# A Survey on Software Defined Network-Enabled Edge Cloud Networks: Challenges and Future Research Directions

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Abstract: The Internet of Things (IoT) era's proliferation of linked devices and data transmission places a significant strain on cloud computing's capacity. Furthermore, the majority of these IoT devices are situated at a network's periphery and have limited resources. Edge cloud-distributed computing networks are emerging as a solution to these problems. Numerous studies examining software-defined networks (SDNs) and network-function- virtualization (NFV) may be crucial due to the dispersed nature of edge cloud networks. Facilitators for resource management, orchestration, and load balancing. With an emphasis on SDN controllers, orchestration, and the role of artificial intelligence (AI) in improving the capabilities of controllers inside edge cloud computing networks, this article offers a thorough overview of these cutting-edge technologies. To be more precise, we offer a comprehensive assessment of research suggestions on the integration of SDN controllers and orchestration with edge cloud networks.

We also present an extensive synopsis of edge cloud use cases and their main obstacles, as well as a comprehensive analysis of SDN-enabled edge cloud networks. Lastly, we discuss some issues and possible avenues for further research in this crucial field.

Keywords: Internet of Things; edge computing; edge cloud network; SDN; SDN controller; ofloading; artificial intelligence; deep learning

## 1. Introduction

The Internet of Things (IoT) emerged as a result of the quick expansion of linked devices enabling smooth connectivity, processing, and data transmission. By 2030, almost 200 billion linked gadgets will be gathering information about how we work, live, and run the machines that depend on us. Several studies predict that by 2040, this number will approach trillions [1,2]. The greatest number of these devices will be placed near the Internet's edge, opening up new applications that will change many facets of our daily lives. Additionally, the performance, security, and dependability of apps may be impacted by IoT devices' limited resources, such as storage and processing capability. As a result, edge cloud-distributed computing systems can improve response times. Furthermore, the performance, security, and dependability of apps may be impacted by IoT devices' limited storage and processing capabilities. Therefore, by putting compute and data storage closer to the application's location, edge cloud- distributed computing systems can increase security, speed up reaction times, and conserve bandwidth.

Cloud computing is a centralized design that provides networking, on-demand elastic storage, and nearly infinite computer capacity [3]. The elastic cloud model has been extremely successful for more than ten years, offering substantial benefits to cloud providers as well as businesses. Additionally, end users access data-intensive services and seemingly limitless resources via the wide-area network. While centralized cloud architecture makes it easier to manage and maintain resources, cloud computing finds it challenging to meet the demands of the emerging trend of latency, bandwidth, and security-sensitive applications in the Internet of Things era. The IoT industry is predicted to increase from USD 245 billion in 2020 to USD 8131 billion by 2030 due to its steady growth [4,5]. The scalability and resilience of the conventional cloud computing models were put to the test by IoT applications like face recognition, ultra-high-definition video, augmented reality (AR), virtual reality (VR), voice semantic analysis, live video analytics, applications of smart city services, smart industry, smart healthcare services, personalized healthcare, and more. Higher processing, latency, storage, and security performance are required for these applications. Furthermore, the backbone network's current limited bandwidth cannot sustain the constant transmission of the quickly expanding amount of data generated by increasingly demanding mobile IoT applications. With an emphasis on lowering latency and backbone bandwidth utilization for real-time applications, edge computing arose as a solution to the problems associated with cloud computing, putting computation and storage closer to the network's edge [3]. However, edge computing has limited storage and computational capacity. A feature-based comparison of cloud and edge computing is presented in Table 1. Additionally, it illustrates the benefits and drawbacks of each.

**Table 1.** Comparison between cloud computing and edge computing. Source: [6,7].

| Features | Cloud Computing | Edge Computing |
|---|---|---|
| Architecture | Centralized | Distributed |
| Latency | High | Low |
| Mobility | No | Yes |
| Computational capacity | High | Medium to low |
| Security | Less secure | More secure |
| Bandwidth usages | High network bandwidth uses | Lower network bandwidth uses |
| Scalability | Easy to scale | Less scalable than cloud |
| Data Processing | Through Internet | Near to the source of the data |

To take advantage of the advantages of both cloud computing and edge computing, edge cloud architecture has emerged. The fundamental concept of edge cloud architecture is the combination of cloud computing, edge computing, and networking to use the benefits of both cloud computing and edge computing paradigms. Edge cloud offers a lot of promise to improve system- level performance in order to meet the demands of the new real-time Internet of Things applications. Because the edge cloud systems are spread over multiple networks, computing power and bandwidth vary greatly between networks.

Effective controllers for distributed edge, ofloading algorithms, resource allocation, traffic load balancing, network routing, and mobility management are essential due to the special characteristics of edge cloud networks [3,8]. As seen below, a number of studies have examined edge cloud networks from various angles. Mobile edge computing (MEC) was examined by Mao et al.
[9] from the standpoint of communication with the goal of combining radio-and-computational resource management. A survey on end edge cloud networks with an emphasis on computing paradigms was given by Ren et al. Additionally, a comparison of MEC, fog, cloudlet, and cloud is presented [10]. The architecture of SDN and multi- tier edge computing was examined by Baktir, Ozgovde, and Ersoy [11]. A survey of multi-access edge computing for allowing Internet of Things applications was carried out by the authors in [12]. Additionally, they talked about MEC and IoT integration security, resource allocation, mobility management, and compute ofloading. A survey examining the major enabling technologies from the standpoint of IoT application delivery on edge cloud was presented by Pan and McElhannon [13]. From the standpoint of an edge cloud approach, Jamil et al.'s study [14] outlined some essential industrial IoT criteria. Along with certain unresolved issues, they also talked about the salient characteristics of several IoT platforms, including ThingsBoard and Microsoft Azure IoT. [15] provides an overview of collaborative deep learning in edge cloud models. Additionally, they identified a few unresolved problems with edge cloud computing's collaborative deep learning. Gkonis et al.'s survey article.

While the polls described above are encouraging, none of them explicitly addressed the significance and incorporation of SDN-enabled controllers and orchestration in edge cloud. In view of the aforementioned, we first provide a thorough

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overview of industry-wide edge cloud use cases, killer apps, and their main obstacles in this study. We then present a comprehensive review of edge cloud networks supported by SDN. The research suggestions on the integration of SDN controllers and orchestration for edge cloud networks are then thoroughly reviewed. Additionally, we stress the use of AI and ML to enhance SDN controller performance in edge cloud networks. The structure of the paper is depicted in Figure 1. It breaks down the research's logical structure into seven major sections, each of which has more in-depth subsections. This method contributes to the provided study's depth and clarity.

Figure 1. Organization of the paper

This is how the remainder of the article is structured. With an emphasis on practical applications, Section 2 highlights some of the major use cases and deployment domains of edge cloud networks.

The basic ideas of SDN-enabled edge cloud architecture are presented in Section 3. This section also covers fixed edge cloud and mobile edge cloud. The fundamental infrastructure of edge cloud systems is covered in Section 4. It investigates networking, processing, and storage in relation to edge cloud systems. An in-depth analysis of the major edge cloud system enabling technologies is provided in Section 5. Additionally, it examines a number of suggested SDN controllers for an edge cloud setting. The main obstacles to implementing edge cloud are covered in Section 6, including workload distribution, intelligent management, controller placement, dynamic ofloading, federated and interoperated services, and safety. In order to overcome these obstacles and further the field of study, it also suggests possible lines of inquiry. The paper is finally concluded in Section 7.

## 2. Use Cases and Deployment Areas for Edge Cloud

In edge cloud computing, resource management is crucial. SDNs, or software-defined networks, have quickly gained popularity in data center networks and are a promising solution for edge cloud controllers. The division of the forwarding plane from the programmable control plane is the fundamental idea of SDN. In order to enhance resource allocation, security, traffic management, and other areas, numerous researchers have recently suggested using artificial intelligence (AI) and machine learning (ML) in SDN controllers [17, 18]. Therefore, by learning the network's global perspective and facilitating data-driven decision making, a programmable intelligent SDN controller can improve the usage of network resources.

Potential cloud applications include industrial IoT, restaurants, healthcare, retail, manufacturing, construction, transportation, agriculture, energy, and so forth. At the network's edge, it is utilized for data aggregation, interaction, filtering, investigation, processing, and analysis. The main purpose of edge computing is to enable the capabilities of IoT devices and IoT applications with the help of edge servers [13,21]. For instance, restaurants can use predictive analytics to forecast food preparation, what is needed right now, and when more food needs to be made. IoT applications analytics powered by ML and AI to predict how many customers and cars will enter the store. Thus, making a reliable prediction is the stated primary goal of using the edge. If the prediction fails (due to disconnecting) or takes too long (due to transferring a lot of data), the client is left pausing.. Cracks in the wheel could cause it to shatter, derailing the entire train. The bandwidth requirement in this case is extremely bursty, producing gigabytes of data in a short period of time. Cracks must be consistently found and reported within minutes in order to prevent major accidents. The usage of surveillance cameras for traffic control and road safety is also

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growing. In order to make judgments in milliseconds or microseconds, video processing and analytics programs must continuously process and analyse recorded video locally or at the edge. There may be applications for edge computing in smart health as well. The healthcare industry uses devices, sensors, and medical equipment to produce massive amounts of data. For this reason, latency, processing time, and storage requirements are critical.

## 3. Edge Cloud Architecture with SDN Support

The idea behind edge cloud computing, also known as multi-access edge cloud computing, is to place computational and storage resources close to the user. This strategy seeks to satisfy the vast processing demands of newly developed low- latency and data-intensive applications. It minimizes delays associated with ofloading massive amounts of data to the centralized cloud by enabling complicated, data-intensive applications to operate closer to IoT devices. Networking is essential to the implementation of the distributed edge cloud computing architecture. As a result, cloud computing and networking together offer an integrated perspective in both domains [23, 24]. Figure 2 shows a layered architecture view of edge cloud computing and networking enabled by SDN.

Access networks are used by multi-tenant user applications on IoT/access devices to access cloud infrastructure. Millions of embedded systems, sensors, cameras, smart phones, drones, connected cars, smart homes, smart factories, robotics, and more could be found in the IoT device layer. These devices gather massive amounts of data (MBs–PBs) from numerous multi-tenant apps and send them to edge cloud clusters over wire, LTE, 5G, Wi-Fi, and multi-access networks. High bandwidth, low latency, and a dependable connection between the access device or devices and the edge cloud layer are all provided by the access network. The user application or applications receive the necessary networking, computation, and storage capabilities from the edge cloud layer. Since edge clouds are dispersed, data will be handled close to the actual locations where users are connected.

On an IoT/access device, multi-tenant user applications make advantage of edge cloud infrastructure via access networks. Millions of embedded systems, sensors, cameras, smartphones, drones, connected cars, smart homes, smart factories, robots, and more could be found in the IoT device layer. Large-scale (MBs–PBs) data is gathered by these devices from several multi-tenant apps and sent to edge cloud clusters via LTE, 5G, Wi-Fi, and cable as multi-access networks. Between the access device or devices and the edge cloud layer, the access network offers high bandwidth, low latency, and a dependable connection. The user application or applications receive the necessary processing, storage, and networking services from the edge cloud layer. Because edge clouds are dispersed, data will be handled close to the actual locations where users are connected.

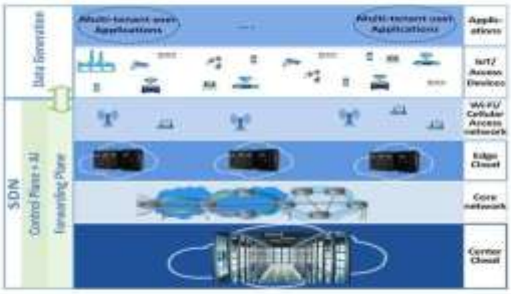



Figure 2: Multi-access edge cloud network design with layers

A number of factors, including processing, propagation, transmission, routing, and switching delays (in an SDN-enabled network), affect an application's overall end-to-end latency. Equation
(1) can be used to express the overall latency for cloud-only models.

$$L_{CC} = \alpha * d_{min}(ED, AP) + \beta * d(AP,CC) + t_{node} \quad (1)$$

LCC is the total cloud latency in Equation (1), $d_{min}(ED, AP)$ is the distance between the end device and the closest access point (AP), d(AP,CC) is the distance between the access point and the central cloud, α and β are the proportionality constants, and $t_{node}$ is the total amount of time a task spends at the central cloud. Equation (2) provides a representation of the overall latency for the edge cloud network.

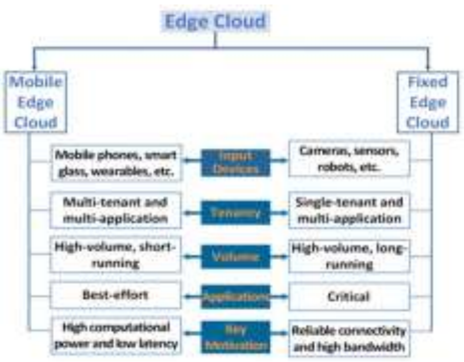
$$L_{EC} = \alpha * d_{min}(ED, EC) + t_{node} + ds \quad (2)$$

Equation (2) uses ds for the control plane switching latency, d min (ED, EC) for the distance between the end device and the edge cloud, and LEC for the total edge cloud latency [8]. Infrastructure, virtualization, and software-defined networks (SDN) are two possible sublayers of the edge cloud layer. The two primary enabling technologies for managing network, compute, and storage devices and virtualizing resources are virtualization and SDN. These two sublayers will be covered in more detail in Sections 3 and 4. Many new services can be implemented at edge sites that are near users or clients. As a result, there is less strain on the centralized cloud server and less traffic on the main networks.

The core network has thousands of IP backhaul lines installed. Edge cloud clusters will be linked to the central cloud via these IP backhaul cables. IP networks, IP/MPLS, optical networks, satellites, cellular, SD-WAN, and other key network technologies are among them. Bandwidth from the edge cloud to the central cloud may be constrained by excessive latency; in rural locations, links may occasionally be faulty. The distant center cloud will be under less strain because the majority of the data will be processed at the edge.

Mobile edge cloud and stationary edge cloud are the two forms of edge cloud that may be distinguished based on deployment characteristics [19]. A comparison of mobile and stationary edge clouds in terms of several important features is presented in Figure 3.

Figure 3: A comparison of fixed and mobile edge clouds




## 3.1. Cloud Mobile Edge

In order to improve the performance of high- throughput applications and lower latency, mobile edge cloud (MEC) is a network architecture concept that puts cloud-like functionality closer to the network's edge. MEC improves service delivery by being closer to end consumers, but it also presents load balancing and resource allocation issues. These issues are brought on by things like network load and user mobility. Virtualization has made it possible for dynamic service migration to manage user mobility and MEC system loads through the use of virtual machines and lightweight containers. To accomplish the objectives of load balancing, fault tolerance, and system maintenance, dynamic resource transfer strategies are crucial. In particular, container migration is showing promise as a way to facilitate effective resource movement across virtualized networks and MEC settings [9,25]. Figure 4 depicts the mobile edge cloud's conceptual design.


Mobile edge cloud architecture (Figure 4).

## 3.2. Cloud Fixed Edge

As previously indicated, the initial goal of edge computing was to improve the limited local resources of mobile devices by using nearby edge servers to perform data-intensive, high-bandwidth, low-latency applications. However, onsite edge deployment, also known as edge-site or fixed-edge deployment, is required for today's mission and safety-critical industrial applications and video analytics. For instance, restaurants must estimate how much food to prepare based on the number of patrons and vehicles arriving at the location; railroads use high-definition cameras to detect wheel cracks; offshore oil rigs must analyze live video to identify safety hazards, etc. Fixed edge cloud for all of the above industrial applications are the scarcity of bandwidth and outage of cloud due

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to unreliable network links [19]. Figure 5 presents the simplified architecture of a fixed edge cloud in a enterprise environment. For all of the aforementioned industrial applications, fixed edge cloud adoption is primarily motivated by bandwidth constraints and cloud outages brought on by unstable network connections [19]. The simplified architecture of a fixed edge cloud in an enterprise setting is shown in Figure 5.


Figure 5: An enterprise setting using a fixed edge cloud deployment architecture [19].

# 4. Infrastructure for Edge Clouds

The idea of both MEC and FEC is to locate network, compute, and storage components close to the users. By offering low latency, high bandwidth, and dependable network connectivity, this strategy seeks to satisfy the demanding computing requirements.

The edge computing paradigm is not a centralized architecture; rather, the edge data centers are dispersed at the network edge since storage and processing resources are closer to the users. Furthermore, one application may require to distribute among several edge servers in edge cloud computing, whereas numerous apps are placed into a single server in cloud computing. As a result, networking between edge data centers (DCs), between DCs, between DCs and cloud DCs, and between DCs and user devices is crucial in edge computing architecture.

Infrastructure, networking, resource virtualization, and control are therefore crucial factors to take into account in order to accomplish the aforementioned objectives. We outline the essential infrastructure elements needed to construct an edge cloud computing system in this section [26, 27].

## 4.1.Storage

Cloud DCs continue to be a component of the edge cloud architecture's storage infrastructure. Furthermore, distributed computing and storage are features of edge computing (edge DC). resources positioned near the devices of end users. Compared to cloud DCs that are usually positioned within or at the periphery of the metro network, it is smaller. It is also referred to as a MEC server situated near the RAN's edge in the context of MEC. Additionally, a number of studies that enable the storage and retrieval of computational data consider cooperative network caching. To enhance resource usage, machine learning and deep learning are suggested for cacheable content recommendation, cache placement, cache methods, and real-time data search [28, 29]. This information is retrieved. These data can be used for local computation after being retrieved from sensors or end-user devices. Backhaul can be reduced by up to 22% by using proactive caching [30].

## 4.2. Computing

Similar to storage, edge cloud computing reduces the drawbacks of a centralized cloud server by bringing processing capacity closer to the customer and offering quicker replies. Data from user apps can avoid making the long trip to a cloud DC by being served at the network edge. Therefore, edge cloud can reduce the danger of congestion, disruption, and cyberattack as well as transmission latency. According to experimental results published by Gao et al. [31], edge clouds can increase response time by roughly 51%. Corneo et al. [24] demonstrated that latency can be reduced by 6% to 40% depending on where the edge DC is placed.

## 4.3. Networking

As we previously discussed, networking in the edge computing paradigm offers connectivity between edge DCs, user devices, and edge DCs to cloud DCs. End users can connect to the computing and storage resources through one of the three access technologies: wired LAN, wireless LAN, or cellular networks. In general, networks between edge DCs and cloud DCs do not differ much from cloud architecture; in this case, the connection between edge DCs and cloud DCs could be established by WAN, cellular, or satellite technology. The deployment of edge servers can reduce operating costs by up to 67% for compute-intensive and bandwidth-intensive applications [27, 30]. Additionally, Silvestro et al. [32] showed that network latency in edge cloud networks.

Workloads are far more dispersed, localized, and varied since edge cloud DCs are heterogeneous and situated close to clients, as we previously discussed. It is crucial to be able to connect interedge DCs flexibly in order to distribute load and offer redundancy. Virtualization and SDN controller integration with edge cloud fulfills these needs quite effectively.

## 5. Crucial Facilitators

Data processing, data communication, and data storage are the emphasis of computing, networking, and storage, respectively. All three zones are now combining due to cloudification. Resource allocation is more challenging in edge clouds than in centralized data centers because of their widely distributed nature. Additionally, edge clouds must manage users with a high degree of application unpredictability. Therefore, virtualization and SDNs are the two main synergistic enabling technologies to enhance the scalability, utilization, and effective control of computing, storage, and networking resources at the edge cloud platform.

### 5.1. Virtualization

By separating from the physical hardware, virtualization technology provides network resources, services, and functions in an abstract layer. Edge cloud design changes from a specialized physical component to a hybrid physical and software-based solution by using virtualization techniques. Compute, storage, and network resources can be created, managed, optimized, and shared among several applications thanks to virtualization. By utilizing commodity servers and storage, virtual compute functions (VCF), virtual network functions (VNF), and virtual storage functions (VSF) are implemented as software instances atop an abstract layer.

### 5.2. Software Defined Networking

Another important enabler that might provide flexible architecture for edge cloud networks is software defined networking (SDN), which separates controlling and forwarding operations.

Improved network management, control, and traffic engineering may result from the separation of SDNs' control plane and forwarding plane. Depending on an application's requirements, an SDN controller can dynamically compute a path [37]. Figure 7 depicts an SDN network's simplified architecture. As previously discussed, edge cloud is a large-scale distributed network architecture that puts computation and storage closer to the consumer. In edge cloud networks, decoupling the control and data planes might be essential for improved user data management, control, and handling.

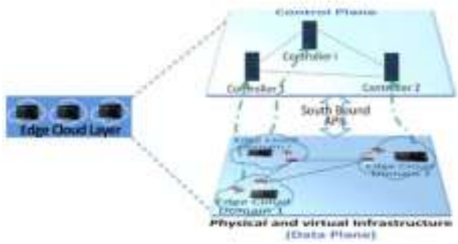


Figure 7. Simplified SDN architecture

### 5.3. Edge Cloud Software-Defined Controllers

SDNs are one of the main technologies that enable edge cloud networks, as we discussed in the previous section. They are essential for managing, keeping an eye on, and coordinating the network because of their capacity for network programming. This section discusses various edge cloud systems that make use of SDN controllers.

#### 5.3.1. SDN Controller for Home Cloud

One project that aims to bring NFV and SDNs closer together for edge clouds is Home Cloud. Developing effective edge cloud orchestration and dynamic IoT application delivery is one of this open framework's goals. SDNs are taken into consideration for network configuration, control, and management, whereas NFV is taken into consideration for enabling computation, storage, and networking closer to the user. The Home Cloud framework's architecture and the interactions between its various functional units are depicted in Figure 8.

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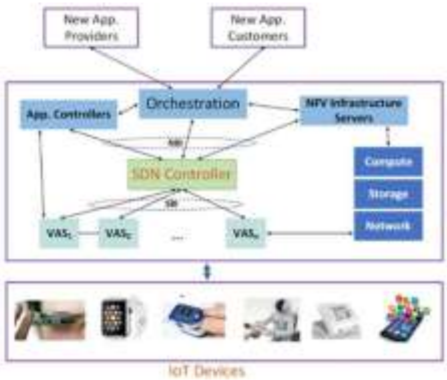


Figure 8. Home Cloud architecture [64].

In the aforementioned architecture, the SDNcontroller uses southbound interfaces (SBIs) to program, control, configure, and monitor overlay networks and northbound interfaces (NBI) to communicate with the application controller, orchestration, and NFV infrastructure server. Network resources like storage, processing power, bandwidth, etc. are distributed and managed via NFV infrastructure. With the help of the SDN controller, orchestration transforms SLA into actual application deployment. Lastly, the SDNcontroller assists the application controller in tracking and monitoring application-level entities [64].

5.3.2. Resource Allocation SDN Controller The increasing quantity and variety of user applications greatly depend on edge cloud networks' processing, storage, and network capabilities. Resource management is therefore one of the most important tasks for enhancing the performance of edge cloud networks. By offering a global perspective of the network and automating resource allocation, SDNs can improve the utilization of network resources [52]. In light of this, Zaman, Jarray, and Karmouch [52] suggested infrastructure as-a-service (IaaS) provisioning leveraging SDNs as a framework for resource allocation. According to this framework, an SDN controller can be used to better coordinate node and link provisioning in the edge cloud. The SDN- based edge cloud resource allocation framework's simplified design is depicted in Figure 9.

Figure 9. Architecture of SDN-enabled resource allocation framework for edge cloud networks [53]

### 5.3.3. LSTM-Based SDN Controller for Load Prediction and Balancing

With the rise of new delay-sensitive and resource- hungry applications and services, optimizing resource allocation and load balancing in the edge cloud environment has become crucial. SDNs play a key role in enabling load balancing between computing nodes as well as distributed SDN controllers. Abderrahime et al. proposed a pre- emptive load bal ancing approach between controllers for delay-sensitive applications within a distributed SDN-enabled edge cloud architecture [50]. In this proactive mechanism, they use a Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) model, which is capable of remembering information from prior stages to make predictions with high accuracy.

## 6. Difficulties and Prospects for Research

We have found a number of issues that require improvement after analyzing and presenting numerous relevant studies. With an emphasis on the integration of SDNs in edge cloud networks, we outline some major research issues and potential future paths in this section.

### 6.1. Distributed Architecture Design for Converged NFV, SDNs, and Edge Cloud

Edge cloud is a distributed system with significant heterogeneity in computing, storage, and network resources that is needed to exchange network status like computational resources, load, bandwidth, etc. It must be integrated into a common infrastructure and managed holistically. As we previously discussed, SDNs separate the control plane and data plane of networks; the control plane could be designed to exchange computational capability, load, bandwidth, etc. NFV-created virtual network functions (VNFs) can be dynamically started or stopped in response to requests [8,23]. The aforementioned problems may be resolved by integrating AI with SDNs and NFV in edge cloud architecture [51]. Thus, by utilizing programmability and configurability of the infrastructure layer and service layer, integration of an AI-enabled SDN controller, NFV, and edge cloud could improve system performance and flexibility. Additionally, the confluence of SDNs, NFV, and edge cloud may create a new path for the development of affordable services and application delivery. As a result, this is a very promising field for further study.

## 6.2 Dynamic Ofloading

Researchers and industry experts are using data and compute ofloading to overcome the restricted processing power, storage, and battery life of IoT and mobile devices. This method improves performance and lowers service delays, which include computation and connection time, by enabling devices to transfer demanding processing jobs to closer, more potent edge servers. Devices that ofload activities run more quickly and use less energy, which reduces CO2 emissions overall. To control where and how tasks are ofloaded—to a single edge server or to several servers simultaneously—a variety of methods have been devised. Determining when and where to ofload duties dynamically is still a significant difficulty, though. These days, a lot of research focuses on deep reinforcement learning (DRL) methods to address this. For instance, Zhu et al. integrated LSTM networks with reinforcement learning to generate more dependable and energy-efficient decisions, while Nieto et al. presented a distributed DRL model to enhance task ofloading decisions and maximize user experience (QoE). In order to provide smarter, quicker, and more energy-efficient services, software-defined networking (SDN) and edge cloud research have made the integration of AI-driven controllers for dynamic ofloading a major focus.

## 6.3. Integration of Mobile Edge and Fixed Edge Computing

At the periphery of cellular network architecture, MEC offers processing power and service contexts. Future 5G or next-generation cellular networks are being embraced by mobile networks, which may offer a setting for extensively used edge computing. One of the main differences between FEC and MEC is that FEC depends on the Internet, whereas MEC is mostly based on cellular networks. Furthermore, the needs of 5G networks, such as ultra-dense heterogeneous networks, high-precision location- aware services, and ultra-low latency, will add new implementation complexity [23,82]. Another topic of research on edge cloud networks is the potential difficulty of deploying edge computing with 5G networks and combining that with FEC.

## 6.4. Workload Distribution and Flow Control

In an SDN-enabled edge cloud network, machine learning (ML) has the potential to assist with resource management, workload distribution, and flow control because ML algorithms can predict outcomes or classify objects using training data and improve their performance with repeated experience on the task. ML has achieved great success in a number of areas, including speech recognition, web search, purchase recommendation, encrypted network traffic classification, etc. Today, IoT or end devices generate unprecedented volumes of data that need to gather, process, and analyze, which consumes very high network resources [18,57,93,94]. A hybrid deep learning technique for efficient task distribution for edge cloud IoT networks was suggested by researchers in [18]. on order to reduce the average job completion time, Wanget al. [95] suggested a preemptive approach for scheduling dispersed machine learning tasks on edge cloud networks. A framework for flow control in SDN edge cloud networks that permits real-time predictions based on IoT sensor data was proposed in the study of Ryoichi et al. [96]. They employed a Random Forest machine learning technique in this architecture. Industry and academic researchers began working in this field, but much more has to be done.

### 6.5. Orchestration and Intelligent Management

The management and orchestration (MANO) of virtualization still faces a number of issues, including placement, chaining, scaling, and fault diagnosis. A federated DRL-based approach for SFC orchestration was suggested by the authors of the work published by Rui et al. [97]. Bunyakitanon et al. propose an autonomous system based on machine learning for VNF prediction and placement [36]. An intelligent orchestration for edge cloud networks is shown in Reference [98]. The OpenNebula SDN controller and machine learning models serve as the foundation for this orchestration. Another interesting field of study in edge cloud networks is intelligent management and orchestration, or iMANO.

## 7. Results

From the studies reviewed, a few clear patterns began to emerge about the use of SDN within edge- cloud environments. Most works agree that separating the control and data planes helps the network respond faster to changing workloads, and several experiments reported noticeable reductions in latency once SDN controllers were introduced at the edge. A number of papers also explored AI- based controllers, and although the approaches vary, they generally showed better performance in predicting traffic changes, managing ofloading decisions, and adjusting resources on the fly. Another observation is that mobile and fixed edge deployments behave differently; when the two are combined, the system tends to be more stable and flexible, especially for IoT applications that depend on real-time processing. While the evidence comes from different testbeds and assumptions, taken together, these results suggest that the joint use of SDN, NFV, and lightweight AI techniques can make edge-cloud systems more dependable and easier to manage.

## 8. Conclusions

Cloud computing, which is usually implemented in a distant data center, is a centralized design that provides nearly infinite processing power and storage. However, when supporting new real-time applications, this method frequently suffers from excessive latency, high bandwidth consumption, and poor security. Conversely, edge computing is a distributed design that brings networking, storage, and processing power closer to the Internet of Things devices. Edge computing improves security, lowers latency, and uses less bandwidth. However, it is constrained by comparatively low processing power and storage capacity. Edge cloud architecture has become a viable way to close the technical divide between these two paradigms. Even though edge cloud architecture has a lot of potential, there are still a few technological issues that need to be resolved before its advantages can be completely realized. We have produced a thorough list of edge cloud deployment areas, applications, and related difficulties through our literature study. Many studies suggest integrating AI-enabled SDN controllers with edge cloud to improve network management, resource allocation, task ofloading, controller placement, security, etc. in order to address these issues. Thus, this survey paper illustrated the architecture of SDN-enabled edge cloud to give an overview of how AI-assisted SDN controllers can be integrated with edge cloud. We also presented a thorough survey on suggested solutions for integrating intelligent SDN controllers and orchestration with the edge cloud networks to improve network management, computation ofloading, dynamic load balancing, resource management, and security. Lastly, this paper discussed the main research challenges that we believe need to be addressed along with possible future research directions.

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