Decentralized Edge-to-Cloud Load-balancing: Service Placement for the Internet of Things

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Abstract—The Internet of Things (IoT) has revolutionized everyday life and expanded the scope of smart services to a broad range of domains. In ubiquitous environments, fog computing has emerged leveraging the resources in the edge-to-cloud continuum to improve the quality of service, while reducing the traffic on cloud infrastructure and networks. In such a distributed ecosystem with heterogeneous resources of various sizes and inherent dynamics such as varying service demand over time, managing resources and services is a major challenge. This paper studies two optimization objectives and formulates a decentralized load-balancing problem for IoT service placement: (global) IoT workload balance and (local) quality of service, in terms of minimizing the cost of deadline violation, service deployment, and unhosted services. The proposed solution, EPOS Fog, introduces a decentralized multi-agent system for collective learning that utilizes edge-to-cloud nodes to jointly balance the input workload across the network and minimize the costs involved in service execution. The agents locally generate possible assignments of requests to resources and then cooperatively select an assignment such that their combination maximizes edge utilization while minimizing service execution cost. Extensive experimental evaluation with realistic Google cluster workloads on various networks demonstrates the superior performance of EPOS Fog in terms of workload balance and quality of service, compared to approaches such as First Fit and exclusively Cloud-based. The findings demonstrate how distributed computational resources on the edge can be utilized more cost-effectively by harvesting collective intelligence.

Keywords—Internet of Things, service placement, load-balancing, edge computing, cloud computing, edge-to-cloud, fog computing, distributed optimization, collective learning, agent

I. INTRODUCTION

The Internet of Things (IoT) has unprecedented impact on how data are shared and processed. Gartner¹ expects the growing number of devices connected to IoT networks to reach 20.8 billion by this year. These devices generate a large volume of data and transmit it to cloud data centers for processing, which results in overloading of data centers and networks. However, despite several advantages of cloud computing as a shared pool of resources and services, some emerging IoT applications cannot work efficiently on the cloud. Applications, such as wind farms and smart traffic light systems, have particular characteristics (e.g., large-scale, geo-distribution) and requirements (e.g., very low and predictable latency) [2].

Running services on the cloud entails challenges: high latency, low bandwidth, privacy and security issues, as well as unexploited resources distributed at the network edges. (i) The centralized nature of cloud computing makes it challenging to process data quickly in terms of involved latency, thereby resulting in high communication delay between the end-devices and remote cloud nodes. (ii) Due to low bandwidth, it is not efficient or even feasible to quickly transmit the high-frequency traffic generated at the network edges across the Internet. (iii) Privacy and security concerns prohibit transferring sensitive data to a remote data center across the public Internet. Maximizing the locality of data storage and processing provides privacy-by-design [3]. (iv) There is a large number of available edge nodes that are generally deployed in less centralized locations compared to centralized cloud centers [4]. The unexploited resources can be utilized, leading to the reduction of the load on data centers and networks.

The challenges mentioned above are tackled by the introduction of edge computing that brings the computation, storage, and networking close to the network edges where the data is being generated [5]–[9]. There are, however, use cases, where the cloud computing provides advantages over the edge paradigm, such as storing long-term collected data for cumulative analytic purposes. Hence, despite several differences between resources at the edge and the cloud, they complement each other and are often used in combination. Fog computing is a system-level architecture that utilizes the resources along an edge-to-cloud hierarchy (i.e., fog continuum [2], [10] to reduce traffic on the network and improve quality of service (QoS) [10]. Although the federation from edge to cloud leads to new opportunities, it also raises new challenges [5]. [8]. Distribution of IoT services on available resources is one of the most critical challenges concerning the federation.

IoT service placement, which is the subject of this paper, is a process that aims at the placement of services on the edge-to-cloud resources, to adhere to the QoS expectations of the services. The service placement acts as a middleware service aimed at finding one or more eligible deployments, and

¹In terms of size, type (computing and sensing capability), heterogeneity, distribution and location in the network.
²This paper considers QoS in terms of service execution delay and delay threshold.
is a multi-constrained and NP-hard problem [11]. Moreover, as a result of the dynamic nature of IoT workload [11–13], inefficient service placement and load-balancing result in degradation in QoS [15, 16]. The load-balancing requirements for IoT service placement can be demonstrated via two IoT-based application scenarios: online video broadcasting [17] and health-monitoring systems [16].

Online video broadcasting is intended to provide on-demand and live video content to audiences, no matter where they are located. Any unexpected peak in service requests might result in a disturbance in serving the requests and quality of experience (QoE) deterioration [17]. In this context, the load-balancing service placement provides the flexibility to add or remove servers as demand dictates [18, 19]. In addition, avoiding over-loaded and under-loaded nodes prevents peak load situations, resulting in better responses to the incoming requests of different requirements and service level agreement (SLA).

An IoT-based health-monitoring system, involving wearable devices, wireless body sensor networks, cloud servers, and terminals, is aimed at providing high-quality health care services [20]. Wearable devices monitor vital signs, such as blood pressure, and inform responsible agencies of any abnormality or emergency. In this system, a late notification may lead to serious consequences, such as a late response to the emergency. In addition, overburdened servers may break-down and delay urgent real-time detection [16, 20, 21]. Other than a reduced service delay, the balanced distribution of workload over the network ensures high availability and sufficient capacity of nodes to reliably forward requests to appropriate nodes [16].

Cloud infrastructures are managed in a centralized model and usually deployed in fully controlled environments. However, IoT service provisioning becomes increasingly challenging when considering the distribution of edge-to-cloud nodes and the demand for emerging distributed applications, such as smart traffic light systems [22, 23]. Moreover, depending on the connectivity of the system, IoT network nodes usually have only a partial view of the whole network without centralized control over the whole system [11, 12, 24]. Instead, this paper studies a fully decentralized management strategy, in which network nodes cooperate in allocating available resources.

This research introduces a decentralized load-balancing placement of IoT services in a distributed edge-to-cloud infrastructure, taking into consideration two objectives: achieving a desirable workload balance (global objective) and minimizing service execution cost (local objective). While the design of service placement algorithms for fog computing has received considerable attention in recent years [25–27], agent-based cooperative service placement, aimed at decentralized load-balancing, is a relatively new and timely topic.

The contributions of this work to addressing the service placement problem are as follows:

- The introduction of a model that formalizes the IoT service placement problem in a fog computing (i.e., edge-to-cloud) infrastructure, and two objectives that aim at balancing workload over the network and minimizing the cost of service execution.
- The introduction of a new methodology to locally and autonomously generate eligible deployments for IoT requests by reasoning based on local network context (i.e., system view) and the characteristics of the received requests (i.e., service view).
- The applicability of L-EPOS, the Iterative Economic Planning and Optimized Selections [28], as a general-purpose decentralized learning algorithm, in solving the IoT service placement problem.
- A comprehensive understanding of how several parameters, e.g., workload distribution method, hop-level allowed for service deployment (host proximity constraint), and network size, influence the optimization objectives.
- New quantitative insights about the comparison of three IoT service placement approaches in terms of QoS metrics and workload distribution.
- New insights and quantitative findings on performance trade-offs. They can be used to design effective incentive mechanisms that reward a more altruistic agent behavior required for system-wide optimization.
- A new open dataset for the community containing service assignment plans of agents. It can be used to compare different optimization and learning techniques as well as encourage further research on edge computing for the Internet of Things.

The remainder of this paper is organized as follows. Section II outlines existing proposals in the field of IoT service placement in the edge-to-cloud infrastructure. Section III formulates the IoT service placement problem. Section IV introduces our distributed service placement approach called EPOS Fog. After this, Section V discusses evaluation results regarding the proposed approach, in comparison with Cloud and First Fit approaches. Finally, Section VI presents a summary, along with some open directions for future work.

II. RELATED WORK

Resource provisioning and service placement are major research challenges in the field of cloud computing [29–31]. Given the heterogeneity of computational resources on the edge, cloud service provisioning solutions are not easily applicable in the fog area [32]. In this section, some of the most important recent studies on service provisioning at the edge-to-cloud computing system are discussed.

Souza et al. [33] introduce a QoS-aware service allocation for fog environment to minimize the latency experienced by services with regard to capacity constraints. This objective is modeled as a multi-dimensional knapsack problem aimed at co-minimizing the overall service execution delay and overloaded edge nodes (in terms of processing capacity and energy consumption). A two-step resource management approach is presented by Fadahunsi and Maheshwaran [34], whose goal is to minimize the response time it takes for services to get served

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1Load-balancing refers to the distribution of workload uniformly across network resources to enhance resource utilization and network efficiency [14].

2Available at https://figshare.com/articles/Agent-based_Planning_Package/7806548 (last access: May 2020).
while using as little edge nodes as possible. First, for each device, a home edge and a pool of backup edge nodes are chosen. Their objective is to find the edge nodes such that the latency between them and the device is minimum. Subsequently, upon receiving IoT requests, the requested services are hosted on the allocated edge nodes guaranteeing the desired response time. Another work with the same objective as the researches above \cite{33, 34}, is proposed by Xia et al. \cite{35}. Based on a back track search algorithm and accompanied heuristics, the proposed mechanism makes placement decisions that fit the objective.

Skarlat et al. \cite{36} present a conceptual service placement framework for the edge-to-cloud system. Their objective is to maximize the utilization of edge nodes taking into account user constraints and is solved using a genetic algorithm. The authors introduce the concept of fog cell: software running on IoT nodes to exploit them toward executing IoT services. In addition, an edge-to-cloud control middleware is introduced, which controls the fog cells. Also, a fog orchestration control node manages a number of fog cells or other control nodes connected to it. The later enables IoT services to be executable without any involvement of cloud nodes. Song et al. \cite{15} focus on maximizing number of services that are served by edge nodes while granting the QoS requirements such as response time. They solve the problem using an algorithm that relies on relaxation, rounding, and validation. Similar to the previous works \cite{15, 36}, Tran et al. \cite{37} provide a service placement mechanism that maximizes number of services assigned to edge nodes. The proposed approach leverages context information such as location, response time, and resource consumption to perform service distribution on the edge nodes.

Deng et al. \cite{38} formulate workload allocation in an interplay between edge and cloud nodes. The trade-off between power consumption and transmission delay in the interplay is investigated and solved in approximation. Simulation and numerical results provide a useful guide for studying the cooperation between edge and cloud nodes. A similar approach proposed by Yousefpour et al. \cite{13} formulates the trade-off between monetary cost (cost of processing, deployment, and communication) and service delay in the edge-to-cloud platform. The proposed framework, named Fogplan, periodically minimizes the trade-off. Fogplan monitors the incoming IoT traffic to the edge nodes and decides when it is necessary to deploy or release a service.

Kapsalis et al. \cite{39} present a four-layer architecture that includes the device, hub, fog, and cloud layers to manage the resources in an IoT ecosystem. The hub layer acts as a mediator between the device layer and the other layers. The fog layer is responsible for service management and load-balancing that applies a score-based function to decide which host is more suitable for each service. For this purpose, the fog layer profits context information such as nodes’ current utilization, battery level, and latency. Xu et al. \cite{40} propose another load-balancing resource allocation method called DRAM. DRAM first allocates network resources statically and then applies service migration to achieve a balanced workload over edge nodes dynamically. Donassolo et al. \cite{41} offer an Integer Linear Programming (ILP) formulation for IoT service provisioning problem, taking into consideration two objectives: minimizing deployment cost (comprising of the costs of processing, memory, and data transfer) and increasing service acceptance rate. The proposed solution uses Greedy Randomized Adaptive Search procedures \cite{42}, which iteratively optimize the provisioning cost while keeping a load-balancing between network nodes.

Despite the solid contributions in the aforementioned studies on IoT service placement, the proposed approach in this paper is distinguished as highly decentralized (Novelty 1) and is designed for scalable IoT networks. Furthermore, to our knowledge \cite{43}, most of the existing resource management schemes \cite{13, 15, 33, 39, 44} only study one objective (e.g., load-balancing, minimizing monetary cost) in the context of IoT service provisioning. In contrast, the present research studies two opposing objectives (Novelty 2) that can be extended to account for any criteria regarding the preferences of users or service providers such as energy-saving. Moreover, contrary to this research, the approaches \cite{40, 41} presented for the purpose of load-balancing neglect the costs related to the deadline violation which is critical for delay-sensitive IoT services. Table. 1 presents an overall comparison of the related studies and the proposed work.

| Reference | Heterogeneity | QoS | Load-balance | Distributed | Multi-Objective |
|-----------|---------------|-----|--------------|-------------|-----------------|
| Souza et al. \cite{33} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Fadahunsi et al. \cite{34} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Xia et al. \cite{35} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Skarlat et al. \cite{36} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Song et al. \cite{13} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tran et al. \cite{37} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deng et al. \cite{38} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Yousefpour et al. \cite{13} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Kapsalis et al. \cite{39} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Xu et al. \cite{40} | ✓ | ✓ | ✓ | ✓ | ✓ |
| Donassolo et al. \cite{41} | ✓ | ✓ | ✓ | ✓ | ✓ |
| EPOS Fog | ✓ | ✓ | ✓ | ✓ | ✓ |

**III. PROBLEM FORMULATION**

We define the load-balancing IoT service placement problem, as follows: given a set of IoT service requests and their requirements (e.g., processing power/CPU, memory, storage, and deadline) and a set of edge-to-cloud nodes and their capabilities (e.g., CPU, memory, and storage), find a mapping between the requests and the available nodes (i.e., service placement plan) considering two objectives: workload balancing across the edge-to-cloud nodes and minimizing the cost of service execution with minimal information about the nodes in the network. This section provides insights into the problem; first, fog computing infrastructure and IoT service model are defined and then, the problem formulation is explained.

\[1\] The proposed solution handles heterogeneity of devices without assuming any particular type of node or network \cite{9}. 

**TABLE I. FEATURES OF THE CITED PAPERS IN THE LITERATURE IN COMPARISON WITH EPOS FOG.**
A. Fog computing: infrastructure and services

Fig. 1 shows the general architecture for the fog computing environment. The lowest layer of the edge-to-cloud architecture is the Things layer, where the IoT end-devices (such as mobile phones, sensors, smart wearable devices, and smart home appliances) are located. These physical devices often have low computational power, and are distributed in different geographic locations [45]. Hence, they are connected to the upper layers in order to get their services executed. The next lower layer serves as the edge computing environment. This layer involves edge devices such as WiFi access points and home switches. The top layer represents the cloud computing environment, which consists of large-scale data centers and third-party cloud servers usually physically far from the Things layer. The fog continuum, where fog computing occurs, expands from the edge network to the cloud layer (i.e., edge-to-cloud) to expand the computational capabilities of cloud computing across the fog [2], [9]. As the nodes that reside in the fog continuum cooperate as a universal system to execute services, they are referred to in this paper as fog nodes, unless stated otherwise [46], [47].

An IoT application may be composed of a set of interrelated modules named service. These services such as authentication and encryption are normally implemented as virtual machines (VMs) and containers that can run in different locations [13], [32]. Since containers share host operating system, they are lightweight and offer lower set-up delay compared to VMs [48]. IoT services can be requested from any edge-to-cloud node, and some are delay-sensitive and have tight delay thresholds (i.e., deadline), while others are delay-tolerant. Consequently, to satisfy their QoS requirements, such services may need to run close to the data sources (e.g., at the edge layer) or may be deployed farther from the data sources (e.g., in the cloud) [13]. Heterogeneous fog nodes, depending on their specification and capacity (e.g., processing power and storage space), could host requested services. In the present work, it is assumed that IoT services can be run independently (i.e., single-service application) and are implemented in the form of containers. As future work, it is interesting to examine how the dependencies within multi-service applications affect the performance results.

B. Edge-cloud system model

This section presents the notations and variables used in the problem formulation. As demonstrated in Fig. 1 a physical network is modeled as an undirected graph denoted by \( G = (V; E) \), where \( V \) indicates the set of edge-to-cloud nodes belonging to the different layers, and \( E \) indicates the edge-set, including the logical links between them. It is worth noting that \( V = (C \cup F) \), where \( F \) corresponds to the set of fog nodes, and \( C \) includes the cloud nodes. Each node \( f \) is characterized by its available capacity as i) CPU \( P(f) \) in MIPS, ii) memory \( R(f) \) in bytes, iii) storage \( S(f) \) in bytes. Respectively, each service \( a \) has the specific requirements in terms of deadline and resource demands as i) CPU \( P(a) \) in MIPS, ii) memory \( R(a) \) in bytes, iii) storage \( S(a) \) in bytes.

IoT service requests reach the nodes via a local area network (LAN). The receivers, i.e., associated fog nodes, are responsible for deciding on where to place and execute the received requests. For a requesting node, an associated fog node is defined as a node (e.g., switch, router, and server) that acts as a portal for the requester to connect to the IoT network and is directly accessible to that node. The solution to the service placement problem is a service placement plan that contains placement decisions (i.e., binary variables), which place each service either on a fog node or on a cloud node. The binary variables \( x_{i,j} \), \( x_{i,j} \), and \( x_{i,k} \) denote whether service \( a_i \) has to be placed on the associated fog node \( f_j \) or the non-associated fog node \( f_j \) (i.e., other neighboring nodes) or the cloud node \( c_k \), respectively. We denote the initial configuration of the service \( a_i \) on the fog node \( f_j \) with \( \pi_{i,j} \), which indicates whether the node \( f_j \) currently hosts the service. These binary variables are input to the optimization problem to find future placement for requested services. The notations used in this document are listed in Table. II.

C. Objectives and constraints

This research formulates the load-balancing IoT service placement problem using two objective functions consist of MIN-COST and MIN-V AR. The MIN-COST function aims at minimizing the cost of accomplishing requested services arising from deadlines violation rate, unhosted services (as the QoS requirements) and imposed deployment traffic on the network. The MIN-V AR function intends to minimize the utilization variance among edge-to-cloud nodes as a measure of workload balance across fog continuum. The problem is formulated below following the two stated functions and problem constraints to be satisfied.

1) Cost minimization: Three components are considered as the elements of service execution cost: number of deadline violations, service deployment traffic, and number of unhosted services. The higher the number of unhosted services and deadline violations, the lower the QoS. The more traffic imposed on the network, the lower the network performance. Equation (1) formulates the overall cost involved in executing
### TABLE II. A OVERVIEW OF THE MATHEMATICAL NOTATIONS.

| Meaning | Notation |
|---------|----------|
| **Network** | |
| Number of fog nodes | $|F|$ |
| Number of cloud nodes | $|C|$ |
| Number of network nodes | $N = |F| + |C|$ |
| Link delay between node $i$ and $j$ | $\ell_{i,j}$ |
| **Cloud** | |
| Set of cloud nodes | $C$ |
| Cloud node $k$ | $c_k$ where $k \in \{1, \ldots, |C|\}$ |
| Processing capacity of $c_k$ (in MIPS) | $P_{c_k}$ |
| Memory capacity of $c_k$ (in bytes) | $R_{c_k}$ |
| Storage capacity of $c_k$ (in bytes) | $S_{c_k}$ |
| **Fog** | |
| Set of fog nodes | $F$ |
| Fog node $j$ | $f_j$ where $j \in \{1, \ldots, |F|\}$ |
| Processing capacity of $f_j$ (in MIPS) | $P_{f_j}$ |
| Memory capacity of $f_j$ | $R_{f_j}$ |
| Storage capacity of $f_j$ | $S_{f_j}$ |
| **Service** | |
| Set of services $A$ | |
| Service $i$ | $a_i$ where $i \in \{1, \ldots, |A|\}$ |
| CPU demand of service $a_i$ (in MIPS) | $P_{a_i}$ |
| Memory demand of service $a_i$ (in bytes) | $\bar{R}_{a_i}$ |
| Storage demand of service $a_i$ (in bytes) | $\bar{S}_{a_i}$ |
| Expected response time for service $a_i$ on $f_j$ | $\tau_i,f_j$ |
| Deadline for $a_i$ | $\tau_i$ |
| Traffic arrival rate to $f_j$ for $a_i$ (in MIPS) | $z_{i,j}$ |
| Processing time for service $a_i$ hosted on $f_j$ | $p_{i,j}$ |
| Waiting time for service $a_i$ | $w_i$ |
| Deadline violation of service $a_i$ hosted on $f_j$ | $\delta_{i,j}$ |
| **Binary Variables** | |
| Binary decision for $a_i$ on associated node $f_j$ | $x_{i,j}$ |
| Binary decision for $a_i$ on non-associated node $f_j$ | $x_{i,j}$ |
| Binary decision for $a_i$ on cloud node $c_k$ | $x_{i,k}$ |
| $a_i$ is currently hosted on $f_j$ | $\pi_{i,j}$ |
| **Plan** | |
| Number of plan generations (iteration) | $t$ |
| Service placement plan $q$ | $\delta_q$ |
| Set of possible plans for node $f_j$ | $\Delta_j$ |
| Number of possible plans | $|\Delta_j|$ |
| Selected plan for node $j$ at iteration $t$ | $\delta_{t,f_j}$ |
| Binary vector of possible plan $\delta$ | $\chi_{\delta}$ |
| Utilization vector of possible plan $\delta$ | $\nu_{\delta}$ |
| Predicted utilization variance of plan $\delta$ | $\sigma_{\delta}$ |
| Realized utilization variance of plan $\delta$ | $\delta_{\delta}$ |
| **Cost Functions** | |
| Cost of deadline violation for plan $\delta$ | $O_{\tau,\delta}$ |
| Cost of service deployment for plan $\delta$ | $O_{\delta}$ |
| Cost of un-hosted services for plan $\delta$ | $O_{\delta}$ |
| Total cost for plan $\delta$ | $O_{\delta}$ |
| Local cost function for global plan at iteration $t$ | $L_{g,t}$ |
| Global cost function for global plan at iteration $t$ | $G_t$ |
| Weight controller for global and local costs | $\lambda$ |

The service placement plan $\delta$.

\[
O_{\tau,\delta} = (O_{\tau,\delta} + O_{\delta,\delta} + O_{\delta,\delta})
\]

where $O_{\tau,\delta}$, $O_{\delta,\delta}$, and $O_{\delta,\delta}$ specify the deadline violation cost, the services deployment cost, and the cost of un-hosted services, respectively.

### Cost of deadline violation

The response time for an IoT service is defined as the time span between the moment an end-device sends the service request and the moment it receives the first response for the request. We need to check if the response time ($e_{i,j}$) for the service $a_i$ assigned to the fog node $f_j$ meets the delay threshold $\tau_i$ defined in SLA. The binary variable $\delta_{i,j}$ indicates the violation of the service deadline as follows.

\[
\delta_{i,j} = \begin{cases} 
0 & \text{if } e_{i,j} = \tau_i \\
1 & \text{otherwise}
\end{cases}
\]

As shown in Equation (3), expected response time for any services results from two metrics [13], [32]: waiting time and processing time:

\[
e_{i,j} = w_i + p_{i,j}
\]

where $w_i$ indicates the *waiting time*, which accounts for the time already passed between receiving the service request $a_i$ and deciding on its placement, and $p_{i,j}$ accounts for the *processing time* of the request. The processing procedure in fog node $f_j$ for service $a_i$ can be viewed as an M/M/1 queuing system [29], [50]. If the traffic arrival rate (in MIPS) to fog node $f_j$ equals to $z_{i,j}$ and the processing capacity (in MIPS) of $f_j$ equals to $P_{f_j}$, the computational delay (waiting time at the queue plus service time) is as follows.

\[
p_{i,j} = \frac{1}{P_{i,j} - z_{i,j}}
\]

\[
z_{i,j} = \sum_{a \in A} p_{a,i} \pi_{i,j}
\]

The queuing system at the fog node $f_j$ is stable if the following constraint is met.

\[
z_{i,j} < P_{f_j}
\]

It is possible that the processing of a service occurs at a fog node other than associated fog node (i.e., other neighboring nodes or cloud nodes). Considering Fig. 2, assume the end-device $m$ is associated with the fog node $f_j$. The service $a_i$ is supposed to be executed on the neighbor fog node $f_j$ or the cloud node $c_k$. As a consequence, the required data for processing must be transferred from $m$ to the fog node $f_j$, and then, to $f_j$ or $c_k$ for processing. Hence, we need to account for the communication delay between the end-device and the destination node. The average propagation delay between the source node $n$ and the destination node $f_j$ is represented by $l(m,n)$. Note that IoT requests are input to associated fog nodes, which are usually located in the vicinity of end-devices, through a local area network (LAN). While the requests that are dispatched from fog nodes to cloud servers through a wide area network (WAN) that covers a large geographic area from edge to core network. Thus, the LAN communication delay could be omitted compared to the WAN [13], [38]. Accordingly, the response time is as follows [32], [38].
the cloud is omitted. Equation (9) calculates this cost [13].

\[
\begin{align*}
\epsilon_{i,j} &= \left( \frac{1}{P_{t,j} - z_{t,j}} + w_i \right) x_{i,j} + \\
&\left( \frac{1}{P_{j',j'} - z_{j',j'}} + 2 f_{j',j'} + w_i \right) x_{i,j'} + \\
&\left( \frac{1}{P_{c,k} - z_k} + 2 f_{j,k} + w_i \right) x_{i,k}
\end{align*}
\]  

(7)

As a result, the communication cost for service deployment on unlimited storage space and can host services for a long time. and deployed locally. Note that a cloud center theoretically has a service not hosted locally, the service must be downloaded deployed service is low, its host node may release that service deployment, from cloud to fog nodes. When the demand for a

Cost of service deployment

Deployment cost is the communication cost of service deployment, from cloud to fog nodes. When the demand for a deployed service is low, its host node may release that service to save more space. So, if a fog node accepts requests for a service not hosted locally, the service must be downloaded and deployed locally. Note that a cloud center theoretically has unlimited storage space and can host services for a long time. As a result, the communication cost for service deployment on the cloud is omitted. Equation (9) calculates this cost [13].

\[
O_{\delta,\delta} = \sum_{j=1}^{C \cup F} \sum_{i=1}^{A} x_{i,j} \tau_{i,j} S_{a,i}
\]  

(9)

where \(x_{i,j}\) denotes whether service \(a_i\) has to be placed on the node \(f_j\), the binary variable \(\tau_{i,j}\) indicates if the node \(f_j\) currently hosts the service \(a_i\), and \(S_{a,i}\) is the required amount of storage resource for deploying the service \(a_i\) on the node \(f_j\).

Cost of unhosted services

If a service placement plan cannot serve all of the requests received by network nodes due to insufficient resources, this is defined as an SLA violation. To measure this, we count the number of services that have no hosts, according to Equation (10).

\[
O_{a,\delta} = \sum_{i=1}^{A} \left( 1 - \sum_{j=1}^{C \cup F} x_{i,j} \right)
\]  

(10)

2) Workload balance: The second objective function consists in minimizing utilization variance among network nodes to achieve an equitable load sharing across the network. On the one hand, utilizing fog nodes can improve resource efficiency at the edge networks and help the execution of delay-sensitive IoT services. On the other hand, load balancing by avoiding bottlenecks (e.g., overloads and low-loaded nodes) leads to a flexible network. As a consequence, the need for horizontal and vertical scaling up (including service migrations) due to system changes (e.g., peak times, node failures) is reduced. [22], [40], [51].

Network nodes have different capacities, and the workload allocated to them must not exceed this capacity. Thus, the workload-to-capacity proportion is applied to formulate the utilization of the nodes. Equation (11) shows how balanced the workload is distributed among all nodes.

\[
\sigma_\delta = \frac{1}{|F| + |C|} \sum_{j=1}^{C \cup F} \left( x_{i,j} - \frac{\sum_{j=1}^{C \cup F} x_{i,j}}{|F| + |C|} \right)^2
\]  

(11)

Note that the resource demands for a service placed on a certain node \(f_j\) must not exceed the available resources (i.e., processing power, memory, and storage) of that node. The following three conditions ensure the capacity constraints.

\[
\sum_{i=1}^{A} P_{a,i} x_{i,j} < P_{t,j}
\]  

(12)

\[
\sum_{i=1}^{A} R_{a,i} x_{i,j} < R_{t,j}
\]  

(13)

\[
\sum_{i=1}^{A} S_{a,i} x_{i,j} < S_{t,j}
\]  

(14)

Finally, the placement of services is constrained so that each service must be hosted on at most one computational resource, i.e., the fog node \(f_j\), or the cloud node \(c_k\). Formally,

\[
0 \leq \sum_{j=1}^{C \cup F} \sum_{i=1}^{A} x_{i,j} \leq |A|
\]  

(15)

Note also that the memory and processing costs in the fog nodes are assumed to be the same as the cloud. Hence, we do not account for these costs in the objective functions.

3) Putting it all together: In order to perceive the general problem of this paper, the two proposed objective functions are combined into one summation as follows.

\[
\min(O_{c,\delta} + \sigma_\delta) = \min(O_{\tau,\delta} + O_{a,\delta} + O_{a,\delta} + \sigma_\delta)
\]  

(16)

Subject to Equations (6), (12) - (15).

The above formulation places IoT services while minimizing the service execution cost and ensuring a satisfactory load-balancing among fog nodes. Emphasized that, in some scenarios, a particular cost may be the preference factor in this summation. Hence, we propose to use a weight controller (i.e., \(\lambda\)) for these factors, which leads to a more general and
adapted solution supporting various circumstances. The next section introduces such a mechanism that controls the trade-off between the two objectives.

IV. COOPERATIVE SERVICE PLACEMENT FOR IoT

This paper introduces EPOS Fog, an agent-based load-balancing mechanism for IoT service placement, as the means to meet a local (individual) and a global (system-wide) objective: (i) MIN-COST and (ii) MIN-VAR. The former aims at reducing the cost of service execution formulated in Subsection III-C1. In the direction of keeping the cost at a minimum, each node autonomously generates its plans, in which it greedily makes host choices only concerning the fulfillment of its received requests and satisfying their QoS. From that perspective, each node assigns the requests to its local neighboring nodes in favor of reducing the local cost, regardless of the impact of the assignments on the other nodes or the state of the entire system. The latter purposes at minimizing utilization variance among network nodes formulated in Subsection III-C2] as a measure of load uniformity. For this purpose, network nodes collaborate and exchange information with nearby nodes to reach a global state, i.e., load-balancing.

There is no centralized monitor in the IoT network, and EPOS Fog uses distributed agents to solve the placement problem. Each fog/cloud node is equipped with a software agent that autonomously generates a predefined number of possible service placement plans determining which service is deployed on which host in the neighborhood of the agent. Possible plans represent service placement flexibility, and each may cause a varied level of cost according to Equation (1). Each agent ranks its possible plans, from low to high, according to the cost. For example, a plan including further hosts (proximity in terms of hop count from source node) costs higher than a plan with closer hosts. This is because the execution of requests in further hosts imposes more traffic on the network and may result in more violations of deadlines.

Agents are structured in a self-organized tree topology over which they perform collective decision-making. They make coordinated selections of their possible plans considering the objectives. The process of generating and selecting placement plans repeats, agents, self-adapt their choices, and collectively learn how to optimize the objectives. Finally, the collective outcome of the choices, i.e., the global service placement plan, is the aggregation of the selected plans for each agent.

A. Proposed solution

In the above overview, an overall understanding of the proposed load-balancing strategy has been presented. Subsequently, this subsection discusses the strategy details in the view of the two aforementioned objectives.

IoT devices generate service requests and submit them to the fog nodes for placement decisions and execution. It is assumed that the receiver nodes/agents know the requirements of the received requests and the capabilities of their neighboring nodes. All receiver agents take part in a two-step procedure consists of (i) generation of local plans and (ii) plan selection. In the first step, each agent generates a set of possible plans, and in the second step, the agent selects one of them. Finally, according to the selected plan, the agents forward the received requests to the selected hosts for execution. This procedure is repeated for all new requests that enter the network. Fig. 3 shows the global view of the proposed service placement mechanism, which is elaborated below.

![Global view of EPOS Fog](image)

1) Generation of local plans: This section illustrates how agents can locally and autonomously generate service placement plans for requested IoT services respecting the local objective. Agents prefer to minimize their local cost, which concerns deployment traffic, service deadline violations, and unhosted services. The motivation here is that if the nodes closer to data sources (i.e., service requesters) can be selected as hosts, deadline violations and imposed traffic on the network are minimized, resulting in higher QoS.

Each agent, upon receiving IoT requests, locally generates a certain number of assigning/mapping “requests to resources” called possible service placement plan, concerning the local cost as Equation (1). As shown in Fig. 3, each agent, for
the plan generation, reasons locally based on its view of the system and requested services. For each agent, the system view represents a profile of the neighboring nodes of the agent and their features (such as capacity and distance), and the service view shows a profile of the services requested from it and their specifications (such as demands and deadline). Possible plans are the representation of agents’ possible options, that encode selected hosts in the form of a binary vector, and resource utilization in the form of a real-valued vector. The structure of a typical plan whose specifications are described below is shown in Fig. 4.

- **Binary vector:** An n-dimensional (n refers to the number of nodes in the network) 0-1 value vector represents the mapping of requested services to the available resources in the network.
- **Utilization vector:** A 2n-dimensional real-valued vector that represents the resource utilization as the ratio of the assigned load to the capacity for each node. In this manner, we account for the heterogeneity in the capabilities of these nodes. Memory and CPU are considered as two metrics for the load; One half of the vector is appointed to CPU and the other half to memory. Although the vector can be extended to account for other metrics such as storage. However, for simplicity and to keep the size of the vector in minimal, it is omitted as future work.

Algorithm 1 illustrates the procedure for plan generation. Upon receipt of requests, agents run this procedure every μ second. As a matter of design, the agents make a greedy decision to grant closer fog resources to the requests that have spent a high waiting time for deployment, with respect to their deadline.

To generate one possible plan, each agent arranges its received requests, from low to high, in terms of the difference between the service deadline and its waiting time \( \tau_i - w_i \) (line 8). Subsequently, the agent randomly chooses the required number of available neighboring nodes as candidate hosts (line 9). It then arranges these hosts ascending, according to their distance (in terms of hop count) from itself (line 10). After that, the agent assigns one to one of the sorted requests to the sorted hosts while keeping the placement constraints and the heterogeneity of the hosts (Equations (6), (12) - (15)) into consideration (lines 13-19). It is assumed that up to 95% of the capacity of each node is allocated to the requested services, and the rest is reserved for maintenance. Finally, lines 20-24 determine the service assignment to the closest cloud node if there is not enough capacity at the candidate host in line 13. Meanwhile, utilization and binary vectors are updated accordingly. The first part of the utilization vector, i.e., CPU criterion, by lines 17 and 22, the second part of the utilization vector, i.e., memory criterion, by lines 18 and 23, and the binary vector in lines 19 and 24 are updated. For each node, the resource utilization is measured as the ratio of the assigned load to the capacity. Note that the workload accounts for the already assigned workload (which is indicated with bar mark in Algorithm 1) plus the new assigned workload to reach a better balance over the network. After generating a certain number of plans (which is controlled by loop for in line 5), the agent calculates the local cost for them and orders accordingly.

The possible plans are released as open dataset² for the broader community to encourage further research on distributed optimization and learning edge-to-cloud computing.

2) **Plan selection:** Traffic dynamics [11], [12] inherent to IoT applications motivate a balanced service placement throughout the network. As a result, more flexible assignments can be applied under various future scenarios, such as node failures and peak demand periods [52], [53], leading to a higher QoS and a more robust network. In this perspective, the global objective for optimizing the placement of IoT services, i.e., MIN-VAR, aims at minimizing utilization variance among the network nodes, as a measure of load-balancing and peak-shaving. The MIN-VAR objective function, as shown in Equation (17), is a quadratic cost function [54] that requires
Algorithm 1 Local plans generation

Input:
A: set of requested services; N: set of network nodes; 
Output:
\(\Delta\): set of possible plans; 
5: for \((q = 1\) to \(|\Delta|\)) do
   Initialize \(\Delta_q\); 
   Sort \(A\) in the order of \((u_i - w_i)\) from low to high; 
   \(\Delta\) \(\leftarrow\) select \(|A|\) neighboring nodes from \(N\); 
   Sort \(H\) in terms of proximity from low to high; 
   \(i, j \leftarrow 0;\)
   while \((A\) is not empty) do
      if \((f_j\) satisfies the constraints based on Equations \([6, 12, 14]\)) then
         Update \(\delta\): 
         \(V_{q}[j] \leftarrow (P_{a,i} + P_{f,j})/P_{t,j};\)
         \(V_{q}[j + n] \leftarrow (R_{a,i} + R_{f,j})/R_{t,j};\)
         \(X_{i,j} \leftarrow 1;\)
         Update the capacity for \(f_j;\)
      else if \((\) the cloud node \((c_k)\) has enough capacity\) then
         Update \(\delta\): 
         \(V_{q}[k] \leftarrow (P_{a,i} + P_{f,k})/P_{t,k};\)
         \(V_{q}[k + n] \leftarrow (R_{a,i} + R_{f,k})/R_{t,k};\)
         \(X_{i,k} \leftarrow 1;\)
      end
   end
   Calculate \(O_{a,b}\) according to Equation \([10]\); 
   Remove \(a_i\) from \(A\) and \(f_j\) from \(H;\)
   \(i++;\) \(j++;\)
end while
30: Calculate \(O_{a,b}\), \(O_{r,s}\) according to Equations \([6, 9]\); 
   Calculate \(O_{r,s}\) according to Equation \([4]\).
end for
35: Sort \(\Delta\) in the order of \(O_{a,b}\) from low to high;
Return \(\Delta\).

coordination among agents’ selections. When the autonomous agents locally generate multiple (alternative) placement plans, the placement coordination problem turns out to be a multiple-choice combinatorial optimization problem, which is NP-hard [55].

\[
\min\left(\frac{1}{|F| + |C|} \sum_{j=1}^{F+C} \left( \frac{z_{t,j}}{P_{t,j}} - \frac{z_{l,j}}{P_{l,j}} \right)^2 \right) \quad (17)
\]

EPOS Fog employs the I-EPOS system [28, 56], as a fully decentralized and privacy-preserving learning mechanism for coordinating the planning of IoT requests. I-EPOS has been studied earlier in load-balancing of bike-sharing stations [28] and in demand-response of residential energy consumption [56–58]. This research contributes a new application of I-EPOS in fog service placement and provides fundamental insights on how the provisioning of IoT services can be modeled as a multiple-choice combinatorial optimization problem.

As a result of the plan generation step, each agent comes with a certain number of possible plans and their corresponding cost. In the second step, all agents collaborate to choose their selected plans from these possible plans in terms of two objectives; MIN-COST and MIN-VAR. Agents are self-organized in a tree overlay topology as a way to structure their interactions with which they perform a cooperative optimization. The optimization is performed by a set of consecutive learning iterations consisting of two bottom-up (leaves to root) and top-down (root to leaves) phases. At each iteration, agents change their selected plans combining the two objectives in a weighted sum of costs as Equation \((18)\) to reduce the costs compared to the previous iteration. Linking the objectives using a weighted summation can suit the solution to various circumstances regarding the network status and QoS preferences.

\[
\lambda L^t + (1 - \lambda) G^t \quad (18)
\]

where \(\lambda \in [0, 1]\), and the higher value of the weight expresses a stronger preference toward minimizing the corresponding objective. When \(\lambda = 1\) agents make random selections, in terms of global cost while the minimization of local cost is maximized.

The cost functions take as an argument the global plan at the iteration \(t\)-1, which is the sum of all utilization vectors in the agent network. The global cost function (MIN-VAR objective) is formulated as follows:

\[
G^t = \sigma(g^t), G^t \in \mathbb{R} \quad (19)
\]

The following cost function minimizes the average cost (MIN-COST objective) of all selected plans:

\[
L^t = \min \frac{1}{N} \sum_{j=1}^{N} l(\delta_j), L^t \in \mathbb{R} \quad (20)
\]

where \(l(\cdot)\) extracts the cost of the selected plan \(\delta\) of the agent \(j\) at iteration \(t\).

Regarding I-EPOS termination criteria, the system run-time completes when the global cost does not any longer change, or a certain number of iterations are performed. After the iterations, based on the selected plans, agents propagate their received requests to the selected hosts. Accordingly, the hosts execute the requests while receiving new requests and starting the placement process again for new placements.

In terms of performance, earlier work demonstrates the computational and communication complexity of I-EPOS as well as its superior cost-effectiveness compared to state-of-the-art [28]: (i) Low communication cost achieved via efficient information propagation in a network topology self-organized in a tree structure. (ii) Monotonous rapid learning performance in very few learning iterations. In terms of optimality, I-EPOS reaches solutions close to top- 3% and above in optimization landscapes with over 1M of possible solutions. Recent findings expand the analysis with optimality profiles in large-scale networks [24].

V. Evaluation

Studying the proposed solutions in the context of IoT comes with several significant challenges [59, 60]. The scale and complexity of this system make it infeasible to use a realistic IoT prototype [60, 61], while constructing

1Available at: http://epos-net.org (last accessed: April 2020)
2Further elaboration on the I-EPOS algorithm is out of the scope of this paper and is available on earlier work [28].
a testbed, is complex, costly, and time-intensive. In such a context, mathematical modeling employs graphs to model the relationships between data centers [62], fog infrastructure [63], and load-balancing environments [64]. Hence, in this research, various network topologies are modeled through three well-known graph models that consist of Barabasi-Albert (BA) [65], Watts-Strogatz (WS) [66], and Erdos-Renyi (ER) [67]. More details on the characteristics of these models are presented in Appendix A. Experimental evaluation is performed using a Java software that emulates a network of edge-to-cloud nodes. Besides, graph modeling and analysis are performed using a Java library, i.e., GraphStream [68]. Appendix B outlines the structure and class diagram of the software.

As the input workload, the Google cluster trace 2 is used, which contains data collected from a variety of input workloads on 12500 machines for 30 days. Fig. 5 displays the incoming workload and corresponding requests during the first 130 minutes of the trace in the form of 300-second periods (i.e., profile). For the experiments, workload interval is considered equal to \( \mu \). However, it is interesting to examine the performance of EPOS Fog with different values of these two parameters. In order to have a comprehensive evaluation, the profiles 0-4 have been tested, in which the input workload is highly variable.

Most of the experimental parameters and their corresponding values are listed in Table III Each service request is accompanied by a set of resource requirements that consist of CPU, memory, and storage demands. Similar to the Google cluster, exact numbers of CPU cores and bytes of memory are unavailable; instead, resource demand information is provided in normalized units.1 The cloud and network capacity values in Table III are specified in such a way that there is enough capacity available in the network to respond to all requests received. Note that because the Google trace does not contain any value as a service deadline, 22 delay-sensitive services \[71\], \[72\] are considered as a variety of IoT services, and their deadline values are associated with all input service requests, listed in Table IV.

![GraphStream Diagram](image-url)

**Fig. 5.** 130 minutes of Google cluster trace 69 as input workload and the frequency of incoming requests per 5-min profiles.

### Table III. Experimental settings.

| Experimental Parameter | Choices           |
|-------------------------|-------------------|
| \( \mu \)                | 300 seconds       |
| \( \lambda \)            | \( \lambda \in \{0, 0.1, \ldots, 1\} \) |
| Network topology        | Barabasi-Albert, Watts-Strogatz, Erdos-Renyi |
| Workload dataset        | Google cluster trace |
| Number of agents         | 200, 400, 600, 800, 1000 |
| Number of possible plans per agent | 20 |
| Plan dimension           | 400, 800, 1200, 1600, 2000 |
| Number of iterations     | 40 |
| CPU capacity of network  | 704.0 unit         |
| Memory capacity of network | 792.5 unit       |
| Storage capacity of network | 313.5 unit     |
| Cloud CPU capacity       | 400 unit           |
| Cloud memory capacity    | 500 unit           |
| Cloud storage capacity   | 200 unit           |

### Table IV. IoT services and corresponding allowable deadlines \[71\], \[72\].

| Service                                  | Deadline |
|------------------------------------------|----------|
| Big data file download, off-line backup   | 100s     |
| YouTube, home automation, video surveillance | 10s     |
| Web search, sensor readings              | 1s       |
| Interactive web site, smart building, analytics | 100ms   |
| Broadcast                                | 50ms     |
| Web game                                 | 30ms     |
| Virtual reality, smart transportation, finance, accelerated video | 10ms   |
| Health care                              | 5ms      |
| Augmented reality                        | 2-10ms   |
| Haptics, robotics, real-time manufacturing, self-driving | 1ms    |

The conducted experiments analyze the relationships between the approaches evaluated and the following configuration parameters.

- **Network size (N):** To study the scalability of the proposed work, different numbers of nodes are considered for the network: 200, 400, 600, 800, 1000.
- **IoT workload distribution:** The workload distribution parameter determines the distribution of IoT requests over the network. Though, the availability of openly available datasets about the distribution of requests in real IoT scenarios is scarce \[73\]. Therefore, considering the literature \[27\], \[6\], this paper explores the effect of two different distributions that consist of a random distribution (denoted as Rand in the experimental results \[75\]) and a Beta distribution \[76\] as Beta (2.0, 5.0) on the performance results.
- **Host proximity (H):** This parameter investigates the impact of the distance between source nodes (i.e., service requesters) and corresponding destinations (i.e., hosts) on the evaluated metrics. Different distances in terms of hop counts include: 1-hop (direct neighbors), 3-hop, and \( \infty \)-hop (unlimited). Note that the host proximity constraint is applied in selecting host nodes in the plan generation step (line 9 in Algorithm 1).

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1Available at: [http://graphstream-project.org](http://graphstream-project.org) (last accessed: April 2020)
2Available at: [https://commondatastorage.googleapis.com/clusterdatalabels-2011-2](https://commondatastorage.googleapis.com/clusterdatalabels-2011-2) (last accessed: March 2019).
3Measurements are expressed relative to the capacity of the most powerful machine.
Fig. 6 shows the simulation process of EPOS Fog with respect to the sequence of application of these parameters.

![Simulation procedure with respect to various simulation parameters.](image)

**A. Strategies and Evaluation Metrics**

Three approaches are considered for evaluation and comparisons:

- **Cloud**: This approach assumes that the fog infrastructure is not available, and all services are sent directly to the cloud.
- **First Fit** [32, 77]: In this approach, each node traces the latency of communication link between itself and other nodes, makes a sorted list of its direct neighbor nodes. Then, upon the receipt of each request, the list is checked, and if any node in the list meets the requirements of the request, it is sent to the node. Otherwise, the request is propagated to the cloud.
- **EPOS Fog**: The proposed approach outlined in section IV

In order to show how the proposed service placement approach meets the objectives, the following metrics are evaluated:

- **Utilization variance**: Utilization variance of network nodes measures the workload balance among the nodes. To establish precise measurements for the load-balancing, three parameters of CPU, memory, and overall (CPU along with memory) load are considered.
- **Utilization of the fog infrastructure**: This criterion shows to what extent fog nodes are utilized and is determined as a ratio of the workload placed on the network resources to the capacity of the resources.
- **Average deadline violations**: This metric indicates the ratio of the number of services whose deadlines have been violated.
- **Average service execution delay**: The difference between service deadline and its response time, measured as $|r_j - e_{i,j}|$.
- **Utilization variance error**: This metric measures how far the predicted utilization variance (the results obtained by I-EPOS) is from the realized one (the results of applying the I-EPOS plans on the network), as $|\sigma_i - \hat{\sigma}_i|$. This paper focuses on the relation between this error and the $\lambda$ parameter that regulates the trade-off between the local and global objectives based on which the plan selections are performed. Higher $\lambda$ values decrease the degree of freedom to choose the plans with lower variance, while distribute services mostly across local regions deployed close to data sources. As a result of increasing the number of high-load nodes, the likelihood of capacity constraints violation increases, thereby limiting the load-balancing potential.

**B. Results and discussion**

This section assesses the execution of service placement plans provided by various approaches, i.e., EPOS Fog, First Fit, and Cloud. Due to space limitation, only the results for 200- and 400-node networks, as well as the first and second profiles, are shown.

1) **Utilization variance**: This studied aspect examines how well balanced the workload is distributed on the network. The Cloud approach does not perform any load-balancing by design, and therefore, it is excluded from this evaluation.

In all scenarios, the utilization variance, i.e., global cost, in the First Fit approach is between 40% to 90% higher than the EPOS Fog approach. This is because for First Fit, services are located on direct neighboring nodes where possible. Otherwise, they are forwarded to the cloud. In contrast, for EPOS Fog, the range of hosts is controlled by a host proximity constraint that can distribute services to a broader range of nodes. Fig. 7 illustrates the difference between the utilization variance (i.e., reduction in utilization variance) of EPOS Fog and First Fit for a 400-node network. The detailed figures on utilization variance, are presented in Appendix C.

With respect to EPOS Fog, the following observations can be made. In the case of different topologies, utilization variance of WS is lower than BA up to 37%, and utilization variance of ER is lower than the other two topologies up to 45%. This is due to the different characteristics of these topologies, such as average path length and clustering, which result in different load-balancing level.

In general, for EPOS Fog, increasing the host proximity parameter from one to infinity decreases the utilization variance; the higher the degree of freedom to choose host nodes the more uniform the distribution of workload over the network. In around 90% of the scenarios with random service distribution, the utilization variance is lower than the same scenarios with Beta distribution. This is because it is harder to achieve a balanced distribution when the input workload is not distributed uniformly. Upon considering the workload distribution and host proximity together, it is observed that the difference of utilization variance between a random distribution scenario
and the same scenario with Beta distribution increases with decreasing host proximity. In the case of 1-hop, the difference reaches 65%. This is because, on the one hand, requests are not distributed uniformly with a Beta distribution, and on the other hand, as the host proximity value decreases, the range of the nodes that can be selected as host, becomes limited. However, this is not the case when there is no forwarding constraint (i.e., $\infty$-hop), which results in hosting the services on any distant nodes to achieve a higher balance. Note that these situations are only two cases among 18 configurations (i.e., 11%).

It is worth noting that the utilization variance does not change significantly when comparing the results for networks with 200 and 400 nodes. This indicates that with increasing the number of nodes (with the constant workload and fixed network capacity), the workload balance remains the same, indicating the scalability of the proposed approach.

![Graph showing workload balance improvement](image)

**Fig. 7.** Difference between overall (CPU along with memory) utilization variance of EPOS Fog and First Fit under varied parameters (Profile=1, N=400).

2) **Utilization of the fog infrastructure:** Fig. 8 shows the utilization of network nodes for several scenarios. In each scenario, the nodes are sorted in a descending order according to their utilization value. For the Cloud approach, 100% of placements are in the cloud node, and the fog resources are not utilized. Concerning First Fit, some nodes are used extensively (more than 90% of capacity is occupied), while other nodes have very low load (less than 10% of capacity is occupied). This is an artifact of the service placement strategy in First Fit: despite the free capacity in non-neighboring fog nodes, these available resources are not optimally utilized. EPOS Fog service placement employs fog resources more effectively, leading to reduced cloud utilization. For instance, regarding EPOS Fog [H=3, Rand], EPOS Fog [H=$\infty$, Rand], EPOS Fog [H=3, Beta], and EPOS Fog [H=$\infty$, Beta] in topology ER, it is observed that almost all fog nodes have the utilization in the range [30%, 80%], while the utilization of cloud node is less than 10%.

Given the increasing host proximity parameter in EPOS Fog, network nodes are allowed to select a broader range of fog nodes as host, and therefore, the utilization of these nodes increases while load-balances the network. This higher balanced distribution confirms the results of the previous subsection, i.e., variance reduction due to higher flexibility in host choices. With respect to input profiles, although in both approaches nodes’ utilization increases with a growing workload resulting from subsequent profiles. However, in contrast to First Fit in which nodes’ utilization varies in the range [0%, 100%] for both first and second profiles, EPOS Fog distributes the workload more uniformly, which indicates a significant potential of EPOS Fog as a load-balancer under various input profiles. For instance, in EPOS Fog [H=$\infty$, Beta], nodes’ utilization grows from the range [40%, 65%] in the first profile to the range [60%, 80%] in the second profile. It is worth to be noticed that ER topology provides a more uniform distribution of workload compared to other topologies, confirming the results of Section V-B1, i.e., the improvement of workload balance due to the type of topology.

3) **Average deadline violations and service execution delay:** Because of the theoretically infinite resources of the cloud centers, requested services are executed immediately after submission and do not violate deadlines. Therefore, the Cloud approach is excluded from this evaluation. For the first profile, the average of deadline violations in First Fit is approximately 0.6, which is 1% to 3% higher than EPOS Fog. Moreover, this higher rate increases for the subsequent profiles. Although different topologies have no considerable effect on this criterion in First Fit, however, in EPOS Fog, the deadline violation for ER is slightly lower than WS, and the violation rate for WS is lower than BA.

In order to study the response time of services in more detail, the average execution delay that services experience is assessed. While the delay for the EPOS Fog and First Fit approaches in the first profile is approximately the same, in the second profile, this criterion is 1% to 25% higher in First Fit than in EPOS Fog. This is due to the fact that in First Fit, with increasing the number of requested services and decreased capacity in neighboring nodes, the forwarding of services to the cloud node increases, resulting in higher delay. Increasing the host proximity parameter results in 2% to 17% lower service delay in EPOS Fog compared to First Fit. This is because, with a higher load-balance, the number of overloaded nodes decreases, thereby reducing the service delay and the probability of deadline violated. Moreover, it is interesting to know that even in the scenarios with a value of one for the proximity parameter (i.e., H=1), EPOS Fog provides from 1% to 25% lower delay than First Fit. That is because of the load-balancing strategy of EPOS Fog, which results in a reduced service delay. The reduction in service delay from EPOS Fog to First Fit is depicted in Fig. 9. Detailed results are included in Appendix [C] for more comprehensive comparisons.

Upon considering service execution delay and utilization results together, it is concluded that EPOS Fog can provide both better fog utilization and lower service delay than First Fit. Note that the better performance even enhances in subsequent profiles. This is because, at the beginning, more resources are available, which makes the placement of requests easier for all strategies. However, in subsequent profiles, as the number of requests increases, the placement has a higher impact on the utilization of the nodes.

4) **Utilization variance error:** The error in the utilization variance is measured against different trade-offs in the optimization of local agent preference vs. system-wide load-balance. Given the $\lambda$ values in the range [0, 1], Fig. 10 evaluates the error as the difference between the predicted
Utilization variance and the actual one. Note that the error is provided using the max-min normalized values and the actual values.

Generally, as $\lambda$ increases the error experienced increases. This is because the higher $\lambda$ values lead to agents preferring lower local cost plans, which results in a more overloaded network and a higher probability of high-load nodes. Consequently, the execution of I-EPOS plans in the unbalanced network increases the probability of capacity constraints violation in the overloaded nodes, and therefore prevents the realization of predicted variance. With respect to topology impact, the BA topology shows the highest error rate, and the ER topology presents the lowest error value for the same values of $\lambda$. This is because the ER topology, with short average paths and low clustering coefficients, provides higher load-balancing (as discussed in Section V-B1) than BA, resulting in the lower error. Fig. 10 confirms the significant increase of the error rate for the scenarios with Beta service distribution and (1 and 3)-host proximity values that generally provide the lowest load-balance in comparison with other scenarios.

It is worth noting that by comparing the results obtained from the networks with 200 and 400 nodes, it is observed that by doubling the number of nodes (at a constant network capacity), the error rate is reduced up to 80%. This is because the increasing number of nodes reduces the probability of high-load nodes to a high extent, and thus the predicted variance is significantly realized.

In brief: when agents make plan choices in favor of their individual (local) objective (high $\lambda$ values), collective (global) objective (i.e., utilization variance) is sacrificed and the network is more overloaded. As a result, the planned variance reduction deviates more from the actual one. Reward mechanisms are means to encourage agents to change the choices of $\lambda$ as well as their selected plan in line with a preferred objective. Employing various incentivize mechanisms with respect to the location of nodes in different layers of the network is subject of future work.

5) Summary of findings: A summary of the key findings in the performed experiments is given below.

- EPOS Fog outperforms other approaches in both (i) minimizing the cost of service execution (Fig. 9) to improve the QoS and (ii) load-balancing of input workload (Figs. 7, 13, 14, and 15) to enhance resource utilization and prevent peak load situations.

- EPOS Fog better utilizes edge-to-cloud nodes (Fig. 8) to allocate the resources effectively and reduce data traffic over the network.

- Even though the deadlines in EPOS Fog have lower violated rates than First Fit, though to a very low extent, the delays in service execution are significantly lower in the EPOS Fog (Figs. 9, 16, and 17) compared to First Fit.

- For EPOS Fog, an increasing number of agents (i.e., nodes) in a fixed network capacity decreases global cost and lowers utilization variance error and deadline violation, indicating the scalability of the proposed approach.
The same results are valid for an increase of a host proximity parameter.

- Concerning EPOS Fog, workload distribution and network topology have the potential to improve the objectives even further. Topologies with short paths and low clustering measures such as ER, and uniform workload distributions such as random result in better overall performance.
- The planning the utilization of the network is more effective (lower utilization variance errors for lower λ values that prioritize system-wide optimization over the optimization of local objectives. Fig. 10).

In summary, the advantages of EPOS Fog can be observed under various input workloads and experimental scenarios due to its flexibility on the objectives and better exploring the computation resources at the fog continuum.

VI. CONCLUSION AND FUTURE WORK

Resource provisioning in the evolving IoT infrastructure is crucial for tackling the limitations in cloud-based technologies while meeting a broad range of IoT services requirements. This paper studies how the optimization of IoT service placement using MIN-VAR and MIN-COST objectives improves the performance of IoT services, such as response time, and obtains a balanced distribution of workload while utilizing resources on the network edges. The proposed approach, EPOS Fog, introduces a local plan generation mechanism, and employees I-EPOS, a cooperative plan selection methodology, for the IoT service placement. While the distributed load-balancing resource allocation increases system robustness, the objectives can be extended, e.g., energy-saving or monetary costs.

The extensive experimental findings using real-world input profiles on various networks confirm that EPOS Fog, via a better utilization of edge-to-cloud nodes provides a higher QoS and more balanced distribution of workload over the network, compared to the First Fit and Cloud approaches. These results, under many experimental scenarios, confirm the scalability of EPOS Fog and its applicability to various circumstances.

Future work includes the mobility of the nodes in the network and an improved QoS using social information, such as users’ profile, in such a context. Another aspect is to study delay-tolerant IoT services along with delay-sensitive ones, to find a good benchmark for choosing the best approach in different situations.

APPENDIX A

GRAPH MODELS

Complex networks like the Internet are the graphs with non-trivial topological features [78]. The Internet illustrates two fundamental properties: small-world phenomenon and scale-free phenomenon [78]. The small-world phenomenon states that distances in real-world networks are quite small [79], and the scale-free phenomenon declares that the degrees in real-world networks show an enormous amount of variability [80]. Considering mathematical modeling as a viable method for analyzing the behavior of systems [81], [82], three graph models include Barabasi-Albert (BA) [65], Watts-Strogatz (WS) [66], and Erdos-Renyi (ER) [67], [83] have opted as network models in this research.

Barabasi-Albert is a model for scale-free networks such as the World Wide Web (w3), characterized by a highly heterogeneous degree distribution and high modularity (groups of the nodes that are more densely connected together than to the rest of the network). Erdos-Renyi model, known as a random network, has low heterogeneity, short average paths, and low clustering [84], [85]. Watts-Strogatz is a model for small-world networks which are very close structurally to social networks. Small-world networks have higher clustering than random networks but the average path length as them. Fig. 11 shows the network graphs of the three selected models for a 200-node network.

APPENDIX B

EPOS FOG AND ITS COMPONENTS

The main classes of EPOS Fog are depicted in Fig. 12. The Simulator class simulates a customized fog environment with specified parameters (such as network size and workload distribution) and begins and ends a simulation. The implementation of EPOS Fog is constituted by three sets of components composed of physical, input, and management components.

The physical components are organized in a hierarchical order, which include the Infrastructure, Graph, and Node classes. A network is modeled as an undirected graph, the
Fig. 11. Three graph topologies used to model a 200-node network.

vertices represent network nodes that perform processing on hosted services and edges denote paths between the nodes. The major attributes of these physical classes are hardware characteristics of the nodes (e.g., available processing power, memory, and storage size) and their connections (i.e., the paths in the network) to each other. Methods in these classes define how the resources of a node are assigned to the services running on it.

The input components that consist of the Workload and Service classes are considered as a collection of independent services, which are the input processing elements in the IoT networks. For each incoming service request, a Service instance creates the request and specifies its resource demands. Finally, based on workload distribution method, the Service objects are submitted to the network Nodes.

The management component of EPOS Fog, i.e., Agent, determines how services are placed across network nodes. The Agent objects according to the requirements of requested services, available resources of the nodes, and configuration parameters (such as host proximity) generate a set of possible plans (i.e., IEPOSPlans). Following the generation of IEPOSPlans, Agents participate in a plan selection provided by IEPOS. When the plan selection is terminated, these Agents place the services according to the output (information flow) of IEPOS. The Agents periodically manage (deploy and release) the Services and the Nodes in the network.

Fig. 12. Fundamental classes of EPOS Fog.

APPENDIX C
EVALUATION RESULTS IN DETAIL

Figs. 13, 14, and 15 and Figs. 16 and 17 illustrate the measurements of utilization variance and service execution delay in detail. Results are illustrated considering the studied aspects: input profiles, host proximity constraint, network topology, and network size.

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REFERENCES

[1] M. Hung, “Leading the iot, gartner insights on how to lead in a connected world,” Gartner Research, pp. 1–29, 2017.
[2] R. Buyya and S. Srirama, Fog and Edge Computing: Principles and Paradigms, ser. Wiley Series on Parallel and Distributed Computing. Wiley, 2019. [Online]. Available: https://books.google.com/books?id=cdSvtQEACAAJ
[3] F. Computing et al., “Fog computing and the internet of things: Extend the cloud to where the things are,” in Technical Report. Cisco Systems, 2016.
[4] F. Bonomi, R. Milito, P. Natarajan, and J. Zhu, “Fog computing: A platform for internet of things and analytics,” in Big data and internet of things: A roadmap for smart environments. Springer, 2014, pp. 169–186.
[5] Z. Nezami and K. Zamanifar, “Internet of things/internet of everything: structure and ingredients,” IEEE Potentials, vol. 38, no. 2, pp. 12–17, March 2019.
[6] M. Chiang and T. Zhang, “Fog and iot: An overview of research opportunities,” IEEE Internet of Things Journal, vol. 3, no. 6, pp. 854–864, 2016.
[7] M. Verma, N. Bhardwaj, and A. K. Yadav, “Real time efficient scheduling algorithm for load balancing in fog computing environment,” Int. J. Inf. Technol. Comput. Sci, vol. 8, no. 4, pp. 1–10, 2016.
Fig. 13. Utilization variance for different scenarios under varied parameters (N=400, Topology=BA).

Fig. 14. Utilization variance for different scenarios under varied parameters (N=400, Topology=WS).

[8] M. Verma and N. B. A. K. Yadav, “An architecture for load balancing techniques for fog computing environment,” *International Journal of Computer Science and Communication*, vol. 8, no. 2, pp. 43–49, 2015.

[9] A. Yousefpour, C. Fung, T. Nguyen, K. Kadiyala, F. Jalali, A. Niankanlahiji, J. Kong, and J. P. Jue, “All one needs to know about fog computing and related edge computing paradigms: A complete survey,” *Journal of Systems Architecture*, 2019.

[10] O. C. A. W. Group *et al.*, “Openfog reference architecture for fog computing,” OPFRA001, vol. 20817, p. 162, 2017.

[11] A. Brogi and S. Forti, “Qos-aware deployment of iot applications through the fog,” *IEEE Internet of Things Journal*, vol. 4, no. 5, pp. 1185–1192, 2017.

[12] G. Colistra, “Task allocation in the internet of things,” Ph.D. dissertation, Universita’degli Studi di Cagliari, 2015.

[13] A. Yousefpour, A. Patil, G. Ishigaki, I. Kim, X. Wang, H. C. Cankaya, Q. Zhang, W. Xie, and J. P. Jue, “Fogplan: A lightweight qos-aware dynamic fog service provisioning framework,” *IEEE Internet of Things Journal*, 2019.

[14] N. Kumar, S. Agarwal, T. Zaidi, and V. Saxena, “A distributed load-balancing scheme based on a complex network model of cloud servers,” *ACM SIGSOFT Software Engineering Notes*, vol. 39, no. 6, pp. 1–6, 2014.

[15] Y. Song, S. S. Yau, R. Yu, X. Zhang, and G. Xue, “An approach to qos-based task distribution in edge computing networks for iot applications,” in *2017 IEEE International Conference on Edge Computing (EDGE)*. IEEE, 2017, pp. 32–39.

[16] H. A. Khattak, H. Arshad, S. ul Islam, G. Ahmed, S. Jabbar, A. M. Sharif, and S. Khalid, “Utilization and load balancing in fog servers for health applications,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2019, no. 1, p. 91, 2019.

[17] U. Bulkan, T. Dagiuklas, M. Ibkal, K. M. S. Huq, A. Al-Dulaimi, and J. Rodriguez, “On the load balancing of edge computing resources for on-line video delivery,” *IEEE Access*, vol. 6, pp. 73 916–73 927, 2018.

[18] R. G. Rajan and V. Jeyakrishnan, “A survey on load balancing in cloud computing environments,” *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 2, no. 12, pp. 4726–4728, 2013.

[19] Y. Deng and R. W. Lau, “Heat diffusion based dynamic load balancing for distributed virtual environments,” in *Proceedings of the 17th ACM Symposium on Virtual Reality Software and Technology*. ACM, 2010, pp. 203–210.

[20] T. N. Gia and M. Jiang, “Exploiting fog computing in health monitoring,” *Fog and Edge Computing: Principles and Paradigms*, pp. 291–318, 2019.

[21] A.-M. Rahmani, N. K. Thanigaivelan, T. N. Gia, J. Granados, B. Negash, P. Liljeberg, and H. Tenhunen, “Smart e-health gateway: Bringing intelligence to internet-of-things based ubiquitous healthcare systems,” in *2015 12th Annual IEEE Consumer Communications and Networking* Conference, 2015, pp. 1–6.
Fig. 15. Utilization variance for different scenarios under varied parameters (N=400, Topology=ER).

Fig. 16. Service execution delay for different scenarios under varied parameters (N=200).

[22] S. Banerjee and J. P. Hecker, “A multi-agent system approach to load-balancing and resource allocation for distributed computing,” in *First Complex Systems Digital Campus World E-Conference 2015*. Springer, 2017, pp. 41–54.

[23] M. D’Angelo, “Decentralized self-adaptive computing at the edge,” in *2018 IEEE/ACM 13th International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS)*, May 2018, pp. 144–148.

[24] J. Nikolic and E. Pournaras, “Structural self-adaptation for decentralized pervasive intelligence,” in *2019 22nd Euromicro Conference on Digital System Design (DSD)*, Aug 2019, pp. 562–571.

[25] J. Santos, T. Wauters, B. Volckaert, and F. De Turck, “Resource provisioning in fog computing: From theory to practice,” *Sensors*, vol. 19, no. 10, p. 2238, 2019.

[26] A. A. Alsaffar, H. P. Pham, C.-S. Hong, E.-N. Huh, and M. Aazam, “An architecture of iot service delegation and resource allocation based on collaboration between fog and cloud computing,” *Mobile Information Systems*, vol. 2016, 2016.

[27] Q. Fan and N. Ansari, “Application aware workload allocation for edge computing-based iot,” *IEEE Internet of Things Journal*, vol. 5, no. 3, pp. 2146–2153, 2018.

[28] E. Pournaras, P. Pilgerstorfer, and T. Asikis, “Decentralized collective learning for self-managed sharing economies,” *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*, vol. 13, no. 2, p. 10, 2018.

[29] V. Cardellini, V. Grassi, F. Lo Presti, and M. Nardelli, “Optimal operator placement for distributed stream processing applications,” in *Proceedings of the 10th ACM International Conference on Distributed and Event-based Systems*. ACM, 2016, pp. 69–80.

[30] Z.-H. Zhan, X.-F. Liu, Y.-J. Gong, J. Zhang, H.-S. Chung, and Y. Li, “Cloud computing resource scheduling and a survey of its evolutionary approaches,” *ACM Computing Surveys (CSUR)*, vol. 47, no. 4, p. 63, 2015.

[31] P. Leitner, W. Hummer, B. Satzger, C. Inzinger, and S. Dustdar, “Cost-efficient and application sla-aware client side request scheduling in an infrastructure-as-a-service cloud,” in *2012 IEEE Fifth International Conference on Cloud Computing*. IEEE, 2012, pp. 213–220.

[32] O. Skarlat, M. Nardelli, S. Schulte, M. Borkowski, and P. Leitner, “Optimized iot service placement in the fog,” *Service Oriented Computing and Applications*, vol. 11, no. 4, pp. 427–443, 2017.

[33] V. B. C. d. Souza, W. Ramirez, X. Masip-Bruin, E. Marin-Tordera, G. Ren, and G. Tashakor, “Handling service allocation in combined fog-cloud scenarios,” in *Communications (ICC), 2016 IEEE International Conference on*. IEEE, 2016, pp. 1–5.

[34] O. Fadahunsi and M. Maheswaran, “Locality sensitive request distribution for fog and cloud servers,” *Service Oriented Computing and Applications*, pp. 1–14, 2019.

[35] Y. Xia, X. Etchevers, L. Letondeur, T. Coupaye, and F. Desprez, “Combining hardware nodes and software components ordering-based
Fig. 17. Service execution delay for different scenarios under varied parameters (N=400).

heuristics for optimizing the placement of distributed IoT applications in the fog,” in Proceedings of the 33rd Annual ACM Symposium on Applied Computing. ACM, 2018, pp. 751–760.

[36] O. Skarlat, M. Nardelli, S. Schulte, and S. Dastidar, “Towards qos-aware fog service placement,” in Fog and Edge Computing (FECFEC), 2017 IEEE 1st Annual Conference on. IEEE, 2017, pp. 89–96.

[37] M.-Q. Tran, D. T. Nguyen, V. A. Le, D. H. Nguyen, and T. V. Pham, “Task placement on fog computing made efficient for iot application provision,” Wireless Communications and Mobile Computing, vol. 2019, 2019.

[38] R. Deng, R. Lu, C. Lai, T. H. Lu, and H. Liang, “Optimal workload allocation in fog-cloud computing toward balanced delay and power consumption,” IEEE Internet of Things Journal, vol. 3, no. 6, pp. 1171–1181, 2016.

[39] A. Kapsalis, P. Kanseis, I. S. Venieris, D. I. Kakkalanis, and C. Z. Patrikakis, “A cooperative fog approach for effective workload balancing,” IEEE Cloud Computing, vol. 4, no. 2, pp. 36–45, 2017.

[40] X. Xu, S. Fu, Q. Cai, W. Tian, W. Liu, W. Dou, X. Sun, and A. X. Liu, “Dynamic resource allocation for load balancing in fog environment,” Wireless Communications and Mobile Computing, vol. 2018, 2018.

[41] B. Donassolo, I. Fajjar, A. Legrand, and P. Mertikopoulos, “Load aware provisioning of iot services on fog computing platform,” in ICC 2019 - 2019 IEEE International Conference on Communications (ICC), May 2019, pp. 1–7.

[42] T. A. Feo and M. G. Resende, “Greedy randomized adaptive search procedures,” Journal of global optimization, vol. 6, no. 2, pp. 109–133, 1995.

[43] C. Mouradian, D. Naboulsi, S. Yangui, R. H. Glitho, M. J. Morrow, and P. A. Polakos, “A comprehensive survey on fog computing: State-of-the-art and research challenges,” IEEE Communications Surveys & Tutorials, vol. 20, no. 1, pp. 416–464, 2017.

[44] S. Agarwal, S. Yadav, and A. K. Yadav, “An efficient architecture and algorithm for resource provisioning in fog computing,” International Journal of Information Engineering and Electronic Business, vol. 8, no. 1, p. 48, 2016.

[45] H. Gupta, A. Vahid Dastjerdi, S. K. Ghosh, and R. Buyya, “ifogsim: A toolkit for modeling and simulation of resource management techniques in the internet of things, edge and fog computing environments,” Software: Practice and Experience, vol. 47, no. 9, pp. 1275–1296, 2017.

[46] O. C. A. W. Group et al., “Openfog reference architecture for fog computing,” 2017, URL: https://www.openfogconsortium.org/wp-content/uploads/OpenFog_Reference_Architecture_2 _09_17-FINAL.pdf.

[47] M. Iorga, L. Feldman, R. Barton, M. J. Martin, N. S. Goren, and C. Mahmoudi, “Fog computing conceptual model,” Tech. Rep., 2018.

[48] K. Kaur, T. Dhand, N. Kumar, and S. Zeadally, “Container-as-a-service at the edge: Trade-off between energy efficiency and service availability at fog nano data centers,” IEEE wireless communications, vol. 24, no. 3, pp. 48–56, 2017.

[49] Y. Xiao and M. Krunz, “Qoe and power efficiency tradeoff for fog computing networks with fog node cooperation,” in INFOCOM 2017 - IEEE Conference on Computer Communications, IEEE. IEEE, 2017, pp. 1–9.

[50] R. F. Serfozo, “Little laws for utility processes and waiting times in queues,” Queueing Systems, vol. 17, no. 1, pp. 137–181, Mar 1994. [Online]. Available: https://doi.org/10.1007/BF01158693.

[51] S. Ningning, G. Chao, A. Xingshuo, and Z. Qiang, “Fog computing dynamic load balancing mechanism based on graph repartitioning,” China Communications, vol. 13, no. 3, pp. 156–164, 2016.

[52] Z. Liu, A. Wierman, Y. Chen, B. Razon, and N. Chen, “Data center demand response: Avoiding the coincident peak via workload shifting and local generation,” Performance Evaluation, vol. 70, no. 10, pp. 770–791, 2013.

[53] H. Zhang, J. Zhang, W. Bai, K. Chen, and M. Chowdhury, “Resilient datacenter load balancing in the wild,” in Proceedings of the Conference of the ACM Special Interest Group on Data Communication. ACM, 2017, pp. 253–266.

[54] R. T. Rockafellar, S. Uryasev et al., “Optimization of conditional value-at-risk,” Journal of risk, vol. 2, pp. 21–42, 2000.

[55] E. Pournaras, M. Vasirani, R. E. Kooij, and K. Aberer, “Measuring and controlling unfairness in decentralized planning of energy demand,” in 2017 IEEE International Energy Conference (ENERGYCON). IEEE, 2017, pp. 1–9.

[56] E. Pournaras, M. Yao, and D. Helbing, “Self-regulating supply–demand at fog nano data centers,” in Proceedings of the Conference of the ACM Special Interest Group on Data Communication. ACM, 2017, pp. 253–266.

[57] E. Pournaras, S. Jung, S. Yadhunathan, H. Zhang, and X. Fang, “Socio-technical smart grid optimization via decentralized charge control of electric vehicles,” Applied Soft Computing, vol. 82, p. 105573, 2019.

[58] E. Pournaras, M. Yao, and D. Helbing, “Self-regulating supply–demand systems,” Future Generation Computer Systems, vol. 76, pp. 73–91, 2017.

[59] E. Pournaras, M. Vasirani, R. E. Kooij, and K. Aberer, “Measuring and controlling unfairness in decentralized planning of energy demand,” in 2014 IEEE International Energy Conference (ENERGYCON). IEEE, 2014, pp. 1255–1262.

[60] E. Pournaras, M. Yao, and D. Helbing, “Self-regulating supply–demand at the edge: Trade-off between energy efficiency and service availability at fog nano data centers,” IEEE wireless communications, vol. 24, no. 3, pp. 48–56, 2017.

[61] Y. Xiao and M. Krunz, “Qoe and power efficiency tradeoff for fog computing networks with fog node cooperation,” in INFOCOM 2017 - IEEE Conference on Computer Communications, IEEE. IEEE, 2017, pp. 1–9.

[62] R. F. Serfozo, “Little laws for utility processes and waiting times in queues,” Queueing Systems, vol. 17, no. 1, pp. 137–181, Mar 1994. [Online]. Available: https://doi.org/10.1007/BF01158693.

[63] S. Ningning, G. Chao, A. Xingshuo, and Z. Qiang, “Fog computing dynamic load balancing mechanism based on graph repartitioning,” China Communications, vol. 13, no. 3, pp. 156–164, 2016.

[64] Z. Liu, A. Wierman, Y. Chen, B. Razon, and N. Chen, “Data center demand response: Avoiding the coincident peak via workload shifting and local generation,” Performance Evaluation, vol. 70, no. 10, pp. 770–791, 2013.

[65] H. Zhang, J. Zhang, W. Bai, K. Chen, and M. Chowdhury, “Resilient datacenter load balancing in the wild,” in Proceedings of the Conference of the ACM Special Interest Group on Data Communication. ACM, 2017, pp. 253–266.

[66] R. T. Rockafellar, S. Uryasev et al., “Optimization of conditional value-at-risk,” Journal of risk, vol. 2, pp. 21–42, 2000.

[67] E. Pournaras, S. Jung, S. Yadhuhanathan, H. Zhang, and X. Fang, “Socio-technical smart grid optimization via decentralized charge control of electric vehicles,” Applied Soft Computing, vol. 82, p. 105573, 2019.

[68] E. Pournaras, M. Yao, and D. Helbing, “Self-regulating supply–demand systems,” Future Generation Computer Systems, vol. 76, pp. 73–91, 2017.

[69] E. Pournaras, M. Vasirani, R. E. Kooij, and K. Aberer, “Measuring and controlling unfairness in decentralized planning of energy demand,” in 2014 IEEE International Energy Conference (ENERGYCON). IEEE, 2014, pp. 1255–1262.

[70] ——, “Decentralized planning of energy demand for the management of robustness and discomfort,” IEEE Transactions on Industrial Informatics, vol. 10, no. 4, pp. 2280–2289, 2014.

[71] A. V. Dastjerdi and R. Buyya, “Fog computing: Helping the internet of things realize its potential,” Computer, vol. 49, no. 8, pp. 112–116, 2016.

[72] S. Svorobej, P. Takako Endo, M. Benedchache, C. Filelis-Papadopoulos, K. M. Giannoutakis, G. A. Gravvanis, D. Tzovaras, J. Byrne, and T. Lynn, “Simulating fog and edge computing scenarios: An overview and research challenges,” Future Internet, vol. 11, no. 3, p. 55, 2019.
[61] M. Ficco, C. Esposito, Y. Xiang, and F. Palmieri, “Pseudo-dynamic testing of realistic edge-fog cloud ecosystems,” IEEE Communications Magazine, vol. 55, no. 11, pp. 98–104, 2017.

[62] S. Filiposka and C. Juiz, “Complex cloud datacenters,” IERI Procedia, vol. 7, pp. 8–14, 2014.

[63] I. Lera, C. Guerrero, and C. Juiz, “Availability-aware service placement policy in fog computing based on graph partitions,” IEEE Internet of Things Journal, vol. 6, no. 2, pp. 3641–3651, 2018.

[64] Z. Zhang and X. Zhang, “A load balancing mechanism based on ant colony and complex network theory in open cloud computing federation,” in 2010 The 2nd International Conference on Industrial Mechatronics and Automation, vol. 2. IEEE, 2010, pp. 240–243.

[65] A.-L. Barabási and R. Albert, “Emergence of scaling in random networks,” science, vol. 286, no. 5439, pp. 509–512, 1999.

[66] D. J. Watts and S. H. Strogatz, “Collective dynamics of small-world networks,” nature, vol. 393, no. 6684, p. 440, 1998.

[67] P. Erdős and A. Rényi, “On random graphs, i,” Publicationes Mathematicae (Debrecen), vol. 6, pp. 290–297, 1959.

[68] A. Dutot, F. Guinand, D. Olivier, and Y. Pigné, “Graphstream: A tool for bridging the gap between complex systems and dynamic graphs,” in Emergent Properties in Natural and Artificial Complex Systems. Satellite Conference within the 4th European Conference on Complex Systems (ECCS’2007), 2007.

[69] C. Reiss, J. Wilkes, and J. L. Hellerstein, “Google cluster-usage traces: format+ schema,” Google Inc., White Paper, pp. 1–14, 2011.

[70] J. Wilkes, “More Google cluster data,” Google research blog, Nov. 2011, posted at http://googleresearch.blogspot.com/2011/11/more-google-cluster-data.html.

[71] C. C. Byers, “Architectural imperatives for fog computing: Use cases, requirements, and architectural techniques for fog-enabled iot networks,” IEEE Communications Magazine, vol. 55, no. 8, pp. 14–20, 2017.

[72] W. Wang, Y. Zhao, M. Tornatore, A. Gupta, J. Zhang, and B. Mukherjee, “Virtual machine placement and workload assignment for mobile edge computing,” in Cloud Networking (CloudNet), 2017 IEEE 6th International Conference on. IEEE, 2017, pp. 1–6.

[73] M. Amadeo, G. Ruggeri, C. Campolo, A. Molinaro, V. Loscri, and C. T. Calafate, “Fog computing in iot smart environments via named data networking: A study on service orchestration mechanisms,” Future Internet, vol. 11, no. 11, p. 222, 2019.

[74] V. A. Barros, J. C. Estrella, L. B. Prates, and S. M. Bruschi, “An iot-daas approach for the interoperability of heterogeneous sensor data sources,” in Proceedings of the 21st ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. ACM, 2018, pp. 275–279.

[75] E. Çınlar, Probability and stochastic processes. Springer Science & Business Media, 2011, vol. 261.

[76] N. L. Johnson, S. Kotz, and N. Balakrishnan, “Chapter 21: beta distributions,” Continuous Univariate Distributions, vol. 2, 1995.

[77] R. P. Brent, “Efficient implementation of the first-fit strategy for dynamic storage allocation,” ACM Transactions on Programming Languages and Systems (TOPLAS), vol. 11, no. 3, pp. 388–403, 1989.

[78] M. E. Newman, “The structure and function of complex networks,” SIAM review, vol. 45, no. 2, pp. 167–256, 2003.

[79] J. Kleinberg, “The small-world phenomenon: An algorithmic perspective,” Cornell University, Tech. Rep., 1999.

[80] L. A. Schintler, A. Reggiani, R. Kulkarni, and P. Nijkamp, “Scale-free phenomena in communication networks: A cross-atlantic comparison,” 2003.

[81] S. C. Chapra, R. P. Canale et al., Numerical methods for engineers. Boston: McGraw-Hill Higher Education,, 2010.

[82] I. U. Din, M. Guizani, S. Hassan, B.-S. Kim, M. K. Khan, M. Atiquzzaman, and S. H. Ahmed, “The internet of things: A review of enabled technologies and future challenges,” IEEE Access, vol. 7, pp. 7606–7640, 2018.

[83] R. Van Der Hofstad, Random graphs and complex networks. Cambridge university press, 2016, vol. 1.

[84] I. Sohn, “Small-world and scale-free network models for iot systems,” Mobile Information Systems, vol. 2017, 2017.

[85] R. V. Solé and S. Valverde, “Information theory of complex networks: on evolution and architectural constraints,” in Complex networks. Springer, 2004, pp. 189–207.