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Energy Optimization in IoT Multi-Path Channels via Deep Learning on G6 Networks

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Abstract

In this research, optimization methods for energy resource allocation are investigated to improve energy efficiency in 6G-IoT networks. By utilizing energy harvesting techniques from hybrid sources such as wind, water, and solar, efforts have been made to provide sustainable energy for IoT networks. However, uncertainty in variable temporal environments does not guarantee continuous connectivity and sustainable energy resources for all network nodes. This research addresses the problem of power allocation in multi-path channels with the aim of identifying influential parameters and employing an LSTM neural network for data-driven predictions based on historical data. The results indicate that the computational load of the algorithm is very low, and optimal responses are achieved by the fourth iteration. As the number of IoT devices increases, the response time grows, and an increase in the Signal-to-Noise and Interference Ratio (SINR) leads to a decrease in energy efficiency. Additionally, an increase in the number of IoT devices results in higher power consumption and reduced efficiency. The average power for a maximum transmission power of 10 megabits per joule has been determined.

Keywords: 6G Mobile Network, Optimal Power Allocation, LSTM Neural Network, Python

Introduction

In recent years, the world has witnessed an unprecedented surge in global mobile data usage. According to projections by the International Telecommunication Union (ITU), global mobile data traffic is expected to reach 607 exabytes (EB) per month by 2025 and soar to 5016 EB per month by 2030 (Andrae, 2019; Shayea et al., 2019; Arifin and Habibie, 2020). Similarly, data traffic per subscriber is anticipated to climb to approximately 39 EB by 2025 and around 257 EB by 2030 (Alsabah et al., 2021; Grasso et al., 2023). This explosive growth in data consumption is driven by the increasing number of mobile phone subscribers, projected to reach nearly 70% of the global population by 2025, with 60% utilizing mobile internet services (Martins and Wernick, 2021; del Portillo et al., 2021; Oughton et al., 2023).

The burgeoning data traffic demands more than just an increase in bandwidth; it necessitates highly reliable, ultra-fast wireless communication systems with exceptionally low latency (Huq et al., 2019; Mumtaz et al., 2021). This demand is largely fueled by the proliferation of personal computers, laptops, tablets, smartphones, sensors, and Internet of Everything (IoE) devices (Masoud et al., 2019; Tyagi and Nair, 2020), which primarily consume data for video content rather than voice traffic (Morley et al., 2018). Furthermore, the anticipated rise in internet users, mobile subscribers, Machine-to-Machine (M2M) connections, and connected devices worldwide underscores the urgent need for advancements in wireless communication infrastructure (Sudarmani et al., 2022; Montori et al., 2018).

The existing generation of wireless technologies is increasingly strained by the volume and complexity of data traffic and the emergence of new applications (Zhang et al., 2019). To address these challenges, the development of the next generation of wireless communication systems, commonly referred to as 6G networks, is underway (Alsharif et al., 2022). 6G networks promise to revolutionize communication through advanced physical layer solutions, novel modulation schemes, sophisticated multiple access techniques, energy harvesting capabilities, edge computing integration, exploration of new spectrum bands, and the incorporation of both terrestrial and non-terrestrial communications (Khalid et al., 2021; Lee et al., 2020). Moreover, 6G networks are expected to leverage blockchain technology, quantum technologies, and artificial intelligence (AI) to further enhance their capabilities.

Despite these promising advancements, the implementation of 6G networks faces significant challenges. These include high processing power demands, limited frequency availability, elevated energy consumption, and substantial costs. As this technology is still in its early stages, developing nations, in particular, are striving to overcome these hurdles. In this context, the need to research and optimize energy efficiency in 6G networks becomes paramount. Artificial intelligence, especially entropy-based techniques, plays a crucial role in this optimization process, enabling self-sustaining and intelligent systems that enhance service quality (Behara and Saha, 2022; Singh et al., 2023).

This study addresses the pressing need for efficient energy allocation and optimization in 6G networks by leveraging deep learning techniques. Specifically, it focuses on two key components: 1) elucidating the governing equations related to channel dynamics, power allocation strategies, and optimization problems, and 2) detailing the flowchart of deep learning methodologies for optimizing energy consumption. By addressing these aspects, this research aims to contribute to the development of more efficient and intelligent 6G communication systems, aligning with global advancements and supporting the progress of technology in developing nations.

Material and Method

In this study, we delve into power allocation and energy optimization utilizing deep learning techniques, particularly applied to 6G networks. The research problem is delineated into two components: 1) elucidating the governing equations in channels, power allocation strategies, and optimization problems, and 2) elucidating the flowchart of deep learning methodologies in optimizing energy consumption. Both aspects are comprehensively addressed in this chapter.

IoT Network Model

In our investigation, we scrutinize a downlink Internet of Things (IoT) system comprising a pool of Base Units (BUs) interconnected to N Remote Radio Units (RRUs), as depicted in Figure 1 (Gbadamosi et al., 2020). Each RRU is adequately equipped with an antenna unit to cater to K IoT devices for the transmission and reception of radio frequency signals (Bjering and Prasad, 2018). System resources are allocated orthogonally to IoT devices to mitigate interference among them. The maximum number of antennas on a large-scale RRU is denoted as Lmax, where RRU activation enhances the efficacy of communication among IoT devices (Kodheli et al., 2018). Resource allocation in IoT systems is enhanced by allocating power to different IoT devices based on channel conditions, prioritizing higher power allocation to IoT devices experiencing weaker channel conditions (Ramezani et al., 2018). Leveraging excellent Channel State Information (CSI) at the transmitter, RRUs temporally store energy for transmitting data to neighboring IoT devices. Additionally, an IoT device opportunistically senses the sub-channel via RRU while being assigned to an RRU. RRUs function as relay protocols, transmitting received signals from IoT devices to the Centralized Band Unit (BU). The uncertainties inherent in communication channels are independent and adhere to a uniform (Gaussian) distribution to meet fading requirements. Figure 2 shows the network model

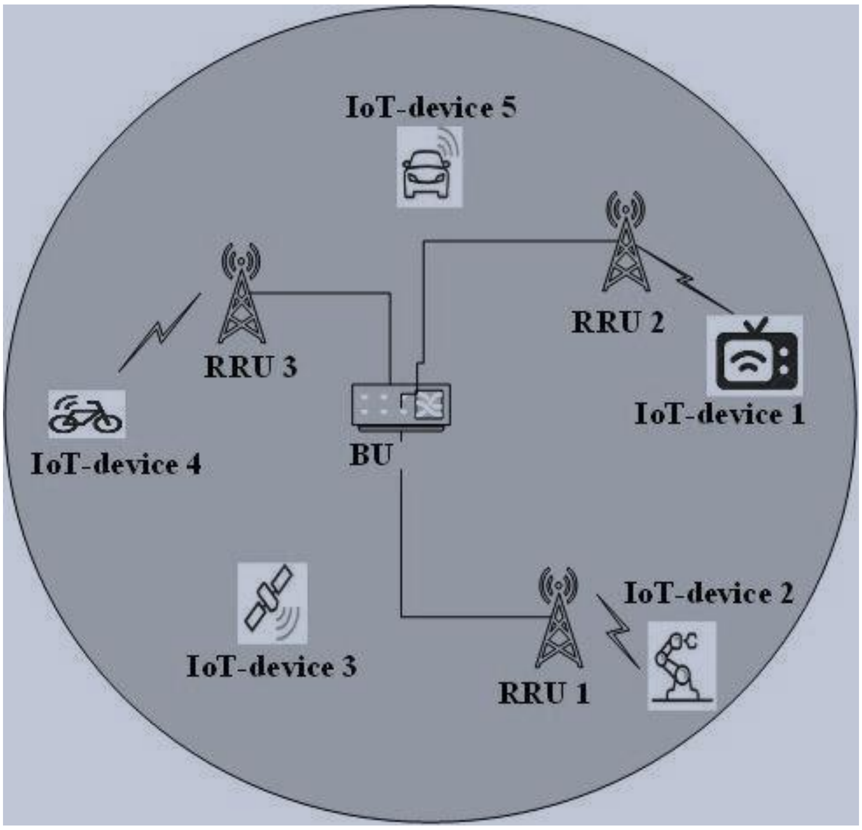

Figure 1. Internet of Things Systems Image (Ansere et al., 2023).

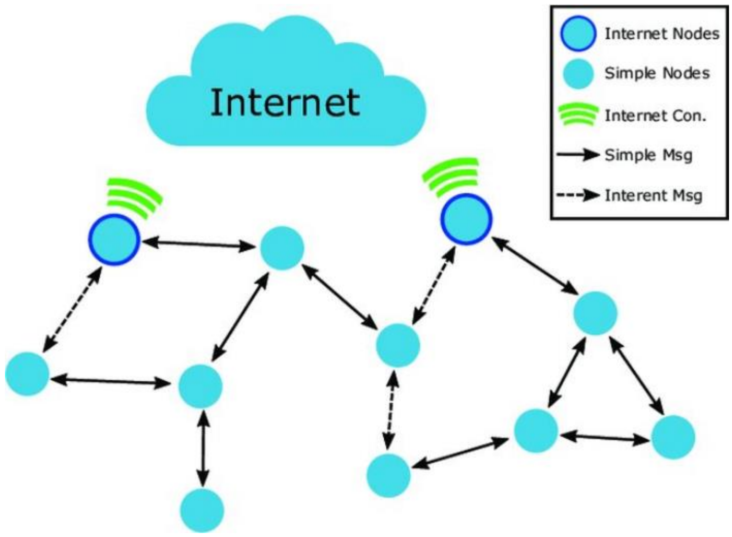

Figure 2. Network model.

Channel Model and Estimation

Considering the downlink training phase, it is assumed that all IoT devices simultaneously transmit pilot signals for channel estimation in $\tau \geq K$, where the size of each pilot τ is identical. A set of orthogonal pilots $\varphi = [\varphi_1, \varphi_2, \dots, \varphi_K] \epsilon C^{\tau * k}$ autonomously assigned to IoT devices $\varphi^H \varphi_{= I_K}$ fulfills this, assuming all antennas are active in this phase. The received signal is provided at the nth Remote Radio Unit (RRU) (Rezaei et al., 2023).

$$\mathbf{Y}_k = \sum_{k=1}^{K} \sqrt{p_k} \mathbf{H}_k^T \mathbf{\Phi} + Z_k^T$$

(1)

The term "pk" in this context represents the power transfer capability of the k-th IoT device. $C^{L_{max}} \times K_{= I_K}$ $H_n = [h_{n,1}, h_{n,2}, \dots, h_{n,k}] \epsilon$ The channel matrix from the n-th RRU to the k-th IoT device is denoted by, and ZkT represents complex Gaussian noise with a distribution of

$CN(0, \sigma_K^2)$. The communication channel is modeled as $\mathbf{h}_{n,k} = \sqrt{\alpha_{n,k}} g_{n,k}$, and the channel vector is depicted for the n-th RRU and k-th IoT devices. Additionally, both $\alpha_{n,k}$ and $g_{n,k} \in \mathbb{R}^{N \times 1}$ respectively indicate the fading coefficients for large and small-scale fading channels between IoT devices n and k.

The Path Loss Model helps IoT networks by predicting signal strength over distance, ensuring adequate coverage. The Fading Model maintains consistent signal quality despite environmental changes. The Multipath Model improves signal reception by managing interference from multiple paths.

Assuming access to channel estimation gains, it is presumed that $\tilde{\mathbf{y}}_{n,k}$ is predicted as Φ_k

$$\tilde{\mathbf{y}}_{n,k}^T \triangleq \mathbf{Y}_n^T \Phi^H = \tau \sum_{k=1}^{K} \sqrt{p_k} \mathbf{h}_{n,k}^T + \tilde{Z}_k^T$$

(2)

By employing the Minimum Mean Square Error (MMSE) channel estimation method (Xia and Jorent, 2019), the estimated channel, hn,k, from the n-th RRU to the k-th IoT devices is provided.

$$\tilde{\mathbf{h}}_{n,k} = \frac{\mathbb{E}\left\{\mathbf{h}_{n,k} \tilde{\mathbf{y}}_{n,k}^*\right\}}{\mathbb{E}\left\{\left|\tilde{\mathbf{y}}_{n,k}^*\right|^2\right\}} \tilde{\mathbf{y}}_{n,k}^*$$

$$= \frac{\sqrt{p_k} \alpha_{n,k}}{\tau p_k \alpha_{n,k} + \sigma_k^2} (\tau \sqrt{p_k} \mathbf{h}_{n,k} + \phi_k Z_k^T)$$

(3)

Therefore, the channel estimation error, $\epsilon_{n,k} = h_{n,k} - \hat{\mathbf{h}}_{n,k}$, is expressed as with a distribution of $\epsilon_{n,k} \sim \mathcal{CN}(0, \alpha_{n,k} \boldsymbol{I}_K)$

Data Transmission Model

It can be assumed that each deployed RRU transfers data to connected IoT device $g_{n,k} \in \mathbb{R}^{N\times 1}$ and $\mathbf{h}_{n,k} \in \mathbb{R}^{N\times 1}$, respectively, represent the RRU and the channel vector from the nth RRU to the kth IoT devices. However, denotes the signal sent to the kth IoT device, representing it as the kth IoT device. This is calculated using the following relationship (Etiabi and Amhoud, 2024). Data Rate helps in optimizing the speed of data transfer, ensuring that large volumes of IoT data are transmitted efficiently. Latency is crucial for reducing delays in communication, which is essential for real-time applications. Error Rate aids in assessing and enhancing the reliability of data transmission by predicting and managing errors.

$$x_{n,k} = \sum_{k=1}^{K} \sqrt{p_{n,k}} \hat{\mathbf{h}}_{n,k} g_{n,k}$$

(4)

As a result, the received signal of the kth IoT device is calculated using the following relationship under the channel $i \in \{1, 2, 3, \dots K_n\}$.

$$y_{n,k} = \sum_{n=1}^{N} \sqrt{p_{n,k}} \mathbf{h}_{n,k}^{T} x_{n,k} + \mathbf{z}_{n,k}$$

$$= \sum_{n=1}^{N} \sqrt{p_{n,k}} \mathbf{h}_{n,k}^{T} \tilde{g}_{n,k} x_k + \sum_{n=1}^{N} \sum_{l=1, l\neq k}^{K_n} \sqrt{p_{n,l} s_{n,l}} \mathbf{h}_{n,l}^{T} \tilde{g}_{n,l} x_l + \mathbf{z}_{n,k}$$

(5)

In which, Zn,k represents Gaussian noise with zero mean and unit variance, and Sn,l denotes the subchannel. The achievable rate for the nth RRU to the kth IoT devices is determined.

$$r_{n,k} = B\log_2(1 + \gamma_{n,k})$$

(6)

Where B represents the bandwidth, $\gamma_{n,k}$ and is the Signal-to-Interference-plus-Noise Ratio (SINR) [27]. $r_{n,k} = B\log_2(1 + \gamma_{n,k}) \gamma_{n,k}$ is given in the following formula.

$$\gamma_{n,k} = \frac{p_{n,k} \left| \mathbf{h}_{n,k}^{T} \tilde{g}_{n,k} \right|^2}{\sum_{l=1, l\neq k}^{K} \sum_{n=1}^{N} \left| \mathbf{h}_{n,k}^{T} \tilde{g}_{n,k} \right|^2 p_{n,l} s_{n,l} + \sigma_{n,k}^2}$$

(7)

Therefore, the maximum achievable rate, Rn,k, for the nth RRU to the kth IoT devices is expressed in this formula.

$$R_{n,k} = \sum_{n=1}^{N} r_{n,k}$$

(8)

Power Consumption Mode

Power consumption in RRUs and power amplifiers constitutes the majority of the total power consumption in the downlink system (Zhang et al., 2020). The total power consumption includes RF transmission power, constant power consumption for site cooling and load processing, and circuit power consumption from active RRUs. As a result, the total power consumption is modeled. The Power Consumption Model helps IoT by optimizing energy use, extending battery life, and reducing operational costs. It enables efficient management of device power modes to balance performance with energy consumption. This ensures that IoT devices and networks operate sustainably and cost-effectively.

$$P_T = P_{\text{FIX}} + P_t + P_c$$

$$P_T = P_{\text{FIX}} + \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{1}{\eta_e} p_{n,k} + p_s \sum_{n=1}^{N} \mathcal{L},$$

(9)

Here $P_c = p_s \sum_{n=1}^{N} \mathcal{L}$, ps represents circuit power consumption, and the cost of power is allocated for servicing deployed RRU units. $\mathcal{L}$ specifies that the deployed RRU units on a large scale are determinative. Pt $= \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{1}{\eta_e} p_{n,k}$ equals transmission power, illustrating the power amplifier efficiency. $\{0,1\}\eta_e \in$

power consumption in IoT networks

In IoT networks, power consumption is a key factor that influences how effectively and efficiently devices operate. For many IoT devices, such as sensors and smart home gadgets, which typically run-on batteries, efficient power consumption directly affects battery life. Devices that use power more efficiently can operate for longer periods before needing new batteries or recharging, leading to reduced maintenance and lower operational costs. Moreover, managing power consumption can significantly impact overall energy costs. In large-scale deployments, such as smart cities or industrial IoT systems, reducing power usage translates into substantial savings on energy bills. Efficient energy use also helps in prolonging the lifespan of devices, as less power consumption generally results in less wear and tear on components. This extends the operational life of the devices, minimizing the need for early replacements and maintenance.

Additionally, lower power consumption has positive environmental implications. By reducing the amount of energy required to run IoT networks, the environmental footprint of these systems is decreased. As the number of IoT devices continues to grow, managing power consumption becomes increasingly important for both economic and environmental reasons. Thus, understanding and optimizing power consumption is crucial for developing IoT systems that are cost-effective, sustainable, and reliable.

Problem of Resource Allocation and Optimization

This section endeavors to tackle the challenge of resource allocation by formulating an optimization problem aimed at maximizing the energy efficiency performance.

Energy Efficiency Optimization

Energy efficiency, denoted as *h*, is defined as the achievable rate *Rn*,*k* to the total energy consumption *PT* of the system (bits/Joule) (Tang et al., 2019). Therefore, energy efficiency *h* can be expressed in terms of power allocation *P*, active *RRU* selection *A*, user selection *U*, and subchannel allocation *S* (You et al., 2020). Energy Efficiency Optimization improves IoT by reducing power consumption, which extends device battery life and lowers operational costs. It enhances device longevity, reducing maintenance needs. Additionally, it supports better system performance and scalability by managing energy resources effectively.

$$\eta(\mathcal{P},\mathcal{A},\mathcal{U},\mathcal{S}) = \frac{R_{n,k}(\mathcal{P},\mathcal{A},\mathcal{U},\mathcal{S})}{P_T(\mathcal{P},\mathcal{A},\mathcal{U},\mathcal{S})}$$

(10)

Formulation of Optimization Problem

The joint optimization of power allocation *P*, selection of active RRUs *A*, user selection UU, and subchannel allocation *S* has been elucidated. Mathematically, the formulated optimization problem for the system is represented as (Xia et al., 2022):

$$\begin{aligned}
&P1: \max_{\mathcal{P},\mathcal{A},\mathcal{U},\mathcal{S}} \eta(\mathcal{P},\mathcal{A},\mathcal{U},\mathcal{S}) \\
&C1: \sum_{n=1}^{N}\sum_{k=1}^{K} s_{n,l}p_{n,k} \leq \eta_e P_{\max}, \forall k, \forall n \\
&C2: \sum_{n=1}^{N}\sum_{k=1}^{K} s_{n,l}R_{n,k} \geq R_{\min}, \forall k, \forall n \\
&C3: \sum_{n=1}^{N} p_{n,k} \leq \delta_o, n \in \psi \\
&C4: \sum_{n=1}^{N} s_{n,l} = 1, s_{n,l} \in \{0,1\}, \forall n, l \\
&C5: \sum_{n=1}^{N} u_{n,k} = 1, u_{n,k} \in \{0,1\}, \forall n, k \\
&C6: p_{n,k} \geq 0, \forall k, \forall n \\
&C7: 0 \leq \mathcal{L} \leq \mathcal{L}_{\max}, \mathcal{L}_{\max} \in Z^{+}
\end{aligned}$$

(11)

Formulating Optimization Problems helps IoT by defining clear goals and constraints, ensuring efficient resource allocation and system performance. It guides the system in balancing factors like energy use, throughput, and latency. This systematic approach leads to optimized and cost-effective IoT solutions. However, the objective function in *P1* presents a complex nonlinear optimization problem that is NP-hard, with constraints involving nonlinear functions, rendering it challenging to find an optimal solution. *P1* entails a mixed-integer combinatorial optimization over multidimensional decision variables. Moreover, addressing *P1* becomes increasingly difficult in polynomial time as the size of the optimization problem escalates. Consequently, achieving an optimal solution in dynamic and large-scale Internet of Things environments is computationally inefficient. Therefore, we opt to transform the considered system problem into a convex form and devise a novel dynamic resource allocation technique to efficiently address it.

Deployment of Deep Learning Algorithm in Energy Optimization

The efficacy of the "end-to-end learning" framework is contingent upon an extensive training dataset and substantial computational resources due to the multitude of parameters inherent in general-purpose neural networks (NNs), which function as global function approximators. The diminished training efficiency of general NNs poses a barrier to their application in dynamic wireless networks and large-scale scenarios. Moreover, in forthcoming 6G wireless networks, where high-quality training samples such as Channel State Information (CSI) may not be readily available, the performance of general deep neural networks (DNNs) may deteriorate significantly, potentially undermining conventional algorithms. Additionally, general NNs are often perceived as "black boxes," rendering it challenging to decipher the functionality of each layer and ensure NN performance. The lack of interpretability in black-box DNNs can pose a significant constraint in wireless network optimization endeavors, where reliability and predictability are paramount (Aklilu and Bounahmidi, 2024).

To overcome these challenges, a novel algorithmic approach has surfaced, establishing a coherent and systematic linkage between classical iterative algorithms and deep neural networks. This approach involves unrolling an iterative algorithm and transferring its parameters to the training parameters of a neural network. Consequently, the unrolled neural network enables the interpretation of each layer and may even offer theoretical guarantees (Xu, 2023). Given the potential to develop efficient neural networks with high performance and theoretical guarantees using reasonably sized training sets, the burgeoning adoption of unrolling algorithms in both theoretical research and practical applications is noteworthy (see Figure 2).

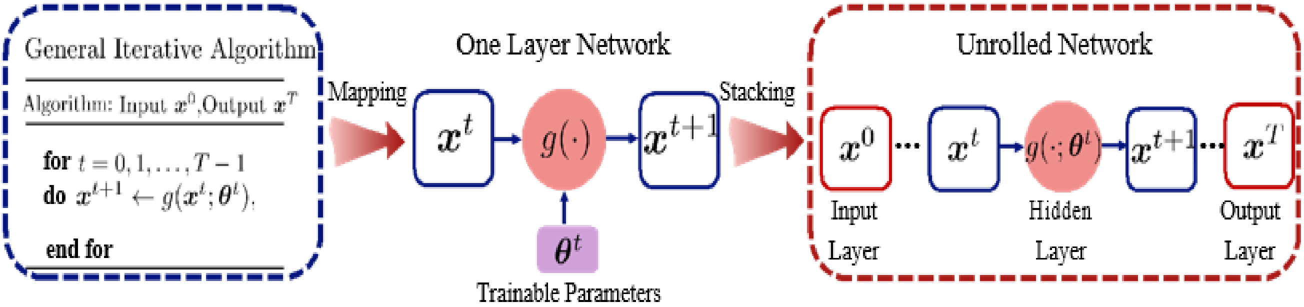

Figure 2. Deep Learning-Based Algorithm Framework.

The algorithmic framework, initially introduced by Gregor and LeCun (Zhou, 2020), opened up by accelerating ISTA to enhance the computational efficiency of sparse coding.

The core concept revolves around mapping each iteration of Iterative Shrinkage-Thresholding Algorithm (ISTA) to a neural network layer and subsequently stacking these layers atop each other. This process can be perceived as the execution of multiple ISTA iterations by a layered neural network. Such techniques can be extended to encompass a broader range of iterative algorithms, particularly those where the update form is data-driven.

$$x^{t+1} = g(x^t; \theta^t), \quad t = 0, 1, 2, \cdots, T$$

(12)

In this context, $x^t \in \mathbb{R}^n, t = 1, \cdots, T$ represents the vector of iterative variables (e.g., a signal to be reconstructed or a variable to be optimized $g(\cdot; \cdot) : \mathbb{R}^n \to \mathbb{R}^n$ denotes the iterative function of a specific iterative algorithm, and $\theta^t \in \mathbb{R}^m, t = 1, \cdots, T$ encompasses the trainable parameters (including model parameters and tuning coefficients) of the algorithm. The fundamental principle of unrolling the algorithm is to unfold a particular iterative algorithm into a deep network by mapping each iterative function (g) in a network layer and stacking a limited number of layers together. The forward process of the neural network corresponds to the execution of the iterative algorithm. Therefore, the unrolled network architecture depends on the underlying iterative algorithm (e.g., ISTA unrolled into a Recurrent Neural Network (RNN) (Zhou, 2020), as a single-layer network has a similar structure to the iterative function (g). The details of unrolling the algorithm are illustrated in the figure. The trainable parameters $\theta^t \in \mathbb{R}^m, t = 1, \cdots, T$ can be learned through an end-to-end approach.

$$\underset{\Theta_T}{\text{minimize}} \ \mathcal{L}\left(x^{T+1}(\Theta_T)\right)$$

(13)

In which (L) is the loss function for training, $\Theta_T = \{\theta^t\}_{t=0}^{T}$ represents all trainable parameters of the entire network with T layers, and $x^{T+1}(\cdot)$ is the output function of the unrolled network. Given the custom structure of the neural network (NN), end-to-end training may suffer from local minima, gradient explosion, or vanishing during the training process. Instead of directly solving (2), a common training strategy adopted for unrolled networks is the layer-wise training method (Gesbert et al., 2007), which, due to better parameter initialization, can achieve more efficient training. This means the entire training process can be divided into consecutive training processes for each layer (t). For the (t)-th sub-training process, our goal is to adjust the trainable parameters specific to (t) using a two-stage method. The first stage is dedicated to optimizing the (t)-th parameters independently, while the second stage jointly optimizes all (t) by fixing the learned (t) as the initialization. During the evaluation phase, feeding data forward through the unrolled network with learned parameters is equivalent to executing the optimized iterative algorithm for a limited number of iterations.

Deploying deep learning algorithms for energy optimization in IoT networks involves several key steps. Here's a step-by-step explanation, along with pseudocode and a flowchart to simplify the process:

Step-by-Step Explanation

1. Data Collection:

Gather data related to energy consumption, such as power usage, device activity, and environmental conditions. This data forms the basis for training the deep learning model.

Example Data: Sensor readings, device operational states, environmental factors (temperature, humidity).

2. Data Preprocessing:

Clean and preprocess the data to make it suitable for model training. This includes normalizing values, handling missing data, and splitting the dataset into training and testing sets.

Tasks: Normalize values, remove outliers, handle missing values.

3. Feature Selection:

Identify the most relevant features (input variables) that will be used by the deep learning model to predict energy consumption and optimize usage.

Example Features: Device type, usage patterns, time of day.

4. Model Selection:

Choose a suitable deep learning model architecture. Common choices for energy optimization include neural networks, convolutional neural networks (CNNs), or recurrent neural networks (RNNs), depending on the nature of the data.

Example Models: Multi-layer Perceptron (MLP), Long Short-Term Memory (LSTM) networks.

5. Model Training:

Train the selected deep learning model using the preprocessed training data. This involves feeding the model with input features and adjusting weights based on the predicted versus actual outcomes.

Tasks: Configure hyperparameters, train the model, validate performance.

6. Model Evaluation:

Evaluate the model's performance using the testing data. Metrics such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE) are used to assess accuracy.

Tasks: Compute performance metrics, adjust model if needed.

7. Deployment:

Deploy the trained model into the IoT network environment where it can process real-time data and make predictions for energy optimization.

Tasks: Integrate the model with IoT systems, ensure real-time data feeding, and monitor performance.

8. Continuous Monitoring and Updating:

Continuously monitor the model's performance and update it with new data to maintain accuracy and effectiveness over time.

Tasks: Collect new data, retrain the model periodically, adjust based on performance feedback.

The codes of this method are:

1 .Load and preprocess data

data = load_data("energy_consumption.csv")

data = preprocess_data(data)

2 .Select features

features = select_features(data)

3 .Choose model

model = choose_deep_learning_model("MLP")

4 .Train model

model.train(features, labels)

5 .Evaluate model

```
performance = model.evaluate(test_data)
if performance < acceptable_threshold:
model.adjust_parameters()
```

6 .Deploy model

```
integrate_model_with_IoT_system(model)
```

7 .Monitor and update

```
while True:
new_data = collect_real_time_data()
predictions = model.predict(new_data)
monitor_performance(predictions)
if performance_drops:
model.retrain()
```

Results and Discussion

Essential Simulation Parameters

To implement the proposed algorithm through computer simulations, it is imperative to define several variables, including the bandwidth of the wireless channel, operating frequency, signal-to-noise ratio (SNR), and the number of Internet of Things (IoT) devices. The optimization of energy allocation revolves around IoT devices communicating with a base station, taking into account the impact on 6G mobile communication. For this purpose, a specific operating frequency of 36 gigahertz has been selected to represent the high-frequency bands characteristic of 6G communication systems. The placement of IoT devices serves as a parameter influencing power allocation and loss assessment. In this scenario, a total radius of 1 kilometer is considered, with IoT users distributed randomly and uniformly within a distance of 40 meters from the reference signal. The spatial distribution of IoT devices in a two-dimensional space is depicted in Figure 3. Moreover, the transmitting antenna is associated with a gain, which is set at 8 megahertz in this context. Path loss is another critical parameter, which is set at 4 in the threshold discussion. Additionally, the signal-to-noise threshold is adjusted to 2 decibels. Various other parameters are outlined in Table 1.

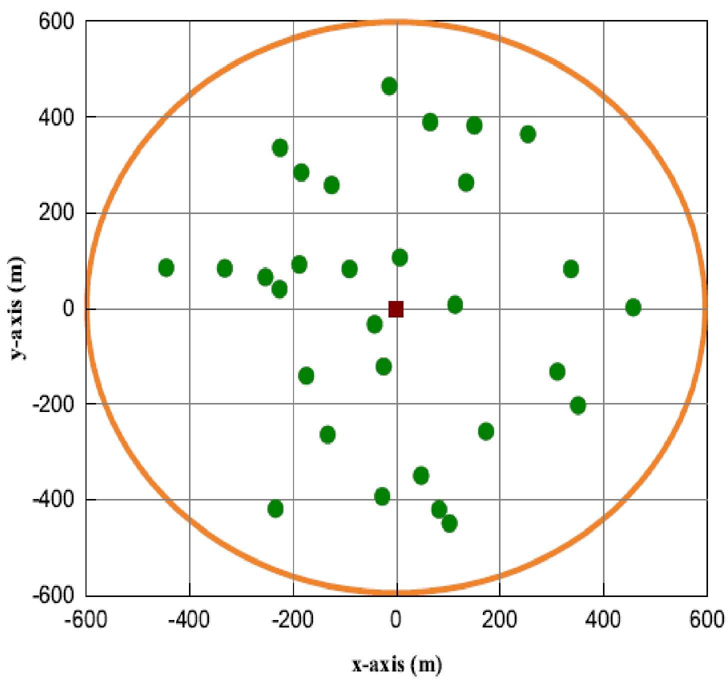

Figure 3. Internet of Things Network with 30 IoT devices and a 6G mobile communication service provider center.

Table 1. Configured Values for Simulation Parameters.

Parameter	Value
Operating Frequency	3.8 Gigahertz
Total Channel Bandwidth	8 Megahertz
Transmitter Antenna Gain	12 Decibels
Path Loss	4
Back-off Constant	0.3
Noise Power per Sub channel	-167 dBm
Power Amplifier Efficiency	0.2
Number of Sub channels	32
Power Consumption	-50 dBm
Minimum Data Rate	4.2 Megabits per Second
SINR Threshold	2 Decibels

Power Allocation Simulation Results

Effects of Power Transfer on Energy Efficiency

Figure 4 illustrates the energy allocation versus the maximum transfer power, denoted as P_{max}. In this simulation setting, parameters such as P_{max} = 80 dBm, 10 repetitions, R_{min} = 2 bps/Hz, and 20 IoT devices are considered in the P_{max} < 35 dBm regime. As observed in Figure 4, algorithms exhibit similar energy efficiency performance, linearly increasing with the rise in P_{max}.

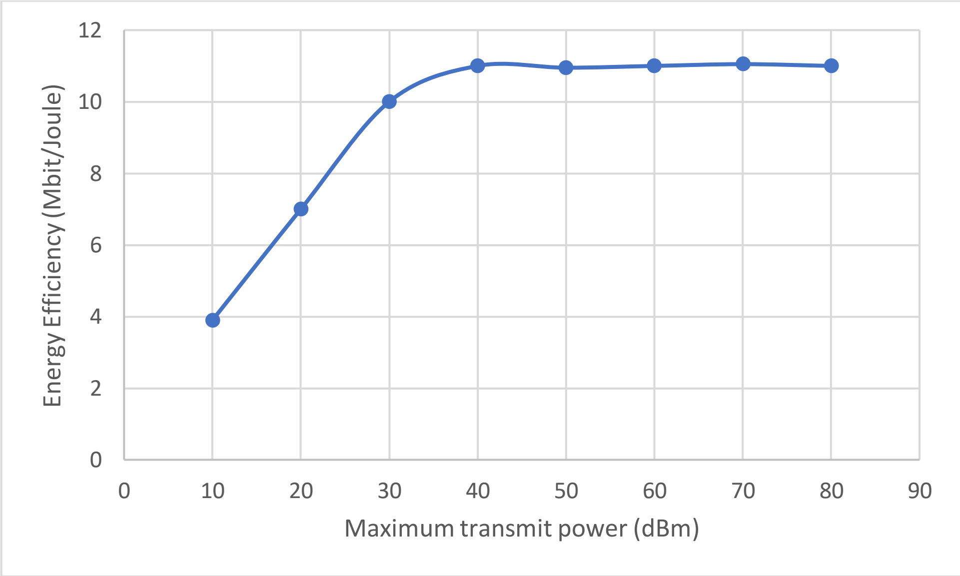

Figure 4. Energy Efficiency versus Maximum Transfer Power.

Impact of Transfer Power on Average Power Allocation

Figure 5 depicts the average system power for the P_{max} scenario with 20 IoT devices at R_{min} = 3 bps/Hz and 10 repetitions. As expected, the operational system power increases with the growth of P_{max}. Notably, beyond P_{max} > 40 dBm, a significant stabilization of operational power is observed. Furthermore, at P_{max} < 30 dBm, values uniformly increase, indicating the influence of signal-to-noise and interference on system performance.

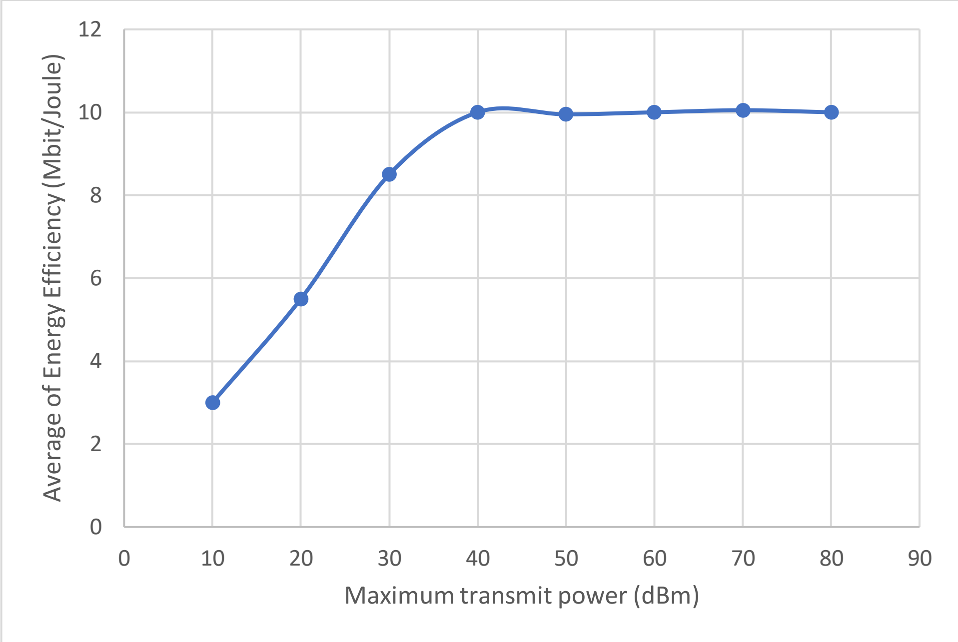

Figure 5. Average System Power versus Maximum Transfer Power.

Effects of Power Transfer on Total Power Consumption

Figure 6 shows the average energy consumption across a wide range of P_{max} values with 20 IoT devices and 10 repetitions. Results are divided into two sections: P_{max} < 30 dBm and P_{max} > 30 dBm. Before P_{max} = 30 dBm, energy consumption decreases linearly. However, beyond 30 dBm, energy consumption stabilizes.

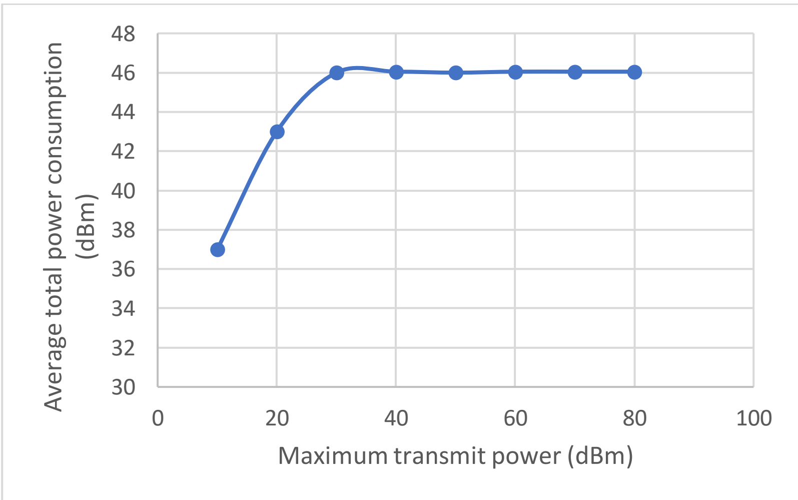

Figure 6. Average Power Consumption.

Impact of the Number of IoT Devices on Energy Allocation

In general, the number of IoT devices significantly affects energy consumption and efficiency. This aspect is also examined in power allocation, and the results are presented in Figure 7. In this simulation with 10 repetitions, P_{max} = 40 dBm, R_{min} = 3 bps/Hz, and 20 IoT devices, an incremental increase in the number of IoT devices leads to a gradual improvement in energy efficiency performance. The performance gap among JEERA, JUSAP, and JPAUP algorithms widens with increased minimum data rate requirements, providing degrees of freedom for effective resource allocation.

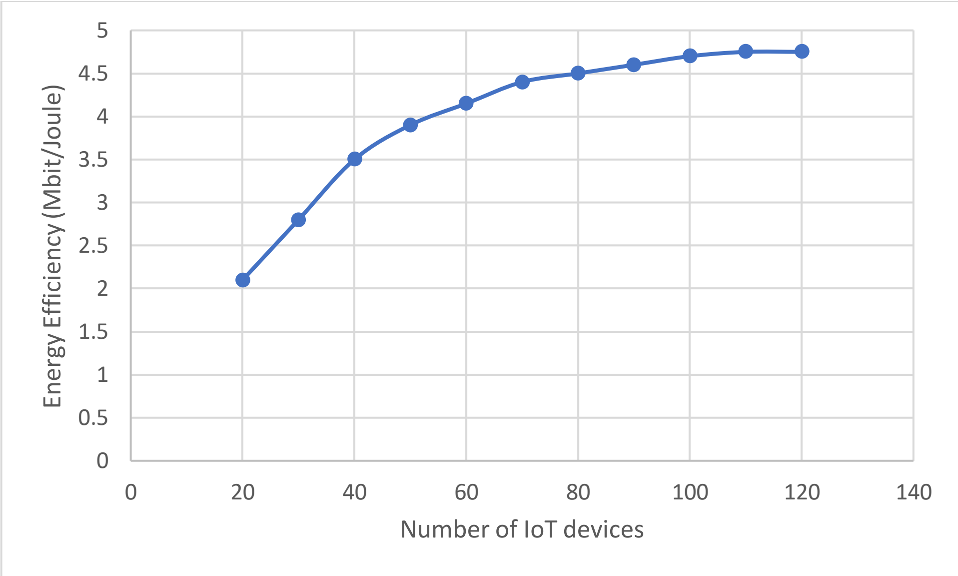

Figure 7. Energy Efficiency with the Number of IoT Devices.

Convergence of the Proposed Iterative Algorithm

As the number of repetitions increases, the obtained results tend to converge, demonstrating a convergence pattern. This convergence becomes apparent from repetition 4 onwards, where values exhibit minimal fluctuations with subsequent repetitions. Figure 8 visually represents this convergence phenomenon. The choice of the number of repetitions is crucial, and in this thesis, a repetition count of 4 is selected, yielding satisfactory results. Computational complexity also plays a pivotal role, favoring simpler algorithms with fewer calculations to achieve convergence within a shorter timeframe.

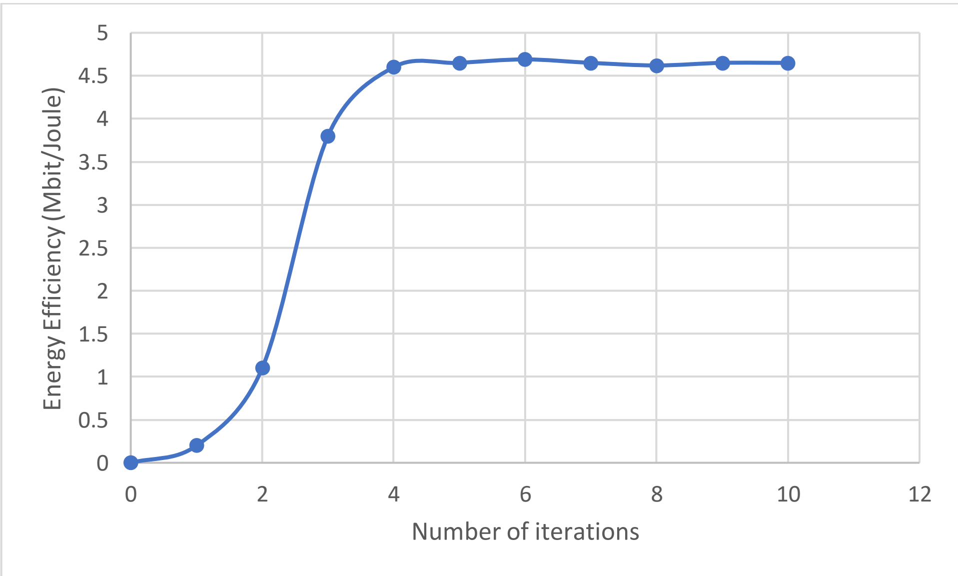

Figure 8. Convergence of Energy Efficiency Results with Repetitions.

To further evaluate the proposed algorithm, Figure 9 illustrates the average response time as a function of the number of IoT devices, expressed in milliseconds. As depicted, there is a natural increase in response time with an increase in the number of IoT devices. Optimal allocation necessitates determining the ideal number of IoT devices for each network, ensuring both high convergence and timely responsiveness. Therefore, engineering parameters must be carefully adjusted to strike a balance between system requirements, performance indices, and variables.

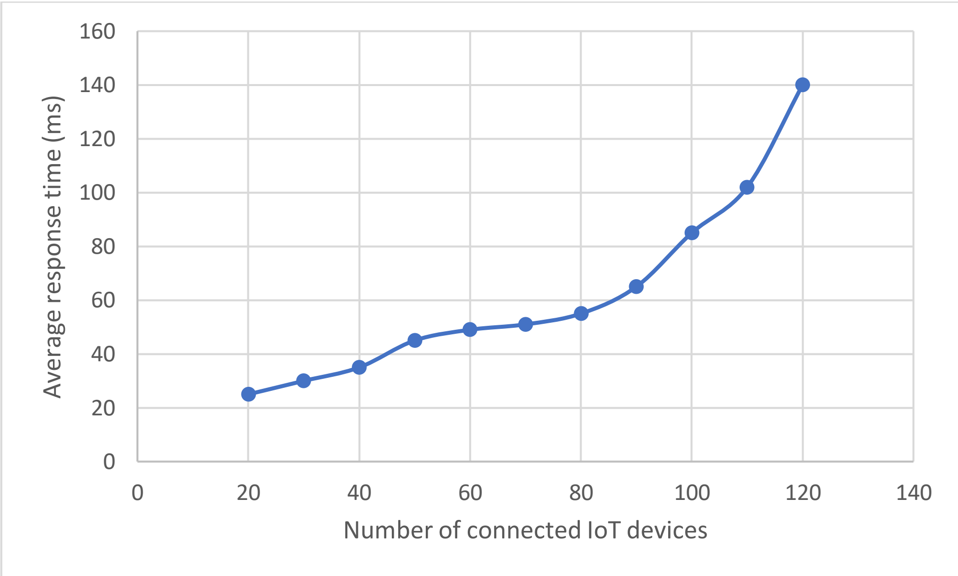

Figure 9. Average Response Time versus Number of IoT Devices.

Impact of SINR Constraints on Power Allocation and Efficiency

Figure 10 illustrates the effects of threshold adjustment on energy efficiency. As evident, as the signal-to-noise ratio threshold increases, energy efficiency decreases. In a specific experiment, it is noted that initially, with an increase in P_{max}, energy efficiency begins to decrease. In the g > 20 dB regime, baseline algorithms reduce energy efficiency.

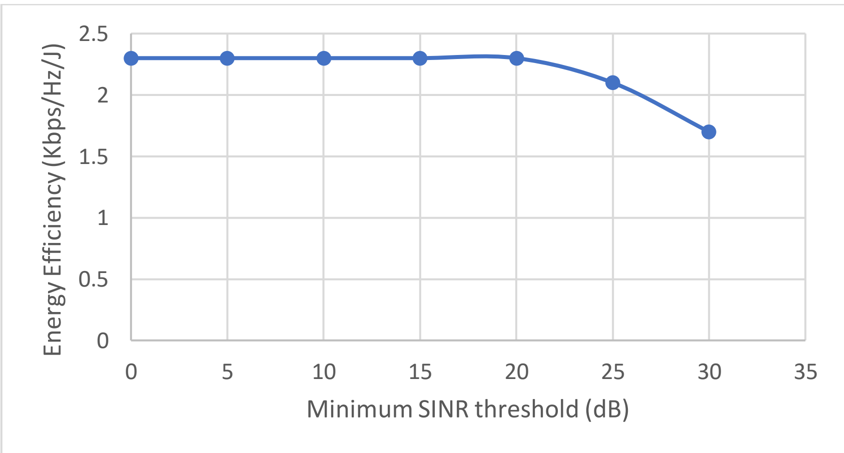

Figure 10. Energy Efficiency at Different SINR Thresholds.

Effects of Active 6G Radio Service Networks on Power Transfer

Figure 11 illustrates the influence of active 6G service provider networks on power allocation and energy efficiency. In other words, one of the variables influencing power allocation and energy efficiency is the number of service providers. This factor contributes to a reduction in the distance between the source and IoT devices, thereby minimizing losses and enhancing overall efficiency. However, excessive increases in the number of service providers may lead to undesired consequences.

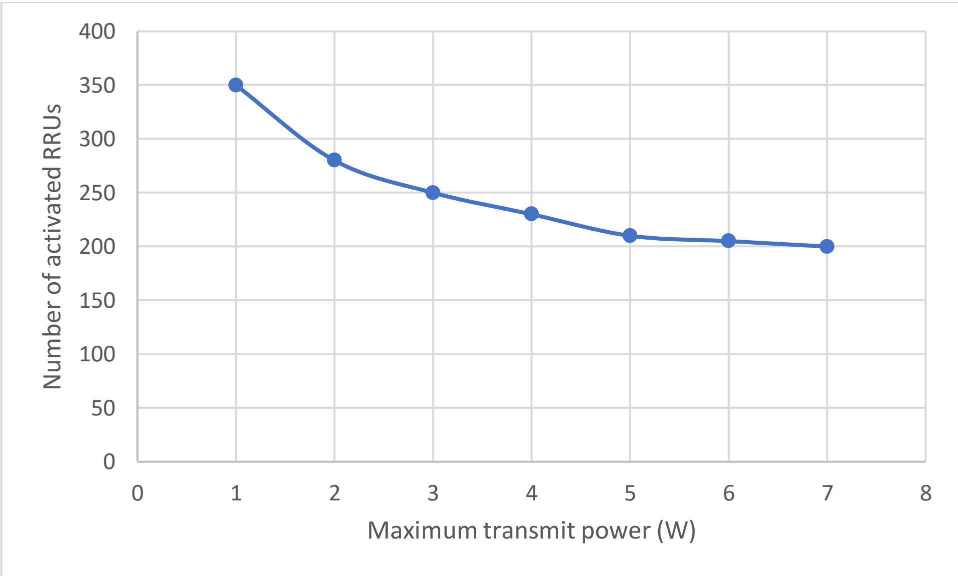

Figure 11. Performance of Active 6G Service Provider Count with Maximum Transfer Power.

LSTM Neural Network Results in Power Allocation Estimation and Prediction

In this section, the Kaggle dataset is leveraged, containing power levels recorded at different hours. A Python-implemented Long Short-Term Memory (LSTM) neural network is utilized to explore the feasibility of predicting allocated power levels. This is paramount for attaining a deeper comprehension of IoT device consumption within a 6G network linked to a radio communication center and for optimizing resources effectively. The LSTM neural network represents a generalized version of the Recurrent Neural Network (RNN), equipped with both short-term and long-term memory capabilities. Memory retention is a critical aspect, and LSTM networks find application in various domains such as data prediction, text classification, and video classification. Multiple platforms, including Python and MATLAB, are available for implementing neural networks. However, this tutorial focuses on MATLAB implementation. Five distinct datasets were employed for this task of predicting energy levels. The workflow encompasses several steps, including:

Data Preprocessing, Value Loss Management, Data Smoothing (Exponential Smoothing), Handling Outliers (Using Standard Deviation), Data Normalization (Scaling values between [0, 1]), Resampling of Data, Dataset Splitting, Training Set, Validation Set and Test Set Prediction results are performed hourly and for a 24-hour period, which can be observed in figures 12 to 16, respectively.

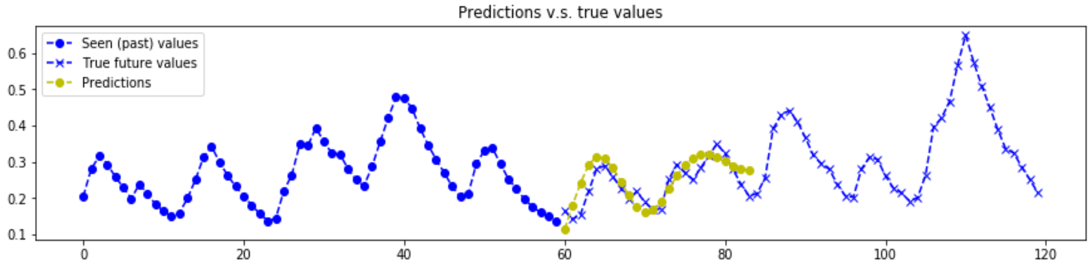

Figure 12. LSTM Results and Optimal Energy Allocation for the First Dataset.

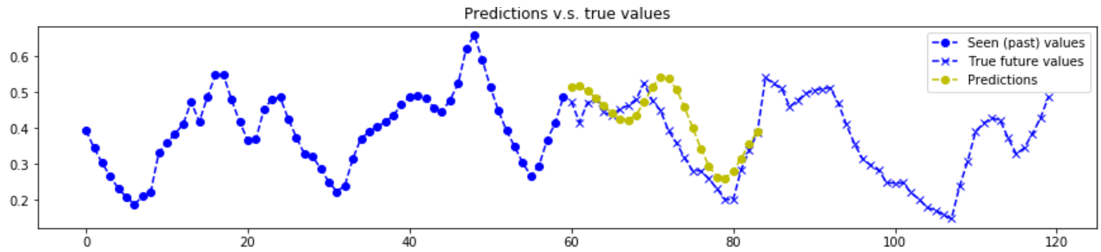

Figure 13. LSTM Results and Optimal Energy Allocation for the Second Dataset.

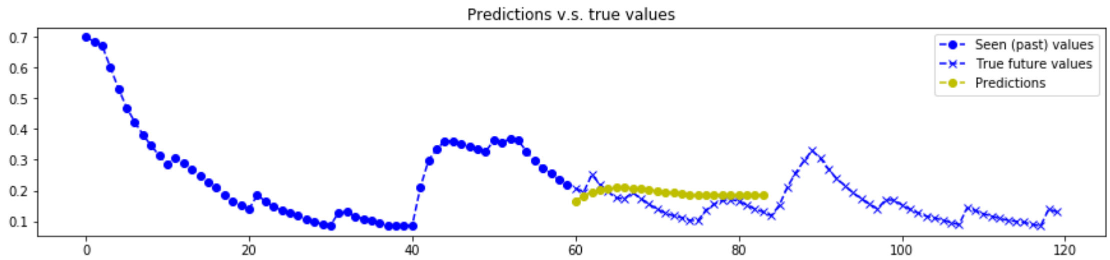

Figure 14. LSTM Results and Optimal Energy Allocation for the Third Dataset.

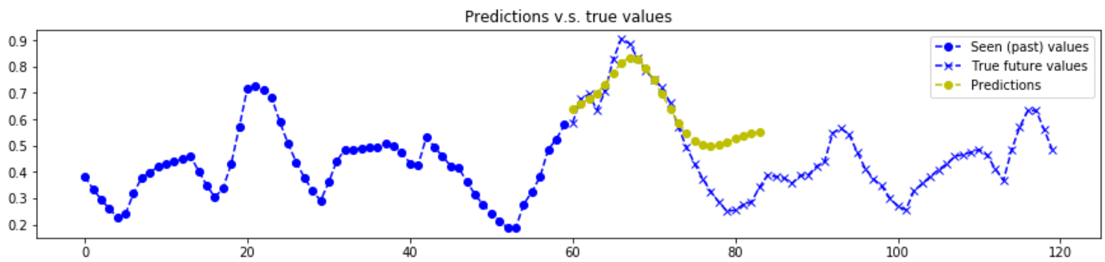

Figure 15. LSTM Results and Optimal Energy Allocation for the Fourth Dataset.

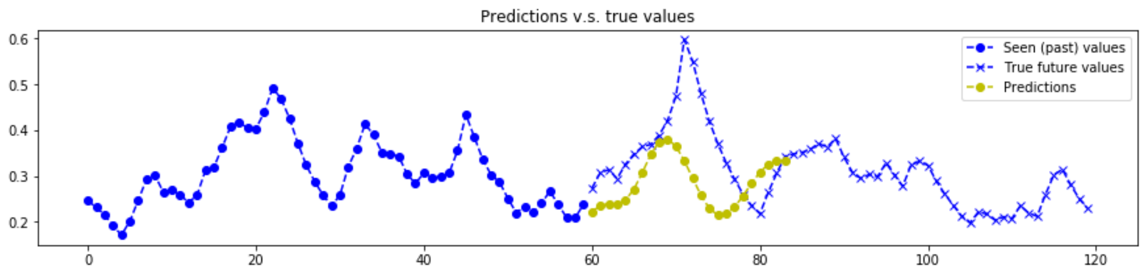

Figure 16. LSTM Results and Optimal Energy Allocation.

In Figures 12 to 16, it is evident that the allocated power exhibits variations at different time instances, taking into account the parameters investigated previously. This variability is influenced by factors such as the number of IoT devices, the number of 6G radio service providers, coverage radius, signal-to-noise ratio, and various other parameters. As a result, predicting the allocated energy and network conditions becomes crucial for optimizing power allocation. Essentially, predicting the required power in channels enables efficient power allocation. By understanding the energy requirements, coupled with prediction and determining upper and lower bounds along with error margins, power allocation can be optimized effectively. The obtained results also clearly highlight the efficacy of utilizing LSTM neural networks for this purpose in the field of electrical engineering.

Rejeb et al. (2023) conducted a study on the Internet of Things in healthcare, focusing on both current advancements and future directions. The analysis of the co-citation network reveals other significant topics, including authentication schemes, fog computing, cloud-IoT integration, and cognitive smart healthcare. Overall, this review provides researchers with a better understanding of the current state of IoT research in healthcare and identifies knowledge gaps for future research. It also informs healthcare professionals about the latest advancements and applications of IoT in the healthcare sector.

Qadir et al. (2023) conducted a study on the progression towards 6G IoT, highlighting recent advancements, use cases, and open challenges. While 5G networks show high potential for supporting various IoE-based services, they are insufficient for meeting the full requirements of emerging smart applications. Therefore, there is a growing demand for forecasting 6G wireless communication systems to overcome the major limitations of existing 5G networks. Additionally, the integration of artificial intelligence in 6G offers solutions to complex network optimization issues. The study also explores new technologies such as THz and quantum communications to add more value to future 6G networks. Future wireless communication requirements will need to support massive data-centric applications and an increasing number of users. Unlike existing works, this paper highlights recent activities and trends towards 6G technology, network needs, essential technologies for 6G networks, and a detailed comparison between 5G and 6G networks. Moreover, it examines emerging 6G connectivity solutions, such as holographic beamforming, AI-driven IoT networks, edge computing, and backscatter communications for smart communities. Several future research directions for implementing 6G-based IoT networks are also outlined. The results of this research are in line with the mentioned researches

Conclusion

The continuous proliferation of interconnected devices, particularly within the Internet of Things (IoT), has catalyzed the evolution of novel Information and Communication Technologies (ICT). Recently, numerous IoT applications and businesses have expanded globally. In 2019, Ericsson’s Mobility Report projected a surge to 7.4 billion smartphone subscriptions and 8.9 billion mobile broadband connections by the culmination of 2025. It's noteworthy that ICT infrastructure currently accounts for approximately 3% of energy consumption and contributes nearly 2% of global carbon dioxide emissions, making the ICT industry a significant environmental factor. In addition to environmental considerations, telecommunications network operators encounter financial pressures associated with energy consumption, as these costs can substantially diminish overall revenue in operational and capital expenses. The advent of 6G, coupled with integration with IoT networks, promises extensive connectivity on a massive scale, ultra-low latency, and exceptionally wide bandwidth. Energy efficiency in the development of 6G-IoT networks is paramount, given that these ubiquitous IoT applications and services are anticipated to connect billions of devices and consume substantial amounts of energy. Therefore, the implementation of efficient IoT programs will not only have a discernible impact on the environment but also assist network operators in achieving long-term profitability.

Typical IoT devices are systems with limited energy resources and batteries. However, managing battery replacement and charging, particularly in scenarios where IoT devices are deployed in remote or harsh environments, can present significant challenges and costs. To address this issue, energy harvesting techniques have been proposed as promising solutions to provide continuous energy to IoT networks on a large scale. These systems harvest energy from hybrid sources such as wind, water, and solar energy to activate independent power sources. However, due to uncertainties in time-variable environments, these methods cannot guarantee uninterrupted communication and a consistent power source for all nodes in an IoT network. Currently, there is a growing focus on the development of optimal energy resource allocation methods aimed at increasing energy efficiency for IoT systems. This thesis also tackled the power allocation issue in multipath channels, aiming to identify influential parameters and leveraging the LSTM neural network as a method capable of providing insights into the future based on past data. Various factors including computational problems, algorithmic complexity, the number of iterations, the number of followers, and the number of IoT devices were examined, and their results were presented.

Overall, the results showed that the computational load of the algorithm is very low, achieving optimal responses by the fourth iteration. However, it was demonstrated that with an increase in the number of IoT devices, response time increases. Additionally, increasing the Signal-to-Interference-plus-Noise Ratio (SINR) threshold results in a decrease in energy efficiency. Moreover, the increase in the number of IoT devices corresponds to an increase in power consumption, which subsequently reduces efficiency. The average power versus maximum transfer power was determined to be 10 megabits per joule.

Based on the current research results and their alignment with broader studies, several avenues for future research emerge:

Enhanced Energy Harvesting Technologies: Future research should focus on advancing energy harvesting techniques to address the limitations posed by environmental variability. This includes developing more reliable and efficient methods for harnessing renewable energy sources, such as integrating hybrid energy systems that can dynamically adapt to changing environmental conditions.

Optimized Power Allocation Algorithms: While current research has demonstrated the effectiveness of LSTM neural networks in power allocation, there is room for improvement. Future studies should explore more sophisticated algorithms and hybrid approaches that combine different machine learning models to enhance accuracy and efficiency in predicting and managing energy consumption.

Integration of 6G with Energy-Efficient Technologies: Investigating the intersection of 6G technology and energy efficiency is crucial. Research should focus on developing new architectural designs and protocols that maximize energy efficiency while supporting the high data rates and massive connectivity promised by 6G networks. This includes exploring novel materials and technologies that can reduce energy consumption in 6G infrastructure.

Scalability and Performance Analysis: Future research should address the scalability of energy optimization solutions as the number of IoT devices increases. This involves examining how optimization algorithms perform under varying scales and conditions, and developing strategies to maintain efficiency and performance as networks grow.

Real-Time Energy Management Systems: Developing real-time energy management systems that can adapt dynamically to network conditions and usage patterns is essential. Research should explore systems that can provide real-time feedback and optimization, integrating advanced analytics and AI to continuously refine energy usage strategies.

Economic Impact Studies: Further studies should analyze the economic impact of implementing advanced energy optimization techniques in IoT networks. This includes assessing the cost-benefit ratios of various energy-efficient technologies and their effects on overall network profitability and sustainability.

Environmental Impact Assessment: Comprehensive environmental impact assessments of different energy optimization strategies should be conducted. Research should focus on quantifying the potential reductions in carbon emissions and other environmental benefits resulting from the adoption of energy-efficient practices in IoT networks.

Cross-Domain Applications: Exploring the application of energy optimization techniques across different domains such as smart cities, industrial IoT, and healthcare can provide valuable insights. Research should investigate how these techniques can be tailored to meet the specific energy needs and challenges of various sectors.

By pursuing these research directions, future studies can build upon the current findings to develop more effective, scalable, and sustainable solutions for managing energy consumption in the rapidly expanding field of IoT and 6G networks.

References

Aklilu, E. G., & Bounahmidi, T. (2024). Machine learning applications in catalytic hydrogenation of carbon dioxide to methanol: A comprehensive review. *International Journal of Hydrogen Energy*, *61*, 578-602.

Alsabah, M., Naser, M. A., Mahmmod, B. M., Abdulhussain, S. H., Eissa, M. R., Al-Baidhani, A., ... & Hashim, F. (2021). 6G wireless communications networks: A comprehensive survey. *Ieee Access*, *9*, 148191-148243.

Alsharif, M. H., Hossain, M. S., Jahid, A., Khan, M. A., Choi, B. J., & Mostafa, S. M. (2022). Milestones of Wireless Communication Networks and Technology Prospect of Next Generation (6G). *Computers, Materials & Continua*, *71*(3).

Andrae, A. S. (2019). Comparison of several simplistic high-level approaches for estimating the global energy and electricity use of ICT networks and data centers. *International Journal*, *5*(51), 2414-2077.

Ankapong, E. (2023). Impacts of Internet accessibility and cost on SMEs in Ghana.

Ansere, J. A., Kamal, M., Khan, I. A., & Aman, M. N. (2023). Dynamic resource optimization for energy-efficient 6G-IoT ecosystems. *Sensors*, *23*(10), 4711.

Arifin, A. S., & Habibie, M. I. (2020). The prediction of mobile data traffic based on the ARIMA model and disruptive formula in industry 4.0: A case study in Jakarta, Indonesia. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *18*(2), 907-918.

Behara, R. K., & Saha, A. K. (2022). Artificial intelligence methodologies in smart grid-integrated doubly fed induction generator design optimization and reliability assessment: A review. *Energies*, *15*(19), 7164.

Bjering, O., & Prasad, L. (2018). An Energy Efficient Radio Base Station.

Cisco, U. (2020). Cisco annual internet report (2018–2023) white paper. *Cisco: San Jose, CA, USA*, *10*(1), 1-35.

del Portillo, I., Eiskowitz, S., Crawley, E. F., & Cameron, B. G. (2021). Connecting the other half: Exploring options for the 50% of the population unconnected to the internet. *Telecommunications Policy*, *45*(3), 102092.

ESCAP, U. (2021). Towards meaningful connectivity: insights from Asia-Pacific case studies.

Etiabi, Y., & Amhoud, E. M. (2024). Federated distillation based indoor localization for IoT networks. *IEEE Sensors Journal*.

Gbadamosi, S. A., Hancke, G. P., & Abu-Mahfouz, A. M. (2020). Building upon NB-IoT networks: A roadmap towards 5G new radio networks. *IEEE Access*, *8*, 188641-188672.

Gesbert, D., Kountouris, M., Heath, R. W., Chae, C. B., & Salzer, T. (2007). Shifting the MIMO paradigm. *IEEE signal processing magazine*, *24*(5), 36-46.

Grasso, C., Raftopoulos, R., & Schembra, G. (2023, May). OSCAR: A Contention Window Optimization Approach Using Deep Reinforcement Learning. In *ICC 2023-IEEE International Conference on Communications* (pp. 459-465). IEEE.

Huq, K. M. S., Busari, S. A., Rodriguez, J., Frascolla, V., Bazzi, W., & Sicker, D. C. (2019). Terahertz-enabled wireless system for beyond-5G ultra-fast networks: A brief survey. *IEEE network*, *33*(4), 89-95.

Kadhim, K. T., Alsahlany, A. M., Wadi, S. M., & Kadhum, H. T. (2020). An overview of patient’s health status monitoring system based on internet of things (IoT). *Wireless Personal Communications*, *114*(3), 2235-2262.

Khalid, W., Yu, H., Ali, R., & Ullah, R. (2021). Advanced physical-layer technologies for beyond 5G wireless communication networks. *Sensors, 21*(9), 3197.

Kodheli, O., Andrenacci, S., Maturo, N., Chatzinotas, S., & Zimmer, F. (2018, September). Resource allocation approach for differential doppler reduction in NB-IoT over LEO satellite. In *2018 9th Advanced Satellite Multimedia Systems Conference and the 15th Signal Processing for Space Communications Workshop (ASMS/SPSC)* (pp. 1-8). IEEE.

Kumar, R., Gupta, S. K., Wang, H. C., Kumari, C. S., & Korlam, S. S. V. P. (2023). From Efficiency to Sustainability: Exploring the Potential of 6G for a Greener Future. *Sustainability*, *15*(23), 16387.

Lee, Y. L., Qin, D., Wang, L. C., & Sim, G. H. (2020). 6G massive radio access networks: Key applications, requirements and challenges. *IEEE Open Journal of Vehicular Technology*, *2*, 54-66.

Martins, S. S., & Wernick, C. (2021). Regional differences in residential demand for very high bandwidth broadband internet in 2025. *Telecommunications policy*, *45*(1), 102043.

Masoud, M., Jaradat, Y., Manasrah, A., & Jannoud, I. (2019). Sensors of smart devices in the internet of everything (IoE) era: big opportunities and massive doubts. *Journal of Sensors*, *2019*.

Montori, F., Bedogni, L., Di Felice, M., & Bononi, L. (2018). Machine-to-machine wireless communication technologies for the Internet of Things: Taxonomy, comparison and open issues. *Pervasive and Mobile Computing*, *50*, 56-81.

Morley, J., Widdicks, K., & Hazas, M. (2018). Digitalisation, energy and data demand: The impact of Internet traffic on overall and peak electricity consumption. *Energy Research & Social Science*, *38*, 128-137.

Mumtaz, S., Menon, V. G., & Ashraf, M. I. (2021). Guest editorial: Ultra-low-latency and reliable communications for 6G networks. *IEEE Communications Standards Magazine*, *5*(2), 10-11.

Oughton, E., Amaglobeli, M. D., & Moszoro, M. M. (2023). *Estimating digital infrastructure investment needs to achieve universal broadband*. International Monetary Fund.

Qadir, Z., Le, K. N., Saeed, N., & Munawar, H. S. (2023). Towards 6G Internet of Things: Recent advances, use cases, and open challenges. *ICT Express*, *9*(3), 296-312.

Ramezani, P., Zeng, Y., & Jamalipour, A. (2018). Optimal resource allocation for multiuser Internet of Things network with single wireless-powered relay. *IEEE Internet of Things Journal*, *6*(2), 3132-3142.

Rejeb, A., Rejeb, K., Treiblmaier, H., Appolloni, A., Alghamdi, S., Alhasawi, Y., & Iranmanesh, M. (2023). The Internet of Things (IoT) in healthcare: Taking stock and moving forward. *Internet of Things*, 100721.

Rezaei, F., Galappaththige, D., Tellambura, C., & Maaref, A. (2023). Time-spread pilot-based channel estimation for backscatter networks. *IEEE Transactions on Communications*.

Sharma, S., Deivakani, M., Reddy, K. S., Gnanasekar, A. K., & Aparna, G. (2021, March). Key enabling technologies of 5G wireless mobile communication. In *Journal of Physics: Conference Series* (Vol. 1817, No. 1, p. 012003). IOP Publishing.

Shayea, I., Azmi, M. H., Rahman, T. A., Ergen, M., Han, C. T., & Arsad, A. (2019). Spectrum gap analysis with practical solutions for future mobile data traffic growth in Malaysia. *IEEE Access*, *7*, 24910-24933.

Singh, P. R., Singh, V. K., Yadav, R., & Chaurasia, S. N. (2023). 6G networks for artificial intelligence-enabled smart cities applications: a scoping review. *Telematics and Informatics Reports*, *9*, 100044.

Sudarmani, R., Venusamy, K., Sivaraman, S., Jayaraman, P., Suriyan, K., & Alagarsamy, M. (2022). Machine to machine communication enabled internet of things: a review. *International Journal of Reconfigurable and Embedded Systems*, *11*(2), 126.

Tang, F., Kawamoto, Y., Kato, N., & Liu, J. (2019). Future intelligent and secure vehicular network toward 6G: Machine-learning approaches. *Proceedings of the IEEE*, *108*(2), 292-307.

Tyagi, A. K., & Nair, M. M. (2020). Internet of Everything (IoE) and Internet of Things (IoTs): Threat Analyses, Possible Opportunities for Future. *Journal of Information Assurance & Security*, *15*(5).

Xia, Q., & Jornet, J. M. (2019). Expedited neighbor discovery in directional terahertz communication networks enhanced by antenna side-lobe information. *IEEE Transactions on Vehicular Technology*, *68*(8), 7804-7814.

Xia, X., Fan, Z., Luo, W., Lu, A., Wang, D., Zhao, X., & You, X. (2022). Joint uplink power control, downlink beamforming, and mode selection for secrecy cell-free massive MIMO with network-assisted full duplexing. *IEEE Systems Journal*, *17*(1), 720-731.

Xu, Z. (2023). *Randomized Algorithms for Mega-AI Models* (Doctoral dissertation, RICE UNIVERSITY).

You, L., Xiong, J., Ng, D. W. K., Yuen, C., Wang, W., & Gao, X. (2020). Energy efficiency and spectral efficiency tradeoff in RIS-aided multiuser MIMO uplink transmission. *IEEE Transactions on Signal Processing*, *69*, 1407-1421.

Zhang, C., Patras, P., & Haddadi, H. (2019). Deep learning in mobile and wireless networking: A survey. *IEEE Communications surveys & tutorials*, *21*(3), 2224-2287.

Zhang, Y., Di, B., Wang, P., Lin, J., & Song, L. (2020). HetMEC: Heterogeneous multi-layer mobile edge computing in the 6 G era. IEEE Transactions on Vehicular Technology, 69(4), 4388-4400.

Zhou, Y., Liu, L., Wang, L., Hui, N., Cui, X., Wu, J., ... & Xing, C. (2020). Service-aware 6G: An intelligent and open network based on the convergence of communication, computing and caching. *Digital Communications and Networks*, *6*(3), 253-260.