Search-Based Software Engineering for Self-Adaptive Systems: One Survey, Five Disappointments and Six Opportunities

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Abstract—Search-Based Software Engineering (SBSE) is a promising paradigm that exploits computational search to optimize different processes when engineering complex software systems. Self-adaptive system (SAS) is one category of such complex systems that permits to optimize different functional and non-functional objectives/criteria under changing environment (e.g., requirements and workload), which involves problems that are subject to search. In this regard, over years, there have been a considerable amount of work that investigates SBSE for SASs. In this paper, we provide the first systematic and comprehensive survey exclusively on SBSE for SASs, covering 3,740 papers in 27 venues from 7 repositories, which eventually leads to several key statistics from the most notable 73 primary studies in this particular field of research. Our results, surprisingly, have revealed five disappointed issues that are of utmost importance, but have been overwhelmingly ignored in existing studies. We provide evidences to justify our arguments against the disappointments and highlight six emergent, but currently under-explored opportunities for future work on SBSE for SASs. By mitigating the disappointed issues revealed in this work, together with the highlighted opportunities, we hope to be able to excite a much more significant growth on this particular research direction.

Index Terms—Search-based software engineering, self-adaptive software, self-adaptive system, multi-objective optimization, decision making.

1 INTRODUCTION

ENGINEERING software systems with the ability to reason and adapt themselves under changes (e.g., on its states, requirements and the environment) has emerged as a successful paradigm for handling runtime dynamics and uncertainty. The resulted software system, namely self-adaptive systems (SASs), has become one of the most complex artifacts that have ever been created by human. Many complex software systems require optimization in the engineering process and the SASs are of no exception. For example, the configuration of SASs’ adaptable parameters is a very typical optimization problem in which the best configured values (and possibly sequence) need to be searched in order to achieve optimality on different functional and non-functional objectives/criteria [1]. However, optimizing SASs is important yet challenging, as human intervention is profoundly limited and there may be an explosion of the possible adaptation solutions, together with multiple conflicting objectives under resources constraints and feature dependencies [2]. As a result, intelligent search is required to fulfill the requirement of optimization in various domains of SASs.

Search Based Software Engineering (SBSE) [3] is one example of a form of Intelligent Software Engineering that has been widely applied across many software engineering domains that demand optimization, including requirements [4], design [5], testing [6] and refactoring [7]. Specifically, SBSE applies computational search, i.e., various search algorithms, to automatically and dynamically seek solutions for minimizing/maximizing objective(s) or for satisfying certain constraint(s) in software engineering. In particular, SBSE can be either single objective, where a single fitness would be used to guide the search that leads to a single optimal solution; or multiple objectives, in which the search is steered to discover a set of Pareto-optimal solutions [8], i.e., Pareto-based multi-objective search [9].

Over years, there have been some successful attempts on exploring SBSE for SASs [10] [11] [12] [13] [14]. Indeed, as pointed out by Harman et al. [15], the very natural requirement of dynamic and automated reasoning in SAS provides a perfect place for SBSE, which targets exactly such a need. Nevertheless, the work on such direction is still arguably much less active comparing with the other problems of software engineering, e.g., software testing [3], where SBSE has become a standard. We believe that one of the reasons for this is because, to the best of our knowledge, there have been no explicit survey on the topic of SBSE for SASs. As such, we lack a general overview and hence the practitioners of SASs are struggle to understand, e.g., what search algorithms to use and how they can be tailored, in what contexts, and how the search results can be assessed.

1. We interchangeably use ‘Pareto-based multi-objective search algorithms’ and ‘Pareto-based search algorithms’ to refer to any algorithms that seek to search for the Pareto front, including those indicator- and decomposition-based multi-objective algorithms.
This is what originally motivates this paper, in which we aim to bridge such gap by conducting a systematic survey on 3,740 searched papers over 27 venues and 7 repositories, based on which 409 ones were identified for detailed review and eventually 73 primary studies were extracted for the analysis. The survey has in fact led to a surprising result: we have identified five disappointed phenomena in the current research on SBSE for SASs, which are mainly due to non-compliance of the best practices in the SBSE and Computational Optimization community. This is perhaps another reason that prevents a significant growth of the research on computational Optimization community. This is perhaps another research on SBSE for SASs, which are mainly due to non-...
2.2 Self-Adaptive Systems

The ever increasing complexity of engineering software systems has led to the high demand of software systems to be versatile, resilient and dependable to changes in its operational contexts, requirements and environments. This cannot be made possible without the notion of self-adaptation—an ability of software system that permits it to modify its own behaviors according to the perceptions about its interior states and the exterior factors. Although at the first glance of the term ‘self-adaptation’, one may think that it is only related to the running software systems, the engineering processes of SASs are in fact spread over both design time and runtime. For example, design time profiling or maintenance of the SAS can often provide useful insights to future improve runtime self-adaptation. In this paper, we therefore include not only the work on SASs runtime, but also the design time studies of SASs as long as they serve as significant understandings for runtime self-adaptation.

Self-adaptations of a SAS are certainly not being conducted for no reason, they are designed to serve certain purpose: to improve the quality of software systems, including both functional and non-functional quality. While there are certain quality dimensions that are widely applicable to any domains, e.g., latency, throughput and availability, the actual parts by which a SAS can modify itself, namely the adaptable features, are highly diverse case by case. In theory, any adaptable software systems can form a SAS, providing that some, if not all, of the adaptable features can be changed as the software system runs. Because of this, from the software engineering research community, it is not uncommon to find that research of SASs have been conducted under different themes, such as Dynamic Software Product Line. In addition to software engineering, SAS research has been spread over the other communities, e.g., System Engineering, Service Computing and Cloud Computing. In the real-world scenarios, it is also not difficult to find a software system that can potentially achieve self-adaptation. For example, MySQL, which is one of the most popular Relational Database Management Systems, has around one third of its configurations that can be changed at runtime. Our survey therefore does not restrict only to software engineering research, but also to any other communities following our review protocol introduced in Section 2. Other overviews of the SASs are available from the literature, see [1] and [2].

Because of the above reasons, engineering SASs can be abstracted as developing automated and dynamic methods that involves tuning (searching) different parts or processes of the software systems, with an aim to improve functional or non-functional quality. This fits precisely with the purpose of SBSE and therefore raise a perfect marriage between the two fields. Our work is the very first endeavour that aims to survey the state-of-the-art on SBSE for SASs, providing the foundation that enables us to evidence about some of the overwhelming issues in existing studies and raise the discussions of future opportunities, which, in turn, will hopefully excite a much more significant growth of this particular research direction.

3 RESEARCH METHODOLOGY

To understand the state-of-the-art on exploring SBSE when engineering SASs, we conducted a systematic literature review covering the papers published from 2009 to 2019. The review methodology follows the best practice of systematic literature review for software engineering, consisting of clear search strategy, inclusive/exclusive criteria, formal data collection process and pragmatic classification. Our review has two goals: (i) to provide summative statistics on the state-of-the-arts of engineering SASs where SBSE have been involved and studied, particularly with respect to the aforementioned RQs; (ii) to identify the issues that derive our disappointments on actively promoting this direction of research, particularly with respect to the common practice drawn from the research fields of SBSE, Computational Optimization and Evolutionary Computation.

3.1 Search Strategy

All the studied papers in this work were carefully selected from a wide range of scientific literature sources, including ACM Library, IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar, DBLP and the SBSE repository maintained by the CREST research group at UCL.

The defined search string aims to cover a variety of search-based optimization applied in the context of self-adaptive software. Synonyms and keywords were properly linked via logical operators (AND, OR) to build the search term. The final search string is shown as below:

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("optimization" OR "search algorithm" OR "search based" OR "multi-objective") AND ("adaptive software" OR "adaptive system" OR "dynamic software product line" OR "autonomic")
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When necessary, the search string was adopted to the particular scientific literature source. For each source, different semantically equivalent version of the string were conducted as pilot searches, e.g., whether to keep hyphen. Then, the one that returns the highest number of results was used.

According to the results from the above search strategy, we conducted a snowballing, manual examination on the...
title and abstract of the paper, in order to exclude those that do not relevant to our goal of review, e.g., those neither relevant to SBSE or focus on a domain that is outside software and system engineering. Following the process, we aim to reduce the found references to a much smaller and more concise set, namely the candidate studies. Finally, by using the inclusion and exclusion criteria (see Section 3.2), we carried on rigorous review on the candidate papers and keep only the most relevant ones, which are known as primary studies.

3.2 Inclusion and Exclusion Criteria

For the selected candidate papers, we firstly identify the primary studies by using the inclusion criteria as below; papers meeting all of the criteria were temporarily chosen as the primary studies:

1) The paper should discuss the design, or application, of computational search algorithm as a major part in the solution to a problem of engineering SASs. If this is not the case, the paper should at least present a formulation of the SAS problem that can be subject to computational search.

2) The problem is concerned with SAS runtime, or it is a design time problem that provides significant insights for runtime self-adaptation of SASs.

3) While we do include work that focus on a particular domain of a SAS (e.g., Cloud, Services, Internet-of-Things and Cyber Physical Systems), the paper should explicitly or implicitly discuss, or at least made assumptions about, the generality of the problem and solution when engineering SASs to the wider context.

4) The problem to be solved by SBSE should be derived from a software and system engineering perspective.

5) There is no restriction about the particular search algorithm(s) that is used to solve the problem.

6) The paper should include quantitative experimental results with a clear instruction on how the results were obtained.

7) There is no restriction about what quality indicator(s) and methods were used to assess the experimental results.

Subsequently, papers meeting any of the exclusion criteria below are filtered out from the temporary primary studies:

1) The paper neither explicitly nor implicitly mentions about SBSE, where the computational search is the key; or the search problem is not considered as an important part of the approach.

2) The paper is not well-recognized or being followed. We used the citation information form Google Scholar as a single metric to assess the reputation and sustainability of a paper. In particular, we follow a pragmatic strategy: a paper has 5 citations per year from its year of publication is deemed as sustainable and respectful, e.g., a 2010 paper would expect to have at least 45 citations.

4) We do not exclude self-citations here as they would still be regarded as the authors’ own initiatives to prompt the same direction of research, which can still be important for expanding the area of SBSE for SASs.

5) The citations were counted by the time that this paper was written, i.e., September 2019.

The only exception is for those papers published in the years of writing this article (i.e., 2019), where we consider any published papers, or pre-press papers that have not yet been given an issue number, regardless to their citation counts.

3) The paper is a short paper, i.e., shorter than 8 pages (double column) or 15 pages (single column).

4) The paper is a review, survey or tutorial type of study.

5) The paper is published in a non-peer reviewed repository.

Finally, if multiple papers of the same research work are found, we applied the following process to determine if they should all be considered as primary studies (after considering both inclusion and exclusion criteria). The same procedure is applied if the same authors have published different papers for the same solution, and thereby only the significant contributions are analyzed for the review.

- All papers are considered if they report on the same problem but have different solutions.
- All papers are considered if they report on the same problem and solutions, but have different assumptions about the nature of the problem or having new findings.
- When the above two criteria do not hold, only the latest version or the extended journal paper is considered.

Finally, error checks and investigations were also conducted to correct any issues found during the search procedure.

3.3 Summary of Results

As shown in Table 1, after the execution of the search process and removing redundancy, a total of 3,740 references from different well-known conferences and journals were discovered. Then, we reduced the found references down to 409 candidate papers based on the their abstracts. Finally, according to the inclusion and exclusion criteria, we further brings the reference down to 73 primary studies. Figure 1 shows the distribution of the 73 primary studies with respect to the year of publication. It is clear to see that the number of studies increases in a steady pace, achieving a 5 times increment in 2019 (by September) compared with 2009. This evidences the increasing popularity of the research on SBSE for SASs.

It is worth noting that, we do not only review papers published in top software engineering venues, but also...
those relevant ones that were published in system engineering conferences/journals as well as those in computational optimization venues, as long as they are related to problems in engineering SAS and comply with the inclusive/exclusive criteria.

4 Results Analytics

In this section, we present and analyze the survey results with respect to our RQs.

4.1 RQ1: What Problems of SAS have been Tackled by using SBSE?

SBSE is a broad paradigm that covers all aspects of the software engineering process, thus it is important to understand what engineering problems of SASs have already been studied.

We have found that all the SAS problems where SBSE have been studied are aimed for optimizing different functional (e.g., bugs) or non-functional quality (e.g., performance) of the SASs. However, the aspect by which the SASs can be adapted and searched are varied. As shown in Table 2, most of the primary studies (78%) on SBSE for SASs have been focusing on configuration during adaptation, which is perhaps the most important problem. In this case, the adaptation is concerned with the parameters of the SASs, which can be almost changed immediately. A considerable amount of work, counted as 11%, target the deployment of SAS. Here, the adaptation is related to, e.g., connections of components, allocation of virtual machine, or topology of the systems, which may cause certain extent of the delay once an adaptation decision has been made. The other problems form the minority of the primary studies.

**Findings:** The configuration of SASs are the most popular problem (78%) to be addressed by SBSE. The problem on SAS deployment is ranked the second, contributing to 11% of the primary studies.

4.2 RQ2: What Search Algorithms are Studied?

Being one of the most important parts of SBSE, understanding what search algorithms have been studied on SBSE for SASs is essential.

Figure 2 depicts the top 10 search algorithms for optimizing single (aggregated) objective in SASs. Clearly, we...
see that when searching on single or aggregated objectives, the search algorithms used are varied, ranging from exact algorithms, e.g., Exhaustive Search (ES) and Branch-and-Bound (BB), to stochastic ones, e.g., Genetic Algorithm (GA), Random Search (RS) and Hill Climbing (HC). In particular, the ES and GA are significantly more popular than the others, both of which appear in 15 primary studies. Indeed, ES is the simplest algorithm that is guaranteed to find the optimal solution by evaluating every possible solution, yet it is applicable only when the search space is small. GA, on the other hand, is a population-based metaheuristic that requires no information about the problem to be optimized. In a nutshell, GA does not visit all solutions, but it proceeds the search through the rule of survival of the fittest, where better solutions have a higher chance to produce their offspring by reproduction operators (i.e. crossover and mutation). Because of such, it fits well with the computationally intractable search space of the SASs but does not guarantee to reach the optimality. Those two search algorithms represent two completely opposite assumptions of the SASs: either it is simple to be optimized (for ES) or it is too complex to be tuned exactly (for GA). Mixed Integer Programming (MIP) solvers, appeared in 10 primary studies, are general tools for solving problems formulated as MIP. We have seen that a variety of solvers are used (e.g., CPLEX\(^7\), LINDO\(^8\), and SCIP\(^9\)) on SBSE for SASs, but the actual search algorithms chosen on each solver have not been explicitly stated. Random search (RS), which performs iterated search based on a pure random exploration of better solution without gradient, is also ranked the third place. It is the simplest search algorithm for SASs with an intractable search space. Compared to GA, RS retains the benefits of simplicity but tends to be slow in convergence due to the lack of heuristic operators. There are also other exact or stochastic search algorithms from Figure 2 forming the remaining minority of the search algorithms on SBSE for SASs.

Fig. 2: Top 10 considered single and aggregated objective search algorithms (with reported results) in the primary studies.

![Fig. 2: Top 10 considered single and aggregated objective search algorithms (with reported results) in the primary studies.](image)

4.3 RQ3: What Domain Information is Used to Specialize the Search Algorithm?

Most SBSE tasks inevitably require specializing the search algorithms in order to make them better serve the purpose, therefore it is important to understand what domain information of the SAS problems have been considered in such specialization when investigating SBSE for SASs.

Noteworthily, the domain information can be distinguished between the nature of the problem, which is the basic elements required to specialize the search algorithm, and the engineers’ domain knowledge, which is specifically related to the engineering problem to be addressed and is often deemed as optional, but desirable. In essence, what makes the additional engineers’ domain knowledge differs from the basic problem nature is that, the natural information of the problem serves as the ‘facts’ about the problem context, where the search algorithms have to comply with in order to be used, e.g., the range of parameters, various equality and inequality constraints. In contrast, the domain knowledge is represented as or produced by typical software and system engineering methods, practices and models. Often, such domain knowledge is not naturally intuitive form the problem context, but can be extracted through rigorous reasoning processes. This is what makes the work on SBSE for SASs rather unique and tailored to the SAS problems. By additionally considering the domain knowledge in the search, specialization turns the search algorithms to be less general (i.e. typically not able to apply to other problems), but they are expected to work better under...
the given SAS where the knowledge lies. However, this does mean that more internal elements of the search algorithms need to be modified, e.g., on the way of producing new solutions and handling constraints, thus rendering an extra complexity.

As shown in Figure 4, surprisingly, 79% of the work on SBSE for SASs extends only the necessary parts in order to apply the search algorithms, i.e., a generic solution encoding and fitness function, using the nature information of the problem. In contrast, the remaining 21% further specialize the search algorithms by additionally incorporating different means of the domain knowledge from the engineers.

Within those 21% primary studies, 8% of them inject knowledge of the feature model, which models the variability of a SAS designed by the engineers, into the search algorithms, creating tailored encoding and heuristic operators that are aware of the dependencies between features. In this regard, the domain knowledge from the feature model acts as a driver that directly steers the search behaviours. Similarly, in 7% of the primary studies, engineers’ knowledge can be encapsulated as “seeds”—a set of specifically selected solutions for a SAS following the software engineering practice—for the search algorithms to start working with. Again, those seeds serve as guidance that can impact the exploration and exploitation of the search. Other domain knowledge, i.e., the goal model and abstract syntax tree of the code, forms the remaining 6% of minority.

**Findings:** The search algorithms are specialized with only the nature information of the problem for majority of the primary studies (79%). For others, additional domain knowledge from the engineers is used to further specialize the search algorithms by means of feature model, seeds of solutions, goal model and abstract syntax tree of the code.

4.4 RQ4: How Multiple Conflicting Objectives are Defined and Handled?

When engineering SASs, dealing with multiple conflicting objectives are not uncommon. As a result, understanding how multiple objective are defined and handled during the search is crucial on SBSE for SASs.

As illustrated in Figure 5, our reviews discovers that on SBSE for SASs, for 52 of the primary studies that do consider multiple conflicting objectives, the search is optimized in certain form of aggregation which effectively turns the problem into a single objective one. Among such, majority of them (46) use the weighted sum while the remaining (6) applies the weighted product. In essence, the weighted aggregation relies on the assumption that the relative importance between objectives exists and they can be precisely quantified. We also found that, as depicted in Figure 5, 31 primary studies have assumed that the weights are provided by the engineers, which forms the majority. There are also a considerable amount of primary studies (20) rely on the assumption and general belief that equal importance amongst the objectives can be achieve by setting equal weights, which would lead to a balanced solution. Apart from those statically specified weight, only 1 primary study has considered dynamic weights update.

There are 20 primary studies, which is over two times less than the weighted aggregation work, have relied on
Pareto-based multi-objective search, where the assumption is that there is no explicit preference towards any of the objectives and/or it is too difficult to quantify their importance in the context of SBSE for SASs. As mentioned, since Pareto-based multi-objective search would provide a set of solutions, it is important to know how a single solution is selected for fulfilling the SAS problem. As shown in Figure 7, leaving such a decision to the engineers tends to be the most popular treatment (14 cases). Another 3 primary studies use the knee point, which represents a balanced compromise among objectives. Surprisingly, an additional weighted sum aggregation is assumed in two studies based on which a solution is selected following a Pareto-based multi-objective search. We have also identified one study assume strong preference toward an objective (minimizing cost), and therefore a solution is selected with the best value of such objective giving that the requirement thresholds of other objectives are satisfied.

**Findings:** For the primary studies that do consider multiple conflicting objectives, weighted aggregation is assumed in 52 primary studies. To this end, the actual weights are mostly assumed to be either given by the engineers, or are set equally for all objectives. There are 20 studies have relied on Pareto-based multi-objective search, within which leaving the selection of the final solution to the engineers to decide is the most common way.

### 4.5 RQ5: What Quality Indicators are Used to Assess the Results under Multiple Conflicting Objectives?

When optimizing SAS that involves only a single objective, the quality of the SBSE approach can be simply evaluated by using that objective value. However, in case multiple conflicting objectives are involved, selecting appropriate quality indicator(s), which assess the quality of a solution(s) produced by a search algorithm, becomes a critical yet challenging task since different solutions may be incomparable on the basis of Pareto dominance. Therefore, it is of great significance to understand what quality indicators are currently used to serve such purpose.

Figure 8 shows the top 5 quality indicators used in the primary studies. As can be seen, utility (weighted aggregation) which shows the value for each objective individually are predominated ways to evaluate the quality of adaptation solutions. They are perhaps the most convenient indicators to assess the solutions under multiple conflicting objectives.

The remaining four quality indicators are designed for Pareto-based multi-objective search so as to evaluate/compare solution sets. All of them are very popular indicators in the SBSE and Evolutionary Computation community. The first three indicators Hypervolume (HV) \[100\], Inverted Generational Distance (IGD) \[101\] and \(\epsilon\)-indicator \[102\] can (partially) reflect all quality aspects of solution sets (i.e., convergence, spread, uniformity and cardinality), despite each having different preferences \[103\]. Specifically, the HV measures the volume of the union of the hypercubes determined by each of the solutions in a solution set and a reference point, and prefers knee points of the set. The IGD measures how close the Pareto front is to a solution set by calculating the average distance of each point of a reference set (which represents the Pareto front) to the solution set, and prefers the set with uniformly-distributed solutions. \(\epsilon\)-indicator measures the maximum difference between two solution sets, and prefers the set who has a better “poorest solution” compared with the other set. The last indicator Generational Distance (GD) \[104\] is solely for evaluating the convergence of a solution set. Opposed to IGD, GD measures how close a solution set is from the Pareto front by calculating the average distance of each solution in the set to the Pareto front.

**Findings:** When multiple conflicting objectives are considered in SASs, a weighted utility or descriptive statistics of each objective values are predominated ways to assess the results on SBSE for SASs (found in 68 primary studies). Four quality indicators for Pareto-based multi-objective search, i.e., HV, IGD, \(\epsilon\)-indicator and GD, occupy the 2nd to 5th most common quality indicator on SBSE for SASs.

### 4.6 RQ6: What and How Many Subject SASs are Studied in Order to Generalize the Conclusion Drawn?

Research on SBSE for SASs would inevitably involve stochastic behaviors, either caused by the search algorithms and/or from the underlying SAS to be optimized. As a result, it is important to understand what and how many subject SASs have been used in the evaluation.

From Figure 9 we can see that both simulator and real system are the most commonly used types of subject SASs when exploring SBSE for SASs, as they are investigated in...
TABLE 3: Top 10 subject SASs and their characteristics considered in the primary studies.

| Subject SAS     | Domain     | Search Space   | Freq. |
|-----------------|------------|----------------|-------|
| Synthetic system| service    | up to $5.6 \times 10^{18}$ | 11    |
| Synthetic system| mobile     | $2.4 \times 10^{14}$   | 3     |
| Synthetic system| cloud      | up to $10^{17}$      | 3     |
| UUV             | vehicle    | up to $3.9 \times 10^{14}$ | 3     |
| CrowdNav        | navigation | $10^{16}$        | 3     |
| Travel system   | web        | $3.0 \times 10^{23}$ | 2     |
| Zinn            | unknown    | $3.4 \times 10^{12}$ | 2     |
| WS-DREAM        | service    | up to $3.4 \times 10^{12}$ | 2     |

Table 3 shows the top 10 subject SASs from the primary studies. We can see that those subject SASs are highly diverse, coming from a wide range of domains. It is not uncommon to see that most of the top 10 subject SASs exhibits different, but rather large, search space, which is one of the key motivations to leverage SBSE. Notably, SASs from the web (4 cases) and service (2 cases) domains are the most commonly used subjects. Synthetic system, as created by some generators, appears in 11 primary studies, which is significantly higher than the other SASs. RUBiS, a well-known web-based benchmark, has been ranked the second as it appears in 4 primary studies. The other SASs are varied but their differences on popularity are marginal.

With regard to how many subject SASs are considered in a primary study, as shown in Figure 10, our review has indicated that there are 65% primary studies consider only one SAS, a further 12% and 10% consider two and three SASs, respectively. Note that here, the SASs are differentiated based on their structure, i.e., they are said different even if the study considers the same system under a given domain, as long as they have different structures, e.g., the same service-based systems with a different number of services to be composed from. If we differentiate the SASs based on their domains, as shown in Figure 11, then the portion of primary studies that considers one SAS becomes 74%, and the number of studies that consider less than three subject SASs is increased to 97%.

Fig. 10: Distribution on the number of different subject SAS considered in the primary studies.

Fig. 11: Distribution on the number of different subject SAS from distinct domains considered in the primary studies.

49 and 37 primary studies, respectively. The simulator is easy to setup and cheap to carry out the experiment runs with reproducible outcomes. However, they may not be able to capture the complex characteristics of real-world SASs. The real systems, on the other hand, are either standard benchmark or widely used SASs, but they are often complex to be deployed, requiring lengthy experiments and the results can be difficult to the replicated as they may be highly restricted to the experimental environment. Apart from these, 8 primary studies have used real-world dataset, which contains data collected from the real systems, whilst at the same time, does not entail the complication associated with the real system. However, such datasets are difficult to obtain and the readily available real-world dataset for SASs is rather limited.

5 DISAPPOINTED ISSUES
In this section, we present in-depth discussions of the disappointed issues derived from the survey results, together, supported by justifiable evidence.

5.1 Unjustified Bias on the Selection of Search Algorithms
The long history of Computational Optimization community has witnessed a wide range of effective search algorithms. The other problems in SBSE have also attempted to explore various search algorithm over the last decade [20]. However, as discussed in Section 4.2 it is disappointed.
to find that when investigating SBSE for SASs, there is an unjustified bias on the selection of search algorithms, i.e., GA and ES are predominated for single or aggregated objective case; NSGA-II is significantly more common in Pareto-based multi-objective cases.

Indeed, certain search algorithms are 'better known' than some others, but such a large bias is what we did not expect. In fact, the selections have not been well-justified: undoubtedly, ES will not work for those widely used subject SASs with an explosion of search space, as shown in Section 4.6. While both GA and NSGA-II are arguably one of the most popular algorithms out of their own category, there has been no scientific evidences to prove that they are universally fit to all contexts, especially considering that the dynamics and uncertainty are heavily involved in the search problems of SAS. In particular, given the extremely active research within the computational optimization domain, it is possible that alternative algorithms perform much better for SAS optimization, which is not uncommon in other SBSE problems. For example, in the software product line optimization problem, IBEA [93] has been shown to be able to find solutions with better convergence and diversity than NSGA-II. This is also highly plausible on SAS problems. In fact, it is essential to 'try' a good range of alternative search algorithms and report the results, especially when the knowledge of the problem is not very clear.

In the Computational Optimization and Evolutionary Computation community, it is not uncommon to investigate between four to six algorithms for majority of the work in order to fully evaluate the effectiveness of the proposed approach and justify the choice. This has also been becoming a standard practice in SBSE. For example, on the test case generation [105] and refactoring [7] problem, existing work (excluding empirical studies) has also studied and presented results based on more than three competitive search algorithms. Sometimes, there can be 9 search algorithms.

Another (probably more important) issue is to select search algorithms for comparisons according to the properties of the problem considered. It is known that every algorithm does have their own "comfort zone". But people tend to work by analogy; that is, using the algorithm which was (widely) used before. This may cause the risk of not being fully aware of their limitations. For example, ES is apparently not workable on large scale SASs; GA may not be suitable for time-critical SASs; NSGA-II typically does not work on SAS problems with four and more objectives [107]. Therefore, selecting an algorithm suitable for the considered SAS problem is crucial, which demands a well understand-

11. Excluding empirical studies where the number of the compared algorithms may easily be over a dozen.
ing of both the problem and the algorithm. This, however, can emerge as a future opportunity on SBSE for SASs, as we will discuss in Section 6.2.

We therefore urge the researchers and practitioners in SBSE for SASs to consider a much wider and deeper investigation on the different search algorithms, as well as a more scientifically justifiable selection of algorithms based on the understanding between SAS problems and search algorithms where possible.

5.2 Limited Synergy between Domain Knowledge and Search Algorithm

Given the very nature of the optimization involved in engineering SASs, exploring SBSE, or more generic sense of search algorithms, for SASs is certainly not new. Yet, disappointingly, from Section 4.3, we have failed to see how the advances of SBSE for SASs can be differed from “another application domain of the search algorithms”, as 79% of the primary studies merely specialize the search algorithm with the nature information about the problem.

Since SBSE is relatively new to SAS research, this result is predictable, but we did not expect such a significant discrepancy. The key challenge that underpins this disappointment is how to exploit the expertise and domain knowledge of engineers to tailor which aspects of the search algorithms, in order to reach better specialized and improved optimization results. This is perhaps a more general issue on a wider context of SBSE problems, but there has been some very successful attempts in capturing and synergizing such knowledge into the algorithms on other SBSE research. For instance, for the software testing problems addressed by SBSE, the search algorithms are often manipulated to work with various types of seeds, which were specifically designed to match the contexts of the code to the test bed [6]. There are also a considerable amount of work that focuses on specializing the operators of search algorithms to better serve the context [8, 10].

Ignoring the strong domain knowledge from engineers is a non-trivial issue on SBSE for SASs and can be an unwise waste of such valuable knowledge. For example, a recent work by Chen et al. [13] on SBSE for SASs has shown that, instead of allowing the algorithm to search from scratch, seeding the search algorithm with high quality seeds, which were selected based on engineers’ expertise, can largely improve the optimization result (i.e., the HV value) when configuring 10 different service-based SASs. An example has been illustrated in Figure 15.

As shown in Section 5.3, we do see a few very good example work (e.g., [14, 15, 18, 21]) on better synergizing domain expertise and search algorithms when exploring SBSE for SASs, which constitutes to the renaming 21% of the primary studies. This, as shown in those 21% work, is in fact a win-win strategy, where on one hand, the search algorithm can be potentially made more controllable and explainable, on the other hand, the strong domain knowledge can serve as strong guidance to steer the search, achieving results that would be otherwise difficult to obtain. Further, the nature of complexity in SAS can actually provide more opportunity to design a better tailored and specialized search algorithm for the context.

We therefore seek to increase the 21% of primary studies and urge the community that when investigating SBSE for SASs, a better and more thorough synergy between domain knowledge and the search algorithms should be carefully considered. This disappointed issue also raise the need of highly specialized search algorithm that also consider the characteristics of the algorithm itself, and human centric SBSE for SASs, in which the human (engineers) is permitted to control the search algorithms, rendering the results more explainable. We will further discuss these new opportunities for future research in Section 6.1 and 6.5 respectively.

5.3 Limited and Inaccurate Definition of Multi-Objective Search for SAS

Multi-objective search, in the context of Computational Optimization community and other SBSE problem, refers to simultaneously optimizing multiple (usually conflicting) objectives, thus resulting in a set of trade-off solutions, called Pareto optimal solutions. Searching for all Pareto optimal solutions (or a good approximation of them) provides the engineers with diverse choices from which they can choose their preferred one, but also with the knowledge/information of the optimization problem (e.g., correlation between the objectives, actual dimensionality of the Pareto front, and the location of knee points) for better understanding of the problem.

However, as shown in Section 4.4, our review discovers that on SBSE for SASs, the multi-objective search can refer to the fact that there are multiple conflicting objectives, but they are optimized in certain form of aggregation (i.e., weighted sum or product). We were disappointed to see that, this form of optimization is predominantly referred to as multi-objective search and constitutes to 52 primary studies, compared with 20 others that rely on the alternative, and perhaps more accurate way of multi-objective search using Pareto-based relation.

In essence, the aggregation of objectives implies that certain preferences over the objectives are available and they can be precisely quantified using weights, as we showed that the majority of them have either assumed the weights can be provided by the engineers or they are equally weighted by default. Indeed, if this is the case, then the...
aggregation way of search-based optimization can be ideal. However, it is not uncommon that a precise quantification of the weights are very difficult, if not impossible, especially given the complexity of SAS. In particular, despite being adopted in 20 primary studies, it is in fact an inaccurate assumption that setting equal weights to the objectives implies an equal importance and thereby leading to a fair solution, because the search pressure guided by the weighted fitness and a single objective search algorithm may not be able to discover certain solutions in the first place. For example, in Figure 16 we compare the case of searching with equally weighted sum of objectives (GA) and the Pareto-based multi-objective search (NSGA-II) on DTLZ2, a well-known bi-objectives test function from the Evolutionary Computation community. Clearly, after very few generations (less than 20), the GA converges to a single point while the NSGA-II produces a much more diverse set of Pareto optimal solutions, finally representing a full spectrum of the trade-off surface in the problem. It is interesting to note that, even equal weights have been given to the two objectives under the same scale, the final solutions are far from being balanced. In fact, it shifts towards the extreme where one objective is preferred more, i.e., close to the boundary points of the problem’s Pareto front. This has apparently contradicted with the general belief that equally weighted objectives represent fair importance. The fundamental cause of this is that (i) the boundary points have higher aggregated fitness than inner points due to the concave shape of the Pareto front, and (ii) the gene drift phenomenon in GA easily lead the population to converge into one point.

The minority of the Pareto-based multi-objective search on SBSE for SASs, on the other hand, does not require weights specification during the search, which precisely addresses the shortcoming of weighted sum and product of the objectives. However, one challenge of Pareto-based multi-objective search is how to select a single solution from the produced nondominated trade-off set. When no preference information is available, it is ideal to provide the engineers with all nondominated solutions found to keep them informed in the decision-making process. When certain preferences exist, the selection of the single solution can be tailored with such. Yet, unlike the case of weighted aggregation, such preferences do not require explicit quantification. As we have shown in Section 4.4 this can be achieved with human intervention when possible (14 studies), or automatically completed by selecting a solution from certain regions, e.g., the knee point selection.

In our review, we have also observed that certain work apply both, e.g., [72] [52], in which the search is conducted in a Pareto-based multi-objective way while the final solution is selected using one single weighted aggregation. This is an approach that we are particularly against, as it arises a clear contradiction: the fact that the weighted aggregation is used implies that certain preferences over the objectives are available and can be quantified, which contradicts with the fact that Pareto-based multi-objective search is usually conducted when such a clear quantification does not exist. Sadly, those studies have not explicitly discussed the rationals behind the choice.

As a result, Pareto-based multi-objective search is what should be investigated more, at least in a comparative amount of attentions to the weighted aggregation, when exploiting SBSE for SASs. With this regard, a future direction on how to capture and model preference on SBSE for SASs has emerged as a new research opportunity, as we will discuss in Section 6.2.

5.4 Unjustified Quality Indicator Selection under Multiple Objectives

When multiple conflicting objectives of the SAS are involved, we have shown in Section 4.5 that using utility or the value for each objective individually are predominated ways to assess the quality of solutions. Despite their popularity, it is disappointed that our review finds no systematic justification on the choice of utility and objective value as quality indicators for multiple objectives. This is important, because as shown in Table 4 the utility can collectively assess all objectives of a single solution only under the assumption that preferences are available and can be precisely quantified. However, as mentioned, it is not uncommon in SAS optimization that the preferences are not available or too difficult to be quantified. The objective value, on the other hand, is exempted from such prerequisite but only provides assessment on a single objective at a time. This is apparently not accurate as it ignores the quality of the solutions on other objectives. When there is a need to assess a solution set, such a way of considering objectives separately may lead to a situation that a solution set is evaluated better than another on all objectives individually, but it turns out that the engineer would never prefer it under any circumstance. The other quality indicators, e.g., HV, IGD, $\epsilon$-indicator and GD, are exactly designed to compare

### Table 4: The prerequisite and characteristics of the top 5 quality indicators considered in the primary studies.

| Prerequisite | utility | objective value | HV, IGD, $\epsilon$ and GD |
|--------------|---------|-----------------|----------------------------|
| Comparing the solution(s) on all objectives? | Yes | No | Yes |
| Comparing solution sets? | No | No | Yes |
TABLE 5: The eight most frequently-used quality indicators for assessing solution set in SBSE [16].

| Convergence | GD | ED | ε-indicator | GS | PFS | IGD | HV | C |
|-------------|----|----|-------------|----|-----|-----|-----|---|
| Spread      | +  | +  | +           | +  | -   | +   | +   | - |
| Uniformity  | -  | +  | +           | +  | +   | -   | -   | - |
| Cardinality | -  | -  | +           | -  | -   | +   | -   | - |

Diversity consists of spread (i.e., coverage) and uniformity. “+” means that the indicator can well reflect a specific quality aspect and “−” means that the indicator can partially reflect a quality aspect.

Fig. 17: Two Pareto-based nondominated solutions sets, A and B, for optimising dependency compliance and the cost of SAS adaptation. A is evaluated better than B on all the eight commonly used quality indicators in SBSE: $GD(A) = 0.02 < GD(B) = 0.26$, $ED(A) = 0.5 < ED(B) = 0.89$, $\epsilon(A) = 0.1 < \epsilon(B) = 0.3$, $GS(A) = 0.15 < GS(B) = 0.46$, $PFS(A) = 5 > PFS(B) = 4$, $IGD(A) = 0.02 < IGD(B) = 0.27$, $HV(A) = 0.77 > HV(B) = 0.43$, $C(A) = 0.8 > C(B) = 0.25$. However, B is in fact more preferred (specifically solution β) when full dependency compliance is more important than possible low cost.

In Section 4.6, we have shown that a variety of subject SASs are considered on SBSE for SASs. Yet, disappointedly, our review has indicated that there are 65% primary studies consider only one SAS, and 87% consider less than three. It becomes even more disappointing if we differentiate the SASs based on their domains, as discussed in Section 4.6 where the portion of studies that considers one SAS increases to three quarters, with the number of studies that consider less than three subject SASs increase to 97%. From the research work on other SBSE problems, it is not uncommon to see a wide range of subject software systems have been used (even excluding empirical studies), for example, SBSE for software product line engineering often involve more than 10 distinct subject systems [108]. In the Computational Optimization and Evolutionary Computation community, we urged the community on this thread of research to carefully consider the selection of multi-objective quality indicators, which itself could potentially be a promising research area. This disappointed issue is again related to the new research opportunity of how to capture and model preference on SBSE for SASs, which we will discuss in Section 6.2.

5.5 Weak Generalization of Results across the Subject SASs

In Section 4.6, we have shown that a variety of subject SASs are considered on SBSE for SASs. Yet, disappointedly, our review has indicated that there are 65% primary studies consider only one SAS, and 87% consider less than three. It becomes even more disappointing if we differentiate the SASs based on their domains, as discussed in Section 4.6 where the portion of studies that considers one SAS increases to three quarters, with the number of studies that consider less than three subject SASs increase to 97%. From the research work on other SBSE problems, it is not uncommon to see a wide range of subject software systems have been used (even excluding empirical studies), for example, SBSE for software product line engineering often involve more than 10 distinct subject systems [108]. In the Computational Optimization and Evolutionary Computation community, we urged the community on this thread of research to carefully consider the selection of multi-objective quality indicators, which itself could potentially be a promising research area. This disappointed issue is again related to the new research opportunity of how to capture and model preference on SBSE for SASs, which we will discuss in Section 6.2.

The actual meaning of cost depends on the context, e.g., it could be the time or resources required to realize adaptation.
the number of test functions used to evaluate a search algorithm is also most commonly to be more than 10 (excluding empirical studies). Comparatively, the number of subject SASs considered is current work on SBSE for SASs is rather limited, even when pure empirical studies are included.

This can be a crucial issue when conducting research on SBSE for SASs, as it weakens the generalization of the conclusion drawn. An example from Pascual et al.’s work [11] has been shown in Table 6 in which the GD results produced by the search algorithms on configuring 8 different SASs are compared. It is unclear to claim whether NSGA-II or SPEA2 can generally outperform the other as they are subject SASs are compared. It is unclear to claim whether NSGA-II or SPEA2 can generally outperform the other as they are

| SAS        | NSGA-II (95% CI) | SPEA2 (95% CI) |
|------------|------------------|---------------|
| Sensor     | 1.39(1.8E+3)     | 1.79(1.4E+3)  |
| Game       | 2.41(1.7E+3)     | 2.79(1.4E+3)  |
| Tank War   | 2.08(6.7E+2)     | 2.09(6.3E+2)  |
| Media      | 2.96(1.2E+3)     | 2.90(1.1E+3)  |
| Guide      | 1.58(3.8E+2)     | 1.72(3.7E+2)  |

The better one is highlighted.

### 6 Opportunities

Despite of having several disappointed and overwhelming issues, SBSE for SASs is still a vital research direction which also bears many opportunities. In this section, we specify those opportunities and outline their promising research directions, as well as the related challenges to be addressed.

#### 6.1 Justifiably Selecting Search Algorithm according to Problem Instances on SBSE for SASs

An interesting phenomenon in SAS as well as SBSE is that in spite of the considerably large number of search algorithms currently available, the primary studies adopt/compare just very few of them, as we shown in Section 4.2. Several algorithms have a clear preference, such as GA and ES for a generic optimization case and NSGA-II for the multi-objective optimisation case. Indeed, every search algorithm has their own merit, which makes them well-suited to a particular class of problems. For a generic optimization case, it is clear that if the scale of the problem is small enough to allow enumerating all solutions (with a given time budget), then ES can be a good option as it can guarantee the optimal solution. Some algorithms are designed for a particular class of problems, and it is expected that these algorithms may produce better solutions than algorithms designed for generic problems, for example Branch and Bound (BB) for some combinatorial problems. The algorithms RS, Greedy Search (GS), HC and GA cannot guarantee an optimal solution. As its name suggests, RS visits the space randomly and the final solution can be rather different in each run of the algorithm. As opposed to RS, every iteration (step) in GS is determined (to make the current optimal choice), in order to the overall optimal way to solve the entire problem. HC may be deemed as a combination of RS and GS, as it starts from a random initial point in the search space and iteratively finds the best neighbor of the current solution. Compared to RS, GS and HS, GA (and other metaheuristics) is a sophisticated optimization algorithm. Its population-based search strategy with a diversity preservation can help to some extent the search jump out of local optimum. A particular benefit of such population-based search is dealing with multi-objective problems, where each individual in the population can be used to approximate a unique trade-off between objectives.

For the multi-objective case, as shown in Figure 3, most of the algorithms considered belong to GA or its variants. Consequently, the range of problems that the algorithms are suitable for is narrow and overlapping. Nevertheless, different multi-objective GAs do have their own “comfort zone”. For example, the algorithms which compare solutions by Pareto dominance and density, such as NSGA-II [90] and SPEA2 [91], typically do not work well on many-objective problems where the number of objectives is larger than three [107]. The decomposition-based algorithms (e.g., MOEA/D [92] and its variants MOEA/D-STM [96] and NSGA-III [110]) scale up well in terms of objective dimensionality, but may struggle on problems with an irregular Pareto front shape (e.g. degenerate, disconnect or highly-nonlinear) [111]. The indicator-based algorithms (e.g., IBEA [93]) are often insensitive to the Pareto front shape, but may suffer from the dominance resistance solutions (i.e. solutions with an extremely poor value on at least one of the objectives but with (near) optimal values on the others [112]), thereby with their solutions concentrating in the boundaries of the Pareto front [113].

Overall, it is important to understand the behavior and advantages/drawbacks of search algorithms available, which, together with the problem knowledge, will certainly help to choose an appropriate algorithm that is well-suited to the problem in hand. To achieve that, there are several challenging research questions desirable for us to address.

- What kind of information/knowledge of the SAS problem can be obtained/extracted, and how.
- What kind of search algorithm can make better use of such information/knowledge, which can greatly inform the algorithm selection.
- Or further, how to generically develop a specialized search algorithm specifically for a SAS problem.
6.2 Capturing Preferences of the Engineers in SBSE for SASs

Preferences refer to one’s satisfaction on certain aspects of the SAS, and they can come from the software and system engineers, who have specific software engineering expertise, and would make various decisions in engineering SAS. While preference exist even for the single objective case, it is often greater importance when there are multiple conflicting objectives for the SAS. According to the software engineering expertise of the engineers, s/he might only be interested in a handful of selected solutions that meet their preference most, instead of the entire set of solution obtained by a Pareto-based multi-objective search algorithm. As a matter of fact, this has been a long standing topic in the Computational Optimization community over half a century.

As we discussed in Section 4.4, 14 primary studies on SBSE for SASs, which constitute to the majority, have captured preferences in a posteriori manner, where a set of widely spread trade-off alternatives are obtained by a search algorithm before being presented to the engineers. However, this obviously increases the engineers’ workload and will incorporate much irrelevant or even noisy information during the decision-making process. To alleviate the cognitive burden of the engineers, some pre-screen techniques have been introduced to help select a handful of representative solutions before handing over to the engineers. These, as shown in Section 4.4 include selecting only the knee point(s) or solutions that are significantly superior on certain preferred objectives. Indeed, a posteriori manner mainly captures preferences based on the natural cognition of engineers rather than their software engineering expertise, as the captured preference cannot influence the search process.

The above has raised the research opportunity of SBSE for SASs on handling preference in a priori or even an interactive manner. In this regard, the former means that the preference information can also be elicited a priori and is used as a criterion to evaluate the fitness that drives the search towards the region of interest along a pre-defined preferred direction. For example, the preference information can be represented as one or more reference points, each dimension of which represents the engineers’ expectation at the corresponding objective [114], [115]. Such information can be formally extracted from some software engineering design notations, such as the goal model. However, capturing the preferences only occur at the beginning of the search. The latter, i.e., the interactive manner, permits continuous refinement of the preferences and thus allowing more accurate capture. Such an interactive preferences capture is a point we will further elaborate in Section 6.5. To achieve a priori or interactive capture of preferences, there are several challenging research questions need to be addressed:

- How to automatically extract the stockholders’ preference information in an efficient and cost effective manner.
- How to structuralize the preferences in a way that is understandable by the search algorithm.
- What parts of the stockholders’ preferences, expressed in some software engineering representations, can be correlated to which quality aspect of the solution.

6.3 Effective and Efficient Fitness Evaluation in SBSE for SASs

A crucial part of SBSE is how the fitness of a solution can be evaluated, which serves as the key to drive the search process. This, in the context of SASs, is often related to how the behaviors of the systems can be changed with different adaptation solutions. In certain scenario, it is possible to profile the SAS at design time, or at runtime where the profiling only affect the SAS in certain aspects rather than changing the whole system [78]. However, most commonly, such profiling is expensive and time consuming. In contrast, surrogate models that are based on machine learning has been explored as an alternative, given that they are relatively cheap in terms of the fitness evaluation as the search proceeds [116]. Yet, this comes with the cost of high complexity in building such model, which may still be lack of accuracy or difficult to capture the up-to-date changes of SASs. Further, the amount of examples required to train the model can also hinder the effectiveness of the search.

The situation raises the research opportunity of investigating effective and efficient fitness evaluation in SBSE for SASs. In particular, the key difficulty lies in the question on how to keep the overhead of fitness evaluation low, while maintaining a reasonable accuracy and cost of building the surrogate model. A promising direction on this is the research area of incremental online learning, where the model can be learned with limited data samples and can be efficiently updated as new data is collected while providing adequate accuracy [116]. The other possible direction is to explore so-called novelty model that does not required to observe the behaviors of SASs when using SBSE [117]. Such a model mimics the natural phenomenon where the evolution would never be solely guided by explicit objectives, but also the biological novelty of the individuals. In such a way, the fineness can be assessed without the need to affect or acquire data from the SASs, and thus mitigating expensive evaluation. However, more research questions need to be addressed in order to better incorporate online learning with SBSE for SASs, such as the following:

- Whether the frequency of model update could have an impact to the search results.
- How to handle the trade-off between the cost of model building and the accuracy (or relevance) of the model, if any.
- What are the correlations between the accuracy (or relevance) of a model to the improvement of SBSE for SASs.

6.4 Just-in-Time Handling of Changes in SBSE for SASs

SAS would inevitably face with changes on the requirements, environment or its internal states, either at design time or at runtime. Despite the fact that SBSE is capable of naturally handling dynamics to some extents, the more fundamental problem is how often should the optimization runs in order to ensure that the results can cope with the new changes. Current researches on SBSE for SASs have almost ignored this point or simply assume that the search algorithm can be re-triggered when there is a need (e.g., according to a fixed frequency or upon the occurrence of
changes). Yet, such a strategy would suffer the limitation that no changes can be captured during the run of the search algorithm.

To this end, recent advances on so-called dynamic optimization [118] and dynamic SBSE [119] is a promising, but under-explored solution for SAAs. Here, the key idea is to allow the search algorithm to automatically pick up any new changes during the search process, and therefore the new information can be used to steer the search or old and useless information can be discard in order to prevent misleading. Such a very nature is a perfect fit to various problems with ‘changes’ that are faced by modern SAAs. However, there are some crucial challenges on this particular direction of research on SBSE for SAAs, for example:

- What are the mappings between the changes on SAAs and the changes with respect to the search algorithm.
- What are the changes can be handled while the search is under processing, and how they can be fed into the search.
- Whether it is possible to generically consolidate any given search algorithm.

6.5 Human-Centric SBSE for SAAs

The main purpose of engineering SAAs is to reduce the levels of human intervention on the running software systems. However, it has been shown that there are scenarios where human involvement is essential [120], or human knowledge has been proven to be able to greatly improve the behaviors of SAAs. Similarly, SBSE is also motivated from the same origin: to automatically generate the software engineering process and thus free the software engineer from tedious and error-proven tasks. Recently, there is an ongoing demand to engineer human-centric SBSE, such that the search approach does not make the final decision on its own, but serving as an assistant to add insight for human to make decisions. Those two facts, together, imply a perfect match between the two fields in terms of the human-centric aspect.

In particular, human can refer to a wide range of engineers with certain software engineering expertise around SAAs, including but not limited to, developers, requirements analyst, architects and testers. Among others, interactive SBSE, in which the human’s domain knowledge of expertise can be used to explicitly control the search process with explainable outcomes, is a promising research opportunity for this thread of research.

Specifically, the interactive SBSE is an emerging paradigm for decision making for software engineering problems on the fly. Combing together with the preferences capturing discussed in Section 6.2 interactive SBSE enables the human to progressively learn and understand the characteristics of the SAS problem at hand and adjust towards more appropriate capture of the preferences information. As a result, solutions can be gradually driven towards the region of interest [121], allowing the human to have more controllability over the search algorithm using their software engineering expertise [122]. This would also create more inspirations to build specialized search algorithms, which should work the best under the SAS where the knowledge lies. Yet, the challenges can be related to:

- What forms of human knowledge/expertise can explicitly influence which aspects of SBSE for SAAs.
- How human can be placed in the loop in order to facilitate timely interaction with SBSE for SAAs.
- How to ensure the information provided by human is reliable, i.e., how to prevent immature inputs.

6.6 Incorporating SBSE with Other Approaches for SAAs

SBSE would never be the sole approach for tackling problems in SAAs. In fact, given the nature of “optimization” implied in SBSE, there is a variety of opportunities to incorporate SBSE and other approaches for SAAs, such as control theory, verification, machine learning and so forth. Our review has witnessed a few successful work that specifically incorporates SBSE with the other approaches, for example, Gerasimou et al. [51] have adopted SBSE, guided by probabilistic verification model, to search for optimal adaptation solution; Maggio et al. [68] have also applied control-theoretic adaptation that is tuned using SBSE. However, there is a lack of general guideline about the possible forms of incorporation. This is important, especially given the wide applicability of SBSE and other approaches for engineering SAAs. In particular, challenges can be raised by the following new directions of research:

- What are the patterns involved when incorporating SBSE with the other approaches for engineering SAAs.
- Whether there could be a “symbiotic” relation exist between SBSE and the other approach, i.e., both SBSE and the other can benefit from each other, which collaborates together to improve the SAS.
- How to codify a generic methodology that guides the practitioners of SAAs on incorporating SBSE with the other approaches.

7 Threats to Validity

Threats to construct validity can be raised by the research methodology, which may not serve the purpose of answering our research questions. We have mitigated such threats by following the systematic review protocol proposed by Kitchenham et al. [22], which is a widely recognised search methodology for conducting survey on software engineering research.

Threats to internal validity may be introduced by having inappropriate classification and interpretation of the papers. We have limited this by conducting multiple rounds of paper reviews amongst all the authors. Error checks and investigations were also conducted to correct any issues found during the search procedure.

Finally, threats to external validity may restrict the generalizability of the results. We have mitigated such by conducting the systematic survey wider and deeper: it covers 3,740 searched papers published between 2009 and 2019, on 27 venues from 7 repositories; while at the same time, extracting 73 most notable primary studies following the exclusion and inclusion procedure.
8 Conclusion

In this work, we have systematically surveyed the research on SBSE for SASs published between 2009 and 2019, leading to 3,740 searched papers over 27 venues, based on which 409 primary studies were selected for the analysis. Several key statistics have been extracted from the state-of-the-art with respect to the RQs:

- **To RQ1**: The configuration of SASs are the most widely studied problem for SBSE for SASs on 78% of the work. The problem of SAS deployment is ranked the second with 11%.
- **To RQ2**: GA and ES, both appear in 15 primary studies, are the most commonly studied search algorithm for single (aggregated) objective in SAS. NSGA-II is the predominated solution (13 primary studies) on Pareto-based multi-objective search.
- **To RQ3**: 79% of the primary studies have used only nature information of the problem to specialize a search algorithm. The other minority of additional domain knowledge include feature model, seeds of solutions, goal model and abstract syntax tree of the code.
- **To RQ4**: When handling multiple conflicting objectives on SBSE for SASs, weighted aggregation is predominated in 52 primary studies. The Pareto-based multi-objective search form the minority of the remaining 20 primary studies.
- **To RQ5**: Weighted utility or descriptive statistics of each objective values are predominated ways to assess the results on SBSE for SASs under multi-objectivity, found in 68 primary studies. HV, IGD, $\epsilon$-indicator and GD appear in 21 studies.
- **To RQ6**: Simulator and real system are the most commonly used types of subject SASs in 49 and 37 primary studies, respectively. The most common SAS is the synthetic service system, which appears in 11 work. The number of studies that consider less than three subject SASs is 87%, which forms the majority. This figure is increased to 97% when the SASs are differentated based on their domains.

The results have also revealed five disappointed phenomena from the most notable primary studies, namely:

- Unjustified bias on the selection of search algorithms
- Limited synergy between domain expertise and search algorithm
- Limited and inaccurate definition of multi-objective search for SASs
- Unjustified quality indicator selection under multiple objectives
- Weak generalization of results across the subject SASs

Those overwhelming issues are mainly due to the non-compliance of the best practices from the research community of SBSE and Computational Optimization. We provide evidences to justify the issues and also highlight six emergent opportunities that are currently under-explored for research on SBSE for SASs, theses are:

- Justifiably selecting search algorithm on SBSE for SASs
- Capturing preferences of the engineers in SBSE for SASs
- Effective and efficient fitness evaluation in SBSE for SASs
- Just-in-time handling of changes in SBSE for SASs
- Human-centric SBSE for SASs
- Incorporating SBSE and other approaches for SASs

Our work provides useful insights that can hopefully excite a much more significant growth of this particular field of research, attracting not only the SA practitioners, but also the researchers from the other fields, such as general SBSE, Computational Optimization and Evolutionary Computation.

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