# Applications of Dynamic Parameter Control in Evolutionary Computation

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## Instructors

**Gregor Papa** is a Senior researcher and a Head of Computer Systems Department at the Jožef Stefan Institute, Ljubljana, Slovenia, and an Associate Professor at the Jožef Stefan International Postgraduate School, Ljubljana, Slovenia. He received the PhD degree in Electrical engineering at the University of Ljubljana, Slovenia, in 2002. His research interests include meta-heuristic optimisation methods and hardware implementations of high-complexity algorithms, with a focus on dynamic setting of algorithms' control parameters. He regularly organizes conferences and workshops in the field of nature-inspired algorithms from the year 2004 till nowadays. He led and participated in several national and European projects.



- **Previous tutorials:** A series of tutorials by Carola Doerr, followed by our common tutorials
  - Theoretical, shortened first part, is based on previous slides of Carola [80] (some texts and figures are taken from there)
- **Version Management:** Slides are regularly updated. You can find the latest version on:
  - http://cs.ijs.si/papa/files/GECCO2021tutorial.pdf
- **Reference of this tutorial:**

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```



## Survey Articles

Summaries of the state-of-the-art techniques and a good starting point for your research can be found in the following surveys
(extensive reference list is at the end)

- **Empirical works**
  - Karafotias, Hoogendoorn, Eiben, 2015 [KHE15]
    (detailed survey of empirical works)
  - Aleti, Moser, 2016 [AM16]
    (systematic literature survey with additional pointers)
  - Eiben, Hinterding, Michalewicz, 1999 [EHM99]
    (classic seminal paper, introduced a widely accepted classification scheme)
  - Lobo, Lima, Michalewicz, 2007 [LLM07]
    (book on parameter selection, includes chapters on tuning and control)
- **Theoretical works**
  - Doerr, Doerr, 2020 [DD20]
    (surveys theoretical works which prove performance bounds with mathematical rigor; introduces the revised classification scheme)

## Outline of the Tutorial

- **Part 1:** Introduction
  *What are the goals of parameter control?*
- **Part 2:** Motivation
  *What are the basics?*
- **Part 3:** Taxonomy of Parameter Control Mechanisms
  *Which parameter control techniques exist?*
- **Part 4:** Real-world optimization
  *What are the characteristics of the real world problems?*
- **Part 5:** Applications of Parameter Control
  *Where is parameter control used in practice?*
- **Part 6:** Wrap Up
  *What's next?*

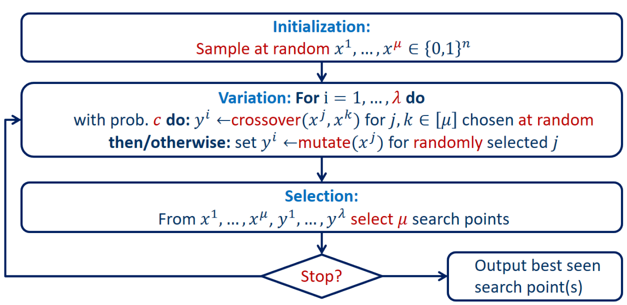


**Introduction**



## Parameters in iterative / evolutionary optimization

A "typical" evolutionary algorithm, a $(\mu+\lambda)$ GA with crossover




$\rightarrow$ There are several parameters that need to be decided: population size, crossover rate, mutation rate, selective pressure, etc.



## The importance of control parameter values

- The very early days of EC:
  - "EAs are robust problem solvers" and need no tuning of parameters
- It was soon realized that this is not true
  - i.e., the "no free lunch" theorem [104]

$\rightarrow$ It is widely acknowledged today that the control parameter values have a decisive influence on the performance of an EA.

## The importance of control parameter values

**How to find good parameter values?**

- Finding optimal parameter values is far from being trivial
- Small changes in one parameter can cause huge performance gaps
- The optimal parameter values for one problem, might be much different for similarly-looking problems
- Optimal parameter values can change during the optimization process



## Goals of Parameter Control

- To identify good parameter values "on the fly"
  - When prior training or tuning is not possible
  - $\rightarrow$ Integrate the tuning procedure into the optimization process
- To track good parameter values when they change during the optimization process
  - They are not only constant factors
  - Significant performance gains are possible



## Controlling Multiple Parameters

- Most EAs have several parameters
- There is no reason to not control more than one or even all of them
- Some works on controlling more than one parameter exist, [55]
- The problem how to best control several parameters at the time is widely open



**Motivation**

## The LeadingOnes Problem

- Classic benchmark problem often studied in the theory of evolutionary computation [85]
  - One of the simplest examples of a non-separable function
  - to test the performance of evolutionary algorithm
- Function

  $\text{LO}:\{0,1\}^n \to \mathbb{R}, x \mapsto \text{LO}(x) = \max\{i \in [n] \mid \forall j \leq i : x_i = 1\}$

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |

  - LO $= 2$ (two initial ones)



## The (1+1) EA example

> Initialization:

Choose $x \in 0, 1^n$ uniformly at random

> Optimization: in iteration $t = 1, 2, \ldots$ do

1. Mutation:
   - create $y$ from $x$ by standard bit mutation (flip each bit with probability $p$, independently of other bits)
2. Selection:
   - if $f(y) \geq f(x)$ $\rightarrow$ replace $x$ by $y$

**Critical parameter**

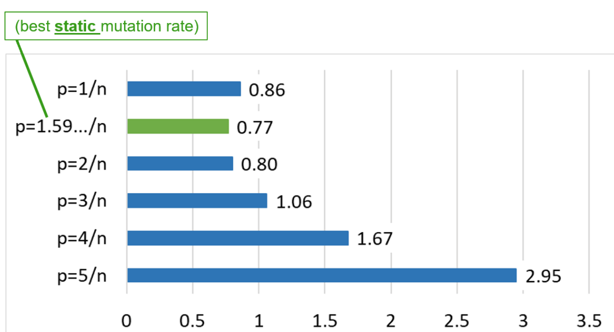
- The mutation rate $p$

  $\rightarrow$ often recommended as $p = 1/n$



## Theoretical Optimization Times

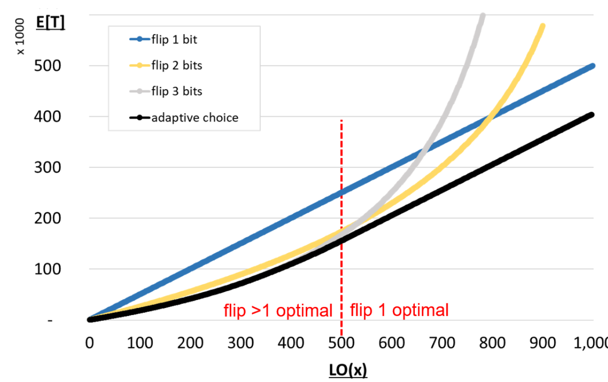
- The expected optimization time of the (1+1) EA on LeadingOnes [12]
  - $\frac{1}{2p^2}\left(\frac{1}{(1-p)^{n-1}} - 1 + p\right)$





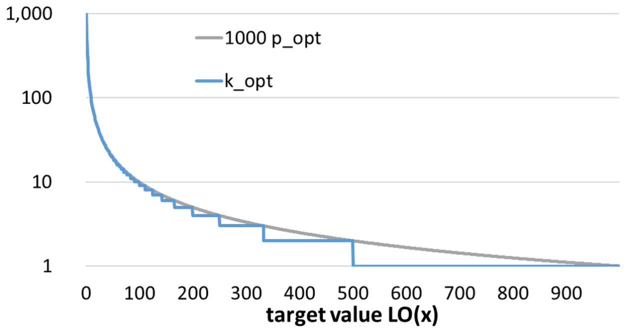

## Fixed-Target Running Times

- Expected fixed-target running times for dimension n=1000



## Mutation Rates Optimality

- Expected fixed-target running times for dimension n=1000

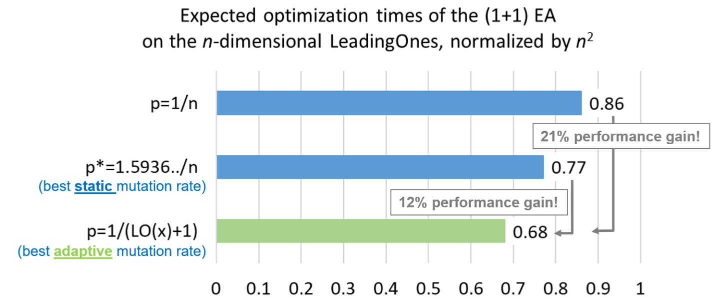



$p_{opt} = \frac{1}{\mathrm{LO}(x)+1}$ [12, 92]

$k_{opt} = \lfloor \frac{1}{\mathrm{LO}(x)+1} \rfloor$ [37, 35]



## Gain of Dynamic Mutation Rates




Measured results from [12]



## (1+1) EA with Adaptive Mutation Rates

> Initialization:
  Choose $x \in 0, 1^n$ uniformly at random

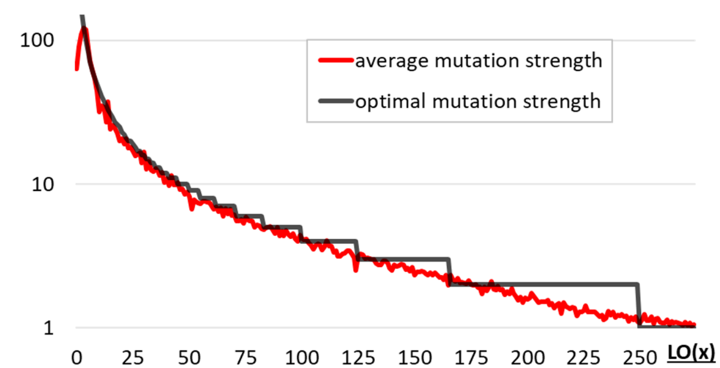
> Optimization: in iteration $t = 1, 2, \ldots$ do
  1. Mutation:
     - create $y$ from $x$ by standard bit mutation (flip each bit with probability $p$, independently of other bits)
  2. Selection + Update:
     - if $f(y) \geq f(x)$
       $\rightarrow$ replace $x$ by $y$
       $\rightarrow$ replace $p$ by $Ap$
     - if $f(y) < f(x)$
       $\rightarrow$ replace $p$ by $bp$

- Based on a variant from [37]



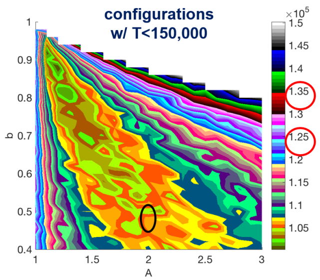
## Tested mutation rates

- Results for LeadingOnes $n$=500, based on [37]
  - Update strengths: $A = 2$, $b = 1/2$
  - Plot compares average number of bits flipped (red) vs. optimal number (black)
  - Logarithmic scale with zoom into $\mathrm{LO}(x) \leq 250$



## Fitness Landscape of Tuning Problem

- The performance gain is not very sensitive with respect to the choice of the hyper-parameters $A$ and $b$ [37]
- Heatmap on average optimization time for combinations of $A$ and $b$ for the adaptive (1+1)EA on $n = 500$ LeadingOnes
  - $A = 2$, $b = 1/2$ gives an average runtime of ≈104,000 function evaluations
  - the static (1+1) $EA_{>0}$ needs ≈135,000 function evaluations
  - RLS needs ≈125,000 function evaluations






## The 1/5-Success Rule

- One of the most famous success-based parameter adaptation rule
- Rechenberg observed that for the sphere function and a corridor landscape the optimal success rate of the (1+1) ES is around 1/5 [82]
- Approach:
  - If (observed success rate $> 1/5$) → increase mutation rate
    Informal interpretation: we seem to be in an easy part of the optimization problem → increasing mutation rates might result in larger progress per step
  - If (observed success rate $< 1/5$) → decrease mutation rate
    Informal interpretation: we could be approaching an optimum and should focus our search → decrease mutation rate for a more conservative search

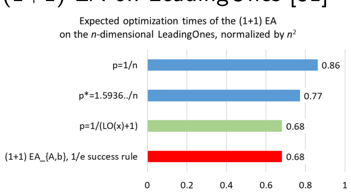
> Similar rules have been proposed by [89] and [29]

> The same idea can also be used to control other parameters, such as the population size, crossover probabilities, etc.

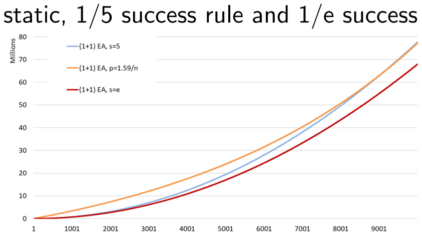


## 1/5 Success Rule in Discrete Optimization

- The 1/e success rule yields optimal mutation rates for the (1+1) EA on LeadingOnes [31]




- Average Fixed-Target Running Times for the (1+1) EA with static, 1/5 success rule and 1/e success rule mutation rates






**Taxonomy**

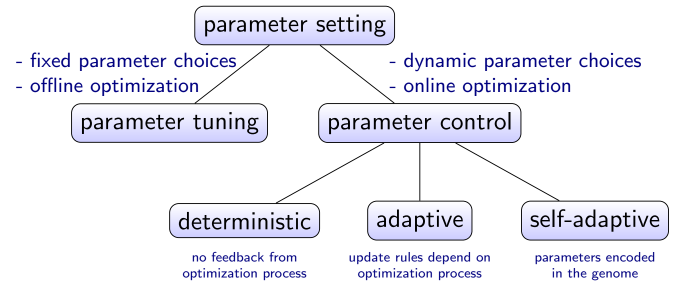
## Main Questions in Parameter Control

1. Which parameter is adapted? (and what is affected: individual / population)
   - Population size
   - Mutation rate, Crossover probability
   - Selection pressure
   - Fitness function (e.g., penalty terms for constraints)
   - ...
2. What is the basis/evidence for the update?
   - Time elapsed: number of evaluations, generation count, CPU time
   - Progress (e.g., in terms of absolute or relative fitness gain)
   - Diversity measures
   - ...
3. How do we update the parameter(s):
   - Multiplicative updates
   - Learning-inspired parameter selection
   - Endogenous/self-adaptive parameter selection
   - Hyper-heuristics
   - ...



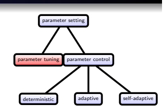
## Initial Classification Scheme

The most popular classification scheme is the one of Eiben, Hinterding and Michalewicz [39]





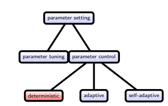

## Parameter Tuning



- Typical tuning approach
  - Run some initial tests and observe how the performance depends on the chosen parameter values
  - Choose the parameter values that seem the most promising
  - → Requires a (large) budget for the training
  - Recent survey on automatic parameter tuning methods for metaheuristics [50]
- Several parameter tuning tools are available
  - irace [68], SPOT [8], GGA [3], ParamILS [52], SMAC [51], HyperBand [62], BOHB [40], ...
  - Advantage: automated identification of reasonable parameter values → supports human and reduces bias
  - Disadvantage: recommended parameter values are static!
  - Note: even when focusing on dynamic parameter choices, parameter tuning can be very essential to select good hyper-parameters [9]

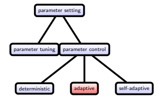


## Deterministic Parameter Control



- Optimal parameters often follow a similar pattern
  - E.g. first allow for exploration, then for exploitation
  - Time-dependent parameter settings can be used
    - time = number of generations, fitness evaluations, wall-clock time, etc.
- Examples:
  - Cooling schedule of the selective pressure ("temperature") in Simulated Annealing
  - Start with some (large) mutation rate $p(0)$, decrease $p$ after every 10,000 fitness evaluations
  - After each 1,000 iterations, draw a random mutation probability
- More suitable terms would be "time-dependent" or "scheduled" update scheme
- Note: finding the optimal deterministic update rules requires tuning

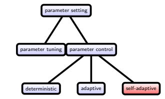
## Adaptive Parameter Control



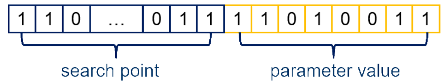
- Global estimate for parameter quality, not individual-based
  - Feedback from the optimization process
  - Change the parameters according to some pre-described rule
- Relevant feedback includes
  - Function values of the search points in the population
  - Diversity of the search points
  - Absolute or relative progress obtained within the last $\tau$ iterations
- Examples
  - 1/5-success rule
  - CMA-ES update of covariance, step size, population size
  - ...



## Self-Adaptive Parameter Control



- Use an EA to determine parameter values
- Many different ways to do this
  - Create a new population of parameter values, choose from this parameter values, possibly apply variation to them, and employ them in EA, select based on progress made
  - Append to the solution candidates a string which encodes the parameter value, first mutate the parameter value part, then use this parameter to change the search point, selection as usual

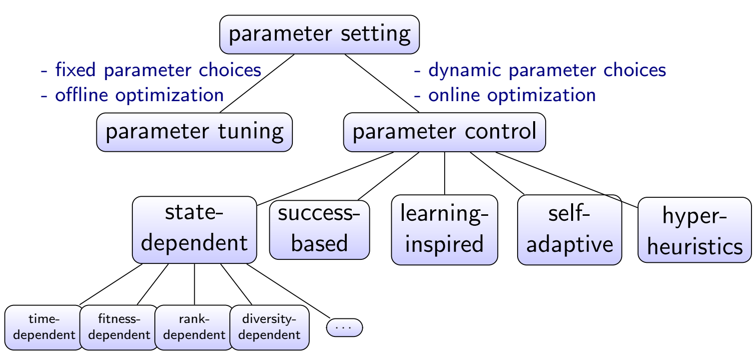



  - Improve parameter selection and fitness at the same time
- Some theoretical works on a self-adaptive choice of the mutation strength, [24] and [34]



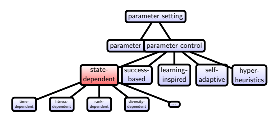
## Revised Classification Scheme

Revised classification from Doerr and Doerr [30] to better fit current research directions and allow more consistent use of terms

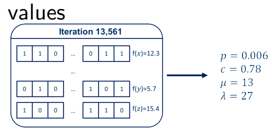





## State-Dependent Parameter Selection

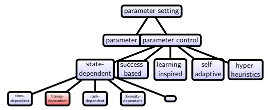


- Selection mechanisms do not depend on the history of the optimization process, but on the current state
  - E.g., a snapshot of the current population is maped to parameter values




- Most commonly used indicators
  - Time elapsed (# fitness evaluations, iteration counter, CPU time, ...) → corresponds to "deterministic" parameter setting in the classification of [39]
  - Function values (absolute values, diversity, ranks, etc.)
  - Genotypic properties (e.g., diversity of the population)

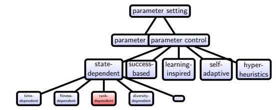
## Fitness-Dependent Parameter Selection




- Requires a good understanding of how the parameters should depend on the function values
- Empirically
  - [5], [6], [41] for OneMax
- Theoretically
  - [20], [32], [7] for OneMax and [35], [36], [66] for LeadingOnes



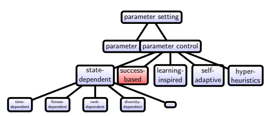
## Rank-Dependent Parameter Selection




- Bad search points should undergo large variation ($\rightarrow$ large mutation rates)
- Good individuals should be modified only moderately ($\rightarrow$ small mutation rates)
  - Example, from [23]
    - Rank search points in the current population
    - Each search point is assigned a mutation rate that depends on its rank:
      rank 1: mutation rate $p_{min}$ // best individual of population
      ...(linear interpolation)
      rank s: mutation rate $p_{max}$ // worst individual of population
    - The rank-based GA first selects an individual from the population and then modifies it with the mutation rate given by this ranking



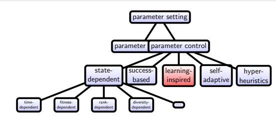
## Success-Based Parameter Selection




- After each (or after every $\tau$) iteration(s) adjust the current parameter value depending on whether or not the last ($\tau$) iteration(s) have been successful
  - Examples
    - Finding a strictly better search point
      this is probably the most common measure
    - Finding a search point that is integrated into population
      used by the adaptive (1+1) $\text{EA}_{>0}$
    - Finding a fitness-increase of at least x%
    - Finding point(s) that increase the diversity of the population
    - ...
  - Success-based parameter selection is classified as "adaptive parameter control" in the taxonomy of [39]



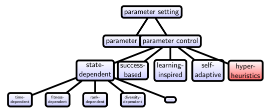
## Learning-Inspired Parameter Control




- To have a set of possible parameter values according to some rule
- Test one (or some) of these values based on the feedback from the optimization process
- Update the likelihood to employ the tested value
  - Example through multi-armed bandits (MAB)
    - $\kappa$ experts in each round
    - You have to chose one of them and you follow their advice
    - You update your confidence in each expert depending on the quality of their forecast
  - Key questions:
    - How to UPDATE the confidences?
    - How to SELECT based on the confidences (greedy, random in proportion to confidence, etc.)

## Hyper-Heuristics

- Hyper-heuristics covers much more than controlling parameters
  → the main idea is to control the whole algorithm, in the sense of dynamically choosing which heuristic is best at a given state
- Surveys: [19], [93]
- Recent theoretical works: [66], [33], [67]






**Real-world optimization**



## Real-world optimization

- Real-world optimization problems occur in many applications
  - Engineering design,
  - Scientific modelling,
  - Image processing,
  - Production,
  - Transportation,
  - Bioinformatics,
  - Finances, etc.
- Real-world systems are, in general, large and very complex. They need to process a large amount of data, to perform complex optimization and make decisions fast [56].



## Real-world optimization

- Real-world problems in general
  - Contain non-linear objective functions of mixed design variables (i.e. continuous and discrete)
  - Contain linear as well as non-linear constraints
  - Might have several local optima
- For a wide range of real-world optimization problems, a near-optimal or a better-than-known solution is considered a satisfactory result of an optimization problem.

## Real-world optimization

- There are several characteristics that increase the complexity of the optimum solution search and for which parameter control could be advantageous
  - **Number and type of variables**: a large number of decision variables, including mixed-integer problems, where different types of variables are optimised
  - **Dynamic problems**: problems that are changing over time
  - **Problems under uncertainty**: the variables of the problem have some uncertainty
  - **Number of objectives**: problems that require optimizing more than one objective function simultaneously and need to be solved by a multi/many-objective approach
  - **Nested problems**: multi/bi-level optimization, where one optimization problem has another optimization problem as a constraint
- Some problems have combination of these characteristics



## Real-world optimization

- Properly defined control parameters play a crucial role in effectively handling the mentioned characteristics and solving such problems.
  - For example: with increasing dimensionality of the problem its landscape complexity grows and the search space increases exponentially.

**But**

An optimization algorithm must still be able to explore the entire search space efficiently



**Large scale global optimization**



## Large scale global optimization

- LSGO [75] - the problem dimension $D$ (the number of variables to be optimised) has an order of magnitude of up to several thousand (for real values) or even billions (for integer or binary values)
- An active research field due to the growing number of large-scale optimization problems in engineering, manufacturing and economy applications (such as bio-computing, data or web mining, scheduling, vehicle routing, etc.) [21], [64]
  - Advances in machine learning and the wide use of deep artificial neural networks result in optimization problems with over a billion variables [49]

## Large scale global optimization

**A major challenge of large-scale optimization**

Most engineering problems have an exponential increase in the number of required decision variables [76], [98]

- The challenges motivated the design of many kinds of efficient, effective, and robust kinds of metaheuristic algorithms to solve LSGO problems with high-quality solutions and high convergence performance as well as with low computational cost [72]



## Large scale global optimization

- To achieve acceptable results even for the same problem, different parameter settings along with different reproduction schemes at different stages of optimization process are needed
- Several techniques (e.g., [110], [26]) have been designed to adjust control parameters in an adaptive or self-adaptive manner (instead of a trial-and-error procedure)



## Large scale global optimization

- Some examples of LSGO
  - Data analytic and learning problems [116]
  - Shape design optimization for aircraft wings and turbine blades [106]
  - Satellite layout design [95]
  - Parameter calibration of water distribution system [103]
  - Seismic waveform inversion [100]



**Dynamic optimization**

## Dynamic optimization

- Real-world optimization problems are usually subject to changing conditions over time
- The effects of these changes could influence several aspects of the problem, such as the objective function, the problem instance, its constraints, etc.
- The optimal solution of the problem might change over time.

**Dynamic optimization**

Changing problems, when solved by an adaptive optimization algorithm on-the-fly, are called dynamic optimization problems (DOPs) [74]



## Dynamic optimization

- The algorithm is expected to be able to track the current optimal solution as well as the changing optimal solution over time
- The optimization procedure has to be able to detect these changes and react quick enough
  - This also requires dynamic change of the ratio for exploration and exploitation parts of the search
  - Both adaptive [101] and self-adaptive [17] parameter control can be used



## Dynamic optimization

- Based on a comprehensive survey [13], four different strategies can be used to help evolutionary/population-based algorithms to adapt in dynamical environments:
  - **Increasing diversity** of the population after a change is detected, (e.g., by increasing mutation rate every $N$ generations)
  - **Maintaining diversity** throughout the run, to avoid convergence of the population on one point
  - **Memory based approaches**, taking into consideration older solutions and sometimes making predictions based on historical data
  - **Multi-population approaches**, where many small populations track their own peaks as the environment changes



## Dynamic optimization

- Some examples of dynamic optimization
  - Production scheduling [109]
  - Energy demand optimization [44]
  - Transportation [108], [65]
  - Financial optimization [48]

**Optimization under uncertainty**



## Optimization under uncertainty

- The presence of (a range of) uncertainties has to be taken into account for solving many real-world applications with evolutionary algorithms
- [54] categorize the uncertainties that influence EA performance into four types
  - When there is some **noise in the fitness function**
  - When there are changes of **design and environmental parameters after the optimization**
  - When **fitness function is an approximation**
  - When the **optimum changes over time** (as in dynamic optimization).



## Optimization under uncertainty

- Methodologies for addressing noisy fitness function
  - *Explicit averaging* by calculating the average of the fitness values over a number of randomly sampled disturbances [47], [71]
  - *Implicit averaging* sample size as an inverse function of the population size [42]
  - *Fitness inheritance* where the offspring inherits also the mean and standard deviation of the objective value [18]
  - *Selection modification* [94]
- These methods assume that the search space follows a homogeneous noise distribution, such as a uniform or a normal distribution [97]



## Optimization under uncertainty

- Some examples of optimization under uncertainty
  - Financial optimization [48]
  - Transportation in unknown environments [111]
  - Space applications [99], [10]

**Multi-objective optimization**



## Multi-objective optimization

- Multi-objective (and also many-objective) optimization approaches are used for optimization problems where several criteria need to be optimised, but they are equally treated and not merged (e.g., by weights) into one single objective
- The output of multi-objective optimization is a set of solutions that approximates the Pareto front
- There is no unique measure that would indicate how good a current approximation of the Pareto front is

**In multi-objective cases**

Adaptive parameter control is a bit more complicated to design and additional considerations are needed to design phenotype feedback collection part



## Multi-objective optimization

- Possible assessment of the optimization process stage
  - Monitor the proportion of non-dominated solutions in the population [105]
  - Convergence detection [73]
- The most common indicators that are also used as input to parameter control are the crowding distance and the contributing hyper-volume [53], [11]



## Multi-objective optimization

- Other metrics can also be applied
  - $\varepsilon$-dominance
  - Generational distance
  - Delta indicator
  - Two set coverage, and so on [83].
- Compared to adaptive control, self-adaptive control is easier to design and implement because less modifications are needed to upgrade an existing multi-objective optimization algorithm [102] [22].

## Multi-objective optimization

- Some examples of multi-objective optimization
  - Engineering design [46]
  - Transportation [88], [61]
  - Production [45], [4]



**Multilevel optimization**



## Multilevel optimization

- In many real-world processes there is a hierarchy of decision-makers and decisions are taken at different levels [70]
  - The constraint domain associated with a multilevel problem is implicitly determined by a series of optimization problems which must be solved in a predetermined sequence
- The simplest form of a multilevel problem has two levels (i.e., bi-level optimization problem)
  - The optimization of such problem aims to achieve the optimum solution of the upper level, while the optimum of the lower optimization level is also taken into account
  - Since the lower level landscape changes for every upper level vector, parameter control seems to be useful approach



## Multilevel optimization

- An interesting application of bilevel optimization is connected to parameter tuning of EAs as bilevel optimization problem
  - [91] propose the parameter tuning problem as an inherently bilevel programming problem involving algorithmic performance as the objective(s)
  - [1] created a bilevel framework for parallel tuning of optimization control parameters, and compared it to irace proving that it can be competitive
  - Bilevel control parameter tuning can be used to design a parameter control mechanism [2]

**Examples**



## Image processing: Feature selection

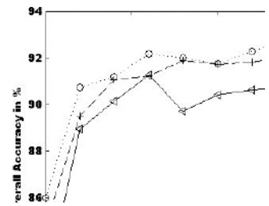
LS

- Feature selection for reducing the dimensionality in classification of hyperspectral images [27]

**Self-adaptive differential evolution SADE is used**

- SADE is used in combination with Fuzzy kNN classifier
- Compared to GA-based and ACO-based approaches [87]

- Significant improvement for overall classification accuracy and Kappa coefficient






## Image processing: Animated Tree Reconstruction

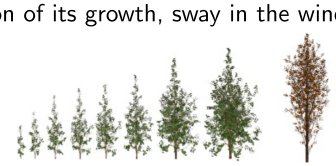
LS UN

- Feature extraction to reconstruct three dimensional procedural models of trees; to lower problem dimensionality needed for encoding local parameters [112]
- The reconstruction is iteratively optimized using DE, which samples procedural tree model parameters to obtain a parameterized procedural model for instantiating a geometrical model

**jDE is used**

- DE with self-adaptive control parameter settings [14]

- Examples of reconstructed model animation are shown, such as simulation of its growth, sway in the wind, or adding leaves





## Intravascular Ultrasound Image Analysis: Medicine

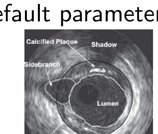
DY UN

- To optimize for the parameters of feature detectors in the multi agent image analysis system to detect lumen, vessel, shadows, sidebranches, and calcified plaques in IVUS images [63]

**MIES (mixed integer evolution strategies) algorithm is used**

- implements self-adaptation of the width of the mutation distribution (step size) [63]
- step size control is used for real, integer, and categorical variables

- The results show that MIES solutions performed better than or equal to the default expert solution
- MIES drawn contours are more smooth than contours detected with the default parameter settings



## Production: Scheduling

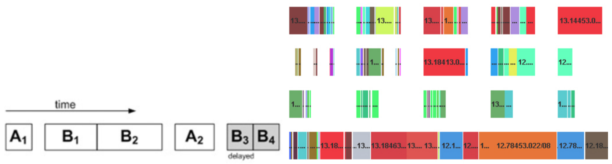
DY

- Optimal operations scheduling in the production of different components considering various constraints [81]

**PLES algorithm is used**

- PLES is based on general GA with modified implementation of functions that allow varying population size, mutation and crossover [79]
- Compared to standard non-adapting GA and GA with customized local search [58]

- Faster convergence of PLES and comparable results to GA for various problem instances






## Transport: Scheduling

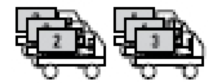
DY

- Solving a constrained transportation scheduling problem, for transporting goods in emergency situations [57]

**PLES algorithm is used**

- PLES is based on general GA with modified implementation of functions that allow varying population size, mutation and crossover [79]
- Compared to non-adaptive Ant-stigmergy algorithm [60]

- The satisfying performance in finding solutions and escaping from local optima, for different transportation modes





## Power systems: Scheduling

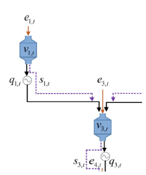
LS
DY

- Addressing total fuel costs and emissions minimization by appropriate hydro and thermal generation schedules [44]

**NPdyn$\epsilon$jDE and PSADEs algorithms are used**

- NPdyn$\epsilon$jDE is based on jDE self-adaptation [15], population size reduction [16], and $\epsilon$ level adjustment [113]
- Surrogate parallel self-adaptive DE (PSADEs) is based on self-adaptation [43], with pre-computed surrogate model

- The satisfied 24-h system demand is obtained by using a new DE architecture





## Optical network wavelength allocation

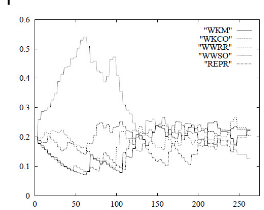
LS
DY

- Determining the route and wavelength to be used by each of the individual traffic requirements of multi-wavelength all-optical transport networks [90]

**GA algorithm is used**

- every few generations probabilities were recalculated, according to the success of the predecessors of the improved solution

- The results compare different sizes of adaptation



## Water pipeline system: Parameter calibration

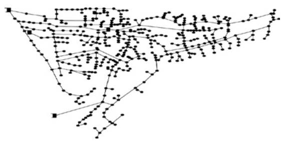
LS

- Parameter calibration strengthens the model accuracy of the water distribution system. Many factors influence the reliability of WDS simulation [103]

**ensemble optimization evolutionary algorithm (EOEA) is used**

- Combining global shrinking stage (to shrink the searching scope to the promising area) [16] and local exploration [107] stage with self-adaptive group sizing
- Different problems were constructed/tested: 100D, 200D, 300D and 454D

- Results show good scalability of EOEA on this real-world application





## Seismic waveform inversion: Configuration

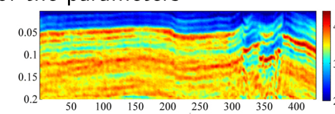
LS UN

- Waveform inversion for whole Earth geophysics and exploration geophysics, to develop an accurate Earth model and for understanding of subsurface structures [100]

**cooperative coevolutionary DE (CCDE) algorithm is used**

- All subcomponents are cooperatively evolved to solve high-dimensional optimization problems through decomposition
- The next generations are selected according to the global fitness values
- The parameter adaptation scheme of jDE [14] is used

- The CCDE results are very effective and have significant advantages over some other methods. CCDE is not sensitive to the size of the parameters






## Underwater glider: Path planning

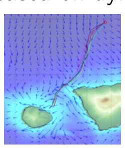
DY UN

- Optimization of a short-term sea trajectory, with opportunistic sampling of dynamic mesoscale ocean structures (eddies), which offer short-term opportunities for underwater glider path optimization [114] [111]

**jDE is used**

- Slightly modified jDE [14], combining DE and underwater glider path planning (UGPP)

- Gliders operational capabilities benefit from improved path planning, especially when dealing with opportunistic short-term missions focused on dynamic structures





## Underwater glider: Path planning 2

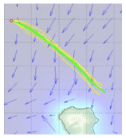
DY UN

- Optimization of a sea trajectory for underwater glider path optimization [115]

**Success-History Based Adaptive Differential Evolution Algorithm (SHADE) including Linear population size reduction (L-SHADE) is used**

- $L - SHADE_5$ was used including different population sizes and population sizing strategies

- Increased opportunity for mission scenario re-tests or in very hard scenarios



## Electrical motor: Geometry selection

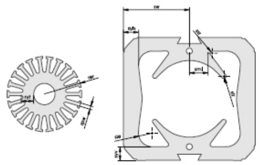
UN

- Optimization of geometrical parameters of the electrical motor rotor and stator geometry [78]

**PLES algorithm is used**

- PLES is based on general GA with modified implementation of functions that allow varying population size, mutation and crossover [79]
- Compared to generational evolutionary algorithm (GEA) [96] and multilevel ant stigmergy algorithm (MASA) [59]

- The results show fast convergence of the PLES but is not always able to find global optimum





## Target shape design: optimization

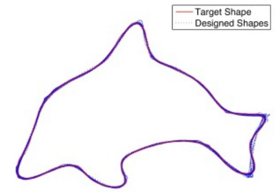
LS MO

- To tackle the target shape design optimization problems (TSDOPs) with B-spline as the geometry representation [106]

**CMA-ES-CC algorithm is used**

- CMA-ES with Cooperative Coevolution was implemented
- Compared with CMA-ES, iES [77], RCGA [28]

- The performance of CMA-ES-CC was stable, and the results of CMA-ES-CC were significantly better than with other EAs for TSDOPs






## Structure topology optimization

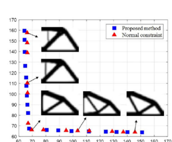
MO

- Topology optimization was performed with two different compliances (structure in different load cases are used as two different objective functions to be minimized) were considered as conflicting objective functions [86]

**Adaptive weight multi-objective algorithm is used**

- Conflicting objective functions are converted to a single objective function by applying weights, and these weights are adaptively updated to find evenly distributed solutions on the Pareto front.

- The results confirm that optimized solutions, obtained by using the proposed method, are evenly distributed on the Pareto front





## Robotic hand: configuration

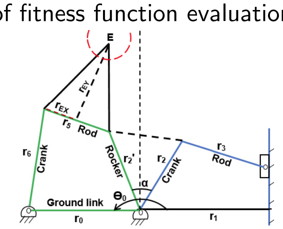
DY

- Design of a three-finger end effector of the robot [69]

**Differential Evolution with Combined Variants (DECV-S)**

- Dynamic control mechanism was added for the *F* parameter of DE
- Compared against the fine-tuned original version of the algorithm (DECV) and against the fine-tuned version of a DE-based approach

- DECV-S was able to provide similar results to those of the fine-tuned compared approaches, but with a considerable lower number of fitness function evaluations



## Robotic hand: configuration 2

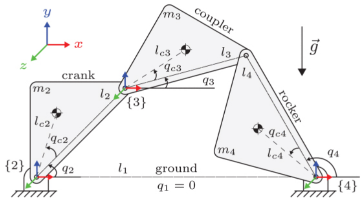
- The speed regulation of four-bar mechanisms in industrial processes [84]

DY MO

**multiobjective metaheuristic optimizers**

- Comparison of NSGA-II, multiobjective evolutionary algorithm based on decomposition and DE (MOEA/D-DE), S-metric selection evolutionary multiobjective algorithm (SMS-EMOA), nondominated sorting genetic algorithm III (NSGA-III), and HV-MODE

- The proposed adaptive controller tuning strategy shows to be effective for speed control of the FBM






## Pendulum: Reinforcement learning

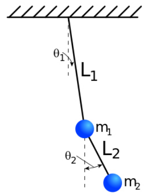
- Considers modeling of inverted pendulum and double-pendulum swing-up [25]

DY

**CMA-ES algorithm is used**

- CMA-ES uses reproducing kernel Hilbert space (RKHS)
- Compared to standard CMA-ES and adaptive CMA-ES direct policy search CMA-ES-A

- The results show that CMA-ES-RKHS is able to avoid local optima and clearly outperformes other methods





## Urban mass rapid transit: Transport

- Multi-objective simulation-based headway optimization for complex urban mass rapid transit systems in Vienna [88]

DY MO

**CMA-ES algorithm is used**

- multi-objective version of CMA-ES (MO-CMA-ES) is compared to single objective version (SO-CMA-ES) and NSGA-II

- The results show similar performance of all tested algorithms




## Aerobic fermentation process: Production

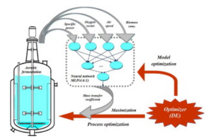
- The optimization of the oxygen mass transfer coefficient in stirred bioreactors, where the oxygen transfer in the fermentation broths has a significant influence on the growth of cultivated microorganism [38]

DY MO

**SADE-NN-1 algorithm is used**

- An improved, simple, and flexible self-adaptive variant of DE, in combination (hybridized) with neural networks

- The improvements (hybridization) of the algorithm resulted in higher efficiency of the whole methodology



**Summary**



## Summary

The distribution of presented cases according to problem characteristics

| large-scale | dynamic | uncertain | multi-objective |
|---|---|---|---|
| 7 | 6 | 12 | 5 |

The distribution of topologies (as presented earlier) used in presented cases:

- some state-dependent
- mostly success-based
- a few learning-inspired



## Summary 2

The need for dynamic parameter control.

- High
  - Traffic
  - Logistics / Transportation
  - Energy demand
- Moderate
  - Production
  - Finances
  - Data analytics
- Low
  - Parameter calibration



## Wrap Up

- You should be (now) convinced that
  - Dynamic parameter choices can help to significantly improve the performance of your EA
  - Already quite simple mechanisms can be surprisingly efficient
  - Research and work on parameter control can be fun ☺
  - Non-static control parameter values should be the new standard in the field ☺
- A lot needs to be done to make this change happen
  - Do not get frightened by the fact that (quite) some work has already been done.
    There is still much room for creativity and we are just starting to understand how good mechanisms look like!

→ If you get to work on parameter control, we would be very much interested in your results, positive and negative!

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