Heuristic Model for Computationally Enhanced Multi-Access Offloading for Ultra-Dense NOMA-Enabled Networks

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Abstract: The growing concerns for effective computational offloading in complex networks face obstruction-related issues that must be necessarily addressed in modern telecommunication networks. Addressing such network obstruction issues enhances the computational effectiveness of the telecommunication system. Therefore, concepts like Non-Orthogonal Multiple Access (NOMA) networks, the principles of frequency division multiple access (FDMA), and Mobile Devices (MDs) are integrated and analysed. The network operations are affected by the obstruction issues. The challenges, like the mixed integer nature and non-linear considerations of the optimization problems, resulted in the development of a novel heuristic approach. The proposed approach utilizes an Improved Tunicate Swarm Algorithm with a Refined Random Number (ITSA-RRN) based heuristic model. This suggested ITSA-RRN heuristic model is effective in tackling challenges like computational complexity and convergence issues. To analyze the effectiveness of the ideal multi-access NOMA network, the suggested ITSA-RRN heuristic model is comparatively evaluated with various existing approaches. The developed ITSA-RRN approach allows for a wide range of analysis of network issues faced during the multi-access offloading and enhances the robustness of the ultra-dense NOMA-enabled networks. With the aim of increasing the system's effectiveness, the suggested approach is compared with other existing approaches.

Keywords: Non-Orthogonal Multiple Access; formatting; Multi-Access Offloading; Mobile Devices; Heuristic Model; Improved Tunicate Swarm Algorithm with Refined Random Number

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Nomenclature

Abbreviation	Description
NOMA	Non-Orthogonal Multiple Access
MEC	Multi-Access Edge Computing
MD	Mobile Device
ITSA-RRN	Improved Tunicate Swarm Algorithm with Refined Random Number
TSA	Tunicate Swarm Algorithm
FSA	Flamingo Search Algorithm
SCO	Single Candidate Optimizer
ABOA	African Bison Optimization Algorithm
VR	Virtual Reality
FDMA	Frequency Division Multiple Access
RIS	Reconfigurable Intelligent Surface
VEC	Vehicular Edge Computing
LMM	Lagrange Multiplier Method
KKT	Karush-Kuhn-Tucker
SAGE	Secured Adaptive Generalized Edge
IWOA	Improved Whale Optimization Algorithm
CPU	Central Processing Unit
STD	Standard Deviation
BEST	Best performance metric value
WORST	Worst performance metric value
MEAN	Mean performance metric value
MEDIAN	Median performance metric value

1. Introduction

The technological advancements in the 5G telecommunication domain paved the way for developments in domains such as VR, smartphones, wearable devices and others etc [6]. Moreover, the development in such fields also shows various limitations regarding the power

capacity, energy efficiency and latency [7]. These issues have direct impacts on the end-user experience of real-world telecommunication applications [8]. So, it is important to tackle these issues to enhance the robustness of the telecommunication systems by enhancing the task offloading operations in the NOMA networks [9]. The ultimate goals of the NOMA networks are to enhance the security and reliability concerns in the computation task with lower energy consumption and shorter time [10].

Traditional system data transmission in communication networks does not focus on enhanced resource utilization in resource-constrained scenarios and on fragmenting the task offered to each node during long-distance data transmission [11]. An effective task-scheduling approach in communication networks can enhance the system's robustness in performing rapid data transfers [12]. It also decreases the load imbalance issues faced by the base station and positively enhances the system stability to improve the computational task offloading procedure [13]. The distance and other factors related to the computational offloading of the assigned task in ultra-dense networks are mainly dependent on the well-equipped MEC servers [14]. With the application of MEC servers, the coverage area of the servers assigned to complete the specified task is increased with low computational overhead and time [15]. Moreover, the implementation of the MEC servers in such task-offloading applications faces some challenges [16].

Those challenges can limit the system's performance by making the system vulnerable to potential malicious threats [17]. Malicious intrusion into the servers can elevate the energy consumption and resource utilization within the system [18]. Therefore, it is important to enhance the system performance with effective computational tasks offloading in ultra-dense NOMA networks [19]. This performance enhancement in the telecommunication system limits resource utilization in constrained network environments and enhances system stability and reliability in data transmission for assigned tasks within server networks [20]. Hence, this developed work implements the task offloading strategy in ultra-dense NOMA networks with the integration of a novel heuristic approach to enhance real-time telecommunication applications.

1.1 Key Contributions

This section delves into the research contributions of the proposed work.

- To implement a secure task offloading model in ultra-dense NOMA networks using a heuristic strategy to elevate the system stability and power allocation with low computational cost, energy consumption, and latency. This makes the developed model suitable for target-specific task offloading applications in NOMA networks. Thus, the developed heuristics model mitigates potential issues in the task offloading procedure and strengthens the effectiveness of ultra-dense NOMA networks.
- To design a novel optimization approach for enhanced task offloading in the telecommunication system. The developed ITSA-RRN heuristic model uses simulation parameters to provide optimal task offloading outputs by optimizing the necessary resource assignment to the targeted server. Therefore, system performance in the applied telecommunication task offloading can be improved.

Organization: The organization of the research work is as follows: related works are discussed in section 2; the system model and problem formulation are presented in section 3; the proposed methodology and problem formulation are described in section 4; results and discussion appear in section 5; and the conclusion is offered in section 6.

2. Related Work

2.1 Review of Traditional Computation Offloading Strategies

The scholars of the telecommunication field suggested various works related to the development of secure task offloading model, which have served as a motivation for implementing such research work. The research work of Baaki et al. [1] developed the decentralized task offloading procedure in the VEC systems with RIS assisted NOMA networks. In this work, the real-world analysis of the vehicular movements was analyzed with the assistance of the LMM and KKT conditions. This model offered enhanced numerical results demonstrating the superiority of the system performance in the delay and energy consumption.

An article by Xu et al. [2] stated that a novel task offloading strategy was developed to address the persistent problems encountered in improving the robustness of computational task

offloading. It was effectively achieved through the application of a multi-user computational analysis strategy. This model underwent a comparative evaluation to analyze the superiority of the system's significance on the target application.

The research work of Subramanian et al. [3] presented the SAGE based reinforcement learning framework for task offloading in MEC environments. This model offered enhanced system robustness with low latency and dynamic resource allocation in constrained scenarios.

A cost-effective task offloading system was proposed by Chu et al. [4] for the seamless specialization of cloud servers. The services provided by this model were effective in offering resource allocation and task scheduling strategies to reduce the load on the server during data transmission.

The analysis of resource allocation in ultra-dense NOMA networks was conducted by Zhou et al. [5]. This model developed a nonlinear mixed-integer formulation integrated with an IWOA to minimize cost factors and latency issues during the resource allocation.

2.2 Limitations in Existing Secure Offloading Models

Secure task offloading is an important task in telecommunication systems to enhance data transmission while minimizing resource allocation and other related factors. However, existing approaches, though beneficial, exhibit limitations that make them unsuitable for real-time applications in modern telecommunication systems.

Conventional task offloading models face issues such as security and privacy vulnerabilities, higher energy consumption, cost inefficiencies, computational overhead, lack of dynamicity and adaptability, and centralized architectures. These limitations have made existing models not to survive the dynamically developing communication technologies. Therefore, the development of a novel secure task offloading model is necessary to enhance privacy concerns during data transmission in ultra-dense NOMA network applications.

3. System Model and Problem Formulation

3.1 System Model

The implications of a small base stations are applied to the MEC servers. The total count of MDs present in the servers can be represented from 1 to E in the set of values $\mathrm{E} = \{1,2,\ldots.E\}$, and the total count of the base stations $\wp$ of the system is depicted as $\wp = \{1,2,\ldots,P\}$.

The computational task offered to the MDs e may be fragmented into $K+1$ various subtasks. Here, the term K represents the subtasks that are assigned to each base station and may vary in size. These assigned tasks are executed by the base station or provincially by the MDs of the system. The offloaded computational tasks made by the system are depicted as $\hat{\mathrm{K}} = \{1,2,\ldots,k\}$. The subtasks executed by the MDs are presented with the values $k = \hat{\mathrm{K}} \cup \{0\}$.

With the assumption of e MDs are correlated with the p base station for yielding strong channel gains. The indexed base station associated with the MDs the set of values can be denoted as $\Im_h = \{T_{h,1}, T_{h,2}, \ldots, T_{h,k}, \ldots, T_{h,K}\}$ where the term $T_{h,k}$ is the indexed base station p with the MDs e and subtasks assigned k.

To address the interference issues during data transmission, the total system bandwidth S is applied to the sub-channel bandwidth s. In the case of clustering, the total bandwidth utilized per cluster can be represented as $L = u\left(S/sV\right)$. The range of allocated bandwidth can be represented as $L + \{1,2,\ldots,\Gamma\}$. Therefore, this assumptions help obtain accurate task assignments for the MDs associated with the base stations. The structural illustration of the NOMA-based network model is presented in Fig. 1.

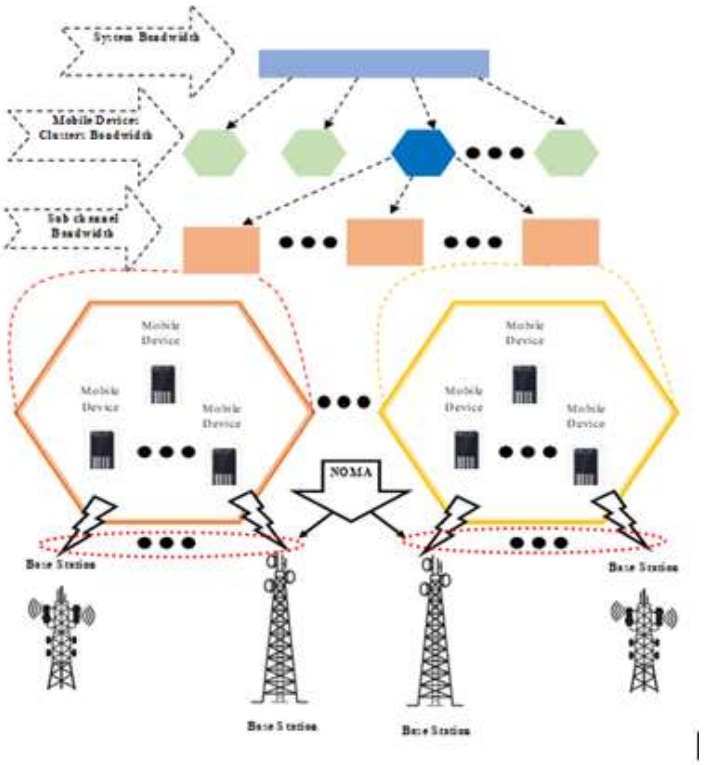


Fig.1 Structural Illustration of the NOMA-based Network Model

3.2 Security Model

The assumptions related to the security features required for the developed offloading system can be assigned using the set mathematical expressions as follows: The indexed set of encryption tools for addressing security concerns is depicted as $A=\{1,2,\ldots,a\}$ with the security concerns related to the various levels of operations are suggested as $Y=\{y_1,y_2,\ldots,y_a,\ldots,y_A\}$ where y_a is the security level protection offered by the encryption algorithm a. The encryption and decryption of data in each CPU cycle are represented as $\ddot{\tilde{\vartheta}}_a$ and $\tilde{\vartheta}_a$ respectively. Since the time required for encryption and decryption processes differs, the CPU cycles are also different. Factors such as time, energy consumption, and latency may vary depending on the encryption algorithms used. The energy consumption parameter of the encryption algorithm is represented as $\breve{\vartheta}_a$. In case where intensive encryption tools are required for the offloading process, the system may experience time delays, which negatively affect communication and reliability. Here, the selected MDs e with the encryption algorithms a for a probability value can be represented as in Eq. (1).

$$\breve{Z}_{e,k,a}=\begin{cases}1-\exp\left(-\alpha_{e,k}\left(\tilde{y}_{e,k}-y_a\right)\right), & if \quad y_a<\tilde{y}_{e,k}\\ 0 & ,else\end{cases} \tag{1}$$

Here, the term $\alpha_{e,k}$ is the security coefficient of the subtask k with the MD values e and $\tilde{y}_{e,k}$ is the expected protection level. The probability of task failure affects the overall stability of the system with the increased cost factor. Therefore, the cost factor of the system can be represented in Eq. (2).

$$\omega_j=\sum_{T\in\Im_h}\sum_{k\in K}\sum_{a\in A}b_k,d_{e,k,a},\breve{Z}_{e,k,a} \tag{2}$$

Here, the terms, b_k is the financial loss that happened due to the privacy issues, $d_{e,k,a}=1$ represent the subtasks of the MDs in the base stations. This condition is applied $\breve{Z}_{e,k,a}=0$ in case no encryption is required for the assigned tasks. Therefore, the performance of the task offloading system can be quantified.

3.3 Simulation Parameter

The input simulation parameters of the developed task offloading mode are provided in the following Table 1.

Table. 1 Input Simulation Parameters

Parameters	Range
Computation capacity	$20GHz$
Data size	$200 \sim 500KB$
Deadline	$1 \sim 2s$
Expected security level	$\{5,6\}$
Minimal rate	$1MB/s$
Noise power	$10^{-11}mW$
Number of cryptographic algorithms	6
Security risk coefficient	$1 \sim 3$
Size of population	30
System bandwidth	$20MHz$

These simulation parameters are collectively represented as TF_n^{AP}.

4. Proposed Methodology and Problem Formulation

This section explains the flow of the proposed work regarding the secure task offloading strategy using the developed ITSA-RRN heuristic model to address the challenges in the prior approaches and overcome them. The simulation parameters of the ultra-dense NOMA network are collected and provided as input to the developed ITSA-RRN heuristic model. Then, the ITSA-RRN heuristic model trains the system to enhance the task offloading performance with the objectives of minimizing the energy consumption, system latency and cost by optimizing the necessary parameters for particular task assignments to the server. The output provided by the system will be the task-offloaded result. Therefore, the system performance in the ultra-dense NOMA applications can be ultimately enhanced. The schematic generalization of the proposed secure task offloading architecture is represented in Fig. 2

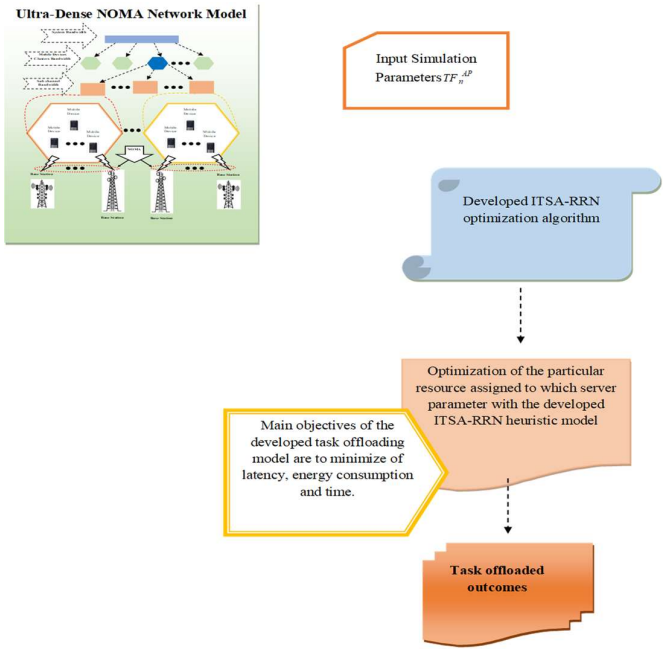


Fig. 2 Schematic Generalization of the Proposed Secure Task Offloading Architecture

4.1 Development of ITSA-RRN

The enhancement of the security features is an essential factor in the telecommunication system to ensure reliable data transmission in the ultra-dense NOMA networks. So, the ITSA-RRN heuristic approach is developed to attain the specific security concerns related to the task offloading system to be effective in resource-constrained environments with objectives of minimizing energy consumption, implementation cost, and latency of the developed task offloading model.

The ITSA-RRN heuristic approach is the successor to the ancestral TSA [21]. The influence of the ancestor TSA heuristic model is based on the biological nature of the tunicate in search of food by swarming intelligence and jet propulsion in the ocean currents. Advantages such as faster convergence, adaptability, and reduced parameter tuning nature made it suitable for the specific task offloading task analysis in the developed model. The objective function of the ancestral TSA optimization approach is provided in Eq. (3)

$$TD_{\vec{is}} = \left| \vec{TS}_{\vec{pos}} - ND_{rand} . \vec{T}_{uni}(k) \right| \tag{3}$$

Here, the term represents the distance $TD_{\vec{is}}$, position of the nutrient source is $\vec{TS}_{\vec{pos}}$ and ND_{rand} is the random uniform number that is present within the range of $[0,1]$, $\vec{T}_{uni}(k)$ represents the position of the tunicate in the ocean currents and k is the iteration. This generated random uniform number of the ancestral TSA optimization approach is not suitable for utilization in the proposed task offloading study. However, the ND_{rand} value of the ancestral TSA optimization approach foresees premature convergence and local optima trapping issues. So, it is important to modify the random number of the ancestral TSA optimization approach in Eq. (3) based on the adaptability concept that is conferred in the following Eq. (4).

Novelty: The presented ITSA-RRN heuristic approach tackles the aforementioned issue by updating the random uniform number of the ancestral TSA optimization approach to enhance the effectiveness of the task-offloading strategy with Eq. (4).

$$ND_{rand} = \frac{TM_{ean}}{TW_{orst} + TC_{urrent} + TB_{est}} \tag{4}$$

Here, the ND_{rand} is the modified random uniform number that exists in the range of $[0,1]$ and TC_{urrent} is the current fit, TM_{ean} mean fit, TW_{orst} worst and TB_{est} best fit of the system respectively. The disadvantages of the ancestral TSA optimization approach are eliminated with the modified random uniform number with the optimization of the system parameter particular task assignment to the server. Thus, this applied modification enhances the random number of the system to enhance the security features in the ultra-dense NOMA system for task offloading.

4.2 ITSA-RRN-based Task Offloading Model

The task offloading is an important feature of telecommunication systems. They offer the resources to each server to perform intensive computational operations. The main aim of applying heuristics in the task offloading model is to enhance resource allocation in constrained environments with lower cost, latency, and energy usage. These issues are generally foreseen based on the bandwidth, latency and security factors of the system during the data transmission. Initially, the process of task offloading is initiated with the analysis of the task. The task analysis evaluates the suitable mode for the transmission of data in the server. Then, the decision is made for the task offloading procedure based on the prior steps. Thirdly, the allocation of resources is accomplished to communicate with the target devices in servers or networks.

In the proposed work, the devices in the ultra-dense NOMA networks are considered for device communication to achieve secure task offloading. Simultaneously, data transmission occurs with the goals of minimizing latency, energy consumption and cost. The task offloading procedure is accomplished through integration with the improved ITSA-RRN heuristic approach. It optimizes the server-specific parameter assignment to improve the offloading result with security guarantees and reduced cost, latency and energy usage. The application of the heuristic approach enhances the intensive computational procedures in the edge servers for characterizing the security and other related issues in data transmission. The developed ITSA-RRN heuristic approach offers secure task offloading with faster model convergence and avoidance of local optima issues. By addressing these issues, system robustness in task assignment and scheduling improves, making it ideal for ultra-dense NOMA networks.

Therefore, the developed ITSA-RRN heuristic approach is well-suited for the resource-constrained environment to tackle the volatile network issue and make it adaptive and flexible for various network-related applications.

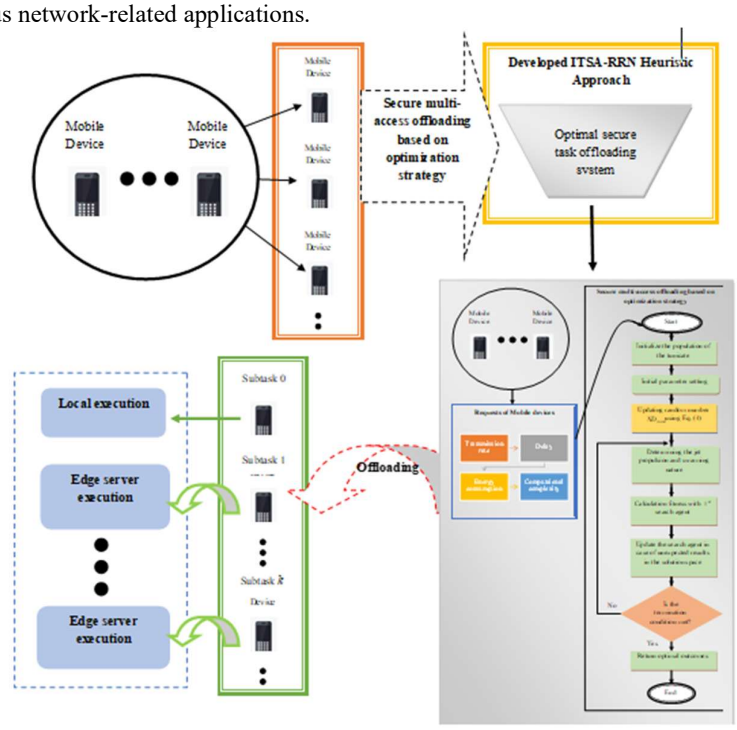


Fig. 3 Pictorial Representation of the Developed ITSA-RRN-based Task Offloading Model

4.3 Multi-objective Constraints

The objective function analysis is a mathematical analysis used to analyze the adeptness of the system offered by effective model training with the developed ITSA-RRN heuristic approach. This integration of the heuristic approach enhances the security features of the task offloading in ultra-dense NOMA networks. The objective function of the developed ITSA-RRN heuristic approach is suggested in Eq. (5)

$$KD_n^{ob} = \arg\min_{\{PRS_N^{AP}\}} \left(TL_{atency} + TE_{con} + TM_{time} \right) \tag{5}$$

Here, the term PRS_N^{AP} is the particular resource assigned to which server parameter that is present within the range of $[1,250]$, TL_{atency} is the latency, TE_{con} represents energy consumption and TM_{time} is the time. The main objective of the developed ITSA-RRN heuristic approach is to minimize the latency, energy consumption and time factors of the task offloading system to enhance the security in ultra-dense NOMA networks. Eq. (6), (7) and (8) represent the latency, energy consumption and time factors of the system respectively.

$$TL_{atency} = \frac{req_{task(l)}}{\kappa_{transrate(l)}} \tag{6}$$

$$TE_{con} = PoW_r . \frac{req_{task(l)}}{\kappa_{transrate(l)}} \tag{7}$$

$$TM_{time} = \frac{\left(1-\phi_g(l)\right).F_g(l)}{Q_{exqtask}} \tag{8}$$

Here, the term PoW_r represents the transmission power and $req_{task(l)}$ is the task request and $\kappa_{transrate(l)}$ is the transmission rate time taken $\left(1-\phi_g(l)\right)$ is the proportion of the executed task, $F_g(l)$ is the computational complexity and $Q_{exqtask}$ is the task execution capacity.

5. Results and Discussion

5.1 Simulation Set-up

The task offloading model based on the heuristic approach was evaluated with the Python simulation tool using a population size of 10, a chromosome length of 5, and 50 maximum iterations. The developed ITSA-RRN heuristic model was comparatively evaluated with various optimization algorithms such as FSA [22], SCO [23], ABOA [24] and TSA [21] to analyze the reliability of the task offloading in ultra-dense NOMA networks. The developed ITSA-RRN heuristic approach was evaluated for various performance metrics such as average waiting time, energy consumption, latency, makespan, residual energy, response time, resource utilization, task delay, throughput, total time consumption, and total cost to determine the adeptness of task offloading in ultra-dense NOMA networks. Therefore, the ITSA-RRN heuristic approach based on secure task offloading was developed for ultra-dense NOMA networks.

5.2 Convergence Analysis of the Developed Model

Fig. 4 represents the cost function evaluation of the developed ITSA-RRN heuristic approach for secure task offloading in ultra-dense NOMA networks. The convergence analysis of the developed ITSA-RRN heuristic approach enhances the system's stability and robustness with the objectives of lower cost, latency and energy consumption. So, the cost function evaluation is important to analyze the effectiveness of the developed ITSA-RRN heuristic approach. Here, the developed ITSA-RRN heuristic approach is compared with various existing optimization algorithms such as FSA, SCO, ABOA, andTSA to evaluate the effectiveness of the developed ITSA-RRN heuristic approach for secure task offloading in ultra-dense NOMA networks. The developed model ITSA-RRN heuristic approach outperformed the specific task with values of 75% of FSA, 66.667% of SCO, 61.538% of ABOA, and 68.750% of TSA. Hence, the developed secure task offloading in ultra-dense NOMA networks is effective in maintaining system stability by reducing time and cost while maximizing resource allocation.

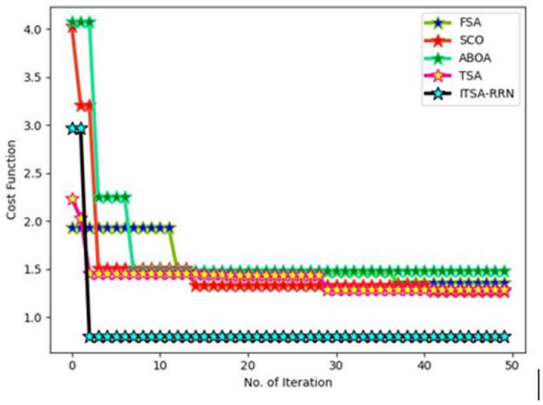


Fig. 4 Convergence Analysis of the Developed Model

5.3 Performance Analysis by Varying Tasks in the Developed Model

The performance analysis of varying assigned tasks in the developed ITSA-RRN heuristic approach is depicted in Fig. 5. The developed ITSA-RRN heuristic approach is compared with various existing optimization algorithms such as FSA, SCO, ABOA, and TSA. The comparative evaluation is carried out to analyze the adeptness of the system in the particular secure task offloading task. There exist 5 different ranges of tasks assigned to each server denoted from 50 to 250. By analyzing Fig. 5 (b), the energy consumption of the developed ITSA-RRN heuristic approach is evaluated and it offered superior performance with the values 19.231% over FSA, 22.222% over SCO, 25% over ABOA, and 8.696% over TSA. Hence, the results show that the developed ITSA-RRN heuristic approach is very effective in enhancing security concerns by minimizing the cost, energy consumption and latency of the system in the NOMA networks.

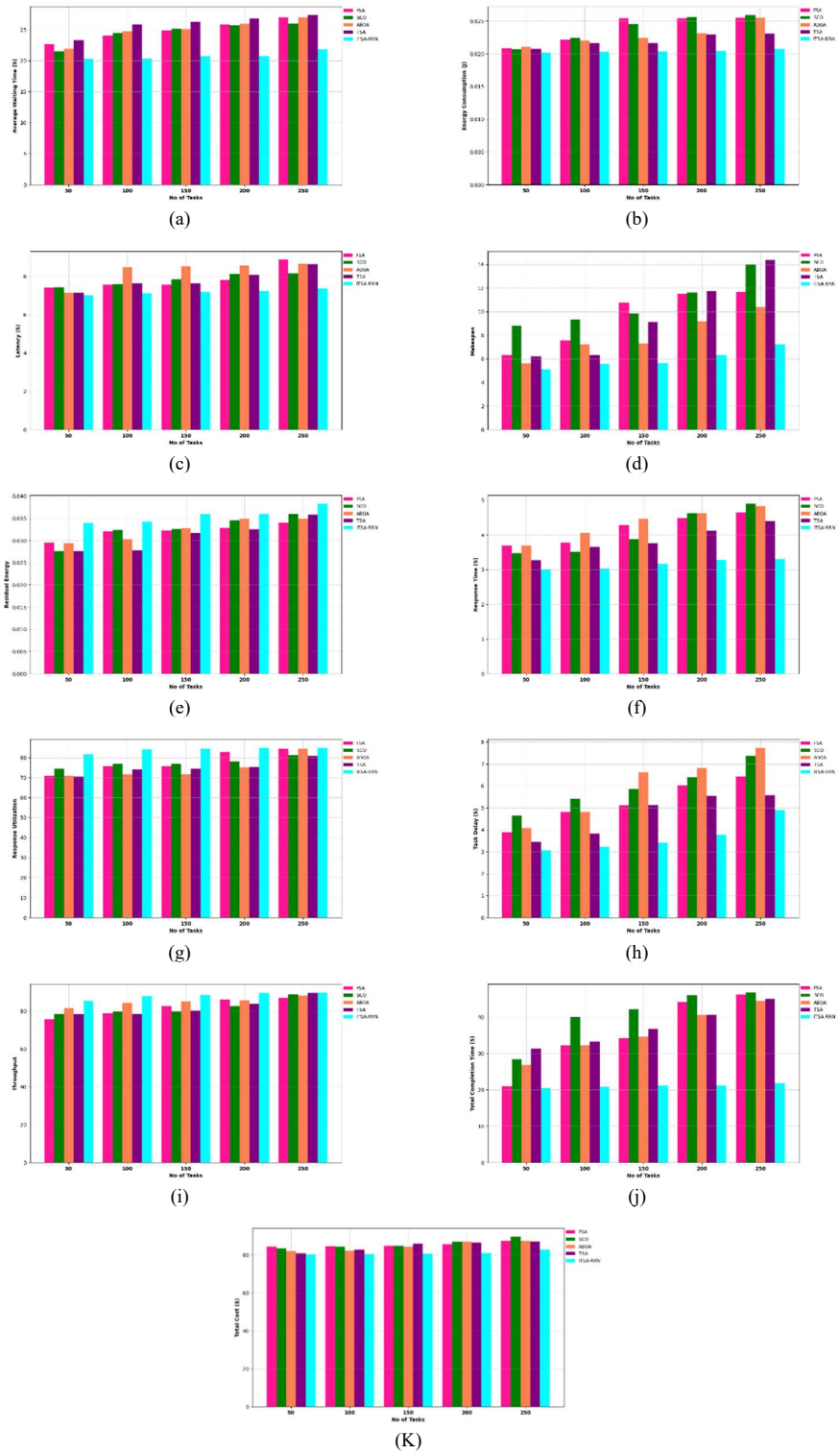
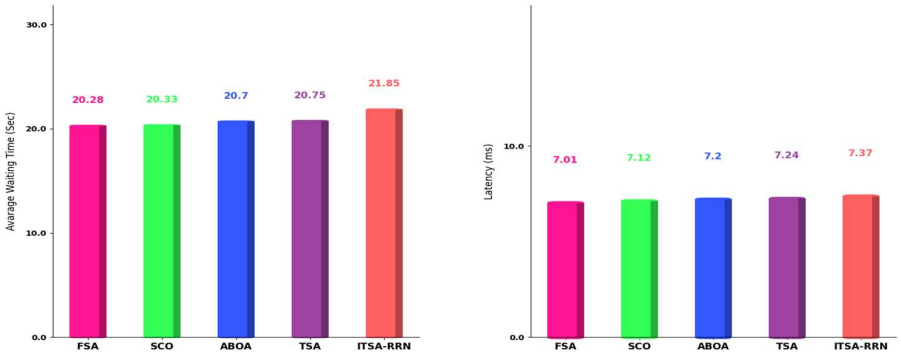


Fig. 5 Performance Analysis by Varying Tasks in the Developed Model regarding (a) Average waiting time, (b) Energy consumption, (c) Latency, (d) Makespan, (e) Residual Energy, (f) Response time, (g) Resource Utilization, (h) Task Delay, (i) Throughput, (j) Total Time consumption, and (k) Total cost

5.4 Varying Server-related Task Performance Analysis of the Developed Model

A varying server-related task performance analysis of the developed model is offered in Fig. 6. The developed model is comparatively evaluated with the existing optimization algorithms such

as FSA, SCO, ABOA, and TSA to analyze its performance in different network conditions. Time is an important factor in the analysis of the task offloading functions. So, the developed secure task offloading system in an ultra-dense NOMA network was evaluated for the average waiting time and latency. The latency value of the developed model is very low when compared to the other heuristic approaches with values of 5.136% over FSA, 1.936% over SCO, 2.361% over ABOA and 1.796% over TSA. Therefore, the end-user experience of the system is enhanced, which elevates the task-loading application in the advancing telecommunication system.



(a) (b)

Fig. 6.Varying Server-related Task Performance Analysis of the Developed Model regarding (a) Average waiting time and (b) Latency

5.5 Statistical Analysis of the Developed Approach

Table 2 offers the statistical evaluation of the developed ITSA-RRN heuristic approach for secure task offloading in ultra-dense NOMA networks. The statistical analysis is examined for various conditions such as BEST, WORST, MEAN, MEDIAN, and STD for various existing optimization algorithms such as FSA, SCO, ABOA, and TSA. The relationship between the training and validation of the developed ITSA-RRN heuristic approach is analyzed and executed with the assistance of statistical analysis. Analyzing the STD values suggests that the developed ITSA-RRN heuristic approach is well-suited for the secure task offloading in the ultra-dense NOMA networks with the values of 92.760% over FSA, 18.077% over SCO, 32.701% over ABOA, and 153.571% over TSA. Therefore, the developed ITSA-RRN heuristic approach is very effective for enhancing the robustness of the task offloading with the features of secure data transmission at low cost.

Table 2 Statistical Analysis of the Developed Approach

ALGORITHMS	FSA [22]	SCO [23]	ABOA [24]	TSA [21]	ITSA-RRN
BEST	1.354	1.264	1.484	1.289	0.796
WORST	1.934	4.031	4.070	2.233	2.968
MEAN	1.550	1.486	1.700	1.408	0.883
MEDIAN	1.468	1.329	1.484	1.434	0.796
STD	0.221	0.520	0.633	0.168	0.426

6. Conclusion

The secure task offloading model was developed in the current study. The ultimate aim of the developed secure task offloading model was to enhance the data transmission in ultra-dense NOMA networks with low cost, reduced energy consumption and minimal latency. The simulation parameters of the ultra-dense NOMA networks were utilized as the inputs to analyze the offloaded outcomes with the application of the ITSA-RRN heuristic approach. The server-specific task assignment parameter was optimized to strengthen the security features of the presented task offloading model. The developed ITSA-RRN model was comparatively evaluated with other existing optimization algorithms such as FSA, SCO, ABOA, and TSA. The ultimate aim of the task offloading system was achieved with the results of the energy consumption as 19.231% over FSA, 22.222% over SCO, 25% over ABOA, and 8.696% over TSA. Hence, the results provide a clear demonstration that the developed ITSA-RRN model was very effective in enhancing the user experience in the ultra-dense NOMA networks by reducing energy usage, transmission time and latency.

Limitations and Future Scope: The developed task offloading model offered various advantages. However, some challenges are also foreseen in this application such as complexity of handling heterogeneous resources across multiple servers and increasing task complexity. These limitations led the developed model to be explored in future applications with advancing computer vision technologies to sort out the existing challenges and enhance the future of telecommunication.

References

[1] Yakubu, AB., Abd El-Malek, AH., Abo-Zahhad, M., Muta, O., Elsabrouty, MM., "Task offloading and resource allocation in an RIS-assisted NOMA-based vehicular edge computing", IEEE Access, Sep 5, 2024.

[2] Xu, H., Zhou, J., Wei. W., Cheng, B., "Multiuser computation offloading for long-term sequential tasks in mobile edge computing environments", Tsinghua Science and Technology, 28(1):93-104, 2022.

[3] Subramanian, NS., Krishnan, P., Jain, K., Kumar, KA., Pandey, T., Buyya, R. "Blockchain and RL-Based Secured Task Offloading Framework for Software-Defined 5G Edge Networks", IEEE Access, Mar 25, 2025.

[4] Chu, W., Yu, P., Yu, Z., Lui, JC., Lin, Y., "Online optimal service selection, resource allocation and task offloading for multi-access edge computing: A utility-based approach", IEEE Transactions on Mobile Computing, 22(7):4150-67, 2022.

[5] Zhou, T., Fu, Y., Qin, D., Nie, X., Jiang, N., Li, C., "Secure and multistep computation offloading and resource allocation in ultradense multitask NOMA-enabled IoT networks", IEEE Internet of Things Journal, 11(3):5347-61, 2023.

[6] MidhulaSri, J., Ravikumar, CV., "Offloading computational tasks for MIMO-NOMA in mobile edge computing utilizing a hybrid Pufferfish and Osprey optimization algorithm", Ain Shams Engineering Journal, 15(12):103136, 2024.

[7] Guo, K., Liu, R., Dong, C., An, K., Huang, Y., Zhu, S., "Ergodic capacity of NOMA-based overlay cognitive integrated satellite-UAV-terrestrial networks", Chinese Journal of Electronics, 32(2):273-82, 2023.

[8] Taneja, A., Rani, S., Boulila, W., "Resource Control in IRS Assisted Multi-Access Edge Computing for Sustainable 6G IIoT Networks", IEEE Open Journal of the Communications Society, Mar 3, 2025.

[9] Xia, S., Yao, Z., Li, Y., Xing, Z., Mao, S. "Distributed computing and networking coordination for task offloading under uncertainties", IEEE Transactions on Mobile Computing, 23(5):5280-94, 2023.

[10] Pupo, EF., Gonzalez, CC., Iradier, E., Montalban, J., Angueira, P., Murroni, M., "Multi-rate multicasting aided NOMA for addressing the multiuser diversity in beyond 5G", Computer Networks, 258:111041, 2025.

[11] Akbar, A., Ahmed, A., Zafar, A., Jangsher, S., "An energy-efficient JT-CoMP enabled framework with adaptive OMA/NOMA in HetNets", Computer Networks, 254:110733, 2024.

[12] Yin, Y., Huang, C., Wu, DF., Huang, S. "Joint computation offloading and resource allocation in space-air-terrestrial integrated networks for IoT Applications", Ad Hoc Networks, 150:103267, 2023.

[13] Bisen, S., Bhatia, V., Brida, P., "Successive interference cancellation with multiple feedback in NOMA-enabled massive IoT network", EURASIP Journal on Wireless Communications and Networking, 2024(1):71, 2024

[14] Ding, J., Han, L., Li, J., Zhang, D., "Resource allocation strategy for blockchain-enabled NOMA-based MEC networks", Journal of Cloud Computing, 12(1):142, 2023.

[15] Kim, D., Kim, JB., Jung, H., Lee, IH., "DNN-based algorithm for joint SIC ordering and power allocation in downlink NOMA-enabled heterogeneous networks", ICT Express. 10(6):1301-7, 2024.

[16] Ahmed, M., Alshahrani, HM., Alruwais, N., Asiri, MM., Al Duhayyim, M., Khan, WU., Nauman, A., "Joint optimization of UAV-IRS placement and resource allocation for wireless powered mobile edge computing networks", Journal of King Saud University-Computer and Information Sciences, 35(8):101646, 2023.

[17] Sang, Y., Wei, J., Zhang, Z., Wang, B., "A Hybrid Heuristic Service Caching and Task Offloading Method for Mobile Edge Computing", Computers, Materials & Continua, 76(2), 2023.