Evolutionary Multitask Optimization: Are we Moving in the Right Direction?

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Abstract
Transfer Optimization, understood as the exchange of information among solvers to improve their performance, has gained a remarkable attention from the Swarm and Evolutionary Computation community in the last years. This research area is young but grows at a fast pace, being at the core of a corpus of literature that expands day after day. It is undeniable that the concepts underlying Transfer Optimization are formulated on solid grounds. However, evidences observed in recent contributions and our own experience in this field confirm that there are critical aspects that are not properly addressed to date. This short communication aims to engage the readership around a reflection on these issues, to provide rationale why they remain unsolved, and to call for an urgent action to overcome them fully. Specifically, we emphasize on three critical points of Evolutionary Multitasking Optimization, which is arguably the paradigm in Transfer Optimization that has been most actively investigated in the literature: i) the plausibility of the multitask optimization concept; ii) the acclaimed novelty of some proposed multitasking methods relying on Evolutionary Computation and Swarm Intelligence; and iii) methodologies used for evaluating newly proposed multitasking algorithms. Our ultimate purpose with this critique is to unveil weaknesses observed in these three problematic aspects, so that prospective works can avoid stumbling on the same stones and eventually achieve valuable advances in the right directions.

Keywords: Transfer Optimization, Multitasking Optimization, Evolutionary Multitasking, Multifactorial Evolutionary Algorithm.

1. Introduction
In the last decade, the existence of high-quality data has become a common factor in almost any discipline of knowledge. Industrial sectors traditionally reluctant to the advent of digital technologies (e.g. energy, manufacturing plants) have gone at a par with this vigorous information blossoming. As a result, Artificial Intelligence (AI) has encountered a magnificent opportunity to provide practical value and achieve unprecedented levels of performance over complex modeling tasks.

In this context, the increase in the number of tasks and data flows that coexist in a certain scenario has motivated a major shift towards AI algorithms capable of coping with several tasks. This is the case of multitask learning [1], which focuses on the development of learning models (for e.g., image classification) that can address several related tasks at the same time; or continual learning [2], which generalizes

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the former paradigm to handle tasks that can dynamically emerge, change or disappear over time. Gains
derived from addressing these tasks via multitask learning come in the form of shorter training periods,
models of smaller size or a lower demand for annotated data, all benefiting from the proper exploitation
of the synergistic commonalities between the modeling tasks at hand. Besides multitask learning, other
research areas in Machine Learning that also promote the exchange of information between modeling
tasks to boost their generalization performance are transfer learning [3] and domain adaptation [4].

This trend has also permeated the optimization research area with the advent of the so-called Transfer
Optimization paradigm [5], which has gathered significant attention from the community. Similar to its
modeling counterparts, the raison d’être of this young research area is to leverage the knowledge acquired
when solving one optimization problem to better address other problems, whether they are related or not.
Embracing this overarching goal, three different paradigms have been identified in the landscape of Trans-
fer Optimization: i) sequential transfer, in which optimization tasks are solved sequentially (knowledge
flows from one task to another once the former has been solved), ii) multitasking, whose objective is
to tackle several concurrent problems in a simultaneous fashion; and iii) multiform multitasking, which
addresses a single optimization problem by deriving alternative formulations and solving them simultane-
ously. Among these three categories, multitasking can be considered to be the one in the limelight of the
research community, partly due to the capital role played by Evolutionary Computation in the develop-
ment of renowned multitasking solvers. This noted relevance has forged the term Evolutionary Multitask
Optimization (also regarded as Evolutionary Multitasking [6]), which refers to the adoption of concepts,
operators and search strategies conceived within Evolutionary Computation for tackling multitask opti-
mization scenarios.

In Evolutionary Multitasking, methods to realize knowledge transfer between the optimization tasks
under consideration are central for the overall effectiveness of the multitasking algorithm itself. As a
result, many works arising in this research area have striven for new knowledge transfer mechanisms,
targeting to promote the exchange of information among related tasks and to minimize the potentially
negative impact of transferring information among unrelated problems on the convergence of the search
process. Although this motivation suffices for pursuing new research endeavors along this direction, there
are more urgent needs in the field. These concerns can be described by fundamental questions (FQ) that
lie at the very heart of the field itself:

FQ1  Why? Does the Evolutionary Multitasking paradigm address a scenario that can be considered plausible
in practical settings? Does the simultaneous optimization of several related problems occur
in real-world applications? Are there scenarios that can be approached using multitask optimization?
In essence, is the main motivation of this research area justified by an informed evidence of its real-world applicability?

FQ2  What? Are evolutionary algorithms used for multitask optimization called by their preexisting names?
Are we using the correct terminology and avoiding ambiguities? Are advances made in this area
coherent with the state of the art in meta-heuristic optimization, Evolutionary Computation and
Swarm Intelligence?

FQ3  How? Is the performance of multitask optimization approaches measured fairly? Are benchmarks
created on purpose for pairing problems with already known correlation properties? Should research studies account not only for the fitness improvements yielded by knowledge transfer, but also the implications of multitasking in terms of the computational effort required for the purpose? When solving real-world optimization problems, do we really obtain a profit by addressing them together via multitasking when compared to the case when the problems are solved in isolation from each other with competitive single-task optimization algorithms?

After years of activity that have been summarized in recent surveys on Evolutionary Multitasking [7,8], we firmly believe that it is the moment to expose and reflect these crucial concerns. Solid and informed
answers to these fundamental questions are still lacking, which can lead to undesirable developments and outcomes of no practical value in the future of this field. To avoid them effectively, we herein spur an open constructive debate around the above issues, establishing the reasons why this discussion is of paramount importance for the evolution and practicality of the research area.

The rest of this manuscript is structured as follows: Section 2 describes briefly the basic concepts of Evolutionary Multitasking, as well as friction points that this paradigm maintains with other areas of Evolutionary Computation. Section 3 elaborates on the three fundamental questions stated above. Finally, Section 4 ends this short communication by offering our prospects for the area, based on the conclusions drawn from the discussion held on the fundamental questions.

2. Evolutionary Multitask Optimization: Concept and Friction Areas of Evolutionary Computation

As mentioned before, multitasking postulates that different yet concurrent optimization problems or tasks are simultaneously solved together. The goal is hence to obtain a good solution to every one of such problems, possibly exploiting as efficiently as possible the knowledge of every problem captured by the solver over the search. Mathematically, a multitasking environment comprises $K$ optimization tasks $\{T_k\}_{k=1}^K$, defined over as many search spaces $\{\Omega_k\}_{k=1}^K$. Without loss of generality, we assume that each task $T_k$ is a single-objective optimization problem driven by its own fitness function $f_k : \Omega_k \to \mathbb{R}$, where $\Omega_k$ is the search space over which the argument $x$ of $f_k(\cdot)$ is defined. If we assume that all tasks should be minimized, the main goal of multitasking is to find a set of solutions $\{x^*_1, \ldots, x^*_K\}$ such that

$$x^*_k = \arg \min_{x \in \Omega_k} f_k(x).$$

Considering this formulation, two algorithmic strategies for tackling multitasking scenarios can be identified in the existing literature, which motivate the widespread adoption of meta-heuristic evolutionary and swarm intelligence solvers in the area:

- The execution of a single search procedure on a unique population $P = \{x^p\}_{p=1}^P$ of candidate solutions. Since all the solutions are contained in a single population, the challenge is to define a unified search space $\Omega_U$ over which candidates can be encoded, evolved, and decoded back to the specific search spaces $\Omega_k$ of every problem for their evaluation. Therefore, individuals evolve over $\Omega_U$, translating them to each independent search space $\Omega_k$ when required by means of an encoding/decoding function $\xi_k : \Omega_k \mapsto \Omega_U$. An evident benefit of this approach is the implementation of a single set of search operators, which gives rise a lower computational complexity of the search process. By contrast, it requires a proper design of the unified search space and encoding/decoding functions, which is not always straightforward to realize. This strategy is adopted by the family of multifactorial optimization methods, which resort to the concept of skill factors to drive the exchange of knowledge among tasks through the crossover operator and the unified search space. Among them, the influential Multifactorial Evolutionary Algorithm (MFEA) is without any doubt its most representative algorithm [9].

- The execution of different search processes running in parallel, one for each problem under consideration. In accordance with a knowledge sharing policy, information is exchanged between such search processes, either periodically or conditioned on the partial results of the search (e.g. a significant phenotypical change in the best solution of the task). Under this strategy, each search procedure operates on a task-specific population of individuals $P_k = \{x^p_k\}_{p=1}^P$. In this case, each population runs over the search space $\Omega_k$ in which the task $T_k$ is defined. Regarding the sharing of genetic material, this is usually materialized through the exchange of individuals among different populations, involving this fact the existence of a mapping function $\Gamma_{k,k'} : \Omega_k \mapsto \Omega_{k'}$ for the translation of a solution $x^p_k \in \Omega_k$ to the search space $\Omega_{k'}$ of task $T_{k'}$. In this second strategy the design of the search operators applied locally on each $P_k$ is straightforward, as it only depends on the characteristics of the problem and its search space $\Omega_k$. By contrast, it generally scales worse with increasing $K$ than the previous single-population
strategy, and requires defining a policy for the exchange of individuals that could increase even further the overall complexity of the multitasking solver. Devising problem-specific populations and search algorithms are the strategy adopted by multipopulation-based multitasking approaches.

Based on the above description, the reasons for the marriage between Evolutionary Computation and Evolutionary Multitasking become clear and evident: populations serve as the knowledge base of the search algorithm, whereas the application of customized crossover operators (unified search space) or the exchange of individuals (multipopulation approaches) allow for the transfer of knowledge between problems. Therefore, many research areas in Evolutionary Computation and Swarm Intelligence can be largely influential for the Evolutionary Multitasking paradigm. Key concepts such as co-evolution, multi-population strategies, archiving criteria, estimation of distribution algorithms, parallel evolutionary algorithms and cellular genetic algorithms have been already considered by the community when proposing new multitasking solvers. From a general standpoint, any research avenue in Evolutionary Computation that permits to split search resources can be thought to be capable of accommodating different tasks over the search process. Consequently, it can be extrapolated for multitasking setups by solely considering the existence of multiple problems in their inner working. Thus, mechanisms such as sub-populations, sub-archives, heuristics running in parallel or different neighborhood topologies (including cellular automata) are being actively investigated in the context of Evolutionary Multitasking.

A further consequence of the above symbiosis is the controversy that often ignites around the similarity between multitasking optimization and multi-objective optimization, i.e., problems that comprise more than one objective function, all defined over the same search space and possibly conflicting with each other. The fact that multi-objective optimization consider several objectives and that such problems are often approached via Evolutionary Computation have propelled even further this controversy. Certainly, conceptual overlaps exist among both research areas (such as the optimization of a group of objective functions), but both paradigms are different from each other. First, Evolutionary Multitasking aims to leverage the parallelism that brings a population of solutions in order to harness potential synergies between the problems at hand. Each of these tasks has its own solution space, often requiring the use of an encoding/decoding strategy for knowledge transfer. Furthermore, multitasking pursues the provision of one solution for each problem. On the contrary, multi-objective seeks a set of solutions that balance different conflicting objectives defined on a unique search space. There is not a single solution for a given multi-objective optimization problem, but rather a set of solutions that meet each objective to a certain extent. Both paradigms can actually coexist in a multitasking setup, in which the solving tasks are multi-objective optimization problems.

Other areas of friction can be found in the connection between multitask learning and multitask optimization, in the sense that we can construct data-based models capable of learning to solve several modeling tasks at the same time as a multitask optimization problem. To this end, solutions \( \{x^*_k\}_{k=1}^K \) sought by multitask optimization should represent the parameters of a model (as done, for instance, in symbolic regression with evolutionary programming). We can conceive multitask optimization as a possible alternative to deal with multitask learning problems, but it is not the only way to do it, nor is multitask learning the unique application for Evolutionary Multitasking.

3. Fundamental Issues in Evolutionary Multitask Optimization

Despite the upsurge of contributions and progressive maturity noted in Evolutionary Multitasking, we follow up our claims anticipated in the introduction by emphasizing on the fundamental questions that need to be clarified at the time being. In this section, we go deep into these main issues, exposing the main concerns that should be addressed by the community on each of these aspects: plausibility of the problem statement (Section 3.1), novelty of algorithmic advances in the field (Section 3.2) and rigor evaluation methodology (Section 3.3). Figure 1 summarizes such concerns.
3.1. **FQ1 (Why?): Is Multitask Optimization a real-World problem that occurs in practice?**

The first issue that requires urgent attention from the whole multitasking community is the lack of convincing reasons why optimization problems should be solved in a simultaneous fashion. Although this claim may sound superficial, the whole paradigm relies on the idea of a temporal concurrence of optimization problems, i.e., multiple problems originate at the same instant of time. Historically, the optimization field has focused on solving single problems under different circumstances: landscapes with challenging properties (e.g., ruggedness, multimodality), dynamic objective functions/constraints, long fitness evaluation processes...). There have been specific cases when information about a problem has been reused for improving a new search process, either for the same problem (as in dynamic optimization, due to the non-stationary nature of its objectives and constraints) or for other related tasks (a change in the parameters defining the problem is usually tackled by feeding the population with previous solutions and restarting the search). In all such cases, tasks among which information has been transferred appear sequentially over time.

Given this prior art, which suggests that in practice problems emerge sequentially, the research community should clarify, supported by verifiable proofs and evidence, whether optimization problems really appear simultaneously in real-world environments. At this point it is worth acknowledging the advance taken in this regard in a preprint recently made available in [11], where several real-world applications are described for multitask optimization. However, we advocate for a step beyond these efforts: studies must not only report that multitasking can be applied to real-world scenarios and problems, but also prove that multitasking is utilized to solve real-world problems by virtue of its provided performance gains. A large fraction of the works reviewed in [11] can be considered speculative and do not stem from a situation or a scenario encountered in practice. In other words: feasibility does not imply practical applicability.

Further along this line, real-world optimization problems are known to be largely diverse in their search spaces, objective functions and/or constraints. Given this heterogeneity, can it be expected that concurrently originating real-world optimization problems will feature any complementarity or synergy when tackled simultaneously via multitasking in practical settings? The origins of this specific concern trace back to the inception of the multitasking research area itself. Almost all areas of research in the optimization field depart from a need or problem observed in a real-world setup. Multitasking, how-
ever, started from conjectural premises about the similarity between the solutions to different problems. Symptomatically, application fields such as logistics, medicine or energy have afforded several real-world benchmarks for modeling and optimization. On the contrary, evolutionary multitask optimization has so far dealt with synthetic benchmark comprising functions that are embedded with synergies that foster the consideration of multitasking optimization. That is, the research has gone from the technique to the synthetic problem creation rather than from the real-world problem to the technique, which ensures that scientific advances naturally flow towards practical impact. For academic purposes, insights can be surely drawn by hypothesizing on the problem based on intuition and common reasoning. But conversely, the lack of supporting evidence for the formulated hypotheses hinders and puts to question whether multitasking effectively contributes to the ultimate objective of optimization research: to solve real-world problems as efficiently as possible [12].

This issue also rises another concern: are multitasking benchmarks created with highly correlated problems to show that algorithms perform well by exploiting such correlations? In contributions related to evolutionary multitasking it is common to have the proposals validated over benchmarks comprising synthetic functions, which are used for evaluating the quality of the developed methods. These benchmarks are often highly biased, as they intentionally combine correlated problem instances that altogether create a favorable scenario for multitasking approaches. Prospective authors should provide rationale whether the simultaneity of real-world problems in any given practical scenario 1) allows for the existence of synergies between tasks that makes its exploitation worthwhile; and 2) that approaching such problems with a multitasking solver is compliant with the non-functional requirements of the scenario (e.g. would any driver be willing to share the source/destination node of his/her route with a machine in the cloud? Is the sharing of industrial production schedules across different plants a reasonable premise?). For this reason, we should avoid independent/separate comparison of methods using tailored benchmark problems without any connection to the limitations of real-world scenarios.

This lack of applicability can be also noted in the fora where works related to Evolutionary Multitasking are currently published. It is often the case that new contributions springing in this area are reported in high-quality journals and tier-one conferences dedicated to Artificial Intelligence, with emphasis on Evolutionary Computation and Swarm Intelligence. On the contrary, contributions dealing with evolutionary multitask optimization are rarely published in conferences and journals specialized in a certain application field. This can be a sign of the questionable applicability at the time being of the field, since these latter scientific venues are more concerned with the feasibility of the technical proposal in real-world settings. Contributions are more strictly evaluated in terms of the plausibility of the scenarios and the proposed solution rather than its algorithmic sophistication. Prospective real-world applications of evolutionary multitasking for readerships that are experts on such applications will have a significantly higher soundness than more algorithmic proposals evaluated over favorably created synthetic benchmarks.

On a positive note, we eagerly encourage authors to embrace the use of previously gathered knowledge when facing new real-world optimization tasks, even if this exploitable knowledge is generated by solving synthetic problems that may provide useful information for the optimization process. In any case, we call for a deep reflection around the adequacy of solving real-world problems in a simultaneous fashion. A more reasonable paradigm in practice is to consider huge archives of previously gathered knowledge (solutions to other problems) before solving a new problem, discover which previous problems are most similar to the one to be solved (e.g., by virtue of meta-features extracted from each problem), and use stored solutions as a starting point for addressing the new task (for instance, by seeding the initial population). This sort of sequential knowledge transfer can be more impactful in real-world applications.

3.2. FQ2 (What?): Are evolutionary algorithms used for multitask optimization coherent with the state of the art in meta-heuristic research?

If we compare Evolutionary Multitasking to other areas in optimization research, it is undeniable that it still remains in an early stage of development, with a long road ahead plenty of challenges and
discoveries. Despite its infancy, this area is already approaching similar practices to the controversial ones observed in Evolutionary Computation and Swarm Intelligence: the explosion of many methods, each claiming to portraying a set of own algorithmic peculiarities, but very similar in their essence to other solvers that have prevailed in the field for decades [13][14]. This trend has lead to myriads of meta-heuristic approaches with scarce differences at their core, both among them and with respect to traditional optimization heuristics.

In the context of Evolutionary Multitasking, however, the algorithmic essence of every new proposal should concentrate on novel strategies to allocate resources among tasks and/or the way knowledge is modeled and transferred among tasks. By all means, they should leave aside the evaluation of sophisticated-yet-already-existing search operators that do not account for the correlation between tasks whatsoever. For this reason, authors should work on properly highlighting the true contribution of their proposed method to the multitasking community.

In connection to this issue, we have also noted name-change research trends, i.e., some algorithmic strategies for Evolutionary Multitasking, when inspected closely, can be found to be refactored versions of already existing concepts in meta-heuristic optimization research. Archive memory, multiple populations, estimation of distributions along the search, topologies, or migration strategies have been considered in different contributions over the short history of Evolutionary Multitasking, and should continue stimulating new developments in the area. But prospective studies using them should avoid any refurbishing of their names, and should clearly and explicitly analyze whether new proposals skim any established area in Evolutionary Computation and/or Swarm Intelligence.

This name changing trend affects beyond certain multitasking approaches proposed to date, permeating into the roots of the Transfer Optimization paradigm. As anticipated in the introduction, three different paradigms are identified in Transfer Optimization: sequential transfer, multitasking optimization and multiform multitasking. Although the last two paradigms introduce new concepts and research pointers, sequential transfer has been extensively studied in the literature along the years. Reusing what has been learned in the past for expediting the search process when optimization a new task (or a new version of it) is a well-known strategy in dynamic optimization, particularly in the case with recurring change patterns. In most schemes departing from the latter casuistry, the solver must store and retrieve from a memory solutions encountered in the past, injecting them into the population towards better accommodating changes in its formulation and/or constraints. This design principle evidently overlaps what is pursued in sequential transfer.

Summarizing, in FQ3 we underscore the fact that many methods proposed in the context of Evolutionary Multitasking and Transfer Optimization can – and must – be regarded as extensions of already published methods in meta-heuristic optimization research. This is specially noteworthy in dynamic optimization, where several approaches for information transfer among time-varying problems (essentially, to reuse past solutions) have been proposed in the recent past [15]. Such variants have been also used in the context of Transfer Optimization and Evolutionary Multitasking (e.g. archive memories in [16] or surrogate modeling assisted information transfer in [17]). Unfortunately, in many cases these variants come along with a change of terminology, which unfairly corresponds other areas of optimization research. We firmly advocate for studies in which the connections of the newly proposed algorithms to traditional areas of optimization research are clearly identified, so that ambiguities are minimized and illusory advances are avoided.

3.3. FQ3 (How?): Are evolutionary multitasking approaches evaluated properly, with right metrics and in fair comparison benchmarks?

The last issue we bring to discussion in this short communication relates to the practices adopted for evaluating the performance of Evolutionary Multitasking solvers. To begin with, a bad practice observed in studies related to this area often conduct their experiments by comparing new solvers to other multitasking methods, mostly in terms of fitness value (or any other indicator of the quality of the solutions
encountered for the tasks under consideration). This comparison is needed for verifying that the proposed solver attains gains with respect to the state of the art in Evolutionary Multitasking. For the sake of a fair experimental analysis, discussions held around the results should clarify, in an informed fashion, whether the gains can be attributed to better search operators, more effective knowledge transfer mechanisms, a more fine-grained parameter setting, or any other aspect of the multitasking solver. But beyond all, experiments should be completed with a rigorous and mandatory comparison of the evolutionary multitasking solver to the alternative case where tasks are solved separately from each other, using competitive state-of-the-art algorithms, and subject to a similar computational effort budget. Advances in evolutionary multitasking are of no practical impact if the exploitation of the synergies among tasks is outgained by more efficient and outperforming single-task solvers.

Furthermore, experiments held over multitasking environments should consider quantitative measures beyond fitness value statistics. One of the reasons to opt for a joint optimization of several tasks at the same time is to reduce the computational effort of the search for their solutions. This implies either a lower number of function evaluations needed for discovering solutions of a given level of quality or, alternatively, better solutions found under the same computational budget. This requires a major rethink on how results in Evolutionary Multitasking should be normalized and interpreted considering the amount of resources (memory, function evaluations) consumed over the search, not only in what refers to function evaluations, but also regarding the additional computation burden imposed by estimating, transferring and exploiting knowledge among tasks.

Finally, another concern with experimental methodologies followed to date by the Evolutionary Multitasking community is the examination of the performance of the developed multitask solvers in environments composed by unrelated tasks. In accordance with our reflections in Section 3.1 a large fraction of the works emerging lately in this area still conduct experiments over benchmarks composed by synthetic functions, in which synergies among tasks are forced to favor its exploitation during the multitask search. Besides the handcrafted nature of these benchmarks (which we already discussed in FQ1), experiments should be augmented with EM scenarios composed by unrelated tasks, so that the discussion is fed with performance results of the method when facing favorable and unfavorable scenarios given the purpose the multitask solver was designed for. Until there is an algorithm proven to effectively pair the related problems to be solved collectively, effectively and universally, a large number of experiments comprising related and unrelated problems selected fully at random should be conducted, including a mandatory comparison against solving each optimization task by competitive state-of-the-art methods. Should such a pairing approach eventually exist, the computational resources required to pair up problems from a large pool of problems should be considered as well.

We again emphasize that in real-world scenarios, optimization tasks with synergies and commonalities rarely occur (let alone arise simultaneously). For this reason, the degradation of the results in environments with unrelated tasks should be thoroughly evaluated, as it is the circumstance that the algorithm will most frequently encounter in practice. Naturally, we should solve optimization problems as efficiently as possible as soon as they arise in the real world, rather than waiting for some time until several tasks are collected (which brings to question how long one can and should wait for, or how long the first problem can be delayed in the process), and showing that better results can be achieved by exploiting synergies in those few cases where they occur.

4. Prospective: Something Else is Needed in Evolutionary Multitask Optimization

Transfer Optimization and Evolutionary Multitasking are at their dawn. A growing corpus of contributions are published on a daily basis, in top conferences and reputed journals. This area has garnered much interest from the community working on optimization, blowing a fresh breeze of new developments and research directions over the field.
Unfortunately, not all that glitters is gold: Evolutionary Multitasking needs urgent, sincere and reflexive thoughts about fundamental questions that threaten the prosperity the area as a whole. Solid grounds are still missing in terms of i) the practical applicability of the multitasking paradigm; ii) the novelty and reciprocity of algorithmic proposal with respect to the state-of-the-art in optimization research; and iii) the fairness and rigor of the methodologies for performance assessment and comparison used to date. As a result, the blossoming strand of literature grows every day from roots weakened by the lack of convincing responses to the aforementioned issues. On a prescriptive note, we advocate for several specific actions that could bring some light to the area:

- Informed evidence of the practical relevance of the multitasking paradigm should be given (e.g. by providing examples of real-world setups where the tasks at hand could co-occur, together with the reasons why they might occur at the same time and why they could feature synergistic relationships with each other).

- More studies showcasing the usage of evolutionary multitasking in real-world (not only realistic) applications published in fora and journals specialized in the field at hand.

- Prospective works should consider and satisfy all specifications, requirements and constraints that one could encounter in a multitasking setup, especially when it comes to information sharing across tasks.

- Algorithmic contributions should focus on improvements that can be attributed to the strategy for knowledge transfer and exploitation, rather than to sophisticated/metaphor-based search operators that do not relate at all to the presence of multiple, potentially correlated optimization tasks.

- Every newly proposed algorithm should be complemented with a thorough analysis of possible algorithmic overlaps with other preexisting areas of Evolutionary Computation and Swarm Intelligence, thereby avoiding name-change research.

- The computational complexity of evolutionary multitasking methods should be regarded as a mandatory aspect for the evaluation of new proposals.

- Comparisons must be done to other multitasking alternatives, but also to competitive single-task solvers from the state of the art subject to the same computational budget.

In no way the intention of this short critique is to condemn the achievements reached in this area to date. Diametrically, we energetically believe that Transfer Optimization and Evolutionary Multitasking deserve proper research attention. However, efforts to be invested in the future must guarantee that the right questions are addressed to dispel the doubts and concerns exposed in this manuscript. Otherwise, the field will maintain an uncontrolled growth without well-grounded conceptual, methodological and practical rationale, eventually leading to a manifold of studies with questionable practical relevance.

A global understanding and assumption of these needs by the community requires an explicit manifesto that serves as a referential point of consensus. This is indeed the ultimate purpose of this open letter. Evolutionary Multitasking is still a young area facing a long road ahead to develop itself and showcase its postulated benefits in real-world applications competing fairly against state-of-the-art single-instance optimizers. It is now the time to ensure that this road can be driven safely, and sure of reaching a meaningful destination.

Acknowledgements

The authors would like to thank the Basque Government for its funding support through the ELKA-RTEK program and the consolidated research group MATHMODE (ref. T1294-19).
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