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Implication of Data stream offloading (DO) in Fog Computing applications: A Comparative Study

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ABSTRACT

In the world of data currency for computational transaction from end user to the edge, then to the cloud, this sequence of digitally encoded coherent signals (homogenous and heterogenous data packets) used to transmit or receive information becomes necessary to understudy. The paper seeks to tabularly survey the implication of data stream workload in various applications vis-à-vis Technology Driver, Defects/Limitations and Support for Big Data Stream mobile Computing (BDSMC). Three major databases, Scopus, ScienceDirect and EBSCO, which indexes journals and conferences that are promoted by entities such as IEEE, ACM, SpringerLink, and Elsevier were explored as data sources. Out of the initial 119 papers that resulted from the first search string, 40 papers were found to be relevant to the research concern after implementing the inclusion and exclusion criteria. In conclusion, it was recommended that research efforts should be geared towards developing scalable frameworks and algorithms that will accommodate data stream offloading, effective resource management strategy and workload issues to accommodate the ever-growing size and complexity of data.

Keywords: Data stream, Stream computing, Data stream limitations, fog computing

INTRODUCTION

In the world of data currency for computational transaction from end user to the edge, then to the cloud, this sequence of digitally encoded coherent signals (homogenous and heterogenous data packets) used to transmit or receive information becomes necessary. Advances in information technology have orchestrated large volume, high-velocity of data, and the ability to store data continuously leading to several computational bottleneck [1, 2, 3]. Due to the nature of big data in terms of volume, velocity, variety, variability, veracity, volatility, and value [4] that are being generated recently, big data computing is a new trend for future computing.

Data Stream Offloading

Now, in connection-oriented networks, data-stream is a sequence of digitally encoded coherent signals (homogenous and heterogenous data packets) used to transmit or receive information that is in the process of being transmitted or retrieved from a service provider. This may contain raw data gathered out of users' devoices or sources. Data streams are useful for big data and AI algorithm integration. Formally, a data stream could be represented by the bipolar ordered pair, where is a sequence of tuple is the sequence of positive real time intervals

Data Stream contains different sets of data, that depend on the chosen data format.

- Attributes – each attribute of the data stream represents a certain type of data, e.g. segment / data point ID, timestamp, geodata.

- Timestamp attribute helps to identify when an event occurred.
- Subject ID is an encoded-by-algorithm ID, that has been extracted out of a cookie.
- Raw Data includes information straight from the data provider without being processed by an algorithm nor human.
- Processed Data is a data that has been prepared (somehow modified, validated or cleaned), to be used for future actions.

Data Stream Contexts

As observed previously, real-time traffic offloading is particularly challenging in BDSMC scenarios especially in cases where applications constantly generate large amounts of data as shown in Figure 3.0 and Table 3.0 looks at the Fog contributions in Big Data Stream mobile Computing (BDSMC) and summary of various research efforts in context.

i. Fog Computing Layer

The work of [5] gave a clear scenario of a distributed data processing in a Fog computing (FC) environment for BDSMC. With the Fog layer, edge computing devices can seamlessly connect to the federated cloud to facilitate data offloading from the cloud. In this case, computing is dynamically distributed across the cloud sites. The network elements for scalability and QoS can be determined.

In Fog Computing (FC), there is no need for storage renting infrastructure or even renting of computing services and applications. Rather, the Fog layer is optimized to support IoT and Internet of Everything (IoE) for seamless resource and interface heterogeneity, handshake with the cloud, and distributed data analytics. This is to address requirements of IoT/IoE applications that require low latency with a wide and dense geographical distribution.

In context, this computing concept leverages both edge and cloud computing. In other words, it uses edge devices for close proximity to the endpoints (edge) and also leverages the on-demand scalability of cloud resources.

The network depends on the wide geographical distribution of Fog system model for real-time Big Data and real-time analytics. Invariably, this will support remote and densely distributed data collection points, thereby enhancing critical Big Data dimensions, that is, volume, variety, and velocity, as the fourth axis.

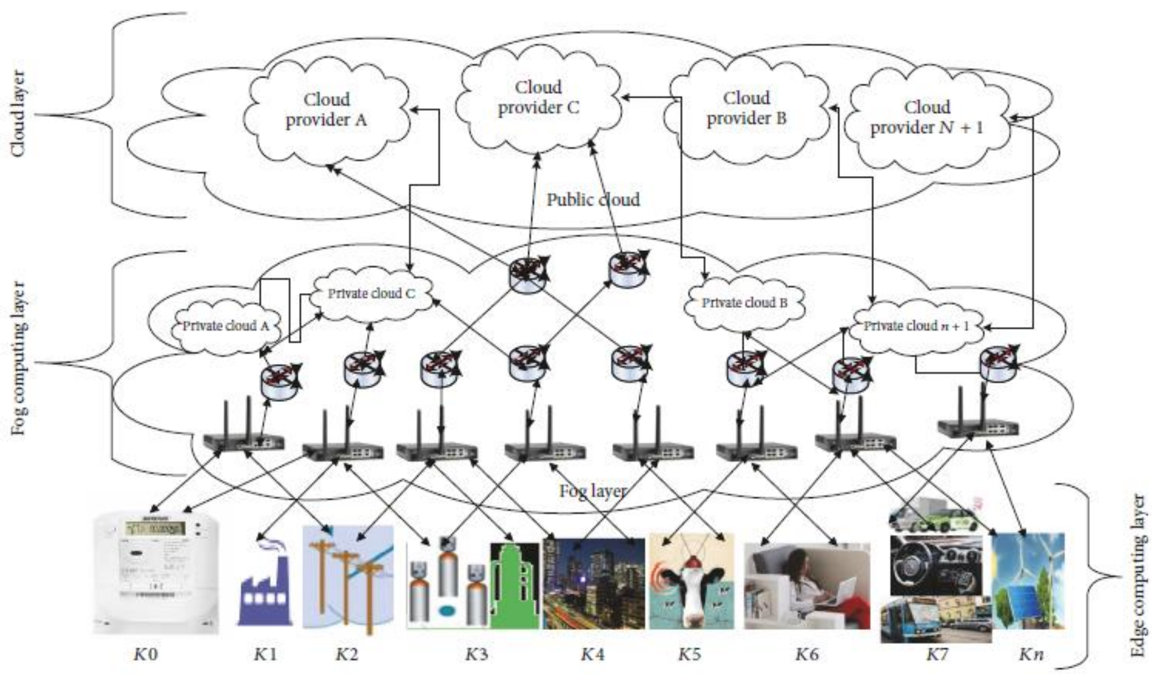

Figure 1: Framework for Fog distributed data processing

Summary of efforts in Fog Computing application context is given in Table 1.0

Table 1.0. Related Fog Computing efforts for BDSMC workload.

Application Context	Technology Driver	Defects/Limitations	Support for BDSCM workload
Real-time smart industrial applications	binary convolutional neural network	deep learning-enabled industrial applications on fog nodes affects latency	Extremely
Internet of Vehicles (IoV)	merger of SDN with IoV and FC	Increased computational resources	Extremely
Vehicular FC service in rural areas	Bidding-Price-based Transaction (BPT)	Trust vulnerability	Unspecified
FC and Conditional Deep Neural Networks (CDDNs)	Learning-in-the-Fog (LiFo)	Trust vulnerability	Extremely
Industry 4.0	Genetic Algorithm (GA) and machine Learning	Increased computational resources	Extremely
Internet of vehicles (IoV)	non-orthogonal multiple access (NOMA)-based FC vehicular (FCV) network architecture	Increased computational resources	Extremely
IoT based Systems	Task Priority based Resource Allocation	Serious Security vulnerability	Extremely
IoT based Systems	Proof-of-Work (PoW)	Increased computational resources	Extremely
Smart Industry	IPv6 over time-slotted channel hopping (6TiSCH)	Serious Security vulnerability	Extremely

Vehicular fog cloud network (VFCN)	Mobility Aware Blockchain-Enabled offloading scheme (MABOS) & linear search based task scheduling (LSBTS) method	Increased computational resources	Extremely
delay-sensitive applications	Ant Colony Optimization (ACO) and Earliest Deadline First (EDF) Algorithm	Increased computational resources	Extremely
Fog-computing radio access network (F-RAN)	Fusion of non-orthogonal multiple access (NOMA) and F-RAN	Increased computational resources	Extremely
Access control system in fog-enabled E-health (AC-FEH).	ciphertext-policy attribute-based encryption (CP-ABE)	Increased computational resources	Extremely

In the development of DCN for efficient data stream offloading and micro-services in the cloud, Figure 2 provided a good framework with support for application enabled management and automation. Some of the attributes include Fog data stream computing, physical and cybersecurity components, data analytics, and cloud network connectivity.

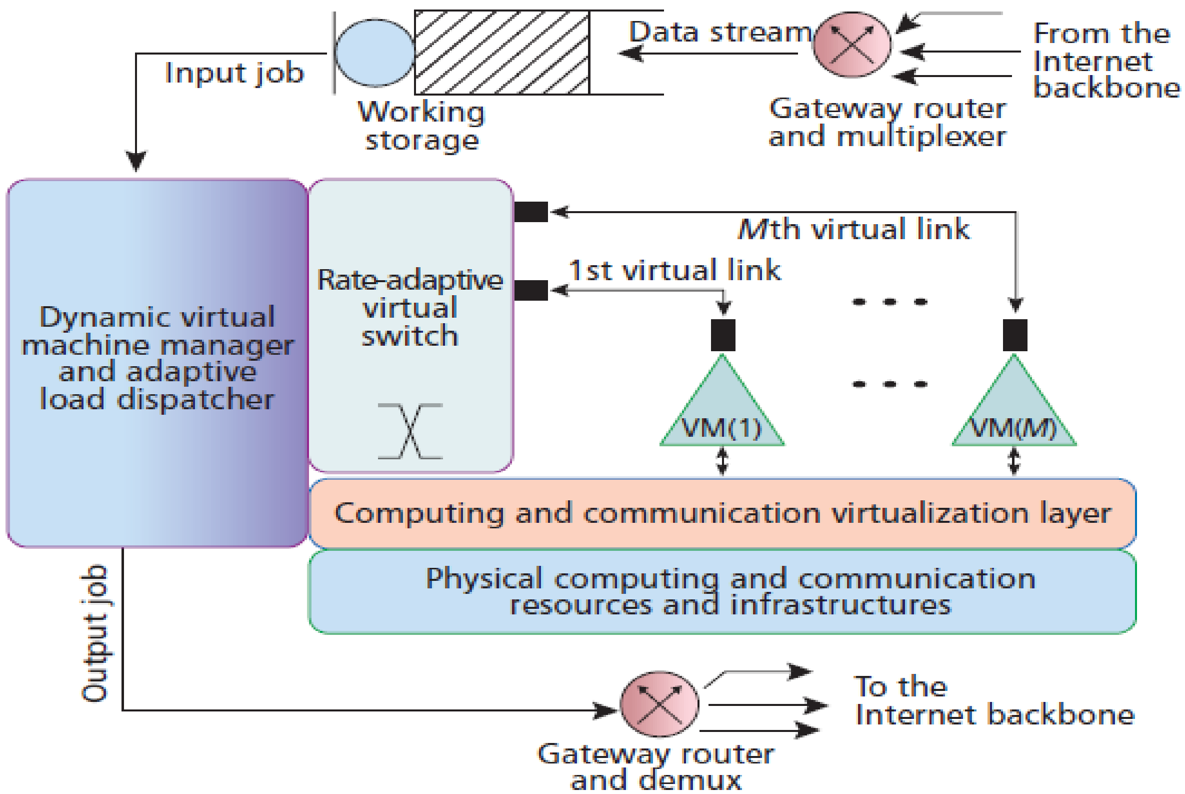

Figure 2: VNetDC architecture of the Stream Cloud platform [6].

However, the local processing of these data is also expensive for resource-limited devices, so real-time offloading of big data streams currently present two main critical issues. The first issue concerns the costs to be sustained by the mobile device in terms of bandwidth consumption, which is induced by the Internet-assisted device-cloud communication, and energy consumption, which stems from the intensive usage of networking wireless interfaces. Therefore, a second issue with the current offloading approaches is that they can only deal with computationally intensive applications that do not need large volumes of input data to be executed. As a consequence, BDSMC applications should not be offloaded, because the cost to send a large volume of data to the cloud actually offsets the gain from remote execution. In principle, data stream traffic offloading could enable devices to balance the energy consumed by the networking interfaces for device-to-cloud communication and the energy saved by running jobs remotely in [7].

Stream Cloud

Stream Cloud is a very important concept in data stream traffic offloading. In table 3.0, the challenges enlisted are addressed by the self-configuring framework recently presented in [8, 9]. This is currently in the prototype phase and is referred to herein as the "StreamCloud paradigm". The paradigm relies on an Internet-assisted peer-to-peer service architecture, which minimizes the energy costs at both the mobile devices and the data centers through adaptive synchronization of the corresponding resource management operations and the real-time hibernation of the underutilized networking/computing servers.

Now, let's look at SeCoM module shown in Figure 3. The VNetDC architecture is subsumed by the StreamCloud paradigm at the cloud side for BDSMC paradigm. It supports the CDroid-server previously reported in [10], which runs at the cloud side on top of the VNetDC as a guest OS. Specifically, Figure 3 platform resides at the middleware layer of the underlying protocol stack. It is composed of multiple reconfigurable VMs interconnected by a switched rate-adaptive virtual LAN (VLAN) and managed by a central controller, (i.e. StreamCloud Manager (SeCoM). According to some recent contributions on the architecture of VNetDCs, the multiplexed big data stream received by the Internet backbone during a time slot undergoes load shedding; hence, it is temporarily buffered by the working storage of Figure 3.1. As shown in the Figure, the black boxes indicate virtual network interface cards. Each virtual link subsumes an end-to-end TCP-based transport connection.

At the beginning of each slot, all the current backlog of the working storage is drained and passed to the VNetDC platform as the current input job. In turn, the VNetDC processes the current input job within a time interval that is limited up to a time slot. This ensures that the overall per-job queue including the computation and communication delay of the VNetDC.

The task of the virtualization layer is to guarantee that the demands for the computing and communication virtual resources of the server are mapped onto adequate computing (e.g., CPU cycles) and communication (e.g., link bandwidths) physical supplies. For this purpose, the virtualization layer of the StreamCloud prototype implements the recently proposed *mClock* and *Second Net* schedulers asserted [11].

The SeCoM module is the “core” engine that performs the adaptive joint management of the virtual communication-plus-computer resources and implements the dynamic virtual manager, load dispatcher and the rate-adaptive virtual switch for streams workload. Two key observations inspired the SeCoM design. First, the workload offered by real-time big data streams is highly time-varying and bursty, so forecasting the instantaneous arrival rate is a challenging task. Second, due to the setup costs, too frequent ON/OFF transitions of the currently underutilized computing/communication servers waste energy. Hence, in order to address with these challenges, this work will introduce data stream hibernation state (DSHS) which allows underutilized devices, physical servers and switches to intuitively move to energy-conservation mode.

Stream Computing Efforts

In [12], the authors focused on the integration of class incremental learning based on deep learning and the Internet of Things (IoT) to achieve transmission costing of data in the edge-cloud architecture. The work demonstrated how training images on the IoT edge device can reduce transmission cost. In [13], the authors highlighted long short-term memory neural networks as a streams model that offers classification accuracy for highly variable and bursty, real-time server traffic flows. The work makes room for heavy data streams thus enabling the employment of optical circuit switching. In [13], voluminous, time-series data streams originating in continuous sensing environments was identified. Its data ingestion and processing challenges lead to an order-preserving sketching algorithm designed for space-efficient representation of multi-feature streams with native support for stream processing related operations.

In their work, observational streams are pre-processed at the edges of the network generating sketched streams to reduce data transfer costs and energy consumption. Ingested sketched streams are then processed using sketch-aware extensions to existing stream processing APIs delivering improved performance. The authors in [14] focused on low latency stream processing on large clusters. The work investigated a tuple scheduler (called Hone) in order to minimize the maximum queue backlog of all tasks over time. Hone leverages an online Largest-Backlog-First (LBF) algorithm with a provable good competitive ratio to perform efficient tuple scheduling. In [15], a multi-service model of a communications system with stream and elastic traffic was investigated on the basis of a two-dimensional Markov process, which approximates the real

process in the considered system. In [16], a novel multi-stream refining based deep multi-task learning scheme that aggregates multi-stage salient embedding features in the network to boost the retrieval performance was presented. In Kim and [17], the authors proposed edge computing-assisted adaptive streaming which provides the opportunity to jointly optimize the QoE of clients, resource utilization, and fairness among clients by shifting the adaptation intelligence from the clients to the edge cloud. The work discussed adaptive streaming framework taking advantage of the capabilities of multi-access edge computing (MEC). Also, an optimization model that jointly considers the main influencing factors in QoE and fairness among clients were highlighted.
The works of [18], looked at data stream classification considering Edge computing (EC) technology for improved the predictive performance. In the research of [19], IoT big data streaming applications were thoroughly investigated considered the important features of IoT data streaming applications (i.e., component dependency and dynamic arrival) and the infrastructure provisioning (i.e., capacity constraint and colocation interference). The work looked at the offloading problem for dynamically arrived IoT data streaming requests on MEC servers in real time while modelling a delay-sensitive multiuser multi-resource online offloading problem. In [20], the authors focused on cardinality estimation in a data stream, under a stringent constraint that the input data stream can be scanned by just one single pass.
Their algorithm addressed traffic monitoring of high-speed networks and query optimization of Internet-scale database and supported the estimation of very large stream cardinalities, even on the Tera and Peta scale. However, the QoS metrics were not highlighted and the approach appears too resource intensive. In [21], proactive caching in mobile-edge computing (MEC) networks was investigated while using data-driven risk-averse optimization to derive a robust strategy for caching and delivery scheduling. A two-stage stochastic mixed-integer programming (SMIP) was employed for operational efficiency.
In [22] works, a real-time streaming controllable clustering edge computing algorithm (SCCEC) was proposed while carrying out clustering analysis and edge-computing algorithm under the framework. The experimental results show that their design can obtain global optimal solution, and deal with massive data with high real-time performance. It can be used for real-time streaming data aggregation under big data background. Other related efforts were studied in kNN STreaming Unit in [22, 23, 24] HTTP adaptive streaming (HAS) in [25], utility maximization framework (UMF), [26], and task caching and offloading (TCO) says [27].

SeCoM Main Open Challenges

In Stream Computing, two main challenges are presented by the BDSMC paradigm. First, due to the inherent real-time constraints, the performance of BDMSC applications also depends on the physical location of the remote servers, their computation load, and the communication latencies introduced by both inter- and intra-data-center networks. As a consequence, a first challenge regards the provision of cloud support to delay-sensitive applications such as BDSMC in Table 3.0. By exploiting the opportunistic access to the communication and computer resources of nearby mobile devices, data stream offloading can easily be achieved.
Current literatures discussed in table 3.0 have not addressed these gaps. Also, multi-tier offloading architectures asserted [28, 29] offered little inputs on Table 3.0. In these instances, a computation resulting from close-by less powerful device for performing low-latency offloading of delay-sensitive "light" applications needs to be improved upon. Besides, the outsourcing of computationally intensive execution of delay-tolerant applications to remote powerful clouds requires a robust network

model. Second, the energy consumed by intra-data-center networks may represent a large part of the energy demand of the overall BDSMC system, especially when the utilized networks are bandwidth-limited. In fact, current virtualized data centers are not designed to support communication/computer-intensive real-time big data applications, such as real-time video coding/ decoding, target recognition, and tracking. Hence, in order to minimize energy consumption, the joint balanced provisioning, scaling, and distributed management of the communication-plus-computer virtual resources of virtualized networked data centers represent a second major challenge. Overall, since the resource management policies reviewed in Table 3.0 are QoS-based, hence an accurate characterizations of resource usage in the supporting data center is the next key focus.

Stream Computing Data Center Designs and Tier Ratings: Data Center Classification

Clearly, the traditional Data Center Networks (DCNs) are suffering from many problems including high energy consumption, high latency, fixed throughput of links and limited reconfigurability to the traffic demand [30]. The classification levels of data centers represent the design certification. A tier depicts the service level and there are 4 tiers of Data centers are [31] submissions:

- Tier 1 Data Center
- Tier 2 Data Center
- Tier 3 Data Center
- Tier 4 Data Center

A tier 1 data center can be little more than a powered warehouse and it is not complex in structure, hence unreliable for stream computing. Tier 4 offer guarantee of uptime and 2N (two times the amount required for operation) cooling and redundant power and infrastructure. Level 4 edge devices does not have issues at the data center infrastructures due to its redundancies. A tier 3 data center can perform repairs without noticeable service disruption. A level 3 provider offer an N+1 (the amount required for operation plus a backup) availability for clients. level 3 is even tolerant of some faults. Tier 4 data centers are considered “fault tolerant.” Unplanned maintenance does not stop the flow of data to a data center Tier 4. Day-to-day operations continue regardless of any support taking place. Availability according to data center Tiers is highlighted below:

- Tier 1 – 99.671% Guaranteed availability
- Tier 2 – 99.741% Guaranteed availability
- Tier 3 – 99.982% Guaranteed availability
- Tier 4 – 99.995% Guaranteed availability

At Tier 3, a data center must adhere to the following:

1. N+1 (the amount required for operation plus a backup) fault tolerance. A Tier III provider can undergo routine maintenance without a downtime in operations. Unplanned maintenance and emergencies may cause problems that affect the system. Problems may potentially affect customer-facing operations.
2. 72 hours of protection from power outages. This provider must have at least three days of exclusive power. This power cannot connect to any outside source.
3. No more than 1.6 hours of downtime per annum. This downtime is allowed for purposes of maintenance and overwhelming emergency issues.

At Tier 4, a data center must adhere to the following:

Zero single points of failure. Tier 4 providers have redundancies for every process and data protection stream. No single outage or error can shut down the system.

1. 99.995% uptime per annum. This is the level with the highest

guaranteed uptime. It must be maintained for a center to maintain Tier 4 ranking.

2. 2N+1 infrastructure (two times the amount required for operation plus a backup). 2N+1 is another way of saying "fully redundant."
3. No more than 26.3 minutes of downtime per annum as a maximum figure. Providers must allow for some downtime for optimized mechanical operations; however, this annual downtime does not affect customer-facing operations.
4. 96-hour power outage protection. A level 4 infrastructure must have at least 96 hours of independent power to qualify at this tier. This power must not be connected to any outside source and is entirely proprietary. Some centers may have more.
5. 99.982 % uptime. This is the minimum amount of uptime that a level 3 provider can produce. The redundancies help to protect this number even if a system suffers unexpected issues.

Big Data Stream Mobile Computing (BDSMC)

BDSMC explains a new generation of mobile or wireless integrated computational networking infrastructures designed to extract hidden value from an ever-increasing volume of space-time correlated heterogeneous data streams in [32]. This is enabled in real time via energy-efficient acquisition, wireless transport, and processing. The characterization of the BDSMC paradigm expresses (i.e., variety (data heterogeneity), volume (ever increasing amount of data to be processed), velocity (data generation at fast and unpredictable rates), value (huge value but hidden in massive datasets at very low density), and volatility (the acquired data streams must be transported and processed in real time). While the first four Vs are common to all big data applications, another last V (i.e., volatility) is introduced for featuring big data stream applications. In general, the value of a stream of data is closely related to both its space and time coordinates, and hence, after acquisition, this value quickly decreases if the computing-plus-communication delay is larger than a suitable quality of service (QoS)-dictated hard threshold.

Big data streams are typically acquired and locally preprocessed by a number of heterogeneous spatially distributed mobile/wireless devices and then transported to remote data centers for further post-processing. Hence, according to the proposed five Vs characterization, we further assume that the life cycle of big data streams is composed of three main phases: data acquisition and local preprocessing at the mobile devices, data transport, and data post-processing at the remote data centers.

Figure 6.0 shows a three-phase life cycle depicting the main functional blocks of an integrated computing- communication technological platform for the support of BDSMC. It is composed by the interconnection of three tiers, that is, the radio access networks (RANs), the Internet backbone, and the remote networked data center. The RANs are directly connected to the mobile devices and bridge them to the Internet backbone. On one hand, RANs suffer from fading and interference, which give rise to fluctuating access bandwidths. On the other hand, mobile devices are energy-limited and equipped with scarce computing/storage resources. This forces them to offload data and computing-intensive application tasks to the remote data center, possibly by opportunistically exploiting the "best" bandwidth/delay/energy consumption mix offered by the available access technologies (e.g., 3G/4G-cellular, WiFi, femto-cellular, WiMAX).

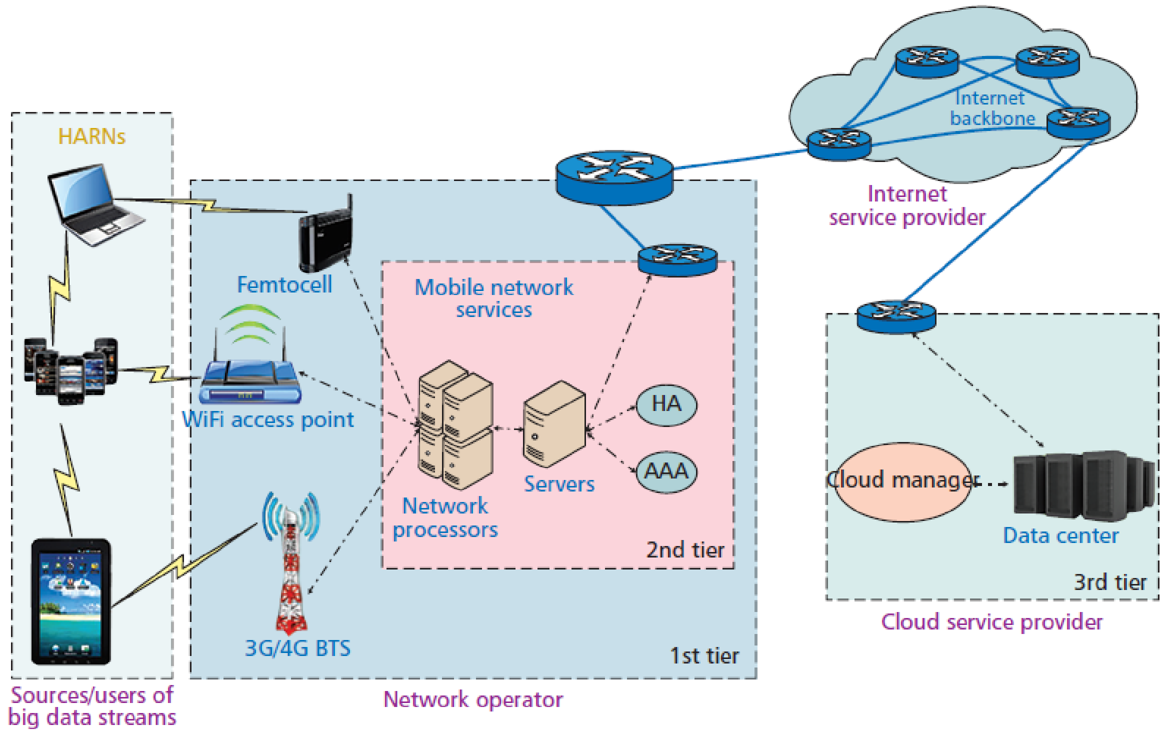

Figure 3.0: Three-tier Internet-assisted BDSMC reference architecture [31].

Thick (thin dashed-dotted) lines indicate TCP-over-IP (data link) connections. HA: home agent; AAA: authentication, authorization, and accounting; BTS: base transceiver station; HRANs: heterogeneous radio access networks.

The Internet backbone multiplexes the traffic streams generated by the RANs and forwards them to the remote data center. In order to support multimedia stream applications (e.g., photo and video sharing), the Internet backbone should guarantee the forwarding of massive data at low latency. Currently, this requirement still creates significant challenges to the Internet backbone says [32], and requires that the traffic offloaded by the mobile devices is dynamically planned by also accounting for the actual utilizations of the Internet backbone and the data center. Hence, streams of big data are post-processed and stored in the data center. Today's virtualization techniques, allow a clone of mobile application to synchronously run in an isolated container (e.g., a virtual machine, VM) hosted by the data center emphasized by [33]. However, in order to both speed up the computing time and reduce the computing energy, modern data centers implement massive parallel processing. This however, requires large amounts of data to be transferred among different VMs. As a consequence, the energy currently consumed by the data center network may represent more than 20% of the overall data center energy consumption, while the inter-VM communication may waste more than 33% of the overall processing time, especially for stream workloads later reviewed. Real-time processing and energy efficiency are two topics of major concern in managing computing-communication technological platforms supporting BDMSC in [34]. It deals with the energy-saving balanced provisioning, dynamic scaling, and distributed QoS management of the communication-plus-computing resources at both the mobile devices and the remote data center of the technological platform as depicted Figure 3.0.

Classification of BDSMC and Opportunities for Quality-of-Service Applications

Resource management must be compliant with the heterogeneous statistical features of the sources of big data streams and the Quality of Service (QoS) requirements of the supported applications. In Table 2.0, a classification of BDSMC operative environments is done based on four main aspects: data sources, content format, data shedding (i.e., compression/fusion) techniques, and QoS supported applications in [35].

Table 2.0. Categories of Big data stream and application-vs.-QoS requirements [36].

SN	Streams Classification	Description
Sources of data stream		
1	*IoT* [37-39]	Thin devices (e.g., smartphones, PDAs, tablets, RFIDs) are identified by IP addresses. Their Internet-based interconnection enables complex services for the support of economic, environmental, and health needs.
2	*Crowdsourcing* [40-47]	Several unskilled users utilize their smartphones as basic sensing units for performing coordinated sensing tasks.
3	*Social Media* [48-54]	It is the source of data generated via URL to share or exchange data in virtual communities and social networks.
Content format		
4	*Structured* [55-57]	Structured data assumes the form of ordered records, and include numbers, words, and dates.
5	*Unstructured* [50]	Unstructured data do not conform to a predefined template. Examples are location information, messages, videos, and social data sets.
6	*Semi-structured* [51]	Semi-structured data are in the form of structured data that are not further organized into relational database models, such as tables and graphs.
Data Shedding Techniques		
7	*Pseudo-random sampling* [52]	It aims to randomly drop segments of acquired data streams while preserving their main statistical features, such as frequencies of symbol occurrences.
8	*Distributed source coding* [53]	It exploits the space-time inter-correlation of the acquired streams for reducing the aggregate data rate of the encoded stream, while preserving the overall information content.

On the basis of Table 2.0 classification, it is feasible to individuate three broad classes of potential "killer" applications for the BDSMC paradigm namely: the mobile Internet of Things (IoT), spatial crowdsourcing (SC), and online social network and nomadic computing (SNNC). Mobile IoT aims to provide Internet connection to a world of heterogeneous mobile smart devices, which must be capable of supporting both machine-to-machine and machine-to-human communications in [45]. The final goal is to make feasible the real-time exchange of information about the surrounding environment by leveraging emerging technologies, such as mobile sensor networks, RFID, and biosensors. Hence, mobile IoT exhibits two basic features that conform to the BDSMC paradigm: a large set of spatially distributed, heterogeneous, and energy-limited wireless devices generate masses of real-time data streams; and IoT data is useful only when it is mined, but this requires a lot of bandwidth and computing resources. In spatial crowdsourcing (SC) application environments, large populations of non-professional clients utilize their smartphones as basic sensing units for timely distribution of sensed tasks and real-time acquisition/processing/diffusion of sensed data streams. Hence, the key feature that conforms SC applications to the BDSMC paradigm is the collective real-time processing of the acquired streams for spatial monitoring and/or decision making. Finally, online social network and nomadic computing (SNNC) applications include context-aware services for personal computing and communication activities running real time and which allow the user to exchange information in real time through cloud-assisted social network platforms. The basic feature conforming SNNC to BDSMC is the requirement of massive sets of inter-stream cross-correlation operations, in order to perform real-time detection of new social trends, similarities, and/or anomalies.

Resource management in Data streams

Resource management in BDSMC systems involves real-time offloading of code and/or data to the remote data center through the available mobile access-plus-Internet network, as well as the corresponding real-time reconfiguration of the networked data center. Table 7.0. shows the categories of big data stream and application-vs.-QoS requirements says Big [46]. The reported numerical data are to be understood as per-class gross upper bounds. IoT: Internet of Things; SC: crowdsourcing; SN &NC: social network and nomadic computing.

Table 3.0: Application vs. QoS requirements of BDSMC systems

Metrics	IoT	SC	SN&NC
Bandwidth	$\leq 10^{-1}(Mb/s)$	$\leq 2\ (Mb/s)$	$\leq 10\ (Mb/s)$
Delay	$\leq 500\ (Mb/s)$	$\leq 150\ (Ms)$	$\leq 4\ (s)$
Delay jitter	$\leq 40\ (Ms)$	$\leq 20\ (Ms)$	$\leq 150\ (Ms)$
Packet loss probability	$\leq 10^{-3}$	$\leq 10^{-5}$	$\leq 10^{-2}$
Block probability	$\leq 10^{-1}$	$\leq 10^{-2}$	$\leq 10^{-1}$

QoS Application	Technology Enabler	Network Type	Protocols/Standards	Context
delay-sensitive interactive	ISP	last-mile connection	Nil	Video feeds
Time-Sensitive Networking (TSN)	Scheduler- size-aware group weighted round robin (SGWRR)	Ethernet	Ethernet protocols	Audio Video Bridging (AVB) traffic and Time-Triggered (TT) traffic,
Service Oriented Architecture	Cloud	HPC convergence	MAS-based control system	Service computing
VoIP and video streaming	Open-source pox controller	5G	WAN	SDN
Best-Efforts	Enhanced Load Balancing and QoS provisioning algorithm (ELBQ)	Tree-DCN	WAN	SDN
Dynamic load balancing	Dynamic QoS routing algorithm	Mobile cloud computing (MCC)	Pastry protocol	SDN
Vehicular to Everything (V2X) communication	Multi-Level QoS (MLQ)	5G	3GPP	Vehicular
Wireless Network	Deep learning empowered QoS-aware adaptive (DLQA) routing algorithm	Unspecified	DLQA	AI
Radio Access	IoT Algorithm	5G	B5G	IoT
Battery-powered RF	Mobility-aware network lifetime maximization	Unspecified	Mixed-integer linear programming	IoT
SDN-IoT network collaboration	Controller group	Multi-technology	Unspecified	SDN
SDN-Data streams	Predictive/proactive heuristic time-	Distributed network	Integer linear programming (ILP)	IoT controlled

	series analysis & fuzzy logic			industrial environments
Narrowband Internet of Things (NB-IoT)	Network calculus	5G	stochastic network calculus (SNC)	Low-power wide-area (LPWA)

The final target is minimization of the overall computing-plus-communication energy consumption under the QoS requirements

Related QoS efforts for Real time traffic workload

CONCLUSION

In conclusion, we recommended that research efforts be geared towards developing scalable frameworks and algorithms that will accommodate data stream offloading, effective resource management strategy and workload issues to cope with the ever-growing size and complexity of data. So far, efforts on QoS workload provisioning have been summarized in Tables 1,2,3. Providing real-time computing support previously highlighted BDSMC applications through remote clouds hosted on virtualized networked data centers (VNetDCs) in the works of [34] is the target for recent management frameworks. These management systems are specifically designed for the real-time support of large-scale BDSMC applications and do not provide automatic and dynamic adaptation to the time fluctuations of the input streams to be processed. Dynamic adaptation of the available computing resources to the ever-changing rate of the input streams is, indeed, provided by the more recent S4-Streams in [34], Time Stream asserted [35,36,37] management frameworks.

However, these frameworks do not consider simultaneous management of network resources; also, they do not enforce hard real-time processing-plus-communication constraints. Among the richer set of articles that cover the more general topic of resource management in delay-tolerant BDSMC applications, some recent contributions may be considered representative of the current state of the art. Specifically, since the workload offered by big data streams exhibits almost unpredictable time fluctuations that are hard to forecast in a reliable way. In [22], a Lyapunov-based technique is used to dynamically optimize the provisioning of computing resources by exploiting the available queue information. Although the approach pursued in [24] is of interest, and relies on an inherent delay vs. utility trade-off, which does not account for the hard constraints on the allowed computing delays in BDSMC applications. Very recently, in [24], the problem of the allocation of computing and networking resources in large-scale data centers is addressed. After recognizing that the resulting optimization problem is NP-hard, a heuristic integrated resource allocator is presented, in order to decide on the admission of dynamically arriving streams of data and allocate resources to the accepted ones. Although performance QoS considering per-stream dedicated minimum bandwidths are accounted for in some reviewed work in this paper, its target is the maximization of the accepted arrival requests.

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