Acronyme / Acronym	NumBBO
Titre du projet / Proposal title	NumBBO - Analysis, Improvement and Evaluation of Numerical Blackbox Optimizers
Axe(s) thématique(s) / theme(s)	☐ 1 ☒ 2 ☐ 3 ☒ 4 ☐ 5
Type de recherche / Type of research	☒ Recherche Fondamentale / Basic Research ☐ Recherche Industrielle / Industrial Research ☐ Développement Expérimental : Experimental Development
Coopération internationale (si applicable) / International cooperation (if applicable)	Le projet propose une coopération internationale / International cooperation with : ☐ avec un ou des pays spécifiquement mentionnés dans l'appel à projets / countries explicitly cited in the call for proposal ☒ autres pays / other countries
Aide totale demandée / Grant requested	642,567.55 €
Durée du projet / Project duration	48 months

CONTENTS

1 EXECUTIVE SUMMARY

Numerical optimization problems are at the core of many present industrial design or development tasks and inherent to some of the decisive issues of our society. Numerical blackbox optimization methods, interpreting a problem as a blackbox where the only available information is the obtained function value for some query points, are the methods of choice when models are non-differentiable, non-convex, multi-modal, noisy, or too complex to be mathematically tractable. Simulation is a cornerstone for the analysis, design and evaluation of those blackbox optimizers as practical algorithms are too intricate to be easily analyzed theoretically or models where theory is possible do not cover the range of problems where we need to understand and evaluate algorithms.

A nowadays standard method for addressing numerical blackbox optimization in practice is the CMA-ES algorithm developed by the INRIA-TAO partner. It is a parameter-free adaptive stochastic search method that addresses properly the questions of solving non-separable, ill-conditioned problems, converging linearly, and being robust to noise and multimodality. In parallel to the development of CMA-ES, various other methods were introduced to address difficult numerical blackbox optimization problems. From a practitioner point of view, it is therefore difficult to know which method to apply. Benchmarking, by allowing to assess performances of different algorithms in the same conditions, offers a way to gain understanding and guide the choice among this variety of optimizers. The framework COmparing Continuous Optimizers (COCO) developed by partners of this project (TAO and TU Dortmund) has been designed to automatize the tedious benchmarking tasks of collecting, postprocessing and visualizing data. It proposes a carefully justified choice of test functions and meaningful quantitative performances measures. It allows to benchmark but is also a natural environment to design better algorithms faster. So far, more than 60 algorithms were benchmarked with COCO by researchers around the world. This data collection opens the way for intensive statistical analysis to perform Exploratory Landscape Analysis whose final goal is to select the best available algorithm for a given problem.

Algorithms benchmarked with COCO are restricted to single-objective unconstrained optimization and concern methods that are not tailored to expensive problems, where only a few hundred function evaluations can be afforded and one has to resort to surrogates of the original problem (expertise of the EMSE partner). Constrained optimization is another important aspect of many real-world problems and is challenging for adaptive methods like CMA-ES. Also, many numerical optimization problems involve the simultaneous optimization of several conflicting objectives where no single optimal solution exist but where Evolutionary Multiobjective Optimizers (EMO) (expertise of the INRIA-DOLPHIN team), can find good sets of solutions showing the trade-offs among the objectives. Like for the single-objective case, benchmarking of EMO is important to understand and assess performance of algorithms.

This project builds on the expertise of the different partners for analyzing, improving, and evaluating numerical blackbox optimizers in the context of single-objective (constrained, large-scale), multiobjective, and expensive optimization with a focus on CMA-ES. One cornerstone of the project is the COCO framework that will be used to gain knowledge about existing methods but also as an environment to design better algorithms faster. We aim here at extending COCO to constrained and multiobjective optimization, exploiting the similarities between the topics and develop further visualization tools. Exploratory Landscape Analysis in single and multiobjective optimization (goal of a submitted DFG proposal by TU Dortmund) will take place using the outcomes of benchmarked algorithms collected with COCO.

2 CONTEXT, POSITION AND OBJECTIVES OF THE PROPOSAL

This project is a fundamental research project. Our goal is to develop novel generic methods that address current challenges in the optimization of difficult numerical functions motivated by industrial real-world problems; develop a general utility benchmarking tool and a database of algorithm performances as a new foundation for an algorithm design process and for the development of methods for algorithm selection. The outcome of the project will serve both the scientific community as well as industry.

While not targeting a specific application, nor involving an industrial partner, we believe that our project is central for improving state-of-the-art methodologies to solve present and future challenging real-world numerical optimization problems. We have a deep experience and understanding of different applications that we gained from industrial partners in previous projects (e.g. the ANR projects OMD, OMD2, the SYTEM@TIC Paris Region project CSDL) as well as from collaboration with different industry partners besides the ANR context (Onera, IFP, Total, IRSN, Renault) such that we plan to model difficulties within test functions with well-understood properties. We also care about designing off-the-shelf methods, an important aspect for transfer of algorithms to industry. We believe that it is important to decouple the algorithm design process from a specific application while keeping our motivation from those real-world problems and that it has been the key of the success of the CMA-ES algorithm. Indeed, the difficulty of an application can often be attributed to specific features which can vary in another application. The life of a project which is centered on a few applications hardly allows the comparative design of optimization algorithms which is however more than ever needed in practice.

2.1 CONTEXT, SOCIAL AND ECONOMIC ISSUES

This research project being fundamental, some points asked (economical trend, market analysis, environmental gain indicator) do not apply here. However, we believe that this project should have a consequent impact for industry and hence for economy as it addresses directly difficult optimization problems in the blackbox setting which is precisely the context of many industrial applications. Because we care in our design of algorithm part to identify robust internal parameters, we can provide off-the-shelf methods that can be directly applied by industry. Finally, we aim at helping practitioners in their choice of algorithm by gaining understanding and having quantitative indicators for which algorithm to use in which context.

2.2 POSITION OF THE PROJECT

Since this project is centered on numerical blackbox optimization, it is in line with the theme *conception and optimization* of the MN call. The project addresses numerical optimization problems where the function is seen as a blackbox that can be the output of numerical simulations. This is the typical scenario in industrial problems mentioned in the call. The *adaptation and evaluation* elements explicitly written in the call are at the core of this proposal as algorithms developed in the context of blackbox optimization are typically adaptive (the distribution used to sample the search space is adapted during the course of the search) and evaluating performances is the primary purpose of the COCO platform. *Large-scale optimization*, also mentioned in the call, is addressed in WP1 for kriging and WP2 for CMA-ES. In addition, all the tasks address the *handling of uncertainties*, as the methods at the core of the project are stochastic, and hence able to cope with uncertainties. The evaluations carried out with the COCO platform are not only on noiseless test functions but explicitly also on *noisy* test functions. A secondary theme of the MN call is *visualization and interactive simulation*. Indeed, Task 5 is about visualization of the different outputs during optimization runs as well as about visualizing post processed data.

This project is connected to the previous ANR projects Optimisation Multidisciplinaire (OMD) and OMDDistribuee (OMD2) involving the TAO and CROCUS teams as well as other academic and industrial partners. Those projects have been organized around test cases proposed by the different industrial partners where meta-model approaches as well as the CMA-ES algorithm were tested. The test case proposed by the Astrium partner for designing a launcher, for example, was so far not solved and has been successfully tackled with CMA-ES during the OMD project. Another outcome of the OMD project which is relevant for this new project, while not being expected at the beginning, was understanding the importance of constraint handling for solving the Astrium test case. It is one motivation for the task on constraint handling in this project. The large-scale optimization task is connected to the SIMINOLE ANR project (involving TAO) where the developments done in the context of both projects will benefit to each respective project. The development of the COCO platform was so far not funded by the ANR but partially by the SYTEM@TIC Paris Region within the Complex Systems Design Lab proposal. The developments proposed in the multiobjective part as well as the Exploratory Landscape Analysis are also new, as far as we know, in the ANR context.

Due to the international visibility of the COCO platform (contribution of different research groups all around the world, organization of three international workshops using COCO with organizers coming from different countries in Europe), of the CMA-ES algorithm and of the different members of the project, the outcomes of this project are expected to have an important impact to the research community at the international level. In addition, the involvement of the German partner TU Dortmund University in this project will allow to further strengthen already existing collaborations between France and Germany and increase the international position of the project.

2.3 STATE OF THE ART

Numerical optimization problems occur frequently in various domains and lie at the heart of many existing industrial problems. When the function relies on complex numerical simulations (where in particular no gradients are available), is non-smooth, non-convex, noisy, multi-modal, or too difficult to be tractable mathematically, numerical blackbox approaches, that do not use any specific properties of the problems, are the methods of choice. Numerical blackbox optimization problems can be successfully tackled with stochastic or surrogate-based optimization methods. The most efficient stochastic methods are adaptive, that is the search distribution used to sample solutions at each iteration is adapted during the course of the algorithm. In particular, the covariance matrix adaptation evolution strategy (CMA-ES) [43, 42] is regarded as the state-of-the-art algorithm for numerical blackbox optimization if we assume that a sufficient budget is available (around 500 times dimension function evaluations). In CMA-ES, the sampling distribution is a multivariate normal distribution whose covariance matrix that encodes second order information is adapted and learns on convex quadratic functions the inverse Hessian. The algorithm has shown superior performance on difficult ill-conditioned, non-separable problems [10, 9] and combined with a smart restart mechanism turns out to be superior for low, moderate, and highly multi-modal functions for problems dimensions between 5 and 40 [39].

In many practical situations, the computational cost of the objective functions or constraints is high, i.e., of the order of hours. This occurs for example when the optimization criteria involve numerical simulations for solving partial differential equations (such as finite elements) or estimating low failure probabilities (through Monte Carlo simulations). The budget affordable for the optimization is then reduced to about 100 simulations for a 10-dimensional problem. It should not be thought that this computational barrier will disappear with increasing computer power: standards for numerical simulation are raised with computer progress so that, in the last 30 years, the same limit on the number of evaluations has characterized expensive optimization problems. The following strategies have been used when confronted to expensive optimization criteria: (i) One can decrease the problem size by merging or fixing some design variables, what is related to the multi-level of design variables [62]. (ii) One can design better optimizers, which has been the common focus of research of all the partners of this project. The EMSE partner has proposed optimizers that account for a limited budget [61, 31]. (iii) Parallel computing is a way to increase the limit on the number of evaluations. The partners of the project have contributed to parallelized optimization algorithms [32, 51]. (iv) The last approach to expensive optimization problems is to replace some of the high fidelity simulations with computationally more efficient models. Such surrogate models, or metamodels, either rely on simplified physical representations (e.g., neglecting viscosity in fluid simulations, neglecting material or displacement non-linearities in solid mechanics, ...) or are statistically learned during the optimization. The introduction of metamodels that are build from past high fidelity simulations in the optimization is a general procedure of high practical interest. Various metamodels for optimization have been introduced—first being used one at a time [53, 73, 34, 55, 87]. Recently, there has been a growing interest in considering multiple metamodels during the optimization [28, 59, 83, 15, 14]. Metamodel based optimization will make one of the work packages of the NumBBO project. The EMSE partner has a large experience with building statistical models based on conditioned Gaussian processes, also known as kriging models [69, 77, 30, 76]. Because the kriging metamodel provides a prediction interval and joined densities for the values of the approximated function in the space of design variables, it has been used by the EMSE partner for optimization [32, 51, 50, 74].

Many different methods exist to address single-objective numerical blackbox optimization: Nelder-Mead or NEWUOA [71], GLOBAL, and pattern search methods are standard *deterministic* methods without derivatives, different bio-inspired techniques including Particle Swarm Optimization (PSO), Differential Evolution, etc. are *randomized* search heuristics. For expensive optimization, we can cite methods like kriging or EGO. Because those methods address general blackbox problems, benchmarking is the only way to quantify and compare performances of the different methods. However, benchmarking is a difficult task. For instance, a bad choice of a testbed can promote algorithms that have a strong bias to solve problems that are irrelevant in practice: it is now well-known that test functions used for testing stochastic bio-inspired algorithms had for years a strong bias towards separable problems (i.e. problems with no correlations between variables that can be optimized by independent 1-dimensional optimization procedures) with the serious consequence to put forward methods like PSO or fast Evolution Strategies exploiting implicitly separability though they perform poorly as soon as variables are correlated as it is the case in difficult real-world applications [44, 41]. Scalability of the test functions is also an important aspect of a good testbed such that performances can be appraised depending on the dimensionality of the problem. Some testbeds present a strong bias towards functions with small dimensions and hence towards easy problems. During the past 4 years, we have developed the COmparing Continuous Optimizers platform[1] to ease the benchmarking process [37]. After carefully choosing a function testbed with the main concern that benchmark functions should reflect the "reality" (include all known relevant difficulties and not be biased towards easy functions), we have developed the platform in order to largely automatize the collection, reporting, presentation, and analysis of data resulting from running stochastic and non-stochastic optimizers on test or real world problems. Contrary to previous attempts to define a clear benchmarking framework which either do not focus on blackbox optimization (such as COCOnut, CUTE-r, and others) or whose overall goal was to determine a winner among all tested algorithms, often solely determined by a single number (sometimes not quantitative), the focus here is on providing meaningful quantitative performance criteria that apply to a single function or a class of function.

Up-to-now, more than 60 algorithms have been benchmarked by different users of the platform across the world. The COCO framework has allowed to assess that CMA-ES is generally the method of choice for dimensions between 10 and 40, budgets larger than 500 times dimension and functions that are neither separable nor have many *uncorrelated* optima. This claim can be made, because it is possible to extract performance for subclasses of functions (unimodal, ill-conditioned, multi-modal with a specific structure, noisy) and hence visualize more precisely strengths and weaknesses of algorithms on those subclasses. For instance, it turned out that for small dimension (not larger than five), the Nelder-Mead method is very fast and reliable [40]. For dimensions between 10 and 40 and smaller budgets, methods based on BFGS [33, 75] and NEWUOA [71] excel. It also opens the way to an immediate validation and comparison such that the design process of new algorithms is eased. Overfitting can and must be prevented by addressing a particular function difficulty in the design process rather than a specific function to be solved. Moreover, exploratory landscape analysis whose ultimate goal is to determine the best available algorithm for a given problem has been started based on the data collected with COCO. It has, for example, been shown that it is possible to accurately predict automatically in which function group (predefined by a human expert) an unknown function of the BBOB'09/10 test set falls by sampling simple mathematical features [65]. Also the best algorithm out of a selected algorithm portfolio of the BBOB contest could be selected automatically with only negligible errors based on cost-sensitive learning [17].

Multiobjective optimization is the natural extension of single-objective optimization when multiple objectives such as cost and performance or profit and risk have to be simultaneously optimized. Due to the typically conflicting nature of the objectives, usually no single optimal solution exists as in the single-objective case but one is rather interested in finding a *set* of solutions which shows the possible trade-offs among the objectives and from which the decision maker or the engineer can then pick a desired solution in the end [68]. Only until recently, multiobjective optimization has been seen from a set-based point of view where the multiobjective optimization problem is transformed into a single-

[1] http://coco.gforge.inria.fr/doku.php

objective *set problem* where the search space is the set of all solution sets of a fixed size and the quality of the sets, formalized by a unary quality indicator such as the hypervolume indicator [90], is then optimized [94, 93]. Hence, the benchmarking of multiobjective optimizers can be studied in a similar fashion than for single-objective algorithms except that one has to compare the achieved sets of solutions (with a certain quality) against the optimal sets with the best achievable quality, i.e., with the actual optimization goal if quality indicator and problem are given. Those sets of size μ have been recently been denoted as *optimal μ-distributions* and some interesting properties of them have been revealed within collaborations between the consortium partners [6, 5, 7, 20] as well as by other researchers [29, 19]. Currently, these properties are only studied for the hypervolume and R2 indicators in the restrictive setting of problems with two objectives with one exception of 3-objective problems [4]. However, the knowledge of the optimal μ-distributions is crucial to be able to transfer important ideas from single-objective blackbox optimization benchmarking such as the computation of the expected runtime (ERT) until a certain accuracy (in terms of the optimal quality indicator value) is reached or the visualization of performance profiles [26, 38] to the multiobjective case.

It has to be noted that first benchmarking exercises in the multiobjective case exist [46, 89]. However, the focus of these organized special sessions at the CEC conference in 2007 and 2009 aimed at determining a winner in a contest-like setting rather than interpreting the results and gaining an understanding of the algorithms. Similar to [45], our focus here is clearly on the latter. Moreover, these benchmarking exercises focused on the vertical view of performance assessment (fixing the number of function evaluations and reporting the reached indicator values) instead of the more preferable horizontal view (fixing target values and reporting the number of function evaluations to reach them) and, thus, the results do not allow to make absolute statements about how much an algorithm is faster than another one. Also with respect to the test functions used in current comparisons of multiobjective optimization algorithms, there are substantial differences to the state-of-the-art in the single-objective case. Most of the available and highly-used test problems in the multiobjective optimization field such as the ZDT, DTLZ, and WFG test suites [91, 24, 47], to our understanding, do not thoroughly reflect the difficulties observed in continuous real-world problems such as large/small basins of attraction, multimodality, or ridges, and to some extend are even separable. Instead, the known benchmark functions were designed to have desired properties in the objective space such as convexity/concavity of the Pareto front, discontinuities in the front, number of local Pareto fronts, etc. To this end, multiobjective test functions typically have two sorts of variables: distance variables which indicate how far a solution is away from the test function's Pareto front and position variables which indicate where a solution on the (local) Pareto front lies [47].

Regarding the algorithms in the field of evolutionary multiobjective optimization, the new set-based view of [94, 93] interestingly did not influence the algorithm development so far. Almost all of the recent research in algorithm design tackled the selection process rather than the variation operators and most of the state-of-the-art methods [16, 88, 11] are using the same basic variation operators than the algorithms proposed a decade ago [23, 92]—which might also be a result of a bias introduced by the highly-utilized multiobjective test problem suites ZDT and DTLZ which, in a sense, do not provide enough different difficulties to the algorithms. Those variation operators, such as the simulated binary crossover or polynomial mutation, are solution-based instead of set-based, can be seen as highly outperformed by CMA-ES-like single-objective variation operators, and do therefore not exploit the new set-based view of multiobjective problems. Even the multiobjective version of CMA-ES [48] is using the standard CMA-ES variation for single-objective optimization (applied to single solutions) and it is expected that set-based variation operators can further improve the efficiency of multiobjective optimizers.

One other challenge in blackbox optimization is related to constraints. Many real-world problems have constraints. For instance, consider the problem of the design of a launcher tackled by some partners of this project in the context of the ANR OMD project: the minimization of the overall recurrent cost of the launcher to send a satellite into orbit involved 23 continuous parameters and 25 equality and inequality constraints related to the trajectory (the launcher, for example, needed to stay in a zone visible from the launching site) or to design [21, 22]. Constraints are classically handled in the blackbox setting either via rejection of solutions violating the constraints—which can be quite costly and even lead to quasi-infinite loops—or by penalization with respect to the distance to the feasible domain (if this information can be extracted) or with respect to the constraint function value. However, the penalization coefficient is a sensitive parameter that needs to be adapted in order to achieve a robust and general method. An alternative method alters the ranking between solutions [78] and is available for rank-based algorithms. The situation is even more intricate in the case of adaptive search algorithms like CMA-ES, because the adaptation process can be jeopardized if constraints are not handled properly. Different adaptive techniques to handle constraints have been tested so far but more work is needed to understand what should be the default way to handle constraints in which circumstances.

It is important to realize that there exists a close connection between constrained and multiobjective optimization [57]: not only can constraints be handled as additional objectives [67] but a multiobjective optimization problem can also be solved by interpreting the objective functions as constraints of a single-objective problem [35]. In this project, we will exploit this close connection in particular to factorize developments for the benchmarking in constrained and multiobjective optimization.

2.4 Objectives, Originality and Novelty of the Project

Single-objective unconstrained blackbox optimization with adaptive search algorithms for problem dimensions up to 100, is certainly at the coming of age that can be witnessed by the fact that CMA-ES starts to be accepted by the classical mathematical community (CMA-ES was included in some special sessions on derivative free methods at the last SIAM conference on optimization, on a session on surrogates and hybrid methods at the last ICIAM conference and recent publications by pattern search specialists investigate CMA-ES [25]). This important change has been made possible by the intensive rigorous benchmarking performed thanks to the unique COCO platform but also by the understanding that comes with the tool that was developed.

In this project, we want to build on the success of CMA-ES for single-objective blackbox unconstrained optimization, on the recent developments of kriging-based surrogates, and on the COCO benchmarking setting to analyze, improve and evaluate numerical blackbox algorithms in the context of expensive optimization, large-scale, constrained optimization and multiobjective optimization. The cornerstone of the project will be the COCO benchmarking platform that will be used to benchmark algorithms but also as an environment for designing faster better algorithms. We provide below a first overview of the different tasks we propose to address:

Analysis and Improvements of Algorithms for Expensive Optimization There is a large amount of previous work where some high fidelity evaluations are replaced by metamodels. One could even consider that most optimizers are based on a model of the points already calculated. When the metamodels specifically aim at replacing a numerically costly simulator, they are usually global in scope, that is defined everywhere in the design space [55, 73, 53, 28]. In this situation, the current literature relies on well-known techniques of statistical model learning or regression to fit these metamodels to already gathered high fidelity points (maximum likelihood, cross-validation, least-squares fit).

In the context of the NumBBO project, we will focus on kriging metamodels as they offer a rich probabilistic interpretation. For example, through Bayesian induction, kriging metamodels are a parameterized way to handling multiple metamodels whose statistical properties (prediction mean and variance) can be calculated. An originality of the works developed will be not to separate the metamodel learning step from the optimization step, but to consider both simultaneously. The methods used to build the metamodel (choice of the kriging covariance kernel, tuning of its parameters, choice of a design of experiments to learn from) will be evaluated from their induced optimization performance, as opposed to the prediction performance of the metamodel.

The other aim of the task on expensive optimization is to clarify through systematic testing the domain of application, in terms of number of variables, computational budget and optimization problem difficulties, of well chosen metamodel-based optimization techniques. The three first candidates are the NEWUOA ([71], which is local and based on quadratic response surfaces with trust regions), the EGO ([54], a global optimization method based on kriging) and the metamodel enhanced CMA-ES algorithms.

Analysis and Improvement of Adaptive Stochastic Search Methods for Single-Objective Optimization While at a coming of age, adaptive stochastic search methods for single-objective unconstrained blackbox optimization still lack rigorous mathematical proofs of the important properties that are the key of their success. The theoretical analyses are difficult because the methods exploit weak information about the objective function, namely updates within the algorithms use solely the ranking of the different solutions with respect to the objective function but not the exact function value itself. This desirable property ensures invariance to monotonic transformation of the objective function which implies that some non-convex, non-continuous functions can be as easily optimized as some convex ones. However, convergence proofs together with convergence rates become then very difficult. In addition, the stochastic nature of the algorithm complicates the proof techniques. In this challenging task, we want to address the proof of the key property of CMA-ES, namely the fact that the covariance matrix of the algorithm can learn the inverse Hessian on some classes of functions including convex quadratic functions. Regarding algorithmic improvements, we want to develop constraint handling techniques that are applicable to CMA-ES, perform well on a broad range of functions and are quasi parameter free. The specific challenge is two-fold. On the one hand, we plan to develop a benchmark testbed that gives a conclusive performance measurement for constrained black-box optimization and is integrated into the COCO framework. On the other hand, we want to arrive at a parameter-free constraint handling technique that is applicable in practice to all kinds of constraints and does not (adversely) interact with other components of CMA-ES. Most likely, this objective cannot be met by solely combining already available concepts. The last subtask is concerned with an extension of CMA-ES to large scale optimization. So far, the algorithm scales quadratically in the dimension, as a full model corresponding and hence a quadratic number of coefficients in the covariance matrix are learned. To extend CMA-ES to problems up to one million variables, reduced models needs to be learned or selection of a few coordinates where to perform optimization needs to be considered. We propose to explore those approaches in this subtask.

Benchmarking Multiobjective Optimizers Although first attempts to benchmark continuous multiobjective blackbox optimizers exist [46, 89], they do not yet offer the same functionality and simplicity of setting up experiments than the current COCO framework provides for the single-objective case and it is one of the main goals of this project to extend the COCO platform also to multiobjective optimization.

With the recently proposed viewpoint of set-based optimization in mind [94], some of the post-processing functionalities of the COCO framework could already be used in the multiobjective setting with only slight modifications of the code—bringing state-of-the-art ideas such as the expected runtime until a target (quality indicator) value is reached or performance profiles to the multiobjective optimization community. However, other fundamental issues have to be tackled as well. The improvement of the available test functions towards building a set of benchmark functions that contain challenges, obtained in real-world applications similar to the single-objective case, is one of these topics—improving our understanding of the optimization goal in set-based optimization another. A third important topic is the design of improved multiobjective optimization algorithms where in previous years, mainly the selection process of evolutionary algorithms was investigated while the variation operators have not been adapted to the new set-based view. We expect that a shift of the focus towards the design of new variation operators for set-based algorithms will improve the efficiency of multiobjective blackbox algorithms significantly.

When extending the COCO framework towards multiobjective optimization, we will exploit the close connection between multiobjective and constrained optimization in order to be also able to benchmark algorithms for constrained optimization with COCO. This will allow us to investigate various constraint handling techniques such as penalization, rank changes, or adaptive techniques specifically developed for CMA-ES in a decent manner and to decide which one should be the default way to handle constraints in the blackbox setting. Another aspect of extending COCO to multiobjective optimization is the integration of new visualization tools such as plotting sets of objective vectors or the plots showing the progress of certain quality indicators over time.

Visualization The visualization of various output data from runs of blackbox optimizers is a challenge on its own right. Based on the COCO framework, we want to develop visualization for single runs in the single-objective case with and without constraints and for multiobjective optimization runs. The specific challenge is to go beyond of what is typically displayed and visualize the distribution of search points over time in a meaningful way. Such display of data has been used with CMA-ES, where it comes naturally with the parameters of the algorithm, and proved to be extremely useful to improve the parametrization of the objective function of practical problems in an iterated design process. For other algorithms, in particular not population-based algorithms, this idea is, to the best of our knowledge, a novel approach. A second objective is to implement comparative visualization for constrained and multiobjective optimization in the framework of COCO.

Elementary Landscape Analysis Elementary Landscape Analysis (ELA), a research topic recently founded by the TU Dortmund University partner, aims at automatizing the selection of the best available algorithm for a given problem by applying statistical analysis and machine learning tools on extensive data of algorithm performances in order to predict which of the many available algorithms should be recommended in practice for a new problem. ELA has been shown to work well in principle for single-objective unconstrained optimization with data obtained via the COCO framework. The aim here is to improve the recently developed algorithm selection methods and their theoretical foundations as well as to extend the focus of ELA towards constrained and multiobjective optimization. Note that another research proposal addressing the topic of ELA has been submitted by the TU Dortmund University partner, involving explicitly already the TAO team, and is currently under review with the Deutsche Forschungsgemeinschaft (DFG).

3 SCIENTIFIC AND TECHNICAL PROGRAM, PROJECT ORGANIZATION

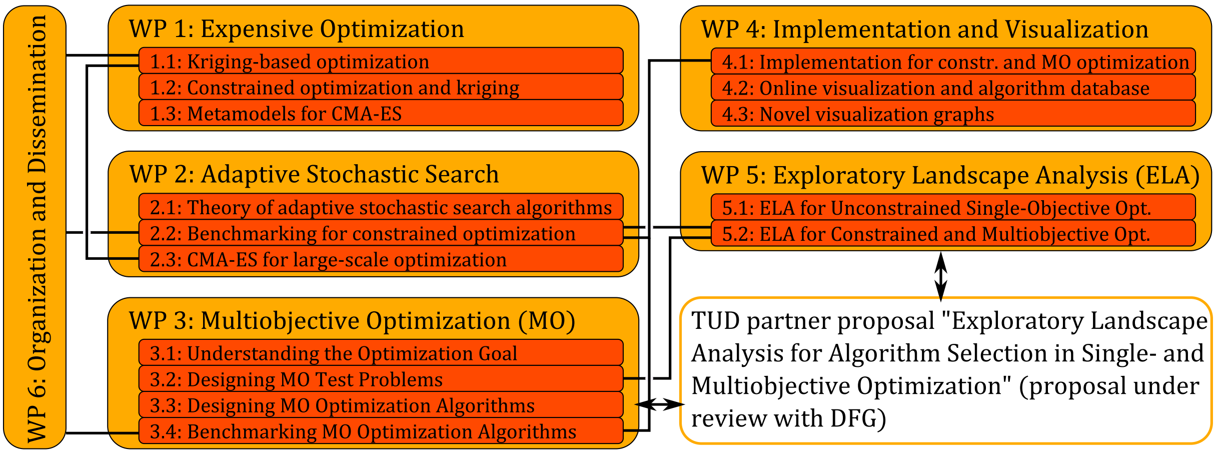

Figure 1: Overview of the scientific program structure. Dependencies and interactions between the tasks and work packages are indicated by lines and arrows. Tasks within a given work package are naturally correlated while, for the sake of clarity, no explicit dependency is indicated in the figure.

3.1 Scientific Program, Project Structure

The scientific program and the project structure is organized around five work packages, each of them being cut into subtasks. In addition, one work package is attributed to the organization and dissemination of the results. The general overview of the work packages, the subtasks as well as the different interactions between the different tasks are presented in Figure 1.

3.2 Project Management

Due to the rather small consortium of the project, the highly related topics covered by the work packages and the already existing collaborations between the different partners, a lean project management will be imposed. We plan to have one overall coordinator (Anne Auger) who is the contact person between ANR and the consortium and responsible for all general tasks. Twice a year, we plan general meetings with the entire consortium to report on the progress and coordinate the next steps and plan more frequent meetings dedicated to further scientific discussion around each work package. We experienced in previous ANR projects (TRAVESTI, OMD) that it is very nice to have a wiki for the project where we can upload bibliographic references and publications related to the project. We will have such a wiki environment for the project.

3.3 Description By Task

3.3.1 WP 1: Analysis and Improvement of Algorithms for Expensive Optimization

Participants: Anne Auger, Xavier Bay, Bernd Bischl, Xavier Delorme, Derrick Fongang-Fongang, Nikolaus Hansen, Rodolphe Le Riche (coordinator), PhD$_3$, *Marc Schoenauer, Diane Villanueva, Tobias Wagner*

Context and Objectives Approaches to deal with costly optimization criteria are based on formulations that decrease the problem size, better optimizers, parallel computing or mixing high fidelity simulations with computationally more efficient models. Such surrogate models, or metamodels, either rely on simplified physical representations (e.g., neglecting viscosity in fluid simulations, neglecting material or displacement non-linearities in solid mechanics, ...) or are statistically learned during the optimization.

In the last decade, a very large number of scientific contributions have proposed to replace some calls to the high fidelity model by calls to metamodel(s). These works were motivated by the simulation cost bottleneck and progress made in the field of statistical learning with the development of neural networks, radial basis functions, support vector machines, kriging, generalized additive models, regression trees, random forests and more recently multiple surrogates. The communities of computer experiments (statisticians which aim at designing experiments for understanding complex softwares) and engineering optimization have started to address the same issue of optimizing expensive functions from two different perspectives, design of experiments and optimization. Although the problem to solve is an optimization problems, within 100 to 10000 simulations it is not clear that a proper convergence can be achieved which explains why the problem can be seen as one of design of experiments. With the multiplication of contributions, we think that a summary work organized around a structured optimization benchmarking campaign would be helpful to the community. Therefore, in this work package, we will focus on statistically learned surrogates and their interaction with high fidelity simulations and optimization algorithms. Obtaining better optimizers, that is optimizers that are adapted to the problem at hand, is a general goal of this project which is addressed by all work packages under various angles unified by a common point, that of properly benchmarking the methods. Other approaches devoted to costly simulations, which are case-dependent, hence not in the blackbox setting, and parallel computing will not be investigated in this project.

The purpose of this work is not to interface new surrogates to optimization algorithms but rather to study the group {surrogate(s), optimization algorithm, interfacing principle} together. Indeed, it is not equivalent to learn a surrogate for approximating a function and for optimizing it [72]. Starting from well-studied, mathematically founded surrogates such as generalized linear models and Gaussian processes, we will highlight working principles according to which surrogates and optimization algorithms should be merged. We will complete these principles. Finally, we will test the groups {surrogate(s), optimization algorithm, interfacing principle} on our test problems database which, because it is structured according to problem difficulties, will allow to better understand the working or failing mechanisms.

Scientific Program This work package is centered on optimization problems where the criteria (objective functions, constraints) are computationally expensive so that only 100 to 10000 evaluations can be afforded. In this work package, all the studied optimization methods target such expensive problems and share the use of surrogates or metamodels. These metamodels are learned from already calculated points.

However, in the context of optimization, the use of metamodels raises specific questions that have not been properly addressed in the literature. Firstly, the point iterates should be seen as following two goals, one of optimization and one of metamodel learning:

1. Optimization first. Optimize the metamodel to get the next iterate. But does this define a good design of experiments for learning the metamodels ?
2. Function approximation first. Define a space filling design that uses all the high fidelity simulations. Then optimize the metamodel(s), that is the metamodel(s) is(are) seen as capturing all the accumulated knowledge about the expensive simulation. But the design of experiments may be

too sparse in important areas of the design space.

3. Approximate and optimize. It is expected that the best strategies will compromise between choosing points for optimization and for metamodel learning. Metamodel based global optimization strategies like EGO [53] already do it implicitly as exploring the design space provides a reasonable design of experiment for globally learning the function. But it is doubtful that it defines the best design of experiment to learn a kriging model in target regions.

Secondly, it is not clear that the way metamodels are learned from data points in the context of function approximation (e.g., likelihood maximization or cross-validation error minimization) is the most appropriate in the context of optimization iterations.

In this work package, the developments made will be benchmarked against state-of-the-art methods such as NEWUOA, a quadratic response surface method for unconstrained optimization without derivatives [71]. The scientific program addressing the aforementioned issues is divided into three tasks.

Task 1.1: Kriging-Based Optimization. Kriging, i.e. conditioned Gaussian processes, provides a probabilistic framework for building metamodels. Because the metamodels come with a prediction measure and can be sampled (as random processes), kriging has been used for global optimization first in the EGO method [53], then in the SUR method [84] or the multipoints expected improvement method [32], for example. Kriging is a particular example of kernel based metamodels as kriging is determined by the choice of a covariance kernel. Some important questions remain opened however. We plan to address them. Firstly, as mentioned above, there is a connection between the way the kriging model is built (choice of kernel and method for tuning it) and optimization which has not been sufficiently studied (it is mentioned around an application in [72]). Secondly, classical kriging models cannot handle more than about 1000 points which leaves the 1000-10000 data points range devoid of state-of-the-art approach. This last aspect is tightly related to the number of optimization variables that can be handled by these methods as more data points are needed to search in higher dimension spaces. Currently, the limit is around 10 to 20 optimization variables. To sum up, we plan on benchmarking and improving *i)* kernels tuning and choices for optimization and *ii)* kriging-based optimization methods for high dimensions. The benchmarking itself is planned to be carried out with the COCO framework for which no modification is needed. It should also be mentioned, as an addition token of project cross links, that kriging-based optimization typically involves internal optimization tasks (likelihood maximization, expected improvement maximization) that are multimodal and for which CMA-ES has been used [50]. This task will be carried out by the EMSE participants in interaction with Tobias Wagner and Bernd Bischl for development related to kriging and with Nikolaus Hansen and Anne Auger for the benchmarking part and large-scale extension related to large scale extension of WP2.3.

Task 1.2: Constrained Optimization with Kriging Surrogates. Another observation that stems from the existing literature is that there is a lack of guidelines for constrained optimization using non local metamodels such as kriging. Sampling criteria have been proposed in [27] and [70] but these works stopped before defining and testing a general optimization method. [58] is a related contribution but it is restricted to integer programming. Constrained optimization with kriging surrogates has been briefly studied as parts of two PhDs : in [13], the probability of satisfying the constraints is one of the objectives; In [80], the expected improvement criterion is multiplied by the probability of satisfying the constraints. The reference [79] is, to the authors knowledge, the main contribution. We propose to develop a metamodel based optimization method for expensive constrained optimization problems. This development will be shared with the work packages on benchmarking for constrained (WP2.2) and multiobjective (WP3.4) optimization. This task will be carried out by the EMSE participants.

Task 1.3: Metamodels for CMA-ES. The CMA-ES algorithm has been coupled with quadratic *local* metamodels built for *each* solution sampled by CMA-ES using an archive of already visited points by minimizing the least square error [56, 18]. Those algorithms loose the invariance to monotonic transformation of the objective function, and by exploiting more about the function (the intrinsic objective function value instead of the relative ranking w.r.t. the function of the solutions) can gain up to factor of 2 w.r.t. CMA-ES. Because invariance to monotonic transformation is desirable, rank-based meta-models using SVM have been investigated in [60] where important improvements were shown, however based on a complete change of the baseline algorithm. In addition it is not clear in which context local metamodels are really needed or whether one global model for the whole population is sufficient. In this task we want to understand how much approaches preserving the rank-based property of CMA-ES (using SVM like in [60] or ordinal regression) can improve over CMA-ES and clarify what are the important ingredients for possible improvements. Ultimately, we want to provide a thoroughly justified metamodel CMA-ES that can become a default baseline algorithm. This task will be carried out by the TAO participants in interaction with R. Le Riche.

Milestones and Deliverables

M1.1 (M12) Comparison of validated version of EGO with CMA-ES in the 100 to 1000 function evaluations range.

D1.2 (M24) Report on a balancing metamodel learning and optimization. This report will compare the effect of various learning techniques (maximum likelihood and augmented likelihood, cross-validation, regularized kriging though nugget effect, scale calculation from data points distribution) not on the metamodel accuracy, but on the optimization convergence speed and robustness. A new method, specifically designed to balance metamodel learning and optimization efficiency will be proposed.

D1.3 (M36) Report on kriging based optimization with large number of points. Report on CMA-ES with meta-models

M1.4 (M36) Version of kriging based optimizers in the 100 to 10000 function evaluations range interfaced with COCO.

D1.5 (M36) Report on kriging based optimization with non linear inequality constraints.

D1.6 (M42) Software: dissemination of all tested methods as opensource code with interfaces with COCO.

M1.7 (M48) Comparison of validated version of kriging based optimizers with CMA-ES in the 100 to 10000 function evaluations range.

Risk and Risk Management It is important that the software/language used to develop the various metamodel based optimization strategies is compatible with the COCO benchmarking platform. For this reason and in order to benefit from a maximum of already existing methods, the developments will be done in R. Apart from that, no blocking point is identified in this WP.

3.3.2 WP 2: Analysis and Improvement of Adaptive Stochastic Search Methods for Single-Objective Optimization

Participants: Anne Auger, Nikolaus Hansen (coordinator), Marc Schoenauer, PhD_0,PhD_1,Postdoc_1

Context and Objectives The CMA-ES algorithm became a standard algorithm to address numerical blackbox optimization for problem dimensions up to the order of 100 variables. One still open question concerns a theoretical proof of the important mechanism in CMA-ES, namely the fact the covariance matrix is able to learn second order information about the problem. In addition, constraint handling in CMA-ES is efficient in the context of box-constraints, however improvements are needed to handle general constraints. Another challenge for CMA-ES is large-scale optimization. The default CMA-ES learns a full covariance matrix associated to the multivariate normal sampling distribution, hence, a number of parameters which is proportional to the square of the dimension and the method needs thus in general a number of function evaluations to solve a problem that scales quadratically in the dimension. To be able to solve high-dimensional problems (of the order of one million variables), a restricted model needs to be learned. We propose to address those three bottlenecks within three different subtasks.

Scientific Program

Task 2.1: Theory of Adaptive Stochastic Search Algorithms The CMA-ES algorithm is an adaptive algorithm where at each iteration a multivariate distribution parametrized by a covariance matrix and a mean vector is adapted after having sampled points and evaluated them on the objective function. This adaptation aims at increasing the probability to sample successful steps in the next iterations and result in the learning of the inverse of the Hessian matrix on convex quadratic functions. After the learning phase is achieved, a linear convergence with rates close to optimal are observed. While the mechanism why this result is achieved is intuitively clear (and drove the design of CMA-ES), the proof of this result is challenging as weak information about the objective function is used within the algorithm, namely the intrinsic ranking of candidate solutions with respect to the objective function and not their exact function value. We believe that the theory of Markov chains for discrete time and continuous state space is the way to go to prove the main result. We indeed want to generalize results already obtained for adaptive algorithms where solely one parameter, the so-called step-size, that scales an identity covariance matrix, is adapted [3]. On classes of functions including convex-quadratic ones, we can exhibit a normalized Markov chain (which is the mean vector divided by this scale parameter) that—if proven to be stable (geometrically ergodic)—implies, using a Law of Large Numbers for Markov chains, linear convergence [66]. We believe that combining the study of Markov chains together with invariance properties of the CMA-ES (to general linear transformation) will lead to the expected result. We know that the stability proof is quite challenging in the CMA case as it involves to find an appropriate drift function and control all the principal directions of the covariance matrix. Note that this result if proven on a convex quadratic function will hold by the invariance property to increasing transformations on non-convex functions as the algorithm is doing the same updates when optimizing a function f or any increasing transformation of f.

In addition to a direct proof on the exact algorithm, we plan to study a continuous time model associated to the algorithm which is given by an ordinary differential equation that was recently formalized [2]. We would like to study in a first time the stability of different stationary points associated to the differential equation and prove in particular that stable points correspond to local optimum of the function to be optimized. We plan to use classical stability tools for differential equation, namely Lyapunov functions. This task will be carried out by Anne Auger, Nikolaus Hansen and *Postdoc*$_1$.

Task 2.2: Benchmarking for Constrained Optimization and Improvement of Constraint Handling in CMA-ES Constrained optimization is challenging for numerical blackbox optimization methods, but is however crucial for real-world problems. COCO has been established as a useful tool to benchmark single-objective blackbox algorithms in the continuous search domain. The first objective here is to extend the concepts used in COCO to constraint handling. This task will be in close connection with the benchmarking of multiobjective optimizers from WP3.4 as indeed in both cases the blackbox returns several objectives instead of one. First, known constrained blackbox test functions need to be reviewed and evaluated. Based on our experience in the single-objective case, we expect to design a new test functions set, that in particular satisfies the demands of non-separability, scalability with dimension, presents a range of difficulties and is well-understood. One difficulty is that constraints come in different "flavors" and testing (combinations of) all of them seems infeasible, from the view point of computational resources and the presentation of results. This task will also develop the necessary and desired requirements for the implementation of the benchmarking procedure in WP4.1.

The second objective is to improve constraint handling in the CMA-ES algorithm and, more generally, get a better insight into different constraint handling techniques and their interaction with continuous blackbox optimizers. The developed methods are most likely not only applicable to CMA-ES only, but at least also to methods that are based on a stochastic natural gradient descent and those developed in WP2.3. A relevant design criterion for constraint handling will be its feasibility in practice, because this objective is highly relevant for many engineering problems. This part of the task serves as the main test case scenario for WP4.1. This task will be carried out by Nikolaus Hansen, Marc Schoenauer and PhD_1.

Task 2.3: CMA-ES for Large-Scale Optimization Stochastic search methods like CMA-ES explore the search space by sampling it. Because of the curse of dimensionality, expression that translates the fact that the search space volume grows exponentially with the dimension, optimization with a stochastic method becomes challenging as soon as the dimension is larger than 3. To overcome the curse of dimensionality for problems with the order of 10 to 100 variables, search is usually done in a neighborhood, whose geometrical shape and size is adapted during the course of the algorithm (for CMA-ES this corresponds to the adaptation of the mean vector and covariance matrix). However this adaptation requires of the order of the dimension square function evaluations which is then too costly for large scale problems where one is interested to optimize millions of variables. However, those problems are important to consider with blackbox methods as they can be non-convex or noisy. We plan to explore large-scale optimization with stochastic techniques using an iterative procedure consisting in selecting a few variables, sampling a few directions in this search space, selecting the best directions within this search space and perform a CMA-ES optimization within the defined subspace spanned by those selected directions. For problems with a moderately large number of variables (of the order of 10^3), we aim at defining a new CMA-ES variant where a restricted model of the covariance matrix is learned. We plan for that to exploit the recent result showing that the CMA update for the parameter of the multivariate normal distribution realizes a natural gradient update step in the Riemannian manifold defined by the multivariate family of distributions [1]. After defining a restricted model for the covariance matrix (generalization of identity matrix plus rank-one matrix for instance [81]), we want to derive the associated natural gradient update step.This task will be carried out by N. Hansen, A. Auger and PhD_0.

Milestones and Deliverables

D2.1 (M12) Analysis of continuous time model for adaptive stochastic search algorithms
D2.2 (M18) Prototype of algorithms for large scale optimization
D2.3 (M36) Prototype of COCO framework extended to constraint handling
D2.4 (M48) CMA-ES with constraint handling and for large-scale optimization
D2.5 (M48) COCO framework for constraint handling

D2.6 (M48) Convergence proof for CMA-ES based on Markov chain

Risk and Risk Management The first subtask includes a high risk as no similarly complicated algorithm was so far analyzed (in particular with Markov chains) and the mathematical tools used are much more difficult to manipulate than on toy examples where they are usually applied. However, this subtask is independent of the other tasks and work packages. The remaining subtasks of this work package are of risk.

3.3.3 WP 3: MULTIOBJECTIVE OPTIMIZATION

Participants: Anne Auger, Dimo Brockhoff (coordinator), Nikolaus Hansen, Arnaud Liefooghe, Olaf Mersmann, Günter Rudolph, Heike Trautmann, Tobias Wagner, PhD$_2$, Postdoc$_2$, Postdoc$_3$

Context and Objectives The goals of this work package are two-fold: benchmarking and algorithm design for multiobjective optimization problems. The former thereby includes the design of a decent suite of benchmark problems that contain difficulties related to real-world problems such as multi-modality, non-separability, ridges, plateaus, and ruggedness similar to the single-objective case (WP3.2) as well as more fundamental issues of performance assessment due to the set-based nature of the algorithm outcomes (WP3.1). The latter goal includes especially the design of new variation operators of multiobjective evolutionary algorithms which has been largely ignored in the field of evolutionary multiobjective optimization (WP3.3). The final goal of this work package is to integrate the research on benchmarking continuous multiobjective optimizers into the COCO framework (WP3.4). This work package offers strong links to constrained optimization (WP2.2) due to the joint need for a conceptionally very similar extension of the COCO framework as well as to WP5 from which especially subtask WP3.2 will profit.

Scientific Program

Task 3.1: Understanding and Formalizing the Optimization Goal The goal of this subtask is to extend our work on formalizing and characterizing the optimization goal in multiobjective optimization in terms of the sets of solutions with a fixed size μ that achieve the optimal indicator value among all possible sets of μ solutions (the so-called optimal μ-distributions) [6, 5, 7, 20]. In particular, further results for other quality indicators than the hypervolume and the R2 indicator are necessary for a thorough benchmarking in the multiobjective case as well as to understand the characteristics of optimal μ-distributions for problems with more than 2 objectives. Furthermore, the optimal μ-distributions have to be investigated for new test problems which are to be developed in WP3.2. The work will be carried out by A. Auger, D. Brockhoff, H. Trautmann, and T. Wagner and is of both theoretical and experimental nature.

Task 3.2: Designing Multiobjective Test Problems Before being able to extend the COCO framework towards multiobjective optimization, the fundamental topic of designing a test problem suite has to be tackled. As in the single-objective case, this task is crucial as one can easily bias the interpretation of the benchmarking by choosing the wrong functions. In multiobjective optimization, there are already several standard test suites available [91, 24, 47], but to our understanding, they do not thoroughly reflect the difficulties observed in continuous real-world problems such as large/small basins of attraction, multimodality, or ridges, and to some extend are even separable.

One possible way to design multiobjective test functions which reflect properties of continuous real-world problems is to simply combine the single-objective functions of the COCO framework. The challenge thereby is to be still able to describe the resulting Pareto fronts of those new problems analytically. This is very helpful in the understanding of the benchmarking results, in particular for computing the optimal μ-distributions in WP3.1. Another possibility is to use the transformations used in the COCO framework to make functions more difficult (random translations, rotations, and disturbances) for already known multiobjective test functions. In the course of the project, there will be a close link to WP5 on elementary landscape analysis, which might give us further insights on which functions we want to have in a multiobjective benchmarking portfolio or which would be needed to extract meaningful data for the algorithm selection. As this subtask is one of the most challenging topics of WP3, we expect to have all participants, mentioned above, working on the design of new multiobjective benchmark functions. In particular, $Postdoc_2$ and $Postdoc_3$ are expected to work on this.

Task 3.3: Designing Efficient Multiobjective Optimization Algorithms In the field of evolutionary multiobjective optimization algorithms, interestingly not much research effort has been spent on the design of variation operators specific to multiobjective problems. The main focus was on the selection and we expect that improvements on variation operators will have a strong impact both on the scientific community as well as for applications. Here, we will focus our effort to design variation operators for the continuous domain which allow to converge faster to a set of solutions than current approaches that variate single solutions. In particular, we are interested in designing fast algorithms that optimize the hypervolume indicator such as the multiobjective CMA-ES [48] or the SMS-EMOA [16]. This subtask highly intersects with module 6 of the DFG proposal submitted by the German partners of TU Dortmund University. A further aspect of this subtask is to reconsider online convergence detection [86, 82, 85] to be used in new restart mechanisms for multiobjective variants of CMA-ES in order to increase its efficiency similar to the improvement observed in the single-objective case [8]—but now in a set-based setting. This subtask will be mainly executed by Dimo Brockhoff, Nikolaus Hansen, Günter Rudolph, $Postdoc_2$, and $Postdoc_3$.

Task 3.4: Benchmarking Multiobjective Optimization Algorithms Within COCO With this subtask, we aim at developing an open-source benchmarking software tool for multiobjective blackbox algorithms based on the COCO framework which helps to conduct and interpret the experiments, including visualizations and postprocessing tools. Besides the actual implementation which is covered already by WP4, and in addition to defining the benchmark functions (WP3.1), several fundamental research questions have to be answered beforehand. For example, we have to decide carefully on a set of (unary) quality indicators which are meaningful and do not bias the algorithm comparison. We shall also transfer standard concepts from single-objective optimization such as the expected runtime (ERT) and performance profiles to the multiobjective case of solution sets. A challenging aspect, which needs to be thereby addressed, is the question of how to compare evolutionary multiobjective optimization algorithms that use different population sizes.

After the COCO extension towards multiobjective optimization is finished, the organization of a workshop on multiobjective benchmarking at a high-quality conference is planned at the end of the project period (see WP6). In contrast to previous comparison contests of new multiobjective optimizers [46, 89], we aim at collecting the performance profiles of at least 10 different state-of-the-art algorithms such as NSGA-II, SPEA2, SMS-EMOA, HypE, MSOPS, and MOEA/D. All results will be made publicly available on the web page of the project for both the scientific community and industry in order to allow to gain insights into which algorithms will perform well in future problems. This subtask will be the main topic of the PhD thesis of PhD_2 and all above mentioned participants are expected to contribute.

Milestones and Deliverables

D3.1 (M12) report about the optimization goal in continuous multiobjective blackbox optimization for a new quality indicator [WP3.1]

M3.2 (M18) decisions about a basic test function suite to include in the multiobjective extension of COCO taken [WP3.2 and WP3.4]

D3.3 (M24) report about a new variation operator for continuous multiobjective optimization [WP3.3]

D3.4 (M27) open-access source code of the new multiobjective optimization algorithm using the proposed variation operator of D3.3 [WP3.3]

M3.5 (M30) prototype of COCO framework extended to multiobjective optimization for internal use [WP3.4]

D3.6 (M48) data of 10+ different (evolutionary) multiobjective optimization algorithms on the proposed multiobjective benchmark functions available online

Risk and Risk Management The extension of the COCO framework to multiobjective optimization is moderately risky—considering the work that was needed for the design of COCO in the single objective case where things like optimization goal and convergence are well defined and the modeling of typical difficulties is much easier. However, the transfer to the multiobjective case seems to be feasible. The largest technical difficulty might come from the fact that for the newly designed benchmark problems, the exact optimal μ-distributions might not be available in which case approximations thereof can be computed numerically up to the machine precision [7]. In any case, the single tasks of this work package are risk-less with respect to a complete failure as any intermediate step will make progress to the overall objective.

3.3.4 WP 4: Implementation and Visualization in COCO

Participants: Anne Auger, Dimo Brockhoff, Nikolaus Hansen (coordinator), Olaf Mersmann, Mike Preuss, PhD_1, PhD_2, $Postdoc_2$, $Postdoc_3$

Context and Objectives Visualization of results is essential to understand the optimization process, track possible bugs in algorithms, quantify and compare performances. This task is often neglected by algorithm developers as it is time consuming, however, it is an important aspect for designing good algorithms. In this work package we want to develop further visualization for single/multiobjective and constrained optimization within the COCO platform in order to assist in understanding the algorithm outcomes. This work package groups also the implementational aspects needed for the extension of the COCO framework towards the four previous work packages.

All participants of the project might actually contribute to this work package, but the people indicated above are expected to be the core developers of the COCO framework. In addition, also other members of the current COCO/BBOB developer team such as Petr Pošik from the Czech Technical University in

Prague[2] are likely to contribute.

The code that we intend to produce in this work package will serve the entire scientific community interested in blackbox optimization algorithm design and benchmarking. We hence expect that this work package contributes grandly to the dissemination of the results of the whole project.

Scientific Program

Task 4.1 Implementation for Extension to Constrained and Multiobjective Optimization Several adaptations are needed to extend the COCO platform to constrained and multiobjective optimization. The *fgeneric* and *cocoexp* wrappers define the interface between the optimizer and the test functions or a testbed and take care of recording the needed data into files. These wrappers need to be redesigned. The output files format needs to be changed as more data need to be recorded. Depending on the feasibility we want to remain compatible with the current version of the code that handles single-objective optimization only. In order to derive a satisfactory solution, we will design from scratch the APIs and the data flows between an MO or constrained optimizer, a testbed and a runtime environment that links both and runs the desired experiments. The new design will be compared to the current status and this will guide the decision whether we will take the path of incremental changes or a new implementation. On the data postprocessing side, the performance evaluation in the constraint case is based on feasible solutions. The time evolution of constraint values and of the percentage of feasible solutions can be displayed. The performance evaluation in the MO case will be based on the use of indicators (like the hypervolume indicator) that will provide a single value for quantifying the quality of a set of solutions. Different indicators will be considered, evaluated and implemented in the platform.

Task 4.2 Online Visualization of Data and Online Database of Algorithms We have so far collected raw data from different benchmarked algorithms. For a given optimizer, those raw data consist in the output of different optimizer (running time to reach a collection of target function values, for all the functions of the test suite, for problem dimensions $2, 3, 5, 10, 20, 40$) necessary for the post-processing. The post-processing produces the different graphs of results for displaying performance of a single algorithm, or comparison of performance of several algorithms. In this task, we organize this collection of raw data into a database that can be queried online and where users can submit their new data online. This database will be used with an online graphical interface that allows to display different graphs for a selection of algorithms the user can choose. The graphical interface will call the post-processing tool already available within COCO for producing the different graphs to display.

Task 4.3 Novel Visualization Graphs In this task, we want to develop new visualization graphs for single runs in order to assist the development of new algorithms. A starting point is the online visualization implemented for CMA-ES algorithms, namely display of the time evolution of parameters of the population in search space. In particular, the step-size in the given coordinate system and the variances in the coordinate system determined by a PCA is of greater interest. In CMA-ES, these parameters are directly available from the algorithm. We want to develop similar features that can be applied to any blackbox optimizer and that are even independent of whether or not a population-based approach is used. This poses a new challenge on the proper (re-)definition of these features. One possible scenario is to generate these features based on an adaptive encoding procedure [36]. This kind of visualization

[2] http://labe.felk.cvut.cz/~posik/

is particularly important to understand how ill-conditioned problems are solved and why they are not solved in case.

In the multiobjective case, it is natural to display solutions in the objective space. For bi-objective problems, we will therefore implement the visualization of solution sets by displaying their objective vectors in a two-dimensional plot while otherwise, parallel coordinates plots [49, 52] will be used. We are planning to also have other plots specific to the multiobjective case, for example a plot displaying the progress of several quality indicator functions over time. For the constrained case, it is also necessary to display the constraint function values to understand the position of a solution with respect to the constraint. Similar plots to the ones planned for the multiobjective case will be implemented.

Milestones and Deliverables

M4.1 (M9) Analysis of work needed for the changes required in COCO for constrained and multiobjective benchmarking
M4.2 (M24) Implementation of visualization graphs for singles runs implemented
D4.3 (M36) Release of the COCO platform ready for multiobjective and constrained benchmarking
M4.4 (M42) Prototype for database and online visualization
D4.5 (M48) Release of database and online visualization, release of visualization graphs for single runs

Risk and Risk Management Task 4.1 is the core of the overall project, several other work packages depend on its progress which is the reason that WP4 is scheduled to start right from the beginning of the project. This task is not too risky and will mainly be carried out by the PhD_1 student who should have good programming skills. In addition, for the work packages WP1 and WP2 only slight modifications of COCO need to be implemented and for multiobjective and constrained optimization, the implementations highly overlap and we can also detect early enough whether we need to focus on only one of these extensions. Task 4.2 is risky because it will depend on the ability of the PhD student to handle technically this task. We might decide to be less ambitious if it turns out to be too difficult with the manpower available. Task 4.3 requires to understand how to deal scientifically with the graphs when a population is not available but it is unlikely to be a complete failure.

3.3.5 WP 5: Exploratory Landscape Analysis Based on COCO Data

Participants: Bernd Bischl, Dimo Brockhoff, Nikolaus Hansen, Olaf Mersmann, Mike Preuss, Günter Rudolph, Heike Trautmann (coordinator)

Context and Objectives Selecting the best available algorithm for a given (unknown) problem is a challenging task and one of the crucial steps in applying blackbox optimization algorithms effectively in practice. Exploratory Landscape Analysis (ELA) is aiming at automatizing this algorithm selection.

Two fundamental issues need to be tackled for algorithm selection. In a first step, one has to understand and formalize the relationship between the performance of an algorithm on specific test functions and the test functions' characteristics. One approach is thereby to use human-defined, high-level features of the test functions, such as ill-conditioning, separability, multi-modality, etc., to distinguish between groups of test functions with similar algorithm performances [64, 12]. In a second step, one can then investigate these high-level features for an unknown problem, decide in which group the new problem falls, and choose the algorithm which shows the best performance on this class of test functions. When automatically selecting an algorithm, however, it has been shown to be beneficial to define easy-to-formalize and efficiently-computable low-level features which can be automatically extracted for a new problem by using systematic sampling of the decision space using a suitable space filling design [63].

For the data collected during the BBOB workshops with the COCO platform, it turns out that the same function groups can be established with the low-level features than if the high-level features based on expert opinions are used [64]. It was also possible to accurately predict the predefined function groups of the BBOB'09/10 test set [65] and to select the best algorithm out of a selected algorithm portfolio of the BBOB contest with negligible errors based on cost-sensitive learning [17].

In the context of the NumBBO project, ELA is planned to be extended towards constrained and multiobjective optimization problems (WP5.2) while also in the unconstrained single-objective case, improvements of the current state-of-the-art are needed (WP5.1). Results of this work package will have immediate impact on the test function design for the extensions of the COCO platform to constrained (WP2.2) and multiobjective optimization (WP3) by gaining insights about where the COCO test function sets need to be adapted and extended as it can be analyzed how well the whole domain of optimization problems is covered by the test functions included in the COCO framework.

The importance of ELA is stressed by the fact that this research field is also addressed in the proposal of the partner from TU Dortmund University for a research grant on "Exploratory Landscape Analysis for Algorithm Selection in Single- and Multiobjective Optimization" with the Deutsche Forschungsgemeinschaft (DFG, currently under review). As the TAO team is already involved in this proposal as well, a strong collaboration between both groups will be required.

Scientific Program

Task 5.1: Improving ELA for Unconstrained Single-Objective Optimization Although ELA has been already proven to be applicable in the unconstrained single-objective case, three research topics are planned to be investigated in the course of this project. First of all, we plan to improve the computational complexity of the ELA features and to determine which features provide the best trade-off between invested function evaluations and revealed problem properties. Second, the current ELA feature set is expected to be extended based on the test sets constructed in WP1–2. Third, the theoretical properties of already used low-level features are going to be analyzed.

Task 5.2: Extensions of ELA Towards Constrained and Multiobjective Optimization In order to extend ELA towards constrained and multiobjective optimization problems, new ELA features need to be designed, especially for characterizing different types of constraints. For the multiobjective case, besides the design of new specific multiobjective ELA features, adequate aggregation techniques will be investigated to transfer characteristics from the multiobjective problem formulation to already existing single-objective ELA features.

Milestones and Deliverables

D5.1 (M18) report about improved computational complexity of given ELA features and redefined and extended feature set specific to expensive and large-scale optimization [WP5.1]

D5.2 (M24) report about theoretical properties of low-level ELA features [WP5.1]

M5.3 (M30) agreement on a set of new ELA features for constrained optimization [WP5.2]
M5.4 (M36) agreement on a set of new ELA features for multiobjective optimization [WP5.2]

Risk and Risk Management The risk of this work package is relatively low and no other work package directly depends on it.

3.3.6 WP 6: ORGANIZATION AND DISSEMINATION

Participants: all, responsible: Anne Auger

This last work package deals with both organizational and disseminative issues. As already explained in Sec. 3.2, this work package covers the internal management of the project (hiring staff, writing intermediate reports, etc.) and the organization of internal meetings of the consortium. To help the participants to share their findings as well as to document their outcomes, an internal wiki page will be set up. A code and paper repository with access by all participants has been already arranged. Furthermore, a web page presenting the project, its members, and its outcomes in terms of reports, papers, talks, etc. will be installed as well.

Regarding the dissemination of results, we plan to present our work at various high-quality conferences and to integrate the state-of-the art in benchmarking into invited tutorials, we regularly give at international conferences. Moreover, we also plan to organize international workshops throughout the project's lifespan. In continuation of the previous and current BBOB workshops[3], we plan for example to further use the extended COCO framework (see WP 4) in future workshops with the goals to (i) establish the COCO framework in the research community and (ii) to collect further data which can be used in WP5. Possible opportunities would be the yearly GECCO and LION conferences as well as the biannual PPSN and EMO conferences. Note that we have been recently invited to organize the next BBOB workshop at the next LION conference in 2012 and consider a possible focus on expensive optimization.

Milestones and Deliverables

D6.1 project web page and internal wiki set up (M3)
D6.2 organization of a BBOB workshop with a possible focus on large-scale or expensive optimization (M24)
D6.3 organization of a BBOB workshop with a possible focus on constrained or multiobjective optimization (M48)

3.4 TASKS SCHEDULE, DELIVERABLES AND MILESTONES

Figure 2 shows the Gantt chart of the project schedule with the main deliverables and milestones as indicated in the detailed scientific program above. As the COCO framework only needs to be slightly adapted for the case of expensive and large-scale optimization, the work packages WP1 and WP2 will be tackled first. work package WP2.2 on constrained and WP3 on multiobjective optimization need a more involved structural change in the COCO framework and will therefore be tackled through the entire period of the project as well as the more or less independent WP1 with the exception of shifting the focus for the multiobjective part to the implementation aspect (WP4) right before the planned BBOB workshop

[3] see http://coco.gforge.inria.fr/doku.php for the details on the 2009, 2010, and 2012 editions

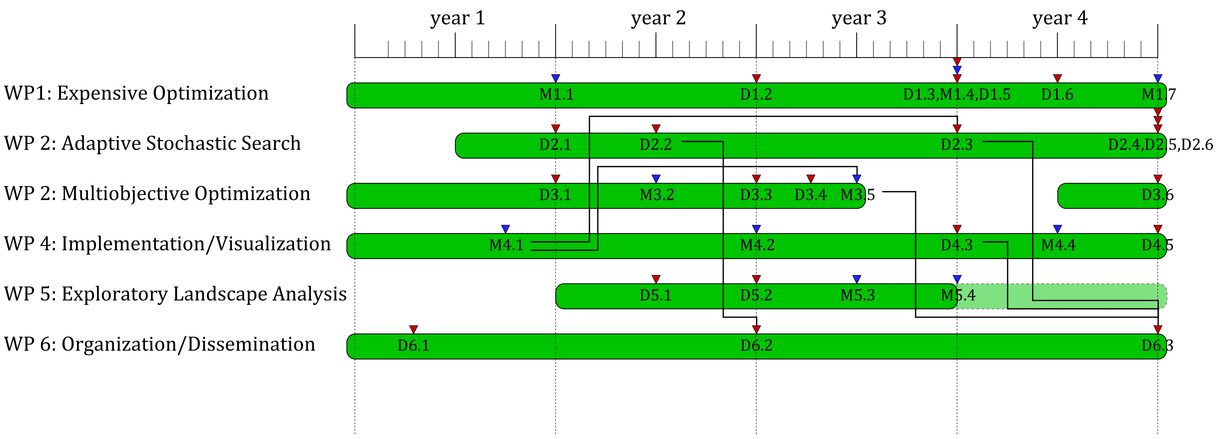

Figure 2: Overview of the projects work packages, milestones, and deliverables and their arrangement over time. Dependencies are denoted by arrows.

on that topic. The work package WP4 on implementation and visualization also covers the entire project period as it is crucial to the final outcomes while the exploratory landscape analysis (WP5) is starting after the first year and is expected to finish at the end of the third year of the project. Depending on the acceptance of the requested funding for the TU Dortmund University partner, WP5 might be continued until the end of the project period, which would be in particular beneficial as it relies on further data collected during the planned BBOB workshops. In case of inter-work package dependencies, enough slack between the milestones and deliverables is planned to not delay the overall progress of the project.

4 DISSEMINATION AND EXPLOITATION OF RESULTS, INTELLECTUAL PROPERTY

We will disseminate our results using the classical channels of conferences and journal publications. We plan to publish the results at the top peer-reviewed conferences in the fields of randomized search heuristics (GECCO, FOGA, PPSN, EMO) as well as of classical optimization (SIAM conference on optimization, ISMP) where we have been already actively publishing during the last years. Moreover, we are also aiming at submitting papers to high-quality journals such as Algorithmica, IEEE Transactions on Evolutionary Computation, Evolutionary Computation Journal, SIAM Journal on Optimization, Journal of Machine Learning Research.

Furthermore, we plan to disseminate our results towards the scientific community through tutorials that we were regularly asked to give at the annual GECCO conference (A. Auger and N. Hansen on CMA-ES since 2008; D. Brockhoff on EMO since 2011; M Preuss on several topics since 2005).

We will set up a wiki page for the project where results will be disseminated and continue to improve the wiki page of the COCO platform where source code is freely available, results are posted and online visualization tools will be set.

We plan to organize two workshops on blackbox optimization benchmarking during this project (in continuation to the previous workshops BBOB 2009, 2010 and 2012) either at GECCO or other high-quality conferences and workshops (see also WP 6 in Sec. 3.3.6). We have been recently invited to run the BBOB workshop at the next LION conference and plan a possible focus on expensive optimization for this workshop.

5 CONSORTIUM DESCRIPTION

5.1 PARTNERS DESCRIPTION & RELEVANCE, COMPLEMENTARITY

The backgrounds of the participants—with training in mathematics, computer science, statistics, and engineering—are complementing each other very well for the multidisciplinary work of search algorithm design for practical applications. This complementarity can be seen in several joint publications as well as within joint projects. The ANR OMD and OMD2 projects, for example, have seen the TAO and CROCUS teams work together closely in a highly industrial project (with involvements of car manufacturer Renault and the SMEs CD-adapco, SIREHNA, and ACTIVEEON). Also between the German partner TU Dortmund University, and the TAO and DOLPHIN teams, ongoing collaborations exist. Here, one should state explicitly the involvement of the TAO team in the recent proposal by the partners from TU Dortmund University for a research grant on "Exploratory Landscape Analysis for Algorithm Selection in Single- and Multiobjective Optimization" with the Deutsche Forschungsgemeinschaft (DFG, currently under review). Within the collaborative research center / transregio CRC/TR30 project[4] Dimo Brockhoff (DOLPHIN), Heike Trautmann (TUD), and Tobias Wagner (TUD) have furthermore collaborated since September 2011 with [20] as a first result. Also regarding the development of the COCO platform and the corresponding BBOB workshops, a close collaboration has been already established between the TAO team and TUD (the COCO platform development and the organizing team for the BBOB workshop include in particular Olaf Mersmann, Mike Preuss from TUD and Anne Auger, Nikolaus Hansen from TAO). More than 10 joint publications with two of the consortium partners have been already written.

TAO TEAM (INRIA SACLAY–ILE-DE-FRANCE, CNRS, AND UNIV. PARIS XI)

The INRIA-Saclay-Ile-de-France (Institut National de Recherche en Informatique et Automatique, site de Saclay) with the Machine Learning and Optimization team (TAO), joint team between INRIA and the Laboratoire de Recherche en Informatique (LRI) from the Paris-Sud University, UMR CNRS 8623 brings together specialists of Evolutionary Computation for Complex Systems and Machine learning and is under the scientific responsibility of Marc Schoenauer and Michele Sebag. The group combines expertise in stochastic optimization (in particular continuous blackbox optimization) and Machine Learning. The expertise of the team ranges from theory (formal proofs of convergence) to algorithm design (Nikolaus Hansen is the inventor of the CMA-ES algorithm) and real-world applications, with in particular several collaborations with industrial partners (Institut Français du Petrôle, Renault, Peugeot, Thales, Astrium, SNCF, ...). The TAO team counts 11 permanent researchers, 18 PhD students and 7 postdocs and engineers. The members involved in the NumBBO project have a high international visibility, Anne Auger, Nikolaus Hansen and Marc Schoenauer are part of the editorial board of the Evolutionary Computation Journal (ECJ), are track chairs for GECCO (the main conference on evolutionary computation), and give regular tutorials since 2007 at the conferences GECCO and PPSN. The TAO team has been introducing and has been the main driving force behind the COCO platform.

DOLPHIN TEAM (INRIA LILLE, CNRS, UNIV. LILLE 1, AND POLYTECH'LILLE)

INRIA's Lille - Nord Europe branch, inaugurated in 2008, currently employs around 300 people, including approximately 200 scientists in its 14 research teams. Recognized for its significant contribution to

[4] Synthesis and Multiobjective Model-based Optimization of Process Chains for Manufacturing Components with Functionally Graded Properties, http://www.isf.de/en/institut/forschung/simulation/tr30-d5.html

the social and economic development of the Nord - Pas-de-Calais region, the INRIA Lille - Nord Europe research center promotes a policy of close cooperation with major businesses and small enterprises. INRIA Lille - Nord Europe has a strong connection to the Laboratoire d'Informatique Fondamentale de Lille (LIFL) at the Université Lille 1 resulting in several joint research teams and made other strategic partnership agreements with CNRS, Ecole Centrale de Lille, Université Lille 2, Université Lille 3, as well as with the CWI in Amsterdam. It is furthermore an associate member of the Université Lille Nord de France cluster of research and higher education (PRES).

The DOLPHIN team is both an equipe-projet at INRIA Lille - Nord Europe and a research group at the LIFL. Its currently 10 permanent staff members and 13 PhD students work mainly on the modeling and resolution of large multiobjective problems using parallel and distributed hybrid techniques (DOLPHIN: Discrete multiobjective Optimization for Large scale Problems with Hybrid dIstributed techNiques). Other research interests are in single-objective and bilevel optimization. The target optimization problems are both generic (such as flow-shop scheduling or vehicle routing) and of industrial nature (mainly in logistics, transportation, energy, and bioinformatics).

CROCUS TEAM AT ECOLE DES MINES DE ST-ETIENNE

The CROCUS team (Calcul de Risque, Optimisation, Calage par l'Utilisation de Simulateurs) is one of the three teams of the LSTI laboratory (Laboratoire des Sciences et Technologies de l'Information, Ecole des Mines de Saint-Etienne, France). It has 5 permanents staff researchers and teachers and from 5 to 10 PhD and postdoctorate students. The CROCUS team carries out research on the use of random processes for metamodeling, design of experiments, sensitivity analysis, optimization and model merging. The application domains of these methods are varied since they concern all activities where decision is based on computationally expensive numerical simulations. CROCUS has collaborated with the aerospace and automotive industries (SNECMA, Airbus, Dassault Aviation, Renault). Other applications have been made in joint projects with the nuclear industry (IRSN, CEA, EDF), the oil industry (Total, IFP) and water resources management organizations (ADEME, Univ. Stellenbosh in S-Africa).

The team is also leading the applied mathematics major and Master's degree at the Ecole des Mines de Saint-Etienne. From July 2012 on, the team will integrate the LIMOS laboratory (Laboratoire d'Informatique, de Modélisation et d'Optimisation des Systèmes, CNRS UMR 6158) at Clermont-Ferrand, France.

TU DORTMUND UNIVERSITY (TUD), GERMANY

TU Dortmund University was founded in 1968 and has developed a unique profile with a special combination of faculties in the natural sciences and engineering, the social sciences and the humanities. This includes a wide spectrum of innovative research and more than 65 bachelor's and master's programs including a broad-based teacher training curriculum in at least 30 subjects.

The TUD team consists of three subgroups of different disciplines, i.e. (computational) statistics, computer science and mechanical engineering, which already worked together on many interdisciplinary research projects in the last decade. The group combines knowledge in statistics, machine learning, computational intelligence as well as single- and multiobjective optimization in general. All group members took part in various collaborative research projects and graduate schools funded by the DFG and are involved in a huge number of international research collaborations.

5.2 Qualification of the Project Coordinator

A. Auger received her Master Degree in applied mathematics from the Paris VI university in 2001 and her doctoral degree in applied mathematics in 2004. She worked as a postdoctoral researcher at ETH Zurich from 2004 to 2006. Since 2006 she holds a permanent research position at INRIA. She is currently chargée de recherche 1st class. She has been involved since 2006 in 3 ANR research proposals, OMD, TRAVESTI and OMD2. She is coordinating for the TAO team the OMD2 project. She is involved in the SYTEM@TIC Paris Region project CSDL and was in the INRIA-Microsoft joint lab on the adaptive search project. Since 2006, she has been supervising 3 postdoctoral fellows, 3 PhD students including one industrial CIFRE with the French Institute for Petrol and 6 Master thesis and research internships.

She has 11 journal publications and 27 peer-reviewed conference articles and collaborated with the 3 other partners of the project: Dimo Brockhoff from DOLPHIN (8 joint conference and journal publications); Rodolphe Le Riche through the OMD and OMD2 ANR joint projects and Mike Preuss and Olaf Mersmann from TUD via the COCO platform and BBOB workshop organizations. She has been organizing several workshops (BBOB 2009,10,12; ThraSH 2010), the Dagstuhl seminar on theory of Evolutionary Algorithms in 2008 and 2010, has been invited to give 8 tutorials in international conferences and workshops. She is in the editorial board of the Evolutionary Computation Journal, has been editing the book “Theory of Randomized Search Heuristics: Foundations and Recent Advances” together with B. Doerr. She is guest editor of a special issue on Theory of Randomized Search Heuristics for the Algorithmica journal and on blackbox-Optimization Benchmarking for the Evolutionary Computation Journal. She is publication chair for GECCO 2012 and was theory track co-chair in 2011.

5.3 Qualification and Contribution of Each Partner

TAO The TAO members involved in the project are expert in stochastic blackbox continuous optimization. They are the main driving force behind the adaptive algorithm CMA-ES. Their expertise ranges from theory to algorithm design and practical application. They have been intensively working on the benchmarking platform COCO the past years, starting its development and making it available and know to the community thanks to the different workshops organized. They are also working on multiobjective algorithms (theory and algorithm design) and meta-models methods based on CMA-ES. They will contribute to WP1, WP2, WP3, WP4: the detail of their contribution is explained within the work package description.

DOLPHIN DOLPHIN’s main expertise lies in the field of multiobjective optimization—both with respect to continuous as well as discrete search spaces and with respect to exact and heuristic approaches. The team members, which are involved in this project, will therefore invest a substantial part of their time into the work package on multiobjective optimization (WP3), but will also actively contribute to the work packages 4–6 with their background in (theoretical) computer science.

CROCUS The CROCUS team is expert on optimization for expensive function using surrogate approaches (kriging, EGO) and develop meta-model approaches, design of experiments using random processes. They have a great expertise in various industrial applications. R. Le Riche has been coordinating the ANR OMD project involving various academic and industrial partners. They will be involved in the expensive optimization part of the project.

TUD TUD comprises a high expertise in statistics, e.g. meta-modeling, model validation, benchmarking techniques and Exploratory Landscape Analysis, which will play a major role in the WPs 1, 3 and 5. Furthermore, the team members' research is focused on both single- and multiobjective evolutionary optimization enhanced by a high expertise in EA theory in the working group of Prof. Rudolph which will be important for WPs 1 as well as 3–5.

6 SCIENTIFIC JUSTIFICATION OF REQUESTED RESOURCES

6.1 PARTNER 1: TAO, INRIA SACLAY – ILE-DE-FRANCE

Equipment We expect to buy six laptops over the period of the project for the 6 persons from the TAO team that will work on the project over the 4 years and two desktops for running benchmarking experiments, totaling to 15k€ .

Staff PhD_1 who will work on WP4 and WP2.2 for a total of 113,906.71€ .
$Postdoc_1$ for 24 months for a total of 97,169.78€ who will work on WP2.1 and WP2.3

Travel Participation in three international conferences outside Europe (3×3k€) and four Europe-based conferences (4×1.5k€) is expected per year. The total is 60k€ for the 4 years. Additional 5k€ are requested to invite the partners from TUD to Paris for scientific exchanges.

Other Expenses The organization of two international workshops on blackbox optimization benchmarking to present the results of the project and to collect additional data for COCO (including costs for invited speakers and the payment of travel expenses of the organizers) needs an additional 2×5k€ = 10k€ .

6.2 PARTNER 2: DOLPHIN, INRIA LILLE – NORD EUROPE

Equipment We budget around 800€ per person year including the laptops/desktops for the two postdocs to be hired within DOLPHIN with a total amount of 5k€ .

Staff $Postdoc_2$: 24 months of postdoctoral fellowship on multiobjective optimization. This person should optimally have a strong background in the field of evolutionary multiobjective optimization and in particular in randomized search heuristics for continuous domain and will mainly work on the subtasks 4.2, 4.3, 4.4, i.e., the design of efficient multiobjective algorithms as well as on the COCO extension to multiobjective optimization during years 2 and 3 of the project.
$Postdoc_3$: 12 months of postdoctoral fellowship on multiobjective optimization. The second postdoc is expected to have a similar background as $Postdoc_2$ and will mainly work on the subtasks 4.3 and 4.4 in the third year of the project in order to amplify the progress towards milestone M4.5 (extension of the COCO framework to multiobjective optimization) as well as towards the planned BBOB workshop on multiobjective optimization (D7.3).

Table 1: Overview of the partners involved in the consortium. Positions to be funded via the current proposal are not included. Abbreviations: person months (PM), principal investigator (PI), multiobjective optimization (MOO), black box (BB), elementary landscape analysis (ELA), evolution strategies (ES), evolutionary computation (EC). A * indicates that the funding depends on the acceptance of the DFG proposal, currently under review. In total, 72PM of postdoc and about 24PM of student research assistants are requested with the DFG proposal.

Partner	Name	First name	Position	PM	Contribution to the project (4 lines max)
TAO	AUGER	Anne	CR1 INRIA	24	PI, participation in all WP, expert in cont. BB opt., CMA-ES and MOO, developer of COCO
	HANSEN	Nikolaus	CR1 INRIA, HDR	14.4	coordinator WP2, participation in all WP, expert in cont. BB opt., developer of CMA-ES and COCO
	SCHOENAUER	Marc	DR1 INRIA, HDR	7.2	WP1, WP3, WP6, expert in EC, developer of COCO
	PhD$_0$		PhD student	36	hired via ministry grant
DOLPHIN	BROCKHOFF	Dimo	CR2 INRIA	24	coordinator WP3, involved in WP3–6, expert in MOO
	LIEFOOGHE	Arnaud	MdC Univ. Lille 1	9.6	WP3, WP4, WP6, expert in MOO
	PhD$_2$		PhD student	36	to be hired via ministry grant, WP3, WP4, WP6
CROCUS	LE RICHE	Rodolphe	CR1 CNRS, HDR	10	coordinator WP1, expert in meta-modeling and optimization
	BAY	Xavier	Maître assistant	4	WP1, expert in probability and optimization
	DELORME	Xavier	Maître assistant	4	WP1, expert in single and multiobjective optimization
	FONGANG-FONGANG	Derrick	PhD student	9	WP1, WP4, PhD in optimization
	VILLANUEVA	Diane	PhD student	9	WP1, WP4, PhD in optimization
TU Dortmund University	RUDOLPH	Günter	Prof. Dr.	4	participation in WPs 3, 5, and 6, co-PI of partner's DFG proposal, expert in theory of ES and MOO
	PREUSS	Mike	PhD student	4	WP4–6, expert in experimental analysis and real-world applications of EC, developer of COCO
	TRAUTMANN	Heike	postdoc	8	coordinator WP5, participation in WPs 3–6, co-PI of partner's DFG proposal, expert in statistics and MOO
	MERSMANN	Olaf	PhD student	0*	expert in statistics and ELA, developer of COCO
	BISCHL	Bernd	PhD student	0*	expert in statistics and machine learning
	WAGNER	Tobias	PhD student	0*	expert in surrogate approaches and MOO

Travel The participation in two Europe-based (1.5k€ each) and two conferences abroad (2.5k€ each) per year is expected for the involved DOLPHIN members throughout the project period (32k€ in total). In addition, about two research meetings of the consortium outside Lille are expected per year with costs of around 200€ per person each (with a total of 5k€). Overall, the expected travel costs are 37k€ .

Other Expenses No other expenses such as subcontracting or costs justified by internal procedures of invoicing are expected.

6.3 PARTNER 3: CROCUS, ECOLE DE MINES SAINT ETIENNE

Equipment The equipment requested corresponds to 3 laptops for $3 \times 2 = 6$k€ .

Staff *PhD*$_3$ The funding of 1 PhD student to help carrying out the work on metamodel assisted optimization for expensive functions (tasks 1.1 and 1.2) is asked for. The cost is 107k€ . The new work on surrogate based optimization (tasks 1.1 and 1.2) will be the focus of this PhD: building kernels for constrained optimization.

Travel The participation by 2 persons to a European and to a further located conference is expected: $2 \times (2 + 1.5) \;=\; 7$k€ .
Two persons will go to Paris 3 times a year for 3 years: $2 \times 3 \times 3 \times 0.2 \;=\; 3.6$k€ .
The PhD student will spend a week in Orsay to interact with other project partners (3 nights) and, once a year, two persons spend a night out-of-town to attend a project meeting for three years: $(3 + 2 \times 3) \times 0.15 \;=\; 1.35$k€ .
The total traveling cost of the EMSE partner is 11.95k€ .

Other Expenses No other expenses such as subcontracting or costs justified by internal procedures of invoicing are expected.

6.4 PARTNER 4: TU DORTMUND UNIVERSITY, DORTMUND, GERMANY

As partner abroad, TU Dortmund University cannot claim any expenses with ANR. However, a proposal entitled "‘Exploratory Landscape Analysis for Algorithm Selection in Single- and Multiobjective Optimization"’ with a slightly different focus than NumBBO is currently under review with the DFG (Deutsche Forschungsgemeinschaft) which has a “bilateral accord” with the ANR. The funding of the involved members of TU Dortmund University mentioned in Sec. 5.3 is ensured. The main overlap between the two proposals is in the multiobjective (WP3) and the exploratory landscape analysis (WP5) work packages of NumBBO.

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A CURRICULA VITÆ OF THE PROJECT COORDINATORS

ANNE AUGER

Education and Experience
Current position: Chargée de recherche premiere classe at INRIA Saclay–Ile-de-France in the TAO team located at the Laboratoire de Recherche en Informatique (LRI) from the University Paris Sud.
Cursus: Master degree in mathematics from Paris VI University (2001) Agrégée of mathematics (2000), PhD in applied mathematics from Paris VI University (2004). Postdoctoral researcher at ETH Zurich (2004–2006). Permanent researcher at INRIA from 2006.

Responsibilities and activities:
⋆ Publication chair for ACM-GECCO 2012, Theory track co-chair of the ACM-GECCO 2011
⋆ Member of the editorial board of the *Evolutionary Computation Journal*. Editor of the book "Theory of Randomized Search Heuristics: foundations and recent advances" together with B. Doerr. Guest editor of a special Issue on Theory of randomized search heuristics for the Algorithmica journal and on BlackBox-Optimization Benchmarking for the Evolutionary Computation Journal
⋆ Organizer of the Dagstuhl seminar on *Theory of Evolutionary Algorithms* in 2008 and 2010; of the ThRaSH workshop in 2010; of the BlackBox-Optimization Benchmarking (BBOB) workshops at GECCO in 2009, 2010, 2012
⋆ Invited tutorials at LION 6 in 2012, ACM-GECCO 2008,09,10,11,12, ThRaSH workshops 2007, 2010

Research interests: Stochastic blackbox continuous optimization including theoretical analysis of randomized search heuristics and design of new algorithms. Benchmarking of algorithms, single and multi-objective optimization

Significant publications:

1. A. Auger, J. Bader, D. Brockhoff, and E. Zitzler. *Hypervolume-based Multiobjective Optimization: Theoretical Foundations and Practical Implications*. Theoretical Computer Science, 2011 (in press).
2. Hansen, N., R. Ros, N. Mauny, M. Schoenauer and A. Auger (2011). Impacts of Invariance in Search: When CMA-ES and PSO Face Ill-Conditioned and Non-Separable Problems. Applied Soft Computing, to appear, Elsevier;
3. Jebalia, M., A. Auger and N. Hansen (2011). Log-Linear Convergence and Divergence of the Scale-Invariant (1+1)-ES in Noisy Environments, Algorithmica, 59(3), pp. 425-460
4. Brockhoff, D., Auger, A. and Hansen, N. Mirrored Sampling in Evolution Strategies With Weighted Recombination, Accepted for GECCO 2011.
5. Auger, A. and Brockhoff, D. and Hansen, N. (2011), "Analyzing the Impact of Mirrored Sampling and Sequential Selection in Elitist Evolution Strategies", Foundations of Genetic Algorithms (FOGA 2011). ACM.

DIMO BROCKHOFF

Education and Experience
Current position: Chargée de recherche deuxieme classe at INRIA Lille - Nord Europe in the DOLPHIN team since November 2011
Cursus: diploma in computer science (Dipl.-Inform.) from University of Dortmund, Germany in 2005; PhD (Dr. sc. ETH) in April 2009 from ETH Zurich, in Zurich, Switzerland; postdoctoral researcher at INRIA Saclay — Ile-de-France in the TAO team from June 2009 till November 2010; postdoctoral researcher at Ecole Polytechnique in the sysmo team between November 2010 and October 2011

Responsibilities and activities:
⋆ organization of several workshops (ThRaSH'2012, ThRaSH'2010, at PPSN'2012 and GECCO'2010) and special sessions (e.g. at MCDM'2011) on evolutionary multiobjective optimization (EMO)
⋆ invited tutorial on this topic at the GECCO'2012 and GECCO'2011 conferences
⋆ published 5 journal papers, 20 peer-reviewed papers at international conferences, 2 invited book chapters, and 11 workshop papers

Research interests: randomized search heuristics for both single- and multiobjective optimization, in particular on theoretical aspects of indicator-based search as well as on the design of derandomized variation operators

Most Significant Publications

J. Bader, D. Brockhoff, L. Thiele, and E. Zitzler. Directed Multiobjective Optimization Based on the Hypervolume Indicator. *Journal of Multi-Criteria Decision Analysis*, 2012. accepted for publication.

A. Auger, J. Bader, D. Brockhoff, and E. Zitzler. Hypervolume-based Multiobjective Optimization: Theoretical Foundations and Practical Implications. *Theoretical Computer Science*, 2012. Online first. DOI: 10.1016/j.tcs.2011.03.012

A. Auger, D. Brockhoff, and N. Hansen. Mirrored Sampling in Evolution Strategies With Weighted Recombination. In *Genetic and Evolutionary Computation Conference (GECCO 2011)*, pages 861–868. ACM, 2011.

D. Brockhoff and E. Zitzler. Objective Reduction in Evolutionary Multiobjective Optimization: Theory and Applications. *Evolutionary Computation*, 17(2):135–166, 2009.

E. Zitzler, D. Brockhoff, and L. Thiele. The Hypervolume Indicator Revisited: On the Design of Pareto-compliant Indicators Via Weighted Integration. In S. Obayashi et al., editors, *Conference on Evolutionary Multi-Criterion Optimization (EMO 2007)*, volume 4403 of *LNCS*, pages 862–876, Berlin, 2007. Springer.

NIKOLAUS HANSEN

Education and Experience

Current position: Chargé de recherche 1ière classe with INRIA Saclay – Île-de-France, in the TAO team located at the Laboratoire de Recherche en Informatique (LRI) of the University Paris-Sud (since September 2009).

HDR: *Variable metrics in evolutionary computation*, February 2010

Ph.D.: *Generalized individual step-size control in the evolution strategy* (in german), Department Bionics and Evolution Technique, Technical University Berlin, Germany, September 1998, advisor: Ingo Rechenberg

Cursus: Studies of medicine (FU Berlin), knowledge engineering (GNB) and mathematics (TU Berlin), software engineer (1989–1992), research assistant/associate (1994–2000, TU Berlin), statistician (2001–2002), senior research associate (2003–2007, ETH Zurich), expert engineer (2007-2009, INRIA).

Research interests

evolutionary computation, stochastic optimization, statistical machine learning

Significant publications

1. N. Hansen, R. Ros, N. Mauny, M. Schoenauer and A. Auger. Impacts of Invariance in Search: When CMA-ES and PSO Face Ill-Conditioned and Non-Separable Problems. *Applied Soft Computing* 11, 5755-5769, Elsevier, 2011.
2. T. Suttorp, N. Hansen, and C. Igel. Efficient covariance matrix update for variable metric evolution strategies. *Machine Learning*, 75:167–197, 2009.
3. N. Hansen, S. P. N. Niederberger, L. Guzzella, and P. Koumoutsakos. A method for handling uncertainty in evolutionary optimization with an application to feedback control of combustion. *IEEE Transactions on Evolutionary Computation*, 13(1):180–197, 2009.
4. C. Igel, N. Hansen, and S. Roth. Covariance Matrix Adaptation for Multi-objective Optimization. *Evolutionary Computation*, 15(1):1–28, 2007.
5. N. Hansen and A. Ostermeier. Completely derandomized self-adaptation in evolution strategies. *Evolutionary Computation*, 9(2):159–195, 2001.

RODOLPHE LE RICHE

Education and Experience
Current position: CNRS first class permanent research associate at the Ecole des Mines de Saint-Etienne, France.
Cursus: Engineering degree from Compiègne University of Technology (France), PhD in aerospace engineering from Virginia Polytechnic and State University (USA), postdoctoral researcher at Ecole des Mines de Paris (1997-97), CNRS permanent research associate from 1998 on (in Rouen and Saint-Etienne, France). Rodolphe Le Riche is 43.

Responsibilities and activities:
⋆ Head of the DEMO team ("Decision in the Enterprise: Modeling, Optimization", a team of the Henri Fayol Institute, Ecole des Mines de Saint Etienne, 10 permanent researchers, since 2011). Head of the CROCUS team ("Calcul de Risque, Optimisation et Calage pour l'Utilisation de Simulateurs", a team of the LSTI laboratory, Saint-Etienne, 5 permanent researchers, since 2010).
⋆ Member of the editorial board of the *Journal of Structural and Multidisciplinary Optimization*
⋆ Principal Investigator of the ANR/OMD project (OMD = MDO = MultiDisciplinary Optimization) from 2006 to 2009.

Research interests: Surrogate-based global optimization, evolutionary optimization, applications in mechanical engineering, identification of behaviour laws in solid mechanics.

Most Significant Publications

J. Janusevskis and R. Le Riche, Simultaneous kriging-based estimation and optimization of mean response. *Journal of Global Optimization*, Springer, DOI 10.1007/s10898-011-9836-5, published online in Jan. 2012.

Ginsbourger, D., Le Riche, R. and Carraro, L., Kriging is well-suited to parallelize optimization. Chapter 6 of *Computational Intelligence in Expensive Optimization Problems*, Springer series in Evolutionary Learning and Optimization, Yoel Tenne and Chi-Keong Goh, Editors, published online in March 2010, ISBN: 978-3-642-10700-9, pp. 131-162, April 2010.

D. Ginsbourger and R. Le Riche, Towards Gaussian-Process based optimization with finite time horizon. Chapter in mODa9 - *Advances in Model-Oriented Design and Analysis* , A. Giovagnoli, A. C. Atkinson and B. Tornsay Ed., Contributions to Statistics series, Physica-Verlag Pub., 2010, pp.89-96.

Gogu, C., Haftka, R. T., Le Riche, R., Molimard, J., Vautrin, A., An Introduction to the Bayesian Approach Applied to Elastic Constants Identification, *AIAA Journal* Vol. 48, No. 5, pp. 893-903, 2010.

Le Riche, R., Picheny, V., Ginsbourger, D., Meyer, A. and Kim, N.-H., Gears design with shape uncertainties using Monte Carlo simulations and kriging, 50th *AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, Palm Springs, USA, May 4-7, 2009, paper No. AIAA-2009-2257.

HEIKE TRAUTMANN

Education and Experience
Current position: Postdoctoral researcher at the Statistics Department, TU Dortmund University, Germany.
Cursus: Statistics diploma in 2000; Consultant in an Automative Company, (2000-2001); Consultant in a strategy consulting company in Munich (2001-2002); ”Graduate School of Production Engineering and Logistics”, TU Dortmund; PhD (Dr. rer. nat.) 2004; DfG (German research foundation) PostDoc research grant in the ”Graduate School of Statistical Modeling”, TU Dortmund (2004-2006); Personal DfG PostDoc research grant, TU Dortmund (2006-2007).

Responsibilities and activities:
⋆ workshop organization (e.g. "Workshop on Automated Selection and Tuning of Algorithms" at PPSN 2012) and special sessions ("Designing Evolutionary Processes" at CEC 2010) on multiobjective optimization
⋆ published 10 journal papers and 21 peer-reviewed papers at international conferences

Research interests: multiobjective (evolutionary) optimisation, in particular preference incorporation, performance assessment and stopping criteria; algorithm benchmarking concepts and Exploratory Landscape Analysis (ELA)

Most Significant Publications

O. Mersmann, M. Preuss, H. Trautmann, B. Bischl and C. Weihs. Analyzing the BBOB Results by Means of Benchmarking Concepts. *Evolutionary Computation Journal*, 2012. accepted for publication.

H. Trautmann, T. Wagner, D Biermann and C. Weihs. Indicator-Based Selection in Evolutionary Multiobjective Optimization Algorithms Based on the Desirability Index. *Journal of Multi-Criteria Decision Analysis*, 2012. accepted for publication.

O. Mersmann, B. Bischl, H. Trautmann, M. Preuss, C. Weihs and G. Rudolph. Exploratory landscape analysis. In *Genetic and Evolutionary Computation Conference (GECCO 2011)*, pages 829–836. ACM, 2011.

T. Wagner and H. Trautmann. Integration of preferences in hypervolume-based multiobjective evolutionary algorithms by means of desirability functions. *IEEE Transactions on Evolutionary Computation*, 14(5):688–701, 2010.

H. Trautmann and T. Wagner and B. Naujoks and M. Preuss and J. Mehnen. Statistical Methods for Convergence Detection of Multi-Objective Evolutionary Algorithms. *Evolutionary Computation*, 17(4):493–509, 2009.