Journal of Network and Computer Applications 219 (2023) 103724

Contents lists available at ScienceDirect

Journal of Network and Computer Applications

journal homepage: www.elsevier.com/locate/jnca

Mobility-aware fog computing in dynamic networks with mobile nodes: A survey

Krzysztof Ostrowski [a],[*], Krzysztof Małecki [a], Piotr Dziurzański [a], Amit Kumar Singh [b]

[a] West Pomeranian University of Technology, Szczecin, Poland
[b] University of Essex, Colchester, UK

ARTICLE INFO

Keywords:
Mobile fog computing
Mobility-aware
Dynamic networks

ABSTRACT

Fog computing is an evolving paradigm that addresses the latency-oriented performance and spatio-temporal issues of the cloud services by providing an extension to the cloud computing and storage services in the vicinity of the service requester. In dynamic networks, where both the mobile fog nodes and the end users exhibit time-varying characteristics, including dynamic network topology changes, there is a need of mobility-aware fog computing, which is very challenging due to various dynamisms, and yet systematically uncovered. This paper presents a comprehensive survey on the fog computing compliant with the OpenFog (IEEE 1934) standardised concept, where the mobility of fog nodes constitutes an integral part. A review of the state-of-the-art research in fog computing implemented with mobile nodes is conducted. The review includes the identification of several models of fog computing concept established on the principles of opportunistic networking, social communities, temporal networks, and vehicular ad-hoc networks. Relevant to these models, the contributing research studies are critically examined to provide an insight into the open issues and future research directions in mobile fog computing research.

1. Introduction

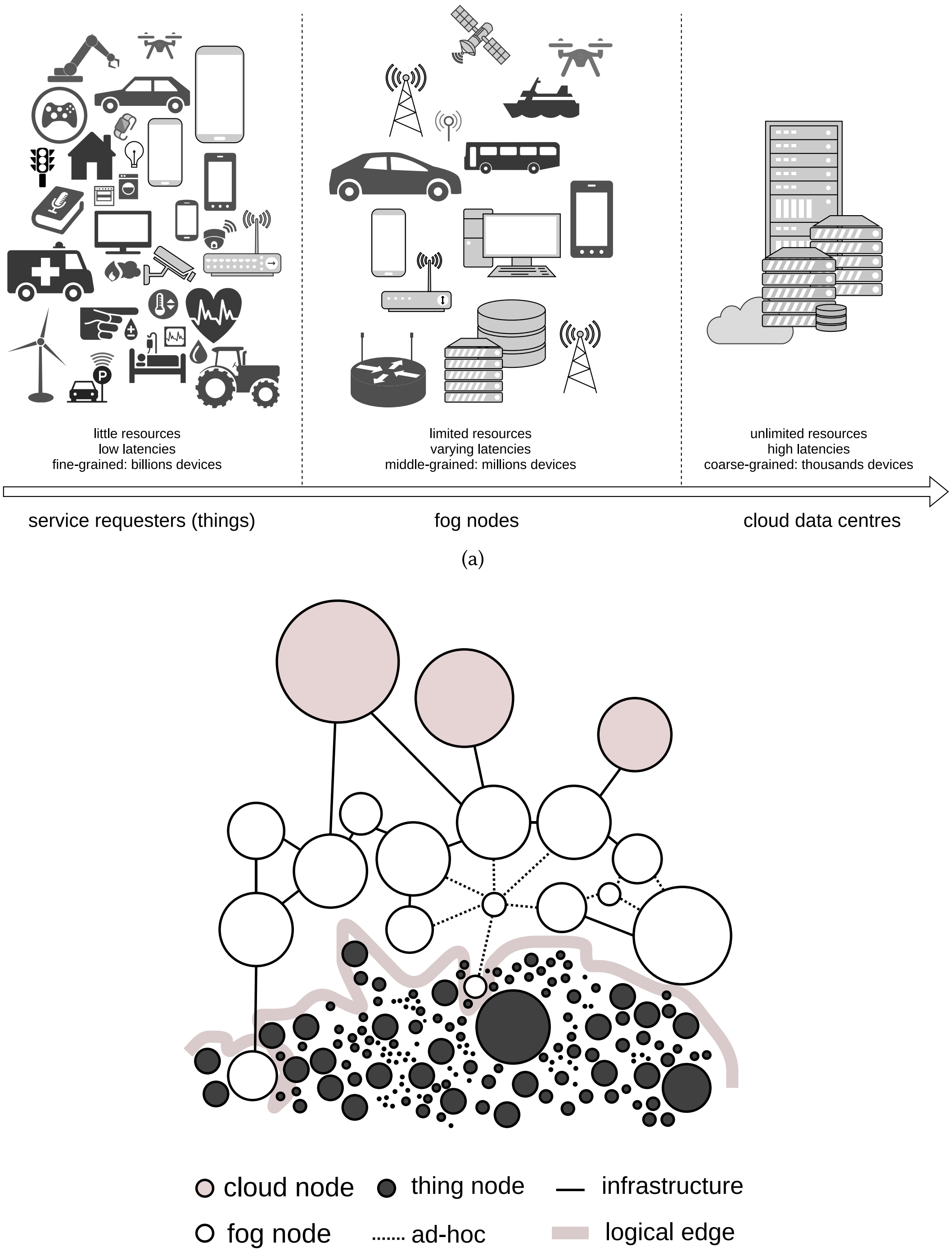
With the proliferation of heterogeneous devices (the things) connected to the Internet of Things (IoT), i.e. networks of sensors and actuators (ITU-T, 2012), the overall volume and velocity of data generated and consumed in IoT networks increases rapidly. Conventional cloud-based centralised solutions deployed in far-end data centres of theoretically unlimited location-independent computing and storage resources, Armbrust et al. (2010) and Mell and Grance (2011), impose significant disadvantages if applied directly to the IoT environment (Yannuzzi et al., 2014; Al-Fuqaha et al., Fourthquarter 2015; Chiang and Zhang, 2016). A significant rise in latency and energy consumption introduced by transfers of data produced by geographically distributed IoT end-users to a centralised cloud is one of the very first observable issues. Furthermore, conventional cloud-based centralised solutions suffer from irrecoverable losses in contextual information that may result in inappropriate judgements based on the situations deduced from the well-formed but no longer valid data. Moreover, a cloud-oriented management of a multitude of constrained end devices of intermittent network connectivity that affects the IoT network's scalability, privacy, and security poses serious challenges. To address the listed issues, several computing paradigms were developed over the years to offer the cloud services, storage and processing resources "closer" to the service requester as represented by an IoT device (Yousefpour et al., 2019). The vast majority of the researched solutions fall into one of two categories of the conceptual computing paradigms, edge computing, and fog computing.

Edge computing is understood as a paradigm that introduces cloud services at the edge of the network by means of network nodes in the proximity of the service requester, Satyanarayanan (2017). Furthermore, edge computing predates the formulation of fog computing, or even cloud computing (as found in a form of distributed data caching services in Dilley et al. (2002), Xie et al. (2002) and Davis et al. (2004)). Edge computing includes a spectrum of concepts, e.g. cloudlet which focuses on microdata centres (Satyanarayanan et al., 2009), or mobile cloud computing (MCC) which delegates tasks from mobile phones to cloudlets (Kumar and Lu, 2010; Dinh et al., 2013; Bou Abdo and Demerjian, 2017), as well as some implementations, which include multi-access edge computing (MEC), formerly known as mobile edge computing. MEC leverages the existing cellular networks infrastructure, and it is deemed to be a step in the evolution of mobile base stations (Hu et al., 2015; ETSI, 2019).

---

* Corresponding author.
E-mail addresses: krzysztof.ostrowski@zut.edu.pl (K. Ostrowski), kmalecki@zut.edu.pl (K. Małecki), piotr.dziurzanski@zut.edu.pl (P. Dziurzański), a.k.singh@essex.ac.uk (A.K. Singh).

https://doi.org/10.1016/j.jnca.2023.103724
Received 5 April 2023; Received in revised form 24 July 2023; Accepted 17 August 2023



(a)

(b)

Fig. 1. Figure (a) presents the context for a fog computing system with the example network devices that take part in building of the cloud-to-thing continuum, and their quantities. Conceptualised visualisation of granularities of the multi-tier fog network (b) with infrastructure and mobile (connected by means of ad-hoc links) fog nodes, cloud computing with localised servers, and thing nodes, where node capabilities increase with node size.

Fog computing (FC) is a conceptual computing paradigm and a standardised system-level hierarchical concept architecture (IEEE, 1934) for a highly virtualised platform that distributes computation, storage, and networking tasks over the autonomous and heterogeneous fog nodes to assist and extend the cloud infrastructure for IoT devices (Bonomi et al., 2012; Byers, 2017). Fig. 1 depicts the context for the standardised fog computing, where the heterogeneity and both the qualitative and quantities granularities of the system actors are emphasised. In fact, any fog-capable device can act as a network node in a fog computing environment (i.e. as a fog node) and actively provide services to end-users and other fog nodes (Bonomi et al., 2014). A fog system may be either a network of connected systems arranged into hierarchies of nodes with controlled lifetimes or a solution folded into a single physical system. Multi-tier computing is at the heart of fog computing. A significant variability in the location, the resulting networking latencies, and the characteristics of fog nodes are visualised in Fig. 1(a), which illustrates the fog computing system with the example network devices that take part in building the cloud-to-thing continuum along and their quantities. As opposed to edge computing, in fog computing, the network nodes can be located anywhere between the cloud and the edge of the network, and benefit from a wide diversity of connected devices (Chiang et al., 2017). Heterogeneity at multiple levels (e.g. device capabilities, network connection, etc.) is inherent in the fog computing paradigm. It may be seen as its primary strength in building distributed systems that integrate things and the cloud. The multi-layered fog network design promotes cooperation with a cloud which, in turn, constitutes a cloud-to-thing continuum, where fog computing is thought of as an extension of cloud-based models that preserves all the benefits brought by cloud computing. Fig. 1(b) figuratively presents the cloud-to-thing continuum composed out of a diversity of interconnected nodes. In particular, fog relies on the cloud and edge ideas to bridge the gap between things and the cloud. Thus it may be seen as the highest evolution of the edge computing principles (De Donno et al., 2019).

Notably, fog nodes are given a high degree of autonomy, so that they are free to actively collaborate with each other and the things, perform analytics to take local decisions independently and efficiently, manage applications, and react to security threats without the involvement of the network operator, or even spontaneously change their location due to node mobility (IEEE, 1934). Recent works in fog computing take advantage of autonomic computing (Kephart and Chess, 2003; Ganek and Corbi, 2003), to cope with the autonomy aspect of fog environments (Tahir et al., 2019; Menascé, 2020). Autonomic computing is founded on the idea of a control loop that monitors the environment. It acts according to adaptable policies that limit the set of decisions and actions the autonomic entity performs (this is known as the monitor-analyse-plan-execute-knowledge, MAPE-K, framework) (IBM, 2006). Coalescing of independent judgements seems to be a major concern in building robust fog solutions.

A reference architecture for fog computing was initially provided by OpenFog Consortium, and later adopted as IEEE (1934) in 2018. The IEEE adoption of the OpenFog reference architecture states that edge computing was originally defined with the exclusion of a cloud. In contrast, fog computing was devised as an extension of a cloud. That implies those two concepts are distinct, and, at most, **fog is a superset of edge computing** (Junior et al., 2021). While the general objectives like, i.a. real-time responsiveness, location awareness, and mobility support are shared between fog and edge, notable differences exist that have a foundation in approach to diversity and location of nodes, as well as in solving network control plane management.

A fog computing network that solely includes infrastructure nodes (i.e. those of fixed locations) manifests mobility in the spatio-temporal behaviour of a service requester (cf. MEC). A ubiquitous computing solution brought by the fog leverages the mobility of nodes in the fog environment, where the mobility concern also applies to adventitious location changes of the service requester node itself. Two directions in mobility-aware fog computing research are leading recently: mobile fog computing (Chang et al., 2020; Gima et al., 2020), and vehicular fog computing (Ostrowski and Małecki, 2023; Ning et al., 2019). Researchers ponder three mobility perspectives: mobility of a service requester, fog nodes, or both. Fog computing is expected to address all of them.

1.1. Dynamic networks

Networks in which nodes may leave and join at any time and where the network connections may disappear and recover as time passes are termed as dynamic networks (Rossetti et al., 2017). Current research studies provide tools to describe and analyse such networks, i.e. temporal networks theory and opportunistic computing paradigm (Newman, 2003; Rossetti and Cazabet, 2018; Conti et al., 2010).

Temporal networks theory, an extension of complex networks, is a mathematical framework to model dynamic structures with relations and interactions (Holme and Saramäki, 2012). Modelling of fog networks as temporal ones provides a tooling to identify and track the mobile fog nodes in relationships (Cazabet and Rossetti, 2019), which is essential to ensure the service continuity property in highly dynamic environments. To the best of our knowledge, none of the related existing surveys neither engaged nor explored the temporal network perspective of fog computing.

The opportunistic computing paradigm evolved from the idea of opportunistic networks, the networks that enable node communication even in the absence of a route between the nodes, to an environment that provides general computing services (Pelusi et al., 2006; Conti et al., 2015). Opportunistic networking exploits the self-organising networks of unstable topologies and high churn rates with locally executed contextual nodal decisions (e.g. routing, scheduling, etc.). Computing services laid over those networks are seen as roots of fog computing (Das, 2018; Mascitti et al., 2018) that employ complex network theory to reason about (Conti and Passarella, 2018). In contrast to this survey, the related existing surveys predominantly describe the mobile user perspective while discussing mobility in fog computing. Moreover, none of those works strictly discusses the mobility of computing fog nodes, neither discover various models of fog computing that share the opportunistic foundation. Note that UAV-assisted solutions constraint the mobility with pre-planned moving dynamics and strictly defined flying paths (Motlagh et al., 2019; Zhu et al., 2021b) which effectively preclude self-decided node mobility and, in turn, factor out UAV research from this survey.

1.2. Contribution

The existing surveys emphasise the mobility of a service requester as a main determinant of mobility-awareness, while this publication tackles the mobility problem from the perspective of fog network dynamics, where fluctuations in the network topology are natural. As found out during careful examination, the available review articles tend to point out differences rather than search for commonalities in the identified models of fog computing, its predecessors (e.g. where fog computing is the most general and complete representative Yousefpour et al., 2019), and in the discovered similar ideas. Few of the latest studies use the pillars and the concept defined by OpenFog as evaluation criteria (Bellavista et al., 2019; Puliafito et al., 2019), and most works are unaware of them. Nevertheless, multiple of them only refer to the arbitrarily selected properties. While most of the papers describe solutions to a problem of the end-user mobility (i.e. when IoT device changes its geographical or topological location), or do not state the used mobility perspective at all, only three of them actually clearly distinguish between network and user mobility perspectives (Mouradian et al., 2018; Mahmud et al., 2020; Gill and Singh, 2021). Interestingly, nearly all the examined surveys emphasise the cruciality of further research in the mobility-awareness aspect of fog computing. To the best of our knowledge, none of the available surveys in fog computing directly addresses the node mobility concerns in mobile fog computing environments. Furthermore, this paper puts emphasis on the relationship between node mobility and the application (i.e. sets of executed tasks) level, thus, elaborations on models of communication channels and related signal processing aspects are minimal.

According to the authors' knowledge, there exists no survey publication entirely dedicated to mobility-awareness in fog computing that provides a complete view on that aspect under the umbrella of the fog computing concept and its models. Furthermore, the available survey publications briefly mention the related mobility issues while discussing other characteristics of fog computing. Therefore, the authors argue that this survey is the very first attempt to systematically review the research efforts in fog computing with mobile fog nodes. A detailed evaluation of the existing surveys is provided in Section 2.

In this survey, a critical evaluation of mobility-aware solutions that contribute to the models of fog computing architecture with mobile computing nodes is presented. The main contributions are as follows:

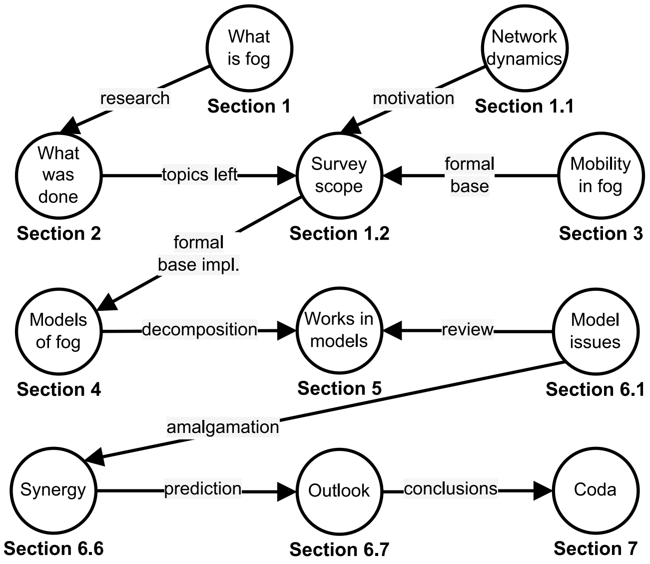


Fig. 2. Illustration of the relationship between the sections of this survey.

(1) Rely on well-established definitions. Highlight mobility concerns that are expressed in the standardised fog computing architecture compliant with IEEE 1934.
(2) Apply a synergistic approach. Identify models of the fog computing concept that contribute to the mobility pillars, and which combination leads to a robust mobility-aware fog solution.
(3) Find the mature building blocks. Provide a comprehensive insight into the latest research efforts related to mobility-aware models of fog computing focused on computing network mobility in particular.
(4) Provide directions. Present open issues and research opportunities.

The foundations of the review criteria rely on the several key ingredients of opportunistic networking and computing applicable to OpenFog definition of fog computing (e.g. nodal collaboration, mobility management, resource management, etc.) considered in the environment of dynamic networks. Examined research works include publications from years 2021, 2020, 2019, and earlier with percentage quantitative contributions of 39%, 34%, 20%, and 7%, respectively.

The remainder of this article is organised as follows. Section 3 provides details of the fog computing concept focused on the mobility-related features. In Section 4, models of the mobility-aware fog computing concept architecture are described. Related surveys are presented in Section 2. Section 5 categorises existing research works in the area of mobile fog computing by the fog computing models and the addressed problems. Identified open issues and research challenges are discussed in Section 6. Finally, Section 7 concludes this article. Fig. 2 illustrates the relationships between the sections.

2. Related surveys

This section summarises current review articles that consider the mobility facet of fog computing. The selection of the survey publications covers the related works available in June, 2022. Detailed screening of the papers led to the final quality-oriented selection of the survey papers from the initially qualified ones.[1] Table 1 summarises the evaluated existing 15 surveys in fog computing that allude to aspect of mobility. A work is OpenFog-complaint if it directly references the standardised architecture, applies the in there settled terminology, and conducts considerations according to the framework defined therein.

Authors of Mahmud et al. (2018) discuss a centralised context-aware scheduling. Node mobility is considered during the scheduling process, which consumes the application context. Only the user mobility is discussed, with no reference to the standardised fog computing architecture.

Papers (Mouradian et al., 2018; Ren et al., 2019) bring evaluations of fog system architectures and algorithms according to the in there developed six criteria. While Ren et al. (2019) roughly discusses the mobility phenomena using an unspecified perspective, Mouradian et al. (2018) identifies mobile computing nodes in vehicular setups only.

Discussions hinged on OpenFog reference architecture for fog computing are found in Bellavista et al. (2019) and Puliafito et al. (2019). Authors of Bellavista et al. (2019) point out the impact of mobility on the communication, and briefly present mobility-aware protocols for resource discovery and routing. Mobility-sensitive system components (e.g. migration) are discussed from the angle of the end-user mobility. Similarly, Puliafito et al. (2019) discusses the impact of the end user mobility on the fog platforms and migration policies. However, the moving computing nodes are not taken into account.

A work in Rejiba et al. (2019) outlines several possible migration scenarios that consider both the end user and node mobility, as well as the migration assisted by infrastructure nodes. The authors stress the role of nodal cooperation as an important factor in providing complete migration solutions. Migration in conjunction with mobility of nodes, and consequently, of nodes and users, is not covered.

A comparison of selected constrained models of the fog computing concept is provided as either a background study or as a basis to point out the future directions of fog computing evolution in Yousefpour et al. (2019). The exploitation of the opportunistic computing to further decentralise and manage the dynamic networks is not covered. The mobility perspective is not explicitly specified.

Authors of Mahmud et al. (2020) elaborate on a logically distributed application management. Mobility aspects are discussed in the event-driven iterative application placement strategy that is sensitive to node failures and mobility. Solutions that reflect the dynamic changes of an application architecture in the fog network topology are not discussed.

Work in Salaht et al. (2020) presents a literature review in solutions to the online service placement with distributed orchestration. Mobility is defined as a characteristic of a placement strategy which, in turn, is materialised in the form of a service migration, and discussed from

---

[1] Following query was used to obtain a list of existing mobility-related fog computing surveys: `TITLE-ABS-KEY(‘‘fog computing’’) AND (PUBYEAR > 2017) AND (LIMIT-TO (DOCTYPE, ‘‘re’’))`.

Table 1
Existing surveys in fog computing with notion of mobility-awareness versus this survey.

Reference	Year	Area	OpenFog compliant	Mobility perspective	Identified models of fog computing, and similar concepts
Mahmud et al. (2018)	2018	comp. paradigms and taxonomy	No	User	MEC, MCC
Mouradian et al. (2018)	2018	System arch., algorithms	Partially	User, network	Cloudlet, MEC
Ren et al. (2019)	2019	Hierarchical comp. arch.	Partially	Mixed	Transparent comp., MEC, cloudlet
Bellavista et al. (2019)	2019	IoT-oriented fog solutions	Yes	User	–
Puliafito et al. (2019)	2019	Software and hardware platforms	Yes	User	MCC, cloudlet, MEC
Rejiba et al. (2019)	2019	Migration	Yes	User, network	Cloudlet, MEC, vehicular clouds
Yousefpour et al. (2019)	2019	Multiple (general overview)	Partially	Mixed	MEC, cloudlet, (others discussed)
Mahmud et al. (2020)	2020	app. arch., placement, and maintenance	Partially	User, network	MEC, mist comp., dew comp.
Salaht et al. (2020)	2020	Service placement w. eval. environs.	Partially	Mixed	–
Gill and Singh (2021)	2021	Simulation frameworks	Partially	User, network	–
Islam et al. (2021)	2021	res. scheduling w. context classification	No	User	–
Martinez et al. (2021)	2021	net. design, res. mgmt., eval. environs.	Partially	Mixed	MEC, cloudlet
Costa et al. (2023)	2022	Orchestration	No	Mixed	MEC
Bukhari et al. (2022)	2022	Discovery	No	Mixed	Osmotic comp.
Songhorabadi et al. (2023)	2023	app. to smart cities	Yes	Mixed	–
(This paper)	2023	Architectures and algorithms	Yes	Network	(spatial) crowdsourcing, drop comp., osmotic comp., vehicular fog comp., opportunistic fog comp., (MEC and others discussed)

app.: application, arch.: architectures, comp.: computing, eval.: evaluation, net.: network, res.: resource.

the angle of the end user, which effectively bypasses the subject of fog network mobility.

Authors of Gill and Singh (2021) survey the fog computing simulation frameworks. Although authors are aware of the computing node mobility, the service requester mobility is generally discussed. Handling migration procedures triggered by either fog node mobility, node failures, or both are not covered. Split into fog computing models is not introduced.

The categorisation of the sources of context-awareness given in Islam et al. (2021) classifies mobility as an inherent characteristic of fog computing that originates from multiple levels of the contextual knowledge. Contexts of a user, device, and environment are marked as crucial in the mobility management. The authors do not reference the standardised fog architecture and discuss the end user mobility only.

Authors of Martinez et al. (2021) discuss orchestration techniques for the networks of infrastructure (fixed), and non-fixed nodes. Horizontal and vertical migration techniques are summarised. However, those techniques are mainly centred in end-user behaviour. Solutions for fault-tolerant dynamic fog networks of hybrid infrastructures with explicit computing node mobility are not covered.

Authors of Costa et al. (2023) notice the dynamicity of the fog computing environments and enumerate its impact on fog orchestration. However, they do not discuss setups with predominant mobile fog nodes. Recent works loosely refer to OpenFog while discussing fog computing in smart cities (Songhorabadi et al., 2023), however, they do not clearly emphasise the value of mobile computing nodes (Songhorabadi et al., 2023; Bukhari et al., 2022).

3. Mobility in the fog computing concept

IEEE 1934's fog computing is built on nine pillars: security, manageability, scalability, openness, autonomy, reliability-availability-serviceability (RAS), agility, hierarchy, programmability (IEEE, 1934). While all the pillars are crucial in the delivery of a complete fog computing network, few of them play pivotal role in the mobility-awareness characteristics, namely: autonomy, agility, manageability, scalability, and RAS (Fig. 3a).

Autonomy is an essential enabler for decision-making, in the decentralised and distributed forms, across the layers of the hierarchical network. Autonomic behaviour enables fog nodes to cooperate, create the intelligence at the network edge, monitor the environment, and react promptly to ensure uninterrupted operations. Agility provides a context (Dey, 2001) out of the data generated by things and fog nodes, effectively driving context-aware decisions that deal with dynamic nature of fog deployments. Agile fog networking aims to respond quickly to change through both the sophisticated application placement, and an insight into the structure and semantics of the information flows. Manageability involves means to discover and orchestrate fog nodes, which covers procedures to i.a. control life cycle, resource provisioning, monitor, and recover them from severe failures. Scalability is observable in dynamic adaptation to the workload and changing system needs. It addresses multiple dimensions of fog networks including fog nodes, fog network, fog functionalities and their characteristics. RAS metrics constitute criteria against which the operations brought by the selected pillars are evaluated.

Mobility is perceived as an essential property of fog computing, and various aspects of it are discussed within the text of IEEE 1934. It is worth to note that OpenFog references neither particular mobility models nor specific implementations. The phenomenon of mobility in the networked distributed computing environments can be observed if either the end-user device changes its location, or the computing network modifies its topology in reaction to the node internal behaviour (Xu et al., 2018). Although OpenFog sees great gains in the latter, it is usually overlooked in research considerations. Handling of the end-user device mobility requires mechanisms to track and predict the trajectory of the service requester. Those include procedures related to handovers and migration of services (Pollini, 1996; Stemm and Katz, 1998). User mobility is well studied by researchers. In contrast, mobility of the fog computing network introduces extensive changes to the computing environment on multiple levels which, in turn, trigger various operations starting from the recovery of the network links (physical connection channels), through multi-hop routing to rebuild the node communication graph, along with re-provisioning of the workload according to the offloaded application characteristics, and ending with the migration of services to candidate nodes proposed by the service discovery feature. Spontaneous node mobility poses serious challenges, but also offers great opportunities to fog systems.

4. Mobility-aware models of fog computing

Due to standardised formulation of the fog computing as a concept, i.e. an abstract notion, there exist various models of fog computing that strive to strip away layers of its complexity in order to materialise bases for implementations. Several of them are identified in this section as either following the analogy of gas-to-liquid phase transitions of matter (e.g. fog, drop), or imitating the related processes (e.g. osmosis), or applying the concept in custom domains (e.g. automotive, maritime, aviation). Although some of the models seem to overlap, they have sprung from different roots to address disparate objectives, and therefore are considered on an individual basis. Following sections briefly introduce designs identified as models of fog computing concept, along with rationales behind, base scenarios and application environments.

4.1. Osmotic computing

Osmotic computing is a system concept for distributed and federated virtualised environments that aims to automatise opportunistic deployment of possibly decomposed applications that span the cloud-to-thing continuum of heterogeneous devices (Villari et al., 2016). The idea behind this form of computing comes form chemistry, where osmosis describes a process of movement of matter from a region of higher concentration to a region of lower concentration. In osmotic computing, osmosis is modelled as a dynamic migration of services to satisfy the infrastructure and application goals that vary over time (Villari et al., 2019). Osmotic computing contributes to fog computing as defined by OpenFog in the areas of scalability and manageability, where it is seen as a distributed application framework for fog environment (Sharma et al., 2018).

Osmotic computing environment is formulated as a regular three-tier system (things–fog–cloud Kaur et al., 2020) composed out of microelements that provide a single abstraction to build data flows that span the whole system. Microelement (MEL) abstraction serves as either a microservice, an information stream, computation unit for a certain class of problems, or a manager that alters or controls the state of a resource. Microelements involved into a dataflow may be deployed to any node in system, including the cloud and things. Fig. 3b presents the idea of osmotic computing in the fog computing context.

Osmotic computing focuses on logical decomposition of the application into a set of cooperating microelements (cf. function as a service concept). Once decomposed, and deployed to virtual components or containers, microelements are subject to aggressive migration. Migration happens between nodes in dimensions constrained by requirements put by the application graph. These include conventional bottom-up offloading from things to a fog, reversed offloading from a cloud to things (Villari et al., 2016), and nodal collaboration. Although the available simulation frameworks for osmotic computing utilise prior global knowledge on network elements and topology (Alwasel et al., 2021), osmotic computing does not put restrictions on decentralised decision-making, and operation in dynamic ad-hoc mobile environments.

4.2. Drop computing

Drop computing is a concept of decentralised computing introduced in Ciobanu et al. (2019b), and later refined in Ciobanu et al. (2019a,c). It is founded on ad-hoc dynamic collaboration of mobile devices enhanced by a human input (social component). Drop computing aims to provide computation and data offloading services in the highly mobile cloud-to-thing continuum. That is, computing nodes and service requesters are assumed to be extremely mobile and heterogeneous. Multi-hop opportunistic communication with relay nodes constitute its mobile ad-hoc networking skeleton.

Drop computing adds social characteristics to fog computing concept. Capabilities of a mobile device are extended by the resources available in the crowd of neighbour devices. Furthermore, direct communication between things takes into account their social familiarity to determine the level of detail for exchanged information. A social graph is either introduced by a human factor, or deduced by the devices independently using trust mechanisms.

Applications in drop computing are partitioned into fine-grained tasks. The offloading process starts with the distribution of tasks to nearby nodes. Participation in offloading is voluntary and rewarded. Nodes are allowed to autonomously re-distribute the assigned tasks to the ad-hoc social clusters (communities). Duplication of offloading requests is used to increase the offloading success rate. Based on the availability of different types of computing architectures and the complexity of the tasks, drop computing executes offloading processes either within the crowdsourcing-like system without access to infrastructure nodes, by means of a cloud, or by utilising all the available computing networks. In case of insufficient resources, drop computing routes the offloading request to cloud computing data centres (fallback). Fig. 3c visualises social relationships between nodes, and task offloading characteristics in drop computing.

4.3. Crowdsourcing

Crowdsourcing forms a system to offload the tasks to a group of heterogeneous worker nodes (Brabham, 2008). The offloading process is managed by a centralised node located in a cloud. Such a cloud-based crowdsourcing service provider discovers the workers, executes task placement and migration, handles incentives mechanisms, and brokers all the bidirectional interactions between the service requester and workers (Jiang et al., 2018). Broker server may be modelled as a distributed system, and, in particular, as a fog computing instance (Yang et al., 2017). Fig. 3e visualises the main characteristics of a crowdsourcing system.

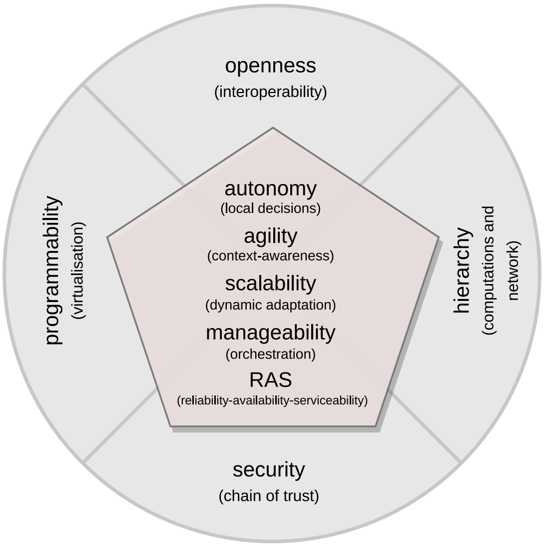
Although crowdsourcing systems tend to be centrally managed, their worker nodes are given a high degree of autonomy. Workers make decisions on task selection and execution through direct interaction with the broker, while indirectly cooperating to build a workflow (Ni et al., 2017). A Set of the accepted tasks specifies a worker's functional role in the system. Workers can be focused on gathering of the sensor data, processing of the collected sensor data, or both. Worker nodes can interact with a human to consume the human input, or execute some trivial tasks (e.g. yes-no questions, etc.). Processing of the sensors' data can be delegated to a broker, and then offloaded to the cloud data centres. In a crowdsourcing system, a service requester can actively build an ad-hoc network from the willing to participate worker nodes available in its vicinity.

The spatial form of crowdsourcing extends its capabilities with a location awareness property of offloading requests. In such a system, computing nodes are required to be available at certain physical locations to take part in computation offloading (Kazemi and Shahabi, 2012). A spatial crowdsourcing system is able to instruct a subset of worker nodes to physically travel to particular locations in order to perform the requested tasks. Locations of mobile workers are observed by a centralised broker node as streams of position changes which, in turn, enable the prediction of workers' location from the collected historical data.

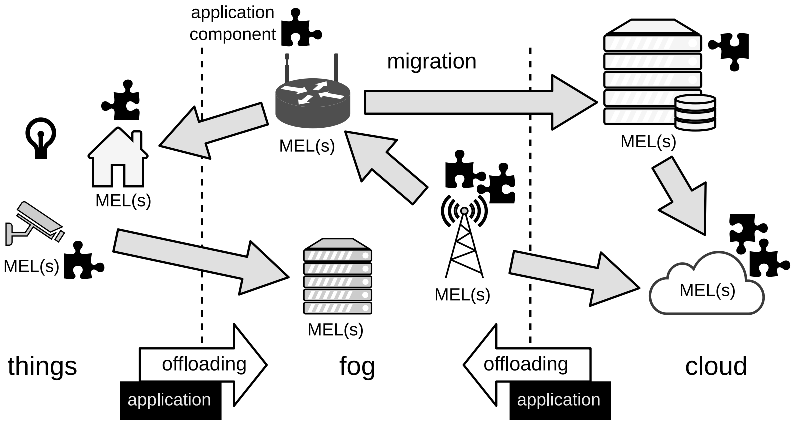
4.4. Opportunistic fog computing

Opportunistic fog computing contributes to mobility-awareness aspects of fog networks in which fog nodes operate in hazardous environments of high density, where resource availability, mobility, and connectivity change dynamically and rapidly (Silva et al., 2017; Fernando et al., 2019). Opportunistic fog computing utilises efficient network scaling to cope with generally unpredictable fog node lifetime. So characteristic for this model of fog computing, a highly adaptive deployment with limited access to infrastructure and cloud data centres, benefits from the dynamic context-aware selection of offloading strategies driven by the properties of the offloaded application.

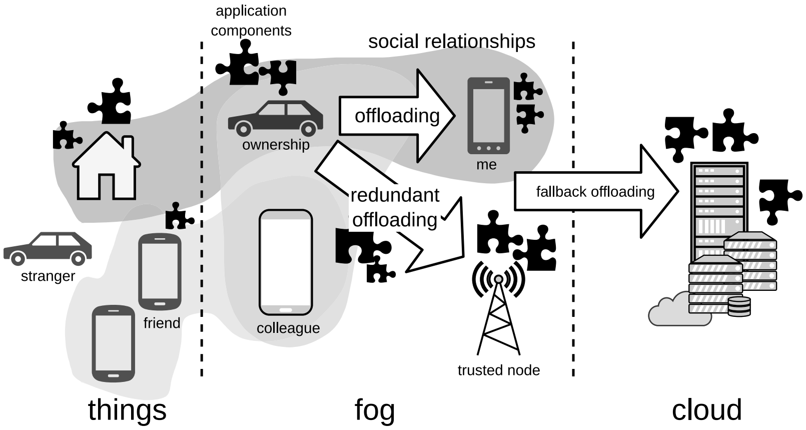
In response to a service requester mobility, varying network context, and offloading statistics, the peer-to-peer cooperation between opportunistic fog nodes enables dynamic clustering, as well as further load balancing and task migration (Brogi et al., 2020). A dynamic cluster is locally managed by a fog node of transferable cluster head role (Baker et al., 1984). Both the structure and functional properties of a dynamic cluster vary over time. Fig. 3f visualises the key characteristics of opportunistic computing.



(a) fog computing pillars

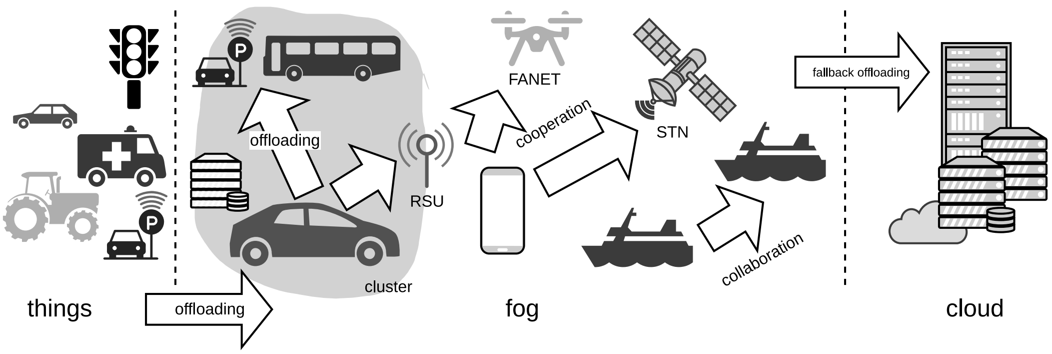


(b) osmotic computing

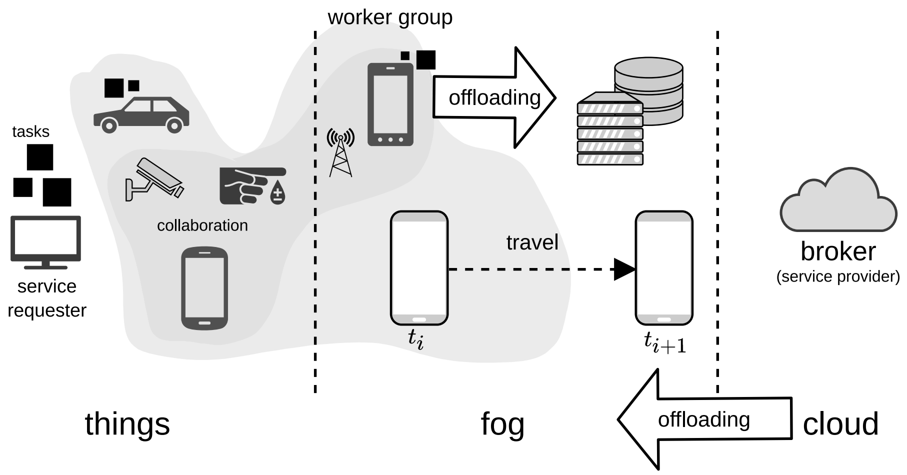


(c) drop computing

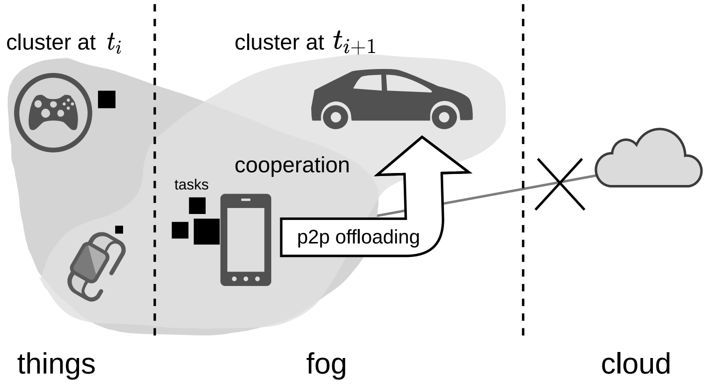
Fig. 3. Osmotic computing (b), drop computing (c), opportunistic fog computing (f), vehicular fog computing (d), and crowdsourcing (e) as models of fog computing that contribute to its pillars (a).



(d) vehicular fog computing



(e) crowdsourcing



(f) opportunistic fog computing

Fig. 3. (*continued*).

4.5. Vehicular fog computing

An increasing computational power offered by the on-board units installed in vehicles, and the opportunity of a spontaneous setup of the wireless ad-hoc networks between them (Chlamtac et al., 2003), gave rise to several vehicular computing paradigms (Kai et al., 2016; Fadhil and Sarhan, 2020). Depending on the presence of infrastructure network nodes (e.g. road side units (RSUs), etc.), some authors differentiate between the vehicular edge, and the vehicular fog computing (Hou et al., 2016), while others use both terms interchangeably. The networking foundation highly influences the key characteristics of those paradigms. Certain mobility perspectives can be implicitly excluded from further consideration (Reis et al., 2017; Pereira et al., 2019), while cooperation in offloading and migration processes restricted (Liu et al., 2020; Ning et al., 2019). Moreover, due to network scalability reasons (Kosch et al., 2006), vehicular nodes are usually organised into clusters (Kuklinski and Wolny, 2009), where an elected cluster head manages the cluster members, and brokers the broadcast-based communication.

Albeit it is desirable because of simplification in mobility predictions, vehicular fog computing does not have to be limited to road vehicles (Marín-Tordera et al., 2017; Zeadally et al., 2020). For example, sparsely distributed mobile service requesters can execute cooperative

Table 2
Comparison of a fog computing concept with its models that contribute to mobility-awareness.

Objective	Osmotic computing (OC)	Drop computing (DC)	Crowdsourcing (CS)	Opportunistic fog computing (OFC)	Vehicular fog computing (VFC)	Fog computing (FC)
Roots	Distributed computing	Social computing	Wireless sensor networking	Opportunistic networking	Mobile ad-hoc networking	Cyber foraging
System architecture	Hierarchical decentralised	Brokered, peer-to-peer	Cloud-brokered distributed	Dynamic distributed	Brokered, peer-to-peer	Hierarchical decentralised, peer-to-peer, brokered
Tiers	Three	At least one	Three	At least one	At least one	At least three
Applicability	Multi-tier architectures	Crowdsourced systems	Distributed sensing	Dynamic network environments	Vehicular environments	Generic
OpenFog pillar	Manageability	Scalability	Agility	Autonomy	Agility	(All)
Mobility perspective	n/a	User, network	User, network	User, network	User, network	User, network
Context awareness	High	Very high	Very high	Very high	High	High
Virtualisation	Supported	Supported	Optional	Supported	Supported	Supported
Nodal collaboration	Horizontal, vertical[a]	Horizontal, vertical	Horizontal[a]	Horizontal, vertical	Horizontal, vertical	Horizontal, vertical

[a] Brokered.

offloading towards satellite fog nodes within a satellite–terrestrial network (Zhang et al., 2019), while others can benefit from scalability improvements (Madan et al., 2020; Liao et al., 2021; Mohamed et al., 2017) introduced by fog-capable flying ad-hoc networks of unmanned aerial vehicles of strictly defined moving dynamics and paths (Motlagh et al., 2019; Zhu et al., 2021b). Furthermore, aerial, ground, and marine vehicles are expected to cooperate and collaborate to provide a robust fog computing environment (Chen et al., 2020). Vehicular fog computing, pictured in Fig. 3d, constitutes a fertile soil for connecting various ideas, and holds great promise for implementations in the near term.

4.6. Summary

This section presented a selection of the mobility-aware models of fog computing. The authors are well aware of numerous computing architectures that either laid the foundation for fog computing (Satyanarayanan, 2001; Balan et al., 2002; Puliafito et al., 2019) or loosely fall under the IEEE 1934 concept (e.g. dew Cristescu et al., 2019, mist Preden et al., 2015; Wang et al., 2019, social dispersed Conway et al., 2019; García-Valls et al., 2018; Yang et al., 2021, or moisture Tufail et al., 2021 computing, etc.). Various computing paradigms matching OpenFog's concept were devised, and the new ones are likely to come up. Five mature models discussed in this section demonstrate how node mobility can be addressed to build the complete computing solutions that span network layers of multiple heterogeneous devices. Each of the described solutions focuses on particular processes within a specific networking environment. Although vehicular fog computing seems to be the most evolved paradigm, the features from the remaining paradigms are required to assure all the benefits of fog computing. Table 2 summarises the characteristics of the discussed five models.

5. Examined research efforts

In this section, a detailed insight into the existing, largely theoretical, research works devoted to fog computing deployed over networks of mobile nodes is presented. The collected publications are discussed using a unified terminology, and analysed from the two major perspectives: models of fog computing applied by the authors, and the system aspects they contribute to. The applied model is inferred from contents of a research paper, although it usually matches the original classification provided by its authors. The review process aims to answer the research questions presented in Table 3 using a method described in Section 5.6.1. Papers are grouped by topics they address. For certain topics, the literature coverage is considerably low which results in few or single representatives works.

Research questions in Table 3 enclose the rudimentary ones that bring the subject of each reviewed article closer, and the three novel categories that focus on: multi-tier cooperation within the network, autonomic collaborative behaviour with functional safety aspects, and decentralised application handling during the fog operation. While rudimentary criteria are likely to be required and present in most of the surveys, the remaining three categories are unique to this survey.

A common terminology that follows OpenFog (IEEE, 1934) is established. Discussion on the contents of the reviewed works adheres to the introduced vocabulary. An entity that provides resources for either computation or storage task execution is termed as a fog node, while the entity that issues such a task is known as a service requester. Fog node is labelled as an infrastructure fog node if it does not change its position, otherwise it is referred to as a mobile fog node. Fog nodes may execute tasks originated from service requesters and other fog nodes. In general, offloadees run tasks of the offloaders. A structure that organises fog nodes is a fog network. Tasks are allocated to fog nodes in the fog network to provide fog computing services to the service requesters. Task allocation requires prior resource provisioning to reserve the computational and memory resources within the fog nodes for use by the service requesters (Martinez et al., 2021).

5.1. Osmotic computing

5.1.1. Network function virtualisation (NFV) in the vehicular environment

Authors of Mouradian et al. (2019) propose a solution to a tree-structured application placement onto a network of a hybrid fog–cloud architecture. Applications are modelled as graphs of heterogeneous application components interacting through different types of substructures (e.g. execution ordering relations, loops, conditional selection). NFV framework is utilised as a base for the deployment of the designed algorithms, thus the application placement problem comes down to the mapping of a virtual network function forwarding graph (VNF-FG) onto NFV infrastructure. Allocation of tasks to both tiers of the cloud and mobile fog nodes, as well as the iterative migration decisions, are centralised in the orchestrator functionality. The solution runs a heuristic that relies on aggressive reassignment of tasks until reaching a near-optimal placement, but the impact of migration and its details are not covered. Although placement jointly targets two tiers of a network, the evaluation considers scenarios with a predominant share of cloud nodes. Proposed a priori optimisation depends on the fog node location (estimated from the synthetic mobility model), and a fixed weighting parameter to control the target tier. A single fog node may host multiple application components at a time, however, applications do not arrive dynamically to the system. Replicas are not considered. Both the assumed lower bounds on fog-to-fog link bandwidth capacities, and the maximum task sizes seem unrealistic in practice.

Table 3
Description of symbols used in Table 4.

Section	Column	Description[a]			
Overview	M.	What is the implied model of fog computing addressed by the authors? Refer to Table 2 for glossary.			
Overview	Problem	How the problems is defined by the authors?			
Overview	Optimisation	What is formulated as an optimisation objective?			
Overview	Form.	How the problem is formulated mathematically? Glossary follows.			
		GrT	Graph theory	NLIP	Non-linear integer programming
		ILP	Integer linear programming	(N)LP	(non-)linear programming.
		MILP	Mixed integer-linear programming	(PO)MDP	(partially observable) Markov decision process
		(·)	Inferred from the text		
Overview	Sol.	How the formulated problem is solved? Glossary follows.			
		A	Analytical/numerical approach	GA	Genetic algorithm
		ACO	Ant colony optimisation	GmT	Game theory
		AAE	Adversarial autoencoder	GrT	Graph theory
		BPSO	Binary particle swarm optimisation	H	Custom heuristic
		(C)MAB	(combinatorial) multi-armed bandit	LP	Linear programming
		CNT	Complex network theory	MA	Memetic algorithm
		ConT	Contract theory	ML	Machine learning
		MchT	Matching theory	SAC	Soft actor–critic
		DQL	Deep Q-learning	(S)DP	(stochastic) dynamic programming
		FC	Field calculus	TS	tabu search
		FL	Fuzzy logic		
Overview	Env.	What is the target execution environment?			
Overview	T:N	What is the relation between a task and a mobile fog node? Glossary follows.			
		1:1	Deployment of a task to a fog node	M:1	Implies multi-tenancy and possible virtualisation
		1:N	Placement of a task divided into sub-tasks	M:N	Combination of M:1 and 1:N
Fog network	C01	Which simulator (evaluation environment) is used by the authors to evaluate their solution?			
Fog network	C02	How the solution exploits the fog hierarchy? Possible values: F (offloading fallback), E (decision escalation).			
Fog network	C03	Is the cloud cooperation (other than offloading fallback) included in the solution?			
Fog network	C04	Is the temporal network structure explicitly modelled?			
Mobile fog node	C05	Is the mobility of the either generated out of real traces (T), of synthetic model (G) or a mathematical mobility model is applied (M)?			
Mobile fog node	C06	Is the mobile node specialised in the set of accepted applications (A), the taken role (R)?			
Mobile fog node	C07	Is the collaboration hybrid (H: between infrastructure and mobile nodes) or nodal (N: between mobile nodes)?			
Mobile fog node	C08	Is the mobile node redundancy applied?			
Mobile fog node	C09	Is the mobile fog node autonomic (i.e. takes operator-independent decisions)?			
Fog operation	C10	Is the fog computing solution managed in a centralised (C), decentralised (D), or hybrid (H) way?			
Fog operation	C11	Is the processed application monolithic (I: indivisible), segmented (S)			
Fog operation	C12	Is the processed application structural?			
Fog operation	C13	Is the data caching modelled?			
Fog operation	C14	Is the application placement modelled?			
Fog operation	C15	Is the computation offloading process modelled?			
Fog operation	C16	Is the application (task) redundancy applied?			
Fog operation	C17	Is the task migration applied?			

[a] Dash character (–) in a cell of Table 4 denotes either information missing in the paper, or a non-applicable metric.

5.1.2. *Resource auction among fog clusters*

A cloud-to-thing continuum architecture proposed in Sun et al. (2020b) relies on the contract-based resource-sharing mechanisms established among dynamic fog clusters. Clusters are classified by functional domains of IoT applications possible to be handled by cluster members. Cluster heads are nominated by the centralised scheduling algorithm based on their betweenness centrality metric, computing performance, and communication delay to service requesters. Heads subsequently run aggregation of other fog nodes through application of spectral clustering methods. Fog nodes of low mobility are favoured as cluster heads. In the proposed resource-sharing auction, a cloud data centre acts as a trusted third-party, and is engaged in the centralised global task scheduling. The proposed scheduling algorithm aims to overcome the negative impact of fog node mobility by combining the dynamic construction of functional domains with resource sharing among fog clusters. Modelling of fog node mobility is limited to a fog cluster leave–join events. Authors assume fixed high-capacity (1Gbps) links between end devices and fog clusters, and a single cluster to logically cover all the end devices in a city. Migration through nodal collaboration, task decomposition, and reliability are not discussed thoroughly.

5.1.3. *Collaborative execution of a workflow graph*

A mobile fog environment with fog clusters managed by a distributed fog network controller is proposed in Alam et al. (2019). A controller is an autonomic offloading reinforcement learning-based agent that makes local decisions based on the observations of the network state, resource demand and availability. Agents collaborate directly to offload the application parts (workflow of "code blocks") to either the cluster members or cloud data centres. An offloading decision is consulted with neighbouring offloading agents to minimise the latency. Initially, a mobile service requester runs the application locally to collect the run time statistics. Collected data drives the application decomposition and flow graph analysis. That way, the interdependencies and estimated resource consumption are determined. Authors leverage existing cellular networks to i.a. run load balancing between fog networks, but details are not provided. Neither the performance footprint of statistics gathering, nor mobility simulation details are presented.

5.1.4. *Allocation of sub-tasks with linear relationships*

Research in Kimovski et al. (2021) discusses application placement of a graph of optionally sequentially inter-dependent sub-tasks onto virtualised resources of heterogeneous nodes in the cloud-to-thing continuum. The authors describe node mobility with Markov model to reduce the problem space of the meta-heuristic used to solve the multi-objective optimisation problem. State changes of a mobile node are observed at regular time intervals, and modelled as handovers between higher-level network gateways. Real mobility traces are used

Table 4
Surveyed publications.

Ref.	Overview							Fog network (C01–C04)				Mobile fog node (C05–C09)					Fog operation (C10–C17)							
	M.	Problem	Optimisation	Form.	Sol.	Env.	T:N	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15	C16	C17
Mouradian et al. (2019)	OC	Placement	Latency, resources	ILP	TS	Vehicular	M:N	–		★		M[c]	R	H			C	S	★		★	★		★
Sun et al. (2020b)	OC	Task sched., res. sharing	Latency	ILP	ConT, GrT, GA	Generic	M:N	iFogSim	FE	★		M[b]	RA	NH		★	C	S			★	★		
Alam et al. (2019)	OC	Offloading	Latency	MDP	DQL	Generic	1:1	MATLAB	FE	★		–	R	NH		★[d]	D	S	★			★		★
Kimovski et al. (2021)	OC	Placement	Latency, resources	LP	GA	Generic	1:1	iFogSim	E	★		T[a]					C	S	★		★			
Ciobanu et al. (2019a)	DC	Offloading	Latency, resources, energy	LP	H	Hybrid[e]	1:1	MobEmu		★		MT[f]		N		★	D	S				★		
Nistor et al. (2021)	DC	Task sched., migration	Task completion ratio	–	GmT	p2p	M:N	MobEmu	F	★		M	A	N		★	D	IS	★		★			★
Wang et al. (2021a)	CS	Node selection	Task completion cost	(ILP)	H[g]	IoT[h]	1:1	–		★		T[i]	R			★	C	I			★			
Zhu et al. (2021a)	CS	Task allocation	Latency	MDP	DQL	Vehicular	1:1	SUMO, other[j]				T[k]	R				C				★			
Sun et al. (2020a)	CS	Privacy protect.	Latency	–	H	Vehicular	1:1	Veins/OMNeT, SUMO	E	★	★	M	R	N		★	D	I						
Wang et al. (2020b)	CS	Movement path calc.	Latency, energy	(ILP)	H	Generic	1:1	MATLAB		★	★	M[l]				★	C							
Belli et al. (2020)	CS	net. scaling w. mobile nodes	net. coverage, connectivity	(ILP)	CNT[m]	Generic[n]	–	–				T[o]	R	H		★	C							
Wang et al. (2021b)	OFC	Offloading	Task completion time	MDP, LP	H	Vehicular	1:1	MATLAB	E	★		M[p]	R	H		★	D	S	★			★		
Audrito et al. (2021)	OFC	distrib. centrality meas.	Error of estim. harmonic centr.	GrT	FC[q]	Generic	1:1	Other[r]				M[s]	R	N		★	D							
Yang et al. (2020)	OFC	Offloading	Offloading success rate	(ILP)	H	Vehicular	1:N	SUMO, other[j]				G	R			★	D	I				★	★	
Asensio et al. (2020)	OFC	Service continuity	Latency, energy	MILP	ML[t]	Generic	–	Other[j]	E	★		M	R	N	★	★[u]	CH[v]	I					★	
Mseddi et al. (2019)	OFC	Offloading	Serving user requests	ILP	DQL	Urban	1:1	Other[x]		★		T[ab,ac]	R			★[d]	D	I				★		★
Du et al. (2020)	OFC	Offloading	Sensing cov., coverage overlap	(ILP)	ML[w]	Vehicular	1:1	Other[x]				T[y]	R			★	D	I				★		
Buda et al. (2020)	OFC	Offloading	Task completion ratio	(ILP)	FL	Vehicular	M:1	NS				M[z]	R	N		★[aa]	D	S			★	★		
Zhu et al. (2019a)	OFC	Offloading	Latency	POMDP	SDP	Vehicular	1:1	SUMO, other[j]			★	T[k]		NH		★[ad]	D	I				★		
Radenkovic et al. (2018)	OFC	Caching	Latency	(ILP)	GmT, CNT	Generic	M:N	Other[ae]			★	T[i,af,ag]	R	N		★	D	S		★			★	
Lv et al. (2021)	VFC	Offloading	Latency	MDP, ILP	DQL	Vehicular	1:1	Other[j]				T[k]	R			★	C	S				★		
Ye et al. (2016)	VFC	Offloading	Latency, incentive payments	LP	GA	Vehicular	1:N	Other				T[av]					C					★		
Zhou et al. (2020)	VFC	Offloading	res. utilisation	ILP	H	Vehicular	1:1	MATLAB				T[k]				★	D	I				★		
Tan and Hu (2018)	VFC	Allocation	Resources	MDP	DQL	Vehicular	1:1	Other[j]	FE			M[au]		H			C	S		★	★	★	★	
Yu et al. (2021)	VFC	Offloading	Cache hit ratio	–	FedSGD, AAE	Urban	1:1	Other[j]		★		M		N			C	I		★		★		
Wu et al. (2021)	VFC	Offloading	Latency	ILP	GrT[ai]	Urban[aj]	1:1	SUMO, NS	F			G[ak]		NH			C	I				★		
Tang et al. (2021)	VFC	Clustering	Clust. joining reward	ILP	GA	Vehicular	–	Other[j]				—[b]		NH		★	DH							
Sorkhoh et al. (2020)	VFC	Offloading	Offloading success rate	MILP	A[ar]	Vehicular	1:1	SUMO, other[j]				MG					C	I				★		
Cha et al. (2021)	VFC	Offloading	Latency	(ILP)	H	Vehicular	1:1	Veins/OMNeT, SUMO	F			MG	R	N		★	D	S				★		
Hameed et al. (2021)	VFC	Offloading	Offloading success rate	(ILP)	H	Vehicular	1:1	NS		★		M[c]	R	N		★	CH	I				★	★	★
Sun et al. (2021)	VFC	Offloading	Latency	NLP	CMAB	Vehicular	M:N	SUMO, MATLAB	FE			MG	R	H		★	DH	I				★	★	
Liu et al. (2021)	VFC	Offloading	Task completion ratio	(ILP)	H	Vehicular	M:1	MATLAB	F			M		H		★	D	I				★		
Zhou et al. (2019)	VFC	Offloading	Latency	(ILP)	ConT, MchT, MAB	Vehicular	1:1	SUMO, MATLAB	F			G[ak]	R			★	C	I				★		
Fu et al. (2021)	VFC	Video transcod. and stream.	Video QoS	MDP, (MILP)	SAC	Vehicular	1:1	Other[j]	F			T[k]					C	S	★					
Zhu et al. (2019b)	VFC	Offloading w. migration	Latency, total quality loss	NLP	LP, BPSO	Urban	1:1	Veins/OMNeT, SUMO				GT[at]					C	I				★		★
Liang et al. (2021)	VFC	Caching	Latency	MILP	A	Urban	1:1	SUMO, NS				GT[ah]		N		★	D			★				

(continued on next page)

to evaluate the proposed algorithm. The devised centralised application component placement strategy uses a genetic algorithm to jointly minimise the aggregated task completion time, energy consumption, and economic cost. A case study of a medical application with multiple

Table 4 (*continued*).

Ref.	Overview							Fog network (C01–C04)				Mobile fog node (C05–C09)					Fog operation (C10–C17)							
	M.	Problem	Optimisation	Form.	Sol.	Env.	T:N	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15	C16	C17
Jabri et al. (2019)	VFC	Cluster head election	num. of heads	ILP	ACO, FL	Vehicular[as]	–	SUMO, MATLAB, NS	F	★		MG	R	NH		★	H							
Yadav et al. (2020)	VFC	Offloading	Latency, energy	ILP	H	Vehicular[ap]	1:1	Veins/OMNeT, SUMO, MATLAB				MG[b,aq]					C	I				★		
Sami et al. (2020)	VFC	Allocation	Tasks allocated	(NLIP)	MA	Vehicular	M:1	SUMO, other[an]	FE			GT[ao]	R	NH	★	★	D	S	★		★			
Dong et al. (2020)	VFC	Offloading	Task completion ratio, energy	(NLP)	H[al]	Vehicular[am]	M:N	MATLAB				M	A	N	★	★	D	S				★	★	
Saad and Grande (2020)	VFC	Connectivity model	Connection quality	MDP	A	Urban	–	Veins/OMNeT, SUMO				MG		H		★	C							

[a] CRAWDAD: ilesansfil/wifidog.
[b] Dwell time.
[c] Random waypoint model (RWP).
[d] Controller.
[e] D2D and infrastructure.
[f] HCMM, UPB 2015.
[g] Heuristic based on probability calculations.
[h] Opportunistic IoT.
[i] CRAWDAD: cambridge/haggle.
[j] Custom simulator.
[k] Custom traces.
[l] Straight line movement.
[m] Complex network theory for online community detection.
[n] M^2EC.
[o] ParticipAct.
[p] As defined in Abboud and Zhuang (2014).
[q] Field calculus.
[r] Alchemist.
[s] Lèvy walks.
[t] Machine learning-based heuristic.
[u] Leader.
[v] See the second paragraph in Section 5.4.3.
[w] Heuristic based on machine learning: SVM, (distributed) Li-GRU.
[x] Not stated.
[y] NGSIM I-80, US 101.
[z] Freeway model.
[aa] Head.
[ab] CRAWDAD: ncsu/mobilitymodels.
[ac] CRAWDAD: roma/taxi.
[ad] Requester.
[ae] ONE.
[af] Cabspotting.
[ag] CRAWDAD: upmc/rollernet.
[ah] Europarc roundabout.
[ai] Bipartite matching.
[aj] Segmented road w. crossings.
[ak] SUMO: randomTrips.
[al] Based on discrete Newton method.
[am] Highway.
[an] Mininet-Wifi.
[ao] Google ClusterData2011, VanetMobiSim.
[ap] Two-lane bidirectional road.
[aq] SUMO: LuST.
[ar] Dantzig–Wolfe decomposition.
[as] Vehicular with MEC.
[at] Traces from iData Lab.
[au] Sojourn time.
[av] CRAWDAD: rice/ad_hoc_city.

interacting components is provided. Authors constrain optimisation problem to nodes of low mobility, and rely on fault tolerance in case of erroneous mobility prediction on the service requester. Moreover, fog nodes are not autonomic, and the task migration is not discussed thoroughly.

5.2. Drop computing

5.2.1. Offloading in a hybrid social-aware environment

Research in Ciobanu et al. (2019a) strives to jointly minimise the computation offloading completion time, resource and energy consumption in the scenarios of different network architecture setups, where multi-hop opportunistic networking is engaged to enhance the cloud–fog cooperation. Mobile nodes are clustered by social communities they belong to. Social network connections provided by an external systems are explored in device-to-device (D2D) offloading, and in the next-hop selection criteria of routing. Mobility of nodes is simulated with custom mobility traces, and by application of synthetic home-cell mobility model (HCMM) that approximates the human behaviour. Applications for offloading are meant to be split into multiple tasks with strictly defined real-time characteristics, albeit the corresponding impact on the system is discussed not thoroughly. Mobile computing nodes are restricted to smartphones, while more powerful units (termed "fog nodes") are of fixed positions and underutilised. Both the intra-cluster collaboration, and accidental task redundancy resulting from task dissemination are not explored by the authors.

5.2.2. Strategies for D2D task scheduling

Migration of workload in opportunistic network of mobile nodes with externally-provided social crowd characteristics, and real-time tasks of a stream structure, is discussed in Nistor et al. (2021). Authors elaborate on local, and global (crowd-wide workload balancing and task publishing) scheduling strategies executed by the nodes. Global strategy exploits community knowledge to establish trust between nodes, and to perform task migration. Decomposed tasks form a sequence whose original order is guaranteed by offloadees. Tasks are passed around till they found the appropriate offloadee nodes that meet the requirements. Nodes can reject the collaboration requests. Mobility patterns from HCMM are applied. Cloud data centres are implicitly used as offloading fallback in evaluation. Neither application to networking environments of low density nor exploitation of task semantics and social graph are covered in detail.

5.3. Crowdsourcing

5.3.1. Data collection in urban scenario

Authors of Wang et al. (2021a) propose a system in which a central server delegates the deadline-aware sensor data collection tasks to the recruited mobile nodes (“mobile gateways”). Nodes gather the task-specific sensor data from the fixed-position sensors in their proximity. Devised heuristic chooses the most suitable gateways for given tasks, and reorganises the sequence of sensors to be visited in order to minimise the task completion cost (i.e. reward paid to mobile nodes). Authors utilise real human mobility traces. Calculated time slot-based contact probabilities between mobile nodes and sensors estimate the chances of mobile nodes to collect the task-required sensor data within the deadlines. Whilst passively performing as data mules, mobile nodes exhibit their preferences by rejecting the recruitment offer, however they do not collaborate in data collection. Nodes with stable cloud connection are favoured.

5.3.2. Context-aware task allocation

A centrally managed system in which vehicle nodes gather and process visual data collected by other vehicles within their coverage area is proposed in Zhu et al. (2021a). A central coordinator asks vehicles to either video capture fixed-position targets of interest or process the collected video frames from the other vehicles in one-hop distance. A centralised context-aware task allocation scheme is executed per service zone (in evaluation: a single cell) to learn strategies which increase amount of useful information extracted from the collected data while minimising the processing latency. Proposed task allocation uses complete information of the environment to determine the data collection rate for the sensing vehicles, and assign the processing tasks based on estimated quality of information (QoI) and workload. Authors model fog nodes (data processors) with buses of predefined trajectories, and use real-world mobility data sets in evaluation. Speed and movement direction of the collector vehicles, and the overall number of vehicles are assumed to be constant during a fixed-length decision epoch.

5.3.3. Incentives, and trust management

Sun et al. (2020a) discusses a fog-based privacy protection of the personal data in the bidding process within the designed incentive mechanism. Authors aim to reduce system response time and communication overhead. Collaborating buses are organised into one-hop-range fog clusters (“regions”) that are maintained through a direct communication and broadcasting. Clustering is driven by the temporal information derived from the historical locations of buses. Clusters are concentrated around an area of a high bus traffic, and remain valid until the next bus route planning details update. Vehicles serve as smart sensor platforms, data collectors, or assist in incentive mechanisms. Reward data is routed between clusters in opportunistic manner. Fog nodes proxy task assignment to worker vehicles.

In Wang et al. (2020b), a spatial crowdsourcing setup embedded in a mobile fog computing environment with worker fog nodes visiting the fixed-position heads of sensor clusters forms a test bed for evaluation of a trustworthy data collection with fog node path planning algorithm. Algorithm minimises energy consumption and transmission delay of the task execution. Fog nodes apply direct and indirect metrics to estimate the sensor’ trust values and levels, so that only data from trustworthy sensors is gathered. Direct trust metrics exploit historical communication interactions of the sensor node, while the indirect ones combine trust information from the neighbours. Trust values drive the cluster head election in stable sensor networks, and guide the fog node mobility. Fog nodes do not collaborate with each other, and have limited moving distance.

5.3.4. Community detection to build an overlay network

Belli et al. (2020) extends existing infrastructure networks with mobile nodes elected from candidate mobile user devices by means of periodic application of centralised evolutionary community detection algorithms. Part of the fixed-position nodes take roles of crowdsourcing brokers, while some of the mobile nodes opportunistically collect data from workers and proxy access to the brokers in a cloud. Authors measure effectiveness of the selected community detection algorithms in the identification of evolving communities. Measurements of the members’ centrality metrics drive the designed mobile node selection strategy. Mobility is simulated with real human mobility traces, however application to a real-world use case is not discussed.

5.4. Opportunistic fog computing

5.4.1. Sequential task graph execution

In Wang et al. (2021b), service requesters located in the resource-constrained vehicles offload the structured applications to the selected nearby resource-rich vehicles. An application forms a graph of tasks bound by a data flow, where a task is either run locally or offloaded from a vehicle to a vehicle. Offloadee selection, task allocation, and data transfer happen on a regular basis, however the assigned tasks always run to completion with neither migration nor fault management involved. Evaluation is limited to a single application in a single-tenant environment. Synthetic microscopic mobility model simulates vehicle moves along a unidirectional straight road of a predefined length.

5.4.2. Distributed situation recognition

Audrito et al. (2021) tackles a problem of coordination of the dynamic IoT systems using the distributed centrality measures applied to the incomplete time-varying network graphs with injected faults. Authors use properties of direct neighbourhoods to establish a classification of arbitrary large dynamic networks that preserves locality of interactions. Proposed algorithms are used to nominate local coordinators to support the use cases of situation recognition tasks like network vulnerabilities detection, and election of cluster heads of “fog colonies”. Centrality measures are calculated by nodes locally and asynchronously. Synthetic mobility with Lèvy walks is modelled. Work lacks extensive evaluation in practical setups.

5.4.3. Task replication, and node redundancy

Signalised road intersection scenario and task replication are investigated in Yang et al. (2020) to enhance performance of deadline-aware task offloading. A fixed budget of task copies controls the redundancy level. No recovery mechanisms for partial offloading results are discussed. Offloaders receive an offloadee candidate list at intersections. Joint consideration of traffic data (e.g. traffic lights state) and vehicle movement is exploited to predict the future vehicle position. Although vehicles follow realistic mobility patterns, the environment is semi-static.

In Asensio et al. (2020), a fault-tolerant multi-agent hierarchical system of fog clusters with dynamically elected cluster heads’ backup nodes (“leaders”) guarantees service continuity, and increases the architecture robustness. Once the current head fails or suddenly leaves the network, a backup node retains the access to cloud management functions and a copy of the storage. Leaders are managed by a cloud-based centralised agent, whilst they coordinate the respective cluster members. Centralised agent runs heuristics to derive a set of actions to map the nodes from a physical to a logical topology through iterative connectivity-based *k*-means-based clustering and node role assignment strategies. Cluster heads apply those actions in a decentralised manner. Authors minimise a weighted-sum objective, where mobility of a node is a weighted discrete variable. There is no further evaluation with real-world traces mobility.

5.4.4. Container placement and migration

Mseddi et al. (2019) discusses containerised task offloading to a clustered fog network of nodes classified by their mobility patterns. A cluster head ("domain controller") executes an online resource allocation strategy that deploys containers to cluster members (or fallbacks to a cloud), so that the number of satisfied offloading requests is maximised. Workload migration between nodes happen if the continuously monitored fog-requester communication and processing latencies exceed certain thresholds. Nodes are categorised by their mobility degree (immobile, slow-moving, fast-moving), and evaluate the solution with (respective to the category) real mobility traces. However, cluster head mobility is not discussed thoroughly, and the evaluation considers only a single cluster (neither cluster formation, maintenance, nor cooperation are taken into account).

5.4.5. Cooperative sensing in a platoon

Du et al. (2020) proposes an infrastructure-less vehicular system with clustered adjacent vehicles sharing their sensing, communication, and computation resources to enhance the safety of autonomous driving. Platoon-head vehicle allocates visual sensing tasks to the vehicles of heterogeneous sensing capabilities for cooperative processing in order to maximise the non-overlapping sensing coverage. The head vehicle fuses the task results to get an accurate state of the platoon, and to feed the distributed deep learning-based lane change manoeuvre prediction algorithm. The prediction is limited to mandatory and discretionary situations, and vehicle selection lacks extended context-awareness. Mobility is simulated with real-world traces, however, vehicles are driving at a relatively stable speed and distance (platoon formation condition).

5.4.6. Collaborative task offloading

Buda et al. (2020) formulates a two-stage algorithm for non-monolithic task offloading in a clustered vehicular environment to one- and two-hop offloadees. The first stage leads to a cluster formation, while in the second stage a cluster head either partitions and allocates tasks to members or requests a collaborative processing from neighbouring clusters. Tasks are executed in parallel to boost completion rate. A decentralised fuzzy logic-based heuristic for cluster head election consumes data exchanged between one-hop neighbours, while fuzzy membership functions and offloadee selection take advantage of expert knowledge and context-aware metrics. Mobility is simulated with a freeway model (Wu et al., 2013). Details of collaboration between cluster heads are not covered, while the task and result data sizes are of fixed small values during evaluation.

5.4.7. Temporal-aspect-driven task offloading

In Zhu et al. (2019a), a distributed online offloading scheme ("Chameleon") of image-based object recognition monolithic tasks from vehicular requesters to bus fog nodes aims to process data of higher image quality with lower latency. A spatio-temporal variation in vehicular traffic density is explored to define time periods ("buckets") in which traffic density changes regularly. Workload of a fog node is expected to evolve as a Markov chain within a time bucket of equally-sized time slots. At the beginning of a time bucket, service requester selects an offloadee from the one-hop candidates. Image resolution is adjusted to the workload observations. Evaluation with a visual-based assisted driving application considers both the infrastructure and mobile nodes. Simulation uses custom mobility traces extracted from real data. Neither nodal collaboration, extended context-awareness, nor highly congested situations are addressed in detail.

5.4.8. Social-aware data offloading

Envisioned in Radenkovic et al. (2018), a context-aware peer-to-peer collaborative content sharing scheme applies predictive heuristics to overlay networks of connected infrastructure and mobile nodes in dynamic disconnection-tolerant networks. Overlay networks encode social topologies with relations between the content publishers and subscribers, and nodal temporal perspectives ("ego networks") to model the nodes met. Nodes observe and exchange upon a contact the time-varying local content popularity. Social metrics (e.g. betweenness, centrality) of neighbours are examined to manage heterogeneous chunks of content with individual popularity, and adaptively forward caching requests based on fused local popularity. Nodes run neighbour offloading of least popular content to prevent from resource exhaustion. Although mobility of nodes is simulated with real-world data sets, the solution lacks extended evaluation in real environments.

5.5. Vehicular fog computing

5.5.1. Cooperative offloading

Delegation of tasks to vehicles for cooperative execution can either support the overloaded RSUs (Ye et al., 2016; Lv et al., 2021), or reduce the negative impact of the mobility-induced migrations on task processing (Lv et al., 2021), or optimise resource utilisation in offloading (Zhou et al., 2020; Tan and Hu, 2018). In particular, Lv et al. (2021) enables the vehicles that are passing through two adjacent RSUs' handover area to apply the learnt optimal one-hop offloading schemes, in Ye et al. (2016) bus fog nodes of known positions extend RSU capabilities in incentive-aware task processing, Zhou et al. (2020) splits offloading into two phases: request gathering and issuing of scheduling policy to be locally executed at each fog node, and final fog node selection based on received policies run by a requester, Tan and Hu (2018) discusses coded content caching in short and long time horizons ("timescales"), where the Q-learning model optimises cost of resource allocation.

Vehicles of public transport mobility characteristics, like taxis (Lv et al., 2021) and buses (Ye et al., 2016) are likely to become offloadees in cooperative offloading due to their predictable mobility trajectories. Candidate vehicles are selected either centrally by an RSU: based on the predicted trajectories (Lv et al., 2021), and accurate positions observed in real-time (Ye et al., 2016; Tan and Hu, 2018), or distributively: by requesters, based on scheduling policies calculated by neighbouring fog nodes (Zhou et al., 2020). While Ye et al. (2016) solely nominates vehicles as offloadees, Lv et al. (2021), Zhou et al. (2020) and Tan and Hu (2018) involve infrastructure and mobile nodes as candidates. A fixed radius (Lv et al., 2021; Ye et al., 2016), or a communication range is explored (Zhou et al., 2020; Tan and Hu, 2018) in candidate discovery. Although (Lv et al., 2021) mentions task segmentation to execute partial offloading, no further discussion follows. Coded caching in Tan and Hu (2018) supports costly download of missed data segments from infrastructure nodes, while remaining works deal with monolithic tasks. Neither task redundancy nor multi-tenancy (results from prevailing binary ILP formulation of task assignment) are present. Works do not model the offloadee behaviour (e.g. no task rejection policies, selfishness, etc.), and no autonomous collaboration is found. Dynamic task arrival is rarely explored. Solutions lack evaluation in realistic networking setups.

5.5.2. Caching with federated learning

A self-driving environment, where cellular base stations provide arrival times of vehicles at each RSU is given in Yu et al. (2021) as a background for discussion on tasks offloading of monolithic model training to subsets of neighbour vehicles selected for participation in the federated learning-based content popularity prediction. Vehicles learn the AAE shared model with their private data of diverse quality. Global model at RSU is repeatedly updated by aggregating the locally trained ones. Contents cached in RSUs are cooperatively replaced in assistance of a base station that populates subsequent RSUs with the predicted popular contents. Population happens in response to movement of a vehicle group along the road with adjacent road site units, however only the RSU located at the entrance to the road runs the popularity prediction. Solutions lacks simulation of vehicular mobility with real-world data sets and reliability modelling. Context-awareness is only exploited for the mobile user in the vehicle.

5.5.3. Clustering based on road topology

In Wu et al. (2021) vehicles in the coverage area of an RSU are organised into directional groups (“fog cells”, “subnetworks”) according to their turning directions at the next crossing. Groups aid the centralised monolithic task offloading scheme run by other vehicles. Idle resources in vehicles and RSUs are considered jointly. RSU exploits the complete state information of the network it covers to select the offloadees, and execute offloading. Collaboration for task offloading is only allowed with RSU and within the same group. However, a vehicle can process at most one task simultaneously, and RSU-assisted handover of offloading results is only covered in simulation. Vehicles are expected to obey the traffic rules (e.g. sudden lane change is prohibited), and they follow the generated mobility patterns.

5.5.4. Resource pooling

Resource pools in VFC are modelled as clusters managed by either infrastructure (Tang et al., 2021; Sorkhoh et al., 2020; Hameed et al., 2021) or mobile (Cha et al., 2021) cluster heads. In particular, Tang et al. (2021) sketches a system with incentives offered by RSUs to offloadees on behalf of requesters, in Sorkhoh et al. (2020) RSU schedules the execution of tasks with deadlines either at the RSU or at in-range vehicles, while other works deal with optimal formation of on-demand (Cha et al., 2021) or scheduled (Hameed et al., 2021) clusters that execute tasks within a time limit. Cluster is formed either entirely bottom-up voluntarily through interactions of candidate members with the head (Tang et al., 2021), collaboratively through explicit confirmation of the membership (Cha et al., 2021), or exclusively by the head (Sorkhoh et al., 2020; Hameed et al., 2021). While Tang et al. (2021), Cha et al. (2021) and Hameed et al. (2021) limit set of member types to vehicles, Sorkhoh et al. (2020) includes also RSUs. Stability of a cluster depends on its (re-)construction metrics, and determines its effectiveness in execution of the requested tasks. Tang et al. (2021) considers vehicle’s dwell time in the coverage of RSU, available resources, and cluster joining reward in community formation metrics. Cha et al. (2021) and Hameed et al. (2021) exploit contextual information from V2X safety beacons (e.g. position/distance, velocity, direction, etc. – cf. IEEE 802.11p BSM) to recruit the cluster head (in Hameed et al. (2021)) or members (in Cha et al. (2021) and Hameed et al. (2021)). Cha et al. (2021) proposes a “companion time” (i.e. an upper limit of link duration between two nodes) to measure the cluster lifetime. Furthermore, Sorkhoh et al. (2020) operates within a single global cluster. However, in Cha et al. (2021) vehicles of speeds above a fixed limit are ignored (to favour stable clusters), and Hameed et al. (2021) does not support self-nomination: cluster head is selected by an infrastructure node (“fog gateway”). Although (Tang et al., 2021) aims to decentralise decision making process, there are discussed neither collaboration, respective cost analysis, nor confirmed autonomy of vehicular choices. The evaluated there GA-based optimisation assumes fixed number of vehicles and communities (implies centralised or hybrid management). Fixed number of clusters and cluster members is also present in Hameed et al. (2021). While Sorkhoh et al. (2020) generates mobility patterns for a dozen of vehicles, Cha et al. (2021) runs evaluation in an urban environment with a straight road and limited speeds, Hameed et al. (2021) uses synthetic model (RWP), and a work in Tang et al. (2021) provides no details on mobility simulation.

Performance of the surveyed solutions suffer from high vehicular density (in Tang et al. (2021)) and mobility (in Hameed et al. (2021)). Sorkhoh et al. (2020) experiences notable task rejection rates with increase of the tasks’ requirements or arrival frequency, while service quality in Cha et al. (2021) quickly degrades with growing number of cluster members. Furthermore, Sorkhoh et al. (2020) does not involve sophisticated handling of resource starvation (tasks are just deleted), nodes’ serviceability dynamics are fixed, overall simulation time is short (60s), and system becomes overloaded as soon as task arrival rate reaches 1 Hz. Only (Hameed et al., 2021) suggests task replication and load balancing within and among clusters to circumvent high topology dynamics. Additionally, tasks in Sorkhoh et al. (2020) are monolithic and run to completion once assigned by RSU, While Cha et al. (2021) only allows types of tasks that are blankly splittable by the cluster head (e.g. image recognition, etc. – albeit the mechanics lack modelling). Although (Sorkhoh et al., 2020) classifies tasks by their size, resource and time demands, neither semantic- nor context-awareness are considered. Reviewed papers impose multiple constraints that limit their applicability and scalability. For example, Tang et al. (2021) prohibits shared membership (i.e. overlapping communities), Sorkhoh et al. (2020) limits on-demand adaptive scaling (e.g. one processing unit per node, node orchestration is not taken into account), Cha et al. (2021) handles cluster reconstruction inefficiently (i.e. system actively waits for a new node), Hameed et al. (2021) does not deal well with highly dynamic environments (e.g. highway scenarios).

5.5.5. Task replication

A work in Sun et al. (2021) studies a relation between the number of task replicas and execution delay. The devised two-step approach to the replica number estimation consists of a RSU-centralised rough approximation for a long time horizon (“timescale”) based on statistical network conditions, which is subsequently autonomically fine-tuned by vehicular offloaders for a short time horizon using sequential decisions (CMAB). Goal of an offloader is to choose a subset of offloadees for a replica assignment so that the offloading delay is minimised. Such a hybrid scheme is promising in balancing the management workload while retaining context locality. However, in this work, tasks are strictly homogeneous (incl. deadlines and types) and run to completion (i.e. pending redundant executions are not cancelled), task rejection is not discussed (i.e. it assumed that at least one offloadee accepts the task), no offloadee collaboration happens, cost of local management lacks analysis, replica calculation is not proactive (scheme runs once task becomes a task queue head), and mobility traces are synthetic (generated for a highway scenario).

5.5.6. Multi-period task offloading

Liu et al. (2021) proposes a multi-period offloading which is an extension of Wang et al. (2020a) for hybrid environments. Designed scheme is similar to the two-step approach from Zhou et al. (2020), but with scheduled allocation attempts of the remaining tasks. That is, tasks that are not selected by the offloadee candidates are broadcasted to nodes contacted in the next periods with hope for an acceptance. Simplified incentive mechanism is devised to reward fog nodes in dynamic programming-based decision making. Requesters run a heuristic-based node selection that aims to maximise task completion ratio. There is no task redundancy, reliability aspect is missing (i.e. assumed uninterrupted communication and sufficient dwell time), and the simulated urban mobility scenario lacks details.

5.5.7. Offloading under information incompleteness and uncertainty

Work in Zhou et al. (2019) designs an offloadee selection scheme that combines centralised contract signing and pricing-based iterative matching with local preference learning at the requester. Having a complete information, the operator quantifies resource sharing capabilities of vehicular offloadees (i.e. assigns "types"), while under information asymmetry only estimation of type probability is available. Operator aims to maximise its long-term profit by signing contract items with the willing vehicles, so that certain amount of resources at some price ("matching cost") is shared by given vehicle types. At the other end, a requester with complete information issues a list with preferred offloadees to the central unit for one-to-one matching with an offloadee. However, once having no global outlook, the requester tries to minimise its long-term offloading delay by adjusting the parameters in the preference calculation (i.e. history of selections and observed delays) with online learning (MAB). Authors consider neither context-awareness in preference construction, task redundancy (incl. handling of multiple tasks at each time slot), offloading fallback details, mobility simulation with real traces in scenarios other than a highway, nor incentive system modelling.

5.5.8. Semantic-aware real-time data processing

Authors of Fu et al. (2021) propose a live video transcoding system in C-V2X environment, where RSU allocates transcoding requests to fog nodes (buses, commercial fleets). Time-varying resources and link quality are modelled as fully observable stochastic processes (of values discretised at finite number of levels) to form a MDP for joint optimisation of bitrate adjustment, offloadee selection (no redundancy), and resource allocation. Proposed scheme is centralised at RSU to run SAC learning. Authors evaluate different categories of video streams (e.g. sport, cartoon, etc.), however each such a segment is of a fixed playback time (cf. task deadlines in Sun et al. (2021)). Semantics of a stream category put specific requirements on transcoding resources' consumption. Although custom traces are supposed to drive the mobility, the data set lacks details. Serving latency rapidly increases with growing number of requesters, while large (over 8) number of fog buses leads to serious communication issues.

5.5.9. Event-triggered offloading and migration

Zhu et al. (2019b) devises a task allocation scheme ("Folo") that assigns containerised video streaming and recognition service instances to commercial fleets (e.g. taxis, buses). The existing cellular networks are reused for scheme deployment (base station), communication, node discovery and tracking, and to trigger iterative live migration upon handover events. Additionally, a requester discovers candidate offloadees with 802.11p one-hop broadcasts. Solution maintains a weighted trade-off between the service latency and quality loss (discretised at several levels). Although the complete system information is explored, the scheme suffers from scalability issues during high density of vehicular traffic (simulated with custom traces). Solution exhibits high memory consumption, even though number of video streams is relatively low (up to 8), and simulation time is relatively short (60s).

5.5.10. Improving network connectivity with forwarding and proxying

Apart from task and data offloading, some authors propose solutions to delivery of data sensed by vehicles (Liang et al., 2021), and drain of cellular radio resources (Jabri et al., 2019) within the dynamic environments. In Liang et al. (2021) a fog node rebuilds the data forwarding path at each hop if the current data relay vehicle is likely to leave its communication range. The selected adjacent vehicle serves as a data mule that runs store-carry-forward of as much sensor data as possible towards the processor ("fog node"). Furthermore, Jabri et al. (2019) aggregates cloud-directed traffic by nominating proxies ("gateways") around which a fixed number of vehicles can cluster. Candidate gateways are self-nominated with fuzzy logic scheme which consumes degree centrality and link quality measurements. After vehicles broadcast self-nomination results to neighbours, the ACO-based velocity-oriented clustering happens. Both reviewed solutions are evaluated with urban scenarios (fog nodes are taxis (Liang et al., 2021) or buses (Liang et al., 2021; Jabri et al., 2019)) of low mobility (30–60 km/h (Liang et al., 2021), 0–20 km/h (Jabri et al., 2019)) using real (Liang et al., 2021), simulator-generated (Liang et al., 2021; Jabri et al., 2019), and synthetic (Jabri et al., 2019) traces. While Jabri et al. (2019) assumes that vehicles never leave the service area, and there is a MEC infrastructure (scheme initiator, service fallback) present, Liang et al. (2021) expects that relays have enough time to store and forward the received remaining data. Both works neither include redundancy (in: gateways, auxiliary relays), load balancing (of: communication overhead, and fog process), nor security threat analysis. Liang et al. (2021) deals well with high density traffic, but suffers from unavailability of candidate relays (i.e. applies active waiting), rapid changes in density, and higher mobility of fog nodes. Jabri et al. (2019) observes a lower ratio of connected vehicles in mobile scenario. Interestingly, Liang et al. (2021) analyses the computational cost of its algorithm.

5.5.11. Overloaded node management

Yadav et al. (2020) delegates mobile users' tasks from overloaded infrastructure ("cloudlet nodes") to vehicles of commercial fleets (buses, taxis). Proposed scheme relies on the locally (at a cloudlet) estimated future resource demand. Measurements are collected by a "zone manager" (at a base station) to trigger the task and offloadee selection procedures. Cellular networks' spatial organisation and facilities are reused (cf. Jabri et al. (2019), Yu et al. (2021) and Zhu et al. (2019b)). Collaboration happens neither between zones nor vehicles, thus the devised heuristic-based scheme suffers from varying traffic density, task storm due to number of requesters, and higher velocities. Mobility is simulated with a synthetic model, and generated traces (urban scenario). Authors provide a computational complexity analysis.

5.5.12. Microservices

Scheme in Sami et al. (2020) allocates containerised service instances (cf. Zhu et al. (2019b) and Cha et al. (2021)) to clusters of vehicles. Specification of a service comprises inter-dependent microservices, each mapped to a fog node in the same cluster. Multi-objective maximisation of the deployed services is solved with a genetic algorithm which repairs the infeasible individuals (through container migration, cluster extension, and change in the service specification). A hybrid multi-layer network architecture is exploited in failure handling (e.g. connectivity, head recovery, migration, etc.), approval of the cluster offers by the requester, and intra-cluster load balancing. A cluster head self-election happens locally (QoS-OLSR). Kubeadm tooling is extensively used in the management of clusters. Evaluation with real data sets excludes the node heterogeneity, while connectivity to the orchestrator (head or RSU) is assumed stable. Authors describe multiple features of the devised system, however, there are almost no in-depth descriptions.

5.5.13. Node redundancy to improve computing reliability

Dong et al. (2020) discusses reliability for task offloading to a cluster of vehicles ("helpers") with backup nodes ("followers") that calculate at reduced rates ("shadowing replication"). The designed recovery mechanism substitutes a node upon its failure or cluster leave with the associated replica, speeds up the replica calculation rate, and nominates a replica for it. Leave notification is issued in advance. Through boost in the rate, the execution states of a task segment assigned to the replica and the faulty node are expected to match. That is possible by setting an optimal lower bound on the calculation rate, which is a trade-off between the energy consumption (grows with higher reduced rates) and latency (affects task completion ratio). Followers do not have to belong the followees' cluster, however task halts if they are not present in the head's range during recovery. Overlapping communities are prohibited (i.e. a helper belongs to a single cluster), there is exactly one replica for a node, task segments have no dependencies. Moreover, neither head recovery nor allocation of functional layer (e.g. security management, results assembly, cluster disbanding, etc.) to the hybrid networking environment are discussed in detail. Evaluation does not provide information on the simulated mobility (highway scenario). The number of segments is medium (10), while the number of fog nodes is an order of magnitude larger than the service requesters.

5.5.14. Modelling the effects of mobility

Saad and Grande (2020) devises MDP-based solution to represent and estimate the link quality ("connectivity status") of a vehicle communicating over multiple heterogeneous media (e.g. V2X, LTE, etc.) including handovers, simultaneous and interleaving connections. Locally calculated quality data are comparable (e.g. may extend the ranking metrics in a candidate offloadee selection), and remain valid even if the hops are increased (e.g. due to mobility). RSU records the advertised qualities to run vehicle behaviour estimation. Authors do not discuss the long-term estimations of link quality and intermittent connections. Simulation relies on a single-RSU urban environment and generated mobility traces. Similarly to Dong et al. (2020), the main focus is put on a detailed design of a VFC building block, rather than a whole system of partially modelled components.

5.6. Methodology details

This survey examines selected research works in the domain of fog computing with mobile fog nodes. In order to clearly expose the core ideas taken up by the authors, as well as to facilitate the readers' understanding, the articles were summarised using the developed unified vocabulary. Original wording was additionally given in quotation marks. Next sections outline the details of the adopted methodology, and provide guidance to the presentation of results.

5.6.1. Method

An iterative multi-step method was applied to search for and to qualify the research papers. Although, initially inspired by Kitchenham et al. (2010), the developed selection and qualification methods were loosely based on the presented there process due to the subject specifics resulting in i.a. notably scarce coverage of the matter in publications. The conducted iterative method comprised two stages executed after preliminary abstract screening had filtered out the irrelevant search results.[2] In the first stage (initial screening), a careful inspection of the system model as delineated in each article led to matching a fog computing model. Furthermore, the general characteristics of the modelled problem were gathered and tabularised. First stage was completed with two-way snowballing process that identified valuable references to either be directly included in next iterations, or trigger scheduling of citation alerts, or both. Second stage of the method left aside all the papers that did not involve mobile fog nodes as computation entities. Consequently, the detailed reading of the full texts was started for the qualified papers. Peculiarities of the system models were contrasted with the results of evaluations carried out by the authors. In the meantime, authors ideas were probed to match and extend the developed unified vocabulary. Both the temporal (e.g. conference papers predating the corresponding journal publications), and functional (e.g. equivalent contribution) duplicates were identified and resolved. The devised review method is quality-oriented, thus publications with unclear, incomplete or inconsistent contribution were low ranked.

Execution of the review method led to a qualification of 1172 papers in total. Collected fog computing-related works span over years 2013–2021, however those published after 2017 were considered foremost to increase the probability of OpenFog reference and awareness. Iterative application of the first stage cut down the overall number of articles in a pool to 140 entries. Execution of the second stage left 41 papers presented in this survey. New publication alerts provided by the scheduled search queries, and citation alerts were inspected weekly as the subjects of the review method until mid of October, 2021. Scopus abstract and citation database, and the related tools, were used to query and monitor the peer-reviewed literature.

5.6.2. Presentation

Surveyed articles are categorised, and presented from multiple perspectives using various means. Decimal percent values were rounded up to whole numbers in all the figures to increase diagrams' readability. Table 5 provides a bird's eye view of the reviewed domain, and the related open issues. Domain of a fog computing concept is divided into its models, where the percentage contribution is expressed as a ratio of a number of articles linked to a particular model to the total number of surveyed articles. Bar plot-visualisation of the selected aspects (Table 3) with coverage in fog computing models is given in Fig. 4. Illustration of mathematical frameworks employed, and optimisation goals set by the authors of the surveyed research works without an distinction into fog computing models is provided in Fig. 5. Table 4 provides a summarised information on the surveyed papers.

6. Open issues and research opportunities

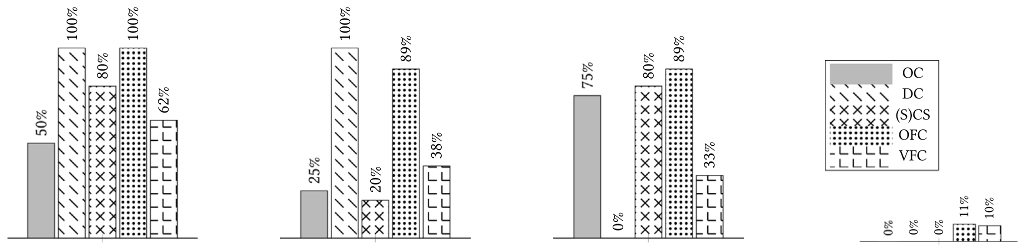
Although formally conceptualised in 2018 with IEEE 1934 as an adoption of the OpenFog Ref. IEEE (1934), the ideas emphasised and incorporated by fog computing were evolving over years. Research studies on providing the computing and storage functionalities to the resource constrained end users led to the emergence of a multitude of overlapping architectures and algorithms to address the selected areas of the problem. Several of those solutions that comply with the fog computing characteristics are considered in this survey under the umbrella of OpenFog formulation. Massively distributed computing environment in which fog is anchored poses numerous challenges on multiple system levels that touch various actors of the system. This survey aims to picture the current state of the academic research on fog computing with mobile fog nodes, where the mobility-awareness is seen as a key enabler for highly scalable adaptive fog solutions. This section outlines the spotted issues, as well as presents the opportunities of further research studies. Table 5 summarises the open points topic-wise.

6.1. Osmotic computing

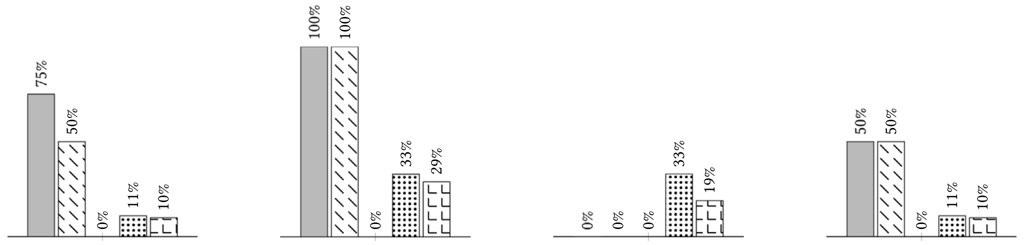
OC offers rapid on-demand flow of tasks in multiple dimensions within the cloud-to-thing continuum. Works that contribute to OC suffer from the highly centralised management (Figs. 4(a), 4(b), 4(o)). **Decentralisation** should improve **scalability** of solutions, enable fine-grained **context-aware decisions** (cf. Mouradian et al. (2019)), and would look kindly on nodes of higher mobility (cf. Kimovski et al. (2021) and Sun et al. (2020b)). Although migration seems to be the main feature of OC, its evaluation is rarely in-depth (Fig. 4(h)). Papers lack comprehensive analysis of the schemes' cost and performance footprint (Mouradian et al., 2019; Alam et al., 2019), incorporation of

---

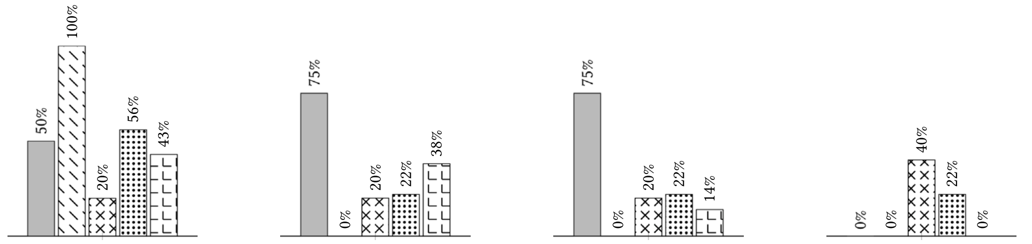
[2] Following queries were used to obtain article search results in Scopus (excluding article citation alerts): `TITLE-ABS-KEY((‘‘fog computing’’ OR ‘‘edge computing’’) AND (‘‘mobility-aware’’ OR ‘‘dynamic network’’ OR ‘‘dynamic topology’’)) AND PUBYEAR > 2017; TITLE-ABS-KEY((‘‘fog computing’’ OR ‘‘edge computing’’) AND (‘‘mobile fog’’) AND NOT (‘‘mobility-aware’’ OR ‘‘dynamic network’’ OR ‘‘dynamic topology’’)) AND PUBYEAR > 2016; TITLE-ABS-KEY(‘‘vehicular fog computing’’) AND PUBYEAR > 2015; TITLE-ABS-KEY(‘‘mobile fog computing’’) AND PUBYEAR > 2015; TITLE-ABS-KEY (‘‘autonomic computing’’ AND ‘‘fog computing’’); TITLE-ABS-KEY((‘‘fog computing’’ OR ‘‘edge computing’’) AND (‘‘opportunistic computing’’ OR ‘‘opportunistic networks’’)); TITLE-ABS-KEY((‘‘fog computing’’ OR ‘‘edge computing’’) AND (‘‘dynamic networks’’ OR ‘‘complex networks’’ OR ‘‘temporal networks’’ OR ‘‘time-varying networks’’)).`



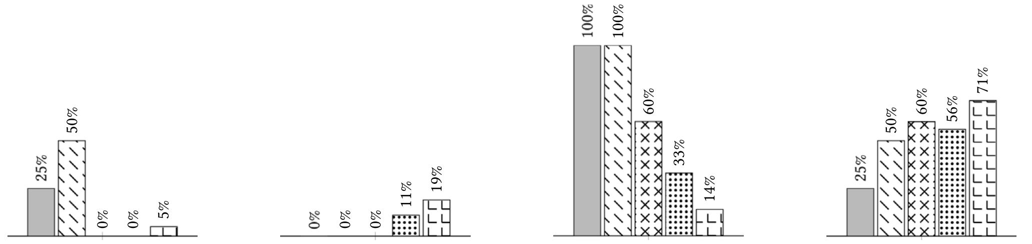
(a) C09: autonomy (b) C10 D: decentralised mgmt (c) C06 R: node roles (d) C08: node redundancy



(e) C12: structural apps. (f) C11 S: segmented apps. (g) C16: app. redundancy (h) C17: migration



(i) C07 N: nodal collab. (j) C07 H: hyb. collab. (k) C02 E: escalation (l) C04: temporal net.



(m) C06 A: app. nodes (n) C10 H: hyb. mgmt. (o) C03: cloud coop. (p) C05 T G: traces

Fig. 4. Percentage contribution to the selected aspects of a fog computing concept distributed over its models in the context of the surveyed publications. Please refer to Tables 2 and 3 for the glossary of acronyms and codes, respectively.

fault resilience (Sun et al., 2020b; Mouradian et al., 2019), and details of interoperability with existing networking environments (Kimovski et al., 2021; Alam et al., 2019). To improve solutions' **reliability**, simulations should run in realistic networking setups with real mobility data sets (Fig. 4(p)).

6.2. Drop computing

DC scales well over hybrid networks through collaborative decisions that take into account the social component. In its current research phase, it is limited to human behaviour, node **heterogeneity** is low (Figs. 4(c), 4(m)), **interoperability** is left implicit, and simulator support lacks alternatives (Ciobanu et al., 2019a; Nistor et al., 2021). Although DC heavily relies on opportunistic networking, neither redundancy nor **hybrid management and hybrid collaboration** are eagerly explored (Figs. 4(j), 4(k), 4(n)). More work is expected in **exploitation and alteration of social graphs** (both the locally-maintained and externally-provided) that result from the context-aware decisions.

6.3. Crowdsourcing

CS services connect its users with remote sensing units (devices and human beings). Current incarnations of CS focus on addressing the topics in centralised management and interfaces towards the users. Local aspects of the worker-side part of the system have no decent coverage yet. CS favours nodes of stable connectivity (Wang et al., 2021a), highly predictable trajectories (Zhu et al., 2021a; Sun et al., 2020a; Wang et al., 2020b), and accurate mobility patterns (Wang et al., 2021a; Belli et al., 2020). Even if a clustered environment is considered (Sun et al., 2020a; Wang et al., 2020b; Belli et al., 2020), cluster structures are either fixed (Sun et al., 2020a) or maintained globally (Belli et al., 2020), and **cluster collaboration** is rare (Sun et al., 2020a). Due to sparse interactions between workers (Sun et al.,

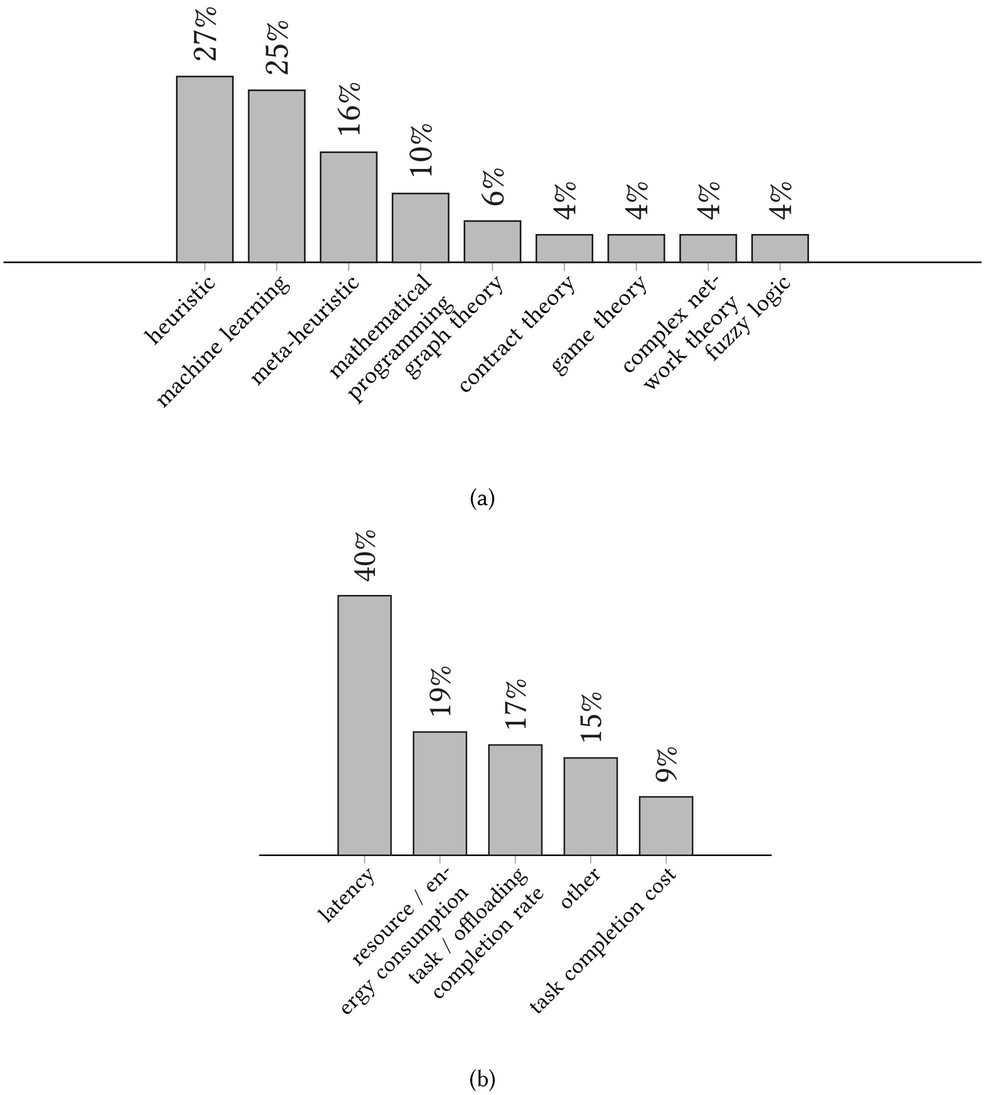


Fig. 5. Solution techniques (a) and optimisation goals (b).

2020a; Wang et al., 2020b; Belli et al., 2020), the distributed **context-awareness** is not satisfactory (Figs. 4(d)–4(i)). Therefore, **scalability** seems to be an afterthought in CS.

6.4. Opportunistic fog computing

OFC brings promise of successful offloading within the highly dynamic infrastructure-less networks (e.g. V2V network of vehicles). Although there exist several attempts to formulate complete solutions, they fall short in many ways. OFC relies on opportunistic networking, thus sophisticated handling of **context-awareness**, proper **fault management** (Audrito et al., 2021; Asensio et al., 2020), and **extensive evaluation** with real data sets and realistic networking conditions are expected, but rarely addressed simultaneously. Furthermore, available OFC solutions lack modelling of the **extended node behaviour** (e.g. for complex situations understanding (Zhu et al., 2019a), collaborative verification of observations (Radenkovic et al., 2018), functional specialisation (Fig. 4(m)), migration (Yang et al., 2020), etc.) that runs within the possibly hybrid environments (Asensio et al., 2020; Mseddi et al., 2019).

6.5. Vehicular fog computing

VFC explores the potential of the hybrid environment of VANETs and the hierarchical infrastructure. VFC scenarios require efficient scalability mechanisms to assure satisfying RAS for their services. Existing solutions rarely model (Fig. 4(l)) and explore the **multi-dimensional collaboration** thoroughly (as for e.g. migration (Zhu et al., 2019b; Lv et al., 2021), results' handover (Wu et al., 2021), control plane redundancy (Dong et al., 2020), incentives (Tang et al., 2021), security, etc.), leaving the long-term **service continuity** aspect uncovered. Works tend to model the complete systems of implicit features, rather than focus on design and **extensive evaluation** of particular components (cf. Dong et al. (2020) and Saad and Grande (2020)). In their current shape, VFC systems are not inclusive enough: fog nodes are limited to certain classes of vehicles of implied behaviour (e.g. buses, taxis, etc.) analysed in the preconfigured environments.

6.6. Synergistic outlook: lessons learnt

To further interpret the review results, we treat the presented fog models as building bricks of a working fog solution. That is, they are neither utterly orthogonal nor undeniably overlap altogether. The underlying fog foundation promotes desirable scalability, and this is the aspect in which most of the presented papers do not meet the

Table 5
Topics addressed by the surveyed papers and their percentage share in total.

M.	Share	Topic	Refs.	Open points
OC	10%	Network function virtualisation (NFV) in the vehicular environment	Mouradian et al. (2019)	Context-aware offloadee selection/migration/case study/eval. w. rwmds.[a], pne.[b]
		Resource auction among fog clusters	Sun et al. (2020b)	Service reliability/migration/scalability/eval. w. rwmds.[a], heterogeneous networking environs.
		Collaborative execution of a workflow graph	Alam et al. (2019)	Offloader cost analysis/load balancing and sharing/explicit node mobility/eval. w. mobility data
		Allocation of sub-tasks with linear relationships	Kimovski et al. (2021)	Service reliability/scalability/migration
DC	5%	Offloading in a hybrid social-aware environment	Ciobanu et al. (2019a)	Heterogeneity/unbounded collaboration/context-aware offloadee selection
		Strategies for D2D task scheduling	Nistor et al. (2021)	Scalability/ext. context-awareness/eval. w. rwmds.[a]
CS	12%	Data collection in urban scenario	Wang et al. (2021a)	Collaboration/node heterogeneity/sensor mobility
		Context-aware task allocation	Zhu et al. (2021a)	Scalability/sensor mobility/eval. w. pne.[b]
		Incentives, and trust management	Sun et al. (2020a) and Wang et al. (2020b)	Heterogeneity/sensor mobility/eval. w. rwmds.[a]
		Community detection to build an overlay network	Belli et al. (2020)	Scalability/case study/eval. w. pne.[b]
OFC	22%	Sequential task graph execution	Wang et al. (2021b)	Scalability/migration/eval. w. rwmds.[a]
		Distributed situation recognition	Audrito et al. (2021)	Scalability/case study/eval. w. rwmds.[a], pne.[b]
		Task replication, and node redundancy	Yang et al. (2020) and Asensio et al. (2020)	Scalability/recovery mechanisms/eval. w. rwmds.[a], pne.[b]
		Container placement and migration	Mseddi et al. (2019)	Cluster cooperation/eval. w. pne.[b]
		Cooperative sensing in a platoon	Du et al. (2020)	Context-aware offloadee selection/eval. w. pne.[b]
		Collaborative task offloading	Buda et al. (2020)	Case study/eval. w. rwmds.[a], pne.[b]
		Temporal-aspect-driven task offloading	Zhu et al. (2019a)	collab. w. context-awareness/scalability/eval. w. pne.[b]
		Social-aware data offloading	Radenkovic et al. (2018)	Extended node behaviour/eval. w. pne.[b]
VFC	51%	Cooperative offloading	Lv et al. (2021), Ye et al. (2016), Zhou et al. (2020) and Tan and Hu (2018)	Collaboration/reliability/eval. w. rwmds.[a], pne.[b]
		Caching with federated learning	Yu et al. (2021)	Reliability/collaboration/eval. w. rwmds.[a], pne.[b]
		Clustering based on road topology	Wu et al. (2021)	Cluster cooperation/eval. w. rwmds.[a], pne.[b]
		Resource pooling	Tang et al. (2021), Sorkhoh et al. (2020), Cha et al. (2021) and Hameed et al. (2021)	Scalability/reliability/eval. w. rwmds.[a]
		Task replication	Sun et al. (2021)	Reliability/collaboration/eval. w. rwmds.[a]
		Multi-period task offloading	Liu et al. (2021)	Reliability/eval. w. rwmds.[a]
		Offl. under inform. incomplet. and uncertainty	Zhou et al. (2019)	Context-awareness/eval. w. rwmds.[a]
		Semantic-aware real-time data processing	Fu et al. (2021)	Scalability/redundancy
		Event-triggered offloading and migration	Zhu et al. (2019b)	Scalability
		Improv. net. connectivity w. forward. and proxy.	Liang et al. (2021) and Jabri et al. (2019)	Scalability/reliability/security
		Overloaded node management	Yadav et al. (2020)	Scalability/reliability/collaboration/eval. w. rwmds.[a]
		Microservices	Sami et al. (2020)	Node heterogeneity/recovery performance/security
		Node redund. to improve computing reliability	Dong et al. (2020)	Scalability/eval. w. rwmds.[a]
		Modelling the effects of mobility	Saad and Grande (2020)	Scalability/eval. w. rwmds.[a], pne.[b]

[a] Real-world mobility data sets.

[b] Practical networking environments.

expectations at most (Table 5). Remarkably, that has roots in the purely theoretical nature of those works, which typically leaves aside tests in practical networking environments. Going even further, insufficient testing efforts lead to mediocre exploitation of multi-tier cooperation and collaboration, which in turn are expected to improve the reliability and continuity of the offered fog services. On the other hand, if we look at the percentage coverage of the topics within the models (Fig. 4), it becomes even more evident that certain aspects are deliberately left as afterthoughts by researchers. Sadly, only a few solutions which claimed to be fog instances were devised with awareness of OpenFog concept. Another observation emphasises a great variety of solution targets undertaken by the authors of the reviewed papers. This has an effect on the low coverage of some of the topics (Table 5). Resource pooling and cooperation during offloading have decent coverage (at least in VFC), while functional safety aspects like redundancy and replication still require work. From the methodology point of view, one-third of all the papers rely on heuristics (Fig. 5, Fig. 5(a)), and even more of them set latency minimisation as the optimisation goal, Fig. 5(b). While reduction of delay seems to be the natural choice for fog computing, a huge share of algorithms with fragile mathematical foundations that require sophisticated tuning do not bode well for deployments.

6.7. Further research

Solutions for fog computing should undoubtedly explore the mobility of fog nodes in providing robust services to its users. It is expected that upcoming works either focus on careful construction of the reliable FC components, or combine the achievements from various FC models to devise scalable systems with a slight number of implicit features. In particular, following aspects should attract researchers' interest:

- **Robustness**. New solutions should tolerate range of discrepancies without negative impact on the behaviour and observed performance (in both QoS and QoE). Researchers are encouraged to clearly indicate the parties obliged to run the devised algorithms, then provide both the computational complexity analysis and thorough performance evaluation. Performance should be measured in the long run using highly heterogeneous setups (at the node and the network levels) and diversity of behaviours (e.g. spontaneous decisions, sudden disruptions, density peaks, etc.). Simulations of mobility should be based on real mobility data sets, which are either publicly available or shared together with the respective article, to enable cross testing and comparisons.
- **Interoperability**. Implementations of fog computing are expected to coexist with extant systems and rely on the firmly established features. Hence, more attention should be paid to ensure and verify the secure information exchange. Example scenarios include integration of third-party solutions (e.g. trust anchors, semantic and social data providers, etc.), benefiting from device and communication media heterogeneity, distribution of decisive power among nodes and the hierarchy, and inclusion of the existing networking and computing systems.
- **Composability**. Deconstruction of complex ideas into interacting entities of high cohesion should be applied to the forthcoming architectures for FC-compliant systems. Therefore, more work is expected in design of mature pluggable components that adapt their behaviours to context changes (i.e. have low decision inertia and reduce possibility to be driven by stale data). Collaboration, rather than cooperation, between the opaque entities over the newly standardised interfaces should become a main concern in providing scalable designs and healthy architectures.

7. Conclusion

This survey discusses mobility-aware fog computing with mobile fog nodes in highly dynamic environments, where the time-varying modifications of the fog network topology are present. Five mobility-aware fog computing models of the fog computing concept compliant with OpenFog adoption as in the IEEE 1934 standard document are identified and described. The conducted systematic review study adopts the multi-aspect broadened perspective on fog computing to highlight the coverage of the OpenFog pillars that are crucial for fog computing with mobile nodes. As discovered, the reviewed papers address the arbitrary aspects of the problem with varying quality and consistency. Therefore, further research is urgently required to compose the complete solutions out of the building blocks designed by various authors, rather than starting from ground zero. Authors believe that, as with mobile fog computing and mobile nodes, agile collaboration is a key here.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Abboud, Khadige, Zhuang, Weihua, 2014. Stochastic analysis of a single-hop communication link in vehicular ad hoc networks. IEEE Trans. Intell. Transp. Syst. (ISSN: 1558-0016) 15 (5), 2297–2307.

Al-Fuqaha, Ala, Guizani, Mohsen, Mohammadi, Mehdi, Aledhari, Mohammed, Ayyash, Moussa, Fourthquarter 2015. Internet of things: A survey on enabling technologies, protocols, and applications. IEEE Commun. Surv. Tutor. (ISSN: 1553-877X) 17 (4), 2347–2376.

Alam, Md Golam Rabiul, Hassan, Mohammad Mehedi, Uddin, Md.ZIa, Almogren, Ahmad, Fortino, Giancarlo, 2019. Autonomic computation offloading in mobile edge for IoT applications. Future Gener. Comput. Syst. (ISSN: 0167-739X) 90, 149–157.

Alwasel, Khaled, Jha, Devki Nandan, Habeeb, Fawzy, Demirbaga, Umit, Rana, Omer, Baker, Thar, Dustdar, Scharam, Villari, Massimo, James, Philip, Solaiman, Ellis, Ranjan, Rajiv, 2021. IoTsim-osmosis: A framework for modeling and simulating IoT applications over an edge-cloud continuum. J. Syst. Archit. (ISSN: 1383-7621) 116, 101956.

Armbrust, Michael, Fox, Armando, Griffith, Rean, Joseph, Anthony D., Katz, Randy, Konwinski, Andy, Lee, Gunho, Patterson, David, Rabkin, Ariel, Stoica, Ion, Zaharia, Matei, 2010. A view of cloud computing. Commun. ACM (ISSN: 0001-0782) 53 (4), 50–58.

Asensio, A., Masip-Bruin, X., Durán, R.J., de Miguel, I., Ren, G., Daijavad, S., Jukan, A., 2020. Designing an efficient clustering strategy for combined fog-to-cloud scenarios. Future Gener. Comput. Syst. (ISSN: 0167-739X) 109, 392–406.

Audrito, Giorgio, Pianini, Danilo, Damiani, Ferruccio, Viroli, Mirko, 2021. Aggregate centrality measures for IoT-based coordination. Sci. Comput. Programm. (ISSN: 0167-6423) 203, 102584.

Baker, D., Ephremides, A., Flynn, J., 1984. The design and simulation of a mobile radio network with distributed control. IEEE J. Sel. Areas Commun. (ISSN: 1558-0008) 2 (1), 226–237.

Balan, Rajesh, Flinn, Jason, Satyanarayanan, M., Sinnamohideen, Shafeeq, Yang, Hen-I, 2002. The case for cyber foraging. In: Proceedings of the 10th Workshop on ACM SIGOPS European Workshop. In: EW 10, Association for Computing Machinery, New York, NY, USA, ISBN: 978-1-4503-7806-2, pp. 87–92.

Bellavista, Paolo, Berrocal, Javier, Corradi, Antonio, Das, Sajal K., Foschini, Luca, Zanni, Alessandro, 2019. A survey on fog computing for the internet of things. Pervasive Mob. Comput. (ISSN: 1574-1192) 52, 71–99.

Belli, Dimitri, Chessa, Stefano, Foschini, Luca, Girolami, Michele, 2020. The rhythm of the crowd: Properties of evolutionary community detection algorithms for mobile edge selection. Pervasive Mob. Comput. (ISSN: 1574-1192) 67, 101231.

Bonomi, Flavio, Milito, Rodolfo, Natarajan, Preethi, Zhu, Jiang, 2014. Fog computing: A platform for internet of things and analytics. In: Bessis, Nik, Dobre, Ciprian (Eds.), Big Data and Internet of Things: a Roadmap for Smart Environments. In: Studies in Computational Intelligence, Springer International Publishing, Cham, ISBN: 978-3-319-05029-4, pp. 169–186.

Bonomi, Flavio, Milito, Rodolfo, Zhu, Jiang, Addepalli, Sateesh, 2012. Fog computing and its role in the internet of things. In: Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing. In: MCC '12, Association for Computing Machinery, New York, NY, USA, ISBN: 978-1-4503-1519-7, pp. 13–16.

Bou Abdo, Jacques, Demerjian, Jacques, 2017. Evaluation of mobile cloud architectures. Pervasive Mob. Comput. (ISSN: 1574-1192) 39, 284–303.

Brabham, Daren C., 2008. Crowdsourcing as a model for problem solving: an introduction and cases. Convergence (ISSN: 1354-8565) 14 (1), 75–90.

Brogi, A., Forti, S., Guerrero, C., Lera, I., 2020. Towards declarative decentralised application management in the fog. In: 2020 IEEE International Symposium on Software Reliability Engineering Workshops (ISSREW). pp. 223–230.

Buda, S., Guleng, S., Wu, C., Zhang, J., Yau, K.A., Ji, Y., 2020. Collaborative vehicular edge computing towards greener ITS. IEEE Access (ISSN: 2169-3536) 8, 63935–63944.

Bukhari, Afnan, Hussain, Farookh Khadeer, Hussain, Omar K., 2022. Fog node discovery and selection: A systematic literature review. Future Gener. Comput. Syst. (ISSN: 0167739X) 135, 114–128.

Byers, C.C., 2017. Architectural imperatives for fog computing: Use cases, requirements, and architectural techniques for fog-enabled IoT networks. IEEE Commun. Mag. 55 (8), 14–20.

Cazabet, Remy, Rossetti, Giulio, 2019. Challenges in community discovery on temporal networks. In: Holme, Petter, Saramäki, Jari (Eds.), Temporal Network Theory. In: Computational Social Sciences, Springer International Publishing, Cham, ISBN: 978-3-030-23495-9, pp. 181–197.

Cha, N., Wu, C., Yoshinaga, T., Ji, Y., Yau, K.-L. A., 2021. Virtual edge: Exploring computation offloading in collaborative vehicular edge computing. IEEE Access (ISSN: 2169-3536) 9, 37739–37751.

Chang, Chii, Hadachi, Amnir, Mass, Jakob, Srirama, Satish Narayana, 2020. Mobile fog computing. In: Fog Computing. John Wiley & Sons, Ltd, ISBN: 978-1-119-55171-3, pp. 1–41.

Chen, W., Su, Z., Xu, Q., Luan, T. H., Li, R., 2020. VFC-based cooperative UAV computation task offloading for post-disaster rescue. In: IEEE INFOCOM 2020 - IEEE Conference on Computer Communications. pp. 228–236.

Chiang, Mung, Ha, Sangtae, Risso, Fulvio, Zhang, Tao, Chih-Lin, I., 2017. Clarifying fog computing and networking: 10 questions and answers. IEEE Commun. Mag. (ISSN: 1558-1896) 55 (4), 18–20.

Chiang, Mung, Zhang, Tao, 2016. Fog and IoT: An overview of research opportunities. IEEE Internet Things J. (ISSN: 2327-4662) 3 (6), 854–864.

Chlamtac, Imrich, Conti, Marco, Liu, Jennifer J.-N., 2003. Mobile ad hoc networking: Imperatives and challenges. Ad Hoc Netw. (ISSN: 1570-8705) 1 (1), 13–64.

Ciobanu, R.-I., Dobre, C., Bălănescu, M., Suciu, G., 2019a. Data and task offloading in collaborative mobile fog-based networks. IEEE Access (ISSN: 2169-3536) 7, 104405–104422.

Ciobanu, Radu-Ioan, Negru, Catalin, Pop, Florin, Dobre, Ciprian, Mavromoustakis, Constandinos X., Mastorakis, George, 2019b. Drop computing: Ad-hoc dynamic collaborative computing. Future Gener. Comput. Syst. (ISSN: 0167-739X) 92, 889–899.

Ciobanu, R., Tăbuşcă, V., Dobre, C., Băjenaru, L., Mavromoustakis, C.X., Mastorakis, G., 2019c. Avoiding data corruption in drop computing mobile networks. IEEE Access (ISSN: 2169-3536) 7, 31170–31185.

Conti, Marco, Boldrini, Chiara, Kanhere, Salil S., Mingozzi, Enzo, Pagani, Elena, Ruiz, Pedro M., Younis, Mohamed, 2015. From MANET to people-centric networking: Milestones and open research challenges. Comput. Commun. (ISSN: 0140-3664) 71, 1–21.

Conti, Marco, Giordano, Silvia, May, Martin, Passarella, Andrea, 2010. From opportunistic networks to opportunistic computing. IEEE Commun. Mag. (ISSN: 1558-1896) 48 (9), 126–139.

Conti, Marco, Passarella, Andrea, 2018. The internet of people: A human and data-centric paradigm for the next generation internet. COMCOM 40 Years, Comput. Commun. (ISSN: 0140-3664) COMCOM 40 Years, 131.51–65,

Conway, Adrian E., Wang, Michael, Ljuca, Emir, Lebling, P. David, 2019. A dynamic transport overlay system for mission-oriented dispersed computing over IoBT. In: MILCOM 2019 - 2019 IEEE Military Communications Conference (MILCOM). pp. 815–820.

Costa, Breno, Bachiega, Joao, de Carvalho, Leonardo Rebouças, Araujo, Aleteia P.F., 2023. Orchestration in fog computing: A comprehensive survey. ACM Comput. Surv. 55 (2), 1–34.

Cristescu, Giorgiana, Dobrescu, Radu, Chenaru, Oana, Florea, Gheorghe, 2019. DEW: A new edge computing component for distributed dynamic networks. In: 2019 22nd International Conference on Control Systems and Computer Science (CSCS). pp. 547–551.

Das, Sajal K., 2018. Mobility management—a personal perspective. COMCOM 40 Years, Comput. Commun. (ISSN: 0140-3664) COMCOM 40 Years, 131.26–31,

Davis, A., Parikh, J., Weihl, W.E., 2004. EdgeComputing: Extending enterprise applications to the edge of the internet. In: Proceedings of the 13th International World Wide Web Conference on Alternate Track Papers & Posters. In: WWW Alt. '04, Association for Computing Machinery, New York, NY, USA, ISBN: 978-1-58113-912-9, pp. 180–187.

De Donno, Michele, Tange, Koen, Dragoni, Nicola, 2019. Foundations and evolution of modern computing paradigms: Cloud, IoT, edge, and fog. IEEE Access (ISSN: 2169-3536) 7, 150936–150948.

Dey, Anind K., 2001. Understanding and using context. Pers. Ubi Comp. (ISSN: 1617-4909) 5 (1), 4–7.

Dilley, John, Maggs, Bruce, Parikh, Jay, Prokop, Harald, Sitaraman, Ramesh, Weihl, Bill, 2002. Globally distributed content delivery. IEEE Internet Comput. (ISSN: 1089-7801) 6 (05), 50–58.

Dinh, Hoang T., Lee, Chonho, Niyato, Dusit, Wang, Ping, 2013. A survey of mobile cloud computing: Architecture, applications, and approaches. Wirel. Commun. Mob. Comput. (ISSN: 1530-8677) 13 (18), 1587–1611.

Dong, L., Ni, Q., Wu, W., Huang, C., Znati, T., Du, D.Z., 2020. A proactive reliable mechanism-based vehicular fog computing network. IEEE Internet Things J. (ISSN: 2327-4662) 7 (12), 11895–11907.

Du, H., Leng, S., Wu, F., Chen, X., Mao, S., 2020. A new vehicular fog computing architecture for cooperative sensing of autonomous driving. IEEE Access (ISSN: 2169-3536) 8, 10997–11006.

ETSI, 2019. Multi-access edge computing (MEC); framework and reference architecture.

Fadhil, J.A., Sarhan, Q.I., 2020. Internet of vehicles (iov): A survey of challenges and solutions. In: 2020 21st International Arab Conference on Information Technology (ACIT). pp. 1–10.

Fernando, N., Loke, S.W., Avazpour, I., Chen, F., Abkenar, A.B., Ibrahim, A., 2019. Opportunistic fog for IoT: Challenges and opportunities. IEEE Internet Things J. (ISSN: 2327-4662) 6 (5), 8897–8910.

Fu, F., Kang, Y., Zhang, Z., Yu, F.R., Wu, T., 2021. Soft actor–critic DRL for live transcoding and streaming in vehicular fog-computing-enabled iov. IEEE Internet Things J. (ISSN: 2327-4662) 8 (3), 1308–1321.

Ganek, A.G., Corbi, T.A., 2003. The dawning of the autonomic computing era. IBM Syst. J. (ISSN: 0018-8670) 42 (1), 5–18.

García-Valls, Marisol, Dubey, Abhishek, Botti, Vicent, 2018. Introducing the new paradigm of social dispersed computing: Applications, technologies and challenges. J. Syst. Archit. (ISSN: 1383-7621) 91, 83–102.

Gill, Monika, Singh, Dinesh, 2021. A comprehensive study of simulation frameworks and research directions in fog computing. Comp. Sci. Rev. (ISSN: 1574-0137) 40, 100391.

Gima, Kosuke, Oma, Ryuji, Nakamura, Shigenari, Enokido, Tomoya, Takizawa, Makoto, 2020. A model for mobile fog computing in the IoT. In: Barolli, Leonard, Nishino, Hiroaki, Enokido, Tomoya, Takizawa, Makoto (Eds.), Advances in Networked-Based Information Systems. In: Advances in Intelligent Systems and Computing, Springer International Publishing, Cham, ISBN: 978-3-030-29029-0, pp. 447–458.

Hameed, Ahmad Raza, ul Islam, Saif, Ahmad, Ishfaq, Munir, Kashif, 2021. Energy- and performance-aware load-balancing in vehicular fog computing. Sustain. Comput.: Inform. Syst. (ISSN: 2210-5379) 30, 100454.

Holme, Petter, Saramäki, Jari, 2012. Temporal networks. Temporal Networks, Phys. Rep. (ISSN: 0370-1573) Temporal Networks, 519 (3).97–125,

Hou, X., Li, Y., Chen, M., Wu, D., Jin, D., Chen, S., 2016. Vehicular fog computing: A viewpoint of vehicles as the infrastructures. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 65 (6), 3860–3873.

Hu, Yun Chao, Patel, Milan, Sabella, Dario, Sprecher, Nurit, Young, Valerie, 2015. Mobile edge computing a key technology towards 5G. ETSI White Pap. No 11 16.

IBM, 2006. An architectural blueprint for autonomic computing. IBM White Pap. 31.

IEEE, 1934. IEEE standard for adoption of OpenFog reference architecture for fog computing.

Islam, Mir Salim Ul, Kumar, Ashok, Hu, Yu-Chen, 2021. Context-aware scheduling in fog computing: A survey, taxonomy, challenges and future directions. J. Netw. Comput. Appl. (ISSN: 1084-8045) 180, 103008.

ITU-T, 2012. Recommendation ITU-T Y.2060. overview of the internet of things.

Jabri, Issam, Mekki, Tesnim, Rachedi, Abderrezak, Ben Jemaa, Maher, 2019. Vehicular fog gateways selection on the internet of vehicles: A fuzzy logic with ant colony optimization based approach. Ad Hoc Netw. (ISSN: 1570-8705) 91, 101879.

Jiang, Jiuchuan, An, Bo, Jiang, Yichuan, Lin, Donghui, Bu, Zhan, Cao, Jie, Hao, Zhifeng, 2018. Understanding crowdsourcing systems from a multiagent perspective and approach. ACM Trans. Auton. Adapt. Syst. (ISSN: 1556-4665) 13 (2), 8:1–8:32.

Junior, Francisco Ferreira de Mendonça, Dias, Kelvin Lopes, d'Orey, Pedro M., Kokkinogenis, Zafeiris, 2021. FogWise: On the limits of the coexistence of heterogeneous applications on fog computing and internet of vehicles. Trans. Emerg. Telecommun. Technol. (ISSN: 2161-3915) 32 (1), e4145.

Kai, Kang, Cong, Wang, Tao, Luo, 2016. Fog computing for vehicular ad-hoc networks: Paradigms, scenarios, and issues. J. Chin. Univ. Posts Telecommun. (ISSN: 1005-8885) 23 (2), 56–96.

Kaur, A., Kumar, R., Saxena, S., 2020. Osmotic computing and related challenges: A survey. In: 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC). pp. 378–383.

Kazemi, Leyla, Shahabi, Cyrus, 2012. GeoCrowd: Enabling query answering with spatial crowdsourcing. In: Proceedings of the 20th International Conference on Advances in Geographic Information Systems. In: SIGSPATIAL '12, Association for Computing Machinery, New York, NY, USA, ISBN: 978-1-4503-1691-0, pp. 189–198.

Kephart, J.O., Chess, D.M., 2003. The vision of autonomic computing. Computer (ISSN: 1558-0814) 36 (1), 41–50.

Kimovski, Dragi, Mehran, Narges, Kerth, Christopher Emanuel, Prodan, Radu, 2021. Mobility-aware IoT applications placement in the cloud edge continuum. IEEE Trans. Serv. Comput. (ISSN: 1939-1374) 1.

Kitchenham, Barbara, Pretorius, Rialette, Budgen, David, Pearl Brereton, O., Turner, Mark, Niazi, Mahmood, Linkman, Stephen, 2010. Systematic literature reviews in software engineering – a tertiary study. Inf. Softw. Technol. (ISSN: 0950-5849) 52 (8), 792–805.

Kosch, T., Adler, C.J., Eichler, S., Schroth, C., Strassberger, M., 2006. The scalability problem of vehicular ad hoc networks and how to solve it. IEEE Wirel. Commun. (ISSN: 1558-0687) 13 (5), 22–28.

Kuklinski, S., Wolny, G., 2009. Density based clustering algorithm for VANETs. In: 2009 5th International Conference on Testbeds and Research Infrastructures for the Development of Networks Communities and Workshops. pp. 1–6.

Kumar, Karthik, Lu, Yung-Hsiang, 2010. Cloud computing for mobile users: Can offloading computation save energy? Computer (ISSN: 1558-0814) 43 (4), 51–56.

Liang, Junbin, Zhang, Jie, Leung, Victor C.M., Wu, Xu, 2021. Distributed information exchange with low latency for decision making in vehicular fog computing. IEEE Internet Things J. (ISSN: 2327-4662) 1.

Liao, Z., Ma, Y., Huang, J., Wang, J., Wang, J., 2021. HOTSPOT: A UAV-assisted dynamic mobility-aware offloading for mobile edge computing in 3D space. IEEE Internet Things J. (ISSN: 2327-4662) 1.

Liu, Lei, Chen, Chen, Pei, Qingqi, Maharjan, Sabita, Zhang, Yan, 2020. Vehicular edge computing and networking: A survey. Mobile Netw. Appl. (ISSN: 1572-8153).

Liu, Chunhui, Liu, Kai, Ren, Hualing, Xu, Xincao, Xie, Ruitao, Cao, Jingjing, 2021. Rtds: Real-time distributed strategy for multi-period task offloading in vehicular edge computing environment. Neural Comput. Appl. (ISSN: 1433-3058).

Lv, Baiquan, Yang, Chao, Chen, Xin, Yao, Zhihua, Yang, Junjie, 2021. Task offloading and serving handover of vehicular edge computing networks based on trajectory prediction. IEEE Access (ISSN: 2169-3536) 9, 130793–130804.

Madan, Naman, Malik, Asad Waqar, Rahman, Anis Ur, Ravana, Sri Devi, 2020. On-demand resource provisioning for vehicular networks using flying fog. Veh. Commun. (ISSN: 2214-2096) 25, 100252.

Mahmud, Redowan, Kotagiri, Ramamohanarao, Buyya, Rajkumar, 2018. Fog computing: A taxonomy, survey and future directions. In: Di Martino, Beniamino, Li, Kuan-Ching, Yang, Laurence T., Esposito, Antonio (Eds.), Internet of Everything: Algorithms, Methodologies, Technologies and Perspectives. In: Internet of Things, Springer, Singapore, ISBN: 978-981-10-5861-5, pp. 103–130.

Mahmud, Redowan, Ramamohanarao, Kotagiri, Buyya, Rajkumar, 2020. Application management in fog computing environments: A taxonomy, review and future directions. ACM Comput. Surv. (ISSN: 0360-0300) 53 (4), 88:1–88:43.

Marín-Tordera, Eva, Masip-Bruin, Xavi, García-Almiñana, Jordi, Jukan, Admela, Ren, Guang-Jie, Zhu, Jiafeng, 2017. Do we all really know what a fog node is? Current trends towards an open definition. Comput. Commun. (ISSN: 0140-3664) 109, 117–130.

Martinez, I., Hafid, A.S., Jarray, A., 2021. Design, resource management, and evaluation of fog computing systems: A survey. IEEE Internet Things J. (ISSN: 2327-4662) 8 (4), 2494–2516.

Mascitti, Davide, Conti, Marco, Passarella, Andrea, Ricci, Laura, Das, Sajal K., 2018. Service provisioning in mobile environments through opportunistic computing. IEEE Trans. Mob. Comput. (ISSN: 1558-0660) 17 (12), 2898–2911.

Mell, Peter, Grance, Tim, 2011. The NIST Definition of Cloud Computing. Technical Report NIST Special Publication (SP) 800-145, National Institute of Standards and Technology.

Menascé, Daniel A., 2020. Self-managed computer systems: Foundations and examples. In: Filipe, Joaquim, Śmiałek, Michał, Brodsky, Alexander, Hammoudi, Slimane (Eds.), Enterprise Information Systems. In: Lecture Notes in Business Information Processing, Springer International Publishing, Cham, ISBN: 978-3-030-40783-4, pp. 17–36.

Mohamed, Nader, Al-Jaroodi, Jameela, Jawhar, Imad, Noura, Hassan, Mahmoud, Sara, 2017. Uavfog: A UAV-based fog computing for internet of things. In: 2017 IEEE SmartWorld, Ubiquitous Intelligence Computing, Advanced Trusted Computed, Scalable Computing Communications, Cloud Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI). pp. 1–8.

Motlagh, N.H., Bagaa, M., Taleb, T., 2019. Energy and delay aware task assignment mechanism for UAV-based IoT platform. IEEE Internet Things J. (ISSN: 2327-4662) 6 (4), 6523–6536.

Mouradian, C., Kianpisheh, S., Abu-Lebdeh, M., Ebrahimnezhad, F., Jahromi, N.T., Glitho, R.H., 2019. Application component placement in NFV-based hybrid cloud/Fog systems with mobile fog nodes. IEEE J. Sel. Areas Commun. (ISSN: 1558-0008) 37 (5), 1130–1143.

Mouradian, C., Naboulsi, D., Yangui, S., Glitho, R.H., Morrow, M.J., Polakos, P.A., 2018. A comprehensive survey on fog computing: State-of-the-art and research challenges. IEEE Commun. Surv. Tutor. (ISSN: 1553-877X) 20 (1), 416–464.

Mseddi, A., Jaafar, W., Elbiaze, H., Ajib, W., 2019. Intelligent resource allocation in dynamic fog computing environments. In: 2019 IEEE 8th International Conference on Cloud Networking (CloudNet). pp. 1–7.

Newman, M.E.J., 2003. The structure and function of complex networks. SIAM Rev. 45 (2), 167–256.

Ni, Jianbing, Zhang, Aiqing, Lin, Xiaodong, Shen, Xuemin Sherman, 2017. Security, privacy, and fairness in fog-based vehicular crowdsensing. IEEE Commun. Mag. (ISSN: 1558-1896) 55 (6), 146–152.

Ning, Z., Huang, J., Wang, X., 2019. Vehicular fog computing: Enabling real-time traffic management for smart cities. IEEE Wirel. Commun. (ISSN: 1558-0687) 26 (1), 87–93.

Nistor, Silvia-Elena, Grosu, George-Mircea, Hampau, Raluca-Maria, Ciobanu, Radu-Ioan, Pop, Florin, Dobre, Ciprian-Mihai, Szynkiewicz, Paweł, 2021. Real-time scheduling in drop computing. In: 2021 IEEE/ACM 21st International Symposium on Cluster, Cloud and Internet Computing (CCGrid). pp. 720–727.

Ostrowski, Krzysztof, Małecki, Krzysztof, 2023. An insight into the state-of-the-art vehicular fog computing with an opportunistic flavour. In: Wyrzykowski, Roman, Dongarra, Jack, Deelman, Ewa, Karczewski, Konrad (Eds.), Parallel Processing and Applied Mathematics. Springer International Publishing, Cham, pp. 502–513.

Pelusi, L., Passarella, A., Conti, M., 2006. Opportunistic networking: Data forwarding in disconnected mobile ad hoc networks. IEEE Commun. Mag. (ISSN: 1558-1896) 44 (11), 134–141.

Pereira, Jorge, Ricardo, Leandro, Luís, Miguel, Senna, Carlos, Sargento, Susana, 2019. Assessing the reliability of fog computing for smart mobility applications in VANETs. Future Gener. Comput. Syst. (ISSN: 0167-739X) 94, 317–332.

Pollini, G.P., 1996. Trends in handover design. IEEE Commun. Mag. (ISSN: 1558-1896) 34 (3), 82–90.

Preden, Jürgo S., Tammemäe, Kalle, Jantsch, Axel, Leier, Mairo, Riid, Andri, Calis, Emine, 2015. The benefits of self-awareness and attention in fog and mist computing. Computer (ISSN: 1558-0814) 48 (7), 37–45.

Puliafito, Carlo, Mingozzi, Enzo, Longo, Francesco, Puliafito, Antonio, Rana, Omer, 2019. Fog computing for the internet of things: A survey. ACM Trans. Internet Technol. (ISSN: 1533-5399) 19 (2), 18:1–18:41.

Radenkovic, Milena, Huynh, Vu San Ha, Manzoni, Pietro, 2018. Adaptive real-time predictive collaborative content discovery and retrieval in mobile disconnection prone networks. IEEE Access (ISSN: 2169-3536) 6, 32188–32206.

Reis, A.B., Sargento, S., Tonguz, O.K., 2017. Parked cars are excellent roadside units. IEEE Trans. Intell. Transp. Syst. (ISSN: 1558-0016) 18 (9), 2490–2502.

Rejiba, Zeineb, Masip-Bruin, Xavier, Marín-Tordera, Eva, 2019. A survey on mobility-induced service migration in the fog, edge, and related computing paradigms. ACM Comput. Surv. (ISSN: 0360-0300) 52 (5), 90:1–90:33.

Ren, Ju, Zhang, Deyu, He, Shiwen, Zhang, Yaoxue, Li, Tao, 2019. A survey on end-edge-cloud orchestrated network computing paradigms: Transparent computing, mobile edge computing, fog computing, and cloudlet. ACM Comput. Surv. (ISSN: 0360-0300) 52 (6), 125:1–125:36.

Rossetti, Giulio, Cazabet, Rémy, 2018. Community discovery in dynamic networks: A survey. ACM Comput. Surv. (ISSN: 0360-0300) 51 (2), 35:1–35:37.

Rossetti, Giulio, Pedreschi, Dino, Giannotti, Fosca, 2017. Node-centric community discovery: From static to dynamic social network analysis. Online Soc. Netw. Media (ISSN: 2468-6964) 3–4, 32–48.

Saad, A., Grande, R. E. De, 2020. MDP-based vehicular network connectivity model for VCC management. In: 2020 IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications (DS-RT). pp. 1–8.

Salaht, Farah Aït, Desprez, Frédéric, Lebre, Adrien, 2020. An overview of service placement problem in fog and edge computing. ACM Comput. Surv. (ISSN: 0360-0300) 53 (3), 65:1–65:35.

Sami, H., Mourad, A., El-Hajj, W., 2020. Vehicular-OBUs-as-on-demand-fogs: Resource and context aware deployment of containerized micro-services. IEEEACM Trans. Netw. (ISSN: 1558-2566) 28 (2), 778–790.

Satyanarayanan, M., 2001. Pervasive computing: Vision and challenges. IEEE Pers. Commun. (ISSN: 1558-0652) 8 (4), 10–17.

Satyanarayanan, Mahadev, 2017. The emergence of edge computing. Computer (ISSN: 1558-0814) 50 (1), 30–39.

Satyanarayanan, Mahadev, Bahl, Paramvir, Caceres, Ramon, Davies, Nigel, 2009. The case for VM-based cloudlets in mobile computing. IEEE Pervasive Comput. (ISSN: 1558-2590) 8 (4), 14–23.

Sharma, Vishal, Kim, Jiyoon, Kwon, Soonhyun, You, Ilsun, Leu, Fang-Yie, 2018. An overview of 802.21a-2012 and its incorporation into IoT-fog networks using osmotic framework. In: Lin, Yi-Bing, Deng, Der-Jiunn, You, Ilsun, Lin, Chun-Cheng (Eds.), IoT As a Service. In: Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, Springer International Publishing, Cham, ISBN: 978-3-030-00410-1, pp. 64–72.

Silva, R., Silva, J. S., Boavida, F., 2017. Opportunistic fog computing: Feasibility assessment and architectural proposal. In: 2017 IFIP/IEEE Symposium on Integrated Network and Service Management (IM). pp. 510–516.

Songhorabadi, Maryam, Rahimi, Morteza, MoghadamFarid, AmirMehdi, Haghi Kashani, Mostafa, 2023. Fog computing approaches in IoT-enabled smart cities. J. Netw. Comput. Appl. (ISSN: 1084-8045) 211, 103557. http://dx.doi.org/10.1016/j.jnca.2022.103557, URL https://www.sciencedirect.com/science/article/pii/S1084804522001989.

Sorkhoh, I., Ebrahimi, D., Assi, C., Sharafeddine, S., Khabbaz, M., 2020. An infrastructure-assisted workload scheduling for computational resources exploitation in the fog-enabled vehicular network. IEEE Internet Things J. (ISSN: 2327-4662) 7 (6), 5021–5032.

Stemm, Mark, Katz, Randy H., 1998. Vertical handoffs in wireless overlay networks. Mob. Netw. Appl. (ISSN: 1572-8153) 3 (4), 335–350.

Sun, Gang, Sun, Siyu, Yu, Hongfang, Guizani, Mohsen, 2020a. Toward incentivizing fog-based privacy-preserving mobile crowdsensing in the internet of vehicles. IEEE Internet Things J. (ISSN: 2327-4662) 7 (5), 4128–4142.

Sun, Huaiying, Yu, Huiqun, Fan, Guisheng, 2020b. Contract-based resource sharing for time effective task scheduling in fog-cloud environment. IEEE Trans. Netw. Serv. Manag. (ISSN: 1932-4537) 17 (2), 1040–1053.

Sun, Y., Zhou, S., Niu, Z., 2021. Distributed task replication for vehicular edge computing: Performance analysis and learning-based algorithm. IEEE Trans. Wirel. Commun. (ISSN: 1558-2248) 20 (2), 1138–1151.

Tahir, Mohammad, Mamoon Ashraf, Qazi, Dabbagh, Mohammad, 2019. Towards enabling autonomic computing in IoT ecosystem. In: 2019 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech). pp. 646–651.

Tan, L.T., Hu, R.Q., 2018. Mobility-aware edge caching and computing in vehicle networks: A deep reinforcement learning. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 67 (11), 10190–10203.

Tang, Chaogang, Xia, Shixiong, Li, Qing, Chen, Wei, Fang, Weidong, 2021. Resource pooling in vehicular fog computing. J. Cloud Comput. (ISSN: 2192-113X) 10 (1), 19.

Tufail, A., Namoun, A., Sen, A.A.A., Kim, K.-H., Alrehaili, A., Ali, A., 2021. Moisture computing-based internet of vehicles (iov) architecture for smart cities. Sensors 21 (11).

Villari, M., Fazio, M., Dustdar, S., Rana, O., Jha, D.N., Ranjan, R., 2019. Osmosis: The osmotic computing platform for microelements in the cloud, edge, and internet of things. Computer (ISSN: 1558-0814) 52 (8), 14–26.

Villari, Massimo, Fazio, Maria, Dustdar, Schahram, Rana, Omer, Ranjan, Rajiv, 2016. Osmotic computing: A new paradigm for edge/cloud integration. IEEE Cloud Comput. (ISSN: 2325-6095) 3 (6), 76–83.

Wang, Desheng, Ding, Wenting, Ma, Xiaoqiang, Jiang, Hongbo, Wang, Feng, Liu, Jiangchuan, 2019. Mifo: A novel edge network integration framework for fog computing. Peer-to-Peer Netw. Appl. (ISSN: 1936-6450) 12 (1), 269–279.

Wang, J., Liu, K., Li, B., Liu, T., Li, R., Han, Z., 2020a. Delay-sensitive multi-period computation offloading with reliability guarantees in fog networks. IEEE Trans. Mob. Comput. (ISSN: 1558-0660) 19 (9), 2062–2075.

Wang, T., Qiu, L., Sangaiah, A.K., Xu, G., Liu, A., 2020b. Energy-efficient and trustworthy data collection protocol based on mobile fog computing in internet of things. IEEE Trans. Ind. Inform. (ISSN: 1941-0050) 16 (5), 3531–3539.

Wang, Pengfei, Yu, Ruiyun, Gao, Ningwei, Lin, Chi, Liu, Yonghe, 2021a. Task-driven data offloading for fog-enabled urban IoT services. IEEE Internet Things J. (ISSN: 2327-4662) 8 (9), 7562–7574.

Wang, Zhe, Zhao, Dongmei, Ni, Minming, Li, Lu, Li, Cheng, 2021b. Collaborative mobile computation offloading to vehicle-based cloudlets. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 70 (1), 768–781.

Wu, Celimuge, Ohzahata, Satoshi, Kato, Toshihiko, 2013. Flexible, portable, and practicable solution for routing in VANETs: A fuzzy constraint Q-learning approach. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 62 (9), 4251–4263.

Wu, Yalan, Wu, Jigang, Chen, Long, Zhou, Gangqiang, Yan, Jiaquan, 2021. Fog computing model and efficient algorithms for directional vehicle mobility in vehicular network. IEEE Trans. Intell. Transp. Syst. (ISSN: 1558-0016) 22 (5), 2599–2614.

Xie, Xing, Zeng, Hua-Jun, Ma, Wei-Ying, 2002. Enabling personalization services on the edge. In: Proceedings of the Tenth ACM International Conference on Multimedia. In: MULTIMEDIA '02, Association for Computing Machinery, New York, NY, USA, ISBN: 978-1-58113-620-3, pp. 263–266.

Xu, Dianlei, Li, Yong, Chen, Xinlei, Li, Jianbo, Hui, Pan, Chen, Sheng, Crowcroft, Jon, 2018. A survey of opportunistic offloading. IEEE Commun. Surv. Tutor. (ISSN: 1553-877X) 20 (3), 2198–2236.

Yadav, R., Zhang, W., Kaiwartya, O., Song, H., Yu, S., 2020. Energy-latency tradeoff for dynamic computation offloading in vehicular fog computing. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 69 (12), 14198–14211.

Yang, Haigen, Li, Gang, Sun, GuiYing, Chen, JinXiang, Meng, Xiangxin, Yu, HongYan, Xu, Wenting, Qu, Qiang, Ying, Xiaokun, 2021. Dispersed computing for tactical edge in future wars: vision, architecture, and challenges. Wirel. Commun. Mob. Comput. (ISSN: 1530-8669) 2021, e8899186.

Yang, B., Sun, M., Hong, X., Guo, X., 2020. A deadline-aware offloading scheme for vehicular fog computing at signalized intersection. In: 2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops). pp. 1–6.

Yang, P., Zhang, N., Zhang, S., Yang, K., Yu, L., Shen, X., 2017. Identifying the most valuable workers in fog-assisted spatial crowdsourcing. IEEE Internet Things J. (ISSN: 2327-4662) 4 (5), 1193–1203.

Yannuzzi, M., Milito, R., Serral-Gracià, R., Montero, D., Nemirovsky, M., 2014. Key ingredients in an IoT recipe: Fog computing, cloud computing, and more fog computing. In: 2014 IEEE 19th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD). pp. 325–329.

Ye, Dongdong, Wu, Maoqiang, Tang, Shensheng, Yu, Rong, 2016. Scalable fog computing with service offloading in bus networks. In: 2016 IEEE 3rd International Conference on Cyber Security and Cloud Computing (CSCloud). pp. 247–251.

Yousefpour, Ashkan, Fung, Caleb, Nguyen, Tam, Kadiyala, Krishna, Jalali, Fatemeh, Niakanlahiji, Amirreza, Kong, Jian, Jue, Jason P., 2019. All one needs to know about fog computing and related edge computing paradigms: A complete survey. J. Syst. Archit. (ISSN: 1383-7621) 98, 289–330.

Yu, Zhengxin, Hu, Jia, Min, Geyong, Zhao, Zhiwei, Miao, Wang, Hossain, M. Shamim, 2021. Mobility-aware proactive edge caching for connected vehicles using federated learning. IEEE Trans. Intell. Transp. Syst. (ISSN: 1558-0016) 22 (8), 5341–5351.

Zeadally, S., Guerrero, J., Contreras, J., 2020. A tutorial survey on vehicle-to-vehicle communications. Telecommun. Syst. (ISSN: 1572-9451) 73 (3), 469–489.

Zhang, Z., Zhang, W., Tseng, F., 2019. Satellite mobile edge computing: Improving QoS of high-speed satellite-terrestrial networks using edge computing techniques. IEEE Netw. (ISSN: 1558-156X) 33 (1), 70–76.

Zhou, Z., Liao, H., Zhao, X., Ai, B., Guizani, M., 2019. Reliable task offloading for vehicular fog computing under information asymmetry and information uncertainty. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 68 (9), 8322–8335.

Zhou, Y., Liu, K., Xu, X., Guo, S., Wu, Z., Lee, V., Son, S., 2020. Distributed scheduling for time-critical tasks in a two-layer vehicular fog computing architecture. In: 2020 IEEE 17th Annual Consumer Communications Networking Conference (CCNC). pp. 1–7.

Zhu, C., Chiang, Y.-H., Mehrabi, A., Xiao, Y., Ylä-Jääski, A., Ji, Y., 2019a. Chameleon: Latency and resolution aware task offloading for visual-based assisted driving. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 68 (9), 9038–9048.

Zhu, Chao, Chiang, Yi-Han, Xiao, Yu, Ji, Yusheng, 2021a. FlexSensing: A QoI and latency-aware task allocation scheme for vehicle-based visual crowdsourcing via deep Q-network. IEEE Internet Things J. (ISSN: 2327-4662) 8 (9), 7625–7637.

Zhu, S., Gui, L., Zhao, D., Cheng, N., Zhang, Q., Lang, X., 2021b. Learning-based computation offloading approaches in UAVs-assisted edge computing. IEEE Trans. Veh. Technol. (ISSN: 1939-9359) 70 (1), 928–944.

Zhu, C., Tao, J., Pastor, G., Xiao, Y., Ji, Y., Zhou, Q., Li, Y., Ylä-Jääski, A., 2019b. Folo: Latency and quality optimized task allocation in vehicular fog computing. IEEE Internet Things J. (ISSN: 2327-4662) 6 (3), 4150–4161.

Krzysztof Ostrowski received M.Sc. degree in the area of software defined radios for navigation systems in 2009. He is currently pursuing the Ph.D. degree in computer science. As a professional, for the last two decades, contributed to projects carried out in different locations around the world, and in various domains, from web, through telecommunication, to automotive. He is an active member of the V2X working group in the AUTOSAR consortium, and works as a software architect in the automotive industry. His research interests include fog computing, temporal networks, and social behaviours.

Amit Kumar Singh received the B. Tech. degree in Electronics Engineering from Indian Institute of Technology (Indian School of Mines), Dhanbad, India, in 2006, and the Ph.D. degree from the School of Computer Engineering, Nanyang Technological University (NTU), Singapore, in 2013. He was with HCL Technologies, India for year and half before starting his Ph.D. at NTU, Singapore, in 2008. He worked as a post-doctoral researcher at National University of Singapore (NUS) from 2012 to 2014, at University of York, UK from 2014 to 2016 and at University of Southampton, UK from 2016 to 2017. Currently, he is a Lecturer at University of Essex, UK. His current research interests include system level design-time and run-time optimisations of 2D and 3D multi-core systems with focus on performance, energy, temperature, and reliability. He has published over 60 papers in the above areas in leading international journals/conferences. Dr. Singh was the receipt of ICCES 2017 Best Paper Award, ISORC 2016 Best Paper Award, PDP 2015 Best Paper Award, HiPEAC Paper Award, and GLSVLSI 2014 Best Paper Candidate. He has served on the TPC of IEEE/ACM conferences like ISED, MES, NoCArc, ESTIMedia, ICESS, and DATE.

Piotr Dziurzanski received the M.Sc. and Ph.D. degrees in computer engineering from the West Pomeranian University of Technology in Szczecin, Poland, in 2000 and 2003, respectively. Currently, he is an Associate Professor at the West Pomeranian University of Technology in Szczecin, Poland, where he acts as the head of the Chair of Computer Architecture and Telecommunications, and a visiting researcher at the University of York, UK. In the past, he was working at the Computer Science Department at the University of York, UK, and the School of Computing at Staffordshire University, UK. He was involved in the DreamCloud and SAFIRE EU-funded research projects and a national project funded by EPSRC (UK). He was also PI or CI in 3 national projects funded by the National Science Centre in Poland. His main research interest is related to resource allocation, cloud computing, parallel processing, and reconfigurable hardware. He has published more than 50 papers in international journals and conferences.

Krzysztof Malecki received the Ph.D. degree (in 2000) and DSc degree (in 2020) in computer science from West Pomeranian University of Technology (Szczecin, Poland). Currently, he is an Associate Professor at the West Pomeranian University of Technology. He was involved in four EU-funded research projects and now he is a R&D manager in a national project focused on public transport and data in the cloud network (National Centre for Research and Development, Poland). He authored more than 100 peer-reviewed articles including journals, chapters and proceedings. His research focuses on cellular automata, multiagent systems, computer simulation of complex discrete systems, soft computing methods, decision analysis and optimisation, and digital image processing.