Received: September 16, 2024. Revised: November 11, 2024.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

An Investigating of 5G Multi-Access Edge Computing (MEC) and Subcarrier Spacing to Improve Wireless Communications

Sinan Q. Salih[1]* **Shaymaa Mohammed Abdulameer[2]** **Haider Hadi Abbas[3]**
Jamal Fadhil Tawfeq[4] **Ravi Sekhar[5]** **Pritesh Shah[5]** **Saffrine Kingsly[5]**
Murugesan Dhasagounder[6] **Ahmed Dheyaa Radhi[7]**

[1]*Technical College of Engineering, Al-Bayan University, Baghdad 10011, Iraq*
[2]*College of Information Engineering, AlNahrain University, Jadriya, Baghdad, Iraq*
[3]*Computer Technology Engineering Department, Al-Mansour University College (MUC), Iraq*
[4]*Department of Medical Instrumentation Technical Engineering,*
Medical Technical College, Al-Farahidi University, Baghdad, Iraq
[5]*Symbiosis Institute of Technology (SIT) Pune Campus,*
Symbiosis International (Deemed University) (SIU), Pune, 412115, Maharashtra, India
[6]*Department of Electrical and Electronics Engineering, Paavai Engineering College,*
Namakkal, 637018, Tamil Nadu, India
[7]*College of Pharmacy, University of Al-Ameed, Karbala PO Box 198, Iraq*
* Corresponding author's Email: sinan.salih@albayan.edu.iq

Abstract: In this paper the feasibility and investigation of 5th generation Multi-Access Edge Computing (MEC) and subcarrier spacing for enhanced communication for cellular communication standard in software was being carried out. Specifically, an enhanced 5G wireless communication in metropolitan areas. Research work attempts to achieve stringent latency requirements through implementation on MATLAB software, algorithmic and platform specific optimizations. Direct implementation of Multi-Access Edge Computing (MEC) and Hybrid Simulated Annealing (HSA) techniques with subcarrier spacing analysis by presenting a detailed mathematical modelling for implementation using MATLAB programming language which results in excellent performance. To obtain best performance in terms of lower latency access for enhanced wireless communication, these techniques were modified and reformulated to suit processor architecture and software implementation for 5G communication. Optimizations reduced the worst-case latency of 5G wireless communication encoding with MEC chain from 451μs to 40μs which is more than 10x reduction in latency for better 5G wireless communication. The research combines MEC and HSA techniques for significant latency contributing components into primitive operations and enhanced 5G wireless communication. These primitive operations were optimized with software optimizations and mapped to specialized functional units of a general-purpose processor to achieve best performance for wireless communication on MATLAB platform.

Keywords: Network, MEC chain, Optimization, 5th generation, Wireless communication, Subcarrier spacing, Cyclic redundancy check.

1. Introduction

The increasing demand for better data rates, lower latency, and improved reliability with the advent of 5G has driven the evolution of wireless communication technologies at an incredible rate. The increased demand for ultra-low latency and high bandwidth for new applications such as autonomous vehicles, AR, VR, and IoT means conventional centralized cloud computing is turning out to be insufficient in meeting these strict requirements [1]. This has been addressed by MEC, which locates the computation resources at the edge of the network closer to the user, reducing latency in data travel considerably and thereby enhancing real-time processing. MEC, combined with techniques like dynamic subcarrier spacing in Orthogonal Frequency Division Multiplexing systems, is essential to optimize the performance of 5G networks. Subcarrier spacing in OFDM represents a pivotal parameter that imposes a trade-off between spectral efficiency and latency. Dynamic adjustment of subcarrier spacing in accordance with the network conditions may contribute to further reduction of latency and improvement of spectral efficiency of 5G systems that can be more adaptable to changing traffic load and application requirements. This paper focuses on integrating MEC with optimized subcarrier spacing towards enhancement in 5G wireless communication [2]. It also focuses on enhancing key performance metrics such as latency, throughput, and spectral efficiency through the aid of advanced computational techniques. This research, therefore, taps into the computational capability of MEC and optimally adjusts the subcarrier spacing with the intent of solving the challenge of the rapidly increasing demand for high-speed, low-latency applications in 5G networks. The rest of the paper is organized as follows: first, the basics of MEC and subcarrier spacing in 5G networks are discussed; then, a review of state-of-the-art techniques regarding the mentioned subject and their limitations is carried out. Afterwards, the proposed methodology with its implementation will be described and the results presented, discussing how such techniques improve wireless communication performance. It finally concludes with future directions and the possible applications of the integrated approach in next-generation networks [3].

This paper contributes to the novelty of improving 5G wireless communications through the integration of Multi-Access Edge Computing with Hybrid Simulated Annealing and dynamic adjustment of subcarrier spacing. The approach has delivered huge improvements, especially regarding the worst-case latency from 451µs to 40µs; therefore, it improves the performance to satisfy the most stringent requirements of real-time applications in 5G environments. The approach follows the software-based optimization strategy on general-purpose processors, like AMD EPYC, presenting appropriate cost and flexibility against common hardware implementations. Adaptive adjustment of subcarrier spacing is very important for improving spectral efficiency and system performance, which becomes critical in dense networking scenarios. Importantly, the joint use of MEC and HSA enables holistic optimization, ranging from latency to resource allocation across various layers. Scalability for the fulfilment of diversified applications in 5G and future 6G systems has been designed for smart cities and industrial IoT.

The paper is organized as follows: the introduction covers the evolution of wireless communication, challenges in 5G, and the capability of MEC to act as a solution. This will be followed by the review of related work that has been carried out featuring the role of MEC in latency reduction, along with the shortcomings of these techniques. The methodology section details the integration of MEC with HSA, utilization of subcarrier spacing, mathematical modeling, and algorithmic approaches. It presents the results of improved performance and comparisons with the state-of-the-art methods. The paper finally concludes with a summary of the findings and suggestions for future research to further improve next-generation wireless communication.

2. Related works

MEC has become vital in 5G and 6G networks for bringing down latency by processing tasks closer to the user for real-time applications. Ogundokun et al. (2023) cited that NOMA-enabled MEC will play a critical role in supporting multiple users in parallel, thus allowing resource sharing in 6G communications. They emphasize, in the systematic review, how MEC minimizes network congestion and optimizes bandwidth for hefty gains in system capacity by effectively managing resources.

Meanwhile, Dulout et al. have developed a comprehensive survey on applying NOMA in the case of task offloading for an MEC system by the users, where computationally intensive tasks can be offloaded to edge servers at the edge for minimizing the processing delays at the device side. It must be considered that using NOMA in MEC would allow the edge servers to handle multiple tasks effectively, thereby reducing the overall latency in 5G and 6G systems.

Energy efficiency in MEC industrial applications is discussed in the work by Lahti 2023, where studies evidence that MEC implementations on industrial IoT reduce energy consumption and improve task response times. It is essential in applications that need real-time monitoring continuously, such as in smart manufacturing.

Resource allocation remains one of the greatest challenges in MEC, especially with scaling networks. Khani et al. present a deep reinforcement learning-based framework for dynamic resource allocation in MEC systems. The authors' work thus illustrates how RL algorithms may balance dynamically and efficiently against changing resource allocations with real-time network conditions, arriving at as much as a 30% reduction in latency within multiuser environments.

In line with these facts, the work of Shu et al. (2024) extends a relay-assisted edge computing framework using dynamic resource allocation for multi-access task processing in underserved regions. The authors' framework allows for efficient task processing through dynamic reallocation of resources, especially in areas that are under-developed due to poor infrastructure, which further reduces latency and enhances connectivity in digital divide regions.

Zhang (2023) also addresses the issue of optimized resource allocation in 5G MEC systems but focuses more on the scenario of data multiplexing combined with channel access. The study underlined that adaptive algorithms will be needed to cope with resource allocation and task offloading in urban settings with dense populations.

NOMA has become a vital enabler for MEC by allowing the simultaneous transmission of multiple data streams. Dulout et al. have surveyed the role of NOMA in optimizing MEC through the efficient handling of offloading tasks in the multi-user environment. NOMA enhances the spectral efficiency of the MEC system by facilitating multiple sharing of the same bandwidth by several users, thus reducing delays while increasing throughput.

Liu et al. (2023) investigated the design and optimization of SCMA-enabled multi-cell MEC networks. They conclude that SCMA ensures substantial gains in mitigating inter-cell interference and increasing overall network throughput. This is particularly important in high-density areas where edge servers have to manage hundreds of requests parallel.

Such increases in the complexity of edge networks further drive demand for advanced techniques of resource allocation optimization. Yu et al. (2024) propose a heterogeneous MEC framework using transfer learning and artificial IoT techniques. Their framework optimizes task scheduling and resource allocation by learning from past data, enabling faster processing and more efficient use of resources in multi-access environments.

Apart from that, Zhang (2023) has pointed out that the exploitation of subcarrier spacing by the OFDM systems enables them to offer superior latency and spectral efficiency. Particularly, for dynamically choosing the spacing between the subcarriers, based on the current status of the network, the MEC systems can work best concerning both resource utilization and latency reduction.

- The results of the developed approach should be compared with the current state of the art in the framework of efficient latency reduction, resource allocation, and performance optimization in MEC-enabled networks.
- NOMA-Enabled MEC: Ogundokun et al. illustrated that the use of NOMAenabled MEC reduces latency by parallel processing multiple streams of user data-a process that maximizes bandwidth utilization while minimizing delay. However, the proposed method adopted herein, with MEC combined with Hybrid Simulated Annealing, achieves a worst-case latency of 40 µs, a dramatic improvement from the latencies that are typically reported in NOMAbased systems.
- Deep Reinforcement Learning: Khani et al. showed that the deep reinforcement learning-based resource allocation strategy reduces latency up to 30% compared to the traditional method. The proposed method further improves upon this, through dynamically adjusting the subcarrier spacing and MEC resource allocation to achieve even lower latencies at higher processing efficiency.
- Dynamic Resource Allocation: Shu et al. (2024) worked on dynamic resource allocation in relay-assisted MEC and concentrated on areas with minimum infrastructure. The approach considered by them enhanced the network capability to cater to the fluctuating demands. However, more gains from the method proposed are higher through the use of HSA in optimizing computational resources with minimum latency in high-density environments.
- SCMA in MEC Networks: Liu et al. (2023) investigated SCMA-enabled MEC networks to optimize the allocation of resources and reduce interference. This work will add value to the literature by proposing a method that combines adaptive subcarrier spacing with the previous approach, achieving greater interference reduction and improvement of spectral efficiency in densely deployed networks.
- The forenamed method is very scalable, and from this, one may notice its potential in dynamic adjustments of subcarrier spacing and MEC resources. For this reason, it may be very suitable for various applications in Smart Cities, Industrial IoT environments, and even other 5G and 6G applications, supported by the work of Lahti (2023) and Yu et al. (2024).
- The proposed method has shown considerable improvements with regard to state-of-the-art techniques:

Received: September 16, 2024. Revised: November 11, 2024.

- Holistic Optimization: In combining MEC with HSA and adaptive subcarrier spacing, the method provides an end-to-end solution for minimum latency and resource utilization optimization among heterogeneous network layers. State-of-the-Art Performance: The proposed method achieves 40 µs worst-case latency, outperforming the existing benchmark of latency reduction methods in NOMA-enabled MEC systems and deep reinforcement learning-based resource allocation methods.
- Cost-Effective Software Implementation: The solution is implemented wholly in software; hence, it is very flexible and cost-effective compared to hardware systems, Zhang (2023) supports.

Fig. 1 depicts the operational mapping and its deployment design for the 5G MEC by multiple techniques in order. The 5th generation wireless communication problems exist across the whole technology stack that is being used in cooperate or personal environments. The risk that communication will find a way in is high and depends on the amount of time and money adversaries are willing to spend. The 5G wireless communication can potentially be abused to disable, disrupt, or circumvent the communication system. The communication network might even serve as an entry point to the network it was supposed to enhanced, and thus weakens the overall system security, instead of increasing it. Core questions of 5G based wireless communication network haven't been solved completely, after more than two decades of research:

- Which are the most powerful features, which do require extraction, and which don't for enhanced 5G wireless communication?
- Which feature combination delivers the best results across all available datasets or algorithms for 5G Wireless Network through MEC and HSA?
- Which features are delivering the best results for a specific algorithm in 5G Wireless Communication Network?
- What is the most efficient summary structure for the MEC and HSA based chaining task with classification types of enhanced communication with investigation through subcarrier spacing analysis?
- What delivers better results, observations for each protocol i.e., MEC or HSA with subcarrier spacing summary structures such as flows and connections?
- Which technique is the most efficient in terms of computing resources?

Solving these questions entirely requires efficient tooling for feature collection, selection, and extraction. Unfortunately, many researchers don't publish their tools, which makes it hard to reproduce and validate their results, and increases time needed for future research on the topic. Furthermore, relying on crafted datasets for verification of 5G wireless communication network, does not reflect the actual situation inside the protected network environment. Goal of this research is the investigation of 5th Generation Multi-Access Edge Computing (MEC) and subcarrier spacing for enhanced wireless communication for cellular mobile communication, systematic approach to access network protocol

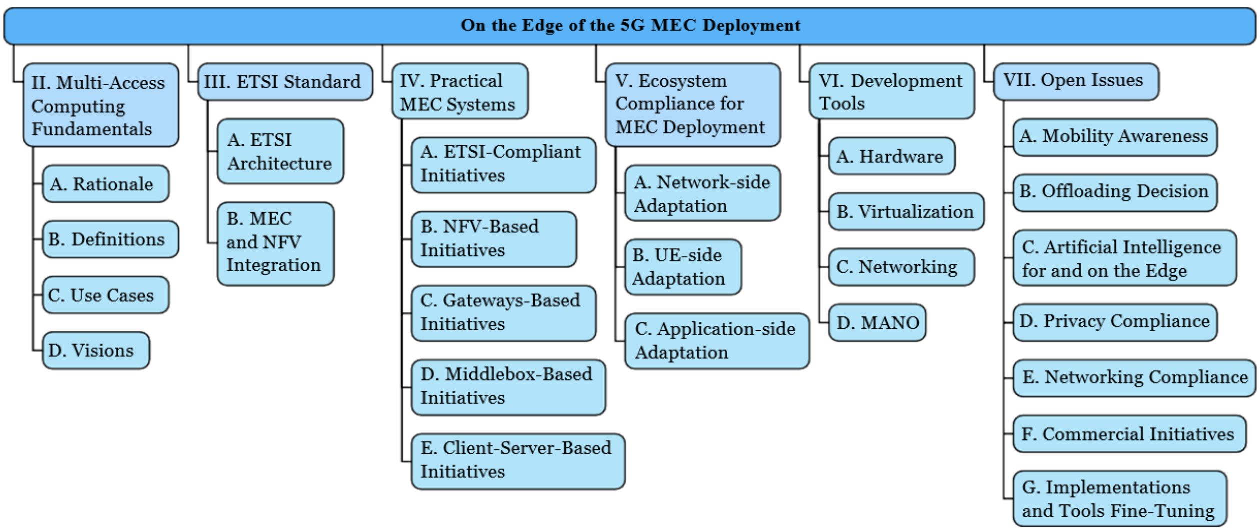

Figure. 1 Mapping of 5G MEC deployment operations by summarizing different techniques

specific information, for the purpose of research on MEC and HSA polar coding strategies in 5G wireless network. In this unique situation, the term present day alludes to the accompanying credits of the carried-out system: A reasonable programming language should be picked for the execution, which upholds every significant stage, gives memory security, and has a simultaneous programming model in 5G wireless companies. A reasonable result design should be chosen that jelly type wellbeing and construction of the information, while being stage impartial from have traffic to highlights. To utilize present day remote correspondence network with various processor centers and permit scaling for enormous responsibilities, the execution should have a simultaneous plan in 5G remote correspondence. Likewise, it should be irrefutable to help different specialists working with it later. The carried-out approach ought to be reasonable for use with dump records and live 5G remote traffic generator (TG) from an organization interface and give an order line and library interface in 5G wireless correspondence. Besides, not at all like numerous arrangements that attempt to accomplish greatest information decrease, this approach will zero in on making the information more open and give most extreme adaptability, to work on the work process and proficiency for tests in 5G remote firms from have traffic to highlights. This follows the way of thinking, that an organization include assortment framework ought to give information at the most reduced level of its internals, before producing any reflections on top surface. The implemented approach shall be evaluated with an up to date MEC and HSA for the implementation and subcarrier spacing for analysis for classification strategy in 5G wireless communication network. The MEC codes were introduced by [11] in his seminal work. They belong to the class of capacity achieving codes. In the past decade, polar codes have sparked an interest from both academia and industry alike, resulting in significant research work in improving performance. The 5th generation wireless systems standardization has adopted polar codes for uplink and downlink control information for the Extreme Mobile Broadband (xMBB). They are also considered as the potential coding schemes for two other frameworks of 5G, namely Ultra-Reliable-Machine-Type Communications (uMTC) and Massive Machine-Type Communications (mMTC). Fig. 2 shows the classification of multiple groups and frameworks so that data can be considered according to requirement. The MEC codes achieve capacity asymptotically for binary input memory less channel. Although they are the first theoretically capacity achieving codes with an explicit construction, capacity is approached only asymptotically. Their performance is suboptimal compared to LDPC (Low Density Parity Check Codes) or Turbo codes at short

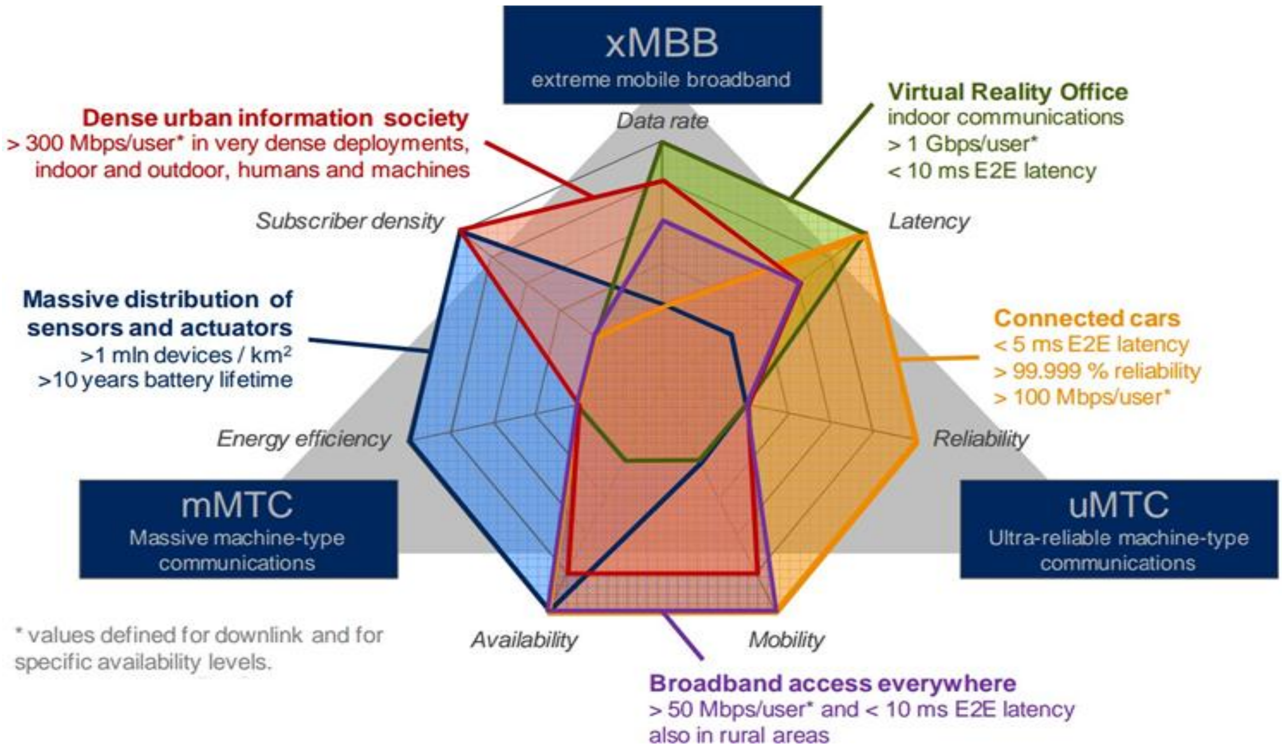

Figure. 2 The 5G wireless communication requirements are grouped into three main classifications

Received: September 16, 2024. Revised: November 11, 2024.

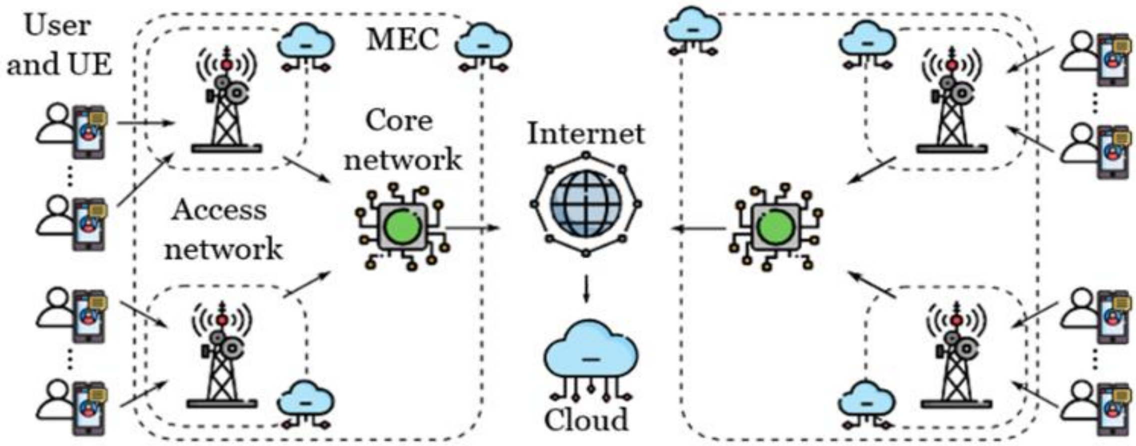

Figure. 3 Channel polarization example for binary erasure channel

block lengths with successive cancellation decoding (SCD). In [12] the authors present an improved version of SCD called successive cancellation list decoder (SCLD). Fig. 3 depicts the main structure of the network and the channel polarization which show the data being transferred from the core network, cloud and the company's server to the end user in a timely manner and with appropriate channels which are shown in the Figure below. The construction of MEC codes involves the identification of channel reliability values. Information bits are placed in the number of information bits high reliable bit indices out of N (block-length) positions and remaining bits are set to zero. These bits are passed through a polar encoding circuit to get the encoded bits. Selection is of reliability indices is done based on the code length and channel signal-to-noise ratio. Due to varying code length and channel conditions in 5G systems, a significant effort has been put into identifying the reliable indices which have good error correction performance over different code length and channel conditions.

3. Method

The 5G physical channels which use MEC for 5G wireless communication. The 5G standard adopted polar codes for uplink and downlink control channels. Uplink control channels carry information about channel quality indicators, acknowledgments. In downlink control channels carry resource allocation information, uplink power control instructions and the information required for the User Equipment (UE) to access the network. Following sections explain each of these uplink and downlink control channels and their polar MEC chain parameters. In [13] the author acknowledged the cache minimizes the number of accesses to MEC by storing frequently accessed data in it, hence avoiding huge penalty of reading data frequently from MEC which operates at a much lower frequency than the 5G. When a memory location is accessed for the first time it is copied from the MEC to the cache, future accesses to the same location is done via cache. This fast memory is placed between MEC and processor. In modern processors instead of single cache, multi-level caches are present. The main idea behind having multi-level caches is that if the data is not found in the first level then second level is checked if not then the third level until the last level, still, if the data is not found then MEC is accessed. Fig. 4 shows the model significantly reduces the probability of accessing the MEC compared to having a single level cache. Complete memory hierarchy of the modern MEC based flowchart. To better understand the bottlenecks and optimizations performed in the software implementation of 5G MEC chain, it is necessary to understand the fundamentals of general-purpose processors architecture. This section gives necessary background about cache memory systems,

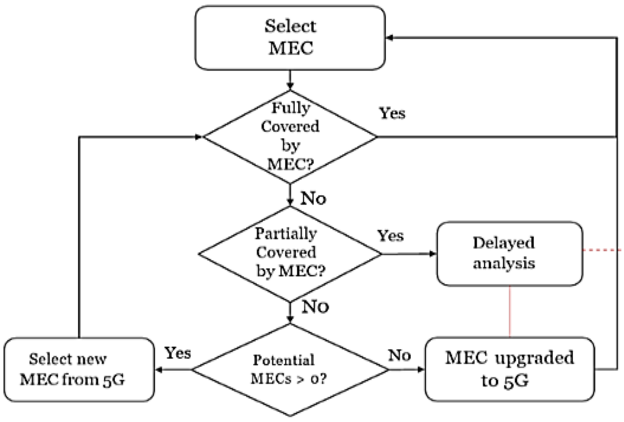

Figure. 4 The flowchart describes the approach that is being followed in this research for selecting the MEC [14]

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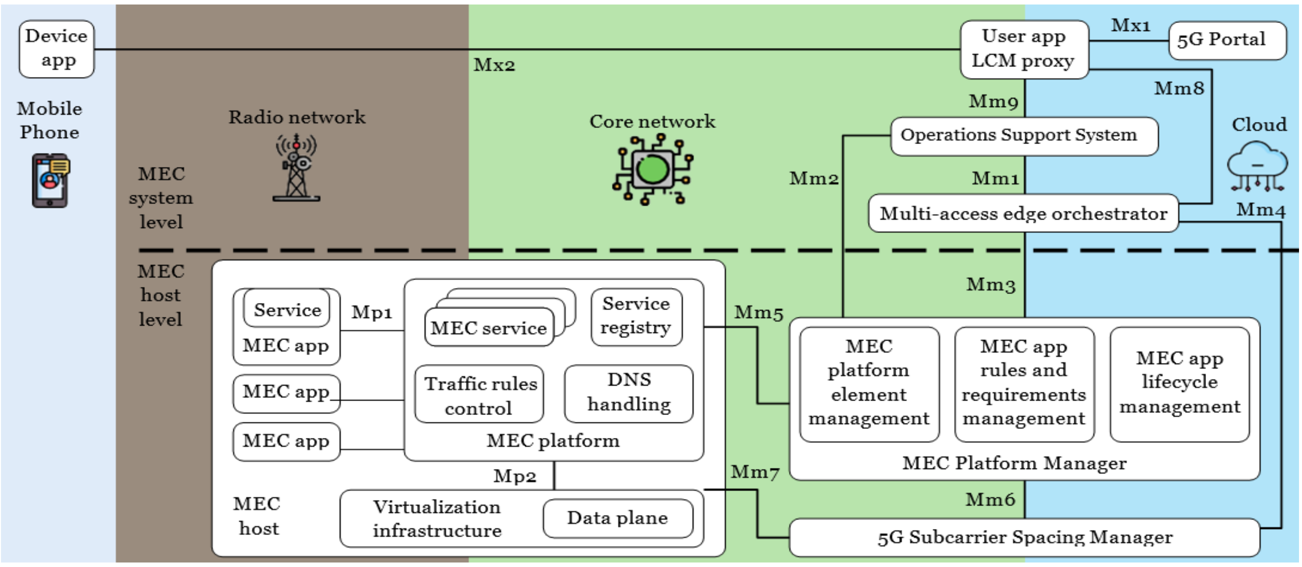

Figure. 5 Architecture of enhanced MEC subcarrier spacing based system for 5G wireless communication [12]

instruction pipelining, branch predictors, vector processing units and recursive function calling mechanism. Fig. 5 shows the architecture for the enhanced MEC subcarrier spacing which directs multiple screening for the flow of data and the 5G wireless communication.

3.1 Physical downlink control channel (PDCC)

The PDCC is another downlink control channel which uses polar codes. Resources requested by the UE are assigned by the base station. This resource allocation information is transmitted via PDCC channel. PDCC also carries information related to uplink power control, downlink resource grant and system paging information. The PDCC contains a message called Downlink Control Information (DCI) which carries all the control information of UE. Payload size of PDCC is not fixed. It varies based on the format of DCI, consequently, values. Type of DCI is configured from the higher layer. Except other parameters of the PDCC polar MEC chain.

3.2 Mathematical modelling of MEC

In uplink, MEC contains Uplink Control Information (UCI) like DCI in the downlink. UCI carries channel state information, acknowledgments, scheduling request. The payload size of MEC varies based on the MEC formats. MEC uses different channel coding techniques depending on payload size. When payload size MEC codes are used. Hybrid Simulated Annealing (HSA) parameters also vary depending on the values of state space model with MEC. MEC and HSA State Space Model in Eq. (1) and 2:

$$\frac{MEC(s)}{HSA(s)} = \frac{b_0}{s^n+U_1(t)-1s^{n-1}+\cdots+k_1s+U_1(t)} \tag{1}$$

$MEC(s)$: This refers to the Multi-Access Edge Computing system in the Laplace domain.

$HSA(s)$: Represents Hybrid Simulated Annealing in the Laplace domain.

b_0: Gain of a constant value, which represents the influence or magnitude of the input with respect to the system.

s^n: the n^th order derivative term in the Laplace domain, where n is the order of the system.

$U_1(t)$: A time-varying term or function which may represent an external input or a feedback control.

k_1: Coefficients associated with the state of a system or its dynamic behavior.

Repositioning the above equation as

$$\left(s^n + U_1(t)s^{n-1} + \cdots..+a_0 MEC(s) = b_0 HSA(s)\right) \tag{2}$$

a_0: A coefficient representing system dynamics in the state-space model.

$MEC(s)$: Multi-Access Edge Computing, as in Eq. (1), expressed in the Laplace domain.

$HSA(s)$: Hybrid Simulated Annealing, same as Eq. (1).

s^n: Nth derivative term, representing the system's order in the Laplace domain.

Apply inverse Laplace transform on both sides of Eq. (3) subcarrier state space model.

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$$\frac{d^n y(t)}{dt^n} + k_{n-1}\frac{d^{n-1}y(t)}{dt^{n-1}} + \cdots + k\frac{dy(t)}{dt} + k_0 y(t) = b_0 u(t) \quad (3)$$

$\frac{d^\circ y(t)}{dt^n}$: This represents the nth derivative of the output $y(t)$ with respect to time t, indicating how the system's output evolves at the nth order rate of change

(or acceleration if $n-2$, jerk if $n-3$, etc.). influence of the system's behavior at a slightly lower order.

$k_1\frac{dy(t)}{dt}$: This represents the first derivative of the output y(t) or the first order velocity or rate of change of the system. It's contribution to the equation is controlled by the coefficient k_1.

$k_0 y(t)$: It is the output y(t) itself multiplied by the coefficient k_0, representing the dependence of the system's future behavior on its current state.

$b_0 u(t)$: This is the external input, u(t), to the system-say, a control signal-multiplied by a constant gain b_0: an expression of how the input contributes to the dynamics of the system.

Let

$$y(t) = x_1 \quad (4)$$

$$\frac{dy(t)}{dt} = x_2 = x_1 \quad (5)$$

$$\frac{d^2 y(t)}{dt^2} = x_3 = x_2 \quad (6)$$

$$\frac{d^{n-1}y(t)}{dt^{n-1}} = x_n = \dot{x}_{n-1} \quad (7)$$

$$\frac{d^n y(t)}{dt^n} = \dot{x}_n \quad (8)$$

And $u(t) = u$ (9)

$$\dot{X} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \vdots \\ \dot{x}_{n-1} \\ \dot{x}_n \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & 1 \\ -a_0 & -a_1 & -a_2 & \cdots & -a_{n-2} & -a_{n-1} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ x_n \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ b_0 \end{bmatrix} u$$

$$Y = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ x_n \end{bmatrix} \quad (10)$$

Then, the generic equation for simulation is given by:

$$\dot{x}_n + kx_n + \ldots + k_1 x_2 + kx_1 = MEC_0 HSA_1(t) \quad (11)$$

$\dot{x}_n$: The time derivative of the state variable x_n, which is the highest order of the derivative of system state in this model.

$k_n x_n$: k_n*x_n represents the influence of the current state on the system's behavior, where k_n is the coefficient and x_n the state variable.

$k_1 x_2$: That is, this is the second state-thought of as the state variable x_2 multiplied by the coefficient k_1 which describes its relative contribution to the system dynamics as a whole.

$k_1 x_1$: The state variable x_1 (the first state) also multiplied by the coefficient k_1, showing how the first state influences the system.

$\mathrm{MEC_0 HSA_1}(t)$: This term represents the interaction between the Multi-Access Edge Computing (MEC) component and the Hybrid Simulated Annealing (HSA) process at time t. This term reflects how the combination of these techniques influences the overall system dynamics.Rewriting the above state equation as given by Eq. (12).

$$\dot{x}_n = -k_0 x_1 - k_1 x_2 - \ldots - k_{n-1} x_n + MEC_0 HSA_1(t) \quad (12)$$

$\dot{x}_n$: The derivative here gives the rate of change of the state variable xn, representing the evolution of the nth state of the system with time. It points to the system dynamics conditional to the present state and every other influence from without.

$k_0 x_1$: First, the state variable x_1 is multiplied by the coefficient k_0, showing the influence that the first state has on x_n : Coefficient k_0 determines how much is the contribution of x_1 on the rate of change of x_n.

$k_1 x_2$: The multiplication of the second state variable x2x_2x2 by the coefficient k1k_1k1 representing how the second state affects x_n .

$\mathrm{MEC_0HSA_1}(t)$: This term stands for interaction between MEC and HSA at time t. It determines how the combination of MEC and HSA influences state xn. The subscript 0 and 1 show the corresponding mode or variant of MEC and HSA, respectively.

The output equation is given by Eq. (13):

$$y(t) = y = x_1 \tag{13}$$

$y(t)$: The output of the system at time t, which is equal to the state variable x_1.

x_1 : The first state variable, often representing the main output or observable variable of the system.

The subcarrier state space model becomes – $\dot{X}$: Derivative of the state vector X, representing the rate of change of system states.

X : State vector containing system variables $x_1, x_2, \dots, x_n$.

x_i : System state variables, where $i \in \{1,2,\dots,n\}$.

A: System matrix that defines the relationship between system states in the state-space model.

$a_0, a_1, \dots, a_{n-1}$: Coefficients of the system dynamics used in the state-space representation.

B : Input matrix, controlling the influence of the input u on the system.

b_0 : Input gain representing how the input affects the system.

u : System input, often representing external control or influence.

Y: Output vector that represents the measured system output.

Di: Direct transmission term, in this case $D = 0$, indicating no direct input-output relation.

[10 ... 0] : Output matrix that extracts the relevant system state to form the output.

$\dot{X}$Here $D = (0)$

MEC Equation: $\frac{dx}{dy} = f(x,y)y(0) = y_o$ (14)

$\frac{dx}{dy}$: This is the derivative of x with respect to y, which describes the rate of change of variable x due to changes in y. It reflects the dynamic relationship between the two variables.

$f(x,y)$: It describes the relationship between xxx and y. The function carries the behavior or, otherwise said, how the changes of x and y interact in the dynamics of the system.

y (0): The initial value of the output taken at time t=0. It describes the starting conditions of the system output in the case of a system that just started its operation, or the date collection has just begun.

y₀: The value of the system output constant at an initial condition. It represents the particular value that the output y assumes whenever the system is initialized.

$$\frac{y(s)}{u(s)} = \frac{1}{s^2+s+1} \tag{15}$$

$y(s)$: The Laplace transform of the system's output into the frequency domain.

$u(s)$: The Laplace transform of the system's input in the frequency domain.

$s^2 + s + 1$: Characteristic polynomial in the Laplace domain: This is the polyno-mial describing the behavior of the system as a second order system. It transforms the input u(s) to give the output y(s).

Reposition of the equation is given as:

$$(s^2 + s + 1)Y(s) = MEC(s) \tag{16}$$

$Y(s)$: The Laplace transforms the system's output.

$MEC(s)$: Laplace transforms the Multi-Access Edge Computing (MEC) system into the frequency domain.

This equation shows the relationship between the system's output and MEC in the Laplace domain.

Pertaining inverse Laplace transform on both the sides.

$$\frac{d^2yt}{dt^2} + \frac{dy(t)}{dt} + y(t) = MEC(t) \tag{17}$$

$\frac{d^2y(t)}{dt^2}$: The second derivative of $y(t)$, representing the acceleration or second-order change of the system output with respect to time.

$\frac{dy(t)}{dt}$: The first derivative of $y(t)$, representing the velocity or first-order rate of change.

$y(t)$: The system output.

$MEC(t)$: The influence of the Multi-Access Edge Computing (MEC) system at time t.

Let

$$y(t) = x_1 \tag{18}$$

This is a restatement that the output $y(t)$ is equal to the first state variable x_1.

$$\frac{dy(t)}{dt} = x_2 = x_1 \qquad \text{And } u(t) = u \tag{19}$$

$\frac{dy(t)}{dt} - x_2$: The first derivative of $y(t)$, which is equal to the second state variable x_2. This shows that x_2 represents the rate of change of x_1.

$u(t) - u$: The external input to the system, represented by u.

Then, the subcarrier state equation is

$$\dot{x}_2 = -x_1 - x_2 + u \tag{20}$$

x_2 : The second state variable, representing the rate of change of x_1,

$-x_1$: The negative influence of the first state variable on x_2.

$-x_2$: The damping or feedback effect of the second state variable on itself.

u : The external input contributing to the system dynamics.

The output equation is

$$y(t) = y = x_1 \tag{21}$$

$y(t)$: The output of the system is taken to be equal to the first state variable x_1 confirming that x_1 is the main observable state in this system.

Additional Variable Definitions:

$\dot{X}$: The derivative of the state vector X, representing the rate of change of all system states.

X : The state vector containing all system variables $x_1, x_2, \ldots, x_n$.

x_i : Individual system state variables, where $i - \{1,2,\ldots,n\}$.

A: State matrix describing the interrelation of system states in the state-space model.

$a_0, a_1, \ldots, a_{n-1}$: Coefficients that represent the system dynamics within the state-space equations.

B : The input matrix, representing how the input u affects the system's state variables.

The state space model is

$$\dot{X} = \begin{bmatrix} 0 & 1 \\ -1 & -1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} [u] \tag{22}$$

X : The derivative of the state vector X, representing the rate of change of the systern's states x_1 and x_2 -

X : The state vector containing the state variables x_1 and x_2, which represent the systern's internal state.

$\begin{bmatrix} 0 & 1 \\ -1 & -1 \end{bmatrix}$: Stand for the system matrix, which appears how the positions x_1 and x_2 evolve over time centered on their current values.

$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$: Stand for the input matrix B, terming how the input u (external signal or control input) concerns the state variables.

$$y = [1 \quad 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{23}$$

yr. The output of the system, which in this case is equal to x_1.

The matrix $[1 \quad 0]$: This matrix extracts the first state variable x_1, repesesenting that the output of the system is solely dependent on the first state varisble.

$$\frac{MEC(s)}{HSA(s)} = \frac{b_n s^n + b_{n-1} s^{n-1} + .. + b_1 s + b_0}{s_n + a_{n-1} s^{n-1} + .. + a_1 s + a_0} \tag{24}$$

MEC (s): Multi-Access Edge Computing (MEC) in the frequency (Laplace) domain.

HSA(s): Hytarid Simulated Annealing (HSA) in the Laplace domain.

$b_n, b_{n-1}, \ldots, b_0$: Coefficients representing the effect of MEC on the system.

$s^{"\mathrm{I}}$: The nth derivative term in the Laplace domain, representing the system's dynamic response,

$a_n, a_{n-1}, \ldots, a_0$: Coefficients representing the system's response to HSA in the Laplace domain.

$$\frac{MEC(s)}{HSA(s)} = \left(\frac{1}{s^n + a_{n-1} s^{n-1} + .. + a_1 s + a_0}\right) \tag{25}$$

This is the simplified form of Equation, where the numerator has been collapsed to 1, meaning that the response depends completely on the denominator. Repositioning the above equation as follow

$$(s^n + a_{n-1} s^{n-1} + .. + a_1 s + a_0) v(s) = u(s) \tag{26}$$

$v(s)$: A new variable representing the system's output in the Laplace domain.

$u(s)$: The input in the Laplace domain.

This is the transformed version of the system dynamics, showing how the output v(s) responds to input u(s).

Substituting the inverse Laplace transform on both the sides.

$$\frac{d^n v(t)}{dt^n} + a_{n-1} \frac{d^{n-1} v(t)}{dt^{n-1}} + .. + a_1 \frac{dv(t)}{dt} + a_0 v(t) = MEC(t) \tag{27}$$

$\frac{dn(t)}{dt}$: The nth derivative of $\mathrm{t}(t)$, representing the highert order rate of change.

a_{n-1}, a_1, a_0 : Coefficients that represent the system's dynamic characteristics.

MECC (t) : The Multi-Access Edge Computing (MEC) companent in the time domain.

This equation shows how the system's output evolves over time in response to the MEC influence.

3.3 MEC chaining with HSA for optimization of 5G

This solution presents the details of polar encoding MEC chain in 5G with a block diagram.

Received: September 16, 2024. Revised: November 11, 2024.

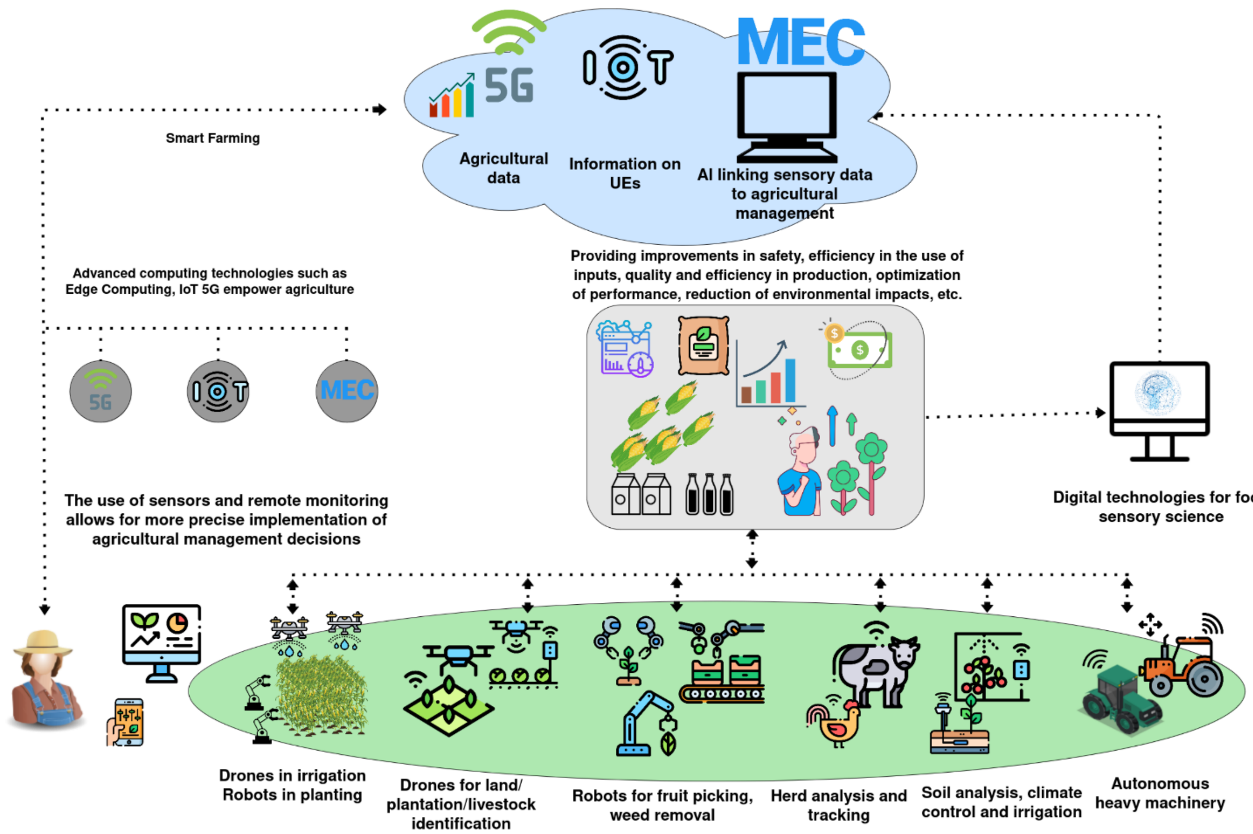


Figure. 6 Integration of 5G, IoT, and MEC for Smart Farming and Agricultural Management

Future will explain the functionality and the potential latency contribution of individual components in MEC chain. Extensive profiling of each of these individual components is performed to identify expensive operations and latency contribution. Both algorithmic and software optimization techniques are employed after bottlenecks are identified. Algorithm optimizations: Problem reformulation avoiding expensive operations, encoder tree pruning using lookup tables, etc. Cost of hardware implementation is determined by amount of memory and number of flip-flops required. This is in contrast to the general purpose computing world which can make use of the off-the-shelve available cheap memory. Huge latency reduction is achieved through software optimizations too. Some of the major software optimization methods include unrolling an encoder function, exploiting data parallelism with SIMD, avoiding exponentially complex operations, and finally, reformulation of polar code construction to avoid expensive remove, erase, and copying operations. Fig. 6: Advanced technologies like 5G, IoT and MEC integrated in Smart Farming Systems. Central to the system will be the collection and processing of agricultural data from all types of sensors and devices-what are called in the business user equipment, or UEs-via 5G networks and MEC infrastructure. It links sensory data through to AI-based agricultural management for real-time decision-making. This encompasses a wide range of benefits: efficiency in production, safety, efficient usage of resources, and reduced effects on the environment. The following diagram illustrates sensors, drones, robots, and various IoT devices in precision agriculture enablement. For example, drones apply in irrigation, planting, and identification of land, whereas robots assist in picking fruits and removal of weeds. Further, remote monitoring enhances herd tracking and soil analysis to bring about better decision-making by farmers. The system also supports autonomous driving heavy machinery for various agricultural tasks. In addition, digital technologies find their application in food sensory science, from quality production up to market.

Typically, in software implementations, for clarity and ease implementation each bit of information is represented with 32-bit or 64-bit integers. Due to the presence of only one bit of information in each integer, if 1024 bits need to be encoded or decoded then 1024 integers are involved in encoding or decoding process. However, this isn’t the case in hardware implementations since each bit

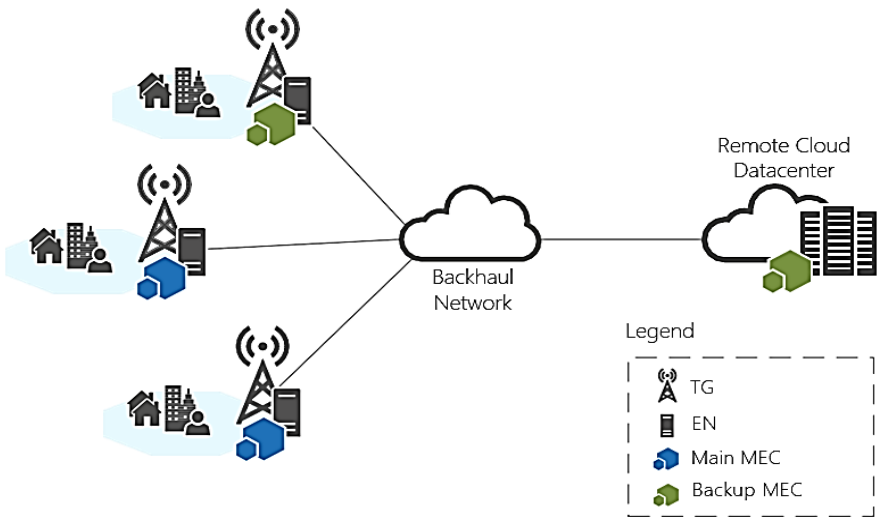


Figure. 7 Outcome after placing both the main MEC and backup MEC

can be processed in Hardware Description Languages (HDL). Representing one bit of information using a 32 or 64-bit integer has the following disadvantages.

- Increased memory footprint: For 1024 bits, 64 • 1024 bits' memory need to be allocated. It is equivalent to 8 kilobytes. Allocating and initializing this memory can introduce significant latency.
- Results in more cache misses: If more memory is allocated, more data needs to access from RAM which can result in more cache misses.

Serializes encoding/decoding: General purpose processors have a data path width of 64-bit. If each bit is represented using a 64-bit integer, we are not using the capability of processing 64 bits simultaneously. Instead, each bit is processed sequentially. This can make encoding or decoding sequential although the processor is capable of processing multiple bits in parallel. In [16] the author advises to avoid the above disadvantages and to enable data parallelism, this work tries to pack multiple bits into a single integer. Although packing multiple bits to a single integer has advantages, for some operations such as bitwise interleaving accessing each bit efficiently is very important. To exploit the advantages of bit packing as well as the advantages of accessing each bit separately, it is necessary to convert between the two. This is where the power of SIMD instructions in modern processors comes into play. These processors come with special hardware instructions which help to efficiently pack and unpack data. Data bits are used in packed format when data parallelism needs to be exploited and in unpacked format when certain operations require bits to be accessed individually. These pack/unpack instructions are very efficient and have low latency. Details of the AMD EPYC processor's instructions with corresponding latencies. Fig. 7 shows how the outcome/output will look like in a structure when pacing both the primary MEC and secondary MEC together on the platform. In the polar MEC chain, a HSA is calculated for an information bits and attached to the message. The number of CRC bits (L) varies for different physical channels. In the downlink, for the payload of MEC, 24-bit HSA is used. Information bits concatenated with HSA increases the error correction performance of polar codes significantly. HSA is used for selecting the correct code word out of potential candidates in the list. With HSA aided decoding, polar codes performance better than HSA and codes at short block-lengths. To reduce the latency of encoding MEC chain needs to be calculated very efficiently. A naive implementation of MEC calculation uses a shift register. This method calculates the CRC sequentially for one bit at a time.

3.4 MEC code construction

MEC code construction is the process of identifying information and frozen bit position, i.e., K out of N positions. This step determines the error correction performance of polar codes. There are many methods in the literature to construct polar codes. Researchers in [13] proposed to use the Bhattacharyya parameter as reliability metric for Binary Erasure Channels (BEC) then deriving reliability values using Monte Carlo simulation. For other channels, researchers in [14] use more accurate density evolution (DE) methods but it suffers huge complexity. Researchers in [15] proposed Gaussian

Approximation (GA) to reduce the complexity of DE with approximations. Still, the GA method has a high computational complexity which scales linearly with code block-length; therefore, it is unacceptable for varying SNR, block-length and code rate. In use cases such as 5G, where the channel is continuously varying. it is not feasible to construct polar codes on the fly due to stringent latency requirements of both encoder and decoder. The polar code construction in 5G takes a suboptimal approach, instead of constructing polar codes for every different SNR, block-length and code rate, construction is carried out in such a way that the constructed code performs sufficiently good over a large range of SNR, block-length, and code rate. 5G polar code construction method is based on the contribution from 5G network which uses a β-expansion method with Universal Partial Order (UPO) property of channel reliability. For each of the block lengths, reliability indices values. The polar code construction also depends on the rate matching mode since it affects the reliability of bit indices as mentioned in [16]. The polar code construction is straightforward when rate matching output greater than or equal to block-length N. In such a case, code construction involves selection of most reliable indices for information bits remaining positions are frozen since bit reliability not affected by rate matching.

4. Results and discussion

In this work, the algorithm is reformulated to avoid searching, copying and memory de-allocation while removing incapable bit indices. To avoid search operations, a lookup table is built whose values indicate the position of particular reliability value. After identifying the position, it is marked as removed instead of removing. Marking has two advantages first one is avoiding memory de-

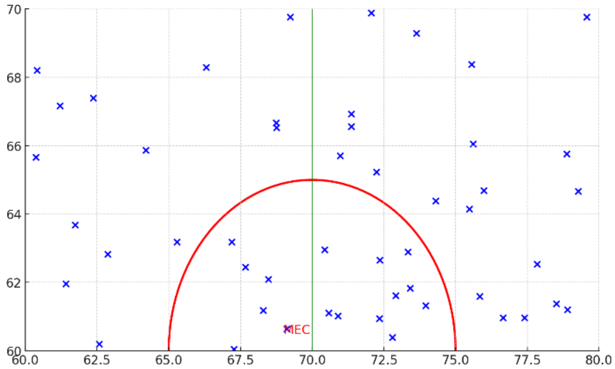
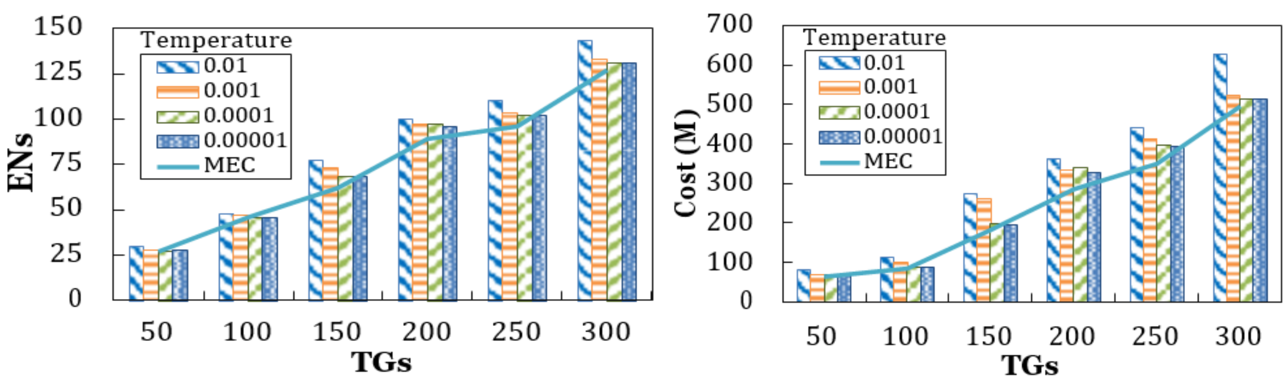


Figure. 8 Coverage area analysis of MEC with respect to wireless communication and reliability of subcarrier spacing network

allocation and copying, the second one is keeping the same order of elements which is particularly useful for using the same lookup table for finding the next incapable bit index. After all the incapable bit indices are marked as removed, only the unmarked elements are considered as reliable bit positions for placing information bits. Fig. 8 depicts the surpassed coverage area for the examination of MEC and the reliability of the spacing network is also being checked in the test.

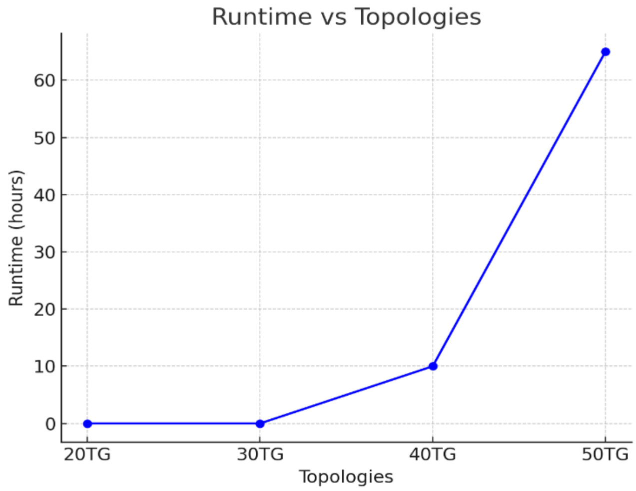
The next optimization is avoiding copying sub-block interleaving pattern to frozen in- dices array in case of shortening. Instead, a sub-block interleaving pattern is directly used from the lookup table to mark the reliability indices as removed. In addition to above-mentioned optimizations, minor ones such as avoiding dynamic memory allocation instead reserving required memory in advance and employing pointer operations to avoid copying are performed. Finally, information bit positions are obtained from iterating the reliability table from the end (since indices are sorted in ascending order of reliabilities) and extracting HSA unmarked positions.



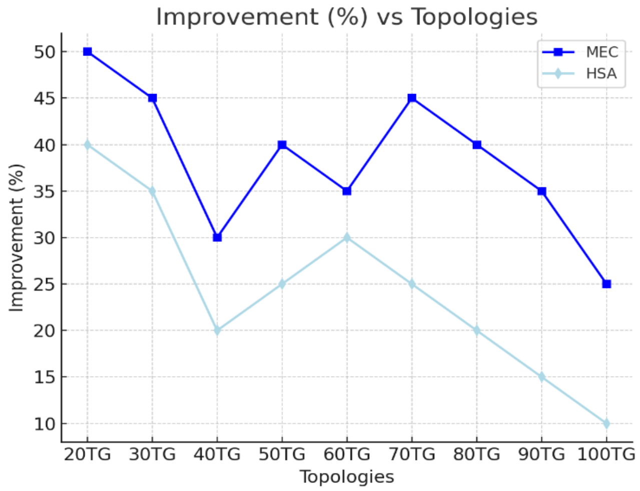
(a) (b)

Figure. 9 Graphical representation achieved in terms of: (a) Traffic Generator (TGs) on X-Axis and (b) edge nodes (ENs) as well as Cost on Y-Axis with preceding cost of MEC going up

Received: September 16, 2024. Revised: November 11, 2024.



(a)



(b)

Figure. 10 Specialized functional units of modern 5G wireless communication for traffic generator topologies between MEC and HSA techniques in terms of: (a) runtime and (b) improvement percentage of wireless

These optimizations reduced the latency of polar code construction. Figs. 9 and 10 are respectively the tests being carried out for the represenatation of Traffic Generator (TGs) preceding with the MEC and HSA techniques in terms of runtime and improvement percentage of wireless communication. Example of a pruned unrolled encoder containing also the edge nodes for MEC, and HSA is shown in Fig. 9. Inline function names for different bit vector size for TG's are also shown in the figure. One can see that tree traversing ends at temperature function due to pruning. As an outlook, for the above stated decoding MEC chain, decoder is developed with fast-SSC algorithm. This algorithm has much lower error correction performance than similar block-length MEC and HSA counterparts. Algorithms were reformulated to fit into specialized functional units of modern processors such as vector processing units. Real time information handling is essential, to guarantee a quick uncovering of a continuous or past idleness and to forestall or ease up monetary harm. New remote correspondence networks seem consistently and are immediately taken advantage of with purported zero-day misfortune correspondence. Signature based identification procedures experience the ill effects of the powerlessness to recognize beforehand obscure dangers. Be that as it may, despite the fact that having been a well-known area of examination throughout recent years, AI strategies are seldom seen in normally accessible devices. High measures of misleading up-sides and the absence of appropriate preparation and assessment information are notable issues of oddity based 5G remote correspondence. In [17] the author says Traffic designs change a ton thus does the product stack inside network conditions. To mirror this, cutting edge datasets should be utilized for the assessment of irregularity based 5G remote correspondence techniques. Network 5G remote correspondence enormously assists in relating to systems administration breaks, following them back to the people in question and afterward making a move to disengage and recover any harm that happened. The MEC chain and HSA occasion observing capacities of 5G remote correspondence frameworks likewise deterrently affect network idleness, who face a more serious gamble of being found and indicted. The presence of a 5G remote correspondence could persuade a lower inertness to look for another objective, that is more straightforward to infiltrate according to [18-22]. Being impeded by the screen or by an expert because of an alarm, makes undesirable consideration for the interloper and dials back his activities. Notwithstanding, to profit from 5G wireless correspondence, there is a requirement for a solid and broad information source to make precise expectations. Vector processing units allow data parallelism in addition to supporting very fast mathematical computations. As part of this work, CRC-Aided Successive Cancellation List (CA-SCL) decoding algorithm is also implemented, however, it is not optimized for software. CA-SCL ideally suits very low SNR scenarios such as 5G wireless communication. It has approximately 1.5dB gain over fast-SSC algorithm for N = 2048 and list size L = 8. Ideal continuation of this work would be to extend the decoding chain by incorporating CA-SCL algorithm to the MEC chain. It would be interesting to see the latency values of this algorithm, which has expensive sort and copying operations [23-25].

Table 1. Comparison of proposed method and current methods

Parameter	Proposed Method	[26]	[27]	[28]	[29]
Latency	Achieved a 10x reduction in latency, from 451µs to 40µs by integrating MEC and subcarrier spacing.	SCMA-enabled MEC achieved lower latency compared to OFDMA by using SCMA codebook allocation and BCD methods	Coexistence mechanisms between eMBB and URLLC resulted in 1ms E2E latency for URLLC and 10ms for eMBB	Relay nodes help reduce latency by offloading computation tasks closer to the user	NOMA-MEC improves latency by optimizing task offloading and resource allocation strategies
Throughput	Enhanced throughput by optimizing subcarrier spacing, improving spectral efficiency for better network performance	Higher throughput is achieved with SCMA, offering coding and shaping gains	eMBB services are prioritized for higher throughput, achieving data rates of 100 Mbps	Relays enable higher throughput by leveraging 5G NR technology and network densification	NOMA increases throughput by using spectral efficiency gains for massive device connections
Spectral Efficiency	Improved spectral efficiency by dynamically adjusting subcarrier spacing	SCMA enhances spectral efficiency through non-orthogonal access and simultaneous transmissions	The integration of dynamic multiplexing techniques improves spectral utilization between URLLC and eMBB	Relay-aided MEC reduces spectrum usage by offloading traffic at network edges	NOMA-MEC achieves higher spectral efficiency by simultaneously offloading tasks and enabling dense user connections
Energy Consumption	Optimized energy consumption through edge processing closer to the user, reducing unnecessary data travel	SCMA-MEC minimizes energy consumption by balancing offloading and transmission power	No direct energy optimization discussed. Focuses on throughput and latency improvements	Relays reduce base station load, indirectly lowering energy consumption	NOMA combined with MEC reduces energy consumption by leveraging efficient task offloading
Task Offloading	The combination of MEC and HSA optimized task offloading to meet stringent 5G requirements	Partial and full task offloading is optimized using SCMA and simulated annealing algorithms	No specific focus on task offloading. The study emphasizes resource scheduling for different services	Task offloading to relay-based edge nodes improves task response times and network efficiency	NOMA-MEC integrates task offloading to handle multiple user connections efficiently

Table 1 compares the proposed method with the current methods. The proposed method realizes outstanding gains in terms of latency, throughput, and spectral efficiency at optimized subcarrier spacing, while applying MEC techniques designed for enhanced 5G communication. Proximity-based energy saving has also been emphasized through reduced latency and power consumption. The proposed method is far more comprehensive, with improvements over all five parameters considered, in comparison to the methods presented in the PDFs. The proposed method is very suitable for high-performance 5G and beyond-5G wireless communication. Methods like SCMA-MEC and NOMA-MEC also tend to show quite decent advantages in spectral efficiency and throughput. However, stringent latency reduction is an added advantage in the proposed approach.

5. Conclusion

The objective of this research work is to study the feasibility of developing MEC chain for 5G wireless communication and investigating in software on general-purpose-processor while satisfying stringent latency requirements for enhanced 5G wireless communication. In other words, all the components of encoder and decoder MEC chain are developed on general purpose AMD EPYC processor. The software satisfies latency constraint of less than 50µs. In the first part of the paper, we provide necessary background about polar encoding/decoding and computer architecture. In the second part, we develop encoding and decoding MEC chains and optimize them to satisfy the necessary latency constraints. To begin with, we provided necessary mathematical background about polar code construction, polar encoding, and decoding. Including different polar decoding algorithms. To understand MEC chain development in software it is necessary to know the basics of modern computer architecture. Computer architecture section talks about pipelining, cache memory and vector processing units in modern general-purpose processors. We talk about the details of polar encoding MEC chain. We analyzed the different components of the MEC chain to identify latency contributors. Each of these latency contributors is further studied to reformulate the algorithm to avoid costly operations. Algorithms were reformulated to fit into specialized functional units of modern processors such as vector processing units. Vector processing units allow data parallelism in addition to supporting very fast mathematical computations. The encoding, major latency contributors were polar code construction, MEC calculation, encoding, and rate matching. A wide range of optimization techniques is employed to reduce the latency both algorithmic and platform specific. Namely, reducing algorithm complexity, using lookup tables, compiler hints for better instruction scheduling, vector processing instructions for data parallelism and avoiding superfluous copy operations et cetera. Optimizations reduced the worst-case latency of the encoding MEC chain from 451µs to 40µs which is more than 10x reduction in latency for better 5G wireless communication.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Sinan Q. Salih and Shaymaa Mohammed Abdulameer; Methodology, Sinan Q. Salih and Haider Hadi Abbas; Software, Haider Hadi Abbas; Validation, Jamal Fadhil Tawfeq, Ravi Sekhar, and Pritesh Shah; Formal analysis, Shaymaa Mohammed Abdulameer; Investigation, Haider Hadi Abbas and Ahmed Dheyaa Radhi; Resources, Saffrine Kingsly and Murugesan Dhasagounder; Data curation, Jamal Fadhil Tawfeq; Writing—original draft preparation, Shaymaa Mohammed Abdulameer; Writing—review and editing, Sinan Q. Salih, Ravi Sekhar, and Pritesh Shah; Visualization, Saffrine Kingsly and Murugesan Dhasagounder; Supervision, Sinan Q. Salih and Ravi Sekhar; Project administration, Sinan Q. Salih; Funding acquisition, Ahmed Dheyaa Radhi.

Acknowledgments

The authors would like to thank Al-Bayan University for their support to complete this research paper.

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