

# Reinforcement Learning based Orchestration for Elastic Services

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*Abstract*—Due to the highly variable execution context in which edge services run, adapting their behavior to the execution context is crucial to comply with their requirements. However, adapting service behavior is a challenging task because it is hard to anticipate the execution contexts in which it will be deployed, as well as assessing the impact that each behavior change will produce. In order to provide this adaptation efficiently, we propose a Reinforcement Learning (RL) based Orchestration for Elastic Services. We implement and evaluate this approach by adapting an elastic service in different simulated execution contexts and comparing its performance to a Heuristics based approach. We show that elastic services achieve high precision and requirement satisfaction rates while creating an overhead of less than 0.5% to the overall service. In particular, the RL approach proves to be more efficient than its rule-based counterpart; yielding a 10 to 25% higher precision while being 25% less computationally expensive.

*Index Terms*—edge computing, fog computing, reinforcement learning, self-adaptive systems

## I. INTRODUCTION

Increased data traffic and network utilization are one of the biggest challenges for network operators nowadays. One of the reasons is the massive amount of data generated by devices in the edge in the context of the Internet of Things (IoT). Edge computing [7] allows network operators to reduce network stress and improve service responsiveness by allocating computation closer to data producers and consumers. Nonetheless, edge processing hardware is constrained and heterogeneous, which makes it hard to provide cloud-like elasticity features (i.e., scale out) that are necessary to react to the burstiness of typical IoT loads (e.g., loads that are based on user behavior or interaction). For example, the load of a local edge server that serves an augmented reality (AR) application [4] is directly correlated to the number of active users. Too many active users result in exhaustive response times and poor user experience.

To address such problems, we proposed in our previous work [6], edge hosted services need to dynamically adapt to the current execution context to better comply with their non-functional application requirements or Service Level Objectives (SLOs) together with the execution framework. We call this concept “Elastic Services”. However, adapting service behavior to a given context is a challenging task, because it is hard to anticipate the scenarios the software might encounter (e.g., different loads or wireless link quality [2]) as well as to assess the impact that each behavior change will produce.

In this work, we propose a Reinforcement Learning (RL) based orchestration to adapt services and applications be-

havior during runtime so they best adhere to non-functional requirements like response time. Our approach starts exploring different behavior alternatives, and learns –based on its own experience– the best behavior for the current and potentially complex execution context. We implement and evaluate a prototype of this approach that provides high satisfaction of service requirements while being computationally inexpensive.

Our main contributions are as follows:

- Definition of a RL based approach and its elements—actions, states and reward—to adapt services to their current execution context.
- Evaluation of the RL based approach and its comparison to a Heuristics based approach, by means of simulation.

## II. MOTIVATION

To illustrate the complexity of dynamically deciding on the best adaptation, we introduce a typical video analysis application: the Lost Child Application. The application works in the following way: if a child goes missing, law enforcement asks their parents for photographs of the child and a facial recognition classifier is trained with them. Then, a service is deployed using existing connected cameras and edge servers in the city to analyze the video feeds and to locate the child. When a matching face is found, a notification is sent to nearby law enforcement officers. This application can be split in two components: (1) an offline module, which is trained with pictures of the child in a server and (2) an online module, a face detection and matching service that is deployed in several devices and is in charge of finding the child. We will focus our attention on the latter.

The face detection and matching service is composed by the following steps, translated as functions of the service:

- 1) **Capture image:** the image is captured by the camera.
- 2) **Image preprocessing:** different preprocessing steps such as resizing, colorization, etc., are performed to improve the accuracy of the face detection and recognition.
- 3) **Face detection:** a face detection classifier is applied to the preprocessed image and each face is extracted and returned.
- 4) **Face Recognition:** for each face that was found in the image, the previously trained classifier that matches the face of the lost child is applied.
- 5) **Notify law enforcement:** a notification is sent to nearby police officers indicating the location of the child.

A small end-to-end latency is necessary to ensure a high frame sampling rate, so the event of missing the child is unlikely to happen, even if it only appears briefly on the video feed, e.g., when the child is moving. The requirement is to have at least one frame analyzed per second, which is translated into having a maximum end-to-end latency of 1 s for each analyzed frame. At the same time, it is desired that the service performs with the highest precision possible.

In order to comply with these requirements, it is necessary to adapt the service behavior to the current execution context:

- The hardware capabilities of the device in which the application or service executes affects its performance, e.g., a device that can use a graphic accelerator to speed up matrix multiplication will be able to process faster neural network algorithms than one without.
- Different camera input results in different performance. For example, in the face detection and matching service, analyzing a frame with 5 persons is less computationally expensive than analyzing a frame with 100 persons. All of these factors generate different latencies for processing images and therefore affect the requirements satisfaction.

#### A. Adaptation Knobs

For each function of the service, a number of parameters can be modified in order to modify the service’s performance. The optimal parameters configuration varies according to the specific requirements of the service, its execution context and its inputs. This means that these values need to be changed for every device and also during runtime, in order to obtain the best possible performance.

Furthermore, the number of alternative behaviors grows exponentially with the number of parameters and the values each parameter can assume. As shown in Figure 1, even for a simple service with three different functions many parameters can be adapted. There are six adaptable parameters, three of them have four different values (image\_resize, scale\_factor and min\_neighbors), and three of them have two different values (colorization, face detection algorithm and face\_recognizer). This means that there are  $4^3 \cdot 2^3 = 512$  different configurations that can be used to adapt the service’s behavior to a given execution context.

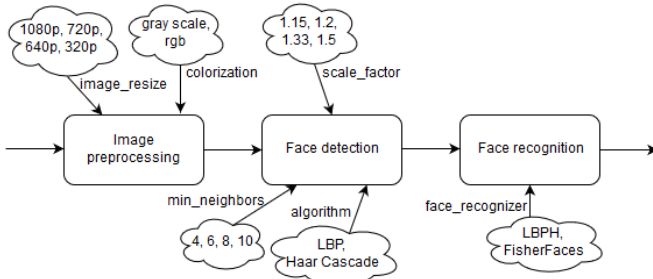


Fig. 1. Different behavior adaptations for the face detection and matching service

Because of the high number of configurations together with the uncertainty of their impact on service requirements, finding the best configuration of parameter values for a given execution context is a complex task. Choosing this configuration

manually is also ineffective, as there is no universal set of values that works properly across all devices and contexts. An automatic approach is needed, one that is able to learn from the service, its inputs and its execution context, to decide what is the best parameters configuration for the current execution context.

### III. ELASTIC SERVICES

In this section we introduce the programming model for service developers to easily define elastic services and also the underlying edge computing framework to support such a programming model.

#### A. Programming Model of Elastic Services

To simplify the development of elastic services, we extend the traditional dataflow-based programming model [1] to support service elasticity in the following way.

First, service developers break down the logic of their services into small processing functions. Each processing function is called an **operator**. However, different from the traditional dataflow programming model, these operators are parameterized to change their internal execution during runtime, meaning that each operator is associated with a set of parameters, and by changing these parameters, we can control the behavior of the operator on the fly. For example, a clustering operator can use a parameter to control which clustering algorithm should be applied for this operator at runtime. The implementation of an operator can be mapped to various of dockerized application images that are deployable and executable in any docker-based environment, either in the cloud or at edges.

Once operators are defined and their implementation images are provided, service developers can start to specify a **service topology** to represent the abstract processing logic of their service. A service topology consists of a set of linked tasks and each task is an annotated operator with a specific granularity. The granularity of a task determines how many task instances of the same operator should be instantiated at runtime, based on the available data.

A service topology must be triggered explicitly by a user-definable **requirement**, issued by a consumer or any application on-demand. The requirement defines when and how the defined service topology should be instantiated, which is the main challenge to be addressed by service orchestration in general. One important part of the requirement is to cover the QoS defined by users in terms of required latency, reduction of bandwidth consumption, or any other high level metrics. The goal of our service orchestration is to achieve and ensure the required QoS continuously by making orchestration decisions adapted to the ongoing workload and also any environment changes.

#### B. FogFlow: Edge Computing Framework for Elastic Services

FogFlow[5] is a distributed execution framework that dynamically orchestrates elastic services over cloud and edges, in order to reduce internal bandwidth consumption and offer low latency. The unique feature of FogFlow is context-driven,

meaning that FogFlow is able to orchestrate dynamic data processing flows over cloud and edges based on three types of contexts, including:

**System context:** available resources which are changing over time. The resources in a cloud-edge environment are geo-distributed in nature and they are dynamically changing over time; As compared to cloud computing, resources in such a cloud-edge environment are more heterogeneous and dynamic.

**Data context:** the structure and registered metadata of available data, including both raw sensor data and intermediate data. Based on the standardized and unified data model and communication interface, namely NGSI, FogFlow is able to see the content of all data generated by sensors and data processing tasks in the system, such as data type, attributes, registered metadata, relations, and geo-locations.

**Usage context:** high level intents defined by all different types of users (developers, service consumers, data providers) to specify what they want to achieve. For example, for service consumers, they can specify which type of results is expected under which type of QoS within which geo-scope; for data providers, they can specify how their data should be utilized and by whom.

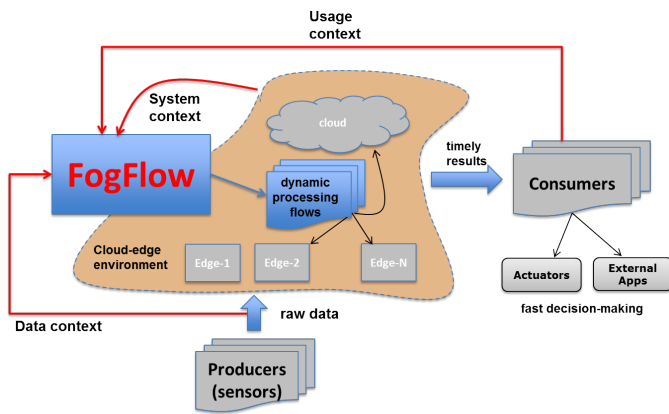


Fig. 2. FogFlow System Overview

As shown in Figure 2, by leveraging these three kinds of context, FogFlow is able to orchestrate elastic IoT services in a more intelligent and automatic manner. The overall design of FogFlow has been presented in our previous paper [5]. In this paper we focus on the algorithms of service orchestration, which can be applied by the FogFlow system framework to support elastic services.

#### IV. DYNAMIC ORCHESTRATION

In order to generalize our approach over services with different numbers and types of requirements, we model the problem as a constrained optimization problem. Specifically, (1) we model requirements as constraints, e.g., to process documents with an end-to-end latency less or equal than 1s or to run at a cost of less or equal than \$10 per hour and (2) we model service performance, such as precision, accuracy or battery consumption, as objective. There is an important difference between the objective and the constraints: whereas the constraints define a maximum or minimum value for the

variable involved (e.g., latency, cost, etc.), the objective does not have a minimum or maximum value expected. In this way, we can define the service requirements as:

$$\begin{aligned} & \underset{\theta}{\text{maximize}} && O(\theta) \\ & \text{subject to} && c_i(\theta) \leq C_i, i = 1, \dots, N \end{aligned}$$

where:

- $\theta$ : is the configuration of parameters used for all of the operators
- $O(\theta)$ : represents the objective of the service, which is determined by the configuration of parameters used
- $c_i(\theta)$ : is a constraint to the service (such as latency), also determined by  $\theta$
- $C_i$ : is the constraint target (e.g., 1 s)
- $N$ : is the total number of constraints.

The developer is in charge of defining the service requirements along with the metrics to monitor them, as well as the parameters that can be adapted and the values they can assume. During runtime, the system is in charge of finding the best configuration of parameter values that maximize (or minimize) the objective while respecting the constraints.

To ensure the correct functioning of the service, the dynamic orchestration has two main requirements:

- **Rapid response.** It must adjust the service behavior rapidly to keep up with the context changes during runtime. A slow response might mean the violation of the requirements if the resources are further constrained, or the loss of improvement in the objective if more resources become available.
- **Low overhead.** The dynamic orchestration must not create a considerable overhead for the system, so most of the execution time is still used for the service.

We present two approaches that implement this constraint optimization for service orchestration: (1) a heuristic based approach and (2) a reinforcement learning based approach.

##### A. Heuristics based Orchestration

First, we develop a heuristic that is based on the assumption of a linear trade-off between the objective of the service and its constraints. This linear trade-off is often seen in algorithms: more computing intensive implementations are slow, but produce more accurate results, while less computing intensive algorithms are faster but result in less accurate results. Note that even though this trade-off is present in the use case of the face detection and matching service for the Lost Child application (see Section II) this is an assumption which highly depends on the service implementation and the chosen algorithms. Current online streaming services use a similar adaptive logic, but in these cases this adaptive behavior must be specifically implemented for the service, whereas in our approach the service developer is abstracted from its implementation.

Our heuristic works as follows: to begin, all of the different possible configurations of parameter values are constructed and sorted by their objective value (e.g., expected accuracy).

The configuration with the highest objective value is used to process the first input. Service requirements are monitored and if they are not satisfied, the performance is degraded by using the immediate lower configuration, which is expected to improve the requirements satisfaction. If the requirements are met for a number of continuous steps, then the performance is upgraded. If this upgrade still satisfies the requirements, then the process is repeated until requirements are not satisfied anymore, and then the performance is degraded by utilizing the last configuration that worked within the requirements. Figure 3 shows a control flow diagram for this approach.

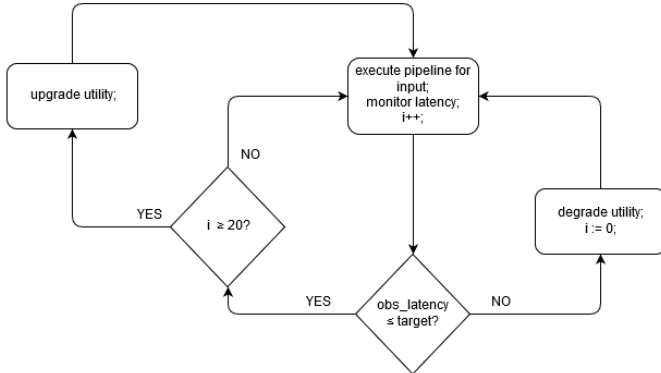


Fig. 3. Control flow diagram of the heuristics based orchestration  
B. *RL based Orchestration*

Second, we develop a Reinforcement Learning (RL) based optimization to find the best configuration of parameter values during runtime. The RL based orchestration does not require a linear trade-off between service objectives and constraints. Instead, it learns through its own experience. This makes the RL based orchestration more flexible and able to generalize over more services than the implemented heuristic.

In RL, an agent can sense its environment and take actions that affect the state of the environment and generate a numerical reward. The agent does not know in advance what actions should be taken in each state, its objective is to find the action that will create the highest reward for each different state [11].

In our RL setup the agent represents the service, and its environment can be seen as its execution context. The agent can take actions to adapt to different states of its context, in order to achieve its goal of performing with the highest possible performance while respecting the given constraints. Also, we frame our problem in a discrete time setting, in which each time step corresponds to the full processing of an input.

In order for the RL approach to be computationally inexpensive, we use tabular Q-learning [12]. Tabular Q-learning defines what action should be taken in each state by maintaining a table in which there is one row for each state, and one column for each action. The value in each cell is the expected reward of taking a specific action while being in a given state. Because of this, it is of particular interest the definition of the actions and states. In our case, we define them as:

- Actions: each different configuration of parameter values
- States: the current execution environment’s status, the requirements’ satisfaction in last step and the last configuration of parameter values used

When the service has just started, different parameter configurations are chosen at random and profiled in an online manner. After this process has been performed a number of times, the agent knows which configurations perform better in each state by using the  $Q$  table.

More specifically, two different states-actions configurations are defined and implemented:

#### Configuration 1

- States: Last latency as % of target [3 values (0-80, 80-100, 100- $\infty$ )], number of last configuration used
- Actions: Number of configuration to be used

#### Configuration 2

- States: Last latency as % of target [3 values (0-80, 80-100, 100- $\infty$ )], current CPU availability % [3 values (0-50, 50-80, 80-100)], number of last configuration used
- Actions: Number of configuration to be used

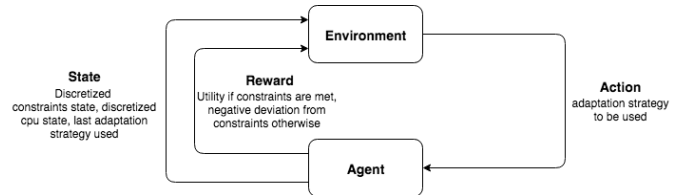


Fig. 4. Diagram of the RL based orchestration, configuration 2

The reward indicates how well the agent is performing according to its objective. In our case, the reward is defined as the objective (measured in a metric selected by the developer e.g. precision) if requirements are satisfied, or the negative deviation of its performance according to the requirements if these are not fulfilled. Mathematically, we define the reward function for taking an action  $a$  in a given time step  $t$  as:

$$R_{t,a} = \begin{cases} O_{t-1}, & \text{if } \forall c_i \leq C_i \\ -\sum_{i=0}^N \frac{c_{i,t-1}}{C_i} \forall c_{i,t-1} > C_i, & \text{otherwise} \end{cases} \quad (1)$$

## V. EVALUATION

### A. Simulator

To test the orchestration approaches, we have implemented a simulator in which developers can define elastic services, by defining a pipeline of operators, and the adaptable parameters for each operator. Once a service has been defined, its functioning can be profiled on a set of inputs and devices by using a profiler which tests all of the different parameters configurations repeatedly and record the metrics that will be later used by the simulator.

We implement the face detection and matching service for the Lost Child application in this framework and profile it on a Raspberry Pi 3B+ device with different inputs. The inputs used are collages with different numbers of faces, from 6 to 192, taken from the dataset Faces94 [10].

### B. Environments and Datasets

To define the RL framework, we specify different environments with the states-actions configurations. The implemented interface has been inspired by OpenAI Gym environments [3].

We simulate the service execution on a shared device, which means that the CPU availability varies over time due to the other services concurrently running. In every step, the environment simulates the CPU availability as a Markov Chain varying from 0.3 to 1.0. In this chain, the CPU availability for a new step has a probability of changing with respect to the previous step of 0.1, and the variation will be randomly drawn from a  $N(0.1, 0.1)$  distribution.

We create three different datasets by combining the inputs previously defined:

- 1) Fixed input: 1000 frames with 48 faces each.
- 2) Variable input: 1100 frames with varying number of faces in each image, from 6 faces to 192. The dataset is composed by blocks of 100 continuous frames with the same number of faces. The blocks are arranged in the following way: 6, 12, 24, 48, 96, 192, 96, 48, 24, 12, 6; where each number represents the amount of faces in the block of 100 frames.
- 3) Full day input: a dataset that simulates the whole input of a full day at a train station was built. There are 86400 images, one for every second of the day. The inputs from the previous item were used, but the number of faces varies over time to simulate peak and low traffic hours.

In addition, we implement another version of the RL environment. This version models the random CPU availability as the previous version but incorporates random inputs. The inputs have different number of faces and are chosen at random from the inputs used by the variable input dataset. Because the number of faces in each input does not change every second in reality, in each step there is a 0.1 probability of changing the input with a random sample and 0.9 probability of keeping the same input as in the previous step.

### C. Results

We simulate the face detection and matching service 50 times with each dataset and orchestration approach. In the case of RL based approaches, the Q-table is started with 0 values for the first simulation and the following ones use a prepopulated Q-table using the values produced by the previous simulations. Table I depicts the results.

Firstly, we implement and test a static service with two different configurations: one optimized for a high precision service, and another one optimized for a high latency satisfaction. We can see that the high precision service has a precision of 1 –this impressive high value can be achieved thanks to the simple dataset used– but fails to satisfy the latency requirement very often. The high latency satisfaction service does the opposite, complies with the latency requirement in most cases but offers a very low precision.

Secondly, we implement and test an elastic service using the Heuristics based dynamic orchestration. We can see how the elasticity of the service helps it to get a good trade-off between precision and latency satisfaction rates.

Finally, we also test an elastic service using both configurations of RL for its dynamic orchestration. Both RL configurations offer a high latency satisfaction as the Heuristics

		Static		Elastic		
Input		High Precision	High Lat. Satisfaction	Heur.	RL1	RL2
Precision	Fixed	100	41.95	82.71	91.92	91.44
	Variable	100	41.95	75.81	76.36	82.66
	Full day	100	41.95	69.99	68.65	77.79
	Random	100	41.95	66.26	72.21	83.45
% Latency Satisfaction	Fixed	79.06	95.78	93.02	94.72	95.00
	Variable	66.38	84.97	82.43	81.36	79.04
	Full day	72.15	82.22	79.20	79.31	79.06
	Random	67.27	86.19	80.22	80.89	83.03

TABLE I  
PERFORMANCE OF STATIC AND ELASTIC SERVICES, USING DIFFERENT DYNAMIC ORCHESTRATION APPROACHES

approach while improving the application’s precision by a margin of 10–25%, as shown on figure 6. Moreover, the RL configuration 2 – which uses the last requirement’s satisfaction, last configuration used and current CPU availability—shows a better performance than the other configuration; because the agent can take better decisions with more information.

Regarding the requirements for the dynamic orchestration, our RL based approach uses less than 0.5% of the total execution time of the application, and produces even a lower overhead than the Heuristics based approach. This is visible in the results obtained in Table II. In addition, the learning based orchestration adapts rapidly to changes as it can be seen in Figure 5. When the CPU availability drops around step 485, the logic automatically changes the configuration, reducing the expected precision but managing to keep functioning within the latency requirement. Afterwards, when the CPU availability increases again in step 515, the orchestration changes again the configuration to take advantage of the higher resources availability and improving the expected precision.

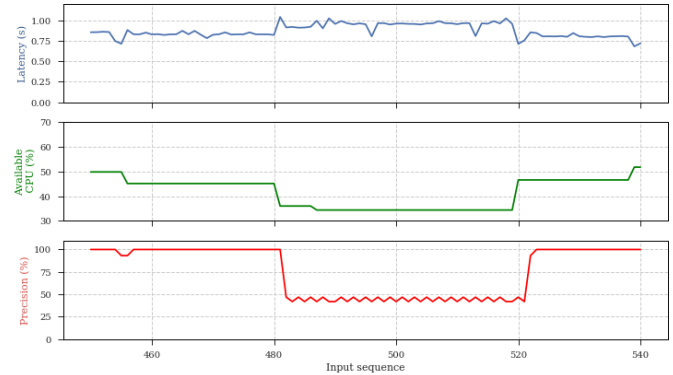


Fig. 5. Response to changes of RL2 based orchestration

		Orchestration	Total	Impact in total latency
<b>Intel Core i5-3210M</b>	Heur.	0.29ms	70.52ms	0.42%
	RL	0.21ms	70.44ms	0.30%
<b>Raspberry Pi 3 B+</b>	Heur.	1.31ms*	313.24ms*	0.42%*
	RL	0.93ms*	312.86ms*	0.30%*

TABLE II  
OVERHEAD OF THE ORCHESTRATION TO THE OVERALL SERVICE. TOTAL EXECUTION TIMES ARE CALCULATED AS THE TIME USED FOR THE ORCHESTRATION AND PROCESSING A FRAME OF 6 FACES USING THE FASTEST PARAMETER CONFIGURATION. (\*) PROJECTED TIMES.

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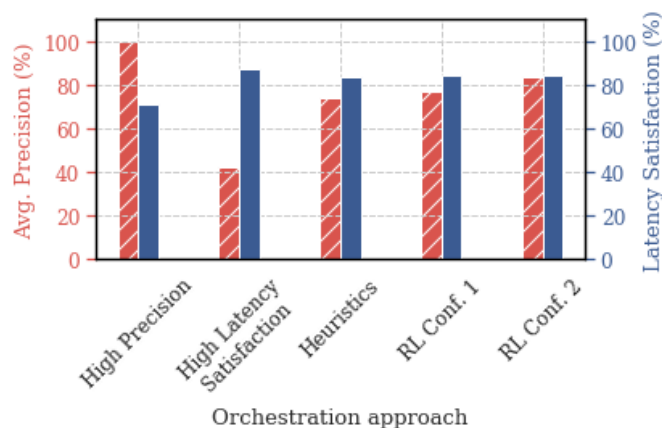


Fig. 6. Average precision and latency satisfaction over all datasets for the different orchestration approaches.

## VI. RELATED WORK

There is extensive research in the fields related to our work, such as self-adaptive systems and utilization of AI to optimize the performance of applications.

Natural Adaptive Video Streaming with Pensieve [9] presents a system that generates adaptive bit rate (ABR) algorithms using Reinforcement Learning. These algorithms are used for video streaming and must balance a variety of QoE goals. This work successfully uses a variant of deep RL, A3C, to create algorithms that adapt to a wide range of environments and QoE. The NN model runs on the server in order to avoid the overhead on the client, something which is not always possible in edge computing.

In Chameleon [8], the performance of video analytics applications is optimized by performing automatic adaptation of its configurations. The application’s behavior is customized to the execution context by selecting different parameter configurations; the best parameter configuration is selected by a logic inspired by greedy hill climbing combined with periodical online profiling. However, this research is centered around applications that use deep convolutional neural networks for video analytics, while we aim to offer a flexible solution that can be applied to any kind of application or service.

## VII. CONCLUSIONS

Thanks to Elastic Services, developers are able to create services that adapt to their current execution context, achieving high requirement satisfaction rates. By using our RL based orchestration to adapt their behavior, services can achieve an even better performance with a lower overhead to the system.

This work has shown the efficiency of the RL based orchestration through multiple simulations, improving on the results of the Heuristics based approach. The RL based orchestration achieves a 10–25% higher precision, while having a smaller system overhead, consuming 25% less execution time. In addition, thanks to its capability of learning through its own experience, the RL based orchestration offers a flexible and adaptable logic that can be used with very different services.

In the future, we plan to optimize our approach to be able to handle a large number of parameters and parameter



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values, something that is challenging for the tabular Q-learning method used in this work. In order to do so, we are looking into hierarchical RL models that will be distributed between the different processing nodes.

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