Faster Multi-Goal Simulation-Based Testing using DoLesS (Domination with a Least Squares Approximation)

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ABSTRACT
For cyber-physical systems, finding a set of test cases with the least cost by exploring multiple goals is a complex task. For example, Arrieta et al. reported that state-of-the-art optimizers struggle to find minimal test suites for this task. To better manage this task, we propose DoLesS (Domination with Least Squares Approximation) which uses a domination predicate to sort the space of possible goals to a small number of representative examples. Multi-objective domination then divides these examples into a “best” set and the remaining “rest” set. After that, DoLesS applies an inverted least squares approximation approach to learn a minimal set of tests that can distinguish best from rest in the reduced example space.

DoLesS has been tested on four cyber-physical models: a tank flow model; a model of electric car windows; a safety feature of an AC engine; and a continuous PID controller combined with a discrete state machine. Comparing to the recent state-of-the-art paper attempted the same task, DoLesS performs as well or even better as state-of-the-art, while running 80-360 times faster on average (seconds instead of hours). Hence, we recommend DoLesS as a fast method to find minimal test suites for multi-goal cyber-physical systems. For replication purposes, all our code is on-line: https://github.com/hellonull123/Test_Selection_2021.

KEYWORDS
Search-based software engineering, Machine learning with and for SE, Software testing, Modeling and Model-Driven Engineering, Validation and Verification, Embedded and cyber-physical systems

1 INTRODUCTION
Simulation models play an important role in many domains. Engineers build such models to simulate complex systems [29]. In the case of cyber-physical systems, these models are sometimes shipped along with the actual device, which means that analysts can now access high-fidelity simulations of their systems. Hence, much of the work on cyber-physical testing focuses on taking full advantage of high-fidelity simulators, prior to live testing [3]. For example, analysts can use the simulators for test suite minimization; i.e. they can explore many tests in the simulator in order to remove tests that do not need to be explored in the real world.

However, using these models for test case minimization can be a very difficult process [3]. These simulation models are built to simulate complex systems such as electronic and physical models. Hence executing these simulation models can be very time consuming [5]. This problem gets even worse for multi-goal problems (e.g. minimizing runtime and maximizing the number of bugs found) since it is necessary to run the models multiple times for different subsets of the goals [5]. For example, Arrieta et al. reported that testing a high fidelity simulation model can take hours to days [3, 19, 37].

Further, they warned that state-of-the-art multi-goal optimizers (e.g. NSGA-III and MOEA/D) struggle to find minimal test suites for this task.

Recently, Chen [10] and Agrawal et al. [1] reported successes with a variant of optimization called “DUO” (data mining using used-by optimizers). In this approach, a data mining method firstly divides the problem space, and then an optimizer executes in each small division. Inspired by that DUO approach, in this work, we apply a sorting method on the objective space to divide the multi-objective test suite minimization problem into several smaller partitions. Our DoLesS algorithm (Domination with Least Squares Approximation) applies a domination predicate to sort the example space to a small number of representative data points. Multi-objective domination divides these data points into a “best” set and the remaining “rest” set. After all that, DoLesS applies an inverted least squares approach to learn a minimal set of tests that can distinguish the best from the rest in the reduced example space.

To evaluate our proposed test case selection approach for simulation models, we compare DoLesS with the most recent state-of-the-art approach produced by Arrieta et al. [3]. In that companion, we ask the following research questions.

RQ1: Can we verify that test case selection for multi-goal cyber-physical systems is a hard problem? Arrieta et al. [3] reported that standard multi-goal optimizers such as NSGA-III and MOEA/D failed in this task. This is an important observation since, if otherwise, there will be no clear motivation for this paper. Accordingly, as a first step, we replicate their results in our experiment.

RQ2: Can DoLesS find better ways to select test cases which result in test suites with higher effectiveness measure (objective scores)? Section 3.1 of this paper reviews five effectiveness measurement metrics which are used to select test cases for cyber-physical systems in the previous study [3]. Our results show that on those five metrics, general performances of DoLesS is better than previous state-of-the-art method.

RQ3: Do selected test cases by DoLesS beat the prior state-of-the-art? Apart from the five effectiveness measurement metrics used by Arrieta et al. [3], two other evaluation scores of interest are (a) reduction in the number of test case and (b) faults detection performance with the reduced test cases. As shown in our result section §5, DoLesS usually performs as well, if not better, than the prior state-of-the-art.

RQ4: Is DoLesS far more efficient than prior state-of-the-art in terms of running time? For all the reasons stated above,
we need methods that offer faster feedback from models of cyber-physical systems. In this regard, it is significant to note that DoLesS runs 80-360 times faster than the prior state-of-the-art. Based on the above, we say our novel contributions are:

(1) We propose a novel test generation method (DoLesS).
(2) We verify that DoLesS solves a hard problem (test case selection for multi-goal cyber-physical systems). This is a problem that defeats state-of-the-art optimizers (NSGA-III and MOEA/D).
(3) We clearly document the value of doing DoLesS. When testing on four cyber-physical models, DoLesS finds test suites as good, as even better, than those found by Arrieta et al.’s approach [3]. Further, DoLesS does so while running 80-360 times faster (seconds instead of hours, mean time). Hence, we recommend DoLesS as a fast method to find minimal test cases for multi-goal cyber-physical systems.

The rest of this paper is structured as follow. Section 2 introduces the background and related work in test case selection for simulation-based testing. Section 3 introduces the problem of studying effectiveness measurement metrics in cyber-physical systems and illustrates how they are calculated by mathematical formula. Moreover, multi-objective optimizers and our proposed approach are introduced in this section as well. Section 4 introduces the case studies, performance evaluation metrics, and statistical analysis method used in this study. Section 5 shows our experimental results. Section 6 explores threats to validity and Section 7 makes the summary of our study and states the possible future work.

Based on the above, we can conclude that DoLesS is faster, yet more effective, than prior results since:

- DoLesS can handle multiple goals (in our experiment, 5 goals) simultaneously. Hence it does not need to loop the algorithm \(n\) times (where \(n\) is the number of subsets for the goals) like the prior state-of-the-art method.
- DoLesS's sorting procedure uses continuous domination to very quickly divide candidates into a very small “best” set (that we can focus on) and a much larger “rest” (that we can mostly ignore). Like much research before us, we argue that continuous domination is more informative than binary domination [38, 42, 52].
- Chen et al. [10] argues that some SE optimization problems can be solved better by over-sampling than via evolutionary methods. For example, the evolutionary NSGA-II method mutates 100 individuals for 250 generations (these parameters were selected to ensure comparability to the prior study). On the other hand, our DoLesS over-sampling method explores 10,000 individuals for one generation. This result suggests that cyber-physical system testing might be another class of problem that better to be solved via the over-sampling methods which stated by Chen et al [10].

2 BACKGROUND

A repeated result is that test suites can be minimized (i.e. we can run fewer tests) while still being as effective (or better) than running the larger test suite [2, 15, 44, 45, 49]. Note that “effective” can mean different things in different domains, depending on the goals of the testing. For example, at FSE’14, Elbaum et al. [16] reported that Google could find similar number of bugs, but after far fewer tests execution. This was an important result since, at that time, the initial Google test suites were taking weeks to execute. Such long test suite runtimes is detrimental to many agile software practices.

Research has found many test case selection techniques such as DejaVu based, firewall based, dependency based, and specification based techniques [17]. We note that different test suite minimization methods need different kinds of data. For example, in 1995, Binkley et al. proposed a semantic-based method which takes the use of differences and similarities of two consecutive versions to select test cases [8]. Rothermel et al. developed a test case selection technique for C++ software on 2020 [36]. In 2001, Chen et al. developed test case selection strategies based on the boolean specifications [11]. In 2005, a fuzzy expert system was developed in test case selection by Xu et al. [47]. In 2006, Grindal et al. presented an empirical study on evaluating five combination strategies for test case selection [20]. In 2011, Cartaxo et al. implemented a similarity function for test case selection in model-based testing [9]. Pradhan et al. [35] proposed a multi-objective optimization test case selection approach which can be used with limited time constraints. Arrieta et al. also used test case execution history to select test cases [5]. Also in 2017, Lachmann et al. [23] did an empirical study on several black-box metrics and made comparisons on their performance in selecting test cases in system testing.

Due to the data requirements, many of the above methods are unsuitable for cyber-physical systems, for two reasons.

Firstly, cyber-physical systems are embodied in their environment. Hence, it is not enough to explore static features of (e.g.) the code base. Rather, it is required to test how that code base reacts to its surrounding environments. Hence, using just static information such as (e.g.) code coverage metrics is not recommended for testing cyber-physical systems.

Secondly, at least for the systems studied here, cyber-physical systems make extensive use of process control theory. In that theory, the feedback controller is used to compare the value or status of process variables with the desired set-point. This controller then applies the difference as a control signal to bring the process variable output of the plant to the same value as the set-point (for example, see the steam governor of Figure 1). Hence, for test suite minimization of process control applications, the requirement is data collected from the feedback loops inside the cyber-physical systems. Accordingly, here we use input and output signals in the simulation models instead of execution history or coverage information.

In one of the IST’19 journal paper, Arrieta et al. [3] explored issues associated with test suite minimization by using the data extracted from feedback loops. They noted that feedback loops
have anti-patterns; i.e. undesirable features that appear in a time series trace of the output of the system. Figure ?? shows three such features correspondingly from left to right in the red dash rectangle: instability, discontinuity, and growth to negative infinity correspondingly. The alarming patterns are shown in red marks.

Figure 2: Examples of anti-patterns seen for systems under feedback. The name of anti-patterns from left to right are instability, discontinuity, and growth to negative infinity correspondingly. The alarming patterns are shown in red marks.

we will optimize for the anti-patterns and effectiveness measures seen in process control systems. But unlike that prior work, we will offer methods that simultaneously succeed across many goals (without needing anything like the pairwise heuristic used in Arrieta et al.). Further, we show that all this can be achieved without additional runtime cost.

2.1 Testing Simulation models
Cyber-physical system developers often use simulation tool (e.g. Simulink) to build cyber-physical models [12]. For an example Simulink models, see Figure 3. This is a model with two hierarchical levels [3]. A complex model will have far more blocks and operators.

In Simulink models, the inputs and outputs are all signals (here signal means a time series function). This means at each simulation time step $\Delta T$, there will be a value in each input and in each output regarding to that time step. For example, if we simulate a model for 5 seconds in real time and the time step $\Delta T$ is 0.05, then there will be $5/0.05 + 1 = 101$ simulation steps, which means each input or output should be a vector of length 101.

Assuming an initial set of $n$ test cases $\{t_1, \cdots, t_n\}$ for a simulation, each test simulates the model from a set of unique input signals $\{i_{s1}, \cdots, i_{sk}\}$ to a set of $l$ output signals $\{o_{s1}, \cdots, o_{sl}\}$ [3, 29].

Our goal for this study is to select representative test cases from the initial test suite to minimize the test execution time, but not influence the testing performance. Here we can define the test selection problem as follow:

Given an initial set of $n$ test cases $T = \{t_1, t_2, t_3, \cdots, t_n\}$, we want to find a subset of that set of test cases $TS = \{i_{s1}, i_{s2}, \cdots, i_{sk}\}$ which can test the model as initial test suite does $\text{Perform}(TS) = \text{Perform}(T)$ with $1 \leq |TS| \leq |T|$.

If we search in the space which contains all the subsets of the initial test suite, then the search space will be very large. For example, with only 100 test cases, there will be $2^{100} - 1$ possible subsets. Thus, cost-effectively selecting test cases is a significant problem.

3 EXPERIMENTAL METHODS
3.1 Simulation Effectiveness Metrics
In this study, we implement five out of seven effectiveness measurement metrics which Arrieta et al. [3] used in their study. The first three metrics are also widely used in previous studies [27, 28, 43], and the forth metric is proposed by Arrieta et al. [3].

Aside: We exclude two of the metrics explored by Arrieta et al. (Input & Output-based test similarity metrics) since these two metrics will always result similar normalized values (0.95-0.99) with different test case selections. Such similar normalized values can affect the performance of multi-objective optimization algorithms. We will introduce the remaining five metrics in the rest of this section.

3.1.1 Test Execution Time. Total test execution time is the first metric we implement in our study. Wang et al. [43] stated that the number of selected test cases can be treated as the measurement for selecting representative test cases from the initial test suite. However, Arrieta et al. pointed out the problem that each test case has different execution time [3]. In our study, we use the similar
calculation that Arrieta et al. [3] did in their study to deal with the test execution time. The test execution time is calculated as follow:

\[
\text{TimeSelect} = \sum_{a=1}^{n} \text{TET}_{sa} / \sum_{b=1}^{m} \text{TET}_{ib}
\]

In our study, we want to minimize this metric because the goal of test case selection is to decrease the test execution time.

3.1.2 Discontinuity in Output Signal. Discontinuity is the second metric we implement in our study. As Matinnejad et al. [27] stated, the discontinuity of the output signal is a duration of quick and frequent oscillations in the output signal, which means the output signal increase and decrease repeatedly in a duration of time. If executing a test case causes instability in the output signal, then that test case detects the undesirable impact on physical process [27]. Assume we have \( N \) output signals \( \{O_1, O_2, \ldots, O_N\} \). For instability score of each output signal \( \text{instability}(O_j) \) where \( 1 \leq j \leq N \), Matinnejad et al. calculated it with [27]

\[
\text{instability}(O_j) = \sum_{i=1}^{k} \left| \text{sig}(i \cdot \Delta t) - \text{sig}((i-1) \cdot \Delta t) \right|
\]

where \( k \) is the total number of simulation steps and \( \Delta t \) is the time stamp in the simulation model for each step.

The instability score of a set of selected test cases is calculated as follow:

\[
\text{IS}_{\text{Select}} = \sum_{a=1}^{n} \text{IS}_{sa} / \sum_{b=1}^{m} \text{IS}_{ib}
\]

With same definition of test case above, let \( DC_{sa} \) denotes the discontinuity score of the test case \( T_{sa} \) in \( \text{TC}_{\text{Select}} \), and \( DC_{ib} \) denotes the discontinuity score of the test case \( T_{ib} \) in \( \text{TC}_{\text{Init}} \). The total discontinuity score of a set of selected test cases is [3]

\[
\text{DC}_{\text{Select}} = \sum_{a=1}^{n} DC_{sa} / \sum_{b=1}^{m} DC_{ib}
\]

\[
DC_k = \frac{\sum_{i=1}^{N} \text{discontinuity}(O_k)}{\max_{i} \left( \text{discontinuity}(O_i) \right)} \text{ is the normalized discontinuity score of the test case } k \text{ among } N \text{ output signals } \{O_1, O_2, \ldots, O_N\}.
\]

In our study, we want to maximize this metric because the goal is to detect more discontinuity in the output signal.

3.1.3 Instability in Output Signal. Instability is the third metric we implement in our study. As Matinnejad et al. [27] stated, the instability of the output signal is a duration of quick and frequent oscillations in the output signal, which means the output signal increases or decreases to instability in a very short time, and recovers back to normal. If executing a test case causes instability in the output signal, then that test case detects the undesirable impact on physical process [27]. Assume we have \( N \) output signals \( \{O_1, O_2, \ldots, O_N\} \). For instability score of each output signal \( \text{instability}(O_j) \) where \( 1 \leq j \leq N \), Matinnejad et al. calculated it with [27]

\[
\text{instability}(O_j) = \sum_{i=1}^{k} \left| \text{sig}(i \cdot \Delta t) - \text{sig}((i-1) \cdot \Delta t) \right|
\]

where \( k \) is the total number of simulation steps and \( \Delta t \) is the time stamp in the simulation model for each step.

The instability score of a set of selected test cases is calculated as follow:

\[
\text{IS}_{\text{Select}} = \sum_{a=1}^{n} \text{IS}_{sa} / \sum_{b=1}^{m} \text{IS}_{ib}
\]

With same definition of test cases above, let \( IS_{sa} \) denotes the instability score of the test case \( T_{sa} \) in \( \text{TC}_{\text{Select}} \), and \( IS_{ib} \) denotes the instability score of the test case \( T_{ib} \) in \( \text{TC}_{\text{Init}} \). The total instability score of a set of selected test cases is [3]

\[
IS_{k} = \frac{\sum_{i=1}^{N} \text{instability}(O_k)}{\max_{i} \left( \text{instability}(O_i) \right)} \text{ is the normalized instability score of the test case } k \text{ among } N \text{ output signals } \{O_1, O_2, \ldots, O_N\}.
\]

In our study, we want to maximize this metric because the goal is to detect more instability in the output signal.

3.1.4 Growth to Infinity in Output Signal. This is the forth metric we implemented in our study. As Matinnejad et al. [28] pointed out, the growth to infinity of the output signal is the phenomenon that the output signal increases or decreases to infinity value. If executing a test case causes growth to infinity in the output signal, then that test case detects the faulty behavior in the model. Assume we have \( N \) output signals \( \{O_1, O_2, \ldots, O_N\} \). For growth to infinity score of each output signal \( \text{infinity}(O_j) \) where \( 1 \leq j \leq N \), Matinnejad et al. calculated it with [28]

\[
\text{infinity}(O_j) = \max_{i=1}^{k} |\text{sig}(i \cdot \Delta t)|
\]

With same definition of test cases above, let \( DO_{sa} \) denotes the growth to infinity score of the test case \( T_{sa} \) in \( \text{TC}_{\text{Select}} \), and \( DO_{ib} \) denotes the growth to infinity score of the test case \( T_{ib} \) in \( \text{TC}_{\text{Init}} \). The total growth to infinity score of a set of selected test cases is [3]

\[
DO_{\text{Select}} = \sum_{a=1}^{n} DO_{sa} / \sum_{b=1}^{m} DO_{ib}
\]

\[
DO_k = \frac{\sum_{i=1}^{N} \text{infinity}(O_k)}{\max_{i} \left( \text{infinity}(O_i) \right)} \text{ is the normalized growth to infinity score of the test case } k \text{ among } N \text{ output signals } \{O_1, O_2, \ldots, O_N\}.
\]
where \( k \) is the total number of simulation steps and \( \Delta t \) is the time stamp in the simulation model for each step.

The growth to infinity score of a set of selected test cases is calculated as follow:

\[
IF_{\text{Select}} = \frac{\sum_{a=1}^{n} IF_{sa}}{\sum_{b=1}^{m} IF_{sb}}
\]

(7)

\[
IF_k = \frac{\sum_{i=1}^{N} \text{infinitly}(O_{ki})}{\max_{i=1}^{N}(\text{infinitly}(O_{i}))} \cdot N
\]

(8)

\( IF_k \) is the normalized infinity score of the test case \( k \) among \( N \) output signals \( \{O_1, O_2, \ldots, O_N\} \).

In our study, we want to maximize this metric because the goal is to detect more growth to infinity in the output signal.

### 3.1.5 Output Minimum and Maximum Difference in Output Signal

This is the last metric we implemented in our study. Arrieta et al. proposed this metric in their work because the difference between maximum output signal and minimum output signal can indicate the level of how a model is being tested. If executing a test case results in large maximum and minimum difference in the output signal, then that test case can detect more parts in the simulation model. Assume we have \( N \) output signals \( \{O_1, O_2, \ldots, O_N\} \). For output minimum and maximum difference score of each output signal \( \text{minmax}(O_j) \) where \( 1 \leq j \leq N \), Arrieta et al. calculated it with [3]

\[
\text{minmax}(O_j) = \left| \max_{i=1}^{k}(\text{sig}(i \cdot \Delta t)) - \min_{i=1}^{k}(\text{sig}(i \cdot \Delta t)) \right|
\]

(8)

where \( k \) is the total number of simulation steps and \( \Delta t \) is the time stamp in the simulation model for each step.

The difference of output minimum and maximum of a set of selected test cases is calculated as follow:

\[
\text{MMDSelect} = \frac{\sum_{a=1}^{n} \text{MMD}_{sa}}{\sum_{b=1}^{m} \text{MMD}_{sb}}
\]

(9)

\[
\text{MMD}_k = \frac{\sum_{i=1}^{N} \text{minmax}(O_{ki})}{\max_{i=1}^{N}(\text{minmax}(O_{i}))} \cdot N
\]

(9)

where \( \text{MMD}_{sa} \) and \( \text{MMD}_{sb} \) denotes the output minimum and maximum difference of the test case \( T_a \) in TSelect, and \( \text{MMD}_{sb} \) denotes the output minimum and maximum difference of the test case \( T_b \) in TInit. The total output minimum and maximum difference score of a set of selected test cases is [3]

In our study, we want to maximize this metric because the goal is to coverage more parts that can be tested.

### 3.2 Algorithms

#### 3.2.1 Binary vs Continuous Domination

In the following, all the algorithms use binary domination except for DoLessS that uses continuous domination.

**Binary domination** decides one individual is better than another if it is better on at least one goal and worse on none. Numerous studies [38, 42, 52] warn that binary domination is hard to distinguish candidates once the number of goals grows to three or more.

For many-goal problems, Zitter’s continuous domination predicate [52] is useful [38, 42, 52]. Continuous domination judges the domination status of pair of individuals by running a “what-if” query which checks the situation when we jump from one individual to another, and back again. Specifically:

- For the forward jump, we compute \( s_1 = -\sum_i e^w_i (a_i - b_i)/n \).
- For the reverse jump we compute \( s_2 = -\sum_i e^w_i (b_i - a_i)/n \).

where \( a_i \) and \( b_i \) are the values on the same index from two individuals, \( n \) is the number of goals (in our case \( n = 5 \)), and \( w_i \) is the weight [-1,1] if we are minimizing or maximizing the goal \( i \) correspondingly. According to Zitter [52], one example is preferred to another if we lost the least jumping to it; i.e., \( s_1 < s_2 \).

Specifically, in this work, we use this predicate to select better goal sets that (a) minimize test execution time, (b) maximize discontinuity score, (c) maximize instability score, (d) maximize growth to infinity score, and (e) maximize output minimum & maximum difference.

#### 3.2.2 NSGA-II

NSGA-II is a common evolutionary genetic algorithm [14]. Firstly, it generates an initial set of population as the starter of the entire algorithm. Secondly, these candidates will evolve to offsprings in a series of generations by implementing the crossover and mutation operators with their individual probability. In our reproduction experiment, we use single point crossover with 0.8 probability and bit-flip mutation with 1/N probability (N is the number of test cases). Thirdly, parents for next generation will be selected by selection operator, which utilizes a non-dominated sorting algorithm to select top non-dominated solutions [32]. In the situation where a front needs to be divided because it exceeds the total number of population, NSGA-II uses the crowding distance to split candidates in that group.

#### 3.2.3 NSGA-III

NSGA-III is an improved NSGA-II algorithm [13]. In NSGA-III, all procedures such as initial population generation, crossover, and mutation are similar to NSGA-II, except selection procedure. In NSGA-III, the selection procedure is applied based on a set of reference points. The reference points are uniformly distributed on the normalized hyper-plane with some division number \( p \) [13]. After that, each objective point is normalized adaptively and associated with a reference point by calculating its distance to the corresponding reference line. Niche-Preservation operation is then applied to select candidates which will be used in the next generation [13].

#### 3.2.4 MOEA/D

MOEA/D is the first multi-objective optimization algorithm which utilizes decomposition technique [50]. More specifically, MOEA/D explicitly decomposes the problem into multiple sub-problems with less objectives in each subgroup and solves these sub-problems simultaneously [50]. To so, prior to inference, all examples get random weights assigned to their goals. Examples are then clustered by those weights such that all examples know the space of other examples that weighted in a similar direction. Next, during the execution, if one example \( X_0 \) finds a way to improve
itself, its local neighborhood will move in the same direction as $X_0$ does.

3.2.5 DoLesS. Figure 4 shows the entire framework of our approach. Unlike above evolutionary algorithms, our proposed approach DoLesS (Domination with Least Squares Approximation):
- Uses continuous domination (defined below, see the first block in Figure 4) to reduce the size of initial large random sets of goals and find a “best” group of representative samples.
- For each data entry in the “best” group, DoLesS then uses a least square approximation technique (the third block in Figure 4) to inversely predict the test selection outcomes which can fit the representative sets of goals best. This least square approximation technique is discussed below.

After sorting on the domination score, DoLesS divides data into:
- The $\sqrt{n}$ “best” items. In our case study, we randomly generate 10000 initial candidates, hence the first 100 candidates with highest domination score are grouped into the “best” group.
- And the remaining “rest” items.

Here we select the number of final population as 100 with two reasons: (a) 10000 random initial population is large enough to cover a wide range of possible outcomes and (b) to make comparison fair, we select same number of final candidates as previous work [3].

In the data processing stage of Figure 4, we take data from each model (which Arrieta et al. also used in their study [3]), and then processes it into the form of least square approximation structure by combining with the representative goals generated from continuous domination. Table 1(i) shows a simple example of effectiveness measurement data collected from the models. We can find that each test case will have a single score for all effectiveness measurement data ($a_{ij}$ means the score of test case $i$ in effectiveness measure $j$). The corresponding matrix equation system for the above example is shown in Table 1(ii). This equation shows the linear relationship of test selection outcomes and the final effectiveness measure scores (e.g. the final score of effectiveness measure 1 can be obtained by $em_1 = a_{11} \cdot t_1 + a_{12} \cdot t_2 + a_{13} \cdot t_3 + a_{14} \cdot t_4$ where $t_i$ is the outcome of test selection). In this example, our goal is to find the best outcomes of $t_1$ to $t_4$ which can result $em_1$ to $em_5$. To summarize the above example, in our approach, we collect effectiveness measurement data for $n$ test cases (like Table 1(i)) and want to find the best set of outcomes for $t_1$ to $t_n$ which can get the closest scores to representative goals which are selected by continuous domination.

Linear Least Squares Approximation is a method which predicts the best value of a set of unknown variables that fits the relationship between expected and observed sets of data. In general, solving a system of linear equations ($Ax = b$) will result no solution or infinite solutions. This always happens when (a) the number of constraints (equations) greater than the number of variables (overdetermined) or (b) the number of variables greater than the number of constraints (underdetermined). The way to find the best approximate solution is called the linear least square approximation. As mentioned in Section 3.2.5, in our study, we have 5 goals and $n$ number of test cases (where $100 \leq n \leq 150$). Thus, our equation system contains 5 equations (5 goals) and $n$ variables (where $n$ must greater than 5). In this case, finding possible selections of test cases becomes a underdetermined least square approximation.

Table 1: An example of (i) collected effectiveness measurement data ($EM$ means effectiveness measure) and (ii) its corresponding matrix equation form

| $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ |
|-------|-------|-------|-------|-------|
| $em_1$ | $a_{11}$ | $a_{12}$ | $a_{13}$ | $a_{14}$ |
| $em_2$ | $a_{21}$ | $a_{22}$ | $a_{23}$ | $a_{24}$ |
| $em_3$ | $a_{31}$ | $a_{32}$ | $a_{33}$ | $a_{34}$ |
| $em_4$ | $a_{41}$ | $a_{42}$ | $a_{43}$ | $a_{44}$ |
| $em_5$ | $a_{51}$ | $a_{52}$ | $a_{53}$ | $a_{54}$ |

Table 1(ii)

\[
\begin{vmatrix}
\begin{array}{cccc}
11 & 12 & 13 & 14 \\
21 & 22 & 23 & 24 \\
31 & 32 & 33 & 34 \\
41 & 42 & 43 & 44 \\
51 & 52 & 53 & 54
\end{array}
\end{vmatrix}
\]

The problem is to find $x$ that minimize
\[
\min ||Ax - b||_2^2 + ||x||_2^2 \tag{10}
\]

In the formulation $Ax = b$, where $x$ is an outcome vector of test cases, we want to predict the value (0/1) for each entry of $x$. The final outcome of $x$ is a vector of float numbers (ranged from 0 to 1 by controller) which indicates lower effect to the final score with
Table 2: Summary of number of I/O signals, number of test cases, and number of mutants in four case studies

| Project Name | Two Tanks | CW | AC Engine | EMB |
|--------------|-----------|----|-----------|-----|
| # Input Signals | 11 | 15 | 4 | 1 |
| # Output Signals | 7 | 4 | 1 | 1 |
| # Test Cases | 150 | 133 | 120 | 150 |
| # Mutants | 6 | 96 | 12 | 18 |

coefficient → higher effect to the final score with coefficient from 0 → 1. Since test selection outcomes can only have 0 (discard that test) and 1 (select that test), we use the threshold of 0.5 to indicate higher probability or lower probability. A value < 0.5 means higher chance to be 0 and a value > 0.5 means higher chance to be 1. For each representative candidate found by continuous domination, **DoLesS** finds the test selection which can get the closest score to that candidate. Although there exists delta between original ideal scores and truth scores generated by predicted results because of the approximation procedure, our results show that least square approximation can find adequate test cases which perform as well or better as the previous state-of-the-art. Our implementation of above step uses `scipy.optimize`, a python library, and uses the function called `lsq_linear`, which solves the above problem by using either dense QR decomposition technique or Singular Value Decomposition technique.

Finally, in the Evaluation stage of Figure 4, **DoLesS** selects the Pareto front set from the final population as Arrieta et al. did in their study [3]. All evaluations are made through 20 repeats for each of algorithm.

4 EXPERIMENTAL SETUP

4.1 Case Studies

We use four Cyber-physical system (CPS) models to evaluate our proposed approach. These four models come from the previous state-of-the-art study [3]. We implement the test cases and mutants that Arrieta et al. generated from these four models. The summary of number of initial test cases and number of mutants are shown in Table 2. In that table:

- Two Tanks project is a model that simulate the incoming and outgoing flows of the tanks [30];
- CW project is a model that simulate the electrics and mechanics of four car windows [3];
- AC Engine project is a model that simulate some safety functionalities in the AC engine [4, 6];
- and EMB project simulates the software model controller which includes a continuous PID controller and a discrete state machine [27].

At first glance, the case studies in Table 2 may appear to contain very small test cases. But appearances can be deceiving; e.g. the number of input signals is a poor measure of the internal complexity of a cyber-physical system. As shown in our RQ1 results, the systems of Table 2 are so complex that, for the purposes of test suite minimization, they defeated state-of-the-art optimizers (NSGA-III and MOEA/D).

4.2 Performance Criteria

To evaluate the selected test cases, we use two evaluation metrics from prior work [3]. These two evaluation metrics are (a) normalized test execution time and (b) mutant detection score. Previous study used these two metrics to calculate the hypervolume indicator and average weighted sum of mutation score and normalized test execution time [3], while in our study, we directly compare the performance of algorithms in these two metrics.

**Normalized test execution time** (TET): Our goal for selecting test cases from the initial test suite is to speed up the testing process. Thus, test execution time is a very important indicator which can indicate whether selected test cases can significantly reduce the cost of testing. In this study we want to minimize this value since, as discussed in our introduction, the whole point of this paper is to reduce the time required for testing cyber-physical systems.

**Mutant detection score** (MS+): If a set of selected test cases can significantly reduce the test execution time, but cannot detect most of the mutants, then such a selection is a bad choice. Our goal for selecting test cases is detecting as much as mutants when minimizing the test execution time. Therefore, mutant detection score becomes another important evaluation metric. In this study we want to maximize this value since higher value means the test suite is better since it can detect more mutants.

That is, a good test case selection approach can both (a) minimize the test execution time and (b) maximize the mutant detection score.

4.3 Statistical Analysis

In our study, we record the value of above two evaluation metrics in 20 repeats. To compare the total performance of different algorithms, we implement A Scott-Knott analysis [31]. The Scott-Knott analysis can sort the candidates by their values, and assign candidates to different ranks if the values of candidate at position i is significantly

Table 3: RQ1 results: Reproduction results of Arrieta et al.’s study [3]. The metric with “+” means less is better while “*” means more is better. The light gray cell in each project means that approach wins others significantly (as computed by the statistical method in §4.3).

| Project   | Approach | TET | MS+ |
|-----------|----------|-----|-----|
| Two tanks | NSGA-II  | 0.30 | 1   |
|           | NSGA-III | 0.49 | 1   |
|           | MOEA/D   | 0.34 | 1   |
| CW        | NSGA-II  | 0.39 | 0.99|
|           | NSGA-III | 0.61 | 0.98|
|           | MOEA/D   | 0.68 | 0.99|
| AC Engine | NSGA-II  | 0.38 | 0.73|
|           | NSGA-III | 0.61 | 0.72|
|           | MOEA/D   | 0.65 | 0.73|
| EMB       | NSGA-II  | 0.37 | 1   |
|           | NSGA-III | 0.54 | 1   |
|           | MOEA/D   | 0.63 | 1   |

1In multi-objective optimization, the Pareto front of a set of individuals are all examples not dominated by anything else.

2https://github.com/aitorarrietamarcos/IST2019Paper
Table 4: RQ2 results: Scores of five effectiveness measurement metrics calculated by sets of selected test cases. All entries report the median score of 20 repeats. In the title row, the metric with “+” means we want to maximize that metric. The light gray cell in each project means that approach wins over another approach significantly (as computed by the statistical method of §4.3) in that metric. Last column counts the number of wins for each approach.

| Project   | Approach | Best Combination       | Time- | Discontinuity+ | Infinity+ | Instability+ | MinMax+ | Wins |
|-----------|----------|------------------------|-------|----------------|-----------|--------------|---------|------|
| Twotanks  | NSGA-II  | Time, Infinite, Minmax | 0.30  | 0.54           | 0.65      | 0.55         | 0.65    | 1    |
|           | DoLessS  |                        | 0.30  | 0.56           | 0.67      | 0.56         | 0.67    | 5    |
| CW        | NSGA-II  | Time, Instability      | 0.39  | 0.55           | 0.34      | 0.64         | 0.34    | 2    |
|           | DoLessS  |                        | 0.36  | 0.50           | 0.58      | 0.44         | 0.58    | 3    |
| AEngine   | NSGA-II  | Time, Discontinuity, Instability | 0.38  | 0.53           | 0.49      | 0.49         | 0.49    | 4    |
|           | DoLessS  |                        | 0.30  | 0.47           | 0.44      | 0.41         | 0.44    | 1    |
| EMB       | NSGA-II  | Time, Instability      | 0.37  | 0.50           | 0.49      | 0.57         | 0.50    | 1    |
|           | DoLessS  |                        | 0.36  | 0.61           | 0.61      | 0.48         | 0.61    | 4    |

RQ1, we replicate Arrieta et al.’s experiment [3]. Table 3 shows our replication results with 20 repeats (with different random number seeds). Two algorithms differ significantly if they separate in different ranks in the Scott-Knott analysis.

As seen in Table 3, we can found the approach with NSGA-II that Arrieta et al. proposed [3] performs better than other multi-goal optimizers (MOEA/D and NSGA-III). Specifically, NSGA-II has higher performance in both test execution time and mutation score in four case studies. However, even though NSGA-II beats the other methods, we cannot sanction its use. NSGA-II has all the problems discussed in §2. Specifically, NSGA-II can only handle pairs of goals. Hence, it has to be re-run multiple times to explore all pairs of five goals. As shown below, we can achieve better results, orders of magnitude faster. Therefore, we can answer RQ1 as follow:

Test case selection for multi-goal cyber-physical models is a hard problem that cannot be solved by merely applying, off-the-shelf, the latest optimizer technology.

These RQ1 results motivate the rest of this paper where we develop a fast approach, which can handle multiple goals simultaneously for the cyber-physical systems.

RQ2: Can DoLessS Find Better Ways to Select Test Cases which Result in Test Suites with Higher Effectiveness Measure (Objective) Scores? To answer RQ2, we calculate the scores of effectiveness measures (test execution time, discontinuity, growth to infinity, instability, minimum and maximum difference) after we generate the subsets of selected test cases.

Table 4 shows our simulation results. For each project, we use Scott-Knott statistical analysis to compare the performance across 20 repeats. Table 4 reports the median scores for each effectiveness measurement metric. To visualize the final results, we mark the winning approach in each metric by light gray, and count the number of wins in the last column.

As seen in Table 4, DoLessS wins in three out of four projects (in Twotanks, CW, and EMB). Moreover, in Twotanks and EMB, our proposed approach results higher scores on most of the effectiveness measurement metrics while previous approach only wins in one DoLessS wins in all effectiveness measurement metrics in Twotanks and wins in 4 out of 5 effectiveness measurement metrics in EMB). These outcomes can indicate that in most of the cases, our proposed

different (by more than a small effect size) to the values of candidate at position \( i - 1 \) [24].

More precisely, Scott-Knott sorts the candidates by their median scores (and in our study, the candidates are the test case selection approaches). Scott-Knott method will split the sorted candidates into two sub-lists which maximize the expected value of differences in the observed performances before and after division [41]. After that, Scott-Knott will declare the one of the split as the best split. The best split should maximize the difference \( E(\lambda) \) in the expected mean value before and after the split [40, 46]:

\[
E(\lambda) = \frac{|l_1|}{|l|} \frac{\text{abs}(l_1 - \bar{l})^2}{|l|} + \frac{|l_2|}{|l|} \frac{\text{abs}(l_2 - \bar{l})^2}{|l|}
\]

where \(|l|, |l_1|, \text{and } l_2|\) are size of list \( l \), \( l_1 \), and \( |l_2| \) are mean value of list \( l \), \( l_1 \), and \( l_2 \).

After the best split, Scott-Knott then implements some statistical hypothesis tests to check the division. If two items \( d_1 \) and \( d_2 \) after division differ significantly by applying hypothesis test \( H \), then such division is defined as a “useful” division. Scott-Knott will run recursively on each half of the best division until no division can be made. In our study, we use cliff’s delta non-parametric effect size measure as the hypothesis test. Cliff's delta quantifies the number of difference between two lists of observations beyond p-values interpolation [46]. The division passes the hypothesis test if it is not a ‘small' effect (\( \Delta \geq 0.147 \)). The cliff’s delta non-parametric effect size test explores two list \( A \) and \( B \) with size \( |A| \) and \( |B| \):

\[
\Delta = \frac{\sum_{x \in A} \sum_{y \in B} \{ +1, \text{if } x > y \} - \{ -1, \text{if } x < y \}}{|A||B|}
\]

Cliff’s delta estimates the probability that a value in the list \( A \) is greater than a value in the list \( B \), minus the reverse probability [25] in the above formula. This hypothesis test and its effect size is supported by Hess and Kromery [21].

5 RESULTS

Returning now to the research questions offered in the introduction, we offer the following results.

RQ1: Can We Verify that Test Case Selection for Multi-goal Cyber-physical Systems is a Hard Problem? To answer
approach gets significant improvement than previous approach in these five metrics. Moreover, in half projects, the state-of-the-art approach concentrates on optimizing the Time metric and Instability metric (because of the algorithm design). However, by using DoLesS, we can find that most of the “goals” are equally optimized. Hence, DoLesS can handle multiple goals all the time while state-of-the-art method can only handle one or two goals in some cases.

By summarizing above findings, we answer RQ2 as follow:

**DoLesS** can find better test selections than state-of-the-art approach in terms of five effectiveness measurement metrics.

**RQ3**: Do selected test cases by DoLesS beat the prior state-of-the-art? To answer RQ3, we compare scores of TET- (normalized test execution time) and MS+ (mutant detection score) between the prior state-of-the-art and DoLesS. It is important to have higher performance on these two evaluation metrics since they directly indicate whether a test case selection is good or not. Table 5 shows our simulation results (note that TET - test execution time & MS - Mutation Score). For each method in each project, we repeat experiment 20 times and calculate the value of two evaluation metrics for each repeat. To obtain the final conclusion, we implement Scott-Knott statistical method to check if our approach significantly differ to state-of-the-art approach in each metric. The light gray cells mark the winning method (in the first rank) resulted from the Scott-Knott test. Moreover, we count the number of higher performance in these two evaluation metrics for each algorithm and record the number of wins in the last column.

As seen in Table 5, DoLesS gets better performance in both two evaluation metrics in two out of four projects (ACEngine & EMB). Moreover, in Twotanks, DoLesS and state-of-the-art method achieve the same performance (both two evaluation metrics are tied in the first rank). In the CW project, DoLesS has higher performance in minimizing test execution time when state-of-the-art method gets a little bit higher mutation score than DoLesS. Taking above comparisons together, we can conclude that test cases selected by DoLesS can achieve similar or better performance in minimizing test execution time and detecting more mutants in all projects.

By summarizing above findings, we answer RQ3 as follow:

**Table 5: RQ3 results: Scores of two evaluation metrics calculated by sets of selected test cases. All entries are reported the median score of 20 repeats. In the title row, the metric with “-” means less is better while “+” means more is better. The light gray cells mark the winning approach (computed by the statistical method in §4.3) in that metric. Last column counts the number of wins for each approach.**

| Project | Approach | TET | MS+ | Wins |
|---------|----------|-----|-----|------|
| Twotanks | NSGA-II | 0.30 | 1 | 2 |
| | DoLesS | 0.30 | 1 | 2 |
| CW | NSGA-II | 0.39 | 0.98 | 1 |
| | DoLesS | 0.36 | 0.95 | 1 |
| ACEngine | NSGA-II | 0.39 | 0.72 | 1 |
| | DoLesS | 0.30 | 0.72 | 2 |
| EMB | NSGA-II | 0.37 | 1 | 1 |
| | DoLesS | 0.35 | 1 | 2 |

Table 6: RQ4 results: Runtime comparison for our proposed DoLesS and the state-of-the-art approach. The light gray cell marked the fastest approach in each project. The last column marks how many times DoLesS faster than state-of-the-art.

| Project | Approach | RunTime (s) | Speed Up (times faster) |
|---------|----------|-------------|------------------------|
| Twotanks | NSGA-II | 11964.6 | 83 |
| | DoLesS | 144.7 | 1 |
| CW | NSGA-II | 15409.9 | 362 |
| | DoLesS | 42.6 | 1 |
| ACEngine | NSGA-II | 14042.1 | 179 |
| | DoLesS | 78.6 | 1 |
| EMB | NSGA-II | 12585.6 | 319 |
| | DoLesS | 39.5 | 1 |

In all projects, comparing to the state-of-the-art, DoLesS can get similar or better performance on minimizing the execution time of selected test cases while keeping to detect most of the mutants.

**RQ4**: Is DoLesS far more efficient than prior state-of-the-art in terms of running time? To answer RQ4, we count the execution time for both algorithms during the experiment. To make comparison fair enough, we run both two algorithms on the same 64-bit Windows 10 machine with a 4.2 GHz 8-core Intel Core i7 processor and 16 GB of RAM. Moreover, when running experiments, we make sure no huge process is starting or ending in our machine.

Table 6 shows the recorded runtime for each project. For each method, we repeat experiments 20 times and record the total runtime. The light gray cells mark the fastest approach.

As seen in Table 6, in both four projects, DoLesS runs significantly faster (80-360 times faster) than the previous method. By analyzing our proposed algorithm and state-of-the-art approach, we find previous approach implemented NSGA-II as their multi-objective optimization, which designed for 2 or 3 objectives [32]. To handle this issue, Arrieta et al. group objectives into 21 different combinations with two or three objectives in each combination, and select one of the best combinations by repeating their approach in those 21 groups [3]. However, in our approach, we just need continuous domination to find “ideal goals” and approximate corresponding test cases inversely.

By summarizing above findings, we answer RQ4 as follow:

In both four projects, DoLesS run significantly faster (80-360 times) than the previous method. In other words, DoLesS is far more efficient than state-of-the-art approach.

Even though our current empirical results can only boost a speed of (up to) 300 times faster, we can make a theoretical case that, if the number of goals increases, our technique would be even more comparatively faster (please note that in the following counts, test execution time is the metric that must be in every combination):

- 5 goals will result 10 different combinations of 2 or 3 objectives.
- 7 goals will result 21 different combinations of 2 or 3 objectives.
- 9 goals will result 36 different combinations of 2 or 3 objectives.
• The above pattern shows that with more goals being utilized, the number of repeats for state-of-the-art NSGA-II approach increases exponentially. However, our approach can handle multiple goals simultaneously in one time. This can show the efficiency of our approach.

6 THREATS TO VALIDITY
This section discusses issues raised by Feldt et al. [18].

Construct validity: The construct validity threat mainly exists in the parameter settings of algorithms. For example, in our replication experiment, we use one point crossover with 0.8 crossover probability and bitflip mutation with 1/(number of variables) mutate probability as prior studies did in order to keep consistent. For another example, in least square approximation, we use 0.5 threshold to indicate whether a test case has large probability to be chose or not. Moreover, we use the default setting of Python least square solver in our algorithm. Changing these parameters can result differences in selecting test cases. Therefore, our observation may differ when different parameters are used. We would consider hyper-parameter tuning [39, 40] in future work to mitigate this threat.

Conclusion validity: The conclusion validity threat in this study is related to the random variations of our algorithm. To reduce the effect caused by this threat, we repeat all experiments 20 times in the same machine. Moreover, we apply Scott-Knott statistical test to compare if the outcomes of our proposed approach and the previous methods differ significantly.

Internal validity: Internal validity focuses on the correctness of the treatment caused the outcome. In this study, we constraint our simulations to the same data set. Moreover, we evaluate our approach and the previous approach in the same workflow. Another internal validity threat can refer to the mutants generated from the projects. To mitigate this threat, we use the same mutants that Arrieta et al. [3] used in their study, which they have removed duplicated mutants.

External validity: External validity concerns the application of our algorithm in other problems. In this study, we generate our simulations to the same data set. Moreover, we apply Scott-Knott statistical test to compare if the outcomes of our proposed approach and the previous methods differ significantly.

As to further work, apart from extending this exploration of feedback loop anti-patterns, we conjecture that our methods could be useful for other multi-objective reasoning tasks. Standard practice in this area is to mutate large populations across a Pareto frontier. This has certainly been a fruitful research agenda [26, 33, 48, 51]. But perhaps the testing community could reason about more goals, faster, if used our domination methods and least squares methods to “reason backwards” from goal space to decision space. Hence, future works can be conducted with

• Finding more simulation projects which can strength our approach.
• Developing more effectiveness measurement metrics which can better indicate representative test cases.
• Adjusting our approach based on the testing scenarios of different projects. Moreover, in some cases, a new test case selection approach is needed for those projects.

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