Reinforcement Learning-based Autoscaling of Workflows in the Cloud: A Survey

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Abstract

Reinforcement Learning (RL) has demonstrated a great potential for automatically solving decision making problems in complex uncertain environments. Basically, RL proposes a computational approach that allows learning through interaction in an environment of stochastic behavior, with agents taking actions to maximize some cumulative short-term and long-term rewards. Some of the most impressive results have been shown in Game Theory where agents exhibited super-human performance in games like Go or Starcraft 2, which led to its adoption in many other domains including Cloud Computing. Particularly, workflow autoscaling exploits the Cloud elasticity to optimize the execution of workflows according to a given optimization criteria. This is a decision-making problem in which it is necessary to establish when and how to scale-up/down computational resources; and how to assign them to the upcoming processing workload. Such actions have to be taken considering some optimization criteria in the Cloud, a dynamic and uncertain environment. Motivated by this, many works apply RL to the autoscaling problem in Cloud. In this work we survey exhaustively those proposals from major venues, and uniformly compare them based on a set of proposed taxonomies. We also discuss open problems and provide a prospective of future research in the area.

1. Introduction

Workflows, originally from the business world, have been introduced into engineering and scientific disciplines due to they are very useful for the design and management of engineering and scientific applications. The existing advances in tools and technologies to exploit workflows have allowed people without programming knowledge to contribute in the design of these applications. Generally, workflows allow users to describe a complex functional objective through the composition of a set of tasks (i.e., sub-objectives) and their dependencies. In addition, workflows facilitate the reuse of predefined software components and provide a clearer overview for the analysis of very complex applications. In this sense, scientific workflows are increasingly used for modeling experiments in various disciplines such as Geoscience \cite{1}, Astronomy \cite{2,3}, Bioinformatics \cite{4}, and so on. Scientific workflows usually consist of hundreds or thousands of tasks with different duration that can range from hours or days, to even weeks. In addition, workflow tasks present different requirements in terms of computational resources (CPU, RAM, storage, network bandwidth). On the other hand, the dependencies between workflow tasks determine a variable workload during workflow execution, with intervals where many tasks can be executed in parallel, and intervals with long executions of sequential tasks. This variable workload generates a resource demand that is also variable at all times.

Cloud computing appears as an efficient alternative for the execution of engineering and scientific workflows, since it facilitates the elastic access to the computational infrastructure required by such type

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of application [5][6]. Particularly, the IaaS Cloud service model allows users to create and destroy different types of Virtual Machine (VM) instances under a pay-per-use scheme. In this way, it is possible to dynamically adjust the infrastructure according to the variations in the resources demand that occur during the execution of workflows. This feature of Clouds together with the need to achieving efficient workflow executions, encourages the study and development of autoscaling strategies for workflows in the Cloud [7][8]. These strategies are aimed to optimize the application execution based on different objectives such as execution time and economic cost, as well as compliance with restrictions or the Service Level Agreements (SLA), if specified. The SLA represents an agreement between a service provider and its users to define quality aspects of the service offered by the provider based on user requirements [9].

Autoscaling strategies periodically solve two interrelated optimization problems, scaling and scheduling. The scaling consists of adjusting the number and type of Cloud resources acquired (e.g., VMs) according to the application demand. On the other hand, the scheduling consists in assigning each task to the acquired resources. Both subproblems are NP-hard so they are usually approached with heuristics. Considering that the variability in Cloud performance represents an important factor of uncertainty in the execution of applications, several recent investigations propose solutions based on Reinforcement Learning (RL) to solve some of the involved subproblems, the scaling stage [10][11][12][13][14][15][16][17][8] or the scheduling stage [17][18][19][20][21][22][23].

RL is one of the three basic machine learning paradigms together with supervised learning and unsupervised learning. Specifically, the RL proposes a computational approach that allows an agent to learn the appropriate behavior to achieve its objective by interacting with a stochastic environment [24]. The agent periodically takes an action that modifies the state of the environment and observes a reward signal that allows the agent to evaluate the immediate effect of the action taken. Actions also have long-term consequences that are not immediately perceptible. Therefore, the RL purpose is to let the agent learn appropriate policies –i.e., mapping the states to actions– in order to generate the greatest long-term benefit in accordance with the agent objective. RL-based strategies are being widely used and very encouraging results have been obtained in areas such as game theory [25][26], which has motivated its study and application in other areas, concretely autoscaling in Clouds.

It is also important to highlight that some of the benefits of addressing the autoscaling problem of workflows in Cloud from the perspective of the RL are the following: a) policies are transparent, i.e., they not dependent on human intervention or a deep knowledge domain, since the scaling and scheduling policies are learned through interaction with the environment; b) policies are dynamic, i.e., the learned policy determines the most adequate action based on the current state of the environment and the application execution, instead of a static plan previously computed as it happens in solutions based on meta-heuristics; and c) policies are adaptable, i.e., the online learning of policies facilitates policy improvement and constant update, this is learned policies are able to adapt to the changes that occur in the dynamics of the Cloud environment, unlike policies learned in offline mode [17][8] that are prone to become obsolete in time.

Hence, we have conducted a literature review of relevant works that address the Cloud autoscaling problem for workflows via solutions based on RL. We have classified the surveyed works based on a taxonomy according to the type of RL-based technique used. From the analysis of the state of the art in the application of RL strategies for autoscaling in Cloud, noticeable findings are that none of the works jointly solves the scaling and scheduling subproblems. In addition, very few works have been proposed for workflow applications, and those who consider workflows only focus on the scheduling without taking into account the scaling problem. These fact altogether evidence not only the promissory nature of RL-based workflow autoscaling in Clouds but also the fertile characteristic of the area in terms of prospective future improvements.

This article is organized as follows. In Section 2, the background is presented, explaining underpinning concepts such as workflow applications, the Cloud Computing paradigm and related provisioning models and the autoscaling problem. Section 3 discusses the relevant works in the area in detail. Then, in Section 4 the limitations of the surveyed works and open problems are highlighted. Section 5 concludes the survey. Finally, in Appendix A we introduce the basic concepts of RL as well as an overview of different relevant techniques under such learning paradigm exploited by the surveyed approaches.
2. Background

In this section, the theoretical and technical foundations underpinning the present paper are discussed, namely those related to workflows applications, Clouds as execution environment, and the concept of workflow autoscaling. For this, the concepts and fundamental characteristics of workflows are presented in subsection 2.1. Then, the Cloud computing environment and its different service models are analyzed in subsection 2.2. Finally, in subsection 2.3 we describe the Cloud autoscaling problem for workflow applications by integrating the two previous topics.

2.1. Workflow Applications

The term “workflow” has its origins in the business world and is closely linked to the automation of business processes. In order to meet the needs of commercial companies, a whole industry of tools and technologies dedicated to the management of workflows [27] has been developed and marketed.

Broadly, workflows describe a complex objective through the composition of a set of tasks and their dependencies. On the other hand, workflow technology has been focused on the development of applications that use readily-available software components. This approach allows people without experience in programming languages, but with knowledge of the problem domain, to contribute in the development of new applications. Currently, workflows are widely used in the modeling of complex research experiments in several disciplines such as Geoscience [1], Astronomy [2, 3] and Bioinformatics [4], among many others. Hence, workflows built in this context are termed “scientific workflows”.

2.1.1. Workflow Representation

Workflows are commonly represented as directed acyclic graphs (DAG), where the nodes represent the tasks and the edges represent the dependencies among them, as shown in Figure 1. The structure of dependencies in a workflow determines the order in which the tasks can be executed. There are two types of dependencies between tasks [28]: data dependencies, where it is necessary to transfer data from one task to another so this latter can actually execute, and flow control dependencies, where one task can not start until another task has finished. In both cases, a task \( t_1 \) is considered the child of a task \( t_2 \), when \( t_1 \) must wait for the completion of the execution of \( t_2 \) to begin its own execution (\( t_1 \) depends of \( t_2 \)). In addition, in such case \( t_2 \) is considered the parent of \( t_1 \). Generally, a workflow task cannot start running until all of its parent tasks have been completed. Then, those tasks that do not have a parent are considered initial task or workflow input tasks, and tasks that do not have children are considered final tasks or workflow output tasks.

2.1.2. Metrics

When a complex computational process is represented through a workflow, dividing it in specific tasks and their dependencies, the next step is to facilitate their execution in some type of computing infrastructure. In order to complete the execution of a workflow all of its tasks must be executed while considering their dependencies. Then, for the efficient execution of a workflow, one of the main issues to consider is the total execution time, or makespan. The makespan of a workflow is closely related to the start times and the durations of the tasks that compose it.

Let \( T \) be the set of tasks that compose a workflow, then, the makespan is computed as:

\[
\text{makespan} = \max_{t \in T} \{ \text{EST}(t) + d_t \} - \min_{t \in T} \{ \text{EST}(t) \}. \tag{1}
\]

where \( d_t \) is the duration of a task \( t \). In practice, \( d_t \) is mostly unknown beforehand and hence workflow schedulers aiming at minimizing makespan have to estimate \( d_t \) by using a performance prediction mechanism [29]. \( \text{EST} \) is the earliest start time and accounts for the minimum time at which a task can start its execution taking into account its parent tasks, i.e. the preceding tasks according to workflow dependencies. Moreover, the EST of a waiting task \( t \) is computed as:

\[
\text{EST}(t) = \max_{1 \leq k \leq p} \{ \text{EST}(t_k) + d_k \}, \tag{2}
\]
where $t$ is a waiting task, $t_k$ is one of the $p$ parent tasks of $t$ and $d_k$ is the estimated duration of $t_k$. Then, for tasks that are ready to execute, the EST is set to the current time.

Figure 1 shows an example of a workflow composed of 5 tasks and 5 dependencies. The red color indicates the path formed by critical tasks. The critical tasks are those tasks that if delayed cause an increment of the workflow makespan.

Computing the EST of tasks allows the workflow scheduler to estimate the next workload of the application. For example, it is possible to determine how many tasks will be ready to execute in the next hour, by checking if the EST of the tasks are in the corresponding range. In order to compute the value of EST prior to the execution of the tasks, it is necessary to estimate the duration of the tasks based on the characteristics of the computation infrastructure available (e.g. expected machine load). For this, existing performance prediction mechanisms can be used [30, 29]. However, such mechanisms come with unavoidable estimation errors that will affect the computed value of EST. In order to mitigate discrepancies between the actual and estimated values, it is important that the estimated values be frequently adjusted, based on updated information on the application status and the execution infrastructure.

2.1.3. Basic Workflows Structures

A workflow essentially represents a flow with different individual processing steps, and each of these steps or tasks can be defined by the following three elements:

1. Entry description: data required to complete the task.
2. Procedure: algorithm that performs the purpose of the tasks.
3. Output description: elements generated by the task, which are usually used as input in subsequent tasks (dependent tasks).

Bharathi et al. [31] describes different basic structures that can be found in workflows, and particularly scientific ones. These structures are often repeated multiple times creating more complex patterns especially in workflows composed of hundreds or thousands of tasks. Figure 2 shows such basic workflow structures.

Process structure is the simplest because it only consists of a task that takes an input and produces an output. Then, if several of these processing tasks are sequentially combined, a pipeline structure is created. The pipeline structure is quite common in workflows and consist of tasks that use as input the output of the previous task, in turn, each output is the input to the next task. On the other hand, there is the distribution structure where the tasks are used for two types of objectives: generate data which is consumed by multiple tasks, or divide a very large data input into smaller chunk to be processed by other subsequent tasks. These types of structures can consume a lot of time and computing resources, but then they usually bring the workflow to higher levels of parallelism (in terms of number of parallel workflow tasks). Achieving higher levels of parallelism is the main interest when it comes to dividing large data. Then, the aggregation structure links and processes the outputs of several individual tasks, generating a combined output. These types of tasks also tend to consume a lot of time and resources, and moreover, represent a reduction in the parallelism degree of the workflow. In some cases, the previously aggregated data is then redistributed. This type of redistribution structure represents a synchronization point from the perspective of data processing. Although redistribution tasks usually represent potential bottlenecks, the parallelism increases again in the next state of the workflow.

Figure 2 show two examples of scientific workflows where the different basic structures are illustrated with different colors. First, Figure 2a shows an example of a small (20 nodes) Montage workflow. Montage
is a toolkit created by the Infrared Processing and Analysis Center (IPAC) at NASA aimed to generate custom mosaics of the sky from a set of input images. The geometry of such input images is used to compute the geometry of the final mosaic. The geometry is used to re-project the images into the same scale and rotation. Then, the images are corrected for standardizing the different background emissions to the same level. Re-projected and corrected images are added together into the final mosaic. Figure 3a illustrates the aggregation, distribution and pipeline basic structures shown in Figure 2.

Then, Figure 3b illustrates the redistribution and aggregation structures in the Laser Interferometer Gravitational Wave Observatory (LIGO) workflow. LIGO is in the crusade for the detection of gravitational waves resulting from several events in the universe according to Einstein’s theory of general relativity. The LIGO’s Inspiral Analysis Workflow [3] analyzes data from the coalescing of binary neutron stars and black holes. Time-frequency data from events captured by each of the three LIGO detectors is split into smaller chunks for analysis. Each chunk is used to generate a subset of wave forms within a given parameter space later used for computing a matched filter output. When a true inspiral is detected, a trigger is generated and it is checked against triggers from the other detectors.

The execution of scientific workflows, which in general are data-intensive and/or CPU-intensive, requires a large amount of computational hardware and software resources that include computing power, high-speed networks, storage capacity, techniques and sophisticated administration tools, among others. In addition, as discussed above, the structures that describe the workflow dependencies directly impact the variability of the workload during execution. On the one hand, high potential parallelism might arise, followed by bottlenecks or long sequential tasks periods, and viceversa. Such variability determines instants of time where an infrastructure with greater or lesser capacity is required. In this context, the elasticity of the Cloud computing model makes it an excellent candidate to meet the computational requirements of this type of applications [5][6]. The following section discusses the main features of this computing model.

2.2. Cloud Computing

The National Institute of Standards and Technology (NIST) defines Cloud Computing as “a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction [32]”. Under this definition, Cloud Computing is composed of five essential characteristics, three service models, and four deployment models. The essential characteristics are:

1. On-demand self-service: A consumer can unilaterally request computing capabilities, such as server time and network bandwidth as needed, and automatically, i.e. without requiring human interaction with each available service provider.
Figure 3: Examples of workflow structures in real scientific workflows (adapted from [31]).

2. **Broad network access**: Such capabilities are available over the network and accessed through standard communication mechanisms that promote the use of heterogeneous platforms (mobile phones, tablets, laptops, and workstations).

3. **Resource pooling**: A provider’s computing resources—storage, processing power, memory and network bandwidth—are pooled to serve multiple consumers using a multi-tenant model, with different physical and virtual resources dynamically assigned and reassigned according to consumer demand. There is a sense of location independence in that the customer generally has no control or knowledge over the exact location of the resources but might be able to specify a location at a higher level of abstraction (country, state, or datacenter).

4. **Dynamic elasticity**: Capabilities can be elastically provisioned and released, in some cases automatically, to scale up and down rapidly according to resource demands. To the consumer, the capabilities available for provisioning often appear to be unlimited and hence can be acquired virtually in any quantity at any time.

5. **Accounted service**: Cloud infrastructures automatically control and optimize resource usage by leveraging a metering capability at some level of abstraction according to the type of resource or service (storage, processing, bandwidth, active user accounts, and so on). Usage can be monitored, controlled, and reported, providing transparency for both the provider and consumer of the utilized resource or service.

A Cloud infrastructure consists of the physical layer (hardware) and the abstraction layer (software) that enable for these five essential characteristics. The physical layer consists of the hardware resources that are necessary to support the Cloud services that are provided on top of them. The abstraction layer consists of the software implemented in the physical layer, which manifests the essential characteristics of Cloud Computing. Conceptually, the abstraction layer is above the physical layer.

### 2.2.1. Service Models

The tendency to expose Everything as a Service (XaaS) when it comes to Cloud capabilities describes a widely adopted scenario in which service-oriented architecture and design principles underpin the development and implementation of software services in Clouds [33]. In this sense, NIST defines the three following service models in the Cloud:

- **Infrastructure as a Service (IaaS)**, where “service” means resource: Is the most basic but at the same time ubiquitous model by which an IT infrastructure is deployed in a datacenter as VMs.
Moreover, IaaS Clouds often offer additional resources such as disk image libraries, raw (block) and file-based storage, low-level network services (e.g., firewalls), load balancers and elastic IP addresses. The providers supply these resources on-demand from their large resource pools installed in datacenters. An IaaS Cloud enables on-demand provisioning of computational resources in the form of VM deployed in a datacenter, minimizing or even eliminating associated capital costs for users, and letting those users adding or removing capacity from their IT infrastructure to meet peak or fluctuating resource demands. Examples of IaaS providers include Amazon EC2, Windows Azure Services Platform and Google Compute Engine.

- Platform as a Service (PaaS), where “service” means platform-level functionality: In this model, the user can create their own software using tools and/or libraries from the provider, including operating systems, programming languages, databases, and Web servers. The user also controls software deployment in the Cloud and configuration settings. PaaS facilitates the deployment of Cloud applications without the cost and complexity of buying and managing the underlying hardware and software layers, while offering hosting capabilities. Some examples are Google App Engine and Windows Azure Cloud Services.

- Software as a Service (SaaS), where “service” means application: Under this model providers install and operate application software in the Cloud, which is accessed by users by using a Web Service API. Cloud users do not manage the Cloud infrastructure and platform where the application runs, i.e., users only interact with installed Cloud applications through the Internet, but they do not know where these applications are running or the implementation and installation details. This model eliminates the need to install and run the application on the user’s own machines, which simplifies maintenance and support. Such Cloud applications can scaled by cloning them onto multiple virtual machines at runtime to meet changing demands. Examples of SaaS are Google Apps, Microsoft Office 365, and Dropbox.

- Function as a Service (FaaS), where “service” is referred to as a “serverless architecture”: It is based on the functions which can be triggered by a given event, so FaaS is also an event-based architecture. Building an application following this model means just writing functions without pondering about concerns such as deployment, server resources, scalability, etc. The most prominent example is AWS Lambda, but there are others alternatives such as Google Cloud Functions, Microsoft Azure Functions, and Webtask.io.

On the other hand, there are different deployment models of Cloud depending on the type of users \[32\]. Private Clouds are for the exclusive use of an organization/company with multiple members. Communities Clouds are for the exclusive use of a community within an organization that share some common objective (such as mission, security requirements, compliance, jurisdiction, etc.). On the other hand, public Clouds are open to the general public and can be owned and managed by business, academic or government organizations, or some combination of them. Finally, hybrid Clouds are those composed of two or more infrastructure types (private, community or public).

2.2.2. IaaS in Public Clouds

This work is placed in the context of the service model IaaS offered by public Clouds providers because the surveyed works mainly focus on how the virtual infrastructure is scaled when running resource-intensive workflow applications. Some of the most recognized providers are Amazon EC2\[1\] and Google Cloud Platform\[2\].

One of the main features of the IaaS model is the elasticity at the infrastructure level, which allows users to dynamically acquire and adjust the computing infrastructure according to their needs. The elasticity in IaaS is supported from a technical perspective through the use of virtualization technologies \[6\]. Virtualization technologies allow us to share the resources of a single physical machine (PM) among several independent VM instances. Several VMs might co-exist in the same PM and have no visibility or

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1Amazon Elastic Compute Cloud: https://aws.amazon.com/ec2
2Google Cloud Platform: https://cloud.google.com/
control over the configuration of the PM that hosts them or over the neighboring VMs. Depending on the configuration, each VM has assigned a portion of the physical resources available in the PM (CPU, RAM, storage and network bandwidth). Then, a VM monitor installed in the PM is responsible for controlling the access of each VM to the physical resources. The VM monitor tries to isolate individual VMs from its environment for security reasons and possible failures, but not to improve performance [34, 35]. Consequently, the unpredictable performance of the VMs [34, 35] becomes one of the main obstacles facing the Cloud computing model [36].

Another key feature of the IaaS model is the eradication of costs associated with the maintenance of the infrastructure, since users only pay for the resources they use. In this way, users are granted access to various types of VMs under a pay-per-use scheme, with a wide range of hardware and software configurations. Typically, prices differ according to the types of VM acquired, but may also vary according to their price model. In this sense, IaaS providers offer various VM options with varying prices, including at least reserved VM instances, on-demand and spot [37]. Existing pricing models offered by Amazon and Google are described below:

**Reserved/Google Committed Use Discounts instances.** This price model is suitable for users with predictable and constant demands, since it allows users to pay a single rate in advance and reserve VM instances for a long period (usually weeks, months or even years). During the reservation period, the use is free or charge with a significant discount compared to on-demand/Non-preemptible instances. However, how much the user can benefit from the reservation scheme depends on how well the resource demand patterns of their application can be foreseen and estimated. Due to the in-advance payment of reservation fees, cost savings with reserved instances are achieved only when the accumulated use of the instances during the reservation period exceeds a certain threshold.

**On-demand/Non-preemptible instances.** This price model is suitable for users with sporadic and bursting demands, since the on-demand option allows users to rent resources more accurately than the reservation option. However, on-demand instances generally have higher prices than reserved instances, considering the same computing capabilities for acquired VMs. In addition, the on-demand option adopts billing cycles generally per hour of use, so partial use of the instances is rounded up to one hour[^3].

**Spot/Preemptible instances.** Clouds providers generally have unsold computing capacity during certain periods. In order to encourage users to buy additional capacity, they offer the option of spot instances. The prices of spot instances fluctuate over time, but they are usually much lower (up to 90% in some cases) than the prices of on-demand instances, considering the same computing capabilities. Then, the user makes an offer with the maximum value (exceeding the spot price) that is willing to pay for the instance and will be charged only with the spot price at any time. On the one hand, spot instances can be used to reduce the economic cost, but when the spot price exceeds the user offer. The fluctuation of the prices in the Amazon spot market based in a bid price are not longer used since March 2018 [38]. Factors that condition the interruption of a spot instance are still internal to the provider and cannot be known without a deep and detailed understanding and analysis of the AWS infrastructure. In the new model, the spot prices are more predictable, updated less frequently, and are determined by supply and demand for Amazon EC2 spare capacity, not bid prices. Then, it is important to consider, together with the economic advantages of spot instances, the fact that spot instances are less reliable, since the tasks they execute are subject to terminations. User-provided checkpoints mechanisms are necessary to avoid losing task progress when the instance in which the task is running is terminated by the infrastructure.

For simplicity, from now on we will refer to the different instances types according to the terminology used by Amazon (reserved, on-demand and spot). In practice, the use of a mixed infrastructure that considers spot and on-demand instances results in an interesting alternative for the execution of workflow applications in Clouds [7], since this allows users to exploit the benefits of both price models while ensuring acceptable reliability. On the one hand, spot instances can be purchased at a lower cost but are less

[^3]: Amazon recently made adjustments to its pricing policies by switching to a billing variant per second, in this way the user pays only for the time used [https://aws.amazon.com/es/ec2/pricing/](https://aws.amazon.com/es/ec2/pricing/)
reliable, while on-demand instances offer maximum reliability at a higher cost. The cost model of a mixed Cloud infrastructure is formally defined below.

Let $I^{\text{type}}$ be the set of supported types of instances (in terms of hardware and software capabilities) and $I^{\text{scheme}}$ the set of three price models previously described (reserved, on-demand and spot instances), the current state of a Cloud infrastructure $I = (I^{\text{type}} \times I^{\text{scheme}} \rightarrow \mathbb{N}_0)$ is defined as the number of reserved, on-demand and spot instances of each type of VM acquired. Then, the computation of the associated cost of such infrastructure $\text{cost}(I)$ depends on the prices of the reserved, on-demand and spot instances that compose it. Formally, an estimated value of the infrastructure cost can be computed as:

$$\text{cost}(I) = \text{cost}_r(I) + \text{cost}_{od}(I) + \text{cost}_s(I),$$

where $\text{cost}_r$ and $\text{cost}_{od}$ are functions that compute the cost of the on-demand and spot instances, respectively. Concretely, the on-demand cost $\text{cost}_{od}$ is computed as:

$$\text{cost}_{od}(I) = \sum_{i \in I^{\text{type}}} \text{price}_{od}(i) \cdot \text{onDemand}(i, I),$$

where $\text{price}_{od}(\cdot)$ is the on-demand price for the instance type $i$ and $\text{onDemand}(\cdot)$, returns the number of on-demand instances of the type $i$ in the current state of the Cloud infrastructure $I$. On the other hand, the spot cost $\text{cost}_s$ is computed as:

$$\text{cost}_s(I) = \sum_{i \in I^{\text{type}}} \text{price}_s(i) \cdot \text{spot}(i, I),$$

where $\text{price}_s(\cdot)$ is the actual spot price for the instances of type $i$ and $\text{spot}(\cdot)$ returns the number of acquired spot instances of type $i$ in $I$.

This IaaS public Cloud model offers to the users, on the one hand, (i) a wide range of options to shape the infrastructure they need for the execution of their applications, and on the other hand, (ii) the elasticity that enables the dynamic reconfiguration of such infrastructure. In this context, the need to develop strategies that take advantage of the elastic capacity that characterizes Cloud infrastructures arises, in order to make workflow execution more efficient. This means to make an intelligent use of available resources to optimize objectives such as execution time and economic cost. For this, it is necessary to take appropriate decisions that allow us scaling the infrastructure according to the current computational needs of workflows, as well as efficiently schedule the execution of the tasks in the available VM. The following section zooms in on these issues.

2.3. Workflow Autoscaling in Clouds

Workflows used in scientific settings perform experiments that can be compute-intensive and/or require the processing of large volumes of data. These workflows usually involve hundreds or thousands of tasks with varying durations that can range from a few minutes to several days or weeks, optionally processing from MiB to TiB of input data. When executing workflows in a Cloud, the duration of the tasks may differ depending on the type of VM acquired. Besides, since tasks usually have different execution profiles (processing load and memory usage), some types of instances may be more suitable for certain instance types than others. For example, Amazon offers different instances type to be used according to the type of problem to solve. Some of them are General Purpose instances, which provide a balance of compute, memory and networking resources, and are suitable for applications that use these resources in equal proportions such as Web servers and code repositories. Moreover, Compute Optimized instances are ideal for compute bound applications that benefit from high performance processors, for example media transcoding, high performance computing (HPC), scientific modeling, dedicated gaming servers, and machine learning inference.
In addition, in public Clouds, the use of resources has an economic cost and moreover, the different types of instances differ in their price. This makes acquiring an appropriate infrastructure (number, types of VM and price models) to efficiently and cheaply execute a workflow a complex problem.

Autoscaling strategies have to deal with the dynamic scaling of the infrastructure according to the application needs (i.e. determining the number and type of instances) and the on-line scheduling of such tasks on the running infrastructure. These are two interdependent problems that must be solved in tandem [7]:

1. **Scaling**, which consists in determining and allocating the appropriate number of instances for each VM type and price models.
2. **Scheduling**, which consists of assigning workflow tasks for execution in the acquired VM instances.

Both subproblems are NP-hard and, therefore, the solutions proposed to date are mainly based on heuristics [39][7][40][41].

In a Cloud infrastructure, the demand of resources fluctuates over time, and the VMs located in the same PM constantly compete for the resources they share. In addition, the potential variations in network traffic impact the communication speed between physically separated VMs. All these elements makes the performance of the Cloud infrastructure to vary. This variability in Cloud performance represents an important uncertainty factor in the decision-making processes behind scaling and scheduling, since the real duration of tasks usually differs from the estimated values. Then, the autoscaling strategies need to frequently update the information they have available for taking those decisions, considering that:

- workflows present variable workload patterns at different stages,
- models that estimate task durations are imperfect, and
- Cloud infrastructures are characterized by variable performance.

This dynamism allows adapting the execution and mitigating the effects of discrepancies between the available information about tasks (estimations) and the real progress of the execution. Broadly, autoscaling strategies need to monitor the state of the environment (infrastructure and workflow) to make appropriate scaling and scheduling decisions at runtime. Then, autoscaling strategies are executed periodically as shown in Figure [4]. In each update interval autoscaling strategies adjust the number of instances for each VM type and price model, and assign the tasks to the currently available VMs.
In each update interval, the autoscaling strategy addresses an optimization problem based on certain objectives of interest such as load balancing, throughput, flowtime, energy consumption, makespan and cost. It is important to mention that both the makespan and cost, or a combination of both, are the optimization objectives most addressed by researchers in the context of Cloud scheduling [42]. More formally, given the set $I^{\text{type}}$ of types of instances (in terms of hardware and software capabilities) considered for autoscaling, the set $I^{\text{scheme}}$ of three price models (reserved, spot and on-demand instances), and the set $I$ of available instances in the current infrastructure, then, in each update interval the autoscaling strategies generate:

- $X^{\text{sca}} = \{I^{\text{type}} \times I^{\text{scheme}} \rightarrow \mathbb{N}_0\}$, a scaling plan that indicates the required number of reserved, on-demand and spot instances of each type, and

- $X^{\text{plan}} = \{T \rightarrow I\}$, a set of scheduling decisions that map each $t \in T$ to one of the $i \in I$ instances.

The estimation of $\text{makespan}(X^{\text{sca}}, X^{\text{plan}}, S)$ depends on the current state of the application and infrastructure as well as the estimation of the start times and tasks durations that have not yet been executed. Then, makespan is computed as shown in Eq. (1). The estimate of the cost of $X^{\text{sca}}, U^{\text{bid}}$ depends on the instance prices which in turn are defined by the used pricing models. Then, the cost is computed as shown in Eq. (3).

The problem of optimizing the execution of workflows in Cloud with autoscaling strategies can be addressed from different perspectives: the execution of individual workflows from different users, the execution of multiple workflows from the same user, or many workflows from different users. In all cases, it is important to consider that when exploiting non-dedicated IaaS Cloud, the performance can be affected by workloads external to the workflows being executed themselves.

Thus, although most of the proposed solutions for the autoscaling problem of workflows in Cloud are based on heuristics, several recent research aims to apply reinforcement learning approaches to solve any of the subproblems involved, the scaling [10, 11, 12, 13, 14, 15, 16, 8] or scheduling [17, 18, 19, 20, 21, 22, 23], which are characterized in Cloud by the conditions of uncertainty.
3. Review of Cloud Autoscaling based on RL Techniques

The two subproblems associated with Cloud autoscaling—i.e. scaling and scheduling—have been addressed in the literature as decision-making problems in stochastic environments. The actions related to scaling consist of increasing or reducing the number of VMs in the virtual infrastructure, while the actions related to scheduling consist of assigning each task to a specific acquired VM. The uncertainty in these problems is associated with the variability in the performance of the Cloud infrastructure. In this sense, proposals that model the autoscaling problem as an MDP and use different RL techniques to learn adequate scaling policies [10, 11, 12, 13, 14, 15, 16, 8] or scheduling [17, 18, 19, 20, 21, 22, 23] have appeared. These policies allow an autoscaler to determine which action is more convenient at any time, in order to optimize in the long-term one or more objectives from the point of view of the execution of one, or a set of applications/workflows.

As we describe in Appendix A, there are different techniques for obtaining adequate policies for this type of problem. On the one hand, there are DP-based techniques, which by nature require a perfect model of the environment. DP-based techniques through algorithms like Value Iteration (see subappendix A.2) allow an autoscaler to compute an appropriate policy in offline mode. On the other hand, there are TD-based algorithms such as Q-learning and SARSA (see subappendix A.3). The strategies do not need to have a perfect model of the environment to compute a policy. In a process of continuous interaction (online) between the policy and the value function of the states $Q(s,a)$, both policies are updated and improved over time. As we mentioned earlier, RL techniques are usually affected by large state spaces, which directly impacts the performance of the aforementioned algorithms in terms of the time to compute a solution and the memory usage. In this sense, the use of non-linear functions to approximate $Q(s,a)$ has been proposed, and moreover, solutions that combine RL with deep neural networks, i.e. Deep Reinforcement Learning (DRL) (see subappendix A.5) have appeared. There are also proposals that use Fuzzy Logic (FL) to represent rules capable of “fuzzily” encompassing multiple states in the context of RL, i.e. Fuzzy Reinforcement Learning (FRL) (see subappendix 5).

In the next subsections, relevant works for addressing the Cloud autoscaling problem via solutions based on RL are described and analyzed. The works are first organized according to the type of technique used as defined in taxonomy depicted in Figure 5. On the first level of the taxonomy, proposals based on DP and TD are presented. Then, on a second level, proposals based on TD are classified in three groups. First, are those proposals that apply the technique in its original or pure formulation. These techniques are further subdivided into sequential or parallel, since the variant of RL given by (multi-thread or multi-process) parallel learning is distinctive. Second, we present the proposals that combine TD with neural networks, and finally, the proposals that combine TD with FL.

![Diagram](image_url)

Figure 5: Classification of the RL based techniques applied to the Cloud autoscaling problem.

Although in the state of the art it can be found other articles that address the Cloud autoscaling problem with the RL based techniques illustrated in Figure 5, in this work we focus on the analysis of articles published in scientific journals of impact and prestigious international conferences.
3.1. Approaches based on Dynamic Programming

There are only two proposals [17, 8] based on DP techniques. Both proposals have in common that, on the one hand, the probability distribution of the transition between states is estimated based on the requirement to have a complete model of the environment to derive the policy. On the other hand, both works share the limitation of learning the policies in an offline mode while operating in a dynamic environment (Cloud infrastructure).

Barrett et al. [17] propose an approach for the efficient scheduling of workflows in Cloud with the aim of minimizing the makespan and monetary cost. First, a genetic algorithm allows the approach to evolve different execution plans, where each workflow task is assigned to one of the available VMs. Then, through an MDP formulation and Value Iteration, a policy that dynamically chooses among the evolved plans the most suitable one for the moment is obtained. This policy considers the current state of the infrastructure. In [17], since there is no perfect model of the environment, the probability distribution of the transitions between states is estimated from the information obtained from multiple previous workflow executions. In this sense, there is a limitation by which the quality of the obtained policy will depend directly on the quality of the estimate of $P(s, a)$.

Then, Gari et al. [43, 8] study the learning of budget allocation policies for the autoscaling of workflows in Clouds. In such works, through the outputs of multiple workflow executions, an MDP model is built, and then through the use of Value Iteration appropriate policies are derived. The derived policies are instead used by an autoscaling strategy called SIAA [7] to determine in each autoscaling cycle, the adequate proportion of spot versus on-demand instances that must be maintained. The policies consider conditions of the environment related to the workload, the current budget limit, and the probability of failures of the acquired spot instances. Both in [8] and [17] there is a limitation given by the quality of the obtained policy depends on the quality of the estimate performed of $P(s, a)$. In addition, the fact that the policy is learned in an offline mode does not the autoscaler to smoothly adapt to changes in the environment at runtime. For example, the prices of the spot instances and/or the probability of their failures could be subject to variations. Therefore, if the policy was learned in online mode, it could incorporate the experience of new executions and adapt to changes accordingly.

3.2. Approaches based on Temporal Differences

Unlike DP-based methods, TD-based methods adopt an online learning strategy and do not require a perfect model of the environment. This type of methods are usually more appropriate for dynamic environments such as Cloud infrastructures. In this group is the largest number of related works in the area of this survey and we will categorize them according to the classification depicted in Figure 5: pure proposals with sequential learning (subsection 3.2.1), pure proposals with parallel learning (subsection 3.2.2), proposals combined with neural networks (subsection 3.2.3) and proposals combined with fuzzy logic (subsection 3.2.4).

3.2.1. Pure Proposals with Sequential Learning

In this section are the works that use TD-based techniques in their original formulation, as opposed to the proposals based on DRL or FRL, and with a sequential learning process. At each decision time, the value of a single state is updated in the table of values $Q(s, a)$. In this sense, these proposals are more likely to have long training times since the speed of convergence of the RL algorithms depends directly on the dimension of the state space and actions.

Peng et al. [18] propose an approach for optimizing task scheduling in Cloud. The proposal is based on RL and queuing theory. The authors use a state aggregation technique to accelerate the learning process with $Q$-learning. Then, for experimentation in CloudSim [44] two types of methods for task submission were defined: individual and grouped scheduling methods. In individual scheduling, user requests arrive continuously (as in regular Web requests or database queries) and an immediate response is required. In this context, the proposal outperformed in terms of response time to strategies such as FIFO, fair-scheduling, greedy-scheduling, and random-scheduling. On the other hand, in grouped scheduling, user requests arrive in groups (e.g. scientific calculations or business statistics) and it is required that the scheduler be able to optimize the arrangement of tasks according to their resource requirements and the current state of the infrastructure. This approach outperforms two competitors: genetic-algorithm and
**modified-genetic-algorithm** [47] in terms of makespan. This work is limited in terms of achieved algorithm scalability since both the dimensions of the state space and the number of actions depend on the number of used VMs, which could make the problem difficult to solve in a context of tens of VMs. In fact, the authors perform the experiments with a maximum of 10 VMs and only considered homogeneous VMs. An heterogeneous infrastructure would make it possible to use VMs that best fit the resource requirements of different types of tasks, which helps to achieve a higher execution efficiency.

Xiao et al. [19] propose a distributed mechanism for scheduling independent tasks in the context of hybrid Clouds. The authors aim to maximize the capacity of the available processing entities (PE) (physical or virtual machines) by considering a cooperation scheme between the schedulers of the different Clouds. The approach tries to guide the scheduling decisions based on experience, and therefore, the problem of each scheduler is modeled as an MDP and *Q-learning* is used to obtain the appropriate scheduling policy. For the definition of the states, the authors consider the task type and the workload of the PE to which tasks can be assigned. The authors use an aggregation strategy to reduce the state space based on a predefined granularity parameter. The actions correspond to the selection of the PE where a task will be assigned. In this sense, the proposal could have algorithm scalability problems since the space of actions depends on the number of PEs, which might be large in a real Cloud. Then, the reward is defined as an inversely proportional function to the response time associated with the scheduling, i.e. the reward corresponds to the objective of the optimization problem. The results show that the work [19] improves the response time compared to five state-of-the-art scheduling algorithms [48]: opportunistic-load-balancing, minimum-execution-time, minimum-completion-time, switching-algorithm, and k-percent-best.

Duggan et al. [20] propose an RL-based strategy to schedule migrations of VMs, taking into account the current use of network resources in a Cloud. The idea is to learn to determine the most appropriate time to migrate a group of VMs from an overloaded PM to another with less use. The proposal aims to reduce the saturation of network resources during rush hours, as well as to reduce the migration time of the involved VMs. The authors define a state space based on the current bandwidth and an estimation of the potential level of network saturation in the near future (increase, decrease, stable). The actions to be carried out are: perform or delay the migration of a particular VM by using a negative reward based on the migration delay. The RL-based algorithm used is *Q-learning*. For comparison the authors used an algorithm called *minimum-migration-time* [49]. This heuristic algorithm decides the migrations of the VMs based on the amount of RAM used. In addition, the authors define a cost function to evaluate the migrations based on the network saturation level at the time of migration, the migration duration and a penalty in case of waiting. The proposal [20], in comparison with the minimum-migration-time algorithm, was able to reduce migration cost, as well as the use of network resources measured as the extra amount of Gb consumed from the link. The results also show that the RL-based strategy learns to perform the migrations when there are less network traffic. Moreover, this strategy contributes to reduce the network saturation during rush hours and reduces the duration of the migrations.

Soualhia et al. [22] propose ATLAS+, a MapReduce-based task scheduler for Hadoop [51]. ATLAS+ is dynamic, adaptable and its goal is to minimize tasks failures (unforeseen events in the Cloud environment such as data lost in storage systems, hard-drive failures, etc.). The proposed framework is based on 3 components: (i) a machine learning algorithm (Random Forest) to predict the probability of task failures, (ii) a dynamic predictor of possible infrastructure failures and (iii) a scheduler based on policies generated by an MDP. For scheduling purposes the life cycle of the task that transits through different stages is modeled (submitted, scheduled, waiting, running, completed, failed). Then, the possible actions to change the status of a task are: process, reschedule, or kill the task. The objective of this proposal is to reduce the tasks failures to have a minimum impact on their execution time. To learn the policy a variant of RL that starts with the SARSA algorithm (for further exploration of the policies) in the first 30 minutes is proposed, and then, *Q-learning* is used for further exploitation of acquired knowledge. Experiments show that this proposal outperforms other Hadoop schedulers as *FIFO*, *Fair* y *Capacity*. Reductions of 59%, 40% and 47% in the number of failed tasks, the total execution time and the task execution time, respectively, were observed. In addition, the approach also reduces the use of CPU and memory in 22% and 20%, respectively.

Dutreilh et al. [19] present VirtRL, an autonomous solution to the problem of dynamic adaptation of the amount of resources allocated to Cloud applications. VirtRL is based on the *Q-learning* algorithm. In VirtRL, the number of user requests per second, the number of VMs assigned to the application and
the average response time of requests are considered for the definition of the states. Then, the actions represent the increase, reduction or maintenance of the number of VMs while the reward considers the cost of acquire or maintain the VMs and a penalty for Service-Level Agreement (SLA) violations. A SLA is a commitment between a service provider and a client. Particular aspects of the service such as quality, availability and responsibilities are agreed between the service provider and the service user. Concretely, the main contribution of this work \cite{10} is to include and integrate in an automatic Cloud autoscaler the following elements, (i) an initialization of the function $Q(s, a)$, (ii) acceleration in the convergence at regular intervals of observations and, (iii) a mechanism for detecting changes in the performance model.

Moreover, Ghobaei-Arani et al. \cite{14} propose an RL-based resource provisioning approach for Cloud service applications. The $Q$-learning algorithm is used for a decision-making agent to learn when to add or remove VMs in order to find satisfactory compensation between SLA and costs. The authors define 3 possible states based on the CPU utilization degree of the infrastructure and 3 possible actions: expand, reduce or maintain the infrastructure. The performance was evaluated with real workloads and the approach was compared with 3 state-of-the-art strategies: Cost-aware-LRM \cite{52} and Cost-aware-ARMA \cite{53}, both based on workload predictions, and DRPM \cite{54}, a multi-agent system to monitor and provision Cloud resources. The results showed that this approach was able to reduce by 50% the total cost and increase the use of resources by 12%.

Dezhabad et al. \cite{15} address the automatic autoscaling of virtualized firewalls in a Cloud. The authors propose GARLAS, a solution that combines RL with a genetic algorithm and queue theory. The idea of this work is to determine the number of firewalls that must be active at all times according to the intensity of the input load and the proportion of requests that each one handles. This approach aims to optimize the balance between the firewalls use degree and compliance with SLA related to system performance (for example, response time). On the one hand, an automatic autoscaler based on RL that decides when it is convenient to increase or reduce the number of active firewalls, dynamically adjusting the system to avoid overloading or wasting resources, is proposed. On the other hand, a genetic algorithm is responsible for deciding the appropriate proportion of requests that each of the firewalls must handle, thus balancing the load to minimize the system response time. For the RL-based autoscaling problem, states that consider the current request rate and the number of active firewalls are defined. The actions consist of increasing, reducing or maintaining the amount of active firewalls, and the reward is responsible for penalizing overload or low load states, as well as SLA violations. Then, through the Q-learning algorithm it is possible to converge to an appropriate scaling policy. The proposal was compared with static strategies (number of fixed firewalls) and based on rules (number of firewalls varies according to fixed rules based on load levels). The results show that GARLAS was able to significantly reduce the response time of the system (by more than 80%) and also offers improvements in the use of resources (more than 9%). This is due to a better load balance and a more precise automatic scaling algorithm.

Finally, Wei et al. \cite{55} propose an approach based on the Q-learning adjustment algorithm (QAA) to help SaaS providers make optimal resource allocation decisions in a dynamic and stochastic Cloud environment. The goal of this work is to reduce renting expenses as much as possible while providing sufficient processing capacity to meet customer demands. For this, the authors have considered different VM pricing models, including on-demand and reserved instances. The reward function is calculated based, on the one hand, on the profit that SaaS provider earned by providing service to his end users, and on the other hand, on the performance (the gain of application performance), which depends on the resource utilization levels. If SaaS provider owns sufficient VM instances to execute customer workloads, a positive reward will be received. In contrast, a penalty will be caused if application processing capacity is lower than the customers’ demands. The value of reward or penalty is related to the distance between the offered processing capacity and the real customer workload. SaaS provider keeps learning from previous renting experiences and enriching its knowledge. This accumulated information can help provider know the best choices in different situations and then generate an efficient renting policy for each decision period. Through a series of experiments and simulations, the authors evaluate QAA under different pricing models (on-demand and reserved instances) and compare it with two other resource allocation strategies: empirically based adjustment algorithm (EAA) and threshold-based adjustment algorithm (TAA). EAA adopts a simple strategy to generate new renting policy. Since SaaS provider does not know the upcoming customer workload when making decisions, provider adjusts the number of rental VM instances according to the last workload. TAA is similar to EAA but does not change the renting policy each time. Only when the difference between cus-
tomer workload and processing capacity offered by the SaaS provider exceeds a specific threshold, a new renting policy will be generated.

3.2.2. Pure Proposals with Parallel Learning

In this section we describe those works from the literature that use TD-based techniques in their original formulation (as opposed to proposals based on DRL or FRL), but with a parallel learning process. With the aim of reducing training time, proposals that use several learning agents in parallel and sharing the knowledge acquired have arisen. In this way, the table $Q(s, a)$ is updated at a faster speed, so it is possible to obtain a higher quality policy faster, at the expense of higher approach design complexity.

Barret et al. [11] propose CloudRL, a method based on MDP and $Q$-learning for dynamic scaling in IaaS, in response to changes in workload and infrastructure performance. The states are defined based on the number of user requests, the number of VMs and the Coordinated Universal Time (CUT). Actions are either requesting, maintaining or canceling instances, while the reward includes the cost and a penalty in case of SLA violations. Particularly, the authors have proposed a strategy with multiple agents learning in parallel to mitigate the problem of long convergence time of $Q$-learning. The long convergence time of $Q$-learning is due to it does not have a good initial approximation of $\pi$ and a good initialization $Q(s, a)$. The authors also suggest that the parallel learning is scalable in terms of resource growth, because the number of learning agents can be determined based on the number of available computational resources. In this sense, the proposal should also be scalable in terms of the number of user requests. If we take into account the algorithm scalability in both dimensions, the state space would grow considerably. As a consequence, this would have an impact not only on the parallel computing capacity of the agent but also on the storage capacity to keep accessible information shared between them and the mechanisms for sharing such information.

Benifa et al. [16] present RLPAS, an RL-based approach for automatically scaling virtualized resources in a Cloud. The objective of the proposal is to dynamically configure resources to minimize response time while maximizing resource utilization and performance. The states are defined based on the number of user requests, the infrastructure utilization degree (relationship between acquired and used VMs), as well as the response time and performance observed for each task during a pre-determined period of time. Then, actions are either increasing, reducing or maintaining the number of VMs, while the reward is based on the relationship between performance and the infrastructure use degree. This approach, based on the SARSA algorithm, reduces convergence time and combines parallel learning with the approximation of the function $Q(s, a)$. This approximation is performed by the gradient descent method. For experimentation, reference applications with dynamic workloads were used and RLPAS was compared with the pure variants of $Q$-learning and SARSA, as well as with the approach proposed in [11] and discussed in the previous paragraph. RLPAS outperformed its competitors in terms of CPU utilization, response time, performance (number of requests processed per second) and convergence time.

Nouri et al. [56] present a decentralized RL-based technique for responding to volatile and complex arrival of tasks through a set of simple states and actions. The technique is implemented within a distributed architecture that is able to not only scale up quickly to meet rising demand but also scale down by shutting down excess servers to save on ongoing costs. The states consist of two types of attributes: system state and applications state. System state reflects the level of utilization of resources of a server such as CPU, and the application state represents the performance of each application hosted on the server in terms of metrics such as its response time. In order to make the state–space discrete, the system states and application states are classified into three categories: normal, warning and critical. On the other hand, the actions are categorized in two groups: scale-down and scale-up. Scale-up actions would be suitable when the system is not able to meet the SLA and needs more computing resources. In contrast, scale-down actions would suit situations that the system is in normal condition and it is able to release idle resources so as to minimize the cost. The application actions involve either duplicating, or creating extra instances of an application, or move, wherein an application is shifted to a different server with more available resources. In this approach it is feasible to share the state, take actions and receive rewards among the servers in order to speed up the learning process. Hence, if a server reaches a state which has not been observed by itself, it tries to find knowledge of the state from the shared knowledge. In case that the look-up procedure produces no result, it will take the best possible action using the learning policy. Furthermore, this procedure allows new servers to initialize their knowledge database using the existing shared knowledge. The authors evaluate the
decentralized control technique using workloads from real-world use cases and demonstrate that it reduces SLA violations while minimizing cost of provisioning infrastructure.

3.2.3. Proposals combined with Neural Networks

In this section we describe the works that propose solutions based on DRL (see subappendix 5), combining techniques of RL with DNN to mitigate the problem of the state dimensionality associated to RL-based techniques in its purest variant. When including the use of DNN in the decision-making process, it is important to consider that the solution becomes more complex, in addition to the problems inherent to DNN [57]. On the one hand, deep learning models usually include a high number of hyper-parameters (for example, learning rate, batch size, momentum, and weight decay) [58] and finding the best configuration for these parameters in a large dimensional space is not trivial. On the other hand, DNNs require a large volume of data and consequently a lot of training time. Nevertheless, DRL has proven to be a promising technique since it allows working with very complex state spaces and actions. In this sense, the following works show a first approach to applying DRL to the area of autoscaling in Clouds.

Liu et al. [21] propose a hierarchical framework to solve two important problems in the context of Cloud Computing: task scheduling and the management of energy consumption of the infrastructure. The framework consists of a global layer for the scheduling problem and a local layer for distributed energy management in local PM. At the global framework level, a DRL-based strategy capable of handling the complex state space and actions that characterizes the problem is proposed. In the states definition, infrastructure information (use degree of each PM) and task information (resource requirements and estimated duration) is represented. The actions correspond to the assignment of the tasks to some of the existing PM. The DRL-based strategy consists of an offline construction stage of the DQN, which represents the correlation between the estimated values of Q and the proposed state-action pairs. Then, the strategy continues to operate in an online stage of decision-making and learning based both on Q-learning and the update of the DQN previously trained. On the other hand, the local level of the framework is responsible for energy management, with a distributed mechanism to selectively turn on and off the PMs. This level includes a workload predictor based on a Long Short-Term Memory (LSTM) neural network [59]. Then, an RL-based adaptive energy manager controls the status of any PM based on the workload predictions made by the LSTM. The authors use Google server logs for experiments and the Round-Robin scheduling method for comparisons. The results show that the RL-based proposal achieves significant energy savings, as well as the best relationship between latency (defined as the time span between the arrival of a task and its completion) and energy consumption.

Cheng et al. [23] present DRL-Cloud, an approach based on DRL for workflow scheduling in Clouds. The objective of this strategy is to minimize the energy cost from the perspective of public Clouds providers. For them, the authors propose a process based on DRL, which is highly scalable and adaptable. The definition of the states include infrastructure information (CPU and RAM availability) and workflow task information (deadlines, and CPU/RAM requirements) are used. DLR-Cloud is fully parallelizable and uses training techniques [26] (target-network, experience-replay) to accelerate convergence. The proposal was compared with two methods: Fast and Energy-Aware Resource Provisioning and Task Scheduling (FERPTS) [60] and Round-Robin. Results show significant improvements in the reduction of energy costs, the number of rejected applications (due to deadline violations) and the execution time.

Wang et al. [61] explore the use of RL techniques for horizontal scaling in Cloud. The idea of this work is to learn policies capable of adjusting the infrastructure, achieving a balance between performance and costs. The authors show a preliminary study of 3 strategies of RL: tabular-Q-learning (QL), deep-Q-network (DQN) y double-dueling-Q-network (D3QN), first in the CloudSim simulator and then in the Amazon Cloud. QL corresponds to a classic variant of Q-learning where the function Q is represented in tabular form. DQN uses a deep neural network to estimate the Q function. D3QN is another variant which

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4This kind of neural networks is widely used for predicting time series sequences.

5Target Network: strategy that proposes the use of a second «objective» network, during the training of a DQN, to calculate the updated values of Q. In this way a more stable training is achieved, since the weights of this second network are updated less frequently than those of the original network.

6Experience Replay: strategy that proposes to store the agent’s experiences and then use random data for the training of the DQN. In this way, correlations in the observation sequences are eliminated and changes in data distribution are smoothed out.
uses a second neural network (Double Q-Network [62]) to stabilize the training process and to update the value of the states in a more robust and decoupled form from the specific actions (Dueling Q-network [62]). The study compares a dynamic scaling method based on predefined thresholds of CPU usage (threshold-based method) with the three above mentioned methods based on RL. The results show the superiority of the proposed DRL-based methods. Besides, D3QN significantly outperformed DQN in terms of the accumulated reward and learning speed.

3.2.4. Proposals combined with Fuzzy Logic

This section discusses the works that combine RL-based techniques with elements of FL as another alternative to the dimensionality problem that arises in the purest variants of RL.

Arabnejad et al. [13] address the problem of horizontal resources scaling in Cloud with the aim of reducing application costs and ensuring SLA compliance. In this work the authors propose and compare two strategies based on RL and a FL system. The modified versions (Fuzzy Q-learning and Fuzzy SARSA) of the classic RL algorithms are able to learn and modify fuzzy scaling rules during execution. Both proposals are implemented and compared on the OpenStack Cloud platform. The results show that both proposals are able to handle different workload patterns, reduce operational costs and prevent SLA violations, with acceptable performance in terms of response time and the number of used VMs. It is important to note that the authors use an environment limited to a maximum of 5 VMs to evaluate the strategies together with high workloads.

Veni et al. [12] present an approach for vertical scaling of virtualized resources in Clouds. The proposal is based on neuro-fuzzy reinforcement learning, combining RL with neural networks and the approximate reasoning of fuzzy logic. This combination aims to mitigate the limitations of the most basic variants of RL in a space of large states. The main objective of this work is to dynamically configure the resources of each VM based on the current workload to achieve the maximum overall system performance with minimum resource utilization. For defining the states, three characteristics (related to CPU and memory) are used for each VM. Three actions –increasing, reducing or maintaining– determine the setting of each resource of the VM. The reward considers the relationship between the overall performance of the system and the resource utilization degree. The proposal was compared with a basic variant of RL (Basic-RL) and with a strategy that combines RL and neural networks (VCONF [63]). The results show that the proposal achieves significant improvements in system performance and scalability. Recall that vertical scaling is limited by the underlying hardware. This means that the characteristics of the VMs can be improved only as far as resources are available in the PMs that allocate them. For the scaling problem of applications in Cloud, it would be interesting that this proposal combines vertical scaling with some variant of horizontal scaling to better mitigate hardware limitations.

3.3. Classification of the Reviewed Approaches

For the sake of organizing the surveyed related works, in this section we present three taxonomies that describe the autoscaling problem in Cloud (see subsection 3.3.1), the types of executed applications (see subsection 3.3.2), and the optimization objectives that are addressed in each work (subsection 3.3.3), respectively. Then, in subsection 3.3.4, a deeper comparative analysis based on the surveyed works and defined taxonomies is presented.

3.3.1. Taxonomy of Autoscaling Problems

To identify the specific problem in each surveyed work, in Figure 6 we present a taxonomy of the main addressed problems in the context of autoscaling in Cloud, where the scaling and the scheduling component are dealt as two different complex optimization problems with particular characteristics that we will see next. However, it is important to mention that an important objective for both scaling and scheduling consist of using the highest amount of available resources to achieve the best performance in the objectives that are intended to be optimized. The optimization objectives (for example, execution time and cost) guide the search of possible policies, determining when one policy is more convenient than another. On the other hand, the constraints (for example, response time < 5 seconds) reduce the search space to include

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7OpenStack: Open Source Platform for Cloud Computing (https://www.openstack.org/).
only acceptable policies, leaving out those that do not allow compliance with the constraints defined for the problem. Besides, there are also SLAs, which represent an agreement between the user and the service provider. This agreement defines which aspects must be respected in the quality of the provided service and also represent the constraints for the problem. Although optimization objectives and constraints may have a non-empty intersection, it is important to consider that they have different roles within the optimization problem.

![Autoscaling Problem Taxonomy](image)

Figure 6: Taxonomy of autoscaling problems in Cloud addressed with RL techniques.

The **scaling problem** consists in determining the appropriate decisions behind provisioning and releasing virtualized resources, according to the fluctuations in their demands and with the goal of achieving a more efficient use of them. In other words, an automatic mechanism is required to increase or reduce the infrastructures based on the current needs and taking advantage of the elasticity inherent to Clouds.

Scaling can be classified in horizontal scaling or vertical scaling [64]. In horizontal scaling, the number of VMs assigned to an application is increased or reduced. The idea is to provide the application with the appropriate number of VMs according to the needs at a given time, to fully exploit the capabilities of parallelization in high demand periods and reduce the number of resources in low demand periods. This type of scaling requires spending time for initialization of the VMs and may not be appropriate for all types of applications, for example, database-oriented applications where splitting and distributing data is not trivial. Then, in vertical scaling, the resource settings (CPU, memory, I/O) are dynamically updated, increasing or reducing the VMs capabilities, without hindering the services that VMs are running. The idea is to constantly provide the VMs with the necessary capabilities and update them again when they are no longer required. This type of scaling usually requires less time for resource configuration (< 0.5 seconds) than the time required for horizontal scaling (5 minutes) [64].

On the other hand, the **scheduling problem** in Cloud consist of automatically determining the appropriate decisions about when and/or where a task should be executed to achieve the greatest possible efficiency within the limits defined by the existing constraints. From a temporal perspective, this problem decides which is the most appropriate time for the execution of a task. In the context of workflow scheduling, this type of decision is primarily subject to the order established by the structure of dependencies between
tasks. The scheduling problem can be addressed from the perspective of prioritizing the execution of critical tasks [7] because of the impact they have on the workflow makespan. On the other hand, from a spatial perspective, the problem of scheduling aims to make the connection between each of the tasks and the most appropriate resources to perform their execution. For this, the scheduler usually uses information related to the characteristics of the tasks and the resources available to support the decision-making process. When the scheduler does not have information about the characteristics of the tasks, estimations are used, usually for task durations.

3.3.2. Taxonomy of Application Types

In the context of Cloud Computing we can find different types of applications that need to be efficiently executed, either because they involve many hours/days of computation, because they require many resources or because immediate results are needed for multiple user requests. All these distinctive elements are the ones that usually determine the most convenient type of strategy for making decisions when performing the autoscaling process. In this sense, it is important to classify the applications and analyze their characteristics. Figure 7 shows a taxonomy according to the application types targeted by the works analyzed in the previous sections.

Figure 7: Taxonomy of Application Types.

Workflow applications (see Section 2.1) are increasingly used for modeling of complex scientific experiments. Workflows are usually composed of hundreds or thousands of computing-intensive and/or data-intensive tasks with different durations and resource requirements. The dependencies between workflow tasks determine the order in which they must be executed, since a task cannot begin its execution until all the tasks on which it depends have been completed. The complex structures of dependencies between workflow tasks determine a variable workload during execution. This variability is evident when many tasks can be executed in parallel (high demand for resources). In other cases, bottlenecks may occur, and it is necessary to wait for the completion of some tasks for starting the execution of other tasks (low demand of resources). In this sense, the dependencies between workflow tasks add an important degree of difficulty to the autoscaling problem. When the workflow structure is known in advance, it is possible to use workload estimates to support proper decision-making in the autoscaling process.
Other applications are composed of independent tasks. In some cases the tasks are randomly initialized by the users so they arrive individually and continuously, while in other cases the tasks arrive in batches. When tasks arrive individually and a quick response is required, the autoscaling decisions are based only on the characteristics of the current task and on the state of the infrastructure. In this sense, autoscaling strategies are intended to provide immediate responses. On the other hand, when the tasks arrive in batches, the amount of options to consider is exponentially increased, so strategies that search in the space of possible solutions are often used. An example of this type of applications in the scientific field are the parameter sweep experiments (PSE), a very popular way of conducting simulation-based experiments, used by scientists and engineers, through which the same application code is run several times with different input parameters resulting in different output data \cite{55,56}. PSEs involve large-scale computer modeling and simulation, and often requires large amounts of computer resources to satisfy the ever-increasing resource intensive nature of their experiments. Running PSEs involves managing many independent tasks. It is important to mention that, moreover, an independent tasks application can be considered as a special type of workflow where there are fictitious start and end tasks, and all other tasks are intermediate tasks within the workflow structure \cite{40}.

A third type of application is Cloud services. These applications represent a software product running on Cloud, that can be accessed through the Internet either with a Web browser or with an API. For example, applications for Big Data Analytics enable data scientists to tap into any organizational data to analyze it for patterns and insights, find correlations, make predictions, forecast future crisis and help in data backed decision making. Cloud services make mining massive amounts of data possible by providing higher processing power and sophisticated tools. Generally, each Cloud service application is composed of one or more services that together perform the functions of the application. In this type of applications the response time to users requests is critical. It is important that the applications are scalable in managing the number of requests, which usually generate high demand peaks. Although anatomically these applications do not always strictly comply to a workflow-like structure, we also consider them in this survey as these are heavily used in practice to execute resource-intensive models and data analyses on Cloud infrastructures.

Considering the different Clouds service models (SaaS, PaaS and IaaS) described in Section 2.2, it is interesting to highlight that from the surveyed works, the Cloud services applications are designed under the SaaS model, while workflows and independent tasks based works are intended for IaaS and PaaS models.

### 3.3.3. Taxonomy of Optimization Objectives

When optimizing the execution of applications in the Cloud, different objectives have been addressed. It is very important to identify these objectives because they represent the direction in which the efforts will move in guiding the search among possible solutions. The optimization of multiple objectives is also a recurring issue, and in some cases, the objectives are conflicting between each other, as in the classical trade-off between time and cost in paid Clouds \cite{41}. Figure 8 presents a taxonomy of the most relevant objectives found in the surveyed works.
First, there are the objectives related to Time. On the one hand, it is important to optimize the makespan in applications consisting of compute-intensive or long-duration tasks, as is usually the case of workflow applications. Note that optimizing workflow makespan is more complex than optimizing the execution time of each of the tasks that compose a workflow, since the makespan also depends on the order in which these tasks are executed. On the other hand, the waiting time refers to the time between a task is submitted and finally begins to execute. The waiting time is usually due to overloaded infrastructures with high demand peaks and it is of special interest in applications that process independent tasks. In the case of workflows, the waiting time is also understood as the delay in starting the execution of a task after the execution of all the tasks on which this task depends. For workflow applications the waiting time is also indirectly optimized since it impacts makespan. Finally, in the context of service applications, the response time that represents the delay in the response to a user request is usually optimized. This delay may be due to the overload of the application that needs to be scaled. Both for workflow applications and independent tasks, the response time is considered as the sum of the waiting and execution times.

Secondly are the objectives associated with the Economic Cost. From the perspective of IaaS users, it is of special interest to reduce the economic cost associated with the use of VMs (referred as VM cost). This cost is determined by the pay-per-use schemes defined by public Clouds providers. Each instance type has an assigned price (usually per hour of use) according to its computational performance. In this sense, the optimization can be achieved through a more efficient use of the acquired infrastructure, reducing the computation time required to execute the application. It is also possible to reduce the execution cost with a dynamic and adequate selection of the VM types and the most convenient pricing models. For example, the use of spot instances represents an interesting opportunity. Then, from the perspective of public Cloud providers, it is important to reduce the costs associated with energy consumption, due to their environmental responsibility. The rapid growth of energy consumption and CO2 emission of Cloud infrastructures has become a key environmental concern \[67, 68, 49\]. Therefore, solutions focused on energy efficiency are required to ensure that the Cloud computing model is sustainable from an environmental perspective. On the other hand, by reducing expenses on electric bills, public Cloud providers can also increase their profit margins. Then, the reduction of energy consumption costs has become an important objective of optimization, generally associated with the efficient use of available resources.

Third, an objective group common to all types of applications are those that describe the Resource Utilization degree. It is common to optimize the use of CPU, memory and network. Also, in some cases it is sought to reduce the number of used VMs, and consequently, the computational cost (memory and extra CPU) associated with their administration, and the energy consumption.

Another objective that is evidenced in the literature is to maximize the Performance of the system. Performance is usually defined considering the number of user requests attended per second, being of special interest in service applications. For independent tasks and workflows applications it is also important to minimize the failures of the tasks, which may be due to hardware or software problems in the infrastructure, or particularly, the failures associated with the use of unreliable VM instances (spots or preemptible ones). Finally, the SLA Violations are considered. It many surveyed works, the objective of minimizing the number of SLA violations agreed between the service provider and the users is present.

### 3.3.4. Comparative Analysis

Table 1 shows a summary of the analyzed works in relation to the taxonomies defined above. First, the works are classified in terms of the applied RL technique (RL Technique column, see Figure 5). Furthermore, the RL algorithms used in each case (RL Algorithm column) is shown. Then, the works are classified based on the specific addressed problem (Problem column, see Figure 6), the Optimization Objectives (Objectives column, see Figure 8) and the Application Type (Application column, see Figure 7), respectively.

From the analysis of the characteristics of the surveyed works in the Table 1, the following observations are highlighted.

Regarding the applied RL techniques, most of the works (16/18) have proposed solutions based on TD and only two works use DP \[8, 17\], which is convenient in a context where changes in the environment dynamics are likely to occur. In this sense, the proposals for online learning seem to be more adequate because they are able to adapt to these changes. In addition, there are Cloud autoscaling proposals that attempt to address classical problems inherent to RL, such as (a) the management of large state spaces \[12\]...
Table 1: Comparative summary of the relevant works in the literature that apply RL techniques for Cloud autoscaling.

| Reference          | RL Technique | RL Algorithm | Problem       | Objective(s)                  | Application Type |
|--------------------|--------------|--------------|---------------|------------------------------|------------------|
| Gari2019 [8]       | DP           | Value Iteration | Scaling (H)   | Time, Cost                  | Workflow         |
| Barret2011 [17]    | DP           | Value Iteration | Scheduling    | Time, Cost                  | Workflow         |
| Pen2015 [18]       | TD-Pure-Sequential | Q-learning | Scheduling    | Time                         | Independent Tasks|
| Xiao2017 [19]      | TD-Pure-Sequential | Q-learning | Scheduling    | Time                         | Independent Tasks|
| Duggan2017 [20]    | TD-Pure-Sequential | Q-learning | Scheduling    | Time, Res. Utilization, Resource Use | Independent Tasks |
| Soualhia2018 [22]  | TD-Pure-Sequential | Q-learning & SARSA | Scheduling | Failures                     | Workflow         |
| Dutreih2011 [10]   | TD-Pure-Sequential | Q-learning | Scaling (H)   | Cost, SLA                    | Services         |
| Ghobaei2018 [14]   | TD-Pure-Sequential | Q-learning | Scaling (H)   | Cost, SLA                    | Services         |
| Dezhabad2018 [15]  | TD-Pure-Sequential | Q-learning | Scaling (H)   | Res. Utilization, SLA        | Services         |
| Wei2019 [55]       | TD-Pure-Sequential | Q-learning | Scaling (H)   | Time, Performance            | Services         |
| Benifa2018 [16]    | TD-Pure-Parallel | SARSA        | Scaling (H)   | Time, Res. Utilization, Performance, SLA | Services |
| Barret2012 [11]    | TD-Pure-Parallel | Q-learning | Scaling (H)   | Resource Utilization, SLA    | Services         |
| Nouri2019 [56]     | TD-Pure-Parallel | Q-learning | Scaling (H)   | Cost, SLA                    | Services         |
| Arabnejad2017 [13] | TD-FRL       | Q-learning & SARSA | Scaling (H) | Time, Res. Utilization, SLA | Services         |
| Veni2016 [12]      | TD-FRL       | SARSA        | Scaling (Y)   | Time, Res. Utilization, SLA  | Services         |
| Wang2017 [61]      | TD-DRL       | Deep Q-learning | Scaling (H)   | Cost, Resource Utilization   | Services         |
| Liu2017 [21]       | TD-DRL       | Deep Q-learning | Scheduling   | Time, Resource Utilization   | Independent Tasks|
| Cheng2018 [23]     | TD-DRL       | Deep Q-learning | Scheduling   | Cost                         | Workflow         |

8 In this case the problem modeled with MDP is budget distribution to support scaling decisions
9 The tasks consist of the migration of VMs.
10 MapReduce tasks are used [50].
the poor initial performance [10] and (d) the slow convergence [10].

Regarding the RL algorithms (particularly in the 16 TD-based works), the use of Q-learning (12/16) predominates compared to SARSA (2/16). However, in most cases the selection of Q-learning or SARSA is not much argued. It is interesting to note that one of the works [22] proposes a combined solution that begins learning with SARSA for further exploration in the policy space, and then continues with Q-learning to ensure a more direct convergence towards an appropriate policy. On the other hand, in [13] the authors combine the use of FL with RL. In this work, modified versions of both algorithms (Fuzzy-Q-learning and Fuzzy-SARSA) are used and no significant performance differences are obtained.

Regarding the problem, it can be seen that both scaling (11/18) and scheduling (7/18) have been subject of study from the RL perspective. For the scaling problem, most of the works focus on horizontal scaling, which means that there is a niche area to explore, i.e. vertical scaling applying RL. No proposals that solve both problems together (scaling and scheduling) from a perspective of RL have been found.

Regarding the optimization objectives, in most works the optimization of multiple objectives are pursued. Concretely, most of the surveyed works have proposed to reduce time and costs, to achieve a more balanced resources use, to improve performance, and to reduce failures as well as the violation of restrictions.

Regarding the application type, it is observed that service applications are more associated with the scaling problem. This may be related to the nature of these types of applications, which need to be able to scale to the fluctuating demands generated by multiple user requests while maintaining adequate performance and minimizing cost. On the other hand, both the independent task and workflows applications are more associated with the scheduling problem, assuming a fixed infrastructure. For this type of applications, usually intensive in terms of computation power or data processing, it is intended to distribute the execution of the tasks in the available resources with the aim of maximizing efficiency in terms of time, cost and use of resources. In this sense, it should be noted that 4 proposals consider workflows per se, or the above defined special type of workflow composed of independent tasks (4 works), and therefore, workflows is a type of application which is still to be explored in the area.

4. Discussion

This section analyzes the limitations and scope of the previously surveyed related works. First, the limitations regarding the type of addressed problem, the type of application and the optimization objectives are analyzed. Then, other more theoretical limitations, related to the RL techniques used in the proposals, are discussed. Finally, discussion of open problems and ongoing developments in the area are also discussed.

4.1. Limitations Related to the Autoscaling Problem Formulation, Application Type and Addressed Objectives

«Scaling and scheduling issues are addressed independently». There are no works that aim to solve both issues together from the RL perspective. Especially, for workflows applications and independent tasks, both problems are interrelated and have an impact on the execution efficiency, so it is important to design proposals that address both problems. Due to the fact that the decisions regarding scaling and scheduling are of a different nature (for scaling the actions are related to the reconfiguration of the infrastructure and for scheduling the actions respond to where and/or when the tasks will be executed) it could be necessary to define different models and/or the combination of different techniques to address both problems.

«Mix of works with workflow applications». Among the 18 analyzed works, 8 of them consider pure workflow applications and independent tasks applications. Besides, most works that consider this type of application focus only on scheduling and not on scaling, except the work in [8]. However, the approach in [8] does not scale purely with RL since it also uses a heuristic-based autoscaling strategy. Most scaling proposals are still based on service applications. It is important to note that there is a difference in the nature of workflow applications (long-term tasks, data-intensive or compute-intensive tasks, high-parallelism or bottleneck stages) compared to service applications (generally short tasks under high demand peaks). Then, the strategies designed for service applications are not the most suitable ones for workflows in general, since they try to optimize processes of a different nature. In this sense it is necessary to expand the study on the application of RL techniques in the context of scaling for the efficient execution of workflows in Clouds.
«For the scaling problem, the particular characteristics of the application in relation to the type of required VM are not considered». Particularly, most of the works define the characteristics of the environment based mainly on the state of the infrastructure, the number of available VMs and/or the resource utilization degree, and so on. Some works include information regarding the state of application execution for evaluating the workload. In addition, several authors use homogeneous infrastructures [10, 23]. Although using homogeneous infrastructures is a common choice in HPC on the Cloud, in many cases, using heterogeneous infrastructures leads to better time and cost optimizations. From the works where the authors have considered the use heterogeneous infrastructure [14, 16, 11], only one work [16] represents in the actions of the model the selection of different types of VMs. The surveyed works are mostly based on service applications, where the characteristics of acquired VMs may not be relevant. Conversely, for workflow and independent tasks applications, the characteristics of acquired VMs are very important since they are usually composed of long duration tasks which are intensive in computation/data. Therefore, it is necessary to consider the tasks requirements in terms of CPU, memory and data transfer, to determine the type of VM where tasks execution is viable and/or more efficient.

«Different price models are not considered». Most of the work in the area focuses on the classical payment scheme, where the provider defines for each type of VM a fixed price per hour of use. The Cloud flexibility is also found in the different options that providers offer in terms of price models. For example, Amazon spot instances, whose price fluctuates according to existing demand, have significant cost reductions (up to 90% in some cases), compared to the fixed price model. Considering that the economic cost is one of the main objectives of optimization in this type of problems and it is also usually present in the SLA, it is interesting to exploit the Cloud options in terms of the different price models.

4.2. Limitations Related to the RL Techniques

**Dinamic Programming: «A perfect model of the environment is required»**. This is one of the main limitations of the DP-based methods since in many problems the actual distribution of the transition probabilities between the states is unknown [24]. Even in dynamic environments, these probabilities could change over time. Estimates of the function \( P(s, a) \) are usually used, but it is necessary to take into account that the quality of the obtained policy depends directly on the quality of these estimates. In the works surveyed in this category [17, 8], to obtain an estimation of \( P(s, a) \), the information generated by multiple previous executions of Cloud applications is used. Although it is true that major public Cloud providers (Amazon, Microsoft and Google) have access to a large amount of information regarding executions, and moreover, such information could be used to generate this type of estimated models [8], complexity must be considered for determining the type and amount of information that should be used to avoid the classic problems of over-adjustment and sub-adjustment when approximating functions.

**Dinamic Programming: «Offline policies might no longer be adequate due to changes in the dynamics of the environment»**. The fact that in DP-based approaches the policy is learned offline from a predefined fixed model does not allow it to adjust to changes in the dynamics of the environment. In the context of Cloud a change in the instances prices, for example the price of spot instances, represents a possible case of variation in the environment dynamics. When the execution cost is considered as an optimization objective, the previously computed policy could no longer be adequate since the learning of the environment that the policy represents has become obsolete. If the model continues to be updated and a new policy is recomputed every certain period of time, the resources (time, capacity) required for such computation in an online context should also be considered. In addition, if possible, it is necessary to determine the periodicity with which to perform such updates. In this line, the approaches in [17, 8] present this limitation because the policies are learned in offline mode.

**Dinamic Programming/Temporal Differences: «Difficulty to manage large state spaces»**. This limitation generally affects both DP-based and TD-based methods. In the case of DP the computational complexity of the algorithms is polynomial in the number of states and actions defined in the model. From the two analyzed DP works [8, 17] it can be seen that the state space and actions are limited. On the other hand, in the works based on TD methods [18, 19, 20, 22, 10, 14, 15, 16, 11, 55], the problem of managing many states and actions is associated not only with the requirements to store the function \( Q(s, a) \) but also with the time and amount of data needed to update it. For example, the use of many features (or dimensions) for the definition of the model generates a combinatorial explosion of states that is very difficult to handle. Besides, when the used model is required to be scalable in some of the defined variables, the number of
states increases considerably depending on the possible values of those variables. In this sense, since the problem of the dimension of the state space (also known as dimensionality problem) is one of the main limitations of RL, different alternatives have been studied to try to mitigate its effects. An alternative to this problem consists of the aggregation of states by defining certain ranges of values for the variables that define them, grouping similar states. A second variant is the use of non-linear approximations of \( Q(s, a) \). A second alternative are the proposals that use deep neural networks. A third option is the use of fuzzy logic combined with RL, for evolving rules that enable approximate reasoning.

**Temporal Differences: «Slow convergence»**. In the basic variants of TD algorithms, the function \( Q(s, a) \) is updated when an action is executed, but only the visited state value at that time is updated. Although convergence is guaranteed, this usually involves a long training time, especially when it comes to problems with many states and/or many actions. To reduce training time there are proposals with multiple agents that learn in parallel and share the obtained information. On the other hand, in the authors propose to accelerate convergence using ideas from DP. For this, frequent phases of updating the function \( Q(s, a) \) are defined using estimations of the obtained states values by recording the observations made of the visited states, transitions and rewards.

**Temporal Differences: «Poor initial performance»**. Considering that at the beginning of the learning process there is not an adequate policy (cold start effect), the initial performance of the strategy is usually poor and it will be improved as it converges to an appropriate policy. From all surveyed works, only in we found a proposal to solve this problem using an initial approximation of \( Q(s, a) \).

### 4.3. Open Possibilities

RL has demonstrated a great potential for automatically solving decision making problems, particularly because of their ability to consider long-term consequences of the available actions. Some of the most impressive results have been shown in Game Theory, but the potential of RL can be also extended to many other areas. Specifically, in the case of Cloud autoscaling, only the first steps have been taken and much remains to be done. From the analysis of the State of the Art, it becomes evident that there is a long list of current limitations which in turn means that there is a wide spectrum of research opportunities regarding RL techniques in the area of Cloud autoscaling. In the general sense, there is a wide number of unexplored combinations derived from the taxonomies outlined earlier in Section that could be explored.

In this context, it is interesting to design and develop autoscaling strategies for scientific applications in Cloud that combine a scheduler and scaler, both based on RL. These strategies could be based on the learning of appropriate scheduling and scaling policies, which allow dealing with the inherent uncertainty in the execution of applications in the Cloud. In addition, when policies are learned in an online mode, they would be able to adapt to changes in the dynamics of the environment. In the context of the execution of applications in Cloud, the uncertainty comes from the variability in the performance of the Cloud infrastructure, and also, the changes in the environment may be due to adjustments in the instances prices (as resource prices depend on market-like fluctuations) and even due to the appearance of other types of instances with different performance-cost trade-offs. The scaling policy could aim to adjust the infrastructure dynamically according to the variable demand of the application, while the scheduling policy could determine the most appropriate resource for the execution of each task, considering the characteristics of each task and the available infrastructure. Both policies would be learned from past experience in the interaction with the Cloud environment, modifying it and observing the resulting effects.

Regarding the learning process, parallel learning is a topic that deserves to be explored more deeply. Parallel-learning schemas update the Q values in parallel speeding up the process of policy learning. In real Cloud settings, this kind of schemes might have special importance since multiple autoscaling agents could share the feedback derived from their actions and update the Q-values collectively. From a theoretical point of view, this accelerates policy convergence but also allows that an enormous amount of agents function as feedback collectors while at the same time are benefited from the latest Q updates making the information instantly available to all of the agents.

Nowadays, one-step, tabular, model-free TD are the most widely used RL methods. This is probably due to their great simplicity, but these algorithms can be extended making them slightly more complicated and significantly more powerful (i.e multistep forms, various forms of function approximation rather than
In the area of Cloud autoscaling, the majority of approaches still use the simplest variants of RL methods. Therefore, it is possible to study, in-depth, the applicability of different variants of the basic RL strategies and their combinations with other machine learning methods such as deep neural networks, i.e. Deep Reinforcement Learning. Please refer to Appendix 5 for more details.

Also, the particular states, actions and how they are represented can strongly affect the performance of the implemented approach. In RL, as in other areas of Machine Learning, such representational choices are, nowadays, more an art than a science [24]. In the area of Cloud autoscaling, it is fundamental to study the specific implications of such representational choices (states and actions) and how they impact on the performance of autoscalers. For example, an interesting questions to answer in this matter are: (a) What information from a real Cloud environment is relevant to learn a policy properly? (b) What could be an adequate representation for this information to accelerate the learning process?

On the other side, the problem of Cloud autoscaling is closely related to Multi-objective Optimization (MOO). The reader might have noticed that in almost all surveyed papers, multiple optimization objectives are present. Even more, conflicting objectives (such as economic cost and execution time) are very common in this context. Current proposals usually combine these objectives in the reward function trying to optimize all of them at the same time. However, many other possibilities are being investigated in the active area of research called Multi-objective Reinforcement Learning (MORL) [69], which basically combines the concepts and strengths of two important fields: MOO and RL. Needless to say that the study of MORL techniques in Cloud autoscaling is a fundamental future line of research but yet it is incipient.

5. Conclusions

The flexibility and elasticity offered by the Cloud Computing paradigms has opened opportunities to the study of autoscaling strategies for the efficient execution of workflows, independent tasks and Cloud service applications. On the one hand, the variability in Cloud performance generates an important uncertainty factor for making scaling and/or scheduling decisions during application execution. In this sense, RL-based strategies allows autoscalers to learn appropriate policies through interaction with a stochastic environment. In this context, several recent research are focused on the application of RL-based strategies to some of the autoscaling subproblems, i.e. scaling and/or scheduling.

Motivated by these facts, in this paper we have analyzed relevant works for addressing the autoscaling problem in Cloud by solutions based on RL. We have classified the surveyed works in a taxonomy according to the type of RL-based technique used. On the first level of the taxonomy, proposals based on Dynamic Programming (DP) and Temporal Differences (TD) are presented. Then, on a second level, proposals based on TD are classified in three groups. First, are those proposals that apply the technique in its original or pure formulation. These techniques are further subdivided into sequential or parallel, since the variant of RL given by parallel learning. Second, we present the proposals that combine TD with neural networks, and finally, the proposals that combine TD with Fuzzy Logic (FL).

As was evidenced in the analysis of the reviewed literature, algorithms based on RL such as Q-learning and SARSA have shown to be effective in the online learning of scaling and scheduling policies in the Cloud. A 45% of the surveyed works are based on the autoscaling problem in Cloud for workflow and independent tasks applications, which are applications with distinctive features (long-term tasks, data-intensive or computational-intensive tasks, high workload variability with high parallelism and bottleneck stages) mostly used in engineering and scientific settings, while a 55% of the works focus on Cloud service applications, mostly used in e-commerce and business settings. However, a major finding is that neither of the surveyed works propose a solution that covers both the scaling and scheduling problems. Hence, the inception of full-fledged autoscalers purely based on RL techniques for either types of Cloud applications remains to be seen in the area.

As final comments, it is important to note that RL is a key technology for the future development of distributed computing systems. In particular, through RL it would be possible to develop autonomous infrastructure management platforms that meet the objectives of:

- Transparency: Implementation and operation details of the applications would be hidden to the user. The use of these systems would not depend on human intervention nor would demand to have access to a deep domain knowledge since it is expected that scaling and planning policies are learned
through the interaction with the environment. Such a scenario would be different from the actual one in which, for example, the scaling approaches that public clouds [70] use, are based on explicit thresholds for resource use. Such thresholds are usually defined by experts based on the available metrics such as CPU or memory usage.

- **Dynamism**: At any moment, the learned policies would allow the provider taking the necessary actions given the current state of the environment and the state of the applications. In such a scenario, the system would not have to rely on static plans nor in rule-based actions defined manually.

- **Adaptability**: Thanks to online learning, policies can be constantly improved and updated. In such a way, the policies would be able to adapt to the changes that occur in the dynamics of the Cloud environment. Such a characteristic is fundamental compared with policies learned in offline mode [8] that are prone to become obsolete in time.

Although the potential benefits are important, many efforts are still necessary towards making these goals a reality and transform the Cloud into the infrastructure of the future.

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**References**

[1] Philip Maechling, Ewa Deelman, Li Zhao, Robert Graves, Gaurang Mehta, Nitin Gupta, John Mehringer, Carl Kesselman, Scott Callaghan, David Okaya, Hunter Francoeur, Vipin Gupta, Yifeng Cui, Karan Vahi, Thomas Jordan, and Edward Field. SCEC CyberShake workflows-automating probabilistic seismic hazard analysis calculations. In Ian J. Taylor, Ewa Deelman, Dennis B. Gannon, and Matthew Shields, editors, *Workflows for e-Science: Scientific Workflows for Grids*, pages 143–163. Springer London, 2007.

[2] G. B. Berriman, Ewa Deelman, John C. Good, Joseph C. Jacob, Daniel S. Katz, Carl Kesselman, Anastasia C. Laity, Thomas A. Prince, Gurmeet Singh, and Mei-Hu Su. Montage: a grid-enabled engine for delivering custom science-grade mosaics on demand. volume 5493, pages 221–232, 2004.

[3] Duncan A. Brown, Patrick R. Brady, Alexander Dietz, Junwei Cao, Ben Johnson, and John McNabb. A Case Study on the Use of Workflow Technologies for Scientific Analysis: Gravitational Wave Data Analysis, pages 39–59. Springer London, London, 2007.

[4] Jonathan Livny, Hidayat Teonadi, Miron Livny, and Matthew K. Waldor. High-throughput, kingdom-wide prediction and annotation of bacterial non-coding mas. *PLoS ONE*, 3(9):1–12, 09 2008.

[5] Christian Vecchiola, Suraj Pandey, and Rajkumar Buyya. High-performance cloud computing: A view of scientific applications. *I-SPAN 2009 - The 10th International Symposium on Pervasive Systems, Algorithms, and Networks*, pages 4–16, 2009.

[6] R Buyya, C Yeo, S Venugopal, J Broberg, and I Brandic. Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility. *Future Generation Computer Systems*, 25(6):599–616, 2009.

[7] David A. Monge, Yisel Garí, Cristian Mateos, and Carlos García Garino. Autoscaling scientific workflows on the cloud by combining on-demand and spot instances. *International Journal of Computer Systems Science and Engineering*, 32(4 Special Issue on Elastic Data Management in Cloud Systems), Jul 2017.

[8] Yisel Garí, David A. Monge, Cristian Mateos, and Carlos García Garino. Learning budget assignment policies for autoscaling scientific workflows in the cloud. *Cluster Computing*, Feb 2019.
[9] Keven T Kearney and Francesco Torelli. Security in Service Level Agreements for Cloud Computing. *Proceedings of the 1st International Conference on Cloud Computing and Services Science, (CLOSER)*, pages 636–642, 2011.

[10] Xavier Dutreilh and Sergey Kirgizov. Using reinforcement learning for autonomic resource allocation in clouds: towards a fully automated workflow. In *7th International Conference on Autonomic and Autonomous Systems*, pages 67–74, 2011.

[11] Enda Barrett, Enda Howley, and Jim Duggan. Applying reinforcement learning towards automating resource allocation and application scalability in the cloud. *Concurrency Computation Practice and Experience*, 2012.

[12] T. Veni and S. Mary Saira Bhanu. Auto-scale: automatic scaling of virtualised resources using neuro-fuzzy reinforcement learning approach. *International Journal of Big Data Intelligence*, 3(3), 2016.

[13] Hamid Arabnejad, Claus Pahl, Pooyan Jamshidi, and Giovani Estrada. A comparison of reinforcement learning techniques for fuzzy cloud auto-scaling. In *Proceedings - 2017 17th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing, CCGRID 2017*, pages 64–73, 2017.

[14] Mostafa Ghabaei-Arani, Sam Jabbehdari, and Mohammad Ali Pourmina. An autonomic resource provisioning approach for service-based cloud applications: A hybrid approach. *Future Generation Computer Systems*, 78:191–210, 2018.

[15] Naghmeh Dezhabad and Saeed Sharifian. Learning-based dynamic scalable load-balanced firewall as a service in network function-virtualized cloud computing environments. *The Journal of Supercomputing*, 2018.

[16] J. V. Bibal Benifa and D. Dejey. RLPAS: Reinforcement Learning-based Proactive Auto-Scaler for Resource Provisioning in Cloud Environment. *Mobile Networks and Applications*, pages 1–16, 2018.

[17] Enda Barrett, Enda Howley, and Jim Duggan. A learning architecture for scheduling workflow applications in the cloud. *Proceedings – 9th IEEE European Conference on Web Services, ECOWS 2011*, pages 83–90, 2011.

[18] Zhiping Peng, Delong Cui, Jinglong Zuo, Qirui Li, Bo Xu, and Weiwei Lin. Random task scheduling scheme based on reinforcement learning in cloud computing. *Cluster Computing*, 18(4):1595–1607, 2015.

[19] Zheng Xiao, Pijun Liang, Zhao Tong, Kenli Li, Samee U. Khan, and Keqin Li. Self-adaptation and mutual adaptation for distributed scheduling in benevolent clouds. *Concurrency Computation*, 29(5):1–12, 2017.

[20] Martin Duggan, Jim Duggan, Enda Howley, and Enda Barrett. A network aware approach for the scheduling of virtual machine migration during peak loads. *Cluster Computing*, 20(3):2083–2094, Sep 2017.

[21] Ning Liu, Zhe Li, Zhiyuan Xu, Jielong Xu, Sheng Lin, Qinru Qiu, Jian Tang, and Yanzhi Wang. A Hierarchical Framework of Cloud Resource Allocation and Power Management Using Deep Reinforcement Learning. In *IEEE 37th International Conference on Distributed Computing Systems (ICDCS)*, pages 866–876, 2017.

[22] M. Soualhia, F. Khomh, and S. Tahar. A Dynamic and Failure-aware Task Scheduling Framework for Hadoop. *IEEE Transactions on Cloud Computing*, XX(XX):1–16, 2018.

[23] Ji Li Mingxi Cheng and Shahin Nazarian. DRL-Cloud : Deep Reinforcement Learning-Based Resource Provisioning and Task Scheduling for Cloud Service Providers. In *Design Automation Conference (ASP-DAC), 2018 23rd Asia and South Pacific*, pages 129–134, 2018.
[39] Ming Mao and Marty Humphrey. Scaling and scheduling to maximize application performance within budget constraints in cloud workflows. In Parallel & Distributed Processing (IPDPS), 2013 IEEE 27th International Symposium on, pages 67–78. IEEE, 2013.

[40] David A. Monge, Elina Pacini, Cristian Mateos, and Carlos García Garino. Meta-heuristic based autoscaling of cloud-based parameter sweep experiments with unreliable virtual machines instances. Computers and Electrical Engineering, 69:364–377, 2018.

[41] D.A. Monge, E. Pacini, C. Mateos, E. Alba, and C. García Garino. CMI: An online multi-objective genetic autoscaler for scientific and engineering workflows in cloud infrastructures with unreliable virtual machines. Journal of Network and Computer Applications, 149:102464, 2020.

[42] E. Pacini, C. Mateos, and C. García Garino. Distributed job scheduling based on Swarm Intelligence: A survey. Computers & Electrical Engineering, 40(1):252–269, 2014. 40th-year commemorative issue.

[43] Yisel Garí, David A. Monge, Cristian Mateos, and Carlos García Garino. Markov Decision Process to Dynamically Adapt Spots Instances Ratio on the Autoscaling of Scientific Workflows in the Cloud, pages 353–369. Springer International Publishing, Cham, 2018.

[44] Rodrigo N Calheiros, Rajiv Ranjan, Anton Beloglazov, César A F De Rose, and Rajkumar Buyya. CloudSim: a toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms. Software: Practice and Experience, 41(1):23–50, 2011.

[45] J. Jang, J. Jung, and J. Hong. k-LZF : An efficient and fair scheduling for Edge Computing servers. Future Generation Computer Systems, 98:44–53, 2019.

[46] Ziqian Dong, Ning Liu, and Roberto Rojas-Cessa. Greedy scheduling of tasks with time constraints for energy-efficient cloud-computing data centers. Journal of Cloud Computing, 4(1), 2015.

[47] Shaminder Kaur and Amandeep Verma. An Efficient Approach to Genetic Algorithm for Task Scheduling in Cloud Computing Environment. International Journal of Information Technology and Computer Science, 4(10):74–79, 2012.

[48] Fatos Xhafa and Ajith Abraham. A compendium of heuristic methods for scheduling in computational grids. In Emilio Corchado and Huajun Yin, editors, Intelligent Data Engineering and Automated Learning - IDEAL 2009, pages 751–758, Berlin, Heidelberg, 2009. Springer Berlin Heidelberg.

[49] Anton Beloglazov and Rajkumar Buyya. Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in Cloud data centers. Concurrency and Computation: Practice and Experience, 24(13):1397–1420, 2012.

[50] Kyong-Ha Lee, Yoon-Joon Lee, Hyunsik Choi, Yon Dohn Chung, and Bongki Moon. Parallel data processing with mapreduce: A survey. SIGMOD Rec., 40(4):11–20, January 2012.

[51] D. Glushkova, P. Jovanovic, and A. Abelló. Mapreduce performance model for hadoop 2.x. Information Systems, 79:32–43, 2019. Special issue on DOLAP 2017: Design, Optimization, Languages and Analytical Processing of Big Data.

[52] Jingqi Yang, Chuanchang Liu, Yanlei Shang, Bo Cheng, Zexiang Mao, Chunhong Liu, Lisha Niu, and Junliang Chen. A cost-aware auto-scaling approach using the workload prediction in service clouds. Information Systems Frontiers, 16(1):7–18, 2014.

[53] Nilabja Roy, Abhishek Dubey, and Aniruddha Gokhale. Efficient autoscaling in the cloud using predictive models for workload forecasting. Proceedings - 2011 IEEE 4th International Conference on Cloud Computing, CLOUD 2011, pages 500–507, 2011.

[54] Mahmoud Al-Ayyoub, Yaser Jararweh, Mustafa Daraghmeh, and Qutaibah Althebyan. Multi-agent based dynamic resource provisioning and monitoring for cloud computing systems infrastructure. Cluster Computing, 18(2):919–932, 2015.
[55] Y. Wei, D. Kudenko, S. Liu, L. Pan, L. Wu, and X. Meng. A reinforcement learning based auto-scaling approach for SaaS providers in dynamic cloud environment. *Mathematical Problems in Engineering*, pages 1–11, 2019.

[56] S.M.R. Nouri, H. Li, S. Venugopal, W. Guo, M. He, and W. Tian. Autonomic decentralized elasticity based on a reinforcement learning controller for cloud applications. *Future Generation Computer Systems*, 94:765–780, 2019.

[57] Gary Marcus. Deep Learning: A Critical Appraisal. *arXiv e-prints*, page arXiv:1801.00631, Jan 2018.

[58] Leslie N. Smith. A disciplined approach to neural network hyper-parameters: Part 1 – learning rate, batch size, momentum, and weight decay. *arXiv e-prints*, page arXiv:1803.09820, Mar 2018.

[59] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9(8):1735–1780, 1997.

[60] Hongjia Li, J. Li, Wang Yao, S. Nazarian, X. Lin, and Y. Wang. Fast and energy-aware resource provisioning and task scheduling for cloud systems. In 2017 18th International Symposium on Quality Electronic Design (ISQED), pages 174–179, March 2017.

[61] Zhiguang Wang, Chul Gwon, Tim Oates, and Adam Iezzi. Automated Cloud Provisioning on AWS using Deep Reinforcement Learning. *arXiv e-prints*, page arXiv:1709.04305, Sep 2017.

[62] Ziyu Wang, Tom Schaul, Matteo Hessel, Hadir van Hasselt, Marc Lanctot, and Nando de Freitas. Dueling Network Architectures for Deep Reinforcement Learning. *arXiv e-prints*, page arXiv:1511.06581, Nov 2015.

[63] Jia Rao, Xiangping Bu, Cheng-Zhong Xu, Leyi Wang, and George Yin. Vconf: A reinforcement learning approach to virtual machines auto-configuration. In *Proceedings of the 6th International Conference on Autonomic Computing*, ICAC ’09, pages 137–146, New York, NY, USA, 2009. ACM.

[64] Simon Spinner, Samuel Kounov, Xiaoyun Zhu, Lei Lu, Mustafa Uysal, Anne Holler, and Rean Griffith. Runtime Vertical Scaling of Virtualized Applications via Online Model Estimation. *International Conference on Self-Adaptive and Self-Organizing Systems*, SASO, 2014-December(December):157–166, 2014.

[65] N. Makris. Plastic torsional buckling of cruciform compression members. *Journal of Engineering Mechanics*, 129(6):689–696, 2003.

[66] C. García Garino, M.S. Ribero Vairo, S. Andía Fagés, A.E. Mirasso, and J.-P. Ponthot. Numerical simulation of finite strain viscoplastic problems. *Journal of Computational and Applied Mathematics*, 246:174–184, July 2013.

[67] Saurabh Kumar Garg, Chee Shin Yeo, and Rajkumar Buyya. Green cloud framework for improving carbon efficiency of clouds. In Emmanuel Jeannot, Raymond Namyst, and Jean Roman, editors, *Euro-Par 2011 Parallel Processing*, pages 491–502, Berlin, Heidelberg, 2011. Springer Berlin Heidelberg.

[68] Anton Beloglazov, Rajkumar Buyya, Young Choon Lee, and Albert Zomaya. *A Taxonomy and Survey of Energy-Efficient Data Centers and Cloud Computing Systems*, volume 82. Elsevier Inc., 1 edition, 2011.

[69] C. Liu, X. Xu, and D. Hu. Multiobjective reinforcement learning: A comprehensive overview. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 45(3):385–398, March 2015.

[70] Amazon. Autoescaling. [http://aws.amazon.com/autoscaling/](http://aws.amazon.com/autoscaling/) January 2020. [Online; accessed May-2020].

[71] Richard Bellman. *Dynamic programming*. Princeton University Press, New Jersey, 1957.
Appendix A: Reinforcement Learning

Reinforcement learning (RL) [24] is one of three basic machine learning paradigms, alongside supervised learning and unsupervised learning. RL is concerned with how a software agent ought to take actions in an environment so as to maximize some notion of cumulative reward. In other words, the computational approach where an agent, acting in an environment with uncertainty, learns to associate situations with actions while maximizing a numerical reward signal is considered reinforcement learning. At the beginning, the agent does not know what actions to take, and as the time passes, it must discover which are the actions that produce the greatest long-term benefit, trying again and again different options. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. Making the most appropriate decision requires taking into account the indirect consequences of the actions, therefore, some kind of foresight or planning is necessary. These two characteristics, trial-and-error search and delayed reward, are the two most important distinguishing features of RL [24].

One of the challenges that arise in RL, is the trade-off between exploration and exploitation. To obtain a lot of reward, a RL agent must prefer those 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 has already experienced in order to obtain reward, but it also has to explore in order to make better action selections in the future, at the potential expense of less reward. The dilemma is that neither exploration nor exploitation can be pursued exclusively without failing at effective learning. The agent must try a variety of actions and progressively favor those that appear to be best. On a stochastic task, each action must be tried many times to gain a reliable estimate of its expected reward.

There are four fundamental elements in the RL learning process: the policy, the reward signal, the value function, and optionally, the model of the environment:

1. A policy defines how the learning agent behaves at a given time. A policy is a mapping from perceived states of the environment to actions to be taken when in those states. The policy is the core of an RL agent in the sense that it alone is sufficient to determine behavior.

2. A reward signal defines the goal in an RL problem. On each time step, the environment sends to the RL agent a single number called the reward signal. The reward signal defines what are the good and bad events for the agent. For example, in a biological system, we might think of rewards as analogous to the experiences of pleasure or pain. They are the immediate and defining features of the problem faced by the agent. The reward signal is the primary basis for altering the policy: if an action selected by the policy is followed by low reward, then the policy may be changed to select some other action in that situation in the future.
3. A **value function** specifies what is good in the long term. The value of a state is the total amount of reward an agent can expect to accumulate over the future, starting from that state. Whereas rewards determine the immediate, intrinsic desirability of environmental states, values indicate the long term desirability of states after taking into account the states that are likely to follow, and the rewards available in those states.

Rewards are in a sense primary, whereas values, as predictions of rewards, are secondary. Without rewards there could be no values, and the only purpose of estimating values is to achieve more reward. Nevertheless, values mostly drive making and evaluating decisions. In real life, for example, people look for actions that bring about states of highest value, not highest reward, because these actions obtain the greatest amount of reward for us over the long run. Unfortunately, it is much harder to determine values than rewards. Rewards are basically given directly by the environment, but values must be estimated and re-estimated from the sequences of observations an agent makes over its entire lifetime. In fact, the most important component of almost all RL algorithms is the method for efficiently estimating values.

4. The **model of the environment** is the fourth and final element. The model mimics the behavior of the environment and allows agent to infer about how the environment will behave. For example, given a state and an action, the model might predict the next state and next reward. Models are used for deciding on a course of action by considering possible future situations before they are actually experienced. Methods for solving RL problems that use models are called model-based methods, as opposed to simpler model-free methods that are explicitly trial and error learners.

A.1 Markov Decision Processes

Markov decision processes (MDP) [71] provide a formal framework widely used in RL to define the interaction between a learning agent and its environment in terms of states, actions and rewards (see Figure 9). An MDP constitutes an intuitive and fundamental formalism for decision-making problems under uncertainty and comprises a set of states and a set of possible actions to take on each state, with the goal of determining a sequence of actions that minimize/maximize some performance criterion. MDPs have become the de facto standard formalism for learning sequential decision-making [72] and it has been applied to autoscaling problems in Cloud [73, 17, 11]. The classical model of an MDP is defined as a 5-tuple \((S, A, P, (\cdot, \cdot), R, (\cdot, \cdot, \gamma))\), where:

- \(S\) represents the environmental state space;
- \(A\) represents the total action space;
- \(P_a(s, s') = Pr(s_{t+1} = s' \mid s_t = s, a_t = a)\) represents the probability that action \(a\) in state \(s\) at time \(t\) will lead to state \(s'\) at time \(t + 1\);
- \(R_a(s, s')\) represents the (expected) immediate reward received after transitioning from state \(s\) to state \(s'\) due to action \(a\);
- \(\gamma \in [0, 1]\) (or discount factor) is the difference in importance between future and immediate rewards. When \(\gamma\) is close to 0, rewards in the distant future are viewed as insignificant. When \(\gamma\) is 1 all rewards are equally important (i.e. additive rewards).

As shown in Figure 9, the agent and the environment continuously interact in a constant exchange process. At each time \(t\), the agent receives a representation of the environment state \(s_t \in S\), and then selects an action \(a_t \in A\). In the next step, and as a consequence of the executed action, the agent receives a numerical reward signal \(r_{t+1} \in R \subset \mathbb{R}\) and goes to a new state \(s_{t+1}\). The boundaries between the agent and the environment are determined by everything that the agent may or may not control, and not by those things the agent knows or does not know. For example, the agent can have knowledge of the current status or how the reward is computed, but only has control over the actions he takes. The reward is a numerical signal and the agent goal is to maximize the total amount of received reward. In general, the agent attempts to maximize the expected gain \(G_t\) that is defined as a specific function of the reward sequence. In the simplest case, the gain is the sum of the rewards: \(G_t = r_{t+1} + r_{t+2} + \ldots + r_T\) where \(T\) is a final time step. Then, considering the discount factor \(\gamma\), which determines the degree of importance
of future rewards compared to the immediate rewards, the agent will attempt to select the action \( a_t \) so that the sum of the discounted rewards is maximized. In this case the expected gain is calculated as:

\[
G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} \cdots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}.
\]

![Figure 9: MDP interaction process between an agent and the environment. Figure adapted from [24].](image)

According to the MDP definition, a policy is a function \( \Pi : S \rightarrow A \) with the form:

\[
\Pi(s) \leftarrow \arg \max_a \sum_{s'} P_a(s, s') [R_a(s, s') + \gamma V_k(s')], \tag{7}
\]

where \( V_k(s') \) is a value function that represents the utility of the state \( s' \) reachable from the state \( s \). The value function is defined as:

\[
V_k(s) = \max_a \sum_{s'} P_a(s, s') [R_a(s, s') + \gamma V_{k-1}(s')]. \tag{8}
\]

When solving an MDP –i.e. obtaining an appropriate policy– there are two fundamental processes that are present in the different resolution strategies used:

- The process of predicting or evaluating the policy, where the values of the states are estimated and the value function \( V(s) \) is updated, generally based on the current estimated policy and the information of the environment (either from the model or from experience, according to the technique).

- The process of control or improvement of the estimated policy, where \( \Pi(s) \) is computed, based on the current estimated values of the states.

Both processes determine a continuous interaction between the different approximations of the value function and the policy. This interaction in time converges to the optimal values for both functions [24]. Two of the most commonly used methods to solve MDPs are Dynamic Programming methods (DP) and Temporal Difference methods (TD), which are described below. Then, more complex resolution variants, which exploit Neural Networks and Fuzzy Logic, are described afterwards.

### A.2 MDP Resolution via Dynamic Programming

Dynamic programming (DP) in this context refers to a collection of algorithms that can be used to compute optimal policies given a perfect model of the environment as an MDP. Methods based on DP compute the policy based on a complete model of the environment. In the process of estimating the states values, the probability distribution of the transitions between the states is used. This often becomes a limitation, since it is not always possible to have a perfect model of the environment. In some cases the probability distribution of the transitions is estimated from data obtained in previous experiences. The DP methods offer an offline learning variant, where the policy is obtained by iterating over the model and not based on the dynamics of current experiences. It is important to note that prior estimates of other states are used in the process of estimating the values of the states (technique known as bootstrap). The most important DP algorithms are policyIteration and valueIteration. Both algorithms have polynomial complexity in the number of states and actions, so it is important to consider the dimensions of these spaces when using DP. However, the search performed with DP is much more efficient than an exhaustive exploration in the space of all possible policies.
The policyIteration algorithm (see Algorithm 1) is defined based on the iterative repetition of the evaluation and the improvement of the policy until convergence is achieved. In this way, the algorithm generates the following sequence of value functions and policies $v_0 \rightarrow \pi_0 \rightarrow v_1 \rightarrow \pi_1 \rightarrow ... \rightarrow \pi^*$ until to reach an appropriate policy. On the other hand, the valueIteration algorithm (see Algorithm 2), first includes the search for the appropriate value function and then, the computation of the associated policy. These steps are not repeated because once the value function is adequate, so is the associated policy. The search for the appropriate value function can be understood as a combination of the policy improvement process and a truncated evaluation of the policy (the values are reassigned after a single sweep of the states) without losing convergence [24]. In this way the algorithm generates the sequence of value function updates $v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow ... \rightarrow v^*$ and then, it computes the suitable policy $\pi^*$.

Both algorithms, policyIteration and valueIteration, formally require an infinite number of iterations to converge exactly to the appropriate policy. In practice, both algorithms stop when the difference between two successive approximations is less than a limit $\Theta$, which usually within a much lesser number of iterations[24].

Algorithm 1 The Policy Iteration algorithm.

1: procedure POLICY ITERATION($S, A, P, R, \gamma, \Theta$):
2: 1. Initialize $V(s)$ y $\pi(s)$ arbitrarily $\forall s \in S$
3: 2. Policy Evaluation
4: repeat
5: $\Delta \leftarrow 0$
6: for each $s \in S$ do
7: $v \leftarrow V(s)$
8: $a \leftarrow \pi(s)$
9: $V(s) \leftarrow \sum_{s'} P_a(s, s')[R_a(s, s') + \gamma V(s')]$
10: $\Delta \leftarrow \max(\Delta, |v - V(s)|)$
11: until $\Delta < \Theta$ (a small positive number)
12: 3. Policy Improvement
13: stablePolicy $\leftarrow$ true
14: for each $s \in S$ do
15: oldAction $\leftarrow \pi(s)$
16: $\pi(s) \leftarrow \arg \max_a \sum_{s'} P_a(s, s')[R_a(s, s') + \gamma V(s')]$
17: if oldAction $\neq \pi(s)$ then stablePolicy $\leftarrow$ false
18: if stablePolicy then stop and return $V \approx v^*$ and $\pi \approx \pi^*$

Algorithm 2 The Value Iteration algorithm.

1: procedure VALUE ITERATION($S, A, P, R, \gamma, \Theta$):
2: Initialize array $V$ arbitrarily $\forall s \in S$
3: repeat
4: $\Delta \leftarrow 0$
5: for each $s \in S$ do
6: $v \leftarrow V(s)$
7: $V(s) \leftarrow \max_a \sum_{s'} P_a(s, s')[R_a(s, s') + \gamma V(s')]$
8: $\Delta \leftarrow \max(\Delta, |v - V(s)|)$
9: until $\Delta < \Theta$ (a small positive number)
10: Output a deterministic policy $\pi \approx \pi^*$ such that:
11: $\pi(s) \leftarrow \arg \max_a \sum_{s'} P_a(s, s')[R_a(s, s') + \gamma V(s')]$

A.3 MDP Resolution via Temporal Difference

Unlike methods based on DP, methods based on TD do not require a perfect model of the environment, since the policy learning process is based on the observed dynamics during its experimentation. In this
sense, these methods offer an approach with a greater ability to adapt to changes in the environment, since unlike DP-based methods, learning through TD occurs in an online way. Similarly to DP, to estimate new states values, the previously estimated values are used (i.e., bootstrap is performed). Then, the function \( Q(s, a) \) that associates the states value to the selection of a given action is computed. This is usually represented in tabular form.

The most important algorithms in this area are Q-learning \[74\] and State-Action-Reward-State-Action (SARSA). It is important to highlight that one of the main limitations in RL is that the convergence time of these algorithms depends directly on the dimension of the state space and actions. Moreover, since these algorithms do not have an adequate initial policy they have a poor initial performance that will have a greater or lesser impact depending on the addressed problem and the time taken for training. To make inappropriate decisions at the beginning of the autoscaling of workflows in Cloud, which is necessary in the exploration process, can have a direct impact on the makespan and the economic cost, so it is convenient to have an acceptable initial policy. This could also reduce the needed time to learn the right policy. In any case, it is necessary to consider that obtaining an acceptable initial policy is not always trivial \[75\].

The distinctive characteristic of Q-learning (see Algorithm 3) is that it uses two different policies (off-policy), one to select the next action and another to update \( Q \). In other words, Q-learning tries to evaluate \( \pi \) while following another policy \( \mu \). Alternatively, SARSA (see Algorithm 4) uses the same policy all the time (on-policy). The most important difference between the two above mentioned algorithms is how \( Q \) is updated after each action. Q-learning updates \( Q \) with the action that maximizes the gain for the next step. This makes Q-learning follows an \( \varepsilon \)-greedy policy\[11\] with \( \varepsilon = 0 \), i.e., there is no exploration. In contrast, SARSA updates \( Q \) by following exactly an \( \varepsilon \)-greedy policy, since the action is extracted from it. Both algorithms include the \( \alpha \in (0, 1] \) parameter relative to the size of the step in the learning process, and the \( \varepsilon > 0 \) parameter that determines the exploration degree of new policies.

Algorithm 3 Q-learning (DT off-policy).

1:  procedure Q-LEARNING\((S, A, P, R, \gamma, \alpha, \varepsilon)\):
2:     Initialize \( Q(s, a) \) arbitrarily \( \forall s \in S, a \in A \) y \( Q(terminalState, .) = 0 \)
3:     for each (episode) do
4:         Initialize S
5:         repeat:
6:             Select A from S using the policy derived from de Q (\( \varepsilon \)-greedy)
7:             Take action A, observe R, S'
8:             \( Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma \max_a Q(S', a) - Q(S, A)] \)
9:             S \leftarrow S'
10:        until S is terminal

Algorithm 4 SARSA (DT on-policy).

1:  procedure SARSA\((S, A, P, R, \gamma, \alpha, \varepsilon)\):
2:     Initialize \( Q(s, a) \) arbitrarily \( \forall s \in S, a \in A \) y \( Q(terminalState, .) = 0 \)
3:     for each episode do
4:         Initialize S
5:         Select A from S using the policy derived from Q (\( \varepsilon \)-greedy)
6:         repeat:
7:             Take action A, observe R, S'
8:             Select A' from S' using the policy derived from Q (\( \varepsilon \)-greedy)
9:             \( Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma Q(S', A') - Q(S, A)] \)
10:            S \leftarrow S', A \leftarrow A'
11:        until S is terminal

\[11\] \( \varepsilon \)-greedy: a policy that with an \( \varepsilon \) probability selects a random action, but most of the times it selects an action with the maximum estimated value.
A.4 MDP Resolution via Neural Networks

Large state spaces in an RL problem leads to the need to find non-tabular representations of the $Q$ function, not only for the memory required to store large tables, but also for the time it would take to fill it. Algorithms capable of generalizing in more complex and sophisticated state space contexts are then consequently needed. In this sense, non-linear approximations of $Q$ with artificial neural networks appeared. A type of neural network that has proven very successful in RL applications [26, 25] is Deep Convolutional Neural Networks, which are specialized in the processing of large-scale data organized in spatial matrices. Then, the strategy that combines RL with Deep Neural Networks (DNN) is called Deep Reinforcement Learning (DRL). Finally, the DNN used to approximate the $Q$ function are called Deep QNetworks (DQN) and the learning algorithm that uses DQN is referred to as Deep Q-learning. Later in this survey we will use this terminology to analyze proposals designed based on DRL for autoscaling in Cloud [21, 61, 23].

Figure 10 shows an example of a DQN. The input corresponds to a state $s$ of the environment and the output represents the estimated value of function $Q$ for the state $s$ and all possible actions. In the process of training the network the objective is to minimize the approximation error between the result of the network and the optimality equation of Bellman [26]. Thereby, the same problem as with the classical DP and TD techniques is solved, but now using a nonlinear approach based on deep neural networks.

![Diagram of a DQN](image)

Figure 10: Example of the structure of a DNQ.

A.5 MDP Resolution via Fuzzy Logic

Fuzzy Logic (FL) appears as another alternative to address the dimensionality problem of RL strategies. The idea is to reduce the state space using a diffuse representation of the information.

Broadly, FL systems attempt to represent knowledge inaccurately, similar to how human beings do, and as opposed to classical numerical forms. In this sense, the FL works with fuzzy sets in which the elements have some membership degree. To define the membership function of these sets, triangles or trapezoid curves are usually used (see Figure 11). For example, in Figure 11 a fuzzy membership function is represented for a Cloud workload variable with three fuzzy sets (Low, Medium, High) that define the membership degree of the variable to each of them. Thus, in the presence of a workload $\alpha$, it is possible to affirm that it belongs both to the Low and Medium fuzzy sets with a 50% of probability, and hence the diffuse nature of this representation.
These concepts from FL allow reasoning based on rules of the form:

\[
\text{if (antecedent) then (consequent),}
\]

where the antecedent and consequent values are expressed in a fuzzy way. Based on the previous example, one possible rule is: if the workload is high then more VM must be requested.

FL has been applied in different fields, from control theory to artificial intelligence. A control process based on FL consists of the following steps:

- Mapping of input data to fuzzy set labels (Fuzzifier)
- The inference process based on fuzzy rules (Fuzzy Reasoning)
- Fuzzy output mapping to clear values (Defuzzifier)

Fuzzy Reinforcement Learning (FRL) is the strategy that combines the strength of fuzzy reasoning with RL. FRL allows handling problems with large state spaces without affecting the performance of the RL algorithms. For this, in the learning process is used a fuzzy representation of the information that considerably reduces the number of states.

Motivated by this benefit, some authors [13, 12] have proposed approaches based on FRL for autoscaling in Cloud. Figure 12 shows the interaction between the components involved in these approaches. First, the Cloud platform and the running application that compose the environment, which is continuously observed by a monitoring process. The monitoring process retrieves data of interest about the state of the environment and reports it to the Automatic Controller (AC). One of the main components of the AC is the
FL-based control process called Fuzzy Controller (FC). The FC is composed of the Knowledge Base (or rules), the Fuzzifier, the Inference Engine and the Defuzzifier. In this way, the FC receives the signal of the environment state, transforms it to its diffuse representation, reasons based on the rules, and obtains a diffuse output that is finally returned to its clear representation. This output or action is used by the actuator process to modify the environment. The second component of the FC is precisely the RL process, which also receives the signal of the environment state and, guided by the optimization objectives, is responsible for learning the most appropriate set of rules to update the knowledge base of FC. Each member of the table of values $Q$ is assigned to a specific rule (which describes some action-state pairs). Then, these values are updated during the learning process. In this way, it is possible to take advantage of the strengths of RL and FL strategies to design an automatic controller capable of evolving fuzzy rules that allow to make an approximate reasoning.