SOLVeR: A Blueprint for Collaborative Optimization in Practice

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ABSTRACT

Collaboration among different stakeholders in achieving a problem-solving task is increasingly recognized as a vital component of applied research today. For instance, in various research areas in engineering, economics, medicine, and society, optimization methods are used to find efficient solutions. Such a problem-solving task involves at least two types of collaborators – optimization experts and domain experts. Each collaborator cannot solve a problem most efficiently and meaningfully alone, but a systematic collaborative effort in utilizing each other's expert knowledge plays a critical and essential role. While many articles on the outcome of such collaborations have been published, and the justification of domain-specific information within an optimization has been established, systematic approaches to collaborative optimization have not been proposed yet. In this paper, methodical descriptions and challenges of collaborative optimization in practice are provided, and a blueprint illustrating the essential phases of the collaborative process is proposed. Moreover, collaborative optimization is illustrated by case studies of previous optimization projects with several industries. The study should encourage and pave the way for optimization researchers and practitioners to come together and embrace each other's expertise to solve complex problems of the twenty-first century.

Keywords: Collaborative Optimization, Industrial Optimization, Multi-disciplinary Design Optimization, Domain-specific Expert, Optimization Expert

1. INTRODUCTION

Interdisciplinarity is a critical component of any applied research nowadays. Multiple branches of knowledge coming together require not only to master each discipline independently but also their intersections. A discipline playing an essential role in various sciences regarding problem-solving tasks is (mathematical) *optimization*. The interdisciplinary character of optimization becomes apparent by studying related literature in various research fields, such as engineering, economics, medicine, and society [1]–[4]. While reading different kinds of studies, one will realize that some publications focus on the domain and others more on the optimization method itself; however, most of the attention is paid to the investigation's outcome and not the collaborative process. Since collaboration is vital for success, this paper focuses on aspects of collaborative research in the context of optimization, which will be referred to as *collaborative optimization* in the remainder of this study.

Collaborations are essential in an interwoven discipline like optimization, which requires knowledge in optimization itself and one or multiple other domains. Because domain knowledge is the foundation for the algorithm's design, its incorporation requires a fundamental or even deep understanding of the domain and the desired method's requirements. Naturally, this demonstrates the need for the domain and optimization knowledge, which is realized by initiating a collaboration. The attempt of *separately* solving the domain-specific and optimization-related tasks is likely to fail; however, this is still carried out even nowadays in practice. For instance, such a clear separation of tasks can be realized by having a domain expert formulating the problem statement on its own and the optimization expert to develop from there on the algorithm without any further feedback from the domain expert. Even though each task should have a collaborator responsible and take the lead, communication and agreements are vital for true collaboration and success. Thus, in collaborative optimization, the outcome is more than the sum of its parts, and success is achieved by effectively addressing the fusion of multiple research fields.

This paper's focus shall lie on the research collaboration in any kind of discipline where optimization is needed and applied. Thus, the different phases of collaboration and all supporting activities are of importance. Furthermore, in this study, collaborative optimization is based on human-human interactions; however, human-machine interaction can be a component of the problem description. Nevertheless, related works specify collaborative optimization only in the context of multi-disciplinary design optimization [5], this study considers collaboration in a more generic context. Moreover, it is worth mentioning that the term collaborative optimization has also been used to refer to a specific type of algorithms to solve large-scale optimization problems [6], [7], which shall also not be the focus of this study.

In the remainder of this paper, we first discuss work related to different aspects of collaborative optimization. In Section 3, we propose a blueprint for collaborative optimization by describing primary and supporting activities. Illustrative case studies are provided in Section 4 and conclusions are discussed in Section 5.

2. RELATED WORK

Collaboration can be defined as "the situation of two or more people working together to create or achieve the same thing" [8]. The aspect of sharing the same goal while working together is essential to understand the word's meaning. Another definition emphasizes the existence of conflicting goals, which shall be reduced to a common denominator and the fact a collaboration to be more contentious than a coordination or cooperation [9]. In the field of optimization, well-studied subjects characterize collaboration by projects and project management, interdisciplinarity, communication, and (applied) research. Even though all of them have to be mastered simultaneously in collaborative optimization, related work shall consider them independently for now. A more precise definition of collaborative optimization and these aspects' interactions will be provided later on in this study.

Projects have been well-studied throughout the literature and are a fundamental part of the economics literature. Especially techniques to measure the success of a project have been of interest. A well-known method for measuring success is the so-called iron triangle, describing success as a trade-off of time, cost, and quality [10]. Whereas most authors agree with the criteria being used are critical, the model has also been criticized for being too simple. Thus, more sophisticated models have been proposed to measure the success or failure of a project. In general, there is an agreement that for projects in general, measuring success is challenging, not least because of subjective views of stakeholders or the time dependency [11]. During a project, the time is also referred to as the project life cycle, which can be divided into different phases: conceptualization, planning, executing, termination [12]. More modern approaches, however, are not following the traditional waterfall model; instead, they pursue a flexible and iterative project management strategies [13].

Projects with goals regarding more than one discipline have to deal with interdisciplinary challenges. Interdisciplinary is characterized by a suitable combination of knowledge from different specialties to achieve that the combinations' values exceed the sum of all contributions individually [14]. A successful fusion of disciplines requires to unify separate ways of understanding and approaching problems across disciplines [15]. Rooting interdisciplinary research more in society was attempted by promoting work across disciplines on many research universities' campuses in the United States in the past years. However, the general superiority of interdisciplinary over disciplinary knowledge has also been critically assessed [16].

Collaboration across disciplines has to ensure efficient communication. Unavoidably, communication is a practical discipline and a vital skill for many different sciences [17]. It is a widespread belief that interpersonal and social problems are caused by impaired communication and can be alleviated by good communication [18].

Besides essential aspects of collaboration itself, successful collaborations in optimization are evident by studying the literature. Various studies show optimization is almost ubiquitous, for instance, in Agriculture [1], Engineering [2], Medicine [3] , or Economics [4]. Different research studies use different kinds of collaborations among different stake-holders. Collaboration are also set up in different ways, for example, in the same laboratory between researchers, across departments and research groups, across research institutes in the same of different countries, or between academia and industry.

3. SOLVER: COLLABORATIVE OPTIMIZATION

Collaborative optimization describes a procedure involving at least two stakeholders – a domain-specific and optimization expert – pursuing to solve an optimization problem *interactively*. The domain-specific expert initially provides the problem to be solved with the optimization expert's knowledge and experience. The interaction between both experts is crucial to successfully solve the problem and can occur at different levels of involvement.

Even though collaborations are carried out in different manners and have different challenges, they often have analogous phases and supplemental activities. Thus, collaborative optimization shall be schematized to track the overall progress and highlight important aspects for a successful collaboration. A blueprint for collaborative optimization is shown in Figure 1, presenting not only the phases but also the supporting activities. The primary phases follow the *SOLVeR* acronym: Specification of the Problem ('S'), Optimization and Algorithm Design ('O'), Live Test ('L'), Verification of Method and Results ('Ve'), and Repetitions and Lessons Learned ('R'). For each phase, the domain and the optimization expert's roles and responsibilities differ and shall be discussed in detail. Moreover, the arrows between the phases on the bottom indicate that multiple iterations of phases are inevitable in practice and an essential part of a collaboration. Furthermore, the phases are accompanied by supporting activities, such as project management, communication, interdisclinarity and the type of collaboration. The blueprint's split of primary and supporting activities is inspired by the well-known value chain model [19] with similar characteristics. Both the primary, as well as supporting activities are essential to reach the goals. In the following, the five *SOLVeR* phases are discussed, and additionally, an overview of each phase's characteristics is provided in Figure 2. Moreover, all supporting activities are described in detail.

(i) Specification of the Problem ('S'): In the first phase, all collaborators shall get a clear understanding of the optimization method's overall goal. For the optimization expert, this often requires understanding the fundamentals of a foreign research field. Thus, the domain expert's responsibility is to communicate efficiently and to define domain-related terminology if necessary. The primary goal is not for all collaborators to understand every little detail but to grasp what the problem is about. Thus, abstraction should be made whenever possible. Moreover, possible requirements and meta-information about the problem should be discussed, for instance, the evaluation time of a single design or the type and number of variables to be considered. After the problem has been defined verbally, it shall be stated mathematically, defining the objective(s), constraints, and the underlying search space. With fundamental knowledge about the domain, the optimization expert will often take the lead for the mathematical problem formulation. Nevertheless, the domain expert's feedback is crucial to ensure the formulation fits the specifications and the domain expert's expectations. For instance, a target measure could be either incorporated into the problem formulation as a constraint or an objective. Whereas

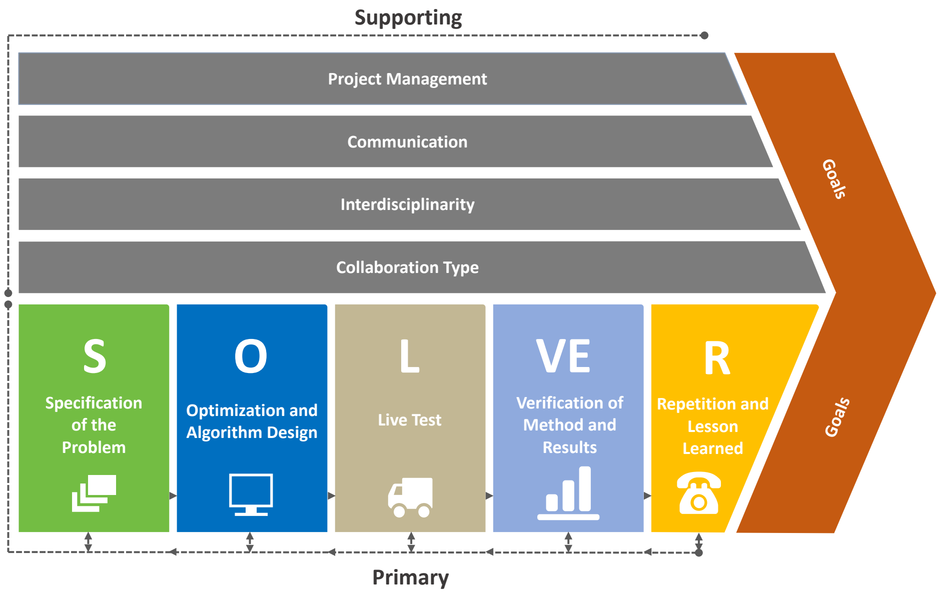

Figure 1: SOLVeR – Collaborative Optimization Practice.

both options might be legitimate ways of considering this metric, domain knowledge can favor one or the other. The domain knowledge, together with the optimization expert's knowledge about each option's benefits and drawbacks in an optimization sense, demonstrates the benefits of a close collaboration from the beginning.

(ii) Optimization and Algorithm Design ('O'): After the problem has been defined mathematically, the design of a suitable algorithm shall be of most interest. The selection or design of an algorithm requires experience in optimization and can be rather challenging. Before starting with the algorithm's design, all problem-dependent information shall be analyzed. For instance, does the evaluation also provide information about the gradient? How many function evaluations are affordable? However, some characteristics can only be assumed and are not known beforehand. For example, a vital question to ask is the modality of the function's fitness landscape because it determines whether a local or global search might be appropriate. If there is an explicitly defined equality constraint, one of the variables can be replaced in terms of other variables – a process that eliminates one variable, and also every modified solution will automatically satisfy the equality constraint. The use of such information to redefine an original problem requires collaboration between optimization and domain-specific experts at the start of the optimization process. A standard optimization algorithm can be modified to suit the supplied problem information. This can happen in modifying different operators of the algorithm. For example, the initial solution(s) can be repaired to satisfy certain constraints so that the search can begin from a good solution(s). The generative operations for creating new solutions can be motivated by the problem information so that new solutions satisfy the supplied problem information.

The fact that the mathematical problem definition and the optimization method are directly linked to each other demonstrates the interdependence of the first two phases and the importance of collaboration. After completing phase two, an algorithm has been developed, possible bugs during development have been fixed, and source code or a binary file for running the method exists.

(iii) Live Test ('L'): In the third phase, the developed algorithm is run in a live environment to observe its performance on the real-world optimization problem. The testing phase is crucial to ensure that the algorithm's design is suitable for the original problem. This might require interfacing between different programming languages or setting up the computational resources to run the method in a live environment. The domain and optimization expert's responsibilities in this phase depend on the type of collaboration and agreements. On the one hand, the algorithm design might be driven by test problems with similar characteristics as the real-world optimization problem because of the lack of computational resources or software licenses on the algorithm developer's end or the industrial partner preferring not to make the problem accessible to the outside. On the other hand, the problem's evaluation function might be delivered to the optimization expert – either open or closed source – and be directly used during the algorithm's design. In some cases, the problem might have been only defined vaguely from the beginning on, and the developer needs to implement a representative live environment from scratch, for instance, by generating synthetic data with reasonable assumptions. The variety of live tests' realizations show that different collaboration types require a different amount of collaborative effort in this phase. However, no matter what type has been chosen, this phase's outcome is a method and results that have to be analyzed.

(iv) Verification of Method and Results ('Ve'): In the fourth phase, the goals and requirements defined initially need to be critically assessed and verified. The verification is based on the results obtained in the previous phase. Even though the verification procedure will vary from collaboration to collaboration, some tasks employed in practice are to analyze the

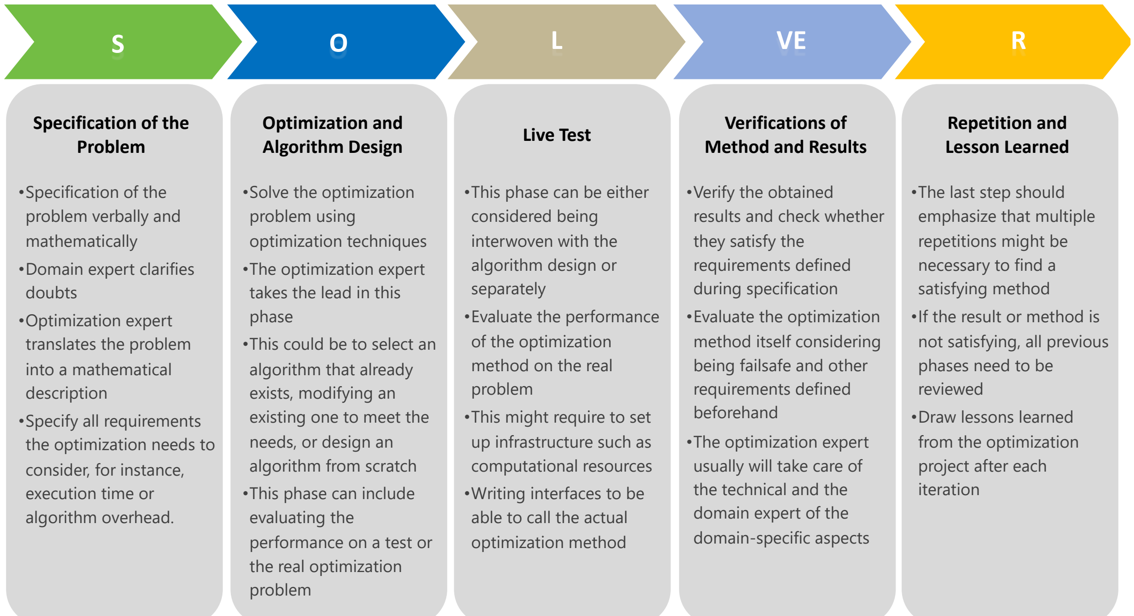

Figure 2: SOLVeR – The phases and responsibilities.

algorithm's convergence over time and carefully inspecting the solutions being found. In some collaborations, the optimization is only performed once, and most attention is paid to the obtain solution(s) itself, and the method plays a minor role. The obtained solutions need to be closely examined and made sure that all requirements are satisfied. The examination often involves checking correctness, feasibility, and the visualization of solutions and results. If discrepancies have been observed, the mathematically defined problem might need to be refined or even entirely redefined, and a reiteration to phase one be necessary. Other collaborations might focus more on the method itself, primarily when the algorithm is run repetitively, for instance, daily or weekly. Then, a thorough test of the method, including possible boundary scenarios, is of importance. Moreover, for stochastic algorithms, not a single run's performance but a statistical analysis of a set of runs shall be done to address the underlying randomness and ensure the method's robustness. No matter where the priority of the collaboration lies, the verification is crucial to measure the overall success.

(v) Repetition and Lesson Learned ('R'): As recommended for projects in general, the last phase consists of reflecting on the collaboration and critically assessing the progress made. Practitioners will agree that no projects on without any future work being done and possible new collaborations being initiated. Thus, drawing lessons learned to avoid possible pitfalls helps improve efficiency and productivity long-term.

Besides primary activities classified into phases, supporting activities are an essential part of collaborative optimization. The supporting activities accompany any of the primary phases and play a different role anytime during the collaboration.

Project Management: A project is characterized by a project schedule with a clearly defined beginning and end. Moreover, the project's outcome is typically defined by milestones and project goals, which should be achieved during or at the end of the project. In practice, goals can also be conflicting, for instance, in a university-industry research collaboration where the researchers prioritize a seminal publication. In contrast, the industry might want to keep the findings confidential to keep a competitor's advantage. Agreeing on the goals initially and keeping track of them is good advice in all collaborations. Moreover, project management includes all matters regarding funding more resources and workforce during the collaboration.

Communication: Efficient communication is essential on many levels. The collaboration is accompanied by communication throughout all phases. The availability of collaborators and the communication frequency can have a significant impact on the project's outcome. While some collaborators prefer frequent feedback, such as daily or weekly, others favor less frequent meetings, for instance, monthly or biannually. Besides the frequency of regular meetings, the collaboration should define several milestone meetings, consisting of at least a kick-off and final meeting. The type of communication often depends on the geographical distance between collaborators. A relatively small distance and convenient commute shall allow in-person meetings. Often, however, this is not the case, and mostly online meetings are scheduled. Modern technology that allows to turn on a webcam, share the screen, or even take over screen control can become handy to increase such meetings' productivity. Moreover, consistent e-mail correspondence and a hybrid style of in-person and online communication are often carried out in practice. Challenges in communication commonly occur through domain-specific terminology, which is not clear to all collaborators or even language barriers in international collaborations.

Interdisciplinarity: Many collaborations have their origin of a subject being of an interdisciplinary manner. Therefore, an expert for the involved disciplines significantly speed up the research process or make meaningful insights possible at all. In collaborative optimization, interdisciplinarity is given by the presence of optimization itself and one other discipline. For some projects, even multiple other disciplines might be involved with possible conflicting objectives. In the literature, such a situation related to optimization is also referred to as Multi-disciplinary Design Optimization (MDO). During the collaboration, especially during the initial problem specification phase, a fundamental understanding of each discipline is essential. Even only rudimentary knowledge helps develop an appreciation for each other's research fields and facilitate meaningful discussions.

Collaboration Type: The type of collaboration has a significant impact on each collaborator's responsibility. With the type of collaboration, we refer to aspects related to the involvement, type, and the number of collaborators. In a *light* collaboration, details of the optimization problem regarding complete problem formulation are available to the optimization experts, thereby not requiring much collaboration between the two expert groups. In a *medium* collaboration, besides the details of the problem formulation, further information is required either due to the complexity involved in the problem or due to the nature of the problem. Optimization experts must share intermediate results with domain-specific experts to get further information to improve the optimization method. In a *strong* collaboration, both groups must engage in more collaboration to solve the problem. This can happen if the objective and constraint functions cannot be shared with the optimization experts due to the confidentiality issues or unavailability of computing resources with the optimization group.

4. CASE STUDIES

The blueprint for collaborative optimization can put into practice in different ways. We demonstrate two case studies to illustrate.

Case Study 1: Cylinder Head Water Jacket. As a case study, the collaboration with an automobile company regarding the optimization of a Cylinder Head Water Jacket is discussed. A study focusing on the optimization itself has already been published [20]; however, details of the collaborative process itself were not part of the study. Initially, the industrial partner with domain-specific expertise was looking for an optimization expert to solve an industrial design problem that could not be solved suitably with a commercial solver. Most commercial solvers are generic and not ideal candidate solution methods to find an acceptable solution with a budget of solution evaluations. Thus, a collaboration was initiated. The industrial collaborator had a background in engineering and more than a decade of experience in engineering design. The optimization experts are specialized in multi-objective and evolutionary optimization, and the team consisted of one professor and two Ph.D. students. The goal to design an algorithm that can deal with a constrained multi-objective optimization problem where each evaluation requires computationally expensive simulation was defined (phase 'S'). Due to the time-consuming evaluation function, the overall evaluation budget was limited to only 120 simulations per optimization run. However, the algorithmic overhead could be significantly higher and even reach a couple of minutes to find new solutions in each iteration. Secondly, the algorithm was first developed on test problems with similar characteristics but computationally inexpensive functions (phase 'O'). Even though the algorithm has been designed from scratch, the usage of existing modules and algorithms of pymoo [21] – a Python framework for multi-objective optimization – was handy for prototyping and sped up the algorithm's development. Bi-monthly discussions between all collaborators accompanied the research process. Thirdly, multiple runs on the live environment (phase 'L') optimizing the Cylinder Head Water Jacket have been employed. Because the optimization experts did not have access to the simulation software, the optimization run was carried out manually by sending engineering designs back and forth via e-mail. This way, multiple experiments have been run, and at the same time, the results were verified (phase 'Ve'). Thus, the execution of phase 'L' and 'Ve' happened simultaneously. As the method has been confirmed to be suitable for the optimization problem, the source code has finally been delivered to the industrial partner. Delivering the source code ensured the algorithm to be used in the future for similar kinds of problems (phase 'R'). Moreover, a final meeting discussing the method and assessing the project's success has taken place between all collaborators and coworkers from related departments.

Case Study 2: Engine Design. In another auto-industry project, the initial task of the industry designers was to reduce the weight of an automobile engine from its current weight by 10 kg (phase 'S'). The problem involves 145 discrete variables, which can be varied within specified lower and upper bounds, 146 constraints which all must be satisfied, and six conflicting objectives which all must be optimized. The objective and constraint functions were not available in explicit form; rather, a black-box executable was supplied. Initial collaborations between the two groups revealed that the functions' gradients were also available from the executable routine. The availability of gradient information allowed the optimization experts to devise a new operator – a gradient-based local search approach – to improve a solution locally. Another study revealed that when 2.5 million random solutions were evaluated, no single solution was found to be feasible. The majority of the search space being infeasible prompted optimization experts to devise an algorithm to infinitely emphasize every feasible solution. A generic many-objective optimization algorithm (NSGA-III [22]) was modified to develop a customized method (phase 'O') to find a feasible non-dominated solutions. The customized algorithm was directly applied to solve the engine design problem (phase 'L'). The developed method resulting from a close collaboration found a new engine, 17 kg lighter than the current design, which is 7 kg better than originally desired (phase 'Ve'). Further information on obtained results can be found from [23]. This study mostly used a light collaboration mode.

The power of collaborative optimization came next from the designers. The multiplicity of designs obtained by customized NSGA-III motivated the designers to set the next goal (phase 'R') to find *multiple* engines with identical weight. This promoted the whole 'SOLVeR' procedure to a new specification (phase 'S'). Optimization experts then introduced the concept of *niche-preservation* – survival of similar solutions as clusters – to develop a new optimization method (phase 'O'). Niche preservation is a new optimization technique that was possible to be developed only by a collaborative problem-solving approach. The method was applied to the real problem (phase 'L'), and three different pairs of engines, each having an identical weight, were obtained (phase 'Ve'). The SOLVeR approach's ability to reduce the engine weight by more than 10 kg motivated the designers to repeat the process (phase 'R') to a third cycle in which they aspired to reduce the weight further by relaxing the constraint bounds.

Relaxation of constraints to improve objective function was dealt with by formulating a two-objective optimization problem (phase 'O'). One of the objectives was to minimize the amount of constraint violation from the current best solution; the second conflicting objective was to maximize the amount of weight reduction from the current best solution. The bi-objective optimization method found multiple trade-off solutions with different combinations of constraint violations and weight reductions (phase 'L'). The solutions allowed designers to better understand the trade-off before choosing a final solution for implementation (phase 'Ve').

None of these extensions achieved with specific and innovative optimization methods were academic, nor were they standard optimization practices. However, they revealed alternate solutions close to the designers' interests, so they had a plethora of pertinent solutions before choosing one. Such a design feat was possible only with a collaborative optimization procedure.

5. CONCLUSIONS

Optimization is an interdisciplinary research field and a substantial part of various sciences. Thus, collaboration is vital to tackle problem-solving tasks in all kinds of disciplines successfully. Whereas most studies focus on the outcome of such collaborative optimization, this study puts the center of attention on the collaborative process itself. To guide the process of collaboration, we have proposed a blueprint following the *SOLVeR* approach consisting of five phases: Specification of the Problem, Optimization and Algorithm Design, Live Test, Verification of Method and Results, and Repetitions and Lesson. We have defined the domain and the optimization expert's roles and responsibilities for each phase and highlighted the other supporting activities during collaborative optimization. Moreover, two case studies have illustrated how the blueprint for collaborative optimization was implemented in practice.

This paper has demonstrated the importance of performing a collaborative optimization rather than a silo-based optimization without any intermediate interactions from the domain-specific experts. Collaborative optimization does not only allow large-scale challenging problems to be solved for finding optimized solutions quickly but also opens up new avenues for more flexible and practical optimization studies that would not have been possible to comprehend without collaboration between domain experts and optimization specialists.

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