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Enhancement of energy and spectral efficiency for mm-wave based 5G communication network

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ABSTRACT

5G network is an enhanced communication network, designed to converge the requirements of quality of service (QoS) parameters, data and capacity, by means of signals with high QoS and high-speed data rate. Several state-of-art technologies are involved to obtain the requirement of energy efficient communication system with increased number of users, devices, higher data rate with low latency. This paper presents a system which demonstrates the energy and spectral efficiency achieved for various number of nodes in a specific area. This study addresses the improvement in energy and spectral efficiency when the proposed algorithm is used. The proposed algorithm is a combination of swarm based artificial bee colony (ABC) algorithm with neural network. Experimental results have been carried out to observe the performance of QoS parameters such as bit error rate (BER), throughput, power consumption and mean square error (MSE). The maximum energy efficiency achieved is 34% and Spectral efficiency is 36%.

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1. INTRODUCTION

Fifth-generation (5G) telecommunications technology, introduced in 2019, has been hailed as the internet of things (IoT) panacea for problems such as mobile phone tariffs. The mobile phone industry has committed to net zero emissions by 2050, and 5G specifications call for a 90% reduction in energy consumption (per unit of data transfer) compared to 4G. These promises are great, but 5G is still in its infancy and the limitations of existing infrastructure and design make these promises far-reaching. The main improvements that 5G promises are primarily the use of millimeter-wave line, which allows communication of the direction of radiation. This means 5G can focus data transfers over a short distance, rather than illuminating the entire area behind you, bathing a somewhat bulb-like target with electricity. The second is the huge increase in communication speed; This will help improve self-management and tools (reduced latency) and the growth of IoT devices, paving the way for innovation and optimization.

The number of 5G connections is increasing by 217% every year, and there will be approximately 100 billion information and communications technology (ICT) connections (40 billion of which are IoT sensors) by 2025. In the next decade, mobile data usage will increase sixfold in developing countries and threefold in developing countries. When new models are introduced (such as the transition from 3G to 4G), mobile data always increases energy consumption, but this is not due to increased data traffic, but to the addition of new hardware for the network. Most of the energy used in ICT systems is not used to send information; is wasted due to heat loss, idle time and other inefficiencies. The components that form the digital core of ICT networks (switches and data centers) are down 72% of the time, and 57% of the network power is needed by cellular stations. The key to the problem is the way current ICT systems are designed and built in all their forms. The problem is that the communications industry in general is almost focused on sending as many items per second as possible. However, little attention is paid to the use of fire electricity that comes with it. The power efficiency of 2G is 60%. This means that for every 10 watts used, 6 watts are used for data transmission. In 4G systems, this efficiency drops to 20%, while in 5G systems it is only 10%, which means that every 9 watts used to send data is wasted. Things are even worse for 5G networks that run on 4G hardware and use millimeter waves. Wave: This product uses only 1% energy. This is worse than old fashioned incandescent lamps. Business pressures will limit the use of 5G technology unless steps are taken to increase these levels of energy efficiency. 5G networks using millimeter waves should be faster than 4G within 300 meters of a mobile phone. Organizations use small mobile phones to extend millimeter wave lines beyond this limit when needed. 5G small cells are necessary to increase mm-Wave coverage, capacity and speed. The terms “millimeter wave” and “5G” are often used interchangeably. However, there are important differences between the two. 5G refers to existing cellular networks, while millimeter baud refers to the radio spectrum in the range of 24 and 100 GHz. This is called millimeter wave (mmWave) band 5G and is best for use in densely populated areas rather than short distances. According to the studies carried out the power consumption for 5G network at peak hours is around 300% greater than 4G power consumption. Due to the energy constraints and versatile network requirements traditional methods are not enough for network optimization. And thus, learning techniques based on ML are engaged which allow the system to learn from the data and optimize the network [1].

Energy efficiency as defined is inverse to energy consumed per transmitted bit or can also be defined as the number of bits transmitted for every unit of energy consumed. In the communications domain, consumption of power and energy-related pollution resulting out of it are becoming major concerns in operational and economical terms [2]. As 5G is expected in claiming to connect large number of devices together, hence large amount of transmit power will be required resulting in huge amount of energy consumption. This is directly going to result in emission of greenhouse gases along with large percentage of carbon dioxide produced by these connected devices and this increases by few million tons [3]. The IoT devices in 5G networks are entangled with multiple of multiple-input and multiple-output (MIMO) transmission interfaces. Now that MIMO is more frequently available on IoT devices an efficient clustering strategy for quickly growing IoT systems is absent and is urgently required so as to handle a variety of user situations. As a result, many novel techniques in load balancing based on network optimization using routing protocol for 5G wireless communication networks are proposed by researchers [4].

Along with enhancement of energy efficiency (EE), spectral efficiency (SE) must also be taken into account, as studies have focused that if we increase the EE, SE decreases and vice-versa [5]. Mittal *et al.* [6] has proposed routing protocols in collaboration with neural network to overcome problem of limited battery power for wireless sensor nodes (WSN). Sharma *et al.* [7] has proposed modified power consumption models that would accurately depict the power consumption for 5G base stations. Rostami *et al.* [8] suggested a wake-up signaling for 5G control plane in order to reduce energy consumption of cellular module in downlink. Aslam *et al.* [9] proposed energy-efficient path planning routing protocols are to deal with the fluctuation of network deployments and adaptive transmission range of WSNs. In [10], the LEACH–energy betweenness (LEACH-EB) model is proposed by taking energy consumption as a constraint condition. Zhang *et al.* [11] proposed combined optimization of spectral efficiency along with power control of massive MIMO networks. Panda [12] has proposed an algorithm which improve the overall spectral efficiency uplink and downlink combined. The achievable effective SE of a massive MIMO system was analyzed by Chen and Zhang [13]. In [14], an ant colony optimization routing algorithm with window reduction for LEO satellite networks, is proposed to achieve load balancing. A 3-hop non-orthogonal multiple access-unmanned aerial vehicle (NOMA UAV)-aided green communication network framework is proposed by Wang *et al.* [15], where UAVs serve as aerial relays to support two groups of ground users. In [16], a novel resource allocation scheme is proposed to maximized the sum throughput of the wireless-powered NOMA internet-of-things (IoT) network. Khuntia *et al.* [17] focuses to review and introduce to the techniques used for enhancement of the energy efficiency gains provided by MIMO systems, providing an overview of MIMO technology, emphasizing the necessity for realistic power consumption models tailored to these systems. Pradhan *et al.* [18] has provided an evaluation of latest trends in a various of D2D domain names, aid allocation and optimization for D2D packages for 5G technologies and the invention technique for sustainable verbal exchange in 5G community with effective usage of energy. Khan and Pesch [19] have investigated the performance of two MIMO precoding techniques in terms of achievable sum rates for massive MIMO. Nataraju *et al.* [20] provides an overview of the opportunities, challenges, and benefits of the 5G-IoT ecosystem toward the sustainable development of green smart cities (GSC). To tackle the cellular networks energy efficiency issue, Tiwari *et al.* [21] investigates energy efficiency in D2D-enabled heterogeneous cellular networks. To effectively improve the user experience, Wang *et al.* [22] has proposed a novel approach, which embraces resource allocation and power control along with deep reinforcement learning (DRL) for 5G communication network. In [23], highlighting at the problem of high energy consumption and improved quality of service demands by the D2D users, this paper proposes a novel scheme to effectively improve the user fairness and satisfaction based on the user grouping into clusters.

Sangeetha *et al.* [24] proposed a novel energy-aware scheduling model that takes into consideration the specific characteristics of 5G green communication systems, to address the challenges of achieving optimal resource utilization and minimizing energy consumption in these systems. In [25], as optimization of energy efficiency has thus become a major challenge for this new generation communication system, several strategies are utilized to improve energy efficiency. This article presents a review and a comparative analysis of these different strategies, those relating to the base station, the organization of the network, software defined networks and those based on machine learning. Premlatha *et al.* [26] has introduced an optimized nature-based cluster sleep technique to reduce the power consumption in the base station and in the network using Firefly algorithm, which benefited the system to improve connectivity among the base stations in an energy-efficient way. A 5G network is a dynamic system and consumes energy continuously in response to spikes in network activities. Major consumption of energy is due to elements at base stations, antennas and radio units. In the areas such as backhaul, core cooling and computing processes, there is a scope for improvement of 5G energy efficiency. The ICT industry is responsible for around 4% of the consumption of the world's electricity. With 5G projected to increase capacity up to 1,000 folds and high frequency millimeter wave (mmWave) transmission driving exponentially higher cell density, this percentage could exceed around 20% by 2030. Thus, incorporating machine learning techniques with 5G network would be beneficial in achieving an improvement in spectral and energy efficiency for 5G communication network steering the ICT industry towards greener electricity sources. To address the challenges in achieving the energy efficiency for 5G network, following objectives are presented in the article:

- To locate a certain number of antennas (nodes) in a specified area and establish a communication link between the nodes for data transmission to takes place.
- To perform channel estimation and obtain quality–of–service (QoS) parameters
- To observe enhancement in QoS parameters by applying proposed hybrid algorithm.
- To assess how well suggested algorithm performs in terms of energy and spectral efficiency calculations.

Thus, the paper claims following contributions owing to integration of 5G network with machine learning techniques:

- Locating different number of antennas in a 1000×1000 m area and using ad-hoc distance vector routing (AODV) routing scheme to setup communication link between source to destination node.
- By performing channel estimation at receiving end obtain a dataset containing parameters such as bit error rate (BER), throughput and mean square error (MSE).
- Apply the proposed algorithm i.e. artificial bee colony (ABC) with artificial neural network (ANN) to optimize and train the network and obtain enhancement in QoS parameters.
- Compare the values of QoS parameters before and after applying proposed algorithm and calculate spectral efficiency (SE) and energy efficiency (EE) taking into account different number of nodes.

2. METHOD

Figure 1 shows the implementation flow of the proposed system. The proposed solution is designed into two segments in which the first segment is used for deploying a communication network and perform channel estimation. In the second segment, machine learning technique is used to optimize the network.

2.1. Network model

In the first stage of the study, we generated a dataset containing QoS parameters such as throughput, BER and MSE. For obtaining the dataset, initially we create a network of 1,000×1,000 m area and plot random number of antennas (nodes). To establish the communication link between the source and destination antennas, we use AODV scheme. In the next stage, channel estimation is carried out to understand and analyze the communication channel's properties. Channel estimation helps to improve the QoS parameters and determine the optimal communication path. Thus, at the receiving end channel estimation is performed considering 8,000 subchannels, 8 number of pilots, 4^{th} order quadrature phase shift keying (QPSK) modulation technique over channel length of 32 for 1,000 iterations, which in turn generates a database containing QoS parameter values. In 5G communication system, the large number of users can utilize the frequency spectrum after fulfilment of certain objectives such as minimizing BER, maximizing throughput and minimizing power consumption.

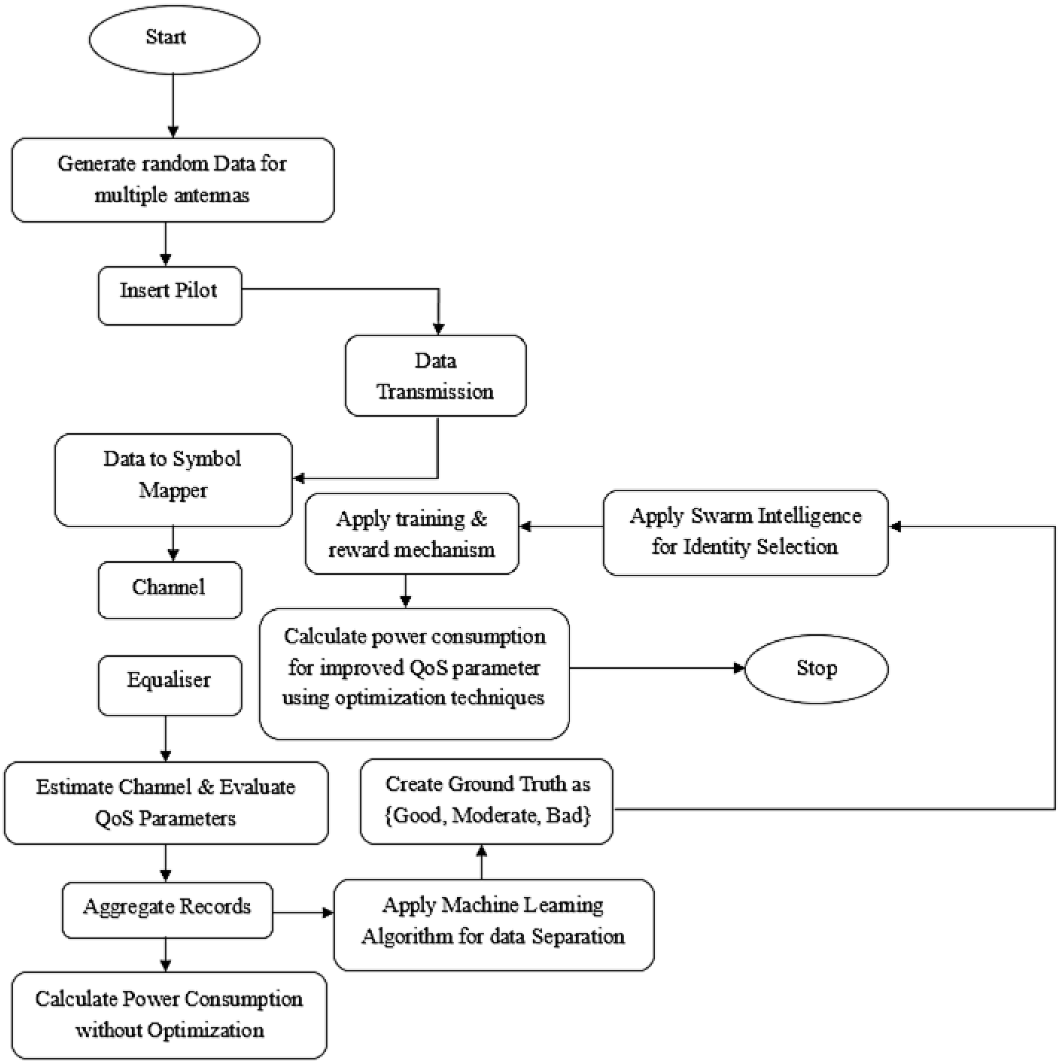

Figure 1. Flow chart of proposed system

2.2. Proposed model

This is the second phase of the study. The proposed algorithm is a combination of artificial bee colony (ABC) algorithm and artificial neural network (ANN). The ABC algorithm is responsible for maximizing the accuracy of each class and ANN is used to train the system. The ABC algorithm is the swarm-based optimization algorithm which includes four phases. In the initialization phase, the initial food sources are produced randomly using expression (1),

$$x_m = l_i + rand(0,1) * (u_i - l_i) \tag{1}$$

where u_i and l_i are upper and lower bound of the solution space of the objective function. Next is the Employed bee phase, in which the neighbor food v_{mi} is evaluated by using (2),

$$v_{mi} = x_{mi} + \phi_{mi}(x_{mi} + x_{ki}) \tag{2}$$

where i is a randomly selected parameter index, x_k is a randomly selected food source, ϕ_{mi} is a random number within a range [-1, 1].

The fitness function is calculated by using (3),

$$fit_m\,(x_m) = \frac{1}{1+ f_m(x_m)}, f_m(x_m) > 0 \tag{3}$$

where $f_m\ (x_m)$ is the objective function value of x_m. The third phase is Onlooker bee phase, the quantity of the food is evaluated by its profitability ($P_{m)}$ using (4),

$$P_m = \frac{fit_m(x_m)}{\sum_{m=1}^{SN} fit_m(x_m)} \tag{4}$$

where $fit_m(x_m)$ is the fitness of x_m. Onlooker bees search neighbourhoods of food source using the expression (2). In the fourth phase, scout bee pahse, the new solutions are randomly searched by the scout bees using (1).

The proposed algorithm selects the best suitable bees against each class defined and passes to Levenberg oriented feed forward back propagation neural networks (FFBPNN). The network trains the system with 10 layers of propagation and 100 propagation epochs. Levenberg is a gradient oriented, sigmoid based training model which propagates in a backward direction to attain minimum mean squared error.

2. RESULTS AND DISCUSSION

The aim is to study the energy and spectral performance of the system. Energy efficiency describes how much energy is consumed per received information bit, measured in bits/joules. Spectrum efficiency is the amount of transmitted data over a given spectrum with the minimum number of errors. The simulation results demonstrate the response of BER, throughput, MSE, power consumption, and routing overhead for a range of SNR values ranging from 5 to 25 dB for different numbers of nodes placed in a 1,000×1,000 m area. Each parameter is analyzed in two different conditions: when the proposed algorithm is not applied, i.e., without optimization, and when the proposed algorithm is applied, i.e., with optimization.

3.1. Simulation results with different number of nodes

The graphical representation of the above results for different parameters is shown in Figure 2. Figure 2(a) shows the positioning of 80 antennas, which are placed randomly in a 1,000×1,000 m area. It shows the communication path set between the source and destination antennas, established with the help of the AODV routing protocol. Figure 2(b) demonstrates that for a network with 80 nodes, the power consumption is reduced when the proposed optimization algorithm is used. The aim behind this study is to maximize the energy efficiency of the communication network, for which the power consumption should be as low as possible.

Figure 2(c) shows that the value of MSE when the optimization algorithm is applied is less than when the optimization algorithm is not applied. Ideally, the value of the mean square error (MSE) is expected to be as low as possible, as it signifies better accuracy of the predictive model. It is the metric that indicates the errors between the actual and predicted values for each data point. Figure 2(d) demonstrates the performance of throughput with respect to the change in SNR. It shows improvements in throughput when optimization is performed, which indicates the maximization of the user's data.

In general, the value of BER should be 10^{-3} for a wireless communication system, which indicates better transmission accuracy and higher data integrity. Figure 2(e) demonstrates that the value of BER when the optimization algorithm is used is less than when the optimization algorithm is not used. To achieve improvement in spectral efficiency, the value of BER has to be minimized. The efficiently utilized spectrum has a low BER value with minimum errors on the receiver side. Routing overhead refers to the additional data, time, and processing required to manage the routing information of a communication network. As seen from Figure 2(f), the routing overhead required when optimization is performed is less than the condition without optimization. In a similar way, the responses of parameters such as BER, throughput, MSE, power consumption, and routing overhead can be obtained for different numbers of nodes. Tables 1, 2, and 3 show the simulation results for 80, 100, and 150 nodes, respectively.

2.2. Energy efficiency calculation results

Tables 1, 2, and 3 demonstrate the performance of various parameters such as BER, MSE, power consumption, throughput, and routing overhead measured under two different conditions, i.e., without optimization performed and with optimization performed. Accordingly, Table 4 shows the percentage improvement in EE and SE by taking into account both conditions. The EE is computed depending on the power consumption values, and the SE is computed using BER values. Maximizing SE and EE while maintaining quality of service is a top priority for next-generation wireless networks. However, there is a notable trade-off when optimizing both SE and EE parameters simultaneously. Table 4 shows that when there is improvement in EE, SE decreases, and vice versa. The maximum EE achieved is 34%, and the maximum the maximum SE achieved is 36%.

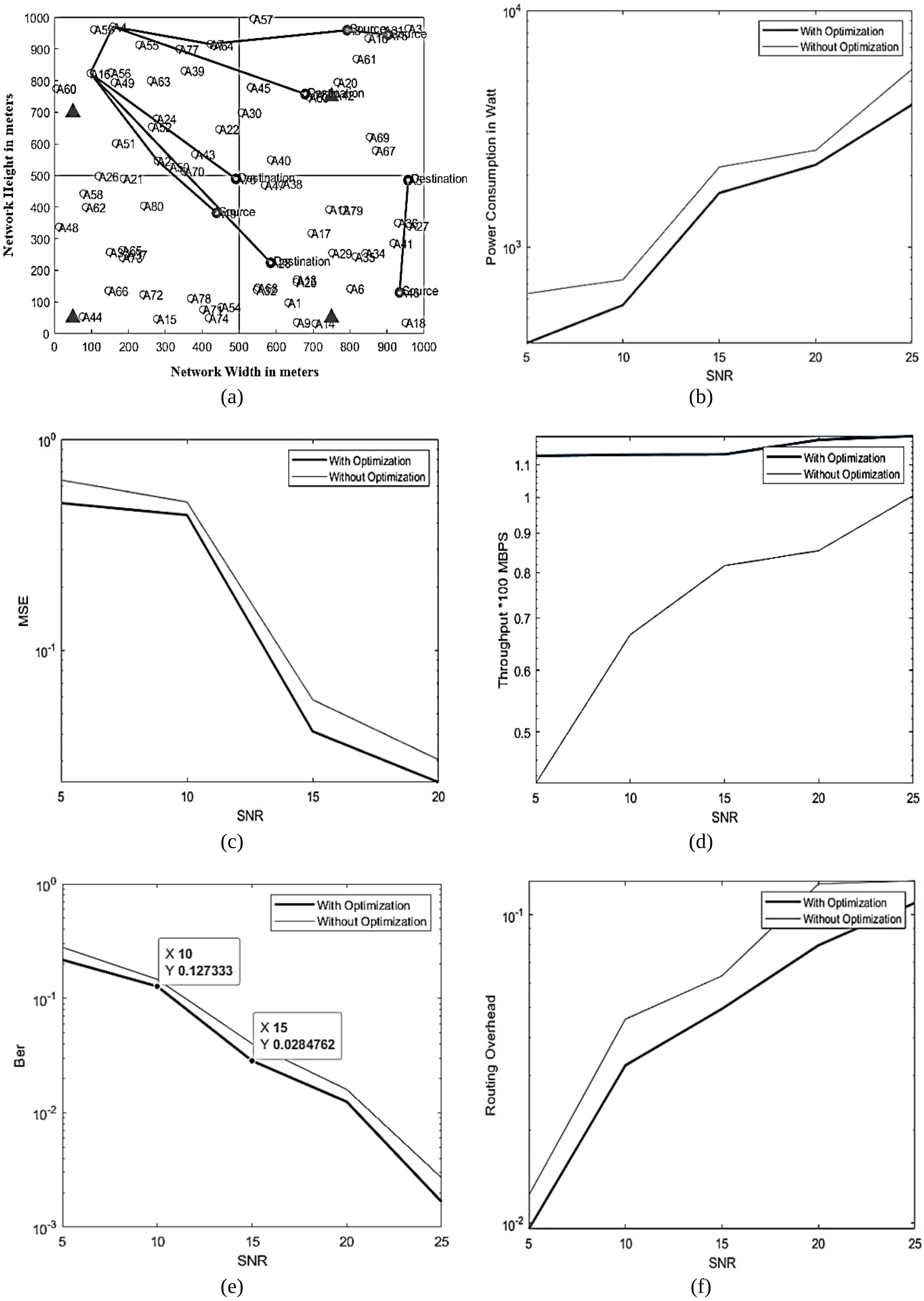

Figure 2. Simulation results for 150 nodes in a network (a) communication scenario with 80 nodes, (b) power consumption vs SNR, (c) MSE vs SNR, (d) throughput vs SNR, (e) bit error rate vs SNR, and (f) routing overhead vs SNR

Table 1. Simulation results for 80 nodes in a network

QoS parameters		Signal-to-noise ratio (dB)				
		5	10	15	20	25
BER	Without optimization	0.28	0.146	0.04	0.016	0.003
	With optimization	0.28	0.127	0.03	0.012	0.002
Throughput*100 Mbps	Without optimization	0.43	0.66	0.82	0.85	1.005
	With optimization	1.129	1.134	1.135	1.184	1.2
MSE	Without optimization	0.64	0.5	0.06	0.03	0.043
	With optimization	0.5	0.43	0.04	0.02	0.03
Power consumption (Watts)	Without optimization	633.4	725.3	2171.98	2557.52	5634.96
	With optimization	391.1	566.9	1687.96	2220.99	3988.17
Routing overhead	Without optimization	0.0123	0.046	0.063	0.126	0.128
	With optimization	0.009	0.032	0.049	0.079	0.11

Table 2. Simulation results for 100 nodes in a network

QoS parameters		Signal-to-noise ratio (dB)				
		5	10	15	20	25
BER	Without optimization	0.28	0.111	0.063	0.032	0.012
	With optimization	0.21	0.091	0.036	0.018	0.006
Throughput*100 Mbps	Without optimization	0.056	0.32	0.32	0.73	0.92
	With optimization	1.13	1.13	1.14	1.67	1.21
MSE	Without optimization	0.81	0.36	0.14	0.04	0.013
	With optimization	0.57	0.3	0.08	0.025	0.0067
Power consumption (Watts)	Without optimization	1636.95	2076.32	13598.6	15338.9	18175.8
	With optimization	951.398	1717.73	7863.98	7925.26	13018.5
Routing overhead	Without optimization	0.015	0.046	0.091	0.179	0.248
	With optimization	0.01	0.038	0.047	0.104	0.145

Table 3. Simulation results for 150 nodes in a network

QoS parameters		Signal-to-noise ratio (dB)				
		5	10	15	20	25
BER	Without optimization	0.43	0.128	0.022	0.0097	0.0092
	With optimization	0.23	0.09	0.021	0.0075	0.0048
Throughput*100 Mbps	Without optimization	0.097	0.155	0.709	0.809	1.06
	With optimization	1.129	1.13	1.137	1.156	1.22
MSE	Without optimization	1.325	0.27	0.072	0.0014	0.022
	With optimization	0.707	0.195	0.072	0.0011	0.012
Power consumption (Watts)	Without optimization	906.2	2662.96	9472.54	9815.18	25784.1
	With optimization	483.93	1920.37	7379.97	9201.78	13473.5
Routing overhead	Without optimization	0.023	0.024	0.025	0.113	0.178
	With optimization	0.017	0.019	0.023	0.059	0.95

Table 4. Energy efficiency (EE) and spectral efficiency (SE) for 80, 100, and 150 nodes

Nodes	SNR	EE (%)	SE (%)
80	5	38	25
	10	22	13
	15	22	25
	20	13	25
	25	29	33
Average		25	24
100	5	42	25
	10	17	18
	15	42	43
	20	43	44
	25	28	50
Average		34	36
150	5	44	45
	10	28	30
	15	22	25
	20	26	23
	25	46	42
Average		33	33

4. CONCLUSION

In this article, we present a novel hybrid swarm-based machine learning algorithm with the perspective of optimizing a wireless network for enhancement in both EE and SE. We presented an analysis of QoS parameters under two different conditions, i.e., without optimization and with optimization. This study is based on the QoS parameter values based on which EE and SE are calculated. We highlighted that the system not only improves EE and SE but also shows a reduction in the trade-off between the two. The results show that, on average, the maximum EE achieved is 34% and SE is 36%. Improvement in EE indicates less power consumption, and improvement in SE indicates minimum transmission errors in the received signal. The increase in energy and spectrum use efficiency in 5G compared to 4G is due to the addition of more antennas, which in turn increases circuit power. Moving forward, if it is possible to lower circuit power through more energy-efficient methods, the energy efficiency of green points will rise, but the spectrum efficiency of green points will fall. It is likely that the efficiency of the spectrum will significantly improve in upcoming 6G communications and beyond, indicating that the energy efficiency of green points will decrease even more, and the use of power will speed up. Should the wireless communication sector adopt this pattern, the resulting carbon emissions will surely rise. Thus, it is crucial for industries to overcome the trade-off between spectrum and energy efficiency, enhancing the energy efficiency of systems while keeping the spectrum efficiency high. So, incorporating newly introduced machine learning techniques with existing systems could be beneficial for further contributing to a greener society. in future, fuzzy logic architecture can be utilized to label the categorize data as it can manage numerical data and handle the linguistic information at the same time. On the other hand, we can also utilize swarm-based optimization algorithms, such as Firefly algorithm for better tuning of the system's parameters resulting in enhanced communication throughput, enabling the communication system to operate more efficiently.

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