[1]* Mr. A. Ramesh

[2] Dr. K. Kamali

Energy Efficiency and Network Lifetime Optimization with Adaptive Power Control for IoT Networks

Journal of Electrical Systems

Abstract:- The main objective of this paper is to optimize the energy efficiency and network lifetime of Internet of Things (IoT) devices using meta-heuristic optimization technique. It also aims to adjust the transmit power of the nodes based on network connectivity and signal strength. Hence in this paper, Energy Efficiency and Network Lifetime Optimization with Adaptive Power Control (EENLO-APC) technique for IoT networks is proposed. In this technique, energy efficiency and network lifetime of IoT devices are optimized by applying Electric Fish Optimization (EFO) algorithm. After this, the transmit power of the IoT end device is adaptively adjusted based on the connectivity and Signal to Noise Ratio (SNR) metrics. By simulation results, it has been shown that EENLO-APC achieves maximum energy efficiency and packet delivery ratio with reduced packet loss rate, while varying the number of nodes and data rate.

Keywords – Internet of Things (IoT) , Energy Efficiency, Network Lifetime, Electric Fish Optimization (EFO), Adaptive Power Control

1. Introduction

By incorporating the idea of intelligence or smartness, the Internet of Things (IoT) is revolutionising and expanding fundamental study domains into new dimensions. A few instances of this transformation are the new domains, which include intelligent transportation systems, autonomous vehicles, smart homes, smart cities, smart industries, and smart healthcare. Other well-known IoT application domains include automated grids for industrial metering, automated security devices like alarms and surveillance systems, vehicle telematics for fleet management and navigation, remote maintenance for industrial automation and vending machine control, and manufacturing control for production chain monitoring [1]. The aim of inventions towards a smarter and greener society for sustainability reasons is what has led to the incorporation of IoT in nearly every area of human existence. The number of IoT use cases being implemented is growing daily. There were 500 million Internet-connected devices in 2003, compared to 6.3 billion people on the planet. By 2022, there will likely be over 50 billion linked devices worldwide, which is four times as many people as there are on Earth. This predicted high growth demonstrates both our reliance on IoT-enabled devices and the exponential rate at which the Internet of Things is expanding globally [2].

Two main obstacles stand in the way of smaller and smarter devices realising a smarter world through IoT enabled connected gadgets: communication and computational power limitations resulting from limited energy resources. The majority of sensor-enabled Internet of Things devices primarily rely on batteries for power. When sensors are in operation, these devices use battery power to gather and transmit data among nearby devices. Data analysis improves the sensed and gathered information's accuracy. Nevertheless, the analysis results in an increase in IoT device energy usage [3]. In order to enable the automation of intelligent decision-making, sensor-enabled smart devices continuously sense, receive, compute, and distribute information. The power supply to the terminals is a significant barrier to the growth of the Internet of Things. It is very crucial to research the upkeep of terminals' sustainable operation, as wired and battery power are unable to adequately address the issue of energy scarcity in terminals. In order to prolong the running duration of network terminals, energy harvesting technology is regarded as a crucial way to lower system energy consumption and prolong device operation. Numerous terminals are installed indoors, where solar energy supply is not suitable, because traditional renewable energy sources like wind and solar are sporadic and unpredictable [4].

The incorporation of sustainability in recent greener and smarter world research has made the optimisation of energy usage in sensor-enabled Internet of Things devices one of the basic challenges. Various energy-efficient ways have been established for sensor-enabled Internet of Things (IoT) devices by technical standardisation groups as the European Telecommunications Standard Institute (ETSI), 3rd Generation Partnership Projects (3GPP), and the Institute of Electrical and Electronics Engineering (IEEE) [5].

In IoT, effective power control is essential for a number of reasons. Because IoT devices frequently run on tiny batteries or restricted energy sources, they require an effective power management system to increase their operational lifetime and reduce the frequency with which they need to be replaced or recharged. By optimising energy use and minimising waste and resource conservation, efficient power regulation in IoT is essential to

[1] Assistant Professor, Dept. of CSE, Annamalai university, Annamalainagar, Chidambaram-608002, Tamilnadu, India.
*rameshmkdn@gmail.com
2Assistant Professor, Dept. of CSE, Annamalai university, Annamalainagar, Chidambaram-608002,Tamilnadu ,India
Kamaliaucse2006@gmail.com

lowering ecological impact. Furthermore, good power management makes it possible for IoT devices to function dependably in a variety of settings and conditions, assuring continuous operation and improving overall efficacy and performance. Ensuring sustainability, extending the lifespan of equipment, and maximising the functionality of connected devices all depend on effective power regulation in the IoT [6].

Because a variety of computing and communication factors are taken into account for scalable IoT use case implementation scenarios, cross layer optimisations have been demonstrated to be superior in the literature. Because of the inherent complexity and variety of requirements of IoT systems, cross-layer approaches must be implemented. Enhancing the efficiency, dependability, and performance of IoTs networks is made possible by integrating cross-layer techniques, which promote better coordination and communication among various protocol layers. Cross-layer approaches provide optimised resource utilisation, decreased latency, greater security, and better adaption to dynamic IoT environments by enabling information flow and coordination across many layers, including the physical, data connection, network, transport, and application layers. By addressing the issues of scalability, QoS, and energy efficiency, this method makes IoT systems more adaptable and responsive, supporting the unique requirements of many applications and enhancing the resilience and functionality of IoT networks [7][8].

1.1 Problem Identification

The challenges posed by IoT devices with limited resources will be overcome by developing cross-layer approaches that are adapted to their constraints. Methods for reducing energy usage need to be examined while maintaining acceptable performance levels on devices with constrained memory, processing power, and battery life. The domain of standardisation efforts and interoperability protocols must be explored for cross-layer approaches in IoT. These optimisations should be made universally applicable to a broad range of IoT devices, platforms, and communication protocols for maximising energy efficiency and facilitating seamless integration and adoption. The possibility of combining artificial intelligence and machine learning techniques need to be examined to create cross-layer optimisations.

This research work aims to

- optimize the energy efficiency and extend the network lifetime of IoT using meta-heuristic optimization technique.
- adjust the transmit power of the nodes based on network connectivity and signal strength.

2. Related Works

ELITE, a cross-layer OF is proposed that uses less energy and introduces the Strobe per Packet Ratio (SPR) as a routing parameter [9]. The number of transmitted strobes per packet as a result of the MAC layer's Radio Duty Cycling (RDC) regulations is indicated by SPR. This newly defined metric can distinguish between nodes based on the relative phase shift that currently exists between them when communicating. It is intended to be used in conjunction with asynchronous MAC protocols. ELITE attempts to choose a path that requires its nodes to receive fewer strobe transmissions.

As a smart agriculture application, we put forth an IoT-based WSN architecture with various design tiers [10]. Agricultural sensors first gather pertinent data, then use a multi-criteria decision function to identify a collection of cluster heads. In order to accomplish reliable and effective data transmissions, SNR is also used to measure the strength of the signals on the transmission connections. By employing the linear congruential generator's recurrence, data transfer from agricultural sensors to base stations is secured.

In order to maximise energy efficiency in wireless LoRa networks made up of LoRa end devices and a flying GW and prolong the network lifetime, deep reinforcement learning (DRL) is suggested [11]. Given the air-to-ground wireless link and the availability of spreading factors, the skilled DRL agent can assign TPs and spreading factors to end devices in an efficient manner. Furthermore, the flying GW is allowed to allocate resources online and modify its optimal policy while on-board. Retraining the DRL agent with a smaller action space allows for this.

An open-source cross-layer assessment framework is designed for Low Power Wide Area networks (LPWANs) [12]. With energy models, downlink messages, and adaptive data rate characteristics, it expands on the state-of-the-art. Thus, it is possible to test and assess theories and transmission strategies. The LoRaWAN protocol is evaluated as a representative scenario. In order to effectively realise LPWANs in terms of energy efficiency and throughput, a cross-layer is essential. Broadcasting longer packets on quasi-static networks can reduce energy consumption by up to a factor of three. However, there will be an energy penalty in unfavourable dynamic circumstances.

Through performance monitoring of underlying communication technologies, an energy-efficient framework is built for an ideal balance between the energy spent by connected devices in a complex and time-critical IoT system [13]. It also focuses on addressing the trade-off between network performance for communicating nodes and energy consumption. After the nodes for time-sensitive Internet of Things systems are modelled using Reinforcement Learning (RL), an Energy Harvesting MAC protocol is created.

3. Proposed Methodology

3.1 Overview

This paper proposes an Energy Efficiency and Network Lifetime Optimization with Adaptive Power Control (EENLO-APC) technique for IoT Networks. Figure 1 shows the block diagram of this technique. As seen from the figure, in this technique, the energy efficiency and network lifetime of IoT devices are optimized by applying EFO algorithm. After this, the transmit power of each IoT end device is adaptively adjusted based on the connectivity and link quality metrics.

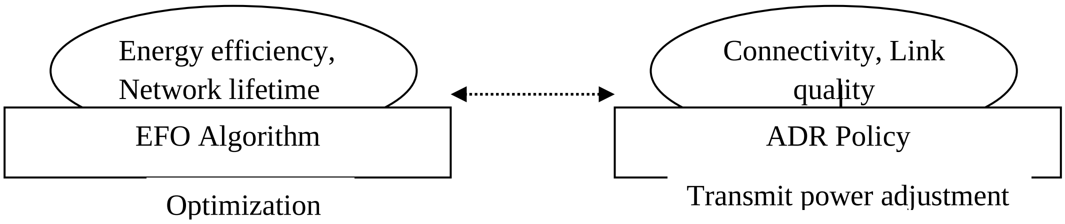

Figure 1 Block diagram of EENLO-APC technique

3.3 Optimizing Energy Efficiency using meta-heuristic Optimization

In this phase, energy efficiency and network lifetime of IoT devices are optimized using Electric Fish Optimization (EFO) algorithm. In this algorithm, a fitness function is derived in terms of energy efficiency and network lifetime. Then the nodes with maximum fitness function are selected.

3.3.1 Estimation of Fitness function

The energy efficient (EE) is defined using the following equation:

$$EE = \frac{T}{(P_T + P_C)} \quad (1)$$

Where, T is the sum rate of the system and P_c is the circuit consumption power and P_T is the transmission power
The network lifetime (NL) is derived in terms of the energy consumption (E_c) and the number of data packets p as given below:

$$NL = \frac{E_c}{p} \quad (2)$$

Then a fitness function of the i^{th} node is derived as given by the following equation

$$f_i = v_1 \frac{NL_{\max}}{NL_i} + v_2 \frac{EE_{\max}}{EE_i} \quad (3)$$

Where v_1, v_2 and v_3 are weight values in the range of (0,1), NL_{max} and EE_{max} are the maximum values of NL and EE, respectively

3.3.2 EFO Algorithm

Based on the fitness function derived in Eq. (3), energy efficiency and network lifetime of the IoT devices are optimized, using Electric Fish Optimization (EFO) algorithm [15].
EFO is motivated by the growth of many optimization algorithms. In this technique, electric fish solutions are randomly initialized in the search space within the region limits, as specified in the following equation

$$q_{ij} = q_{\min} + rand(q_{\max} + q_{\min}) \quad (4)$$

Where q_{ij} indicates the j^{th} position in the i^{th} solution, max and min indicates the maximum and minimum limits of the region, respectively.
In EFO, positions with higher occurrence utilize active electrolocation and other positions utilizes passive electrolocation.
The occurrence value is defined within the maximum (f_{max}) and minimum (f_{min}) values of the fitness function.

$$f_i(t) = f_{min} + \left(\frac{f_w - f_i}{f_w - f_b}\right)(f_{max} - f_{min}) \quad (5)$$

where $f_i(t)$ denotes the fitness of i^{th} solution at t^{th} iteration,
f_w and f_b denote the worst and best fitness values.
The amplitude cost of the i^{th} solution (A_i) is computed as

$$A_i = s(A_i(t-1)+(1-s)f_i \quad (6)$$

where s is a value in range [0, 1].
The EFO algorithm has the following major steps:

1. Construct the population q as defined by the below equation

$$q_{ij} = (UB_j - LB_j) * rand + UB_j - LB_j,\ j = 1,2,...N \quad (7)$$

Where N is the number of individuals and D is the dimension of each solution.

2. While ($t < t_{max}$),

Change each q_i into binary mode as

$$bq_i = \begin{cases} 1 & if\ q_{ij} \geq 0.5 \\ 0 & otherwise \end{cases} \quad (8)$$

3. Compute the fitness value of each q_i based on δ and L_{nw} as specified in the following qquation.

$$f_i(t) = \gamma_1.\delta(i) + \gamma_2.L_{nw}(i) \quad (9)$$

Where γ_1, γ_2 are weight values between (0,1)

$$f_i(q_i) = z_i \times e \quad +(1-z_i) \times \left(\frac{\text{BQi}}{D}\right) \quad (10)$$

Where, e is the error classification factor

z is the parameter that normalizes the components of the fitness function

4. Find the best individual q_b.
5. Select the nodes with maximum fitness function.
6. Evaluate the performance with various measures.

3.4 Adaptive Transmit Power Adjustment based on Connectivity

After optimizing the energy efficiency using EFO, the transmit power (P_T) of the node is adaptively adjusted based on the connectivity using Adaptive Data Rate (ADR) policy.

3.4.1 Connectivity

Due to the mobility of the nodes, the connectedness or number of connections (CC) of the system follows a probability (P_r). The greater the network connectivity, the higher the value of CC.

The network connectivity probability is defined based on binomial theory, using the following equation:

$$\Pr(x = CC) = \sum_{x=0}^{n} \binom{n}{x} \left[\frac{\pi r^2}{s} \left(1 - \frac{\pi r^2}{s}\right)^{n-x} \right] \quad (11)$$

where r is the radius of the nodes.

3.4.2 Link Quality

Measuring the link quality (LQ) at every node helps balance the load between nodes. The link quality can be measured in terms of Interference Rate (IR) and noise rate. As long as they both use the same radio link and are in range of each other's interference, transmissions on one wireless link may interfere with those on another. Noise may also have an impact on this. The achievable data rate is therefore greatly influenced by transmission interference and noise.

3.4.3 Adaptive Data Rate (ADR) Policy

ADR is a policy for optimizing the data rates and power consumption in the network. While optimizing the power consumption of the devices, it also ensures that the data can be retrieved at the gateways. In this policy, either the transmit power is reduced or the data rate is increased.

After receiving the data, each gateway executes the ADR policy. The gateway requires the SNR values from each received uplink data and LQ along the link l_j.

The margin value λ is measured as

$$\lambda = (SNR_{mes} - SNR_{req}) + LQ_j \quad (12)$$

where SNR_{req} and SNR_{mes} represent the required and measured SNR values at each gateway.

Then the following steps are executed:

ADR Policy

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1. Check Pr(x=CC)
2. If Pr $\geq$ 1, then
3. Measure λ

If λ > 0 and $\lambda > \lambda_L$ then

Decrease P_T

Else if λ < 0

Increase P_T

Else if λ = 0

Keep the same P_T

Else

Keep the same P_T

In this policy, initially the connectivity of the nodes is checked using Eq. (10). It there exist at least one connection, then the transmit power is adjusted by estimating the margin value. If the margin λ is non-zero and higher than a threshold λ_L , then the additional P_T is reduced . If it is negative, then the insufficient power is increased. If it is exactly becomes 1, then P_T is not adjusted. On the other hand, if there is no active connection or Pr=0, then P_T is not adjusted and kept the same value.

4. Experimental Results

4.1 Simulation Settings

The proposed EENLO-APC technique has been implemented in the LoRaWAN cross-layer simulation framework [12]. The performance is compared with the existing Mean-Field Game (MFG) technique [8]. 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 Nodes	10 to 50
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

A. Varying the nodes

The performances of the techniques are evaluated by varying the number of nodes from 10 to 50.

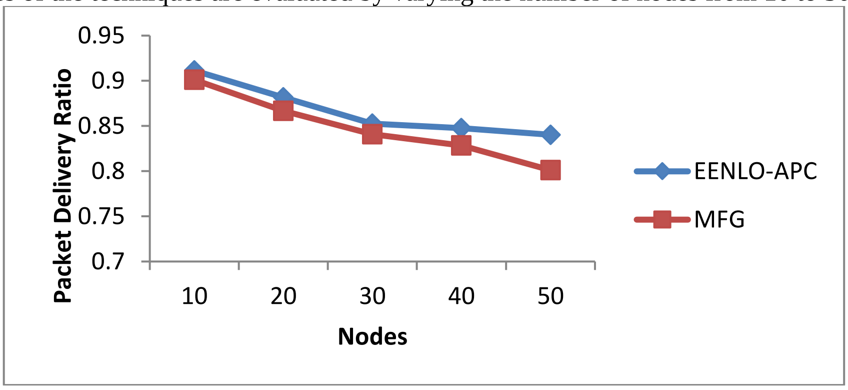

Figure 2 Results of Packet delivery ratio Vs Nodes

The packet delivery ratios of all the protocols are shown in Figure 2. From the figure, it can be seen that EENLO-APC has 2.2% higher delivery ratio than MFG.

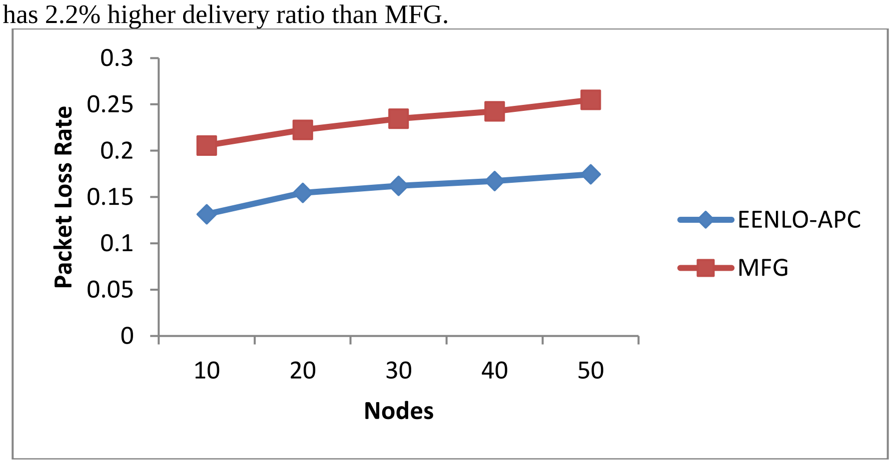

Figure 3 Results of Packet loss rate Vs Nodes

The average packet loss rates of all the protocols are shown in Figure 3. From the figure, it can be seen that packet loss rate of EENLO-APC is 32% lesser than MFG, for varying the nodes.

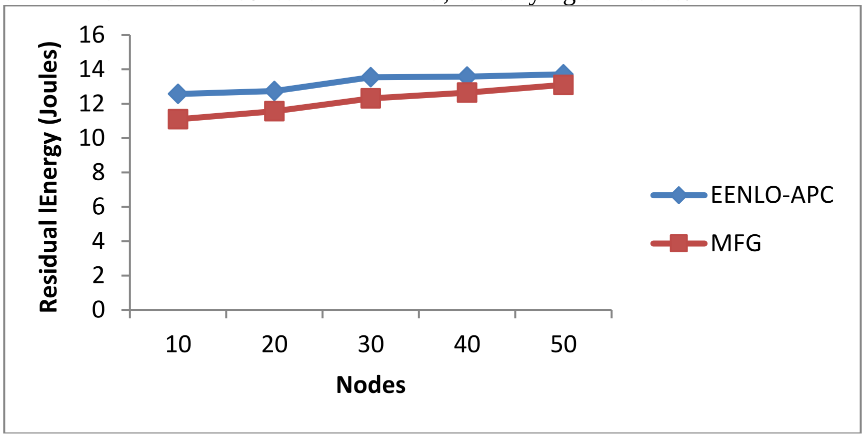

Figure 4 Results of Residual Energy Vs Nodes

The average residual energies of all the protocols are shown Figure 4. From the figure, it can be seen that residual energy of EENLO-APC is 8.2% higher than MFG, for varying the nodes.

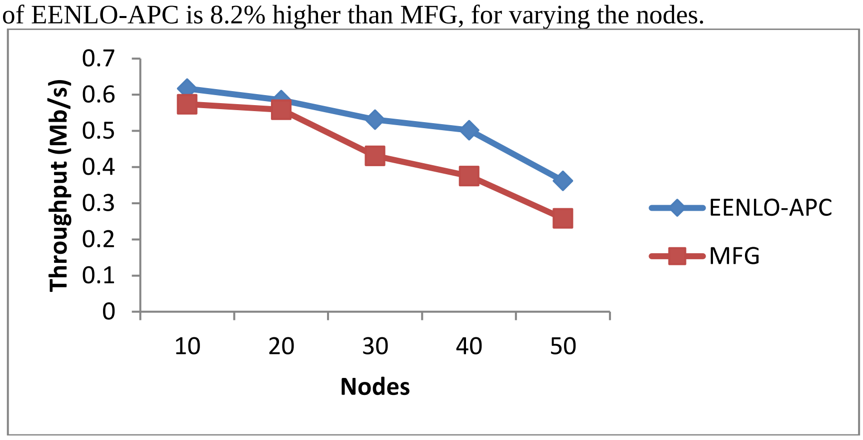

Figure 5 Results of Throughput Vs Nodes

The throughput measured for all the protocols are shown Figure 5. From the figure, it can be seen that throughput of EENLO-APC is 17% higher than MFG, for varying the nodes

B. Varying the data rate

The performances of the techniques are evaluated by varying the data rates from 50 to 250Kb/s

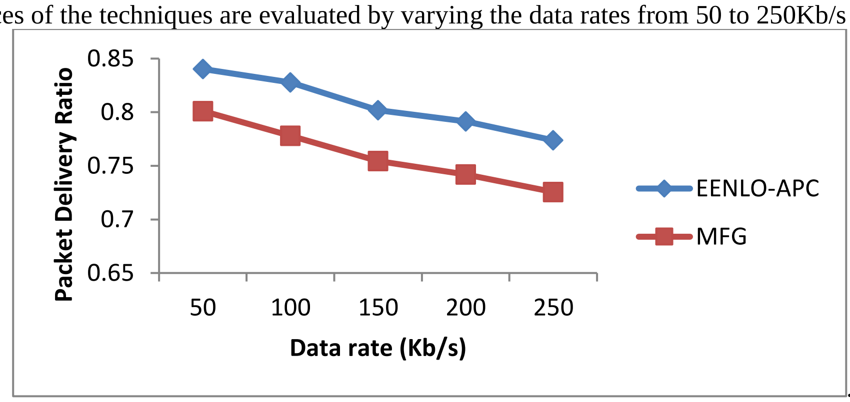

Figure 6 Results of Packet delivery ratio Vs Data rate

The packet delivery ratios of the two techniques are shown in Figure 6. From the figure, it can be seen that EENLO-APC has 8% higher delivery ratio than MFG, for varying the rates.

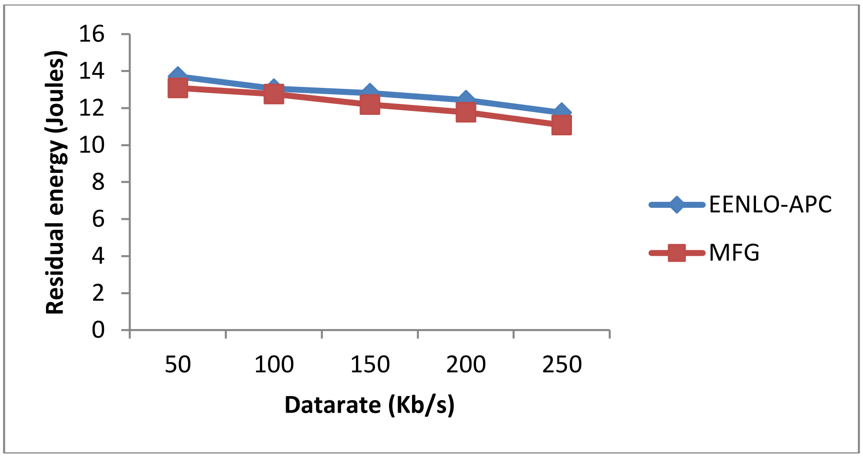

Figure 7 Results of Residual Energy Vs Data rate

The average residual energies of the two techniques are shown Figure 7. From the figure, it can be seen that residual energy of EENLO-APC is 4% higher than MFG, for varying the rates.

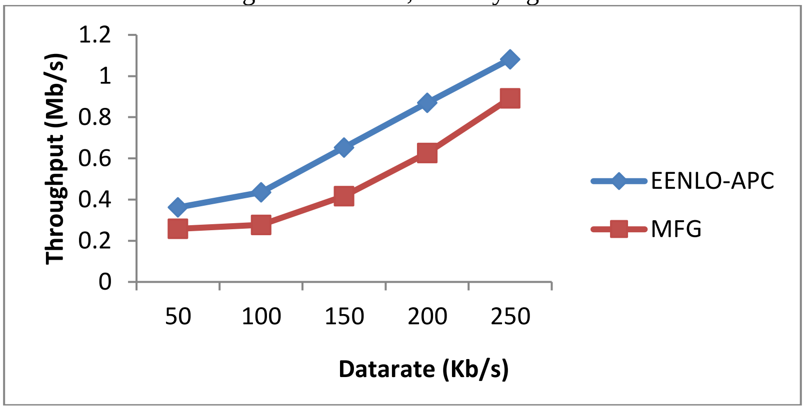

Figure 8 Results of Throughput Vs Data rate

The throughput measured for all the protocols are shown Figure 8. From the figure, it can be seen that throughput of EENLO-APC is 32% higher than MFG, for varying the rates.

5. Conclusion

In this paper, we propose Energy Efficiency and Network Lifetime Optimization with Adaptive Power Control (EENLO-APC) technique for IoT Networks. In this technique, the energy efficiency and network lifetime of IoT devices are optimized by applying EFO algorithm. After this, the transmit power of each IoT end device is adaptively adjusted based on the connectivity and SNR metrics. The performance of EENLO-APC technique is compared with the existing MFG technique in terms of packet delivery ratio, packet loss rate, average residual energy and throughput. By simulation results, it has been shown that EENLO-APC achieves maximum energy efficiency and packet delivery ratio with reduced packet loss rate, while varying the number of nodes and data rate.

Funding: The authors didn't get any funding support for this research.

Conflict of Interest: The authors don't have any conflict of Interest

Data Availability: The authors didn't use any third party data materials in their research.

Authors Contribution: In this manuscript preparation author 1 prepared the concept and author 2 prepared the implementation part and author 3 prepared the english grammatical errors.

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