals become unable to deal with other objectives.

That is the case of the length minimization objectives.

In the VorEAl case

- Tried to improve VorEAl by adding a length minimization objective.
- Severe diversity loss.
- Ended up having a lot of small individuals (in terms of number of sites).
- This could also happen in multi-objective genetic programming when one objective is meant to reduce bloat.



Progressive Addition of Objectives (PAO)[31]

PAO starts with a set of 'primary' objectives selected *a priori* and progressively adds objectives that are the least disruptive.

- A VorEAl instance is evolved until convergence is detected by the OCD method.
- Different combinations of objectives are tested in a limited number of iterations.
- The least disruptive one is selected.

Intrigued? — More on this in GECCO 2017. (the paper is available online)

[31] Martí, L., Fansi-Tchango, A., Navarro, L., and Schoenauer, M. (2017). Progressively adding objectives: A case study in anomaly detection. In *Proceedings of the 2017 Annual Conference on Genetic and Evolutionary Computation (GECCO'17)*, pages 1–8, New York, NY, USA. ACM Press. in press

Outlook

Salient issues: Comparing criteria

- Testing stopping criteria is an awkward task, but;
- comparing them is even more.

We need to come up with a set of problem+algorithm pairs.

- Different convergence rates;
- incorrect parameter setup, in particular;
- population sizes.

Available software

- Matlab taxonomomy of stopping criteria:
  `http://github.com/lmarti/emo-stopping-criteria-taxonomy`.
- Python implementation of current state of the art:
  `http://github.com/lmarti/py-emostop`.
  - Can be used as in conjunction with `DEAP` and `inspyred`.
- Python implementation of entropy-based termination criteria:
  `https://github.com/mbelmadani/moea-automatic-termination`.
  - Includes the implementation of the MOEAs involved in the paper.

Final remarks

- There is room for improvement;
- **indicators**: assume elitism, take into account diversity, etc.
- **evidence gathering**: many tools available: statistics, Markov, filters, etc.
- Ideas from anomaly detection, time-series processing and/or outlier detection.
- *A posteriori* analysis.
- The most recent review on the topic is still valid[32].

[32] Wagner, T., Trautmann, H., and Martí, L. (2011). A taxonomy of online stopping criteria for multi-objective evolutionary algorithms. In Takahashi, R. H. C., Deb, K., Wanner, E. F., and Greco, S., editors, *6th International Conference on Evolutionary Multi-Criterion Optimization (EMO 2011)*, volume 6576, pages 16–30, Berlin/Heidelberg. Springer

Eskerrik asko!

Thank you!

Obrigado!

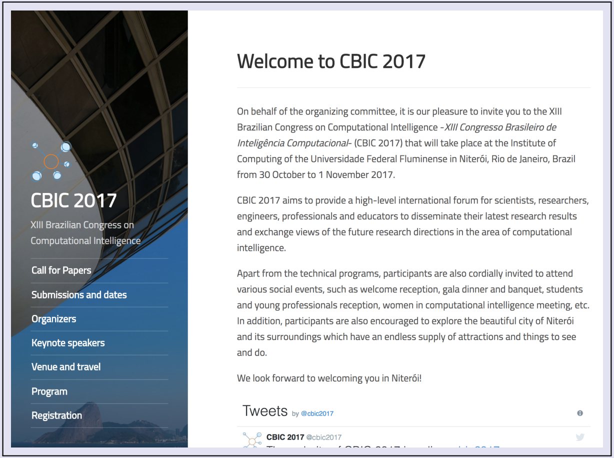
¡Gracias!

- nayat@ime.uerj.br; lmarti@ic.uff.br
- http://lmarti.com/stopping

One final comment

XIII Brazilian Congress on Computational Intelligence (CBIC 2017)

`http://cbic2017.org` — `@cbic2017`



Bibliography I

Aytug, H. and Koehler, G. J. (2000).
New stopping criterion for genetic algorithms.
European Journal of Operational Research, 126(3):662–674.

Bosman, P. A. N., Grahl, J., and Thierens, D. (2013).
Benchmarking parameter-free amalgam on functions with and without noise.
Evolutionary Computation, 21(3):445–469.

Bui, L. T., Wesolkowski, S., Bender, A., Abbass, H., and Barlow, M. (2009).
A dominance–based stability measure for multi–objective evolutionary algorithms.
In *2009 IEEE Congress on Evolutionary Computation (CEC '09)*, pages 749–756, Piscataway, New Jersey. IEEE Press.

Deb, K., Abouhawwash, M., and Dutta, J. (2015).
Evolutionary Multi-Criterion Optimization: 8th International Conference, EMO 2015, Guimarães, Portugal, March 29 –April 1, 2015. Proceedings, Part II, chapter An Optimality Theory Based Proximity Measure for Evolutionary Multi-Objective and Many-Objective Optimization, pages 18–33.
Springer International Publishing, Cham.

Dias de Mello Jr, H., Martí, L., Abs da Cruz, A. V., and Rebuzzi Vellasco, M. M. B. (2016).
Evolutionary algorithms and elliptical copulas applied to continuous optimization problems.
Information Sciences, 369:419–440.

Dutta, J., Deb, K., Tulshyan, R., and Arora, R. (2013).
Approximate KKT points and a proximity measure for termination.
Journal of Global Optimization, 56(4):1463–1499.

Fonseca, C., Gandibleux, X., Korhonen, P., Martí, L., Naujoks, B., Thiele, L., Wallenius, J., and Zitzler, E. (2009).
Working group on EMO for interactive multiobjective optimization (1st round).
In Deb, K., Greco, S., Miettinen, K., and Zitzler, E., editors, *Hybrid and Robust Approaches to Multiobjective Optimization*, number 09041 in Dagstuhl Seminar Proceedings, Dagstuhl, Germany. Schloss Dagstuhl — Leibniz–Zentrum fuer Informatik.

Bibliography II

Goel, T. and Stander, N. (2010).
A non-dominance-based online stopping criterion for multi–objective evolutionary algorithms.
International Journal for Numerical Methods in Engineering.

Guerrero, J. L., García, J., Martí, L., Molina, J. M., and Berlanga, A. (2009).
A stopping criterion based on Kalman estimation techniques with several progress indicators.
In Raidl, G., Alba, E., Bacardit, J., Bates Congdon, C., Beyer, H.-G., Birattari, M., Blum, C., Bosman, P. A. N., Corne, D., Cotta, C., Di Penta, M., Doerr, B., Drechsler, R., Ebner, M., Grahl, J., Jansen, T., Knowles, J., Lenaerts, T., Middendorf, M., Miller, J. F., O'Neill, M., Poli, R., Squillero, G., Stanley, K., Stützle, T., and van Hemert, J., editors, *GECCO'09: 11th Annual Conference on Genetic and Evolutionary Computation*, pages 587–594, New York, NY, USA. ACM Press.

Guerrero, J. L., Martí, L., García, J., Berlanga, A., and Molina, J. M. (2010).
Introducing a robust and efficient stopping criterion for MOEAs.
In *2010 IEEE Conference on Evolutionary Computation (CEC), part of 2010 IEEE World Congress on Computational Intelligence (WCCI 2010)*, Piscataway, New Jersey. IEEE Press.

Jain, B. J., Pohlheim, H., and Wegener, J. (2001).
On termination criteria of evolutionary algorithms.
In Spector, L., Goodman, E. D., Wu, A., Langdon, W., Voigt, H.-M., Gen, M., Sen, S., Dorigo, M., Pezeshk, S., Garzon, M. H., and Burke, E., editors, *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO 2001)*, page 768, San Francisco, California, USA. Morgan Kaufmann.

Karush, W. (1939).
Minima of functions of several variables with inequalities as side constraints.
Master's thesis, Department of Mathematics, University of Chicago, Chicago, IL, USA.

Kuhn, H. W. and Tucker, A. W. (1951).
Nonlinear programming.
In Neyman, J., editor, *Proceedings of Second Berkeley Symposium on Mathematical Statistics and Probability*, pages 481–492, Berkeley, LA, USA. University of California Press.

Bibliography III

Loshchilov, I. (2013).
CMA-ES with restarts for solving CEC 2013 benchmark problems.
In *IEEE Congress on Evolutionary Computation (CEC)*, pages 369–376. IEEE.

Martí, L., Dias de Mello Jr, H., Sanchez-Pi, N., and Rebuzzi Vellasco, M. M. B. (2016a).
SMS-EDA-MEC: Extending copula-based EDAs to multi-objective optimization.
In *Proceedings of the 2016 IEEE Congress on Evolutionary Computation (IEEE CEC 2016) part of the 2016 IEEE World Congress on Computational Intelligence (IEEE WCCI 2016)*, pages 3726–3733. IEEE Press.

Martí, L., Fansi-Tchango, A., Navarro, L., and Schoenauer, M. (2016b).
Anomaly detection with the Voronoi diagram evolutionary algorithm.
In Handl, J., Hart, E., Lewis, R. P., López-Ibáñez, M., Ochoa, G., and Paechter, B., editors, *Proceedings of the 14th International Conference Parallel Problem Solving from Nature (PPSN XIV)*, pages 697–706. Springer International Publishing.

Martí, L., Fansi-Tchango, A., Navarro, L., and Schoenauer, M. (2016c).
VorAIS: A multi-objective Voronoi diagram-based artificial immune system.
In *Proceedings of the 2016 Annual Conference on Genetic and Evolutionary Computation (GECCO'16)*, pages 11–12, New York, NY, USA. ACM Press.

Martí, L., Fansi-Tchango, A., Navarro, L., and Schoenauer, M. (2017).
Progressively adding objectives: A case study in anomaly detection.
In *Proceedings of the 2017 Annual Conference on Genetic and Evolutionary Computation (GECCO'17)*, pages 1–8, New York, NY, USA. ACM Press.
in press.

Martí, L., García, J., Berlanga, A., and Molina, J. M. (2007).
A cumulative evidential stopping criterion for multiobjective optimization evolutionary algorithms.
In Thierens, D., Deb, K., Pelikan, M., Beyer, H.-G., Doerr, B., Poli, R., and Bittari, M., editors, *GECCO'07: Proceedings of the 2007 GECCO Conference Companion on Genetic and Evolutionary Computation*, page 911, New York. ACM Press.

Bibliography IV

Martí, L., García, J., Berlanga, A., and Molina, J. M. (2009).
An approach to stopping criteria for multi–objective optimization evolutionary algorithms: The MGBM criterion.
In *2009 IEEE Conference on Evolutionary Computation (CEC 2009)*, pages 1263–1270, Piscataway, New Jersey. IEEE Press.

Martí, L., García, J., Berlanga, A., and Molina, J. M. (2010).
A progress indicator for detecting success and failure in evolutionary multi–objective optimization.
In *2010 IEEE Conference on Evolutionary Computation (CEC), part of 2010 IEEE World Congress on Computational Intelligence (WCCI 2010)*, Piscataway, New Jersey. IEEE Press.

Rudenko, O. and Schoenauer, M. (2004).
A steady performance stopping criterion for pareto–based evolutionary algorithms.
In *The 6th International Multi–Objective Programming and Goal Programming Conference*, Hammamet, Tunisia.

Rudolph, G. and Agapie, A. (2000).
Convergence properties of some multi–objective evolutionary algorithms.
In *2000 IEEE Congress on Evolutionary Computation (CEC 2000)*, volume 2, pages 1010–1016, Piscataway, New Jersey. IEEE Press.

Saxena, D. K., Sinha, A., Duro, J. A., and Zhang, Q. (2016).
Entropy-based termination criterion for multiobjective evolutionary algorithms.
IEEE Transactions on Evolutionary Computation, 20(4):485–498.

Stewart, T. J. (1997).
Convergence and validation of interactive methods in mcdm: simulation studies.
In *Essays in Decision Making*, pages 7–18. Springer.

Trautmann, H., Ligges, U., Mehnen, J., and Preuss, M. (2008).
A convergence criterion for multiobjective evolutionary algorithms based on systematic statistical testing.
In *Parallel Problem Solving from Nature — PPSN X*, pages 825–836. Springer, Heidelberg.

Bibliography V

Wagner, T., Trautmann, H., and Martí, L. (2011).
A taxonomy of online stopping criteria for multi-objective evolutionary algorithms.
In Takahashi, R. H. C., Deb, K., Wanner, E. F., and Greco, S., editors, *6th International Conference on Evolutionary Multi-Criterion Optimization (EMO 2011)*, volume 6576, pages 16–30, Berlin/Heidelberg. Springer.

Wagner, T., Trautmann, H., and Naujoks, B. (2009).
OCD: Online convergence detection for evolutionary multi–objective algorithms based on statistical testing.
In Ehrgott, M., Fonseca, C. M., Gandibleux, X., Hao, J.-K., and Sevaux, M., editors, *5th International Conference on Evolutionary Multi–Criterion Optimization (EMO 2009)*, volume 5467 of *Lecture Notes in Computer Science*, pages 198–215. Springer.