Performance Testing Using a Smart Reinforcement Learning-Driven Test Agent

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Abstract—Performance testing with the aim of generating an efficient and effective workload to identify performance issues is challenging. Many of the automated approaches mainly rely on analyzing system models, source code, or extracting the usage pattern of the system during the execution. However, such information and artifacts are not always available. Moreover, all the transactions within a generated workload do not impact the performance of the system the same way, a finely tuned workload could accomplish the test objective in an efficient way. Model-free reinforcement learning is widely used for finding the optimal behavior to accomplish an objective in many decision-making problems without relying on a model of the system. This paper proposes that if the optimal policy (way) for generating test workload to meet a test objective can be learned by a test agent, then efficient test automation would be possible without relying on system models or source code. We present a self-adaptive reinforcement learning-driven load testing agent, RELOAD, that learns the optimal policy for test workload generation and generates an effective workload efficiently to meet the test objective. Once the agent learns the optimal policy, it can reuse the learned policy in subsequent testing activities. Our experiments show that the proposed intelligent load test agent can accomplish the test objective with lower test cost compared to common load testing procedures, and results in higher test efficiency.

Index Terms—performance testing, load testing, workload generation, reinforcement learning, autonomous testing

I. INTRODUCTION

Performance as an important quality characteristic plays a key role in the success of software products. Performance assurance is of great importance particularly in the domains where quality assurance of both functional and non-functional aspects of system’s behavior is essential. For example, enterprise applications (EAs) [1] with Internet-based user interfaces such as e-commerce websites are examples of systems whose success is subject to performance assurance. EAs are often the core parts of the business organizations and their performance is a prerequisite for acceptable execution of business functions [2].

Performance, which is also called efficiency in classifications of quality attributes [3]–[5], generally describes how well the system accomplishes its functionality. It presents time and resource bound aspects of a system’s behavior, which are indicated by some common performance metrics such as throughput, response time, and resource utilization. Performance analysis is conducted to meet the primary objectives as I) evaluating (measuring) performance metrics, II) detecting the functional problems emerging under specific execution conditions such as heavy workload, and III) detecting violations of performance requirements [6].

Performance modeling and testing are considered common approaches to accomplish the mentioned objectives at different stages of performance analysis. Although performance models [7]–[9] provide helpful insight into the behavior of a system, there are still many details of the implementation and the execution environment that might be ignored in the modeling [10]. Moreover, building a precise detailed model of the system behavior with regard to all the factors at play is often costly and sometimes impossible.

Load testing is a type of performance testing that focuses on analyzing the performance of the system when subjected to workloads. Load is often configured as a set of concurrent (virtual) users doing different transactions on the software under test (SUT), which often mimic the behavior of the real users of the system [11]. Different transactions do not have the same impact on the performance, and generating an effective test workload in an optimal way is challenging. Common load testing approaches such as the techniques using source code [12] and system model analysis (e.g., performance and UML models) [13]–[17], and also use case-based [18], [19] and behavior-driven [20]–[22] techniques all mostly rely on the artifacts that are not always available during the testing. Meanwhile, in the black-box testing, in order to efficiently generate an effective workload identifying the performance effects of the transactions involved in the workload is important and still challenging. Therefore, this paper is organized based on addressing the following question:
Research Goal. How can we efficiently and adaptively generate test workload resulting in reaching the performance test objective for a SUT without relying on the source code and performance/system models?

Contribution. In this paper, we present a self-adaptive model-free reinforcement learning load testing agent (RELOAD), which learns how to generate an effective test workload efficiently without relying on the system model or source code, and is able to reuse the learned policy in further testing scenarios. The test objective is defined as reaching a status under which a certain performance requirement gets violated.

Solution proposal. The proposed reinforcement learning-driven load testing agent identifies the effects of different transactions involved in the workload and learns how to adjust the transactions to meet the test objective. It assumes two learning phases: initial and transfer learning phases. It learns the optimal policy (way) to generate an effective workload in the initial learning. Then, in the transfer learning it is able to reuse adaptively the learned policy in further testing scenarios, i.e., with different test objectives. It uses Q-learning, a model-free reinforcement learning (RL) algorithm, as the core learning with an adaptive action selection strategy to be able to reuse the learned policy in the transfer learning. RELOAD uses a well-known load test actuator, i.e., Apache JMeter [23], to execute the designed workload on the SUT.

Experimental evaluation. We present a two-fold experimental evaluation, i.e., efficiency and sensitivity analysis, of the proposed approach on a functional e-commerce web application as SUT. In the experimental evaluation we address two main research questions which are as follows:

RQ1: How efficiently can RELOAD generate an effective test workload to meet the test objective?

RQ2: How is the efficiency of RELOAD affected by changing the learning parameters?

We consider test cost saving (reduction) and compare the efficiency of RELOAD based on four configurations of the proposed learning with a random (exploratory) and a standard baseline load testing approaches. According to the results of the efficiency analysis, after the initial learning RELOAD generates a more accurate and finely-tuned workload to meet the test objective with around 32% and 17% test cost saving compared to baseline and random approaches respectively. Moreover, once it learns how to tune the transactions to reach the objective, it reuses the learned policy and keep the efficiency, i.e., preserve around 25% and 13% test cost saving compared to baseline and random approaches respectively, in further testing scenarios without a need to redo the learning. Lastly, we also study the behavioral sensitivity of RELOAD to the learning parameters influencing the learning mechanism.

The rest of this paper is organized as follows: Section II presents the architecture and technical details of the proposed RL-assisted load testing agent. Section IV presents the research method and experiments’ setup. Section V discusses the experimental results, answers to RQs and the threats to validity. Section VI gives an overview of the related work. The conclusion and future research directions are presented in Section VII.

II. MOTIVATION AND BACKGROUND

Any anomalies in the performance behavior of the system (e.g., performance requirement violation) could be mainly a consequence of emerging bottlenecks at the level of platform or application [24], [25]. A bottleneck can make the system fail or not perform as required, and can happen due to the full utilization of the component capacity, exceeding a usage threshold or occurrence of contention [26].

Possible defects in source code or architecture and some issues related to platform resources could be often the root causes of the emergence of bottlenecks. Moreover, all transactions do not have the same effect on the performance and some of them are more critical to lead to the emergence of performance bottlenecks. Therefore, due to the existing interplay between the involved factors, drawing a detailed model expressing the performance behavior of the system, is not easily possible. This issue makes room for model-free machine learning techniques, such as model-free reinforcement learning (RL) [27] to play an interesting role in addressing the related challenges, in particular from testing perspective. RL algorithms are mainly intended to address decision-making problems and have been widely used to build self-adaptive intelligent systems.

In model-free RL the intelligent agent can learn an optimal behavior to achieve an intended objective based on the interaction with the environment (i.e., the system under test in this problem) without access to the source code or a model of SUT. Furthermore, the agent is able to store the gained knowledge and reuse the learned behavior in further potential testing situations such as regression testing or testing of SUT with regard to different test objectives. Model-free RL algorithms are not intended to build or learn a model of the environment. Instead, they learn optimal behavior to accomplish the objective through various episodes of interaction with the environment. They are apt for the problems where the model (i.e., the dynamics) of the environment is unknown or costly to be built, but the experience of interaction with the environment can be sampled and used.

A. Reinforcement Learning

Using RL, the agent learns the optimal behavior to meet the objective through being rewarded or punished in the interaction with the environment. At each step of the interaction, the agent observes the state of the system. It takes one possible action. The system undergoes changes upon actions. Then, the agent receives a reward signal showing how good the action was to direct the agent towards
accomplishing the objective. The overall goal of the agent is formulated in terms of maximizing the cumulative long-term reward. The agent decides how to behave at each step of the interaction and based on optimizing the long-term received reward, learns the optimal behavior function which is called optimal policy. The agent uses an action selection strategy to interact with and apply actions to the system. The action selection is often based on trying the available actions, i.e., exploration of the action space, or relying on the learned policy which leads to selecting highly valued actions, i.e., exploitation of the gained knowledge.

III. RELOAD TEST AGENT FOR OPTIMAL TEST WORKLOAD GENERATION

In this section, we present an overview of the architecture of our proposed RL-driven load testing agent, RELOAD, and describe the technical details of the learning procedure.

How it learns. It assumes two phases of learning, i.e., initial and transfer learning. During the initial learning, the test agent learns the optimal policy to generate an effective workload to accomplish the test objective. During the transfer learning, the learned policy is reused in further potential testing scenarios, e.g., regression testing scenarios or testing with regard to different test objectives. In the transfer learning phase, the agent also still continues with the learning to keep the policy updated.

We use Q-learning, a model-free RL algorithm, as the core learning technique. Fig. 1 shows the architecture of RELOAD. The main constituent parts of each learning step in RELOAD are detecting state, taking actions and computing reward (See Section II-A). We have formulated these parts in RELOAD as follows:

State Detection. Average response time and error rate, as two performance metrics, are used to indicate the performance state of the SUT. The values of these performance metrics are classified under a number of discrete classes, which are described as Low, Normal and High for response time and Low and High for error rate. The threshold (boundary) values for defining these classes are selected empirically and could be updated based on the requirements. The combinations of these classes form the discrete classes for the state of the system, as shown in Fig. 2. Actually, different transactions do not have the same impact on the performance of the SUT, and test workloads with different configurations, i.e., in terms of constituent transactions, might lead the SUT to different performance states. The agent fetches these metrics from the test actuator at each learning step and identifies the state of the SUT.

Actions. At each learning step, the test agent takes one action after detecting the state of the SUT. We define the actions as adjusting the load of constituent transactions in the workload, in terms of numbers of virtual users running each transaction. Table I presents the list of transactions for the SUT in our case study, which is an e-commerce web application.

Each transaction involves a certain function together with its functional dependencies. For example, transaction Add to cart involves performing login, accessing the search page, and selecting the product as well, since all those functions are prerequisites for function Add to cart. Therefore, the function in each transaction of the workload is considered together with its functional dependencies. Then, the set of actions for the test agent is defined as follows:

$$\text{ActionList} = \{\cup \text{action}_k, \; 1 \leq k \leq |\text{List of Transactions}| \}$$

$$\text{action}_k : \{W_{T_j}^{T_j} = W_{T_{j-1}}, \; for \; j \neq k, \}$$

$$\text{action}_k : \{W_{T_j}^{T_j} = W_{T_{j-1}} + \frac{W_{T_j}}{3}, \; for \; j = k, \}$$

where $$T_j$$ indicates a transaction of the SUT, $$W_{T_j}^{T_j}$$ indicates the load of transaction $$T_j$$ at time step $$n$$, i.e., the number of users running this transaction. After the agent decides on an action, a test plan is generated by the agent, and then is executed on the SUT by the test actuator, i.e., Apache JMeter.

TABLE I: List of transactions for the SUT

| Operation       | Description              |
|-----------------|--------------------------|
| Home            | Access to home page      |
| Sign up page    | Access to sign up page   |
| Sign up         | Register and add a new user |
| Login page      | Access to login page     |
| Login           | Sign in at the system    |
| Search page     | Access to search page    |
| Select product  | See the details of the selected product |
| Add to cart     | Add the selected product to the cart |
| Payment         | Access to payment page   |
| Confirm         | Confirm the order (payment) |
| Log out         | Log out                  |

Reward Signal. After taking the selected action and running the tuned workload, the test agent receives a reward signal which shows how effective the applied action was in
leading the test agent to reaching the test objective. We define a function to represent the reward signal as follows:

\[ R_n = \left( \frac{RT_n}{RT_{\text{threshold}}} \right)^2 + \left( \frac{ER_n}{ER_{\text{threshold}}} \right)^2 \]  \hspace{1cm} (3)

where \( R_n \), \( RT_n \), and \( ER_n \) indicate the reward, the average response time, and the average error rate respectively, in step \( n \). Also \( RT_{\text{threshold}} \) and \( ER_{\text{threshold}} \) are the response time and error rate thresholds related to the test objective.

**Learning Procedure.** In RL, the agent is intended to learn the optimal policy to accomplish the objective of the problem. The policy determines which action to be taken by the agent, given a certain state. The key idea for finding the optimal policy is the use of an iterative policy iteration process at each step of the learning, which consists of policy evaluation and policy improvement. At each step of the interaction, the agent performs both evaluation and improvement. First, it evaluates the policy which it follows, then it tries to improve it through a greedy approach (e.g., \( \varepsilon \)-greedy). Finally, this process will converge on the optimal policy.

In model-free RL, there are generally two approaches to realize this: learning the policy directly and indirectly. In the Q-learning algorithm, the agent learns an optimal value function, i.e., an action-value function \( Q^*(s, a) \), from which the optimal policy can be obtained. The optimal action-value function, \( Q^*(s, a) \), gives the expected long-term return, given state \( s \), taking an arbitrary action \( a \), and then following the optimal policy. It is presented as follows:

\[ Q^*(s, a) = \max_a E^\pi [q_n|s_n = s, a_n = a] \]  \hspace{1cm} (4)

\[ q_n = \sum_{k=0}^{\infty} \gamma^k R_{n+k+1} \]  \hspace{1cm} (5)

where \( \gamma \) is a discount factor for future rewards and \( q_n \) is the long-term return in terms of cumulative discounted reward.

In general, the optimal policy selects the action maximizing the expected return given starting from state \( s \). Moreover, according to the definition of \( Q^*(s, a) \), given \( Q^* \), the optimal action for state \( s \), \( a^*(s) \), is obtained as:

\[ a^*(s) = \max_a Q^*(s, a') \]  \hspace{1cm} (6)

In order to obtain the optimal policy, Q-values are stored (e.g., in a Q-table or a neural network) and considered the experience of the agent. During the learning, the Q-values are updated incrementally according to Eq. 7:

\[ Q(s_n, a_n) = (1 - \alpha)Q(s_n, a_n) + \alpha \left[ R_{n+1} + \gamma \max_{a'} Q(s_{n+1}, a') \right] \]  \hspace{1cm} (7)

where \( \alpha, 0 \leq \alpha \leq 1 \) adjusts the rate of learning which controls the impact of new Q-values on the previous ones.

In this study, the research problem, i.e., generating an effective workload to meet an intended test objective, is regarded as a sequential decision-making problem. Model-free RL is proposed as a beneficial learning solution to this problem since the SUT (environment) and execution platform are supposed to be initially unknown to the test agent. Then, in the proposed model-free RL-driven solution, the agent finds (learns) the optimal policy to generate an effective workload to accomplish the test objective through a built-in iterative policy evaluation-improvement process. Algorithms 1 and 2 present the procedure of the learning in the proposed RL-driven load testing agent.

In model-free RL, \( \varepsilon \)-greedy is a well-known method for action selection, when RL is used to find the optimal policy in a decision-making problem. It guarantees the sufficient continual exploration required for finding the optimal policy, and meanwhile provides a proper trade-off between exploration of the state-action space and exploitation of the learned value function. In \( \varepsilon \)-greedy, the value of \( \varepsilon \) adjusts the degree of exploration versus exploitation, as it leads the agent to select a high-value action based on the learned value function with probability \((1-\varepsilon)\) or a random possible action with probability \( \varepsilon \), given a certain state. In addition to Q-learning, we also implemented RELOAD with DQN [28], which is a combination of Q-learning and deep neural networks and suits the large scale problems where due to the big number of states and actions using tabular methods (i.e., Q-table) is not practical.

**IV. Method**

We perform empirical evaluations of RELOAD by running experiments on a mature open-source software, an e-commerce web application. Our target SUT is based on the widely-used WooCommerce platform and deployed using...
Algorithm 1 Adaptive Reinforcement Learning-Driven load Testing

Required: \( S, A, \alpha, \gamma; \) 
Initialize Q-values, 
\[
Q(s, a) = 0 \forall s \in S, \forall a \in A \text{ and } \varepsilon = v, 0 < v < 1;
\]
while Not (initial convergence reached) do 
| Learning_Episode (with initial action selection strategy, e.g., \( \varepsilon \)-greedy, initialized \( \varepsilon \)) |
end
Store the learned policy; 
Adapt the action selection strategy to transfer learning, i.e., tune parameter \( \varepsilon \) in \( \varepsilon \)-greedy; 
while true do 
| Learning_Episode with adapted strategy (e.g., new value of \( \varepsilon \)) |
end

Algorithm 2 Learning_Episode

repeat 
1. Detect the state \((S_n)\) of the SUT; 
2. Select an action (See Eq. 1) according to the action selection strategy, e.g., \( \varepsilon \)-greedy: select \( a_n = \arg \max_{a \in A} Q(s_n, a) \) with probability \((1-\varepsilon)\) or a random \( a_k, a_k \in A\) with probability \( \varepsilon \); 
3. Take the selected action: Tune the workload and run the modified workload on the SUT; 
4. Detect the new state \((S_{n+1})\) of the SUT; 
5. Compute the reward, \( R_{n+1} \); 
6. Update the Q-value of the pair of previous state and taken action 
\[
Q(s_n, a_n) = (1 - \alpha)Q(s_n, a_n) + \alpha[R_{n+1} + \gamma \max_{a' \in A} Q(s_{n+1}, a')]
\]
until meeting the stopping criteria (reaching the test objective);

Figure 3 shows an overview of the experimental setup.

XAMPP on an Apache web server with PHP 7.4.13 and MariaDB 10.4.17. The experiments’ environment consists of two virtual machines (VMs), as one of them hosts the SUT and the other one runs the load testing agent together with the test actuator. Each VM has 2 CPUs at 3.1GHz, 8GB of RAM, and Linux Ubuntu 16.04. We use Apache JMeter 5.2.1 as an actuator to execute the test workload on the SUT.

We design a series of experiments to assess the efficiency and sensitivity of RELOAD. The experiments investigate how different learning configurations (setups) affect the outcome of RELOAD. For comparative purposes, we also report results from random (exploratory) testing and a standard (naive) testing baseline. For all experimental runs, we translate differences in the number of generated concurrent virtual users to reduced testing costs.

Figure 3 shows an overview of the experimental setup. The Dependent Variable (DV) in all experimental runs is the number of generated virtual users. The Independent Variable (IV) defining different experimental runs is the test generation technique. We explore six discrete levels of the IV: A1) RELOAD with \( \varepsilon = 0.2 \), A2) RELOAD with \( \varepsilon = 0.5 \), A3) RELOAD with decaying \( \varepsilon \), A4) RELOAD with DQN; B) Standard Baseline; C) Random Testing. In A1)-A3) RELOAD is based on Q-learning together with \( \varepsilon \)-greedy with different values for \( \varepsilon \).

Section III describes the details of the RELOAD configurations in A1)-A4). The Standard Baseline (B) applies an initial workload that contains all the transactions with the same number of users per each transaction, then increases the number of users in fixed steps by 33% until accomplishing the test objective. In Random Testing (C), a transaction is chosen randomly at each step, and then the number of virtual users allocated for the selected transaction is increased by 33%. The process is repeated until the test objective has been met.

The experimental runs corresponding to the six test generation techniques (i.e., values of the IV) are executed the same number of times, i.e., the same number of episodes. In RL each learning episode constitutes one complete sequence of states and actions in RL till reaching the objective (i.e., equivalent to one epoch in supervised learning). The agents’ properties including the value function and policy are updated gradually over the learning episodes. Despite the lack of learning in the Baseline and Random testing, we refer to one complete execution for those techniques as an episode too.

In the efficiency analysis, we report results corresponding to the two learning phases of RELOAD. First, we analyze the initial learning. Second, we study how efficiently RELOAD performs during the transfer learning, i.e., when the agent reuses learned policies in new similar testing scenarios.

In the sensitivity analysis, we investigate the performance sensitivity of RELOAD to two learning hyperparameters, i.e., the learning rate \( \alpha \) and the discount factor \( \gamma \). We explore the two hyperparameters by changing one parameter while keeping the other one constant. As the sensitivity analysis followed the efficiency study, we based the design on our empirical observations at that point.

In the efficiency experiments, we use baseline values of \( \alpha = 0.5 \) and \( \gamma = 0.5 \). In the sensitivity experiments, we conduct four experimental runs to analyze the sensitivity of RELOAD. First, we set \( \alpha \) to 0.1 and decaying values while keeping the value of \( \gamma \) fixed at 0.5. Second, we set the \( \gamma \) to 0.1 and 0.9,
V. RESULTS AND DISCUSSION

This section presents our experimental results, answers the RQs, and discusses the main threats to validity.

A. Experimental Results

Efficiency Analysis. Initial Learning. To see how it works during the initial learning, we compare the efficiency of RELOAD for the learning configurations A1)-A4) (i.e., \(\epsilon = 0.2, 0.5\), decaying \(\epsilon\), and DQN) with the Standard Baseline and Random Testing. In particular, we are interested in studying the behavior of RELOAD after the initial convergence in comparison with other approaches. The convergence happens after around 30 episodes in Q-learning with \(\epsilon\)-greedy (A1-A3) and in some episodes later for the DQN configuration (A4), i.e., after roughly 37 episodes. We consider the performance of the learning-based approach during the last 10 episodes after the convergence. We also run the Standard Baseline (B) and the Random Testing (C) 40 episodes. The test objective is reaching a performance status under which 1) the response time of the SUT exceeds 1,500ms or 2) the error rate in the received responses exceeds 20%.

Fig. 4 shows the number of generated virtual users in all approaches to produce an effective workload accomplishing the test objective. Table II presents the resulting test cost saving at the last 10 episodes in RELOAD, i.e., the last 10 episodes show the behavior of the RL approach when it has almost achieved an initial convergence. We proceed by discussing the performance of RELOAD using the four configurations A1)-A4).

Q-learning with \(\epsilon\)-greedy. Using \(\epsilon = 0.2\) (A1) makes the agent mainly rely on the stored experience rather than exploring new actions. It might slow down the learning convergence in a varying environment in which more exploration is needed. This issue is observable in terms of high spikes in Fig. 4. The configuration \(\epsilon = 0.5\). (A2) provides an equal likelihood for the exploitation of the learned policy and the exploration of new actions. The decaying \(\epsilon\) setting (A3) decreases \(\epsilon\) gradually over the learning episodes. It makes the agent explore new actions mainly during the early episodes of the learning and do more exploitation of the learned policy in the later episodes. The efficiency of the three configurations (A1)-A3) are comparable, i.e., they converge roughly on the same number of virtual users needed to meet the test objective. DQN (A4) is an extension of Q-learning that uses a deep neural network as a function approximator instead of a Q-table to approximate the Q-values. In this experiment, the A4 obtain roughly the same efficiency as Q-learning with \(\epsilon\)-greedy (A1-A3). This is also in line with previous works on the use of Q-learning for performance assurance purposes [29], i.e., for problems that are not high-dimensional and satisfy the required conditions for Q-learning convergence, it is possible to obtain desired results using Q-learning with a carefully selected configuration. For the transfer learning part, we proceed with the A3 configuration.

Transfer Learning. After the initial convergence, we study the efficiency of RELOAD in reusing the learned policy in further similar testing situations (scenarios) during the transfer learning. In this part of the experimentation, after an initial learning of 40 episodes with RELOAD configuration A3, we continue with 10 additional episodes (i.e., episodes 41-50 in Fig. 5a). For these 10 episodes, we change the test objective and keep the \(\epsilon\) low to guide the agent towards relying on the learned policy. Over the episodes of transfer learning, we alter the threshold of the target performance status (i.e., test objective). We change the target error rate threshold from 0.2 to 0.3 gradually by an increase of 0.01 at each episode and also change the target threshold for response time from 1,500ms to 2,500ms by an increase of 100ms at each episode. Figure 5 shows the efficiency of RELOAD in accomplishing the test objective in the further similar testing scenarios (i.e., represented by the 10 episodes, 41-50, after the initial learning) compared to the Standard Baseline and Random Testing. It indicates that the smart test agent is able to properly reuse the learned policy in the similar testing scenarios, i.e., the episodes with new values of test objectives, and still accomplish the test objective more efficiently. Table III presents the resulting test cost reduction of RELOAD in the transfer learning.

Sensitivity Analysis. We select \(\epsilon\)-greedy with decaying \(\epsilon\) (A3) as the learning configuration in the sensitivity analysis. Figure 6 shows the behavioral performance of RELOAD regarding changing the values of hyperparameters as described in Section IV. It presents how different values for the learning hyperparameters influence the learning behavior, e.g., convergence, and the learning trend, in the proposed RL-driven test agent. We observe that RELOAD does not converge using a low learning rate, i.e., \(\alpha = 0.1\). Furthermore, we find slower convergence using both lower

| TABLE II: Average test cost saving of RELOAD in the initial learning |
|---------------------------------|---------|---------|---------|
| **Test Cost Saving**          | \(\epsilon = 0.5\) | \(\epsilon = 0.2\) | decaying \(\epsilon\) | DQN setup |
| w.r.t Standard Baseline       | 30%     | 30%     | 34%     | 34%       |
| w.r.t Random Testing          | 17%     | 17%     | 20%     | 20%       |

| TABLE III: Efficiency and average test cost saving in the transfer learning |
|-----------------------------|-----------------|-----------------|
| **Range of the number of generated virtual users** | RELOAD (with Q-learning) | Standard Testing | Random Testing |
| 48-62                       | 55-99           | 55-68           |
| RELOAD test cost saving     | 25%             | 13%             |
and higher discount rates, i.e., \( \gamma = 0.1 \) and \( \gamma = 0.9 \).

### B. Revisiting the Research Questions

**RQ1.** As shown in Fig. 4 and Table II, on average RELOAD leads to accomplishing the test objective using fewer virtual users than the Standard Baseline and Random Testing. RELOAD learns how to meet the objective with a more accurate and fine-tuned workload and subsequently leads to a considerable test cost saving. In particular, RELOAD based on \( \varepsilon \)-greedy, decaying \( \varepsilon \) and DQN setup, offers a smoother learning trend and after the convergence results in a slightly higher cost saving, i.e., 34\% and 20\%, compared to other learning configurations. Based on our experiments, we conclude that RELOAD results in 10-30\% increased test efficiency.

The test agent learns the optimal policy to meet the test objective efficiently over the learning episodes. The optimal policy is learned through the value function. The agent stores the learned value function and is able to exploit it in further testing scenarios. The results of the efficiency analysis in the transfer learning (see Fig. 5 and Table III) confirm that the test agent after the initial learning is able to reuse the gained knowledge in subsequent testing scenarios, in which the SUT displays similar characteristics, and maintain its efficiency across scenarios. As shown in Table III, RELOAD leads to 25\% and 13\% test cost saving in the transfer learning compared to the Standard Baseline and Random Testing.

**RQ2.** As shown in Fig. 6 in the sensitivity analysis experiments, fixing the learning rate at a low value such as 0.1 did not lead to a learning convergence. Whereas a higher value such as 0.5 (as used in efficiency analysis) or using a decaying learning rate results in faster updates in the stored Q-table of the agent and works better in this case study.
Moreover, changing the values of the discount factor, e.g., setting it to 0.1 or 0.9, appears to slow down the learning convergence.

Applicability. RELOAD learns how to tune the transactions optimally in the workload to meet the test objective. The smart agent generates an effective workload efficiently without relying on source code or a system model. It is well-suited to operational contexts where the source code, system models, and behavior specifications are not available. Meanwhile, the pay-as-you-go cost for many of the load generation tools on the market is proportional to the number of generated virtual users. Therefore, the efficient generation of an effective workload by the proposed test agent could lead to considerable cost and time savings in the testing process. Moreover, the proposed smart test agent has the capability of reusing the learned policy in further similar testing scenarios. RELOAD keeps the learning running to adapt the learned policy to changes in the environment. This feature is particularly beneficial to DevOps continuous testing activities such as performance regression testing where performance testing scenarios must be repeated for the SUT in a continuous integration process.

C. Threats to Validity

Some of the potential sources of threats to validity of the experimental results are described as follows:

Construct validity. One of the main sources of threat is the formulation of the RL technique to address the problem. Formulating the states, actions, and also the reward function is a major step in building an RL-driven smart agent.

Internal validity. Dependency on the resource availability in the execution environment of the SUT is another common source of threats to the validity of the results in performance testing. To tackle this potential threat, we perform the experiments on dedicated virtual machines, i.e., two separate VMs were used for running the SUT and the test agent.

External validity. In our case, the approach has been formulated based on a particular e-commerce web-application as SUT, which supports a certain set of transactions. Therefore, in order to apply the approach to other types of applications, e.g., other web-based systems, the involved transactions of the new system should be extracted and included in the set of actions.

VI. Related Work

Measuring performance metrics under different execution conditions including various workload and platform configurations [30–32], detecting different performance-related issues such as functional problems or violations of performance requirements [33–35] are common objectives of different types of performance testing. An overview of the techniques used for generating test workload is presented as follows:

Analyzing system models. Analysis of a performance model of SUT in Petri nets using constraint solving techniques [36], using genetic algorithms to generate test load based on the control flow graph of SUT [13], applying genetic algorithms to other types of system models such as UML models to generate stress test load [14–17] are samples of the techniques in this category.

Analyzing source code. Generating test load using the analysis of SUT’s data-flow and symbolic execution [34], [37] are examples of using source code analysis to generate test load and find performance-related issues.

Modeling real usage. Extracting the usage pattern of real users and modeling their behavior using form-oriented models [18], [19], extracting workload characteristics and modeling the user behavior based on Extended Finite State Machines [38] and Markov chains [39] through monitoring submitted requests to SUT, and workload characterization through users clustering based on the business-level attributes extracted from usage data [40] are examples of the techniques used for modeling the realistic workload.

Declarative specification-based methods. Using a declarative Domain Specific Language (DSL) to specify the performance testing process together with a model-driven test execution framework [21], [22] and also using a specific behavior-driven language, to specify load testing process in combination with a declarative performance testing framework like BenchFlow [20] are examples of declarative techniques for performance and load testing.

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**Fig. 5: Efficiency of RELOAD (in the transfer learning) vs. the baseline and random approaches in new similar testing scenarios**

(a) RELOAD in the Transfer Learning
(b) Standard Baseline
(c) Random Testing
techniques such as supervised and unsupervised algorithms are often intended to build models and knowledge patterns from the data, while in other techniques like reinforcement learning algorithms, the intelligent agent learns the way to accomplish an objective through interaction with the environment. Machine learning techniques have been frequently used for analyzing the resulted data, e.g., for anomaly detection [41] and reliability prediction [42]. Machine learning techniques have been also applied to the generation of performance test conditions in some studies. For example, using RL together with symbolic execution to find the worst-case execution path within an SUT in [43], a feedback-driven learning technique which extracts some rules from the execution traces to find the performance bottlenecks, [44], and using RL to build a smart performance testing framework which mainly generates the platform-based test conditions [45]–[47]. Regarding generating performance test conditions, a few studies have also used some other adaptive techniques to generate the test workload. A feedback-based approach using search algorithms to benchmark an NFS server based on changing the test workload in [48], and an adaptive generation of test workload based on using some pre-defined tuning policies in [49] are some other examples of using adaptive approaches for the generation of performance test conditions.

VII. CONCLUSION

System models, source code, and user behavior patterns are common sources of information in load testing techniques for generating test workload to find performance issues. Nonetheless, those artifacts might not be available all the time during the testing. Moreover, in black-box testing approaches, it is important to consider that not all transactions have the same effect on the performance, i.e., tuning the workload optimally is crucial for test efficiency. We proposed RELOAD, a self-adaptive model-free RL-driven load testing agent that learns how to tune transactions in the workload to accomplish the test objective. It learns an optimal policy to generate an effective workload efficiently and is able to reuse the learned policy in further similar testing scenarios, e.g., in performance regression testing. Furthermore, RELOAD adapts the learned policy to continuous changes in the SUT and the execution environment, thus we believe the smart test agent to be particularly well-suited to the continuous performance testing context within DevOps. The smart test agent assumes two phases of initial and transfer learning and uses Q-learning as the core learning algorithm. It performs more efficiently than random and baseline load testing approaches, which enables reduced testing costs.

We conclude that RELOAD provides three main strengths. First, RELOAD provides efficient generation of effective test workloads. Second, the RL approach reduces source code and model dependencies, e.g., system models and user behavior models. Third, RELOAD enables generalizable knowledge representation, i.e., previously learned policies can be reused for other testing scenarios on the SUT. We posit that RELOAD can reduce costs in performance testing. Furthermore, the continuous testing context that permeates contemporary DevOps processes would further amplify the benefits. In future work, we plan to conduct empirical studies to validate our claims.

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