Migrating from Microservices to Serverless: An IoT Platform Case Study

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ABSTRACT
Microservice architecture is the common choice for developing cloud applications these days since each individual microservice can be independently modified, replaced, and scaled. As a result, application development and operating cloud infrastructure were bundled together into what is now commonly called DevOps. However, with the increasing popularity of the serverless computing paradigm and its several advantages such as no infrastructure management, a pay-per-use billing policy, and on-demand fine-grained autoscaling, there is a growing interest in utilizing FaaS and serverless CaaS technologies for refactoring microservices-based applications. Towards this, we migrate a complex IoT platform application onto OpenWhisk (OW) and Google Cloud Run (GCR). We comprehensively evaluate the performance of the different deployment strategies, i.e., Google Kubernetes Engine (GKE)-Standard, OW, and GCR for the IoT platform using different load testing scenarios. Results from our experiments show that while GKE standard performs best for most scenarios, GCR is always cheaper wrt costs.

CCS CONCEPTS
• Computer systems organization → Cloud computing.

KEYWORDS
Microservices, Serverless, Function-as-a-Service, FaaS, Container-as-a-Service, CaaS, Performance Analysis

ACM Reference Format:
Mohak Chadha, Victor Pacyna, Anshul Jindal, Jianfeng Gu, Michael Gerndt. 2022. Migrating from Microservices to Serverless: An IoT Platform Case Study. In Eighth International Workshop on Serverless Computing (WoSC ’22), November 7, 2022, Quebec, QC, Canada. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3565382.3565881

1 INTRODUCTION
Cloud computing is the corner-stone of modern day corporate and consumer IT. For companies it provides a multitude of advantages such as outsourcing of costly infrastructure, scalability, elasticity, and fault tolerance. To this end, the architectures of cloud native applications have adjusted to the ever increasing demand of migration to the cloud. Most prominent among them is the microservices architecture that displaced the prevalent monolithic architecture [6]. This architecture enables the development of applications as a suite of small independent services communicating with each other via well-defined interfaces. A microservices-based architecture provides several advantages such as better modularization, enhanced isolation, and easier maintainability [20]. Moreover, each service can be scaled up or down on-demand, or be deployed in multiple availability zones to eliminate single point of failures. However, this has led to an increase in complexity of deployment and provisioning of services, resulting in developers having to develop their application as well as take care of its operation, i.e., DevOps [14]. To this end, an emerging computing paradigm called serverless computing that abstracts infrastructure management away from the user has gained popularity and widespread adoption in various application domains such as edge computing [15, 24] and machine learning [4, 12].

Function-as-a-Service (FaaS) and serverless Container-as-a-Service (CaaS) are key enablers of serverless computing that allow developers to focus on the application logic, while responsibilities such as infrastructure management, resource provisioning, and scaling are handled by the cloud service providers. In FaaS or serverless CaaS, the developer implements fine-grained functions that are executed in response to external triggers such as HTTP requests and deploys them into a FaaS platform such as Apache OpenWhisk (OW) [25] or a serverless CaaS platform such as Google Cloud Run (GCR) [22]. On invocation, the platform creates an execution environment, i.e., function instance which provides a secure and isolated language-specific runtime environment for the function. Serverless computing offers several advantages such as scale-to-zero for idle functions, a pay-per-use billing policy, and rapid fine-grained automatic scaling on a burst of function invocation requests. However, serverless functions are stateless and any application state needs to be maintained through external transactions with a database or a data store.

Both architectures, i.e., either microservices or serverless have their advantages and disadvantages and the decision to adopt one over the other depends on several factors. In this paper, we investigate these two competing software architectures for an IoT platform application. Towards this, our key contributions are:

• We migrate a microservices-based IoT platform application developed by us onto OW and GCR.
• We comprehensively evaluate the performance of the IoT platform across different deployment strategies, i.e., Google Kubernetes Engine (GKE) standard, OW, and GCR with different load testing scenarios wrt performance and cost.
We highlight the important lessons learned from our migration. All code artifacts related to this work are available at\(^1\).

## 2 IOT PLATFORM

We designed and developed the IoT platform to enable numerous IoT applications such as room monitoring and occupancy estimation. The platform provides a scalable infrastructure for managing multiple users, devices, and sensors. Furthermore, it provides persistent storage for sensor data that is received via HTTP, WebSocket or MQTT protocols and supports secure communication with end devices through JWT tokens. Finally, it supports visualization of data in various formats to enable smart data analytics.

### 2.1 Data Model

The IoT platform’s data model consists of four main entities, i.e., users, devices, sensors, and consumers. Users are the main components responsible for interacting with the IoT platform. Their attributes include name, credentials of a username and a password, and a role, which is either admin or user. Users can have multiple devices associated with their account and each device can have multiple sensors associated with it. Consumers are responsible for retrieving sensor data from the IoT platform. A user can have multiple consumers, that each allow access to a self-administered set of the user’s sensors. Prior to retrieving data, the user has to grant a consumer access to one or multiple sensors (§2.2). The relationship between the different entities and their attributes is shown in Figure 1.

### 2.2 System Design

The IoT platform consists of several independent microservices that interact with each other to provide the different functionalities described in §2 and §2.1. The different components of the platform are shown in Figure 2.

At the center of the platform is the IoTCore which is implemented as a web application with a React based front-end and a Node.js based backend. It enables users to manage devices, sensors, and authentication/authorization tokens for secure communications with the end devices. All data related to the users, devices, and sensors is stored in the relational database management system MariaDB. The end devices can send data to the platform using three different gateways, i.e., HTTP, WebSocket or MQTT. The main purpose of the gateway is to check the sensor’s authentication token and verify its data schema. Currently our platform supports sending and storing data in various formats such as string, integers, or as floating point values. Moreover, it supports complex data types such as tuples and arrays. Following a successful verification by the gateway, the received sensor data is forwarded to Kafka. Kafka is a scalable streaming platform and incorporates a publish-subscribe pattern. One or multiple producers publish data records to a topic, the core abstraction of Kafka that is used to store and process data record streams. A single topic can then be subscribed by zero, one or multiple consumers (subscribers). Each sensor is matched to a separate Kafka topic in our current implementation. As a result, the received sensor data is logged under its own Kafka topic. Furthermore, for scalability purposes, each Kafka topic has a corresponding

\(^1\)https://github.com/CAPS-Cloud/IoT-Platform-Migration

![Figure 1: Data Model of the IoT platform.](image)

![Figure 2: System Design](image)
4 EXPERIMENTAL RESULTS

In this section, we present results wrt performance and cost for the microservices and serverless versions of the IoT platform. In addition, we highlight the lessons learned from our migration. To limit the total number of experiments, we only focus on six relevant API endpoints (§4.2, §4.3). For all our experiments, we follow best practices while reporting results.

4.1 Experiment Setup

To compare the performance of the original microservice architecture of our IoT platform with our migrated versions (§3), we consider three deployment strategies: (i) Google Kubernetes Engine (GKE) in standard mode [11], (ii) OW on top of GKE, and (iii) GCR.

4.1.1 Deployment Configuration. To guarantee fairness between the microservice and serverless deployment strategies, we deploy all off-the-shelf software components (§2.2) to a separate Kubernetes cluster with a fixed resource configuration of three VMs of type e2-standard-4 [7], i.e., 4vCPUs and 16 GiB of memory. This cluster contains all components except the IoTCore and the HTTP gateway. All services were exposed using internal load balancers that make them accessible only within the project's virtual private cloud (VPC). This also guarantees that access times were comparable between all three deployments strategies.

Following this, for the first deployment strategy, we deploy the services under investigation on a GKE cluster with a node pool of two VMs of type e2-standard-8 [7] and 100 GiB of persistent disk memory. We set the maximum number of nodes for the GKE cluster to five and enable on-demand cluster-autoscaling [8]. We configure the IoTCore and the HTTP gateway deployments to request 0.5vCPU and use a maximum of one vCPU per pod. Furthermore, we enable horizontal pod autoscaling (HPA) for the GKE cluster [17] with a maximum limit of 40 pods for the two different services. For our experiments, we consider two different HPA configurations, i.e., 50% CPU utilization (GKE-50) and 80% CPU utilization (GKE-80). For our OW setup, we use a GKE cluster with a node pool of five VMs of type e2-standard-8. We set the initial number of nodes to five to keep the performance results comparable with our first deployment strategy. The individual OW functions were configured with a maximum memory of 256 MiB (§3). Moreover, we modify the default configurations of the different components of OW to enhance scalability [1]. Towards this, we set the number of controllers and invokers to two, enable request concurrency, increase the user pool memory to 10 GiB, disable logging, and set the heap space for the controller and invoker to 2 GiB and 1 GiB respectively. In addition, we limit the number of action invocations to 25000 per minute and the maximum concurrent invocations to 9999. For the third deployment strategy, we configure the individual GCR functions to use one vCPU with 256 MiB of memory. We set the maximum number of instances for a GCR function to 20 and limit the request concurrency to 100. Moreover, we connect the GCR functions to the shared services with a serverless VPC connector [10], that enables access to the internal load balancers of the off-the-shelf services.

4.1.2 Load Testing Scenarios. For generating load at the different API endpoints (§2.2), we use the open-source performance and regression testing tool k6. It uses a script for running the load tests where the API endpoint along with the request parameters are specified. Tests in k6 are based on virtual users (VUs), which are entities that make HTTP(s) requests and try to perform a given test as often as possible. The number of requests per second (RPS) generated by k6 depends on the number of VUs and the time taken by each request to complete. For our experiments, we consider three different scenarios that mirror different workloads. First, linear, i.e., a 30 minutes (mins) linear increase to a target of 100 VUs. Second, random, i.e.,
60 VUs at 7 mins, 30 VUs at 14 mins, 100 VUs at 21 mins, 40 VUs at 28 mins, and zero VUs after 30 mins. The transitions between targeted values are linear. Third, spike, i.e., a plateau of 10 VUs is reached after one min. Following this, a spike of 100 VUs is created between 14 and 16 mins. After the spike, the plateau of 10 VUs is held for another 13 mins before the VUs are linearly decreased to zero. All scenarios are executed for 30 mins.

For our experiments on the different API endpoints, we create dummy users and data on the IoT platform. For each load test, a random user with the appropriate parameter is selected. All load tests are executed on a VM instance hosted on the LRZ compute cloud [18] with a configuration of 10vCPUs and 45 GiB of RAM. We ensure sufficient time between each test to allow the different deployment strategies to scale back to their initial state.

4.2 Comparing Performance

To compare the performance across the different deployment strategies (§4.1.1) and load testing scenarios (§4.1.2), we consider metrics based on request response times, i.e., average and p(95), and the number of successful requests, i.e., requests with a status code of 200. The performance results for the Sensor–Get API endpoint for the different load testing scenarios are shown in Figures 3a, 3b, and 3c. For the linear workload, we observe that GKE-80 was able to serve 343,343 total requests with an aggregated p(95) response time of 19.63 milliseconds (ms), while GKE-50 served 343,158 requests with a p(95) response time of 19.72ms. On the other hand, GCR served 319,046 requests within 53.74ms and OW served 161,053 requests within 94.15ms. We observe a significant increase in the p(95) response time for OW for greater than 2000 requests per ten seconds. This can be attributed to the overhead for executing sequence actions in OW (§3) for a large number of concurrent requests. Moreover, we observe that all requests were successfully handled in GKE-50, GKE-80, and GCR deployment strategies, while with OW eight requests failed. For the random workload, GKE-50 and GKE-80 served 346,864 and 346,620 requests within 19.54ms and 19.65ms aggregated p(95) response times respectively. GCR served 321,963 requests within 52.86ms, while OW served only 175,065 requests within 86.75ms. Similarly, for the spike workload GKE-50 served a total of 87,132 requests, GKE-80 87,085 requests, GCR 79,628 requests, and OW 68,409 requests. The aggregated p(95) response times for the different strategies were 19.59ms, 19.76ms, 65.11ms and 69.73ms respectively. For both random and spike workloads GKE-50, GKE-80, and GCR were able to serve all requests successfully, while with OW nine and four requests failed. The initial peaks in the p(95) response times for GCR can be attributed to cold starts.

In contrast to the Sensors–Get API endpoint, we observe that with the HTTP-Gateway, serverless deployments, i.e., GCR and OW perform better than GKE-50 and GKE-80 as shown in Figures 3d, 3e, and 3f. For the linear workload, OW served 322,721 requests with an aggregated p(95) response time of 39.33ms, while GCR served 299,420 requests within 108.39ms. GKE-50 and GKE-80 served
295,154 and 283,433 requests within 113.41ms and 123.64ms respectively. For the random workload, OW and GCR served 326,900 and 311,514 requests with aggregated p(95) response times of 37.63ms and 88.38ms respectively. On the other hand, GKE-50 and GKE-80 served 297,088 and 283.071 requests within 109.61ms and 130.61ms respectively. Similarly for the spike workload OW served 81,971 requests within 33.61ms, GCR served 81,029 requests within 30.98ms, GKE-50 served 75,969 requests within 148.34ms, and GKE-80 served 76,256 requests within 152.55ms. For all workloads GKE-50, GKE-80, and OW were able to serve all requests successfully, while with GCR nine and four requests failed for the linear and random workloads. The low p(95) response times observed for OW across the different workloads as compared to the different deployment strategies can be attributed to the high initial resource provisioning for our OW setup, i.e., five VMs (§4.1.1). Moreover, while GCR limits the amount of CPU resources allocated to a function, with OW no such limit is enforced leading to better performance. Furthermore, implementation of the gateway function in OW does not require action sequencing.

Table 1 summarizes the performance results for the different API endpoints across the different deployment strategies and workloads. From our experiments, we observe that for the API endpoints Sensors-Get, Users-Get, and Devices-Get, the GKE standard deployment strategies outperform the serverless deployments. For the HTTP gateway OW performs best, while for the Devices-Add endpoint GCR delivers best performance. Although OW has lower response times for certain workloads than GCR for the Devices-Add endpoint, the number of requests served are significantly lower. Moreover, for the Consumer–Consumer–Get endpoint OW performs best for the linear and random workloads, while GKE-50 has the lowest average response time and maximum number of served requests for the spike workload. This endpoint is responsible for obtaining data from ES (§2.2) and also does not require action sequencing. Across the different load testing scenarios, we observed that GKE setups scaled well to handle the incoming requests. This behaviour was closely matched by GCR which delivered robust performance across the different scenarios and endpoints. However, with OW, we observed significantly higher response times at the peak of the different workload patterns leading to request failures (e.g. Figure 3a).

GKE-50 performs slightly better as compared to the GKE-80 deployment strategy. This can be attributed to the HPA configuration in GKE-50 which initiates execution of new pods earlier as compared GKE-80.

### 4.3 Comparing Costs

Table 2 shows the comparison between cost per 1000 requests for the different deployment strategies across the different workloads. For estimating the costs for GKE and OW, we use the computational model used by Google based on the VM type, the amount of persistent storage, the experiment duration, and the cluster management fee [16]. On the other hand for GCR, we use the number of invocations, the allocated memory, and the execution duration for estimating costs [23]. Across all endpoints, we observe that GCR leads to the lowest cost per 1000 requests across all load testing scenarios. This can be attributed to two reasons. First, GCR serves a high amount of requests per second, while at the same time it lacks expensive fixed costs. Second, the reservation-based fees of the GKE and OW setups are charged independently of the workload that actually occurs. For instance, for the User–Get endpoint with the linear workload, the GKE-50 cluster would need to serve 2.24x number of requests (405,744) with the same execution duration to match the costs of GCR. However, invocation costs with GCR will not be cheaper if the request response times become significantly higher than the GKE and OW deployments. For these scenarios, the fixed cost structure benefits the other two deployment strategies.

### 4.4 Lessons Learned

From our migration and performance analysis, we highlight three lessons learned. First, FaaS and serverless CaaS technologies suffer from significantly high initial response times on a burst of function invocation requests due to function cold starts as shown in Figure 3. Although, mitigating cold starts is an active area of research in serverless computing [3], with solutions such as pre-warming function instances before incoming requests on commercial cloud providers [2], it can lead to a significant number of application SLO violations if not accounted for by the developers. Second, the
microservices based deployment strategies outperform the serverless deployment strategies for simple API endpoints responsible for fetching the required data from the database. For instance, for the Users-get endpoint GKE-50 was 1.1x faster than GCR and served 2682 more requests. To this end, for better performance, the developers should consider using a microservices-based architecture for similar API calls that are invoked frequently and have a static response size. Third, the process of migrating a microservices-based application is mostly ad-hoc, time consuming, and costly. As a result, developers should consider the percentage of existing code that can be reused as an important criterion before initiating the migration process (§3). Moreover, language of the application and the choice of the serverless platform is also important. For instance, while GCR functions in any programming language, Google Cloud Functions (GCF) supports limited function runtimes with no support for languages such as C++.

5 RELATED WORK
Due to the rising popularity of serverless computing and its various advantages, there are increasing debates about the architecture design of modern cloud native applications when it comes to choosing microservices, serverless, or a hybrid approach. Towards this, some prior work [5, 13, 14] has focused on migrating and comparing the performance of microservices and serverless deployment strategies. Fan et al. [5] migrate a simple employee time sheet management application onto AWS Lambda and compare its performance with Amazon's Elastic Container Service. Jindal et al. [14] build on this and present comparison results for a simple cinema application across GKE, OW, and Google Cloud functions. In contrast to our work, the applications chosen for migration are relatively simple with only one off-the-shelf software component. Jin et al. [13] migrate four stateful microservices applications onto OW. The authors highlight lessons learnt from the migration and describe methods to minimize code changes while maintaining a similar performance. However, in contrast to our work they only present preliminary performance results. Moreover, none of the previous works present a cost comparison between the different deployment strategies.

6 CONCLUSION & FUTURE WORK
In this paper, we migrated a complex IoT platform application based on the microservices architecture onto OW and GCR. We comprehensively evaluated the performance of the application using different deployment strategies, i.e., GKE, OW, and GCR across different load testing workloads. From our experiments, we observed that GKE performed best for most scenarios followed by GCR and OW. However, using GCR led to least costs across all scenarios. In the future, we plan to migrate a suite of different complex microservices applications and provide detailed guidelines and performance measurements that will enable architects to make reasoned decisions about the architecture to use for their applications.

7 ACKNOWLEDGEMENT
The research leading to these results was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation)-Projektnummer 146371743-TRR 89: Invasive Computing. Google Cloud credits in this work were provided by the Google Cloud Research Credits program with the award number 64c92de5-fb62-4386-8c5b-ff3f480390bb.

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