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OMPA Optimization framework for Energy Efficiency & Long-term Communication in IoT Networks

1*Mr.A.Ramesh 2 Ms.K.Kamali

Assistant Professor, Dept. of CSE, Annamalai university, Annamalainagar, Tamilnadu

Assistant Professor , Dept. of CSE, Annamalai university, Annamalainagar, Tamilnadu

Abstract

In Internet of Things (IoT) networks, every device that is connected to a network should ideally be able to communicate with other devices connected to the network. The availability of intermediary nodes in the network and their proper operation are necessary for node connectivity. To increase the connectivity, the bandwidth and spread factor of each relay should be assigned maximum. As each link will have its respective time of transmission, the optimization should minimize the transmission time thus minimizing energy consumption. In this work an optimization framework using Opposition based Marine Predators Algorithm (OMPA) is designed for energy efficiency and long-term communication in IoT networks. The fitness function is derived in terms of bandwidth, spread factor, total transmission time and energy consumption ber bit. Then relay nodes are selected based on maximum fitness function. By simulation results, it has been shown that OMPA-OF achieves maximum energy efficiency and packet success rate with reduced packet loss rate.

Keywords

Internet of Things (IoT) , Opposition based Marine Predators Algorithm (OMPA), energy efficiency, connectivity

1. Introduction

The Internet of Things (IoT) is a network of networked devices that transfer and gather data via a wireless network without the need for human involvement. Applications for it include asset detection, automated building, security, surveillance monitoring, and health care. Periodically, the IoT-based data gathering system gathers physical environment data. These systems can be used in a variety of industries, including remote monitoring, big data analytics, and video surveillance [1]. The network has been applied to performance improvement in a number of ways. This cloud-based technology handles a variety of tasks that users from anywhere in the world can assign it to do. Using a router, it links various devices, including PCs, tablets, and smartphones, to the Internet. After that, the data is relayed to the mini-computer via Bluetooth, Wi-fi, and other comparable technologies. IoT has fueled urban infrastructure experimentation and analysis in the context of smart cities, enabling innovation in energy systems, transportation, and healthy environments to benefit the populace as a whole.

In all types of networks, IoT—connectivity is an essential requirement. Every device that is connected to a network should ideally be able to communicate with other devices connected to the network. Stated differently, the network needs to maintain connectivity among all accessible devices. The availability of intermediary nodes in the network and their proper operation are necessary for node connectivity. If a mobile node in a drone or car network moves, the communication channels between its neighbours will also shift. In the worst scenario, losing or moving a node could cut off communication to a large number of functional nodes and waste a lot of active resources if there isn't another redundant way [3][4].

One of the main issues with low-power wide area networks (LPWANs) used in mMTC situations is the trade-off that takes into account power consumption and relatively long reaches [5]. The communication protocol adopted in LoRaWAN also helps to tackle IoT difficulties connected to long-range connectivity, as well as to reduced energy usage, at the expense of poor data rates.

Energy efficiency is what the IoT should be all about in order to power the sustainable smart world [6]. Additionally, there will be a further large increase in energy usage due to the increased interest and acceptance from numerous organisations. As a result, it is imperative that green IoT be developed, with an emphasis on lowering IoT power usage. IoT devices with low power supply ought to have optimised interfaces, and optimised communication protocols ought to lower energy usage. There are still many options for optimising protocols based on the needs of the network, depending on a number of variables like data characteristics, data transfer method, and network size [7].

2. Related works

A region-based clustering and cluster-head election methodology was proposed by Priyanka et al. [1] to increase the energy efficiency of IoT networks used in agricultural environments (REAN). In order to deliver energy-efficient software and Internet of Things applications, the suggested methodology makes use of the Region Clustering and Cluster Head Selection (RCHS) algorithm and the Shortest Routing and Less Cost algorithm (SRLC).

Laguidi et al. [4] have suggested an IoT approach that can enhance an IoT object's connectivity. This method entails utilising the NB-IoT's wider coverage to increase the Wi-Fi zone's coverage, which does not go beyond a few metres.

Surenther et al. [7] offer a Deep Learning based Grouping Model Approach (DL-GMA) that optimizes energy utilization in WSNs. DL-GMA utilises cutting-edge deep learning methods, specifically Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM), to improve energy efficiency by selecting, forming, and maintaining Cluster Heads (CH) in an efficient manner. By utilising deep learning and intelligent grouping, this method increases data transmission efficiency and prolongs the lifespan of WSNs. With its ability to maximise network potential and improve data transmission efficiency while addressing the issues of scarce energy resources, DL-GMA marks a major breakthrough in energy optimisation for WSNs.

Lee [8] aimed to improve the performance of enormous MIMO with enormous IoT connectivity by employing the dropping technique that drops the IoT devices that demand high power consumption. Numerous scheduling and power control strategies have been put forth to improve Massive MIMO systems' energy and spectrum efficiency. The Internet of Things devices that ought to be discontinued are determined by a falling coefficient factor. Power control methods that demand higher power consumption benefit more from this technique.

A RIS-assisted SI-cancellation method is suggested by Sultan et al. [9] to assist in reducing the SI level in the analogue domain. Furthermore, the main goal is to maximise the DL-IoT total rate without inadvertently degrading the transmissions of macro-DL users.

Wang et al. [10] suggest using the temporal correlation in user activity to increase detection performance; that is, a device that was active during a prior time slot is more likely to be active during the present time slot. Explicit quantitative correlation is found between the real activity pattern at the previous and current time slots and the activity pattern estimated by approximate message passing (AMP) at the prior time slot. This helpful SI is integrated into the design of the AMP framework's minimal mean-squared error denoisers and log-likelihood ratio test-based activity detectors, based on the well-defined temporal correlation.

A variety of green IoT technologies and concerns are presented by Singh et al. [11]. Additionally, it examines green cloud computing (CC), green data centres (DC), and green machine-to-machine (M2M) ICT. Furthermore discussed in this study are the difficulties of achieving green IoT communication through the use of effective activity scheduling techniques that save energy. In conclusion, the green IoT-Home Service (GIHS) model is suggested, which offers effective energy management for home automation systems.

Shen et al. [12] developed a novel activation/inactivation strategy for long-term IoT network operation. In this strategy, a machine learning model is adopted to adaptively select the unneeded sensors to be inactivated during network operation. Moreover, to maintain high sensor data processing performance during long-term operation, by only using the basic sensor data (e.g., temperature and humidity), they selected the unneeded sensor candidates which are periodically updated.

2.1 Research Gaps

A scarcity of comprehensive studies occurs, specifically addressing the practical implementation and validation of the existing framework, potentially impeding its real-world applicability. Moreover, there is a limited importance on the dynamic nature of IoT environments and the adaptability of the existing methods to diverse network conditions. The scalability of the multi-criteria framework, mainly in wide-ranging IoT deployments, remains inadequately investigated. Moreover, a detailed analysis is needed to understand the influence of security considerations on energy efficiency and long-term communication. Finally, the existing methods did not considered cost-efficiency during implementation, providing valuable insights for IoT industry. Addressing these research gaps will lead to a more comprehensive understanding and successful implementation of the multi-criteria framework in order to improve energy efficiency and long-term communication in IoT networks.

3 Proposed Methodology

3.1 Overview and System Model

In this work an OMPA-OF is designed for energy efficiency and long-term communication in IoT networks. The fitness function is derived in terms of bandwidth, spread factor, total transmission time and energy consumption ber bit.

The network is modeled as a graph G = (V, E), where V is the set of sensor nodes and E is the set of edges that indicate the links. Apart from these, it consists of relays and the Gateway. The system model considers that the end devices are connected by LoRa wireless links and the relays are able to receive LoRa signals from the end devices and forward them to a Gateway.

The optimization model aims to determine the position of each device and optimize the resources using in order to establish the best links.

3.2 Estimation of Parameters

3.2.1 Energy consumption

The energy consumption per bit (E_{bit}) metric is used to evaluate the energy usage of the LoRA devices, which is given by

$$E_{bit} = \frac{P_c.(N + N_p + 4.25).2^{SF}}{8.PL.BW} \quad (1)$$

Where, P_c denotes the consumed power based on the transmitted power P_T,

N denotes the number of symbols used to transmit the payload

N_p denotes the number of packets transmitted

SF denotes the spread factor

PL denotes the path loss

BW denotes the bandwidth

The transmission power P_T is evaluated based on the following link budget equation

$$P_R = P_T + G - PLoss \tag{2}$$

Where P_R is the received power, G is the system gain, PLoss is the link attenuation in dB.

3.2.2 Transmission time

The transmission time (T_t) depends on the value of SF which is directly proportional to E_{bit}

$$T_t = T_{pr} + T_L \tag{3}$$

where T_{pr} and T_L are the preamble duration and payload duration.

3.2.3 Fitness Function

To increase the connectivity, the BW and SF of each relay should be assigned maximum. As each link will have its respective T_t, the optimization should minimize the maximum T_t of each schedule, thus minimizing E_{bit}. Hence the fitness function is derived as follows:

$$F = \sum_{i=1}^{N}(SF_i + BW_i) - \sum_{i=1}^{N} E_{bit}(i) \tag{4}$$

For optimization, the Opposition based Marine Predators Algorithm (OMPA) is used.

3.3 Opposition based Marine Predators Algorithm (OMPA)

A network is considered as non-connected when at least one of its devices is not able to provide connectivity between its pairs, according to the assigned values of BW and SF. The optimization process is repeated until a network-connected solution is defined.

The minimized objective function (OF) takes into account the (E_{bit}) metric and the total network data collection time T_{data}

3.3.1 MPA

Recently, the optimization techniques have played a major role in selecting features plays major role. The wrapper (optimization) based feature selection models identify the best sub-set of features. Hence, this work presents a wrapper based feature selection model for selecting the necessary features for weather forecasting. MPA is one of the metaheuristic models that portray the biological relation among the MP (marine predators) and prey. The standard MPA doesn't have capacity to develop large productivity, is trapped by optima and lacks in exploration and exploitation.

MP utilizes the wide-spread foraging characteristic known as Brownian and Levy's flight. When the focus of prey in the hunting region is large, the Brownian is utilized and when the focus of prey in the hunting region is large, the Levy's flight is utilized. This wide-spread foraging characteristic is defined as:

$$\vec{Y_j} = \vec{Y}_{\min} + \vec{rand} \otimes \left(\vec{Y}_{\max} - \vec{Y}_{\min}\right) \tag{5}$$

where $\vec{Y}_j$ is the j^{th} member of prey's initial population, $\overrightarrow{rand}$ is the random number, $\vec{Y}_{\max}$ and $\vec{Y}_{\min}$ are the maximum and minimum bounds. The fitness function is used for measuring the every member's fitness. Best member is selected on the basis of best fitness value and the Elite matrix is computed as:

$$E = \begin{bmatrix} Y^B_{1,1} & Y^B_{1,2} \cdots Y^B_{1,d} \\ Y^B_{2,1} & Y^B_{2,2} \cdots Y^B_{2,d} \\ \vdots & \vdots \quad \vdots \\ Y^B_{m,1} & Y^B_{m,2} \cdots Y^B_{m,d} \end{bmatrix} \qquad (6)$$

where Y^B is the best member of MP population, m is the size of population and d is the dimension. The individual of prey is given as:

$$P = \begin{bmatrix} Y_{1,1} & Y_{1,2} \cdots Y_{1,d} \\ Y_{2,1} & Y_{2,2} \cdots Y_{2,d} \\ \vdots & \vdots \quad \vdots \\ Y_{m,1} & Y_{m,2} \cdots Y_{m,d} \end{bmatrix} \qquad (7)$$

The foraging characteristic is split to the three major stages by the proportion of prey and velocity of MP.

Proportion of high velocity: In this stage of MPA, the exploration stage is carried out and the MP moves slower than the prey. It is represented as:

$$while\ iteration < \frac{1}{3} * \max\_\ iter$$

$$\vec{S}_i = \vec{R}_B \otimes \left(\vec{E}_i - \vec{R}_B \otimes \vec{P}_i \right) \qquad (8)$$

$$\vec{P}_i = \vec{P}_i + C \times \vec{R} \otimes \vec{S}_i \qquad (9)$$

where $\vec{R}_B$ is the random value, $\otimes$ is the multiplication operator, C is the constant number and $\vec{R}$ is the random vector.

Unit velocity: When both prey and MP move in the same manner and the population is split into two stages. Half of the population used for exploration is given in Equations (8-9) and the next half of the population used for exploitation is given in Equations (10-11).

$$while\ \frac{1}{3} * \max\_\ iter < iteration < \frac{2}{3} * \max\_\ iter$$

$$\vec{S}_i = \vec{R}_Q \otimes \left(\vec{E}_i - \vec{R}_Q \otimes \vec{P}_i \right) \qquad (10)$$

$$\vec{P}_i = \vec{P}_i + C \times \vec{R} \otimes \vec{S}_i \qquad (11)$$

where $\vec{R}_Q$ is the random value which depends on the Levy's distribution and $\vec{S}_i$ is the step size.

$$\vec{S}_i = \vec{R}_U \otimes \left(\vec{R}_U \otimes \vec{E}_i - \vec{P}_i \right) \tag{12}$$

$$\vec{P}_i = \vec{E}_i + C \times AV \otimes \vec{S}_i \tag{13}$$

where $\vec{R}_Q$ is the random value and AV is the adaptive variable.

Proportion of low velocity: It is the final stage of the MPA, when the prey moves slower than the MP and the exploitation stage is completed. It is expressed as:

$$while\ iteration > \frac{2}{3} * \max\_\ iter$$

$$\vec{S}_i = \vec{R}_Q \otimes \left(\vec{E}_i - \vec{R}_Q \otimes \vec{P}_i \right) \tag{14}$$

$$\vec{P}_i = \vec{E}_i + C \times AV \otimes \vec{S}_i \tag{15}$$

After all iterations, every solution of the candidate is updated on the basis of the best solution and fitness. This mechanism is expressed as:

$$\vec{P}_i = \begin{cases} \vec{P}_i + AV\left[\vec{Y}_{\min} + \vec{R} \otimes \left(Y_{\max} - \vec{Y}_{\min} \right) \right] \otimes \vec{W} & when\ r \le FAT \\ P_i + \left[FAT(1-r) + r \right] \left(\vec{P}_{r1} - \vec{P}_{r2} \right) & when\ r > FAT \end{cases} \tag{16}$$

where $\vec{P}_{r1}, \vec{P}_{r2}$ are the randomly selected preys, FAT is the fish aggregation tool, $\vec{W}$ is the vector having binary number, $\vec{Y}_{\max}$ and $\vec{Y}_{\min}$ are the maximum and minimum limits.

Figure 1 shows the flowchart of MPA.

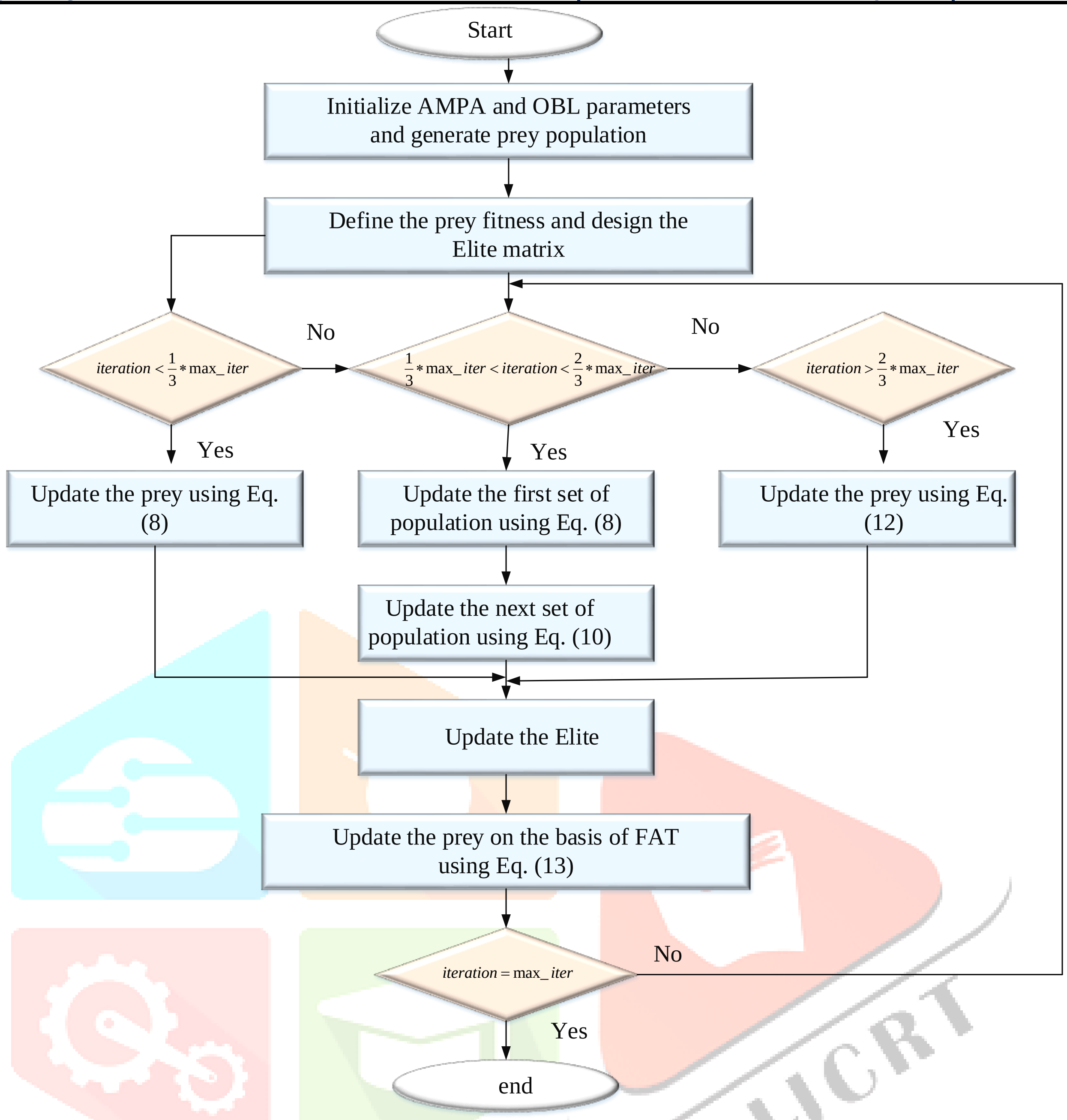

Figure 1: Flowchart of MPA

3.3.2 Opposition based learning

Opposition based learning is used for boosting the performance of MPA. It generates new opposition on the basis of present solution for improving the search process. For formulating the learning, let us consider the Y^o is the opposite value and $Y \in [l_b, u_b]$ is expressed as:

$$Y^o = l_b + u_b - Y \qquad (17)$$

The opposite value $Y = (Y_1, Y_2, ...Y_n)$ is the value in $Y_1, Y_2, ...Y_D$ and $Y_j[l_{bj}, u_{bj}]$. It is given as:

$$Y_j^o = u_{bj} + l_{bj} - Y_j \qquad (18)$$

Here, Y^o and Y are the solutions obtained by the fitness function. Hence, the best solution is stored and the remaining is eliminated. This opposition based learning in MPA produces a highly distribution initial population and balances the trade off among the exploration and exploitation. Due to this efficiency, the MPA model selects the essential features needed for the classification process.

4. Experimental Results

4.1 Simulation Settings

The proposed OMPA optimization framework (OMPA-OF) has been implemented in the LoRaWAN cross-layer simulation framework [13]. The performance is compared with the existing Basic Variable neighborhood search (BVNS) [5] optimization model. The performance metrics packet delivery ratio, packet loss rate, average residual energy and throughput are measured, by varying the nodes. Table 1 shows the simulation settings.

Number of Devices	20 to 100
Size of the topology	150m X 150m
Propagation Model	Two Ray Ground
Antenna Model	OmniAntenna
MAC protocol	IEEE 802.15.4
Traffic Source	CBR
Packet size	512 bytes
Traffic Rate	50Kb
Initial Energy	12 Joules
Transmit power	0.3 watts
Receiving power	0.3 watts
Simulation time	100 seconds
Transmission range	30m

Table 1 Simulation Settings

4.2 Results & Analysis

The performances of the techniques are evaluated by varying the number of devices from 20 to 100.

Devices	**OMPA-OF**	**BVNS**
20	0.9713	0.9311
40	0.9455	0.9169
60	0.9261	0.9028
80	0.9216	0.8823
100	0.9093	0.8511

Table 2 Results for Packet success rate

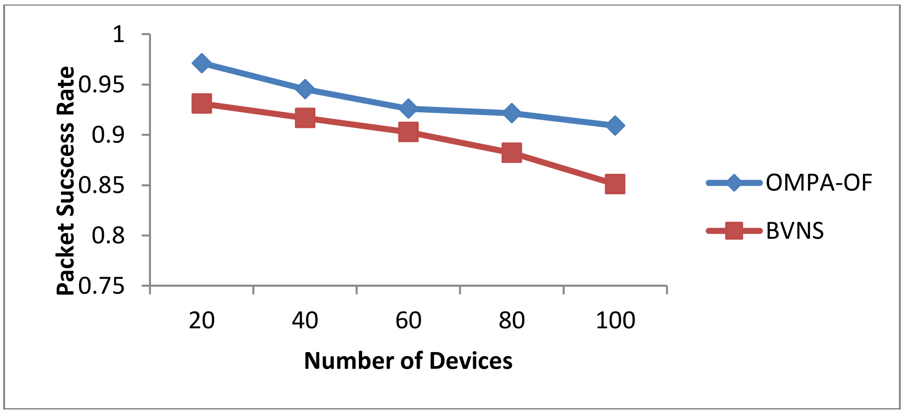

Figure 2 Results of Packet success rate

The packet delivery ratios of all the protocols are shown in Table 2 and Figure 2. From the figure, it can be seen that OMPA-OF has 4% higher success rate than BVNS.

Devices	OMPA-OF	BVNS
20	0.1015	0.1758
40	0.1144	0.1825
60	0.1221	0.2036
80	0.1273	0.2086
100	0.1345	0.2149

Table 3 Results for Packet loss rate

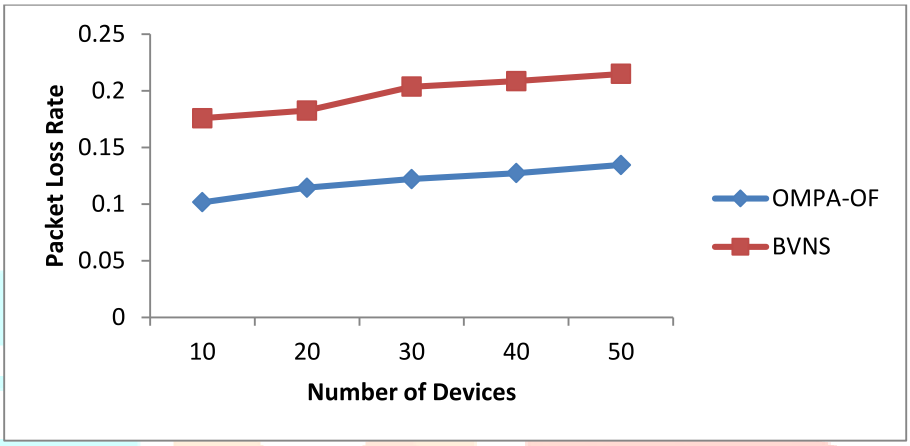

Figure 3 Results of Packet loss rate

The average packet loss rates of all the protocols are shown in Table 3 and Figure 3. From the figure, it can be seen that packet loss rate of OMPA-OF is 39% lesser than BVNS, for varying the devices.

Devices	OMPA-OF (Joules)	BVNS (Joules)
20	14.56	12.96
40	14.37	12.56
60	13.54	12.15
80	13.38	11.74
100	13.14	11.37

Table 4 Results for Residual energy

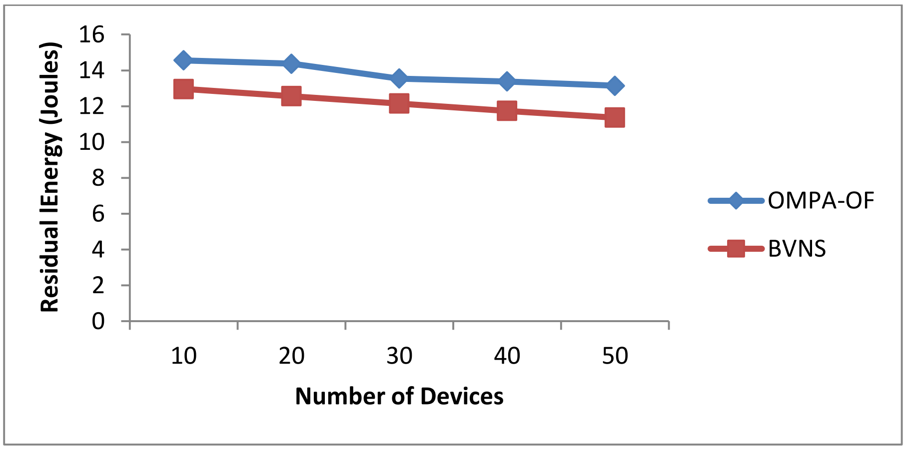

Figure 4 Results of average Residual Energy

The average residual energies of all the protocols are shown in Table 4 and Figure 4. From the figure, it can be seen that residual energy of OMPA-OF is 12% higher than BVNS, for varying the devices.

Devices	OMPA-OF (Mb/s)	BVNS (Mb/s)
20	0.783	0.614
40	0.734	0.599
60	0.658	0.534
80	0.615	0.512
100	0.562	0.478

Table 5 Results for Throughput

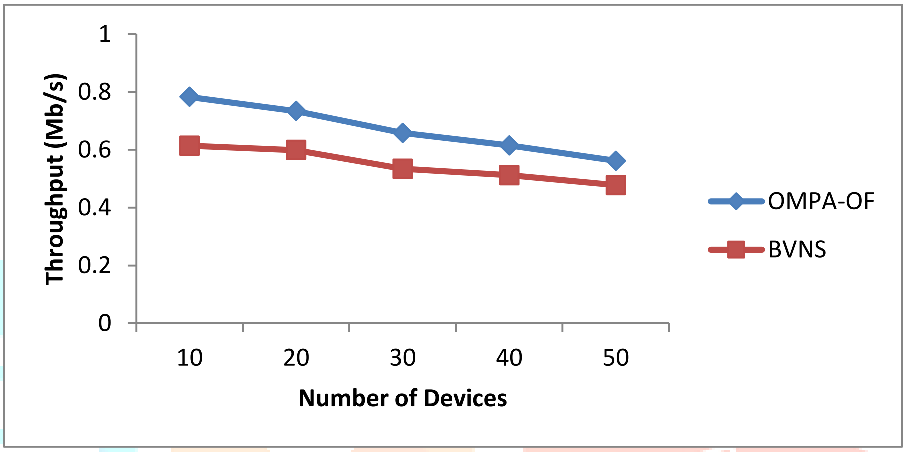

Figure 5 Results of Throughput

The throughput measured for all the protocols are shown in Table 5 and Figure 5. From the figure, it can be seen that throughput of OMPA-OF is 18% higher than BVNS, for varying the devices.

5. Conclusion

In this work an OMPA-OF is designed for energy efficiency and long-term communication in IoT networks. The fitness function is derived in terms of bandwidth, spread factor, total transmission time and energy consumption ber bit. Then relay nodes are selected based on maximum fitness function. The proposed OMPA-OF has been implemented in the LoRaWAN cross-layer simulation framework. The performance is compared with the existing (BVNS optimization model. By simulation results, it has been shown that OMPA-OF achieves maximum energy efficiency and packet success rate with reduced packet loss rate.

References

1. Priyanka, B., Udayaraju, P., Koppireddy, C. S., & Neethika, A. (2023). Developing a region-based energy-efficient IoT agriculture network using region- based clustering and shortest path routing for making sustainable agriculture environment. *Measurement: Sensors*, *27*, 100734. https://doi.org/10.1016/j.measen.2023.100734

2. Davanam, G., Kalyanasundaram, S., Singh, N., Gunjan, V. K., Roy, S., Rahebi, J., Farzamnia, A., & Saad, I. (2022). Multi-Controller model for improving the performance of IoT networks. *Energies*, *15*(22), 8738. https://doi.org/10.3390/en15228738

3. Akram, V. K., & Challenger, M. (2021). Connectivity maintenance in IoT-based mobile networks: Approaches and challenges. *Computer Science and Information Systems (FedCSIS), 2019 Federated Conference On*. https://doi.org/10.15439/2021f102

4. Laguidi, A., Tamtam, S., & Mejdoub, Y. (2023). A technique to improve IoT connectivity based on NB-IoT and D2D communications. ITM Web of Conferences, 52, 01010. https://doi.org/10.1051/itmconf/20235201010

5. Gava, M. A., Rocha, H. R. O., Faber, M. J., Segatto, M. E. V., Wörtche, H. J., & Silva, J. a. L. (2023). Optimizing resources and increasing the coverage of Internet-of-Things (IoT) networks: an approach based on LORAWAN. *Sensors*, *23*(3), 1239. https://doi.org/10.3390/s23031239

6. Gočal, P., & Macko, D. (2019). EEMIP: Energy-Efficient Communication using timing channels and Prioritization in ZigBee. *Sensors*, *19*(10), 2246. https://doi.org/10.3390/s19102246

7. Surenther, I., Sridhar, K., & Roberts, M. K. (2023). Maximizing energy efficiency in wireless sensor networks for data transmission: A Deep Learning-Based Grouping Model approach. *Alexandria Engineering Journal*, *83*, 53–65. https://doi.org/10.1016/j.aej.2023.10.016

8. Lee, B. M. (2023). Enhancing IoT Connectivity in Massive MIMO Networks through Systematic Scheduling and Power Control Strategies. *Mathematics*, *11*(13), 3012. https://doi.org/10.3390/math11133012

9. Sultan, R. (2022). IoT connectivity optimization in RIS-Assisted Full-Duplex massive MIMO networks. *2022 IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*. https://doi.org/10.1109/pimrc54779.2022.9977635

10. Wang, Q., Liu, L., Zhang, S., & Lau, F. C. M. (2021). On Massive IoT Connectivity with Temporally-Correlated User Activity. *2021 IEEE International Symposium on Information Theory (ISIT)*. https://doi.org/10.1109/isit45174.2021.9517805

11. Kalyanasundaram, S., Madda, R. B., Chen, C., Patan, R., & Cheelu, D. (2018). Low energy aware communication process in IoT using the green computing approach. *IET Networks*, *7*(4), 258–264. https://doi.org/10.1049/iet-net.2017.0105

12. Shen, Z., Yokota, K., Tagami, A., & Higashino, T. (2019). Energy-Efficient Activation/Inactivation Strategy for Long-term IoT Network Operation. *2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation*. https://doi.org/10.1109/smartworld-uic-atc-scalcom-iop-sci.2019.00161

13. Gilles Callebaut, Geoffrey Ottoy, Liesbet Van der Perre, “Cross-Layer Framework and Optimization for Efficient Use of the Energy Budget of IoT Nodes”, 2019 IEEE Wireless Communications and Networking Conference (WCNC).