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Edge Cloud Server Deployment with Machine Learning for 6G Internet of Things

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Abstract: Cloud computing is an important technology that may be used to provide client devices access to a large pool of elastic resources. This can be accomplished via a variety of methods. The greatest issue of these systems, the considerable distance between users and servers, has been solved by the creation of edge cloud computing, in which the cloud servers are positioned at the edge of the network. This kind of cloud computing is a variant of traditional cloud computing. The vast majority of them ignore the decision of where the edge servers should be located, despite the fact that this might have a substantial influence on the effectiveness of the system. In the future, networks like those found in the Internet of Things and 6G Networks will need to be able to support very large numbers of users and servers simultaneously. As a direct consequence of this, we need solutions that are capable of being expanded. In light of these two issues, we propose a server deployment strategy that is based on machine learning and data mining for 6G Internet of Things scenarios. Our method has been shown to be one that is not only effective but also time-saving. In addition, we show that our method is superior to more conventional deployment tactics for Edge Cloud Computing servers in terms of reduced lag time and higher utilisation of available resources. These benefits may be attributed to our methodology. In this article, we do in-depth research of the convergence of 6G and the ML (6G and IOT) in order to examine the new possibilities afforded by 6G technologies in IOT networks and applications. Specifically, we are interested in how 6G technologies might improve the efficiency of IOT networks.

Keywords: *Edge Cloud Computing, Machine Learning, 6G, IOT.*

1. Introduction

Recent years have seen a rise in interest in cloud computing due to the fact that it offers a convenient method of supplying consumer devices with resources such as memory and processing power. It's possible that this trend is due to the cost-effectiveness and scalability of cloud computing. Customers are able to rent and use the resources that are housed on cloud servers in exactly the quantity that they need and at exactly the time that they want it. When compared to the traditional method of acquiring resources of this kind, this method of providing services is often more cost-effective for customers who don't make frequent use of the services in question. In addition, since cloud computing allows for the dynamic distribution of resources, the service is not significantly impacted even if consumers have an unforeseen demand for more of those resources. This is because more and more people are using online computer services. Virtualization is what makes all of this possible. It takes a single physical server and splits it up into multiple different virtual servers. Each of these virtual servers is in responsible of delivering services to a different user group. Cloud computing has a lot of potential, but it cannot now handle applications that cannot tolerate any kind of delay. This is despite the fact that cloud computing has a lot of promise. This is because standard cloud servers may sometimes be found in locations that are some distance distant from the bulk of their clients. Because of this, the amount of delay required to reach such servers can make the transaction prohibitively costly. Real-time applications, such as those dealing with healthcare, intelligent video streaming, and other real-time tasks, are often incompatible with traditional cloud computing.

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Table 1: Key Distinctions Between 6g Networks and Those That Came Before It, According To Published Research.

Current and 5G networks	6G networks
For optimal performance in edge devices, learning models should be pre-loaded.	Edge nodes are able to independently conduct learning algorithms because of the characteristics they possess.
Gigahertz frequencies represent the upper limit of what is practicable in terms of human communication.	Terahertz and millimetre wave frequencies are both potentially accessible to the wireless channel technology.
networks based on microcells that have a low degree of densification	As a result of extensive densification, there will be a significant increase in the number of base stations and servers.
In pre-Internet-of-Things systems, there were fewer vices per user.	When the Internet of Things achieves its full potential, there will be a very large number of devices that are connected to one another.

Edge cloud computing (ECC), which involves the deployment of cloud servers outside of the network, was developed as a solution to address this vulnerability. As a direct consequence of this, the amount of time that consumers have to wait since they are physically nearby is decreased. As a direct consequence of this, real-time applications are now able to make use of the resources that are made available by the cloud. It is important to have a big number of servers available in order to provide the customer the assurance that they will always be in close proximity to one of the servers. As a result of the fact that the servers themselves use less resources than those in conventional cloud computing, ECC is more cost-effective than traditional cloud computing despite the need for a greater number of servers. As a consequence of this, we sometimes refer to them as cloudlets. Because each cloudlet may host fewer customers than typical cloud computing servers, the service model is unaffected by the decreased capabilities of the cloudlets [1].

Recently, research on sixth-generation (6G) wireless networks and the related technological developments have garnered significant interest from a variety of sectors, including academic institutions as well as industry. Because of this, the Internet of Things (IoT) and other areas of technology have been able to make progress. It is anticipated that 6G would provide an entirely new level of service quality and improve consumers' ability to connect with existing Internet of Things (IoT) technologies. This is because 6G will have qualities that are superior to those of preceding network technology generations, such as those seen in 5G and 4G. These characteristics include consumer services that are based on satellite technology, exceptionally high throughput, vast autonomous networks, and communications with extremely low latency. These levels of capacity will be unequalled in the fields of data sensing for the Internet of Things, device connection, wireless communication, and administration of 6G networks. In addition to this, they will speed up the applications and rollouts of 6G-based Internet of Things networks. Research in this potentially fruitful field has gotten a great deal of attention, which has been made feasible by the huge potential that the 6G Internet of Things has. For example, Finland provided funding for both the 6Genesis 6G project and the world's first experimental 6G-IoT research environment. Both of these endeavours were carried out in Finland. The creation of a vision for future 6G systems that would integrate the human, digital, and physical worlds within the framework of future IOT networks is the objective of the new European 6G flagship research programme that Nokia will launch on January 1, 2021. This initiative will begin operations in Europe. The formation of a collaboration with a number of Europe's most illustrious academic institutions, communication service providers, and network manufacturers is going to be the means by which this objective will be met. In addition, the United States Federal Communications Commission (FCC) has opened up the Terahertz frequency spectrum, which makes it possible for engineers and researchers to test the functioning of 6G on mobile communications systems and Internet of Things (IoT) devices. In addition, the government of South Korea has plans to initiate a demonstration project for a 6G mobile service in the year 2026. In order to test and evaluate the functionality of 6G systems as part of this project, one of the five essential IOT domains will be used. Some examples of developments in these areas are autonomous cars, smart cities and factories, and immersive digital material related to healthcare. It is projected that the first commercially available 6G networks will go operational in the year 2028, and it is anticipated that the technology will become generally available in the year 2030. Researchers are already investigating the vast potential of 6G-IoT and using fundamental technologies to pave the way for future 6G-IoT connection in order to fulfil the requirements of the intelligent information society that will exist in the 2030s. This is being done in order to meet the demands of the society that will exist in that decade. Figure 1 provides a visual representation of the concept of 6G-IoT applications, which will be the subject of discussion in the following paragraphs [2].

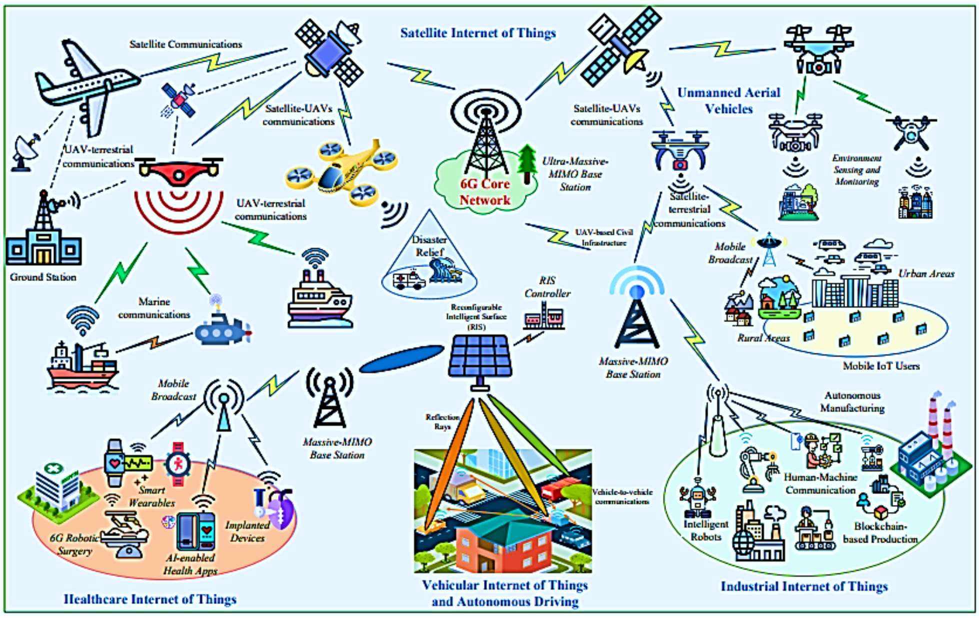

Fig 1: Iot Applications In The Future With A 6g Base.

The artificial intelligence (AI) technique known as federated learning (FL), which is a distributed collaborative AI, is now undergoing research and development with the intention of altering edge and fog intelligence architectures. FL is a distributed AI strategy that, in its most basic form, enables the training of high-quality AI models without having direct access to the local data by averaging local updates from numerous learning edge clients. FL was developed by Facebook and is an example of an artificial intelligence (AI) technique that was developed by Facebook. This is accomplished by a procedure known as averaging the local updates. For the purpose of performing neural network training, for instance, eight IoT devices that are located in different parts of the world might operate together with a data aggregator and an edge server within the framework of intelligent IoT networks. During this procedure, the only thing that the devices would need to do is trade parameters with one another; trading raw data would not be necessary [3]. This is seen in Figure 2 below.

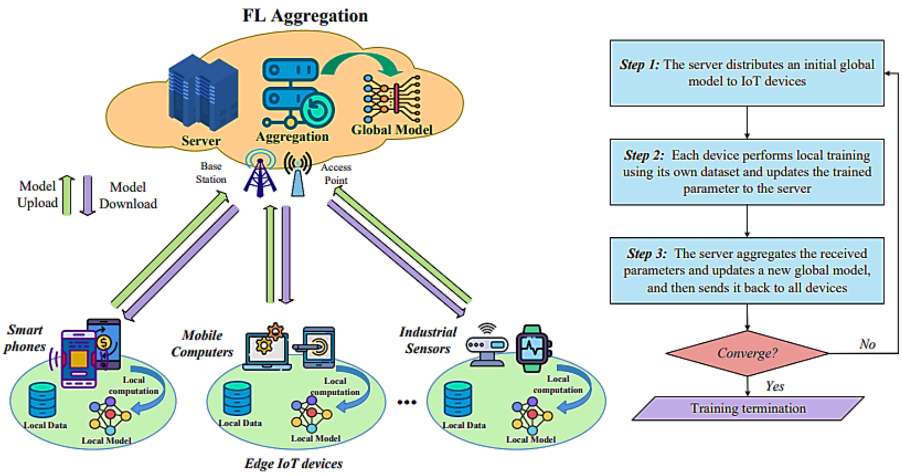

Fig 2: Iot Wireless Networks With Edge Intelligence Using Fl.

FL may be able to construct IOT networks that have a variety of specific properties; however this ability is dependent on the operational paradigm that it utilises. One of the most important aspects is the capacity to enhance data privacy based on distributed model training without supplying raw data to external servers. This is one of the most important characteristics. This is without a doubt one of the most essential characteristics. Because of increasingly stringent regulations for the preservation of data privacy, such as the General Data preservation Regulation (GDPR), future secure 6G-IoT systems will need the capacity to keep user information in FL. Another advantage is that low-latency network connections may be achieved, which is made possible by the fact that FL prohibits dumping enormous data volumes to a remote server while the training phase is in progress. It's possible that this benefit is connected to the training stage. Additionally, the quantity of network spectrum resources required for iterative data training is cut down thanks to this feature's implementation. The participation of a number of IOT devices in a collaborative effort would make it possible for the FL system to get large-scale datasets as well as processing resources. This will result in increased learning performances, such as higher accuracy rates, for more intelligent 6G IOT services. Additionally, the pace of convergence for the whole training process will pick up as a result of this. The FL system would benefit even more by the inclusion of many IOT devices in the collection of big datasets. In the following, a case study of edge intelligence with FL support operating in a 6G-IoT context will be shown and discussed. Using a technique known as Air Ground Integrated Federated Learning (AGIFL), this research investigates the effect of different tactics for the deployment of hovering places for unmanned aerial vehicles (UAVs), while keeping privacy concerns in mind. The challenges caused by breaches of privacy during the training of AI served as the impetus for the development of this technology. Numerous mobile users who have terrestrial nodes are considered to be clients in this context, and they are invited to take part in the UAV-deployed server-based collaborative training. In this scenario, each participant makes use of their own dataset in order to do local training. The updated parameter is then sent to the UAV, which compiles all of the changes made and generates a global model before sending it back to all of the participants so that they can utilise it during the subsequent phase of training for the site deployment. The AGIFL-based approach that was recommended demonstrates a promising classification accuracy performance when compared to non-federated techniques in the 6G context, with an accuracy rate that reaches up to 95%. This is the case because the accuracy rate of the suggested method may reach this high. This was accomplished by simulating image classification jobs using traditional handwritten digit datasets and using convolutional neural networks, often known as CNNs. A level of accuracy of up to 95% was within grasp of those making the attempt. In the near future, federated training should include attack detection strategies such as access limiting and data authentication in order to ensure the safety of local gradient computing that is performed on UAVs. This will allow the security of the computations to be guaranteed [4].

2. Review of Literature

Cloud computing is an important technology that may be used to provide client devices access to a large pool of elastic resources. This can be accomplished via a variety of methods. The greatest issue of these systems, the considerable distance between users and servers, has been solved by the creation of edge cloud computing, in which the cloud servers are positioned at the edge of the network. This kind of cloud computing is a variant of traditional cloud computing. Because it is considered to be so important for the development of future networks, a significant amount of investigation is being placed into the investigation of technologies that may enable edge cloud computing operate as effectively as is physically feasible. The vast majority of them ignore the decision of where the edge servers should be located, despite the fact that this might have a substantial influence on the effectiveness of the system. In the future, networks like those found in the Internet of Things and 6G Networks will need to be able to support very large numbers of users and servers simultaneously. As a direct consequence of this, we need solutions that are capable of being expanded. In light of these two issues, we propose a server deployment strategy that is based on machine learning and data mining for 6G Internet of Things scenarios. Our method has been shown to be one that is not only effective but also time-saving. In addition, we show that our method is superior to more conventional deployment tactics for Edge Cloud Computing servers in terms of reduced lag time and higher utilisation of available resources. These benefits may be attributed to our methodology [5].

Deep learning is one technique that has the potential to be used in the analysis of raw sensor data that was collected by Internet of Things (IoT) devices that were installed in difficult places. Due to the layered structure of deep learning, it works particularly well in systems that have been designed specifically for edge computing. As a consequence of this, we will start this article by discussing the ways in which deep learning may be applied to Internet of Things scenarios by using edge computing. We also develop an innovative offloading strategy in order to improve the overall performance of edge-based IoT deep learning applications. This is necessary owing to the limited processing capabilities of the edge nodes that are currently in use. During the course of the performance evaluation, we investigate the efficiency of our approach while it is being used to finish a number of deep learning projects in an environment using edge computing. The results of the assessment show that our strategy for improving IOT performance is better to earlier deep learning techniques [6].

The fast increasing number of connected devices, such as sensors, mobile, wearable, and other Internet of Things devices, has resulted in a dramatic increase in the amount of data traffic that travels over the network. It's plausible that the Internet of Things is to blame for this overwhelming amount of data. In order to facilitate machine learning (ML), data collected by devices connected to the Internet of Things (IoT) is routinely uploaded to the cloud or another centralised system. This method is still used despite the fact that it generates latencies and increases the amount of network traffic. Edge computing provides the opportunity to solve issues such as these by moving processing operations to a location that is physically closer to the edge of the network and the data sources itself. On the other hand, owing to its limited processing capability, computing at the edge is not an option for carrying out machine learning tasks. This article employs edge nodes to connect edge computing with cloud computing for IOT data analytics. This helps to reduce the amount of data that has to be sent. The sensors are arranged geographically, and feature learning is performed on the edge node that is geographically closest. This is done so that data may be evaluated near to where it was generated. When making comparisons, the use of processing that is based on similarities is also taken into account for the objective. When it comes to feature learning, deep learning is employed; the encoder component of the learned auto encoder is placed on the edge, while the decoder component is stored in the cloud. The difficulties of extracting information about human activities from sensor data was the primary emphasis of this investigation. When sliding windows are used in the preparation stage, the results show that data may be reduced on the edge by up to 80% with little to no loss in accuracy, and this can be accomplished without the use of any other tools. This may be accomplished without the need for any further equipment [7].

It is anticipated that wireless communication networks of the sixth generation (6G) and the Internet of Things (IOT) would revolutionise consumer services and applications and pave the way for fully intelligent and self-sufficient systems in the foreseeable future. In this article, we do an in-depth research of the convergence of 6G and the Internet of Things (6G and IOT) in order to examine the new possibilities afforded by 6G technologies in IOT networks and applications. Specifically, we are interested in how 6G technologies might improve the efficiency of IOT networks. Beginning with some of the most fundamental aspects of 6G technology, such as edge intelligence, reconfigurable intelligent surfaces, space-air-ground-underwater communications, Terahertz communications, massive ultra-reliable and low-latency communications, and block chain, which are all anticipated to be the primary drivers of upcoming IOT networks, we will begin our discussion. We provide a comprehensive analysis of the potential roles that 6G might play in a wide variety of Internet of Things applications by focusing on five of the most important industries. The Industrial Internet of Things, Unmanned Aerial Vehicles, Satellite Internet of Things, Internet of Things in Healthcare, Internet of Things in Vehicles, and Autonomous Driving are some of the topics that fall under this category. This is particularly true when compared to the results of other polls that are connected in a manner that is analogous to the one being discussed here. In our conclusion, we urge further research on this interesting topic by highlighting some exciting research problems and presenting prospective future lines of investigation. This was accomplished by focusing on several possible future research avenues [8].

3. Machine Learning Solution

As was shown in a previous part of this chapter, the speed with which services are made available is significantly influenced by both the virtual and physical connections made by users. A smart strategy would surely include technologies that make it possible to carefully identify relationships of this kind in order to cut down on delay. Users who, as was said before, have physically attached themselves to the base station that has the strongest signal will have the biggest advantage. Utilising the transmission power level control on the base stations to independently evaluate their transmission power levels and, as a result, govern how many and which users connect to each one would be the easiest way to accomplish this goal. This would also be the most effective method. This is shown by the equation. Direct assignments may be performed in order to determine the virtual affiliations, which are often commonly referred to as "which cloudlet serves which user." In order to calculate the appropriate amount of transmission power, we are going to use PSO in the method that was just presented to you. The research makes use of a machine learning technique in order to find a middle ground between the two distinct approaches taken to the problem of base station communication load. Transmission power, on the other hand, is the factor that governs both the real-world and the simulated exchanges that take place during that activity. This results in a solution that is simple, but it disrupts the configuration that would be optimal since the system will never identify a user combination that is both physically linked to one base station and virtually connected to its cloudlet. This prevents the ideal configuration from being realised. In point of fact, the approach pays no attention at all to a number of the prerequisites. In order to restrict the configuration of PSO to just the transmission power levels and the physical interactions associated with those levels, we are going to make certain modifications to the programme. A digital collaboration will be formed between our organisations and KMC [9].

❖ The Particle Swarm Optimisation

In PSO, a large number of agents work together to search across the space of all the different possible configurations in an attempt to find the optimal solution. Each dot on this diagram represents a possible solution strategy that might be used to address the problem that PSO is working to address. The particles, which stand in for the agents, move across this area and, before moving on to another position, evaluate all of the potential solutions that are associated with the specific location they are now in. They travel along a route that is biassed towards the best solution that has been identified so far around the planet, and as a result, they swarm towards the best solution that has been decided by the collection of all particles. Furthermore, the movement is biassed towards what is known as local best, which is the best solution determined by that particular particle, and biassed towards the direction and speed of their prior movement, which is known as the inertia component. Both of these factors contribute to the movement's overall behaviour. This is done in order to avoid the particle from being ensnared in what are known as local optimal zones. The variables "global best," "local best," and "inertia" are each assigned a weight, and these weights indicate the degree to which each variable influences the search for a solution. In most cases, random variables that may take on any value between 0 and 1 and that change with each iteration also have an effect on the swarming behaviour that occurs around the global/local optimal solutions. These variables can have any value between 0 and 1. The purpose of these portions is to achieve a balance between the exploitation of the swarm that has gathered around the best solutions identified and the exploration of the random search for new components. This balance is achieved by working to establish a balance between the two [10]. This is done to ensure that they do not get mired in a state referred to as a "local optimum."

We are making efforts to determine the transmission power level configuration for this problem that will be most effective for all base stations. As a consequence of this, the transmission power that is supplied by each base station is represented by a tuple of V components in our solutions. PSO can only change the physical connections that exist between entities, supposing that any necessary virtual connections have already been made before the algorithm is executed. Using an objective function that will indicate what the global and local best are, our algorithm will search for the configuration that will result in the least amount of delay for our clients. This will be done by finding the configuration that will cause the least amount of delay. In order to do this, you will need to determine the configuration that: Eq. In the first algorithm, we present our implementation of the PSO.

Algorithm 1 -PSO: implementation for determining transmission power levels for the base stations.

for all particles $\mathbb{P}$ **do** set $q_{\mathbb{P}}$ with random $\mathfrak{V}$ values
for all particles $\mathbb{P}$ **do** set $\mathbb{V}_{\mathbb{P}}$ with random $\mathfrak{V}$ values
for all particles $\mathbb{P}$ **do** $\mathbb{B}^{l}_{\mathbb{P}} \leftarrow q_{\mathbb{P}}$
$\mathbb{B}^{g} \leftarrow \arg\min_{\text{particles } \mathbb{P}} f(\mathbb{B}^{l}_{\mathbb{P}})$
for $\mathbb{R}^{PSO}$ iterations **do**
  for all particles $\mathbb{P}$ **do**
    if $f(q_{\mathbb{P}}) < \mathbb{B}^{l}_{\mathbb{P}}$ **then** $\mathbb{B}^{l}_{\mathbb{P}} \leftarrow q_{\mathbb{P}}$
    if $f(q_{\mathbb{P}}) < \mathbb{B}^{g}$ **then** $\mathbb{B}^{g} \leftarrow q_{\mathbb{P}}$
    $\mathbb{F}^{l} \leftarrow$ random number between 0 and 1
    $\mathbb{F}^{g} \leftarrow$ random number between 0 and 1
    $\mathbb{V}_{\mathbb{P}} \leftarrow \mathbb{W}^{i} \cdot \mathbb{V}_{\mathbb{P}} + \mathbb{F}^{l} \cdot \mathbb{W}^{l} \cdot (q_{\mathbb{P}} - \mathbb{B}^{l}_{\mathbb{P}}) + \mathbb{F}^{g} \cdot \mathbb{W}^{g} \cdot (q_{\mathbb{P}} - \mathbb{B}^{g})$
    $q_{\mathbb{P}} \leftarrow q_{\mathbb{P}} + \mathbb{V}_{\mathbb{P}}$
return $\mathbb{B}^{g}$

R PSO denotes the total number of iterations of the PSO algorithm that we plan to carry out. Within the framework of the symbol system, the particles are represented by the letter P. Both the position and the velocity of a particle may be represented by their corresponding abbreviations, qP and VP. The notation B l P speaks for the best local solution that particle P has found up to this point, while the notation B g stands for the best global solution that all of the particles have discovered up until this point. Following each cycle, the random variables F l and F g, which are integral in the computation of the local and global bests, respectively, shift somewhat. The symbol Wi denotes the inertia weight, while the symbols Wl and Wi stand for the best weights locally and globally, respectively. Wi is the symbol for the inertia weight. In the end, we are going to replace our objective function with the function f().

❖ The K-Means Clustering

Distance is given the highest priority as a criterion in the KMC technique, which is responsible for the clustering of the component components. The entire number of clusters, which will be K, has already been decided upon. The first thing that needs to be done in order to implement this strategy is to choose a node at random to serve as the centroid of each of the K clusters. Because of this, the centre of each element will be defined as the centroid that is situated at the location that is physically closest to the element. After that, the location of each cluster's centroid will be changed to correspond with the point that represents an average of the centres of all of the cluster's component sections. After that, new clusters are assigned to each element in accordance with the newly identified centroids of each element. This process of assigning items to clusters or modifying the centroids to coincide with the elements continues so long as the locations of the centroids do not shift. The initial random centroids that are selected have an effect on how well the procedure works overall. In order to eliminate this bias, the procedure described above is carried out several times using a variety of initial centroids that are positioned in a random starting position. At the end of each iteration, the performance of the final clusters is evaluated with the use of an objective function, and the results of this evaluation are recorded. The KMC output will be comprised of the clusters that demonstrated the highest level of performance during the applicable iteration.

In order to resolve the problem, we are planning on making some adjustments to KMC. In order to identify the specific virtual connections that are associated with each user, we will consult KMC. As a consequence of this, we will choose K clusters and use the technique to allocate one of them to each cloudlet. As a direct consequence of this, the only places where the cloudlets that make up the cluster centroids may be located are in the locations of the base stations. We are going to make the assumption that the physical connections have already been established before to the beginning of the algorithm on the basis of the strongest signal strength that is available for each user, and that KMC will only have an effect on the virtual linkages. Therefore, the decision of which cluster the users would join based on their physical proximity is not the most important factor to take into consideration. Instead, users will unite with cloudlets whose co-located base station has the shortest backhaul connection. The length of this link will be decided by how fast the signal reaches the user with whom it is linked. In the event that two or more users have identical scores, the user's physical distance from the cloudlet will be taken into consideration. Additionally, the algorithm, in its present iteration, has a propensity to lead to cloudlets being overloaded by forming too big of clusters when users assemble close to a base station. This occurs because the programmed creates too many clusters. As a direct consequence of this, there are major delays in processing, which is an issue. In order to ensure that each cluster has the same number of users, we will first determine the largest size that a cluster is permitted to have, which in our case will be U/K. In the end, the cluster layout equation (14), will be used to decide which iteration had the best possible cluster arrangement. The KMC implementation is going to be discussed in the next part.

❖ Submitted Algorithm

PSO will be utilized to build physical linkages, and KMC will be used to construct virtual ties; this is the essential concept that underpins our deployment method. PSO gives users the possibility to actively change the gearbox delay by choosing from a number of different power levels for the gearbox itself. The time in processing might potentially be controlled by KMC by determining which cloudlet(s) customers' workloads are assigned to. To summaries, the issue of backhaul latency is something that can be handled by any technique. PSO may do this by physically attaching a user to a base station that is close to the user's virtual association, or at the very least, by integrating a user's physical and virtual affiliations inside a single base station. Alternatively, PSO may simply combine a user's physical and virtual affiliations. KMC accomplishes this goal by categorizing users according to the manner in which the virtual relationship will influence backhaul propagation. As a direct consequence of this, we have full control over the duration of the delay that the service will experience. In order for the idea to be implemented successfully, the starting transmission power level has to be calibrated the same way across all base stations. This step is conducted so that one may get a head start on resolving issues with bodily associations. After each KMC cycle, the power levels of the gearbox are then calculated by employing PSO. This comes after the KMC has been used to choose the virtual associations. Each and every iteration of the KMC exhibits this tendency always. The output of the algorithm includes virtual affiliations for users, transmission power levels for base stations, and configuration deployment locations for cloudlets. This outcome refers to the iteration that performed the best overall out of all the other iterations that might have been tried.

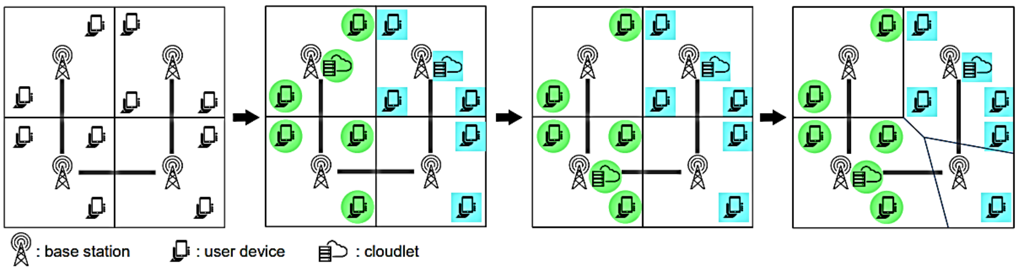

Fig 3: The Proposed Technique Distributes Users Across Cloudlets Using Kmc And Then Uses Pso To Fine-Tune The Transmission Power.

Figure 3, which may be seen at this location, depicts the algorithm's workings. In the first half of the image, both the locations of the users and the locations of the base stations are shown. Before the KMC is performed, the cloudlets are first positioned inside a base station of arbitrary selection. After that, the KMC is applied. Users are dispersed throughout the several cloudlets in a manner that takes into account the amount of backhaul propagation that is necessary to reach each user. This helps ensure that the burden is distributed evenly across all of the servers. The sign that represents the user will either be a circle or a square, and this will be determined by whether or not they are linked to a cloudlet. After then, the KMC will transmit the cloudlets to the base station that is geographically located at the shortest distance from the group of users. This is shown by moving the base station such that it is now at a place where the cloudlet with the circle symbol is visible. After the virtual associations have been formed, the PSO technique is implemented in order to do the calculations necessary to determine the power levels of the gearbox and to alter the particular physical connections. The illustration demonstrates how a single user, represented by the square icon, may access their cloudlet without making use of the backhaul lines as a consequence. Because of this, this particular client does not experience any backhaul delay, and end users that make frequent use of connections of this kind have access to a greater amount of bandwidth. As a direct consequence of this, we may be able to use less power for transmission at the base station in the bottom right corner, which would result in a general reduction in interference. Users will see less overall gearbox and backhaul delay as a consequence of using one of these solutions.

Algorithm 2 -kMC: proposed algorithm for deploying cloudlets and configuring associations.

1: **for all** $v_i \in V$ **do** $\omega_{v_i} \leftarrow$ base transmission power level
2: **for** $\mathbb{R}^{\text{kMC}}$ iterations **do**
3: $\quad \mathbb{V} \leftarrow V$
4: $\quad$ **for all** cloudlets k **do**
5: $\quad\quad$ Choose random $v_i \in \mathbb{V}$
6: $\quad\quad$ Deploy k in v_i
7: $\quad\quad$ Remove v_i from $\mathbb{V}$
8: $\quad$ **repeat**
9: $\quad\quad$ $\mathbb{K} \leftarrow$ all cloudlets
10: $\quad\quad$ **for all** $u_i \in U$ **do**
11: $\quad\quad\quad$ $z_{u_i} \leftarrow k \in \mathbb{K}$ with min. propagation to h_{u_i}
12: $\quad\quad\quad$ In case of ties, choose based on $d_k^{u_i}$
13: $\quad\quad\quad$ **if** z_{u_i} has $\mathfrak{U}/\mathfrak{K}$ users **then** remove z_{u_i} from $\mathbb{K}$
14: $\quad\quad$ $\mathbb{V} \leftarrow V$
15: $\quad\quad$ **for all** cloudlets k **do**
16: $\quad\quad\quad$ Move k to $v_i \in \mathbb{V}$ closest to its users
17: $\quad\quad\quad$ Remove v_i from $\mathbb{V}$
18: $\quad$ **until** no cloudlet changes location
19: $\quad$ Execute **PSO** for setting transmission power levels
20: **return** configuration with best performance

The whole method is shown in Algorithm 2. R Our plan calls for a total of KMC iterations, which brings our total to KMC. By using the auxiliary set known as K, we are able to accurately represent all cloudlets that have not yet amassed the required number of users. Another auxiliary set that we make use of is denoted by the letter V, and its purpose is to store all of the base stations that do not now have cloudlets co-located with them. As shown in lines 15 through 17, the cloudlet centroids are moved to the base station that is geographically located in the closest proximity to the central node of the user group to which they belong. After one cloudlet is relocated to base station vi, vi is then removed from base station V to make sure that no more cloudlets are put there. This is done on the assumption that it is impossible for two cloudlets to coexist at the same base station.

4. Research Methodology

As we go on to the next part of our conversation, we will give a solution to the problem of excessive service latency by utilising the problem statement that has been presented in this section as a basis for our discussion. In order to simplify the procedure and make the model easier to comprehend on the whole, it will be partitioned into a number of subsections.

❖ Problem Definition

It is necessary for us to decide on a location for each of the cloudlets that will make up the total number of cloudlets. In order to make sure that every user is able to use the ECC service, we need to figure out a way to connect every user to a base station and a cloudlet at the same time. This is a prerequisite for each and every user in order for them to be able to use the service. The current work that has to be completed is locating the user relationships and deployment locations that will result in the least amount of service delay possible.

❖ Processing Delay

As was said before, the bulk of the time spent processing is spent during the task's wait at the cloudlet for a processor to become available before it can be carried out. Assume that there is a queue of the size M/M/c that is waiting for the processors, where c is the total number of processors that are included in a single cloudlet. Under the assumptions that each user sends one task to the cloudlet in base station vi per second and that the cloudlet in base station vi has |Gvi| associated users, the task arrival rate to the cloudlet in base station v1 may be approximated as follows.

$$\Lambda_{v_i} = |G_{v_i}| \cdot \Lambda_1.$$

The following equations, all of which are derived from the concept of queueing, have been presented for your ease of use. Calculating the occupancy rate of a cloudlet's processors would be doable if the pace of new requests coming into the cloudlet is known, together with the average number of seconds it takes for a task to finish running once it has gained control of the processor. Where did the information for this employment rate originate from?

$$\rho_{v_i} = \frac{\Lambda_{v_i} \cdot \mu}{c}.$$

A significant indicator is the percentage of rooms that are currently being used. If the rate is more than one, it is obviously not desired since it would lead to an increase in the predicted amount of time spent waiting in line. As a direct consequence of this, it is essential to keep the occupancy rate at or below 1 at all times. Since there are no idle processors when a work gets to the cloudlet at base station vi, we are also able to anticipate the possibility that a task will have to wait for access to a processor by utilising the occupancy rate. This is possible since there are no idle processors. As a direct consequence of this, we are in a better position to distribute our available resources.

$$\psi_{v_i} = \frac{(c \cdot \rho_{v_i})^c}{c!} \cdot \left((1 - \rho_{v_i}) \cdot \sum_{j=0}^{c-1} \frac{(c \cdot \rho_{v_i})^j}{j!} + \frac{(c \cdot \rho_{v_i})^c}{c!} \right)$$

❖ Transmission Delay

Millisecond wave communications are used by the millimeter wave wireless channel that is utilized for the transmission delay of the 6G standard. This is consistent with what was predicted with regard to 6G. As a consequence of this, problems such as route loss, fading, antenna gain, noise, and interference may all have an impact on transmissions. In addition, in order to make the subject matter more understandable, we are going to make the assumption that Shannon and Hartley's theorem is correct for the channel transmission rate. The channel rate is consequently limited to a maximum value that is defined by where STXRX represents the signal strength between a receiver RX and a transmitter TX, B represents the channel bandwidth, IRX represents the interference that is detected at the receiver, and N represents the channel noise (as estimated by an additive white Gaussian noise model).

$$B \cdot \log_2 \left(1 + \frac{S_{\mathrm{RX}}^{\mathrm{TX}}}{B \cdot \mathfrak{N} + I_{\mathrm{RX}}} \right)$$

It is feasible to obtain a downlink transmission rate that is equivalent to the one achieved on the uplink by only switching the capabilities of the receiver and the transceiver. If we state that: "If Brown denotes the entire bandwidth of a base station's downlink channel, then we should be able to determine such a rate for the user interface (UI).", then we should be able to determine such a rate.

$$D_{u_i}^{\mathrm{down}} = B_{u_i}^{\mathrm{down}} \cdot \log_2 \left(1 + \frac{S_{u_i}^{h_{u_i}}}{\mathfrak{N} \cdot b_{u_i}^{\mathrm{down}} + I_{u_i}} \right)$$

We are now able to determine what caused the delay in the transmission. The total amount of time it takes to transmit anything takes into account both the amount of time it takes to send the job over the uplink and the amount of time it takes to send the outcome over the downlink. This takes into consideration, in addition to the uplink and downlink transmission rates, the physical propagation twice between the user and the associated base station. We shall use the notations p up, p down, d j i, and p up, p down, respectively, to refer to the size of the work, the size of the outcome, the speed of light (which is utilised for the transmission of wireless media), and the actual distance that separates i and j. As a direct consequence of this, the user interface's anticipated latency in transmission is

$$T_{u_i}^{\mathrm{delay}} = \frac{p^{\mathrm{up}}}{D_{u_i}^{\mathrm{up}}} + \frac{p^{\mathrm{down}}}{D_{u_i}^{\mathrm{down}}} + 2 \cdot \frac{d_{u_i}^{h_{u_i}}}{\xi}.$$

Analysis and Interpretation

In this part, we will offer the evidence that supports our claim that our proposal can be implemented in a way that is useful for addressing the ECC deployment difficulty effectively. Our objective is to give evidence that the method of randomly distributing servers leads to significant improvements in their overall performance when compared to the conventional approach that has been used in the vast majority of the research that has been published. In other words, we want to show that our method is superior to the regular strategy. The results shown on this page are the product of a simulation that was run. The locations of the base station and the users in each simulation were chosen at random to assure the trustworthiness of the statistical data, and the results shown here are the average of one thousand simulations of the same kind. Unless otherwise specified, the outcomes are represented by the average of all of these simulations. As was said earlier, the backhaul connections are decided upon depending on the distance that separates them, and the collection of links that is produced as a consequence is what constitutes a passive optical network. Even though it is usually thought that the speed is the same as the speed of light, the propagation distance is determined by the distance between the base stations. In addition, the numbers from Table 2 are employed as simulation parameters, unless anything else is specifically stated.

Table 2: Aspects Of The Simulations' Parameters.

user task rate generally speaking	1 task/s
Time spent working, on the whole	50 ms
the amount of processors allocated to each cloudlet	15
intercepting with a significant amount of path loss	75.85 dB
The average value of the path loss exponent	4.77
The whole area of the surface	10000 m^2
There are base stations available.	10

lot of little cloudy things	5
The number of users	10000
a base station's antenna gain potential	24.5 dBi
factor de fadage de Rayleigh	-1.59175
The capacity of users to transmit	27 dBm
Gain for the customer's antenna	2.15 dBi
a great deal of commotion	$4 \cdot 10^{-19}$W/Hz
wireless channels' available bandwidth	1 THz
size of the package	128 KB
Rate of data transmission for each backhaul link	10 Gb/s
Iterations per thousand megacycles, number	5
Iterations of the PSO have been finished.	5
a count of particles for PSO	6
influenced by the inertia of the PSO	3
PSO with a local best bias	19.5
PSO with the best global bias	3.5

- **Optimized Resource Allocation:**

In order to make dynamic adjustments to the transmission power, machine learning algorithms may assess real-time data such as the proximity of devices to one another and the congestion on the network. The effectiveness and reliability of the network may be improved if attention is given to ensuring that Internet of Things devices have access to the right quantity of resources.

- **Low Latency and Responsiveness:**

IoT devices can access computational resources thanks to the deployment of edge cloud servers. This reduces latency and makes it easier to make rapid decisions, making it ideal for applications that need almost instantaneous responses, such as those that involve remote medical procedures and autonomous vehicles.

- **Energy Efficiency:**

It's possible that algorithms that learn from their environment might help save energy by more precisely adjusting gearbox power. This is very important for Internet of Things devices that may operate on battery power for extended amounts of time. Utilising the device's power in an effective manner will lengthen its lifespan and reduce the amount of maintenance that is required.

- **Adaptive Network Management:**

Because of the use of machine learning, the network is able to automatically adjust to changing conditions as they arise. Due to the dynamic nature of IoT environments, which include varying device densities and degrees of interference, the network must be flexible enough to accommodate these changes in order to maintain its integrity.

The use of edge cloud servers, the management of transmission power via the use of machine learning, and the use of 6G IoT all work together to produce a compelling architecture for future networks. It is a solution that is disruptive to the IoT environment since not only does it solve significant technical issues, but it also coincides with sustainability objectives and security concerns. Consequently, it is an all-around better solution.

5. Result and Discussion

The aforementioned figures are in line with what is anticipated for 6G IOT networks. As we work, we are operating on the assumption that the values of the uplink and the downlink are same. The parameters of the machine learning algorithms were built via a process of trial and error to identify what would be most advantageous for dealing with this specific circumstance. In order to test how well our theory applies, we are going to investigate a number of different scenarios. As a point of comparison, we will make use of a deployment approach that is distinct from the one that is often utilised in the research literature. This method employs a random distribution of cloudlets over all base stations that are accessible to users, regardless of the location of those users. the application of backhaul propagation to the process of decision-making about virtual relationships. PSO is used to make decisions on the transmission power levels and the physical associations. In addition, according to a random policy, each cloudlet will be responsible for serving customers located in the United Kingdom, and the amount of work will be distributed evenly among all cloudlets. The second and third criterion imply that the deployment decisions might be directly to blame for the performance disparities. The number of base stations that were used in the first graph is going to undergo some modifications on our end. The findings of the research are shown in Figure 4 below.

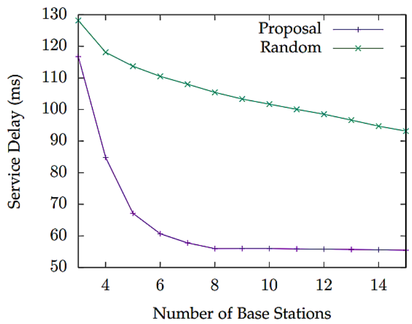

Fig 4: Variation In Ecc Service Latency As Base Station Count Rises.

As was to be expected, the increase in the number of base stations results in a decrease in the lag time experienced by all policies. This makes sense when one considers that as the number of base stations rises, the amount of communication effort required at each base station lowers. This, in turn, results in a reduction in the transmission delay. In order for base stations in regions with a limited number of base stations to communicate with users who are geographically dispersed, they often need to employ a high transmission power level. This often results in a large transmission delay, a worse signal for those users, and more interference over the whole of the system as a whole because of the longer time it takes for signals to propagate. On the other hand, if there are a greater number of base stations, there will be a decrease in the number of users who conduct their activities independently. The performance of the random deployment approach is the worst because it is hard to install cloudlets in the base stations that give the greatest performance. In practise, the greatest variances in performance are seen at the deployment sites identified by our KMC-based approach. These are the locations where the cloudlets are positioned. This disparity is possible to see irrespective of the number of base stations that are included in the system. Our strategy is able to make the most efficient use of the available resources even in locations with a limited number of base stations, which eliminates the advantages that would be gained by installing more base stations. After that point, the restrictions will be looked at once again in the event that the number of servers increases. Figure 5 presents the findings of the study.

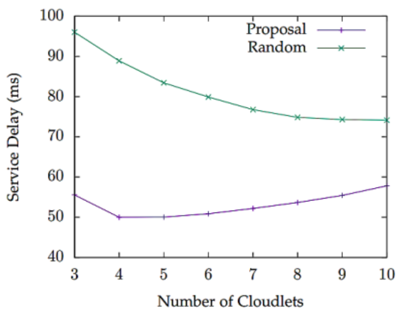

Fig 5: Variation In Ecc Service Latency As Cloudlet Count Rises.

It is interesting to notice that even if the system may have more resources than those mentioned in our plan, the performance of our approach would suffer if more than five servers were added. This is because our strategy is optimised to work best with the current number of servers. The inclusion of cloudlets improves the quality of the service and cuts down on the amount of time that users have to spend waiting by lowering the amount of processing work that is necessary for each cloudlet. When there are fewer people utilising each cloudlet, the processors are able to function in a more efficient manner. If you have a sufficient number of cloudlets, though, this wait time will be so short that it will be completely irrelevant. Because it is necessary for all servers to provide assistance for customers located in the United Kingdom, the quality of the service suffers whenever more cloudlets are made available. As a result of this, increasing the amount of cloudlets after the wait time has already been reduced does not speed up the processing but instead slows down the transmission. This is because it is more likely that a user will be forced to connect to a server that is farther away since the server that is geographically closest to them has already reached its capacity. The reason for this is because of the chance that a user will be forced to connect to a server that is further away. Because there are not enough cloudlets now accessible, the random deployment strategy is unable to conduct a test of this behaviour at this moment. The graph also illustrates how, once again, deciding where to deploy the cloudlets in a random manner decreases the efficiency of the strategy. The technique is always the better option to go with, and this holds true regardless of the number of individual cloudlets that are now present in the scenario.

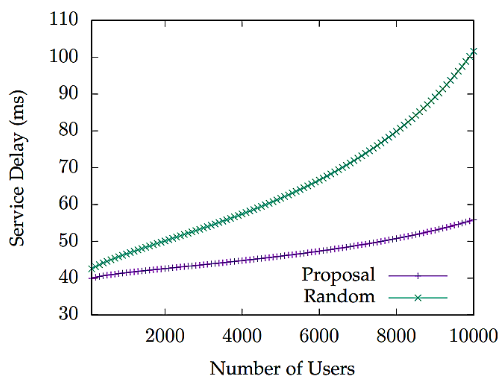

Fig 6: Variation in Ecc Service Latency with Growing User Base.

In the end, a comparison is made despite the fact that the number of users is always changing. The findings of the research are shown in Figure 6 below. When there are more customers, there will inevitably be longer lineups for service, and this is to be anticipated. This phenomenon occurs because users share the same processing and communication resources, which is the simplest explanation for why it occurs. Because of this, there are a greater number of customers who, on average, make use of fewer resources, which leads to longer wait times before receiving services. The situation is rendered much more precarious since there is no deployment option available to alleviate the mounting pressure that is the direct result of the random approach. The graph provides an illustration of one possible configuration for KMC's server placement in order to minimise the impact of service latency on the user's location.

6. Conclusions

ECC is an essential method that must be implemented in order to provide users access to available resources. It makes it possible for several users to share resources in a way that is both cost-effective and on-demand. In addition, the latency that exists between users and servers in modern cloud computing is far shorter than it was in old cloud computing. This makes it possible for even real-time applications to make advantage of the cloud's resources. As a consequence of this, ECC is an important piece of technological equipment. In this body of work, we suggested a deployment strategy for 6G IOT settings that makes use of the PSO and KMC machine learning algorithms. This method was developed for deployment in contexts where 6G is being used. Processing, transmission, and the link to the backhaul are all taken into account within the scope of this technique in order to drastically cut down on service latency. Our answer is not too complicated and can be carried out in a short amount of time; this enables it to be used in scenarios that include a large number of different factors. Because of the large number of users, servers, and requests that these technologies generate, the implementation of ECC with IOT and 6G is contingent on the outcome of machine learning algorithms. The simulations also shown that the notion is far more advantageous than the method of random deployment. This should serve as a reminder of the usefulness of deployment choices in decreasing ECC service latency and the relevance of taking into consideration transmission, processing, and backhaul connection when building a solution. Additionally, this should serve as a reminder of the importance of taking into account transmission, processing, and backhaul connection. This should also demonstrate how significant the role that deployment choices play is in minimising service delay in ECC. If the deployment is not carried out in the appropriate manner, the speed of the service will be substantially reduced. We are able to deliver a service that is completed in a more timely manner by applying our method, which involves meticulously configuring each cloudlet in line with the requirements of the client.

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