Journal of ELECTRICAL ENGINEERING, VOL 74(2023), NO2, 95–101

sciendo

PAPERS

Allocation of power in NOMA based 6G-enabled internet of things using multi-objective based genetic algorithm

Shelesh Krishna Saraswat*, **Vinay Kumar Deolia**, **Aasheesh Shukla**[1]

Sixth generation (6G)-enabled internet of things (IoT) requires significant spectrum resources to deliver spectrum availability for massive IoT's nodes. But the existing orthogonal multiple access limits the full utilization of limited spectrum resources. The non-orthogonal multiple access (NOMA) exploits the potential of power domain to improve the connectivity for 6G-enabled IoT. An efficient quality of service (QoS) aware power allocation approach is required to enhance the spectral efficiency and energy of NOMA based 6G-enabled IoT nodes. The multi-objective genetic algorithm (MOGA) is used to resolve the non-convex problem by considering the successive interference cancellation (SIC), QoS, and transmission power. Extensive experiments are drawn by using the Monte Carlo simulation to evaluate the significant improvement of the proposed model. Experimental results indicate that the proposed power allocation model provides good performance of the NOMA based IoT network.

K e y w o r d s: NOMA, IoT, 6G, genetic glgorithm, power allocation

1 Introduction

Internet of things (IoT) has influenced the world greatly by making the life and work of people smarter. It is not only offering intelligent devices but also play important role in business. In IoT, many devices such as sensors, actuators, and other smart devices are connected over the Internet to carry out communication among things-things and people-things [1]. Due to innovations in IoT, the wireless networks of sensors and intelligent devices have been grown tremendously. A substantial volume of data is generated through these networks [2]. The mobile traffic is continuously growing that requires better connectivity for massive wireless terminals. The fifth-generation (5G) will eventually contend with technical limitations in supporting these massive networks that require diverse services. Therefore, there is a need for a new paradigm for the massive wireless terminals *ie*, sixth-generation (6G) [3].

The highly reliable communication can be made through 6G-enabled IoT. The benefits of 6G-enabled IoT are communication frequency can be increased using terahertz frequency technology, the transmission rate can be increased, and can cover blind areas and provide better coverage than 5G [4]. It may ponder some cutting-edge communication technologies, such as user-centric and scalable cell-free networking, integrated access and backhaul, ultra-massive multiple-input multiple-output, intelligent reflecting surfaces, and integrated satellite and terrestrial networks. It will provide complete-coverage connectivity for massive users rajatheva2020white. But when massive IoT's nodes access the spectrum for mobile communications handling a million clients, the spectrum resources will become limited for IoT nodes. Thus, providing the high availability of spectrum resources for every IoT node is not possible [5, 6]. The existing narrow-band IoT is unable to attain the high-quality internet in 6G network because it is unable to utilize spectrum resources efficiently [7]. Hence, to handle this issue of limited spectrum resources for IoT is the main driving force to implement a 6G-enabled IoT network.

The issue of the limited spectrum can be handled by using non-orthogonal multiple access (NOMA). It can efficiently use the spectrum resources among the huge number of users. It can improve the utilization of spectrum by providing the services to multiple clients in the same block at the same time [8, 9]. Therefore, it is a suitable solution for 6G-enabled IoT to handle the massive users for the limited spectrum resources. The main contributions of this paper are as follows:

- An efficient QoS aware power allocation model is required to enhance the spectral efficiency and energy of NOMA based IoT nodes in 6G era.
- The multi-objective genetic algorithm (MOGA) is used to resolve the non-convex problem by considering the successive interference cancellation, QoS, and transmission power.
- Extensive experiments are drawn by using the Monte Carlo simulation to evaluate the significant improvement of the proposed model.
- Experimental results indicate that the proposed power allocation model provides good performance of the NOMA based IoT network.

[1] Department of ECE, GLA University, Mathura, NH-2, Uttar-Pradesh, India. * Corresponding author: shelesh.saraswat@gla.ac.in

https://doi.org/10.2478/jee-2023-0012, Print (till 2015) ISSN 1335-3632, On-line ISSN 1339-309X

2 Related work

This section discusses related work. Fang *et al* [10] implemented cross-tier interference and co-channel interference based resource assignment optimization issue. The dual-decomposition and convex relaxation approaches were utilized to optimize the subchannel and power assignment issues.

Abozariba *et al* [11] reveal that how the distribution and QoE needs of IoT nodes can affect the required number of radio resources. The extended auction approach by utilizing complementary functions has augmented the efficiency of radio resources.

Muhammed [12] utilized the joint optimization of energy efficiency and fairness among clients by using the power assignment attributes. A greedy subcarrier allocation approach was implemented by using the worst-user first principle. The non-convex optimization was resolved using the fractional programming with sequential optimization of the inter/intra-subchannel power assignment vectors.

Song *et al* [13] designed a power assignment approach to improve the energy efficiency for downlink NOMA. The system model for imperfect channel state information was implemented, in which the optimization issue was formulated by an outage probability aware probabilistic non-convex problem. Thereafter, the optimization problem was decomposed to a non-probabilistic issue with the help of relaxation.

Ali *et al* [14] implemented a model to enhance the achievable rate of a multi-user multi-channel NOMA based cognitive radio system. A channel allocation and power enhancement approach were designed for the secondary clients also the performance of primary clients is ensured by using the interference temperature limits.

Na *et al* [8] designed unmanned aerial vehicle (UAV)-supported clustered NOMA (C-NOMA) system to improve the uplink means achievable summation rate of IoT devices. To handle non-convexity and complication, an iterative approach was utilized. Additionally, for subslot assignment bisection approach and Lagrange multiplier were utilized.

Liu *et al* [9] implemented a NOMA-based hybrid spectrum access for cognitive IoT. The uplink resource assignments were improved by using the decoding PU-first and PU-last approaches. Finally, a C-NOMA was utilized to minimize the inter-user interference.

Khan *et al* [7] designed a power assignment approach for enhancing the spectral efficiency and energy of NOMA based IoT network. The sequential quadratic programming (SQP) was utilized to optimize the non-convex problem.

Li *et al* [15] designed a model to improve the energy efficiency of a hybrid NOMA-enabled multi-access edge computing. In hybrid NOMA, a client can offload its job during a time slot shared with other clients and the remaining job can be uploaded when an exclusive time period is served by orthogonal multiple access. The optimized non-convex energy minimization multilevel programming was utilized. Khan *et al* [16] implemented an optimization model to improve the spectral efficiency of IoT by considering a power domain NOMA. A limited number of frequency blocks in IoT were considered. SQP was utilized to optimize the non-convex problem.

Tian [17] discussed the power assignment issue to improve spectral efficiency and energy efficiency for multi-cluster multi-user applications. The power assignment issue was formulated with the assumptions of the power budget and the minimum rate required by every client. The bisection approach and monotonicity of function was utilized to optimize the power assignment issue.

Pei *et al* [18] designed a mobile edge computing offloading approach for IoT networks with massive NOMA-aided edge servers. The total summation rate was maximized by deriving it as an optimization issue. Finally, an iterative approach was used to solve the defined optimization issue.

To enhance the power savings and bandwidth performance of NOMA-enabled internet of things (IoT) devices, Ju Liu and his team of researchers turned to sequential quadratic programming (SQP) [19]. They use a comparison of the suggested SQP-based methodology and the standard KKT-based optimization method to evaluate his scheme's efficacy. The findings reveal that the performance of the NOMA-enabled IoT network is significantly enhanced by using the suggested SQP-based power optimization architecture.

In a multicell IoT network, Ahmad's team implemented backscatter communication (BC), in which a source in each cell broadcasts a layered signal to its associated IoT devices through non-orthogonal multiple access (NOMA) [20]. This study aims to enhance the IoT network's overall energy efficiency (EE) while considering the service quality of each IoT device. The Dinkelbach approach is then used to perform a transformation on the problem and separate it into two distinct issues. The simulation findings show that the suggested NOMA BC network is more efficient overall than the traditional NOMA network.

From the extensive review, it has been observed that in 6G enabled IoT networks, NOMA is very helpful to utilize limited resources of the network to support massive IoT clients. Recently, many researchers have utilized NOMA to efficiently utilize the limited spectrum resources of IoT networks. NOMA can utilize several IoT resources by a single frequency block to improve the IoT network. Thus, it has been found that due to the potential advantages of NOMA in terms of energy and spectral efficiency, it is promising to utilize NOMA with 6G enabled IoT networks. In NOMA based IoT, massive IoT nodes can offload their respective jobs simultaneously on a similar resource. Consider only a one-time slot is free at a time, and two IoT clients will offload their jobs to the sink. If an orthogonal multiple access transmitter is utilized then only one client can send it and the other have to wait. But

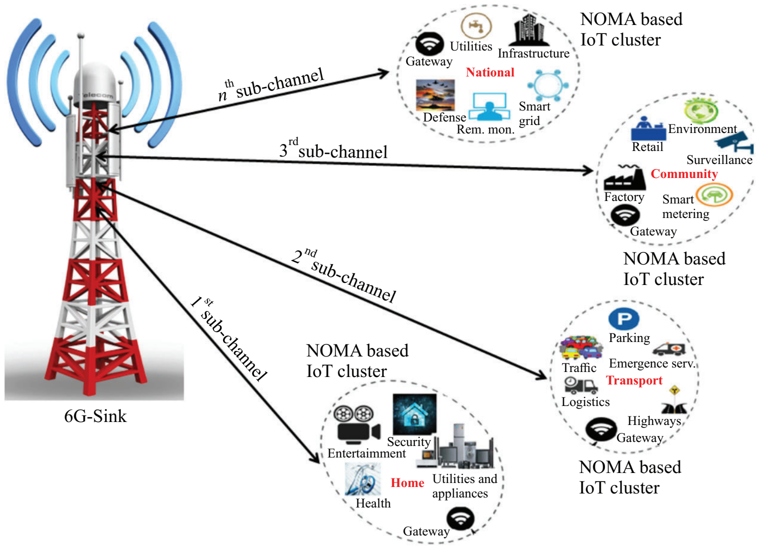

Fig. 1. 6G enabled NOMA based IoT network with n sub channels

Table 1. Nomenclature of NOMA

Symbol	Description
S_{c}	Sub-channel
$R_{l,n}$	Received signal at IoT node l on $n-$th S_{c}
B_n	Group of IoT nodes intercommunicating on $n-$th S_{c}
$H_{l,n}$	Channel coefficient of IoT node l on $n-$th S_{c}
C	Group of S_{c}
I	Group of IoT nodes
$P_{i,n}$	Transmission power of IoT node i on $n-$th S_{c}
$r_{l,n}$	Data rate of IoT node l onn-th S_{c}
$\delta_{l,n}$	Signal to interference and noise ratio of IoT node l on $n-$th S_{c}
ρ^2	Additive white Gaussian noise variation
$V_{\max}$	Total power at sink
$\Gamma_{\min}$	Minimum threshold to ensure QoS requirements of IOT network
β	Minimum distance among IoT nodes powers in B_n to implement SIC
$z_{i,n}$	Data symbol of IoT node i on n-th S_{c}
$N_{l,n}$	Additive white Gaussian noise of IoT node l on n-th S_{c}
$\varpi_{l,n}$	Wheth n-th er S_{c} is allocated to IoT node l
$M_{\max}$	Maximum IoT nodes on n-th S_{c}

in the case of NOMA, both clients can send their respective data to the sink in a simultaneous fashion. Thus, it can minimize the latency due to limited radio resources. Therefore, the computing service in 6G can gain from the integration of NOMA and IoT.

3 Proposed model

Initially, the diagrammatic flow of the proposed work is presented. Thereafter, nomenclature is given. Mathematical formulation of the NOMA based IoT network is then presented. Finally, multi-objective genetic algorithm is presented.

Figure 1 shows NOMA based IoT network with 6G enabled sink. Sink serves l IoT nodes by using n sub-channels (S_{Cs}). This IoT network supports various kind of services by using the NOMA based IoT clusters along with n 100 sub-channels. The information of every IoT node is available at the sink. It is assumed that IoT nodes and transmitters are equipped with an Omni-directional antenna. Every transmission link utilizes independent and identically distributed Rayleigh fading. Every S_{c}, can handle numerous IoT nodes at a time [21].

3.1 NOMA based IoT network

Table 1 shows nomenclature of NOMA based IoT network. Assume that B_n defines group of IoT nodes on n S_{Cs} where $n \in C$, and $z_{i,n}$ defines signal of IoT node i where $i \in B_n$. The received signal of IoT node $l \in B_n$.

on n-th S_c can be defined as

$$R_{l,n} = R_{l,n} = \sum_{i=1}^{B_n} \sqrt{P_{i,n}}\, z_{i,n} + N_{l,n}\,. \tag{1}$$

Here, $H_{l,n}$ defines channel coefficient of IoT node l on $n-$th S_c. $P_{i,n}$ shows the transmission power of IoT node i on n-th S_c, and $z_{i,n}$ defines the data signal of IoT node i on $n-$th S_c Further, $N_{l,n}$ is the additive white Gaussian noise of node l on n-th S_c with zero mean and $\sigma = \rho^2$. An IoT node l implements SIC for IoT node i if $|H_{i,n}|^2 \geq |H_{l,n}|^2$. But an IoT node l is unable to implement SIC for IoT node i if $|H_{l,n}|^2 \geq |H_{i,n}|^2$. On the receiver side, consider the decoding complexity of SIC, it is evaluated that a $n-$th S_c an handle maximum ($M_{\max}$) IoT nodes at a time, *ie* $|B_n| \leq |B_{\max}|$. Thus, the rate of IoT node can be evaluated as

$$r_{l,n} = \log_2(1 + \delta_{l,n})\,. \tag{2}$$

Here, signal to interference plus noise ratio is

$$\delta_{l,n} = \frac{P_{l,n}|H_{l,n}|^2}{|H_{l,n}|^2 \sum\limits_{i=1}^{l-1} P_{i,n} + \rho^2}\,. \tag{3}$$

In power domain multiplexing, at receiver ends NOMA needs SIC [22]. Therefore, it is assumed that the minimum distance among IoT nodes' power in B_n on n-th S_c can attain following assumption

$$P_{l,n}|H_{l-1,n}|^2 - \sum_{i=1}^{l-1} P_{i,n}|H_{l-1,n}|^2 \geq \beta\,. \tag{4}$$

Here, β shows minimum distance between IoT node power in B to successfully implement SIC. A binary variable $\varpi_{l,n}$ is also utilized which defines $n-$th S_c is allocated to IoT node l. Therefore, the goal is to minimize the transmission power of IoT nodes by optimizing the $P_{l,n}, \varpi_{l,n}$. Mathematically, optimization problem can be defined as

$$\min_{\varpi_{l,n}, P_{l,n}} \sum_{n=1}^{C} \sum_{i=1}^{I} \varpi_{l,n} P_{l,n} \quad \text{such that} \tag{5}$$

$$\sum_{i=1}^{l} \varpi_{l.n} \leq B_{\max}, \quad \varpi_{l,n} r_{l,n} \geq \Gamma_{\min}, \tag{5a,b}$$

$$\sum_{n=1}^{C} \sum_{l=1}^{I} \varpi_{l.n} P_{l,n} \leq P_{\max}\,, \tag{5c}$$

$$\sum_{n=1}^{C} \varpi_{l,n} \Big(\sum_{l=1}^{I} P_{l.n} + \frac{\beta}{|H_{l-1,n}|^2} \leq P_{l,n} \Big), \tag{5d}$$

$$\varpi_{l,n} P_{l,n} \geq 0\,, \quad \varpi_{l.n} \in \{0,1\}. \tag{5e,f}$$

Here, (5a) and (5f) control the amount of IoT nodes on n-th S_c n at a time. Equation (5b) handles QoS of IoT node l on n-th, where $\Gamma_{\min}$ defines threshold for QoS requirements. Equation (5c) grantees that the remaining power of all nodes will be minimum as compare to the overall sink power, where $P_{\max}$ shows the remaining power at sink. Also, (5d) is responsible for successful implementation of SIC. Finally, (5e) defines positive powers of IoT nodes. For more details see [7].

3.2 Multi-objective genetic algorithm

The genetic algorithm contains a group of operators to optimize the given problem 23]. Initially, random solutions are obtained using a normal distribution. These solutions are then applied to given problem for evaluating the multi-objective fitness function, see (5). Based on the computed values, the given solutions are ranked for further processing. Thereafter, mutation and crossover operators are applied to the obtained solutions to compute child solutions. Based upon their fitness values they are ranked using non-dominated sorting [24, 25]. Finally, the most non-dominated solution is returned as minimized solution for NOMA based IoT.

To minimize (5), the genetic algorithm for Pareto optimization is discussed in Algorithm 1. It utilizes selection 135 (see Algorithm 2), recombination operator (see Algorithm 3), and nondominated sorting to minimize (5).

Algorithm 1.
Multi-objective genetic algorithm for NOMA based IoT

output: $\min\limits_{\varpi_{l.n} P_{l,n}} \sum_{n=1}^{C} \sum_{l=1}^{I} \varpi_{l,n} P_{l,n}$
input: $\{P_{l,n} \varpi_{l.n}\}$
Begin
  Generate the random R_P;
  /* R_P represents the initial population */;
  Evaluate Eq. 5 according to R_P solutions
  and store values in fitness function (f_c);
  Apply selection process using Algorithm 2.;
  Apply recombination process using Algorithm 3.;
  /* Ranking */ sort the D_s;
  return D_s [1] /* returns the most dominant solution
    wrt fitness function */
end

4 Performance analysis

Table 2 shows the various simulation parameters along with their respective values. It presents the various hyperparameters of the proposed model.

In this paper, Rayleigh fading is considered to compute the mean outcomes from Monte Carlo simulations. The energy efficiency (E_f) in b/J/Hz of MOGA-NOMA based IoT can be evaluated as [25-26]

$$E_f = \frac{\sum\limits_{m=1}^{M} \sum\limits_{k=1}^{K} \log_2\big(1 + \delta_{k,m}\big)}{\sum\limits_{m=1}^{M} \sum\limits_{k=1}^{K} p_{k,m} + P_c}\,. \tag{6}$$

Algorithm 2. Selection process of multi-objective genetic algorithm for NOMA based IoT

---

output: $\min\limits_{\varpi_{l,n}P_{l,n}} \sum_{n=1}^{C}\sum_{l=1}^{I}\varpi_{l,n}P_{l,n}$
input: $\{P_{l,n}, \varpi_{l,n}, D_s\}$
Begin
set $D_s = R_P$; /* D_s denotes final population */
while $S_e! = 0$ or l_G==true **do** /* S_e and l_G represent children elimination and last generation */
Generate random S;/* S denotes children and set $S_e = 0$;
for each S **do**
Compute the fitness of S;
if $f_C \leq f_{D_s}[1]$
remove c;
set $S_e+ = 1$;
Else
set $D_s = S$;
End
end
next generation
end
return D_s /*returns the most dominant solution *wrt* fitness function*/
end

Algorithm 3. Recombination process of multi-objective genetic algorithm for NOMA based IoT

---

output: $\min\limits_{\varpi_{l,n}P_{l,n}} \sum_{n=1}^{C}\sum_{l=1}^{I}\varpi_{l,n}P_{l,n}$
input: $\{P_(l,n), \varpi_(l,n), S_1, S_2, c_3\}$
Begin
while $S_e! = 0$ or l_G==true **do** /* S_e and l_G represent children elimination and last generation */
for *crossover* **do**
select S_1 and S_2 randomly;
/* S_1, S_2, and c_3 are children*/
$S_3 = S_1 \oplus S_2$
Evaluate the fitness of c_3;
if $f_{S_3} \leq f_{S_3}$ or f_{S_2} **then**
remove S_3;
Else
remove S_1, S_2;
End
next generation
end
return D_s /*returns the most dominant solution *wrt* fitness function*/
End

Figure 2 shows the energy efficiency (E_{f}) versus number of IoT nodes (K) for MOGA-NOMA, OFDMA, Benchmark NOMA, and SQP-NOMA approaches. It shows that when the number of IoT nodes is lesser or equal to 15 *ie* , $K \leq 15$ then MOGA-NOMA shows little improvement OFDMA, Benchmark NOMA, and SQP-NOMA, respectively. But with an increase in K *ie* , $K > 15$ then MOGA-NOMA shows significantly more energy efficiency (E_{f}) compared to the existing models. Thus, the proposed model can conserve more energy as compared to the FDMA, Benchmark NOMA, and SQP-NOMA, respectively.

Table 2. Simulation parameters along with their respective values

Attribute	Symbol	Value(s)
Total IoT nodes	I	24
Sub-channels	C	12
Power budget at sink	$V_{\max}$	20 W
Minimum QoS threshold	$\tau_{\min}$	1b/s/Hz
Circuit power	P_c	05 W
Power between IoT nodes for SIC	β	0.2 W
Additive white Gaussian noise variance	ρ^2	0.1 W

Table 3. Energy efficient analysis in joules

No. of IoT devices	OFDMA	Benchmark -NOMA	SQP -NOMA	MOGA -NOMA
1	0.507	0.610	0.656	0.671
3	0.802	0.906	0.955	1.005
5	1.201	1.301	1.354	1.408
7	1.356	1.452	1.508	1.679
9	1.66	1.753	1.806	1.981
11	1.703	1.958	2.056	2.076
13	1.706	2.043	2.159	2.165
15	1.702	2.138	2.253	2.290
17	1.708	2.222	2.358	2.423
19	1.703	2.319	2.458	2.552
21	1.705	2.404	2.554	2.688
23	1.707	2.492	2.656	2.813
25	1.709	2.503	2.701	2.885

Figure 3 shows the energy efficiency (E_{f}) - versus the number of remaining transmission power at the sink for MOGA-NOMA, OFDMA, Benchmark NOMA, and SQP-NOMA approaches. It reveals that when the remaining transmission power at the sink increases then the energy efficiency (E_{f}) of MOGA-NOMA and the existing OFDMA, Benchmark NOMA, and SQP-NOMA, also decreases. However, compared to the existing OFDMA, Benchmark NOMA, and SQP-NOMA, MOGA-NOMA is able to conserve more energy efficiency (E_{f}) . Figure 4 shows the spectral efficiency analysis by scaling the transition power at sink. It is found that there is a positive change in spectral efficiency when we scale the transition

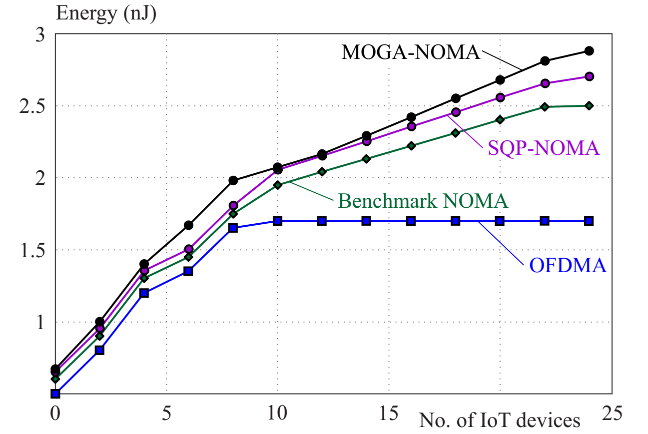

Fig. 2. The energy efficiency (E_f) versus number of IoT nodes (K) for MOGA-NOMA, OFDMA, Benchmark NOMA, and SQP-NOMA approaches

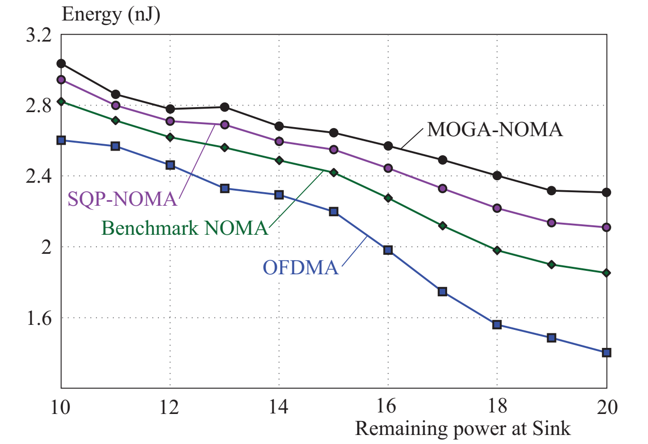

Fig. 3. Energy efficiency (E_f) versus remaining transmission power at sink for MOGA-NOMA, OFDMA, Benchmark NOMA and SQP-NOMA approaches

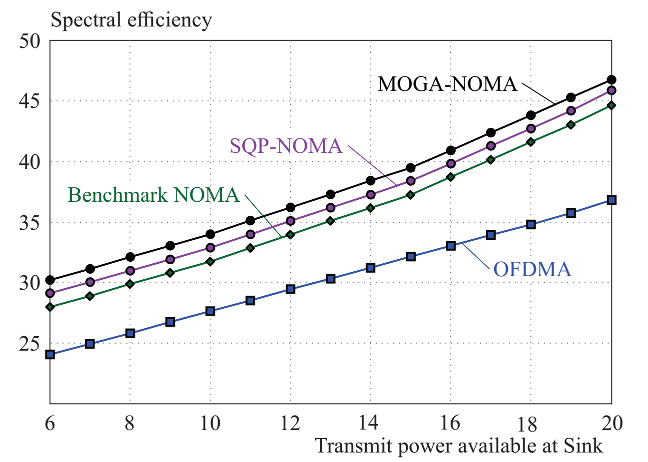

Fig. 4. Spectral efficiency analysis of transmission power at sink of IoT network for MOGA-NOMA, OFDMA, Benchmark NOMA and SQP-NOMA approaches

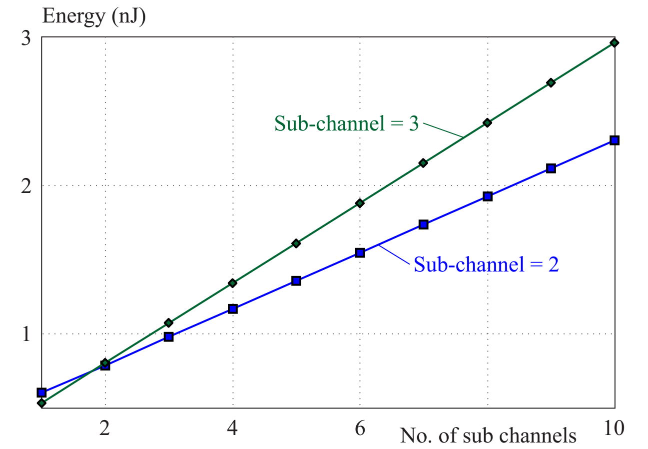

Fig. 5. Energy efficiency (E_f) analysis of MOGA-NOMA, OFDMA, Benchmark NOMA and SQP-NOMA approaches by scaling the number of sub-channels of IoT nodes per sub-channel

power at sink. Compared to the existing OFDMA, Benchmark NOMA, and SQP-NOMA, MOGA-NOMA achieves high spectral efficiency values.

Figure 5 shows energy efficiency (E_f) analysis of MOGA-NOMA by scaling the number of sub-channels of IoT nodes per sub-channel. Scaling is done on a number of sub-channels and each sub-channel contains two and three IoT nodes at a time. It is observed that when the number of sub-channels is 2 or lesser then MOGA-NOMA with sub-channel=2 performs better as compared to MOGA-NOMA with sub-channel=2. But when we scale the number of sub-channels to more than 2 then MOGA-NOMA with sub-channel=3 performs significantly better than MOGA-NOMA with sub-channel=2. Thus, MOGA-NOMA can handle a huge amount of IoT nodes even when the system has limited resources.

5 Conclusion

An optimistic allocation of spectral resources would play a significant role to support 6G enabled IoT networks. NOMA is found to be 160 very helpful to utilize limited resources of the network to support massive IoT clients. Recently, many researchers have utilized NOMA to efficiently utilize the limited spectrum resources of IoT networks. NOMA can utilize several IoT resources by a single frequency block to improve the IoT network. Thus, it has been found that due to the potential advantages of NOMA in terms of energy and spectral efficiency, it is promising to utilize NOMA with 6G enabled IoT networks. In this paper, efficient QoS aware power assignment approach was designed to enhance the 165 spectral efficiency and energy of NOMA based IoT nodes in 6G era. Initially, the non-convex problem was defined by considering SIC, QoS, and transmission power. Finally, MOGA was used to resolve the non-convex optimization issue for power assignment in NOMA based IoTs. Extensive experiments were drawn by utilizing the Monte Carlo simulation to evaluate the significant improvement of the proposed model. Experimental results have shown that the proposed power allocation model achieves good performance for the NOMA based IoT network.

Recently, many metaheuristic techniques such as emperor penguin optimizer [27], seagull optimization algorithm [28], spotted hyena optimizer [29, 30], etc. have been proposed, therefore, in near future we may extend the proposed work by utilizing these kind of the metaheuristic techniques.

References

[1] M. Bolic, M. Rostamian, and P. M. Djuric, "Proximity detection with rfid: A step toward the internet of things", *IEEE Pervasive Computing*, vol. 14, no. 2, pp. 70-76, 2015.

[2] J. Miranda, N. Mãkitalo, J. Garcia-Alonso, J. Berrocal, T. Mikkonen, C. Canal, and J. M. Murillo, "From the internet of things to the internet of people", *IEEE Internet Computing*, vol. 19, no. 2, pp. 40-47, 2015.

[3] L. Zhang, Y.-C. Liang, and D. Niyato, "6g Visions Mobile ultra-broadband, super internet-of-things, and artificial intelligence", *China Communications*, vol. 16, no. 8, pp. 1-14, 2019.

[4] N. Rajatheva, I. Atzeni, E. Bjornson, A. Bourdoux, S. Buzzi, J.-B. Dore, S. Erkucuk, M. Fuentes, K. Guan, Y. Hu, et al, "White paper on broadband connectivity in 6g", *arXiv preprint arXiv*, ¿—2004.14247, 2020.

[5] X. Liu, M. Jia, X. Zhang, and W. Lu, "A novel multichannel internet of things based on dynamic spectrum sharing in 5g communication", *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 5962-5970, 2018.

[6] M. Chen, Y. Miao, Y. Hao, and K. Hwang, "Narrow band internet of things", *IEEE access* 5, pp/ 20557–20577, 2017.

[7] W. U. Khan, F. Jameel, M. A. Jamshed, H. Pervaiz, S. Khan, and J. Liu, "Efficient power allocation for noma-enabled iot networks in 6g era", *Physical Communication* 39, p. 101043, 2020.

[8] Z. Na, Y. Liu, J. Shi, C. Liu, and Z. Gao, "UAV-supported clustered noma for 6g-enabled internet of things", *IEEE Internet of Things Journal*, https—¡//doi.org/10.1109/JIOT.2020.3004432, 2020.

[9] X. Liu, H. Ding, and S. Hu, "Uplink resource allocation for noma- based hybrid spectrum access in 6g-enabled cognitive internet of things", *IEEE Internet of Things Journal*, 2020.

[10] F. Fang, J. Cheng, and Z. Ding, "Joint energy efficient subchannel and power optimization for a downlink noma heterogeneous network", *IEEE Transactions on Vehicular Technology*, vol. 68, no. 2, pp. 1351–1364, 2018.

[11] R. Abozariba, M. K. Naeem, M. Patwary, M. Seyedebrahimi, P. Bull, and A. Aneiba, "Noma-based resource allocation and mobility enhancement framework for iot in next generation cellular networks", *IEEE Access* 7, pp. 29158–29172, 2019.

[12] A. J. Muhammed, Z. Ma, P. D. Diamantoulakis, L. Li, and G. K. Karagiannidis, "Energy-efficient resource allocation in multicarrier noma systems with fairness", *IEEE Transactions on Communications*, vol. 67, no. 12, pp. 8639–8654, 2019.

[13] X. Song, L. Dong, J. Wang, L. Qin, and X. Han, "Energy efficient power allocation for downlink noma heterogeneous networks with imperfect csi", *IEEE Access* 7, pp. 39329–39340, 2019.

[14] Z. Ali, Y. Rao, W. U. Khan, and G. A. S. Sidhu, "Joint user pairing, channel assignment and power allocation in noma based cr systems", *Applied Sciences*, vol. 9, no. 20, p. 4282, 2019.

[15] H. Li, F. Fang, and Z. Ding, "Joint resource allocation for hybrid noma-assisted mec in 6g networks", *Digital Communications and Networks*, vol. 6, no. 3, pp. 241–252, 2020.

[16] W. U. Khan, J. Liu, F. Jameel, V. Sharma, R. Jantti, and Z. Han, "Spectral efficiency optimization for next generation noma-enabled iot networks", *IEEE Transactions on Vehicular Technology*, 2020.

[17] X. Tian, Y. Huang, S. Verma, M. Jin, U. Ghosh, K. M. Rabie, and D.-T. Do, "Power allocation scheme for maximizing spectral efficiency and energy efficiency tradeoff for uplink noma systems in b5g/6g", *Physical Communication* 43 101227, 2020.

[18] X. Pei, W. Duan, M. Wen, Y.-C. Wu, H. Yu, and V. Monteiro, "Socially-aware joint resource allocation and computation offloading in noma-aided energy harvesting massive iot", *IEEE Internet of Things Journal*, 2020.

[19] Khan, W. U., Jameel, F., Jamshed, M. A., Pervaiz, H., Khan, S. and Liu, J., "Efficient power allocation for NOMA-enabled IoT networks in 6G era", *Physical Communication* 39, p. 101043, 2020.

[20] M. Ahmed, W. U. Khan, A. Ihsan, X. Li, J. Li, and T.A. Tsiftsis, "Backscatter sensors communication for 6G low-powered NOMA-enabled IoT networks under imperfect SIC", *IEEE Systems Journal*, vol. 16, no. 4, pp. 5883–5893, 2022.

[21] B. Di, L. Song, and Y. Li, "Sub-channel assignment, power allocation, and user scheduling for non-orthogonal multiple access networks", *IEEE Transactions on Wireless Communications*, vol. 15, no. 11, pp. 7686–7698, 2016.

[22] Z. Ali, G. A. S. Sidhu, M. Waqas, and F. Gao, "On fair power optimization in nonorthogonal multiple access multiuser networks", *Transactions on Emerging Telecommunications Technologies*, vol. 29, no. 12, p. e3540, 2018.

[23] V. Roostapour, A. Neumann, and F. Neumann, "Evolutionary multi-objective optimization for the dynamic knapsack problem", *arXiv preprint arXiv*:2004.12574, 2020.

[24] H. You, Z. Pan, N. Liu, and X. You, "User clustering scheme for downlink hybrid noma systems based on genetic algorithm", *IEEE Access* 8, pp. 129461–129468, 2020.

[25] X. Xue, J. Lu, and J. Chen, "Using nsga-iii for optimising biomedical ontology alignment, CAAI", *Transactions on Intelligence Technolog*, vol. 4, no. 3, pp. 135–141, 2019.

[26] S. A. R. Naqvi, S. A. Hassan, H. Pervaiz, Q. Ni, and L. Musavian, "Self-adaptive power control mechanism in d2d enabled hybrid cellular network with mmwave small cells: An optimization approach, in 2016 *IEEE Globecom Workshops*, pp. 1-6, 2016.

[27] G. Dhiman and V. Kumar, "Emperor penguin optimizer: a bio-inspired algorithm for engineering problems", *Knowledge-Based Systems*, vol. 159 pp. 20–50, 2018.

[28] G. Dhiman and V. Kumar, "Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems", *Knowledge-Based Systems*, vol. 165, pp. 169–196, 2019.

[29] G. Dhiman and V. Kumar, "Multi-objective spotted hyena optimizer: a multi-objective optimization algorithm for engineering problems", *Knowledge-Based Systems*, vol. 150, pp. 175–197, 2018.

[30] G. Dhiman and V. Kumar, "Spotted hyena optimizer: a novel bio-inspired based metaheuristic technique for engineering applications", *Advances in Engineering Software*, vol. 114, pp. 48–70, 2017.

Received 26 February 2023