A Domain-Specific Language for Simulation-Based Testing of IoT Edge-to-Cloud Solutions

Jia Li, Shiva Nejati, Mehrdad Sabetzadeh
University of Ottawa, Ottawa, Canada
{jli714,snejati,m.sabetzadeh}@uottawa.ca

Michael McCallen
Cheetah Networks, Ottawa, Canada
mccallen@cheetahnetworks.com

ABSTRACT

The Internet of things (IoT) is increasingly prevalent in domains such as emergency response, smart cities and autonomous vehicles. Simulation plays a key role in the testing of IoT systems, noting that field testing of a complete IoT product may be infeasible or prohibitively expensive. In this paper, we propose a domain-specific language (DSL) for generating edge-to-cloud simulators. An edge-to-cloud simulator executes the functionality of a large array of edge devices that communicate with cloud applications. Our DSL, named IoTECS, is the result of a collaborative project with an IoT analytics company, Cheetah Networks. The industrial use case that motivates IoTECS is ensuring the scalability of cloud applications by putting them under extreme loads from IoT devices connected to the edge. We implement IoTECS using Xtext and empirically evaluate its usefulness. We further reflect on the lessons learned.

KEYWORDS

Domain-Specific Languages, IoT, Simulation, Stress Testing, Xtext.

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1 INTRODUCTION

Simulation is an important validation and verification activity during the requirements and design stages, and before a proposed system has been built. For certain types of systems, simulation also plays a key role in later stages of development, e.g., when one needs to exercise scenarios that are too risky or too expensive to run in real-world deployments. Notably, simulation is the technique of choice for the validation and verification of systems that have high levels of autonomy, e.g., autonomous vehicles [8, 9, 13], or massive connectivity, e.g., the Internet of things (IoT) [28, 43].

This paper is concerned with simulation in the context of IoT. IoT envisions complex systems that interconnect large numbers of smart devices, embedded with sensors and actuators, through the Internet or other network technology [24]. IoT is already pervasive in several application domains, e.g., emergency response, smart cities, smart agriculture and autonomous vehicles, to name a few. IoT simulation has numerous facets, including simulation of IoT sensors and actuators [3, 26, 52], simulation of IoT edge devices [25, 47] and simulation of IoT networks [4, 14, 27, 36]. Our work in this paper focuses on simulating "edge devices and their interactions with cloud applications." An edge device is a generic term referring to any device that serves as an entry point to a network. In IoT, edge devices typically run applications and protocols for managing groups of sensors and actuators, performing edge computing [20], and sending and receiving data to and from cloud applications.

Specifically, we propose in this paper a model-based approach for creating "edge-to-cloud simulators." An edge-to-cloud simulator executes the functionality of a large number of edge devices that run in parallel and communicate with cloud applications either synchronously or asynchronously [20]. Edge-to-cloud simulators may be employed for purposes such as testing and decision making, e.g., about how frequently edge devices should communicate with the cloud, and how to schedule the data flow from IoT devices so that the overall network traffic remains stable and burst-free [51].

Our work in this paper addresses a specific yet important need in IoT: Scale testing of cloud applications. Scale testing is concerned with understanding how a system behaves under an extreme workload and at the upper limits of its capacity [16]. In our context, the workload originates from the edge devices and is destined for processing and storage by the cloud. Existing feature-rich IoT simulators, e.g., [25, 47], are not good fits for cloud scale testing, noting that a feature-rich simulator may require substantial computational resources (CPU, memory and storage) to simulate thousands of devices. Many IoT providers use hosted services for simulation. The more resource-intensive the simulator, the more difficult it is to set up and the higher is the cost of running it for scale testing.

Figure 1 shows a schematic view of a typical IoT system. In a real IoT system, a network sits in between the edge and cloud layers. In our work, we need to ensure that the network does not act as a limiter for how far simulated edge devices can stress the cloud. We therefore connect the simulated edge layer to the cloud via an ideal network with no loss and minimally low transmission time. For experimentation purposes, we create this ideal network using a single network switch, discussed in Section 4.2.
Contribution. Building a well-functioning edge-to-cloud simulator involves various technical considerations, including proper use of communication protocols, managing the massive concurrency of simulated edge devices, and efficient use of computing resources. Due to these considerations, building an edge-to-cloud simulator from scratch can be a daunting task. To facilitate the construction of edge-to-cloud simulators, we propose a domain-specific language (DSL), named IoTECS (the IoT Edge-to-Cloud Simulation language). IoTECS provides abstractions that shield software engineers from several complexities of edge-to-cloud simulation, while still affording good customizability for different systems and different resource constraints. Specifications (models) written in IoTECS are automatically translatable into operational Java-based simulators. IoTECS has been developed in response to industrial needs and is the outcome of a collaborative research activity with Cheetah Networks – a leading provider of IoT analytics solutions. IoTECS has been already adopted by Cheetah Networks for stress testing some of their cloud applications.

Following ideas and guidelines from the literature on multi-agent simulation [40], IoTECS employs a hierarchical architecture for grouping large arrays of simulated edge devices. The resulting groups can subsequently be emulated through containerization, virtualization, or a combination thereof. IoTECS further supports configurable time gaps for orchestrating the execution of parallel edge devices; this is to ensure that messages between the edge devices and the cloud applications are communicated at a rate that is in line with real-world expectations in a specific IoT system.

Evaluation. We have applied IoTECS for stress testing a benchmark cloud as well as industrial cloud applications at our partner, Cheetah Networks. To evaluate IoTECS, we first ensure that it can reliably simulate a large number of parallel edge devices without incurring data loss. We scale simulation to generate 24000 packets per second using a single conventional laptop computer. These packets represent the data generated by 12000 (simulated) IoT sensors and actuators that communicate with the cloud every 500 milliseconds. We show how IoTECS can help engineers determine in a systematic way the number of IoT and edge devices that the cloud applications under test can handle. We further reflect on our experience and lessons learned using IoTECS in an industrial setting.

Structure. Section 2 motivates our use case for IoT edge-to-cloud simulators. Section 3 presents our DSL. Section 4 describes our evaluation of the configurability and usefulness of the DSL. Section 5 highlights industrial adoption and lessons learned. Section 6 compares with related work. Section 7 concludes the paper.

2 MOTIVATING USE CASE

This research resulted from a collaboration with Cheetah Networks (http://cheetahnetworks.com). Cheetah Networks develops AI-based solutions for real-time monitoring of quality of experience (QoE) in IoT networks. Below, we present the use case that motivated our research. For confidentiality reasons, we do not discuss the use case over our industry partner’s products, noting that some of these products are yet to be announced and released. Instead, we use a generic example from the domain of smart cities [23]; this example has the representative characteristics of IoT edge-to-cloud solutions, which is what our work focuses on.

In a smart city, sensors monitor a wide range of parameters including, among others, weather, lighting, motion, traffic conditions, utility consumption, water chemistry, and air pollution. The information that these sensors collect is used for decision making and giving commands to actuators that control, for example, traffic and street lights, alarms, barrier gates, pumps, and heating and cooling systems. The sensors and actuators that are in close proximity are grouped together and connected in a wired or wireless manner to an edge device, also known as a gateway. Gateways typically have limited computational power, performing only basic data analysis. A gateway sends sensor data – potentially after some processing – to cloud services. The communication between a gateway and the cloud is routed through a core network. Upon receiving unprocessed or semi-processed sensor data, the cloud services perform a more comprehensive processing of the data, generate analytics, determine any necessary course of intervention, and send instructions back to the gateway, which will in turn communicate the instructions to actuators.

Our smart-city example is an instantiation of the IoT architecture in Figure 1. Within this example, consider the various data storage, data analysis, and decision-making services deployed in the cloud. An important question that the providers of these services need to answer is how far their services will scale in the face of extreme loads from a large number of IoT sensors, actuators, and gateways. Simulation is the most practical strategy for answering this question, noting that a physical IoT testbed for stressing cloud applications is often prohibitively expensive to build.

Creating a reliable simulator nonetheless presents its own challenges. In particular, implementing, within a practical budget, the concurrency and network-based communication required for mimicking a large number of IoT gateways connected to an even larger number of sensors and actuators is a complex technical endeavour. In this paper, we set out to develop an edge-to-cloud simulation DSL that abstracts away from much of the complexity of the underlying concurrency and networking technologies. Through this DSL, we aim to enable software engineers to build reliable edge-to-cloud simulators without requiring extensive knowledge of containerization, virtualization, and network protocols.

3 EDGE TO CLOUD SIMULATOR

IoTECS is a domain-specific language (DSL) built on top of the conceptual model shown in Figure 2. This conceptual model aims to support a scalable and parameterizable architecture for capturing the communication between edge devices and cloud applications, and to enable simulation-based stress testing of edge-to-cloud solutions. We explain our conceptual model in Section 3.1. This is followed by a discussion of IoTECS syntax and usage in Section 3.2.

3.1 The IoTECS Conceptual Model

The concepts in the conceptual model of Figure 2 are arranged under two packages: Edge Layer and Cloud Layer. As described in Section 1, these two layers communicate through a network. The topology of this network is abstracted away in our model since, as argued in Section 1, for stress testing of cloud applications, an ideal network is placed between the edge and cloud layers. In our model, network-related information is limited to node IPs, port numbers...
and communication protocols. This information is captured as necessary within the edge and cloud concepts.

Cloud Layer. The Cloud concept shown in Figure 2 represents a cloud application under stress testing. For an edge-to-cloud simulator to be able to connect to the cloud under test, we need the IP address of the cloud’s host and the port at which the cloud receives incoming data. In IoTECS, we can test several cloud applications by instantiating Cloud multiple times.

Simulation Time Management. The top-level Simulator concept in Figure 2 captures the attributes required for managing time. We execute each simulation for a given duration and divide this duration into equal time steps. We use the duration and step attributes to refer to the total simulation duration and to the duration of individual time steps, respectively. For example, Figure 3 depicts a simulation run where the duration is 10s and each step takes 1s.

Simulated Devices. The concepts here are IoT Device and Edge Device. IoT devices encompass sensors (e.g., temperature sensors) and actuators (e.g., traffic lights). IoT devices connect to and communicate periodically with edge devices by wired or wireless links. For example, a temperature sensor may communicate temperature readings to an edge device every 5s. Edge devices can assume a variety of roles, but their primary function is controlling the data flow at the boundary of a network. Edge devices may perform part of the required processing close to the source (IoT devices) instead of relying on the cloud to do all the processing, which is expensive and can further lead to latency. Edge devices nonetheless usually have limited processing and storage capabilities, and their view on data is limited as well. Edge devices are thus not a substitute for the processing and storage done by the cloud.

Ultimately, what we aim to achieve through IoTECS is high-fidelity simulation of edge devices. For this, we do not need to explicitly simulate IoT devices through individual processes or threads. Neither do we need to distinguish between IoT sensors and actuators, noting that both can have two-way communication with edge devices. Instead, as we elaborate below, we incorporate the relevant properties of IoT devices into the execution of (simulated) edge devices. For succinctness, where there is no ambiguity, we refer to a sensor or actuator simply as “device”. In contrast, when we mean an edge device, we use the term “edge device”.

Each instance of IoT Device has a period attribute, indicating the time interval (in terms of the number of simulation steps) between two successive executions of the IoT device. For example, an IoT device with period = 1 executes its function every step and the one with period = 2 executes every other step (e.g., see Figure 3). Given a set of devices, we choose the size of the step for our simulator as the greatest common divisor of the devices’ periods. For example, if we have two devices, one executing every 4s and the other every 6s, then the size of the step for our simulator is set to 2s. IoT devices, whenever they execute, generate a data packet whose size is specified by the payload attribute.

Each instance of Edge Device owns a group of IoT devices. At every time step, each edge device collects the data packets generated by its associated IoT devices. As mentioned earlier, in IoTECS, the IoT device concept does not include executable entities. Instead, each instance of an edge device, which is an executable entity in IoTECS, is responsible for emulating the behaviour of the IoT devices associated with it. We provide a precise characterization of the behaviour of edge devices later, when we discuss Algorithm 1.

Edge devices send the collected packets to the cloud following the communication protocol indicated by the protocol attribute in Edge Device. For example, in Figure 3, suppose that one edge device is associated with IoT devices D1, D2, and D3. At time 0, the edge device sends the packets from all three to the cloud. At time 1s, it sends the D1’s packet, and at time 2s, it sends the packets from D1 and D2 to the cloud. In parallel with sending packets, the edge device performs two more operations: (a) receiving data from the cloud, and (b) performing compute-intensive operations (i.e., edge computing). Edge devices use a workload attribute to specify the time duration, measured in milliseconds or nanoseconds, spent on compute-intensive operations.

In addition to the protocol and workload attributes, Edge Device has a speed attribute that specifies how many packets an edge device sends to the cloud per simulation time step. To illustrate, let the simulation time step be 1s. If we set speed to 100, the edge device sends up to 100 packets over 1s. That is, the edge device waits for 10ms after sending each packet to the cloud. In the above, we say “up to” because the edge device may send fewer packets if its associated IoT devices produce less packets than what the speed attribute allows to be transmitted. Similarly, if we set speed to 1000, the edge device waits for 1ms after sending each packet. To indicate that an edge device can send packets at maximum speed over the time step duration (i.e., without any waiting after sending a packet), one can set speed to a designated value, MAX.

We use speed to control the time gap between the sending of the packets. If a large number of (simulated) edge devices attempt to send all their packets to the cloud without any time gap, the simulator may not be able to cope with all the send requests, or these requests may congest the network. In both situations, one
may experience packet loss or latency at the (simulated) edge or within the network. In view of our goal, which is to stress test cloud applications, we need to make sure that we do not incur packet loss or latency at the edge or in the network. Using the speed attribute, we can pace the send requests in a way that would prevent the simulator and the network from being overwhelmed. This in turn allows us to rule out the simulator and the network as the root causes of packet loss and thus localize packet-loss occurrences to the cloud applications. In our empirical evaluation of Section 4, we demonstrate the impact of speed on our results.

Algorithm 1 formally specifies the behaviour of edge devices in IoTecs. An edge device performs three operations in parallel: sending packets, receiving packets and performing (edge) computing. At every time step \( i \) between 0 to \( \frac{T}{q} \) where \( T \) is the simulation duration and \( q \) is the size of the step, the edge device \( e \) checks each of its associated IoT devices (line 5). If the period of an IoT device indicates that it should be executed at step \( i \) (line 6), then \( e \) sends the associated payload to the cloud (line 7). After sending the data, \( e \) may wait for some time gap whose size depends on the speed parameter of \( e \) (lines 8-9). The loop for sending the IoT devices’ data to the cloud (lines 5-12) ends as soon as the time step \( q \) has elapsed (line 11-12). As a result, if the time step is too short or too many IoT devices are associated to \( e \), some may fail to send their data packets to the cloud.

The receive method is used for receiving packets transmitted from the cloud to edge device \( e \) (lines 13-14). To simulate edge computing in IoTecs, edge devices perform, for the duration specified by the workload attribute, some compute-intensive operation (lines 15-16). Note that to properly simulate edge computing, we need to explicitly perform operations that keep the edge CPU busy so that the CPU is not allocated to other parallel tasks. To this end, we perform a series of floating-point operations. Algorithm 1 stops when the simulation duration \( T \) elapses.

### Algorithm 1: The behaviour of Edge Device \( e \).

**Input:**
- \( T \): Simulation duration
- \( q \): Size of the simulation time step
- \( n \): Number of IoT devices associated to \( e \)

1. run in parallel:
   2. **Send Process:**
      3. for \( i = 0 \) to \( \frac{T}{q} \) do
         4. startTime = getWallClockTime()
         5. for every \( j \in \{1, \ldots, n\} \) do
            6. if \( (i \mod e.devices[j].period == 0) \) then
               7. Send e.devices[j].payload to e.cloud using e.protocol
               8. if e.speed < MAX then
                  9. sleep( \( \frac{q}{e.expired} \) )
               10. currentTime = getWallClockTime()
               11. if \( (q \leq currentTime \cdot start_time) \) then
                  12. Break out of the loop (of line 5)
      13. Receive Process:
      14. Receive packets from e.cloud
      15. Compute Process:
      16. Perform CPU-intensive operations for duration e.workload

### Algorithm 2: The behaviour of Simulation Node \( sn \).

**Input:**
- \( m \): Number of edge devices associated to \( sn \)

1. for every \( i \in \{1, \ldots, m\} \) do
   2. initialize sn.edgeDevice[i]
   3. In parallel, run all sn.edgeDevice[i] (\( i \in \{1, \ldots, m\} \))

Simulation Architecture Management. An important factor in edge-to-cloud simulation is the ability to simulate a large number of IoT and edge devices. As discussed above, each edge device manages the sending of the packets related to its IoT devices sequentially and within the simulation time step \( q \). This assumption matches practice, since in the real-world, edge devices directly handle their related IoT devices. The edge devices themselves, however, run in parallel and are independent from one another. The concepts under Simulation Architecture Management enable a more orderly handling of concurrency, in turn allowing us to optimize the number of edge devices that can run in parallel.

To maximize the capacity of our simulator in terms of the number of parallel edge devices, we introduce an additional tier into our simulator’s architecture to group the edge devices into clusters. This tier is represented by the Simulation Node concept in the model of Figure 2. Each simulation node is associated with a platform, represented by the Platform concept. Edge devices that belong to a given simulation node all execute in parallel and on the platform of the simulation node. The Platform concept has as attributes IP, username and password to enable access to the platform host machine. In IoTecs, Platform is specialized into Native (i.e., running on a native operating system), Virtual Machine and Docker. For a virtual machine (VM), we need to specify the CPU and memory attributes, respectively indicating the CPU and memory allocated to the VM. Docker containers can be unconstrained or constrained. For the latter (i.e., Constrained Docker), similar to a VM, we need to specify the CPU and memory attributes.

The idea of clustering edge devices into simulation nodes in order to scale simulators is inspired by the notion of “super individuals” in massively multi-agent simulators [40]. In our context, such clustering provides a mechanism to reduce contention over CPU, memory and ports. For example, instead of running 100 parallel edge devices on a single computer, we create ten dockers by dividing the single computer resources (CPU, memory and ports) between the dockers equally. We then use each docker to host ten (simulated) edge devices. As we will demonstrate in our evaluation of Section 4, the docker option considerably improves the scalability of our simulator, compared to the native option.

Another motivation for defining simulation nodes is to be able to restrict the amount of resources used for simulation, thus keeping the cost of simulation within reasonable limits when computation resources need to be purchased from third-parties. We will come back to this in our lessons learned (Section 5), when we discuss cost-awareness for simulation.

The behaviour of Simulation Node is specified in Algorithm 2. Each simulation node, upon creation, initializes each of its associated edge devices (lines 1-2). It then executes the edge devices in parallel (line 3). That is, Algorithm 1 is called for each edge device.
Algorithm 3: The behaviour of Simulator sim.

Input:
1. Number of simulation nodes

1. for every i ∈ {1,...,l} do
2. Let p denote sim.sn[i].platform
3. Initialize p
4. Transfer sim.sn[i] to p using p.IP, p.username and p.password
5. In parallel, run all sim.sn[i] (i ∈ {1,...,l})
6. // run Algorithm 2 for each sim.sn[i]
7. sleep (sim.duration)
8. for every i ∈ {1,...,l} do
9. Terminate sim.sn[i] if it is still running
10. Clean up sim.sn[i].platform and sim.sn[i]

Algorithm 3 shows the overall behaviour of our simulator. The simulator starts by initializing the platforms of the simulation nodes (line 3). It then transfers the simulation code to the platforms (line 4). Next, the simulation nodes start to run in parallel on their respective platforms (line 5). The nodes run until the simulation duration elapses (line 6), at which point the nodes and their platforms are cleaned up (lines 7–9).

Our simulator can be configured to represent different numbers of IoT and edge devices. As these numbers increase, the application(s) in the cloud layer are put under more stress. In this way, our simulator makes it possible to determine how far the cloud application(s) under test can be stretched without degradation in their quality of service. Upon the termination of a simulation round, we collect certain metrics, defined in Section 4.3. These metrics help determine (1) whether, given the computational resources made available, the simulator can mimic the desired numbers of IoT and edge devices without getting overwhelmed, and (2) whether the cloud application(s) are able to process and respond in reasonable time to all the messages received from the simulator.

3.2 The IoTECS DSL

IoTECS aims to support practitioners in creating simulators that are instances of the conceptual model of Figure 2. We provide an implementation of IoTECS using Xtend [19]. Specifically, we use Xtext’s grammar language to define IoTECS’s grammar. To generate executable simulators from specifications written in IoTECS, we use Xtend [18]. More precisely, we use Xtend to retrieve all the objects defined in an IoTECS specification; these objects in turn drive the instantiation of a number of a-priori-defined Xtend templates. Our Xtend templates include: (1) Java-based implementations of the algorithms in Section 3.1, (2) scripts for setting up / starting virtual machines and containers, (3) scripts for uploading and running simulator code on remote platforms, (4) scripts for downloading simulation results from simulation nodes, and (5) scripts for analyzing and reporting simulation results.

We make IoTECS’s Xtext grammar and Xtend templates publicly available [6]. In the rest of this section, and noting that the design of IoTECS follows well-established DSL engineering practices using Xtext, we adopt a practitioner-oriented perspective and emphasize examples of IoTECS usage; full details about the design of IoTECS can be found in our artifacts [6].

Cloud. Figure 4 shows a snippet of an IoTECS specification specifying two Cloud instances. For each instance, the IP and port attributes respectively specify the IP address of the cloud application’s host machine and the port at which incoming packets are received. We note that the code for instances of Cloud is not meant to be generated by IoTECS. Rather, each Cloud instance represents an existing cloud application that needs to be stress-tested.

Simulator. Each IoTECS specification has exactly one instance of the Simulator concept. To illustrate, consider the snippet in Figure 5. Here, the simulator has its duration set to 10s and its step to 1s; this results in dividing the simulation into 10 steps of equal length with each step running for 1s. The time unit for duration and step can be in milliseconds (ms), seconds (s), minutes (m) or hours (h). A simulator needs to declare its simulation nodes. This is done as illustrated on line 4 of Figure 5. On this line, we are stating that the simulator has six simulation nodes: five nodes of type SN1 and one node of type SN2. We next illustrate how to define the simulation node types (in this case SN1 and SN2) and their associated execution platforms.

Simulation nodes and platforms. As discussed in Section 3.1, IoTECS uses the notion of simulation node for grouping simulated edge devices and to further specify the platform on which a group of edge devices run. In the snippet of Figure 6, we define two simulation node types, SN1 and SN2, each having a set of edge devices and a platform. Similar to our convention for specifying the simulation nodes contained in a simulator (see Figure 5), we define the edge devices contained in a simulation node via an edge-device type and a number of instances. For example, in Figure 6, SN1 has ten edge devices: seven of type E1 and three of type E2 (we will momentarily illustrate the specification of edge-device types).

Each platform has a type that assumes one of the following values: Native, VM or Docker. To be able to run a simulation node when its platform is remote (i.e., not the local host), the simulation code and scripts need to be transferred to and set up on the platform first. For this purpose, we need to specify an IP and login credentials (username and password) in instances of the Platform concept. This is illustrated by platform P2 (of type Docker) as specified on lines 12-19 of Figure 6. When the platform is local, this information is not needed, as illustrated by platform P1 on lines 9–11 of the same figure. To be precise with respect to our conceptual
model of Figure 2, for a local platform, the username and password can be viewed as being empty and the IP as 127.0.0.1. For a Docker platform that is constrained and for any VM platform, we specify the required attributes indicated in our conceptual model of Figure 2. For example, platform P2 is a constrained docker with 4 CPUs and 2G of memory.

**Edge and IoT devices.** Each edge device has a set of IoT devices associated to it. For example, in the snippet of Figure 7, edge-device type E2 is associated with 10 IoT devices of type D1 and 20 IoT devices of type D2 (we will shortly exemplify IoT-device types).

Each edge device communicates with one cloud application. For example, in Figure 7, E1 is specified as communicating with cloud application C1. The protocol used by an edge device for communication with the cloud is captured by the protocol attribute. Currently, IoTECS supports the UDP, TCP and MQTT protocols. The speed attribute describes the number of packets sent to the associated cloud application in one step. For instance, in Figure 7, the speed is set to 100 for E1 and 1000 for E2. Since step has been set to 1s (see Figure 5), E1 waits 10ms between sending two consecutive packets; this wait time is 1ms for E2. The workload attribute indicates the amount of edge computing to be done by the edge device (lines 15-16 of Algorithm 1). The time unit for workload can be milliseconds (ms), seconds (s) or minutes (m). Note that, in parallel with sending packets and edge computing, an edge device also receives packets from the cloud (lines 13-14 of Algorithm 1). The protocol for receiving data from the cloud is the same as that used for sending data to the cloud (i.e., as specified by the protocol attribute).

Each IoT device (type) has two attributes. The first one is period which determines the frequency of execution. For example, in the snippet shown in Figure 8, device D1 generates a packet every second, while device D2 generates a packet every two seconds. The second attribute is payload. This attribute can be used to specify the actual payload content, e.g., payload: "23C", or alternatively, the size of the packet that the device sends every time the device executes. In the latter case, the payload unit can be bytes (B), kilo bytes (kB) or mega bytes (MB). When a size unit is indicated for the payload, the content of the payload is generated randomly as per the requested size. This option, illustrated in Figure 8, is convenient when the actual payload is unimportant for simulation purposes (e.g., in a simple cloud storage application).

### 4 EVALUATION

In this section, we evaluate the applicability and usefulness of simulators generated from IoTECS specifications for stress testing of cloud applications. We use the term simulator to refer to the executable code generated from instantiating the edge-layer concepts of the model of Figure 2; we use the term cloud to refer to instances of the cloud concept in this model. For our experiments, as we discuss in Section 4.1, we create our own baseline cloud applications. The research questions (RQs) that we investigate are as follows:

**RQ1. (Configuring Simulators)** Can we configure our simulator so that it can successfully simulate a large number of IoT and edge devices? With RQ1, we examine whether the simulator architecture envisaged by the conceptual model of Figure 2 allows one to instantiate a large number of IoT and edge devices as required by our motivating use case (Section 2). For practical reasons, we want the whole simulator to run successfully on a single computer with modest resources. In RQ1, we assess how grouping edge devices into simulation nodes and executing simulation nodes on alternative platforms (native, virtual machine and docker) impacts the ability of simulators to scale. The results of RQ1 lead to a configuration range for simulators in terms of the number of IoT devices, edge devices and simulation nodes as well as the platform types.

**RQ2. (Cloud-Application Stress Testing)** Can our simulator be used for stress testing cloud applications and determining the number of IoT and edge devices that a cloud application can handle? We perform simulations using the configurations identified in RQ1 to assess how well one can push a cloud application to its limits in terms of the number of IoT and edge devices being handled.

### 4.1 Baseline Cloud Applications

Due to confidentiality, for RQ1 and RQ2, we do not report quantitative results over our partner’s cloud applications. Instead, we build...
our own baseline cloud applications and apply to these baselines the same analysis as that performed on our partner’s applications. The results we report for RQ1 and RQ2 are over the baselines. Our baselines implement a simple loop where an instance of the cloud concept receives a packet from an edge device, performs compute-intensive operations for a configurable duration, `cloudComputing`, and sends the received packet back to the sender. The compute-intensive operations are meant at simulating cloud computing. We create three baselines, varying the `cloudComputing` parameter to 0, 1ms, and 5ms, respectively.

### 4.2 Experiment Design

To answer RQ1 and RQ2, we use two computers, one for running the simulator and one for running a baseline cloud application.

Consistent with our objective of abstracting away from the complexities of networks (discussed in Section 1), we connect the simulator to the cloud via a single switch as shown in Figure 9. This setup, while simple, provides a high-fidelity testbed for stress testing of cloud applications, as it routes all network traffic through the switch (ideal network) rather than a real-world network that may not be as reliable or predictable. Requiring the simulator to run on a single machine (laptop) was in line with the needs of our partner; they needed the simulator machine to be portable so that it could be brought to different sites and connected to different networks.

Table 1 shows the configuration parameters for our experiments. We select the duration of simulations to be 2s and the time step to be 0.5s (i.e., four steps in each simulation). For the device payload size, we follow the recommendation of our collaborating partner, and set it to 8B. We set the period of each IoT device to 1 to maximize the number of messages sent in each time step. Based on the recommendation of domain experts, we configure virtual machines and constrained dockers with four CPU cores and 2G of memory. For edge devices, we eliminate edge-computing time by setting the workload to zero, noting that our goal is maximizing communication with the cloud. For the number of IoT devices per edge device and the number of edge devices per simulation node, we followed the recommendation of our partner based on past examples of large-scale IoT rollouts.

To answer RQ1, we executed our simulator using the parameters of Table 1. Specifically, for the speed of edge devices, we insert a time gap of 0ms, 1ms, 2ms, 3ms and 4ms between the consecutive messages sent, resulting in the edge device speed to be set, respectively, to MAX, 500, 250, 167 and 125. Note that further decreasing the speed (i.e., increasing the gap time) leads to inconsistency in our experimental setup since each edge device needs to be able to send 100 messages in a time step (i.e., one message per IoT device). For the number of simulation nodes, the partner was interested in having ten. Nonetheless, the partner was also interested in determining how far the simulation could be pushed on the laptop that we were using without the simulator showing anomalous behaviours. Based on this requirement, we experimented with 10 ± 2 simulation nodes, thus the range of 8 to 12 nodes in Table 1. With these numbers of simulation nodes, we use our simulator to capture between 8000 to 12000 IoT devices where each is sending a message every half second to the cloud. We executed each configuration of our simulator for four platform options: Native, Virtual Machine (VM), Constrained Docker (CDC) and Unconstrained Docker (UDC). We assumed that the cloud is not doing any cloud computing (i.e., `cloud computing` = 0), since the purpose of RQ1 is configuring the simulator. This in turn requires operating under the assumption that the cloud responds as promptly as possible. In total, to answer RQ1, we performed 100 experiments (# of platforms = 4) × (# of speeds = 5) × (# of sim nodes = 5). We repeated each experiment 10 times to account for random variation.

To answer RQ2, we consider the simulation configurations that, based on the results of RQ1, can successfully execute on a single machine and send all messages to the cloud. We then rerun these configurations for two cloud instances where their computing time is set to 1ms and 5ms, respectively. That is, in contrast to the cloud instance used for RQ1, here, we consider cloud instances that have to preform some computing tasks after receiving messages and before responding. For RQ2, we perform 100 experiments (# of platforms = 2) × (# of speeds = 5) × (# of sim nodes = 5) × (# of alternative cloud instances = 2) and repeat each experiment 10 times to account for randomness. Note that, for RQ2, we consider the CDC and UDC platforms only. This is because the VM and Native platforms could not pass the sanity check in RQ1: in our experimental setup, these platforms could not successfully run the simulator without incurring packet loss. We executed our simulator on a machine with a 2.5 GHz Intel Core i9 CPU and 64 GB of memory, and our cloud on a machine with a 2.3 GHz Intel Core i9 CPU and 32 GB of memory. We connected the two machines using an unmanaged NETGEAR GS308v3 Gigabit Ethernet switch.

**Implementation and availability.** We implemented IoTecs using Xtext (version 2.25.0) [19] and Xtend (version 2.25.0) [18]. As noted in Section 3.2, the IoTecs grammar and our code generation tool are publicly available [6].

### 4.3 Metrics

We record two main metrics as the results of our experiments: (1) the number of packets that are dropped during the simulation, and (2) the packet transmission time, i.e., the amount of time it takes for the packets to be transmitted from the simulator to the cloud and be processed by the cloud. In the setup of Figure 9, packets can be dropped (1) on the simulator side when the simulator fails to send all the messages it is expected to send, (2) on the network side when the switch fails to handle the traffic that needs to pass through
it, e.g., due to congestion, or (3) on the cloud side, when the cloud fails to receive all the packets that have reached its host computer, or fails to send responses for the packets it has received. In our experiments, we measure packet drops at the three above locations separately and refer to them respectively as SimDrop, NetDrop and CloudDrop. Note that in order to measure these values, we have to keep track of the packet counts at the level of the simulator, the cloud, and also the network adapters on both host machines. To count the number of packets sent from and received by the simulator side, we use the Wireshark tool which is the world’s most widely-used network protocol analyzer. Using Wireshark, we have determined how well the cloud is able to handle packets at the simulation node and run each simulation node on a separate VM, over a time gap – to send all the packets it is supposed to send. This highlights the importance of the hierarchical structure provided by the Simulation Node concept in IoTecs. Similarly, the VM option, while generating SimDrop values lower than those of the Native option, is unsuitable for stress testing as it still leads to non-negligible packet drop on the side of the simulator.

For the simulation configurations executed on CDC and UDC, SimDrop values are zero (or negligible). For these configurations, the cloud side drops packets, particularly when edge devices send their packets at once and without having any time gap in between, (i.e., when the edge device speed is MAX). By inserting a time gap on the side of edge devices (i.e., lowering the speed), the cloud will receive the packets at a lower rate and can avoid packet drop. Note that transmission time values for the Native and VM options should be discarded. This is because, for these options, there is high packet drop at the simulator, and hence, considerably fewer packets are transmitted from the simulator to the cloud and vice versa. Therefore, the transmission times are computed for a smaller portion of packets, leading to unrealistically small values. For the CDC and UDC options where the simulator is able to complete its task without packet drop, the transmission time decreases as we reduce the speed of the edge devices. This trend is expected, since by reducing the speed, we avoid the cloud side from being overwhelmed, hence reducing the packet transmission time.

The answer to RQ1 is that our simulator can be tuned such that it can, on a conventional laptop, simulate the sending of 24000 packets per second without packet drop. Further, our results show the importance of grouping edge devices into simulation nodes to manage resource usage on the simulator’s host machine and thus enable the simulator to scale as much as possible. In our experimental setup, containerization (through dockers) turned out to be the best option for scaling. Among the main benefits of IoTecs is its support for simulation nodes and its ability to abstract from platform details so that engineers can explore different platform options.

### 4.4 Results

**RQ1.** Table 2 shows the average values for SimDrop, CloudDrop, and packet transmission time obtained by running our simulator using the parameters in Table 1. Here, cloud computing is fixed at zero, i.e., the cloud does not perform any computing (beyond sending and receiving packets). As discussed in Section 4.2, for RQ1, we run our simulator using four different platform options, i.e., Native, VM, CDC and UDC. In the native option, we run all the edge devices in parallel on the simulator host machine without grouping them into separate simulation nodes. In contrast, when we use VM, CDC, UDC, we group every ten edge devices into a simulation node and run each simulation node on a separate VM, CDC or UDC. For each VM and each CDC, we use the CPU and memory sizes specified in Table 1.

As shown in Table 2, there is substantial packet drop on the simulator side when we use the Native option. This indicates that in this architecture where edge devices are not grouped into simulation nodes, the simulator is simply unable – due to resource contention – to send all the packets it is supposed to send. Further, our results show the importance of the hierarchical structure provided by the Simulation Node concept in IoTecs. Similarly, the VM option, while generating SimDrop values lower than those of the Native option, is unsuitable for stress testing as it still leads to non-negligible packet drop on the side of the simulator.

The 4.4 Results section provides detailed analysis and comparison of various simulation configurations on different platforms. The table is used to illustrate the effectiveness of various configurations in terms of packet drop and transmission time. The results indicate that group-based simulation on separate VMs and CDCs shows the best performance, reducing packet drop and improving transmission times compared to the Native option.
Table 3: Average packet drop and packet transmission time values obtained by ten runs of the experiments of RQ2.

| Metric | #Simulation/Node-12 | #Simulation/Node-11 | #Simulation/Node-10 | #Simulation/Node-9 | #Simulation/Node-8 | #Simulation/Node-7 | #Simulation/Node-6 | #Simulation/Node-5 | #Simulation/Node-4 | #Simulation/Node-3 | #Simulation/Node-2 | #Simulation/Node-1 |
|--------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| TransTime (ms) | CloudDrop | CDC_Cloud1ms | CDC_Cloud5ms | UDC_Cloud1ms | UDC_Cloud5ms | CloudDrop | CDC_Cloud1ms | CDC_Cloud5ms | UDC_Cloud1ms | UDC_Cloud5ms | CloudDrop | CDC_Cloud1ms |
| Max | 2873.7 | 3793.1 | 3797.3 | 3794.3 | 3798.9 | 2873.7 | 3793.1 | 3797.3 | 3794.3 | 3798.9 | 2873.7 | 3793.1 |
| Min | 2854.1 | 3794.3 | 3798.9 | 3794.3 | 3798.9 | 2854.1 | 3794.3 | 3798.9 | 3794.3 | 3798.9 | 2854.1 | 3794.3 |
| Mean | 2861.5 | 3797.6 | 3798.9 | 3794.3 | 3798.9 | 2855.0 | 3796.7 | 3798.9 | 3794.3 | 3798.9 | 2854.1 | 3794.3 |

The answer to RQ2 is that as cloud-computing time increases, so does the cloud’s packet drop and packet transmission time. This means that our simulator, without incurring any packet drop on its end, has successfully fulfilled its function, i.e., pushing the cloud application under test to its limits.

5.2 Lessons Learned

UML profiles versus Xtext. In most of our past research with industry, we have relied on UML profiles [55] for addressing domain-specific needs. Examples include a profile for managing safety-certification documents [37] (collaboration with the maritime and energy sector), a profile for simulating tax policies [45] (collaboration with the public-service sector), a profile for traceability analysis between requirements and design [33] (collaboration with the automotive industry), and a profile for hardware-in-the-loop (HIL) testing of cyber-physical systems [42] (collaboration with the satellite industry).

In our current work, we considered UML profiles as an alternative to Xtext. Nonetheless, in view of the contextual factors that we highlight below, we favoured Xtext. First, while the engineers at our partner were familiar with UML, they were not actively using it for product development. We deliberated over a profile-based solution that would mostly hide UML. However, the issue of DSL maintenance lingered. Specifically, the issue is as follows: if the partner company were to independently modify the DSL, considering that UML was not being used, would it be easier for the company to modify an Xtext-based implementation or a profile-based one? Given the context, we deemed an Xtext-based implementation more likely to be maintainable. Another important factor that influenced our decision was whether using UML would lead to a significantly simpler solution. In many situations, tailoring the existing modelling languages in UML is superior to building from scratch and potentially "reinventing the wheel". In the context of our current work though, as the conceptualization and algorithms of Section 3.1 emerged, we determined that a lightweight, UML-independent DSL would be sufficient for meeting our analytical goals. GMF [1] was also considered as an alternative, but a textual notation was found to be more palatable to our partner for the analytical goal at hand.

The lesson learned here is that contextual factors, like in many other aspects of software engineering [11], play an important role in choosing a suitable DSL technology that is fit for purpose.

Making simulation cost-aware. We did not initially anticipate simulation costs to be a factor in our DSL grammar design. The ability to constrain memory and CPU usage for containers and virtual machines was provisioned into IoTecs later and in response to our partner’s feedback about simulation costs. In particular, our partner noted that, in large IoT simulation and testing campaigns involving hundreds of thousands of simulated devices, solution providers often use externally hosted resources for a fee; the fee has since been used independently by Cheetah in several of their testing and demonstration campaigns.
is determined based on the CPU and memory limits set for containers and virtual machines. We believe that accounting for cost factors – in our case, hosting costs – is important for simulation DSLs, as doing so provides a way to optimize the cost of simulation. For example, we are now considering how, through optimization techniques such as search, we can maximize the number of IoT and edge devices that can be simulated while minimizing hosting costs.

6 RELATED WORK

We compare our approach with related work in the areas of IoT simulation, IoT testing and domain-specific languages for IoT.

IoT Simulation. Numerous simulators exist for different components of IoT systems, e.g., IoT sensors and actuators [29, 38], IoT edge devices [25, 50], IoT network [2, 5, 7], and IoT cloud infrastructure [15, 21, 53]. Among these, the closest ones to our work are IoT edge simulators. IoTCloudSamples [50] provides a simulation framework aimed at facilitating the development and operation of edge software systems. IoTSimEdge [25] is an IoT device-to-edge simulator enabling the specification of various IoT-device characteristics, e.g., network connectivity, mobility and energy consumption, and simulating the interactions of IoT devices with edge devices.

The above simulators are focused on covering various features and metrics in the IoT domain. In contrast, IoTECS is not built for feature coverage, but rather to provide a lean, purpose-built simulation framework for cloud scale testing that can simulate, with minimal resources, thousands of devices frequently communicating with the cloud. IoT simulators’ symbolic execution of IoT devices at the edge layer and its simulation architecture management are novel and specifically aimed at minimizing simulation-resource needs.

IoT Testing. Testing IoT systems is a challenging task due to numerous factors, e.g., the sheer scale of IoT systems, the heterogeneity of IoT sensors and actuators, the diversity of network protocols and network topologies in IoT systems, and the tight integration of IoT systems with their environment [12].

Motivated by testing IoT systems, Moawad et al. [31] propose a conceptualization of IoT data at run-time. They then use time-series compression and polynomial segmentation algorithms to synthesize realistic sensor data based on their proposed conceptualization.

EMU-IoT [39] is an IoT testbed based on a microservice architecture. This testbed can emulate IoT devices through containers running on virtual machines, create virtualized gateways, and deploy orchestrators, monitors and load balancers. EMU-IoT has been applied for various testing purposes, e.g., testing the collection of information about resource consumption across an IoT system.

IoTTest [34] is a testbed that enables using resource-constrained containers as IoT components and grouping these components into a device tier, gateway tier and cloud tier. Using IoTTest, one can simulate dynamic changes in the operating conditions of IoT systems and thereby test device capabilities, network performance and load-balancing strategies. Fogify [48] is an edge testbed that focuses on emulating IoT topologies and deployment conditions using containerized descriptions. Fogify further provides a mechanism to alter network quality and inject entity and infrastructure downtime at run-time. UTiIoT (version 3) [30] provides a testbed for integrating real IoT devices with emulated devices that run as containers on virtual machines to support large-scale experimentation. Senderek et al. [41] propose the concept of a software-defined IoT test environment. Their proposed testbed can define virtual environments, virtual sensors and virtual communication devices as software, thereby allowing the combination of virtual and real equipment for testing IoT application and communication protocols.

None of these works support the testing objective that motivates our work, i.e., scale testing of cloud applications. Further, although some of these works use virtualization and containerization methods, none perform systematic experiments that compare containers versus virtual machines and native hosts for simulation. Our experimentation not only demonstrates the applicability of IoTECS, but also the inadequacy of non-hierarchical (native) simulation which does not benefit from our proposed architecture.

Domain-Specific Languages (DSLs) for IoT. Model-driven engineering (MDE) is a well-established thrust in IoT [31, 32, 46]. DSLs are particularly common as a way to abstract away from the complexity of IoT systems and thereby simplify the construction and analysis of this type of systems.

Snips-Snepppe and Namiet [44] propose a web-based DSL to simplify data access in IoT web applications. This DSL supports both synchronous and asynchronous data updates as well as communication between processes and sensors. Tichy et al. [49] present a DSL that supports the declarative specification and execution of IoT system components for quality assurance purposes. Gomes et al. [22] propose EL4IoT, a DSL that aims to simplify the development of IoT-device applications by refactoring the network stack. Amrani et al. [10] propose IoTDSL for specifying and assembling usage scenarios of IoT systems in a way that would be understandable for end-users without programming expertise.

These existing DSLs have helped us better shape our approach; nevertheless, none have not been designed for our use case, and cannot, without very substantial resources, generate large-scale, lossless edge-cloud traffic.

7 CONCLUSIONS

In this paper, we proposed a domain-specific language, named IoTECS, for building simulators that mimic the operation of a large number of edge devices. The main motivating use case for IoTECS is stress testing of IoT cloud applications and systematically measuring how these applications scale. IoTECS was designed, iteratively refined, and empirically evaluated in the context of a collaborative project with industry. IoTECS has been implemented using Xtext and Xtend, and is publicly available [6].

For future work, we would like to enhance IoTECS with high-level constructs that enable a more flexible configuration of the publish-subscribe messaging model in simulators. In addition, we would like to study optimization techniques to optimally balance the total number of simulated IoT devices against simulation costs.

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