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RESEARCH ARTICLE

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Energy-Efficient Communication Protocols For Massive Machine-Type Communications (MMTC)

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Abstract

A foundational component of next-generation wireless networks. Massive Machine-Type Communications (mMTC) allows billions of devices to be connected with little to no human interaction, making it ideal for the Internet of Things (IoT) paradigm. Particularly in reaching energy efficiency without sacrificing network performance, the dramatic increase in device density and traffic volume presents significant difficulties. This work examines the evolution of energy-efficient communication protocols tailored for mMTC conditions. Examining current systems, including NB-IoT, LoRa, and Sigfox, holistically helps one understand their strengths and constraints regarding energy consumption, scalability, and dependability. Building on these observations, we offer an adaptive, energy-aware communication architecture encompassing sleep scheduling, data aggregation, and dynamic resource allocation techniques. Simulation-based assessments reveal that the proposed protocol minimizes energy usage while ensuring reliable communication, especially in ultra-dense network situations. The work advances scalable, environmentally friendly mMTC solutions for future intelligent environments.

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Introduction

Wide-ranging and omnipresent applications spanning domains require mMTC (massive machine-type communication) to be incorporated into 5G and B5G networks, predicting an accommodation of around 106106 devices per km².[1] The sparse deployment of battery-operated devices or machines would enable IoT-based solutions.[21] Sparse burst low-rate transmission at minimal mobility requires the mMTC scenario to have a dense network of nodes. Constraints on size and weight, as well as placement, create a limit on the battery life. Due to the location, the expected lifetime would be over ten years.[22] Giving these devices guaranteed network access is difficult for network operators since significant MAC signaling overhead will compromise the unique energy efficiency of the mMTC devices.[19] High collision counts in contention-based random-access systems cause energy inefficiency and a failure of mission-critical services, including eHealth services, automated traffic control, driving, and environmental monitoring alarms.[2] All things considered, present MTC load control systems rely on rigid grouping criteria and simpler application implementation strategies.[20]. In this regard, the energy behavioral pattern of the devices, which are mostly powered by batteries, is susceptible to random access phenomena, which, if not managed, may lead to a blackout. Energy efficiency in frameworks resolving network congestion and access latency has received considerably less focus. Following our understanding that the continuous presence of battery-operated sensors strategically located in remote areas determines the viability of the sensors, our approach.[3]

Literature Review

Reinforcement Learning

Reinforcement learning involves studying an agent and how it interacts with the environment using actions based on a Markov decision process (MDP). The agent starts receiving feedback in the form of a reward, which can either denote affirmation or negation of the actions taken. [4] The agent, observing the state of the environment at every step, will decide on the action to take that will maximize each reward. Many researchers have been addressing some issues in the wireless network with both groups of RL. Ohtsuki investigates in[1] several ways to facilitate communication in 5G and beyond, employing machine learning techniques.[5] In,[2] the authors analyze some enablers of 6G ultra-reliable low latency communication (URLLC) and apply some interesting machine learning approaches for automated intelligence designed for 6G services, termed massive URLLC. In.[3]

In Wireless Networks, Network Congestion and Signal Overload

3GPP encapsulated one of the initial proposed systems, the access class barring (ABC). It proposes collecting devices and presenting every group as a class. The base station allocates the probability of any device class starting the random-access procedure and gives a banning factor to every class. This assists in decreasing the barring factor's randomness and the attempts at the random-access process. Alves et al. in[5] take on the problem of large access in NOMA-based mMTC. Random backoff for preamble selection was proposed in order to avoid a high likelihood of simultaneous requests from multiple devices initiating the random access procedure. Also, they propose an exponential-decrease back-off window for more efficient access request collisions. The authors of[7] review the scope of 3GPP MTC, radio resource control, and random access and collision in a MTC system were studied. The authors proposed clustering based on device traffic demand specific to grouping-dynamic resource allocation multi user framework improves resource contention. This resulted in smoother traffic congestion and reduced processing complexity. In,[8] clusters of users from the same cell are assigned resources based on predetermined time frames. Lee et al.An optimal number and size of groups are created into a group-based communication system, where a transmission from spatially clustered devices is incorporated to maximize efficiency.[9]

Main Characteristics of Massive Machine Type Communications

With each new generation of MCS, data transfer rates would double that of the previous generation. One of the foremost requisites for the NGMN system, particularly for the 5G MCS, concerns the enhancement of data speeds with a significant reduction in latency. As illustrated in figure 1, there is a marked difference in latency between 4G and 5G networks.[10]

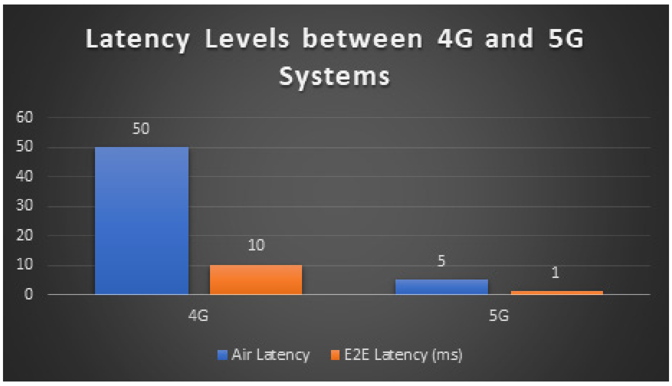

Fig.1: Latency Levels between 4G and 5G Systems

Incorporating new services and applications is crucial to enhancing data transfer speed and/or minimizing latency. The MCS that will implement the complete operation of services based on the IoT conception using its architecture and functionalities will be 5 G. This will enable a novel communication between different classes of machines (M2M, D2D, V2V, etc.) regardless of their mobile, remote, or nomadic state, or relationship with IC access technologies of diverse connections. 5G MCS will widen the scope of Internet access requests through mobile connection (MBB, Mobile Broadband) due to the increasing number of terminal devices and the offering of new services. The interchangeable amount of data augments the controllable transmission rate. Fig 1 shows the data transfer rate for 4G and 5G MCS format files.[11].

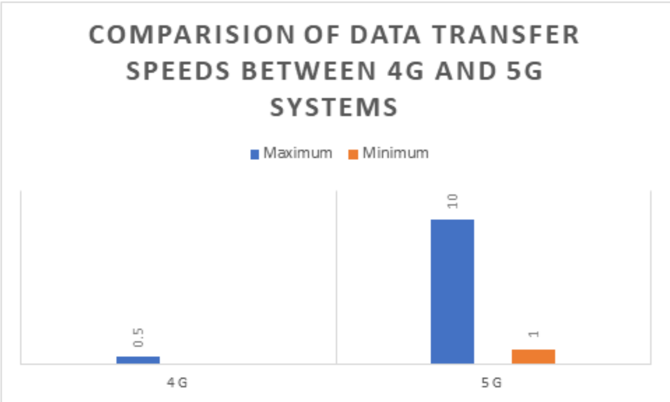

Fig. 2: Comparison of Data transfer speed between 4G and 5G Systems

The range ranges from very low for sensor systems to high for UHD video transmitting. These needs are included in the latency range needed for security applications like e-maintenance of alarm systems, emergency services, and e-calls, which is, in this case, low. Latency notwithstanding, there will be some services and applications that will not be affected.[12] Also, packet size will vary in the small to large spectrum depending on whether they are from a file transfer application or a smartphone application. MCS 5G will enable the ecologically friendly access to numerous software solutions and services that affect the daily life routine of an individual, the continuous development of society as a whole, and lead to a significant reduction of energy consumption. In Fig 2, a comparison of the primary performance parameters of the 4G and 5G networks has been included.[13]

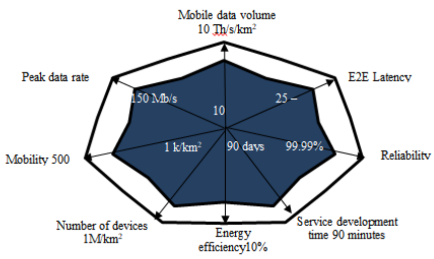

Fig. 3: Range of minimum expected requirements between 4G and 5G Systems

Implementing fig 3 the 5G network must tackle the escalating energy efficiency concern. Considering the infrastructure's considerable expansion by 2020, it is easy to foresee an energy consumption figure that exceeds the envisaged standards. This is mainly because most energy comes from hardware, while antennas contribute only a fraction. To avert energy drain failures on the network, 5G will be able to curtail the required coverage and capacity by deactivating certain infrastructure elements on demand while maintaining essential coverage and capacity. Instead of using current networks, the better utilization of radio frequency and mMIMO (massive Multiple Input Multiple Output) will enable mobile data speeds to surpass 1 Gbps easily. Lowering the latency to 1 ms will allow transmission of broader multimedia content. The capability to connect an arguably trillion terminal devices is expected to be enabled, which will be shrunk in size and equipped with enhanced battery longevity. In order to assure a certain quality of service, then reliability of the system must reach 99.999%. [14]. Additionally, private and business users will benefit from improved privacy and data protection enabled by 5G. The latency levels of the 4G and 5G systems are compared visually in Fig 3. 5 10 20 30 40 50 60 E2E Latency (ms) Air Latency (ms) 5G 4G Fig 3 contrasts the transport speed of data between systems 4G and 5G. 0 1 2 3 4 5 6 7 8 9 10 Throughput minimum 4G 5G (Gbps) Bandwidth maximum (Gbps) 5 The prediction peaks serve as the estimated baseline peaks for each region utilizing these resources. Figure 3 depicts the minimum theoretical needs for 4G and 5G systems. [four] 5G systems will bring considerable value and benefits for the main market participants such as consumers and network operators (Fig 3). The reason is that the next generation core network of the 5G system will be able to control the characteristics of the communication hardware with different industry standards. Having simultaneous integration of cloud-communications, nanotechnology, and other innovations will also take place.

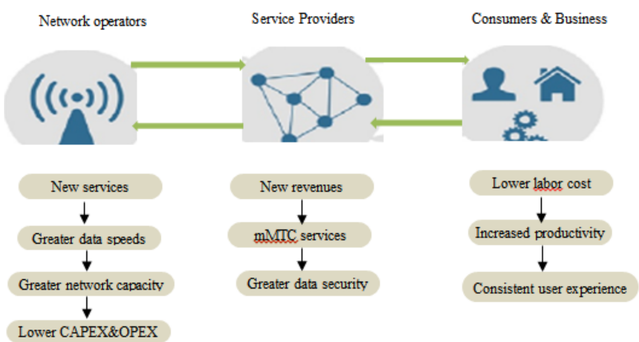

Fig. 4: Summary of main benefits for 5G stakeholders

Moreover, the interfacing of Fig 4 of the IoT concept with the 5G network is expected to occur across multiple sectors, creating the connection and synergetic functioning of industrial plants, medical equipment, and automobiles. About this prospective shift, the advanced paradigm of concept and ecosystem, which shall be termed as Internet of Everything (IoE) is foreseen to emerge so as to provide diverse services such as manufacturing, healthcare, transportation, etc., more economically than 4G technology.[15]

MMTC Model

MMTC Architecture

3GPP provides an architectural design for MTC over LTE networks in References.[38] Some task management components like application servers (MTC ASs) perform an MTC app-to-core network (CN) interconnection using SCS. Each application is bundled with tools that complete the chores before a set time expires. MTC devices await asynchronous messages from MTC AS for authorization completion. MTC-IWF sends the SCS-to-MTC device triggering message. The message triggers a prompt response assessment by the CIoT device towards the bounding set of processes. If the MTC device determines that it sets up a PDN-enabled CN packet for the intended process.[16] During the period commitment bounded by the MTC device, tasks are executed. An MTC server triggers all devices, which respond with a set of defined network-signalized messages. With the SCS-MTC append interface, the CN enables monitoring and task scheduling at the MTC applications on servers. After approval, the MTC interworking function (MTC-IWF) sends trigger commands relayed through the SCS to the MTC devices. The CN provides the MTC PDN connection to enable provisioning procedures to check whether an MTC device can execute the assigned tasks. As described, every application has a set deadline by which it needs to be completed. Therefore, at a high level, MTC operations can be described using applications, tasks, and devices as the primary actors. Recurring MTC applications are very common and have the objectives for large-scale deployment. Moreover, one of the concerns with the vast access system is the energy efficiency. The focus of this paper is on these two issues: signaling optimization and energy saving. We utilize power-saving mode (PSM) to minimize energy consumption, and grouping—sharing the exact identification within a group—also reduces the signaling load.[17]

MMTC Energy Consumption

Both PSM and discontinuous reception (DRX) control their energy expenditure in MTC devices. In this case, PSM is preferable over DRX because the RF modules are off in PSM, hence, the device cannot be paged or reached. In regards to this matter, PSM is better than DRX because with PSM, the link does not need to be reestablished. Unlike DRX, PSM eliminates the need for re-establishing the link since the device stays connected to the network throughout the duration of PSM. This is more desirable for our system design. In this case, PSM is a semi-Markov model with three modes and S2, S3 and S4 states, four states.[18] The total energy spent by a particular device j is defined to be the total energy burnt when in different stages of activity, mathematically defined as:

$$E_j = \sum_{k \in PSM, act, Idle} Ekj \tag{1}$$

$$E_{PSMj} = PSM_j . t_{PSMj} \tag{2}$$

$$E_{idlej} = idle_j . t_{idlej} \tag{3}$$

$$E_{actj} = E_{rachj} . \sum_{q=0}^{R_{max}} y_{j,q} + E_{trxj}$$

$$y_{j,q} = \begin{cases} 1 & \frac{\text{if device } j \text{ collided on attempt } q}{\text{otherwise}} \\ 0 & \end{cases} \tag{4}$$

where, Let us denote the energy consumed by device J in sleep, active, and idle modes respectively as E and describe Rmax as the upper bound of re-transmission. Energy is used in other components of operation RACH as mentioned in,[4] also energy transfer MTC device is in active mode. In the PSM scenario, the MME after receiving the grouping result from AS has to wake the group at the proper time and inform the group members when to go active. In a subset, data transfer by mobile network is allowed only to one device at a time. All other devices pulse (off) until the active phase where they switch to the mobile network for energy-efficient PSM.

The Overall average consumed energy

$$E_{MTC\,ave} = \frac{1}{N} \sum_{j=1}^{N} E_j \tag{5}$$

MMTC Signaling Overload

Two of the most significant challenges in IoT are signal congestion and battery life. The application server has to control the activation messages to switch off the device, but this control ratio is relatively poor compared to data traffic. During busy periods, the EPC sending bursts of messages becomes economically unviable. The traffic model estimates and calculates the payloads and the additional effort involved in the protocol headers. In this case, we ignore the payload size since the bursting is deemed to be within the headers in the signaling. The stack consists of CoAP, DTLS, UDP and IP. With the increase in the number of MTC devices and in expectation of a further increase, the reduction of alerting messages becomes critical. This would help lower the energy consumption of MTC devices in the B5G network and alleviate the congestion problem for the servers. Mounted on the mobile network, the mMTC devices respond to the servers immediately. Its packet is from 4 bytes to 21 bytes in size. Devices equipped with such technologies will not require frequent battery replacements thanks to low-power consumption features.[1]

MMTC Access Delay

In a contention-based environment, the minimum waiting time for the RACH procedure to finish is 15 milliseconds, without considering the wait time at step one. In this inst, we look under the more advanced latency details to observe how collision influences the overall delay. The chances of collision discussed previously existention-based RACH. Once a collision occurs, it impacts the transmission operation delay of the entire device. The overall device latency can be calculated as follows:

$$D_{MTCj(init)} = D_{rach-1}\left(\left(1 + R_{max}\right) * x_j\right) + R_{max}\left(T_{Back} * x_j\right) \quad (6)$$

$$D_{MTCj(final)} = D_{rach-2} + D_{trx} \quad (7)$$

$$D_{MTCj} = D_{MTCj(init)} + D_{MTCj(final)} \quad (8)$$

$$x_j = \begin{cases} 1 & \text{if device } j \text{ collided} \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

Thus, the operating latency of a device that is connecting to the network is proportional to its first several access attempts.

$$D_{MTCave} = \frac{\sum D_{MTCj}}{N} \quad (10)$$

Algorithm

Inputs:
S= {S_1,S_2,..........S_k }:state set representing device characters ics
A:Action set for device grouping
π:Policy function mapping S to A
c (S,a)≤0:constraints on states and actions
▫:Lagrange Multiplier
Initialize RL Model Parameters θ,policy π,state set s,action set A and ▫
for each device in the network do
Observe State s▫S
Determine action a^*=π_θ (s)for device grouping
Execute a^*,grouping the device accordingly
update S with new device grouping
end forfor each action a^* during grouping do
evaluate grouping effectiveness and constraint satisfaction
calculate reward R(s,a)and penalty ▫C (s,a)
update θ using the gradient of R(s,a)+ ▫C(s,a)
adjust ▫ based on constraint violations
end for
output:optimized device groupings with minimal unallocated space adhering to constraints

Performance Analysis

The ensuing subsections will cover all parameters which include configuration settings, simulation settings hierarchy, and the key parameters within the simulation experiments. It also clarifies the consideration pertaining to configuring the simulation scenario together with device enumeration, assignment of tasks, and other pertinent components.

Performance Metrics

The described methodologies are evaluated with the appropriate standard performance metrics as follows: The Miss rate probability which models this metric as the sum of failed devices (meaning devices which either exceed max re-transmission or time bound) over the total N devices trying to access the network through a RACH operation. Total energy consumed: The energy consumed for N devices from the perspective of two staged RACH mechanism. RACH access delay which deals with the statistics, is the mean time for N data packet receptions to be available following the single data packet reception initiation after first reception (preceding RACH attempt). Assume the back-off period is 20 ms and max retransmit is also 20.

Results and Analysis

The collision probability of unrestricted preamble systems relating to resource allocation and control is discussed in greater detail below. From Fig 5, with a fixed 300 lower bound on the number of preambles and devices, the finite capacity lossy queueing network defined in this work shows a specific pattern in its service rates. In the fig 6 mentioned above, it is noted that for every 56 devices that join via these random-access protocols, there is a unique value for the provided set of parameters, with 31 preambles and 124 devices served by 2 devices queued. 50% of device preambles have been proven to themselves almost uniformly at every range of area considered.

Several changes in resource allocation and collision preamble utilizing a feedback control system offer a promising method for managing constant data devices simultaneously sending bursty data throughout the network. Using barrage constrained delay control when data cycles reach the needs of users through distributed control networking background gives rise to redefine set queue models of vast multi programed computers.

Retrying attempts poses that the phenomena instantly unclog themselves can be used promisingly within-domain systems.

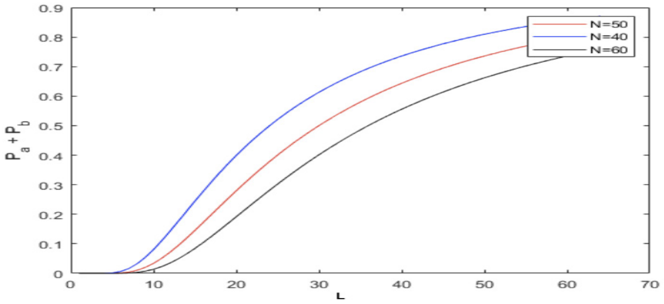

Fig.5: Success Probability

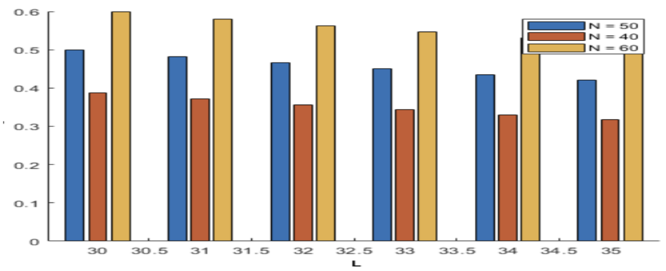

Fig. 6: Failure Probability

Effects of Effective Grouping in the Total MMTC Energy Consumption

In the energy consumption consideration of this subsection, Fig 7 driven by battery, it is necessary to observe how collisions impact the mMTC devices' energy consumption. Also, we compute the total energy spent as RACH steps progress 2 sequentially as 264 μJ. As noted in Fig 7, energy consumption tends to increase exponentially in scenarios with high collision rates. This increase stems from the collision, as the colliding devices must repeatedly re-transmit, hoping for success

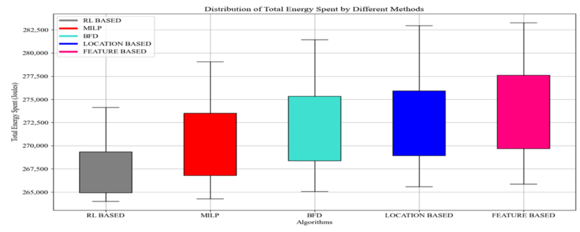

Fig. 7: Total energy consumption per method

in subsequent attempts. As an optimal scheduling policy was built from strict completion times for devices and applications, it can be provided with less renewable energy without impacting performance. When combining the attempts with supply reduction measures, a better energy-saving effect can be achieved. Consequently, low-latency targeted quality of service is more easily provided.

Effects of Effective Grouping on the General MMTC Transmission Delay

The transfer delay represents the average time needed to fetch a data packet. In relation to the energy expenditure, Fig 8 shows that the access delays, as the collision rate goes from 2% to 10%, increase the traffic load exponentially. When a device goes below the RACH due to a clash, it shifts to the back-off timer-set waiting state while newcomers keep entering. This means that new participants are added to the back-off mode, which increases the congestion of devices that have already collided. Hence, other devices will be forced into back-off mode, which instead of waiting, leads to greater congestion (Figure 8.

Overall Rach Access Delay Per Collision Percentage

The current study focuses on the impacts of the proposed learning-based energy-efficient device grouping strategy for machine type communications (mMTCS) in B5G networks. The model incorporates

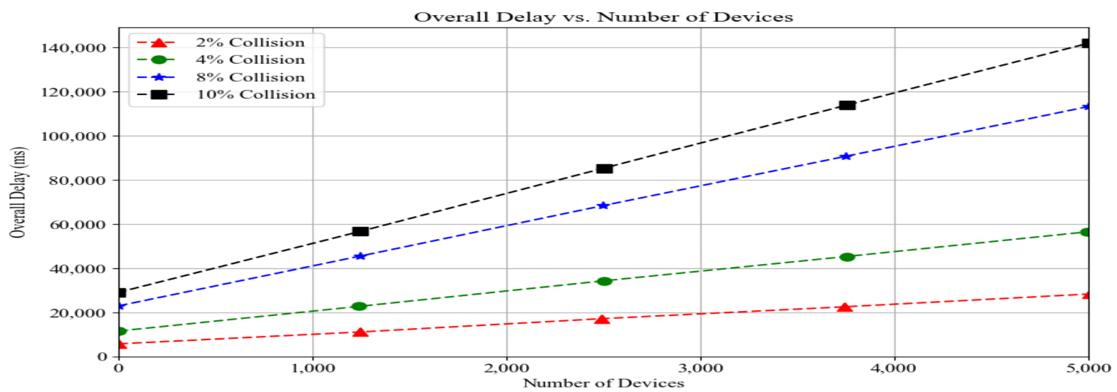

Fig. 8: Overall delay Vs Number of Devices

energy-aware techniques for minimizing miss rates, spending, and access lags in the RACH contention-based architecture by optimizing device clustering and inter-group access scheduling. In B5G networks, energy, access delays, and the rate of successful mMTC device accessed were better in the B5G networks with the RL based model than without it. The program simulated practically by solving optimization problems related to device grouping for large-scale MTCs based on essential parameters, such as deadlines, temporal restrictions, and device heterogeneity. For mMTC scenarios, the results of simulations demonstrated improved gaps compared to existing methodologies which proved effective in other s. However, it is important to highlight the issue of computational complexity when applying the reinforcement learning model (with dynamic, high speed) networks, which might be difficult for low-cost implementation. The model flexibility in adopting various topologies and modes of communication within the network is also unclear, thereby requiring additional evaluation to enhance reliability in other conditions. These issues must be resolved to respond effectively to shifting conditions in the networks.

Conclusion

The rapid growth of Massive Machine-Type Communications (mMTC) in the IoT ecosystem creates an urgent need for energy-efficient communication protocols. The energy economy becomes essential to extend the lifetime of devices and guarantee sustainable network operations since billions of devices are expected to coexist and interact with minimal human participation. We examined and evaluated current low-power communication methods using this work, highlighting their advantages and constraints in mMTC environments. Our proposed adaptive protocol architecture shows notable energy economy by including intelligent resource allocation, sleep scheduling, and data aggregation techniques. Simulation results support the usefulness of these strategies, particularly in dense deployment scenarios. Future work should incorporate machine learning for real-time adaptation, cross-layer optimization, and guaranteeing protocol stability under changing traffic and network conditions. Realizing scalable, dependable, and ecologically sustainable mMTC deployments requires first, generally, energy-efficient protocol design.

References

1. Ohtsuki, T. Machine Learning in 6G Wireless Communications. IEICE Trans. Commun. 2023, 106, 75–83. [Google Scholar] [CrossRef]
2. Liu, Y.; Deng, Y.; Nallanathan, A.; Yuan, J. Machine Learning for 6G Enhanced Ultra-Reliable and Low-Latency Services. IEEE Wirel. Commun. 2023, 30, 48–54. [Google Scholar] [CrossRef]
3. Tang, L.; Du, Y.; Chen, Q.; Liu, Q.; Li, J.; Li, S. Equilibrated and Fast Resources Allocation for Massive and Diversified MTC Services Using Multiagent Deep Reinforcement Learning. IEEE Internet Things J. 2023, 10, 664–681. [Google Scholar] [CrossRef]
4. Guevara, K. G., Guevara, L. A. R., Gonzales, T. V. P., Neyra-Panta, M. J., Gálvez, J. F. E., & Saavedra, N. L. C. (2024). Review of Scientific Literature on Social Networks in Organizations. Indian Journal of Information Sources and Services, 14(4), 125–130. https://doi.org/10.51983/ijiss-2024.14.4.19
5. Li, Y.; Chai, K.K.; Chen, Y.; Loo, J. Smart duty cycle control with reinforcement learning for machine to machine communications. In Proceedings of the 2015 IEEE International Conference on Communication Workshop (ICCW), London, UK, 8–12 June 2015; pp. 1458–1463. [Google Scholar]
6. Sarvi, B., & Pourmozaffar, S. (2024). A review of the reproduction and rearing of clownfish, Amphiprion clarkii, in captivity. International Journal of Aquatic Research and Environmental Studies, 4(2), 145-158. http://doi.org/10.70102/IJARES/V4I2/9
7. Alves, T.A.B.; Abrão, T. NOMA-Based Random Access in mMTC XL-MIMO. IEEE Access 2023, 11, 1944–1954. [Google Scholar] [CrossRef]
8. Harwahyu, R.; Sari, R.; Misbahuddin, M. Performance Evaluation of LTE Random Access Procedure under Distributed Location Data Mining for Road Traffic Monitoring. Int. J. Commun. Netw. Inf. Secur. 2016, 8, 171–178. [Google Scholar] [CrossRef]
9. Arvinth, N. (2024). Integration of neuromorphic computing in embedded systems: Opportunities and challenges. Journal of Integrated VLSI, Embedded and Computing Technologies, 1(1), 26-30. https://doi.org/10.31838/JIVCT/01.01.06
10. Lien, S.Y.; Chen, K.C.; Lin, Y. Toward ubiquitous massive accesses in 3GPP machine-to-machine communications. IEEE Commun. Mag. 2011, 49, 66–74. [Google Scholar] [CrossRef]
11. Wong, S. K., & Yiu, S. M. (2020). Identification of device motion status via Bluetooth discovery. Journal of Internet Services and Information Security, 10(4), 59-69.
12. Rahman, S., & Begum, A. (2024). Applied Mechanics for Mechanical Engineers: Principles and Applications. Association Journal of Interdisciplinary Technics in Engineering Mechanics, 2(1), 13-18.
13. Tsai, A.H.; Wang, L.C.; Huang, J.H.; Lin, T.M. Overload Control for Machine Type Communications with Femtocells. In Proceedings of the 2012 IEEE Vehicular Technology Conference (VTC Fall), Quebec City, QC, Canada, 3-6

September 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 1–5. [Google Scholar] [CrossRef]

14. Vijayarajeswari, R., & Balachandar, N. (2020). Adjustment Restoration Virtual Private Networks and Quality of Service Constraints. International Academic Journal of Science and Engineering, 7(1), 9–16. https://doi.org/10.9756/IAJSE/V7I1/IAJSE0702
15. Lee, K.; Shin, J.; Cho, Y.; Ko, K.S.; Sung, D.K.; Shin, H. A group-based communication scheme based on the location information of MTC devices in cellular networks. In Proceedings of the 2012 IEEE International Conference on Communications (ICC), Ottawa, ON, Canada, 10–15 June 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 4899–4903. [Google Scholar] [CrossRef]
16. Boisguene, R., Althamary, I., & Huang, C. W. (2024). A Learning-Based Energy-Efficient Device Grouping Mechanism for Massive Machine-Type Communication in the Context of Beyond 5G Networks. Journal of Sensor and Actuator Networks, 13(3), 33.
17. Jovović, I., Forenbacher, I., & Periša, M. (2015, November). Massive machine-type communications: An overview and perspectives towards 5G. In Proc. 3rd Int. Virtual Res. Conf. Tech. Disciplines (Vol. 3).
18. Abdullah, D. (2024). Recent advancements in nanoengineering for biomedical applications: A comprehensive review. Innovative Reviews in Engineering and Science, 1(1), 1-5. https://doi.org/10.31838/INES/01.01.01
19. Soh, H., & Keljovic, N. (2024). Development of highly reconfigurable antennas for control of operating frequency, polarization, and radiation characteristics for 5G and 6G systems. National Journal of Antennas and Propagation, 6(1), 31-39.
20. Ahmed, M., & Pandey, S. K. (2024). Digital Innovation Management: A Study of How Firms Generate and Implement Digital Ideas. Global Perspectives in Management, 2(3), 13-23.
21. De Araújo, L. O. N., & Outtagarts, A. (2024, October). Sustainability of AI-Energy consumption estimation of an mMTC admission control. In 2024 7th Conference on Cloud and Internet of Things (CIoT) (pp. 1-7). IEEE.
22. Zigui, L., Caluyo, F., Hernandez, R., Sarmiento, J., & Rosales, C. A. (2024). Improving Communication Networks to Transfer Data in Real Time for Environmental Monitoring and Data Collection. Natural and Engineering Sciences, 9(2), 198-212. https://doi.org/10.28978/nesciences.1569561
23. Ali, M., & Bilal, A. (2025). Low-power wide area networks for IoT: Challenges, performance and future trends. Journal of Wireless Sensor Networks and IoT, 2(2), 20-25.
24. Arthur, L., & Ethan, L. (2025). A review of biodegradable biomaterials for medical device applications. Innovative Reviews in Engineering and Science, 3(1), 9–18. https://doi.org/10.31838/INES/03.01.02
25. Tang, L., Chen, Y., & Zhou, J. (2025). Reconfigurable computing architectures for edge computing applications. SCCTS Transactions on Reconfigurable Computing, 2(1), 1–9. https://doi.org/10.31838/RCC/02.01.01
26. Khan, A. (2025). Challenges and solutions in low-power ASIC design for edge computing applications. Journal of Integrated VLSI, Embedded and Computing Technologies, 2(3), 12–22. https://doi.org/10.31838/JIVCT/02.03.02
27. Alnumay, W. S. (2024). Use of machine learning for the detection, identification, and mitigation of cyber-attacks. International Journal of Communication and Computer Technologies, 12(1), 38-44. https://doi.org/10.31838/IJCCTS/12.01.05