FLASH: A Faster Optimizer for SBSE Tasks

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Abstract—Most problems in search-based software engineering involve balancing conflicting objectives. Prior approaches to this task have required a large number of evaluations—making them very slow to execute and very hard to comprehend. To solve these problems, this paper introduces FLASH, a decision-tree-based optimizer that incrementally grows one decision tree per objective. These trees are then used to select the next sample.

This paper compares FLASH to state-of-the-art algorithms from search-based SE and machine learning. This comparison uses multiple SBSE case studies for release planning, configuration control, process modeling, and sprint planning for agile development. FLASH was found to be the fastest optimizer (sometimes requiring less than 1% of the evaluations used by evolutionary algorithms). Also, measured in terms of model size, FLASH’s reasoning was far more succinct and comprehensible. Further, measured in terms of finding effective optimization, FLASH’s recommendations were highly competitive with other approaches. Finally, FLASH scaled to more complex models since it always terminated (while state-of-the-art algorithm did not).

Keywords—Search based software engineering, optimization, configuration, release planning, agile, NSGA-II, SPEA2, SWAY, MOEA/D, ePAL, Bayesian optimizer.

I. INTRODUCTION

In 2001, Harman and Jones characterized a wide range of SE tasks as an optimization problem; i.e.

One in which optimal or near-optimal solutions are sought in a search space of candidate solutions guided by a fitness function that distinguishes between and worse searches. \cite{15}.

To complete such tasks, some algorithm must navigate through a complex space of constraints. Often “trade-offs” must be made between multiple competing objectives; e.g.

(a) An optimized agile project selects use cases from a backlog that deliver the most requirements in the least time \cite{29};

(b) An optimized waterfall project uses fewest programmers to deliver most code with fewest bugs in least time \cite{22};

(c) An optimized release planner delivers the most functionality with the least cost while minimizing risks and maximizing customer satisfaction \cite{42};

(d) An optimized configuration engine most explores the measure of interest of the stakeholder (such as throughput) after reflecting on the fewest configurations \cite{31}.

A perennial question is which algorithm to use to optimize these tasks. Recent literature reviews report that the search-based SE (SBSE) community makes extensive use of only two or three evolutionary algorithms \cite{6}. This is curious since:

(1) Researchers in software analytics have shown that their standard algorithms can be readily adapted to optimizing SE tasks — sometimes significantly out-performing EA methods \cite{20, 27, 25}.

(2) For such optimization tasks, machine learning researchers prefer non-evolutionary algorithms called “Bayesian optimization” \cite{32, 11, 46, 45}.

(3) Researchers in evolutionary algorithms (EAs) are always improving their algorithms \cite{9, 8, 42}.

Given plethora of methods there are two natural next questions. Firstly, should the SBSE community consider changing their preferred set of algorithms? Secondly, is there any advantage in combining ideas from different research communities?

To answer these questions, this paper experiments with a new optimizer called FLASH that combines ideas from the research communities (1), (2), (3) listed above. When tested on SE tasks (a), (b), (c), (d), FLASH was often a “better” optimizer than any of the standard methods. Here, by “better” we mean FLASH is far faster than the other algorithms studied in this paper. Also, FLASH produces simpler and more comprehensible summaries of its conclusions. Further, FLASH’s proposed optimizations are often just as good as the other algorithms. Lastly, FLASH scales to more complex models since it is the only algorithm in this particular case study that successfully terminated on the (a), (b), (c), (d) tasks.

Accordingly, we make several conclusions. Firstly, SBSE researchers have been unnecessarily limiting themselves due to their algorithm selection. Secondly, better SBSE techniques are now available based on a combination of methods from other fields. As to the specific technical contributions of this work, the unique features of this paper are:

• A demonstration that EAs may not be the preferred approach for some SBSE tasks;

• A proof-of-concept algorithm, FLASH, that demonstrates the value of combining insights and algorithms from several fields;

• An extension of standard SE configuration optimization to multi-objective reasoning;

• A set of experiments showing the value of FLASH;

• A public-domain version of FLASH and public-domain executable versions of models used in (a), (b), (c), (d)\footnote{http://github.com/blinded4review}.

• Guidelines for when not to use FLASH.
II. RELATED WORK

A. Optimizations from Software Analytics

One approach towards optimization of SBSE tasks comes from the software analytics literature. In this approach, standard software analytics learners are applied to data and the resulting model is queried in some way to guide the optimizations. As described below, examples of this approach include GALE [20], SWAY [25], and the CART-based methods [5] used by the software product line community [31, 27].

Software product line researchers warn that developers rarely understand the configurations of their system [41]. Hence, they may ignore most of their configuration options, leaving considerable optimization potential untapped. To address this problem, many researchers have collected performance data from many different configurations, then applied the CART decision tree learner to summarize the results into a comprehensible form [28, 13]. The problem with this approach is the data collection cost—many configurations must be compiled and executed to build CART’s training set. Accordingly, various research teams have tried incremental approaches that learn from some stochastically selected sample of the data. For example, Nair et al. [27] clustered the data then learned from examples selected at random from each cluster. While a useful approach, this method was reliant on CART and hence suffer from the limitations of that algorithm. Specifically: CART learns models for a single goal while the task shown in the Section II require a multi-goal analysis.

Other work from software analytics handles multi-objective optimization. Krall et al. [29] approach optimizations as a clustering problem. Their GALE algorithm recursively bi-clustered decisions using an approximation to the first component of principle components analysis. At each level of the recursion, GALE evaluates the two most distant decisions, then prunes half of the data furthest from a “better” decision (and “better” is defined using the domination predicates discussed below). For each leaf in the resulting tree, GALE sorts two distant decisions, and mutates all the examples towards the better end. Subsequent work by Chen and Nair et al. [25] showed that GALE’s leaf mutation was less important than exploring a large initial population. Hence, while GALE explored populations of 100 randomly generated decisions, Chen and Nair’s SWAY algorithm (shown in Figure 1) used no mutation but just explored populations of 10,000 randomly generated decisions. The key point of SWAY is when it explores 10,000 decisions, then at every level of its recursion, it only evaluates two decisions (plus all the decisions found in the final leaf—typically \( \sqrt{N} \) items). That is, when exploring 10,000 decisions, SWAY terminates after less than 126 \( 2 \log_{2} 10^{4} + \sqrt{10^{4}} \) evaluations. When compared against evolutionary algorithms, SWAY proved to be remarkably effective [25]. That said, as shown below, the algorithm called FLASH is faster since it uses even fewer evaluations.

B. Bayesian Optimization - ePAL

Bayesian optimizers (BO) incrementally update a surrogate model representing a generalization of all examples seen so far. For example, after processing 20 examples, an BO generalizes those examples into some probabilistic regression model that summarizes prior beliefs about the sampled instances. The surrogate model used in practice is usually a Gaussian Process Model [18, 45] but other approximations have been proposed namely Parzen estimators [3], Random Forests [16], just to name a few. Once the surrogate is available, it can be used to decide the next most promising point to evaluate. This ability to avoid unnecessary model executions (by just exploring a surrogate) is very useful in the case of models that take minutes to hours to days to execute.

Most prior work on BO focused on single-goal optimization. Algorithm 2 shows Zuluaga et al.’s ePAL [45], a novel multi-objective extension of BO. The algorithm inputs a large number of unevauated data items. Before entering its main loop, ePAL applies the fitness function to an initial small sample of 20 data items. Then, until it exhausts all the data, the evaluated data are used to build a Gaussian process model. The model is then applied to the remaining data to learn \( \mu, \sigma \) of the model predictions. ePAL then removes all \( \varepsilon \)-dominated points: \( y \) is discarded due to \( x \) if \( \mu_{x} + \sigma_{x} \varepsilon \)-dominates \( \mu_{y} - \sigma_{y} \), where \( x \varepsilon \)-dominates \( y \) if \( x + \varepsilon \geq y \) and “\( \geq \)” is binary domination—see Equation 1 in Table I. ePAL also uses its model to select the next most informative data item to evaluate. For this task, it selects the instance which is furthest away from the known \( \mu + \sigma \) of any objective.

While an interesting technology in some test domains,
Bayesian optimization has certain limitations. Building Gaussian process models can be very challenging for high dimensional data. So far, the state-of-the-art in this area is the optimization of models with around ten decisions [39].

C. Evolutionary Algorithms

EAs (also referred to as MOEA-Multi-Objective EA) evolve a population of solutions, guided by a fitness function, as follows. **Step 1:** Generate an initial population of solutions using an initialization policy for example random sampling. **Step 2:** Evaluate each solution using a problem specific fitness function. **Step 3:** Repeat the following.

- Create a new population using some problem specific reproduction operators; e.g. new individuals are formed by cross-over parts of pairs of parents.
- Evaluate the new population via the fitness function.
- Select solutions from a new population for the next generation. This selection is done using an elitist strategy which mimics the “survival of the fittest”. Table I discusses different kinds of elitism.

**Domination counters** compute \( \Omega_d(x) \) which is a sort order for individuals in a population based on how many other individuals \( y \) that are worse than \( x \), according to a domination definition \( d \). For a sample of different domination definitions, see Table I. One nuance of multi-objective optimization is that when a population is sorted by dominance, there may be more than one “best” individual. This is especially true when using the binary domination \( \Omega_B \) definition of Equation 1 in Table I. Hence, algorithms like NSGA-II [9], rely on a fast “non-dominated sorting” procedure to divide the population into “bands” with the property that items in the first band are better than those in the second, etc. Accordingly, when we seek several useful individuals, we will use \( \Omega_B \). However, when we want a single “best” individual, we will use another dominance counter which is known to return a single individual as “best” (\( \Omega_I \) counter based on indicator dominance— see Equation 2 of Table II).

Two problems with EAs are their long runtimes and comprehensibility. In practice, EA evaluates far more individuals than other algorithms such as SWAY, ePAL, or FLASH algorithm discussed in the next section. For example, when completing tasks (a), (b), (c), (d) from our introduction, ePAL, EAs require (tens, thousands) of evaluations, respectively. For another (very extreme) example, Wang et al. [38] needed 15 years of CPU time for their EAs to tune the parameters of their software clone detection tools. More typically, Harman [13] comments on the problems of evolving a test suite for software if every candidate solution requires a time consuming execution of the entire system: such test suite generation can take weeks of execution time.

As to the comprehensibility problem, when EAs terminate, they return all the individuals in the final population. Valerdi notes that, without automated tools, it can take days for human experts to review just a few dozen examples. In that same time, an automatic tool can explore thousands to billions more solutions. Humans can find it an overwhelming task just to certify the correctness of conclusions generated from so many results. Verrapra and Leiter warn that:

|TABLE I: Three kinds of EA elitist strategies.|
|---|
|1. Decomposition-based algorithms such as MOGLS [17] and MOEA/D [42] divide the problem into a set of sub-problems, which are solved simultaneously in a collaborative manner. For example, at start-up, MOEA/D generates over-lapping clusters of the population to find individuals with similar goal. If any member of a cluster finds a better solution, then it broadcasts the direction of that improvement to all individuals of all its containing clusters.|
|2. Pareto dominance-based algorithms such as NSGA-II [9], PAES [19] and SPEA2 [44] use binary domination to select solutions for the successive generations. When exploring a complex set of competing goals, there may be no best solution that is best over all objectives. Hence, to declare that one solution is “better” than another, all objectives must be polled separately. Given two vectors of decisions \( x, y \) with associated objectives \( o_x, o_y \), then \( x \) is binary dominant over \( y \) when:

\[
\forall o_j \in \text{objectives} \quad |\neg(o_j \prec o_j) | \\
\land \exists o_j \in \text{objectives} \quad o_j \succ o_j \\
\]

where \( obj \) are the objectives and \((\succ, \succ)\) tests if an objective score in one individual is (no worse, better) than the other. Pareto dominance-based algorithm are used in tandem with niching operators to preserve the diversity among the solutions. For example, if binary domination selects too many candidates for the next generation, NSGA-II employs a crowd-pruning heuristic to stop solutions clumping together to closely.

3. Indicator-based algorithms such as HypE [2] and IBEA [43] work by establishing a complete order among the solutions using a single scalar metric \( M \) like hypervolume etc. For example, in IBEA, \( x \) indicator dominates over \( y \) if:

\[
x \succ y = M(y, x) > M(x, y) \\
M(x, y) = \sum_{w=-1}^1 \Delta(j, x, y, n) / n \\
\Delta(j, x, y, n) = w (o_j \prec o_j) / n
\]

In the above \( w \in \{-1, 1\} \) and represents the \( n \) objectives that need to be minimized or maximized.

... for industrial problems, these algorithms generate (many) solutions which make the task of understanding them and selecting one amongst them difficult and time consuming. [36]

D. FLASH: A Hybrid Algorithm

Our understanding of the literature is that the optimization work in software analytics, machine learning, and evolutionary algorithms has evolved on mostly separate lines. But, clearly, these methods were all evolved to achieve similar goals. Therefore, it is reasonable to ask if there is any advantage in combining ideas from these different research directions.

Considerations such as these lead to the design of FLASH as a combination of other methods:

- From the EA community, we took the dominance counters \( \Omega_B \) and \( \Omega_I \) since these can find us find good candidate(s) within a large space of multiple objective options.
- From the Bayesian optimization work, we took the technique of minimizing the calls to the fitness functions; i.e. build a model from the current evaluations then use that model as a surrogate for the real world evaluations.
- From the software analytics community, we took decision tree learning with CART since such trees offer a succinct representation of multiple examples. Another advantage
A. Experimental Design Principle: “Precedented plus Two”

Our reading of the optimization literature is that there exists a very large number of optimizers, models, evaluation criteria that could be used to design experiments with optimizers. No single paper can explore all combinations of the above. Hence, we need some guiding principle for experimental design.

The principle used here is as follows: precedent plus two. As to “plus two”, we think important to not just use past work, but also to extend some parts of that work. Accordingly, to our design, we add one new treatment we wish to test (in this case, FLASH) plus a second new treatment that was rarely used before. In this case, we will apply the MOEA/D evolutionary algorithm (described in Table I) to many of our models. MOEA/D was chosen since it is an example of the newer generation of EA algorithms.

As to “precedented”, this means our experimental methods need to be justified via some prior precedent in the literature. For example, to select our statistical hypothesis test methods, we use the Scott-Knott effect-size endorsed by Mittas and Angelis at TSE’13 [24] and by Hassan et. al. at ICSE’15 [12]. Within Scott-Knott, we use the A12 non-parametric effect size test (to detect, then reject, trivially small differences) since A12 was endorsed by Acura & Briand at ICSE’11 in their paper Statistical tests to assess randomized algorithms in SE [11].

Another paper used to design our experiments is Practical guide to select quality indicators for search algorithms recently published in ICSE’16 [37]. Following their advice, we use two measures to assess the success of a multi-objective optimizer:

- The Generational Distance (GD) [35] measures the closeness of the solutions from by the optimizers to the Pareto frontier i.e. the actual set of non-dominated solutions.
- The Inverted Generational Distance (IGD) [7] is the mean distance from points on the Pareto frontier to its nearest point in the set returned by the optimizer.

Note that, for both measures, smaller values are better. Also, according to Coello et al. [7], IGD is a better measure of how well an optimizer’s solutions spreads across the space of all known solutions. Further, for models other than SS*, obtaining the PF is infeasible in practice [10]. Thus, to obtain a Pareto frontier, we apply \( \Omega_B \) to all solutions found by any algorithms for one model.

Moving on the selection of models, applying “precedented” principle, we use the POM, XOMO, MONRP, SS* models, respectively, to address the Introduction’s tasks (a), (b), (c), (d) since:

- POM and XOMO were used extensively by Chen et al. in their work on SWAY [25], [20].
- MONRP is widely used in the next-release planning community [6].
- The SS* models were used by Zuluga et al. in their publications that report results for BO [45], [13].

For details on these models, see Figure 4 and Figure 5 and III-B (below).

Once the test models are known, the next step is to select optimizers that have been previously applied to those models. For example, Chen et al. made extensive use of NSGA-II and SPEA2 for their studies of POM and XOMO. Also, ePAL was applied by Zuluga et al. to the SS* models so we will do the same. Note that we we will run two version for ePAL:
In this paper, we will say “domination tree” if one of these trees is far smaller and hence easier to browse, understand, and audit.

B. Model Details

Two aspects of our design were described in response with the specific features of our experiments. For example, all our algorithms were written in Python except for ePAL, which uses the Matlab code from the Žuluga et al. group. Since we are comparing implementations in different languages, we do not measure “speed” in terms of runtimes. Rather, we use “number of evaluations” to measure speed since that is a language-independent feature.

Another specific aspect of our design is how we measure model comprehensibility. We assume that software engineers will want to browse, understand and audit the results of any algorithm that has the presumption to tell them to change this or that. One way to present the results of an optimizer is to generate a domination tree, as follows:

- Take all the examples ever evaluated by an optimizer.
- Score each individual by $|\Omega(x)|$, which is the number of other individuals dominated by $x$.
- Use the CART decision tree learner 5 to summarize the decisions that lead to difference domination scores.

In this paper, we will say “domination trees with fewest nodes and leaves are more comprehensible. For example, Figures 6 and 7 show two trees generated from the examples evaluated by FLASH and ePAL while optimizing the LLVM (SS12) model of Figure 5.

These ePAL versions represent two extremes of ePAL from most cautious ($\varepsilon = 0.01$) to most careless ($\varepsilon = 0.3$).

Other aspects of our design were described in response with the specific features of our experiments. For example, all our algorithms were written in Python except for ePAL, which uses the Matlab code from the Žuluga et al. group. Since we are comparing implementations in different languages, we do not measure “speed” in terms of runtimes. Rather, we use “number of evaluations” to measure speed since that is a language-independent feature.

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• Figure 5 shows our models without constraints:
• The #Decs column of these two figures shows how many decisions are used by these models.

These aspects are important since, as seen below, these aspects determine which of our six optimizers (ePAL, FLASH, SWAY, NSGA-II, SPEA2, MOEA/D) succeed on different models.

Our first set models are the “SS*” models of Figure 4. These models are related to configuration control for software system. Adjusting the choice points (configuration) in these models alters the performance objectives (listed on the right-hand side — Objectives, of Figure 4). These SS* models come from (i) Zuluaga et al. [45] (SS2, SS8, SS12) and (ii) Jamshidi et al. [18] (all the rest). Zuluaga et al. explored two chip-design problems (SS2, SS8) and a software configuration problem (SS12), where evaluation of a single point is very expensive. Jamshidi et al. [18] ran three benchmarks (Word Count, Rolling Sort and SOL) on Apache Storm on clusters with different cluster configuration.

The other constrained models are Multi-Objective Next Release Planning problem (MONRP). These are concerned with defining which requirements should be implemented for the next release of a software. The flavor of MONRP used in this paper considers (maximizing) combination of importance of features and corresponding risk, (minimizing) cost and (maximizing) satisfaction. Thus the multi-objective Next Release Planning can be formalized as the process of maximizing \( f_1 \) and minimizing \( f_2 \), defined as follows:

\[
f_1 = \sum_{i=1}^{N} (score_i, (P - x_i + 1) - risk_i, x_i) \cdot y_i
\]

\[f_2 = \sum r_i \text{ and } f_3 = \sum c_i \cdot y_i
\]

subject to:

\[
\sum_{i=1}^{N} cost_i \cdot f_{1,k} \leq budgetRelease_k, \forall k \in 1, \ldots, P
\]

\[x_k \leq x_a, \forall (r_a \rightarrow r_k), \text{(where } r_a, r_k \rightarrow R)\]

where, \( score_i = \sum_{j=1}^{M} wt_j \cdot importance(c_j, r_i) \), the Boolean variable \( y_i \) indicates whether requirement \( r_i \) will be implemented in some release, variable \( x_i \) indicates the number of the release where requirement \( r_i \) is to be implemented. \( budgetRelease_k \) refers to the available budget and \( P \) represents the number of releases. We explore four variants of MONRP, ranging from the least constraint to the most constraint. For example, problem variant MONRP-50-4-5-4-110 refers to a scenario where a software project has 50 requirements and 4 releases. The project involves development of a software for 5 clients, delivered in the form of 4 releases using 110% of the actual cost. For more details refer to [6].

Our next two models are unconstrained. POM and XOMO, were designed for software process control for agile and waterfall systems, respectively. POM was based on the work of Turner and Boehm [4] who observed that agile managers struggle to balance idle rates of developers, completion rates and over all cost of the project. POM is a model to compute completion rates, idle times and overall costs. POM models the agile process by considering a set of inter-dependent requirements. Each requirement consists of a priority value and corresponding cost along with list of dependent requirements, which need to be satisfied before completing the requirements. Since POM models an agile environment, the cost and value of the requirements are constantly changing until the completion of the requirement. The POM model considers minimizing the man hours spent on developing a requirement, salary of the developers and the idle times. We explore four variants of POM ranging for a small highly critical project to large project which is very dynamic in nature. For more details refer to [29], [6].

XOMO combines four waterfall software process models developed by Boehm et. al [23]. The inputs to XOMO are the

![Fig. 7: Another domination tree. Same model (LLVM) and format as Figure 6 but the optimizer is ePAL. This tree is larger than Figure 6 (and hence harder to understand) since ePAL evaluated more examples than FLASH.](image-url)
project descriptors, which can be changed by a management decision. For example, if a manager wants to (a) relax schedule pressure, they set *sced* to its minimal value; (b) to reduce functionality they halve the value of *kloc* and reduce the size of the project database (by setting *data*=2); (c) to reduce quality (in order to race something to market) they might move to the lowest reliability, minimize the documentation work, the complexity of the code, and reduce the schedule pressure to some middle value. In the language of XOMO, this last change would be *rely=1, docu=1, time=3, cplx=1*. The optimization goals considered in this paper are: minimize risk, effort, cost, and time required for a project. We consider 5 variants of the XOMO in this work, which have been taken from NASA’s Jet Propulsion Laboratory [22]. For more details refer to [6].

IV. RESULTS

To comparatively assess FLASH, we repeated the following procedure twenty times (each time with a different random number seed). Firstly, we generate 10,000 random solutions for each model. Next, we give each optimizer however many solutions it wants; specifically, NSGA-II, SPEA2, MOEA/D want 100; the rest take 10,000. The algorithms then run till their internal termination criteria trigger at which point some final *best* set of decisions are returned.

These runs were instrumented to answer three research questions:

- **RQ1**: Is FLASH a fast optimizer?
- **RQ2**: Can FLASH generate a comprehensive and a succinct description of the search space?
- **RQ3**: Is FLASH as effective as other optimizers?

A. RQ1. Is FLASH a fast optimizer?

Figure 8 shows the median number of evaluations used by each optimizer while processing our models. In that figure, the markers , , and represent configuration control, MONRP, POM and XOMO respectively.

Note that the SS13, SS14, SS15 results do not list all the ePAL versions since some of these did not terminate (even after ten hours of execution – a pragmatic choice). The reason for this can be seen in Figure 4: these models use more than 10 decisions and the Gaussian process models used by ePAL does not scale beyond 10 dimensional decisions.

The obvious feature of Figure 8 is that FLASH used fewer evaluations than other methods in 23 of the models run here. Further, for some models (MONRP, POM, XOMO), FLASH terminates after orders of magnitude fewer evaluations. Hence, our answer to **RQ1** is

FLASH evaluates fewer points than the ePAL and EAs. The number of evaluations used by FLASH is an order of magnitude less that the traditional EAs and uses only half the number of evaluations as ePAL-0.3.

B. RQ2. Can FLASH generate a comprehensive and a succinct description of the space?

As discussed above, an easy way to understand the search space is to build a domination tree using the points sampled by an optimizer. Since, a decision maker (human) needs to go through all the branches of the tree it is important that the tree is small. In this paper, we measure comprehensiveness of the optimizer by two measures: (i) number of branch points or nodes and (ii) number of leaves in the decision tree build using the solutions sampled by the optimizers. Figure 8 shows the number of nodes and leaves build on the examples evaluated by
It reasonable to ask whether domination trees generated in this way are of any use to the decision maker. To answer that question, we refer back to Figure 6 and also Figure 10. Recall that Figure 6 shows a summary of the examples evaluated by FLASH as it optimized the LLVM configurations. That tree had a branch marked in gray—this was the branch leading to the examples that dominated most other examples.

Figure 10 shows in black the examples that are selected by the highlighted tree branch of Figure 10. The graph polygon of that figure shows the region covered by those examples. Note that the gray region covers nearly all the Pareto frontier (shown as a blue line).

To summarize, examples sampled by FLASH is much lower than the other optimizer. Further, these few samples can generate very succinct domination trees that can be used to easily read a description of an approximation to the Pareto frontier. Hence we say:

The points sampled by FLASH is useful to build smaller trees, which provides a comprehensive view of the search space.

C. RQ3. Is FLASH as effective as other optimizers?

Figure 11 shows a statistical analysis using the Scott-Knott effect size test. In this figure, cells marked with an “x” show where some optimizer failed to terminate. Note that ePAL rarely terminated for SS13, SS14 and SS15.

In Figure 11, the median values of Generational Distance (GD) and Inverted Generational Distance (IGD) are shown. These values are collected over 20 runs and are generated by different optimizers for various case studies. All these numbers are expressed as ratios of the state-of-the-art result known prior to this paper. Hence:

- A value of 100 means “same as the prior state-of-the-art”;
- Values less than 100 can indicate an improvement;
- Values more than 100 can indicate an optimizer performing worse than the state-of-the-art.
Fig. 11: Statistical comparisons of FLASH, ePAL, NSGA-II, SPEA2, MOEA/D, SWAY. Performance measures are GD (Generational Distance) and IGD (Inverted Generational Distance). For these measures less is better; “x” denotes cases where algorithms did not terminate within a reasonable amount of time (10hrs). All numbers are expressed as percentages of the ePAL-0.01 results (left-hand-side) and NSGA-II results (right-hand-side). That is “100” means “as good as the baseline methods”. Gray cells denote results from a statistical analysis (the Scott-Knot effect size test). Any cell in gray is as “as good as the best” in any row. Cells with a black background summarize how often a model was “as good as the best” within a group of models.

To define those ratios, we used ePAL-0.01, NSGA-II as the state-of-the-art for configuration control and other models. For SS13-15, FLASH has been used as the state-of-the-art since ePAL-0.01 did not terminate for these systems.

Note one quirk of Figure 11: it has many cells with values of “100”. There are two reasons why this so. Firstly, many of these columns are “100” by definition. Recall that we use ePAL-0.01 and NSGA-II as the reference optimizers to define “100”. Hence, all values in those columns will be 100. Secondly, many of the configuration problems have only a few examples of their Pareto frontier; e.g. see the four blue points in Figure 10 that define the LLMV Pareto frontier. When the target is that simple, many optimizers will find the same solutions and, hence, score 100 within our ratio calculations.

As to the gray cells Figure 11, these denote results that are statistically insignificantly different from the best result for any row. That is, any cell in gray is “as good as the best”.

One way to get a quick summary of this table is to read the black cells. These cells count the number of times an optimizer was marked as “as good as the best”. Looking over those black summary cells:

- For the SS* models:
  - FLASH clearly wins over ePAL;
  - This is particularly true for the configuration problems with most decisions such as SS13, SS14, SS15. For those problems, ePAL rarely terminated while FLASH always did.
- For the MONRP models:
  - FLASH ties with SWAY for best place;
  - For the POM models:
    - FLASH performs well, measured in terms of Generational Distance (GD).
    - But when looking at Inverted Generational Distance, NSGA-II and SPEA2 perform best.
- For the XOMO models:
  - FLASH and SWAY are clear losers.

Clearly FLASH is always not the best optimizer– and we should not expect it to be. Wolpert and Macready [40] showed that we can never expect that any optimizer always works well for all problems [41]. Still, there is much here to recommend FLASH:

- FLASH can handle models with many more decisions that ePAL (see the SS13, SS14, SS15 results). For those configuration problems, ePAL rarely worked and FLASH always worked.
- Across all of Figure 11 there are more successes with FLASH than any other approach.
- For some real-world problems, it might be indeed useful to use an optimizer which terminates faster and provide a comprehensible report of the search space rather than producing better performance after a long and expensive optimization process.

That said, there might be a systematic reason why FLASH is failing for models like XOMO and not perform best for models like POM. As noted in Figure 5, XOMO and POM are unconstrained models– which means that good solutions

3Specifically: for any optimization algorithm, any elevated performance over one class of problems is offset by performance over another class.
can be spread across large regions of the decision space. That is, we conjecture that for models with several objectives and no constraints (e.g. POM and XOMO), FLASH might need to be augmented with some solution diversity operator.

To summarize, FLASH is very effective on problems for constrained problems. However, the basic algorithm might need more work for unconstrained problems with objectives greater than 2.

| FLASH is effective for configuration control problem and constrained model like MONRP. However, more work is required for unconstrained problem with dimensions more than 2. |

V. DISCUSSION

A. What is the trade-off between the number of lives and the number of measurements?

FLASH requires that the practitioner defines a termination criterion (lives in our setting) before the optimization process commences. The termination criterion preempts the process of searching when the sampled points does not add to the already seen PF. In our experiments, the number of evaluations depends on the termination criterion (lives). An early termination of the FLASH would lead to sub-optimal solutions, while late termination would result in resource wastage. We performed a careful manual tuning of the stopping criterion and found empirically that the lives=10 is a sweet spot between achieving lower number of evaluations and finding the actual PF. However, in real-world scenarios, budget allocated for optimization would influence ‘lives’.

B. Why Decision Trees is used as the surrogate model?

Decision Trees is a very simple way to learn rules from a set of examples and can be viewed as a tool for the analysis of a large dataset. The reason why we chose CART is two fold. Firstly, it is shown to be scalable and there is a growing interest to find new ways to speed up the decision tree learning process [33]. Secondly, decision tree is able to describe with the tree structure the dependence between the decisions and the objectives, which is useful for induction. These are primary reason for choosing decision-trees to replace Gaussian Process as the surrogate model for FLASH.

C. Why FLASH and not SWAY?

SWAY is a novel technique which uses over-sampling as well as approximated principal component to sample points. However, approximation of the the principal component is particularly challenging since, it require careful selection of the distance function used during its computation. This has been described by the authors and mentions how embedding domain knowledge into the search process can be challenging [6]. However, FLASH makes no such assumption since CART is agnostic distribution of the decision values. This quality makes FLASH a off-the-shelf optimizer which can be used without embedding any domain knowledge.

VI. Threats to Validity

Reliability refers to the consistency of the results obtained from the research. For e.g., how well can independent researchers could reproduce the study? To increase external reliability, we took care to either clearly define our algorithms or use implementations from the public domain (SciKitLearn) [23]. All code used in this work are available on-line.

Validity refers to the extent to which a piece of research investigates what the researcher purports to investigate [30]. Internal validity concerns with whether the differences found in the treatments can be ascribed to the treatments under study.

For the case-studies relating to configuration control, we cannot measure all possible configurations in reasonable time. Hence, we sampled only few hundred configurations to compare prediction to actual values. We are aware that this evaluation leaves room for outliers and that measurement bias can cause false interpretations [21]. We also limit our attention to predicting PF for a given workload, we did not vary benchmarks.

Internal bias originates from the stochastic natural of multi-objective optimization algorithms. The evolutionary process required many random operations, same as the FLASH was introduced in this paper. To mitigate these threats, we repeated the experiments for 20 runs and report the median of the indicators. We also employed statistical tests to check the significance in the achieved results.

It is very difficult to find the representatives sample test cases to covers all kinds of domain. We just selected four most common types of decision space to discuss the FLASH basing on them. In the future, we also need to explore more types of SBSE problems, especially the problem with other types of decisions. We aimed to increase external validity by choosing case-studies from different domains.

VII. Conclusion

Traditionally EAs have been used to solve various SBSE problems, but they requires a large number of evaluations to find a set of non-dominated solutions. This might not be useful in situations where evaluating a single solution is expensive, or users want some succinct justification for why the model is telling them to do this, or that.

Meanwhile, in the machine learning community, Bayesian Optimization is traditionally used for parameter tuning of machine learning algorithms, but it does not scale beyond a moderate number of dimensions.

To overcome these shortcomings of EAs and BO, we introduce FLASH – a hybrid algorithm which is fast in terms of evaluation, scalable when compared to BO and effective for constrained models. The solutions sampled by FLASH during the process of optimization can be used to build small and comprehensible trees which helps in analysis search space.

To compare FLASH with various state-of-the-art optimizers (ePAL, NSGA-II, SPEA2, MOEA/D and SWAY), we conducted a number of experiments on 15 real-world configurable system as well as on 13 variants of 3 different case studies to demonstrate the qualities of FLASH. We observed that FLASH is effective to find the points very close to the Pareto
frontier for multi-objective constrained problems using fewer evaluations than the state-of-the-art optimizers.

In terms of future work, the two clear directions for this research are case studies with more models and newer operators to increase the diversity of solutions found in FLASH.

To conclude, we make two observations. Firstly, EAs is definitely not a silver bullet to solve all types of problems in SBSE. There are various ways to solve a problem and for problems where evaluations is resource intensive, alternative techniques such as FLASH can be very effective. Secondly, different communities tackle similar problems and many not be fully aware of advances in other communities. This paper experiments with ideas from fields of machine learning, SBSE and software analytics to create FLASH. which is a fast, comprehensible, scalable and effective optimizer. We hope this paper inspires other researchers to look further afield than their home discipline.

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