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Internet Of Things (Iot) - Enabled Intelligent Edge Computing For Energy Management In Smart Cities

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ABSTRACT:

Edge computing has emerged as a viable paradigm for delivering cloud-like services to mobile consumers. Edge computing is able to intelligently deliver on-demand services with minimal latency because it takes use of the geographical and social similarities among users. However, a bottleneck in the performance of edge computing has been established as a result of an unprecedented number of activities together with the diverse nature of applications that will be used in future smart cities. Some examples of these applications are healthcare, energy management, transportation, cybersecurity, and so on. Therefore, in order to keep up with the ever-evolving computing environment and to continue to deliver dependable smart services to mobile consumers, edge devices must be outfitted with adaptive machine learning algorithms. In addition to reducing the load on edge servers, a cooperative learning system in which information is sent from the cloud to the edge and the edge to the cloud can improve the efficiency of the learning process. In this work, we develop a smart energy management system for IoT devices using deep reinforcement learning and edge computing. In the first section, we provide a high-level overview of IoT-based smart city energy management. At the end of the paper, a framework and software model for an Internet of Things-based system that employs edge computing are presented. Finally, we describe a deep reinforcement learning-based energy scheduling technique that makes optimal use of the suggested architecture. Lastly, we provide examples of the success of the suggested method.

Keywords. Internet of Things, Smart City, Energy Management, Edge Computing.

1. INTRODUCTION

The Rapid advancements in fields including transportation, healthcare, energy management, and smart homes need the development of intelligent computing networks capable of managing the resulting explosion in data complexity, volume, and heterogeneity [1]. Edge computing provides cloud-like services in close proximity to mobile consumers,

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facilitating efficient administration of compute-intensive and latency-sensitive applications. In addition to facilitating the processing of mobile users' operations on robust servers, edge computing helps alleviate pressures on the central network and preserve data privacy by preventing the transmission of data over the lengthy cloud path [2]. Future computing systems will be increasingly complicated; thus, it will be crucial to equip edge computing nodes with intelligent algorithms that can handle this kind of data. The implementation of efficient learning models may result in a wide range of positive outcomes, some examples of which include the extraction of high-level features from raw data, the anticipation of future requests, and the making of intelligent proactive decisions. Furthermore, edge devices have restricted computational capabilities in comparison to the cloud, despite the abundance of edge resources [3]. As such, using the vast amounts of data and robust cloud resources may provide strong backing for edge intelligence in terms of both resources and expertise. The impact of technology on every area of human existence is undeniable. The processing power of cloud computing has proven inadequate for smart gadgets, sensors, and even self-driving automobiles, despite the proliferation of these technologies in recent years. By overcoming the limitations of cloud computing, edge computing has the potential to greatly enhance the functionality of such gadgets and machineries [4, 5, 6].

As an extension of cloud computing, edge computing brings together at the network's periphery the same set of resources (computing, storage, and network services) that are typically hosted in a data centre [7]. Edge computing, which offloads some calculations to edge devices, has several advantages over cloud computing services, including faster computing, less storage, lower latency bandwidth, better data security, and less restrictions due to physical location. Within the realm of edge computing, several devices will produce vast amounts of data. Data can be calculated on the edge service to save on bandwidth and energy costs rather than being transmitted back to cloud services [8]. To further decrease the need for storage space, edge computing may also prioritise and prioritise the data extracted from the raw data that has been received. Further, many end-users benefit from the efficient, secure services made possible by edge computing. In the context of fifth-generation (5G) mobile communication networks, edge computing has the upper hand over cloud computing because it makes use of the higher bandwidth and lower latency to process and analyse the data quickly and efficiently. As a new way of life, the notion of "smart cities" has gained popularity in recent years. With the help of numerous Internet of Things (IoT) gadgets, smart cities may construct cutting-edge, networked infrastructure that makes life easier for its residents. Smart parking, smart buildings, smart lighting, sophisticated waste disposal, and traffic management are just some of the numerous facilities and applications included in a typical smart city system [9].

Energy efficiency in smart cities is improved with the aid of edge computing thanks to constant monitoring. Monitoring, analysing, and forecasting short-term energy usage also provides information useful for energy policy, infrastructure development, and conservation [10]. Numerous surveys on smart cities have been undertaken in the past. Data management approaches utilised to ensure the reusability, granularity, interoperability, and consistency of

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data from smart IoT devices were examined by [4]. The authors also detailed the methods deployed to ensure citizens' safety and privacy in smart cities. Aside from that, though, we also talk about how new technologies are allowing smart cities. With the use of big data and a variety of initiatives, the authors of [8] explain how to build smart cities. There are four types of reference models that the authors employ to categorise how urban big data is put to use. The difficulties in making sense of smart city data are also discussed. The study [9] examined smart city applications based on the Internet of Things. The authors provide a summary of ongoing IoT-based initiatives. A prototype of an Internet of Things-based real-time monitoring system for smart cities has also been shown. In [50], we get an overview of the features, framework, advances, and difficulties of smart cities. As a result, this method can assist lessen the demands placed on the environment and the economy by cutting down on unnecessary use of resources like power, data transfer, and labour. There is a bigger demand for bandwidth as cities expand because more resources are needed to reduce system delay. This means that edge computing has an advantage over traditional cloud computing due to its superior scalability. The number of Internet of Things (IoT) devices producing data and requiring processing via cloud computing is expanding fast, especially when machine and deep learning techniques are utilised as predictive models [11]. Due to unique environmental factors, the application's offloading bandwidth is inadequate, resulting in a substantial delay in user interaction. As demand for Internet of Things (IoT) devices has skyrocketed, cloud computing has hit a wall due to issues including slow speeds, expensive upkeep, and limited support. Cloud computing's drawbacks are simple for edge computing to overcome. The reduced latency of 5G broadband makes edge computing a viable option for processing data from Internet of Things devices. Although Internet of Things (IoT) gadgets have come a long way in recent years, they are still limited by factors like battery life, memory capacity, and cooling systems. By alleviating these limitations, edge computing helps keep devices operational for longer. The healthcare industry is another important sector that may reap the benefits of edge computing alongside smart city technologies and Internet of Things applications. Computing at the network's edge has the potential to lessen the volume of data in transit and boost healthcare productivity [12].

In addition to assisting medical professionals in decreasing their dependency on distant centralised servers [13], edge computing architecture may also improve data security and ethical integrity [14,15]. Patients with Parkinson's disease, high risk of heart attacks, and other serious conditions are increasingly using wearable gadgets and sensors as a therapy and active monitoring alternative in the comfort of their own homes [16]. Together, these devices and edge computing's capacity to react quickly with low latency might improve dependability and forestall undesirable outcomes.

Edge computing (EC) is a fundamental technology used by IoT-based energy management systems to circumvent this problem [17]. As one of its key features, EC is well-suited for DRL deployment in IoT-based systems because it can provide computing services close to the network's "edge," where IoT devices are often placed. To begin, EC's pre-processing techniques can drastically lessen the amount of data transmitted from devices to

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the DRL agent. Second, EC is capable of satisfying the computational need of energy management while yet respecting the constraints of low-powered devices. Edge computing with dynamic resource balancing (DRL) is introduced in this article as part of an IoT-based energy management system. This technology can speed up processes and enhance energy management performance. In order to simply show off the proposed system, the bare bones of the infrastructure and the software model are described. We outline a difficulty with energy scheduling for demand-side response in the smart grid scenario based on this technology. With the DRL algorithm, we develop two scheduling strategies while taking into account the constraints of EC processing power. The testing outcomes demonstrate the superiority of our solution over previous IoT-based energy scheduling techniques.

2. EDGE COMPUTING

Edge computing is the most important technology that will be used in the future generation of network technologies. Since EC [18] has gained the attention of relevant researchers from around the world because to its ability to perform the crucial computations required to address job scheduling, content caching, collaborative processing, and other issues in large-scale networks. The supply of data computation and services was recommended to be shifted from the cloud to the edge by [19]. Due to the cloud's inability to efficiently handle time-critical and context-aware applications in the Internet of Things age, edge computing has emerged as a viable solution [20]. The purpose of the MEC decision model and solution approach presented in [21] is to stabilise the mobile network system for the next generation of IoT, to balance the network load, and to guarantee the quality of the user service experience. With the use of SDN and NFV, it has been shown that the best MEC centre may be chosen for multi-attribute decision making, which in turn speeds up server responses and enhances the quality of service provided to end users [22]. An efficient approach for calculating edges was presented by [23]. Users of smart IoT devices may quickly shift computationally heavy activities to neighbouring devices, supplementary devices, or edge clouds. In this work, we take a fresh look at mobile computing offloading from the standpoint of resource efficiency, and we develop a robust computing offloading method. Intelligent IoT devices may spend less time running because to the mechanism's combination of a delay-aware task graph division strategy and an optimum virtual machine selection approach. The experimental results verify the effectiveness and enhanced performance of the proposed resource-efficient edge computing system [24]. In [25], the author examined how IoT devices and data-centric networks might benefit from deep learning models including convolutional neural networks, recursive neural networks, and improved learning. The purpose of this research is to make an assessment of the development trend that will be followed by the network architecture in the future. As a result, the convolutional neural model is highlighted as a viable option for Internet of Things applications, allowing for the reliable utilisation of data gathered from highly complicated settings [26]. To further take into consideration the multimodality of data in real-time applications, IoT devices incorporate improved learning and convolutional neural networks. In [27] advocated employing machine learning

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technology to ensure the privacy of users as they roamed using a PBS (position-based service). Using a combination of the decision tree and k-nearest neighbour values, the approach determines the user's current position and then uses a hidden Markov model to predict the user's next destination and monitor their movements from there. The timely delivery of PBSs is ensured by employing a mobile edge computing service strategy. By placing network and computer services close to roaming customers, the mobile edge service concept offers benefits like location anonymity and low latency [28]. According to [29], network security is becoming increasingly difficult due to the proliferation of IoT applications and network physical services. This piece benefits from the adaptability of cloud-based architectures and the most current developments in massive-scale machine learning. Edge computing may make use of complicated limit learning models constructed in advance in the cloud to efficiently execute traffic categorization [30] by offloading activities that demand more processing resources and more storage to the cloud. Machine learning communication technology is the term used to describe the recommendations made by [31] in their study on wireless communication in edge learning. The usefulness of these design recommendations is illustrated with examples [32]. In conclusion, MEC's high performance and minimal latency enable it to deliver satisfying network service experiences to end customers. Despite advances in network technology and access to vast amounts of data, the difficulty of processing speed remains. Existing research have improved the MEC in a similar fashion utilising AI technology, with positive results. Machine learning was proposed as a result of AI progress. In the meantime, nonetheless, there is no equivalent performance test to back up the claims of those researchers who believe machine learning has a positive influence on enhancing MEC. This study employs machine learning techniques to enhance MEC, and the resulting experimental performance is evaluated.

The core components and services of a smart city are managed utilising a suite of intelligent computing technologies, as outlined by [9]. To increase storage capacity and processing speed with elastic, on-demand, and pay-as-you-go cloud computing resources, a centralised cloud-computing architecture has been widely used in smart cities. With the help of several different technologies, such as virtualization and network security, cloud computing improves the efficiency with which physical resources are being used. Cloud computing relies heavily on virtualization technology, which simulates physical hardware in the cloud.

Virtualization enables different operating systems to run simultaneously on a single computer system and maximises the use of a system's computational and storage resources. Virtualization may also be used to create a virtual machine. To reduce the amount of time that resources like CPU, RAM, network, and storage sit idle, cloud computing virtualizes and maintains them in a resource pool to deliver computing services over the network. Users can access and make use of public clouds (like AWS and Azure) by paying a subscription fee. The resources of a private cloud, on the other hand, are often only accessible within a single company and shared among its employees. The capacity to store and access data and applications outside of the local computing environment over computer networks is made

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possible by cloud computing, allowing the smart city to function as a fully functional computing system.

3. IoT-Based Energy Management in Smart Cities

Data collected from buildings should be processed and used in an efficient manner in order to create a more intelligent and humanised building [33]. Smart building energy management may be thought of on three distinct layers: device, system, and inter-system.

Device Level: Devices in smart buildings can provide more widespread entry to enter data (electricity used, temperature, humidity, etc.) that is critical to understanding the building's operating parameters. For energy management in particular, the IoT processing unit should use predictive or adaptive processing to analyse the energy data and then send the results to the appropriate command and control nodes. Then the last actuators may do the required measures.

System Level: Smart buildings' primary purpose is to synchronise the actions of numerous energy-related components at the system level. Short-term, the IoT-supported smart building may automatically modify the building's internal fundamental system to improve energy management and control. Many smart IoT devices are spread out around the system, and they all work together to support the applications that deal with energy.

Inter-System Level: Integration of several independent subsystems into a cohesive whole for the purpose of achieving energy management for smart buildings is what is meant by "inter-system level." In this context, "smart building" refers to a structure with several interconnected systems, such as those that provide power, gas, and heating. Its "smartness" refers to its ability to satisfy energy management through the management, interconnection, and adaptation of diverse assets and functions (including technological, economic, and social variables).

3.1. Smart Power Grid

The smart power grid is an essential element of the plans that are being developed for a more environmentally friendly energy future [11–13]. By using the Internet of Things, they may not only aid in the spread of renewable energy and the electrification of transportation, but also deliver novel value-added services associated with the field of energy. Specifically, the development and implementation of smart grids will propel the revolution in energy management. The intelligence and data flows of smart power grids have the ability to greatly increase their current capacities. The Internet of Things helps make smart power grids citywide, fostering intelligent grid infrastructure and user-friendly engagement. The Internet and the energy industry (including generation, distribution, transmission, storage, and the market) are becoming increasingly integrated, giving rise to a new generation of power management systems known as "smart energy." Some of its defining features are synergistic equipment, numerous energy sources, symmetric information, decentralised supply and demand, a horizontal organisation structure, and transparent transactions [12].

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3.2. Multi-Energy Networks

Large buildings, parks, islands, and towns are only some of the sites where IoT-based multi-energy networks might improve energy efficiency and provide other benefits [14]. In order to offer smart cities with a centralised means of managing all of their energy demands, IoT systems employ information and communication technology to integrate several energy networks, such as the smart electric grid, supply grids of heat and gas, and network traffic. Here are some more positives associated with integrating IoT into a renewable source.

Promoting Deep Fusion of Energy and Information Infrastructure: The Internet of Things (IoT) might be used to coordinate the development of several energy grids (e.g., electric, gas, cool air, heat, etc.) and their respective information infrastructures (e.g., information architectures and storage units). In this way, the information system and the energy system may be integrated in terms of measurement, calculation, control, etc. There is potential for integration to serve as an impetus for standardising the structure and information interface of multi-energy networks.

Developing Smart Energy Management: In the future, smart districts and similar infrastructure, including terminal facilities like smart homes, may be able to create energy-efficient monitoring platforms, provide individualised energy management/saving services, and realise smart customisation and flexible energy transaction.

Cultivating the Emerging Energy Market and Business Models: The Internet of Things (IoT) enables multi-energy organisations to remotely collect and read water, gas, heat, and electricity in unified metres. This benefit of an IoT-based energy system may stimulate the development of a shared market system that allows micro-users like people, households, and distributed energy resources to trade energy on a level playing field via centralised exchanges.

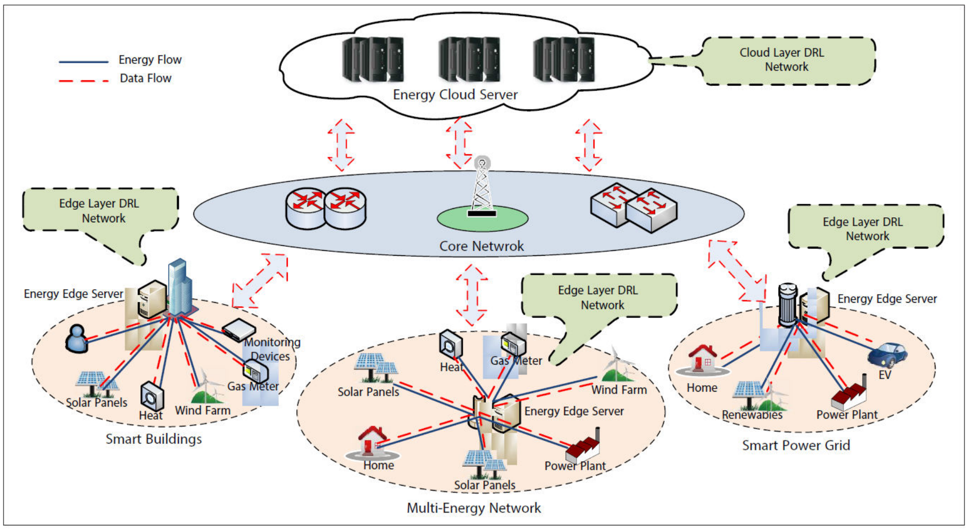

Figure 3.1. IoT-based smart city energy management technology

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3.3. Edge Computing to Digital Twins

In recent years, digital twins have developed into comprehensive digital representations of physical entities ranging from a single product to an entire manufacturing procedure. They take in and synthesise data from several sources in order to mimic the responsiveness of their physical counterparts. To create the most accurate digital twins, however, it is necessary to account for the dynamic nature of the features being modelled [34]. Inconsistent resource availability may wreak havoc on supply chains, while environmental factors like temperature and pressure might alter production methods in the plant. Everything in the real world is in a constant state of flux, and this dynamic is fundamental to their very nature. Time-dependent aspects must be simulated in order to provide an accurate depiction of the entities in question.

Fortunately, cloud computing has provided a solid foundation for bringing together and synthesising these many data sets. Sending data to a remote site for processing can introduce latency problems, but this isn't a problem if the data is stored locally. A delay in this time might result in incorrect representations of private information, systems, or procedures. Costs rise when vital business opportunities are overlooked, product batches are destroyed, and resources are mismanaged. The benefits of cloud infrastructure are just too significant to forego, but a fix for its latency problem is crucial to unleashing digital twins' enormous potential. There, edge computing is positioned to become the next critical component [35].

Internet of Things (IoT) gadgets utilising edge computation have proved critical in developing practical digital twins. However, a complex networking model is required as part of the simulation's architecture. When there are only so many open connections, systems without one are more likely to crash. An efficient solution to this issue is to use an asynchronous design. Distributed load balancing guarantees there are enough processors in the network to deal with high demand [36]. It processes the activities of thousands of devices. As a result, only a single thread is needed to process and send control events from each device to the simulation, where they are combined with other events to form a full state of the environment.

3.4. IoT-Based Architecture with Intelligent Edge Computing

The IoT-based energy management architecture using edge computing on a DRL network is presented in Figure 3.1. The energy devices, energy edge servers, and energy cloud servers make up the key parts of the architecture.

Energy Device: The energy device is any entity, device, or user in the network that can both generate and consume power. Depending on the equipment' capabilities, several forms of energy data can be detected, collected, or generated.

Energy Edge Server: In order to compute, cache, and distribute energy data in a regional network, the energy edge server can be set up at the network gateway, base station, and so on. It communicates with the energy gadgets in a number of ways, including 5G, WiFi, and a mobile ad hoc network (VANET). In addition to doing analysis, the energy edge server may use the information to make operational decisions for a regional energy grid.

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Energy Cloud Server: In order to facilitate energy management, the energy cloud server establishes a connection with the central controller. The energy cloud server's role is twofold: first, to fulfil the computing needs of energy edge servers, and second, to give real-time analysis and calculation to energy devices.

The acquired data is processed by computers at the energy network's periphery, which then sends it to a cloud server through the backbone network. DRL agents are placed in both the cloud server and the edge server. In order to complete a compute task, an energy device communicates with a nearby edge server, where an edge DRL agent is waiting to carry it out. To lessen the load on the edge server's resources, we can pretrain DNNs in the energy cloud server. Next, we communicate the DNN weights to the energy edge server that controls the deep Q-learning procedure once the training phase has concluded. In this scenario, data from energy devices is loaded into energy edge servers, which subsequently send that data to an energy cloud server to be processed.

4. Software Model

This section describes the development of a software model for an Internet of Things-based energy management system, which incorporates smart edge computing (see Fig. 4.1. The proposed software model has four levels, or "layers," that are respectively "sensor," "network," "cognitive," and "application" levels.

Sensing Layer: At the sensor layer, gadgets can produce or detect data about the energy network's usage. The energy edge server is in charge of maintaining connections between devices, or establishing secure channels of communication between them. A primary function of the suggested software paradigm for intelligent edge computing services is the ability to query data. The edge server will queue and categorise the acquired energy data for hierarchical processing, taking into account the diversity of this data in smart cities.

Network Layer: The offloading of tasks from the edge server to the cloud server, as well as the transport of data between energy devices and the energy edge server, are crucial to the success of the proposed IoT-based energy management system. Several different methods exist for transmitting data, including power line communications (PLC), fifth generation (5G) mobile networks, long-term evolution (LTE), and wireless fidelity (Wi-Fi). To store energy data, a "data pool" is produced when the storage capacities of the energy cloud server, the energy edge, and the energy devices are combined into a single source of network storage. Thanks to the standard interface, heterogeneous data in the data pool may be accessed from anywhere, even on any device or server. Energy managers may use the virtual data pool to analyse past data and formulate more effective regulation rules. This register is intended to keep track of the many devices that connect to and disconnect from the planned IoT-based energy network. The registry plays a crucial function in assisting with network setting as the devices may regularly enter and exit the network.

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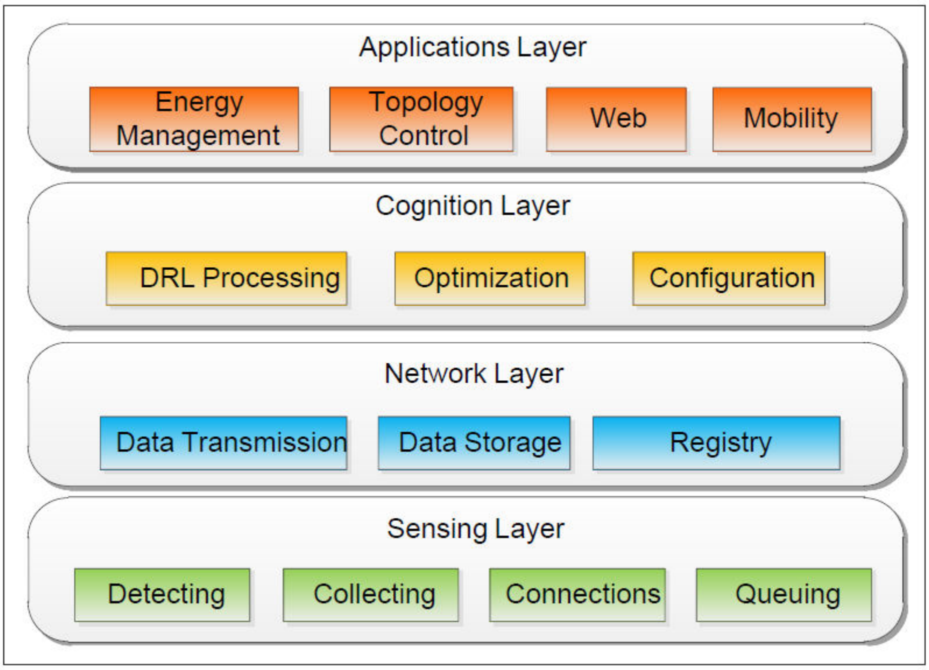

Figure 4.1. The architecture of an Internet of Things-based energy management system's software

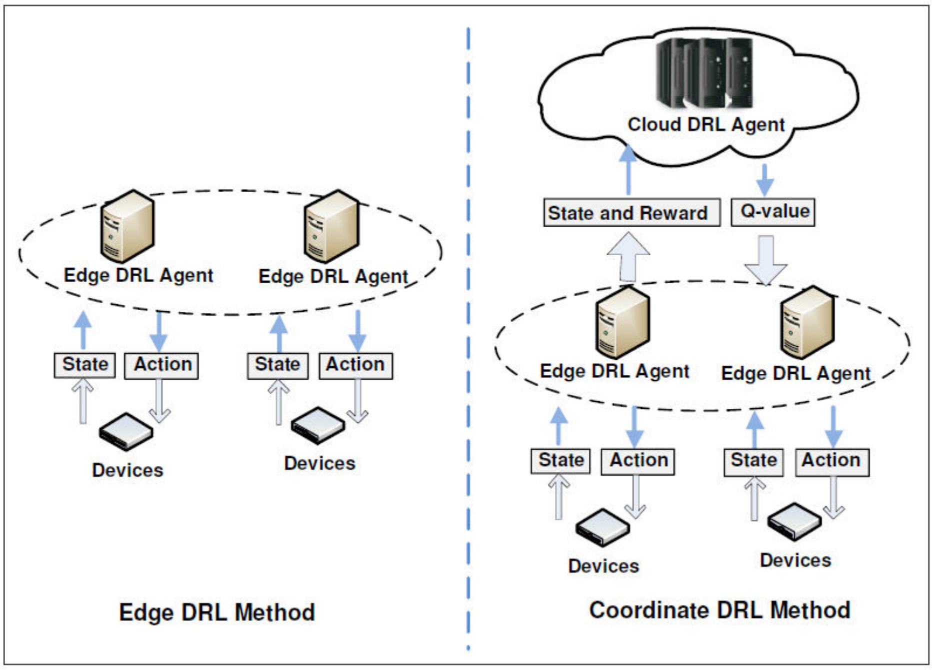

Figure 4.2. The DRL process.

Cognition Layer: The cognitive layer is a crucial component of the proposed architecture, as it is responsible for developing an intelligent consciousness of the energy ecosystem. DRL processing, optimization, and configuration are the three primary functional modules found in this layer. Both the cloud server and the edge server have processing modules for DRL in place. Input from connected users, including their needs and status updates, are recorded by

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the module. The DRL module can then determine the reward based on the outcomes of the most recent action taken. With the help of a robust DNN, the DRL module can make judgments with high precision in estimate and prediction. For a DRL agent to acquire the best possible answer in online deep Q-learning during the course of its whole operating periods, an optimization function is crucial. Since excessive utilisation of edge servers might result in unacceptably high energy consumption, the optimization can also investigate the most cost-effective timetable for utilising edge servers. The setup of edge servers or devices can be achieved in the energy cloud server. On the other hand, the configuration can be managed in an edge server for adjacent devices. It is important to remember that setup may be handled either centrally on a cloud server or dispersed on individual devices or edge servers.

Application Layer: The application layer supplies a suite of operations and utilities for processing data attained from lower levels and determining the network parameters of the proposed IoT-based infrastructure. Specifically, energy management is the essential feature that allows the entities to schedule and regulate the energy from all sides of the system without having knowledge of the situations in the underlying layers. Device exit and entry decisions are made via topology control.

4.1. Effective Energy Scheduling Using Deep Reinforcement Learning

Here, we provide a DRL-based processing architecture (Fig. 4.2) in which DRL agents may be located anywhere, including on-premises, in the cloud, or at the network's periphery. We suggest two different DRL approaches: an edge DRL approach and a cooperative DRL approach. For starters, under the first approach, devices delegate the job of energy scheduling to an edge server. The DRL approach is then used by the edge server to determine the best scheduling options for the devices. The second approach involves the edge server delegating the DNN training to a remote cloud service in order to save money on computational resources, and then using the cloud service's predicted Q-value to guide its own deep Q-learning procedure.

5. EDGE DRL METHOD

Action Space: In each decision epoch, we allow the edge DRL agent to categorise the devices in a new way to better serve the varying needs of the service. To be more specific, the DRL agent decides what kind of devices should be prioritised at the moment. The DRL agent can determine which of a group of devices are now operational after an operation has been performed.

Reward: The incentive is put to use in order to achieve the lowest possible energy usage for the devices and to fulfil the requirements set out by the devices. In this research, we introduce the notion of an instantaneous reward for cloud DRL agents, denoted by $Re = E_{max}$ - E_{real}, where E_{max} is the highest value of the devices' energy consumption and real represents the actual total energy consumption of the devices that may be retrieved at each decision epoch. Q-Learning on the Deep Web: The use of deep Q-learning after offline DNN training may be explained as follows:

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Step 1: The edge DRL agent takes in state-action pairs for each state from devices at the start of each decision epoch, and uses a DNN to estimate the value of the Q function.

Step 2: The e-greedy policy is used to determine the course of action to be taken during execution for a certain category of devices. The highest (1 - e) probability Q-value estimate is used to choose the course of action to take. Probability e is used to pick one action at random from the available set of actions.

Step 3: The edge DRL agent determines the best approach to managing energy consumption for a certain class of devices, and then implements that approach.

Step 4: After seeing the device's immediate payoff and subsequent condition, data about those transitions is stored in the experience memory and sampled.

Step 5: The weights of the DNN are updated at the conclusion of each decision epoch by using the loss function obtained from the sampled state transitions by the edge DRL agent.

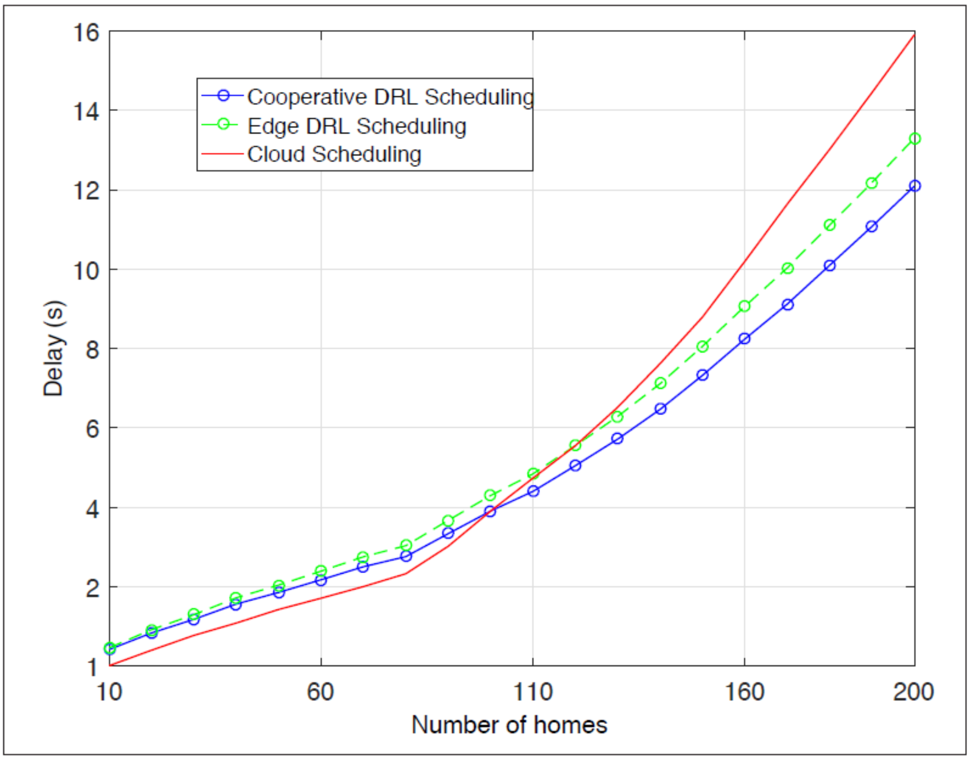

Figure 5.1. Cost comparisons of different energy scheduling schemes

6. Results and Discussion

In this section, we take into consideration five communities, each of which consists of forty households and ten various kinds of renewable resources, and each of which deploys a server for edge computing. In total, we take into account a total of a hundred and ten different types of renewable resources. We use hourly load profiles of several practical demands from the RELOAD database [16] to model these and other needs in a virtual home, including heating and cooling, water heating, lighting, drying and freezing garments, and so on. Grid electricity

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costs p(t) = 0.3 cents between 8:00 and 12:00 noon, according to the market. and midnight, and p(t) = 0.20 cents between midnight and midnight and 8:00 a.m. Both energy use and time are tracked in the simulation. In addition, we contrasted the two DRL-based energy scheduling approaches that we proposed (termed "cooperative DRL scheduling" and "edge DRL scheduling") to a baseline method known as "cloud scheduling," in which a central server handles all energy scheduling for homes that don't employ a DRL approach.

In order to overcome this drawback, function approximators can be used to approximately represent the real value function. In particular, the emerging Deep Reinforcement Learning (DRL) which combines RL and deep learning techniques has achieved great success in applications such as cooling datacentres [35] and playing video games [30]. DRL utilizes a deep neural network (DNN) to build the correlation between each state-action pair and its associated value function.

The edge intelligence layer is an intermediate layer and is closer to users than the cloud. Edge computing servers can process traffic flow scheduling and routing or forward the control flows to the higher layer. Time-sensitive traffic flows can be handled in this layer and reduce the overall service delay. The centralized intelligence layer mainly processes computing-intensive traffic flows or the flows forwarded by the lower layer and sends the response back to the lower users. The DRL module is installed in the data centre to provide higher service and more efficient resource utilization.

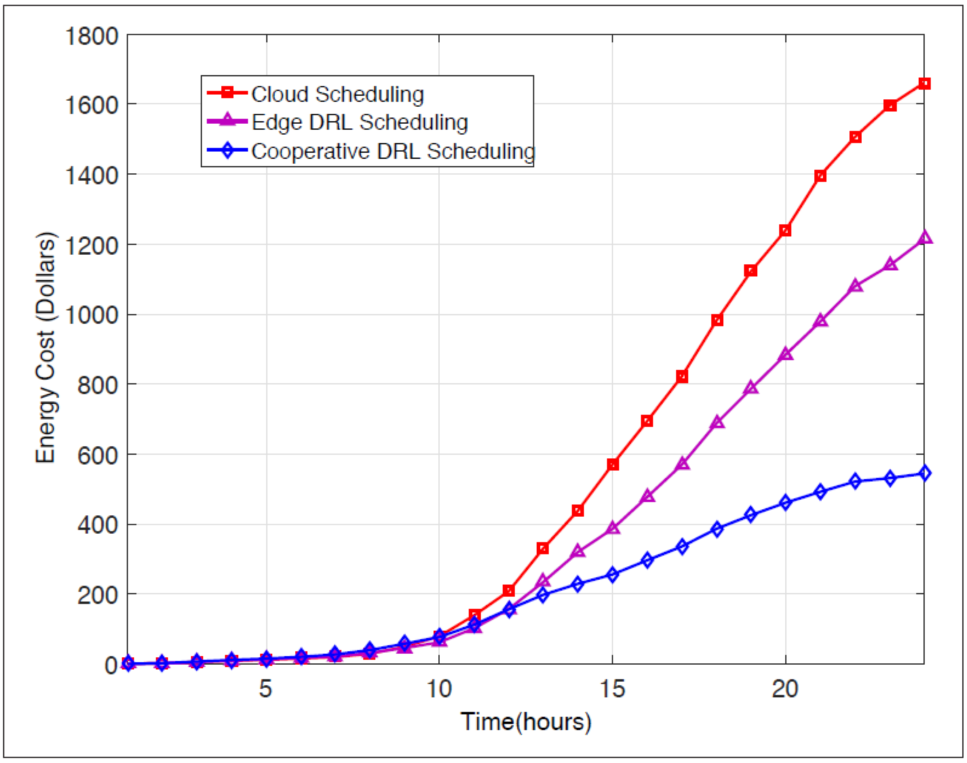

Figure 6.1. Different energy methods are compared for their delay times

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The delay is measured by adding the time it takes for devices to communicate with the higher-level server to the time it takes for each home's activities to be executed (including the cloud server and edge computing server). Scheduling systems such as cooperative DRL scheduling, edge DRL scheduling, and cloud scheduling are compared for latency in Figure 6.1. The completion time of these three plans is likely to lengthen as the population grows. It's fascinating to see how, as the number of houses increases, the cloud scheduling strategy goes from having the lowest delay to having the highest delay compared to the other two suggested DRL-based systems. In other words, in the cloud scheduling system, transmission congestion may occur because the households will all communicate their computing needs to the cloud server at the same time. Therefore, as the population grows, the latency in data transmission will increase dramatically.

There will be less of a delay when using the edge DRL scheduling scheme compared to the cloud scheduling strategy since various classes of houses will have varied priority when it comes to transmitting the requests. However, the execution delay is still there with this technique since the edge server may not be able to process tasks from many devices in a timely way due to its limited computational capabilities. The cooperative DRL scheduling strategy splits the scheduling work into simple (Q-learning) and complicated (DNN training) components, with the former being done on an edge server close to the residences and the latter in the cloud. As the network grows in size, this method can speed up both processing and data transfer for the growing number of households.

7. CONCLUSION

Edge computing is an interesting new computing paradigm with the potential to provide immediate computation and storage to smart cities. Cloud computing is frequently used to supply computational and storage resources to smart devices. However, cloud computing's intrinsic slowness has cleared the way for moving processing and storage resources from a faraway data centre to the network's edge. Adversely, real-time smart city applications need immediate access to analytic services. Edge computing is necessary for these kinds of real-time applications. However, there are considerable challenges to overcome when putting edge computing into practise in smart cities.

The Internet of Things (IoT) energy management framework for a smart city is analysed and assessed in this article. The suggested framework's software model introduces enabling edge computing technologies and works to spread its adoption. Then, a DRL-based energy scheduling system is introduced with the long-term objective of addressing the intermittent and uncertain nature of urban energy sources and needs. We examine the energy scheduling scheme's effectiveness in both the presence and absence of edge servers. Compared to conventional methods, the suggested ones have a lower energy cost and result in less delay, as seen in the illustrative results.

In the future, network slicing will likely be widely used in the development of smart cities. There are currently millions of devices spread throughout urban areas. It is predicted that billions of smart devices and sensors would be added to the world in the near future. Data flow from all these devices necessitates real-time analytics. The availability of low-latency computing resources on demand is one of the main benefits of edge computing, which enables near-instantaneous analytics. Further, data transfer between end devices and edge servers calls for cutting-edge, high-throughput communication solutions. However, smart city development must be long-lasting and trustworthy. In order to implement innovative technologies that make smart cities a reality, a number of stakeholders, including telecommunication network operators, edge computing service providers, cloud service providers, and the IoT service providers, will engage.

8. REFERENCES

[1] Y. Miao, K. Hwang, D. Wu, Y. Hao and M. Chen, "Drone Swarm Path Planning for Mobile Edge Computing in Industrial Internet of Things," in IEEE Transactions on Industrial Informatics, 2022, doi: 10.1109/TII.2022.3196392.

[2] Minh, Q.N.; Nguyen, V.-H.; Quy, V.K.; Ngoc, L.A.; Chehri, A.; Jeon, G. Edge Computing for IoT-Enabled Smart Grid: The Future of Energy. Energies 2022, 15, 6140.

[3] S. Yu, X. Chen, L. Yang, D. Wu, M. Bennis, J. Zhang, "Intelligent Edge: Leveraging Deep Imitation Learning for Mobile Edge Computation Offloading", IEEE Wireless Communications, vol. 27, no. 1, pp. 92-99, February 2020.

[4] M. Chen, Y. Miao, H. Gharavi, L. Hu, I. Humar, "Intelligent Traffic Adaptive Resource Allocation for Edge Computing-Based 5G Networks", IEEE Transactions on Cognitive Communications and Networking, vol. 6, no. 2, pp. 499-508, June 2020.

[5] M. Chen, Y. Hao, K. Lin, Z. Yuan, L. Hu, "Label-less Learning for Traffic Control in an Edge Network", IEEE Network, vol. 32, no. 6, pp. 8-14, 2018.

[6] Y. Miao, J. Xu, M. Chen, K. Hwang, "Drone enabled Smart Air-Agent for 6G Network," The 2022 IEEE International Conference on Communications (IEEE ICC), Gangnam-gu Seoul South Korea, 16-20 May, 2022.

[7] Q. Pham, et al., "A Survey of Multi-Access Edge Computing in 5G and Beyond: Fundamentals, Technology Integration, and State-of-the-Art", IEEE Access, vol. 8, pp. 116974-117017, 2020.

[8] F. Zhou, R. Q. Hu, Z. Li, Y. Wang, "Mobile Edge Computing in Unmanned Aerial Vehicle Networks", IEEE Wireless Communications, vol. 27, no. 1, pp. 140-146, February 2020.

[9] F. Costanzo, P. D. Lorenzo, S. Barbarossa, "Dynamic Resource Optimization and Altitude Selection in Uav-Based Multi-Access Edge Computing," IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020.

[10] Y. Chen, S. Chen, B. Wu, et al, "Cost-efficient computation offloading in UAV-enabled edge computing", IET Communications, vol. 14, no. 1, 2020.

[11] C. Zhan, H. Hu, X. Sui, Z. Liu, D. Niyato, "Completion Time and Energy Optimization in the UAV-Enabled Mobile-Edge Computing System", IEEE Internet of Things Journal, vol. 7, no. 8, pp. 7808-7822, Aug. 2020.

[12] Y. Qian, F. Wang, J. Li, L. Shi, K. Cai, F. Shu, "User Association and Path Planning for UAV-Aided Mobile Edge Computing With Energy Restriction", IEEE Wireless Communications Letters, vol. 8, no. 5, pp. 1312-1315, Oct. 2019.

[13] Y. Luo, W. Ding, B. Zhang , et al., "Optimization of bits allocation and path planning with trajectory constraint in UAV-enabled mobile edge computing system", Chinese Journal of Aeronautics, vol. 33, no. 10, 2020.

[14] Q. Liu, L. Shi, L. Sun , et al., "Path Planning for UAV-Mounted Mobile Edge Computing with Deep Reinforcement Learning", IEEE Transactions on Vehicular Technology, vol. 69, no. 5, pp. 5723-5728, 2020.

[15] K. Valavanis, G. Vachtsevanos (Eds.), "Handbook of unmanned aerial vehicles", Dordrecht: Springer Netherlands, 2015, ISBN 978-90-481-9708-8.

[16] Gouse Baig Mohammad, S Shitharth, Puranam Revanth Kumar. Integrated Machine Learning Model for an URL Phishing Detection, International Journal of Grid and Distributed Computing, vol. 14, Issue 1, pp. 513 – 529, 2020.

[17] Y. Xu, T. Zhang, Y. Liu, et al, "UAV-assisted MEC networks with aerial and ground cooperation," IEEE Transactions on Wireless Communications, vol. 20, no. 12, pp. 7712-7727, 2021.

[18] M. Y. Arafat and S. Moh, "Localization and Clustering Based on Swarm Intelligence in UAV Networks for Emergency Communications," IEEE Internet of Things Journal, vol. 6, no. 5, pp. 8958-8976, 2019.

[19] Gouse Baig Mohammad, S Shitharth. Wireless sensor network and IoT based systems for healthcare application, Materials Today: Proceedings, pp. 1-8, 2021.

[20] Salman Ali Syed, K Sheela Sobana Rani, Gouse Baig Mohammad, Krishna Keerthi Chennam, R Jaikumar, Yuvaraj Natarajan, K Srihari, U Barakkath Nisha, Venkatesa Prabhu Sundramurthy. Design of resources allocation in 6G cybertwin technology using the fuzzy neuro model in healthcare systems, Journal of Healthcare Engineering, vol. 2022, 2022.

[21] Kemal Polat, Raman Dugyala, N. Hanuman Reddy, V. Uma Maheswari, Gouse Baig Mohammad, Fayadh Alenezi. Analysis of Malware Detection and Signature Generation Using a Novel Hybrid Approach, Mathematical Problems in Engineering, vol. 22, Issue. 1, pp. 1-13, 2022.

[22] Rehmani, M.H.; Davy, A.; Jennings, B.; Assi, C. Software Defined Networks-Based Smart Grid Communication: A Comprehensive Survey. IEEE Commun. Surv. Tutor. 2019, 21, 2637–2670.

[23] Zhang, J.; Tao, D. Empowering Things with Intelligence: A Survey of the Progress, Challenges, and Opportunities in Artificial Intelligence of Things. IEEE Internet Things J. 2021, 8, 7789–7817.

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[24] Ghosal, A.; Conti, M. Key Management Systems for Smart Grid Advanced Metering Infrastructure: A Survey. IEEE Commun. Surv. Tutor. 2019, 21, 2831–2848.

[25] Liao, X.; Srinivasan, P.; Formby, D.; Beyah, R.A. Di-PriDA: Differentially Private Distributed Load Balancing Control for the Smart Grid. IEEE Trans. Dependable Secur. Comput. 2019, 16, 1026–1039.

[26] Wang, X.; Liu, Y.; Choo, K.-K.R. Fault-Tolerant Multisubset Aggregation Scheme for Smart Grid. IEEE Trans. Ind. Inform. 2021, 17, 4065–4072.

[27] Mehmood, M.Y.; Oad, A.; Abrar, M.; Munir, H.M.; Hasan, S.F.; Muqeet, H.A.U. Noor-bakhsh Amiri Golilarz, Edge Computing for IoT-Enabled Smart Grid. Secur. Commun. Netw. 2021, 2021, 5524025.

[28] Yaacoub, E.; Abu-Dayya, A. Automatic meter reading in the smart grid using contention based random access over the free cellular spectrum. Comput. Netw. 2014, 59, 171–183.

[29] Bera, S.; Misra, S.; Rodrigues, J.J.P.C. Cloud Computing Applications for Smart Grid: A Survey. IEEE Trans. Parallel Distrib. Syst. 2015, 26, 1477–1494.

[30] Rashid Mahamood, B. Shilpa. Design and Implementation of Framework for Smart City using Lora Technology, Sreyas International Journal of Scientists and Technocrats, vol. 1, Issue 7, pp. 36-43, 2017.

[31] Saleem, M.U.; Usman, M.R.; Usman, M.A.; Politis, C. Design, Deployment and Performance Evaluation of an IoT Based Smart Energy Management System for Demand Side Management in Smart Grid. IEEE Access 2022, 10, 15261–15278.

[32] Chen, S.; Wen, H.; Wu, J.; Lei, W.; Hou, W.; Liu, W.; Xu, A.; Jiang, Y. Internet of Things Based Smart Grids Supported by Intelligent Edge Computing. IEEE Access 2019, 7, 74089–74102.

[33] Xu, X.; Li, H.; Xu, W.; Liu, Z.; Yao, L.; Dai, F. Artificial intelligence for edge service optimization in Internet of Vehicles: A survey. Tsinghua Sci. Technol. 2022, 27, 270–287.

[34] R. Dong, C. She, W. Hardjawana, Y. Li and B. Vucetic, "Deep Learning for Hybrid 5G Services in Mobile Edge Computing Systems: Learn from a Digital Twin," in IEEE Transactions on Wireless Communications, vol. 18, no. 10, pp. 4692-4707, 2019.

[35] X. Xu et al., "Service Offloading with Deep Q-Network for Digital Twinning-Empowered Internet of Vehicles in Edge Computing," in IEEE Transactions on Industrial Informatics, vol. 18, no. 2, pp. 1414-1423, 2022.

[36] Jernej Protner, Miha Pipan, Hugo Zupan, Matevz Resman, Marko Simic, Niko Herakovic, Edge Computing and Digital Twin Based Smart Manufacturing, IFAC-PapersOnLine, Volume 54, Issue 1, 2021, Pages 831-836.