Simulation-Based Estimation of Resource Needs in Fog Robotics Infrastructures

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Abstract: Embedded devices are increasingly connected to the Internet to provide new and innovative applications in many areas. These devices (Edge devices or "Things" in IoT) are heterogeneous sensors, cameras and even robots performing sometimes certain tasks locally. Fog Computing (or Fog robotics) optimizes the management of these tasks, offering data management mechanisms (computation and storage) closer to the data source. Nevertheless, many aspects remain closed to Fog computing environments like resource needs estimation in such environments. Indeed, such a topic remains a critical challenge, as it falls under either solving very complex optimization problems or comparing hypothetical scenarios very time consuming and/or expensive for deployment in a real environment. To help on this challenge we built SERFRI, an approach to estimate the resource needs in Fog robotics environments based on simulation. This approach optimizes simultaneously the duration and the Fog resources utilization cost in order to determine the minimum resource requirements compromising both metrics. We validated this approach on an existing robotics use case. This one aims at deploying a human face detection service on streaming images.

1 INTRODUCTION

The Internet of Things (IoT) has transformed the Internet, enabling communication between every kind of objects (Things). The growing number of sensors and smart devices increased the possibilities of data generation and collection (R. de Oliveira. et al., 2021). These smart devices are robots in our case, making the previous observation more important in the field of robotics (Turnbull and Samanta, 2013; Norman and Bobrow, 1975). Indeed robotics is becoming more and more topical, as it facilitates the automation of tasks and guarantees better accuracy and speed of execution compared to human processing (Kwon et al., 2020; Moniz and Krings, 2016).

Basically, the high level architecture of a robot (Figure 1) consists of: sensors which get information about the robot environment, actuators which allow the robot to move in its environment, micro-controller which manages the actuators' motion, a microprocessor which computes tasks and the battery alimenting the whole system. In the basic running process of a robot, there are two main problems related to the computational capabilities of the robot: (i) the first one is about energy consumption, since this process

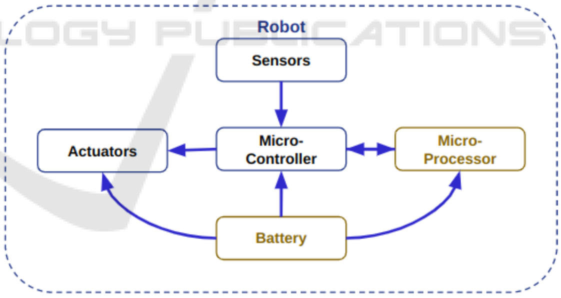

Figure 1: Five main components of a robotic architecture.

runs frequently and asynchronously the battery will be used by the assembly of robot components simultaneously, which makes the activity not feasible in the long term; (ii) the second one is about the fact that in most cases, robots do not have enough computing power or storage capacity to process (for a current service) and post-process (e.g: for the updating of a service) data generated.

In some cases it has been shown that it is more advantageous relative to time constraints to deploy robotic applications (which must be real-time) on remote resources. Figure 2 presents for example a comparison between the ETL (Extract - Transform - Load)

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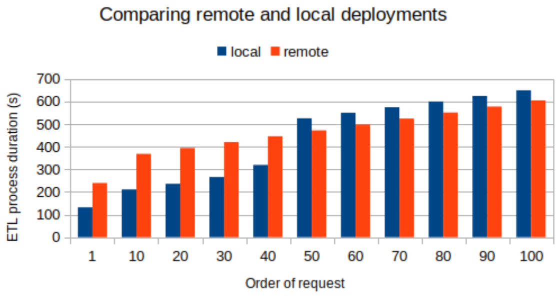


Figure 2: Comparing the ETL process of deploying a human face recognition service locally and remotely.

process duration of deploying a robotic application locally and remotely (36 times more powerful than the robot). This application was made using a Reachy humanoid robot (Mick et al., 2019) that captured 100 images (at the rate of 7 images per second) that were processed locally or on remote resources, to determine whether there was a human face or not. Then by the fiftieth request, the local deployment becomes in average 50s slower than the remote one. Based on the fact that industrial robotics applications often consist of millions of requests and based on the benefits of the Fog Computing (in terms of latency and power computing), it is then really more advantageous to deploy such applications on Fog-based environments.

Fog Computing offers a large computing and storage capacity near data sources (robots in this case, where we talk about Fog Robotics Platform (FRPs) (Gudi et al., 2017)). This is a recent approach that solves the latency problem present in native Cloud environments, for long-term and real-time applications (as in the case of industrial robotics). The architecture of Fog computing consists of three main layers: an IoT layer which contains connected data sources (such as smartphones, sensors, robots, etc.) sending requests (periodic, asynchronous and heterogeneous in the case of robotics applications), a Fog layer which contains resources (static/dynamic and heterogeneous/homogeneous) near the data sources and a Cloud layer which contains static resources far the data sources.

We are interested in two main problems related to such platforms: (i) indeed, in general, setting up certain hypothetical scenarios of Fog platforms is not possible at the real scale (this is sometimes due to high price of industrial robots and the financial cost of reserving or using a certain number of resources); (ii) moreover, the global makespan[1] of the platform often decreases with the number of resources increasing while the financial cost of using these resources does not have a known and specific evolution a priori. Two questions then arise, respectively to the two problems mentioned above: (a) How to simulate the deployment of FRPs in a realistic way? (b) how to estimate, based on a realistic simulation, the sufficient (minimum) number of Fog resources needed to guarantee a fast execution and at a lower financial cost of a robotic application?

This paper presents an approach for Simulation-based Estimation of Resource needs in Fog Robotics Infrastructures (SERFRI). It aims at providing a FRP configuration reducing the activity duration as well as the resources usage cost. More precisely, it determines the minimum number of Fog resources reducing significantly simultaneously: the makespan and the financial utilization cost of Fog Computing nodes. As a proof of concept, this approach has been used on an existing robotics use case. For this use case the IT architecture specification has been estimated to support its activity.

In the following sections of the paper, we present: the case study in Section 2, the related works in Section 3, the core principle of our contribution in Section 4, the experimental settings, results and comments in Section 5 and the conclusion in Section 6.

2 THE CASE STUDY

This section presents the study and the specifications of an existing robotics use case which is about deploying a human face detection service on a stream of images by a Reachy humanoid robot (Mick et al., 2019). Reachy (Figure 3) is a human-scale robotic arm with seven joints from shoulder to wrist, which can help researchers explore, develop and test innovative control strategies (such as tele-operation or gaze control) and interfaces on a human-like robot. Its 3D printed structure and ready-to-use actuators make it inexpensive compared to the price of an industrial-grade robot. Using an open-source architecture, its design makes it widely pluggable and customizable, so it can be integrated into many applications.

In Figure 3 we can see that Reachy has two high definition cameras and several articulations. This allows realizing through its use several use cases. The present use case employs one of Reachy's cameras to capture a stream of images to determine if there is at least one human face in each image. In this case, Reachy will raise the left hand and if not, the right hand. In Section 1 we have shown that for a number of resources that are globally 36 times more powerful than Reachy's NUC, the ETL process (photo capture, image computation, response to Reachy as shown in Figure 5) was faster. Two main challenges appear: (i)

[1]global queries' completion time

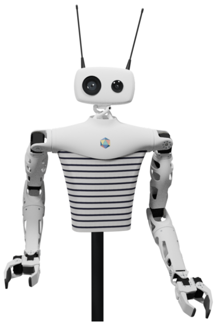


Figure 3: Reachy's Full kit picture: 3D printed MJF Painted - Flexible PU molded - Aluminium Construction; 670x1800x200mm with arms outstretched; 180 W of Max Power consumption and 6.2 kg of weight.

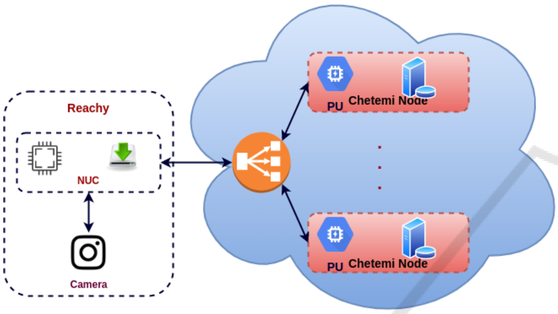


Figure 4: The Reachy use case architecture.

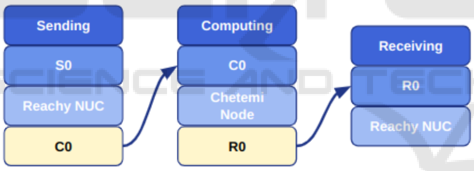


Figure 5: The Reachy use case workflow modeling.

Since the latency between Reachy and the remote resources represents a major parameter (more than 200 ms) in the duration of the ETL process, what type of distributed system would be best suited to deploy such a use case? (ii) To perform the experiment highlighted in Figure 2, 3 Grid'5000 nodes of the *chetemi* cluster [2] (Intel Xeon E5-2630 v4) located in Lille were used (Figure 4), however with 2 nodes of the same type after a certain number of requests or with 1 node of another type of resources, the same type of behavior could be observed; what would be the sufficient (taking less time and less financial cost to run) number of remote computing nodes for this use case? Part of Section 3 gives some clarification on the type of distributed system adequate for the application underlying this use case and Section 4 will provide an element of answer regarding the estimation of the resource requirements on the adequate platform.

3 RELATED WORK

Modeling and simulation technology has become a useful and powerful tool in Large Scale Distributed Systems (LSDS) deployments (particularly in the Cloud computing research community) to deal with performance evaluation and security problems in such environments (Zhao et al., 2012). It is necessary to model both the platform and the application concerned. In this Section, we present: (a) A brief background on the deployment of robotic ecosystems on LSDS in terms of brief comparative study to justify the use of Fog Computing Platforms, (b) some simulators of application deployments on Fog-based environments and (c) some Fog resource needs estimation approaches.

3.1 Deployment of Robotic Ecosystems on Large Scale Distributed Systems

Many works present the deployment of robotic ecosystems on large-scale distributed systems in various paradigms as Service Oriented Architecture (SOA), Cloud Computing, Edge Computing, Fog Computing and peer-to-peer.

Cloud and SOA (Papazoglou and Van Den Heuvel, 2007) offer a high level of security, large computing capacities and interoperability. An initial type of deployment to virtualize robotic hardware and software resources and offer them as services on the Cloud via the web is more and more topical. For example, RobotWeb (Koubaa, 2014) is a SOAP-based web service middleware-based system that binds robot computing resources as services and publishes them to end users. In (Koubaa, 2014), the robots run on the Robotic Operating System (ROS), as it provides a hardware abstraction that facilitates application development.

Edge Computing enables the decentralization of the management of robot functionalities, thus increasing the reliability and reducing the latency of the centralized system (Chen and Hu, 2013). The work presented in (Ray, 2016) proposes a new concept that addresses the problems of supporting control and monitoring activities at deployment sites and industrial automation. In that work, smart objects can monitor peripheral events, induce sensor data acquired from various sources, use ad hoc, local and distributed Artificial Intelligence (AI) to determine the appropriate course of action. The goal is to control or disseminate static or dynamic robotic objects that are aware

[2] https://www.grid5000.fr/w/Lille:Hardware#chetemi

of their position in the physical world in a seamless manner by providing a way to operate them as suggested by the Internet of Robotic Things (IoRT) concept (Ray, 2016).

The use of pairing technologies (Kapitonov et al., 2021) presents a wide decentralization of robotic devices, giving them economic independence by using Peer-to-peer technologies, distributed registry and cryptography. Table 1 (Sakovich, 2020) gives a more explicit comparison of these different approaches.

Table 1: Comparison of distributed system paradigms.

Paradigm	Latency	Data management	Scalability	Computing Capabilities
SOA and Cloud	High	Centralized	High	High
Edge computing (IoT)	High	Decentralized	Low	Low
Fog computing	Low	Decentralized	Low	Low
Peer-to-peer	Very Low	Widely decentralized	Very Low	Very High

The concept of Robot as a Service (RaaS) has made it easier to manage robotic functionalities. Everything is done so that the end user does not have to worry about updating the functionality. The RaaS concept directs the work related to Fog robotics towards the ROS improvement in order to favor in a first step, a large decentralization of the management of robotic functionalities. ROS is a widely used software development framework with packaging tools and communication infrastructure for robotic scenarios, often easily deployed on virtual machines running on Android devices, smart mobile gateways and especially robotic hardware (Quigley et al., 2009).

The work done by (Mushunuri et al., 2017), consists in linking the NLopt optimization library (Johnson, 2014) (which implements several types of optimization algorithms) to ROS. Through this library, they optimize the communication infrastructure of robotic scenarios, thus promoting the management of limited resources in various other mobile IoT environments.

3.2 Simulation in Fog-Based Environments

Simulating application execution in LSDS is very common these days generally speaking in Cloud-based environments. In this Section we will discuss some of the most relevant and existing simulators in Fog environments.

iFogSim (Gupta et al., 2017) is a simulation framework allowing to model IoT, Edge and Fog environments and to measure the impact of resource management techniques on latency, energy consumption, network congestion and the cost of using resources. it also demonstrates strong scalability in terms of memory consumption and execution time. However, it is limited with regard to the network communication model, since it does not deal with device-to-device communications because it considers a hierarchical organization of Fog equipment.

MyiFogSim (Lopes et al., 2017) is a simulation framework that is based on iFogSim, so it inherits all its assets. In addition to these strengths, it supports the analysis of the impact of virtual machine migration policies on the quality of service of applications. It therefore also inherits the network communication modeling limitations present in iFogSim.

YAFS (Lera et al., 2019) is a simulation framework for IoT applications in Fog environments. It has broader functionality than iFogSim and MyiFogSim, in that it deals with both Fog resource management and IoT application placement on Fog devices. In addition, its modeling of Fog environments is much more realistic and strong. However, its cost model is not available, its network model is limited and customization of the mobility model is not supported (Kunde and Mann, 2020).

3.3 Fog Resource Needs Estimation for IoT Applications

Fog Computing brings a recent approach to data management, resource management is very little discussed in Fog-based environments. Previous studies are limited to Cloud and Edge scenarios only.

Reference (Aazam and Huh, 2015) presents a service oriented resource management model for IoT devices, through Fog, which can help in efficient, effective, and fair management of resources. Their work mainly focused on customer type and device based resource estimation and pricing, but they do not take into account IoT device capabilities, like CPU and memory in their model.

Reference (Garcia et al., 2018) analyzes and estimates the real Fog computational capacity in the city of Barcelona, which is one of the world's most popular smart cities. Thus, they do not focus on specific applications or specific types of applications like robotics applications.

Reference (Kattepur et al., 2017) mainly deals with the estimation of the execution times of robotics applications in heterogeneous Fog environments. They implement their approach on applications processing images and videos. However, they do not address the estimation of Fog resource requirements, moreover the model does not take into account the CPU degradation of Fog resources.

This work primarily discusses the Fog resource requirements of robotic devices of the Edge layer, since this kind of deployment is a compromise for the majority of the comparison criteria (good latency, better security, good data management) in Table 1. It differs from existing works about multi-objectives optimization in that it does not focus on resource utilization optimization but on resource needs estimation (whose use can be further optimized). This estimation targets the reduction of two metrics simultaneously: the makespan and financial Fog resource utilization cost; Through robust and reliable simulation based on the well-known simulator, SimGrid[3] (Casanova et al., 2014), which has one of the best network communication models to date.

4 SERFRI's CORE PRINCIPLE

To estimate the resource requirements of an application based on the simulation of its deployment in a FRP, it would be necessary to: (i) model this FRP, (ii) model the robotic application, (iii) set up the simulation and (iv) simulate application deployments on multiple platform scenarios (since simulation is less time-consuming) and compare the metrics (makespan, cost) to determine the best type of resources to use (among numerous types). These steps represent the phases of SERFRI and are the subject of presentation in this section.

4.1 Fog Robotics Platform Modeling

Figure 6 takes up the high-level architecture of a robot already presented in Figure 1 without on-board computing and storage capabilities. In this work, we deal only with homogeneous Fog environments containing static resources.

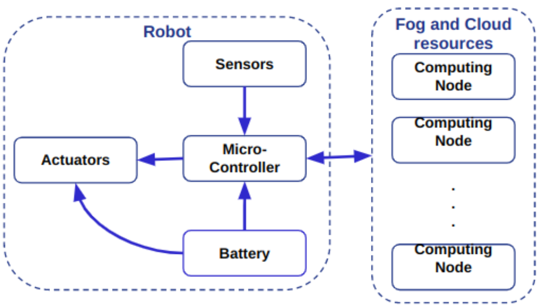


Figure 6: Fog Robotic Platform modeling.

The first objective of this approach is to determine the global resource needs (Workload[4] (W), and Storage (S) capacity) of the application, then to estimate the configuration of resources (storage capacity, and computing power) which satisfy at best the global needs and simultaneously compromises the makespan and the cost of using Fog resources.

To parameterize this situation, we represent a Fog resource of order j by two types of information:

- **the fixed parameters** (without dependency on its activity): the cost of using the resource per unit of time (c_j); resource memory (r_j); and its storage capacity (s_j).
- **the calculated parameters** (depend on its activity): the calculation speed of the node (v_j), which is the product of the number of cores, the clock frequency and the number of operations per instructions cycle of the Fog node; the start computing time (b_j); the completion time of all the requests entrusted to this resource during the activity (m_j).

Finally, a Fog resource of order j (FN_j) can be written according to the expression $FN_j = (r_j, s_j, c_j, v_j, b_j, m_j)$.

Considering n Fog resources, C the resource utilization cost and M the makespan of the Fog layer, then appears the following constraints and relations:

$$S < \sum_{j=1}^{n} s_j \tag{1}$$

$$C = \sum_{j=1}^{n} c_j \times m_j \tag{2}$$

$$M = Max(\{b_j + m_j\}_{j=1}^{n}) - Min(\{b_j\}_{j=1}^{n}) \tag{3}$$

4.2 Robotic Application Modeling

Figure 6 suggests that the application be divided into two sub-applications: a Client application to issue requests and a Server application to process these requests. In the context of robotics, these queries are:

- **periodicals:** for each pair of consecutive requests, there is a constant duration between their emission dates (Equation (5));
- **asynchronous:** sending and processing a request does not prevent the same operations for other requests;
- **heterogeneous:** the quantity of data communicated varies according to the requests.

[3]https://simgrid.org/usages.html

[4]in FLOPs (FLoating Point OPerations)

The i-order request (R_i), is characterized by: a date of issue (e_i), a quantity of data that it communicates (d_i). Finally we write: $R_i = (e_i, d_i)$. And for a set of q periodical (t-periodical (Equation (5))) requests we define a function T giving the completion time of a i-order request processed by the j-order Fog resource by:

$$\begin{array}{cccc} T & : & \{R_i\}_{i=1}^{q} \times \{FN_j\}_{j=1}^{n} & \rightarrow & \mathbb{R}_+ \\ & & (R_i, FN_j) & \mapsto & t_{ij} \end{array} \quad (4)$$

So that:

$$t_{ij} = \begin{cases} value > 0 & \text{if } R_i \text{ is processed by } FN_j \\ 0 & \text{else.} \end{cases}$$

$$e_{i+1} = e_i + t, \forall\, 0 < i < q \quad (5)$$

The workload of the i-order request will then be defined by Equation (6). This workload being the same for the same application even if the resources specification change, helps in compute the corresponding completion time of a request by the new resource, having the completion time of the previous one.

$$W_{ij} = t_{ij} \times v_j \quad (6)$$

Figure 6 suggests also three kind of events[5]: Sending event (which sends the requests), a Computing event (which processes the data communicated by the requests) and the Receiving event (Which load to the data source/an IoT device the results of requests). These events happen in this order: Sending, computing and Receiving; The robot runs the Sending and the Receiving events when the resources handle the Computing event.

4.3 Simulation Settings

Even though there are a very large number of simulators in Fog based environments, there are some limitations on the most known of them, as they are based on other simulators that are limited in terms of network communication models for example. To circumvent this limitation, we used SimGrid which is very powerful for simulations in many types of LSDS and in Cloud and Grid computing in particular. SimGrid has an accurate network communication model, which helps make the simulation realistic (Velho and Legrand, 2010). It has been used in hundreds of projects and helps in both distributed applications and LSDS evaluation. Moreover, there is a very large community around him since it represents more than twenty years of code improvement.

A SimGrid study consists of:

[5] An event means an action (Sending, Computing or Receiving) in this case

- **The description of the platform concerned:** defining the zones of the platform studied, the entities (hosts) which composed them as well as a description of the specifications of these hosts and the connections between them. This can be done through an XML file or an assembly of code instructions, built from the following parameters: resource specifications $\{FN_j\}_{j=1}^{n}$, latency (lt) and bandwidth (bw) of the connection between the IoT layer and the Fog layer;
- **The description of the application:** a set of functions or events that must occur during the execution of a deployment scenario. In SimGrid, they are represented by Classes or Event Functions;
- **The deployment:** which specifies which host executes which event. It can be expressed through an XML file or an assembly of code instructions, built taking into account the workflow described above (Sending - Computing - Receiving) executed by the corresponding hosts (robot - Fog resources - robot).

Our simulation is therefore likened to a $simulate()$ function which finally takes as parameters: $\{FN_j\}_{j=1}^{n}$, lt, bw, the requests sending period t and the function T in Equation (4)). This function ($simulate()$) returns again $\{FN_j\}_{j=1}^{n}$, with suitable values of calculated parameters of each resource related to the execution of the application, since before the execution those parameters were all set to 0. However the workload generated by a request is not known, it is then necessary to find what the function T corresponds to in our simulation. T can be assimilated (depending on the use case) to a mathematical formula, machine learning model or mapping object and so on, that give exactly or estimate the completion time of a request by a Fog resource according to the characteristics of the request and those of the Fog resource. Then an estimation of the query workload is given by Equation (6)).

4.4 Algorithm of the Approach

The objective of SERFRI is to propose a resource type and the optimal number of resources of this type among a set of resource types, in order to simultaneously reduce as far as possible the makespan and the global cost of resources use. The goal is to apply it on each type of resource studied and select the one that optimizes the makespan and the cost. Indeed, according to a specific resource type, for each resource of order j, $FN_j = FN_1$ and $FN_1 = (r, s, c, v_j, b_j, m_j)$ where r, s, c are constant. We do not deal with resource management and assume that the scheduling used for the distribution of requests to resources is the Round-Robin algorithm, and that the scheduling of requests on a node follows the logic of the FIFO algorithm.

The problem that this approach tries to solve can be reformulated as follows: Assuming we have l types of resources ($\{hn_j\}_{j=1}^{l}$) and p configurations[6] ($\{config_k\}_{k=1}^{p}$) possible for each type of resource, what would be the pair $(hn_j, config_k)$ that would best reduce the makespan and financial cost of using the resources (by serving requests in order of arrival, without attempting on line scheduling on them)? The results of the simulations of each pair in $\{hn_j\}_{j=1}^{l} \times \{config_k\}_{k=1}^{p}$ can be represented by two matrices of order $p \times l$: the makespan matrix A (A_{kj} is the makespan when $config_k$ resources of type hn_j are used) and the financial cost matrix B (B_{kj} is the financial cost of using $config_k$ resources of type hn_j).

The problem as formulated can be solved by a Pareto optimization (Ngatchou et al., 2005), whose solution $(hn_{j_0}, config_{k_0})$ verifies that there is no pair (A_{kj}, B_{kj}) so that $A_{kj} < A_{k_0 j_0}$ and $B_{kj} < B_{k_0 j_0}$. This can lead mathematically speaking to several solutions, some of which may not be acceptable in practice.

Algorithm 1 of the SERFRI approach aims at selecting the most practically acceptable solution in the theoretical Pareto front (of couples verifying the Equation (1)). It proceeds by calculating the ratios (Equation (7)) relative to a basic resource type and a basic configuration for each metric and by performing optimization operations on them. This algorithm highlights some functions that we define below:

$$\begin{array}{cccc} \phi & : & \mathcal{M}_{p\times l} & \rightarrow & \mathcal{M}_{p\times l} \\ & & M & \mapsto & \left\{\frac{M_{kj}-min\_cell\_val(M)}{min\_cell\_val(M)}\right\}_{(k,j)\,\in\,\overline{1,p}\,\times\,\overline{1,l}} \end{array} \tag{7}$$

In the ϕ function definition, $min\_cell\_val(M)$ returns the minimum value of the elements of M. This function (ϕ) returns a matrix where each cell has for value, the relative error of the value of the cell of the same position as this one in matrix M, compared to the cell of matrix M whose value is minimal.

$$\begin{array}{cccc} \sigma & : & {\mathcal{M}_{p\times l}}^2 & \rightarrow & \mathcal{M}_{p\times l} \\ & & (M,N) & \mapsto & \{max(M_{kj}, N_{kj})\}_{(k,j)\,\in\,\overline{1,p}\,\times\,\overline{1,l}} \end{array} \tag{8}$$

The σ function returns a matrix where each cell has, for value, the maximum value of two cells of the same position as this one in the matrices M and N.

This algorithm is indeed of complexity $O(p \times l)$, which is faster than first applying a Pareto optimization of exemplary complexity ($O(p \times l \times log(p \times l))$ (Deb et al., 2002)) before implementing a selection algorithm to find the solution of the front that is in practice acceptable. From the pair (k_0, j_0), we then have the type of resources (hn_{j_0}) and the number of resources of this type $(config_{k_0})$ which compromises the simultaneous reduction of the makespan and financial cost of using the resources.

[6] the possible numbers of resources

Algorithm 1: Determine the Fog resource needs.

Require: $A \vee B$
Ensure: k_0, j_0
  $\delta \leftarrow \sigma(\phi(A), \phi(B))$
  $(k_0, j_0) \leftarrow \underset{k,j}{argmin}(\{\delta_{kj}\}_{(k,j)\,\in\,\overline{1,p}\,\times\,\overline{1,l}})$
  return k_0, j_0

5 EXPERIMENTS

In this section, we first validate the simulation of the deployment of the use case expressed in Section 2. And then, we present the estimated resource type specifications (among many types of resources) to optimally set up the infrastructures of this case. The simulator [7] is publicly available on GitLab and contains dataset, source code and instructions to reproduce our results.

5.1 Simulation Validation

To make a simulation reliable, it should be as realistic as possible. One way to validate it is to evaluate its accuracy and its scalability compared to the same scenario in a real environment. We evaluate the accuracy of our simulator by comparing the time-based traces obtained in real situations and in simulation, about the completion time and we evaluate the scalability by evaluating the machine learning models predicting the services' completion times when the number of cores is increasing.

Table 2: Mean Absolute Errors (MAE) and Standard deviations (STD) according to the number of cores. CT stands for Completion Time.

Number of cores	CT MAE (s)	CT STD (s)	Image size STD (KB)
20	22.83	26.07	23.76
40	21.01	17.81	25.79
60	24.12	15.95	16.8
80	20.25	13.4	23.7
100	26.62	9.39	21.8

[7] Our simulator is available at: https://gitlab.inria.fr/lndjieng/fridsim/-/tree/master

5.1.1 Simulation Scalability Evaluation

Equation (4) (Section 4.2) presents a generic function for estimating the completion time of a i-order request on a j-order Fog resource. We said in Section 4.3 that this function can be similar to a mathematical formula, machine learning model or mapping object and so on in our simulation (For each platform setting).

In our use case, we built machine learning models trying to find the optimal correspondence between the data (e_i, d_i) and t_{ij} according to the platform setting. We thus first collected execution traces of the human face detection service on 400 images for each configuration of the Fog layer (1, 2, 3, 4 and 5 *chetemi* nodes). Then a clustering algorithm (KMeans in our case) was applied to 280 random occurrences of the couple (e_i, d_i) in the dataset containing the 400 starting couples. The value of the predicted completion time for each triplet of a cluster was then the mean value of the completion times of the couples of this cluster. We evaluate the accuracy of the model like the percentage of predictions whose absolute errors relative to the actual values are less than a given tolerance. This tolerance should be as small as possible. The CDF on Fig. 7 gives the completion time estimation model accuracy according to the tolerance (and according to the number of nodes), and Table 3 gives the accuracy corresponding to 15 s according to the number of cores. This accuracy increases with the number of nodes, meaning that the simulation reaches the scale-out property.

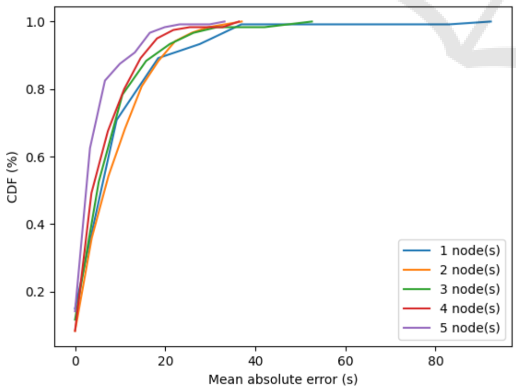


Figure 7: CDF according to the mean absolute error between real completion and prediction. Each *chetemi* node has 20 cores. Reachy sends 400 requests to Fog nodes.

5.1.2 Simulation Accuracy Evaluation

Figure 8 gives the evolution of the life-cycle duration (in real and in simulation) according to the order of the request sent for each configuration of the Fog layer. This life-cycle consists of three steps (extract, transform and load) and is traced for each request in simulation and in real deployment to compare both deployments. According to the number of cores, the difference between both life-cycles duration in average is short (22.97 s by computing mean value of CT MAE column of Table 2 giving an accuracy of 95% in average for the completion time estimation model) . This tolerance can be considered as short because it does not really have an impact on the global makespan, completion time and duration of the activity, since requests are asynchronous. Despite the fact that the data communicated by the queries are of the same order (because standard deviation of image size distribution (Table 2) is very lower than the minimum value of this distribution (Table 4)), the completion times in real life vary greatly (Table 2). This is because at certain times there are many more requests sharing the CPU than at other times. The simulation follows this same observation well with respect to the mean absolute errors of the completion time for each configuration of the Fog layer highlighted in Table 2.

Table 3: Completion time accuracy for a tolerance of 15 s, according to the number of nodes.

Number of cores	Accuracy (%)
20	80.83
40	80.92
60	88.3
80	90.0
100	96.5

5.2 Fog Resource Needs Estimation

To implement SERFRI on the use case presented in Section 2, we consider that Fog instances have similar characteristics to OVHCloud instances[8] designed for data analysis and data-science uses: r2-15, r2-30, r2-60 , r2-120 and r2-240. We simulate the platform scenario made-up of : 2, 4, 8, 16, 32 and 64 resources for each of OVHCloud instance types considered. We present first the simulation settings, then the pareto optimization and finally the SERFRI steps: (i) phi-transformation [9], (ii) sigma-transformation [10] and result expression.

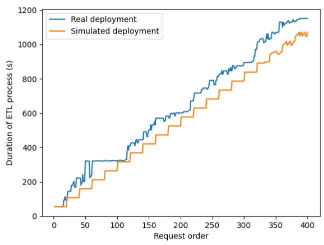
5.2.1 Settings

To perform the simulations with these new instances, we do not rebuild an estimation model but we rely on the models built with the *chetemi* nodes. Indeed, with regard to Equation (6)), the workload of a request i

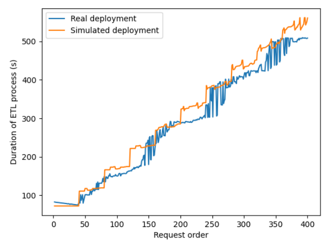
[8]Cloud pricing: Comparison of public Cloud offers-OVH, https://www.ovhCloud.com/fr/public-Cloud/prices/

[9]The application of ϕ function

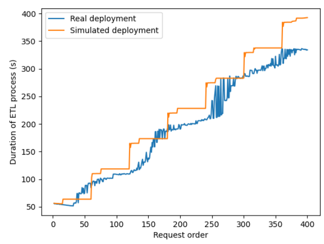
[10]The application of σ function



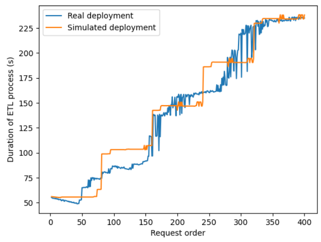
(a) 1 *chetemi* node: 20 processing cores.



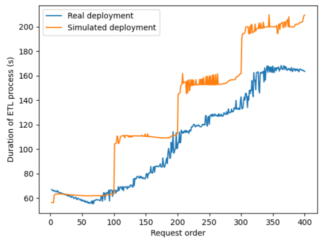
(b) 2 *chetemi* nodes: 40 processing cores.



(c) 3 *chetemi* nodes: 60 processing cores.



(d) 4 *chetemi* nodes: 80 processing cores.



(e) 5 *chetemi* nodes: 100 processing cores.

Figure 8: Requests life-cycle durations. Comparison between Real and Simulation deployments.

on a resource j with speed v_j is written $W_{ij} = t_{ij} \times v_j$, in the same way, this request processed by another type of resource of order j with speed v'_j will have a workload that will be written $W_{ij} = t'_{ij} \times v'_j$. This allows us to deduce the desired completion time: $t'_{ij} = \frac{t_{ij} \times v_j}{v'_j}$.

Table 4: Simulation settings.

Number of requests	5000
Frequency (number of requests/second)	7
Maximum number of instances	64
Bandwidth between Edge and Fog Layers (Mbps)	20
Latency between Edge and Fog Layers (s)	0.005
Data sizes range (B)	420000 - 480000
Response json size (B)	62
Instances (ovh Cloud instances)	r2-15, r2-30, r2-60, r2-120, r2-240

Table 4 gives the values of the simulator inputs. Regarding the characteristics of the instances, the level of granularity is very low, because we consider: the memory, the storage, the number of cores, the resources cost per unit of time, the clock frequency, the maximum number of operations per instruction cycle and bandwidth in a public network. Requests sizes are randomly generated between 420000 B and 480000 B, and we keep this same distribution for all deployment scenarios of the use case.

5.2.2 The Pareto Optimization

Table 5: Makespan (in second) by resource type and configuration.

Configuration	**R2-15**	**R2-30**	**R2-60**	**R2-120**	**R2-240**
2	82182.11	82182.11	41138.88	20610.64	10253.34
4	41138.88	41138.88	20610.64	10592.45	5591.26
8	20610.64	20610.64	10592.45	5591.26	2690.48
16	10592.45	10592.45	5591.26	2772.42	1530
32	5591.26	5591.26	2772.42	1530	869.8
64	2772.42	2772.42	1530	869.8	494.5

Table 6: Financial cost (in euro) by resource type and configuration.

Configuration	**R2-15**	**R2-30**	**R2-60**	**R2-120**	**R2-240**
2	4.43	5.12	5.01	5.04	4.95
4	4.45	5.14	4.98	5.09	5.13
8	4.41	5.1	5.01	5.14	5.05
16	4.46	5.15	5.03	5.12	5.22
32	4.45	5.14	5.04	5.28	5.44
64	4.44	5.13	5.16	5.46	6.4

Table 5 and Table 6 present the makespan and financial costs of using Fog resources, respectively. They are therefore the matrices we referred to in Section 4.4. The graphical transcription of Table 5 (Fig. 9) shows that the makespan decreases as the number of resources increases and more so when the type of resources is more powerful. The graphical transcription of Table 6 (Fig. 10) , on the other hand,

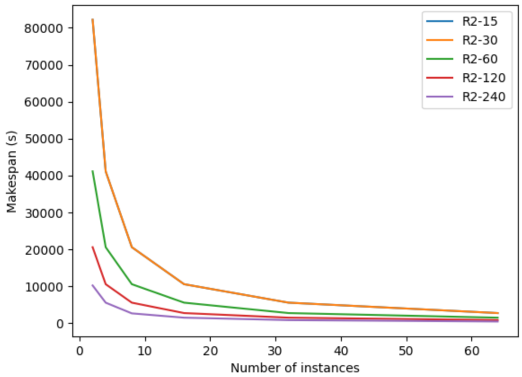


Figure 9: Makespan by the number of resources for each type of resource.

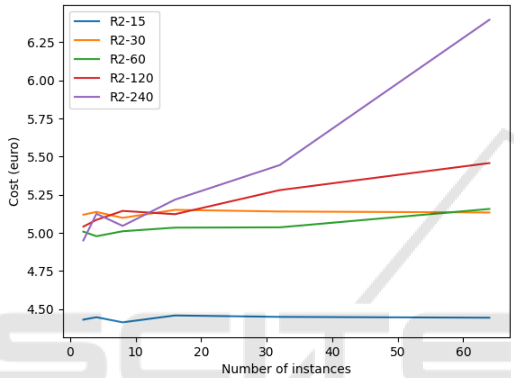


Figure 10: Financial cost by the number of resources for each type of resource.

grows as the number of resources increases and more so when the type of resources is more powerful, that makes the optimization very difficult. By naively applying Pareto optimization to reduce the makespan and the cost of using resources as much as possible, we obtain the following Pareto front: {(r2-15, 8), (r2-15, 64), (r2-60, 64), (r2-240, 8), (r2-240, 32), (r2-240, 64)}.

5.2.3 Phi-Transformation

Table 7 and Table 8 represent the normalized (phi-transformed tables obtained by applying ϕ function of Equation (7)) tables from Table 5 and Table 6 respectively. In other words, we look for the smallest element in Table 5 and we calculate for each element of this table the relative error with respect to this smallest element, and the same thing is done for the Table 6. This allows to bring the makespan and the financial cost into the same dimensional space. The makespan decreases according to the number of resources and the power of resources, but it is an inverted observation for the financial cost ratio. The Pareto front is the same front presented in Section 5.2.2.

Table 7: Makespan ratios by resource type and configuration.

Configuration	R2-15	R2-30	R2-60	R2-120	R2-240
2	165.19	165.19	82.19	40.68	19.73
4	82.19	82.19	40.68	20.42	10.31
8	40.68	40.68	20.42	10.31	4.44
16	20.42	20.42	10.31	4.61	2.09
32	10.31	10.31	4.61	2.09	0.76
64	4.61	4.61	2.09	0.76	0

Table 8: Financial cost ratios by resource type and configuration.

Configuration	R2-15	R2-30	R2-60	R2-120	R2-240
2	0	0.16	0.14	0.14	0.12
4	0.01	0.17	0.13	0.15	0.16
8	0	0.16	0.14	0.17	0.15
16	0.01	0.17	0.14	0.16	0.18
32	0.01	0.17	0.14	0.2	0.23
64	0.01	0.16	0.17	0.24	0.45

5.2.4 Sigma-Transformation

This transformation applies the σ function (Equation 8) on normalized matrices. Maximizing these matrices (Table 7 and Table 8) leads to the creation of the Table 9, according to the Equation (8), from which we can determine the minimum element and therefore the solution of the Pareto front that in practice is the most efficient in terms of time and financial cost: (r2-240, 64). It is indeed, because compared to the other Pareto solutions, it saves much more time than it costs.

Table 9: Maximized ratios by resource type and configuration.

Configuration	R2-15	R2-30	R2-60	R2-120	R2-240
2	165.19	165.19	82.19	40.68	19.73
4	82.19	82.19	40.68	20.42	10.31
8	40.68	40.68	20.42	10.31	4.44
16	20.42	20.42	10.31	4.61	2.09
32	10.31	10.31	4.61	2.09	0.76
64	4.61	4.61	2.09	0.76	0.45

6 CONCLUSION

In this article we address the estimation of Fog resource requirements (number of resources, memory, computing and storage capacity of each resource) of robotics applications. We then proposed an approach (SERFRI) for estimating static and homogeneous Fog resource needs based on the simulation of the deployment of Fog Robotic infrastructures. This approach aims at providing the best resource type and the best number of them, compromising the reduction at best of the makespan and the one of the financial cost of using these Fog resources. We implement the approach on an existing use case (Reachy) which could also have industrial vocation. The validation of the simulator on which the approach is based consisted mainly on the validation of the machine learning models used (accurate on average at 95 % with a prediction margin of 23 s for each request, not really impacting the global life-cycle duration of the application) to estimate the request completion time. This approach can therefore, also greatly help industrial companies (and/or those who base their activities on the use of robots) to have an approximate idea of the budget required for the activities of their robots on Fog resources. This approach also saves the financial budget and the use of the robot's battery, allowing it to perform more tasks. However, a similar approach should be implemented in the generic case of platform, where Fog resources are heterogeneous and dynamic and robots are mobile. The study indeed deserves reflection because it is not just an implementation of the knapsack problem as in the case of static heterogeneous resources.

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REFERENCES

Aazam, M. and Huh, E.-N. (2015). Fog computing micro datacenter based dynamic resource estimation and pricing model for iot. In *2015 IEEE 29th International Conference on Advanced Information Networking and Applications*, pages 687–694.

Casanova, H., Giersch, A., Legrand, A., Quinson, M., and Suter, F. (2014). Versatile, scalable, and accurate simulation of distributed applications and platforms. *Journal of Parallel and Distributed Computing*, 74(10):2899–2917.

Chen, Y. and Hu, H. (2013). Internet of intelligent things and robot as a service. *Simulation Modelling Practice and Theory*, 34:159–171.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation*, 6(2):182–197.

Garcia, J., Simó, E., Masip-Bruin, X., Marí-Tordera, E., and Sànchez-López, S. (2018). Do we really need cloud? estimating the fog computing capacities in the city of barcelona. In *2018 IEEE/ACM International Conference on Utility and Cloud Computing Companion (UCC Companion)*, pages 290–295.

Gudi, S. C. et al. (2017). Fog robotics: An introduction. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Gupta, H., Vahid Dastjerdi, A., Ghosh, S. K., and Buyya, R. (2017). ifogsim: A toolkit for modeling and simulation of resource management techniques in the internet of things, edge and fog computing environments. *Software: Practice and Experience*, 47(9):1275–1296.

Johnson, S. G. (2014). The nlopt nonlinear-optimization package.

Kapitonov, A., Lonshakov, S., Bulatov, V., Kia, B., and White, J. (2021). Robot-as-a-service: From cloud to peering technologies. In *2021 The 4th International Conference on Information Science and Systems*, pages 126–131.

Kattepur, A., Rath, H. K., and Simha, A. (2017). A-priori estimation of computation times in fog networked robotics. In *2017 IEEE international conference on edge computing (EDGE)*, pages 9–16. IEEE.

Koubaa, A. (2014). A service-oriented architecture for virtualizing robots in robot-as-a-service clouds. In *International Conference on Architecture of Computing Systems*, pages 196–208. Springer.

Kunde, C. and Mann, Z. Á. (2020). Comparison of simulators for fog computing. In *Proceedings of the 35th annual ACM symposium on applied computing*, pages 1792–1795.

Kwon, M., Biyik, E., Talati, A., Bhasin, K., Losey, D. P., and Sadigh, D. (2020). When humans aren't optimal: Robots that collaborate with risk-aware humans. In *2020 15th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 43–52. IEEE.

Lera, I., Guerrero, C., and Juiz, C. (2019). Yafs: A simulator for iot scenarios in fog computing. *IEEE Access*, 7:91745–91758.

Lopes, M. M., Higashino, W. A., Capretz, M. A., and Bittencourt, L. F. (2017). Myifogsim: A simulator for virtual machine migration in fog computing. In *Companion Proceedings of the10th International Conference on Utility and Cloud Computing*, pages 47–52.

Mick, S., Lapeyre, M., Rouanet, P., Halgand, C., Benois-Pineau, J., Paclet, F., Cattaert, D., Oudeyer, P.-Y., and De Rugy, A. (2019). Reachy, a 3d-printed human-like robotic arm as a testbed for human-robot control strategies. *Frontiers in neurorobotics*, 13:65.

Moniz, A. B. and Krings, B.-J. (2016). Robots working with humans or humans working with robots? searching for social dimensions in new human-robot interaction in industry. *Societies*, 6(3):23.

Mushunuri, V., Kattepur, A., Rath, H. K., and Simha, A. (2017). Resource optimization in fog enabled iot deployments. In *2017 Second International Conference on Fog and Mobile Edge Computing (FMEC)*, pages 6–13. IEEE.

Ngatchou, P., Zarei, A., and El-Sharkawi, A. (2005). Pareto multi objective optimization. In *Proceedings of the*

13th international conference on, intelligent systems application to power systems, pages 84–91. IEEE.

Norman, D. A. and Bobrow, D. G. (1975). On data-limited and resource-limited processes. *Cognitive psychology*, 7(1):44–64.

Papazoglou, M. P. and Van Den Heuvel, W.-J. (2007). Service oriented architectures: approaches, technologies and research issues. *The VLDB journal*, 16(3):389–415.

Quigley, M., Conley, K., Gerkey, B., Faust, J., Foote, T., Leibs, J., Wheeler, R., Ng, A. Y., et al. (2009). Ros: an open-source robot operating system. In *ICRA workshop on open source software*, volume 3, page 5. Kobe, Japan.

R. de Oliveira., E., Delicato., F., R. da Rocha., A., and Mattoso., M. (2021). A real-time and energy-aware framework for data stream processing in the internet of things. In *Proceedings of the 6th International Conference on Internet of Things, Big Data and Security - IoTBDS,*, pages 17–28. INSTICC, SciTePress.

Ray, P. P. (2016). Internet of robotic things: Concept, technologies, and challenges. *IEEE access*, 4:9489–9500.

Sakovich, N. (2020). Fog computing vs. cloud computing for iot projects.

Turnbull, L. and Samanta, B. (2013). Cloud robotics: Formation control of a multi robot system utilizing cloud infrastructure. In *2013 Proceedings of IEEE Southeastcon*, pages 1–4. IEEE.

Velho, P. and Legrand, A. (2010). Accuracy study and improvement of network simulation in the simgrid framework. In *2nd International ICST Conference on Simulation Tools and Techniques*.

Zhao, W., Peng, Y., Xie, F., and Dai, Z. (2012). Modeling and simulation of cloud computing: A review. In *2012 IEEE Asia Pacific Cloud Computing Congress (APCloudCC)*, pages 20–24.