Microservices-based IoT Applications Scheduling in Edge and Fog Computing: A Taxonomy and Future Directions

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Edge and Fog computing paradigms utilise distributed, heterogeneous and resource-constrained devices at the edge of the network for efficient deployment of latency-critical and bandwidth-hungry IoT application services. Moreover, MicroService Architecture (MSA) is increasingly adopted to keep up with the rapid development and deployment needs of the fast-evolving IoT applications. Due to the fine-grained modularity of the microservices along with their independently deployable and scalable nature, MSA exhibits great potential in harnessing both Fog and Cloud resources to meet diverse QoS requirements of the IoT application services, thus giving rise to novel paradigms like Osmotic computing. However, efficient and scalable scheduling algorithms are required to utilise the said characteristics of the MSA while overcoming novel challenges introduced by the architecture. To this end, we present a comprehensive taxonomy of recent literature on microservices-based IoT applications scheduling in Edge and Fog computing environments. Furthermore, we organise multiple taxonomies to capture the main aspects of the scheduling problem, analyse and classify related works, identify research gaps within each category, and discuss future research directions.

CCS Concepts: • General and reference → General literature; • Computer systems organization → Distributed architectures.

Additional Key Words and Phrases: Edge/Fog computing, Microservice Architecture, Internet of Things, Osmotic computing, Application Scheduling

1 INTRODUCTION

Internet of Things (IoT) paradigm is gaining immense popularity due to its significance in technical, social and economic aspects [8]. IoT transforms everyday objects and infrastructure into intelligent entities that can interact with each other without human intervention, which has resulted in its expansion to a wide range of services, including healthcare, transportation, industrialisation, agriculture, etc. IoT generates enormous quantities of dynamic data composed of various data types to be processed, analysed and stored. Cloud computing was initially identified as a viable solution for hosting such IoT services, giving rise to cloud-centric IoT [33]. Due to the exponential increase in the connected devices, raw data transmission towards centralised cloud data centres increases the network congestion and latency, thus reducing the feasibility of cloud-centric IoT analytics. As a solution, novel computing paradigms like Edge and Fog computing were introduced, bringing data processing and storage closer to the end-user, hence supporting latency-critical and bandwidth-consuming IoT services. Meanwhile, MicroService Architecture (MSA) emerged as a cloud-native application architecture style, enabling the development and deployment of highly reliable and scalable software systems that can undergo frequent updates and deployments [72, 84]. This paved the way for the convergence of Edge/Fog computing, IoT and microservices, thus resulting in the introduction of novel paradigms such as Osmotic Computing that focus on dynamic scheduling and deployment of microservices across federated Edge-Cloud environments.

Microservices-based IoT applications are gaining tremendous momentum due to their potential to improve the performance of IoT services deployed within distributed computing environments [57].

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However, within distributed and heterogeneous Edge/Fog environments, application scheduling remains one of the most critical and challenging areas [32]. To utilise the full potential of the Fog computing paradigm, the scheduling algorithms benefit from awareness of the application model characteristics so that they can properly utilise the strengths of the application architecture while overcoming the challenges introduced. To this end, we aim to understand the features and unique challenges of microservices-based IoT applications scheduling and analyse recent literature to summarise the current status of the research and propose possible future research directions. The following section discusses related surveys and highlights our contribution.

1.1 Related Surveys and Our Contributions

We analyse related surveys belonging to three main areas of research; surveys on Edge/Fog computing, surveys on Osmotic computing, and surveys on MSA, and conduct a qualitative comparison of the aspects covered by each of these surveys to define our contribution.

Existing surveys on Edge and Fog computing cover a wide range of areas such as resource management and application scheduling along with application architecture, infrastructure, optimisation metrics and algorithms. Hong et al. [41] study and classify the architecture of Edge/Fog platforms and algorithms designed for resource management. However, they do not focus on classifying application architectures and identifying their effect on managing resources. Jamil et al. [44] propose a taxonomy of optimisation metrics and algorithms used in resource allocation and task scheduling in Fog computing. However, they do not characterise existing works based on the application models or architectures and fail to analyse optimisation characteristics with respect to them. Brogi et al. [10], Varshney et al. [79], Mahmud et al. [56], Salaht et al. [73] and Goudarzi et al. [32] focus specifically on application placement/scheduling and management related aspects within Edge/Fog environments. They perform a high-level categorisation of existing works based on the application models considering dependencies among application tasks: Brogi et al. [10] analyse the effect of task dependencies as a constraint in scheduling problem formulation, whereas Varshney et al. [79], Mahmud et al. [56], Gaudarzi et al. [32] create taxonomies for application models considering monolithic architecture, distributed architectures such as modular and microservices. However, none of these works specifically focus on MSA-related characteristics and challenges. Brogi et al. [10], and Goudarzi et al. [32] identify Osmotic computing and microservice placement in Edge/Fog computing as future directions that need further attention and deeper analysis.

MSA-related surveys mainly focus on development and operational phase concerns [46] and challenges related to adaptation of MSA for application development [67]. Joseph et al. [46] provide a broad taxonomy using research work that captures development aspects related to MSA such as modelling, architectural patterns, maintenance, testing and quality assurance, along with operational aspects including placement, migration, service discovery and load balancing. Although [46] discusses Osmotic computing and Edge/Fog computing as distributed computing paradigms employing MSA, a categorisation of existing works within these paradigms is not performed. Razzaq et al. [67] studies existing research to identify MSA-related software architectural styles, patterns, models, and reference architectures adapted by IoT systems. However, the scheduling aspects of such applications are out of scope for their study. Thus, microservices-related surveys mainly focus on design, development and maintenance aspects related to MSA in general without focusing on challenges related to their scheduling and deployment within distributed computing paradigms such as Edge and Fog computing.

Osmotic computing-related surveys focus on detailing the concepts and features of the Osmotic computing paradigm along with challenges and future directions [47, 81]. Androcc et al. [5] and Neha et al. [58] conduct a systematic review to capture the current status of Osmotic computing by analysing applications that follow the Osmotic computing principles, Osmotic computing-related
topics addressed and their level of maturity. While these works highlight the concepts and potential of Osmotic computing, they do not analyse existing works based on scheduling related aspects including features and challenges related to modelling, placement, service composition, evaluation with respect to MSA.

Thus, existing surveys fail to provide a thorough taxonomy on microservices-based IoT applications scheduling in Edge and Fog computing environments bringing Edge/Fog computing, Osmotic computing and MSA together. With the increasing popularity of MSA for application development and its potential benefits within distributed Fog environments, it is paramount to study aspects related to modelling of application architecture for IoT applications, formulation of the placement problem within federated Fog-Cloud environments, microservices composition within the said environments and validation of the scheduling approaches while properly highlighting relationships among these aspects. This would provide future research with an opportunity to comprehensively address the challenges of the microservices-based IoT applications scheduling in Edge and Fog computing environments while reaping the benefits of the architecture. The main contributions of our work are as follows:

• We present a comprehensive background on MSA, IoT applications, Edge/Fog computing and their integration to identify unique characteristics and challenges that differentiate "Microservices-based Application Scheduling in Edge/Fog environments" from other application models.
• We review recent research on microservices-based application scheduling in Fog environments and analyse them under application modelling using MSA, application placement, microservice composition, and performance evaluation and propose taxonomies for each of the above perspectives. Our taxonomies capture MSA-related features and challenges we identified during the background study.
• We identify research gaps in microservices-based application scheduling in Fog environments with reference to each proposed taxonomy.
• We identify and propose future research directions that researchers can use to improve the Fog application scheduling further.

1.2 Paper Organization

The rest of the paper is organised as follows. Section 2 presents a comprehensive background study detailing the unique characteristics and challenges of microservices-based IoT applications scheduling in Edge and Fog environments to derive the high-level taxonomy. Proceeding sections introduce and discuss detailed taxonomies under each aspect presented in the high-level taxonomy: Section 3 introduces the taxonomy on modelling microservices architecture for IoT applications and analysing existing works, Section 4 presents the taxonomy for application placement related to MSA and discusses the current works accordingly, Section 5 introduces the taxonomy for microservice composition, and Section 6 presents the taxonomy for performance evaluation. Based on the gaps identified in each section, Section 7 provides future research directions. Finally, Section 8 summarises this survey.

2 BACKGROUND

In this section, we present an extensive background on MSA and IoT applications along with Edge/Fog computing paradigms to identify the characteristics and requirements that make these three areas benefit from their integration. Moreover, we differentiate microservices-based application scheduling from the traditional DAG-based workflow scheduling to derive the problem
definition of "microservices-based IoT applications scheduling within Edge/Fog computing environments". Then we derive the scope, challenges and motivation for this work and derive the high-level taxonomy.

2.1 Comparison between Microservice and Monolithic Architecture for Applications

An enterprise application usually consists of a server-side application that implements its domain-specific business logic, client-side user interfaces supporting different clients such as desktop browsers and/or mobile browsers, and a database to persist the data. Moreover, the application may connect with other third-party applications (through web services or message brokers) and expose APIs for third parties to consume. The design and development of such applications follow different architecture patterns depending on the complexity of the business domain. Fig. 1 presents a general representation of an application developed using Monolithic and Microservice architecture.

In monolithic architecture, the server-side application is a single logical executable that handles HTTP requests from the client side, performs logical operations, communicates with the database and populates HTML views to be displayed on the client-side. The server-side application can be designed and developed either as a single process or a modular monolith where modules invoke each other through method/function calls at the programming language level [59]. Using monolithic architecture is advantageous during the early stages of an application or if the application is quite simple with only a few core functionalities. It provides a better approach to defining requirements and building, testing and deploying a working product quickly and efficiently.

But as the applications grow, they tend to outgrow the monolithic architecture [69]. As all modules of the application are combined into a single unit, the coupling among them increases, and the application becomes too complex to understand, which makes it hard to make changes and improvements to the application. As any modification to the application affects the entire application, end-to-end testing becomes complex, resulting in high deployment delays. Moreover, monolithic architecture lacks flexibility as it requires a single development stack which hinders the adaptation of new technologies or heterogeneous technologies depending on the functionality of each module. Monoliths also lack reliability because a fault in one place results in the failure of the entire application. Moreover, different modules inside a monolith may have different resource requirements, which makes the application challenging to scale. Thus, monolithic architecture lacks support for agile development and limits the rapid growth of applications.

MSA aids in overcoming limitations of the monolithic architecture within rapidly growing software ecosystems. Martin Fowler defines MSA as "an approach to developing a single application as a suite of small services, each running as independent processes and communicating
Table 1. Comparison between Monolithic and Microservice architecture

| Monolithic Architecture                                      | Microservice Architecture                                                                 |
|---------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| Server-side application is a single logical executable        | Server-side consists of independently deployable, multiple microservices                     |
| Modules communicate through language level method invocations | Inter-process communication through REST APIs or lightweight messaging                     |
| Low flexibility                                               | Flexible - different programming languages and technologies can be used based on microservice requirements |
| Less support for scaling                                      | Highly scalable (independently deployable and scalable microservices)                       |
| Longer time from development to deployment                    | Supports rapid and agile development and deployment                                          |
| Unreliable due to single point of failure                     | Higher resilience to failure due to failure isolation and redundancy support                 |

with lightweight mechanisms, often an HTTP resource API [28]. Fig. 1b depicts a microservice application developed using API design pattern where all services are exposed to clients through an API gateway that directs client requests toward microservices. MSA is an evolution of Service Oriented Architecture (SOA), where microservices are fine-grained compared to services in SOA. It uses dumb pipes for the communication among them, unlike in the case of SOA, where services communicate using smart pipes containing business and message processing logic [28].

Thus, microservices are independently deployable and scalable units that are designed around business logic adhering to the single responsibility principle and contain their own database for persisting data [46]. Moreover, microservices are loosely connected components that can be easily integrated to create complex applications. From the software design and development perspective, this allows small teams to work on each service with minimum dependencies among the teams, thus increasing development velocity by supporting independent development and testing of microservices. Due to fine-grained modularity, each microservice can be deployed on hardware that best matches its resource requirements (i.e., CPU-intensive, memory-intensive, I/O-intensive, etc.) and can be deployed and scaled independently according to the load of each service. Unlike monolithic architecture, MSA has better fault isolation as a fault in a certain service only affects that service. Furthermore, independent scalability of microservices improves redundant deployment to achieve fault tolerance. As services are loosely coupled, new technologies that best suit the microservice can be easily adapted. This mitigates the need to stick to a single technology stack and provides the flexibility to evolve with technologies. Table 1 summarises and compares the characteristics of the two architectures.

MSA enables continuous development and deployment of rapidly evolving complex applications, but introduces novel challenges in design, development, deployment and orchestration, described in detail below:

- **Microservice design**: From a software design perspective, defining microservice boundaries can be identified as one of the main challenges of MSA. The level of granularity directly affects the performance of the applications. Dividing the application logic into too many microservices increases the number of remote calls made among microservices, thus increasing the latency of the operations. In contrast, less granularity creates macro modules with lower cohesion and higher coupling. Hence, an optimum level of granularity needs to be achieved by using the domain-driven approach for separation of business concerns so that extensibility and adaptability are supported as the application requirements evolve [38, 76]. Moreover, it results in designing microservices as independently deployable and scalable components.

- **Application scheduling**: Granularity creates complicated dependencies among microservices and complex composition patterns, which results in composite services. Openness in microservice design allows reusability of microservices between multiple composite services.
with heterogeneous QoS requirements [60], conditional branching, which results in alternative data flows within composite services [61], and use of third party microservices [2]. These characteristics need to be considered during the application scheduling to improve performance (i.e., QoS, resilience, scalability, security, etc.) while satisfying competing performance requirements of the services. Moreover, characteristics of the microservices, such as their independently deployable and scalable nature, have the potential to improve the performance if appropriately utilised by the scheduling algorithms. Thus, novel scheduling algorithms are required to handle the above complexities efficiently while using the benefits provided by the architecture [62, 81].

- **Application management**: The increase in the number of moving components per application makes management more complex. At the same time, due to the elasticity of microservices, service instances can be dynamically scaled up and down with the changing workload or system failures. This requires support for automated deployment using orchestration platforms. To overcome the complexities introduced by the number of microservices and their dependencies, proper monitoring is crucial to provide insights (i.e., the health of the microservices/APIs, isolation of failures, demand variations etc.) to make management decisions.

- **Microservices communication**: With the development of applications as a collection of inter-connected modules, proper communication among microservices must be established using different communication patterns. Suitable communication patterns are selected by analysing the nature of the interactions among microservices [76]. Such patterns include Synchronous communication (i.e., request-response methods like HTTP-REST), Publish-subscribe and Asynchronous communication using message queues (RabbitMQ, Apache Kafka, and Apache ActiveMQ [17]).

- **Service discovery**: Within a microservices application, microservices communicate with each other to perform tasks. This requires client microservices to be aware of other available microservices that can be invoked to perform specific tasks. With the distributed nature of the microservices and the dynamism of microservices placement (auto-scaling, migration, service failures), service discovery has become one of the main challenges in using MSA. Dynamic service discovery involves checking the status of existing microservices, detecting and registering new microservices as they become available in real-time, with minimum overhead.

- **Load balancing**: MSA supports horizontal scalability or a combination of horizontal and vertical scalability of the microservices. As a result, to ensure performance, load balancing is required to direct requests among horizontally scaled microservices. Efficient load balancing algorithms have to be designed to minimize the networking and computation overhead and ensure microservice availability through load analysis, link analysis and forecasting to adapt to dynamic scenarios [60, 82]. Thus, load balancing is tightly coupled to service discovery and monitoring of the microservices-based systems.

- **Fault tolerance**: Even though MSA supports higher fault isolation compared to monolith architecture, it still requires fault tolerance methods to handle failures. Having a large number of components means there are more points of failure. Moreover, communication failures among components become a potential cause as well. Fault tolerance mechanisms should be able to tackle such failures and avoid cascading failures as well. To achieve this, MSA aims to handle failures at both the development and deployment phases. Microservice applications integrate methods such as circuit breakers, retries, timeouts and deadlines to the microservice design to minimize the effect of failures, where as redundant placement, checkpoint and
restore, migration, etc., are used at deployment to improve the resilience and availability of
the application under failures.

2.2 Internet of Things (IoT) Applications and their Characteristics

Internet of Things (IoT) refers to connected objects that collect and share data with other devices over the internet [45, 51]. It transforms conventional physical objects into smart objects. With the software/hardware improvements of the connected devices along with bandwidth and latency improvements in telecommunication technologies such as 5G/6G and other wireless technologies like Wifi6, the number and variety of connected devices are increasing rapidly [14, 15, 37]. Cisco predicts that 500 billion devices will be connected to the Internet by 2030, which would result in the generation of a massive amount of data that can be used to generate insights in a variety of IoT application domains such as smart healthcare, smart city, smart home, Industrial IoT (IIoT), smart agriculture and smart transportation [43, 95].

Due to rapid growth in IoT data generation, applications have to undergo fast design, development and deployment cycles to both improve existing IoT services (i.e., moving to new tech stacks, AI augmentation and updating ML models, integration of novel data types, improvements in data processing method/algorithms, etc.) and introduce new services to the end-users. The ultimate vision of IoT is to move away from application development as "point solutions" and evolve towards an "IoT ecosystem" where cross-platform integration of heterogeneous devices, data, communication technologies, and application services occur [19, 86]. To this end, IoT applications should be flexible to change, support service re-usability, and expose open interfaces to enable third-party integration of application services (i.e., big data analytic services, payment gateways, authentication and authorisation services, data visualisation services etc.) [67].

Due to improvements in Radio Access Network (RAN) technologies and consequent growth in mobile IoT devices (i.e., wearable gadgets, smartphones, vehicles, etc.), mobile-IoT workloads keep increasing rapidly. To accommodate such fluctuating workloads, IoT application design has to mainly focus on the scalability of the application deployment [80]. Moreover, IoT applications consist of a large number of diverse services in terms of suitability of development technology stacks (i.e., I/O intensive services using NodeJs, machine learning using Python, etc.) and QoS expectations (i.e., bandwidth-hungry services like Multi-media Internet of Things (M-IoT), latency-sensitive applications like healthcare, tactile internet, etc.).

Due to these characteristics and requirements of IoT applications, their development is moving away from Monolithic architecture towards distributed application architectures, whereas deployment is moving away from cloud-centric deployment towards distributed computing paradigms like Edge/Fog computing.

2.3 Edge/Fog Computing, Osmotic Computing and Related Paradigms

Fog computing is a novel networking computing paradigm which extends cloud-like services towards the edge of the network [54]. Fog computing paradigm was first introduced by Cisco in 2012 as a platform to support the unique requirements of IoT, such as low latency, location awareness, mobility support, and geo-distribution [9]. To this end, Fog computing introduces an intermediate layer between IoT devices and cloud data centres [54], which is organised in a multi-tier architecture. It exploits computation, storage and networking resources that resided within the path connecting end devices to the cloud data centres [68]. Thus, Fog resources consist of a diverse set of resources (i.e., smart routers and switches, personal computers, edge servers, Raspberry Pi devices, micro-datacentres, cloudlets, etc.) that are distributed and resource-constrained compared to cloud data centre resources. To overcome the resource limitations, the Fog computing paradigm maintains federated Fog computing architectures, where distributed Fog resources collaborate to satisfy client
Moreover, the Fog computing layer maintains a seamless connection with the Cloud so that computation-intensive tasks can be carried out using Cloud resources.

Edge computing and Mobile Edge Computing (MEC) computing also follow a similar concept to Fog computing, where their main objective is to move computation toward the users. In literature, Edge and Fog computing are often used interchangeably. However, works such as [54, 56, 90] define Edge computing as a paradigm limited to the edge network, which consists of devices such as mobile phones, access points etc. at the immediate first hop from IoT devices. In contrast Fog extends this concept further to include the core network along with the integration of cloud data centres when necessary to provide IaaS, PaaS and SaaS services in the proximity of the data sources. Mobile Edge Computing (MEC) focuses on mobile end-users and moves processing and storage capabilities to the edge of the mobile network by improving the capabilities of the base stations that reside within the Radio Access Network (RAN) of the 5G/6G networks [21]. However, all these paradigms share common characteristics, such as heterogeneity of resources, and limited and distributed resource availability, along with main goals such as lower latency, lower network congestion and mobility support.

Osmotic computing is a relatively new paradigm, first introduced in [81], especially focusing on microservices-based application scheduling within Fog and Cloud environments. Osmotic computing aims to achieve a balanced deployment of microservices by utilizing both Edge/Fog and Cloud resources to satisfy the requirements defined at different levels of the microservices-based IoT application (i.e., service-level QoS requirements, microservice-level resource requirements etc.). Osmotic computing identifies MSA as a suitable approach for developing IoT applications for deployment within integrated Edge/Fog and Cloud environments due to their fine granularity, fast deployment and elasticity. Thus, this paradigm tries to address microservices specific challenges such as microservice orchestration, networking, monitoring, elasticity control, and dynamic Edge-Cloud placement [5, 81].

In this survey, we consider existing research works that focus on microservices-based application deployment related to all the above paradigms.

### 2.4 Microservices-based IoT Applications and Edge/Fog Computing

In sections 2.1, 2.2 and 2.3, we discussed MSA, IoT applications and Edge/Fog paradigms in detail, highlighting their key characteristics and requirements. This section aims to analyse how those
characteristics fit perfectly together, giving rise to microservices-based IoT applications for Edge/Fog environments. Fig. 3 lists these characteristics and groups them to show their relationships.

Characteristics of IoT Applications can be categorised under three main groups; Design and Development, Deployment and Management, and Service Characteristics. Rapid design, development needs and interoperability, and reusability of services caused by the complexity of the IoT ecosystem can be satisfied by adopting a software architecture that supports higher flexibility to change, reduced time to market, and collaboration among multiple development teams. MSA can enable these requirements with the fine-grained modular design and loosely coupled nature which perfectly conforms with agile design and development principles. From a deployment and maintenance perspective, IoT applications must maintain rapid deployment cycles with minimum service disruptions and support the dynamic workload while maintaining service availability and resilience. These requirements can be successfully satisfied through the use of MSA [2, 12, 75]. MSA decomposes large and complicated applications into independently deployable and scalable modules that can be conveniently packaged using container technologies such as Docker and rktlet. Lightweight containers with considerably lower startup times enable quick deployment and migration, which result in higher service availability and reliability under dynamic conditions. Decomposition of the application into small independent units allows only the updated or newly developed microservices to be re-deployed, and just the performance affected microservices to be scaled within each deployment cycle. Moreover, this enables a proper balance between horizontal and vertical scalability where microservices that are harder to scale horizontally (i.e., services that use relational databases etc.) can be vertically scaled while the rest can be horizontally scaled [52]. Thus, MSA meets the scalability, maintainability, extensible, and interoperability requirements of the large and complex IoT software systems [67]. As a result, MSA is increasingly adopted for IoT application development in many areas such as smart cities, smart healthcare, IIoT [11, 16, 77].

Radio access network (RAN) technologies are improving rapidly to support higher bandwidth (i.e., 5g, 6g, etc.) and lower latency values. However, core network capabilities are still limited, thus making cloud-centric IoT infeasible to support IoT workloads. Sending a large amount of data towards the centralised Cloud through the core network would result in higher network congestion and larger latency values, lowering the QoS satisfaction of the latency-critical IoT services. Edge/Fog computing emerges as the solution to these challenges enabling the data analytics closer to the end devices that generates the data, thus reducing the amount of data sent towards the Cloud. The federation of Fog environments with cloud data centres allows IoT applications to utilise the best of both paradigms. This enables latency-critical, bandwidth-hungry services to be placed closer to the end-user while the rest can use Cloud resources, thus meeting heterogeneous QoS requirements of the IoT application services. Moreover, the distributed Fog architecture creates location awareness, thus providing ubiquitous access to IoT services. With Edge/Fog resources becoming richer in resource availability and telecommunication providers supporting the Edge/Fog implementation, Fog computing is rising in popularity as a viable solution for hosting IoT applications.

In contrast to Cloud data centres, Edge/Fog environments consist of distributed, heterogeneous, resource-constrained devices. Thus, deploying a monolithic application onto such devices is less feasible due to their resource demand. The scalability of such applications is also limited by the said characteristic of Edge/Fog devices. Fine-grained microservices match such environments better due to their modular, loosely coupled nature, which makes the resource requirements of each microservice small enough to be satisfied by the distributed Edge/Fog devices. Independent deployability and scalability of such microservices enable them to adjust to dynamic conditions (i.e., device failures, mobility, workload changes, etc.) while utilising limited Fog resources. Moreover, these characteristics support dynamic and fast migration of microservices across Fog devices and between Fog and Cloud, thus improving deployment flexibility. Thus, MSA demonstrates the
potential to utilise Edge/Fog environments and achieve a balance between federated Fog-Cloud usage to improve application performance and meet QoS requirements.

2.5 Microservices-based IoT Applications Scheduling vs DAG Workflow Scheduling

In this section, we compare the "Microservices-based IoT application placement" problem with the Directed Acyclic Graph (DAG) workflow scheduling problem [70], which is extensively addressed in the existing literature, considering both Fog and Cloud environments. We identify similarities and differences between the two to highlight the unique aspects related to the Microservices-based IoT application placement problem.

DAG-based workflows are used to model business processes as collections of distributed tasks where tasks, their dependencies and data flows are represented using DAGs [70]. Each DAG is characterised by a tuple, \( \{V, E\} \) where \( V \) and \( E \) denote vertices and edges, respectively. In DAG-based workflows, vertices represent the tasks or sub-processes of the main process, and directional edges depict the data flow from the source task to the destination task, where the output from the...
prior task is fed as input for the next task. Thus, each DAG would consist of one or more starting tasks with no incoming edges and an ending task which provides the processed output.

As microservice applications consist of interconnected microservices collaborating to perform domain logic, existing works model such applications as DAGs [25, 34], where microservices are represented by the vertices (V) of the DAG, and edges (E) represent the dependencies among microservices with direction from client microservices to invoked service. Thus, the directional edges denote microservice invocations. However, unlike in the case of DAG workflows, dataflows in microservice applications can not always follow a DAG due to the complex data dependencies among microservices, which can create cyclic dataflows. This can be further explained through the concept of composite end-user services in MSA. In IoT applications, "services" can be defined as functionalities accessed by the end-user expecting a certain output, and each application can consist of one or more such services [63]. Fine-granularity of MSA creates composite services with different dataflow patterns such as chained, aggregator and hybrid [66] (Fig. 4a). Such patterns can result in cyclic dataflows where one microservice invokes other microservices, receives responses from them and finally aggregate and/or further process the responses before returning the results of the composite service.

Moreover, each IoT application consists of multiple composite services with heterogeneous QoS requirements. As an example, in a smart healthcare application for patient monitoring, there can be multiple services, such as an emergency notification services that detect abnormalities in measured vitals in real-time (S1 in Fig. 4b) and latency-tolerant services for predictive analysis to give early warnings about possible health issues to prompt preventive actions (S2 in Fig. 4b) [63]. Herein, large-scale IoT application scheduling has to consider competing QoS requirements of its services. These services can share some microservices among them, which further complicates the placements decisions (in Fig. 4b Feature Extraction microservice - m1 is part of both S1 and S2). In contrast to this, workflow scheduling either defines QoS per workflow or an ensemble of workflows.

Each large-scale IoT application has to support a large user base of distributed users that expect ubiquitous access to the application. Thus, application placement includes challenges related to the application’s scalability based on the number of users, their access locations and time. Moreover, the life cycle of the placement is also perpetual. In contrast to this, workflow scheduling is defined from a user perspective, where each user makes the placement request for their particular use and workflow deployment exists until the request from that client is processed, which makes the life cycle ephemeral. Moreover, MSA creates complex interaction patterns such as shared microservices among composite services, candidature microservices resulting in conditional dataflows based on the users, and third-party microservice usage. [93] discusses electronic payment microservices where users can select one out of many payment options (i.e., PayPal, AliPay etc.) and the requests are directed to the microservice relevant to the selected option (Fig. 4c). This results in multiple possible data paths within a single service and different levels of demand for each payment microservice based on the composition of the users accessing the service. Existing works on workflow scheduling rarely consider such interactions.

Even though microservice applications can be modelled as DAGs, the above-highlighted characteristics differentiate microservices-based application scheduling problem from existing research focusing on DAG-based workflow scheduling within Edge/Fog environments. In this work, we aim to conduct a comprehensive survey on scheduling algorithms designed for the microservices-based application scheduling problem and create a taxonomy based on the discussed characteristics and challenges.
Table 2. Comparison between Microservices-based application scheduling vs Directed Acyclic Graph (DAG) workflow scheduling

| Microservices-based IoT applications Scheduling | DAG workflow Scheduling |
|------------------------------------------------|-------------------------|
| Microservice invocation can be represented by a DAG | Invocation and data flow are represented by a DAG |
| Multiple end-user services per app | Each DAG represents a single service |
| Microservices shared among services/applications | No shared tasks among workflows |
| Per-service QoS with multiple services per app | QoS per workflow/ensemble of workflows |
| Life cycle: perpetual | Life cycle: mostly ephemeral |
| Service access shared among a large number of users | Mostly focus on a particular user |
| Complex interactions (shared microservices, candidate microservices, third-party microservices) | Not a main focus |

2.6 Microservices-based IoT Applications Scheduling within Edge and Fog Computing

2.6.1 Problem Definition and Challenges. Microservices-based IoT Applications scheduling within Edge/Fog computing environments falls under Fog Service Placement Problem (FSPP) addressed in works such as [20, 34, 63]. FSPP addresses application deployment and maintenance, where services with agreed Service Level Agreements (SLA) are deployed onto Edge/Fog and Cloud environments for the shared use by the service users. Thus, FSPP considers scalability, request load balancing, ubiquitous access, location awareness and fault-tolerance to meet the required performance of the applications. This survey considers solving the scheduling of IoT applications developed using microservice architecture to process data streams generated by IoT devices.

The main challenges related to the scheduling problem are listed below:

- **Challenges related to accurate modelling of MSA**: The fine-grained nature of the microservices, and their complex interaction patterns, set MSA apart from other application architectures and adds novel challenges to the scheduling problem formulation. Thus to utilize the full potential of MSA and overcome related challenges, accurate modelling of the applications is of paramount importance. This includes the correct depiction of microservice granularity (i.e., microservice heterogeneity and interactions), service composition (i.e., number of microservices per service and their dataflow patterns) and application composition (i.e., number of heterogeneous services per application and use of shared/candidature/3rd party microservices).

- **Challenges related to microservice placement**: Characteristics of the MSA such as fine-grained design, independently deployable and scalable nature of the microservices can be utilised to reach efficient placements that optimise federated Fog-Cloud usage. Being independently deployable units, microservices can be dynamically moved between Fog-Cloud layers to optimise multiple parameters such as QoS parameters (i.e., makespan, throughput, budget, reliability, etc.), network/computation resource usage and infrastructure provider’s revenue. The placement of microservices is further complicated by the heterogeneity of available resources and resource requirements of the microservices. Thus, a proper balance of vertical and horizontal scaling of microservices should be achieved to reach an optimal placement under resource constraints while ensuring fault tolerance and service availability.

- **Challenges related to microservice composition**: Due to dynamism caused by the distributed deployment, migration and elasticity enabled by the MSA, the composition of microservices to create composite services become a critical challenge affecting the application’s performance. Main challenges related to this include service discovery, load balancing, monitoring, networking etc., that comes with scalability, elasticity, migration, redundant deployment and failures of microservices. Orchestration or choreography frameworks are introduced to handle the dynamic changes and maintain interconnections among microservices minimising adverse effects on service performance.
• **Challenges related to performance evaluation**: Due to the lack of commercial Fog service providers providing Fog platforms as IaaS, PaaS or SaaS, the evaluation of the novel scheduling approaches is mainly handled by simulations or small-scale Fog frameworks developed by researchers. Furthermore, with microservices architecture, simulators and frameworks need to be extended further with container orchestration/choreography support, distributed monitoring, dynamic scheduling etc. Moreover, the workloads used for evaluations should adequately capture the characteristics of the MSA and IoT applications to achieve accurate evaluations.

Fig. 5. Taxonomy for Microservices-based IoT Applications Scheduling

2.6.2 **Motivation for research.** Our background study shows that MSA is becoming exceedingly popular for the design and development of large-scale IoT applications, and the features of the architecture (fine granularity, extensibility, cohesiveness, scalability etc.) demonstrate immense potential to improve the performance of the applications through their efficient scheduling within federated Fog-Cloud environments. Utilising these characteristics introduces novel challenges to the scheduling process that differentiates microservices-based application scheduling from traditional monolithic or modular application placement. Thus, it is vital to analyse existing works that focus on microservices scheduling in Fog environments to identify how these specific challenges are addressed and what research gaps remain for future works.

Existing surveys on Fog application scheduling [10, 56, 73, 79] focus on all application models in general, without delving deep into specific characteristics and challenges of microservices. Surveys on Osmotic computing covers the concepts behind novel paradigm, challenges, and future directions [5, 58], but do not analyse the effect of MSA on designing scheduling algorithms. Hence, in this survey, we study the existing works that model and solve Fog application scheduling for microservices-based IoT applications, propose a taxonomy and map the works to highlight important aspects of the scheduling problem and gaps in current research.

Fig. 5 depicts the main taxonomy designed based on the characteristics and challenges we discussed in previous sections. In the following sections, we discuss each aspect, propose separate taxonomies for them, analyse existing literature under each taxonomy and identify areas of improvement.

3 **MICROSERVICE ARCHITECTURE**

To utilise the capabilities of MSA and overcome the challenges of the architecture within Edge/Fog environments, proper modelling of the applications is of vital importance so that the placement algorithms can capture all aspects of the scheduling problem. To this end, Fig. 6 presents the taxonomy for modelling applications based on MSA where we analyse microservices-based application modelling at multiple levels; granularity at microservice level (**Granularity**), composition
of microservices at service level (**Service Composition**) and composition of services at application level (**Application Composition**). Table 3 maps the existing works to the proposed taxonomy based on how each research work models the microservices-based applications.

![Fig. 6. Taxonomy for modelling of Microservice Architecture](image)

### 3.1 Granularity

Granularity is one of the most important and challenging aspects of MSA. The fine-grained nature of the microservices allows application services to be depicted as a collection of small components communicating together to perform a certain end-user requested service. While this allows QoS-improved placement within resource-constrained Edge/Fog devices and dynamic movement between federated Fog-Cloud environments following the Osmotic computing paradigm, it introduces complexities in interaction patterns among the microservices. Thus, when modelling the application placement problem, the level of granularity should be captured accurately to overcome the challenges while utilising the advantages introduced by the granular design.

Hence, we analyse the microservice granularity within IoT applications as follows:

1. **Microservice count**: MSA decomposes the application into a set of microservices, increasing the complexity of the scheduling problem as the number of microservices increases. Thus, existing works capture different levels of granularity based on the number of microservices in the modelled IoT applications. Each application modelled in [3, 7, 83, 88] consists of a single microservice such that the microservice is designed to perform a specific task requested by the end-user. As an example scenario, [83] introduces an object detection application used by autonomous cars for the detection of other vehicles, pedestrians, road signs etc., that consists of a single microservice for object detection service. To avoid the complexities introduced by having a large number of interconnected microservices, [23] simplifies the placement problem by designing the placement algorithm to handle applications with a fixed number of microservices. [23] proposes the placement algorithm for applications consisting of two microservices: a high throughput microservice that receives data and pe-process it to reduce the throughput, and a low throughput microservice which process the data sent from the first microservice. Works such as [24, 34, 49, 63, 92] remove this constraint and...
Table 3. Analysis of existing literature based on the taxonomy for modelling of Microservice Architecture

| Work Count | Resource Heterogeneity | Dependency | Invocation pattern | Microservice count | Dataflow pattern | Service Composition | Application Composition |
|------------|------------------------|------------|--------------------|--------------------|------------------|---------------------|------------------------|
| [26] Multi-V Captured (R) | Dependent | Ch | Multiple | NA |
| [49] Multi-V Captured (R) | Dependent | DG | Multiple | NA |
| [35] Multi-V Captured (Pc) | Dependent | DG | Multiple | NA |
| [23] Multi-F Captured (R,p,S) | Dependent | Ch | Multiple | Ch |
| [62] Multi-V Captured (R,p,S) | Dependent | DAG | Multiple | NA |
| [34] Multi-V Captured (R) | Dependent | DAG | NA | NA |
| [24] Multi-V Captured (R,p,S) | Dependent | DAG | Multiple | DAG |
| [83] Single | NC | Independent | NA | Single | NA |
| [64] Multi-V Captured (Pc, R) | Dependent | ND | NA | NA |
| [74] ND Captured (R) | Independent | NA | ND | NA |
| [22] Multi-V Captured (Pc) | Dependent | ND | Multiple | Ch |
| [1] Single Captured (Pc) | Independent | NA | Single | NA |
| [25] Multi-V Captured (R,p,S) | Dependent | DAG | Multiple | DAG |
| [92] Multi-V Captured (Pc) | Dependent | Ch | Multiple | Ch |
| [20] Multi-V Captured (R,p,S) | Dependent | Ch | Multiple | Ch |
| [87] Multi-V Captured (Pc, R) | Dependent | NC | Multiple | Ch |
| [42] Multi-V Captured (Pc) | Dependent | Ch | Multiple | Ch |
| [48] Multi-V Captured (Pc) | Dependent | DAG | Multiple | DAG |
| [6] Multi-V Captured (Pc,R,S) | Dependent | DG | Multiple | DG |
| [88] Single | NC | Independent | NA | Single | NA |
| [7] Single | NC | Independent | NA | Single | NA |
| [40] Multi-V Captured (R) | Dependent | Ch | Multiple | Ch |
| [39] Multi-V Captured (R,p,S) | Dependent | DAG | Multiple | Ch, Ag, H |
| [85] Multi-V Captured (Pc, R) | Dependent | DG | Multiple | DG |
| [30] Multi-V Captured (Pc, R, B) | Dependent | DAG | Multiple | DAG |
| [3] Single Captured (R,B) | Independent | NA | Single | NA |
| [29] Multi-V Captured (Pc, R, B) | Dependent | DAG | Multiple | DAG |
| [63] Multi-V Captured (R,p,S) | Dependent | DAG | Multiple | Ch, Ag, H |
| [56] Multi-V Captured (Pc, R) | Dependent | DAG | Multiple | DAG |
| [53] Multi-V Captured (Pc, R) | Dependent | NA | Multiple | UWG |
| [91] Multi-V Captured (Pc) | Dependent | DAG | Multiple | DAG |

Mult-F: Multiple-Fixed, Multi-V: Multiple-Variable, Ch: Chain, Ag: Aggregator, H: Hybrid, DAG: Directed Acyclic Graph, DG: Directed Graph, UWG: Undirected Weighted Graph, R: RAM, Pc: Processing power (CPU), Pg: Processing power (GPU), S: Storage, B: Bandwidth, RU: Resource Units, NC: Not Captured, NA: Not Applicable

model the application as a collection of any number of microservices, thus providing robust placement algorithms that capture the problem-domain dependent granularity levels of MSA more accurately.

(2) Resource Heterogeneity: One of the advantages of decomposing applications into microservices is to achieve functional separation where the application is divided into separate modules following "separation of concern" design pattern. This results in the separation of microservices based on their resource requirements as well (i.e., CPU, GPU, RAM, storage etc.). It’s specially advantageous in Edge/Fog environments where resources are heterogeneous (i.e., Raspberry Pi 1, Jetson Nano 2, Dell PowerEdge XR12 3, Lenovo ThinkEdge SE50 4, etc.) and resource-constrained unlike in Cloud environments. [23, 39, 63] demonstrate this by modelling microservices within the same application to have heterogeneous resource requirements in terms of multiple resource parameters such as RAM, CPU, storage and bandwidth. [25, 91] extend this to include GPU as well, where microservices with GPU requirements may have to be moved to different Fog locations or Fog service providers based on the GPU availability. While the above works represent resource requirements as a vector, some works

1https://www.raspberrypi.com/products/raspberry-pi-4-model-b/specifications/
2https://developer.nvidia.com/embedded/jetson-nano
3https://www.dell.com/en-au/work/shop/city/pdp/spd/poweredge-xr12/aspxr12_vi_vp
4https://psref.lenovo.com/syspool/Sys/PDF/ThinkEdge/ThinkEdge_SE50/ThinkEdge_SE50_Spec.pdf
like [34, 49] simplify the representation by introducing the scalar parameter "Resource Units", with the possibility of extending it to include multiple resource types.

3) **Dependency among microservices**: Microservices are developed as independently deployable units with well-defined business boundaries such that their functionality is exposed to the outside through open interfaces. This allows microservices within applications to easily communicate with each other to create composite services. [1, 74, 83] represent microservices as independent entities without any interconnections among them. In contrast, works such as [26, 49, 62] model them to have dependencies, where microservices communicate with each other through lightweight communication protocols such as REST APIs and message brokers, creating a plethora of IoT services.

4) **Invocation pattern**: The higher level of openness supported by microservices results in different invocation patterns among them, where client microservices invoke other microservices to perform functions required to complete the composite services. [20, 26, 92] models the invocation relationship as a chained pattern. [36, 39, 63] use a more general representation of microservice invocation by modelling it using DAG representation. [35] and [49] model the invocation as directed graphs where the interactions between microservice are depicted using many-to-many consumption relationships.

### 3.2 Service Composition

With granularity comes the concept of composite services, where microservices interact to create services that perform a certain task and provide an output to the user. In this section, we analyse and categorise aspects related to service composition.

1) **Microservice count**: The granularity of the microservices creates end-user services with varying numbers of microservices: "atomic services" consisting of a single microservice and "composite services" that consist of multiple interconnected microservices. [1, 83] represent each service by a single microservice that receives requests from the end-user front-end, completes a task and provides the result back to the user without interacting with any other microservices. Other works like [20, 36, 63] model services with multiple microservices that interact together to perform tasks. [20] describes a smart city application with a smart policing service used by the police to identify suspects where the service is a composition of three microservices, and [62, 63] model a smart healthcare application with an emergency notification service where multiple microservices interact to detect abnormalities in ECG data streams and raise emergency alarms in real-time.

2) **Dataflow Pattern**: Due to different interaction patterns among microservices, the data flow within composite services can take many forms. [22, 23, 26] consider the chained composition of microservices, whereas [39, 63] models the services considering chained, aggregator and hybrid dataflow patterns to create composite services. Works such as [25, 48] model dataflow among microservices as DAGs, assuming the absence of cyclic data flows while [6, 85] include cyclic dataflows and represent the dataflows using DGs. [53] models the interaction pattern using an Undirected Weighted Graph (UWG) where edges are represented using interaction weights irrespective of the direction of communication.

### 3.3 Application Composition

As the capabilities of the IoT applications improve rapidly, they quickly evolve into complex applications covering large business domains due to the flexibility of design and development using MSA. We analyse the aspects related to this as follows:
Service count: With the increase in connected devices and the generation of diverse data, IoT applications have evolved to provide many services to users. Thus, microservices-based IoT applications are modelled as a composition of one or more services. [23, 83] define applications with single services, whereas [22, 35, 48] model applications with multiple end-user services with heterogeneous QoS requirements. [62, 63] model a smart health care application with two primary services; emergency alarm generation service with stringent latency requirements and a latency tolerant long term analysis service. Modelling the applications with multiple services allows the placement problem to capture competing QoS requirements within applications and paves the way to propose placement policies that can utilize Fog-Cloud resources more efficiently.

Advanced Interactions: Due to the fine-grained nature of the microservices, along with well defined functional boundaries and lightweight communication methods, advanced interactions among microservices are possible. [63] models applications where some microservices (i.e., feature extraction, data cleaning etc.) are part of multiple composite services that have heterogeneous latency requirements. [92] models the services to have candidate microservices (i.e., online payment gateways) depending on the payment method used by the user. Thus, the application is modelled to have alternative data paths. [3] handles the concept of having alternative paths by defining control structures for each composite service through conditional branching within some of the microservices. Another advanced capability of microservices is using third party microservices through the use of APIs, which is modelled in the [3] where composite services are created by combining microservices developed by multiple developers, and provided as services by multiple computing service providers.

3.4 Research Gaps

Based on the analysis of existing works presented in Table 3, we have identified the following gaps related to microservices-based application modelling.

1. Existing works show shortcomings in several aspects in capturing the granularity of the MSA, such as lack of use in generalised invocation patterns (i.e., directed graphs) and capturing resource heterogeneity in different microservices within the same application (i.e., use of GPU, databases etc.). Many works use a chained invocation of microservices without considering complex dependency patterns that can occur due to the openness in microservice design. For capturing resource heterogeneity, most of the works consider one or more parameters such as CPU, RAM and storage. However, GPU or TPU requirements are scarcely considered. With the rise of EdgeAI workloads in IoT, such parameters and the constraints imposed by them play an important role in the placement logic.

2. In service composition, the data flow pattern is not properly defined and utilised in the placement process of the majority of the works. Many of the works define chained data flow, or acyclic data flows, disregarding cyclic data flows, which affect the end-to-end latency calculations of the services.

3. Under application composition, most of the works model each application to have a single composite service. Thus heterogeneity in QoS requirements between different composite services within the same IoT application is not captured properly. This also hinders the application from having complex interaction patterns and data flow patterns within the applications.

4. In modelling the applications, most of the works do not consider complex interaction patterns of microservices, including shared microservices among different composite services, candidate microservices and third party microservices. Placement of shared microservices
has to consider multiple, heterogeneous composite services that they are part of and schedule them so that all non-functional requirements of the services are satisfied under resource contention. For efficient placement of the candidate services, knowledge of their demand and usage is vital. The use of third party microservices in applications results in security, reliability and performance challenges (i.e., latency, availability, transaction cost etc.) that are out of the control of the application developers, which need to be accounted for during the scheduling phase to improve performance. The majority of the works that consider these only analyse the effect a single pattern, thus failing to capture the effect of multiple ones.

4 APPLICATION PLACEMENT

Fig. 7. Taxonomy for placement approach for microservices-based applications

MSA introduces novel aspects (i.e., QoS granularity, scalability, lightweight/ independent deployment, etc.) that can be utilised for better placement of the IoT applications while also giving rise to novel challenges (i.e., microservice dependencies, interactions, cascading failures etc.). We
consider these MSA-specific effects in addressing application placement problem and create a novel taxonomy as shown in Fig. 7. Current works are mapped to the taxonomy to identify gaps and possible improvements (see Table 4).

4.1 Placement Mode
Placement mode represents the number of placement requests processed by the placement engine during each execution of the placement algorithm. Placement modes are categorised into two groups: sequential mode, where the placement algorithm queues the placement requests to process one after the other, and batch mode, where a set of applications are considered for placement simultaneously. In the works such as [20, 62, 83], the placement engine uses a First In First Out (FIFO) queue to store and process application placement requests sequentially. [23, 24] prioritise the applications in the queue based on their resource requirements, whereas [49] and [88] prioritise them based on the deadlines of the applications and order them for sequential placement. Placement engines in [34, 48, 63] are designed using meta-heuristic algorithms (i.e., genetic algorithm, particle swarm optimisation) to handle the complexities of the batch placement and navigate the larger solution space successfully. [25] employs a batch placement policy based on a heuristic algorithm to maximise the placement of IoT applications within a multi-domain federated Fog ecosystem under locality constraints imposed on microservices. Some works such as [1, 42, 87] do not properly define placement mode and carry out the evaluations using the placement of a single application.

4.2 Placement Perspective
Placement perspective is identified based on the optimisation parameters/objectives considered during the placement and from whose view point they are addressed from. [6, 23, 24] define the placement problem from the perspective of the Fog infrastructure provider thus aiming to maximize the IaaS provider’s revenue. Other works such as [20, 22, 93] define the placement problem from the application provider perspective, where application providers expect the satisfaction of non-functional requirements (i.e., latency, throughput, reliability etc.) of the services provided by their application, while ensuring budget constraints related to Fog-Cloud deployment. [26, 35] address this from a user perspective where the user sends a request for an application or service along with performance requirements and the placement algorithm ensures the availability of the requested service under requested constraints (i.e., latency, throughput etc.) to satisfy the user expectations.

4.3 Placement Parameters
In this section we analyse the characteristics of the parameters considered by the placement policy.

1. Parameters: IoT application services have multiple heterogeneous QoS parameters (i.e, latency [20, 40, 53, 85, 93], cost [20, 63, 88], throughput [3, 6, 85], energy [87], reliability [64] etc.) negotiated with the Edge/Fog infrastructure provider in the form of Service Level Agreements (SLA). Moreover, placement decisions made from the infrastructure provider perspective consider maximisation of the revenue of the IaaS provider. [23], and [24] formulate the placement problem to maximise the revenue of the Fog provider, whereas [6, 25] consider a federate Fog environment where each provider focus on minimising the total deployment cost while minimising the number of resources rented from external Fog infrastructure providers and the Cloud. Resource utilisation is another parameter considered in current research where [3, 34, 53] consider optimisation of computation resource usage, [36] optimises network resource usage, while [29, 63] consider both. Placement policies focus on optimising one or more of the above mentioned QoS parameters. [26, 35, 62] formulate the placement problem considering the satisfaction of a single parameter and focus on minimising the latency of
Table 4. Analysis of existing literature based on the taxonomy for application placement

| Work | Placement Mode | Placement Perspective | Parameters | QoS-Awareness | QoS Granularity | Placement Parameters | Placement Techniques | Advantages/Service characteristics | Ind. Deployability | Ind. Scalability | Other Objectives |
|------|----------------|-----------------------|------------|---------------|-----------------|----------------------|----------------------|-----------------------------------|-------------------|-----------------|------------------|
| [26] Seq-HIFO | UF | Latency | No | per microservice (Latency) | Heuristic - Greedy | VMs | NC | Latency |
| [49] Seq-P | AF | Latency, Availability | Yes (Latency) | per application (Latency) | Heuristic | Containers | H | - |
| [23] Seq-P | IP | Revenue, Latency, Throughput | Yes (Latency, Throughput) | among microservices (Throughput per application (Latency) | Heuristic-Greedy | Containers | NC | F-C Balance (D) |
| [34] Batch | AF | Latency, RU | No | per service (Latency) | Heuristic | Containers | H | Service Spread |
| [62] Seq-HIFO | UF | Latency | No | per service (Latency) | Heuristic | Containers | H | V | F-C Balance (S) |
| [42] ND | AF | Latency, Cost | Yes | per service (Latency) | Meta-Heuristic | Containers | NC | V | Redundancy |
| [64] Seq-ND | AF | Cost, Reliability, Latency | Yes | per application (All) | Meta-Heuristic | NC | H | - |
| [47] ND | AF | Latency, Energy | No | NC | Meta-Heuristic | Containers | H | Redundancy |
| [1] ND | UF | Latency | Yes (Latency) | per microservice (Latency) | Machine Learning | Containers | H | Fault-tolerance |
| [48] Batch | AF | Energy, Latency | Yes (Latency) | per microservice (Latency) | Mathematical Programming (Lagrangian Multiplier) | Containers | H | - |
| [22] Seq-ND | AF | Energy, Latency | No | NC | Meta-Heuristic | VMs | NC | - |
| [25] Batch | IP | Revenue, Latency, Throughput | Yes (Latency, Throughput) | among microservices (Latency, Throughput) | Heuristic | Containers | NC | Locality-awareness |
| [24] Seq-P | IP | Revenue, Latency, Throughput | Yes (Throughput, Latency) | among microservices (Throughput, Latency) | Heuristic-Greedy | Containers | NC | F-C Balance (D) |
| [63] Seq-HIFO | AP/UF | Latency, Cost | Yes (Latency) | per application (Latency) | Reinforcement Learning | Containers | NC | Mobility-awareness |
| [6] Seq-ND | IP | Latency, Throughput | Yes (All) | among microservices (All) | Heuristic | Containers | H | F-C Balance (D) |
| [58] Seq-P | UF+AF | Latency, Cost | Yes (Latency) | per microservice (Latency) | Heuristic - Greedy | Containers | NC | F-C Balance (D) |
| [39] Seq-ND | AF | Latency, Cost | Yes (Cost) | among microservices (Latency) | Heuristic - Greedy | Containers | H | - |
| [3] Seq-ND | AF | Latency, RU | Yes (Throughput) | per microservice (Throughput, Latency) | Analytical Hierarchy Process (AHP) | Containers | NC | - |
| [30] ND | IP+UF | Latency, Throughput, Cost, RU, RU | Yes (Latency, Throughput) | among microservices (Latency, Throughput) | Approximate Algorithm + Deep Reinforcement Learning | Containers | H | Load-awareness Resource contention |
| [61] Batch | AF | Latency, Cost, Throughput, RU | Yes | per service (Latency) | Meta-Heuristic | Containers | H | V | F-C Balance (D) |
| [56] Batch | UF | Latency, RU | Yes | per service (Latency) | Meta-Heuristic | Containers | H | Location-awareness |
| [53] ND | AF | Latency, RU | No | NC | Deep Reinforcement Learning + Heuristic | Containers | H | Load-awareness |
| [20] Seq-HIFO | AF | Cost, Latency | Yes | per service (All) | Mathematical Programming (Branch and Bound) | Containers | H-V | - |
| [95] Seq-HIFO | AF | Latency | No | per service/application (Latency) | Monte Carlo + Meta-heuristic | Containers | H | Availability |
| [40] Batch | IP | Latency | No | per service (Latency) | Mathematical Programming (Gurobi MILP solver) | ND | H-V | Optimal routing |
| [63] Seq-ND | UF | Latency, Throughput | Yes (Latency, Throughput) | among microservices (Latency, Throughput) | Mathematical Programming | VMs | H | Redundancy |
| [29] ND | IP+UF | Latency, Throughput, Cost, RU, RU | Yes (Latency, Throughput) | among microservices (Latency, Throughput) | Approximate Algorithm + Deep Reinforcement Learning | Containers | H | Load-awareness Resource contention |
| [91] ND | UF | Latency, Throughput | Yes (Latency) | per service (Latency) | Heuristic-Greedy | Containers | NC | - |

FIFO: First-In-First-Out, UF: User Perspective, AF: Application provider Perspective, IP: Infrastructure provider Perspective, RU: Computation Resource Utilisation, RU_N: Network Resource Utilisation, ND: Not Defined, NC: Not Considered, H: Horizontal, V: Vertical, F-C Balance(D): Dynamic Fog-Cloud Balance, F-C Balance(S): Static Fog-Cloud Balance
the services deployed within Edge/Fog environments. Other works like [48, 64, 74] focus on multiple parameters to reach a trade-off between conflicting parameters such as latency, cost, energy etc. by formulating the placement problem as a multi-objective optimisation problem.

(2) **QoS-awareness:** Reduction of service latency and core network congestion are two of the main objective of Edge/Fog computing paradigms. As a result, [35, 42, 93] aim to place the microservices as close as possible to the user to reduce the overall latency of the application. While this is done in a QoS-unaware manner, assuming that all services require low latency, other research works such as [25, 36, 63, 64] consider the QoS requirements of the IoT services before placing them. Such approaches highlight one of the main limitations of Edge/Fog computing which is its resource-constrained nature compared to the cloud data centres. Thus, they aim to capture the QoS heterogeneity of the IoT services and prioritise them based on their QoS requirements (i.e., stringent latency requirements over latency-tolerant services [25, 36], stringent budget constraints over higher budget availability [63, 64], throughput-aware placement/scaling of microservices [23, 63], etc.) and achieve a proper balance between Fog and Cloud resource usage in a QoS-aware manner. MSA further enhances this behaviour due to the ease of moving independently deployable microservices across Fog and cloud data centres dynamically.

(3) **QoS Granularity:** Because of the fine-grained nature of the microservices and their possible composition patterns, QoS parameters are defined at different levels of granularity. Among existing works, QoS parameters are defined at three primary levels: microservice level, composite-service level and application level. [23, 24] define the throughput requirements at the microservice level, where it is presented as the bandwidth requirement between interacting microservices, whereas [1, 26, 74] define latency requirements per each microservice. Several works such as [35, 42, 63] define latency, throughput, cost etc., per each composite service where microservices-based applications can consist of one or more such services. [24, 83] define latency requirement per each application, assuming that the application performs a single function/service requested by the end-user. Most of the works define all QoS parameters at a single level, whereas [23, 24] uses different granularity levels based on the parameter (i.e, throughput at microservice level and latency at application level).

### 4.4 Placement Technique

Different placement techniques are chosen to implement the placement policies based on the complexity of the modelled microservices-based applications, placement mode, optimisation parameters and their granularity, and the dynamism of the considered scenario (in terms of distributed resources, workload, failures etc.). Works such as [20, 40, 74, 85] use mathematical programming to solve microservices-based application placement in Edge/Fog: [40] formulates the problem using Mixed Integer Linear Programming (MILP) and solve it using Gurobi MILP solver. [74] uses the Lagrangian multipliers to solve the optimisation problem under multiple constraints including network QoS, price, resource usage etc. Several works including [26, 35, 62] propose heuristic placement algorithms to optimise a single placement parameter such as latency. Heuristic approaches are proposed by works such as [23, 25, 49] that consider multiple parameters as well. Here, [23], and [25] formulate the placement problem as an Integer Linear Programming problem to solve it using greedy heuristic algorithms. [34, 36, 48] that try to handle batch placement scenarios and multiple placement parameters, propose placement policies based on evolutionary meta-heuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO) to navigate large solution space efficiently. With increased computation power available for

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5[https://www.gurobi.com/products/gurobi-optimizer/]
placement engines, algorithms are moving towards Machine Learning (ML) : [1] uses ML-based forecasting models to make predictive auto-scaling decisions, and [29, 53, 83] use Reinforcement Learning based approaches to tackle the highly dynamic nature of Edge/Fog environments and the microservices. Moreover, existing works use other techniques such as Analytical Hierarchy Process (AHP) [3] which is a powerful decision analysis method used to prioritise and balance multiple criteria, and computation algorithms such as Monte Carlo method [93] used to capture uncertainties in the placement problem introduced by the MSA (i.e., candidate microservices, 3rd party microservices, etc).

4.5 Advanced Microservice Characteristics
The popularity of the MSA for deployment within highly distributed Edge/Fog environments stems from two primary microservices-related characteristics, their independently deployable and scalable nature.

(1) Independent Deployability: Decomposing monolithic applications into a collection of microservices can improve deployment-related aspects such as fault tolerance and reliability due to the independently deployable nature of the microservices. This is further supported by containerisation, which provides a lightweight method for deploying microservices compared to the earlier used Virtual Machines (VMs). [26] proposes a deployment scenario where all microservices of a user-requested service are mapped onto a single VM. The vast majority of existing works [25, 34, 49, 87] improve the deployment through the use of containers (i.e., Docker), which allows rapid deployment by providing microservices with lightweight, isolated environments. The use of containers enables fast deployment of microservices while mitigating single point of failure using distributed placement of microservices. Works such as [62, 74] highlight the importance of using container technology due to their faster spin-up times and analyse resultant performance improvements under dynamic conditions. [20, 63] consider the cost of the containerised microservices by adapting the pricing models used in container platforms provided by the commercial Cloud providers (i.e., Amazon Fargate, Azure Containers).

(2) Independent Scalability: As microservices are independently deployable units with well-defined business boundaries, each microservice can be independently scaled to meet the throughput requirements. This is especially advantageous in Edge/Fog computing scenarios where devices are heterogeneous in their resource capacities, workloads also vary rapidly with the popularity of the services, mobility of the users etc. Scalability of the microservices is used in multiple ways where some works consider only horizontal scalability while others use a combination of horizontal and vertical scalability to satisfy throughput requirements. [34] uses horizontal scalability of the microservices to spread instances of each microservices uniformly across the Fog landscape to support distributed access by users. [62, 63] consider resource heterogeneity of the Edge/Fog devices and use a hybrid approach of vertical and horizontal scalability to meet the throughput requirement. Current works use scalability of the microservices for multiple purposes. Above works focus on satisfying the overall throughput requirement while utilising resource-constrained Edge/Fog devices. Meanwhile, [36] use horizontal scalability to incorporate location awareness, whereas [74, 93] use horizontal scalability to achieve redundancy which improves availability and fault-tolerance of the application.
4.6 Other Placement Objectives

One of the main advantages of using MSA for Fog application development is the ability to easily utilise both Fog and Cloud resources to meet application requirements. This concept is also put forth in Osmotic computing which highlights the importance of dynamically moving microservices between Cloud and Fog and achieving an equilibrium such that the non-functional requirements of the services are met. In some works such as [23, 62] this is handled in a static manner where microservices to be placed on Cloud are predefined per each application based on the deadline requirement of the composite services each microservice belongs to. [6, 24, 35, 63] handle this in a dynamic way: [24] partitions the application based on the throughput requirement to place microservices with higher throughput requirements in the Fog and rest in the Cloud, [35] analyses the popularity of the microservices based on the user requests to move less popular ones to the Cloud, [6] achieves balance by considering the cost of deployment in Fog and Cloud, [63] formulates a multi-objective problem to achieve a trade-off between Fog device usage and network usage to achieve a balance between Fog and Cloud resource usage dynamically.

Locality or location awareness is another aspect that comes with IoT applications due to data security and latency requirements. Sensitive IoT data (i.e., healthcare, security camera footage etc.) can have constraints on geographical locations for processing which requires certain microservices to be placed within certain regions or within certain Fog service providers in federated Fog computing environments. [25] adds locality constraint to their problem formulation and handle it using a heuristic approach. With the distributed nature of the Edge/Fog resources and the users, location awareness can be used to minimise the network resource usage and delay [34, 36]. [36] utilise this concept where user’s location is used to select the microservice instances such that the requests are routed to the closest instances. [34] introduces a metric called service spread which evenly distributes microservices across Fog landscape to improve performance when users are uniformly distributed.

Modularity and scalability of microservices pave the way for efficient redundant placement to improve availability and fault-tolerance of the services. [93] proposes a redundant placement policy for composite services consisting of chained microservices, considering uncertainty of requests and heterogeneity of the resources. This work aims to reduce the outage time under failures through redundant placement of microservices. To address the challenge of cascading failures that occurs in MSA, [48] proposes a fault tolerance method for applications deployed using API gateway pattern where API gateway acts as the access point for requests coming from the users. This work deploys API gateway within cache-enabled edge nodes, so that data related to service requests can be cached proactively in case down stream microservices become unavailable due to failures, until the microservice is redeployed using a reactive fault-tolerance approach.

Due to horizontal scalability of microservices, proper load balancing and routing is required to ensure performance requirements. To address this [40, 42, 87] formulate the application placement problem as a combination of microservice replica placement and determining the optimal data flow path of composite services. [42] uses minimization of service latency and cost (both computation and data transfer costs) to achieve the optimum level of service replication and identification of the request path that minimises latency of the composite services. [87] considers latency and power consumption as optimisation parameters to achieve this. [40] extends this further by incorporating SDN controller placement as part of the problem, where SDN controllers are used for service discovery and determining data flow.

Deploying multiple lightweight containers onto the same Fog device can result in resource contention depending on the resource requirements of each container instance. To overcome this, [29, 30, 91] propose online algorithms to detect shared-resource contentions and afterwards
dynamically adjust resource allocations or migrate microservice instances to other idle nodes to maintain the required level of performance. These works capture different types of resource contentions including I/O [29], GPU global memory bandwidth [91] and computation capacity [30] contentions.

4.7 Research Gaps
Based on the analysis of existing works presented in Table 4, we identified the following gaps related to microservices-based application placement.

1. QoS-granularity and QoS-awareness, together with proper placement mode selection, can improve performance, especially when microservices-based IoT applications are considered. As IoT applications grow in complexity to provide many services with heterogeneous QoS requirements, the granularity of the microservices paves the way for per-service QoS definitions. Together with batch placement or sequential placement with QoS-aware prioritisation, this approach is rarely explored in existing works. Following shortcomings are apparent in existing works;
   - QoS-granularity: Most of the works define QoS requirements among interacting microservices (i.e., latency and throughput requirements between two microservices) which becomes less feasible due to composite services with complex interaction patterns and their agile evolution as applications evolve. As a result, existing works scarcely capture QoS heterogeneity of the composite services within the same application. Thus, MSA-related scenarios like competing requirements that exist due to shared microservices are not handled.
   - QoS-awareness: Many works do not define QoS requirements and capture the heterogeneity but try to minimise overall latency, cost etc. This approach hinders the proper utilisation of limited Edge/Fog resources and limits achieving equilibrium between Fog-Cloud resource usage.

The above gaps are tightly coupled with how the microservices-based application is modelled, and overcoming them requires the proper capturing of MSA as described in the Section 3.

2. In existing works, there’s scope for incorporating advanced microservice characteristics such as the independently deployable and scalable nature of the microservices. Although many of the works use container technology for microservice deployment, they lack proper utilisation of the fast spin-up time, lightweight deployment capabilities and related cost models, whereas, for independent scalability, only a very few works explore the combination of horizontal and vertical scalability to support throughput requirements of the composite services. This can further consider scalability constraints of different microservices (i.e., microservices with databases).

3. Placement objectives of the current works lack emphasis on the following: security challenges related to microservice, utilising microservices for improvement of reliability and fault tolerance, dynamic microservice scheduling under federated Fog architectures, dynamic Fog-Cloud balance, mobility aware scheduling, consideration for load uncertainty, etc.

5 MICROSERVICE COMPOSITION
The complex interaction patterns among microservices, their ability to independently scale up/down to maintain performance and distributed deployment of microservice instances across networked devices are supported through microservice composition mechanisms. Fig. 8 presents the taxonomy for essential aspects of the successful composition of microservices within distributed environments. For this analysis, we use both Edge/Fog frameworks designed for microservice deployment [27, 89] and conceptual frameworks/simulators used in formulating and solving placement problems [20, 39]
as demonstrated in Table 5. We analyse the main functions related to microservice composition in the sections below.

Table 5. Analysis of existing literature based on the taxonomy for microservice composition

| Work | Service Discovery | Load Balancing | Networking | Elasticity | Monitoring | Other |
|------|-------------------|----------------|------------|------------|------------|-------|
| [27] | S-S               | S-S            | Round Robin|            | U-D        | -     |
| [62] | C-S               | C-S            | Weighted Round Robin |           | U          | H-V   |
| [20] | NC                | C-S            | Round Robin | -          | -          | -     |
| [63] | NC                | C-S            | Weighted Round Robin | -          | -          | -     |
| [6]  | S-S               | S-S            | Custom     |            |            |       |
| [53] | S-S               | S-S            | Custom     | (Kubernetes + Istio) | U-D | H | (Prometheus) |
| [42] | ND                | S-S            | Custom     |           |            |       |
| [48] | S-S               | NC             | -          |           |            | Fault-tolerance |
| [39] | ND                | C-S            | Round Robin | -          | -          | -     |
| [89] | S-S               | S-S            | Weighted Round Robin | (Kubernetes + KubeEdge) | U-D | - | (Custom) |
| [55] | C-S               | C-S            | Weighted Round Robin | ✓          | U-D        | H-V   |
| [18] | S-S               | ND             | (MQTT Broker) | ✓          | U-D        | H | (Custom) Fault-tolerance Security |
| [13] | S-S               | S-S            | ND          | (Kubernetes + CNI) | U-D | H | - | - |

C-S: Client-side, S-S: Server-side, U: Up, D: Down, H: Horizontal, V: Vertical, CNI: Container Network Interface, ND: Not Defined, NC: Not Considered

5.1 Service Discovery

Dynamic placement algorithms proposed to handle microservice placement [53, 62, 89] define service discovery mechanisms, so that changes (i.e., scale up/down, failures) in microservice instances are made known to other microservices that interact with them. [55, 62] use client-side service discovery pattern where each client microservice queries a dynamically updated service registry to determine the available service instances. Works such as [48, 53, 89] use server-side service
discovery where the requests are directed to a designated entity (i.e., a load balancer, a proxy etc) that is responsible for directing the requests towards available service instances. "FogAtlas"[27] which is a Edge/Fog computing platform used by multiple works such as [23, 25] and other works such as [6, 89] use Kubernetes as the orchestrator along with its default proxy based, server-side service discovery mechanisms. [48] implements server-side service discovery using an API gateway as the ingress node responsible for service discovery and service composition.

5.2 Load Balancing

(1) **Type:** Current works model load balancing using two primary approaches: *client-side load balancing* [20, 39, 62] where each client is responsible for individually executing load balancing policies, thus enabling application dependent load balancing policies to be implemented, and *server-side load balancing* [6, 53, 89] where a dedicated load balancer sits between client and server microservices to handle load balancing.

(2) **Approach:** Integrating the effect of the load balancing mechanism and introducing novel load balancing policies to improve the performance of the services is vital in microservice application deployment. [20, 63] model the end-to-end service latency based on the existing load balancing policies such as Round Robin and Weighted Round Robin to determine the number of microservice instances to deploy. Meanwhile, some works introduce custom load balancing policies: [6] proposes a load balancing policy for a multi-region Fog architecture where the requests are directed based on the residual CPU of each Fog region, [53] uses the variance of the resource occupancy rate of the edge nodes to determine where to direct the requests, [42] uses a meta-heuristic algorithm to place microservice replicas to identify flow paths by considering parameters such as service cost and service latency.

5.3 Networking

Distributed deployment of containerised microservices makes networking one of the integral functions of microservice compositions. This is further complicated by the federation of Fog and Cloud which results in communication between multiple networking environments and technologies. [27] use Kubernetes to handle the networking among microservices instances where as [53] integrates Istio\(^6\) service mesh framework to handle inter-service communication. [89] integrate Kubernetes with KubeEdge for the edge network. To overcome the limitation Kubernetes network model and assign subnets per host, [6] use Flannel, a Container Network Interface (CNI) and Istio on top of Kubernetes orchestration. [13] explore and compare multiple CNIs including Flannel, Weave, Calico and OVN. [18] uses MQTT Broker, an asynchronous messaging based communication mechanism to transmit messages over the network among decoupled microservices.

5.4 Elasticity

Elasticity indicates the ability of the microservices to be dynamically scaled up and down dynamically in a performance-aware manner. With the use of lightweight deployment technologies such as containers, microservices can be easily auto-scaled to improve the performance of the application while ensuring optimum resource utilisation. Out of the many works that consider horizontal scalability of microservices, the majority consider this during the initial placement of the application to make use of resource-constrained Fog devices but fail to use auto-scaling/elasticity under dynamic changes in the environment (i.e., load changes, failures etc.). Dynamic placement algorithms proposed in works such as [53, 55, 62] consider elasticity. However, we can further analyse it based on the supported type of elasticity: scaling up, scaling down, and the method of

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\(^6\)https://istio.io/
scaling: horizontal, vertical. [62] considers both vertical and horizontal scaling but only considers scaling up as new user requests arrive. [53] proposes a utilisation threshold-based policy to horizontally scale up/down microservices through continuous monitoring of the resources. Practical frameworks and simulators [27, 55] provide the infrastructure required to auto-scale (both up and down, horizontal and vertical) microservices through customised policy implementations.

5.5 Monitoring
Monitoring is the collection of application and platform metrics in such a way that they can be used to detect failures, performance degraded states, etc. and act accordingly to maintain system performance. Highly dynamic nature of the containerized microservices makes monitoring a challenging task, which has resulted in the development of open-source monitoring tools that can handle the large volume of moving parts in microservices-based application deployment. Hence, [6, 27, 53] integrate Prometheus\(^7\) to their orchestration platform to monitor multiple platform metrics (i.e., request number, response times, resource consumption, network communications, etc). Meanwhile [18, 89] implement their own customised monitoring tools to monitor metrics across Edge-Cloud integration.

5.6 Other
Other composition related tasks include fault-tolerance and security. [48] proposes a conceptual framework where API Gateway handles the responsibility of fault-tolerance by data recovery, service re-composition and re-submission of failed request. [18] introduces three main components: health check component, circuit breaker and timeout component to identify and isolate failures to avoid cascading failures under MSA. [18] implements a centralised security components to manage authorisation and authentication required for microservice access.

5.7 Research Gaps
Based on the analysis of existing works presented in Table 5, we identified the following gaps:

1. Current works demonstrate less emphasis on load balancing policies and their effect on formulation of the placement problem.
2. There’s scope for improvement in elasticity (both horizontal and vertical scaling), fault tolerance, microservice security through proper monitoring of the deployed application at the application and platform level.
3. Effect of orchestration components (i.e., service registry, API gateways, load balancers) on the application performance needs to analysed and demonstrated in terms of handling their possible failures, delay overheads, etc.

6 PERFORMANCE EVALUATION
Accurate policy evaluation is one of the vital steps in designing novel placement algorithms for fast-evolving fields such as IoT and Edge/Fog computing. To this end, we propose the final taxonomy by analysing the crucial aspects of the evaluation phase as shown in Fig. 9. Afterwards, current works are mapped to the taxonomy to identify gaps and possible improvements (see Table 6).

6.1 Evaluation Approach
Evaluation approaches can be categorised as Numerical Evaluations, Simulations, use of Practical test-beds and Hybrid approaches consisting of combinations of above methods.

\(^7\)https://prometheus.io/
Fig. 9. Taxonomy for performance evaluation of the placement policy

Table 6. Analysis of existing literature based on the taxonomy for performance evaluation

| Work | Numerical | Simulation | Practical | Synthetical | Real | Hybrid |
|------|-----------|------------|-----------|-------------|------|--------|
| [40] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [42] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [44] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [48] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [50] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [52] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [54] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [56] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [58] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [60] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [62] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [63] | ✓         | -          | ✓ (FogSim)| -           |      |        |
| [64] | ✓         | -          | ✓ (FogSim)| -           |      |        |

**Numerical Evaluations:** In numerical experiments, the algorithm is evaluated by numerically calculating specific metrics that provide insights on the fitness of the resultant placement proposed by the algorithm [23, 24, 39, 40] or/and evaluating performance metrics of the algorithm such as execution time, computation complexity and convergence [34, 39]. [23, 24] use the Gurobi mathematical optimization solver to obtain the optimum solution to the formulated MINLP and compare the solution obtained from their proposed heuristic placement algorithm by calculating metrics such as the number of placed applications, network link usage, etc. numerically. [34] evaluates their approach based on the performance metrics (i.e., the fitness of the best solution, Pareto solution spread, execution time, etc.) of their proposed multi-objective evolutionary algorithm, where as [39] analyses the execution time of the algorithm under different experimental settings to evaluate the scalability of the algorithm, thus deriving the system size the algorithm can handle.

**Simulations:** For the evaluation of microservices-based application placement in Edge/Fog computing environments, both open source simulators (i.e., iFogSim [22, 35, 62, 63], YAFS [49], CloudSim [20, 26]) and custom simulators [6, 83, 93] are used by the current works. Simulators such as iFogSim [55] and YAFS [50] provide in-built microservice related features such as distributed application modeling, service discovery and load balancing, thus enabling the users to simply implement their placement policy within the simulator or implement the algorithm separately (i.e., MATLAB [20], IBM CPLEX [63]) and input the resultant placement to the simulator for evaluations.

**Practical:** To evaluate placement algorithms using practical frameworks, [23] uses "FogAtlas", an open source framework for microservices deployment, and orchestration in Fog environments, [91] implements a framework called "Astraea" for the management of GPU microservices, whereas other works such as [1, 6, 53, 89] implement customised test-beds with functionalities relevant to the placement algorithms. They use popular container-orchestration platforms such as Docker swarm [1], Kubernetes [6, 53], KubeEdge [89] in their implementations.
Hybrid: Some of the works use multiple evaluation approaches to analyse and evaluate the proposed placement policies from multiple perspectives. [6] use both Simulations and practical test-beds for evaluation. Simulations carry out large scale experiments, whereas test beds further verify the results of the simulations by carrying out a selected set of experiments. [63] use a combination of numerical evaluations and simulations where numerical evaluations are used to improve and fine-tune the meta-heuristic placement algorithm, whereas the simulation evaluates the resultant placements.

6.2 Workload

For the analysis of the workload, we consider the nature of the application placement requests used to evaluate the placement policy. We can categorise them as Synthetic, Real, or a combination of the both, denoted as Hybrid.

Synthetic: Synthetic workloads are created either by mimicking specific microservices-based applications [23, 26, 62] (categorised in the taxonomy as MSA) or using generic application models such as DGs or DAGs [24, 25, 39, 49] (categorised in the taxonomy as Other) to generate a workload consisting of multiple applications with heterogeneous resource and QoS requirements. [23] models the applications following a microservices-based IoT application for face recognition consisting of two chained microservices. [62] models a smart-healthcare application and creates a synthetic workload based on the modelled application. [26] models smart city and forest surveillance applications. Meanwhile, [24, 25, 39] generate random synthetic DAGs as microservices-based applications, whereas [49] uses Growing Network(GN) graph structure where graphs are created by adding nodes one at a time to existing nodes to develop microservices-based applications following Directed Graphs as the interaction pattern.

Real: Real workloads include the use of already implemented microservices-based applications (categorised in the taxonomy as MSA) or adapting performance traces of applications that follow other application models (categorised in the taxonomy as Other). [53] use Bookinfo 8, an online book store application following MSA along with the hotel reservation booking application from DeathStartBench 9 [31], which is a benchmark application suite following MSA. [30] also uses benchmark applications from DeathStartBench along with the benchmark application provided in [94]. [91] uses AI-based GPU microservices available in AIbench 10 to create the workload. [48] uses the curated data set available in [65] which consists of 20 open-source projects based on MSA. With contrast to above examples, [88] uses traces from Google Cluster 2019 [78]. These traces provide data on task requests (i.e., CPU, memory, deadline, etc.), and as [88] models microservices as independent components that do not interact with other microservices, the said data set is easily adapted by this work for evaluations.

Hybrid: [34, 35] use a microservices-based e-commerce application know as Sock Shop 11 provided under Apache License 2.0, along with two other synthetic application models (an online EEG tractor beam game and intelligent surveillance application) to create the workload. [6] creates a synthetic workload for simulation-based studies and implements a microservices-based application name "Paper Miner" designed for mining research papers and deploy it on a real-world platform to evaluate the placement algorithm.

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8https://istio.io/latest/docs/examples/bookinfo/
9https://github.com/delimitrou/DeathStarBench/tree/master/hotelReservation
10https://www.benchcouncil.org/aibench/index.html
11https://microservices-demo.github.io/
6.3 Research Gaps

Based on the analysis of existing works presented in Table 6, we identified the following gaps related to the evaluation of placement algorithms developed for microservices-based application placement within Edge/Fog environments.

1. Lack of use in practical test-beds is one of the prominent drawbacks of currently used evaluation approaches. The majority of the available works use numerical evaluations or simulations to evaluate the performance of their placement policies but fail to validate them on real test-beds. Thus, overheads related to orchestration tasks (i.e., service discovery, load balancing, auto-scaling etc.), failure characteristics, resource contention among microservices, etc., are not accurately captured. Moreover, the suitability of the Edge/Fog devices to act as the placement engine that runs the algorithms is not evaluated in practical settings.

2. As Edge/Fog computing paradigms are still relatively new and yet to be adopted by the service providers, simulators play a significant role in evaluating placement policies. However, this requires a standard open-source simulator for use among the research community and continuous improvements through collaboration. As microservices-based application placement in Fog environments is still in its infancy, we see the increased use of custom simulators due to the lack of open-source simulators that capture all related aspects of the microservice orchestration.

3. Lack of real-world traces or actual implementations of applications for the deployment within test-beds is another significant gap in current research. The existing benchmark applications do not include IoT applications, making it harder to capture their characteristics accurately.

7 FUTURE RESEARCH DIRECTIONS

Based on the research gaps identified in previous sections, we propose future directions for microservices-based IoT application scheduling in Edge/Fog environments.

**Dynamic Scheduling Algorithms** - To maintain application QoS under the dynamic nature of the Fog infrastructure and fluctuating workloads, application scheduling algorithms must adapt and make the decisions accordingly. Algorithms can exploit the independently deployable nature of the microservices, which adds dynamic behaviour to them through auto-scaling, migration, proactive redundant placements, Fog-Cloud balanced usage, etc. To this end, the placement techniques can benefit from AI-based techniques such as evolutionary algorithms and ML techniques such as Reinforcement Learning that can adapt to dynamic environmental changes.

**Microservice orchestration platforms for Edge/Fog** - For the evaluation of scheduling policies within Cloud environments, commercial platforms such as AWS, Google Cloud, and Microsoft Azure are available. As Edge/Fog computing is still in its early stages of industrial adaptation, current research uses small, custom-built test beds. However, they lack support for large-scale experiments, thus failing to capture important aspects related to MSA such as distributed, location-aware deployments, load balancing, reliability, security and interoperability of services within the large-scale IoT ecosystem. Moreover, they should reflect novel technologies (i.e., container orchestration, service mesh, monitoring tools, overlay networks, etc.). Hence, scalable and extensible container orchestration platforms for Edge/Fog environments should be implemented for research purposes.

**IoT workloads/ benchmarks related to MSA** - Lack of microservices-based IoT workload traces from large-scale deployments and benchmark IoT applications that follow MSA hinder the evaluation of placement policies considerably. Enterprise workload traces of IoT applications can be used to derive accurate data related to request volumes, patterns, diversity in usage of services,
etc. Collecting such data over a long time within large-scale IoT deployments and making them accessible to the research community is significant for accurately evaluating placement algorithms.

**Security-aware scheduling** - Data privacy is one of the main concerns of data-driven IoT applications. Distributed deployment of microservices across Fog-Cloud, along with the vulnerability of open microservice interfaces, poses a considerable security threat to sensitive data transmission and processing. The independently deployable nature of microservices enables the migration of microservices easily across federated Fog environments and between Fog and the Cloud. However, placement algorithms have to incorporate data privacy and security threats related to such migrations in making deployment decisions.

**Resource contention handling** - Due to concurrent execution of multiple containers within the same edge device, resource limitation in such devices and complex interaction patterns of the microservices, resource contention among microservices can affect application performance negatively. The development of intelligent algorithms that can proactively identify resource contentions during microservice placement, dynamically auto-tune container parameters or migrate containers across the Fog-Cloud continuum has the potential to mitigate this challenge.

**Observability and monitoring driven maintainance** - Deployment of microservices-based IoT applications creates a distributed system of many microservice instances that can be dynamically created and destroyed. Observability and monitoring can be used to detect performance anomalies within such systems. This requires distributed tracing, monitoring and analysis of the system at both application and platform levels, which would create massive amounts of data of different metrics, logs and traces. This poses a big data analysis challenge where data mining and machine learning techniques can be integrated with the placement policy to make performance-aware decisions in handling performance anomalies and failures within the system.

8 SUMMARY

In this paper, we discussed IoT applications designed and developed using MSA and their scheduling within Edge and Fog computing environments. We conducted a comprehensive background study and identified four critical aspects of microservices-based application scheduling: modelling of MSA, application placement, microservice composition and performance evaluation. We proposed taxonomies for each of the aspects, highlighting features related to MSA. Moreover, we analysed and discussed current literature under each taxonomy and identified research gaps. Finally, we compiled future research directions to improve the scheduling of microservices-based IoT applications in Edge and Fog computing environments.

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