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Design of federated learning-based resource management algorithm in fog computing for zero-touch network

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ABSTRACT

The concept of zero-touch networking involves creating networks that are fully autonomous and require minimal human intervention. This approach is increasingly relevant due to the rapid growth of current cloud architectures, which are beginning to reach their limits due to continuous expansion demands from users and within the network core itself. In response, Fog computing, acting as a smart, localized data center closer to network nodes, emerges as a practical solution to the challenges of expansion and upgrading in existing architectures. Fog computing complements cloud technology. However, the realization of zero-touch networks is still in its early stages, and numerous challenges hinder its implementation. One significant challenge is the NP-hard problem related to resource management. This paper introduces an optimal resource management algorithm based on Federated Learning. The effectiveness of this algorithm is evaluated using the iFogSim simulator within the existing cloud-fog architecture. The results demonstrate that the proposed architecture outperforms the current infrastructure in several key aspects of resource management, including system latency, number of resources processed, energy consumption, and bandwidth utilization.

1. Introduction

The International Data Corporation forecasts that an enormous amount of data, approximately 79.4 zettabytes, will be produced by a remarkable 42 billion interconnected devices by the year 2025 (Bendechache et al., 2020; Basheer and Itani, 2023). The traditional method of storing and managing data in one central location, supported by cloud technology, is unable to cope with the vast amount of data being generated. Additionally, clients aim to achieve the highest Quality of Service (QoS) at the lowest cost. The conventional "pay-as-you-go" cloud model needs enhancements to effectively manage resources in a dynamic manner (Bansal et al., 2020).

One possibility of resource management in Cloud infrastructure arises from Network Resources Virtualization. This implies the "creation of a virtual version of something" (Raghunath and Annappa, 2019). This candidate solution for resource management, however, requires the data from each input sensor to be sent over the network to the Cloud for processing and response. It accounts for the considerable latency (Mijuskovic et al., 2021). Besides communication delay, network latency problems may arise from fluctuations in the virtual machines, incoming sensors to software-only bugs, and Distributed Denial of Service attacks (Moghaddam et al., 2019).

One potential solution involves establishing data centers in various locations across a wide geographical area. Consequently, several technologies, such as Fog and Edge Computing, have emerged to support this approach (Bendechache et al., 2020; Aggarwal and Kumar, 2023; Khan and Soomro, 2018; Khan and Soomro, 2021). These newer paradigms enable localized services such as data processing and storage at the node nearer to the connecting device.

Resource scheduling and management within Fog networks pose a complex optimization challenge, as indicated by Ghobaei-Arani et al. (2020). This involves assigning tasks to the most suitable nodes, considering various QoS parameters like cost and deadline. Nodes themselves possess distinct QoS parameters such as hardware setup, memory availability, and bandwidth allocation (Ghobaei-Arani et al., 2020). The difficulty lies in efficiently

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matching tasks with nodes to achieve optimal performance.

In today's context, there is a pressing requirement for an automated system to manage the complexities of networks like the one described. The intricacy and density of such networks make automation necessary (Bendechache et al., 2020). A structured system capable of self-adjustment, self-enhancement, and self-recovery is referred to as a self-organized or cognitive system (Fourati et al., 2021). Implementing automated resource management within each Fog node can decrease response time and enhance network reliability (Mijuskovic et al., 2021), thus mitigating the rate of network deterioration (Moghaddam et al., 2019).

The central concept of zero-touch networks revolves around the idea of self-regulation within computer networks. Different aspects of network management, configuration, and security can be handled through closed-loop automation with minimal human involvement (Demchenko et al., 2015). The TeleManagement Forum (TMF) has defined zero-touch provisioning (ZTP) as part of its broader Zero-Time Orchestration, Operations, and Management (ZOOM) model (Demchenko et al., 2015).

Moreover, cognitive networks offer capabilities to 5G networks, such as self-adjustment with minimal human involvement (Rojas et al., 2020). Furthermore, service delivery should be ensured according to agreed-upon Service Level Agreements (SLAs), which are defined within the Quality of Service/Experience (QoS/E) framework (Laghari et al., 2021). The paper suggests a Federated learning-based resource management algorithm in fog computing for zero-touch networks.

This paper is structured as follows: Section 1 introduces the topic, Section 2 reviews existing literature, Section 3 presents a federated learning-based resource management algorithm in fog computing for zero-touch networks, Section 4 discusses the results of the conducted experiment, and Section 5 concludes the paper while suggesting future research directions. The references are provided at the end.

2. Literature review

The history of zero-touch network and service management originates from the European Telecommunications Standards Institute (ETSI). This specification group was established in 2017. The goal of this group was to specify an end-to-end reference architecture (Benzaid and Taleb, 2020a). This reference architecture would serve as a minimum framework for future networks, enabling agility, automation, and ultra-low latency. It is seen that expenditure on AI-driven networks has increased from $23 million in 2018 to above $1.9 billion by the end of 2021 (Benzaid and Taleb, 2020a). The choice of a specific machine learning technique depends on the problem-related heuristics (Gallego-Madrid et al., 2022). Machine learning leverages the networks by providing flexible learning capabilities (Gallego-Madrid et al., 2022).

There are many challenges lying ahead. These challenges can be classified into one of three major categories namely dynamic spectrum management, automated service and network management, and cross-domain trust (Carrozzo et al., 2020). Additionally, dedicated infrastructure would be required for such an arrangement (Demchenko et al., 2016). This section deals with the architectural layout of the zero-touch network along with the fog computing paradigm.

2.1. Shortcomings in current networks

The challenges faced in the current Cloud Network need to be addressed and expanded upon:

1. Delay for link establishment: The delay in establishing links within Traditional Cloud Networks contributes significantly to latency and intermittent connectivity issues. Packet loss resulting from connection loss exacerbates this problem (Chen et al., 2018).
2. Conveying delay: Time delays occur when data is transferred from source nodes to central control, a problem known as thrashing. Integrating Fog into Cloud-to-Things communication can help mitigate this issue (Zhang et al., 2020).
3. Resource allocation: This encompasses resource assignment to network nodes and is further categorized into resource allocation, migration, and scheduling (Aggarwal and Kumar, 2023).
4. Network latency: The stringent latency requirements of 5G networks, demanding delays of less than 1 ms, pose a challenge in reducing the current latency of around 25ms. This challenge has led to the concept of zero-touch networks (Elbamby et al., 2018).
5. Task allocation: Challenges in task allocation involve cloudlet discovery, multi-resource management, and decentralized scheduling (Lin et al., 2019).
6. QoS degradation: QoS degradation occurs due to packet loss and transmission delays resulting from the challenges mentioned above (Kumari et al., 2019).
7. Datacentric security: With the increasing adoption of information-centric networking, ensuring data security and prevention has become more challenging (Zhang et al., 2018).
8. Remote server verification and validation: Verifying and validating remote servers adds latency to networks and can create potential security vulnerabilities (Ortiz et al., 2020).
9. Control and scheduling: Edge servers play a crucial role in maintaining lower latency, especially for mission-critical operations and applications requiring real-time responses with dynamic policies (Elbamby et al., 2019).
10. Fault tolerance: Human intervention and involvement often lead to a lack of fault tolerance in cloud systems.

11. Economic costs: The economic costs associated with network latency, including energy consumption and other factors like customer retention and penalties for violating SLAs, need to be addressed (López-Pires and Barán, 2017).

2.2. Cloud-fog architecture

The fundamental Cloud-Fog architecture is depicted in Fig. 1 (Basheer and Itani, 2023). Fog is a complementary architecture to Cloud (Khan and Soomro, 2021; Khan and Soomro, 2018). Its most fundamental placement is nearer to the device. These devices can be heterogeneous in nature, ranging from RFID-enabled sensors to IoT-enabled systems (Khan and Soomro, 2018). The arrangement of devices within each layer of the cloud-fog architecture anticipates the IoT, with the fog layer consisting of the system on chips or smart sensors (Khan and Soomro, 2021). The cloud layer encompasses the backbone network, and the nodes connecting to the network exhibit different levels of data generation and processing times (Khan and Soomro, 2021; Khan and Soomro, 2018).

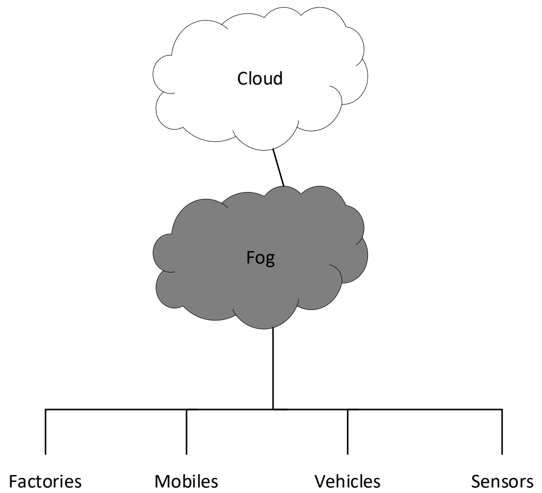

Fig. 1: Cloud-fog architecture (Basheer and Itani, 2023)

At the perceived level of exponential network growth, it is imperative to expand and automate the current cloud-fog architecture. This notion of Self-configuration and self-recovery is the notion behind the zero-touch networks. These futuristic networks lay the foundation for 5G and B5G networks (Basheer and Itani, 2023). The most notable features of these networks include modularity, agility, and scalability. The addition of machine learning techniques to the current Fog-Cloud architecture is one step in the visualization of Zero-touch Networks (Khan and Alam, 2021).

A zero-touch network architecture implies that the networks are autonomous and independent of human interaction. It implies creating a notion of self-learning in the networks. The initial direction points to incorporating machine learning in the Fog-Cloud networks (Khan and Alam, 2021). Many applications support the concept of deploying machine learning in the cloud-fog architecture. One important application is the visualization of green cities and smart buildings. The future of urban living rests with the idea of an autonomous body implying self-sufficiency. Another important paradigm is fully connected, smart vehicles depicting the future of the automobile industry (Khan and Alam, 2021).

Moreover, the application of the smart grid can be found in many paradigms, including Energy conservation and green energy-based systems. Another significant improvement to enhance quality of life can be depicted in Smart homes of the future. These applications indicate that the induction of machine learning algorithms in fog-cloud networks is a progressive and viable paradigm.

A few of the notable machine learning algorithms that are currently deployed in the cloud-fog paradigm are given in Table 1.

An analysis and study of currently existing algorithms indicate that Federated learning-based techniques for resource management have been largely unexplored.

Table 1: Machine-learning algorithms in the cloud-fog network (Khan and Alam, 2021)

Machine learning algorithm	Functional area in fog-cloud
Random forest	Price forecasting Power record faults Behavior/event recognition Tooling wear/error detection
ANN	Traffic flow features, Road-side CO and NO_2 concentrations estimation, travel time prediction
Support vector machine (SVM)	Blackout warning, power line attacks
Bayesian network	Event and behavior detect
Evolutionary computing	Short-term load forecasting
Q- learning-based algorithm	Aided optimal customer decisions for an interactive smart grid
KNN	Short-term load forecasting

2.3. Zero-touch network architecture

The zero-touch architecture is dictated by modularity and flexibility. To meet this vision, the architecture follows certain design goals. The modularity permits a combination of varied services (Benzaid and Taleb, 2020a). Many vendors are implementing versions of this architecture. One such is the 5G ZORRO-Zero-Touch Security and Trust for Ubiquitous Computing (Carrozzo et al., 2020). Data-driven artificial intelligence applications backed by Cloud and Fog networks are the key to the future. This architecture is segmented into various management domains (MD). The resources allocated within each domain are under the supervision of the MD. Fig. 2 depicts the Management domains in a zero-touch network.

As depicted in Fig. 2, modularity is achieved by separating the resources within each cluster (Gallego-Madrid et al., 2022). Each domain unit also includes an E2E (End to End) management along with a logical group of closely related services (Benzaid and Taleb, 2020b). The data collected is based on user requests for services. It is sent for analysis and response to an execution entity. This is effectively defined as closed-loop automation (Dutta et al., 2021). The performance matrices used for selecting a specific node include CPU utilization ratio, load scaling, interdependency, and intra-dependency (Tutschku et al., 2016). Fig. 2 depicts the modular approach for the zero-touch network (Gallego-Madrid et al., 2022). Autonomous management and orchestration (MANO) of these virtualized networks require efficient resource management strategies to ensure the quality of decisions (QoD) (Sciancalepore et al., 2018). The upcoming infrastructure of the Internet requires dynamism and diversity in services at ultra-low latency (Zhang et al., 2019).

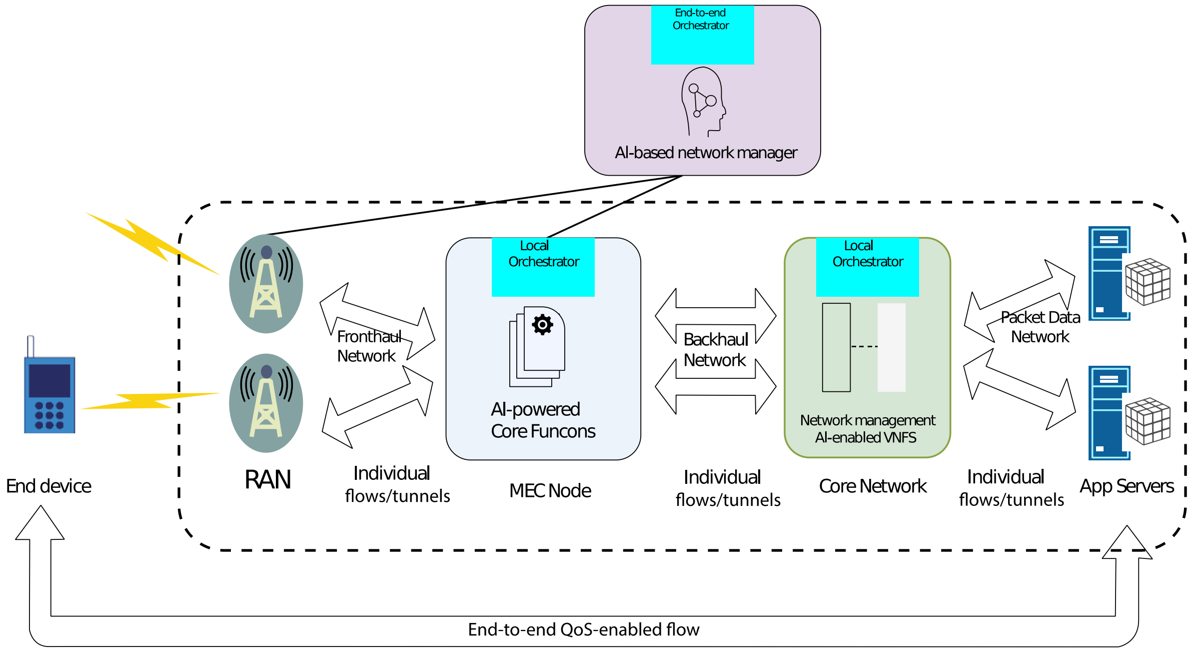

Fig. 2: Management domains

Fig. 3 provides a detailed explanation of the zero-touch architecture, highlighting the importance of management services, functions, and domains. Each component of this architecture is described as follows:

- Management service: This building block provides facilities and serves to address customer requests. At this layer, the connecting nodes may be clustered to receive services from the same provider. Alternately, varied management services can be combined together to accommodate varying user requests (Liyanage et al., 2022).
- Management domains: Management domains offer the fundamental concept of modularity and fine-grained control. These domains imply that each management service acquires the optimal resources to entertain service requests. Service authorization, authentication, and security are also managed by management domains (Gallego-Madrid et al., 2022).
- The E2E service management domain: this domain provides end-to-end delivery of the requested services (Benzaid and Taleb, 2020a; Carrozzo et al., 2020).
- Integration fabric: This component enables communication and service integration between management functions. It supports inter-domain and intra-domain services (Liyanage et al., 2022).

2.4. Resource management in cloud/fog architecture

The resource management in a Cloud/Fog architecture can be segmented into six approaches, as described in Table 2 (Ghobaei-Arani et al., 2020). Table 2 sums up the different approaches towards resource management.

Table 2: Resource management approaches (Ghobaei-Arani et al., 2020; Shafik et al., 2020)

Technique	Definition
Application placement (Ghobaei-Arani et al., 2020)	How and where to place the applications?
Resource provisioning and optimization (Shafik et al., 2020)	How to optimize current fog resources?
Resource scheduling (Liaqat et al., 2017)	How to schedule resources for achieving QoS and QoE?
Resource allocation (Zeng et al., 2019; Madni et al., 2017)	Which resources are required for execution of the specified task?
Task offloading (Ghobaei-Arani et al., 2020)	How and when to offload the task?
Load balancing (Madni et al., 2017)	How to distribute workload evenly among the participating nodes?

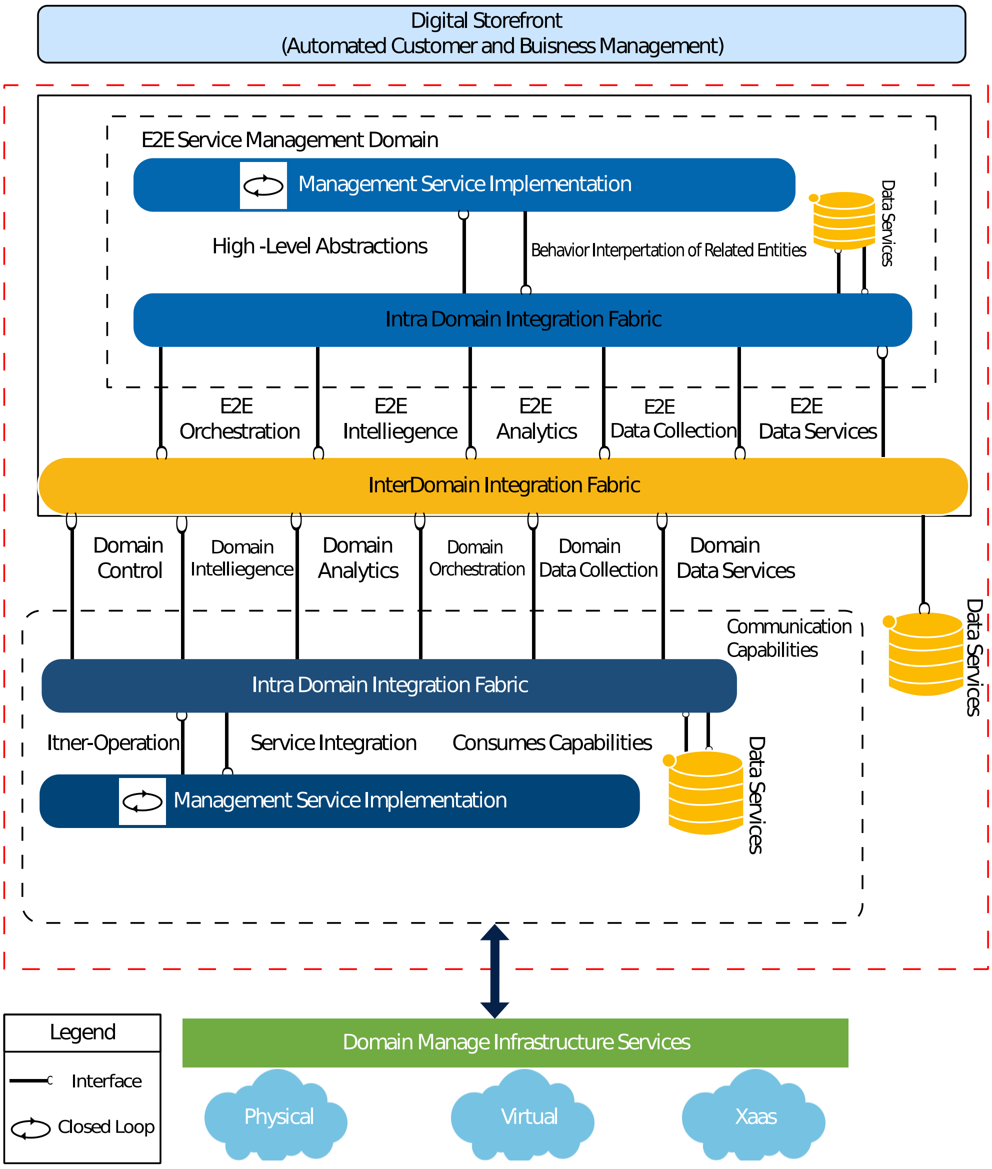

Fig. 3: Zero-touch network architecture (Liyanage et al., 2022)

Besides, there are certain resource management bottlenecks that need to be considered. These include massive channel access, power allocation, interference management, user association, and hand-off management, harmonious co-existence of Human-to-Human and IoT traffic, coverage extension, and energy management (Shafik et al., 2020). Hence, the decision for resource management in the cloud requires complex analysis and decision-making (Liaqat et al., 2017). Additionally, edge resource management requires additional management as it has high dynamics. Therefore, a model-free dynamic perspective that can fit at the run time is desired (Zeng et al., 2019). Several rules govern resource allocation in the cloud-fog continuum, including but not limited to avoiding unnecessary allocation of extra resources, ensuring adequate provisioning of resources, preventing resource congestion, minimizing resource destruction, and addressing resource deficiencies (Madni et al., 2017). VMware is an example of built-in policy control-based solutions in a specific business environment (VMware, 2021).

3. A federated learning-based resource management algorithm

This section discusses FedFog, a federated learning-based resource management algorithm in fog computing for zero-touch networks (Khan et al., 2023). The algorithm is segmented into three basic modules: FedFog-Cloud, FedFog-Fog, and FedFog-Node. Fig. 4 explains the FedFog algorithm pictorially. Each module is explained separately below:

- FedFog-Cloud: This module resides in the cloud and serves to act as a backbone. The function of this layer is to initially broadcast the global parameters to the FedFog-Fog. During random intervals of time, the FedFog-Cloud updates its global model by receiving an updated model from the FedFog-Fog. This is the essence of Federated learning, where the updated model is received by Cloud instead of data.

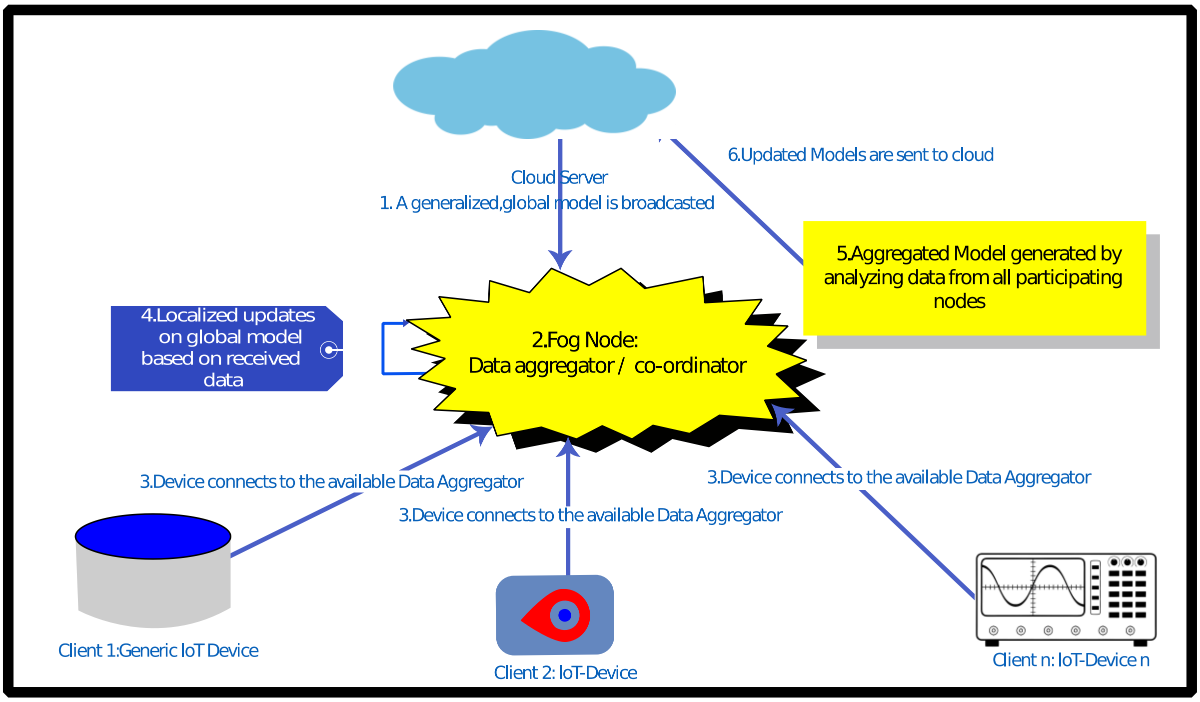

Fig. 4: FedFog-A federated learning algorithm in fog networks (Khan et al., 2023)

- FedFog-Fog: This module is the middle layer between FedFog-Cloud and FedFog-Node. It is at this layer that the majority of resource management decisions occur. FedFog-Fog begins by receiving the global initialization parameters from FedFog-Cloud. It then broadcasts these parameters to the connected nodes *k* and its directly connected neighbors, namely the other Fog Nodes in the cluster. When the connected nodes *k* send some service request through FedFog-Node, the FedFog-Fog checks if the number of incoming requests n_k are less than the number of requests that can be processed at FedFog-Fog n_f, i.e. $n_k < n_f$. In case the current Fog Device is busy or is already processing incoming requests at the maximum capacity, the request is routed to the next-hop neighbor. This ensures task offloading and load balancing at the Fog layer, thereby entertaining maximum incoming requests without affecting the QoS. Alternately, if the incoming request is entertained at the current FedFog-Fog, the model is updated by calculating the gradient using the method *calculate_h*$_k(n_k)$. This, in essence, implies that model parameters are regularly updated at the FedFog-Fog instead of FedFog-Cloud. This ensures nearly zero data thrashing and data routing to the cloud. It improves overall system response time. The *Receive_Update ()* method elaborates on the parameters that are received at the fog level from the node. These include an updated time stamp for service processing t← $t + tf$, an updated number of requests processed at the fog device, n←$n + n_f$, *updated* system weights w← $w + h$, and updated security parameters, s← $s + \Delta$. The Fog device receives these parameters from all the participating nodes and updates the received global model locally. In other words, the model updates occur at the fog layer instead of the cloud.
- FedFog-Node: This module essentially represents the connecting devices. These devices range from RFID-enabled devices to smart buildings, depending on their service requests. These nodes will receive initial global parameters for connecting to the Cloud-Fog Network and later on request FedFog-Fog for service requests and processing. The algorithm is depicted below.

FedFog-Cloud
1. *Begin Broadcast (t, w, s)*
(initial global parameters to be advertised to Fog Nodes for beginning the first round of Federated learning)
t: time stamp,
w: weight,
s: security)
2. *while (T==RANDOM.TIME())*
do
{
Updated_GlobalModel=FedFog-Fog.Receive_Update ()
//t=updated_t, w=updated_w, s=updated_s
}
3. *Broadcast(t,w,s)*
END

FedFog-Fog
1. Receive Broadcast (t, w, s)
2. Global parameter n: Number of requests processed in the current round
3. while (FedFog-Node! =0) do
{
FedFog-Node k in cluster
send sample (t,w) to k
}
4. receive (n_k)
{
if(n_k<n_f) //n_k: Number of incoming service requests from k at FedFog-Fog

calculate h_k (n_k)// n_f: Number of requests that can be processed at FedFog-Fog
else
Send_to_Neighbour(n_k)
}
5. calculate_hk(nk)// h_k: Gradient of the sampled model
{

$$n = \frac{1}{|j|} \Sigma_{k\epsilon j} n_k$$

// j: Nodes that return a value(model)in this round
return n
}
6. Send_to_Neighbour(n_k)
{
while (FedFog-Fog.count! =0)
select least-hop Neighbour
}
7. Receive_Update ()
{
t← $t + tf$// t: updated time stamp// tf: time needed for processing at Fog Node
$n \leftarrow n + n_f$
//n: updated number of resources processed
h←weighted sum (h_k where k ε j)// h: aggregated system gradient
$w \leftarrow w + h$ // w: updated system weights
s← $s + \Delta$
//Δ: updated security parameters

}
END

FedFog-Node
1. *Receive broadcast(t,w)*
2. (t_k,w_k) //k^{th} node receiving system parameters
END

The above-stated federated learning-based resource management algorithm in fog-computing for zero-touch networks, FedFog, has a notable optimization by including task offloading to the nearest neighbor. It is achieved through device polling implemented at the FedFog-Fog using the method *Send_to_Neighbour(n_k).* The specific learning parameters at the FedFog-Cloud include updated time stamp, *t=updated_t,* updated weight stamp, *w=updated_w*, and updated security stamp, s=updated_s. The same learning parameters are learned at the FedFog-Fog node. The difference happens because the FedFog-Cloud learns at random time intervals from the FedFog-Fog while FedFog-Fog learns it from the *FedFog-Node* whenever there is a service request.

4. Results and discussion

The proposed algorithm is simulated in iFogSim and tested against the existing cloud-fog architecture. The specifics of the simulator are depicted in Table 3.

Table 3: Parameters used in the simulation (Khan et al., 2023)

Parameter	Specification	Device type		
		Sensor/Actuator	Fog server	Cloud server
Hardware	x86 architecture	x86 architecture	x86 architecture	x86 architecture
RAM(MB)	256	256	400	4000
Uplink bandwidth	100 MHz	100 MHz	100,00 MHz	100,00 MHz
Downlink bandwidth	100,00 MHz	100,00 MHz	100,00 MHz	100,00 MHz
Level	NA	2	1	0
Batch size		Variable	Variable	NA
System metrics to be considered	Energy consumed, network usage, resources processed, latency			

The algorithm focuses on implementing Federated Learning in the fog rather than the cloud. This improves system response by reducing latency. Load balancing is achieved by polling fog devices and selecting the optimal Fog node for a given task. While traditional Federated Learning operates in the cloud, FedFog brings federated learning to the fog. Additionally, FedFog modifies traditional federated learning by offloading tasks to the nearest neighbor. This occurs when the current fog device is processing user requests at maximum capacity and cannot accommodate additional service requests (Khan et al., 2023). Initial results demonstrate the superiority of FedFog over existing cloud-fog architecture. Stable system response is observed across varying cluster sizes (n=3, 4, and 5) and different time intervals (5000ms, 10000ms, 15000ms, and 20000ms), providing concrete evidence of algorithm reliability (Khan et al., 2023).

Figs. 5-8 illustrate the performance difference between traditional cloud-fog architecture and the FedFog algorithm. Simulation results indicate that the proposed FedFog algorithm achieves an average latency of approximately 75.4ms, compared to traditional cloud-fog architecture, with an average difference of 148.9ms. Moreover, the average number of processed resources is 78% higher in FedFog compared to the traditional architecture. Reduced network usage is observed due to minimal data thrashing from devices to the Cloud, as depicted by Figs. 5-8. Additionally, energy consumption is reduced, providing a cost-effective solution.

5. Conclusion and future directions

The paper proposed a federated learning-based Resource Management Algorithm in Fog Computing for Zero-touch Networks. The resource management in tomorrow's networks is still unanswered. There are numerous advantages of implementing an optimal resource management scheme in Fog computing to enable the notion of zero-touch networks. A few notable advantages are given below:

- Improved resource management: Cognitive systems can help improve the resource management of the local network and the cloud. These cognitive gateways can identify, classify, and schedule resources based on performance parameters, such as available local computations, internet bandwidth, etc., automatically without human intervention (Jalali et al., 2017).

- Efficient route discovery: A zero-touch network can automatically discover an efficient route to the cloud using metrics such as shortest path available, available bandwidth, etc. (Verma et al., 2018).
- Network optimization: Zero-touch control and optimization of low-level network functionalities by providing an efficient, automated, modular, and flexible network control platform (Bonati et al., 2020).

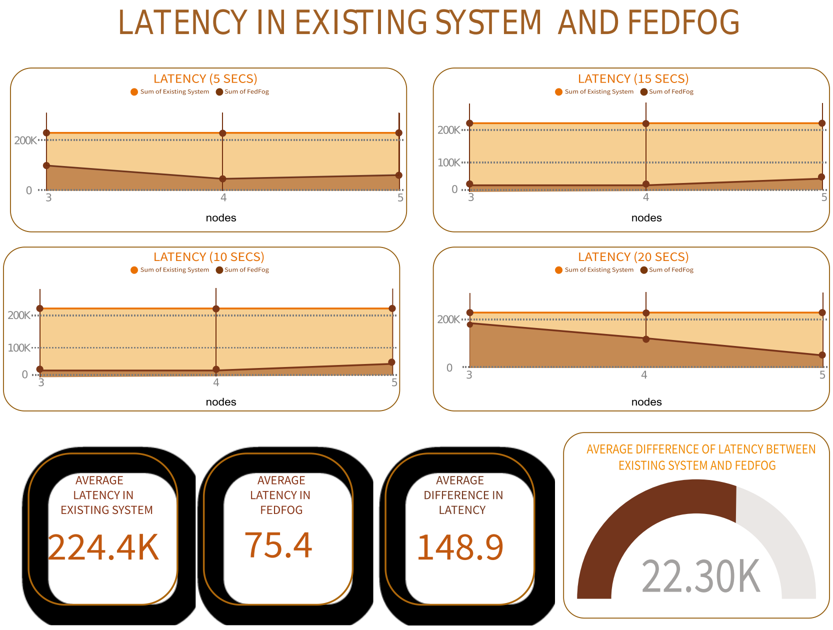

Fig. 5: Latency comparison (Khan et al., 2023)

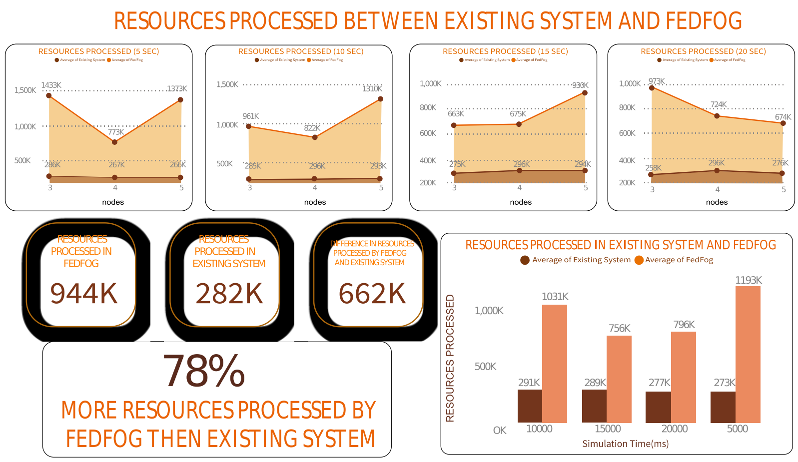

Fig. 6: Comparative number of resources processed (Khan et al., 2023)

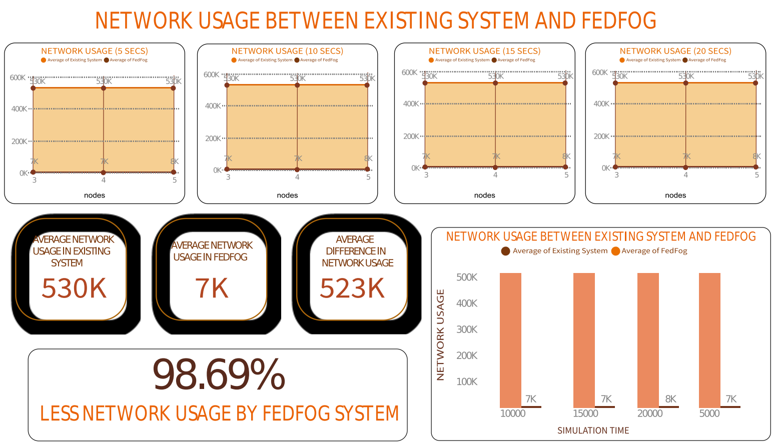

Fig. 7: Comparative network usage (Khan et al., 2023)

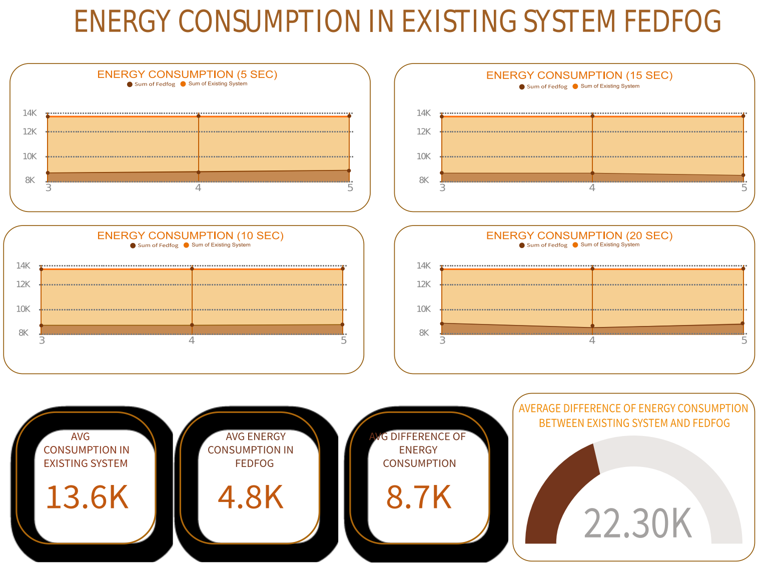

Fig. 8: Comparative energy consumption (Khan et al., 2023)

- Fine-grained control: Improved network performance and fine-grained control can be guaranteed along with flexibility (Ghobaei-Arani et al., 2020).
- Lesser SLA penalties: Zero-touch provisioning permits no human intervention, thereby reducing the violations by scaling the resources automatically (Khan et al., 2023).
- Reliability and fault-tolerance: Zero-touch networks provide better fault tolerance and reliability.
- Financial Benefits: Lesser SLA penalties imply maximization of financial benefits and hence promote profit (Khan and Soomro, 2018; Khan and Soomro, 2021; Khan et al., 2023).

The proposed work provides an open research direction in the field of future networks such as 5G AND B5G. Implementing an effective resource management algorithm at the cloud-fog spectrum to enhance network automation could provide an effective and long-lasting implementation of the IoT.

The literature review indicates that machine learning algorithms utilized in Fog-Computing do not include Federated learning. The novelty of the research is indicated by the fact that a federated learning-based algorithm is utilized at the fog level to optimize resource management.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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