Improving Energy and Capacity-Awareness of Effective Satellite Communication in 6G Heterogeneous Internet of Things

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RESEARCH ARTICLE

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ABSTRACT

The spreading of Sixth Generation (6G) communication within the Internet of Things (IoT) is one of the recent innovations in networking services. As the number of devices becomes increasingly connected through extensive communication network connectivity, energy efficiency has become a significant concern with the widespread use of massive IoT devices. While general lack of energy optimization can lead to several issues, including data loss, link failure, and high-power utilization, directly affect the communication quality of the network. To address these challenges, it is crucial to develop a model that combines effective optimization and resource allocation, based on both Quality of Service (QoS) and energy efficiency. In this study, we propose an Energy with Capacity-Awareness Effective Satellite Communication (ECESC) approach for 6G in an IoT environment. The network environment comprises Base Stations (BS) and User Equipment (UEs), with devices equipped with data transmission models, energy consumption models, and QoS-based service parameters. Our proposed technique is to enhance resource utilization and optimization among devices using the Superior Hidden Markov Model (SHMM) and Improved Neighborhood Field Optimization (INFO) Algorithm, significantly increasing energy and network utility. The ECESC approach was implemented using NS2 and compared with EERS-IoT, SECA-IoT, and DATS-IoT. We evaluated results using varying number of nodes and speeds. The performance metrics include end-to-end delay, throughput, packet delivery ratio, energy efficiency, packet loss, and routing overhead. The experimental results demonstrate that our proposed method achieves significantly improved outcomes in terms of packet delivery, throughput, and energy efficiency compared to earlier studies.

Introduction

In recent years the evolution of sensing technology has resulted in Sixth Generation (6G) technology creation which consists of highly innovative services and applications that are more advanced than the 5G technology, 6G supports massive Internet of Things (IoT) devices that can interconnect to build an intelligent application like creation of robots[1], Unmanned Ariel Vehicles (UAVs), and smart cars[2]. 6G-enabled IoT devices to support ultra-low power, ultra-low la-

tency, and low-cost communication systems[3]. The 6G technology has become trending among the industrial and academic sectors. Although the Fifth Generation (5G) is implemented globally, it still needs improvement because of various shortcomings in delivering, inability, and minimum data that have forced the researchers to come out with the (6G) technology. Due to those drawbacks energy consumption is highly increased reflected in the decrease of the battery power in the IoT devices[4]. That provides a way to highly seamless and intelligent connectivity among the

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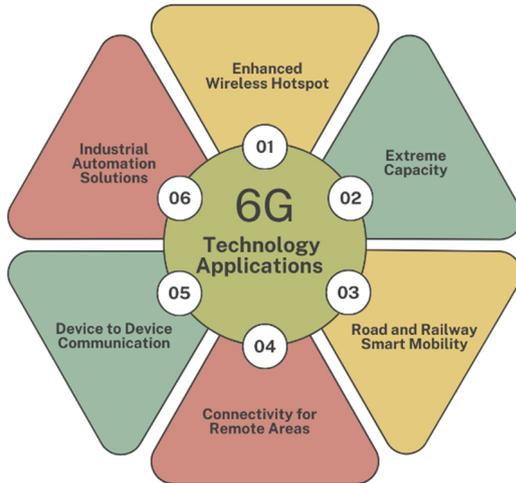
Fig. 1. 6G Technology applications.

devices called (6G) technology[5,6]. The applications of (6G) technology is described in Fig. 1.

Working with ultra-dense networks creates new challenges in IoT communication such as severe interference during inter-beam communication, and as well it creates backhaul burden and energy consumption[7]. Providing proper upgrades in hardware and infrastructure in the (6G) technology is highly complicated and not a cost-effective process. A Certain process like design, development, and maintenance are highly complicated and consist of compatibility issues. The major concentration of this article is all about the energy consumption. With the presence of numerous IoT devices, power utilization is highly increased when accessing advanced IoT capabilities. To get rid of this drawback effective resource allocation model becomes highly essential in (6G) technology. In earlier research, several methods were introduced to overcome this challenge such as mmWave-permitted IAB design, and Markov precise size-aided subchannel distribute model which achieves moderate performance in terms of latency with congestion[8,9]. The research contribution is outlined as follows.

i. To improve the efficiency and reduce the power utilization of the (6G) technology in advanced IoT, resource utilization and optimization are concentrated which is termed as Energy with Capacity Awareness Effective Satellite Communication (ECESC).

ii. To improve the quality of the network model that includes the well-organized communication and energy consumption model, effectual Base Station (BS) and User Equipment (UEs) connectivity, and qualified service parameters, and the fitness analysis.

iii. To attain maximum resource utilization with the best services to achieve high QoS, the SHMM model is developed so that the network energy efficiency is significantly improved.

iv. To transmit the data in the shortest path between the UEs and the BS which is effective path that obtained using the Algorithm of INFO Calculation. Along core assist about certain calculations the lag, routing overhead, packet loss, remain reduced which produce an expand in the throughput along packet delivery ratio in mesh.

The structure of the paper is communicated in such a way: The Section Two elaborates on the associated study about the 6G technology and its drawbacks. Section Three detailed the communication and energy consumption model, effectual UEs and BS connectivity qualified service parameters, and the fitness function. Section Four describes a detailed elaboration of the resource utilization process and optimization process employed in the proposed ECESC approach. Finally, section Five provides the results and discussion in terms of NS2 implementation. The conclusion and the future direction are given in section Six.

Related work

In the related work section, various studies and findings relevant to the topic are reviewed and discussed to provide context and highlight the existing knowledge in the field. In[10] the author Qiao, presented a joint beam-forming design algorithm for the Base station and IoT to reduce the problems in the sixth generation IoT. Though this method provides better performance of energy consumption, data aggregation, and data transmission, the coverage area is not expandable.

Liao Zhuofan et al.[11] proposed Distributed-Two-Stage Offloading (DTSO) to provide solutions for trade-off problems. In addition, Queue theory and Sequential Quadratic Programming are used for optimization problems. However, this method enhances the performance by minimizing latency and energy consumption, but the computational process is complex. Li et al.[6] developed a long preamble sequence to prevent signaling overhead in Low-earth-orbit Scenarios. In addition, Length-alterable Differential Cross-Correlation (LDCC), is used for Carrier Frequency Offset (CFO). This method increases the performance of timing estimation accuracy, and normalized access energy but the computational cost is high.

Jia Ziye et al.[12] developed a heuristic algorithm to minimize the complexities using the Dantzig-Wolfe

decomposition in the internet of Remote things of the sixth-generation network. Though this reduces the complexities and energy consumption, provides high latency. Jia Ziye et al.[13] suggested a restricted three-sided matching algorithm to handle user, HAP, and satellite matching in space air-ground networks. Additionally, a two-tier matching approach to address go-ahead links mediate rocket along HAPs brought on through periodical moving along rocket. This process provides reduced computational time but energy consumption is high.*

Wan et al.[14] proposed a Data-driven Fair-Hierarchical Scheduling method for scheduling the packets to reduce the delay time. In addition, the Particle Swarm Optimization algorithm is used for scheduling optimization problems. The outcomes revealed that the delay time is reduced but computational cost is increased. Liu et al.[15] developed an algorithmic improvement plan to expand network coverage in the wide area of IoT in 6G. Furthermore, time collaboration rest along possible area rest models are used for optimization problems. The network coverage area is expandable but the computational time and cost are high.

Gustavsson Ulf et al.[16] outlined that communication of Satellites can be an essential component of the beyond-5G and 6G communication structure. Huge hardware synergies between tinge swell earthly along rocket final, along amidst innovations in durable rocket initiate manner, may pave path towards cost reductions that would enable widespread implementation. Charbit Gilles et al.[17] designed a revert-united air combine amidst minimum modifications from conventional terrestrial technologies is critical for providing seamless mobility. Additionally, using the 3GPP Narrow-Band IoT (NB-IoT) air combine remains a wireless communication system as an example explains major system elements. However, the Design trade-off provides better performance but expanding network coverage is limited.

Marcano Nestor J et al.[18] developed a unique queuing model that is utilized to enhance the end-to-end delay in LEO satellite constellations for 5G and 6G. In Addition, the Matrix Geometric Method is used for the optimization method. It provides better end-to-end delay with expandable network area but increases computational complexities.

Deebak Bakkiam David et al.[19] presented a dynamically driven congestion control and segment re-routing to take into account network congestion to enhance the quality metrics in the developing IoT environments. Further, Deleroi used a forward-backward interface and superimposed principles to analyze the media access networks. The suggested DD-CCSR is more effective in determining congestion, but energy usage is high. Ansere et.al.[20] designed resource allocation for energy efficient framework to addressing the combined optimization of power allocation, power allocation, subchannel allocation, user selection and number of activated Remote Radio Units in dynamic large-scale 6G-IoT ecosystems. The problematic is formulated as a nonconvex Mixed-Integer Nonlinear Programming model, aiming to enhance efficiency energy through the optimal allocation of resources while considering the dynamic nature of large-scale IoT networks.

Rajak et.al.[21] proposed a hybrid relay-IRS-aided IoT device network to achieve energy efficiency in a Rayleigh fading domain. This hybrid relay-IRS-assisted network is designed to achieve the high reliability, data rate, bandwidth and data transfer requests of 6G communications. Irshaid et al.[22] presents novel energy-efficient multichannel framework with a cross-layer MAC to exploits a non-persistent CSMA protocol for cognitive radio 6G-enabled massive IoT communication systems networks. By coordinating the parameters of both layers physical and MAC, the framework seeks to enhance energy-efficiency for IoT networks. The authors specifically address the energy efficiency maximization per bit, while considering several design constraints. Kouroshnezhad Sahar et al.[23] suggested SEDMAG, a truck-motion rattle on a path preparing calculation, for locating 6th-generation IoT apparatus. In addition, a wise pursuit calculation along with an inverse operation method are used to minimize latency and energy overhead. Though it provides lower localization latency, but provides only a limited coverage area.

López Onel LA et al.[24] studied the CSI-free WET technique to enhance the efficiency of the IoT devices in 6G. To power complicated gadgets with high power consumption requirements, however, this approach can be the perfect solution. Mao et al.[25] proposed 6G communication IoT application in remote zones, focusing on satellite-UAV- assisted IoT systems. The study highlighted several key 6G technologies THz communication, energy efficient, edge computing and discussing where the technologies enhance the efficiency of satellite-UAV- assisted 6G IoT systems. Rana et al.[26] Suggested a network intelligent solution aimed at improving energy efficiency in 6G-enabled expanding IoT networks. This approach leverages cell-free massive multiple-input multiple-output technology and achieves optimal energy efficiency through effective network resource allocation. By optimizing the pilot reuse factor and access point density, while accounting for the number of users and antennas at each access point, the proposed method seeks to maximize energy efficiency.

Table 1. Summary of related studies.

Reference	Approach Details	Benefit	Restriction
[10]	A joint beamforming design algorithm	Maximum Energy Efficiency	Minimum coverage area
[11]	Distributed-Two-Stage Offloading (DTSO)	Minimum latency and final energy use	High computational complexities
[6]	Along preamble sequence	Minimum Energy consumption	High computational cost
[12]	A heuristic algorithm	Minimal Energy consumption	High Latency
[13]	A restricted three-sided matching algorithm	Minimum computational time	Higher Energy Consumption
[14]	Data-driven Fair-Hierarchical Scheduling (DFHS) method	Minimum delay time	High computational cost
[15]	Process-oriented optimization framework	High network coverage area	computational time and cost are high
[16]	Satellite communication	High network coverage area	High Energy consumption
[17]	A backward-compatible air interface	Better Design trade-off	Minimum coverage area
[18]	A novel queuing model	Minimum End-to-End Delay	Higher Computation Cost
[19]	A dynamically driven congestion control and segment re-routing	Minimum congestion	Higher Energy Consumption
[20]	Dynamic resource optimization framework for 6G-IoT ecosystems.	maximize the lifetime of a radio subsystem	Enhance the energy efficiency of IoT networks
[21]	hybrid relay-IRS-aided wireless IoT network for 6G communications	Maximum energy consumption	higher bandwidth and reliable data transmission.
[22]	A Joint cross-layer optimization for Cognitive radio	Maximum Energy Efficiency	Improve energy efficiency
[23]	A semi-dynamic drone trajectory planning algorithm	Minimum localization latency	Minimum coverage area
[24]	CSI-free WET technique	Powering complex devices	High Delay and Routing Overhead
[25]	Satellite-UAV-served 6G IoT system	reducing latency and energy consumed	high transmission efficiency
[26]	Cell-free mMIMO technology in 6G-enabled IoT networks	Maximizes energy efficiency	increased energy efficiency
[27]	High-altitude platforms (HAPs) and low-Earth orbit (LEO) satellites	Effective resource management	Higher Energy Consumption

Jia et al. [27] analyzed Space–Air-Ground Integrated Network (SAGIN) arise to achieve global coverage and seamless service. To perform effective remote area data transmission High Altitude Platforms (HAPs) and Low-Earth Orbit (LEO) rocket remain used which include time expanding graph (TEG) to perform Capacity Aware effective resource management although failing towards transcend packet delivery ratio and energy efficiency during communication. Later dissecting existing research, to appreciate this conveyed communication be effective in satellite-predicated IoT mesh is at rest the field of study. Remains this general, explore work Energy with Capacity aware effective satellite communication is concentrated in the IoT environment. A basically of previous research is construe in Table 1.

The major drawbacks that are analyzed from the earlier research are high computational cost and high-power utilization at the time of processing on advanced IoT devices. Mainly to reduce energy consumption effective optimization and resource allocation among the IoT devices are concentrated.
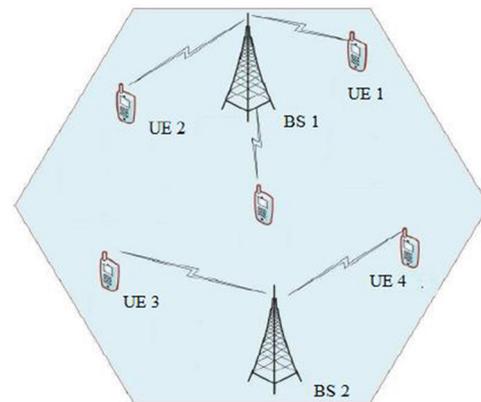
Fig. 2. Illustration of network model [28].

Preliminaries

Considering a downlink packet transmission in the IoT networks, consisting of Base Station (BS) and User Equipment (UEs), as shown in Fig. 2. Sensors are installed in the UEs to improve the reliability of data transmission through sub-channels. Furthermore, UE uses BS to strategically utilize sub-channels;

each UE is only permitted to communicate with one BS. Considering the neighboring UE has the best signal strength between the broadcasting BS and UE receiver, the BS transmits an energy signal toward the UE. To temporarily store energy for data transmission to the target, each UE individually detects accessible sub-channels. The distributed UE and BS sets are described as $n \in \{1, 2, \ldots, N\}$ also $m \in \{1, 2, \ldots, M\}$, accordingly. It is expected that during convergence, the UEs and BS operate on a time-division-duplexing protocol. $q_{m,n} = [q_{m,1,n}, \ldots, q_{m,n,M}]^T \in C^{M*N}$ is considered a compact fading channel matrix from m^{th} BS to n^{th} UE. Let $\alpha_{m,n}$ denotes the channel's large-scale fading coefficient. So, the nth UE and m^{th} BS's communication channel, $h_{m,n}$ thematically expressed in Eq. (1).

$$h_{m.n} = \sqrt{\alpha_{m.n}}\, \hat{q}_{m.n} \tag{1}$$

The minimum mean-square error (MMSE) calculated by q_n of nth UE in Eq. (2),

$$\hat{q}_n = \frac{k_n p_n}{k_n p_n + 1} q + \frac{\sqrt{k_n p_n}}{k_n p_n + 1}\, w_n \tag{2}$$

In Eqs. (1) and (2) the terms q_n implies maximal ratio transmission using the precoding vector, k_n implies the number of pilot symbols required for each coherence interval and where p_n implies transmit power which is the energy flow from the mth BS to the nth UE. The values of $q_{m,n}$ have Gaussian noise power, which is individually and similarly distributed.

Data transmission model

Each BS in the IoT network transmits packets to the linked UEs during the transmission period. Let's assume that each UE links to a single BS, and indicates Im as the set of UEs assist by the mth BS, the packets broadcast from the mth BS is expressed as Eq. (3)

$$x_m = \sum_{n=1}^{Im} \sqrt{p_{m,n}}\, q_{m,n}\, z_{m,n} \tag{3}$$

In Eq. (3) the terms $z_{m,n}$ implies the broadcast symbol. So, the packet transfer signal received from m^{th} BS to nth UE is mathematically expressed in Eq. (4)

$$
\begin{aligned}
y_{m,n} &= x_m h_{m,n}^T + \sum_{i=1,\ i\neq m}^{M} x_m h_{m,n}^T + w_{m,n} \\
&= \sum_{t=1}^{I_m} \sqrt{P_{m,t}}\, h_{m,n\ q_{m,t}\ z_{m,t}}^T + \sum_{i=1,\ i\neq m}^{M} \sum_{t=1}^{I_m} \sqrt{P_{i,t}}\, h_{i,n\ q_{i,t}\ z_{i,t}}^T \\
&\quad + w_{m,n}
\end{aligned}
\tag{4}
$$

It is significant to observe that, from the right side of Eq. (4), the desired signal is represented by the first term, and interference and effective noise are represented by the other terms. The acceptable data rates of mth BS to n^{th} UE is mathematically expressed in Eq. (5)

$$r_{m,n} = \log_2\left(1 + \gamma_{m,n}\right) \tag{5}$$

In Eq. (5) the term $r_{m,n}$ implies the signal-to-interference-plus-noise ratio and optimal achievable rate during the packet broadcast from m^{th} BS to n^{th} UE is mathematically expressed in Eqs. (6) and (7).

$$r_{m,n} = \frac{\sum_{t=1}^{I_m} p_{m,t}\left|h_{m,n\ q_{m,t}\ z_{m,t}}^T\right|^2}{\sum_{i=1,\ i\neq m}^{M}\sum_{t=1}^{I_m} p_{i,t}\left|h_{i,n\ q_{i,t}\ z_{i,t}}^T\right|^2 + \left|w_{m,n}\right|^2} \tag{6}$$

$$R_n = \sum_{m=1}^{M} x_{m,n} \log_2\left(1 + \frac{\mathcal{L}_{p_{m,n}}\lambda_{m,n}}{\sum_{i=1}^{M}\sum_{t=1}^{N} p_{i,t}\alpha_{i,n} + \sigma_{m,n}^2}\right) \tag{7}$$

In Eq. (7) the term $\lambda_{m,n}$ implies the distribution function in $h_{m,n}$. According to these calculations, the data transmission model is described in the IoT environment.

Energy consumption model

As the total power consumption P_T, which consists of circuit energy usage, power efficiency, and power amplifier during the packet transmission process from the BS to UEs, is mathematically expressed in Eq. (8):

$$
\begin{aligned}
P_T &= P_{C_r} + P_t + P_s \sum_{m=1}^{M} k = P_{C_r} + \sum_{n=1}^{N}\sum_{m=1}^{M} \frac{1}{\varphi} P_{m.n} \\
&\quad + P_s \sum_{m=1}^{M} \mathcal{L}
\end{aligned}
\tag{8}
$$

In Eq. (8) the term P_{C_r} implies energy consumption of the circuit, $P_t = \sum_{n=1}^{N}\sum_{m=1}^{M} \varphi\, P_{m.n}$ implies the power transmission, $\mathcal{L}$ implies the number of enabled BS antennas, P_s implies the amount of energy used to serve a BS antenna and φ implies the amplifying devices drain efficiency accordingly.

UE and BS connection

To achieve the accessible sub-channel for packet transmission in IoT networks, the UE is linked to the BS using a collection of integer binary variables. Since there is only one BS that UE connects to, the connection variable $x_{m.n}$ between nth UE and the mth

BS is mathematically expressed in Eq. (9).

$$x_{m,n} = \begin{cases} 1, & if \; n \; UE \; connects \; to \; m \; BS \\ 0, & otherwise \end{cases} \quad (9)$$

QoS-based service parameters

A QoS describes non-constructive characteristics along with benefits such as reaction time, accessibility, cost, and so on. Components that need to be minimized are cost, energy consumption, and response time. Maximizing availability and reliability is also necessary.

Response time, which is determined using Eq. (10), is the service's ability towards carrying out its activities in predetermined circumstances for a specified timeframe.

$$RT_{RK} = \frac{RES_K}{REC_K} \quad (10)$$

In Eq. (10) the term $K = 1, 2, \ldots, m$ implies amount along with jobs deferred towards that repeat in celebrated time, and refers to the amount of appeal. The number of jobs RES_K sent to RK that were repeated during the specified period and REC_K relate to the total number of requests. IoT service availability is defined as being accessible and functional when needed. It is a relationship between time anywhere the service is accessible along a specified time that is necessary or quantifiable for effort. Using Eq. (11), it can be mathematically expressed.

$$AV_{RK} = \frac{A_{QJ}}{S_{NJ}} \quad (11)$$

In Eq. (11) the terms imply the assets and for each, where m implies a total number of services, implies an amount of jobs yield; along with implies a number of jobs accept. Cost is amount of money paid for the requirement for IoT nods, based on bandwidth, recollection, and processes that are used. The cost calculation is mathematically expressed in Eq. (12).

$$Cost = \sum_{i=1}^{k} (A_i * UAT_i) * UAS_i \quad (12)$$

In Eq. (12) the term k implies the capacity of the concrete service, implies the number of nodes assigned to each user's request, implies the duration of the user's access to the nodes, and implies the speed of user's access to nods. The possibility of a network processing the necessary tasks in a time frame without error is demonstrated by reliability. The reliability

calculation is mathematically expressed in Eq. (13).

$$REL_t = \frac{FDD_{fun}}{OP_t} \quad (13)$$

In Eq. (13) the terms imply reliability which represents the possibility of operating in time t, implies operating time, along with implies defeat probability function. The impact of power consumption on devices supporting IoT candidate services is outstanding. Each potential service must then provide a parameter to indicate its energy usage. That melodist barrel then chooses a benefit with optimal power conservation based on this parameter. The energy calculation is mathematically expressed in Eq. (14).

$$Energy = \frac{E_{ep} + E_{zig}}{D_{ca} \; B_{time} \; \sum_{\forall \vartheta_{iev}} \lambda_i} * UAT_i * UAS_i \quad (14)$$

In Eq. (14) the terms imply the power consumption of the entry point, ZigBee energy usage, data packet capacity, beacon broadcast interval, and implies data arrival rate of a node. Fig. 3 demonstrates a three-layered architecture to illustrate a circumstantial representation of IoT benefit composition. Initially, clients' forward services. The request is then sent to the edge layer, which will find service operations depending on the most frequent QoS variables. The service revelation process is initiated when the set of requested services is received by the service coordinator flow. To secure a Service-Level Agreement, reasonable services are also picked from the list of available services. Hence, the model selects the best QoS as the ultimate optimum service composition option for users. Due to their ability to operate in diverse distributed situations, service-oriented systems are particularly significant. These services are offered in various locations and have various QoS parameter values.

Fitness function

The provision of amount of conscious benefit to satisfy changeable limitations along with improve wellness purpose is a fundamental objective of service composition. The values of the QoS parameters should be optimized through the fitness function. Positive and negative parameters prefer to have opposite effects on their evaluation functions. To solve this issue, all QoS should assimilate appropriately (using the next section) so that all their combined negative and positive aftermath meet to one side. The wellness province calculation is mathematically expressed in Eq. (15) where W_i implies the weight factor and the
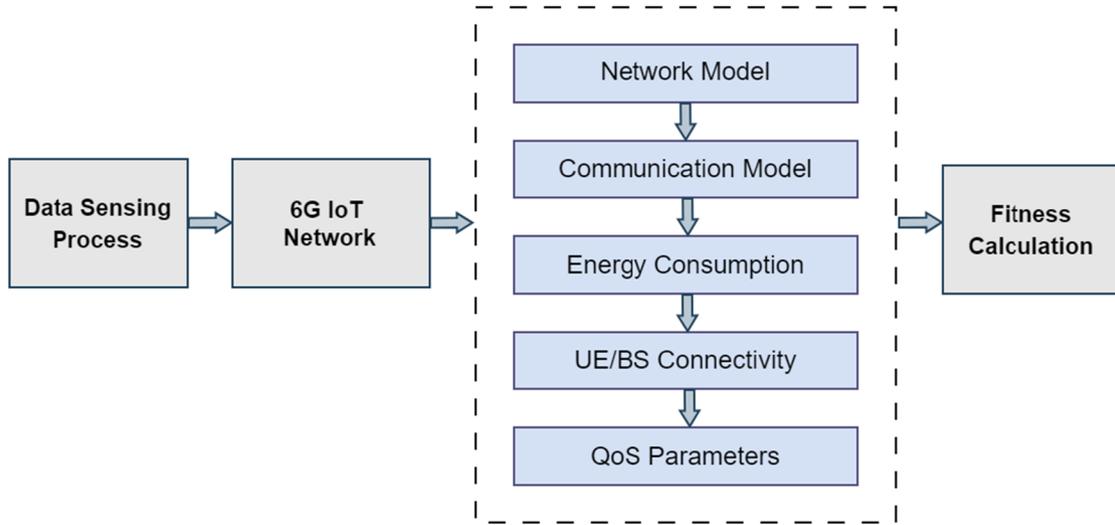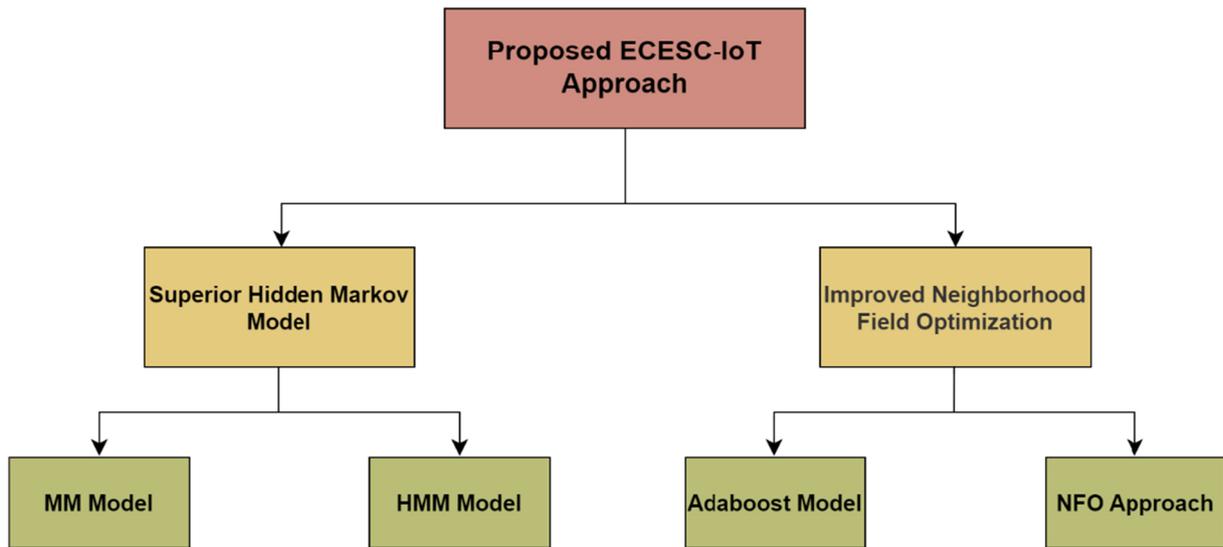
Fig. 3. Three layered architecture.

Fig. 4. ECESC-IoT approach workflow.

Q_i implies the quality factor.

$$Fitness = \sum_{i=1}^{5} W_i * Q_i \qquad (15)$$

Proposed ECESC-IoT approach

The proposed ECESC-IoT approach is developed mainly to improve the 6G communication in IoT. To improve the quality the network model is constructed in an effective way that includes the well-organized communication and Energy Consumption model, effectual UEs and BS connectivity qualified service parameters, and the fitness function. Followed by that

to achieve maximum resource utilization and optimization in the proposed approach Hidden Markov Model (SHMM) and Neighborhood Field Optimization (INFO) Algorithm is used. The proposed workflow of the ECESC-IoT approach is described in Fig. 4.

In the realm of 6G Assisted Heterogeneous IoT, the concept of intelligently integrating energy with capacity-aware satellite communication aims to optimize IoT device performance in diverse network settings. The approach can involve efficiently managing energy consumption and harnessing the potential of satellite communication within 6G networks. Furthermore, it incorporates energy optimization techniques to decrease energy usage, capacity-aware communication strategies to maximize satellite capacity, and robust routing and scheduling mechanisms for

Table 2. A comparison of the ECESC-IoT proposed model with existing methods.

Approach	Advantages	Disadvantages	Parameters Used	Future Uses
ECESC-IoT	Enhanced network performance through improved energy efficiency, packet delivery ratio, reduced consumption and delay, dynamic adaption to network changes, and scalability and flexibility in management.	Complexity in implementation, resource-intensive optimization algorithms, potential overhead from SHMM and INFO algorithm	Communication, energy consumption, UE, BS connectivity, SHMM, INFO parameters	Smart cities, IoT networks, Autonomous vehicles, Urban infrastructure, environmental monitoring
EERS-IoT	Energy-efficient routing strategies	Limited coverage area	Network topology	Healthcare applications
SECA-IoT	Secure communication protocol	Increased computational overhead	Security Protocols	Industrial automation
DATS-IoT	Real-time data aggregation and processing	Complexity in data fusion and analysis	Data aggregation algorithm	Agricultural monitoring

dependable and low-latency communication. With the applying these strategies within 6G networks, IoT devices can experience enhanced performance, improved reliability, resource efficiency, and scalability.

The technique allows for fluency in the integration of energy management and satellite communication, thus showing the full potential of IoT within heterogeneous environments. Moreover, Self-SHMM is a promising tool for capturing complex network dynamics, since future states can be predicted knowingly based on the current state estimation and observations made of it, enabling efficient resource allocation decisions and facilitating optimal device use. To enable efficient resource allocation in device neighbourhoods, INFO Algorithm is presented which embodies cooperative aspects and certain of the optimisation algorithms, which will allow for efficient resource allocation through continued adaptability to the network efficiency. By continuously refining and adjusting strategies in real-time, the model maximizes efficiency and effectiveness in heterogeneous IoT environments. Table 2, discusses the proposed model with an existing model.

Superior hidden Markov model

A Markov cycle with undiscovered (covered up) states is assumed to be the shown system in an actual MM known as the SHMM. A state is apparent in MM, and famous criteria are achievable accordingly between states. The model is hidden in an SHMM, but the output is determined by the mode. A predictive method that is widely used is MM. Many Markov designs, such as the HMM and the semi-Markov, have effectively been derived from MM. Functionality modelling and functionality-forecast analysis have both been done using the SHMM. Using the current state as a starting point, the HMM may read the future state of the desired mechanism. In an SHMM, we are

unable to witness the states, but as you can see, an observation is recorded as the state's anticipation underlings. Each state in group has been given a specific observation as in Eqs. (16) to (21).

$$\{V_1, \ V_{2,....}V_M\}: \ b_j(m) \triangleq P_r\left(O_t = V_m | q_t = S_j\right), \quad (16)$$

where $b_j(m)$ displays possible observational radiation Additionally, hold considered a uniform design among which potential outcomes are sovereign of t. Thus, an observation sequence O is established by the observed amounts. Despite being hidden, the state sequence q can be inferred from the observation sequence O. The SHMM's observable model, in which $b_j(m) = 1$, if $m = 0$ and $m = 0$. The ensuring element assist us summarise and validate the

$$SHMM : S = \{S_1, \ S_{2.....}S_N\} \quad (17)$$

V: count of separate study symbols in alphabet,

$$SHMM : V = \{V_1, \ V_{2.....}V_N\} \quad (18)$$

A is state transfer achievable

$$SHMM : A = \left(a_{ij}\right), \ where \ a_{ij} = P_r(q_t \ + 1 = S_j | q_t \quad (19)$$

Study probabilities,

$$SHMM : B = \left(b_j(m)\right), \ where$$
$$b_j(m) = P_r(O_t = V_m | q_t = S_j) \quad (20)$$

Chief state possibilities,

$$SHMM : \Pi = (), \ where \ \pi_i = P_r(q_t \ + 1) \quad (21)$$

The other variables implicitly determine S and M, $\Lambda = (A, \ B, \ \Pi)$ as the SHMM boundary. Assuming Λ, the model can produce an arbitrary number of

examination succession. While assuming a sequential exercise state, focus is typically on approximating the design features.

Background of neighborhood field optimization (NFO) algorithm

An investigative technique for resolving global optimization issues is the neighborhood field optimization (NFO) method. Wu and Chow proposed the concept[29]. The NFO method leverages a species' local cooperative behavior to identify the location of a global optimal. The genetic algorithm, an investigative machine learning technique, is well recognized[30]. The GA technique employs a random search process to determine the most optimal solutions. Similarly, the NFO method also utilizes a randomized search approach[31]. However, the NFO differentiates itself from the GA by implementing a gradient descent strategy for its search mechanism. This allows for smoother convergence in a local region compared to the GA method. The NFO approach utilizes two neighboring solutions - an inferior one (xw) and a superior one (xc). The current solution is assigned to x, while xc and xw are designated as the superior and inferior neighbors, respectively. The following calculation is made:

$$xv = x + \alpha r_1 (xc - x) + ar_2 (xc - xw)$$
$$+ ar_3 (xc - xw_2) \tag{22}$$

In Eq. (22) the term α implies the learning rate, and, implies two vectors with random numbers.

Improved neighborhood field optimization (INFO) algorithm

Learning might be considered a specific form of optimization. The purpose of machine learning is to find the best possible hypothesis. Mitchell observed that the GA approach is appropriate for the challenging hypothesis task. It should be noted that the NFO approach outperforms other methods while being newer than the GA approach. To complete the optimization goal, this paper attempts to integrate the AdaBoost and NFO approaches. The (INFO) approach is the name of the suggested technique. Fig. 5 contains a flowchart of the approach. Three NFO approaches are combined linearly in the INFO algorithm, as can be seen in Fig. 5. The goal of the INFO method is to combine three weak solvers to develop a powerful solver. A beginning process with a population size N. Deceitful pursuit, usual search, and deceitful search make up an INFO algorithm's main cycle. The main
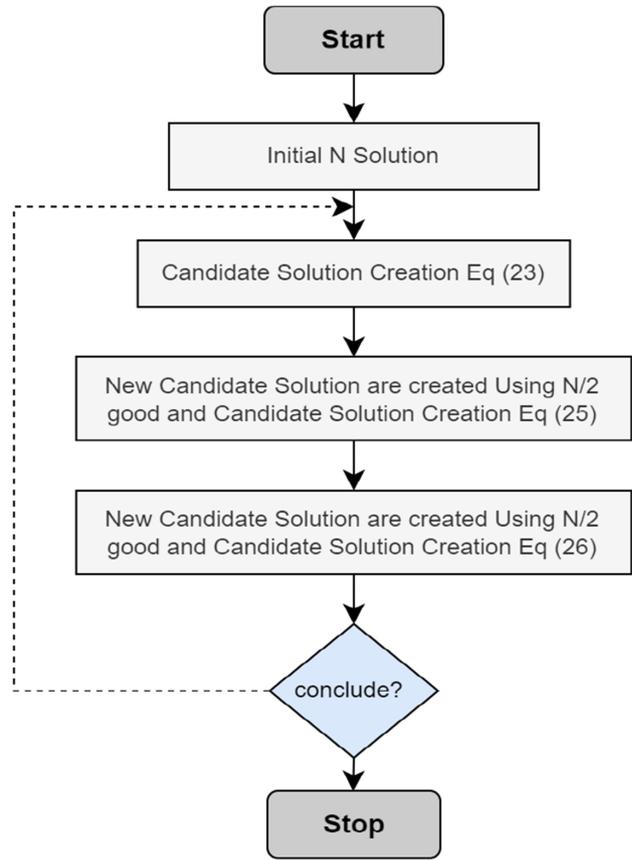

Fig. 5. Flowchart for improved INFO.

cycle is repeated unless the algorithm satisfies the termination requirements in which case it terminates. Exploitative search seeks optimal results about best result with a combination of the AdaBoost model. The Eq. (23) is:

$$xv = \left(x + \alpha r_1 \left(x^{best} - x\right) + \alpha r_2 \left(x^{best} - xw\right)\right.$$
$$\left. + \alpha r_3 \left(x^{best} - xw_2\right)\right) * f(x) \tag{23}$$

In Eq. (23) the terms imply the best solution. The area around be found using the search Equation to guide the search where f(x) implies the Ada-Boost method with the linear combination which is mathematically expressed in the Eq. (24).

$$f(x) = \sum_{i=1}^{N} \alpha_i * C_i(x) \tag{24}$$

In Eq. (24) the term implies the classifier's (x) weight, and x implies the used sample. Similar to the original NFO method, the common search Equation

Algorithm 1. ECESC-IoT Approach.

Input: communication, energy consumption model, UE, BS connectivity parameters.
SHMM parameters: S, V, A, B, Π
INFO Algorithm parameters: α, x_{best}, x_w, x_c, α_i, C_i
Output: Optimized resource utilization and network performance
Step 1. Initialize SHMM, INFO algorithm parameters
Step 2. Construct a network model incorporating a communication and energy consumption model, UE, BS connectivity, and fitness function.
Step 3. Implement SHMM to predict future states based on current observations.
Step 4. Utilize INFO algorithm for optimization with Exploitative Eq. (23), Common Eq. (25), Explorative Eq. (26),
Step 5. Repeat 3 and 4 steps until conditions are met.
Step 6. Evaluate optimized solutions.
Step 7. Output performance metrics.

is mathematically expressed below in Eq. (25).

$$xv = x + \alpha r_1\ (xc - x) + \alpha r_2\ (xc - xw)$$
$$+ \alpha r_3\ (xc - xw_1) * f(x) \qquad (25)$$

The neighborhoods of both superior and inferior neighbors can be searched using the search Equation. Exploratory search is intended to locate the unexplored surrounding area of search space. A search Equation is:

$$xv = x + \alpha r_1\ (x^{worst} - x) + \alpha r_2\ (x^{worst} - xw)$$
$$+ \alpha r_3\ (x^{worst} - xw_2) * f(x) \qquad (26)$$

In Eq. (26) the terms imply the worst solution. The neighborhood of be found using the search Equation. Since parameter α implies a hyper-parameter, it must be defined previously. At each iteration, the parameters are generated again.

These are the processes that are involved in the proposed ECESC-IoT approach and the leader purpose of proposed model is towards improve throughput, packet delivery ratio, energy efficiency, and network by reducing power consumption, routing overhead, delay. The implementation is performed using the networking software NS2 and a detailed evaluation is given in the upcoming sections. Algorithm 1, as described about the parameters of the ECESC-IoT proposed model.

Simulation environments

The principles defined in the suggested approach ECESC-IoT are applied in NS-2 network simulation to evaluate the performance of the nodes. The setup involves defining placements of the nodes, mobility models and communication protocols in the simulation. The evaluation is done in terms of varying

Table 3. Simulation parameters for the generated results.

Parameters	Values
Implementation Tool	NS2
Simulation Duration	500 ms
Coverage Density	2000m*2000m
Nodes Count	500 Nodes
Radio Model	IEEE 802.14.5 [21]
Antenna Model	Omni-directional Antenna
Nodes Mobility	Random Waypoint
UMTS Threshold	–94 dBm
Queue Type	DropTail
Node Speed	3Km/hr to 30Km/hr
Initial Power	1000 [21]

number of nodes and varying speeds, Key parameters such as energy consumption models and routing algorithms are designed to align with the proposed model of ECESC-IoT. The matrices that are considered for varying nodes from 50 nodes to 500 nodes are throughput, packet loss, end-to-end delay, routing overhead, packet delivery ratio, and energy efficiency. The matrices that are calculated for varying speeds from 3 km/Hr to 30 km/Hr are throughput, packet loss, routing overhead, and packet delivery ratio. An measured outcomes are compared with the baseline methods like EERS-IoT [25], SECA-IoT [26], and DATS-IoT [27]. By analyzing the results, insights are gained into the strengths and limitations of the ECESC-IoT model. The essential parameters needed for the implementation are discussed in Table 3.

Results and discussion

Results of number of nodes concerned

Implementation outcomes stay calculated concerning amount along with node and outcomes remain observed graphically for methods like EERS-IoT, SECA-IoT, DATS-IoT, and ECESC-IoT. The matrices used in these calculations are throughput, packet loss,
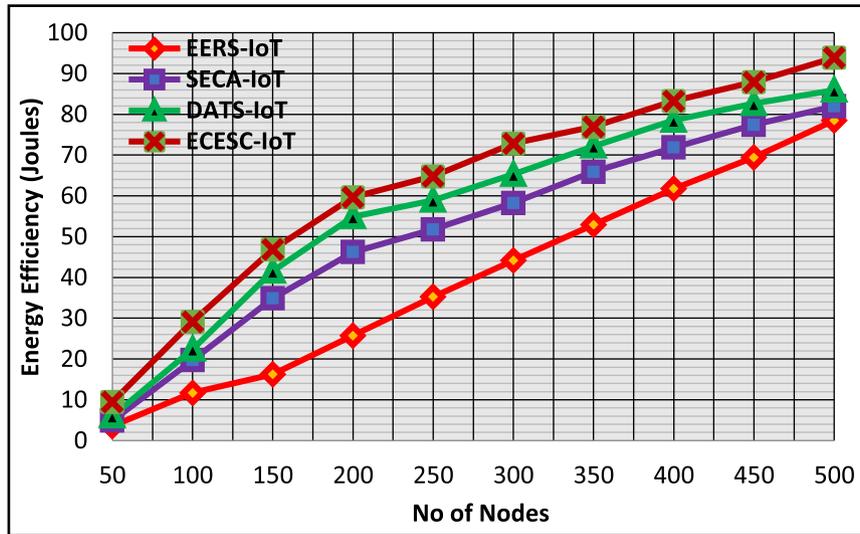
Fig. 6. Energy efficiency calculation concerned with the number of nodes.
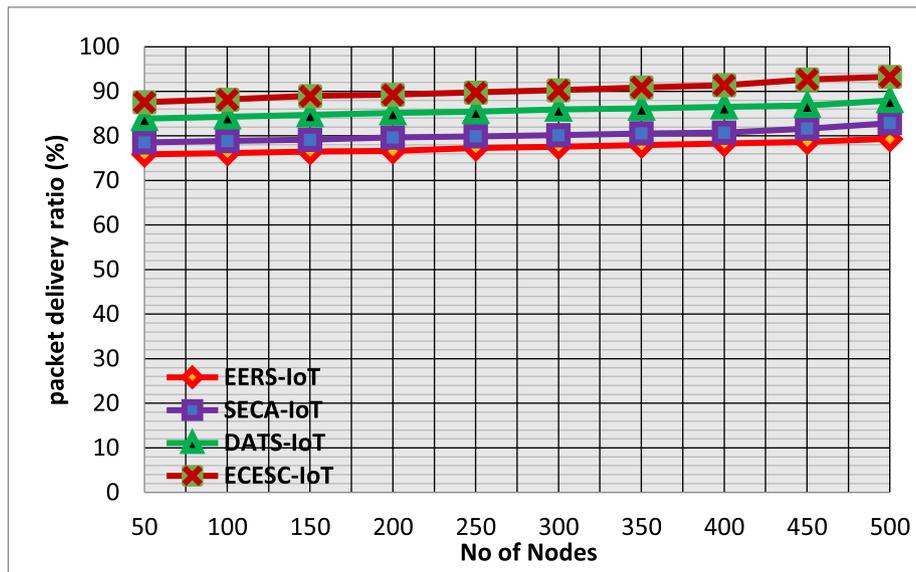

Fig. 7. Packet delivery ratio calculation concerned with the number of nodes.

end-to-end delay, routing overhead, packet delivery ratio, and energy efficiency.

Energy efficiency calculation

The remaining energy is determined after the simulation is finished for different quantities of nodes. the energy efficiency is illustrated in Fig. 6 which shows that ECESC-IoT has the most efficiency in comparison to other methods in the literature like EERS-IoT, SECA-IoT, and DATS-IoT. On the other hand, this method has two major shortcomings: it expends a lot of energy to communicate in an efficient manner, and it poorly manages the allocation of resources. Therefore, the proposed method emphasizes optimization

and resource allocation which has shown to improve efficiency over previous methods considerably.

Packet delivery ratio calculation

The delivery ratio is defined as the ratio of the data received by the recipient with respect to the data sent by the originator of the information. In the graphical representation of the data provided in Fig. 7, the ECESC-IoT model achieves greater performance over the other methodologies including EERS-IoT, SECA-IoT, and DATS-IoT. This novel methodology integrates a proficient soft and hard cooperative strategy with a High-Quality Hidden Markov Model to allow optimal distribution of resources between the
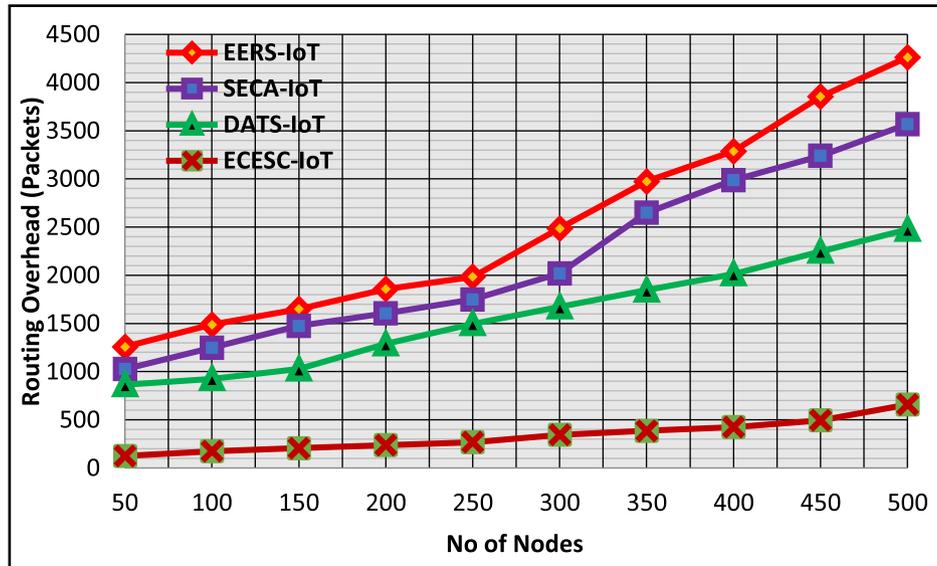
Fig. 8. Routing overhead calculation concerned with the number of nodes.
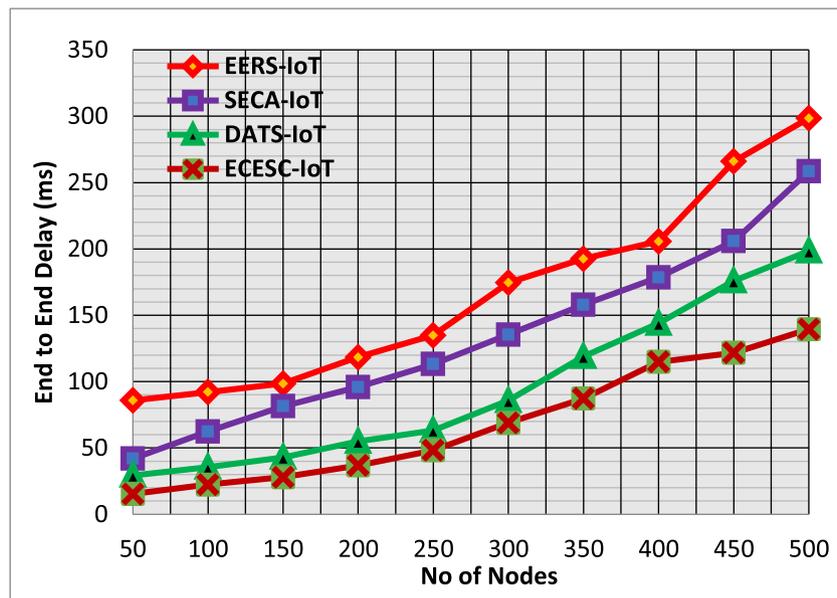
Fig. 9. End-to-end delay calculation concerned with the number of nodes.

user equipment and the base stations in a manner that achieves disruption-free data transfer. The result shows the ECESC-IoT achieves a higher packet delivery ratio than previous studies.

Routing overhead calculation

The evaluation also considered routing overhead the process of determining the total amount of information transmitted by the sender and received by other nodes is known as routing overhead. According to Fig. 8, the ECESC-IoT method produces lower overhead compared to alternative methods such as

EERS-IoT, SECA-IoT, and DATS-IoT. The INFO algorithm effectively decreases the data forwarding ratio between UEs and BS, resulting in a decrease in routing overhead in the IoT network. This improvement in routing overhead has a significant impact on reducing network delay and energy consumption.

End-to-end delay calculation

The process of determining the time it takes for a node to generate information for a successful packet collection response is known as delay calculation. As shown in Fig. 9, this research compares the delay
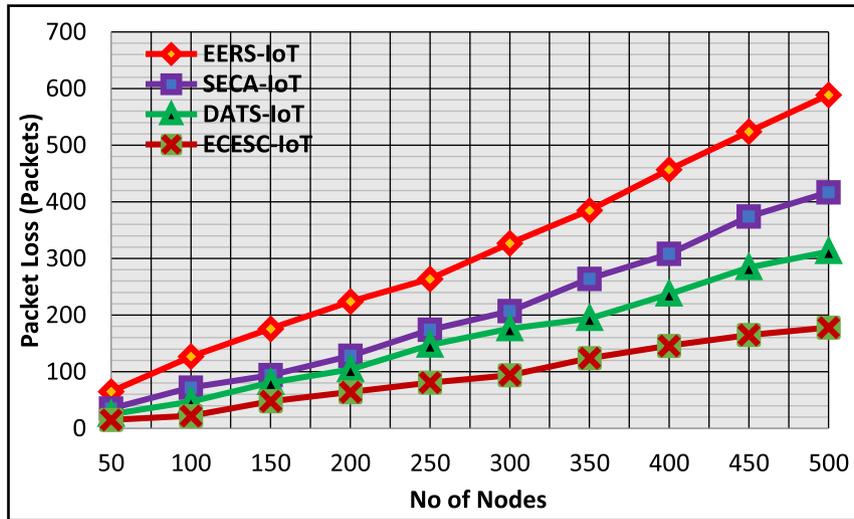
Fig. 10. Packet loss calculation concerned with the number of nodes.

calculations of different methods, and it has been found that ECESC-IoT has a lower end-to-end delay compared to other methods such as EERS-IoT, SECA-IoT, and DATS-IoT. This can be attributed to the fact that earlier methods lack efficient routing utilization during communication, leading to longer delays. To address this issue, the researchers utilized a hidden Markov model for effective resource allocation and monitored network congestion. Through optimization, the best solution was then applied to each destination from the source UEs.

Packet loss calculation

The concept refers to the amount of information that is no longer available after data is sent between different nodes in the diverse IoT network. In Fig. 10, it is shown that the ECESC-IoT method has a lower rate of lost packets compared to other methods such as EERS-IoT, SECA-IoT, and DATS-IoT. Studies indicate that failure to manage resources appropriately causes packet loss, routing delays, and a subsequent rise in energy utilization. To address these and improve performance, the proposed approach uses more efficient hidden Markov models and selects the shortest path using the INFO algorithm. This method also demonstrated considerably less packet loss than other techniques.

Throughput calculation

The initial step involves calculating the highest volume of data that can be communicated between nodes. The ECESC-IoT method achieves higher throughput as shown In Fig. 11 as compared to EERS-IoT, SECA-IoT and DATS-IoT. This is due to the proposed network model's improved resource distri-

bution and optimization, which translates to lesser energy use, delay, and routing overhead. Consequently, the throughput during any transmission period between any UE and BS is significantly improved.

Results and discussion concerned with the number of nodes

This section focuses on the outcomes of the implementation concerning the total count of evaluated nodes to measure the performance of the current techniques beside the ECESC-IoT strategy. The metrics applied for the evaluations are energy efficiency, packet delivery ratio, routing overhead, end-to-end delay, packet loss, and throughput. The corresponding values for the parameters of these metrics are included in Table 4 and Table 5, respectively.

In the term of energy efficiency, ECESC-IoT achieve a surprising 93.86%, followed by DATS-IoT at 85.91%, SECA-IoT at 81.95%, and EERS-IoT at 78.48%. ECESC-IoT further cements its affirmation in energy efficiency by outperforming EERS-IoT by 15.38%, SECA-IoT by 11.91%, and DATS-IoT by 7.95%. This only goes to prove how the ECESC-IoT system utterly surpasses its competitors in energy savings. With regards to Packet Delivery Ratio, ECESC-IoT is ahead of the rest with an impressive packet delivery ratio of 93.27%, thus ensuring effective and efficient delivery of data packets within the network. Following ECESC-IoT in position is EERS-IoT with 79.36%, while SECA-IoT with 82.85%, and DATS-IoT with 87.94% boast a relatively lower packet delivery ratio. Still, it is only ECESC-IoT that dominates the competition with EERS-IoT by 13.91%, SECA-IoT by 10.42%, and DATS-IoT by 5.33%. With
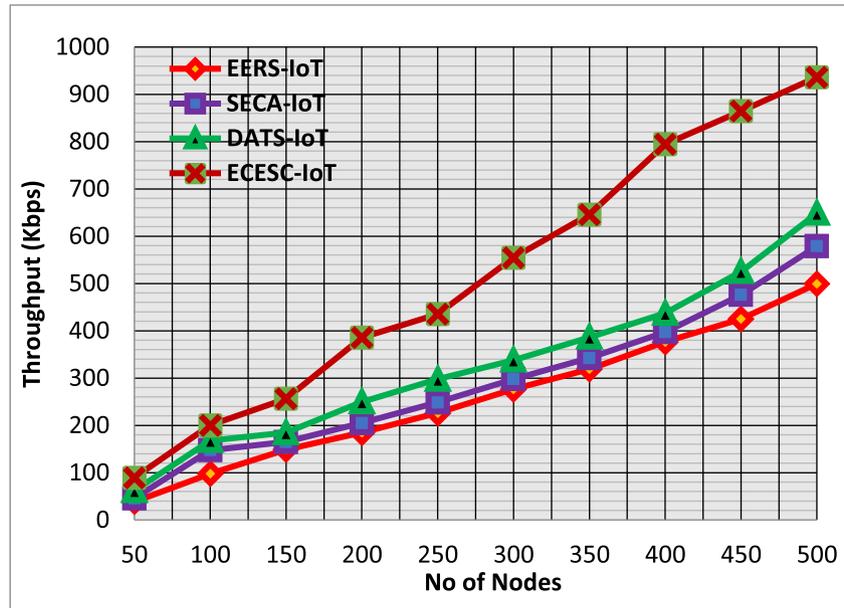
Fig. 11. Throughput calculation concerned with the number of nodes.

Table 4. Calculation of the parameters include energy efficiency ratio, packet delivery ratio, and routing overhead ratio concerning the number of nodes.

No of Nodes	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT
	Energy Efficiency (%)				Packet Delivery Ratio (%)				Routing Overhead (PACs)			
50	3.57	4.89	6.04	9.46	75.87	78.53	83.89	87.58	1258	1025	864	125
100	11.72	19.74	22.41	29.14	76.14	78.85	84.27	88.16	1487	1248	925	174
150	16.24	34.87	41.52	46.85	76.48	79.15	84.75	88.97	1649	1475	1027	205
200	25.74	46.21	54.86	59.67	76.62	79.64	85.16	89.25	1857	1604	1287	238
250	35.28	51.79	58.94	64.82	77.28	79.91	85.47	89.76	1984	1748	1497	267
300	44.17	58.27	65.27	72.85	77.61	80.17	85.97	90.28	2487	2018	1672	345
350	52.94	65.89	72.17	76.94	77.92	80.54	86.19	90.87	2974	2648	1845	386
400	61.75	71.85	78.52	83.27	78.29	80.75	86.52	91.37	3287	2987	2014	425
450	69.47	77.42	82.64	87.92	78.67	81.64	86.84	92.68	3854	3240	2248	494
500	78.48	81.95	85.91	93.86	79.36	82.85	87.94	93.27	4262	3568	2475	658

Table 5. Measurement of end-to-end delay, packet loss, and throughput for concerned with number of nodes.

No of Nodes	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT
	E2E_Delay (ms)				Packet Loss (PACs)				Throughput (Kbps)			
50	85.86	41.96	29.29	15.39	65	35	25	15	38.48	45.78	61.84	89.37
100	92.15	62.48	35.48	22.48	127	72	47	22	97.82	147.52	167.85	200.25
150	98.56	81.47	42.89	27.94	176	94	81	48	148.95	164.85	184.56	256.32
200	118.45	95.86	54.85	36.82	224	128	104	64	184.62	204.96	249.67	385.64
250	134.89	113.25	63.25	48.25	264	174	147	81	225.97	248.63	297.68	435.26
300	174.52	135.43	85.67	68.97	327	207	176	94	276.48	297.85	337.84	554.63
350	192.56	157.89	118.94	87.25	385	264	194	124	318.94	342.56	386.25	645.85
400	205.74	178.56	143.85	114.89	457	308	237	146	376.52	397.15	436.89	794.56
450	265.89	205.85	175.89	121.75	524	374	284	165	425.14	476.23	524.98	864.52
500	298.53	258.53	198.36	139.57	589	417	312	178	499.35	578.73	648.25	936.35

respect to routing overhead, ECESC-IoT has 658 packets while EERS-IoT, SECA-IoT, and DATS-IoT have 4262, 3568, and 2475 packets respectively. This is clear and convincing evidence of efficient resource management. Here too, ECESC-IoT is the clear winner with EERS-IoT, decreasing the Routing Overhead by 3,604 packets and completing SEP by 2,910 packets, and DATS-IoT by 1,817 packets.
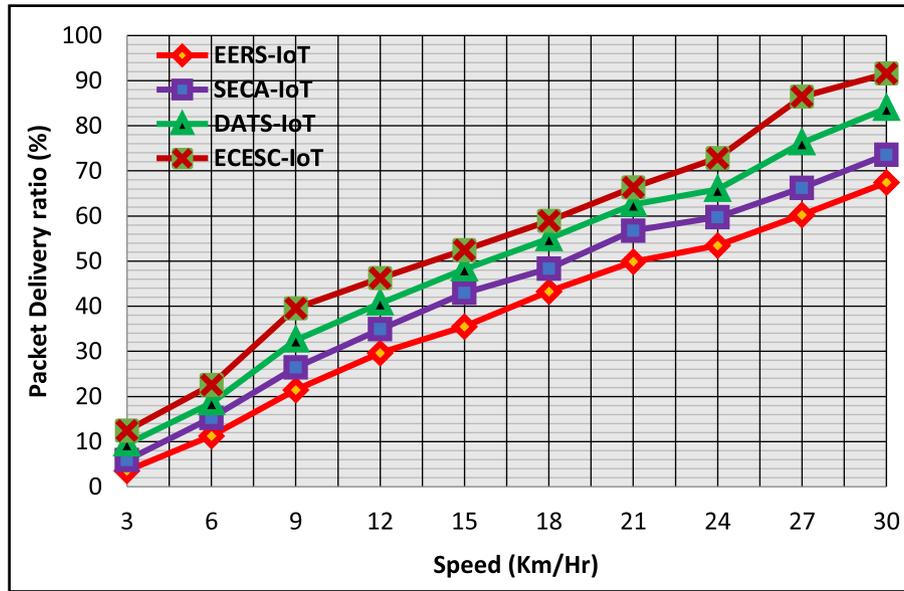
Fig. 12. Packet delivery ratio calculation concerned with varying speed.

The End-to-End Delay remains an important metric for the EERS-IoT which records an End-to-End Delay of 298.53 ms while SECA-IoT seems to perform better with an End-to-End Delay of 258.53 ms. DATS-IoT records 198.36 ms. On the other hand, ECESC-IoT seems to perform very well for minimising delay with an ECESC-IoT End-to-End Delay of only 139.57 ms. ECESC-IoT, with an improvement of 159.96, outperformed EERS-IoT while SECA-IoT was outperformed with an improvement of 118.96 ms. DATS-IoT was outperformed with an improvement of 58.79 ms.

In the metric of Packet Loss, the proposed method ECESC-IoT achieves the highest optimized result, demonstrating a considerably low 178 total packets lost. While the other described methods DATS-IoT, SECA-IoT, and EERS-IoT lost 312, 417, and 589 packets respectively, the ECESC-IoT method demonstrates a 411 packets advantage, which clearly demonstrates dominance over the other methods. In terms of throughput, EERS-IoT remains the lowest in this category with a throughput of 499.35 Kbps, while ECESC-IoT showcases the highest throughput of the methods proposed, totaling 936.35 Kbps and surpassing EERS, SECA, and DATS IoT by 437, 357.62, and 288.1 Kbps respectively. All other methods DATS-IoT, SECA-IoT, and DATS-IoT followed respectively with 648.25 Kbps, 578.73 Kbps, and 936.35 Kbps demonstrating a significant increase.

Results concerned with varying speed

The implementation of Varying Speed results is calculated to number of nods and overcome are observed graphically for the methods like EERS-IoT, SECA-IoT, DATS-IoT, and ECESC-IoT. The matrices used in these calculations are throughput, packet loss, end-end delay, packet delivery ratio, energy efficiency,

Packet delivery ratio calculation

In this metrics, the Fig. 12 indicates the graph of delivery ratio concerned with varying speed from 3Km/Hr to 30Km/Hr from that it is shown that ECESC-IoT attains maximum results than the baseline methods like EERS-IoT, SECA-IoT and DATS-IoT. The exchange of information between the user equipment and base station is achieved through the use of efficient factors such as the data transfer method, power usage, and quality of service offerings.

Packet loss calculation

According to Fig. 13, the packet depicting speed ranging from 3Km/Hr to 30Km/Hr, the ECESC-IoT has demonstrated lower packet loss compared to other methods such as EERS-IoT, SECA-IoT, and DATS-IoT. The achievement of lower packet loss in high-speed communication is a challenging task that requires concentrated efforts in resource utilization and optimization. The proposed model is designed to improve performance and has shown significantly lower packet loss compared to previous research.

Routing overhead calculation

The movement in routing overhead costs in relation to speed from 3Km/Hr to 30Km/Hr are illustrated in the Fig. 14. ECESC-IoT shows much lower overhead costs than other proposed methods EERS-IoT,
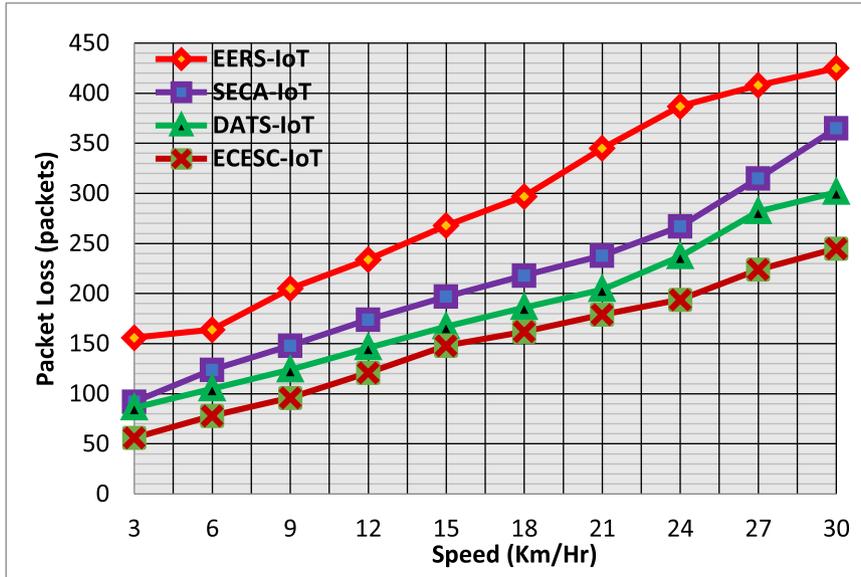
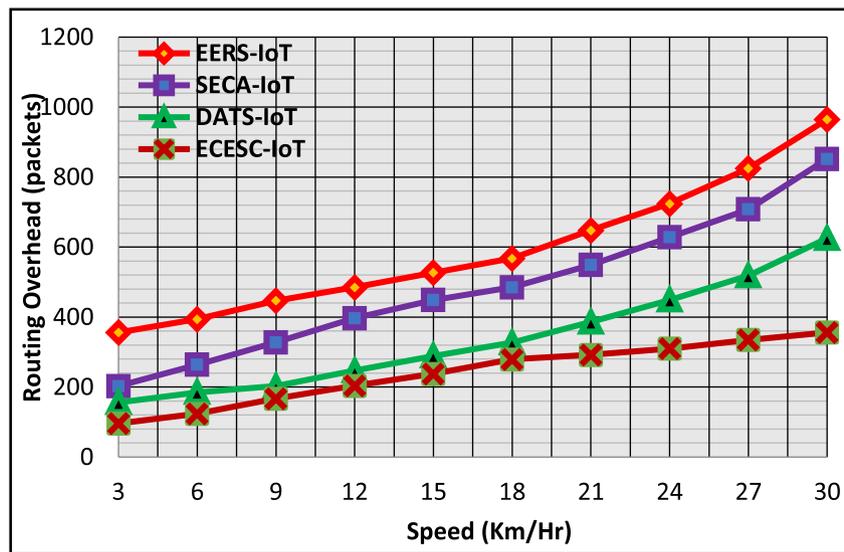**Fig. 13.** Packet loss calculation concerned with varying speed.

Fig. 14. Routing overhead calculation concerned with varying speed.

SECA-IoT, and DATS-IoT. All other factors being equal, and with the increased speed there is increased routing overhead; however, the optimisation model addressed in this paper reasonably minimises the costs of routing overhead and improves enhanced network performance compared to other studies in the current research for all ranges of speeds.

Throughput calculation

To assess the Throughput, Fig. 15 displays the calculation of throughput for speed ranges of 3Km/Hr to 30Km/Hr. The results reveal that ECESC-IoT yields greater throughput compared to other methods such as EERS-IoT, SECA-IoT, and DATS-IoT. Typically, an

increase in speed leads to a decrease in throughput during UE-BS communication. However, with efficient resource utilization in our proposed work, we achieve high throughput in all speed variations. This is evident in the maximum data transmission achieved in the network, surpassing previous research efforts.

Results and discussion concerned with varying speed

The implementation outcomes are deliberated to varying speeds to analyze the performance of baseline works and ECESC-IoT. The matrices used in these
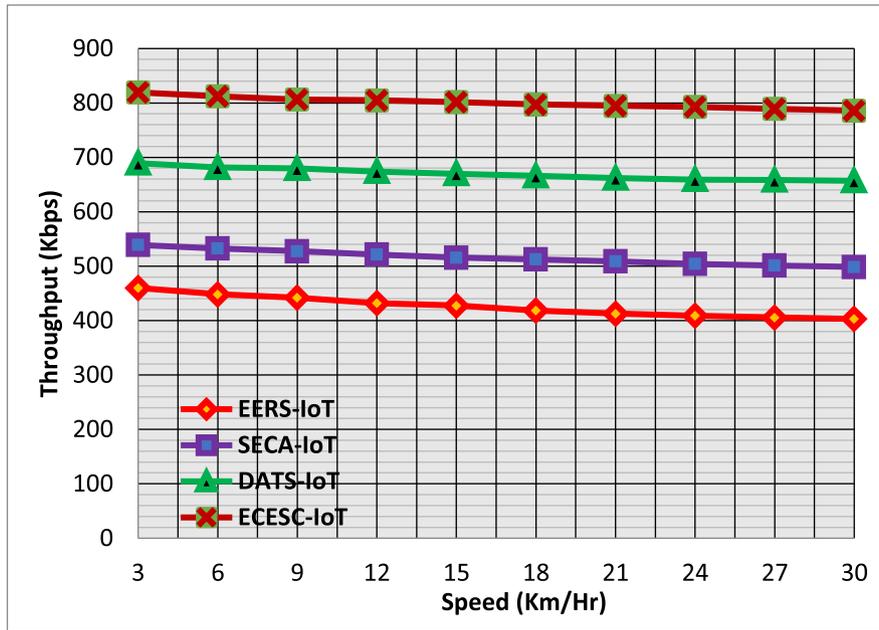
Fig. 15. Throughput calculation concerned with varying speed.

Table 6. Measurement of the parameters such as packet delivery ratio and packet loss concerned with varying speed.

Speed (Km/Hr)	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT
	Packet Delivery Ratio (%)				Packet Loss (PACs)			
30	3.56	5.89	9.46	12.44	156	92	86	56
60	11.25	15.24	18.56	22.54	164	124	105	78
90	21.45	26.42	32.47	39.56	205	148	124	96
120	29.65	34.89	40.68	46.23	234	174	146	121
150	35.48	42.96	48.23	52.47	268	197	167	148
180	43.26	48.32	54.96	58.94	297	218	186	162
210	49.87	56.74	62.57	66.34	345	238	204	179
240	53.47	59.74	65.89	72.87	387	267	237	194
270	60.23	66.23	76.23	86.45	408	315	282	224
300	67.42	73.59	83.84	91.57	425	365	301	245

calculations are packet delivery ratio, routing overhead, packet loss, and throughput. The calculated measurements of those matrices are given in Tables 6 and 7.

In terms of packet delivery ratio, the EERS-IoT achieved a Packet Delivery Ratio of 67.42%, while SECA-IoT demonstrated a slightly higher ratio of 73.59%. DATS-IoT performed as superiority, with a Packet Delivery Ratio of 83.84%. However, the Proposed framework where emerged as the top performer with 91.57%. This exceptional performance indicates that the ECESC-IoT better than EERS-IoT by 24.15 %, SECA-IoT by 18.9 %, and DATS-IoT by 7.73%.

The effects of network packet losses, the EERS-IoT recorded 425 packets lost, while SECA-IoT reported slightly less with 365 packets lost. DATS-IoT, on the other hand, recorded a Packet Loss of 301 packets,

however, the Proposed ECESC-IoT where the most successful with 245 packets lost. This suggests ECESC-IoT framework performed 180 packets better than EERS-IoT, 120 packets better than SECA-IoT, and 56 packets better than DATS-IoT.

In performance of routing overhead, the EERS-IoT established routing overhead of 965 packets, while SECA-IoT, demonstrated lower routing overhead of 852 packets. In addition, DATS-IoT exhibited routing overhead of 625 packets. On the other hand, the Proposed ECESC-IoT exhibited routing overhead of only 356 packets and recorded the lowest routing overhead against the baseline. However, the Proposed ECESC-IoT routed 609 packets less than EERS-IoT, 496 packets less than SECA-IoT, and 269 packets less than DATS-IoT. Regarding throughput, the EERS-IoT recorded a throughput of 402.98 kbps, while SECA-IoT recorded 498.675 kbps. Furthermore, DATS-IoT

Table 7. Measurement of the parameters such as routing overhead and throughput concerned with varying speed.

Speed (Km/Hr)	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT	EERS-IoT	SECA-IoT	DATS-IoT	ECESC-IoT
	Routing Overhead (PACs)				Throughput			
30	356	203	156	96	459.98	538.97	689.24	819.35
60	394	264	185	124	448.23	532.48	681.45	812.45
90	447	328	203	167	442.17	527.46	679.46	806.34
120	485	397	247	204	432.19	521.48	673.82	804.92
150	527	449	289	238	427.63	515.79	669.76	801.56
180	568	485	327	279	418.59	512.63	665.97	797.29
210	648	549	386	292	412.78	508.92	661.81	794.85
240	724	628	449	310	408.97	504.19	659.27	792.68
270	825	708	518	335	405.86	501.28	658.23	789.25
300	965	852	625	356	402.98	498.675	656.89	785.97

recorded 656.89 kbps. Congruent with the others, the Proposed ECESC-IoT method achieved the highest throughput and recorded 785.97 kbps. Hence, EERS-IoT was surpassed by 383.99 kbps, while SECA-IoT and DATS-IoT were surpassed by 287.295 kbps and 129.08 kbps, respectively.

Study limitation

- Exploitation of complex models such as SHMM and INFO algorithms has complexity, potentially hindering straightforward implementation and requiring significant computational resources.
- Assumptions made regarding network behaviour and energy consumption patterns may not always accurately reflect real-world scenarios, leading to discrepancies between expected and observed performance.
- The scalability factor lags behind in regard to numerous large scale IoT deployments. Parameter sensitivity and the demand of fine tuning in relation to the environment outlined directly affect the lacking efficiency.

Conclusion

This research proposes the Energy with Capacity aware Effective Satellite Communication (ECESC) approach to improve the performance of 6G technology in IoT. In this work, the network communication models like the data transmission model, energy consumption model, UE and BS Connection, and QoS-based service parameters are intelligently developed and as well to achieve effective communication SHMM model and INFO Algorithm are introduced. Simulation of proposed ECESC model was full filled in NS2 along overcome among compared with earlier works such as EERS-IoT, SECA-IoT, and DATS-IoT. The overcome calculation is executed in two division like change number of nods and change speed. The matrices that are afford in phrase of change numbers of nods are throughput, packet loss, packet delivery ratio, routing overhead, energy efficiency, packet delivery ratio, end-to-end delay. The matrices that afford to change speed among throughput, packet loss, packet delivery ratio, routing overhead.

The analysis of results proved the superiority of the proposed ECESC approach for nodes and speed. Initial in terms of the nodes number the ECESC which achieves 7.95% to 15.38 % better energy efficiency, 5.33% to 13.91% higher delivery ratio, 1817 to 3604 packets lower overhead, 58.79 ms to 159.96 ms lower delay, 172 packets to 411 packets lower packet loss, 288.1 Kbps to 437 Kbps higher throughput compared to baseline methods. Secondly, in terms of speed, the ECESC achieves a 7.73% to 24.15% higher delivery ratio, 56 packets to 180 packets lower packet loss, 269 to 609 packets lower overhead, and 129.08 Kbps to 383.99 Kbps higher throughput than baseline works.

The use of complex models such as the SHMM and INFO algorithms can be very complex, which can impact ease of implementation and the computational resources required. the assumptions made regarding the network behavior and energy consumption paradoxes do not mirror the true situation, which causes the expectations and the results obtained to be at loggerheads. In regards to the ability to scale, there are severe limitations which arise with the IoT as the scale and cover increases. In regards to dynamic setting, the concerns raised of tuned parameter sensitivity and precision can impact the performance, which can be substantial.

In the future scope, to expand the network density with lower overcrowding and data loss, effective security needs to be focussed. The massive machine-type communication with Artificial Intelligence can be integrated with the (IoT) environment with the presence of certain technologies like edge computing and edge AI in the (6G) heterogeneous network.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for republication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Anbar.

Authors' contribution statement

A M J and K A M conceived the initial idea. A M J developed the theory and conducted the computations. A M J, K A M and F H A verified the analytical methods. K A M and F H A contributed to the manuscript preparation and supervised the research findings. All authors reviewed and approved the final version of the manuscript.

References

1. Qadir Z, Le KN, Saeed N, Munawar HS. Towards 6G Internet of Things: Recent advances, use cases, and open challenges. ICT Express. 2023;9(3):296–312. https://doi.org/10.1016/j.icte.2022.06.006.

2. Rashid AN, Jubair AM Stable Heterogeneous Traffic Flow with Effective Localization and Path Planning in Wireless Network Connected and Automated Vehicles in∼ Internet of Vehicular Things (IoVT). Iraqi Journal for Computer Science and Mathematics. 2024;5(4):10. https://doi.org/10.52866/2788-7421.1213.

3. Wu HT. The internet-of-vehicle traffic condition system developed by artificial intelligence of things. J Supercomput. 2022;78(2):2665–80. https://doi.org/10.1007/s11227-021-03969-0.

4. Jubair AM, Hassan R, Aman AH, Sallehudin H, Al-Mekhlafi ZG, Mohammed BA, et al. Optimization of clustering in wireless sensor networks: techniques and protocols. Appl Sci. 2021;11(23):11448. https://doi.org/10.3390/app112311448.

5. Mukherjee A, Mukherjee P, De D, Dey N. QoS-aware 6G-enabled ultra low latency edge-assisted Internet of Drone Things for real-time stride analysis. Comput Electr Eng. 2021;95:107438. https://doi.org/10.1016/j.compeleceng.2021.107438.

6. Plastras S, Tsoumatidis D, Skoutas DN, Rouskas A, Kormentzas G, Skianis C. Non-Terrestrial Networks for Energy-Efficient Connectivity of Remote IoT Devices in the 6G Era: A Survey. Sensors. 2024;24(4):1227. https://doi.org/10.3390/s24041227.

7. Elamaran E, Murugaveni S, Jyothi S, Prabhu MR, Chitra MP, Talasila V. A novel approach of low complexity distributed UA algorithm is used for traffic load balancing and interference in next generation networks. Opt Quan-

tum Electron. 2024;56(4):525. http://dx.doi.org/10.1007/s11082-023-06105-9.

8. Polese M, Giordani M, Zugno T, Roy A, Goyal S, Castor D, et al. Integrated access and backhaul in 5G mmWave networks: Potential and challenges. IEEE Commun Mag. 2020;58(3):62–68. https://doi.org/10.1109/MCOM.001.1900346.

9. Awad FH, Hamad MM, Alzubaidi L. Robust classification and detection of big medical data using advanced parallel K-means clustering, YOLOv4, and logistic regression. Life. 2023;13(3):691. https://doi.org/10.3390/life13030691.

10. Qi Q, Chen X, Zhong C, Zhang Z. Integration of energy, computation and communication in 6G cellular internet of things. IEEE Commun Lett. 2020;24(6):1333–1337. https://doi.org/10.1109/LCOMM.2020.2982151.

11. Liao Z, Peng J, Huang J, Wang J, Wang J, Sharma PK, et al. Distributed probabilistic offloading in edge computing for 6G-enabled massive Internet of Things. IEEE Internet Things J. 2020;8(7):5298–5308. https://doi.org/10.1109/JIOT.2020.3033298.

12. Jia Z, Sheng M, Li J, Niyato D, Han Z. LEO-satellite-assisted UAV: Joint trajectory and data collection for internet of remote things in 6G aerial access networks. IEEE Internet Things J. 2020;8(12):9814–9826. https://doi.org/10.1109/JIOT.2020.3021255.

13. Jia Z, Sheng M, Li J, Zhou D, Han Z. Joint HAP access and LEO satellite backhaul in 6G: Matching game-based approaches. IEEE J Sel Areas Commun. 2020;39(4):1147–1159. https://doi.org/10.1109/JSAC.2020.3018824.

14. Wan S, Hu J, Chen C, Jolfaei A, Mumtaz S, Pei Q. Fair-hierarchical scheduling for diversified services in space, air and ground for 6g-dense internet of things. IEEE Trans Netw Sci Eng. 2020;8(4):2837–2848. https://doi.org/10.1109/TNSE.2020.3035616.

15. Liu C, Feng W, Chen Y, Wang CX, Ge N. Cell-free satellite-UAV networks for 6G wide-area Internet of Things. IEEE J Sel. Areas Commun. 2020;39(4):1116–1131. https://doi.org/10.1109/JSAC.2020.3018837.

16. Gustavsson U, Frenger P, Fager C, Eriksson T, Zirath H, Dielacher F, Studer C, et al. Implementation challenges and opportunities in beyond-5G and 6G communication. IEEE J Microw. 2021;1(1):86–100. https://doi.org/10.1109/JMW.2020.3034648.

17. Charbit G, Lin D, Medles K, Li L, Fu IK. Space-terrestrial radio network integration for IoT. in 2020 2nd 6G Wireless Summit (6G SUMMIT). 2020; IEEE. https://doi.org/10.1109/6GSUMMIT49458.2020.9083854.

18. Marcano NJ, Diez L, Calvo RA, Jacobsen RH. On the queuing delay of time-varying channels in low earth orbit satellite constellations. IEEE Access. 2021;9:87378–87390. https://doi.org/10.1109/ACCESS.2021.3089005.

19. Deebak BD, Al-Turjman F, Alazab M. Dynamic-driven congestion control and segment rerouting in the 6G-enabled data networks. IEEE Trans Industr Inform. 2020;17(10):7165–7173. https://doi.org/10.1109/TII.2020.3023944.

20. Ansere JA, Kamal M, Khan IA, Aman MN. Dynamic resource optimization for energy-efficient 6G-IoT ecosystems. Sensors. 2023;23(10):4711. https://doi.org/10.3390/s23104711.

21. Rajak S, Muniraj I, Elumalai K, Hosen AS, Ra IH, Chinnadurai S. Energy efficient hybrid relay-irs-aided wireless iot network for 6g communications. Electronics. 2022;11(12):1900. https://doi.org/10.3390/electronics11121900.

22. Rshaid MB, Salameh HB, Jararweh Y. Intelligent multichannel cross-layer framework for enhanced energy-efficiency in 6G-IoT wireless networks. Sustain Energy Technol.

Assess. 2023;57(5):103211. https://doi.org/10.1016/j.seta.2023.103211.

23. Kouroshnezhad S, Peiravi A, Haghighi MS, Jolfaei A. Energy-efficient drone trajectory planning for the localization of 6G-enabled IoT devices. IEEE Internet Things J. 2020;8(7):5202–5210. https://doi.org/10.1109/JIOT.2020.3032347.

24. López OL, Alves H, Souza RD, Montejo-Sánchez S, Fernández EM, Latva-Aho M. Massive wireless energy transfer: Enabling sustainable IoT toward 6G era. IEEE Internet Things J. 2021;8(11):8816–8835. https://doi.org/10.1109/JIOT.2021.3050612.

25. Mao B, Tang F, Kawamoto Y, Kato N. Optimizing computation offloading in satellite-UAV-served 6G IoT: A deep learning approach. IEEE Netw. 2021;35(4):102–8. https://doi.org/10.1109/MNET.011.2100097.

26. Rana A, Taneja A, Saluja N, Rani S, Singh A, Alharithi FS, *et al*. Intelligent network solution for improved efficiency in 6G-Enabled expanded IoT Network. Electronics. 2022;11(16):2569. https://doi.org/10.3390/electronics11162569.27.

27. Jia Z, Sheng M, Li J, Han Z. Toward data collection and transmission in 6G space–air–ground integrated networks: Cooperative HAP and LEO satellite schemes. IEEE Internet Things J. 2021;9(13):10516–10528. https://doi.org/10.1109/JIOT.2021.3121760.

28. Ansere JA, Han G, Liu L, Peng Y, Kamal M. Optimal resource allocation in energy-efficient Internet-of-Things networks with imperfect CSI. IEEE Internet Things J. 2020;7(6):5401–5411. https://doi.org/10.1109/JIOT.2020.2979169.

29. Wu Z, Chow TW. Neighborhood field for cooperative optimization. Soft Comput. 2013;17:819–834. https://doi.org/10.1007/s00500-012-0955-9.

30. Abduljabbar IA, Abdullah SM, An evolutionary algorithm for solving academic courses timetable scheduling problem. Baghdad Sc J. 2022;19(2):0399–0399. https://doi.org/10.21123/bsj.2022.19.2.0399.

31. Zhang X, Wu Z. Study neighborhood field optimization algorithm on nonlinear sorptive barrier design problems. Neural Comput. Appl. 2017;28:783–795. https://doi.org/10.1007/s00521-015-2106-6.

تحسين الطاقة و القدرة على التواصل عبر الأقمار الصناعية الفعالة في G6 و إنترنت الأشياء غير المتجانسة

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الملخص

يعد انتشار اتصالات الجيل السادس (G6) ضمن إنترنت الأشياء (IoT) أحد الابتكارات الحديثة في خدمات الشبكات. مع تزايد عدد الأجهزة المتصلة بالإنترنت من خلال الاتصال بشبكة الاتصالات واسعة النطاق، أصبحت كفاءة استخدام الطاقة مصدر قلق كبير مع الاستخدام الواسع النطاق لأجهزة إنترنت الأشياء الضخمة. لذا يمكن أن يؤدي النقص العام في تحسين الطاقة إلى العديد من المشكلات، بما في ذلك فقدان البيانات وفشل الارتباط واستخدام الطاقة العالية، وكلها تؤثر بشكل مباشر على جودة الاتصال بالشبكة. ولمواجهة هذه التحديات بفعالية، من الضروري تطوير نموذج يجمع بين التحسين الفعال وتخصيص الموارد، بناءً على جودة الخدمة (QoS) وكفاءة الطاقة. في هذه الدراسة، نقترح نهجًا للطاقة مع الاتصالات عبر الاقمار الفعالة للقدرات (ECESC) لشبكات الجيل السادس في بيئة إنترنت الأشياء. تشتمل بيئة الشبكة على محطات قاعدة (BS) ومعدات مستخدم (UEs)، مع أجهزة مجهزة بنماذج نقل البيانات، ونماذج استهلاك الطاقة، واتصالات UE وBS، وآلات الخدمة القائمة على جودة الخدمة. يتمثل مفهوم تقنيتنا المقترحة في تعزيز استخدام الموارد وتحسينها بين الأجهزة التي تستخدم نموذج ماركوف المخفي الفائق (SHMM)، وخوارزمية تحسين مجال الجوار (INFO) المحسنة، وبالتالي زيادة فائدة الطاقة والشبكة بشكل كبير. تم تنفيذ نهج ECESC المقترح باستخدام NS2 ومقارنته بالأعمال السابقة مثل EERS-IoT وSECA-IoT وDATS-IoT. قمنا بتقييم النتائج باستخدام جزأين رئيسيين: العدد المتفاوت للعقد والسرعات المتفاوتة. يتم تقديم مقاييس الأداء بناءً على معلمات مختلفة، بما في ذلك عدد العقد، والتأخير من طرف إلى طرف، والإنتاجية، ونسب تسليم الحزم، وكفاءة الطاقة، وحمل الحزمة، وفقدان الحزمة، وحمل التوجيه. بانت النتائج التجريبية أن طريقتنا المقترحة تحقق نتائج داعمة بشكل ملحوظ من حيث توصيل الحزم والإنتاجية وكفاءة الطاقة مقارنة بالدراسات السابقة.

الكلمات المفتاحية: كفائة الطاقة، إنترنت الأشياء (IoT)، خوارزمية تحسين مجال الجوارالمحسنة، الاتصالات عبر الاقمار، نموذج ماركوف المخفي الفائق، تقنية G6.