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Design and Evaluation of a Scalable Smart City Software Platform with Large-Scale Simulations☆

Arthur de M. Del Esposte[a], Eduardo F. Z. Santana[a], Lucas Kanashiro[a], Fabio M. Costa[b], Kelly R. Braghetto[a], Nelson Lago[a], Fabio Kon[a,*]

[a] *Department of Computer Science - University of São Paulo*
[b] *Instituto de Informática - Universidade Federal de Goiás*

Abstract

Smart Cities combine advances in Internet of Things, Big Data, Social Networks, and Cloud Computing technologies with the demand for cyber-physical applications in areas of public interest, such as Health, Public Safety, and Mobility. The end goal is to leverage the use of city resources to improve the quality of life of its citizens. Achieving this goal, however, requires advanced support for the development and operation of applications in a complex and dynamic environment. Middleware platforms can provide an integrated infrastructure that enables solutions for smart cities by combining heterogeneous city devices and providing unified, high-level facilities for the development of applications and services. Although several smart city platforms have been proposed in the literature, there are still open research and development challenges related to their scalability, maintainability, interoperability, and reuse in the context of different cities, to name a few. Moreover, available platforms lack extensive scientific validation, which hinders a comparative analysis of their applicability. Aiming to close this gap, we propose InterSCity, a microservices-based, open-source, smart city platform that enables the collaborative development of large-scale systems, applications, and services for the cities of the future, contributing to turn them into truly smart cyber-physical environments. In this paper, we present the architecture of the InterSCity platform, followed by a comprehensive set of experiments that evaluate its scalability. The experiments were conducted using a smart city simulator to generate realistic workloads used to assess the platform in extreme conditions. The experimental results demonstrate that the platform can scale horizontally to handle the highly dynamic demands of a large smart city while maintaining low response times. The experiments also show the effectiveness of the technique used to generate synthetic workloads.

Keywords: Smart Cities, Smart Urban Spaces, Middleware, Simulation, Scalability, Open Source, Microservices

1. Introduction

Most large cities around the world are challenged by problems related to population growth, shortage of resources, air pollution, traffic congestion, and public safety, among many other modern urban problems. Research on Smart Cities seeks to mitigate these problems using Information and Communication Technology (ICT) to leverage the city infrastructure and resources as part of a highly integrated, diverse, and large-scale smart cyber-physical environment. The goal is to enable systems and applications that will ultimately turn the city into a smart environment, contributing to improve the quality of life of its citizens.

A number of industry initiatives have been successfully adopted in cities around the world, tackling different urban problems. They combine cyber-physical systems with mobile applications to enable the realization of bike sharing services, bus tracking systems, and smart traffic lights, which are now widespread in large urban centers. Smart navigation systems such as Waze and Google Maps are examples of smart city applications capable of serving millions of users by combining geolocation, crowd-sensing, and real-time data. The early adoption of ICT in the context of urban problems has significantly impacted multiple application domains. Although several of the mentioned systems handle scalable data processing and services, they do not offer an integrated infrastructure to facilitate the development of other smart city applications through facilities that can be shared across multiple domains and services.

In the academia, several efforts have been devoted to the study and development of the smart city paradigm, leading to a proliferation of initiatives around the world, targeting different domains such as urban mobility, energy management, and healthcare. Despite their early success, there is a need for more effective solutions for data integration and sharing as several of those initiatives have been

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*Corresponding author
Email address: kon@ime.usp.br (Fabio Kon)

developed using ad-hoc approaches [1]. They neither follow a common set of practices and standards nor consider the need for data and resource sharing among the different systems in the city [2, 3]. This hinders the development of smart city solutions that are both sustainable in the long term and reusable in cities with different characteristics, thus creating market islands and raising extensibility, adaptability and interoperability issues.

The use of smart city platforms facilitates the fast development, deployment, and operation of integrated, high-quality smart-city services and applications [3]. Such platforms typically implement a set of common functional requirements in the form of reusable services that application developers can use, including services for the integration of Internet of Things (IoT) devices, as well as for data storage and processing, and for context-awareness. Similarly, the architectures of those platforms may meet multiple non-functional requirements such as adaptability, privacy, interoperability, and evolvability, according to the specificities of the problem that they intend to solve. In particular, in this paper, we are mainly interested in designing and evaluating such platforms for scalability, a non-functional requirement for future cyber-physical systems that is specially critical in the context of smart urban spaces, which may encompass entire cities, with millions of sensors, actuators and humans in the loop [3, 4].

A smart city platform must handle a large number of devices that are part of or are integrated with the city infrastructure. It needs to store and process large volumes of data related to the city, which are continuously produced and consumed by devices and client applications. At the same time, the platform must be able to support thousands of requests from users and from services that run on top of it. The scalability demands thus vary according to the characteristics of the city, as well as those of the deployed applications and services. For instance, a city may start with a pilot project in one of its districts and then expand to other parts of the city as the required infrastructure becomes available.

Despite its importance, platform scalability has not yet received the necessary attention in smart city research. According to a previous systematic study of the literature [3], most of the works that supposedly meet scalability requirements only present superficial discussions of design and implementation decisions that can lead to a scalable architecture. Moreover, they often do not provide scientific evidence of the feasibility of their approaches. Sanchez et al. [5] highlighted that several IoT projects were able to present concrete solutions through new technologies and architectural models, but failed to present conclusive validation of the proposed solutions, which are often restricted to proofs-of-concept. However, demonstrating the actual scalability of smart city platforms presents significant challenges due to the lack of available infrastructure for real experimental setups, as well as the lack of comprehensive datasets.

This state of affairs derives from the difficulty in assessing platform characteristics in real-world scenarios. This difficulty stems both from the significant deployment and usage hurdles in most platforms and from the lack of adequate evaluation techniques.

Middleware platforms for smart cities usually implement complex distributed architectures, requiring considerable effort in documentation and automation to run, configure, and test them. Also, these platforms are often implemented as non-open-source software, hampering their use and study by third parties, as well as the reproducibility of results and collaborative development. Consequently, few projects are truly deployed in production environments, as most of the existing infrastructures are experimental and small in scale.

Even if this was not the case, the research community still needs to advance in the direction of more sophisticated methods, tools, and benchmark strategies to enable a comprehensive evaluation of smart city platforms. One challenging related problem is the generation of representative workloads to assess the performance and scalability of smart city software platforms. Two distinct fundamental actors must be accounted for: (1) client applications, which generate requests using the platform facilities, and (2) the underlying IoT devices, which continuously produce sensed data and/or receive actuation commands. In this context, the use of randomly generated synthetic workloads or a failure to consider either of these external actors can result in experiments that, although useful for evaluating the system in a limited context, do not represent realistic scenarios. This has been observed in most of the reported evaluations of smart city platforms, as exemplified by [6, 7, 8].

In a real smart city, citizens dynamically interact with the cyber-physical infrastructure, triggering multiple events and changing the context observed by pervasive devices and systems. Similarly, platform clients, such as end-user applications and city management services, may vary their interaction behavior with the platform due to events observed in the physical world and real-time data provided by the city. This dynamic behavior of citizens and platform clients needs to be captured and modeled to generate meaningful and representative synthetic workloads.

Available benchmark tools focus on generating workloads for Smart Cities or IoT platforms by extrapolating real sensor traces from various contexts or by emulating the behavior of users based on Web traces. The use of smart city simulators can reduce the problems related to workload generation by allowing large-scale experiments on smart city platforms based on more realistic scenarios. Such simulators implement models that reproduce smart city environments based on the behavior of citizens, IoT devices, and other aspects of the city, such as vehicles, buildings, and lamp posts [9]. Although data produced by a simulator is still synthetic, it reflects the individual behavior of involved actors and their interactions, emulating the dynamic behavior of a city and adapting the simulation accordingly. However, making a simulator interact

with a smart city platform is not a trivial task. Notably, the scalability of the simulator itself needs to be addressed, as well as its integration with the target platform.

In 2016, we started the development of InterSCity[1], an open-source, microservices-based platform that provides a cloud-native software infrastructure to support the development of smart city projects, applications, and services. InterSCity has a microservices architecture that contributes to its scalability. Its modularization through small, single-purpose and loosely-coupled interconnected services enables the evolution of its design, which is a valuable property to adequately meet the continuously changing demands of novel smart city contexts and applications.

In this paper, we investigate the scalability of the InterSCity platform using InterSCSimulator, a scalable smart city simulator [9]. In previous work [6], we introduced the InterSCity platform and provided preliminary experimental results indicating the feasibility of our approach towards achieving a scalable architecture. Although we have maintained the main InterSCity modules in relation to our previous work, we have refined important architectural decisions regarding microservices communication and deployment, enabling greater scalability and the integration with the simulator. Also, we have implemented several improvements in the microservices code base related to database queries, caching mechanism, and data serialization to avoid performance issues. This paper brings three new fundamental contributions:

- A detailed exploration of the current architecture and implementation of the InterSCity platform, supported by a deeper discussion of the design decisions made to meet scalability requirements and more comprehensive experiments considering realistic scenarios and covering broader requirements than the ones of the previous version presented in [6].
- Advances on performance evaluation of smart city platforms, with the proposal of a new method for workload generation that addresses the dynamism of smart cities by using large-scale simulations integrated with the platform.
- An application of the simulation-based experimental strategy to evaluate the InterSCity platform based on a Smart Parking application scenario. We provide an extensive analysis of the platform's scalability properties, advancing the knowledge on the use of the microservices architectural pattern to develop smart city solutions.

This paper is organized as follows. Section 2 discusses related work targeting either architectural proposals for scalable smart city platforms or the generation of workloads for scalability and performance evaluation of smart city platforms. Section 3 explores the design and implementation details of the InterSCity microservices architecture related to scalability. Section 4 presents a brief overview of InterSCSimulator, its integration with the InterSCity platform, and the modeled smart city scenario. Section 5 describes the experimental methodology to assess the platform using the modeled scenario and a comprehensive scalability analysis. Finally, Section 6 presents our conclusions and discusses future work.

[1] `http://interscity.org/software/interscity-platform`

2. Related Work

Research on smart city platforms comprises a wide range of areas and related problems. However, in the context of this work, we are mainly concerned with the scalability of these platforms. Therefore, we divide relevant related work into two categories: (1) projects that propose novel smart city platforms that address scalability challenges, and (2) tools and methodologies to generate workloads for experiments on smart city platforms.

2.1. Scalable Smart City Platforms

A number of smart city platforms have been proposed in the literature to address challenges in the development and deployment of smart city applications and services. One of the most relevant smart city initiatives is SmartSantander [10], which includes an infrastructure to collect city data using more than 20,000 IoT devices, together with a software platform to store this data and provide it to other applications. The city of Santander has less than 200,000 inhabitants; we did not find any discussion on the use of this platform in more complex contexts, such as in a large metropolis. Also, to the best of our knowledge, no evaluation of the scalability of the SmartSantander platform has been published yet.

CiDAP [11] is a big data analytics platform for smart cities deployed in the SmartSantander testbed. The main objective of this platform is to use the data collected from the testbed and analyze it to understand the city's behavior. CiDAP uses a set of Big Data tools, such as Apache Spark and NoSQL databases, to improve the scalability of the platform. Access to data collected by the platform is possible through a REST interface. Experiments showed that CiDAP can handle almost 300 sensor data updates per second. However, the authors failed to evaluate their platform scalability considering other city-scale realistic scenarios. Moreover, their platform does not meet key functional requirements to support the development of smart city applications, such as resource discovery and actuator support.

Similarly to CiDAP, the Scallop4SC (SCALable LOgging Platform for Smart City) [12] and the platform proposed by Girtelschmid et al. [13] rely on the use of Big Data tools such as Hadoop and Storm. Both works collect data from the city infrastructure, store the data in NoSQL databases and process the data using services implemented

with such tools. Likewise, the InterSCity project takes advantage of existing open source tools to leverage its functionalities and performance. However, neither of the two projects mentioned above present experiments to demonstrate the maximum workload supported by the platforms.

DIMMER is a microservices-based smart city IoT platform focused on energy efficiency and management [14]. This is one of the few previous works that explore the use of microservices to build smart city solutions, providing important discussions regarding the design and organizational impact of this architectural style in this context. The creators of DIMMER state that microservices enable horizontal scalability, data partitioning, and scaling through functional decomposition. However, no experimental evaluation of the platform was reported to support these statements. In contrast, and supported by experimental results, our work closely examines the impact of adopting a microservices architecture in a more comprehensive smart city context.

OpenIoT[2] is an open source middleware for the development of IoT-based applications. It has an API to manage a Wireless Sensor Network and a directory service to discover deployed sensors; it also has a component for service definition and access. A Smart City project called Vital [15] was built on this platform.

CitySDK is an API that provides data collected from the city for use in the development of smart city applications and services. According to Pereira et al. [16], CitySDK is available for Amsterdam, Helsinki, Lamia, Lisbon, and Rome using a reference implementation of the API. The primary requirements handled by the API is the use of static and dynamic data, caching for enabling offline use, interoperability, distribution, and scalability. The platform provides a set of REST services that call a data management layer which in turn accesses a MongoDB database. Despite the deployments of CitySDK and the stated scalability requirement, for the best of our knowledge, there are no studies about the maximum workload supported, neither numbers about the real scenarios already faced by the platform.

The CityPulse framework facilitates the creation of city services providing a distributed system for real-time data stream processing, data analytics, and semantic discovery. The main goal is to provide cross-domain data integration, tackling the problem of silo applications for smart cities. The framework deals with data from different formats and quality to create reliable city services. Puiu and Barnaghi [17] present a study case of the framework using a Travel Planer application. However, no scalability analyses or discussion is presented in the paper.

FIWARE is a multi-million Euro initiative funded by the European Commission whose goal is to develop a large collection of open source components and tools to facilitate the development of Future Internet applications, including smart cities. To this end, the project specifies a reference architecture composed of Generic Enablers (GE), which are software components that implement general-purpose functions that can be combined through open APIs to provide middleware facilities for application development. FIWARE offers an open specification for each of its GEs, describing its essential functionalities, interfaces, and APIs, along with an open source solution that implements the specification. FIWARE GEs have been exploited in various domains [18, 19, 20, 21]. These works usually combine a very small set of GEs to provide the basis for the development of different prototype applications for end users. Such projects demonstrate that smart applications can benefit from FIWARE components as reusable building blocks. However, these works also evidence the technical disparity between the different GEs in terms of technical quality, maturity, ease of integration, documentation, and provided functionalities.

The projects discussed above describe tools and architectures for the design of smart city platforms whose features and principles have influenced the design of the InterSCity platform. However, most of these works failed to either provide a thorough explanation of how they address the scalability problems or perform scientific validation of the scalability of the proposed platforms. Such problems are heightened in cases where the documentation is lacking or the source code is not available, thus limiting the analysis of scalability and exploratory work by the research community to just considering the discussions that were presented in the original publications. To tackle these problems, our work deepens the discussion about the use of a microservices architecture on smart cities via the open-source InterSCity platform. In addition, this paper introduces reproducible scientific experiments to demonstrate the scalability of the platform. To this end, a companion experimentation package is also made available[3] which can be used and extended by the research community.

2.2. Workload Generation for Smart City Platforms

One of the major difficulties to evaluate the scalability of smart city platforms is workload generation. Such platforms interact with two layers that depend on each other at runtime: the city IoT infrastructure and client applications. The city dynamics (e.g., people and cars moving across the city, car accidents, traffic jams, and weather conditions) directly impact the infrastructure. For example, if in a specific region many cars are moving in a specific direction, intelligent traffic lights should be kept open to optimize the flow. Conversely, changes in the cyber-physical infrastructure affect the city behavior as well. For instance, if a driver is heading to an available parking spot and, in the meantime, a sensor detects that the spot has been occupied by another car, the driver will keep looking for another available parking spot, increasing the number

[2] OpenIoT - https://github.com/OpenIotOrg/openiot

[3] `https://github.com/LSS-USP/interscity-k8s-experiment`

of vehicles moving around. Therefore, a realistic workload in a smart city context must consider the dynamic interaction between the two layers. However, since real-world deployments of smart city platforms are still rare, there is a lack of real traces of this kind of systems that could be used to better characterize workloads.

IoT and smart city benchmarks, such as RIoTBench [22] and CityBench [23], can be used to generate workloads related to a city's IoT infrastructure. These benchmarks are based on real traces of IoT devices scattered across the city. Their main goal is to assess distributed stream processing systems, which are a crucial part of a smart cities platform architecture. RIoTBench includes four stream-based workloads derived from real IoT observations of smart cities and personal fitness devices, with peak stream rates that range from 500 to 10,000 messages/sec, and different frequency distributions[22]. CityBench, in turn, focuses on RDF stream processing engines. It includes real-time IoT data streams generated from various sensors deployed in the city of Aarhus, Denmark [23]. Although these works represent significant steps towards the evaluation of smart city platforms, they are limited to a set of specific functionalities (such as data stream processing and the handling of several IoT devices at the same time) and encompass only the behavior of the underlying IoT layer, failing to consider the behavior of citizens and applications.

Another technique to generate workloads that represent the city's IoT infrastructure is the use of simulation. SenSE (Sensor Simulation Environment) [24] is an open source synthetic traffic workload generator, developed to simulate complex environments, such as smart cities. This tool can generate massive amounts of heterogeneous sensor data simultaneously, being able to simulate tens of thousands of sensors based on pre-defined probability distributions [24]. However, it is also limited to the IoT layer.

To generate workloads representing client applications of smart city platforms, common HTTP workload generation tools can be used, such as ApacheBench[4] and HTTPerf [25]. However, characterizing the workload to represent the frequency and peaks of user requests is not easy. Workload characterization is based on the analysis of measurements collected from the infrastructure during its operation [26]. When real representative traces from smart city applications are not available, workload characterization is not a trivial task. This aspect is important because cities and their citizens do not behave the same way during the course of a day, week, month or year. In addition, there is the occurrence of unexpected events. Thus, a realistic workload must include such variations.

To the best of our knowledge, no previous work explores the dynamic interactions among the different actors in a city to characterize experimental workloads. The approaches described above present significant limitations in generating realistic workloads for smart city platforms as they do not encompass the two layers (city IoT infrastructure and client applications) and their cross-interactions. Our proposal to solve this problem is to use a scalable agent-based smart city simulator that manages the behavior of both the IoT infrastructure and the client applications at the same time, while also enabling the analysis of the consequences of their interactions via the platform during the simulation. The following sections present this approach.

3. The InterSCity Platform

Future smart cities will demand high-quality research in multiple areas. The InterSCity project [27] is a multidisciplinary consortium that aims to develop scientific and technological research to address key challenges related to the software infrastructure of smart cities, focusing on Networking and High-Performance Distributed Computing, Software Engineering, Data Analysis, and Mathematical Modeling. The project aims at enabling the development of reusable open-source technologies and methods to support future smart cities while advancing the state-of-the-art.This section presents the InterSCity platform[5], an open-source, microservices-based middleware to support the development of smart city applications and to enable novel, reproducible research in the field.

The InterSCity platform offers a set of high-level, Web-based services that provide facilities to manage heterogeneous IoT services and resources, as well as to support the discovery of city resources based on context data, to store and process data, and to intermediate actuation commands. These services cover essential features required to support integrated smart city applications in different domains. The InterSCity platform intermediates communication between smart city applications and the IoT services of the city, offering high-level abstractions that hide the complexity of city-scale data management and the inherent particularities of the communication with the underlying IoT devices.

In addition to **scalability**, the main design requirements for the platform include: **flexibility** and **extensibility**, achieved via modular, decoupled, distributed services that enable independent evolution of components and facilitate the addition of new features; **interoperability**, achieved with the adoption of open, well-accepted standards and protocols; code writing **productivity** and **reliability**, achieved with the reuse of robust, highly-tested open-source tools, libraries, and frameworks. By meeting these requirements, we were able to design an evolvable architecture facilitating the addition of new features and resolving performance bottlenecks.

Therefore, the platform design is based on a microservices architecture from the outset, aiming to provide a

[4] `https://httpd.apache.org/docs/2.4/programs/ab.html`

[5] The InterSCity source code is available at `http://interscity.org/software/interscity-platform` under the MPL 2.0 license

modular, evolvable, and scalable middleware infrastructure that can be easily extended and shared among multiple research groups, smart city initiatives, and code development communities. Microservices are an architectural style that promotes the modularity of a system in terms of a set of distributed, fine-grained, independent services that collaborate via network protocols such as Web services or remote procedure calls [28]. The microservices model emerged from the software industry efforts to build large-scale distributed systems combining the guidelines of traditional Service Oriented Architecture, Domain-Driven Design, continuous delivery, on-demand virtualization, infrastructure automation, and small autonomous teams [29].

Up to this date, the InterSCity platform has already been used in four software development courses in different Brazilian universities to support the development of smart cities projects, reaching nearly 100 undergraduate and graduate students. Also, a Smart Cities Hackathon was promoted at the University of São Paulo in which teams developed hardware and software solutions based on the platform. These allowed us to experiment with the platform in different domains such as mobility, health, sports, interaction with social networks, and street lighting. Each of these events served as a valuable opportunity to detect non-optimal design decisions leading to refinements of the platform implementation and documentation. Recently, research groups from other universities started to use the platform as a basis for their research. For example, the authors of ContextNet extended the InterSCity platform to include support for Complex Event Processing [30]. With such experiences, we have been collecting feedback from the users of the platform, which have helped us to refine the endpoints provided in our API and to add new useful features, such as the support for geolocalized searches. Besides, it also motivated some external contributions either through patches of code or bug reporting.

A broader description of the InterSCity platform was presented in a previous paper [6], covering high-level details of its architecture, modules, interfaces, design principles, and development methods, such as DevOps techniques and practices used by open-source communities. Therefore, in this paper, we focus on presenting the refined decisions in the systems-level design and in the implementation of the platform to meet its scalability requirements.

Compared to the previous version of InterSCity, the main enhancements we introduced in the new version described in this paper did not impose significant changes in the high-level system components. The main changes improved platform internal aspects such as deployment procedures, communication mechanisms among the microservices, and improvements in the microservices code base to resolve performance bottlenecks. Such enhancements include using caching mechanisms to save the latest sensor data and avoid database locking when reading from tables that receive many writes; providing finer-grained API endpoints for internal communication between the microservices, avoiding unnecessary overheads of object serialization and deserialization; and refinement of the queries and database indexes most commonly used by applications.

InterSCity leverages the microservices architecture as its base strategy to achieve scalability. This is due to three fundamental reasons, which we explore in further detail in the remaining of this section:

- Functional Decomposition: the microservices architecture promotes modularity via single-purpose, small services that communicate through lightweight mechanisms to achieve a common goal. Also, functional decomposition leads to scalability as the system workload is split among distributed microservices.
- Design and Technology Heterogeneity: different design and technology decisions can be made for distinct microservices, although they do not exclude general choices that apply to the entire system; and
- Independent Deployment: each microservice can be deployed, replicated, and replaced independently.

3.1. Functional Decomposition

By implementing a microservices architecture, the InterSCity platform decomposes its functionalities across a set of small, interconnected, collaborative services. Figure 1 presents an overview of the InsterSCity architecture, exposing its main microservices: Resource Adaptor, Resource Catalog, Data Collector, Actuator Controller, Resource Discovery, and Resource Viewer. The figure also highlights the top and bottom boundaries of the system, which are accessed by smart city applications and by IoT systems, respectively, through Representational State Transfer (REST) APIs over the Hypertext Transfer Protocol (HTTP).

The architecture of InterSCity supports decentralized management of city resources, dividing functional responsibilities and data persistence across the microservices. The Resource Adaptor is a proxy microservice that simplifies communication between external IoT systems and the rest of the platform. It provides a single entry point for the underlying IoT gateways to register and update resources on the platform, post sensed data from those resources, and subscribe to events that indicate actuator commands. As a proxy, Resource Adaptor is responsible for validating the requests, augmenting them with additional metadata and required adaptations. The adaptor either broadcasts the requests to the entire system or calls a specific microservice to handle the request synchronously.

The Resource Catalog is a vital microservice of the InterSCity architecture since it manages the static data of city resources, working as a catalog for these resources. After registering a new resource, the Resource Catalog assigns it a new Universally Unique IDentifier (UUID) and asynchronously notifies the resource creation event to other microservices. Both client applications and IoT gateways

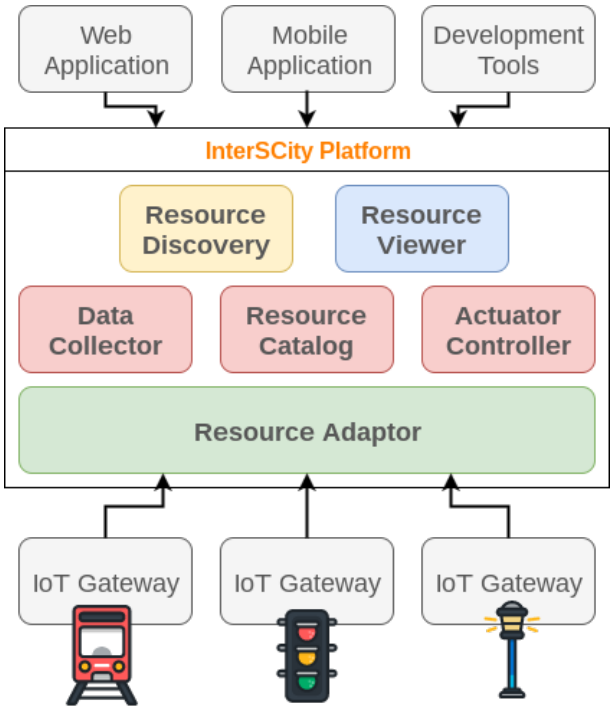


Figure 1: The InterSCity platform architecture (extracted from [6])

must use a UUID in later interactions that target a specific resource, such as to get and publish sensor data.

City resources may have functional capabilities to provide data and receive commands, which are respectively supported by sensors and actuators coupled to the resource. InteSCity splits the responsibility for managing sensors and actuators between two microservices: Data Collector and Actuator Controller. Data Collector is responsible for storing and providing access to data collected by city resources. An item of sensor data consists of either context information or an event linked to a resource capability that is observed at a particular time. Data Collector provides an API to allow access to both current and historical context data of city resources using a rich set of filters that can be accessed via search endpoints. The Actuator Controller microservice, in turn, enables client applications to send commands to change the state of city resources that have actuator capabilities. It is responsible for receiving and validating actuation requests from clients and asynchronously notifying the underlying IoT gateway through Webhooks. This microservice also records the history and tracks the status of actuation requests made through its API.

Client applications need an easy way to find the resources available in the city so they can interact with them through the platform. For this purpose, the Resource Discovery microservice provides a sophisticated context-aware search API. It orchestrates the Data Collector and Resource Catalog to offer a set of filters by combining their results based on location and static data (i.e., resources' type and capabilities), and by matching rules for latest context data. For instance, one may search for all available city resources capable of monitoring the environment located within a radius of 1 kilometer from a specific location, and whose temperature sensors are scoring above 18 °C. Similarly to Resource Dicovery, the Resource Viewer microservice also orchestrates the Data Collector and Resource Catalog to gather both static data and sensor data for visual presentation. It is a front-end microservice for presenting general and administrative information regarding city resources which are useful, e.g., for platform management.

As a result of its functional decomposition, the workload of InterSCity is handled by separate distributed services, cooperating towards its scalability. The partitioning of the system workload is also reflected on the database tier, since each microservice has its database and manages a small set of the system's data. Different smart city contexts may lead to different ways of splitting the workload of the platform among its microservices in a non-uniform way. For instance, in a city with a large number of sensors, two microservices of the InterSCity platform may be used more often: Resource Adaptor and Data Collector. In another type of scenario, a city with actuator resources might have management systems that send actuation commands to the underlying IoT devices, thus placing a higher demand on Actuator Controller.

3.2. Design and Technology Heterogeneity

Since microservices communicate via standardized protocols, each microservice can be built with the most appropriate stack of technologies for its specific purpose. They can also be maintained in separate repositories, enabling polyglot persistence and technology diversity. Table 1 shows the technologies used by InterSCity services.

Although we embrace the diversity of technologies in InterSCity, we apply this principle with some caveats to avoid increasing overall system complexity and the proliferation of practical problems since a radical adoption of technology diversity could lead to an unmaintainable architecture [31]. For this reason, we initially opted to use Ruby-based tools to develop the foundation services of the platform due to the high productivity and flexibility of this language and the smooth learning curve for newcomers who aim to contribute with the InterSCity codebase. Technological and design aspects related to contributions in the form of new microservices are discussed with the project team and may use other technical options according to their purpose. However, if the new microservices are supposed to be maintained within the main platform repository, they must have at least one maintainer that has fluency in the adopted technologies and must conform to the quality requirements of the project, such as having highly automated test coverage.

In addition to the technology aspects mentioned above, several other design decisions permeate the development of a microservice for the platform. One of the main issues is to define strategies to enable a microservice to scale horizontally while offering its functionalities with acceptable

Table 1: Technology Stack of InterSCity Microservices

Service	Language	Framework	Database	Cache
Actuator Controller	Ruby	Ruby on Rails	MongoDB	
Data Collector	Ruby	Ruby on Rails	MongoDB	In-memory MongoDB (Percona)
Resource Adaptor	Ruby	Ruby on Rails	PostgreSQL	Redis
Resource Catalog	Ruby	Ruby on Rails	PostgreSQL	Redis
Resource Discovery	Ruby	Ruby on Rails		
Resource Viewer	Javascript	EmberJS		

performance. Several decisions may affect the internal implementation of a service, such as the use of caching mechanisms, database schema and indexing, the choice of algorithms, and API design. Decisions regarding how a microservice interacts with the whole ecosystem of the platform are also relevant in this perspective, such as communication protocols, discovery of other services, and the handling of asynchronous messages, to name a few.

InterSCity implements two fundamental communication mechanisms to support the scalable orchestration of its microservices: (1) Synchronous communication over HTTP and (2) Asynchronous messaging through the Advanced Message Queuing Protocol (AMQP)[6].

For HTTP communication, we employ the *API Gateway* design pattern[7] by using Kong[8], a distributed, scalable open-source gateway that aims at facilitating the orchestration of microservice APIs. Kong is backed by NGINX[9] and extends its HTTP Web server features to offer a dynamic management layer for the microservices HTTP APIs. In summary, the API Gateway receives all incoming HTTP requests, determines which InterSCity microservice should respond to a specific request, and forwards the request to the identified microservice. For this purpose, we use URI-based rules: the system uses the path part of an HTTP request to identify the target microservice of the request. Figure 2 illustrates this strategy, highlighting the interaction of a client application and an IoT Gateway with the platform through the HTTP APIs of its microservices, which in turn are accessed via the API Gateway.

A clear advantage of implementing the above mentioned API Gateway strategy is that clients only need to interact with a single entry point (host address and port) to access all InterSCity facilities, instead of keeping references to multiple microservices.

The API Gateway also enables scalability as it leverages the load balancing feature of NGINX so that it is possible to easily deploy multiple instances of the same service. Figure 3 illustrates this by presenting the main interactions among clients, the API Gateway, and the available microservice instances. Whenever we run a new instance of a microservice, the microservice uses Kong's REST API, which is an implementation of the *Self-registration* design

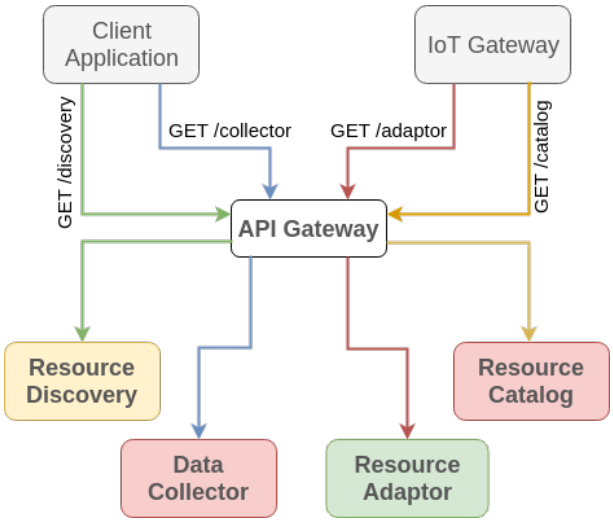


Figure 2: InterSCity API gateway

pattern[10], to register itself with the API Gateway as a target for an existing URI rule. In the example, distinct Resource Catalog instances register themselves as targets for requests that match the */catalog* URI rule, indicated by the black arrows. This approach enables the dynamic creation of new instances of a service to split and distribute the increasing workload using a round-robin strategy, without affecting other parts of the system or requiring further reconfiguration. Round-robin load balancing is represented by the blue and yellow arrows in Figure 3.

The API Gateway constantly monitors the availability of target instances by health checking the endpoints in order to adjust its load balancing accordingly by not sending new requests to unhealthy nodes. It identifies microservice instances as healthy or unhealthy based on the status code in HTTP responses. A success code indicates a healthy endpoint, whereas non-success status codes, timeouts and TCP errors denote an unhealthy endpoint.

As Kong allows the registration of service instances, the API Gateway also supports the *Server Side Discovery* design pattern[11]. This pattern facilitates HTTP-based communication among microservices in the platform since instead of having to manage references to all running in-

[6] https://www.amqp.org/
[7] http://microservices.io/patterns/apigateway.html
[8] https://getkong.org/
[9] https://www.nginx.com/

[10] http://microservices.io/patterns/self-registration.html
[11] http://microservices.io/patterns/server-side-discovery.html

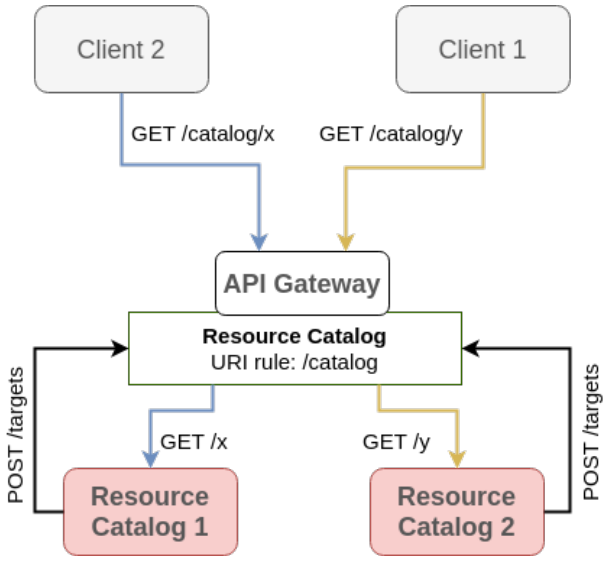


Figure 3: InterSCity load balancing HTTP requests

stances, clients need to know only the address of the API Gateway, using URI-based rules to communicate with the target microservice, as shown in Figure 2. A direct advantage of using the `API Gateway` design pattern is the guarantee that requests for a given microservice will be handled by any of its instances in an independent way, allowing for efficient load-balancing. This is an important feature since the number of service instances and their locations may change dynamically.

Although services provide well-defined RESTful APIs, we adopt asynchronous communication whenever possible to avoid the additional latency of blocking synchronous request-reply interactions. To achieve this, a microservice may use the publish/subscribe design pattern rather than directly exchanging messages with other services. InterSCity carries out asynchronous messaging by using RabbitMQ[12], a widely used, lightweight, open-source messaging middleware that implements the AMQP protocol.

Events of different types may generate data that need to be broadcast to other modules in the platform. Examples are the registration of a new IoT resource, the reception of sensor data, and requests to actuators. Each type of event is mapped to a *topic*, to which interested services can subscribe to receive new messages through queues maintained by RabbitMQ. By default, each subscription will create a new queue. Messages sent to a specific topic are pushed to all of its subscribed queues.

InterSCity thoroughly exploits RabbitMQ messaging features by using routing keys that enable the use of more sophisticated criteria to route messages to subscribers. A routing key is a list of dot-separated strings related to metadata about InterSCity's internal abstractions. They are added by publishers when sending messages to RabbitMQ. When a city resource publishes sensor data on the platform, a new message is published on topic **data_stream** with a routing key of the form **uuid.capability.others**, where *uuid* is the unique identifier of the resource, *capability* is the type of the sensor data, and *others* represents any additional information regarding the posted sensor data that could also be used to build the routing key. Similarly, subscribers must inform a binding key when defining a queue to receive messages from a topic.

Figure 4 shows an example of an InterSCity topic-based message exchange using routing keys. When the Resource Adaptor receives sensor data from the underlying IoT infrastructure, it publishes the data on topic *data_stream*, which has consumer queues for Data Collector, Resource Catalog, and other services interested on the topic. As Data Collector is responsible for saving the history of sensor data, it is interested in any data on this topic (binding key: #). On the other hand, Resource Catalog is only interested in sensor data that contains geolocation information so that it can update the location of moving city resources on its database (binding key: **#.location.#**). Other microservices could be interested in any data from a specific type of sensor, such as temperature data (binding key: ***.temperature.#**), regardless of which city resource provided the data.

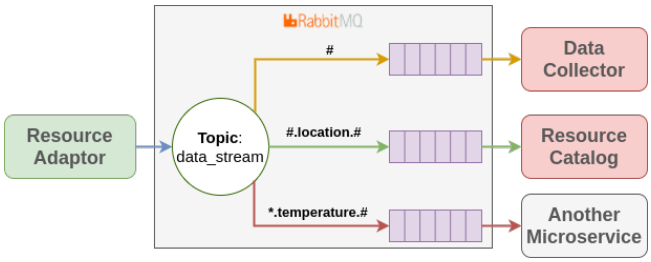


Figure 4: InterSCity Asynchronous messaging

To further decrease the latency of communication among microservices and thus improve its scalability, InterSCity employs a worker-based strategy for asynchronous messaging. InterSCity services that need to receive asynchronous messages from the platform must implement a background worker for each subscribed topic in RabbitMQ. By design, these services support the addition of more workers to improve the processing rate of the queued jobs by implementing the *Competing Consumers* design pattern[32]. Figure 5 presents this design pattern, where additional workers read messages from the same queue concurrently and as fast as possible, enabling parallel processing of background tasks. As workers read from the same queue, messages are not replicated for each of them. Consequently, in the example, messages **X** and **W** will be processed in this order by the first two workers that finish their current jobs, represented by messages **Y**, **Z**, and **A**.

3.3. Independent Deployment

An important aspect of the InterSCity architecture is that its components are designed as single-purpose, inde-

[12] `https://www.rabbitmq.com/`

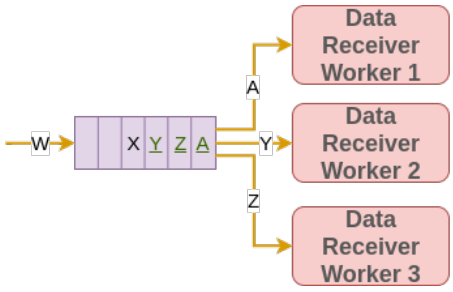


Figure 5: Competing Consumers design pattern

pendently deployable services. Two sets of deployment-related design decisions need to be considered: those related to the entire system, and those that concern individual microservices. The former corresponds to decisions related to the choice of cloud provider, the allocation of computing resources for the system, the packaging of service instances (i.e., virtual machines, containers, and physical hosts), the handling of common procedures (e.g., update, backup, and monitoring), and the deployment of complementary services used by the system (e.g., databases, message brokers, and proxies). The latter concerns the distribution of microservice instances across the available hosts (e.g., single service per host, multiple services per host), service configuration, failure recovery, and scaling of a microservice to appropriately respond to changes in the workload.

Another related issue refers to the deployment of individual microservice instances across the different tiers of the distributed execution environment: cloud, fog, and edge. For instance, a microservice that interacts heavily with city infrastructure resources, such as Resource Adaptor, could be dynamically deployed at the edge to reduce latency. Conversely, a microservice that requires significant computational power or a more global view of the system, such as Resource Viewer, could be deployed in the cloud. This aspect of microservice deployment, especially considering dynamic redeployment, is the subject of ongoing research in the project.

The above examples of decisions related to the deployment of microservices-based systems highlight the multiple trade-offs and challenges faced by engineers, as also observed in [31]. DevOps techniques and tools are very successfull in achieving a reliable and reproducible deployment process, as well as in improving the operating environment [29, 31]. The inherent complexity of the InterSCity distributed microservices environment requires the use of such techniques to automate the necessary procedures. These include automated tests and the upgrading of microservice instances in the production environment, as well as support for more complex tasks, such as scaling and distributing microservices automatically based on the monitoring of services and computational resources.

For this purpose, we packaged all the InterSCity microservices into Docker[13] containers and used them in addition to the containers provided by the community for the supporting tools (i.e., RabbitMQ, Kong, MongoDB). Moreover, we use Kubernetes[14] to support the deployment of Docker containers throughout a cluster of virtual machines in a cloud infrastructure.

Kubernetes is an open source project that aims at automating the management of container-based applications by offering tools for supporting two critical tasks. First, it provides a declarative structure through YAML files for developers to define the desired state for the containers that comprise the managed system [33] in compliance with the *Infrastructure as Code* (IaC) principle, one of the pillars of DevOps [34]. Second, the Kubernetes engine runs the specified configuration on the cloud provider to manage the deployment of the system by scheduling containers across the available machines.

In dynamic smart city contexts, with varying demands throughout the day and random citizen behavior, InterSCity must be able to individually scale out the stressed services to properly support workload fluctuations, rather than scaling the entire system as a whole. As we designed InterSCity microservices as stateless services, we can place several copies of the same microservice behind a load balancer (i.e., Kong). Likewise, multiple instances of the same microservice leverage the worker-based approach to distribute processing jobs across asynchronous workers. By monitoring computational resources used by the platform microservices, Kubernetes is capable of adjusting the number of instances for each microservice to adequately and automatically support a varying workload.

4. Smart City Simulation for Workload Generation

This section discusses the fundamental steps to enable simulation-based workload generation. This approach is meant to support comprehensive performance and scalability experiments on top of the InterSCity platform, especially considering realistic, large-scale smart city scenarios. In particular, we present InterSCSimulator, a smart city simulator for the behavior of city actors and their interactions in large-scale settings. We also describe the simulated scenario and how we implemented the integration between the InterSCity platform and InterSCSimulator to perform the experiments.

4.1. InterSCSimulator

InterSCSimulator is an open-source, scalable simulator for large-scale smart city scenarios [9] developed in the context of the InterSCity project. In its current version, the simulator provides a set of mobility models for cars, pedestrians, buses, and the subway. Previous work shows

[13] https://www.docker.com/
[14] https://kubernetes.io/

that InterSCSimulator is capable of simulating an entire city such as São Paulo, with more than 10 million software agents virtually moving across tens of thousands of streets. The simulator is implemented in Erlang, a language suitable for the development of highly parallel and distributed applications based on the actor model.

Figure 6 shows the simulator architecture. InterSCSimulator builds on top of the Sim-Diasca simulator [35] to perform general-purpose simulation activities such as Simulation Time Management, Random Number Generation, Load Balancing, and Base Actor Modeling. InterSCSimulator contains the city street map graph and the required actors for Smart City simulation such as cars, buses, subways, and sensors. Actors execute tasks during a simulation clock tick, which represents the simulation of one second in the real world. Lastly, the top layer comprises the scenarios that can be implemented using the Smart City Model.

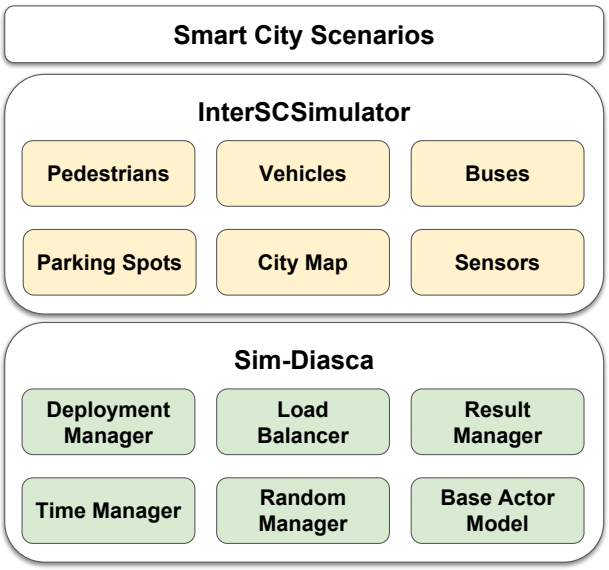


Figure 6: InterSCSimulator Architecture

InterSCSimulator has two main components: **Scenario Definition**, which receives the input files and creates the simulation scenario, and **Simulation Engine**, which executes the algorithms and models and generates the simulation output. For mobility simulations, it receives three required files as input: **map.xml**, with the city street graph, **trips.xml**, describing all the trips that must be simulated, and **config.xml**, with general options such as the total simulation time. There are other optional files depending on the simulated scenario such as **park.xml**, containing all the parking spots and **subway.xml** with the subway network graph of the city. At the end of a simulation, the simulator generates an output file with all the events that occurred during the simulation. Figure 7 presents the InterSCSimulator components and their inputs and outputs.

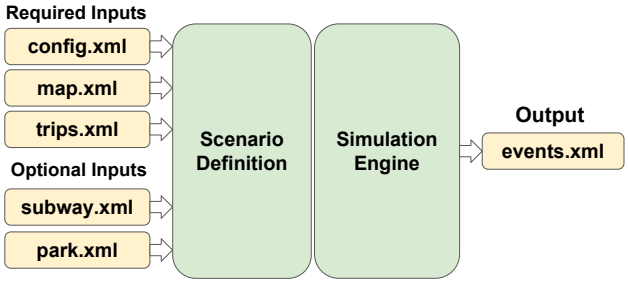


Figure 7: InterSCSimulator components

4.2. Smart City Scenario

To evaluate the InterSCity platform, we implemented a Smart Parking scenario on InterSCSimulator, which uses the existing mobility models in addition to new parking spot actors. This scenario considers several car drivers using a Smart Parking mobile application backed by the InterSCity platform to assist in the difficult task of finding a free parking spot in a large city like São Paulo. This application offers geolocated real-time information about parking spaces. When using the mobile app, a car sends its current location to the server application, which then answers with a list of the closest available parking spots. In this scenario, we simulated the behavior of drivers that use the mobile application, the behavior of the IoT devices installed in parking spots, and the interactions among them.

We extended the simulator with models to support the monitoring of parking spots and to allow drivers to find parking spots in the city. A parking spot actor generates events when a car parks on it or leaves it. It simulates the behavior of a real smart parking infrastructure supported by cyber-physical systems to detect the presence of cars based on technologies that are commonly used in smart parking solutions, such as Wireless Sensor Networks (WSN), Light Dependable Resistor (LDR) sensors, Infra-Red (IR) sensors, and magnetic sensors.

The simulation model consists of the following flow for a single car agent: (I) the car starts its trip from an origin to a destination point; (II) when the car is close to arriving at its destination, it requests the nearest free spots to the Smart Parking application; (III) the application asks the platform to find the nearest available spots considering the user's location; (IV) with the data returned by the platform, the simulator changes the route of the car to the closest parking spot returned; (V) the driver arrives at the spot and finishes its trip; (VI) the simulator updates the status of the chosen parking spot on the InterSCity platform, marking it as unavailable.

If the platform does not find any parking spots that match the request of a car driver, the corresponding simulation agent may return to step **II** increasing the search radius. After three failed attempts, the agent stops using the application and completes its execution in the simulation. Another special case might occur during step **V**,

as the target parking spot might become unavailable (e.g., by being taken by another vehicle), requiring the car to return to step **II**.

The interactions between the InterSCSimulator and the InterSCity platform required the integration of these two systems. Such interactions impose workloads on the platform both at the top layer, as the simulator consumes data as a client application, and at the bottom layer, as it updates the status of the underlying IoT infrastructure of smart parking spaces. The details of this integration will be presented in Section 4.3.

To generate a meaningful workload to evaluate the platform, we modeled a realistic scenario based on real data from the very large city of São Paulo. This data was used as input to the simulator to define the number and distribution of parking spots around the city and the trips undertaken by drivers, including their origins, destinations, and departure times. The data used to generate workloads is detailed bellow:

- **Origin-Destination (OD) Survey:** we created the simulated trips based on the OD survey performed by the subway company of São Paulo[15]. This survey describes the trips of 200,000 people and extrapolates the data to the entire population of the city. The survey includes information on the origin, destination, transportation mode, and departure time. We used this data to define the behavior of car agents. To generate the load for the platform experiments, we simulated the traffic in São Paulo during peak hours, from 5:40 am to 8:40 am. In the OD survey, there are 492,976 cars that start their trips during the considered time interval.

- **OpenStreet Maps:** to create the city graph used in the simulation, we used the map from OpenStreet Maps. This map contains all the streets and junctions of the city, together with a number of attributes, such as length, capacity, and speed limit. Such information is used by the simulator to define the routes taken by cars as they perform their trips, as well as to simulate the impact of traffic on the speed of cars.

- **Parking Spots:** we created the simulated parking spots based on data from OpenStreet Maps and from *Zona Azul*[16] (the rotary parking service of the city of São Paulo).

To show the distribution of parking spaces and drivers destinations throughout the city, Figure 8 presents two heat maps: (a) the simulated distribution of parking spots across the city; and (b) the distribution of trip destinations throughout the entire simulation. It is worth noting that parking spots with IoT infrastructure are significantly more concentrated than trip destinations. This may lead to situations where drivers do not find available parking spots after three attempts. In such cases, the user agent stops using the application and finishes its execution.

4.3. Simulator and Platform Integration

Enabling the scalability evaluation on the InterSCity platform using InterSCSimulator requires an integration of the two systems. To fully explore the dynamics of the Smart Parking scenario on the workload generation, the simulator needs to produce workloads for both the status updates of parking spots (the IoT infrastructure) and the requests performed by drivers to find available parking spaces (using the client application).

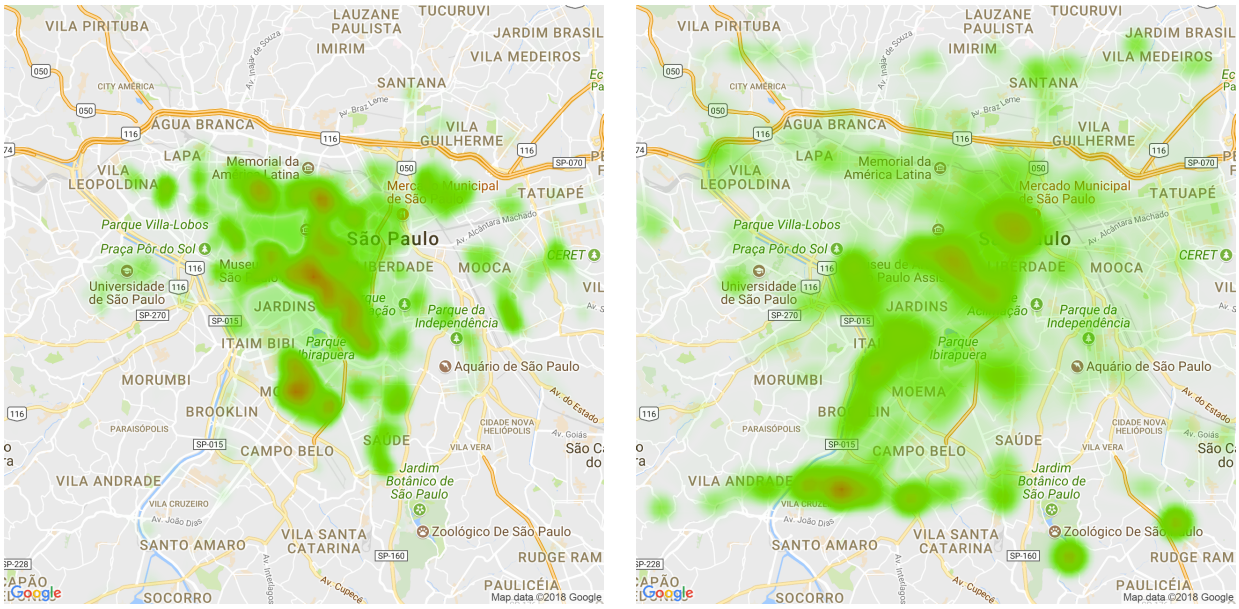
For this integration, we implemented a two-way communication interface between the simulator and the platform. In one direction, the simulator updates the status of the *parking spots* in the platform based on the simulated IoT devices. This is carried out directly via the platform's RabbitMQ instance, by publishing update data on the **data_stream** topic. In the other direction, the simulated users of the application perform synchronous HTTP requests to the platform. To avoid blocking the simulator while clients wait for a reply from the platform (and, therefore, distorting the simulated passage of time), we implemented an intermediate agent that runs independently of the simulation cycle to perform these HTTP requests and wait for the responses.

Figure 9 details, in the context of the Smart Parking scenario, the integration of InterSCity and InterSCSimulator in terms of the interactions between their components. When a car (represented by its simulation agent) is close to arriving at its destination, it asks a controller agent for a nearby available parking space. Note that there are multiple controller agents, each one managing a set of parking spots in the simulation. As we do not want to halt the simulation waiting for the HTTP response from the platform, the controller sends a message to an external Erlang agent asking for an available spot nearby the latitude and longitude of the car's destination. This discovery agent is responsible for actually making the HTTP request to the platform. The agent keeps blocked until it receives the reply. After that, the identifier of the suitable parking spot is sent back to the controller inside the simulator. The controller marks this spot as unavailable and passes its identifier to the car. The car retraces its route to park in the right place. This workflow simulates a single driver using the Smart Parking application. When a parking spot becomes available or occupied, the controller agent sends an AMQP message to the platform, via the RabbitMQ instance, informing the event to the platform.

Finally, we added an idle agent to the simulator which sleeps for a time very close to one second to ensure that the simulator operates in real time (i.e., at the same rate as the actual physical system). Each simulation step (cycle) is a simulated second of the day in which all agents are given the opportunity to perform some action. In its

[15] Origin-Destination Survey - `http://goo.gl/Te2SX7`

[16] `http://www.cetsp.com.br/consultas/zona-azul/mapa-zona-azul/mapa-zona-azul.aspx`



(a) Parking spots distribution (b) Destinations distribution

Figure 8: Heat maps of the distributions of parking spots and car trip destinations in the City of São Paulo

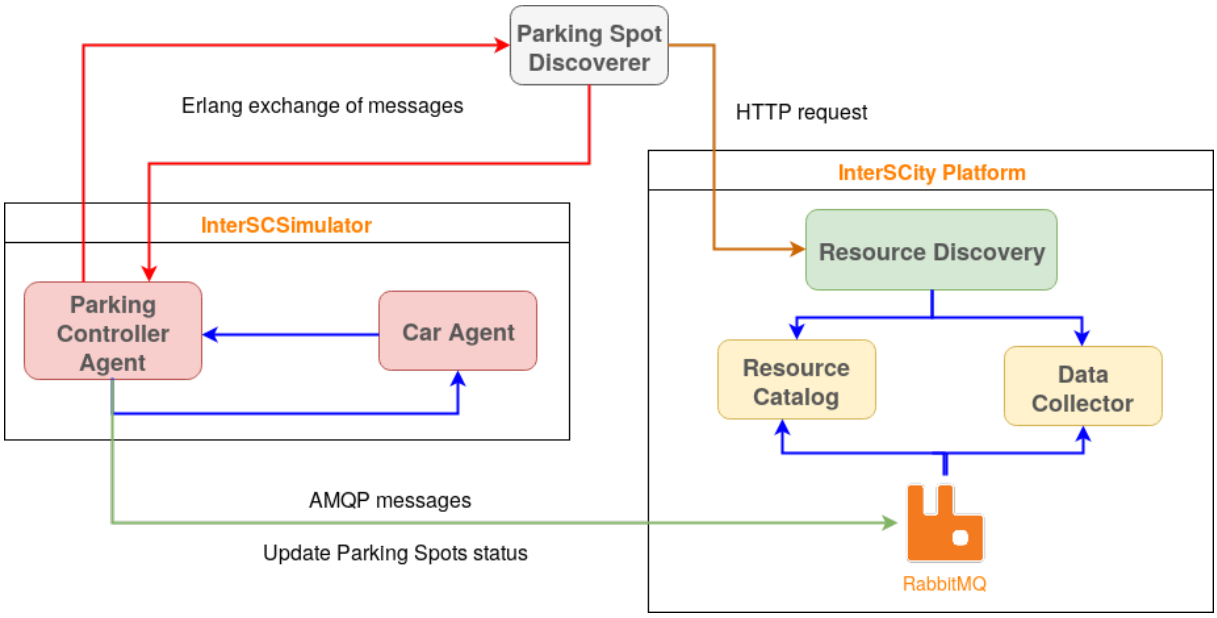


Figure 9: The 2-way integration of the InterSCity platform and InterSCSimulator

normal operation mode, the simulator runs as fast as possible, simulating multiple cycles under one real second. In many cases, this is interesting because the simulation results (which may take hours) come faster. However, in our case, the goal is to produce a realistic load to evaluate the platform, so we want to process as close to real time as possible.

4.4. Simulating Other Scenarios

Note that other scenarios could be simulated by defining a proper model of the city dynamics and creating associated abstractions in the InterSCSimulator. For example, one could consider extending the platform to deal with a Smart Grid scenario in which each home or building in the city could behave both as energy consumer and producer. In this case, one should program new InterSCSimulator agents [9] to model, for instance, the energy consumption behavior of families in a residence, workers in an office, and machines in a factory, as well as a simplified behavior of wind turbines and solar panels (e.g., modeling how much energy they produce). The simulator could then receive as input (1) a map of the city's energy distribution grid,

(2) historical data about the level of solar radiation and wind speed, and (3) a list of buildings and homes capable of producing electricity from solar and wind energy.

With this setting, the simulator would be able to generate a realistic workload, consisting of events related to energy consumption and energy production, generated by the different simulation agents. This workload could then be used to assess, for example, a Smart Grid monitoring and accounting application built on top of the smart city platform.

5. Experimental Evaluation and Analysis

Using the integrated environment described in Section 4, we performed a comprehensive experiment to assess the scalability properties of the InterSCity platform. The experiment consisted of: (I) running a production-like instance of the platform in a cloud environment; (II) enabling an auto-scaling mechanism for the platform's microservices based on the variation of the workload; (III) setting up the simulator in an isolated environment; (IV) starting the simulation of the Smart Parking scenario; (V) monitoring the platform's performance and its usage of the computational resources during the entire simulation; and (VI) analyzing the obtained results.

Section 5.1 details the execution environment of the experiments. In Section 5.2 we discuss the results from a set of repeated rounds of the experiment on the InterSCity platform.

5.1. InterSCity Configuration

To conduct the experiments, a production-like instance of the InterSCity platform pre-populated with the resources available in the city (parking spots) and their initial states (available) is required. Only the microservices Resource Catalog, Resource Discovery, and Data Collector are used in the Smart Parking scenario. The Resource Adaptor is not used since all communication with sensors happens through RabbitMQ (as detailed in Section 4.3), whereas the Actuator Controller is not required as the scenario does not include actuators.

We used Docker containers for InterSCity microservices and supporting services. In all experiments we used the Google Cloud Platform[17] (GCloud), which is an appropriate infrastructure to run InterSCity in a production environment as the platform is a cloud-native system. More specifically, we used the Kubernetes Engine, a set of tools provided by GCloud based on Kubernetes, to schedule the deployment of containers throughout a GCloud cluster. Among other tasks, we used Kubernetes to also automate the restarting, replication, and scaling of containers. Thus, Kubernetes increases the reproducibility of our experiments by ensuring the correct application of deployment rules, configuration, and state. All the code used to perform the experiments, as well as the Kubernetes configuration files, are publicly available in an online repository[18].

We divided the cluster into 5 different node pools so that Kubernetes could schedule the containers to the appropriate pools. Figure 10 presents these node pools and the number and type of the machines used by each one on GCloud[19]. The Platform Pool comprises 25 machines of type *n1-standard-2* (2 virtual CPUs and 7.5GB of memory) and runs both InterSCity microservices and Kong. There are three additional node pools composed of *n1-highmem-2* machines (2 virtual CPUs and 13GB of memory), which execute the support services of the InterSCity environment. Both MongoDB and PostgreSQL pools have 5 nodes running distributed, fault-tolerant instances of their respective database systems, whereas RabbitMQ has a dedicated machine in an isolated node. MongoDB is deployed using the replica set strategy[20] to distribute *read* operations among secondary nodes (slaves), although *write* operations are always performed on the primary node (master). The same strategy is adopted for the PostgreSQL instance for optimizing the *read* operations performed by the Resource Catalog. Finally, the InterSCSimulator runs on its own *n1-highmem-16* machine (16 virtual CPUs and 104GB of memory), isolated from the rest of the services.

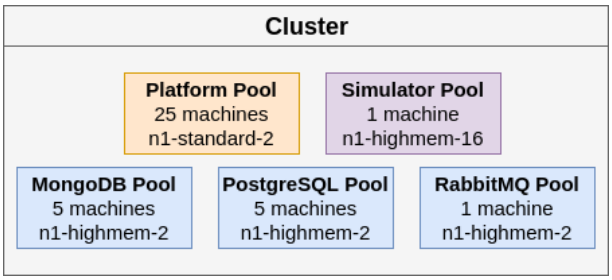


Figure 10: Cluster Node Pools for the experiments

For the Platform Pool, Kubernetes may schedule several containers for the same host depending on the available computational resources. The distribution of containers across the 25 nodes may differ from one experiment to another and is a variable that we did not control for during the performed experiments. To evaluate the impact of such variations on the analysis, we repeated the experiment 15 times and studied the variability of the results.

As we were interested in assessing the platform scalability considering a smart city scenario with a varying workload, we used automatic scaling for the Resource Catalog, Resource Discovery, Data Collector, and Kong services, as they are designed to scale horizontally. For this purpose, we specified a target of 60% of CPU usage for each of those services, enabling the system to increase or decrease the number of containers per service. The system

[17] https://cloud.google.com/

[18] https://github.com/LSS-USP/interscity-k8s-experiment

[19] https://cloud.google.com/compute/docs/machine-types

[20] https://docs.mongodb.com/manual/tutorial/deploy-replica-set/

balances the workload to match the target CPU usage considering the average CPU usage of the running containers, which is measured every 30 seconds. Initially, each service has four containers, which is set as the minimum number of running containers. This number may increase as long as computational resources are available in the Platform node pool. We run the containers behind a load balancing service.

Although we could benefit from GCloud's elasticity properties by automatically adding and removing nodes to our cluster using its auto-scaling feature, this would introduce another level of uncertainty in our experiments, since in our experience the time taken to create new VMs may vary considerably. Thus, we created all the nodes in advance, before starting the experiments, keeping them running throughout the experiment.

5.2. Scalability Evaluation

To better analyze the behavior of the InterSCity platform, we ran multiple rounds of the experiment. Our objective was to minimize the effects of uncontrollable variables inherent to the environment in which the tests were performed, so as to evaluate important aspects of the system and to ensure that the observed results are good estimates for the general behavior of the system.

We performed a total of 15 rounds of the experiment. Each round ran for 3 hours, corresponding to the simulation of the morning peak traffic hours in São Paulo according to the scenario described in Section 4.2. Figure 11 represents the average workload generated by InterSCSimulator on the platform during the experiment and the standard deviation (black lines on top of each bar). It is worth noting the constant increase in the workload during the first 80 minutes. In the approximate interval of one hour between 60 and 120 minutes, we observed the highest load period of the experiment, whereas the maximum peak of requests happens after 80 minutes, corresponding to more than 113,000 requests in 10 minutes. In total, more than one million requests were performed to the platform during the experiment time. Since fulfilling each of these requests requires a complex set of operations with multiple internal steps, this translates to a very large computational load.

Figure 12 shows the dynamic creation and destruction of InterSCity containers due to the application of the auto-scaling strategy in a single round. The initial replication of Kong instances was enough to support the entire workload during the entire experiment since it only performs the low-latency task of forwarding the incoming requests to the proper microservices. In turn, the three InterSCity microservices, which are truly responsible for handling the requests, were replicated according to the increasing workload. Thus, the number of containers for these services varied from 4 to 25. It is important to mention that the InterSCity elasticity mechanism also reduced the number of containers as the demand decreased. As can be seen in Figure 12, among the InterSCity microservices, Data Collector was the microservice that consumed the least CPU time.

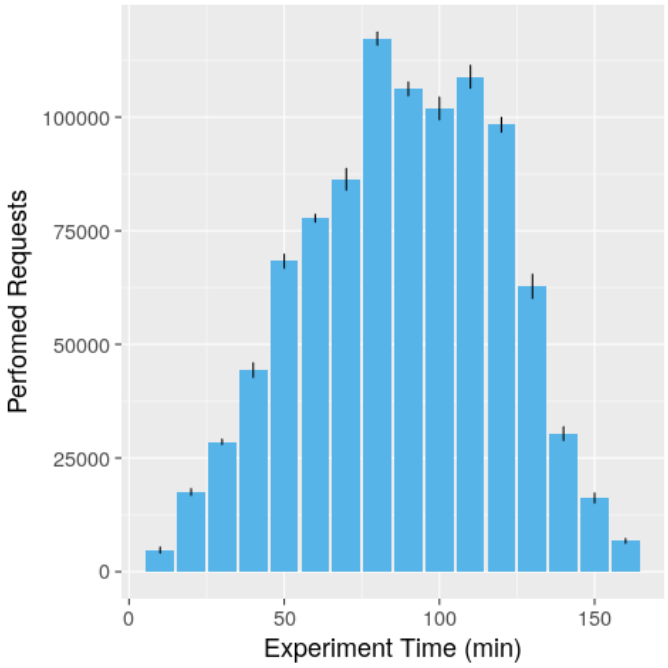


Figure 11: Average workload generated by the InterSCSimulator

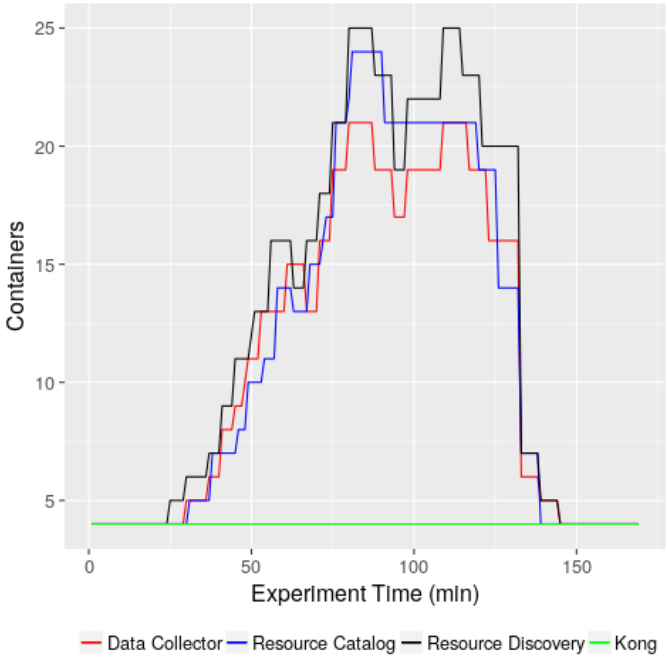


Figure 12: InterSCity services autoscaling

Figure 13 shows the average throughput of the InterSCity platform over the duration of the experiment. The throughput is defined as the rate of successful responses received by the simulator. The result indicates that the throughput closely matches the generated workload, as

can be seen by comparing Figures 11 and 13. Despite the simulated variations in the drivers' behavior throughout the experiment, the platform was able to handle the varying demand thanks to its scalability and autoscaling support features, described in Section 3. However, we should mention that the throughput did not match the generated workload exactly, since some of the requests failed, representing nearly 0.6% of all requests on average. Failed requests include those that had responses with an HTTP error code, as well as those that were not completed due to connection refusal or timeout. But we consider that being able to handle over 99.5% of the requests under high load is satisfactory; a typical user would see a failure every 200 requests, which is very good for this kind of real-time smart urban application.

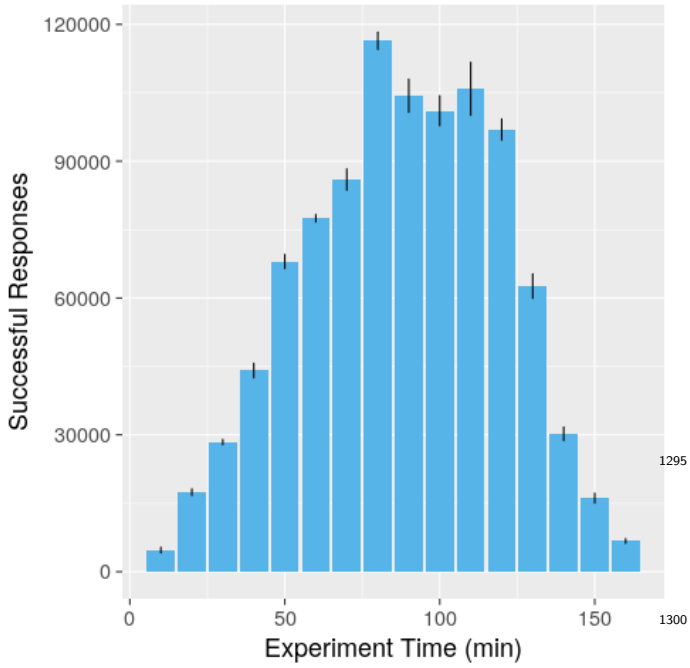


Figure 13: Average InterSCity throughput

Another fundamental aspect of the system assessment is to analyze the performance of the platform to handle application requests with a varying workload. In this respect, we are mainly interested in analyzing the performance degradation and verifying whether the platform is scaling appropriately to serve its clients within acceptable response times. For this purpose, we collected the response time from the client's point of view, as shown by Figure 14. During most of the experiment duration, the platform was able to respond in less than one second. However, different from the throughput, the impact of the highest demand period on the observed response time is noticeable since, during a small time interval (after 110 minutes of execution), the average response time was greater than 1 second. The response time went back down to 500 milliseconds after that. But, we can see that even in periods of high-load, the response time was kept under 2s, which is a very good result for this kind of application.

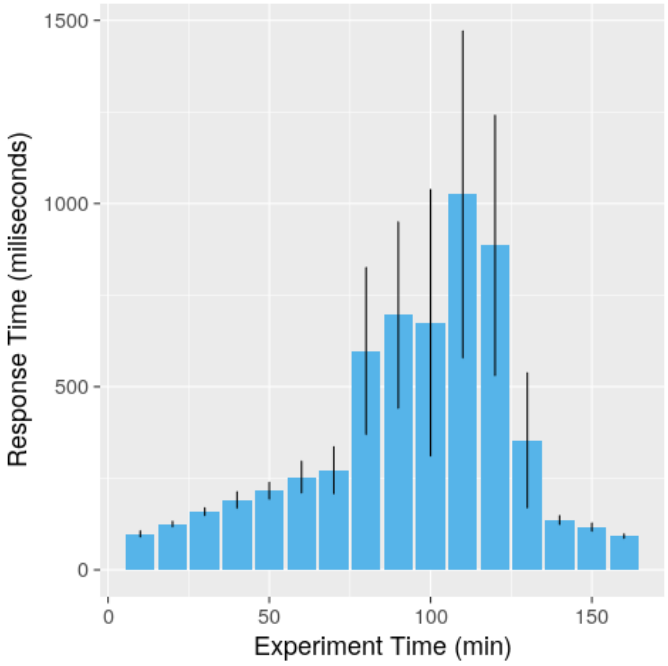


Figure 14: InterSCity Average Response Time

We should recall that the distribution of containers on the available nodes may impact the response time, as several containers may compete for computational resources if they are running on the same host machine. Moreover, although the system handles the autoscaling task every 30 seconds, we have no control over the time it takes for a container to be scheduled and become ready to receive requests. On the other hand, this distribution may also introduce a beneficial effect due to the scheduling of services that constantly interact with each other to the same machine, reducing network latency and unpredictability.

5.3. Threats to Validity

In this section, we clarify and discuss some important aspects of our experiment design as they may threaten the validity of our results and affect reproducibility. Most of the threats are inherent to the environment where the experiments were carried out, as there is considerable uncertainty concerning the provisioning of resources and services in cloud environments [36]. As the Google Cloud Platform is not a controlled environment, it is impossible to have complete knowledge of the system. For instance, we cannot correctly specify all properties related to the communication network used within the cluster, such as network capacity, nor ensure constant bandwidth. Such variables may directly impact results such as the observed response time.

As discussed in Section 5.2, although Kubernetes plays a crucial role in our experiments, it also raises some concerns for their validation. Firstly, we do not control the

way Kubernetes distributes new containers across the available hosts of a node pool, except for the definition of the minimum computing resource requirements for executing a specific container. As a consequence, on each round of the experiment, Kubernetes may distribute microservices differently, which may lead to a different load distribution among the hosts in use. For instance, consider the case of a new container that has the minimum requirement of 30% of available CPU and is allocated on a host whose CPU usage is already at 60%. The container would probably have less CPU time than if it had been allocated on a host with less competition for resources or, at least, manifest higher latencies. Another important aspect regarding Kubernetes is the variation in the time spent for scheduling new containers, especially in the auto-scaling task. In periods of increasing workload, the delay in the allocation of new containers may directly impact the number of failed requests and the response time.

Finally, since we advocate for the use of more appropriate scenarios to test smart city platforms, it is worth mentioning the aspects related to the realism of the smart city simulations performed as part of the experiments. The conformance of the simulations with real-world future smart cities scenarios depends on good models. In this sense, the refinement of the models used to simulate car trips, as well as the behavior of drivers in search for parking spots in a large city might change the workload generated on the platform. Moreover, in addition to Smart Parking, it is essential to evaluate the platform using other smart city scenarios, which may pose different demands and require others functionalities, such as actuation on city resources.

6. Conclusions and Future Work

Appropriate software platforms are critical to the feasibility and widespread adoption of complex smart cyber-physical environments, especially future smart cities, requiring considerable development and research effort to ensure their technical quality. Despite the existence of numerous smart city projects, developing architectures to support city-scale environments and evaluating them is still challenging. Thus, this paper brought a comprehensive discussion on the InterSCity platform microservices architectural design and presented experimental results to demonstrate its benefits on scalability and performance. For this purpose, we introduced a novel approach that uses a smart city simulator to generate realistic workloads, similar to what one would expect in a metropolis with over 10 million inhabitants such as São Paulo. Such workloads are essential to enable the execution of more appropriate experiments and tests.

With respect to the InterSCity platform, the experiment showed that its architecture is capable of scaling up and down horizontally to handle a varying workload. More precisely, it was able to handle more than one million complex requests during approximately 3 hours, considering a Smart Parking scenario during São Paulo's rush hour. Also, the platform response time remained acceptable, mostly 1 second or below, even at the highest demand time interval. We highlight the use of modern tools such as Kubernetes and Docker containers as essential means to achieve these results.

We presented a mechanism to evaluate the scalability and performance of the InterSCity platform via the integration of the platform and the InterSCSimulator. To achieve a more representative workload for assessing the platform, we extended the InterSCSimulator models with real data gathered from a large metropolis. The simulator managed both individual behavior and interactions among IoT devices and the platform users considering a Smart Parking scenario. This approach contributed towards the characterization of more appropriate workloads for smart cities.

As future work, we want to integrate other smart city scenarios, enabling cross-domain experiments. We also intend to devote efforts to decouple the presented integration mechanism to allow experiments and tests of smart city platforms other than InterSCity with the same simulation-based approach.

There are still several open research challenges regarding smart cyber-phisical platforms applied to smart urban spaces, including: (I) meeting other critical non-functional requirements, such as security and privacy; (II) extending the core functionalities to better support application development; and (III) deploying a production instance of the platform on a real city. Also, we intend to perform further experiments to continue exploring the scalability and performance properties of the platform, mostly by considering other smart cities scenarios and features. Finally, based on our open source and open science approach, we encourage the community to leverage the contributions described in this paper and to contribute to the evolution of the field.

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