Improving Search-Based Stress Testing using Q-Learning and Hybrid Metaheuristic Approach

by

Francisco Nauber Bernardo Gois

Submitted to the Doutorado em Informatica Aplicada
in partial fulfillment of the requirements for the degree of

Doctor of Science in Applied Informatics

at the

Universidade de Fortaleza

February 2017

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Abstract

Some software systems must respond to thousands or millions of concurrent requests. These systems must be properly tested to ensure that they can function correctly under the expected load. A common use of stress testing is to find test scenarios that produce execution times that violate the timing constraints specified. In this context, search-based testing is seen as a promising approach for verifying timing constraints. In this thesis, We proposed hybrid metaheuristic approach that uses genetic algorithms, simulated annealing, and tabu search algorithms in a collaborative model using Q-Learning to improve stress search-based testing and automation. A tool named IAdapter, a JMeter plugin used for performing search-based stress tests, was developed. Four experiments were conducted to validate the proposed approach.

Thesis Supervisor: Pedro Porfirio Muniz de Farias
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Acknowledgments

This is the acknowledgements section. You should replace this with your own acknowledgements.

Related Publications

The following publications are related to this thesis:

- **N. Gois, P. Porfirio, A. Coelho, and T. Barbosa**. Improving Stress Search Based Testing using a Hybrid Metaheuristic Approach. In Proceedings of the 2016 Latin American Computing Conference (CLEI), pages 718–728, 2016 [35].

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Chapter 1

Introduction

Many systems must support concurrent access by hundreds or thousands of users. Failure to providing scalable access to users may results in catastrophic failures and unfavorable media coverage [47].

The explosive growth of the Internet has contributed to the increased need for applications that perform at an appropriate speed. Performance problems are often detected late in the application life cycle, and the later they are discovered, the greater the cost to fix them [55].

The use of stress testing is an increasingly common practice owing to the increasing number of users. In this scenario, the inadequate treatment of a workload generated by concurrent or simultaneous access due to several users can result in highly critical failures and negatively affect the customers perception of the company [25] [47].

Stress testing determines the responsiveness, throughput, reliability, or scalability of a system under a given workload. The quality of the results of applying a given load testing to a system is closely linked to the implementation of the workload strategy. The performance of many applications depends on the load applied under different conditions. In some cases, performance degradation and failures arise only in stress conditions [31] [47].

A stress test uses a set of workloads that consist of many types of usage scenarios and a combination of different numbers of users. A load is typically based on an operational profile. Different parts of an application should be tested under various parameters and stress conditions [9]. The correct application of a stress test should cover most parts of an

application above the expected load conditions[25].

Fig. 1-1 shows an example of a system under assessment with three pages (the main page, profile page, and search page) and six possible users. From the combinations of users and application pages, various scenarios can be created, such as scenarios 1 and 2 shown in the figure. The first scenario presents a test that has passed, and the second scenario presents a test that has an HTTP 404 error.

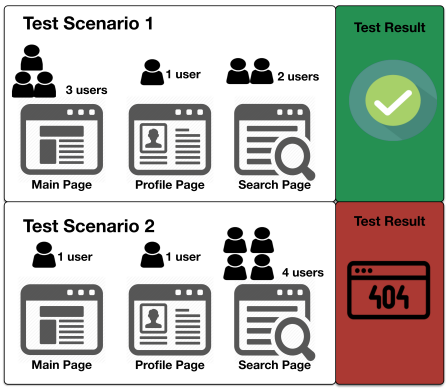

Figure 1-1: Possible test scenarios for a hypothetical application

A stress test usually lasts for several hours or even a few days and only tests a limited number of workloads. The major challenge is to find the workloads that expose a major number of errors and to discover the maximum number of users supported by an application under testing [10].

Search-based testing is seen as a promising approach to verifying timing constraints [2]. A common objective of a load search-based test is to find scenarios that produce execution times that violate the specified timing constraints [71].

This research proposes the use of a hybrid metaheuristic approach that combines genetic algorithms, simulated annealing, and tabu search algorithms in stress tests. A tool named IAdapter (github.com/naubergois/newiadapter), a JMeter plugin for performing search-based load tests, was developed. Two experiments were conducted to validate the proposed approach. The first experiment was performed on an emulated component, and the second one was performed using an installed Moodle application.

Fig. 1-2 shows an example where IAdapter stress test automation finds two test scenarios. The first scenario presents a test that has an HTTP 500 error, and the second scenario

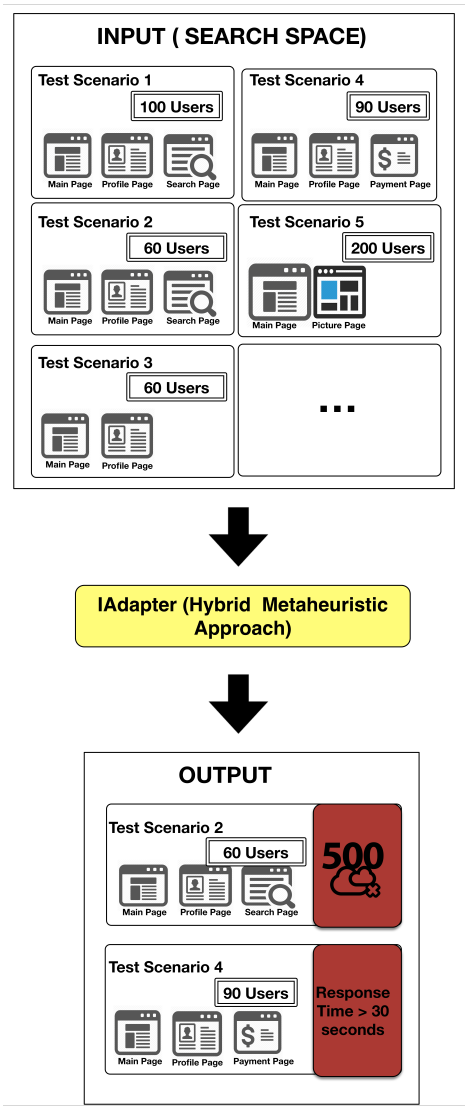

Figure 1-2: Illustrative example showing how IAdapter should be used

presents a test that has a response time higher than 30 seconds.

The research also addresses the problem of comparing the use of several metaheuristics in search based tests. When comparing a new metaheuristic to existing ones, it is advantageous to test on the problem instances already tested by previous papers. Then, results will be comparable on a by-instance basis, allowing relative gap calculations between the two heuristics. In this paper, we propose a flexible testbed tool to evaluate various diversity combining metaheuristics in search based software testing. The IAdapter Testbed is an open-source facility that provides software tools for search based test research. The

testbed tool emulates test scenarios in a controled environment using mock objects and implementing performance antipatterns.

1.1 Motivation

There is strong empirical evidence, that deficient testing of both functional and nonfunctional properties is one of the major sources of software and system errors. In 2002, NIST report found that more than one-third of these costs of software failure could be eliminated by an improved testing infrastructure. Automation of testing is a crucial concern. Through automation, large-scale thorough testing can become practical and scalable. However, the automated generation of test cases presents challenges. The general problem involves finding a (partial) solution to the path sensitization problem. That is, the problem of finding an input to drive the software down a chosen path [42] [21].

Software performance is a pervasive quality, because it is affected by every aspect of the design, code, and execution environment. Performance failures occur when a software product is unable to meet its overall objectives due to inadequate performance. Such failures negatively impact the projects by increasing costs, decreasing revenue or both [80].

Software testing is a expensive and difficult activity. The exponential growth in the complexity of software makes the cost of testing has only continued to rise. Test case generation can be seen as a search problem. The test adequacy criterion is transformed into a fitness function and a set of solutions in the search space are evaluated with respect to the fitness function using a metaheuristic search technique. Search-based software testing is the application of metaheuristic search techniques to generate software tests cases or perform test execution [2] [32].

Performance testing of enterprise applications is manual,laborious, costly, and not particulary effective. When running many different test cases and observing application's behavior, testers intuitively sense that there are certain properties of test cases that are likely to reveal performance bugs. Distilling these properties automatically into rules that describe how these properties affect performance of the application is a subgoal of our approach [37].

Experimentation is important to realistically and accurately test and evaluate search based tests. Experimentation on algorithms is usually made by simulation. Experiments involving search based tests are inherently complex and typically time-consuming to set up and execute. Such experiments are also extremely difficult to repeat. People who might want to duplicate published results, for example, must devote substantial resources to setting up and the environmental conditions are likely to be substantially different.

Below we briefly describe the related research and practices on stress testing:

1.1.1 State of Research on the Search-Based Stress Testing

In the academic context, a number of studies proving the efficacy of metaheuristics to automate test execution can be found in literature. A variety of metaheuristic search techniques are found to be applicable for non-functional testing including simulated annealing, tabu search, genetic algorithms, ant colony methods, grammatical evolution, genetic programming and swarm intelligence methods. However, most research studies are limited to making prototypes [2].

Garousi and Alesio presents functional tools to Systems from safety-critical domains. Garousi presented a stress test methodology aimed at increasing chances of discovering faults related to distributed traffic in distributed systems. Alesio describe stress test case generation as a search problem over the space of task arrival times. The research search for worst case scenarios maximizing deadline misses where each scenario characterizes a test case. The paper combine two strategies, GA and Constraint Programming (CP) [29] [31] [22] [23] [5].

1.1.2 State of Industrial Practices on Stress Tests

The stress testing process in the industry still follows a non-automated and ad-hoc model where the designer or tester is responsible for running the tests analyzing the results and deciding which new tests should be performed [48].

Typically, performance testing is accomplished using test scripts, which are programs that test designers write to automate testing. These test scripts performs actions or mim-

icking user actions on GUI objects of the system to feed input data. Current approaches to load testing suffer from limitations. Their cost-effectiveness is highly dependent on the particular test scenarios that are used yet there is no support for choosing those scenarios. A poor choice of scenarios could lead to underestimating system response time thereby missing an opportunity to detect a performance [37].

1.2 Research Hypothesis

Our underlying research hypothesis is as follows:

> The use of metaheuristics and hybrid metaheuristics in combination with Q-learning can make it possible to automate the stress test execution process, improving the choice of new test cases for each interaction and finding scenarios that maximize the number of users of the application under test and minimize response time or find scenarios with a expected response time.

The purpose of this thesis is to show the validity of this hypothesis through the development of a testbed tool, algorithms that use hybrid metaheuristics and the Q-learning technique and application of validation experiments. This thesis will be useful for load test practitioners and software engineering researchers interested in large-scale testing software systems.

1.3 Thesis Contributions

The major contributions of this thesis are:

1.3.1 Hybrid Metaheuristic Approach applied on Stress Testing

We present a hybrid metaheuristic approach that uses Genetic Algorithms, Simulated Annealing and Tabu Search in a collaborative mode. In the first experiment, The signed-rank Wilcoxon non-parametrical procedure showed that there was a significant improvement in the results with the Hybrid Metaheuristic approach [35].

The second and third experiments ran for 17 generations. The experiments used an initial population of 4 individuals by metaheuristic. All tests in the experiment were conducted without the need of a tester, automating the execution of stress tests with the JMeter tool. In both experiments the hybrid metaheuristic returned individuals with higher fitness scores.

1.3.2 Q-Learning Metaheuristic Approach

1.3.3 IAdapter JMeter Plugin

1.3.4 IAdapter Testbed Tool

1.4 Thesis Organization

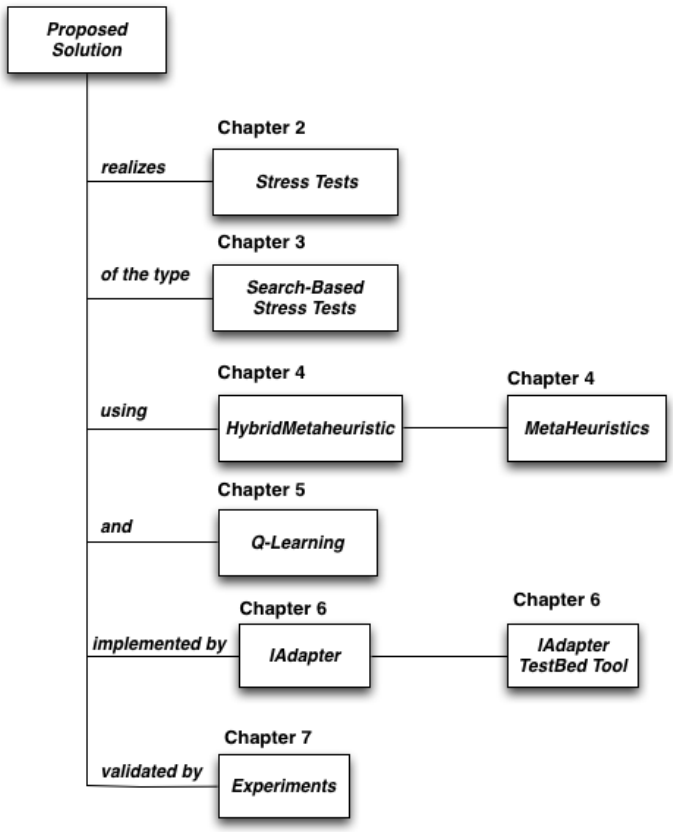

Figure 1-3: Thesis Organization

Chapter 2

A Survey on Stress Testing Software Systems

Load, performance, and stress testing are typically done to locate bottlenecks in a system, to support a performance-tuning effort, and to collect other performance-related indicators to help stakeholders get informed about the quality of the application being tested [65] [19].

The performance testing aims at verifying a specified system performance. This kind of test is executed by simulating hundreds of simultaneous users or more over a defined time interval [24]. The purpose of this assessment is to demonstrate that the system reaches its performance objectives [65]. Term often used interchangeably with "stress" and "load" testing. Ideally "performance" testing is defined in requirements documentation or QA or Test Plans [48].

In a load testing, the system is evaluated at predefined load levels [24]. The aim of this test is to determine whether the system can reach its performance targets for availability, concurrency, throughput, and response time. Load testing is the closest to real application use [55]. A typical load test can last from several hours to a few days, during which system behavior data like execution logs and various metrics are collected [2].

Stress testing investigates the behavior of the system under conditions that overload its resources. The stress testing verifies the system behavior against heavy workloads [65] [48], which are executed to evaluate a system beyond its limits, validate system response in activity peaks, and verify whether the system is able to recover from these conditions.

It differs from other kinds of testing in that the system is executed on or beyond its breakpoints, forcing the application or the supporting infrastructure to fail [24] [55].

This chapter surveys the state of the art literature in stress testing research. The thesis extends the survey presented by Jiang et al. to the Stress Testing context [47]. This survey will be useful for stress testing practitioners and software engineering researchers with interests in testing and analyzing software systems. We proposed the following four research questions:

- How is a proper stress designed?
- How is a stress test executed and automated?
- What are the main problems found by stress tests?
- How are the stress tests results analysed?

The population in this study is the domain of software testing. Intervention includes application of stress test techniques to test different types of non-functional properties.

2.1 Background

Stress testing is boundary testing. Some of the resources that stress testing subjects to heavy loads include [48]:

- Memory
- Networks
- Transaction queues
- Transaction schedulers
- User of the system

The following are the suggested steps for stress testing [48]:

- Perform simple multitask tests.
- After the simple stress defects are corrected, stress the system to the breaking point.
- Perform the stress tests repeatedly for every development spiral.

While load testing is the process of assessing non-functional quality related problems under load. Performance testing is used to measure and/or evaluate performance related aspects (e.g., response time, throughput and resource utilizations) of algorithms, designs/architectures, modules, configurations, or the overall systems. Stress tests puts a system under extreme conditions to verify the robustness of the system and/or detect various functional bugs (e.g., memory leaks and deadlocks) [2]. The next subsections present details about the stress test process, automated stress test tools and the stress test results.

2.1.1 Stress Test Process

Contrary to functional testing, which has clear testing objectives, Stress testing objectives are not clear in the early development stages and are often defined later on a case-by-case basis. The Fig. 2-1 shows a common Load, Performance and Stress test process [47].

The goal of the load design phase is to devise a load, which can uncover non-functional problems. Once the load is defined, the system under test executes the load and the system behavior under load is recorded. Load testing practitioners then analyze the system behavior to detect problems [47].

Once a proper load is designed, a load test is executed. The load test execution phase consists of the following three main aspects: (1) Setup, which includes system deployment and test execution setup; (2) Load Generation and Termination, which consists of generating the load; and (3) Test Monitoring and Data Collection, which includes recording the system behavior during execution[47].

The core activities in conducting an usual Load, Performance and Stress tests are [26]:

- Identify the test environment: identify test and production environments and knowing the hardware, software, and network configurations helps derive an effective test plan and identify testing challenges from the outset.

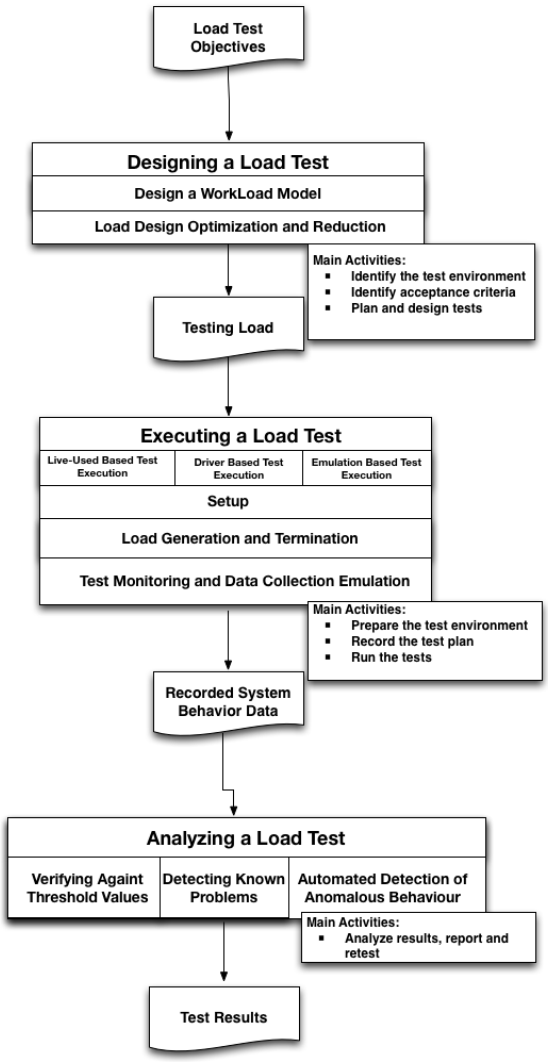

Figure 2-1: Load, Performance and Stress Test Process [47][26]

- Identify acceptance criteria: identify the response time, throughput, and resource utilization goals and constraints.

- Plan and design tests:identify the test scenarios.In the context of testing, a scenario is a sequence of steps in an application. It can represent a use case or a business function such as searching a product catalog, adding an item to a shopping cart, or placing an order [19]. This task includes a description of the speed, availability, data volume throughput rate, response time, and recovery time of various functions, stress, and so on. This serves as a basis for understanding the level of performance and stress testing that may be required to each test scenario [48].

- Prepare the test environment: configure the test environment, tools, and resources necessary to conduct the planned test scenarios.
- Record the test plan: record the planned test scenarios using a testing tool.
- Run the tests: Once recorded, execute the test plans under light load and verify the correctness of the test scripts and output results.
- Analyze results, report, and retest: examine the results of each successive run and identify areas of bottleneck that need addressing.

2.2 Research Question 1:How is a proper stress designed?

The design of a stress test depends intrinsically on the load model applied to the software under test. Based on the objectives, there are two general schools of thought for designing a proper load to achieve such objectives [2]:

- Designing Realistic Loads (Workload Descriptive).
- Designing Fault-Inducing Loads (Workload Generative).

In Designing Realistic Loads, the main goal of testing is to ensure that the system can function correctly once. Designing Fault-Inducing Loads aims to design loads, which are likely to cause functional or non-functional problems [2].

Stress testing projects should start with the development of a model for user workload that an application receives. This should take into consideration various performance aspects of the application and the infrastructure that a given workload will impact. A workload is a key component of such a model [55].

The term workload represents the size of the demand that will be imposed on the application under test in an execution. The metric used for measure a workload is dependent on the application domain, such as the length of the video in a transcoding application for multimedia files or the size of the input files in a file compression application [27] [55] [36].

Workload is also defined by the load distribution between the identified transactions at a given time. Workload helps researchers study the system behavior identified in several load models. A workload model can be designed to verify the predictability, repeatability, and scalability of a system [27] [55].

Workload modeling is the attempt to create a simple and generic model that can then be used to generate synthetic workloads. The goal is typically to be able to create workloads that can be used in performance evaluation studies. Sometimes, the synthetic workload is supposed to be similar to those that occur in practice in real systems [27] [55].

There are two kinds of workload models: descriptive and generative. The main difference between the two is that descriptive models just try to mimic the phenomena observed in the workload, whereas generative models try to emulate the process that generated the workload in the first place [24].

In descriptive models, one finds different levels of abstraction on the one hand and different levels of fidelity to the original data on the other hand. The most strictly faithful models try to mimic the data directly using the statistical distribution of the data. The most common strategy used in descriptive modeling is to create a statistical model of an observed workload (Fig. 2-2). This model is applied to all the workload attributes, e.g., computation, memory usage, I/O behavior, communication, etc. [24]. Fig. 2-2 shows a simplified workflow of a descriptive model. The workflow has six phases. In the first phase, the user uses the system in the production environment. In the second phase, the tester collects the user's data, such as logs, clicks, and preferences, from the system. The third phase consists in developing a model designed to emulate the user's behavior. The fourth phase is made up of the execution of the test, emulation of the user's behavior, and log gathering.

Generative models are indirect in the sense that they do not model the statistical distributions. Instead, they describe how users will behave when they generate the workload. An important benefit of the generative approach is that it facilitates manipulations of the workload. It is often desirable to be able to change the workload conditions as part of the evaluation. Descriptive models do not offer any option regarding how to do so. With the generative models, however, we can modify the workload-generation process to fit the

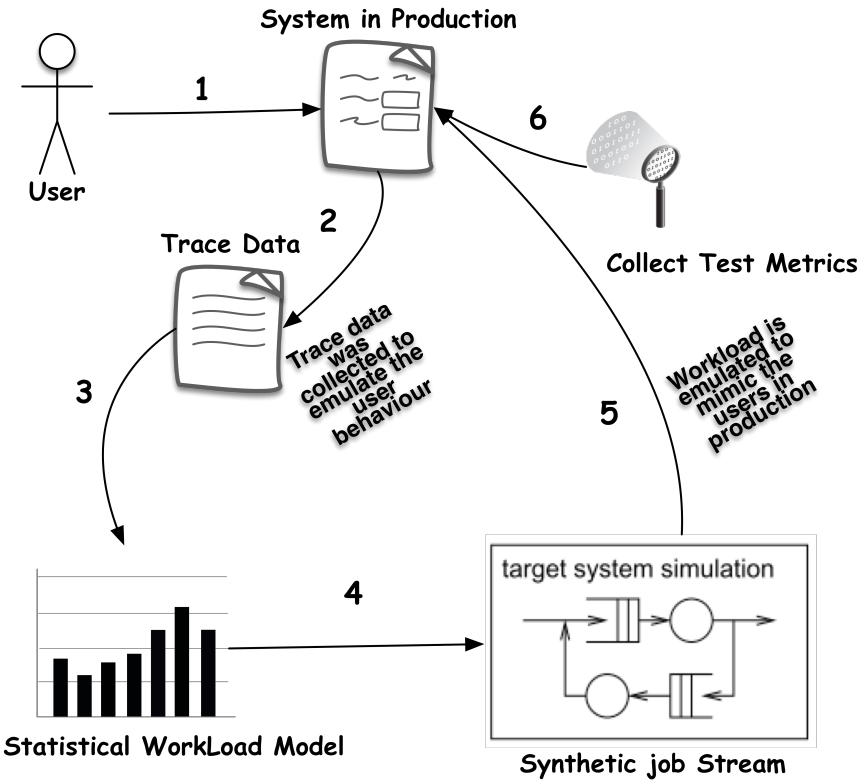

Figure 2-2: Workload modeling based on statistical data [24]

desired conditions [24]. The difference between the workflows of the descriptive and the generative models is that user behavior is not collected from logs, but simulated from a model that can receive feedback from the test execution (Fig. 2-3).

Both load model have their advantages and disadvantages. In general, loads resulting from realistic-load based design techniques (Descriptive models) can be used to detect both functional and non-functional problems. However, the test durations are usually longer and the test analysis is more difficult. Loads resulting from fault-inducing load design techniques (Generative models) take less time to uncover potential functional and non-functional problems, the resulting loads usually only cover a small portion of the testing objectives [47]. The presented research work uses a generative model.

There are several approaches to design generative or descriptive workloads:

- Model-based Stress testing: a usage model is proposed to simulate users' behaviors.
- Feedback-Directed Learning Software Testing: is an adaptive, feedback-directed

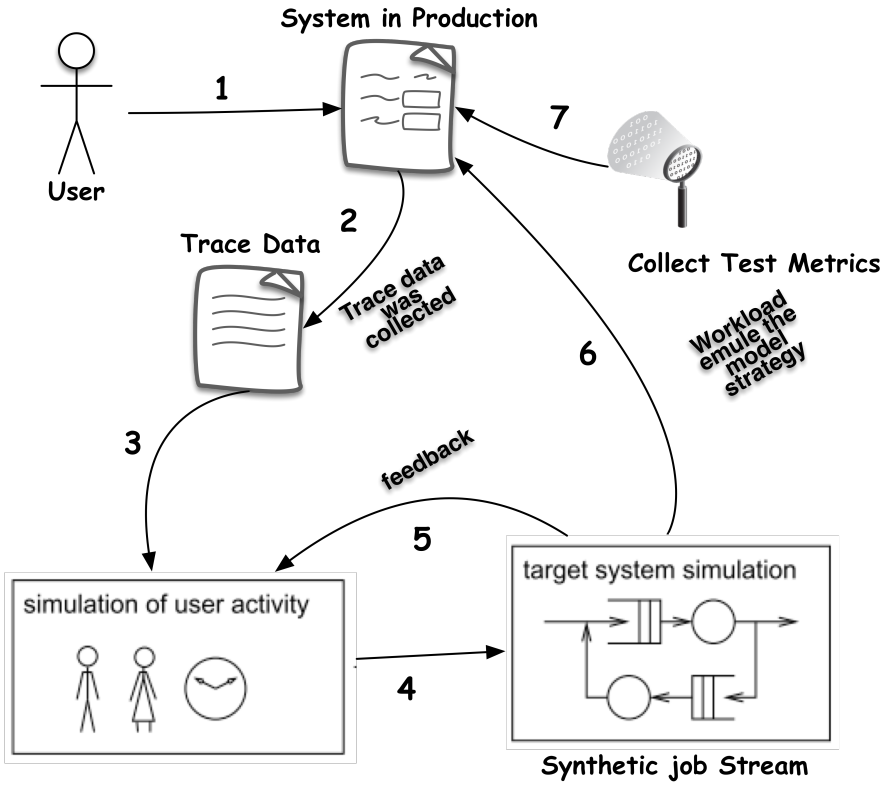

Figure 2-3: Workload modeling based on the generative model [24]

learning testing system that learns rules from system execution [49] [87].

- Search-based Stress testing.

Search-Based Stress testing will be detail explained in the chapter 3.

2.2.1 Model-based Stress Testing

Model-based testing is an application of models to represent the desired behavior of a System Under Test or to represent testing strategies in a test. Some research aproaches proposes models to simulate or generate realistic loads. Model-based testing (MBT) is a variant of testing that relies on explicit behaviour models that encode the intended behaviours of a system under test. Test cases are generated from one of these models or their combination [50] [1].

The model paradgim is what paradigm and notation are used to describe the model.

There are many different modelling notations that have been used for modelling the behaviour of systems for test generation purposes [50] [43].

- State-Based (or Pre/Post) Notations. These model a system as a collection of variables, which represent a snapshot of the internal state of the system, plus some operations that modify those variables. Each operation is usually defined by a precondition and a postcondition, or the postcondition may be written as explicit code that updates the state [50].

- Transition-based Notations. These focus on describing the transitions between different states of the system. Typically, they are graphical node-and-arc notations, like finite state machines (FSMs). Examples of transition-based notations used for MBT include FSMs themselves, statecharts, labelled transition systems and I/O automata [50].

- History-based Notations. These notations model a system by describing the allowable traces of its behaviour over time. Message-sequence charts and related formalisms are also included in this group. These are graphical and textual notations for specifying sequences of interactions between components [50].

- Functional Notations. These describe a system as a collection of mathematical functions. The functions may be first-order only, as in the case of algebraic specifications, or higher-order, as in notations like HOL [50].

- Operational Notations. These describe a system as a collection of executable processes, executing in parallel. They are particularly suited to describing distributed systems and communications protocols. Examples include process algebras such as CSP or CCS as well as Petri net notations. Slightly stretching this category, hardware description languages like VHDL or Verilog are also included in this category [50].

- Stochastic Notations. These describe a system by a probabilistic model of the events and input values and tend to be used to model environments rather than SUTs. For example, Markov chains are used to model expected usage profiles, so that the generated tests scenarios [50].

- Data-Flow Notations. These notations concentrate on the data rather than the control flow. Prominent examples are Lustre, and the block diagrams of Matlab Simulink, which are often used to model continuous systems [50].

A User Community Modeling Language (UCML) is a set of symbols that can be used to create visual system usage models and depict associated parameters [82]. The Fig. 2-4 shows a sample where all users realize a login into the application unde test. Once logged in, 40% of the users navigates on the aplication, 30% of the users realizes downloads. 20% of users realizes uploads and 10% of users performs deletions.

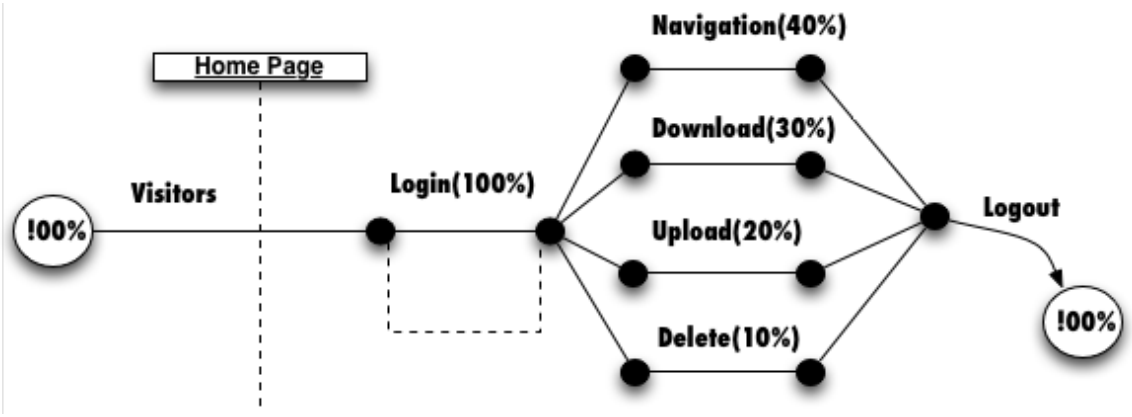

Figure 2-4: User community modeling language [82]

Another technique to create workload models it is Stochastic Formcharts. The work of Draheim and Weber's Formoriented analysis is a methodology for the specification of ultra-thin client based systems. Form-oriented models describe a web application as a bipartite state machine which consists of pages, actions, and transitions between them. Stochastic Formcharts are the combination of formoriented model and probability features. The Fig. 2-5 shows a sample where all users have a probability of 100% of realize a login into the application under test. Once logged in, users have a probability of 40% of navigate on the application and so on [25].

One way to capture the navigational pattern within a session is through the Customer Behavior Model Graph (CBMG). Figure 2-6 depicts an example of a CBMG showing that customers may be in several different states—Home, Browse, Search, Select, Add, and Pay—and they may transition between these states as indicated by the arcs connecting

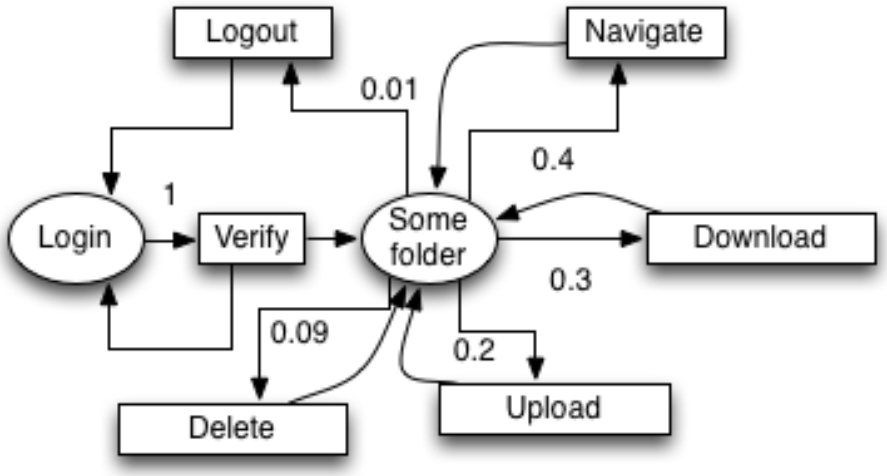

Figure 2-5: Stochastic Formcharts Example [25] [82]

them. The numbers on the arcs represent transition probabilities. A state not explicitly represented in the figure is the Exit state [53] [47] [54].

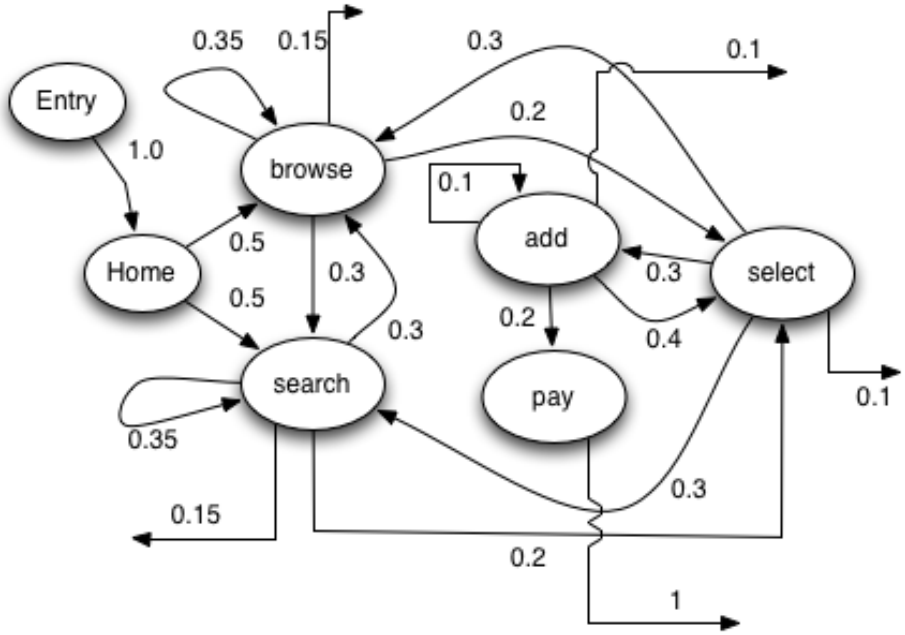

Figure 2-6: Example of a Customer Behavior Model Graph (CBMG) [53] [47] [54]

Garousi et al. proposes derivate Stress Test Requirements from an UML model. The input model consists of a number of UML diagrams. Some of them are standard in mainstream development methodologies and others are needed to describe the distributed architecture of the system under test (Fig. 2-7).

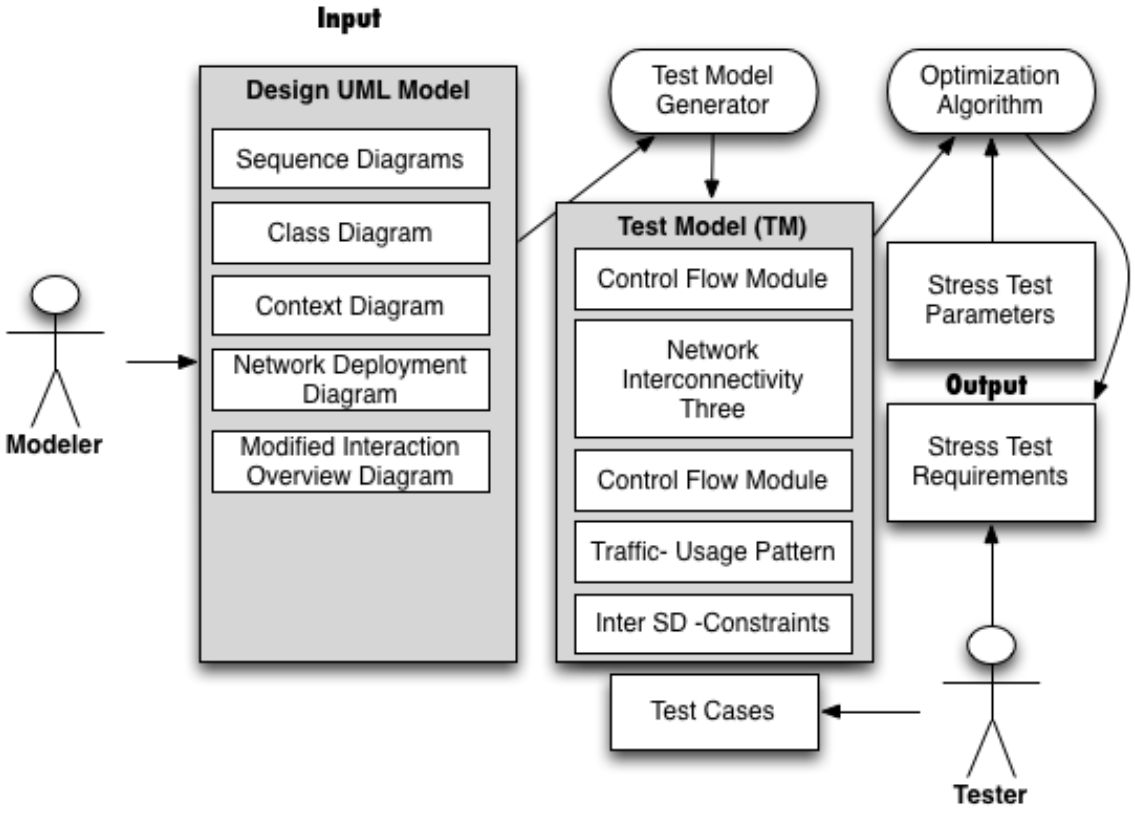

Figure 2-7: Model-based stress test methodology

Vogele et al. presents an approach that aims to automate the extraction and transformation of workload specifications for an model-based performance prediction of session-based application systems. The research also presents transformations to the common load testing tool Apache JMeter and to the Palladio Component Model [81]. The workload specification formalism (Workload Model) consists of the following components, which are detailed below and illustrated in Fig. 2-8:

- An Application Model, specifying allowed sequences of service invocations and SUT-specific details for generating valid requests.

- A set of Behavior Models,each providing a probabilistic representation of user sessions in terms of invoked services.

- A Behavior Mix, specified as probabilities for the individual Behavior Models to occur during workload gen- eration.

- A Workload Intensity that includes a function which specifies the number of concurrent users during the workload generation execution.

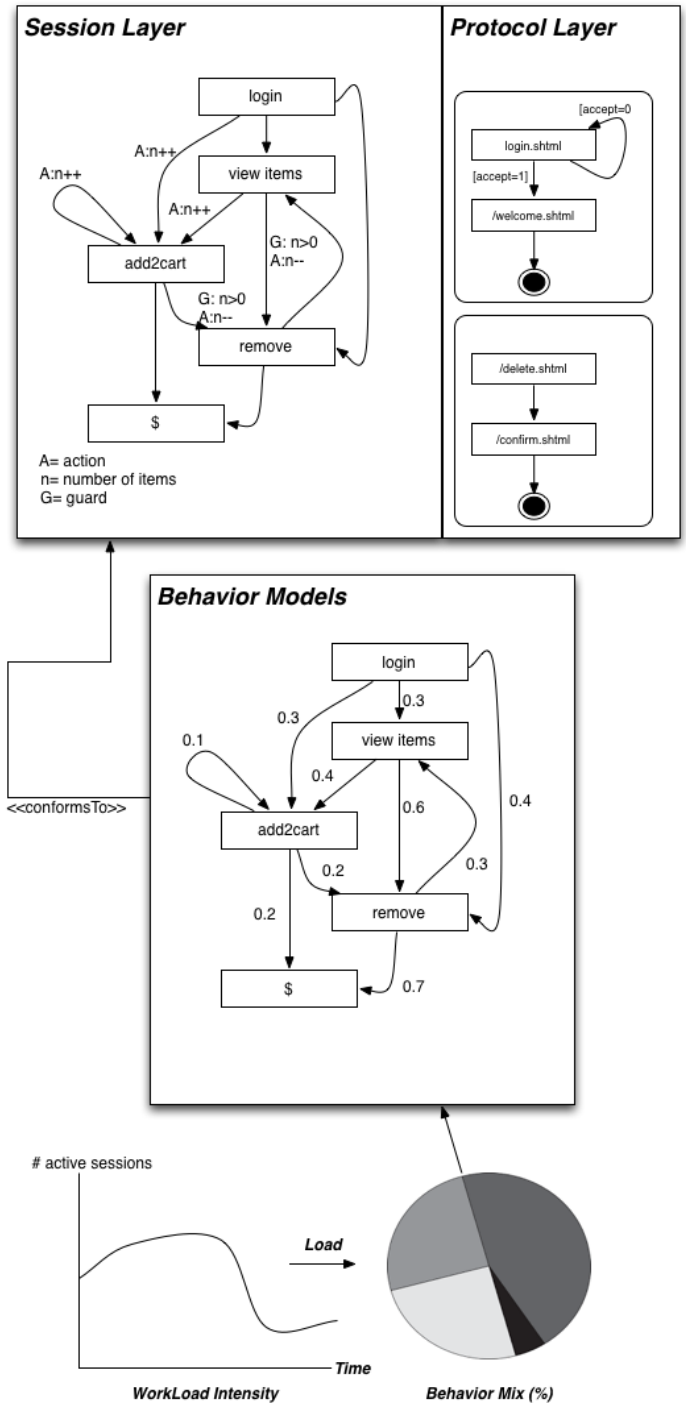

Figure 2-8: Exemplary workload model

2.2.2 Feedback-Directed Learning Software Testing

Feedback-ORiEnted PerfOrmance Software Testing (FOREPOST) is an adaptive, feedback-directed learning testing system that learns rules from system execution traces and uses these learned rules to select test input data automatically to find more performance problems in applications when compared to exploratory random performance testing [37].

FOREPOST uses runtime monitoring for a short duration of testing together with machine learning techniques and automated test scripts to reduce large amounts of performance-related information collected during AUT runs to a small number of descriptive rules that provide insights into properties of test input data that lead to increased computational loads of applications.

The Fig. 2-9 presents the main workflow of FOREPOST solution. The first step, The Test Script is written by the test engineer(1). Once the test script starts, its execution traces are collected (2) by the Profiler, and these traces are forwarded to the Execution Trace Analyzer, which produces (3) the Trace Statistics. The trace statistics is supplied (4) to Trace Clustering, which uses an ML algorithm, JRip to perform unsupervised clustering of these traces into two groups that correspond to (6) Good and (5) Bad test traces.

The user can review the results of clustering (7). These clustered traces are supplied (8) to the Learner that uses them to learn the classification model and (9) output rules. The user can review (10) these rules and mark some of them as erroneous if the user has sufficient evidence to do so. Then the rules are supplied (11) to the Test Script. Finally, the input space is partitioned into clusters that lead to good and bad test cases, to find methods that are specific to good performance test cases. This task is accomplished in parallel to computing rules, and it starts when the Trace Analyzer produces (12) the method and data statistics that is used to construct (13) two matrices (14). Once these matrices are constructed, ICA decomposes them (15) into the matrices for bad and good test cases correspondingly. Finally, the Advisor (16) determines top methods that performance testers should look at (17) to debug possible performance problems.

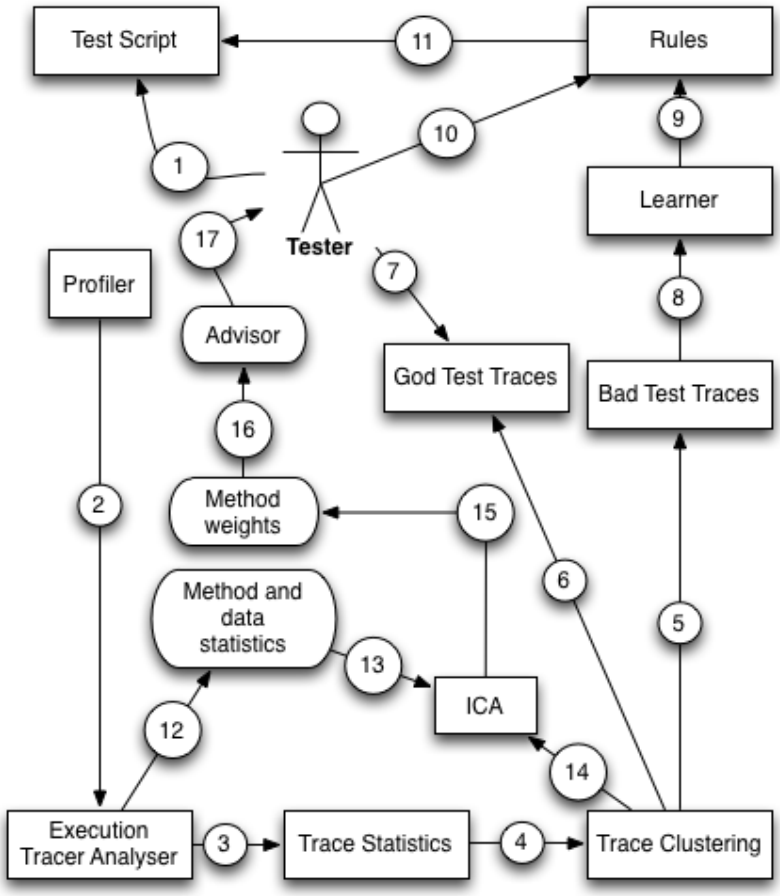

Figure 2-9: The architecture and workflow of FOREPOST

2.3 Research Question 2: How is a stress test executed and automated?

The stress test execution consists of deploy the system and steup test execution ; generating the workloads according to the configurations and terminating the load when the load test is completed and recording the system behavior. There are three general approaches of load test executions [55][47]:

- Live-User Based Executions: The test examines a system's behavior when the system is simultaneously used by many users or execute a load test by employing a group of human testers.

- Driver Based Executions: The driver based execution approach automatically gen-

erate thousands or millions of concurrent requests for a long period of time using a software tool.

- Emulation Based Executions: The emulation based load test execution approach performs the load testing on special platforms and doesn't require a fully functional system and conduct load testing.

Usually, a stress test execution it is performed with Driver Based Executions approach [26] [54] [82]. There are three categories of load drivers [47]:

- Benchmark Suite: specialized load driver, designed for one type of system. For example, LoadGen is a load driver specified used to load test the Microsoft Exchange MailServer.

- Centralized Load Drivers: refer to a single load driver, which generates the load.

- Peer-to-peer Load Drivers: refer to a set of load drivers, which collectively generate the target testing load. Peer-to-peer load drivers usually have a con- troller component, which coordinates the load generation among the peer load drivers.

2.3.1 Load Test Tools

A stress test need to perform hundreds or thousands of concurrent requests to the application under test. Automated tools are needed to carry out serious load, stress, and performance testing. Sometimes, there is simply no practical way to provide reliable, repeatable performance tests without using some form of automation. The aim of any automated test tool is to simplify the testing process.

Workload generators are software products based on workload models to generate request sequences similar to real requests. They are designed and implemented as versatile software tools for performing tuning or capacity planning studies. Workload generators typically have the following components [55]:

- Scripting module: Enable recording of end-user activities in different middleware protocols;

- Test management module: Allows the creation of test scenarios;
- Load injectors: Generate the load with multiple workstations or servers;
- Analysis module: Provides the ability to analyse the data collected by each test interation.

There are several tool to execution of Stress testing. In this tools, the procedure is semi-automated, whereas the execution of the tests itself is performed by a tool, the choice of scenarios to be executed as well as the decision to start new execution batteries are activities of the test designer or tester.

Normally, load test tools uses test scripts. Test scripts are written in a GUI testing framework or a backend server-directed performance tool such as JMeter. These frameworks are the basis on which performance testing is mostly done in industry. Performance test scripts imitate large numbers of users to create a significant load on the application under tests [37].

Comparing Web workload generators is a laborious and difficult task since they offer a large amount and diversity of features. In this section we contrast generators according to a wide set of features and capabilities, focusing on their ability to realize search-based tests or have learning capacities.

WebStone was designed by Silicon Graphics in 1996 to measure the perfor- mance of Web server software and hardware products. Nowadays, both executable and source actualized code for WebStone are available for free. The benchmark generates a Web server load by simulating multiple Web clients navigating a website. All the testing done by the benchmark is controlled by a Webmaster, which is a program that can be run on one of the client computers or on a different one [54] [79] .

TPC Benchmarkt (TPC-W) is a transactional Web benchmark defined by the Transaction Processing Performance Council that models a representative e-commerce evaluating the architecture performance on a generic profile.The models uses a remote browser emulator to generate requests to server under test. TPC-W adopts the CBMG model to define the workloads in spite of this model only characterizing user dynamic behavior partially. The remote browser emulators are located in the client side and generate workload towards

the e-commerce Web application, which is located in the server side (e-commerce server) [54] [53].

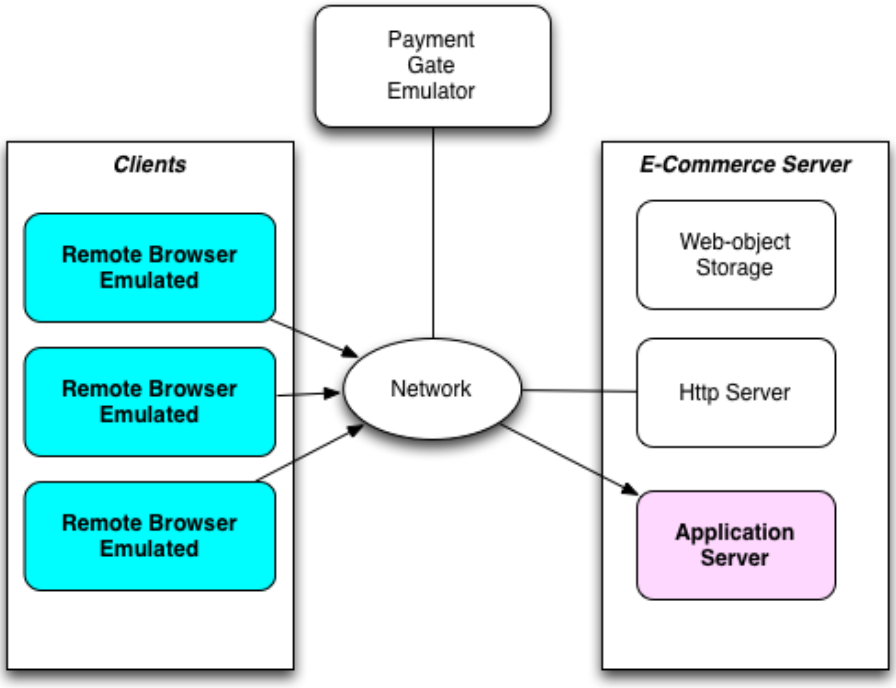

Figure 2-10: TPC-W architecture [54] [53]

Open STA is an open source software developed in C++, and released under the GPL licence. OpenSTA provides a script language which permits to simulate the activity of a user. This language can describe HTTP/S scenario and all the test executions is managed in a graphical interface. The composition of the test is very simple, allowing the tester choose scripts for a test and a remote computer that will execute each test.

LoadRunner is one of the most popular industry-standard software products for functional and performance testing. It was originally developed by Mercury Interactive, but nowadays it is commercialized by Hewlett-Packard. LoadRunner supports the definition of user navigations, which are represented using a scripting language. The basic steps are recorded, creating a shell script. Next, this script is then taken off-line, and undergoes further manual steps such as data parameterization and correlations. Finally, the desired performance scripts are obtained after adding transactions and any other required logic (Fig. 2-11). LoadRunner scripting only permits partial reproduction of user dynamism when generating Web workload, because it cannot define either advanced interactions of

users, such as parallel browsing behavior, or continuous changes in user's behaviors [54].

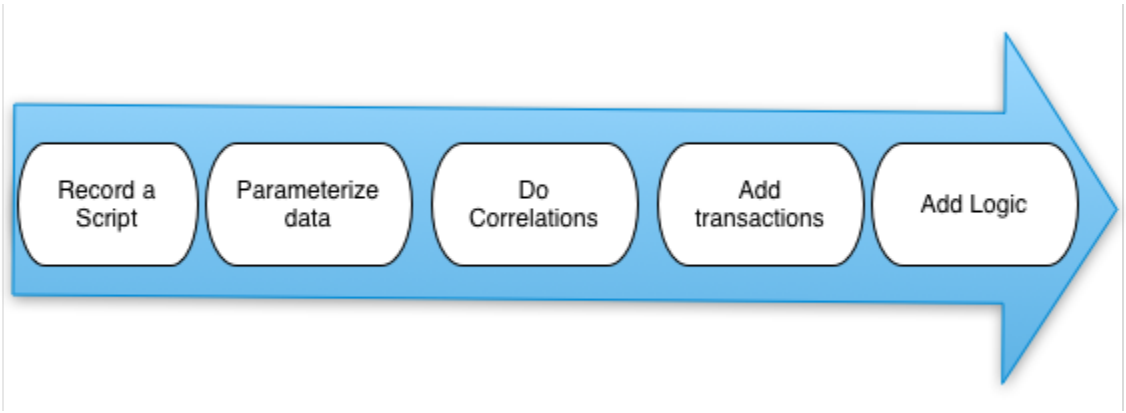

Figure 2-11: Load Runner Scripting

WebLOAD is a software tool for Web performance commercialized by RadView. It is oriented to explore the performance of critical Web applications by quantifying the utilization of the main server resources. The tool creates scenarios that try to mimic the navigations of real users. To this end, it provides facilities to record, edit and debug test scripts, which are used to define the scenarios on workload characterization. The execution environment is a console to manage test execution, whose results are analyzed in the Analytics application. Since WebLOAD is a distributed system, it is possible to deploy several load generators to reproduce the desired load. Load generators can also be used as probing clients where a single virtual user is simulated to evaluate specific statistics of a single user. These probing clients resemble the experience of a real user using the system while it is under load [54].

Apache JMeter is a free open source stress testing tool. It has a large user base and offers lots of plugins to aid testing. JMeter is a desktop application designed to test and measure the performance and functional behavior of applications. The application it's purely Java-based and is highly extensible through a provided API (Application Programming Interface). JMeter works by acting as the client of a client/server application. JMeter allows multiple concurrent users to be simulated on the application [40] [26].

JMeter has components organized in a hierarchical manner. The Test Plan is the main component in a JMeter script. A typical test plan will consist of one or more Thread Groups, logic controllers, listeners, timers, assertions, and configuration elements:

- Thread Group: Test management module responsible to simulate the users used in a test. All elements of a test plan must be under a thread group.
- Listeners: Analysis module responsible to provide access to the information gathered by JMeter about the test cases .
- Samplers: Load injectors module responsible to send requests to a server, while Logical Controllers let you customize its logic.
- Timers: allow JMeter to delay between each request.
- Assertions: test if the application under test it is returning the correct results.
- Configuration Elements: configure detais about the request protocol and test elements.

Table A.2 summarizes the studied workloads generators as well as the grade (full or partial) in which they fulfill the features described bellow. None of the presented tools uses heuristic or learning resources when choosing the scenarios to be tested or the workloads to be applied in the test.

2.4 Research Question 3: What are the main problems found by stress tests?

Performance problems share common symptoms and many performance problems described in the literature are defined by a particular set of root causes. Fig. 2-12 shows the symptoms of known performance problems [86].

There are several antipatterns that details features about common performance problems. Antipatterns are conceptually similar to patterns in that they document recurring solutions to common design problems. They are known as antipatterns because their use produces negative consequences. Performance antipatterns document common performance mistakes made in software architectures or designs. These software Performance antipatterns have four primary uses: identifying problems, focusing on the right level of abstrac-

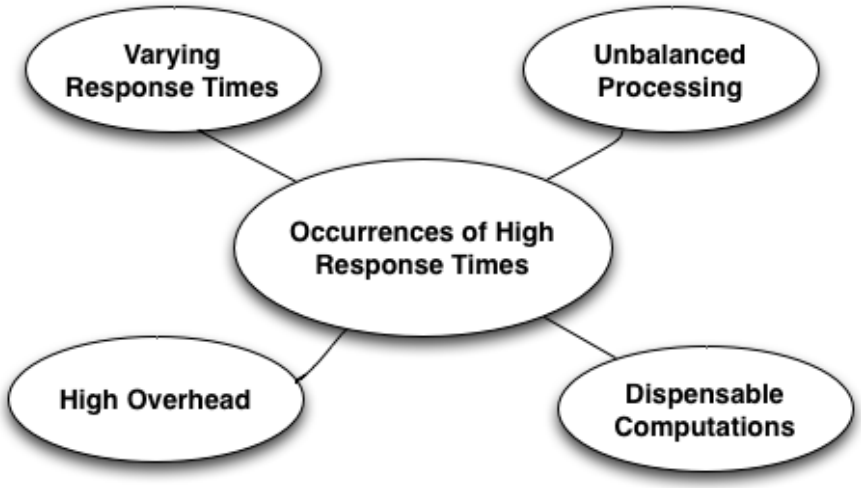

Figure 2-12: Symptoms of know performance problems [86].

tion, effectively communicating their causes to others, and prescribing solutions [17]. The table 2.1 present some of the most common performance antipatterns.

Table 2.1: Performance antipatterns

antipattern	Derivations
Blob or The God Class	
Unbalanced-Processing	Concurrent processing Systems
	Piper and Filter Architectures
	Extensive Processing
Circuitous Treasure Hunt	
Empty Semi Trucks	
Tower of Babel	
One-Lane Bridge	
Excessive Dynamic Allocation	
Traffic Jam	
The Ramp	
More is Less	

Blob antipattern is known by various names, including the “god” class [8] and the

"blob" [2]. Blob is an antipattern whose problem is on the excessive message traffic generated by a single class or component, a particular resource does the majority of the work in a software. The Blob antipattern occurs when a single class or component either performs all of the work of an application or holds all of the application's data. Either manifestation results in excessive message traffic that can degrade performance [20] [68].

A project containing a "god" class is usually has a single, complex controller class that is surrounded by simple classes that serve only as data containers. These classes typically contain only accessor operations (operations to get() and set() the data) and perform little or no computation of their own [68]. The Figures 2-13 and 2-14 describes an hypotetical system with a BLOB problem: The Fig. 2-13 presents a sample where the Blob class uses the features A,B,C,D,E,F and G of the hypotetical system; The Fig. 2-14 shows a static view where a complex software entity instance, i.e. Sd, is connected to other software instances, e.g. Sa, Sb and Sc, through many dependencies [80][86].

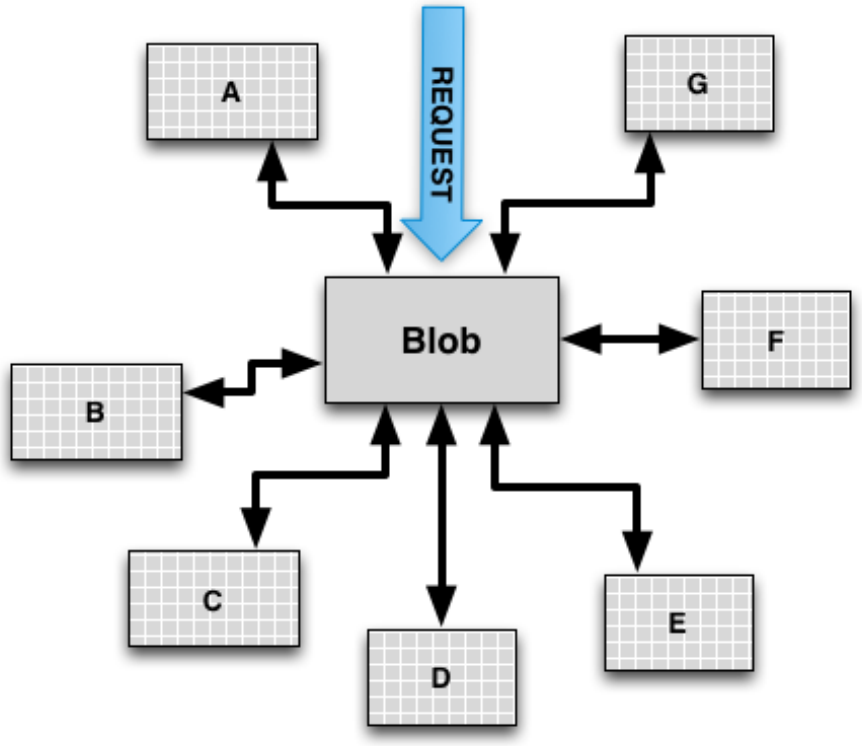

Figure 2-13: The God class[86].

Unbalanced Processing it's characterises for one scenario where a specific class of re-

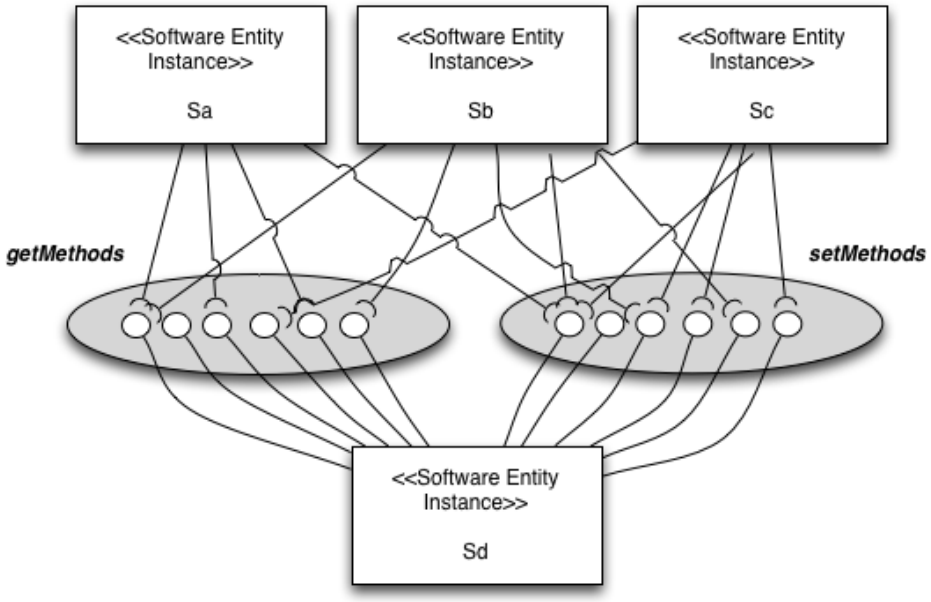

Figure 2-14: The God class[80].

quests generates a pattern of execution within the system that tends to overload a particular resource. In other words the overloaded resource will be executing a certain type of job very often, thus in practice damaging other classes of jobs that will experience very long waiting times. Unbalanced Processing occurs in three different situations. The first case that cause unbalanced processing it is when processes cannot make effective use of available processors either because processors are dedicated to other tasks or because of single-threaded code. This manifestation has available processors and we need to ensure that the software is able to use them. Fig. 2-15 shows a sample of the Unbalanced Processing. In The Fig. 2-15, four tasks are performed. The task D it is waiting for the task C conclusion that are submmited to a heavy processing situation.

The pipe and filter architectures and extensive processing antipattern represents a manifestation of the unbalanced processing antipattern. The pipe and filter architectures occurs when the throughput of the overall system is determined by the slowest filter. The Fig. 2-16 describes a software S with a Pipe and Filter Architectures problem: (a) Static View, there is a software entity instance, e.g. Sa, offering an operation (operation x) whose resource demand (computation = $compOpx, storage = $storOpx, bandwidth = $bandOpx) is quite high; (b) Dynamic View, the operation opx is invoked in a service and the throughput of

the service ($Th(S)) is lower than the required one. The extensive processing occurs when a process monopolizes a processor and prevents a set of other jobs to be executed until it finishes its computation. The Fig. 2-17 describes a software S with a Extensive Processing problem: (a) Static View, there is a software entity instance, e.g. Sa, offering two operations (operation x, operation y) whose resource demand is quite unbalanced, since opx has a high demand (computation = $compOpx, storage = $storOpx, bandwidth = $bandOpx), whereas opy has a low demand (computation = $compOpy, storage = $storOpy, bandwidth = $bandOpy); (b) Dynamic View, the operations opx and opy are alternatively invoked in a service and the response time of the service ($RT(S)) is larger than the required one [80].

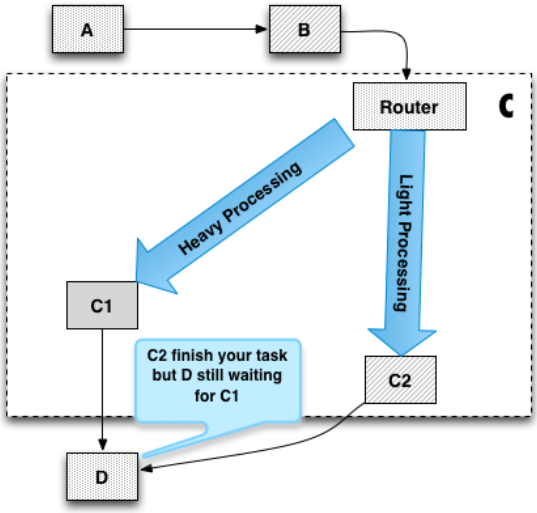

Figure 2-15: Unbalanced Processing sample [86].

Circuitous Treasure Hunt antipattern occurs when software retrieves data from a first componet, uses those results in a second component, retrieves data from the second component, and so on, until the last results are obtained [70] [69]. Circuitous Treasure Hunt are typical performance antipatterns that causes unnecessarily frequent database requests. The Circuitous Treasure Hunt antipattern is a result from a bad database schema or query design. A common Circuitous Treasure Hunt design creates a data dependency between single queries. For instance, a query requires the result of a previous query as input. The longer the chain of dependencies between individual queries the more the Circuitous Treasure Hunt antipattern hurts performance [87]. The Fig. 2-18 shows a software S with a

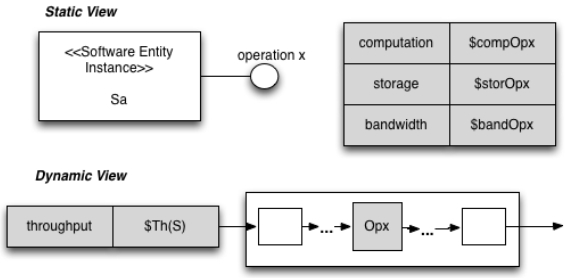

Figure 2-16: Pipe and Filter sample [80]

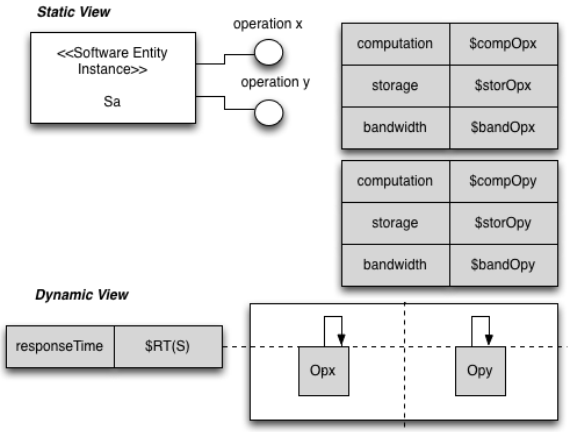

Figure 2-17: Extensive Processing sample [80].

Circuitous Treasure Hunt problem: (a) Static View, there is a software entity instance e.g. Sa, retrieving information from the database; (b) Dynamic View, the software S generates a large number of database calls by performing several queries up to the final operation [80].

Empty Semi Trucks occurs when an excessive number of requests is required to perform a task. It may be due to inefficient use of available bandwidth, an inefficient interface, or both [7]. There are a special case of Empty Semi Trucks that occurs when many fields in a user interface must be retrieved from a remote system. Fig. shows a software S with a Empty Semi Trucks problem: (a) Static View, there is a software entity instance, e.g. Sa, retrieving some information from several instances (Remote Software 1, . . . , Remote Software n); (b) Dynamic View, the software instance Sa generates an excessive message traffic by sending a big amount of messages with low sizes, much lower than the network bandwidth, hence the network link might have a low utilization value [80].

The Tower of Babel antipattern most often occurs when information is translated into an exchange format, such as XML, by the sending process then parsed and translated into an internal format by the receiving process. When the translation and parsing is excessive, the system spends most of its time doing this and relatively little doing real work [69]. Fig. shows a system with a Tower of Babel problem: (a) Static View, there are some software entity instances, e.g. Sa, Sb, . . . , Sn; (b) Dynamic View, the software instances Sd performs many times the translation of format for communicating with other instances [80].

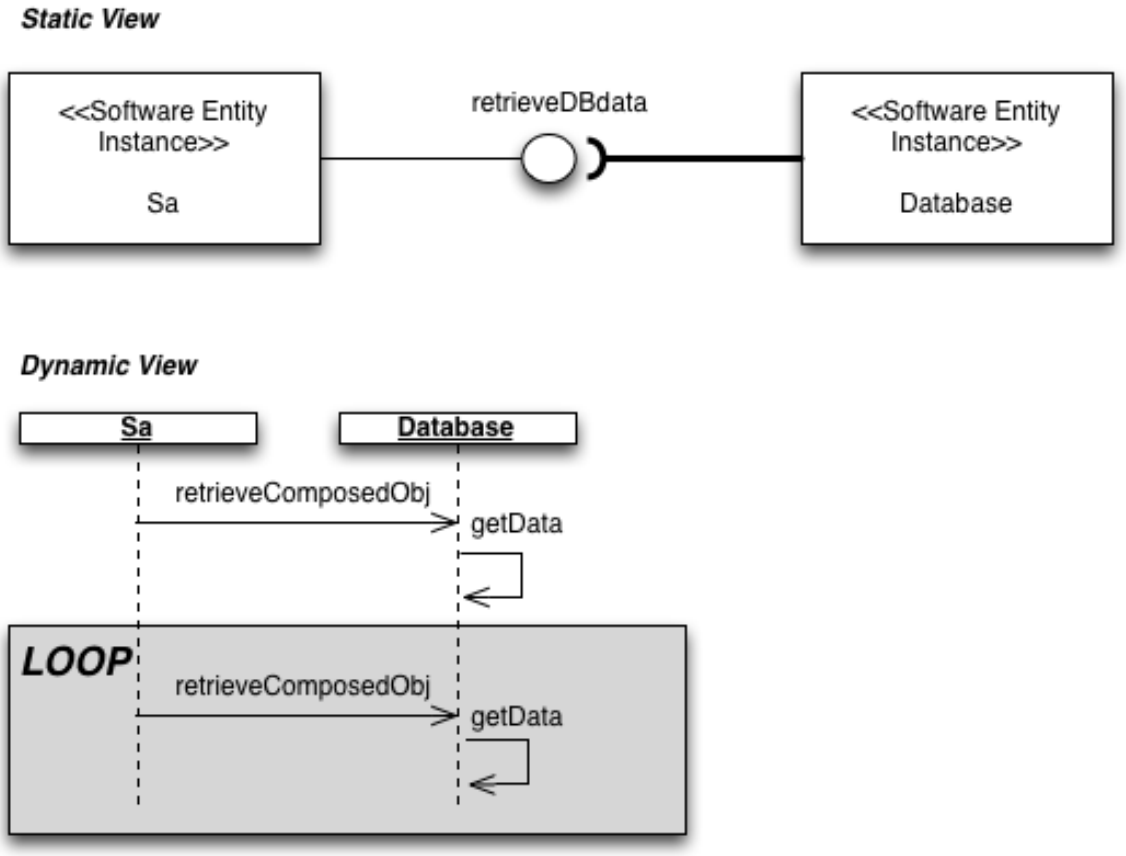

Figure 2-18: Circuitous Treasure Hunt sample [80]

One-Lane Bridge is a antipattern that occurs when one or a few processes execute concurrently using a shared resource and other processes are waiting for use the shared resource. It frequently occurs in applications that access a database. Here, a lock ensures that only one process may update the associated portion of the database at a time. This antipatterns is common when many concurrent threads or processes are waiting for the same shared resources. These can either be passive resources (like semaphores or mutexes) or active resources (like CPU or hard disk). In the first case, we have a typical One Lane Bridge whose critical resource needs to be identified. Figure 3.10 shows a system with a One-Lane Bridge problem: (a) Static View, there is a software entity instance with a capacity of managing $poolSize threads; (b) Dynamic View, the software instance Sc receives an excessive number of synchronous calls in a service S and the predicted response time is higher than the required [80].

Using dynamic allocation, objects are created when they are first accessed and then

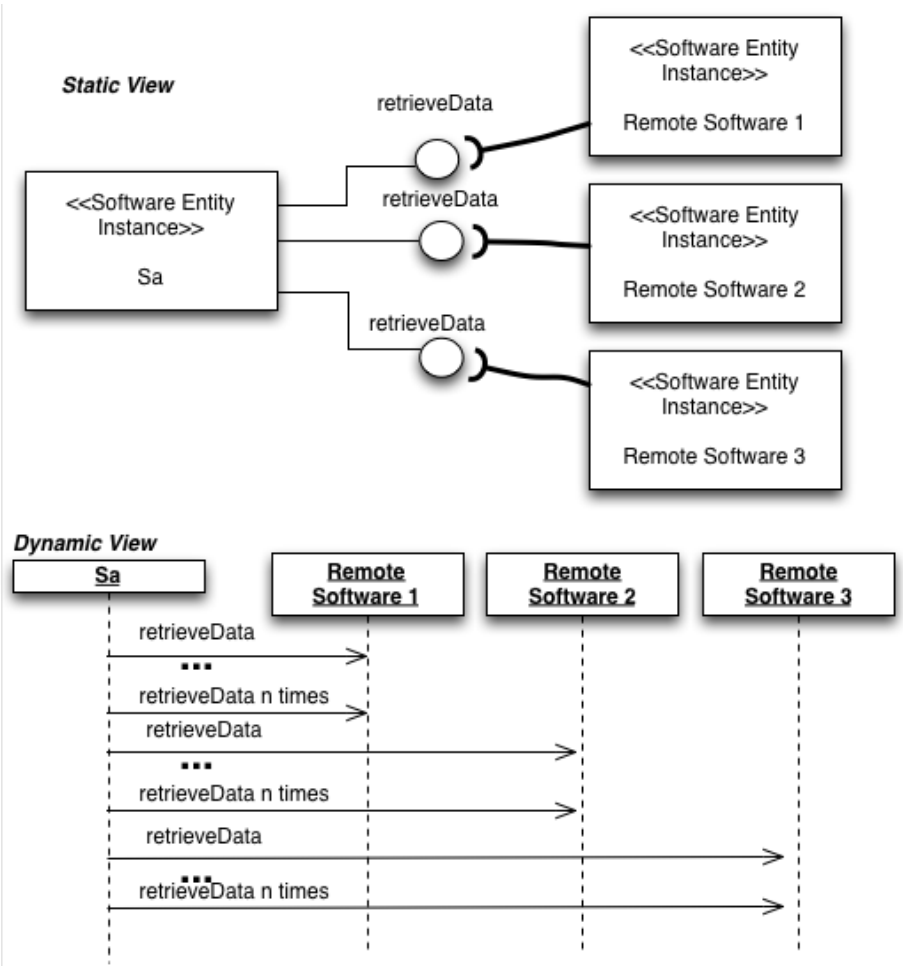

Figure 2-19: Empty Semi Trucks sample [80].

destroyed when they are no longer needed. Excessive Dynamic Allocation, however, addresses frequent, unnecessary creation and destruction of objects of the same class. Dynamic allocation is expensive , an object created in memory must be allocated from the heap, and any initialization code for the object and the contained objects must be executed. When the object is no longer needed, necessary clean-up must be performed, and the reclaimed memory must be returned to the heap to avoid memory leaks [70] [69].

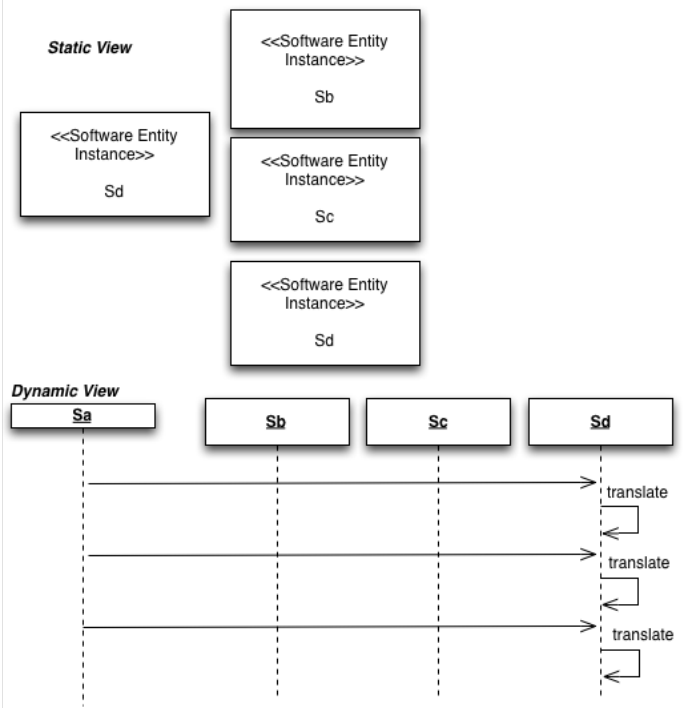

Figure 2-20: Tower of Babel sample [80]

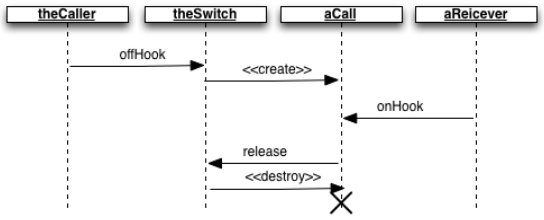

Figure 2-22: Excessive Dynamic Allocation.

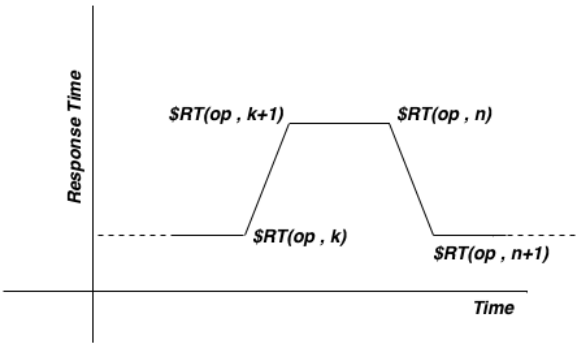

Figure 2-23: Traffic Jam Response Time [80].

The Fig. 2-22 shows a Excessive Dynamic Allocation sample. This example is drawn from a call (an offHook event), the switch creates a Call object to manage the call. When the call is completed, the Call object is destroyed. Constructing a single Call object it is not seem as excessive. A Call is a complex object that contains several other objects that must also be created. The Excessive Dynamic Allocation occurs when a switch receive hundreds of thousands of offHook events. In a case like this, the overhead for dynamically allocating call objects adds substantial delays to the time needed to complete a call.

The Traffic Jam antipattern occurs if many concurrent threads or processes are waiting

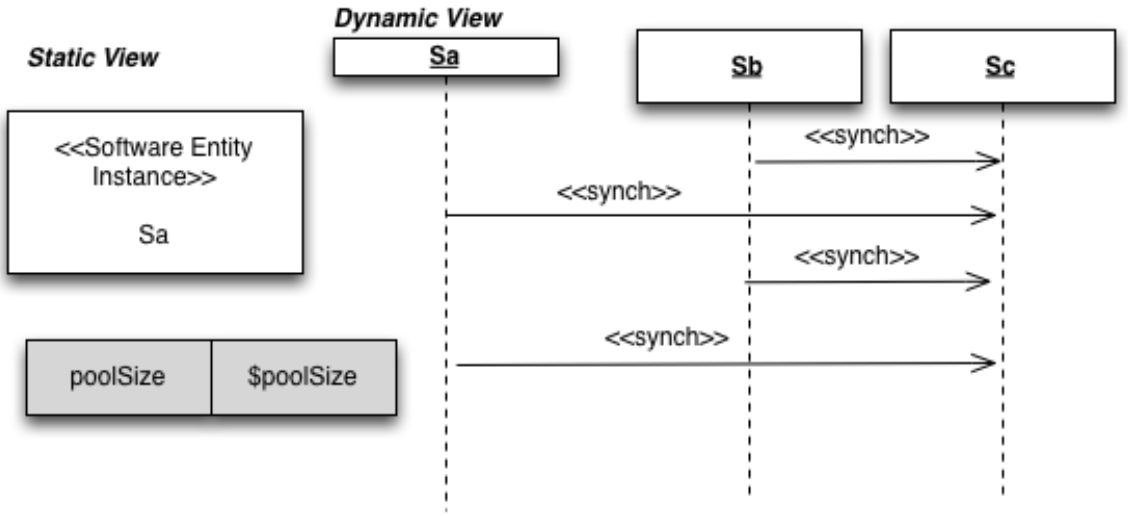

Figure 2-21: One-Lane Bridge sample [80].

for the same active resources (like CPU or hard disk). This antipatterns produces a large backlog in jobs waiting for service. The performance impact of the Traffic Jam is the transient behavior that produces wide variability in response time. Sometimes it is fine, but at other times, it is unacceptably long. Figure 2-23 describes a software with a Traffic Jam problem, the monitored response time of the operation shows a wide variability in response time which persists long [80].

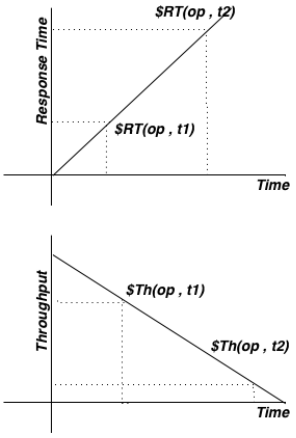

Figure 2-24: The Ramp sample [80].

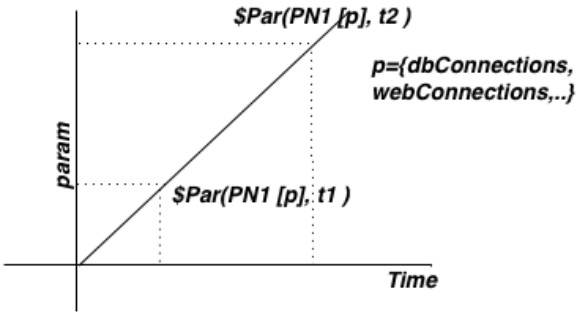

Figure 2-25: More is Less sample [80].

The Ramp it is a antipattern where the processing time increases as the system is used. The Ramp can arise in several different ways. Any situation in which the amount of processing required to satisfy a request increases over time will produce the behavior. With the

Ramp antipattern, the memory consumption of the application is growing over time. The root cause is Specific Data Structures which are growing during operation or which are not properly disposed [87] [69]. Fig. 2-24 shows a system with The Ramp problem: (i) the monitored response time of the operation opx at time t1, i.e. $RT(opx, t1), is much lower than the monitored response time of the operation opx at time t2, i.e. $RT(opx, t2), with t1 < t2; (ii) the monitored throughput of the operation opx at time t1, i.e. $Th(opx, t1), is much larger than the monitored throughput of the operation opx at time t2, i.e. $Th(opx, t2), with t1 < t2.

More is less occurs when a system spends more time "thrashing" than accomplishing real work because there are too many processes relative to available resources. More is Less are presented when it is running too many programs overtime. This antipattern causes too much system paging and systems spend all their time servicing page faults rather than processing requests. In distributed systems, there are more causes.They include: creating too many database connections and allowing too many internet connection. Fig. 2-25 describes a system with a More Is Less problem: There is a processing node PN1 and the monitored runtime parameters (e.g. database connections, etc.) at time t1, i.e. $Par(PN1[p], t1), are much larger than the same parameters at time t2, i.e. $Par(PN1[p], t2), with t1 < t2.

2.5 Research Question 4: How are the stress tests results analysed?

The system behavior recorded during the stress test execution phase needs to be analyzed to determine if there are any load-related functional or non-functional problems [47].

There can be many formats of system behavior like resource usage data or end-to-end response time, which is recorded as response time for each individual request. These types of data need to be processed before comparing against threshold values. A proper data summarization technique is needed to describe these many data instances into one number.

There are three types of data summarization techniques proposed in the literature. Jiang et al. use response time analysis as an example to describe the proposed data summarization

techniques [47]:

- Maximum values;
- Average or Medium Vales;
- Percentile-values.

Some researchers advocate that the 90-percentile response time is a better measurement than the average/medium response time, as the former accounts for most of the peaks, while eliminating the outliers [47].

2.6 Conclusion

Table 2.2: My caption

Test Design	**Test Execution**	**Load Driver**	**Test Tool License**	**Search-Based Stress Test Application**	**Search-Based Test Metaheuris.**	**Test Results**
Model-Based Testing	Live-User Based	Benchmark Suite	Comercial	Real-Time	Genetic Algorithms (GA)	Average
FOREPOST	Driver-Based	Centralized L. Drivers	Open-source	Industrial	Simulated Annealing	90-Percentile
Search-Based Testing	Emulation-Based	Peer-to-peer L. Drivers			Tabu Search	80-Percentile
					Ant Colony	70-Percentile
					Particle Swarm	Maximum
					Hill Climbing	Minimal

Chapter 3

Search-Based Stress Testing

The goal of this Chapter is to describe Search-Based Testing, define recurring solutions in search-based testing

3.1 Introduction

Search-based software engineering (SBSE) is the application of optimization techniques in solving software engineering problems [1,2]. The applicability of optimization techniques in solving software engineering problems is suitable as these problems frequently encounter competing constraints and require near optimal solutions [2] [41].

Search Based Software Testing (SBST) is the sub-area of Search Based Software Engineering concerned with software testing. Search-based software testing is the application of metaheuristic search techniques to generate software tests. SBSE uses computational search techniques to tackle software engineering problems, typified by large complex search spaces. SBSE derives test inputs for a software system with the goal of improving various criteria. The test adequacy criterion is transformed into a fitness function and a set of solutions in the search space are evaluated with respect to the fitness function using a metaheuristic search technique [2] [6] [41].

Stress search-based testing is a application of SBST where the main goal it is to find test scenarios that produce execution times that exceed the timing constraints specified. If a temporal error is found, the test was successful [71].

3.2 Search-Based Testing

Search-Based Testing is the process of automatically generating test according to a test adequacy criterion,encoded as a fitness function, using search-based optimization algorithms, which are guided by a fitness function. The role of the fitness function is to capture a test objective that, when achieved, makes a contribution to the desired test adequacy criterion [42].

Search–Based Testing uses metaheuristic algorithms to automate the generation of test inputs that meet a test adequacy criterion. Many algorithms have been considered in the past, including Simulated Annealing, Parallel Evolutionary Algorithms [4],Evolution Strategies, Estimation of Distribution Algorithms , Scatter Search , Particle Swarm Optimization , Tabu Search and the Alternating Variable Method. An advantage of metaheuristic algorithms is that they are widely applicable to problems that are infeasible for analytic approaches. All one has to do is come up with a representation for candidate solutions and an objective function to evaluate those solution [8].

The application of metaheuristic search techniques to test case generation is a possibility which offers much benefits. Metaheuristic search techniques are high-level frameworks which utilise heuristics in order to find solutions to combinatorial problems at a reasonable computational cost. Such a problem may have been classified as NP-complete or NP-hard, or be a problem for which a polynomial time algorithm is known to exist but is not practical [52].

One of the most popular search techniques used in SBST belong to the family of Evolutionary Algorithms in what is known as Evolutionary Testing. Evolutionary Algorithms represent a class of adaptive search techniques based on natural genetics and Darwin's theory of evolution. They are characterized by an iterative procedure that works in parallel on a number of potential solutions to a problem. Figure 3-1 shows the cycle of an Evolutionary Algorithm when used in the context of Evolutionary Testing [8].

First, a population of possible solutions to a problem is created, usually at random. Starting with randomly generated individuals results in a spread of solutions ranging in fitness because they are scattered around the search–space. Next, each individual in the

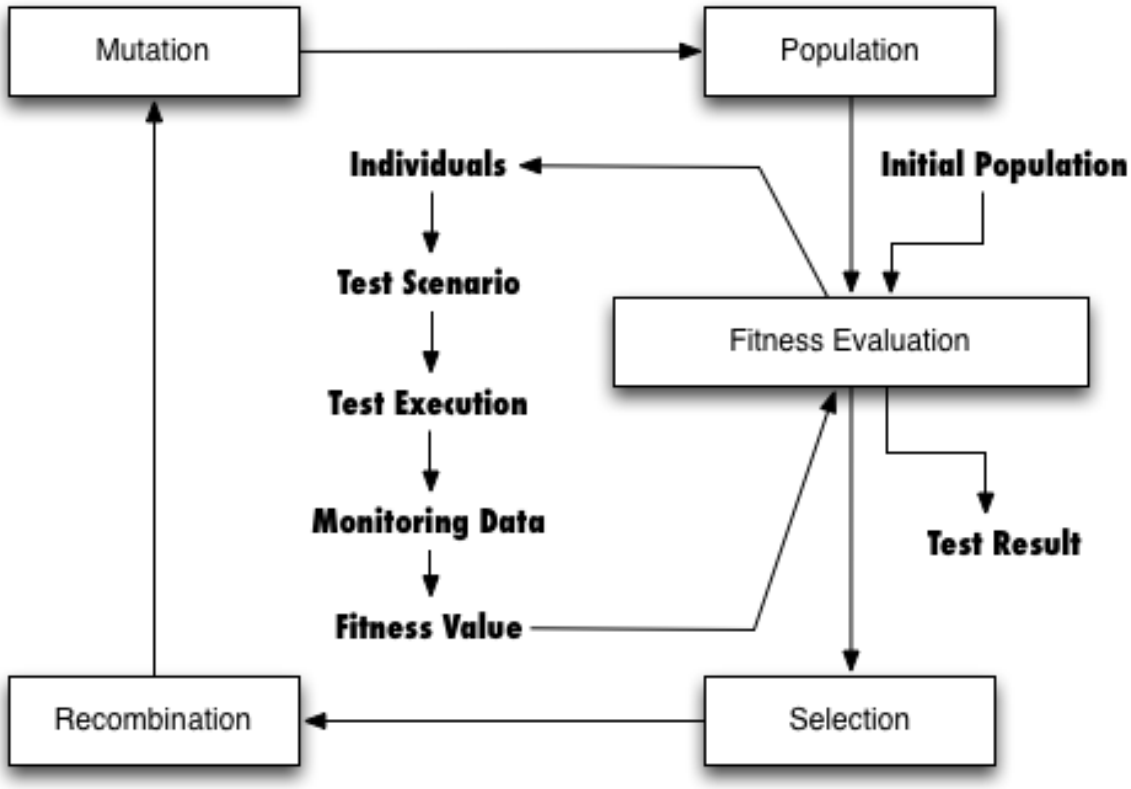

Figure 3-1: Evolutionary Algorithm Search Based Test Cycle[8].

population is evaluated by calculating its fitness via a fitness function. The principle idea of an Evolutionary Algorithm is that fit individuals survive over time and form even fitter individuals in future generations. Selected individuals are then recombined via a crossover operator. After crossover, the resulting offspring individuals may be subjected to a mutation operator. The algorithm iterates until a global optimum is reached or another stopping condition is fulfilled [8].

The fitness evaluation is the most time consuming task of SBST. However, for time consuming functional testing of complex industrial systems, minimizing the number of generated individuals may also be highly desirable. This might be done using an assumption about the "potential" of individuals in order to predict which individuals are likely to contribute to any future improvement. This prediction could be achieved by using information about similar individuals that have been executed in earlier generations.

3.3 Non-functional Search-Based Testing

SBST has made many achievements, and demonstrated its wide applicability and increasing uptake. Nevertheless, there are pressing open problems and challenges that need more attention like to extend SBST to test non-functional properties, a topic that remains relatively under-explored, compared to structural testing. There are many kinds of non-functional search based tests [2]:

- Execution time: The application of evolutionary algorithms to find the best and worst case execution times (BCET, WCET).
- Quality of service: uses metaheuristic search techniques to search violations of service level agreements (SLAs).
- Security: apply a variety of metaheuristic search techniques to detect security vulnerabilities like detecting buffer overflows.
- Usability: concerned with construction of covering array which is a combinatorial object.
- Safety: Safety testing is an important component of the testing strategy of safety critical systems where the systems are required to meet safety constraints.

A variety of metaheuristic search techniques are found to be applicable for non-functional testing including simulated annealing, tabu search, genetic algorithms, ant colony methods, grammatical evolution, genetic programming and swarm intelligence methods. The Fig. 3-2 shows a comparison between the range of metaheuristcs and the type of non-functional search based test.The Data comes from Afzal et al. [2]. Afzal's work adds to some of the latest research in this area ([29] [31] [22] [23] [5] [35]).

3.4 Search-Based Stress Testing

The search for the longest execution time is regarded as a discontinuous, nonlinear, optimization problem, with the input domain of the system under test as a search space [71].

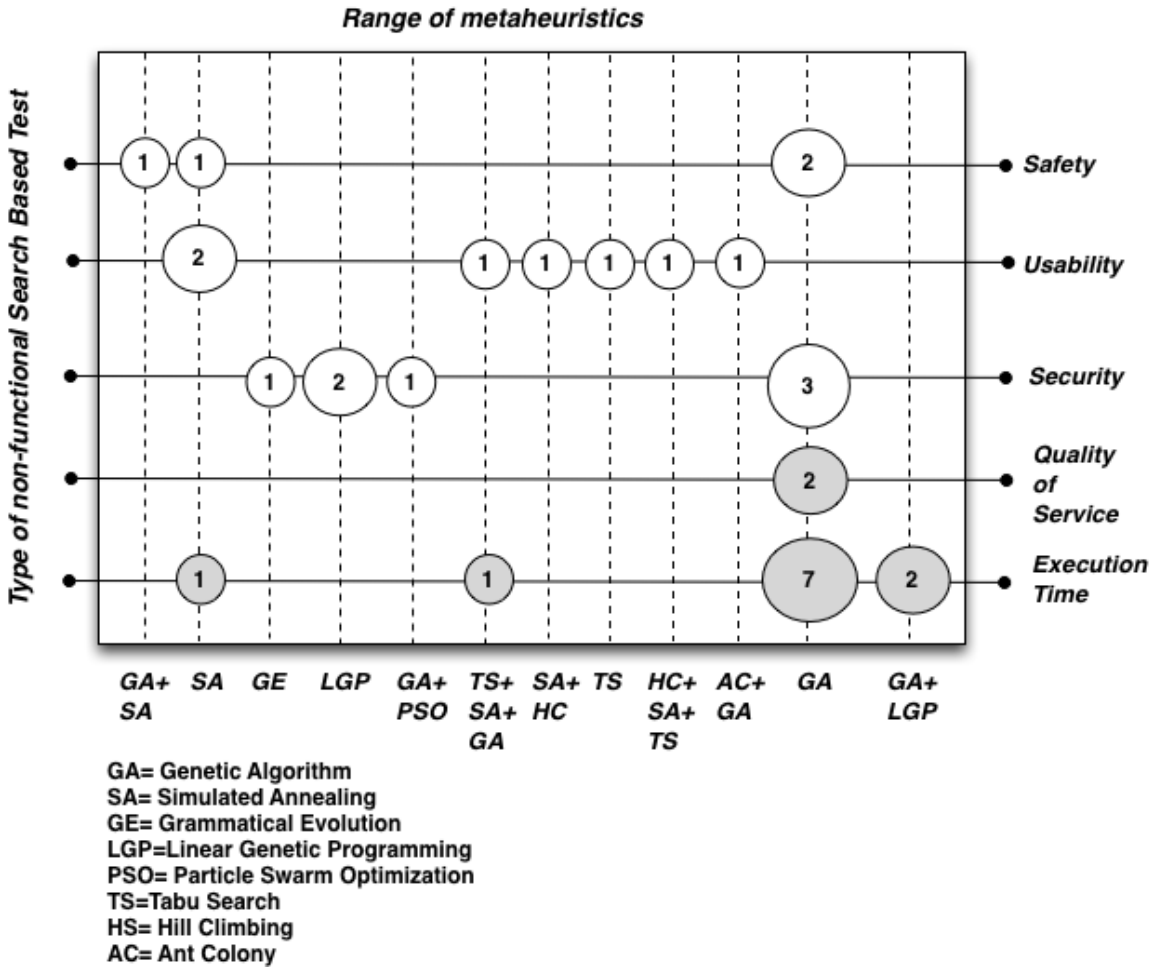

Figure 3-2: Range of metaheuristics by Type of non-functional Search Based Test[2].

The application of SBST algorithms to stress tests involves finding the best- and worst-case execution times (B/WCET) to determine whether timing constraints are fulfilled [2].

There are two measurement units normally associated with the fitness function in stress test: processor cycles and execution time. The processor cycle approach describes a fitness function in terms of processor cycles. The execution time approach involves executing the application under test and measuring the execution time [2] [78].

Processor cycles measurement is deterministic in the sense that it is independent of system load and results in the same execution times for the same set of input parameters. However, such a measurement is dependent on the compiler and optimizer used, therefore, the processor cycles differ for each platform. Execution time measurement is a non deterministic approach, there is no guarantee to get the same results for the same test inputs [2].

However, stress testing where testers have no access to the production environment should be measured by the execution time measurement [55] [2].

Table 3.1 shows a comparison between the research studies on load, performance, and stress tests presented by Afzal et al. [2]. Afzal's work adds to some of the latest research in this area ([29] [31] [22] [23] [5] [35]). The columns represent the type of tool used (prototype or functional tool), and the rows represent the metaheuristic approach used by each research study (genetic algorithm, Tabu search, simulated annealing, or a customized algorithm). The table also sorts the research studies by the type of fitness function used (execution time or processor cycles).

Table 3.1: Distribution of the research studies over the range of applied metaheuristics

	Prototypes		**Functional Tool**
	Execution Time	Processor Cycles	Execution Time
GA + SA + Tabu Search			Gois et al. 2016 [35]
GA	Alander et al.,1998 [3] Wegener et al., 1996 and 1997 [84][45] Sullivan et al., 1998 [71] Briand et al., 2005 [16] Canfora et al., 2005 [18]	Wegener and Grochtmann, 1998 [83] Mueller et al., 1998 [56] Puschner et al. [61] Wegener et al., 2000 [85] Gro et al., 2000 [39]	Di Penta, 2007 [57] Garoussi, 2006 [29] Garousi, 2008 [30] Garousi, 2010 [31]
Simulated Annealing (SA)			Tracey, 1998 [77]
Constraint Programming			Alesio, 2014 [23] Alesio, 2013 [22]
GA + Constraint Programming			Alesio, 2015 [5]
Customized Algorithm		Pohlheim, 1999 [59]	

The studies can be grouped into two main groups:

- Search-Based Stress Tesing on Safety-critical systems.

- Search-Based Stress Testing on Industrial systems.

3.4.1 Search-Based Stress Tesing on Safety-critical systems

Domains such as avionics, automotive and aerospace feature safety-critical systems, whose failure could result in catastrophic consequences. The importance of software in such systems is permanently increasing due to the need of a higher system flexibility. For this reason, software components of these systems are usually subject to safety certification. In this context, software safety certification has to take into account performance requirements specifying constraints on how the system should react to its environment, and how it should execute on its hardware platform [22].

Usually, embedded computer systems have to fulfil real-time requirements. A faultless function of the systems does not depend only on their logical correctness but also on their temporal correctness. Dynamic aspects like the duration of computations, the memory actually needed during program execution, orthe synchronisation of parallel processes are of major importance for the correct function of real-time systems [45] .

The concurrent nature of embedded software makes the order of external events triggering the systems tasks is often unpredictable. Such increasing software complexity renders performance analysis and testing increasingly challenging. This aspect is reflected by the fact that most existing testing approaches target system functionality rather than performance [22].

Reactive real-time systems must react to external events within time constraints. Triggered tasks must execute within deadlines. Shousha develops a methodology for the derivation of test cases that aims at maximizing the chance of critical deadline misses [67].

The main goal of Search-Based Stress testing of Safety-critical systems it is finding a combination of inputs that causes the system to delay task completion to the greast extent possible [67]. The followed approaches uses metaheuristics to discover the worst-case execution times.

Wegener et al. [84] used genetic algorithms(GA) to search for input situations that produce very long or very short execution times. The fitness function used was the execution time of an individual measured in micro seconds [84]. Alander et al. [3] performed experiments in a simulator environment to measure response time extremes of protection

relay software using genetic algorithms. The fitness function used was the response time of the tested software. The results showed that GA generated more input cases with longer response times [3].

Wegener and Grochtmann performed a experimentation to compare GA with random testing. The fitness function used was duration of execution measured in processor cycles. The results showed that, with a large number of input parameters, GA obtained more extreme execution times with less or equal testing effort than random testing [45] [83].

Gro et. al. [39] presented a prediction model which can be used to predict evolutionary testability. The research confirmed that there is a relationship between the complexity of a test object and the ability of a search algorithm to produce input parameters according to B/WCET [39].

Briand et al. [16] used GA to find the sequence of arrival times of events for aperiodic tasks, which will cause the greatest delays in the execution of the target task. A prototype tool named real-time test tool (RTTT) was developed to facilitate the execution of runs of genetic algorithm. Two case studies were conducted and results illustrated that RTTT was a useful tool to stress a system under test [16].

Pohlheim and Wegener used an extension of genetic algorithms with multiple subpopulations, each using a different search strategy. The duration of execution measured in processor cycles was taken as the fitness function. The GA found longer execution times for all the given modules in comparison with systematic testing[59].

Garousi presented a stress test methodology aimed at increasing chances of discovering faults related to distributed traffic in distributed systems. The technique uses as input a specified UML 2.0 model of a system, augmented with timing information.The results indicate that the technique is significantly more effective at detecting distributed traffic-related faults when compared to standard test cases based on an operational profile [29].

Alesio, Nejati and Briand describe a approach based on Constraint Programming (CP) to automate the generation of test cases that reveal, or are likely to, task deadline misses. They evaluate it through a comparison with a state-of-the-art approach based on Genetic Algorithms (GA). In particular, wthe study compares CP and GA in five case studies for efficiency, effectiveness, and scalability. The experimental results show that, on the largest

and more complex case studies, CP performs significantly better than GA. The research proposes a tool-supported, efficient and effective approach based on CP to generate stress test cases that maximize the likelihood of task deadline misses [22].

Alesio describe stress test case generation as a search problem over the space of task arrival times. The research search for worst case scenarios maximizing deadline misses where each scenario characterizes a test case. The paper combine two strategies, GA and Constraint Programming (CP). The results show that, in comparison with GA and CP in isolation, GA+CP achieves nearly the same effectiveness as CP and the same efficiency and solution diversity as GA, thus combining the advantages of the two strategies. Alesio concludes that a combined GA+CP approach to stress testing is more likely to scale to large and complex systems [5].

3.4.2 Search-Based Stress Testing on Industrial systems

Usually, the application of Search-Based Stress Testing on non safety-critical systems deals with the generation of test cases that causes Service Level Agreements violations.

Tracey et al. [77] used simulated annealing (SA) to test four simple programs. The results of the research presented that the use of SA was more effective with larger parameter space. The authors highlighted the need of a detailed comparison of various optimization techniques to explore WCET and BCET of the of the system under test [77].

Di Penta et al. [57] used GA to create test data that violated QoS constraints causing SLA violations. The generated test data included combinations of inputs. The approach was applied to two case studies. The first case study was an audio processing workflow. The second case study, a service producing charts, applied the black-box approach with fitness calculated only on the basis of how close solutions violate QoS constraint. The genome representation is presented in Fig 3-3. The representation models a wsdl request to a webservice.

In case of audio workflow, the GA outperformed random search. For the second case study, use of black-box approach successfully violated the response time constraint, showing the violation of QoS constraints for a real service available on the Internet [57].

Gois et al. proposes an hybrid metaheuristic approach using genetic algorithms, sim-

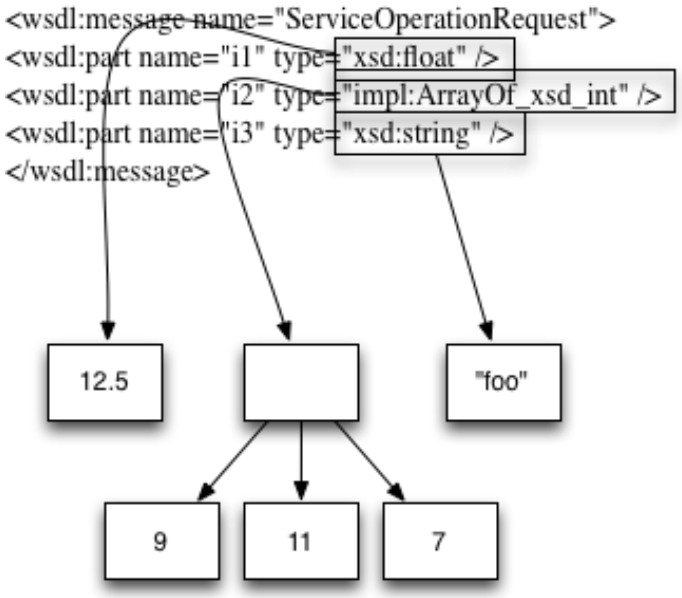

Figure 3-3: Genome representation [57].

ulated annealing, and tabu search algorithms to perform stress testing. A tool named IAdapter, a JMeter plugin used for performing search-based stress tests, was developed. Two experiments were performed to validate the solution. In the first experiment, the signed-rank Wilcoxon non- parametrical procedure was used for comparing the results. The significant level adopted was 0.05. The procedure showed that there was a significant improvement in the results with the Hybrid Metaheuristic approach. In the second experiment, the whole process of stress and performance tests, which took 3 days and about 1800 executions, was carried out without the need for monitoring by a test designer. The tool automatically selected the next scenarios to be run up to the limit of six generations previously established [35].

Chapter 4

Metaheuristics

Following the complexity of the problem, it may be solved by an exact method or an approximate method. Exact methods obtain optimal solutions and guarantee their optimality. Approximate (or heuristic) methods generate high quality solutions in a reasonable time for practical use, but there is no guarantee of finding a global optimal solution [76].

In the computer science, the term metaheuristic is accepted for general techniques which are not specific to a particular problem. A metaheuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space [62].

Metaheuristics are strategies that guide the search process to efficiently explore the search space in order to find optimal solutions. Metaheuristic algorithms are approximate and usually non-deterministic and sometimes incorporate mechanisms to avoid getting trapped in confined areas of the search space. There are different ways to classify and describe metaheuristic algorithm [13]:

- Nature-inspired vs. non-nature inspired. There are nature-inspired algorithms, like Genetic Algorithms and Ant Algorithms, and non nature-inspired ones such as Tabu Search and Iterated Local Search.

- Population-based vs. single point search. Algorithms working on single solutions are called trajectory methods, like Tabu Search, Iterated Local Search and Variable Neighborhood Search. They all share the property of describing a trajectory in the

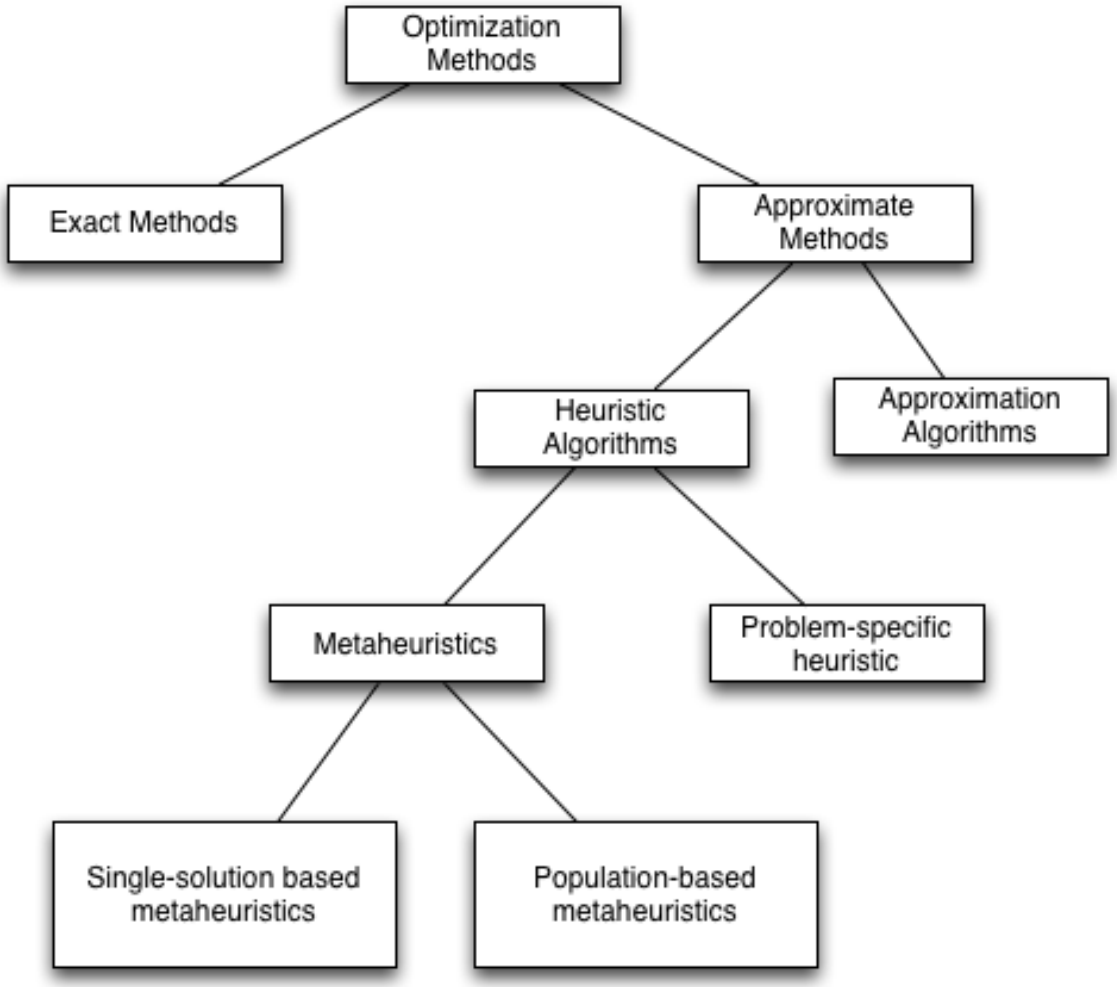

Figure 4-1: Classical optimization methods [76].

search space during the search process. Population-based metaheuristics perform search processes which describe the evolution of a set of points in the search space.

- One vs. various neighborhood structures. Most metaheuristic algorithms work on one single neighborhood structure. In other words, the fitness landscape topology does not change in the course of the algorithm. Other metaheuristics, such as Variable Neighborhood Search (VNS), use a set of neighborhood structures which gives the possibility to diversify the search by swapping between different fitness landscapes.

4.1 Single-Solution Based Metaheuristics

While solving optimization problems, single-solution based metaheuristics improve a single solution. They could be viewed as "walks" through neighborhoods or search trajectories through the search space of the problem at hand.

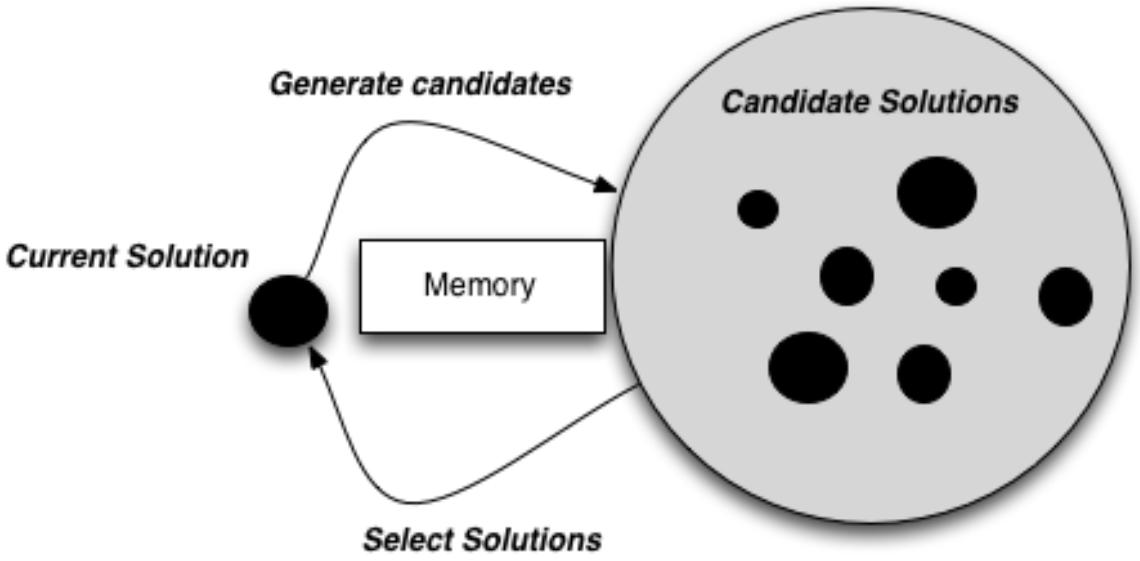

Figure 4-2: Main principles of single-based metaheuristics.

4.1.1 Neighborhood

The definition of Neighborhood is a required common step for the design of any Single-Solution metaheuristic (S-metaheuristic). The neighborhood structure it is a important piece in the performance of an S-metaheuristic. If the neighborhood structure is not adequate to the problem, any S-metaheuristic will fail to solve the problem. The neighborhood function N is a mapping: $N : S \rightarrow N^2$ that assigns to each solution s of S a set of solutions $N(s) \subset$ S [76].

The neighborhood definition depends representation associated with the problem. For permutation-based representations, a usual neighborhood is based on the swap operator that consists in swapping the location of two elements s_i and s_j of the permutation [76]. The Fig. 4-3 presents a example where a set of neighbors is found by permutation.

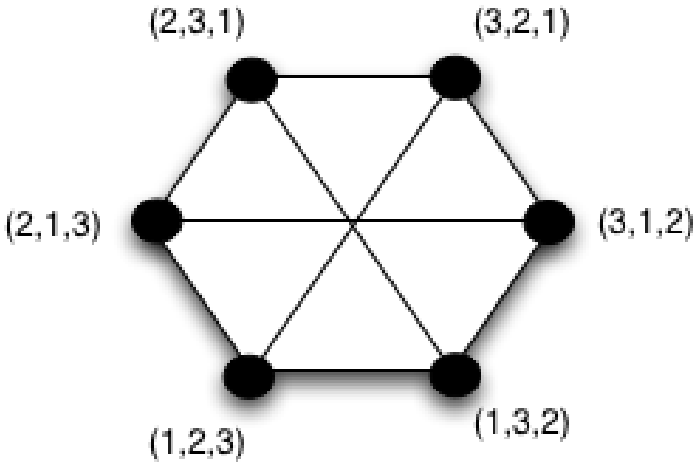

Figure 4-3: An example of neighborhood for a permutation [76].

Single-Solution Based Metaheuristics methods are characterized by a trajectory in the search space. Two common S-metaheuristics methods are Simulated Annealing and Tabu Search.

4.1.2 Simulated Annealing

Simulated Annealing (SA) is a randomized algorithm that tries to avoid being trapped in local optimum solution by assigning probabilities to deteriorating moves. The SA procedure is inspired from the annealing process of solids. SA is based on a physical process in metallurgy discipline or solid matter physics. Annealing is the process of obtaining low energy states of a solid in heat treatment [46].

The algorithmic framework of SA is described in Alg. 1. The algorithm starts by generating an initial solution in function *GenerateInitialSolution()*. The initial temperature value is determined in function *SetInitialTemperature()* such that the probability for an uphill move is quite high at the start of the algorithm. At each iteration a solution s_1 is randomly chosen in function *PickNeighborAtRandom(N(s))*. If s_1 is better than s, then s_1 is accepted as new current solution. Else, if the move from s to s_1 is an uphill move, s_1 is accepted with a probability which is a function of a temperature parameter Tk and s [62].

Algorithm 1 Simulated Annealing Algorithm

```
1:  s ← GenerateInitialSolution()
2:  k ← 0
3:  Tk ← SetInitialTemperature()
4:  while termination conditions not met do
5:      s1 ← PickNeighborAtRandom(N(s))
6:      if (f(s1) < f(s)) then
7:          s ← s1
8:      else Accept s1 as new solution with probability p(s1|Tk,s)
9:      end if
10:     K ← K + 1
11:     Tk ← AdaptTemperature()
12: end while
```

4.1.3 Tabu Search

Tabu Search (TS) is a metaheuristic that guides a local heuristic search procedure to explore the solution space beyond local optimal and search with short term memory to avoid cycles. Tabu Search uses a tabu list to keep track of the last moves, and don't allow going back to these [34].

The basic idea of TS is the explicit use of search history, both to escape from local minima and to implement a strategy for exploring the search space. A basic TS algorithm uses short term memory in the form of socalled tabu lists to escape from local minima and to avoid cycles [64].

The algorithmic framework of Tabu Search is described in Alg. 2. The algorithm starts by generating an initial solution in function *GenerateInitialSolution()* and the tabu lists are initialized as empty lists in function *InitializeTabuLists(TL_1,...,TL_r)*. For performing a move, the algorithm first determines those solutions from the neighborhood *N(s)* of the current solution *s* that contain solution features currently to be found in the tabu lists. They are excluded from the neighborhood, resulting in a restricted set of neighbors $N_a(s)$. At each iteration the best solution s_1 from $N_a(s)$ is chosen as the new current solution. Furthermore, in procedure *UpdateTabuLists(TL_1,...,TL_r,s,s_1)* the corresponding features of this solution are added to the tabu lists.

Algorithm 2 Tabu Search Algorithm

$s \leftarrow GenerateInitialSolution()$
InitializeTabuLists(TL_1,...,TL_r)
while termination conditions not met **do**
    $N_a(s) \leftarrow \{s_1 \in N(s) | s_1$ does not violate a tabu condition, or it satisfies at least one aspiration condition $\}$
    $s_1 \leftarrow argmin\{f(s_2) | s_2 \in N_a(s)\}$
    UpdateTabuLists(TL_1,...,TL_r,s,s_1)
    $s \leftarrow s_1$
end while

4.2 Population-based metaheuristics

Population-based metaheuristics (P-metaheuristics) could be viewed as an iterative improvement in a population of solutions. First, the population is initialized. Then, a new population of solutions is generated. Finally, this new population is integrated into the current one using some selection procedures. The search process is stopped when a stopping criterion is satisfied. Algorithms such as Genetic algorithms (GA), scatter search (SS), estimation of distribution algorithms (EDAs), particle swarm optimization (PSO), bee colony (BC), and artificial immune systems (AISs) belong to this class of metaheuristics [74].

4.2.1 Genetic Algorithms

Genetic Algorithms could be a mean of solving complex optimization problems that are often NP Hard. GAs are based on concepts adopted from genetic and evolutionary theories. GAs are comprised of several components [44] [67] :

- a representation of the solution, refered as the chromossome;
- fitness of each chromossome, refered as objective function;
- the genetic operations of crossover and mutation which generate new offspring.

Algorithm 3 shows the basic structure of GA algorithms. In this algorithm, P denotes the population of individuals. A population of offspring is generated by the application

of recombination and mutation operators and the individuals for the next population are selected from the union of the old population and the offspring population [62].

Algorithm 3 Genetic Algorithm

```
    s ← GenerateInitialSolution()
    Evaluate(P)
3:  while termination conditions not met do
        P1 ← Recombine(P)
        P2 ← Mutate(P1)
6:      Evaluate(P2)
        P ← Select(P2, P)
    end while
```

4.3 Hybrid Metaheuristics

However, in recent years it has become evident that the concentration on a sole metaheuristic is rather restrictive. A skilled combination of a metaheuristic with other optimization techniques, a so called hybrid metaheuristic, can provide a more efficient behavior and a higher flexibility when dealing with real-world and large-scale problems [75].

A combination of one metaheuristic with components from other metaheuristics is called a hybrid metaheuristic. The concept of hybrid metaheuristics has been commonly accepted only in recent years, even if the idea of combining different metaheuristic strategies and algorithms dates back to the 1980s. Today, we can observe a generalized common agreement on the advantage of combining components from different search techniques and the tendency of designing hybrid techniques is widespread in the fields of operations research and artificial intelligence [62].

There are two main categories of metaheuristic combinations: collaborative combinations and integrative combinations. These are presented in Fig. 4-4 [63].

Collaborative combinations use an approach where the algorithms exchange information, but are not part of each other. In this approach, algorithms may be executed sequentially or in parallel.

One of the most popular ways of metaheuristic hybridization consists in the use of trajectory methods inside population-based methods. Population-based methods are better in

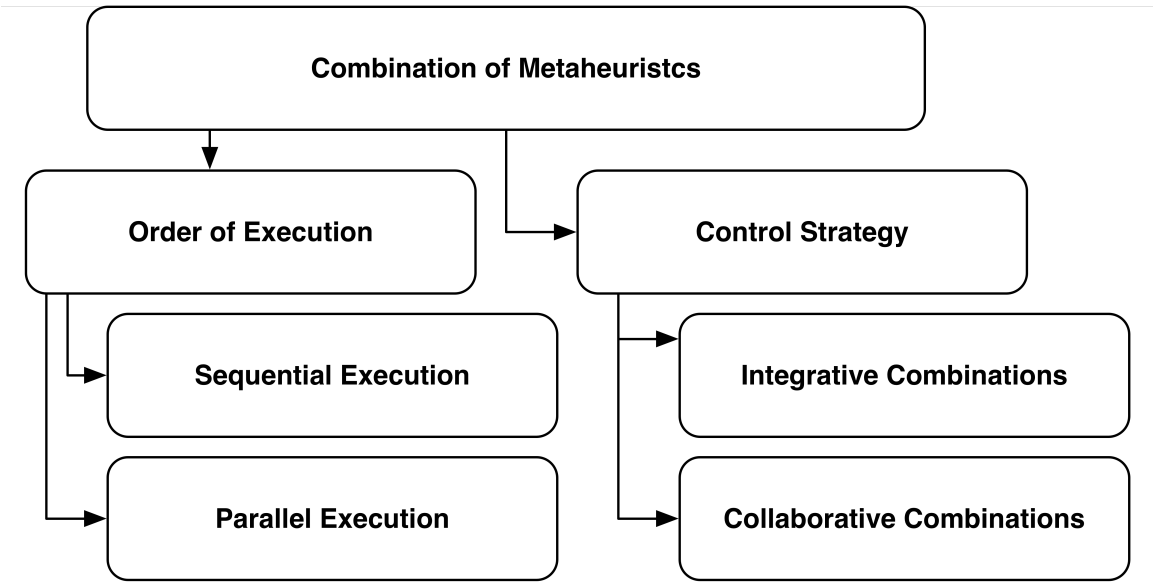

Figure 4-4: Categories of metaheuristc combinations [60]

identifying promising areas in the search space from which trajectory methods can quickly reach good local optima. Therefore, metaheuristic hybrids that can effectively combine the strengths of both population-based methods and trajectory methods are often very successful [62].

The work uses a type of collaborative combination with sequential execution with two trajectory methods (Tabu Search and Simulated Annealing) and Genetic Algorithms.

Chapter 5

Q-Learning

5.1 Reinforcement Learning

Reinforcement learning (RL) refers to both a learning problem and a subfield of machine learning. As a learning problem, it refers to learning to control a system so as to maximize some numerical value which represents a long-term objective. A typical setting where reinforcement learning operates is shown in Figure 5-1: A controller receives the controlled system's state and a reward associated with the last state transition. It then calculates an action which is sent back to the system.

The basis idea of Reinforcement learning is simply to capture the most important aspects of the real problem facing a learning agent interacting with its environment to achieve a goal [72]. Reinforcement learning is learning what to do—how to map situations to actions—so as to maximize a numerical reward signal. The learner need to discover which actions yield the most reward by trying them [72].

In Reinforcement Learning, an agent wanders in an unknown environment and tries to maximize its long term return by performing actions and receiving rewards. The challenge is to understand how a current action will affect future rewards. A good way to model this task is with Markov Decision Processes (MDP), which have become the dominant approach in Reinforcement Learning. There are two types of learning problems:

- Iteractive learning;

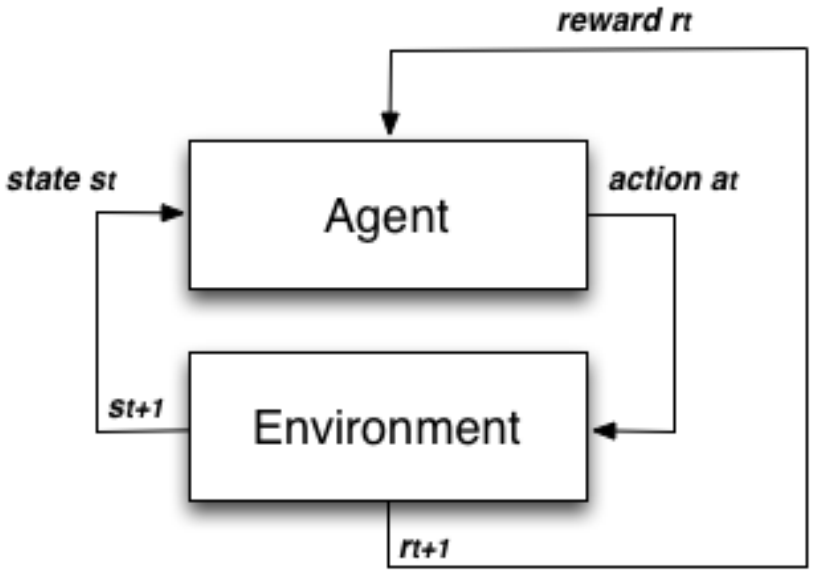

Figure 5-1: Example of a simple MDP with three states and two actions

- Non-interactive learning.

In non-interactive learning, the natural goal is to find a good policy given a fixed number of observations. A common situation is when the sample is fixed. For example, the sample can be the result of some experimentation with some physical system that happened before learning started.

In Interactive learning, learning happens while interacting with a real system in a closed-loop fashion. A reasonable goal then is to optimize online performance, making the learning problem an instance of online learning. Online performance can be measured in different ways. A natural measure is to use the sum of rewards incurred during learning.

Interactive learning is potentially easier since the learner has the additional option to influence the distribution of the sample. However, the goal of learning is usually different in the two cases, making these problems incomparable in general.

In Reinforcement Learging, all agents act in two phases: Exploration vs Explotation. In Exploration phase, the agents tries discover better action selections to improve its knowledge. In Explotation phase, the agents tries to maximize its reward, based on what its already know.

One of the challenges that arise in reinforcement learning is the trade-off between exploration and exploitation. To obtain a lot of reward, a reinforcement learning agent must

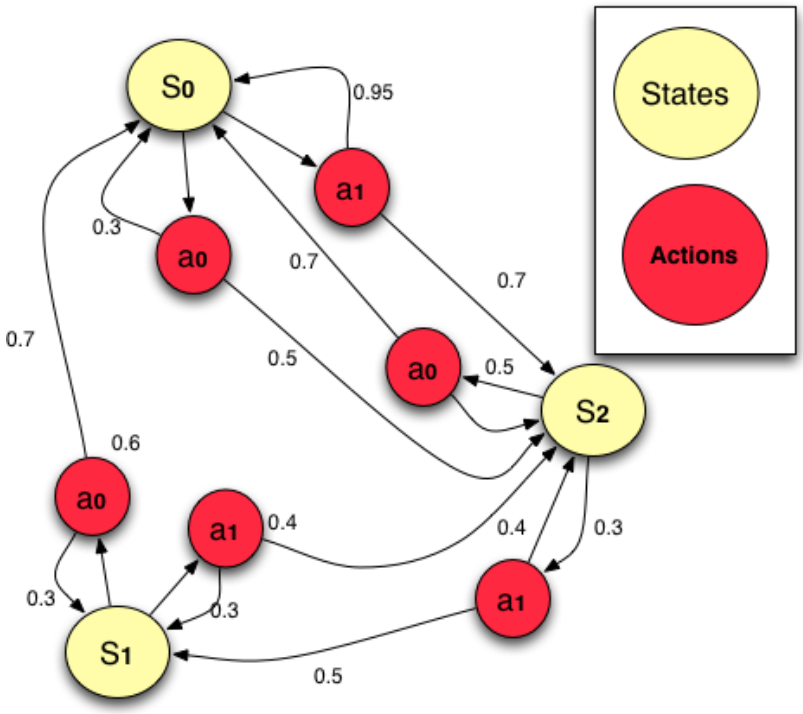

Figure 5-2: Example of a simple MDP with three states and two actions

prefer actions that it has tried in the past and found to be effective in producing reward. But to discover such actions, it has to try actions that it has not selected before. The agent has to exploit what it already knows in order to obtain reward, but it also has to explore in order to make better action selections in the future.

5.1.1 Markov decision processes

Markov decision processes (MDPs) provide a mathematical framework for modeling decision making. A countable MDP is defined as a triplet $M = (\chi, A, P_0)$ [73]. where χ is a set of states, A is a set of actions. The transition probability kernel P_0 assigns to each state-action pair $(x, a) \in \chi xA$

The six main elements of a MDP are:(1) state of the system, (2) actions, (3) transition probabilities, (4) transition rewards, (5) a policy, and (6) a performance metric [72].

The state of a system is a parameter or a set of parameters that can be used to describe a system. For example the geographical coordinates of a robot can be used to describe its state. A system whose state changes with time is called a dynamic system. Then it is not

hard to see why a moving robot produces a dynamic system.

Actions are the controls allowed for an agent. Transition Probability denotes the probability of going from state i to state j under the influence of action a in one step. If an MDP has 3 states and 2 actions, there are 9 transition probabilities per action. Usually, the system receives an immediate reward ,which could be positive or negative, when it transitions from one state to another

A policy defines the learning agent's way of behaving at a given time. Roughly speaking, a policy is a mapping from perceived states of the environment to actions to be taken when in those states. It corresponds to what in psychology would be called a set of stimulus–response rules or associations. Policys mapping from states to actions.

Performance Metric: Associated with any given policy, there exists a so-called performance metric — with which the performance of the policy is judged. Our goal is to select the policy that has the best performance metric.

5.2 Q-Learning

Q-learning is a model-free reinforcement learning technique. Q-learning, it is a multiagent learning algorithm that learns equilibrium policies in Markov games, just as Q-learning learns to optimal policies in Markov decision processes [38].

Q-learning and related algorithms tries to learn the optimal policy from its history of interaction with the environment. A history of an agent is a sequence of state-action-rewards.Where s_n it is a state, a_n it is an action and r_n is a reward:

$$< s_0, a_0, r_1, s_1, a_1, r_2, s_2, a_2, r_3, s_3, a_3, r_4, s_4.... >, \tag{5.1}$$

In Q-Learning, the system's objective is to learn a control policy $\pi = \sum_{n=0}^{\infty} \gamma^{\mathrm{n}} r_t + n$, where π is the discounted cumulative reward, γ is the discount rate (01) and r_t is the reward reiceved after execution an action at time t. The fig. 5-3 shows the summary version of Q-Learning algorithm. The first step it is to generate the initial state of the MDP. The second step it is to choose the best action or a random action based on the reward, the actions with best rewards are chosen.

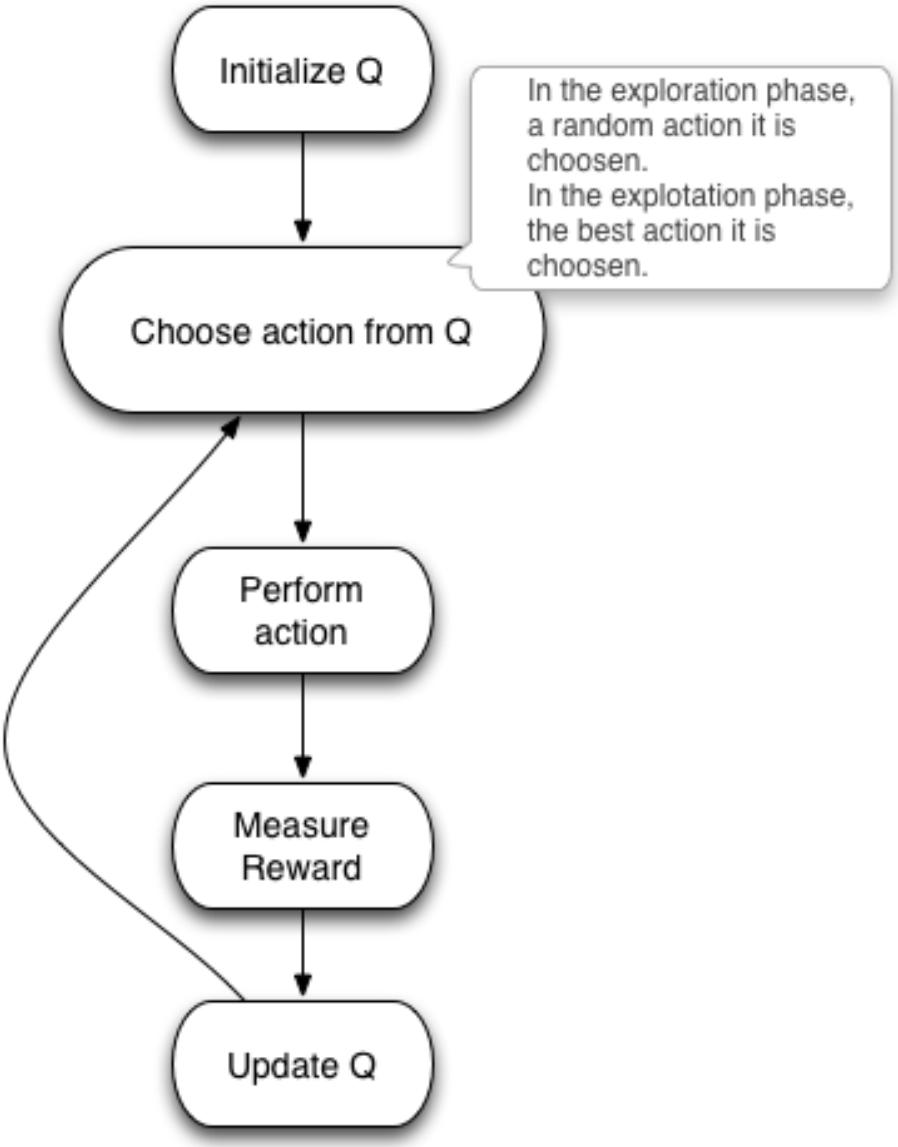

Figure 5-3: Q Learning algorithm

5.3 GridWorld Example

The GridWorld problem is an example of using reinforcement learning with Q-Learning. In this example, The agent's goal is to reach the reward state. There are one rewarding states with value +1 (Gray square at position (3,1)). The agent receives +0.02 of reward if it get closer to the reward state As the agent moves away from the reward state, he receives -0.01 of reward.The agente receive +0 points of reward if it is the same distance to the reward

state.

The Fig. 5-4 shows the initial and final phase on exploration phase. The numbers in the squares shows the Q-values for four available actions: up (u), left (l), right(r) and down(d). The arrows show the optimal action based on the current value function. The initial discount rate is 0.9.

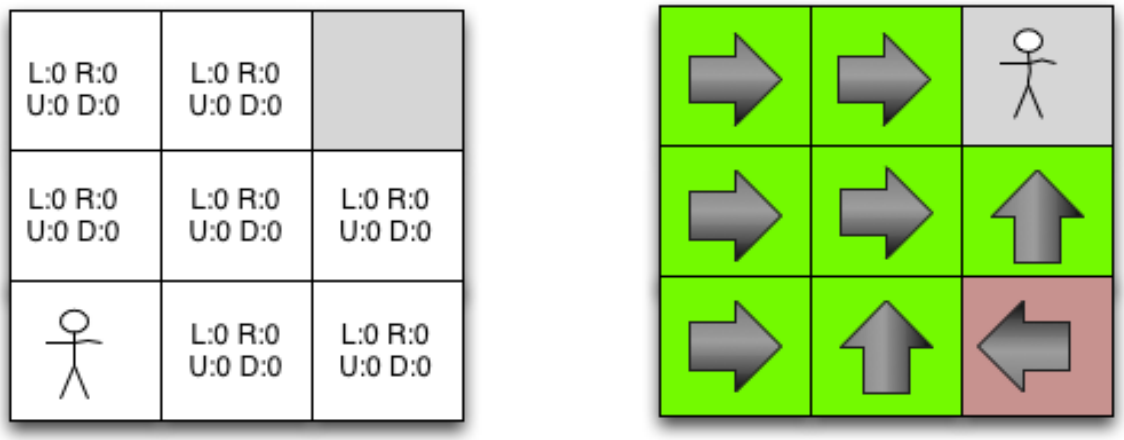

Figure 5-4: GridWorld - initial and final stage on exploration phase

The figure B-1,B-2, B-3 and B-4 shows the states of the game in exploration phase. In the first image, all frames have the accumulated reward value equals to zero. In the second image the reward values increase or decrease as the agent moves.

5.4 Relationships Between Reinforcement Learning and Optimization

Many are the intersections between optimization and Reinforcement Learning. First, approximated versions of optimazation and RL tasks contain challenging optimization tasks, the maximization operations in determining the best action when an action value function is available or the optimal choice of approximation [11]. Both optimization and Machine Learning analysts address real world problems by formulating a model, deriving the core optimization problem, and using mathematical programming to solve it [12] [15].

Gambardella et al. show an Ant metaheuristic with Q-Learning approach (Ant-Q).

They experimentally investigate the functioning of Ant-Q and we show that the results obtained by Ant-Q on symmetric TSP's are competitive with those obtained by other heuristic approaches based on neural networks or local search. The research used Q-Learning to indicate how useful it is to make move in TSP for each ant [28]. Bianchi et at. present a new algorithm, called Heuristically Accelerated Q–Learning (HAQL), that allows the use of heuristics to speed up the well-known Reinforcement Learning algorithm Q–learnin g. The Heuristically Accelerated Q–Learning algorithm can be defined as a way of solving the RL problem which makes explicit use of a heuristic function to influence the choice of actions during the learning process. The HAQL uses a modification Greedy rule to control exploration and exploitation phases [51].

5.5 Software Testing with Reinforcement Learning

Many software systems are reactive. The behavior of a reactive system, especially when distributed or multithreaded, can be nondeterministic. In these cases, a test suite generated offline may be infeasible.

Online testing can be more appropriate than offline tests for reactive systems. The reason is that with online testing the tests may be dynamically adapted at runtime, effectively pruning the search space to include only those behaviors actually observed instead of all possible behaviors. The interaction between tester and the application under test is seen as a game where the tester chooses moves based on the observed behavior of the implementation under test [**?**].

Andre et al. show a method that operationalizes the risk assessment for interoperability testing. Typically high number of possible interaction scenarios makes interoperability testing a complex task. Since it seems impossible to cover all scenarios, their relevance for being tested has to be prioritized. The method uses behavior models of the system under test and reinforcement learning techniques to obtain the relevance of single system actions for being tested [58]. The table 5.1 shows the Q-value for some states of the test.

Sato and Sugihara propose an automatic test pattern generation by applying genetic algorithms in reinforcement learning. The results of evaluation with an ATM system which

Table 5.1: Q-value for some states of the test [58]

State	Action	Q-value
M'1N1O1	M 1 → M 2	2.5
M'2N2O2	M 2 → M 1	1.25
M'2N2O2	M 2 → M 3	0.0
M'1N1O2	M 1 → M 2	0.5

assuming the existence of a bug related to a global variable are reported [66].

Chapter 6

Improving Stress Search Based Testing using Q-Learning and Hybrid Metaheuristic Approach

6.1 Hybrid Approach

A large number of researchers have recognized the advantages and huge potential of building hybrid metaheuristics. The main motivation for creating hybrid metaheuristics is to exploit the complementary character of different optimization strategies. In fact, choosing an adequate combination of algorithms can be the key to achieving top performance in solving many hard optimization problems [60] [14].

The proposed solution makes it possible to create a model that evolves during the test. The proposed solution model uses genetic algorithms, tabu search, and simulated annealing in two different approaches. The study initially investigated the use of these three algorithms. Subsequently, the study will focus in others Population-based and single point search metaheuristics. The first approach uses the three algorithms independently, and the second approach uses the three algorithms collaboratively (hybrid metaheuristic approach).

In the first approach , the algorithms do not share their best individuals among themselves. Each algorithm evolves in a separate way (Fig. 6-1).

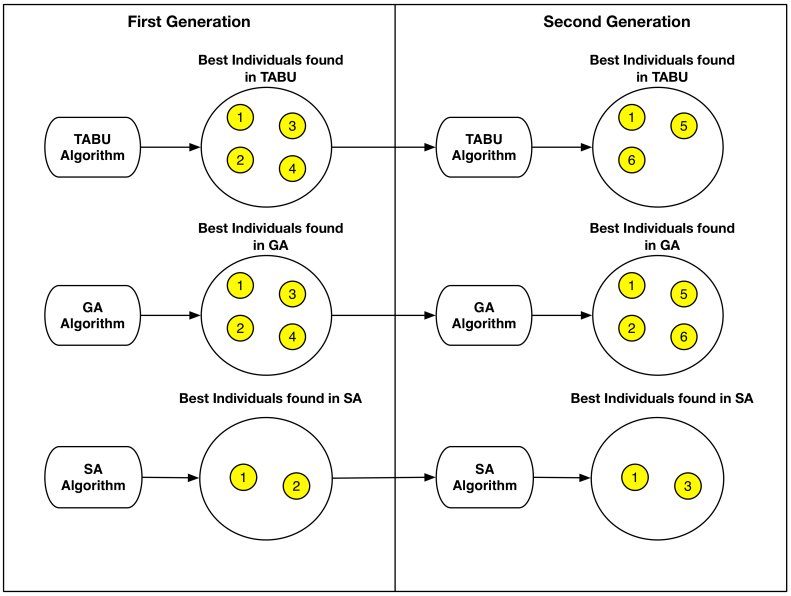

Figure 6-1: Use of the algorithms independently

The second approach uses the algorithms in a collaborative mode (hybrid metaheuristic). In this approach, the three algorithms share their best individuals found (Fig. 6-2). The next subsections present details about the used metaheuristic algorithms (Representation, initial population and fitness function).

6.1.1 Representation

The solution representation is composed by a linear vector with 23 positions. The first position represents the name of an individual. The second position represents the algorithm (genetic algorithm, simulated annealing, or Tabu search) used by the individual. The third position represents the type of test (load, stress, or performance). The next positions represent 10 scenarios and their numbers of users. Each scenario is an atomic operation: the scenario must log into the application, run the task goal, and undo any changes performed, returning the application to its original state.

Fig. 6-3 presents the solution representation and an example using the crossover operation. In the example, genotype 1 has the Login scenario with 2 users, the Form scenario with 0 users, and the Search scenario with 3 users. Genotype 2 has the Delete scenario with 10 users, the Search scenario with 0 users, and the Include scenario with 5 users. After the

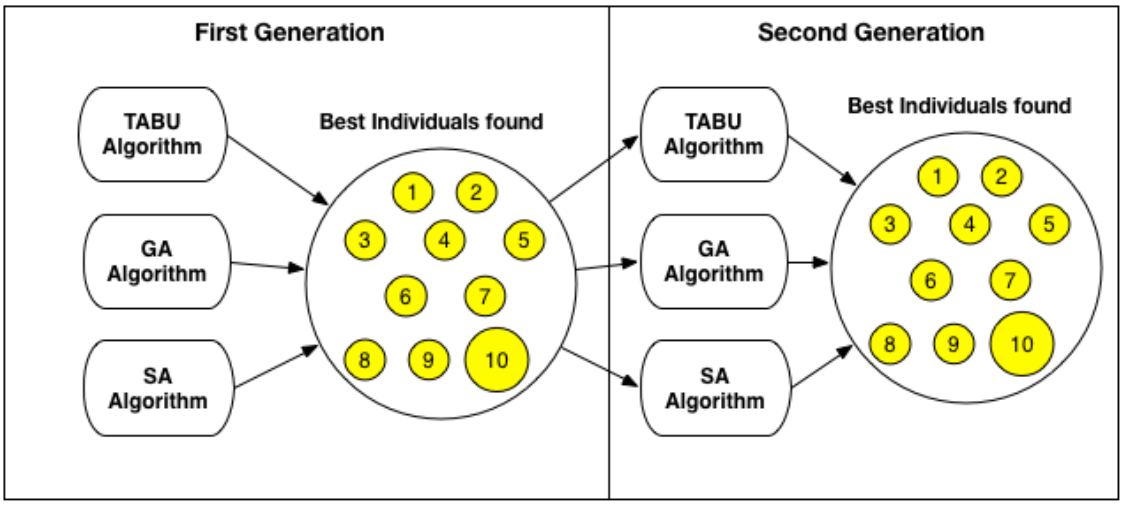

Figure 6-2: Use of the algorithms collaboratively

crossover operation, we obtain a genotype with the Login scenario with 2 users, the Search scenario with 0 users, and the Include scenario with 5 users.

Fig. 6-4 shows the strategy used by the proposed solution to obtain the representation of the neighbors for the Tabu search and simulated annealing algorithms. The neighbors are obtained by the modification of a single position (scenario or number of users) in the vector.

6.1.2 Initial population

The strategy used by the plugin to instantiate the initial population is to generate 50% of the individuals randomly, and 50% of the initial population is distributed in three ranges of values:

- Thirty percent of the maximum allowed users in the test;
- Sixty percent of the maximum allowed users in the test; and
- Ninety percent of the maximum allowed users in the test.

The percentages relates to the distribution of the users in the initial test scenarios of the solution. For example, in a hypothetical test with 100 users, the solution will create initial test scenarios with 30, 60 and 90 users.

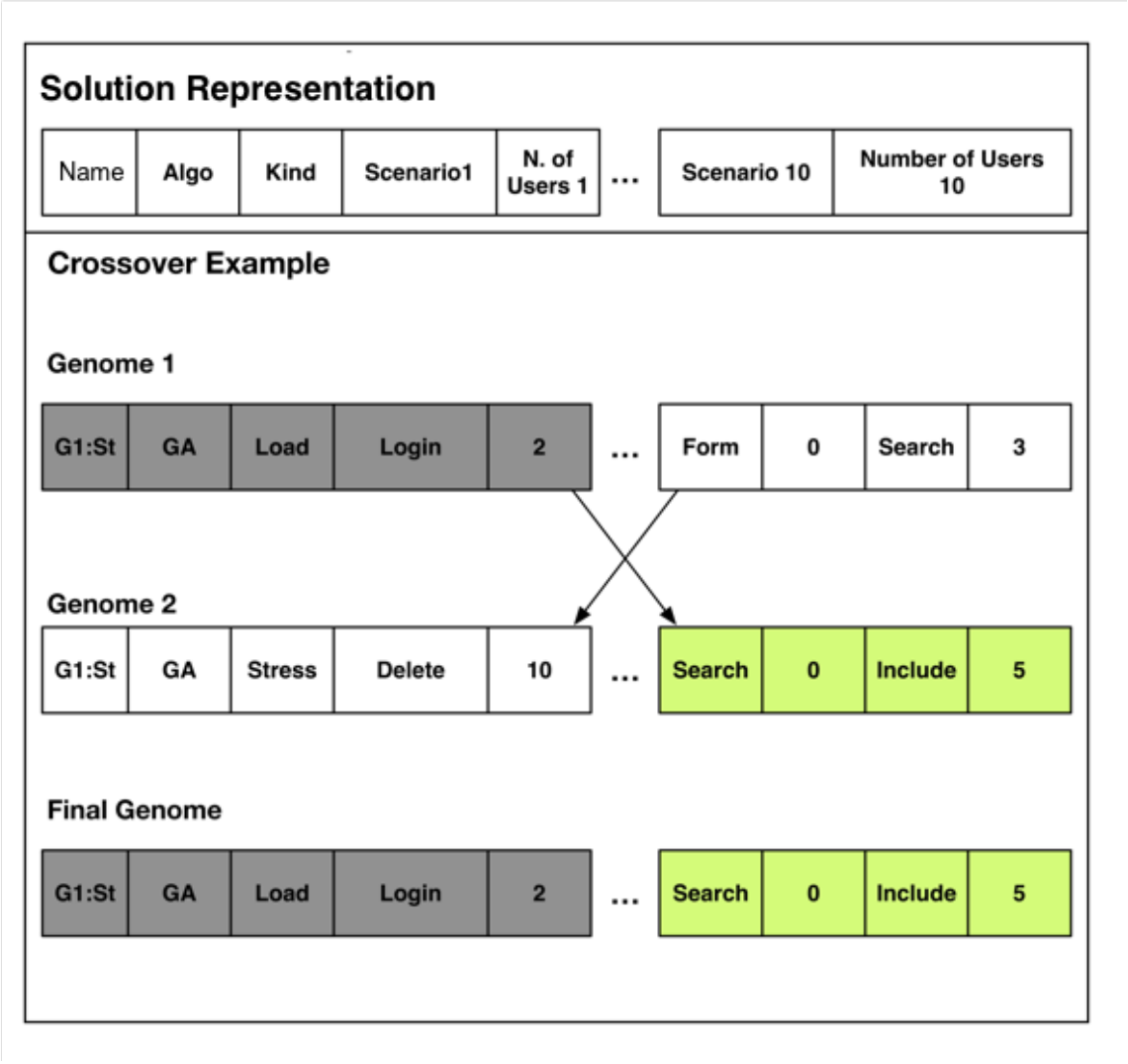

Figure 6-3: Solution representation and crossover example

6.1.3 Objective (fitness) function

The proposed solution was designed to be used with independent testing teams in various situations where the teams have no direct access to the environment where the application under test was installed. Therefore, the IAdapter plugin uses a measurement approach to the definition of the fitness function. The fitness function applied to the IAdapter solution is governed by the following equation:

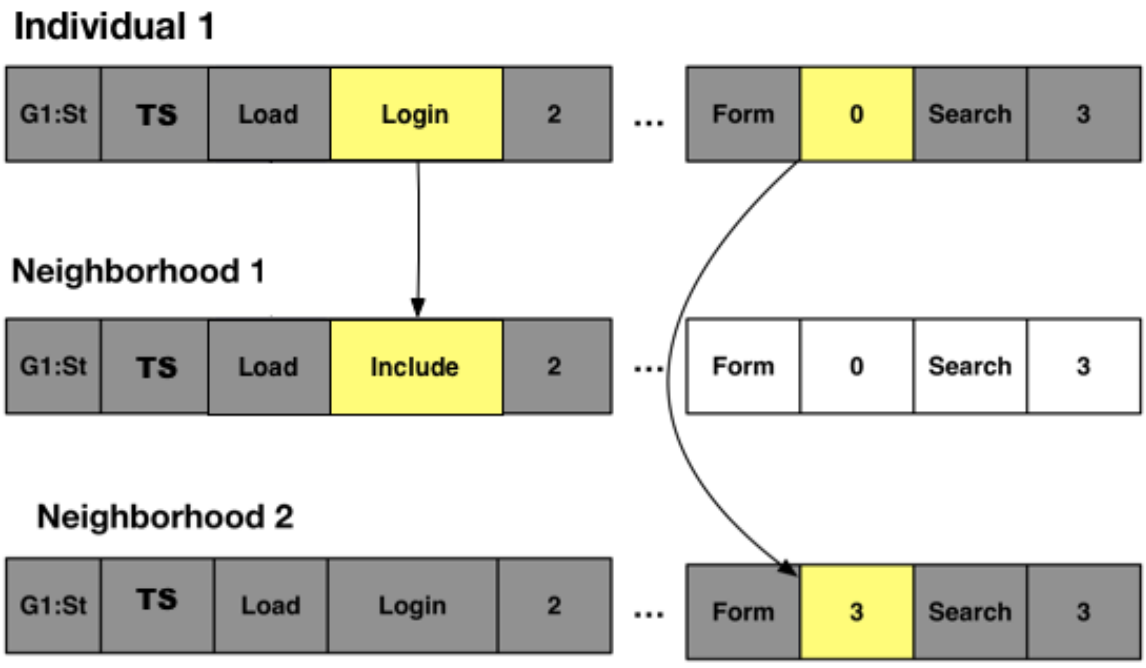

Figure 6-4: Tabu search and simulated annealing neighbor strategy

$$\begin{aligned} fit = {} & 90percentileweigth * 90percentiletime \\ & +80percentileweigth * 80percentiletime \\ & +70percentileweigth * 70percentiletime+ \\ & maxResponseWeigth * maxResponseTime+ \\ & numberOfUsersWeigth * numberOfUsers - penalty \end{aligned} \tag{6.1}$$

The proposed solution's fitness function uses a series of manually adjustable user-defined weights (90percentileweight, 80percentileweight, 70percentileweight, maxResponseWeight, and numberOfUsersWeight). These weights make it possible to customize the search plugin's functionality. A penalty is applied when an application under test takes a longer time to respond than the level of service. The penalty is calculated by the follow equation:

$$\begin{aligned} penalty &= 100 * \Delta \\ \Delta &= (t_{CurrentResponseTime} - t_{MaximumResponseTimeExpected}) \end{aligned} \tag{6.2}$$

6.2 Hybrid Metaheuristic with Q-Learning Approach

The HybridQ algorithm uses the GA, SA and Tabu Search algorithms in a collaborative approach in conjunction with Q-Learning technique.

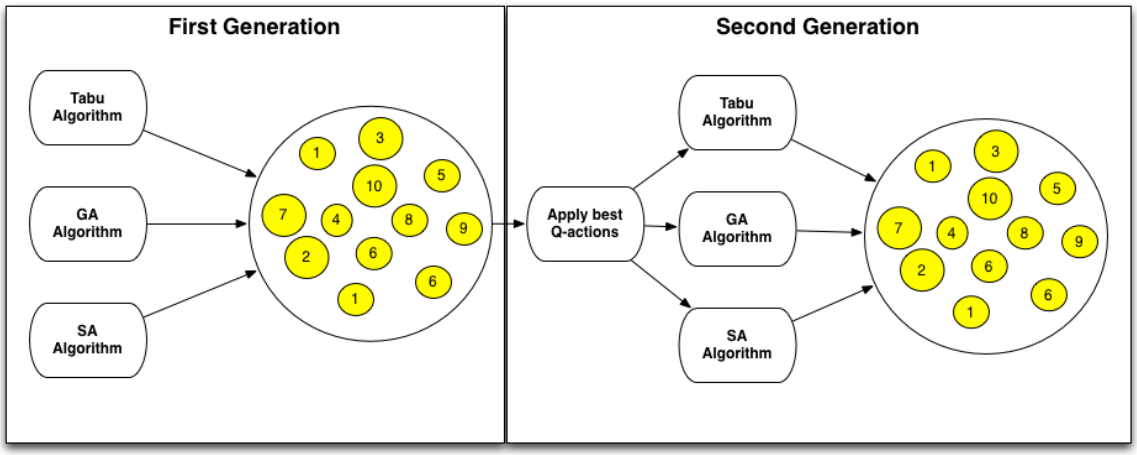

Figure 6-5: Hybrid Metaheuristic with Q-Learning Approach

6.3 IAdapter

IAdapter is a JMeter plugin designed to perform search-based stress tests. The plugin is available on www.iadapter.org. The IAdapter plugin implements the solution proposed in Section 5. The next subsections present details about the Apache JMeter tool, the IAdapter Life Cycle and the IAdapter Components. The IAdapter plugin provides three main components: WorkLoadThreadGroup, WorkLoadSaver, and WorkLoadController.

The Fig. 6-8 show the IAdapter architecture. All metaheuristic class implements the interface IAlgorithm. Test scenarios and test results are stored in a Mysql database. GeneticAlgorithm class uses a framework named JGAP to implement Genetic Algorithms.

The WorkLoadThreadGroup class is the Load Injection and Test Management modules, responsible to generate the initial population and uses the JMeter Engine to realize requests to server under test.

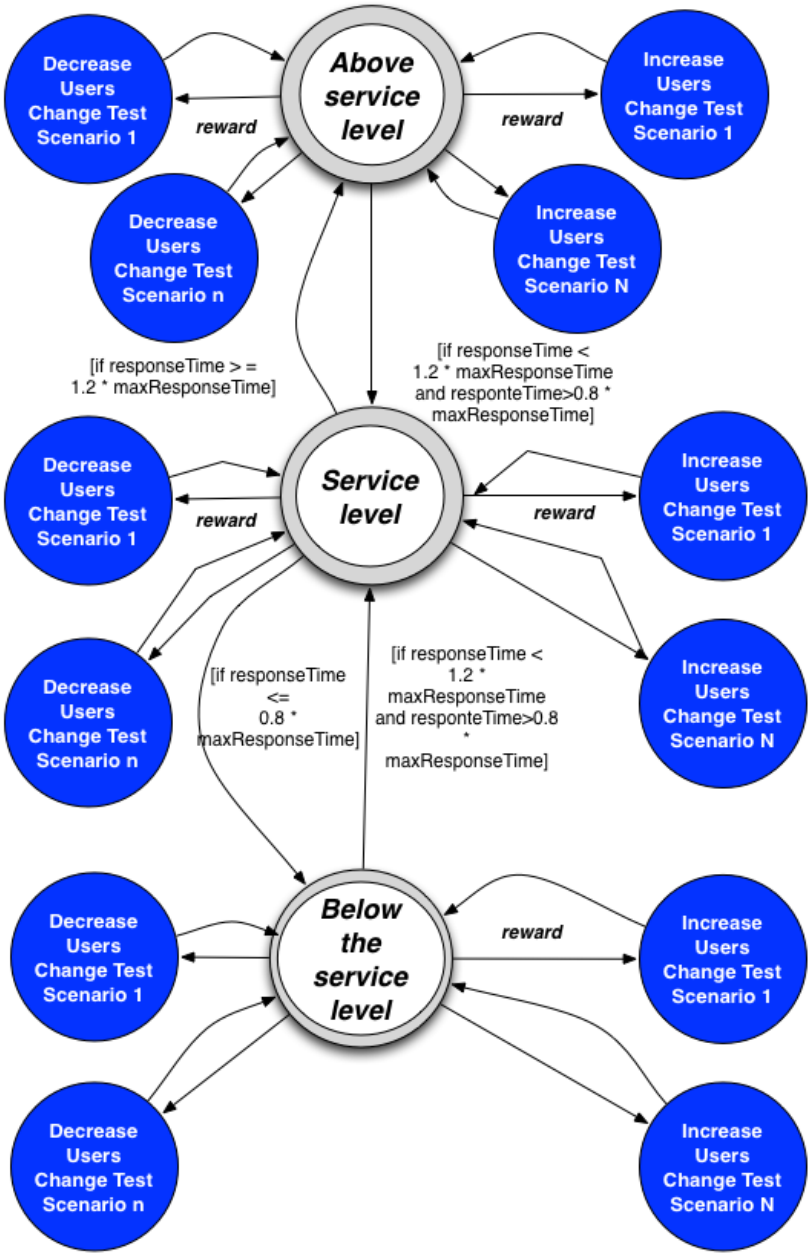

Figure 6-6: IAdapter architecture

6.3.1 IAdapter Life Cycle

Fig. 6-9 presents the IAdapter Life Cycle. The main difference between IAdapter and JMeter tool is that the IAdapter provide an automated test execution where the new test scenarios are choosen by the test tool. In a test with JMeter, the tests scenarios are usually chosen by a test designer.

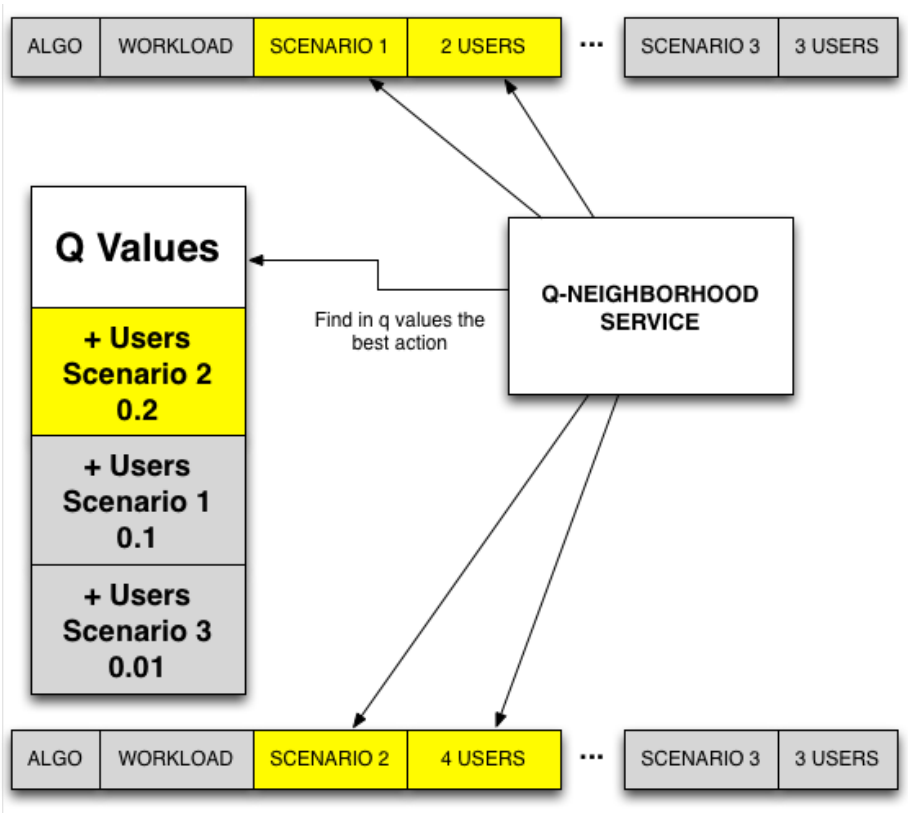

Figure 6-7: IAdapter architecture

6.3.2 IAdapter Components

WorkLoadThreadGroup is a component that creates an initial population and configures the algorithms used in IAdapter. Fig. 6-10 presents the main screen of the WorkLoadThreadGroup component. The component has a name ❶, a set of configuration tabs ❷, a list of individuals by generation ❸, a button to generate an initial population ❹, and a button to export the results ❺.

WorkLoadThreadGroup component uses the GeneticAlgorithm, TabuSearch and SimulateAnnealing classes. The WorkLoadSaver component is responsible for saving all data in the database. The operation of the component only requires its inclusion in the test script.

WorkLoadController represents a scenario of the test. All actions necessary to test an application should be included in this component. All instances of the component need to login into the application under test and bring the application back to its original state.

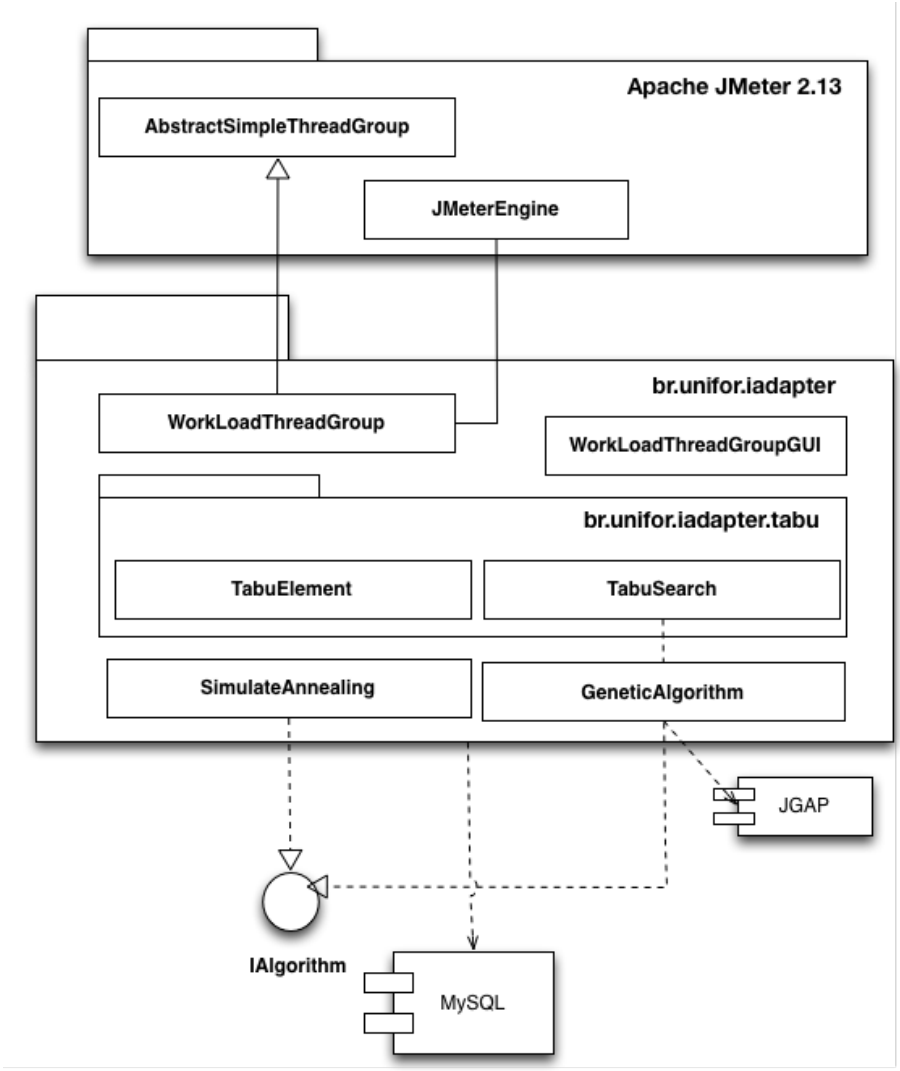

Figure 6-8: IAdapter architecture

6.3.3 IAdapter Testbed Tool

A Testbed makes possible follow a formalized methodology and reproduce tests for further analysis and comparison. It seems natural that one of the most important parts of a comparison among heuristics is the testbed on which the heuristics are tested. As a result, the testbed should be the first consideration when comparing two metaheuristics [33].

In this section, We devise a new testbed that has the ability to reproduce different types of web workloads. The proposed solution extends the IAdapter plugin to create a testbed tool to validade load, performance and stress search based tests approaches [35]. The

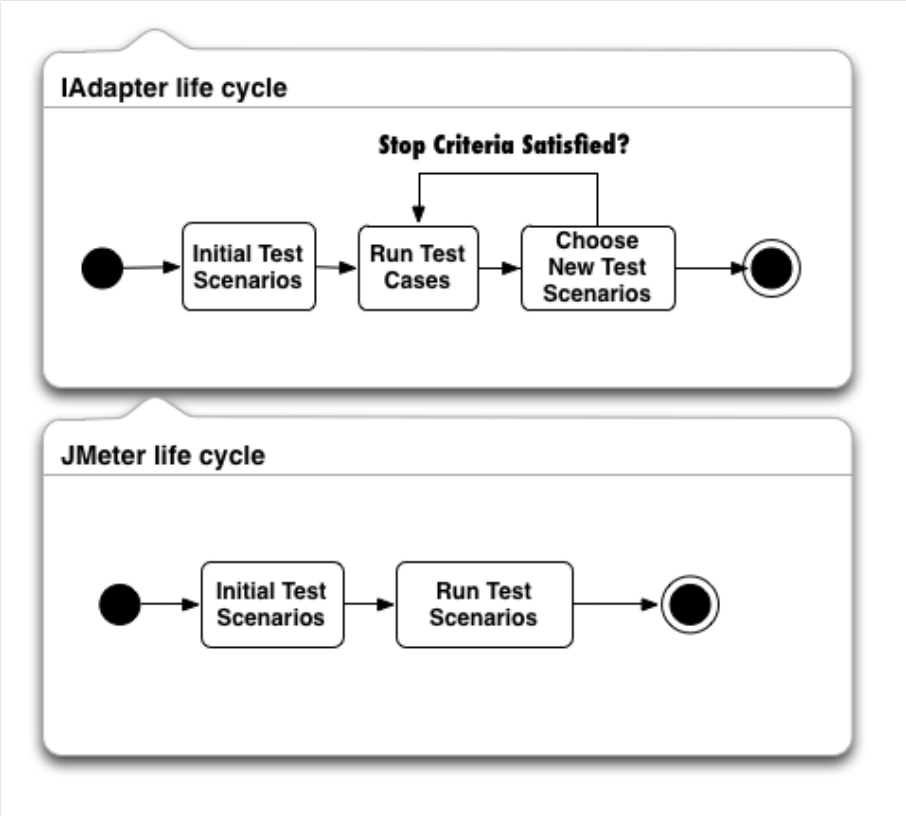

Figure 6-9: IAdapter life cycle

IAdapter is a JMeter plugin designed to perform search-based stress tests.

This new testbed must accomplish three main goals. First, it must reproduce a workload by using an antipattern implementation. Second, it must be able to provide client and server metrics with the aim of being used for web performance evaluation studies. Finally, it is should be extensible, allowing create new test scenarios.

IAdapter Testbed is an open-source facility that provides software tools for search based test research. The testbed tool emulates test scenarios in a controled environment using mock objects and implementing performance antipatterns.

The testbed tool proposed consists of four main elements. The first element is a emulator module that it is responsible to simulate the antipatterns in a specific context. The second it's a module named test module that it is responsible for use a previous selected metaheuristics and perform a search based test. The third module contains the test scenarios representation. The fourth module it is responsible for provide a service of explore the

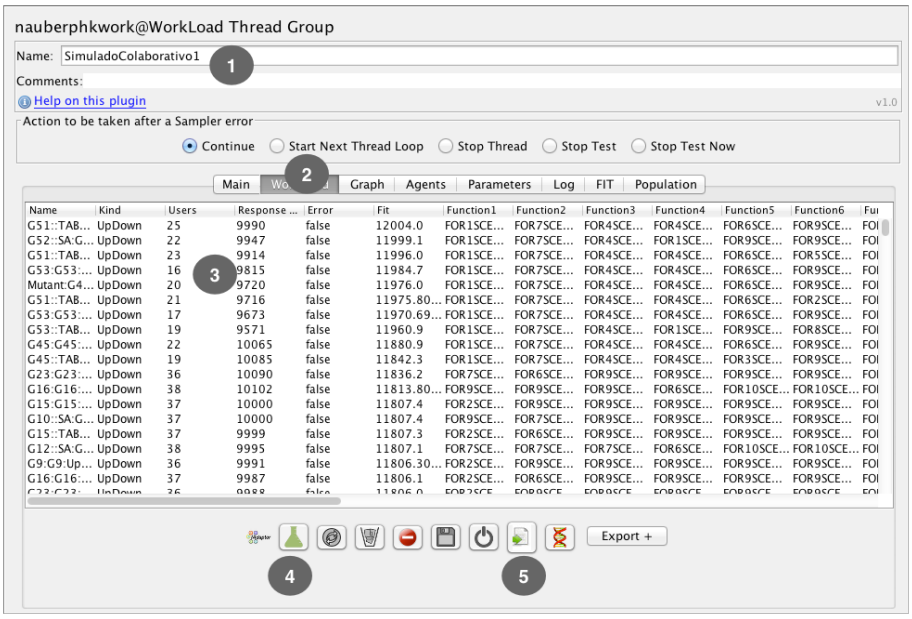

Figure 6-10: WorkLoadThreadGroup component

neighborhood of a given individual.

Testbed Architecture

The Fig. 6-11 presents the main architecture of the Testbed solution proposed. The emulator module provides workloads to the Test module.The Test module uses a class loader to find all classes that extends AbstractAlgorithm in the classpath and run all tests for each metaheuristic found. The Test Scenario Representation and Persistent Module provides the scenario representation used by the metaheuristics and persist the testbed results data in a database. Neighborhood provider service is responsible to search neighbors of some individual provided as parameter to the service.

Test Module

The Test Module is responsible for load all classes that extends AbstractAlgorithm in the classpath and perform the tests under the application. The Emulator Module provides successful scenarios and antipatterns implementations. The heuristics are executed in order to select the scenarios with failures or high response times. The Fig. 6-13 presents the first feature of Test Module where a initial population it is created and IAdapter with JMe-

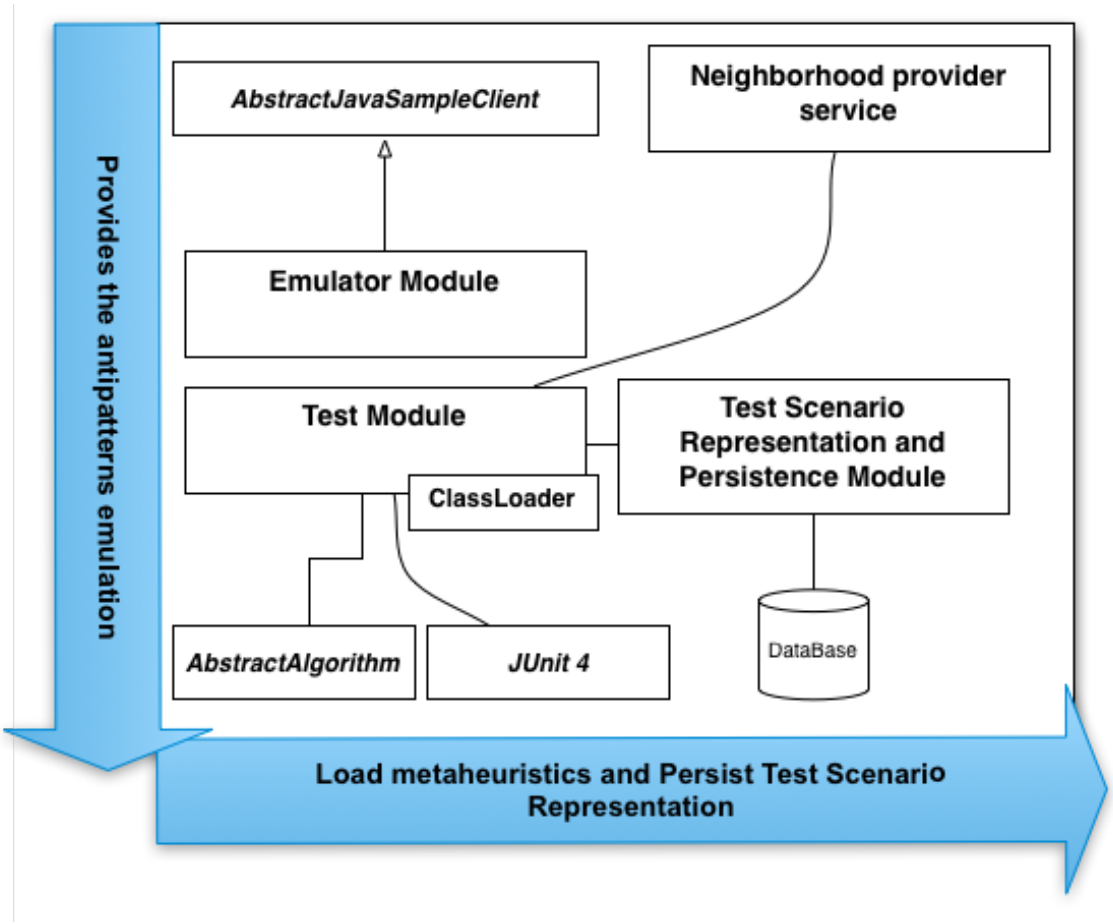

Figure 6-11: testbed main architecture.

terEngine performs all tests and apply a fitness value to each workload.

The Fig. 6-14 presents the Test Module life cycle. The life cycle iterate over two steps: The first step apply a metaheurist to select or generate a new set of workloads based on selection criteria. The second step run each workload with the JMeterEngine and obtain a fitness value based on some objective function. The red circles represent the workload that contain errors. The green circles represents the workloads with no errors and low acceptable response time. The testbed tool uses as default objective function the equation:

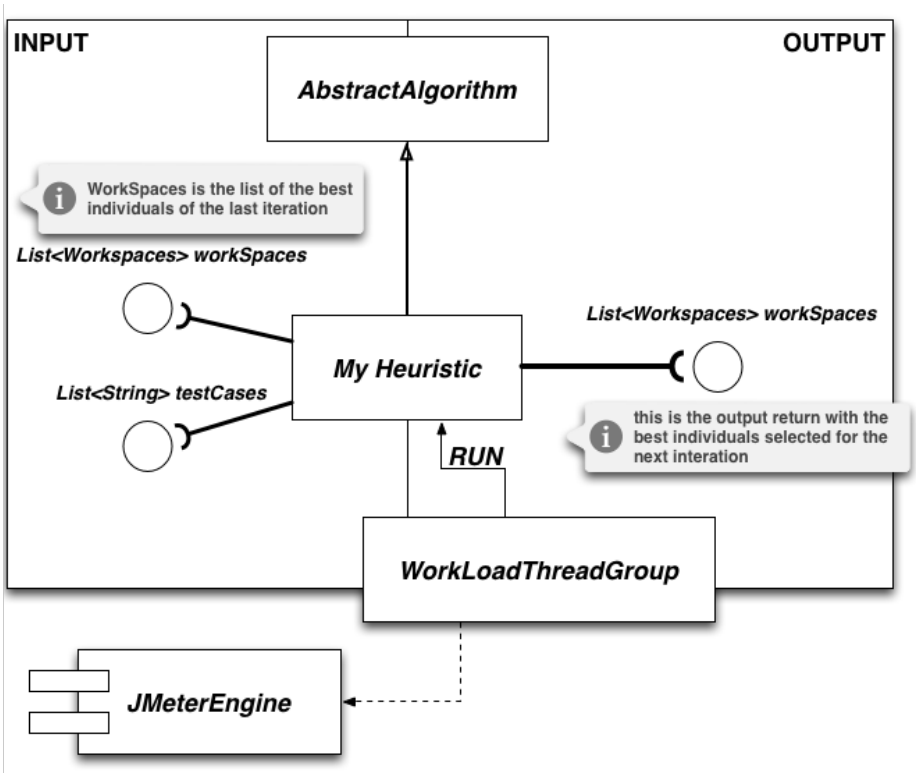

Figure 6-12: Heuristic class diagram.

$$\begin{aligned} fitness = {} & 90percentileweigth * 90percentiletime \\ & +80percentileweigth * 80percentiletime \\ & +70percentileweigth * 70percentiletime+ \\ & maxResponseWeigth * maxResponseTime+ \\ & numberOfUsersWeigth * numberOfUsers - penalty \end{aligned} \tag{6.3}$$

The use of presented fitness value by each metaheuristic it's optional. Each Metaheuristic could define your own objective function. The proposed fitness function uses a series of manually adjustable user-defined weights (90percentileweight, 80percentileweight, 70percentileweight, maxResponseWeight, and numberOfUsersWeight). These weights make it possible to customize the search plugin's functionality. A penalty is applied when an application under test takes a longer time to respond than the level of service. After all these steps the cycle begins until the maximum number of generations it is reached. The Fig. 6-12 shows the class diagram for custom and provided heuristics. All heuristic classes ex-

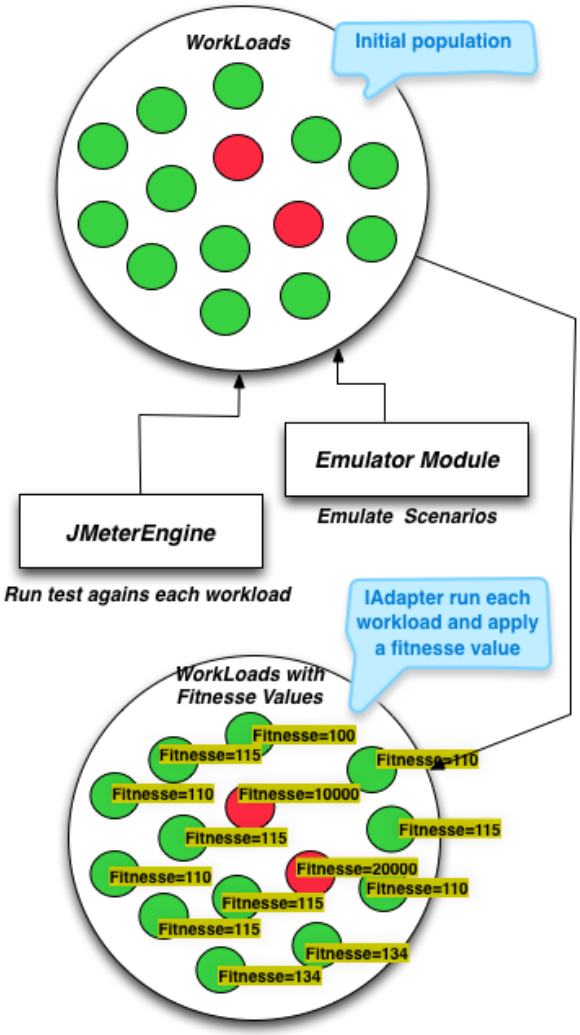

Figure 6-13: Test Module first feature.

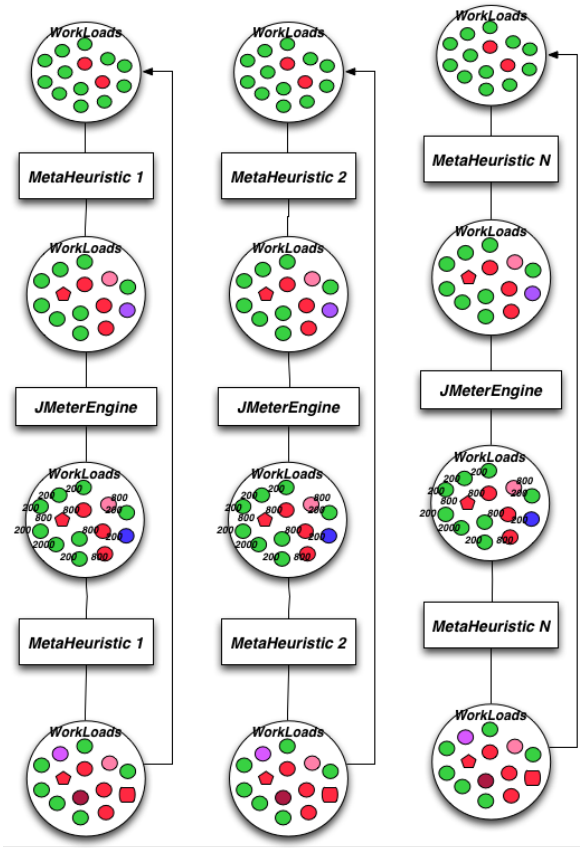

Figure 6-14: Test Module life cycle.

tends the class AbstractAlgorithm. The heuristics receives as input a list of workspaces and a list of testcases. The workspace represents each individual in the search space.

Each metaheuristic class returns a list of workspaces (the individuals selected to the next generation). The Listing presents the method that performs the search of classes that extends Abstract Algorithm

Emulator Module

The Emulator Module is responsible for implement and provide successful scenarios and the most commons performance antipatterns. All classes must extends the AbstractJavaSamplerClient class or use JUnit 4. The AbstractJavaSamplerClient class allows create a JMeter

Java Request. Using JUnit 4, the emulators classes could be called by a JMeter JUnit request. The Fig. 6-15 presents the main features of the emulator module. The module implements 8 test scenarios in its first version.

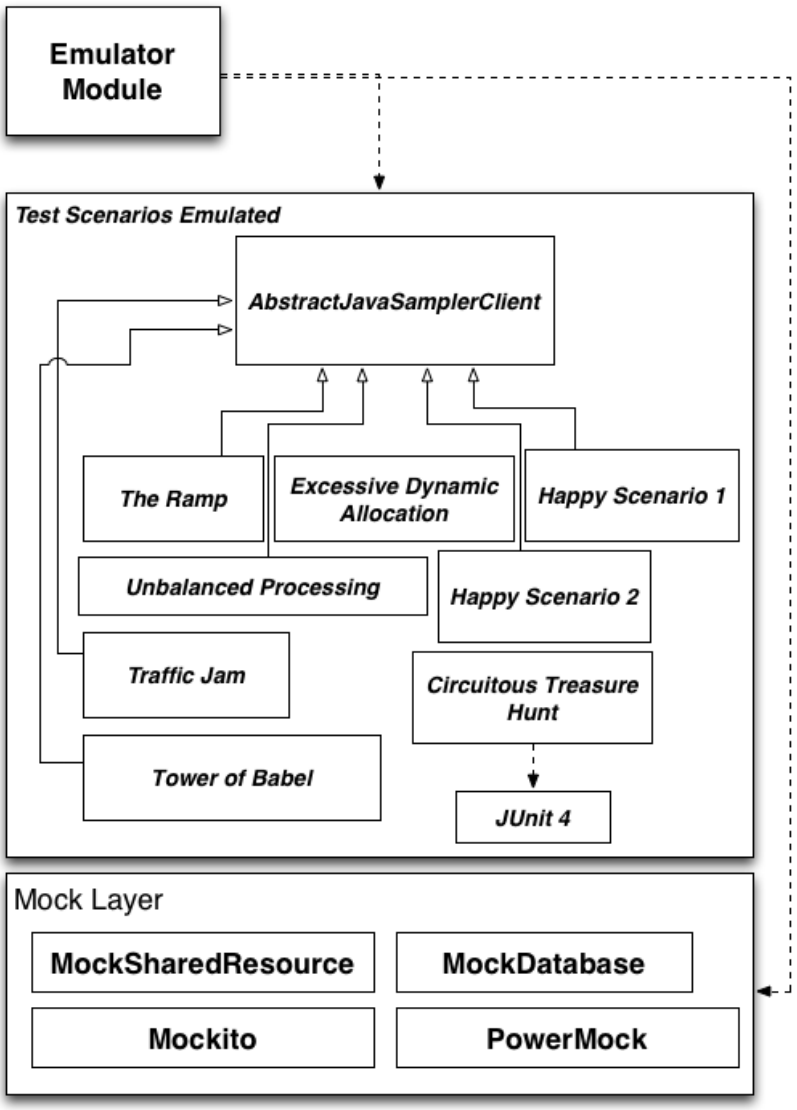

Figure 6-15: Heuristic class diagram.

The Mock Layer provides emulated databases and components to the test scenarios. Each scenario provided by the Emulator Module could be called in JMeter using a Java Request. The algorithm 4 emulates the Unbalanced Processing antipattern. The test scenario C still waiting until A and B scenarios are used by a test.

Algorithm 4 Unbalanced Processing emulate algorithm

```
1: while List of processing scenarios contains A and B do
2:     Processing A and B scenarios
3: end while
4: Processing scenario C
```

The algorithm 5 emulates the Ramp antipattern. The algorithm increase the response time at each time that it has been used.

Algorithm 5 The Ramp emulate algorithm

```
1: if count is null then
2:     count ← 0
3: end if
4: sleep(100* count)
5: count ← count + 1
```

The algorithm 6 implements the Excessive Dynamic Allocation antipattern. The algorithm creates a connection with a emulated database, uses the connection and finally the connection.

Algorithm 6 Excessive Dynamic Allocation emulate algorithm

```
1: for each request do
2:     for int i=0 to 1000 do
3:         Create a connection to a database
4:         Use the connection
5:         Destroy the created connection
6:     end for
7: end for
```

The algorithm 7 presents the Happy Scenario 1. The response time increases for every 10 users.

Algorithm 7 Happy Scenario 1 emulate algorithm

```
1: sleep(2*users)
```

Algorithm 8 Happy Scenario 2 emulate algorithm

```
1: sleep(3*users)
```

A further 4 algorithms were developed for the scenarios Circuitous Treasure Hunt, Happy Scenario 2, Traffic Jam and Tower of Babel.

Chapter 7

Experiments

In this chapter, We present the results of experiments which we carried out to verify the hybrid and q-learning algorithm approaches ,the antipatterns implementation, the fitness objective function and the metaheuristics used by the testbed tool.

7.1 Emulated Class Test Experiment

The first experiment aimed to perform performance, load, and stress testing on a simulated component. The purpose of using a simulated component was to be able to perform a greater number of generations in a shorter time available and eliminate variables such as the use of databases and application servers. The first experiment used a test class named SimulateConcurrentAccess. This class has a static variable named x and a set of methods that use the variable in a synchronized context (Listing 7.1). The experiment was executed using the JMeter Java Request Sampler Component with IAdapter.

The experiment used the following fitness function:

Listing 7.1 SimulateConcurrentAccess class

```
1:  public class SimulateConcurrentAccess {
2:    @Test
3:    public void firstScenario() {
4:      synchronized (StaticClass.class) {
5:        for (int i = 0; i <= 1000; i++) {
6:          StaticClass.x += i;
7:        }
8:        StaticClass.x = 0;
9:      }
10:   }
11:
12:     @Test
13:   public void secondScenario() {
14:     synchronized (StaticClass.class) {
15:       for (int i = 0; i <= 2000; i++) {
16:         StaticClass.x += i;
17:       }
18:       StaticClass.x = 0;
19:     }
20:   }
```

$$\begin{aligned} fitness = 0.9 * 90percentiletime \\ +0.1 * 80percentiletime \\ +0.1 * 70percentiletime+ \\ 0.1 * maxResponseTime+ \\ 0.2 * numberOfUsers - penalty \end{aligned} \tag{7.1}$$

This fitness function is the same function represented in the section VII with the manually adjustable user-defined weights filled out. This fitness function intended to find individuals with the highest percentile of 90%, followed by individuals with a higher percentile time of 80% and 70%, maximum response time, and number of users.

The first experiment ran for 27 generations, and the second experiment performed 6 generations, with 300 executions by generation (100 times for each algorithm), generating 300 new individuals. The experiments used an initial population of 100 individuals. The genetic algorithm used the top 10 individuals from each generation in the crossover operation. The Tabu list was configured with the size of 10 individuals and expired every 2 generations. The mutation operation was applied to 10% of the population on each generation.

Fig.7-1 presents the best results in 27 generations applied in the first experiment. The

figure shows the results obtained with the algorithms with and without collaboration. The x axis represents the generation number, and the y axis represents the best fitness value obtained until the current generation. A higher value in the figure means that the scenario has a greater response time by the application under test. The results of the experiment showed that the use of cooperation between the three algorithms resulted in finding the individuals with better fitness values.

Figure 7-1: Best results obtained in 27 generations

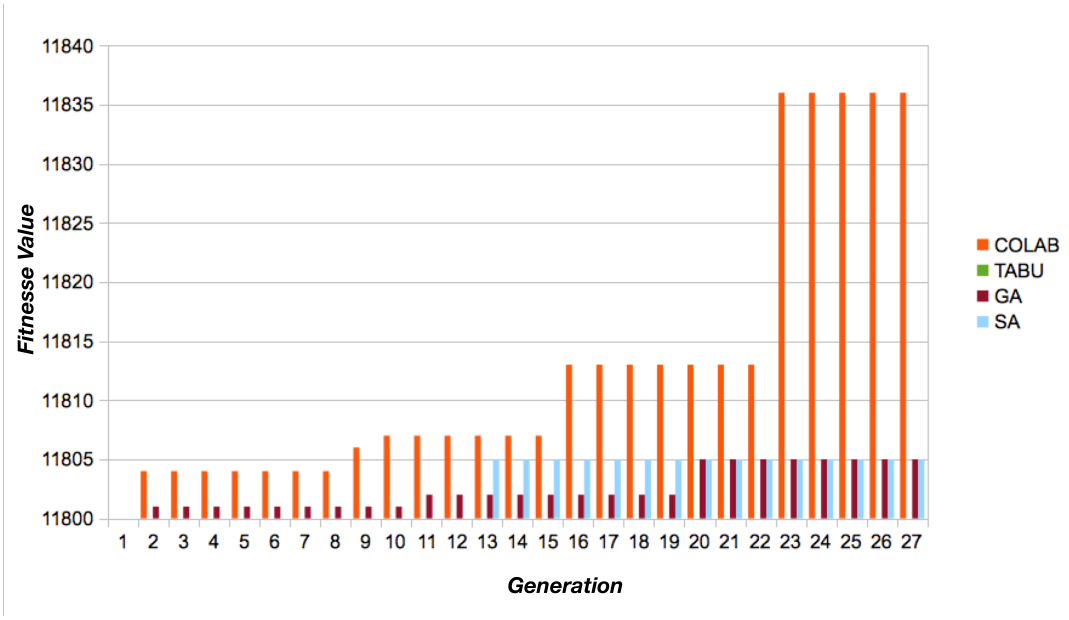

Table 7.1 presents the results obtained by the hybrid metaheuristic (HM) approach, genetic algorithm (GA), simulated annealing (SA), and Tabu search (TS) from 27 generations in the first experiment. The values are the maximum fitness value obtained by each algorithm.

The signed-rank Wilcoxon non-parametrical procedure was used for comparing the results with Z-value and W-value. The significant level adopted was 0.05. The Z-value obtained was -2.2736 and the p-value was 0.0232. The W-value obtained was 78. The critical value of W for N = 25 at $p \leq 0.05$ was 89.The result was significant at $p \leq 0.05$. The procedure showed that there was a significant improvement in the results with the collaborative approach.

Table 7.1: Maximum value of the fitness function by algorithm

GEN	HM	TS	GA	SA
1	11238	11238	11238	11238
2	11804	11596	11801	10677
3	11787	8932	8411	10869
4	11723	9753	9611	10760
5	8164	9780	10738	4794
6	11802	9781	11086	6120
7	9985	5782	11272	11798
8	11803	11749	10084	11309
9	11806	7284	11633	10766
10	11807	9386	11717	4557
11	11802	9653	11802	11151
12	11807	10594	11793	9434
13	11802	10848	10382	11805
14	11801	11551	7219	10237
15	11807	1701	7189	9338
16	11813	6203	11758	5321
17	11805	10720	10805	11748
18	9600	6371	11698	7818
19	11733	8160	11648	11509
20	9589	9428	11805	4813
21	11800	9463	11798	10801
22	11805	11799	11804	6029
23	11836	11655	11800	3579
24	11805	11512	11803	5761
25	11804	11573	11802	9680
26	11800	11575	11403	9388
27	11805	10691	11745	9465

7.2 Testbed Tool Experiments

We conducted two experiments in order to verify the effectiveness of the testbed tool. The experiments ran for 17 generations. The experiments used an initial population of 4 individuals by metaheuristic. The genetic algorithm used the top 10 individuals from each generation in the crossover operation. The Tabu list was configured with the size of 10 individuals and expired every 2 generations. The mutation operation was applied to 10% of the population on each generation. The experiments uses tabu search, genetic algorithms and the hybrid metaheuristic approach proposed by Gois et al. [35].

The objective function applied is intended to maximize the number of users and minimize the response time of the scenarios being tested. In this experiments, better fitness values meaning to find scenarios with more users and a low values of response time. A penalty is applied when the response time is greater than the maximum response time expected. The experiments used the following fitness (goal) function. :

$$\begin{aligned} fitness = 3000 * numberOfUsers \\ -20 * 90percentiletime \\ -20 * 80percentiletime \\ -20 * 70percentiletime \\ -20 * maxResponseTime \\ -penalty \end{aligned} \tag{7.2}$$

The experiments addresses:

- Validate the operation of the testbed tool.
- Find the maximum number of users and the minimal response time.
- Analyze and verify the best heuristics among those chosen to the experiments.

7.2.1 The Ramp and Circuitous Treasure Hunt experiment

The experiment was carried out for 8 continuous hours. All tests in the experiment were conducted without the need of a tester, automating the process of executing and designing performance test scenarios.In this experiment, Scenarios were generated with the Ramp and Circuitous Treasure antipattern as well as scenarios with Happy Scenario 1, Happy Scenario 2 and mixed scenarios. The Fig. 7-2 presents the fitness value obtained by each metaheuristic. HybridQ metaheuristic obtained the better fitness values.

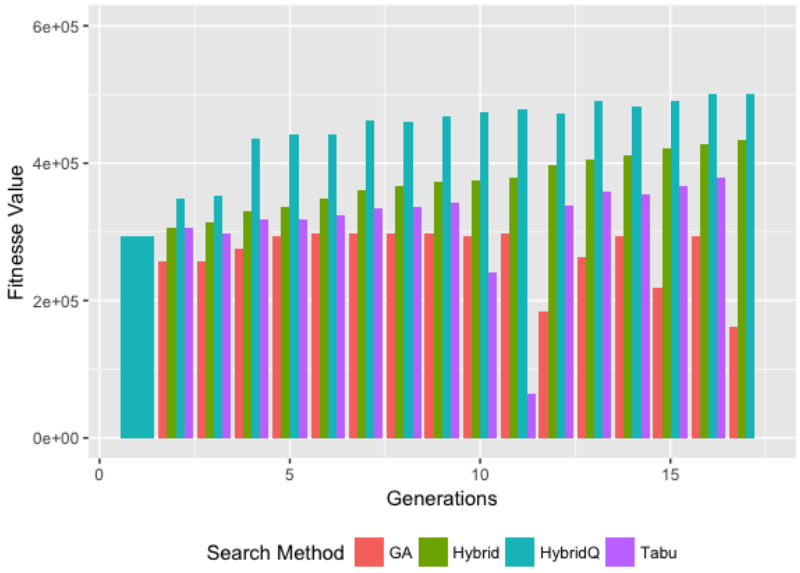

Figure 7-2: fitness value obtained by Search Method

Despite having obtained the best fitness value in each generation, the Hybrid algorithm performs twice as many requests as the tabu search (Fig. 7-3). The HybridQ algorithm obtained the best fitness value The Fig. 7-4 shows the average, minimal e maximum value by search method.

Figure 7-3: Number of requests by Search Method

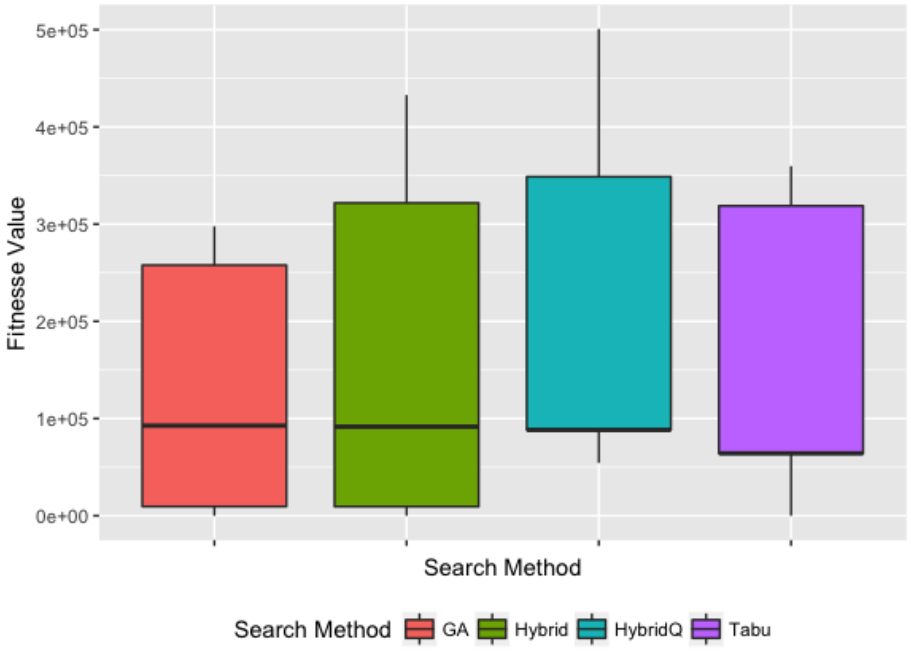

Figure 7-4: Average, median, maximum and minimal fitness value by Search Method

The Fig. 7-5 presents the maximum, average, median and minimum fitness value by generation. The maximun fitness value increases at each generation. The Fig. 7-6 presents the density graph of number of users by fitness value. The range between 100 and 150 users has the highest number of individuals found with higher fitness value.

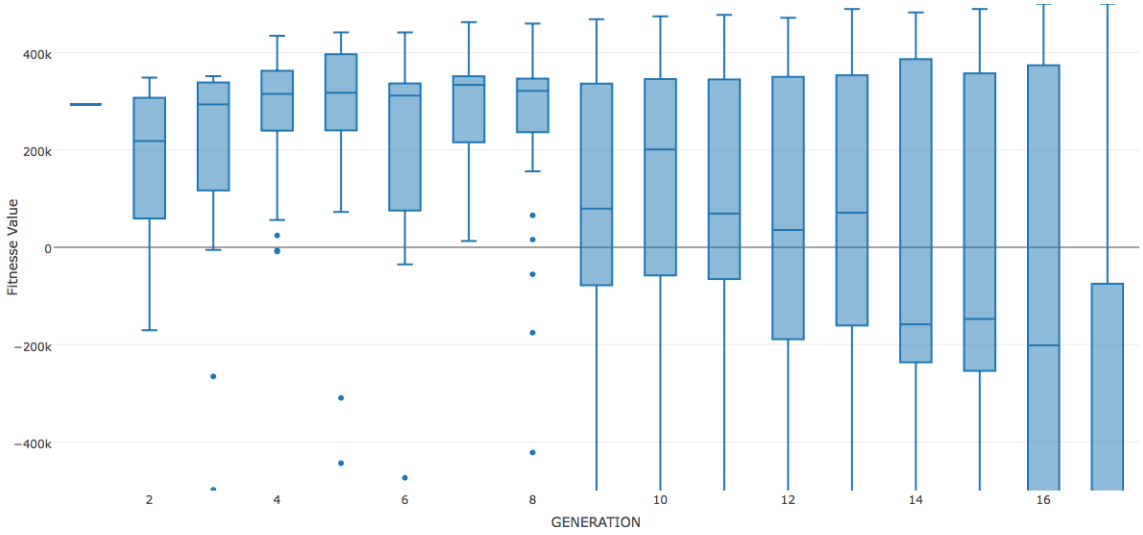

Figure 7-5: fitness value by generation

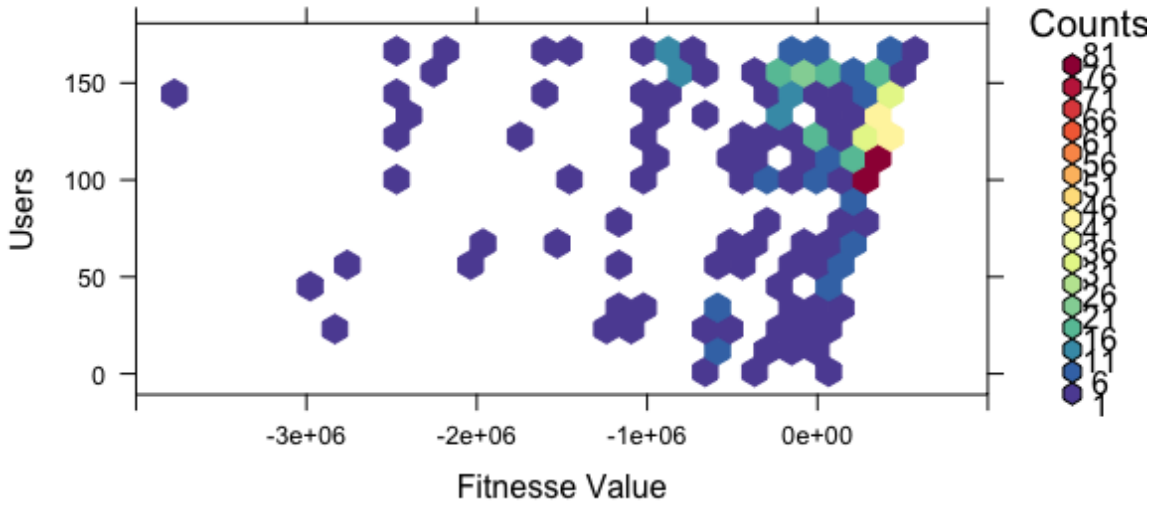

Figure 7-6: Density graph of number of users by fitness value

Table 7.2 shows 4 individuals with 164 to 169 users. These are the scenarios with the maximum number of users found with the best response time. The first individual has 153 users on Happy Scenario 2, 16 users on Happy Scenario 1 and a response time of 13 seconds. None of the best individuals has one of the antipatterns used in the experiment.

Table 7.2: Best individuals found in the first experiment

Search Method	Generation	Users	fitness Value	Happy 2	Happy 1	Resp. Time
HybridQ	17	169	500740	153	16	13
HybridQ	16	169	500700	153	16	15
HybridQ	13	164	489740	149	15	13
HybridQ	15	164	489740	149	15	13

Fig. 7-7 presents the response time by number of users of individuals with Happy Scenario 1 and Happy Scenario 2. The Figure illustrates that the individuals with best fitness value has more users and minor response time. The Fig. 7-8 presents the response time by number of users of individuals with the Ramp and Circuitous Treasure antipatterns

scenarios. The Figure illustrates the smallest number of individuals with the antipatterns when compared to individuals who use the happy scenarios.

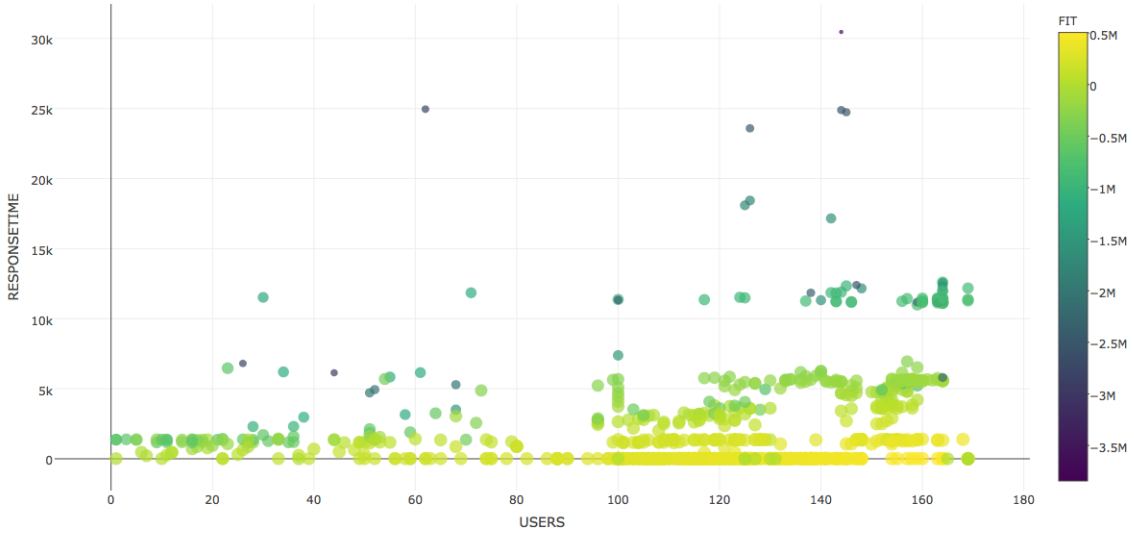

Figure 7-7: Response time by number of users of individuals with Happy Scenario 1 and Happy Scenario 2

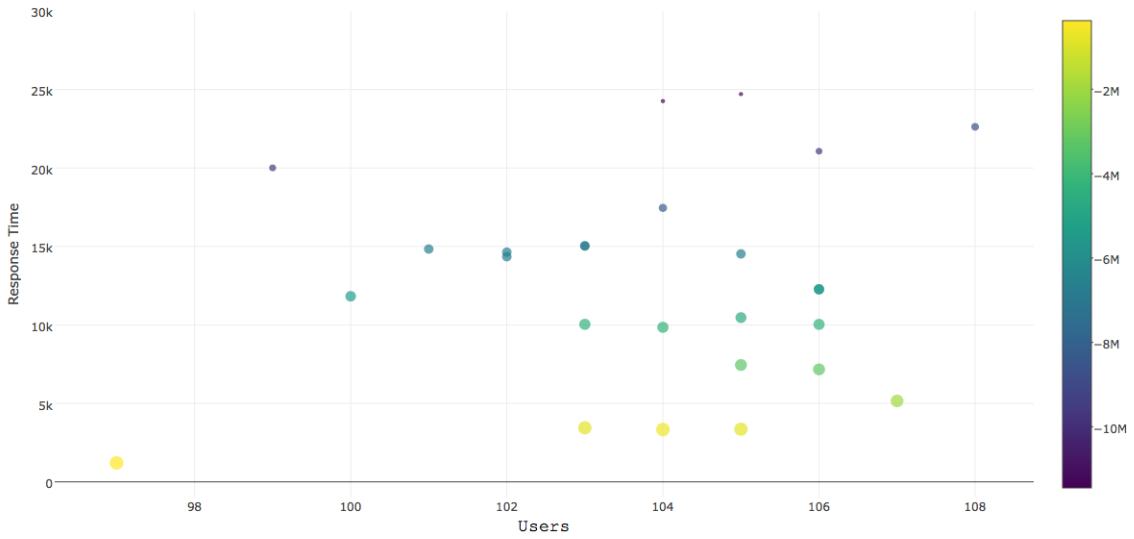

Figure 7-8: Response time by number of users of individuals with the Ramp and Circuitous Treasure antipatterns

Fig. 7-9 presents the markov decision process for the experiment. When the response time it is bellow or equal the service level, the action with major reward it is increase the number of users and include more positions with the Happy Scenario 2 (Happy 2).

When the response time is above the service level, the action with major reward value it is decrease the number of users and include more positions with the Happy Scenario 2. The actions with minor value of reward contais the both antipatterns Circuitous Treasure (CTH) and The Ramp antipatterns (Ramp).

In the first experiment, We conclude that the metaheuristics converged to scenarios with an happy path, excluding the scenarios with antipatterns. The hybridQ and hybrid metaheuristic returned individuals with higher fitness scores. However, the Hybrid metaheuristic made twice as many requests than Tabu Search to overcome it.

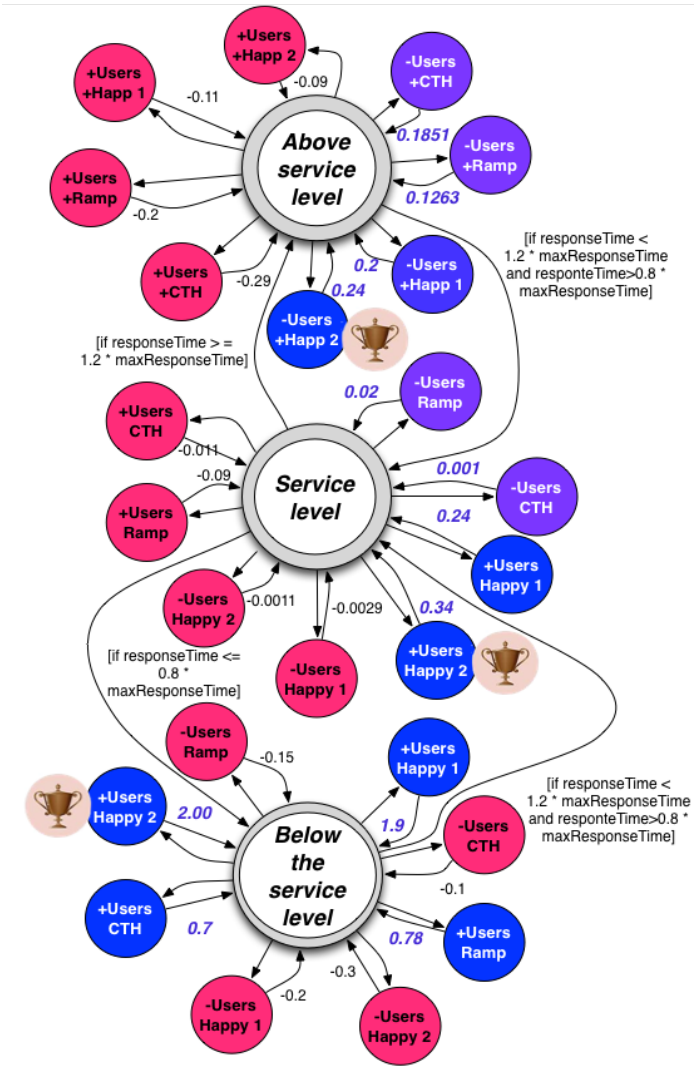

Figure 7-9: Markov decision process of experiment with Circuitous Treasure and The Ramp antipatterns

7.2.2 The Tower Babel and Unbalanced Processing experiment

The experiment was carried out for 6 continuous hours. All tests in the experiment were conducted without the need of a tester. In this experiment, Scenarios were generated with Tower Babel and Unbalanced Processing antipattern as well as scenarios with Happy Scenario 1, Happy Scenario 2 and mixed scenarios. The Fig. 7-10 presents the fitness value obtained by each metaheuristic. The SA algorithm obtained the worst fitness values. Hybrid metaheuristic obtained the better fitness values.

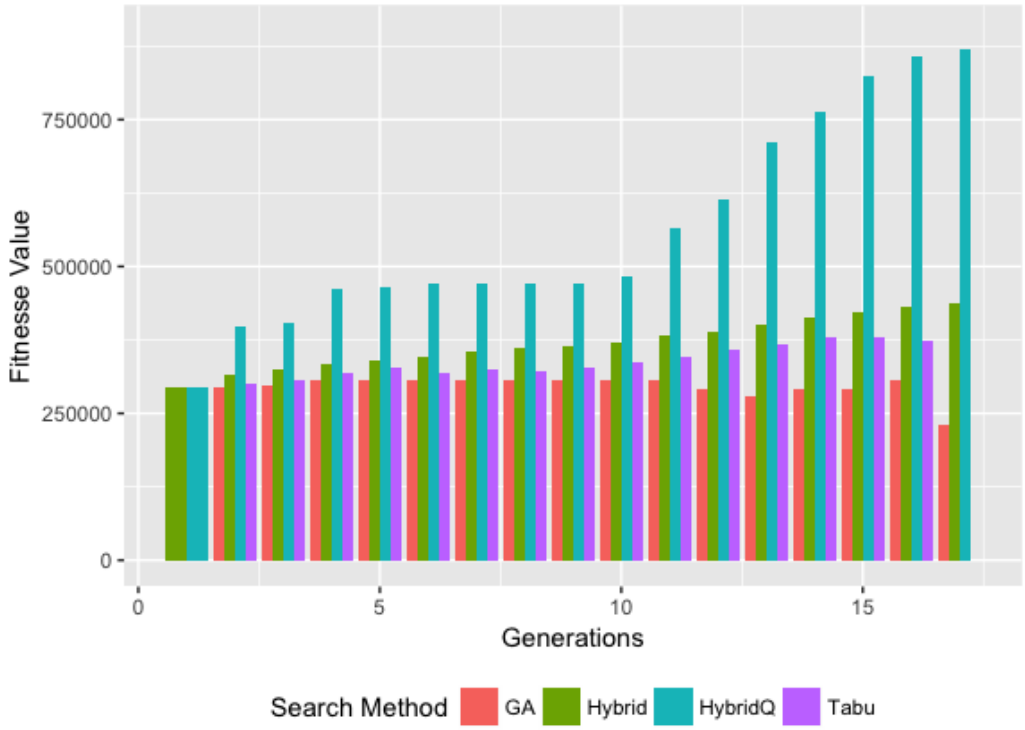

Figure 7-10: Fitness value obtained by Search Method

As in the first experiment, the Hybrid algorithm performs twice as many requests as the second one, the tabu search (Fig. 7-11). The Fig. 7-12 shows the average, minimal e maximum value by search method. The Fig. 7-13 presents the maximum, average, median and minimum fitness value by generation. The maximun fitness value increases at each generation. The Fig. 7-14 presents the density graph of number of users by fitness value. The range between 100 and 150 users has the highest number of individuals found with higher fitness value.

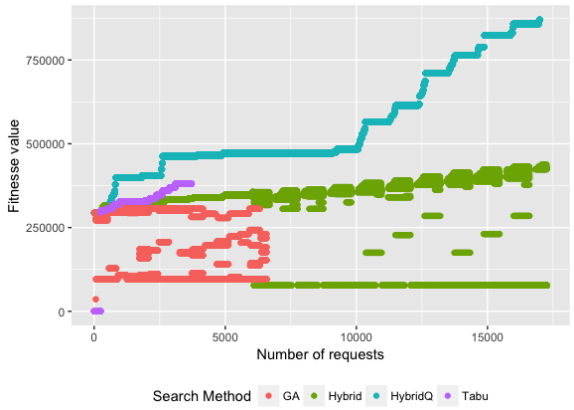

Figure 7-11: Number of requests by Search Method

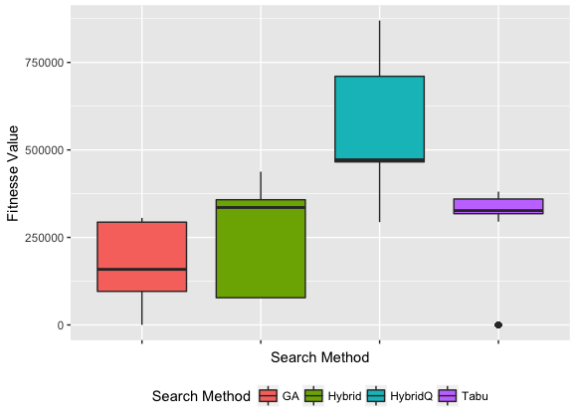

Figure 7-12: Fitness value by generation in all tests

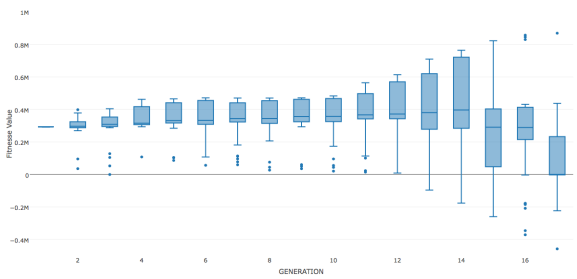

Figure 7-13: Response time by generation in all tests scenarios

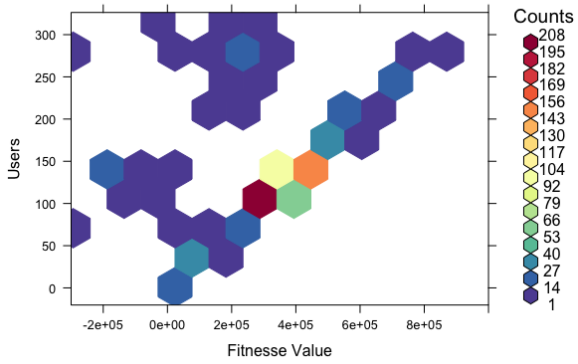

Figure 7-14: Finesse value by generation in all tests

Table 7.3 shows 4 individuals with 279 to 292 users. The first individual has 121 users on Happy Scenario 2, 171 users on Happy Scenario 1 and a response time of 11 seconds. None of the best individuals found implements the Unbalanced Processing or Tower Babel antipattern.

Fig. 7-15 presents the response time by number of users of individuals with Happy Scenario 1 and Happy Scenario 2. The Figure illustrates that the individuals with best fitness value has more users and minor response time. The Fig. 7-16 presents the response time by number of users of individuals with with Unbalanced Processing and Tower Babel antipatterns scenarios. The Figure illustrates the smallest number of individuals with the Unbalanced Processing and Tower Babel antipattern when compared to individuals who

use the happy scenarios and the Tower Babel antipattern.

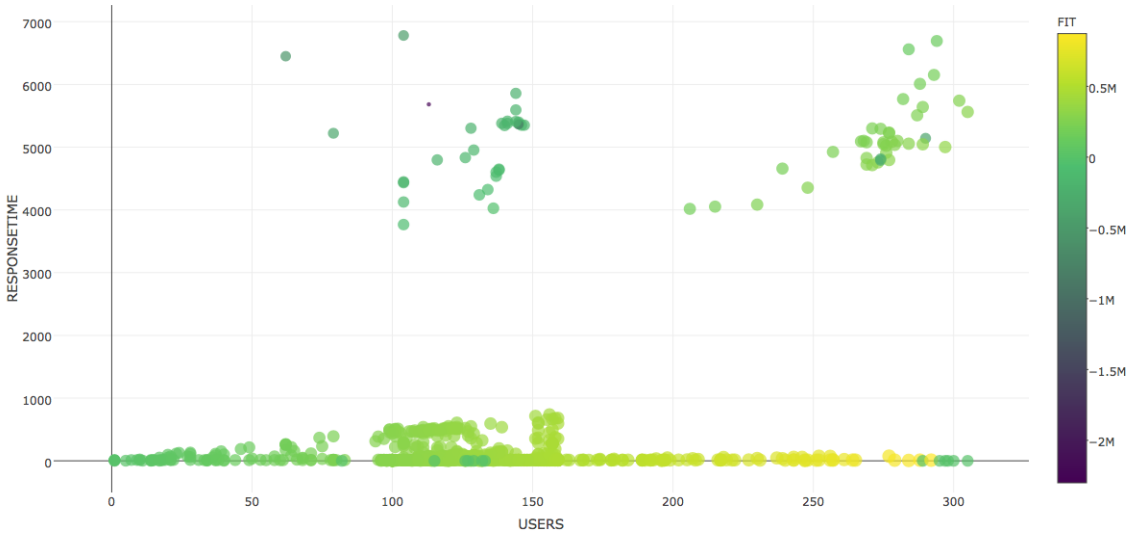

Figure 7-15: Response time by number of users of individuals with Happy Scenario 1, Happy Scenario 2 and Tower Babel antipattern

We conclude that the metaheuristics converged to scenarios with an happy path, excluding the scenarios with Unbalanced Processing and Tower Babel antipattern. The hybrid metaheuristic with Q-Learning (HybridQ) returned individuals with higher fitness scores. The Hybrid metaheuristic (Hybrid) made twice as many requests than Tabu Search to overcome it. The SA algorithm obtained the worst fitness values. The algorithm initially used a scenario with an antipattern and found neighbors that still using an antipattern over the 17 generations of the experiment. The individual with best fitness value has 121 users on Happy Scenario 2, 171 users on Happy Scenario 1 and a response time of 11 seconds.

Table 7.3: Best individuals found in the second experiment

Search Method	Generation	Users	fitness Value	Happy 2	Happy 1	Time
HybridQ	17	292	869780	121	171	11
HybridQ	16	288	857780	103	185	11
HybridQ	16	284	845880	167	117	10
HybridQ	16	279	830780	144	135	11

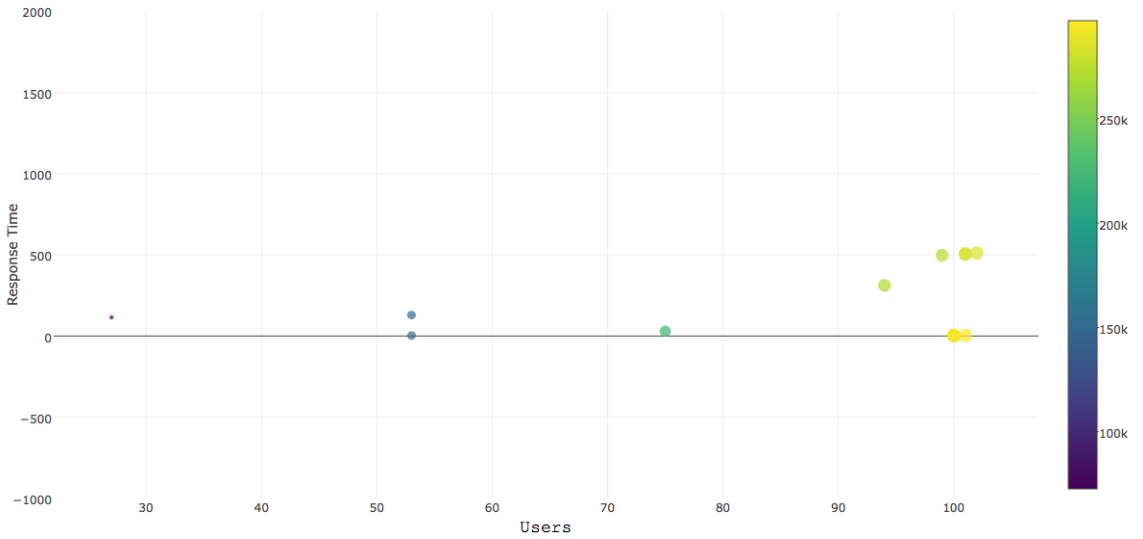

Figure 7-16: Response time by number of users of individuals with Unbalanced Processing antipattern

7.3 Moodle Application Experiment

This experiment used a Moodle application installed in a machine with 500 GB of hard disk space and 8 GB of memory. The study used six application scenarios:

- PostDeleteMessage: This scenario posts and deletes messages in the Moodle application.
- MyHome: This scenario accesses the homepage of the user's application.
- Login: This scenario is responsible for user authentication by the application.
- Notifications: This scenario involves entering the notification page of each user.
- Start Page: This scenario shows the initial start page of the application.
- Badge: This scenario involves entering the badge page.

The experiment used the following fitness function:

$$
\begin{aligned}
fitness = 0.9 * 90percentiletime \\
+0.1 * 80percentiletime \\
+0.1 * 70percentiletime+ \\
0.1 * maxResponseTime+ \\
0.2 * numberOfUsers - penalty
\end{aligned}
\tag{7.3}
$$

The maximum tolerated response time in the test was 30 seconds. Any individuals who obtained a time longer than the stipulated maximum time suffered penalties. The whole process of stress and performance tests, which took 3 days and about 1800 executions, was carried out without the need for monitoring by a test designer. The tool automatically selected the next scenarios to be run up to the limit of six generations previously established.

Table 7.4 presents the maximum fitness value obtained by the hybrid metaheuristic (HM) approach, genetic algorithm (GA), simulated annealing (SA), and Tabu search (TS) in each generation.

Table 7.4: Results obtained from the second experiment

GEN	HM	TS	GA	SA
1	32242	32242	32242	32242
2	34599	32443	26290	35635
3	35800	34896	34584	34248
4	35782	34912	32689	25753
5	35611	31833	34631	8366
6	35362	35041	33397	9706

The small number of samples of the experiment is insufficient to give a statistical significance to the results of the Wilcoxon procedure. However, it is noted that, in four of six generations, the collaborative approach presented the best values. The experiment succeeded in finding 29 individuals whose maximum time expected by the application was obtained. Table 7.5 shows an example of the six individuals with the highest fitness values in the second experiment. The table shows the fitness value (Fit); the name of the scenario (Scenario); the number of users (Users); and the percentiles of 90%, 80%, and 70% (90per, 80per and 70per) in seconds.

Table 7.6 presents the percentage of genes in all test scenarios by generation with and

Table 7.5: Example of individuals obtained in the second experiment

Id	Fit	Scenario	Users	90per	80per	70per
1	35800	MyHome	31	30	29	10
		Badges	4			
2	35795	MyHome	30	30	29	10
		Notifications	2			
		Badges	2			
3	35782	MyHome	32	30	29	10
		Badges	3			
4	35773	MyHome	22	30	29	10
		Notifications	6			
		Badges	9			
5	35771	MyHome	28	30	29	9
		Badges	6			
6	35683	MyHome	27	30	29	8
		Badges	10			

without collaboration. Most of the genes converged to the MyHome feature, which had the highest application response time.

Table 7.6: Percentage of genes in each scenario by generation

Gen/ Scenarios	**Non collaboration approach**						
	Initial	1	2	3	4	5	6
Badges	20	18	16	24	15	16	17
MyHome	**15**	**59**	**55**	**48**	**53**	**50**	**52**
StartPage	15	10	12	11	20	18	19
Notifications	25	5	11	10	9	10	9
Post	8	3	1	3	1	2	1
Login	17	5	5	4	2	4	2
	Collaboration approach						
Badges	20	29	16	25	9	16	9
MyHome	**15**	**29**	**69**	**49**	**74**	**66**	**76**
StartPage	15	22	10	21	10	10	8
Nofications	25	10	1	1	2	1	3
Post	8	2	1	1	1	2	1
Login	17	8	3	3	4	5	3

7.4 JPetStore Application Experiments

Two experiments were conducted to test the use of the HybridQ algorithm in a real implemented application. The chosen application was the JPetStore, available at `https://hub.docker.com/r/pocking/jpetstore/`. The maximum tolerated response time in the test was 10 seconds. Any individuals who obtained a time longer than the stipulated maximum time suffered penalties. The whole process of stress and performance tests, which took 2 days and about 1800 executions, was carried out without the need for monitoring by a test designer. The tool automatically selected the next scenarios to be run up to the limit of eleven generations previously established.

The experiment used the following fitness function:

$$fitness = \begin{cases} n * \{3000 * numberOfUsers - 20 * 90percentiletime - 20 * 80percentiletime \\ -20 * 70percentiletime - 20 * maxResponseTime - penalty\}, \text{where n is the} \\ \text{number of scenarios used by the test in a set of previous selected scenarios} \end{cases} \tag{7.4}$$

7.5 JPetStore experiment

This first experiment tries to find the scenarios with maximal number of users and best response time in a configuration that

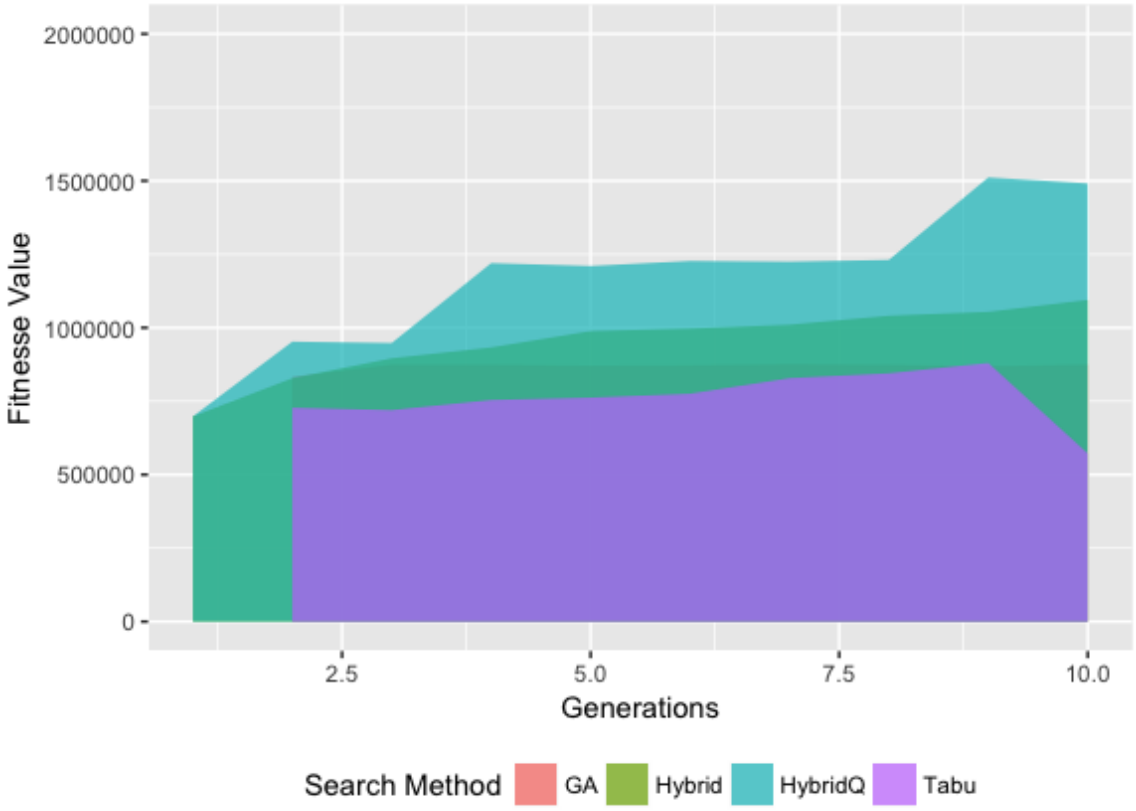

Figure 7-17: GridWorld - exploration phase (Step 10 to 13)

Chapter 8

Conclusion

In this thesis we dealt with the use of hybrid metaheuristics and Q-Learning in Stress Testing.

This thesis presented a hybrid metaheuristic approach that combines genetic algorithms, simulated annealing, and tabu search algorithms in stress tests. A tool named IAdapter (github.com/naubergois/newiadapter), a JMeter plugin for performing search-based load tests, was developed. Two experiments were conducted to validate the proposed approach. The first experiment was performed on an emulated component, and the second one was performed using an installed Moodle application.

IAdapter Testbed is an open-source facility that provides software tools for search based test research. The testbed tool emulates test scenarios in a controled environment using mock objects and implementing performance antipatterns.

The main contributions of this research are as follows: The presentation of a hybrid metaheuristic approach for use in stress tests; the development of a Testbed tool the development of a JMeter plugin for search-based tests and the automation of the stress test execution process.

8.1 Achievements

Four experiments were performed to validate the hybrid metaheuristic and two experiments were conducted to validate the Testbed tool. The experiments uses genetic, algorithms, tabu

search, simulated annealing and the hybrid approach.

The first experiment was performed on an emulated component, and the second experiment was performed using an installed Moodle application. The collaborative approach obtained better fit values. In the first experiment, the signed-rank Wilcoxon non-parametrical procedure was used for comparing the results. The significant level adopted was 0.05. The procedure showed that there was a significant improvement in the results with the Hybrid Metaheuristic approach.

The second and third experiments ran for 17 generations. The experiments used an initial population of 4 individuals by metaheuristic. All tests in the experiment were conducted without the need of a tester, automating the execution of stress tests with the JMeter tool. In both experiments the hybrid metaheuristic returned individuals with higher fitness scores. However, the Hybrid metaheuristic made twice as many requests than Tabu Search to overcome it. The SA algorithm obtained the worst fitness values. The algorithm initially used a scenario with an antipattern and found neighbors that still using the antipatterns over the 17 generations of the experiment.

In the second experiment the metaheuristics converged to scenarios with an happy path, excluding the scenarios with the use of an antipatterns. The individual with best fitness value has 64 users on Happy Scenario 2, 81 users on Happy Scenario 1 and a response time of 12 seconds. None of the best individuals has one of the antipatterns used in the experiment.

In the third experiment, the metaheuristics converged to scenarios with an happy path and Tower Babel antipattern, excluding the scenarios with Unbalanced Processing antipattern. The individual with best fitness value has 72 users on Happy Scenario 2, 30 users on Happy Scenario 1, 46 user with the antipattern Tower Babel and a response time of 11 seconds. Future works include the use of new antipatterns and more experiments with the use of the antipattern Tower Babel.

In the fourth experiment, the whole process of stress and performance tests, which took 3 days and about 1800 executions, was carried out without the need for monitoring by a test designer. The tool automatically selected the next scenarios to be run up to the limit of six generations previously established.

8.2 Open Issues and future works

There is a range of future improvements in the proposed approach. Also as a typical search strategy, it is difficult to ensure that the execution times generated in the experiments represents global optimum. More experimentation is also required to determine the most appropriate and robust parameters. Lastly, there is a need for an adequate termination criterion to stop the search process.

Among the future works of the research, the use of new combinatorial optimization algorithms such as very large-scale neighborhood search is one that we can highlight.

Appendix A

Tables

Table A.1: Best individuals found in the second Testbed Tool experiments

Method	Resp.Time	Users	Fitnesse	Happy 1	Tower	Happy 2	Unbalanced
HybridQ	11	292	869780	171	0	121	0
HybridQ	11	288	857780	185	0	103	0
HybridQ	10	284	845880	117	0	167	0
HybridQ	11	279	830780	135	0	144	0
HybridQ	75	277	823500	147	35	77	18
HybridQ	12	265	788760	127	0	138	0
HybridQ	13	264	785740	170	0	94	0
HybridQ	20	261	776600	160	0	83	18
HybridQ	11	257	764780	181	0	76	0
HybridQ	16	257	764680	135	29	79	14
HybridQ	12	256	761760	150	0	106	0
HybridQ	72	256	760560	157	33	49	17
HybridQ	12	252	749760	191	0	61	0
HybridQ	74	252	748520	130	32	77	13
HybridQ	10	251	746800	130	30	77	14
HybridQ	12	248	737760	130	29	76	13
HybridQ	10	247	734940	155	0	92	0

Table A.2: Comparison study presented by Pen~a-Ortiz on the book Modeling and Simulation of Computer Networks and Systems Methodologies [F- Fully attended feature P-Partial attended feature] [54]

Feature	Webstone	SPECweb	SURGE	Web polygraph	TPC-W
Analytical-Based Architecture	F	F	F	F	F
Distributed Architecture	F	F	F	F	
Business-Based Architecture		P		P	F
Client Parameterization	F	F		P	F
Workload Types		F			F
Multi-platform	F	F	F	F	F
Open Source	F		F	P	F
Search-based Testing or Learning features					
Feature	**LoadRunner**	**WebLoad**	**JMeter**	**S-Clients**	**WebJammma**
Analytical-Based Architecture	P	P	P		
Distributed Architecture	F	F			
Business-Based Architecture	F	F	F		
Client Parameterization	F	F	F		F
Workload Types	F	F	P		
Multi-platform	F	F	F	F	F
Open Source			F	F	F
Search-based Testing or Learning features					
Feature	**Deluge**	**HAMMER HEAD 2**	**PTester**	**Siege**	**Locust**
Analytical-Based Architecture					P
Distributed Architecture					
Business-Based Architecture					F
Client Parameterization					F
Workload Types					P
Multi-platform	F	P	F	P	F
Open Source	F	F	F	F	F
Search-based Testing or Learning features					

Appendix B

Figures

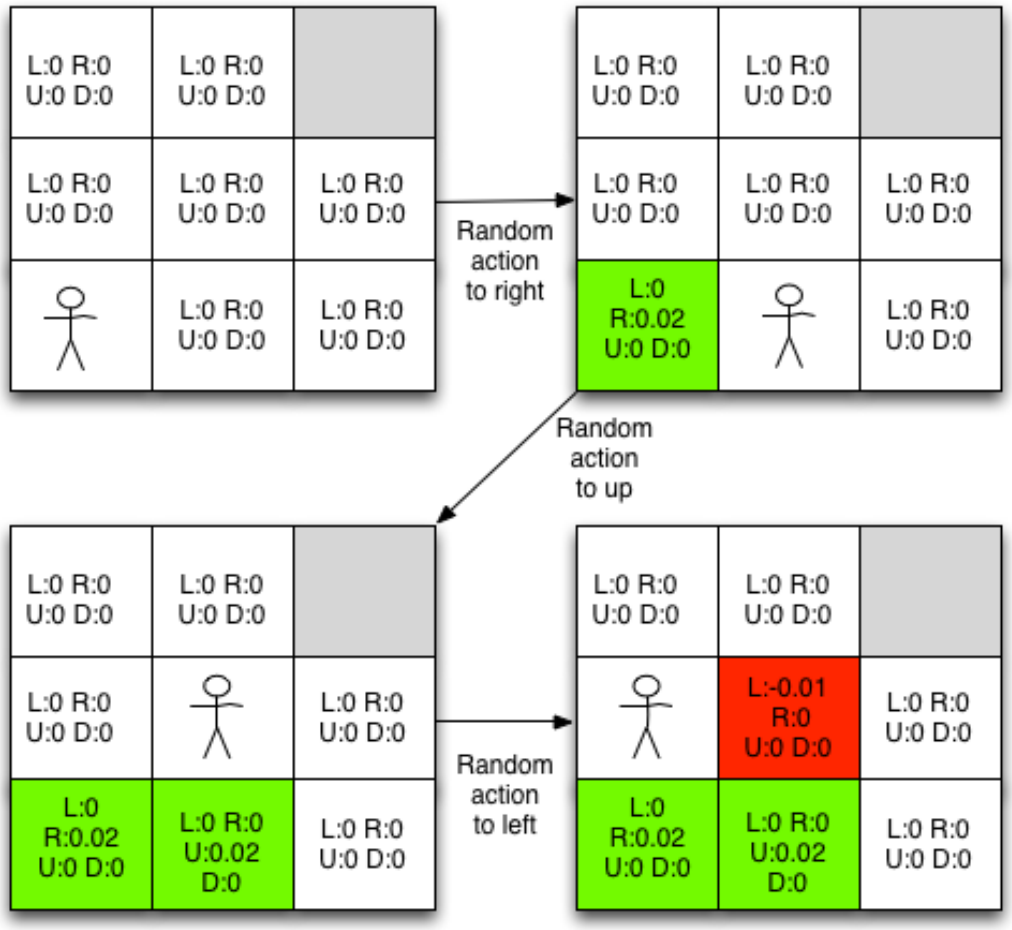

Figure B-1: GridWorld initial states

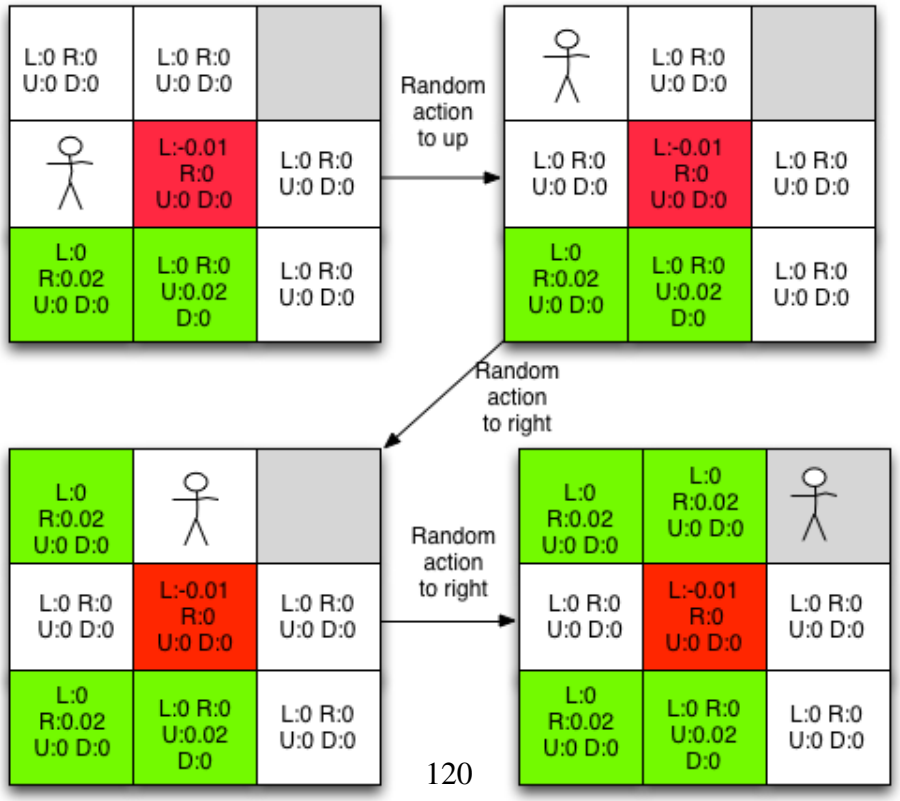

Figure B-2: GridWorld after four initial actions

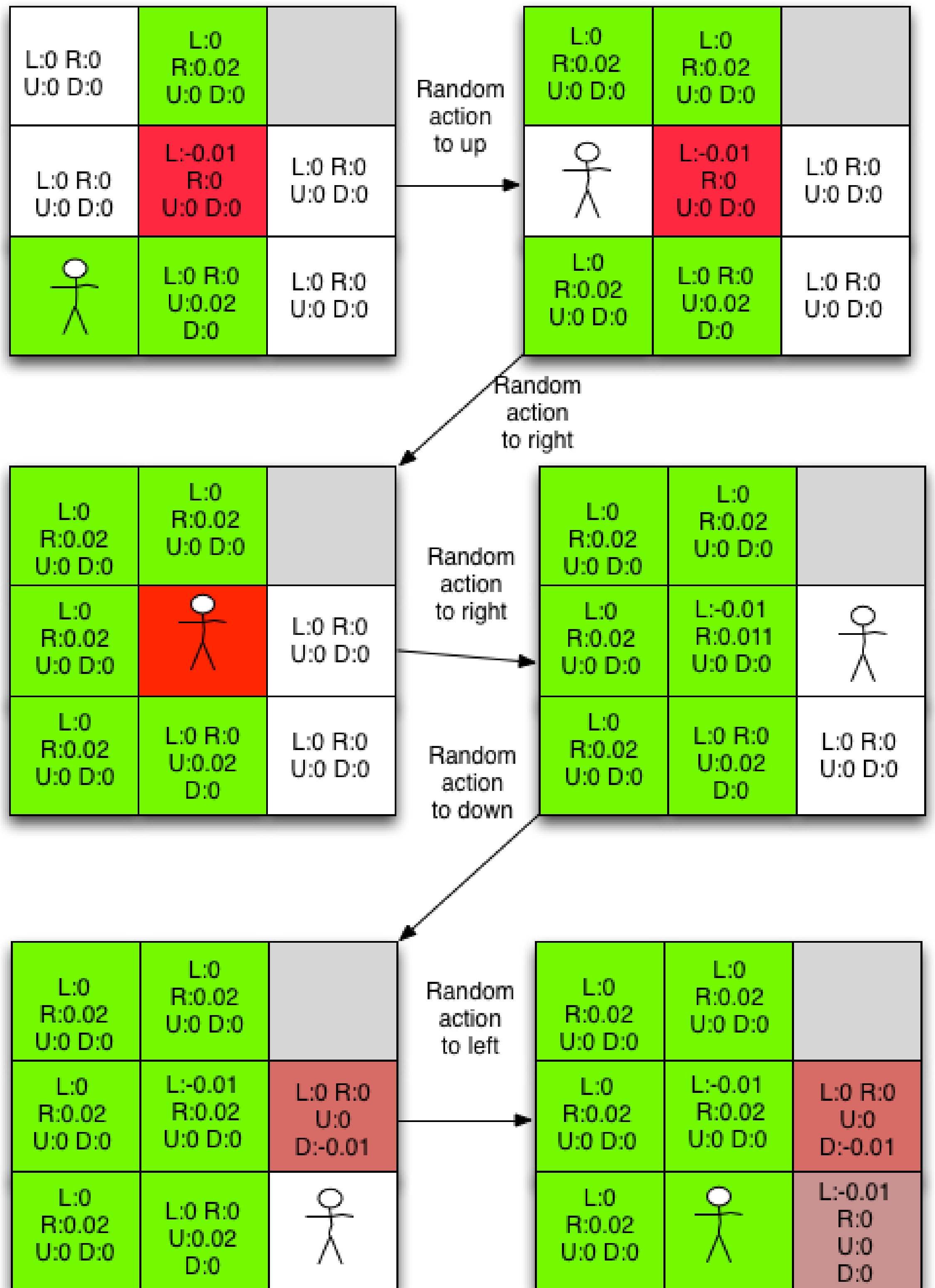

Figure B-3: GridWorld - exploration phase (Step 5 to 10)

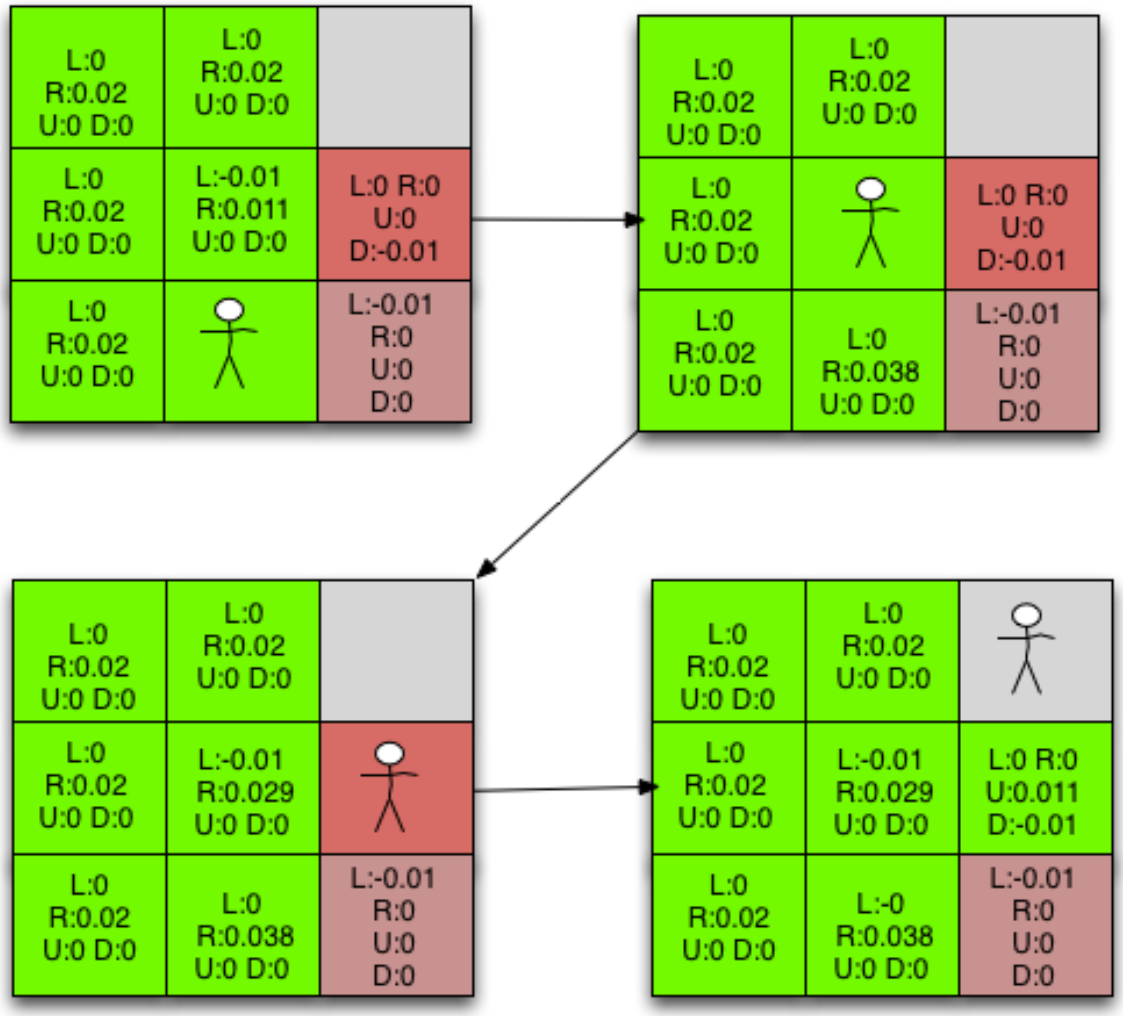

Figure B-4: GridWorld - exploration phase (Step 10 to 13)

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