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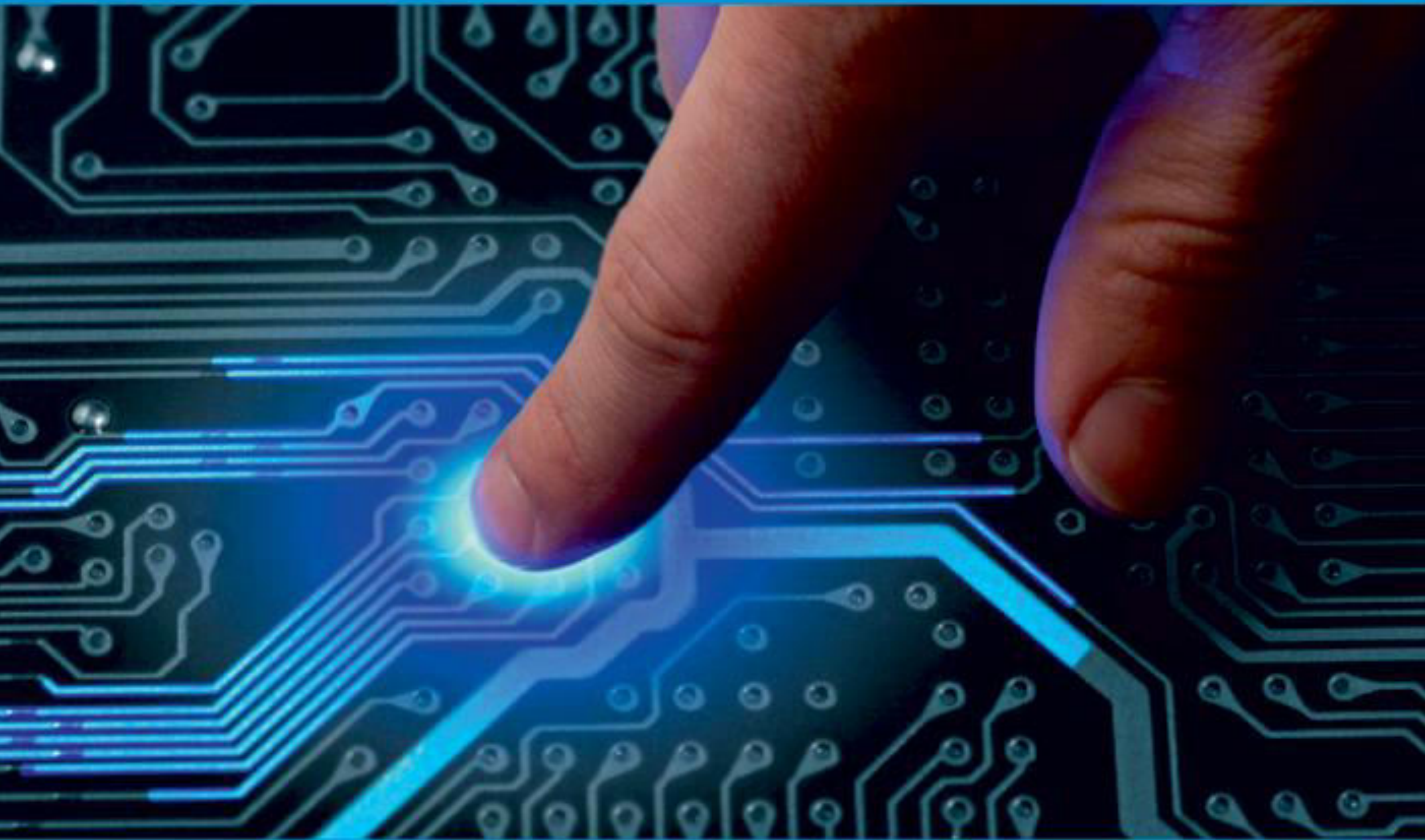

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Energy Efficient Routing Algorithm for Maximizing Network Lifetime of MANETs

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ABSTRACT: Increasing traffic and the number of people using mobile devices are both driving up the energy usage of mobile networks. There must be a focus on energy efficiency in the next generation of mobile networks in order to ensure their long term viability. Increasing the energy efficiency of 5G and beyond networks is addressed in this thesis in two ways, namely by reducing the network's energy usage and designing an energy-efficient network architecture. Base stations (BSs), the most energy-intensive aspect of mobile networks, are the subject of the first section of this thesis. A mobile network provider provides us with a data collection that includes information on network load. It is a challenge to use mobile network traffic data to train ML algorithms for sleep mode management decisions due to the coarse time granularity of data. We propose a method to regenerate mobile network traffic data taking into account the burstiness of arrivals. We propose ML-based algorithms to decide when and how deep to put BSs into sleep. The current literature on using ML in network management lacks of guaranteeing any quality of service. To handle this issue, we combine analytical model based approaches with ML where the former is used for risk analyses in the network. We define a novel metric to quantify risk of decision making. We design a digital twin that can mimic the behavior of a real BS with advanced sleep modes to continuously assess the risk and monitor the performance of ML algorithms. Simulation results show that using proposed methods considerable energy saving is obtained compared to the baselines at cost of negligible number of delayed users. In the second part of the thesis, we study and model end-to-end energy consumption and delay of a cloud native network architecture based on virtualized cloud RAN forming foundations of open RAN. Today large telco players achieved a consensus on an open RAN architecture based on hybrid C-RAN which is studied in this thesis. Migrating from conventional distributed RAN architectures to the network architectures based on hybrid C-RAN is challenging in terms of energy consumption and costs. We model the migration cost, in terms of both OPEX and CAPEX, with economic viability analyses of a virtualized cloud native architecture considering the future traffic forecasts. C-RAN based designs may be more cost-effective than D-RAN in some circumstances, although the infrastructure costs of fronthaul and fibre connections are not obvious. Optimizing the fronthaul using an integer linear programming (ILP) issue reduces the migration expenses. For big problem sizes, we present a heuristic technique based on artificial intelligence to handle the problem optimally. An important challenge in network design and administration is dealing with the tradeoff between energy consumption and latency. As part of a hybrid C-RAN design with many layers, we devise an ILP issue to reduce the network's energy usage while also enhancing latency by storing popular content near the edge. In addition, we look at the trade-off between network bandwidth use and total energy consumption. By finding a middle ground between several performance indicators, we show that intelligent content placement not only cuts down on latency, but also conserves energy. By creating logical networks that are specifically designed and configured for each service, we hope to achieve the same goal of cutting down on network energy usage. There has been a significant reduction in overall energy usage by network slicing, according to the scientific literature. In most research, only radio access network resources are included. When the RAN component of the network is taken into account, energy usage decreases as more bandwidth is supplied to consumers. A new model for energy consumption in the cloud and the fronthaul section of a network, described in this thesis, shows that increasing bandwidth allotment also increases processing energy consumption in both cloud and fronthaul. A non-convex optimization problem is developed to address this issue, and the network's energy consumption is reduced while the quality of service (QoS) of the slices is ensured. The issue is transformed into a second-order cone programming problem, and the optimum solution is found. End-to-end network slicing may reduce the overall energy consumption of the network compared to radio access network slicing, according to our study.

KEYWORDS: 6G, 5G, Energy efficiency, Machine learning, Reinforcement learning, Network architecture, Sleep modes, Mobile networks.

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I. INTRODUCTION

To meet the ever-increasing need for faster data rates and to provide a wide range of services with varying quality-of-service, the ICT sector is swiftly moving toward 5G and beyond networks (QoS). For 5G and beyond technologies, implementing and managing these different needs is a major problem. However, on the other side, 5G designs should meet the needs of various services that need higher bandwidth and reduced latency. As a result of increased data traffic and technology, greater investment costs and increased energy usage [4] are inevitable. Since improved signal processing methods are capable of processing vast amounts of data, it is necessary to review the present network structures and management procedures to take full advantage of these new capabilities. Modern networks are becoming more complicated as they grow in size and number of nodes to govern. Network management is becoming more complicated, and new technologies like artificial intelligence (AI) and machine learning (ML) hold great promise. Traditional methods are no longer sufficient to cope with the new issues created and the increased complexity of 5G and future networks, on the other hand.

Using AI and ML-based strategies, we address the problem of lowering future mobile networks' energy consumption and improving their sustainability after looking into energy and delay-aware resource allocation in mobile networks in [12–25]. We emphasise the possible prospects, constraints, and outstanding issues of energy conservation at various network levels. We're particularly interested in ways to reduce energy at base stations, eco-friendly network topologies, and techniques for cutting consumption while still keeping the QoS that's been promised. Research topics around base station energy conservation will be examined as part of this thesis (BSs). While working to reduce power consumption at the BSs, this section also aims to avoid performance deterioration. This research aims to provide a framework for determining and managing the risk associated with base station energy saving features. This is very important in the network, since energy savings are often accompanied by a decrease in performance. Thus, it is critical to monitor and maintain the lowest feasible performance deterioration.

For the next step, we look into the end-to-end network architecture and investigate the open problems and research gaps in green network architecture design. We argue that the current network architecture is not designed for multitudes and heterogeneous services and we need to move on to the new architecture. Therefore, we investigate different aspects of novel network architectures ranging from migration cost to them, to supporting numerous services, and to tailoring network resources for specific services. In this section of thesis, we mainly focus on end-to-end network design to 1) evaluate the migration costs to the new green architectures, and 2) propose joint network resource allocation for improving the QoS of the users and services while minimizing the energy consumption. The proposed solutions are evaluated with numerical experiments and the experiments results well prove the efficiency of the proposed solutions.

Related work

A. Green Networks

During the previous decade, green networks have been extensively explored in both fixed (44–46) and wireless (47–49) networks. A large number of research in both domains have focused on putting various parts of the network to sleep, decreasing the active portions of the network (such as dependability, throughput, or latency), or using power management to challenge multiple network performance criteria. BSs account for a significant portion of the total network's energy usage, according to research [51]. BS energy reduction must be achieved while avoiding any negative influence on the quality of service (QoS) provided to customers, such as delays in data transmission [25, 52], if these networks are to remain operationally viable. Based on (de)activation time scale, it has recently been demonstrated in [10] that BS transceiver chain components may be separated into four categories by their components. Sleep modes allow a collection of components to be put to sleep at the same time for a predetermined amount of time (SMs). It is possible to save BS electricity by using SM, however this comes at the expense of occasional service disruption. Delays or drops may be more noticeable during the daytime when network traffic is often more congested. Consequently, careful deployment of the SM is necessary to avoid a decrease in quality of service (QoS). BS density and traffic load affect potential energy savings, as the authors in [53] find out when looking at cell DTX in heterogeneous networks. Load-adaptive SM management is the goal of the research in [54], which takes into account long-term, deep SM. An evaluation of how 4G BS sleep affects QoS, such as dropping/delay, is presented in [55]. Based on Tokyo traffic statistics, [56] assesses the ON/OFF status of small-cell mm-wave antennas [56]. An ASM-based stochastic model for adjusting the BSs configuration is proposed in [57].

It's recently become popular to employ machine learning (ML) to handle BS sleep modes (SMs) operations. Implementing such SMs, on the other hand, may reduce BS energy, but at the expense of causing service delays for end customers. ASMs must be used in a way that does not adversely affect the quality of service (QoS) provided to end users. Using ML in ASMs has been shown to result in significant energy savings at BSs [58–63]. Using a predetermined sequence of (de)activation, the authors in [58–60] look at four SMs in detail. They make the decision on how long each SM will last. A heuristic technique for implementing ASMs is provided in [58]. Synchronization

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signalling frequency has an influence on ASMs' ability to save energy. An approach that uses Q-learning to identify the best SM is proposed in [59]. Using a Q-learning algorithm, they offer a traffic-aware technique for creating a codebook that maps traffic load to alternative actions. In these research, the authors assume a predetermined sequencing of actions that may not result in optimum energy savings. According to the researchers in [61], they suggest an algorithm for selecting SMs that takes into account traffic. They do, however, use a predetermined traffic pattern to train their network. The research in [62] suggests a separation of the control and data planes in 5G BSs in order to achieve deeper SMs, such as SM4, or longer SM durations since control signalling may restrict the energy savings of ASMs. Co-coverage situations, where basic coverage cells may convey all periodic control signals but capacity-enhancing ones have a stronger ability to sleep and save energy, may also benefit from this separation. For the sake of [63], we suggest a distinction between "high" and "low" loads, which we refer to as "states." Although this research relies on tabular approaches, it is confined to just two load levels and hence cannot capture long- and short-term temporal relationships.

B. Network Architecture Design

On the one hand, mobile networks are using more energy, while on the other side, more services are being added to the network. It is currently unable to handle diverse services in terms of energy consumption and capacity in a distributed network architecture currently in use. As a result, new designs must take into account a variety of factors, such as energy consumption, cost, operation and maintenance, delay, and handovers. Centralized and virtualized network designs are viable options for a network with a rising number of services and increasing energy usage. C-RAN technology has received a lot of attention lately. It is the primary goal of C-RAN to centralise all digital baseband computing and cooling at selected cluster centres, leaving behind just RF and analogue processing at the cell sites for the purpose of cost and energy consumption reduction." Additional advantages of this centralization include the ability to provide coordinated multipoint (CoMP) technology, which allows for millisecond-scale inter-cell coordination, leading to greater resource efficiency and EE, particularly for users near the cell's edge. CoMP technology. C-RAN designs have several benefits, but there are also some drawbacks that need to be addressed in the literature. The capacity of connections between radio units and the centre cloud may not be sufficient at certain times of the day when all processing units are centralised. Media connecting radio units and cloud must be scalable, low-cost and capable of handling raw I/Q signals for transmission to the cloud at the same time. Furthermore, the network is burdened with an additional transit delay, making it more difficult to handle time-sensitive applications. While attempting to offer as many different services as possible, the C-RAN design has evolved over the last several years in order to minimise its impact on the environment. C-RAN design may be improved by adding another layer of processing, allowing for the distribution of processing duties between the centre cloud and a new layer called edge cloud. As suggested in SooGREEN, this adaptable and semi-centralized architecture is referred to as a hybrid C-RAN (H-CRAN) by us. The physical layer network function splits in H-CRAN are tuned to decrease power consumption and midhaul bandwidth in tandem. In a three-layer design, H-CRAN builds on the prior C-RAN structure by functionally separating the processing responsibilities between CC and EC. As seen in Figure 1, the progression of DRAN to H-CRAN is shown. Each radio unit in DRAN is equipped with a digital unit and is linked to the main network through a backhaul connection. Fronthaul links are used to connect all digital units and RUs in C-RAN to this pool of digital units and RUs. One of the advantages of H-CRAN is that it provides an additional layer of processing that may be dispersed across RUs and DU pools (central cloud). Several research attempts have been made in the aim of creating a practical H-CRAN. EC, CC, and the cell layer make up H-three CRAN's layers. User equipment is served by RUs that are being densely packed in the cell layer (UEs). The ECs and RUs are linked. The data from a set of REs is gathered at an EC, which serves primarily as an aggregate point. MmWave lines are considered to be the primary means of communication between RUs and ECs. Additionally, the ECs send the aggregated data to the CC through midhaul. It is possible to execute function processing on requested material by using DUs in the CC and ECs of this architecture. By pooling their computing resources, these DUs may be used to support any linked RUs. Traffic from cells may be partly processed at the EC so that bandwidth requirements for midhaul connections can be lowered, and the remaining processing will take place in CC. There are more units in an EC than there are in CCs, which means they are less efficient at using energy. As a consequence, by pooling infrastructure resources, the CC is able to save even more energy. The decision is whether to reduce bandwidth and increase delay performance by dispersing functions at the ECs, or to benefit from the inherent power savings that occur with centralising all operations at CC. Delay-sensitive services may be offered at the EC, while delay-tolerant applications can be served at the CC to take use of the energy-saving properties of the cloud in the H-CRAN system. In light of the delay restrictions, we further disperse the processing operations to address the issue of capacity limitation in the fronthaul.

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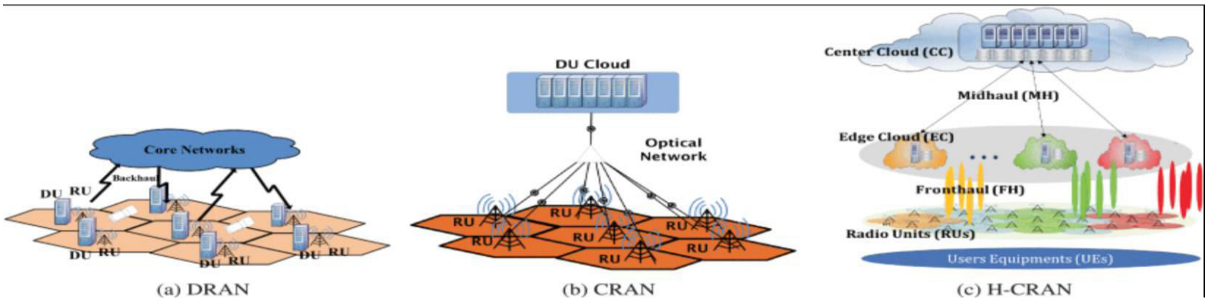

Figure 1: Evolution of RAN (DRAN/C-RAN/H-CRAN) [4].

1. Functional Split

Although the C-RAN concept is intriguing, there are still a number of issues that need to be addressed before it can be implemented in the real world. Fronthaul signal bandwidth may be greatly upscaled by many orders of magnitude compared to its previous DRAN design if all physical layer processing, including channel coding, modulation, and Fast Fourier Transform (FFT), is fully centralised. That is, when technologies like large MIMO are used, such an impact may be considerably more restrictive. This is a problem both upstream and downstream. CoMP joint reception, for example, necessitates an increase in fronthaul bandwidth because of the need for better signal resolution (finer quantization). In order to maintain the scalability advantages of C-RAN while alleviating bandwidth congestion and permitting efficient CoMP coordination for cell-edge users, more convenient and possibly flexible intermediate functional splits must be investigated.

As illustrated in Figure 2, we simulate the functional division of the baseband processing chain for cells and users in order to examine how EC and CC handle function processing. Cell processing (CP) and user processing (UP) are two types of baseband processing services. The cell's signal processing activities are included in the CP, which is part of the physical layer. Serial to Parallel Encoding, FFT, Cyclic Prefix and Resource Mapping are some examples of CP functions. Similar to the physical layer, the upper layer of the UP is responsible for signal processing for each user in a cell and comprises a set of functions. Antenna mapping and forward error correction are just a few examples of UP functions in action. Fig. 1.7 shows that the split might occur either before Split 1 or after Split 7, or anywhere in between these two points. C-RAN is the consequence of a split at Split 1 in which all functions are centralised at the CC. All functions are consolidated at EC when Split 7 occurs, resulting in DRAN. CC and EC are used for functions above and below a split, respectively, when it occurs in between.

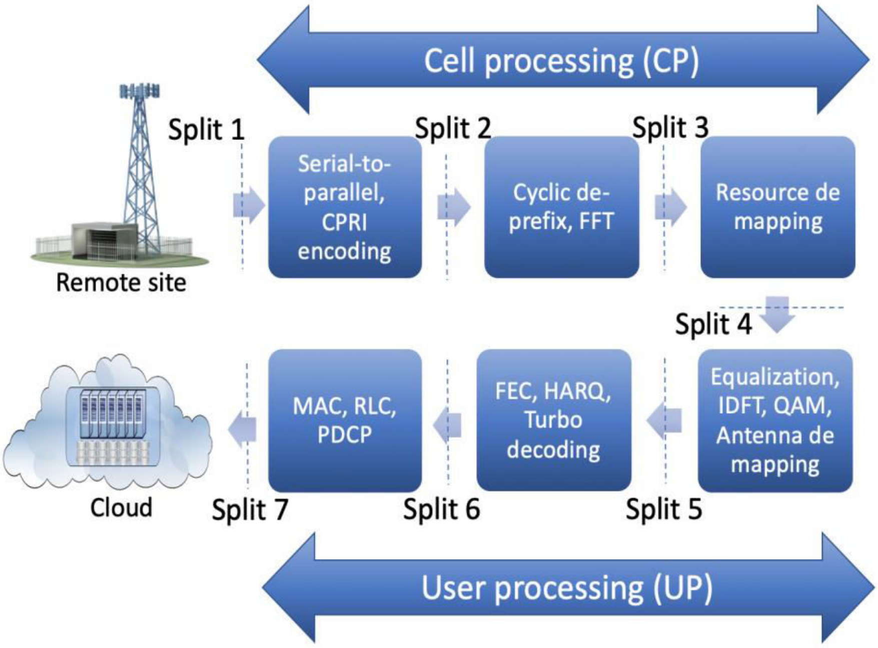

Figure 2: Functional split model [5].

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2. Network Architectures and Migration Costs

C-RAN, despite its many benefits, presents significant obstacles for the operators to implement it. In [64], the advancement of C-RAN and its significant problems are covered. Assuming that all network functions are consolidated in the base band unit (BBU), C-RAN may need 160 Gbps of throughput with a latency of 10 to 250 microseconds [65]. As long as lower physical layer (PHY) functions are maintained in close proximity to the RUs, these criteria become more lenient. Fronthaul transport link requirements for lower-level PHY functions, such as split 4 in Figure 2 (approximately 933Mbps), are only around 40% of those required for a completely centralised scenario. Cell-processing (CP) and user-processing (UP) are two subsets of the baseband processing capabilities shown in Figure 2 Signal processing and physical layer operations, such as serial to parallel, CPRI encoding, and resource demapping, are the focus of CP functions. Per-user signal processing, such as equalisation and turbo coding, is handled by UP. It is feasible to divide this chain of processing using functional splitting in C-RAN [4]. There are different fronthaul requirements depending on the functional split point. As with classic C-RAN, maximum energy savings and virtualization may be achieved when all functions are centralised in the cloud. Although this may not be practicable owing to the restricted fronthaul capacity, employing alternative split points supported by the cost-effective fronthaul is preferred [66]. Table 1 summarises the capacity requirements for fronthaul connections as shown in Figure 2 and Table 1 depicts alternative split places [7, 66]. Passive optical networks are the best choice for fronthaul transport since they meet these criteria [67]. As a result, new design difficulties need to be addressed. Pool location, fronthaul architecture, and network cost are all issues that need to be addressed in order for the processing to be centralised.

Table 1: Fronthaul capacity requirement for different split points

	Capacity requirements (Mbps)						
Split point:	7	6	5	4	3	2	1
Downlink	151	151	173	933	1075	1966	2457.6
Uplink	48	49	452	903	922	1966	2457.6

An energy efficient aggregation network and a pool placement optimization issue were presented by the authors in [68] to address these difficulties. For each DU pool, the authors in [69] devised an optimization problem in order to reduce deployment costs. One of the most significant issues with C-RAN is the fronthaul limitation, which requires a particular latency, infrastructure deployment, and pool location. For next-generation optical access networks, the authors in [70] provided an outline of the fronthaul needs and recommended topologies and transmission technologies. According to [71], the fronthaul restriction may be handled with numerous techniques, including signal compression and quantization as well as coordinated signal processing. The research in [72] examined the effect of cellular network delay performance on wired and wireless backhaul. Backhaul infrastructure costs were also taken into account in this analysis.

A detailed network cost model is necessary to evaluate the financial aspects of the network. The backhaul network's influence on TCO was studied by the authors of [73] who simulated the power consumption of backhaul in several situations. If a backhaul solution like fibre optic architecture is used, the backhauling power consumption will be a tiny percentage of the radio access power consumption. [74] tried to calculate the overall cost of backhauling using two alternative technologies, namely microwave and fiber-optic backhaul. Fiber was shown to be the most promising backhaul technology in terms of capacity and latency, according to this research.

Taking into account all of the network expenses is necessary in order to offer a technological and economic foundation for C-RAN architectures. TCO is used as an assessment parameter in the research [32,75–79]. An approach to evaluating TCO for various technologies was described in [75]. Optical access technology migration costs were the primary focus of this research, which also took into account infrastructure and technological upgrades. Scalability, CapEx and OpEx, as well as the unpredictability in various phases, such as demand and penetration index, are all taken into account in the TCO model given by the authors [76] in their paper. They've found that the highest projected benefit is highly dependent on the allocation of resources. According to [77], the cost of moving to a passive optical network was studied in terms of both infrastructure and technological upgrading costs. Different migration beginning periods, customer penetration, node consolidation and network provider business responsibilities in fibre access networks have all been taken into account in this research by the authors. To evaluate both the TCO and the financial viability of various deployments, researchers in [78] developed a complete techno-economic framework. NPV and cash flow should also be taken into account when evaluating the profitability of alternative designs, according to the authors. Fiber and microwave architectural expenses were modelled and the TCO was estimated for various geographic locations in [79]. Fronthaul design and functional splitting are lacking from their research.

A constraint programming approach was used to construct the TCO reduction issue in [32]. The authors of this research discovered the ideal moment at which a radio unit and a digital unit should be functionally divided. After all,

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the issue of choosing the best site for a swimming pool was not addressed. A fixed wireless access network's x-haul section was analysed in a cost-benefit analysis in [80].

II. AI ASSISTED GREEN MOBILE NETWORKS

A. Risk Aware Sleep Mode Management

In this section, we propose a framework for risk-aware sleep mode management. AI or machine learning algorithms are prone to anomalous and unknown data and their performance can be inadequate or sub-optimal. A mechanism is needed to define the risk, monitor the performance of AI with respect to the input traffic to find out whether re-training is needed. As shown in Figure 3, we use a DT that gets the network data, communicates and mimics the performance of the real system including the AI module, and assesses the risk. Based on this assessment and the risk in the real network, we decide whether to use the AI, retrain the network, or temporarily deactivate the AI module. In the following we explain this approach in detail. First, we introduce the concept of risk associated to the BS sleeping algorithms. We explain the DT model for BS ASM management to estimate the risk. Then, we combine the intelligent sleep mode management and DT and explain the framework for risk-aware BS sleep mode management as is depicted in Figure 4.

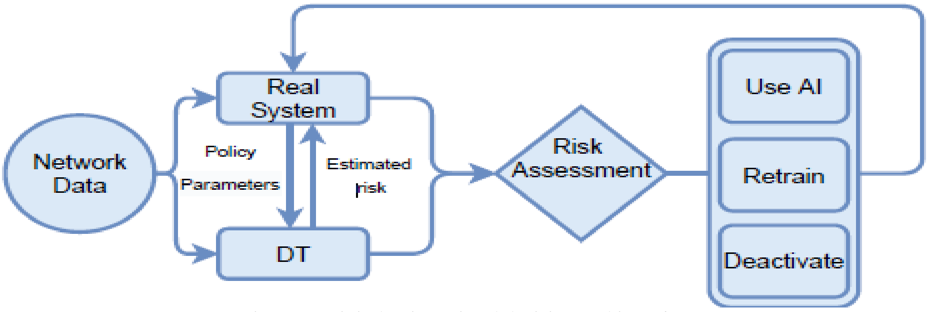

Figure 3: Digital twin assisted decision making [6].

1. Risk Definition

In this study, risk refers to a situation in which SM management algorithm takes sleep decisions resulting in delays in connection setup time of future user arrivals. The more users experiencing delay, the higher value of risk should be associated to the situation. Therefore, if the risk could be measured in advance, BS can avoid delaying large number of users. For this purpose, we utilize the DT concept as a virtual representation of the BS sleeping process.

In Fig.2.3, we illustrate the proposed a DT assisted risk aware SM management framework. In this scheme, the physical network provides the required information, e.g., duration of sleeping, ON/OFF state duration, sleeping time, and arrival rate. The observed information is fed to the virtual network to update the model parameters and predict the RDM in the network using Equation (2.11). Hence, the DT can predict the risk utilizing the Markov model and its updated parameters. The Markov model together with the update parameter step constructs the virtual network. The output of virtual network is used to predict the risk. This risk is compared with the threshold set by the operator and the actual risk (which will be available in future). If the predicted risk is higher than the threshold, the SMs should be deactivated. If the predicted risk is higher than the actual one, it is possible that the algorithm needs to be retrained. Otherwise, if RDM is below the predefined threshold, BS can activate the SMs and benefit from BS sleep mode management algorithms. This algorithm is designed and explained in Paper 3. Using the risk monitoring procedure in Figure 4, the operators can make sure that their sleep mode management algorithm does not take sleep decisions when there are user arrivals or is not missing the opportunity of energy saving when it is safe to save energy

2. Risk Management

In this section, we propose a framework for risk-aware sleep mode management. First, we introduce the concept of risk associated to the BS sleeping algorithms. We quantify the risk and formulate it based on the proposed hidden Markov model for BS ASMs. Then, we propose a solution for BS ASM management to estimate the risk. Finally, we propose a framework for risk-aware BS sleep mode management to combine intelligent sleep mode management and hidden Markov model based risk estimation.

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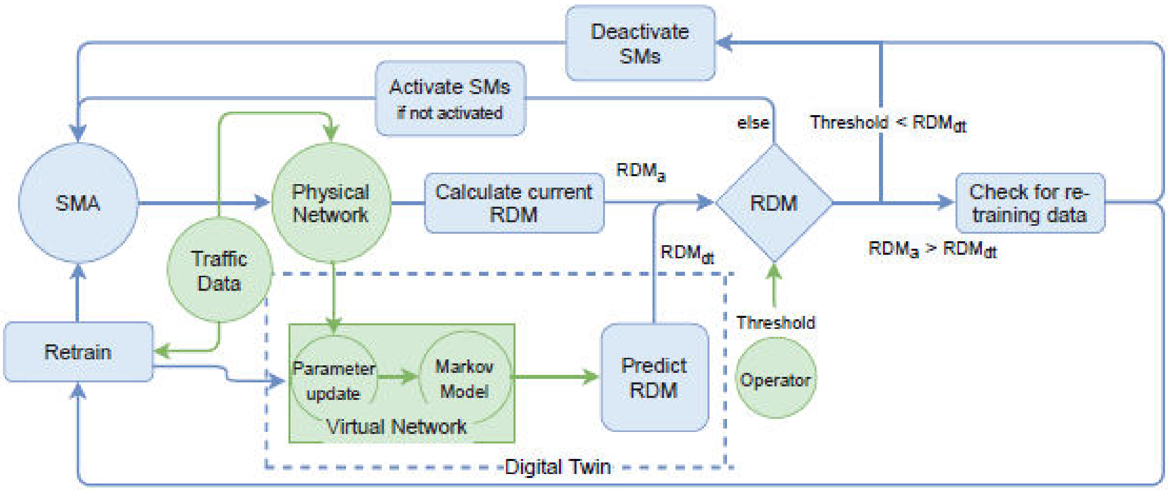

Figure 4: Digital twin based risk aware sleep mode management [6]

In this paper, risk refers to a situation in which SM management algorithm takes sleep decisions resulting in delays in connection setup time of future user arrivals. The more users experiencing delay, the higher value of risk should be associated to the situation. Therefore, if the risk could be measured in advance, BS can avoid delaying large number of users. For this purpose, we utilize the the hidden Markov model, as a virtual representation of a process, in our case BS sleeping. The model is continuously updated from real-time data, and uses machine learning and reasoning to help decision-making. Therefore, it helps us understand the present and predict the future performance of the BS sleeping performance metric, e.g., sleeping duration, probability of delaying users, and the risk for each state of the network. In the following we explain the Markov model for BS sleep mode management algorithm.

3. Digital Twin Model

In this study, as is depicted in Fig.2.3, the digital twin has three main parts, 1) parameter update, 2) network model, and 3) prediction. The former two constructs the virtual network, representative of the physical network. The model is continuously updated from real-time data, and uses machine learning and reasoning to help decision-making. The network is modeled as hidden Markov process and in the prediction phase we use the updated virtual network to estimate and predict the future performance metric of the BS sleeping, e.g., sleeping duration, probability of delaying users, and the risk for each state of the network. In the following we explain the Markov model for BS sleep mode management algorithm.

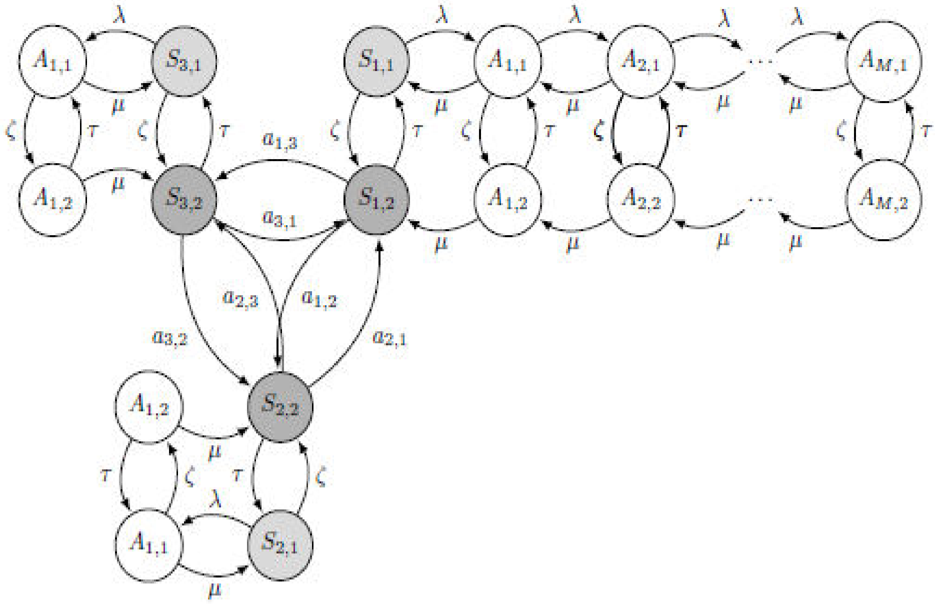

Figure 5: Markov model for advanced sleep mode management [6].

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4. Virtual Network Model: A Hidden Markov Process
In the DT, we require a realistic analytical model that can estimate the actual behavior of ML based BS sleep mode management as a virtual network. In particular, we model the system as a hidden Markov model1 depicted in Figure 5 where the states, input traffic, and model parameters are obtained by the interaction with the physical network environment. The environment is defined as the load in the system and level of sleeping. In the following, we present the hidden Markov model, required information, performance metrics, and a framework for risk monitoring in the system.

III. AI ASSISTED NETWORK ARCHITECTUREDESIGN AND MANAGEMENT

A. Cloud RAN Network Architecture Power and Delay Models

Centralization of RAN operations provides a number of benefits, including improved cooperative solutions, better load balancing, and the ability to share RANs. On contrast, it might present key issues such as migration costs, offering low-latency services, and demanding large bandwidth in the transport layer. Various network topologies and approaches have been developed to overcome these problems. Some lower-layer network operations may stay close to the RU to decrease fronthaul bandwidth needs, for example, which implies that processing functions must be separated [110] and dispersed across two levels of processing in order to reduce centralization. Therefore, a separate layer of network processing is needed to handle the processing of the network services that are not fully integrated. High-speed, low-latency transport links this layer to the core cloud. Because of this, the transportation connection is an essential part of the design of the network An X-haul transport connection might be front- or mid-haul in nature. This connection may be built using several technologies, such as passive optical network (PON), Ethernet network, or time-sensitive network, and it uses CPRI or eCPRI to send data to the cloud. Each of these technologies has its own set of advantages and disadvantages that make it a better choice in a certain context.

1. Conventional C-RAN Architecture
In conventional C-RAN architecture, as depicted in Figure 6, the digital units (DUs) are residing in a central cloud (CC) and are connected to the RUs via fronthaul links. Fronthaul is a transport network that connects the RUs to the central cloud. The central cloud is responsible for the base band processing. The main issue with this architecture is that the fronthaul links may not be enough to transport the I/Q signals from RUs to the DUs. Therefore, we need to lessen the load from the fronthaul. This can be done by adding another processing layer, called edge cloud, between the RUs and central clouds.

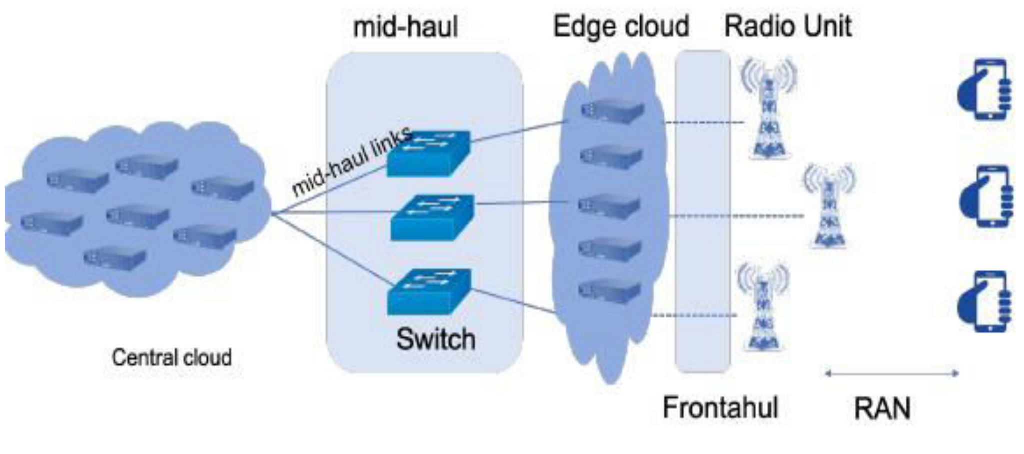

Figure 6: Basic C-RAN architecture.

2. Hybrid C-RAN
There is a central cloud and several edge clouds shown in the figure, where DUs are deployed at both the central cloud and the edge cloud (EC). As a result, central clouds and edge clouds may both be used to disperse baseband processing. Furthermore, both CC and EC may be outfitted with RAM that can be used for caching popular content. Cell layer, edge cloud, and central cloud make up H-three-layer CRAN's architecture. The cell layer is made up of increasingly dense cells, each of which serves a number of UEs.
A DU and an RU may form the edge cloud, which are essentially a DU and an RU. The DU handles a portion of baseband processing, while the CC handles the remainder. The fronthaul connection connects EC and RU and may

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be coaxial cable, fibre optic cable, or Ethernet cable. The midhaul connection between EC and CC may be a fibre link employing various technologies, such as TWDM-PON or Ethernet base networks. In Fig. 3, you can see this design in action. The midhaul/fronthaul connection connections, which connect EC and CC, are known as the common protocol radio interface (CPRI). On the one hand, the midhaul/fronthaul capacity needed in 5G networks is increasing despite the restricted capacity of these linkages. Consequently, there will be an increase in traffic on the linkages between the RUs and DUs. eCPRI (evolved CPRI) is being adopted to guarantee that bandwidth expectations for 5G are not exceeded. This standard supports 5G and allows for enhanced efficiency in order to satisfy 5G network requirements. With the eCPRI standard, the PHY of the BSs may be divided into two separate functional areas, unlike CPRI. A packet-based midhaul/fronthaul network, such as IP or Ethernet, is used for flexible radio data delivery. Due to the lower cost of traffic aggregation and switching provided by packet-based Ethernet midhaul/fronthaul, it may lower network costs compared to more traditional WDM-based networks. [111] Industry is interested in packet-based transport architectures. It is possible to meet the latency, throughput, and reliability requirements of sophisticated 5G applications by using the eCPRI protocol. Because it is an open standard, the eCPRI may be used by a variety of carriers, enabling them to collaborate in a manner that improves global connectivity and speeds [112]. When compared to CPRI, eCPRI has several benefits, including the following:

- Ten-fold reduction of required bandwidth
- Required bandwidth can scale according to the to the user plane traffic
- Ethernet can carry eCPRI traffic and other traffic simultaneously, in the same switched network
- A single Ethernet network can simultaneously carry eCPRI traffic from several system vendors.

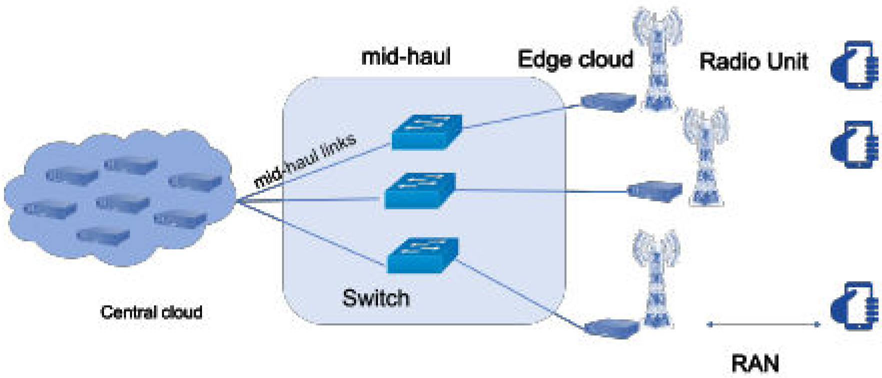

Figure 7: Two layer CRAN architecture.

The EC may share space with RUs in H-CRAN. As an additional option, you might link more than one remote unit (RU) together via an EC. The EC serves as an aggregation point for a set of cells/RUs. It is possible to use wireless communications, such as mmWave links, to connect a cell to an EC. TWDM-PON technology is used to link the ECs to the CC midhaul. For both the edge and central cloud layers, containers for virtualized functions (DUs) are used, which are containers for virtualized functions. As a result, EC is less efficient than CC because of the greater number of DUs at the CC. Figure 8 depicts this design.

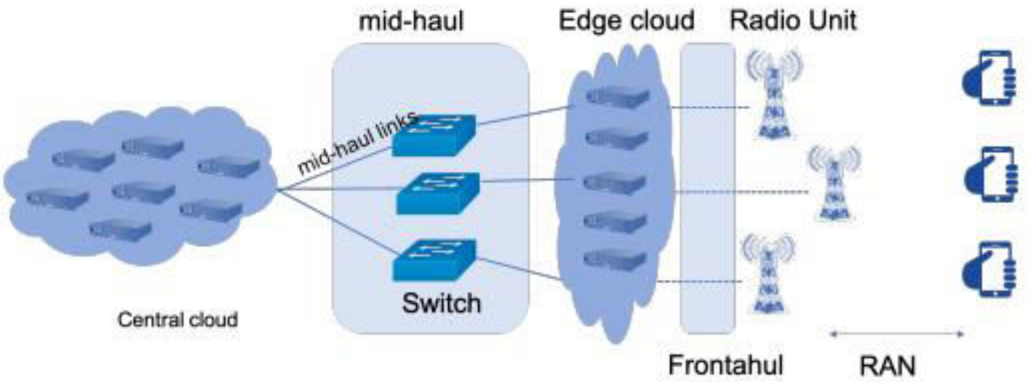

Figure 8: Multi layer C-RAN architecture

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IV. Simulation Results

A. AI Assisted Green Mobile Networks

Python is used to create an event-based numerical simulation, which runs the proposed adaptive algorithm and baseline equivalents alike. Using OBS as an upper limit on energy savings, we compare the SMA algorithm's performance to that of the fixed sleep mode where only SM1 may be employed. All consumers are provided immediately and without any incurred delay in these baselines. A comparison with SARSA algorithm results is also made [63]. There are no surprises when it comes to new users and their active hours in OBS. Inactive intervals may be filled with the appropriate SM if BS scans all inactivity periods. We proceed in accordance with the steps outlined in [63]. This information must be processed before it can be included into our simulation tools. The produced load and the original data set normalised average load are shown in Fig. 9a. Comparing the created data to the original data reveals that the average daily behaviour of the generated data is preserved. The arrivals are shown in Fig. 9b on a time scale of five seconds. The parameter α prioritizes the power saving or incurred delay in the reward function. In Fig. 10 we present the performance of the proposed algorithm, i.e., SMA, with regards to the α. The higher α is, the less weight is assigned to energy saving. We compare the performance of SMA with OBS algorithm defined in [63], as an upper bound on energy saving gain. OBS is always optimal and non-causal due to the knowledge of future information. For α = 0 the total reward includes only energy saving reward. SMA can achieve optimal energy saving but at cost of incurring delay to the users. When latency is more prioritized, the BS becomes more conservative to choose deeper SMs and prefers shallower SMs. Therefore, less energy is saved in favor of less incurred delay. SMA outperforms fixed SM where only SM1 is in use, in which BS cannot benefit from deeper SMs and miss the energy saving opportunities. Moreover, SMA performs better than SARSA algorithm because SMA can find better long-short term dependencies in traffic data and hence leverage this information to find a better energy saving policy. The Fig. 11 illustrates the absolute energy consumption of the SMA compared to the three cases: 1) when no sleeping is used, 2) when only SM1 is used, and 3) the optimal energy saving approach. During the rush hours the SMA mostly chose to go to the shallowest SM hence the performance is very close to the only SM1. Moreover, during these hours there is not room to save energy and hence it is meaningful to be more conservative about delaying users and let the BS be either awake or benefit from the SM1. Figure 12 shows the normalized energy saving performance of the SMA and OBS over 24 hours. The values are normalized with regards to the maximum energy saving of OBS algorithm. Hours between 2:00-6:00 AM are the best hours of a day with the highest energy saving potentials. The least opportunity for energy saving happens in the evening at about 18:00. It is worth mentioning the data set under consideration is for an area which is dominated by the industrial buildings. The traffic pattern and hence the energy saving patterns depend on the type of area.

In Figure 13, we plot the performance of risk aware BS sleeping algorithm. Using the procedure in Fig. 10, BS calculates the risk value and when the risk is high it temporarily deactivates SMs. When SMs are deactivated, BS calculates the potential risks and when the risk is small again for a while, i.e., for duration of T, it activates the SMs again.

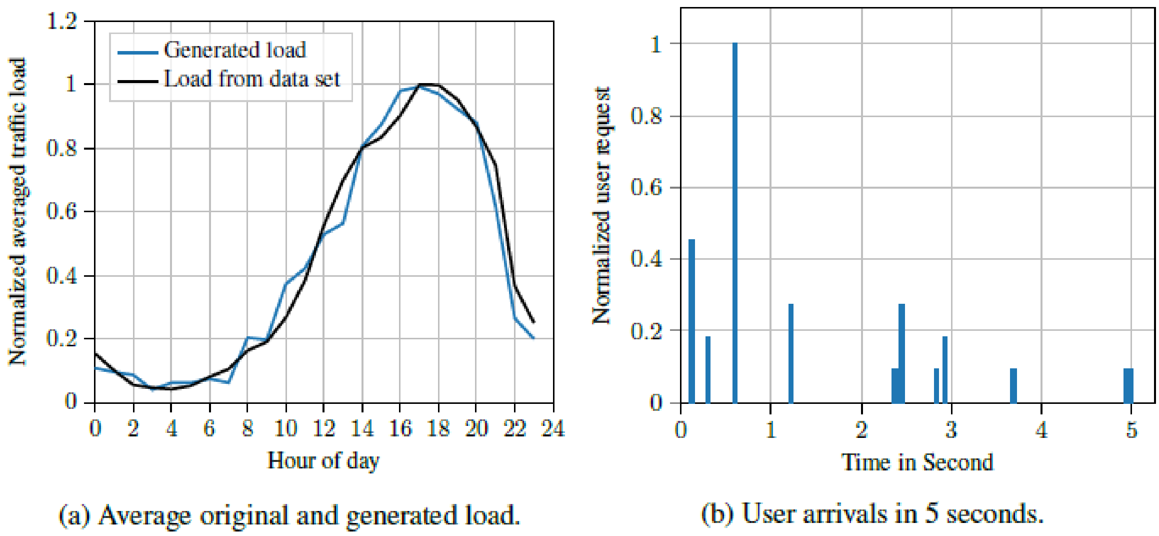

Figure 9: Network load generation as input to the network for τ = 0.1 and ζ = 0.5 [6].

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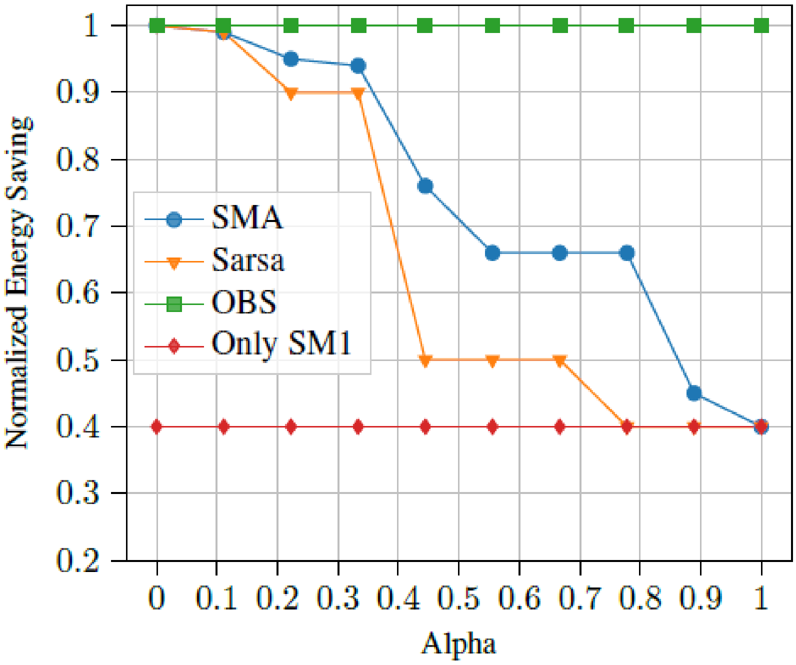

Figure 10: Energy saving vs delay trade-off [6]

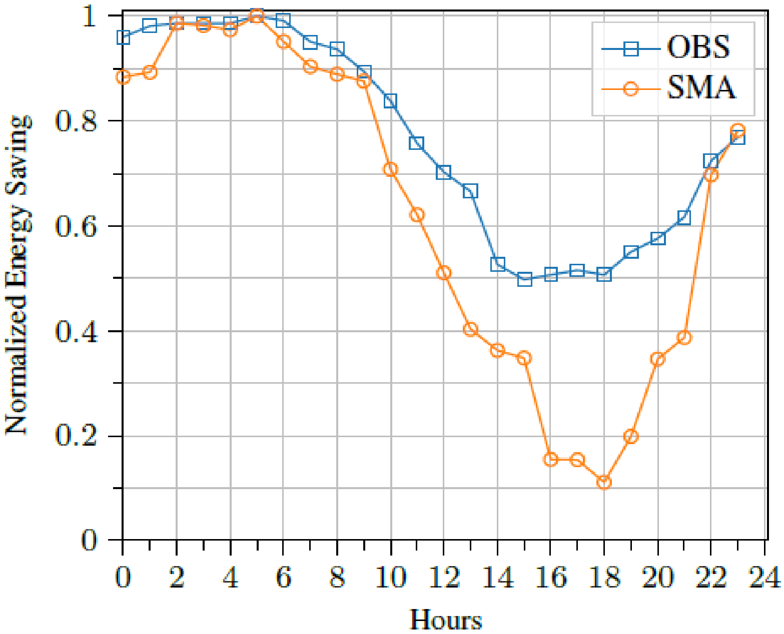

Figure 11: Normalized daily profile of energy saving [6].

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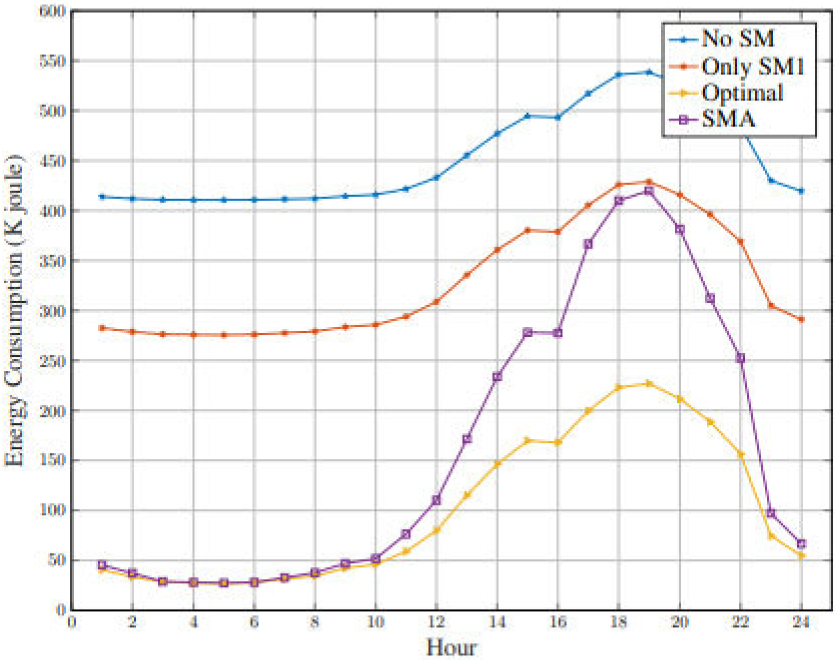

Figure 12: Daily profile of energy consumption.

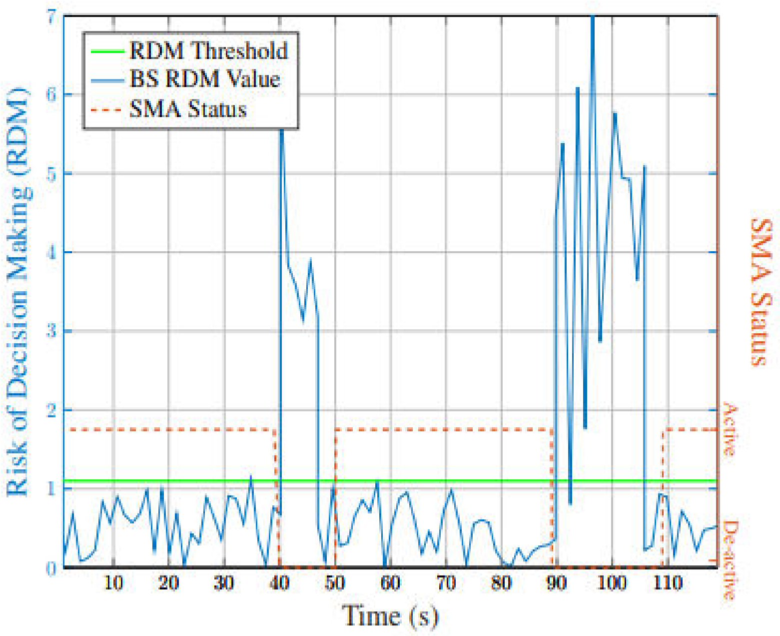

Figure 13: Performance of risk management algorithm [6].

B. AI Assisted Network Architecture Design And Management

In this section, we provide the selected results to evaluate the performance of the proposed end-to-end slicing method, i.e., slice-based resource allocation (SBRA), and compare it with the baselines. In this study, we assume that the expected number of users in each slice is provided to the slice manager in advance. Therefore, the respective optimization problem is solved to reserve resources for the future. We consider a network with |R|= 4 number of RUs and |S|= 4 slices namely, critical MTC, eMBB delay sensitive, eMBB delay tolerant, and massive MTC. The maximum tolerable delays for these slices are 10, 50, 100, 150 ms, respectively. The users' file sizes for each slice are 0.1, 2, 2, 0.1 MB, respectively. We assume that the 5G NR numerology index is 0, otherwise stated. We assume that each BS is equipped with a single RU and DU, and the slice duration (slice window) is T = 1 s. We assume that the processing

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limit of DU of the BS is the same as that of the DUs at the CC. Moreover, the processing resources of the BSs in (3.5) are allocated proportional to the load of each slice

We compare the proposed solution with two cases: RAN slicing and user-based resource allocation (UBRA). With RAN slicing us only allocate the bandwidth to each slice and the computation resources are assumed to be fixed and given. We assume that the allocated computation resources are enough to serve the peak load and this amount is fixed for all loads. Comparing with this baseline, we can highlight the impact of considering computation resource allocation. For UBRA, we create an end-to-end slice per user and we allocate processing resources in CC and bandwidth in RAN to each user. Comparing the SBRA with UBRA, we can demonstrate how the proposed SBRA can decrease the complexity of the network slicing and how close the solution is to optimal solution. In Figure 14, we illustrate the hourly energy consumption of the network for two cases of SBRA and RAN slicing. To generate this figure, we use the real network data from BSs in rural area of Uppsala County. We extracted the number of users belonging to the eMBB delay sensitive and eMBB delay tolerant services in each hour of a weekday as is depicted in the right hand side axis of Fig. 3.13. Since the information on the massive MTC and the critical MTC services is not available in the data set, we set the number of critical MTC users to 1 and the number of connected massive MTC devices to 100. As can be seen from this figure, SBRA performs better in off-peak hours of the day because it will utilize less processing resources and hence can turn off the unnecessary equipment. However, in RAN slicing the processing resources can be only in idle mode, consuming energy. On the other hand, in the peak hours of the day, the network energy consumption difference is smaller because most of resources are in use in both methods. However, still SBRA slightly outperforms RAN slicing due to end-to-end resource allocation. Figure 15a compares the allocated processing resources per user per slice for SBRA. According to this figure, the SBRA will give us an estimate of the average required resources for the next slice window. This figure illustrates that critical MTC slice which has the tightest delay constraints requires more processing resources per user than the other slices. Massive MTC users require the least amount of processing resources due to their relaxed delay constraints. Figure 15b compares the total allocated processing resources per each slice. The total traffic demand in each slice, depicted in Figure 15c, and their delay requirements determine the total required processing at the CC. For instance, in this study since the number of massive MTC devices is higher than other slices, in total it requires more processing resources. Please note that each massive MTC device requires much less processing resources as is depicted in Figure 15a. On the other hand critical MTC devices, despite their lower load than other slices, they require higher processing resources than eMBB slices. Because critical MTC slice has the most stringent delay requirement and hence higher processing resources should be assigned to it, so that the QoS is satisfied. It is worth mentioning that the file size of each user may differ in UBRA, and thus the required processing resources may differ from SBRA. Therefore, compared to SBRA, less processing resources may be assigned to the users in UBRA for one slice and more processing resources be assigned to other slices.

For UBRA the joint communication and computation resource allocation problem is more complex in comparison to the proposed end-to-end slicing SBRA. The reason is that the number of optimization variables as well as the number of constraints for users' QoS linearly scales with number of users while for SBRA the number of constraints is in the order of the number of slices. Therefore, it takes more time to solve the problem of UBRA as is depicted in Figure 16.

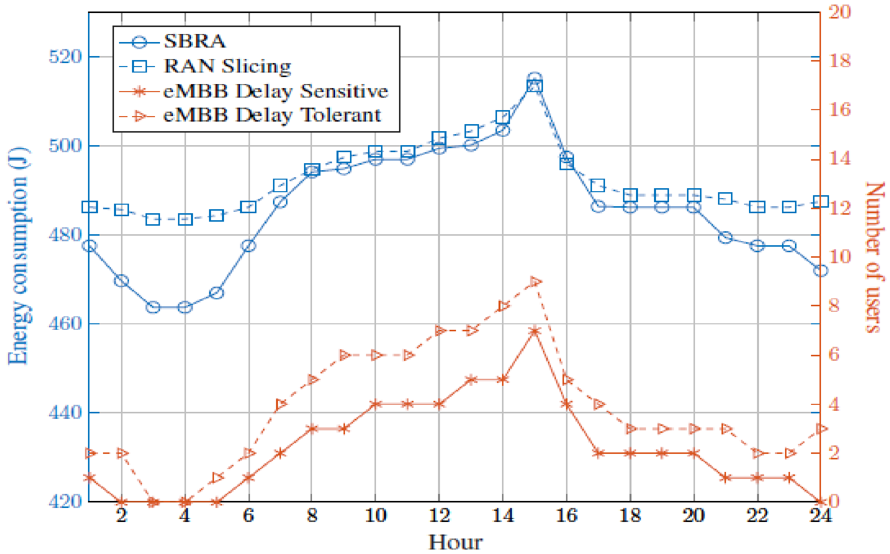

Figure 14: Hourly profile of expected energy consumption and number of users for eMBB delay sensitive and eMBB delay tolerant slices [8].

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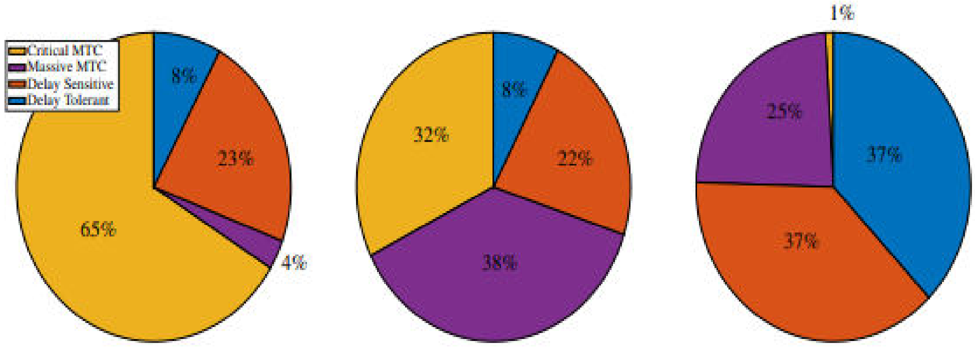

(a) Allocated processing resources per user. (b) Allocated processing resources per slice. (c) Proportion of traffic demands per slice.

Figure 15: Allocated processing resources to each slice and user [8]

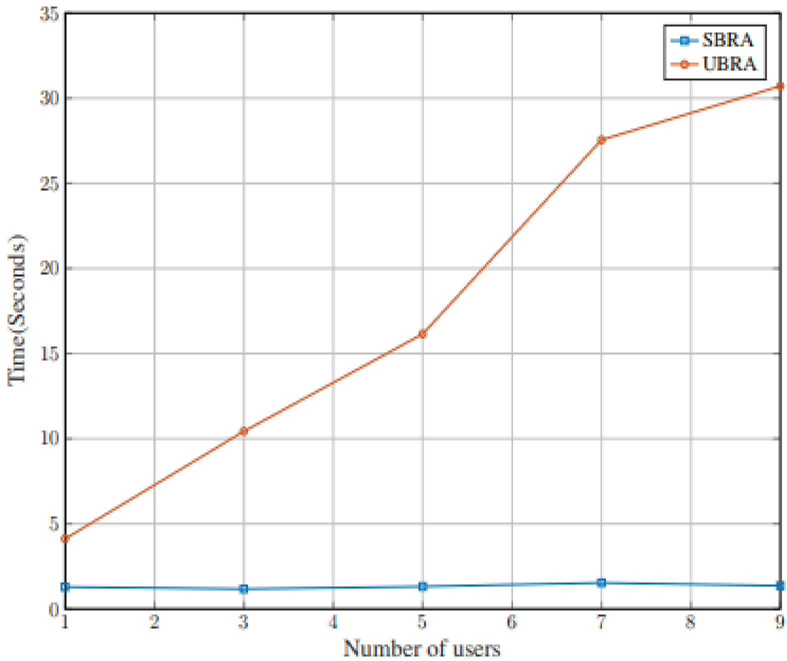

Figure 16: Time complexity performance comparison of SBRA and UBRA [8]

V. Conclusion and Future Work

One to two percent of the world's total energy consumption is used by mobile networks. Because of additional expectations on service providers to improve network capacity, extend geographical coverage, and implement sophisticated technological use cases in 5G and beyond, energy consumption will rise. Improving the energy efficiency of mobile networks is critical to their long-term viability. In this thesis, we looked at methods for increasing the energy efficiency of future wireless networks, such as 5G and beyond. AI-assisted green mobile network, where we lower the energy consumption of the base stations in the network, and AI-assisted architectural design and management of networks, where we look at end-to-end network layouts and resource allocation to increase energy efficiency in networks.

In the journey to beyond 5G networks, energy efficiency will be one of the key pillars of network design and management. On the other hand, in recent years it is possible to obtain mobile networks data. Utilizing the available data can significantly help the mobile operators and vendors, to design, optimize, and maintain their network. Moreover, thanks to the advancement of the field of artificial intelligence and processing technologies which can

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handle processing extensive tasks, it is now possible to benefit from the AI techniques to assist the network management and improve the performance metrics. In this thesis, we cover many aspects of improving the network energy efficiency in the mobile networks. However, there are nevertheless some limitations that this thesis and can be improved and extended.

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