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Long Range (LoRa) Communication Protocol with a Novel Scheduling Mechanism to Minimize the Energy in IoT

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Abstract: The proliferation of IoT devices has increased the concerns about their cohesive energy consumption. Many of these gadgets are portable, but there are also a sizable number that are permanently connected to the internet. Most battery-powered devices need a huge amount of power to operate, however not necessarily for all gadgets. The device has a finite lifespan due to the limitations of its power source. The main objective of this study is on developing a strategy for routing Internet of Things devices and selecting an appropriate frequency range. The unique communication technology LoRa (Long Range), designed for Internet of Things (IoT) devices, has been chosen as the frequency band routing. It is an optimization method based on the modified version of the Environmental Adaptation Method. Our proposed method minimizes the energy consumption as well as throughput of the routing mechanism. The average response time of proposed method is 0.09095 which is lower than other existing metaheuristic approaches such as ACO, GA, K-Means, PSO, DE are 0.11484, 11225, 0.15364, 0.12591, 0.12265 respectively.

Keywords: *Energy, IoT, optimization, routing, Environmental Adaption Method.*

1. Introduction

Devices connected to the Internet of Things (IoT) confront more difficult processing demands as the IoT spreads around the globe. However, IoT devices often have limited processing power and battery life [1]. As the number of Internet of Things (IoT) devices grows to the billions in the next years, so does interest in IoT network optimization. Therefore, the IoT network must be structured to minimize the effect of this traffic on other services that utilize cellular and other kinds of networks. Without a solution to network issues, the Internet of Things (IoT) will not be able to continue to expand [2].

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Developments in transportation, governance, environmental and quality-of-life must be made as a result of the fast expansion in urbanization over the last decade. The Internet of Things (IoT) offers a wide range of sophisticated and ubiquitous applications for smart cities. IoT applications are using more and more energy, while the number and needs of IoT devices are rising [3]. In order to do this, energy-efficient city solutions must be able to cope with the problems that arise from their usage. For the implementation of complex energy systems in smart cities, energy management is viewed as a crucial paradigm [4][5][6]. Communication and networking technologies are used to overcome the challenges posed by urbanization and population increase in a smart city. Smart cities are made possible in large part by the Internet of Things (IoT), which consists of sensors, actuators, and communication and network devices. A wide range of city activities may be detected and monitored in real time using the sensing devices [7][8].

In the near future, common industrial, personal, workplace, and residential devices, equipment, and objects are predicted to be able to sense, transfer, and analyses data. It takes longer for all systems to respond when there is a lot of network traffic [9][10].

System response time is reduced and energy consumption expenses are reduced by selecting the shortest route from source to destination. It is because of the problems that different individuals have different viewpoints about the Internet of Things (IoT). A routing protocol includes a variety of task scheduling techniques.

It is possible to classify these job scheduling methods as either heuristic or metaheuristic. Rather of using metaheuristic methods, which aim for global optimums by exploring the whole solution space, heuristic methods are more suited for finding a local best solution. IoT's colossal number of characteristics makes metaheuristic techniques less useful than they first look. [12]. One of the most well-known algorithms in this meta-heuristic sector is the ACO algorithm or its derivatives, which have been used by several academics to find the shortest route in various routing issues. Using a stochastic local search strategy, the ACO algorithm shapes the routing patterns that a swarm of artificial ants may generate [13].

Our strategy is based on a metaheuristic method that seeks the shortest route while also taking environmental variables into account in order to maximize energy usage. Environmental variables like humidity and temperature have a significant impact on IoT device energy usage. The IoT devices are specifically targeted by these environmental parameters, and a new scheduling technique called Improved Environmental Adaptation Method is given. In addition, our solution incorporates these characteristics depending on the device's location. You may get information about an area of a device by looking up its location in a lookup table, and then using that information, you can determine its average temperature and humidity for a certain time period.

Below is the outline for the rest of the paper: Section 2 describes the related work in a nutshell. The methods employed in this study are discussed in Section 3. The findings and analysis are presented in Section 4. The conclusion and potential implications are discussed in Section 5.

2. Related Work

An optimization issue is often made up of inputs, outputs, restrictions, and several objective functions [14]. The IoT network optimization challenge consists of several components that must be combined in a variety of ways to address a particular network problem. According to our evaluation of past work, there are primarily two approaches to optimizing data. (1) Formulating a solution for the shortest route using an existing and well-known optimization procedure. IoT scheduling issues may be solved by using heuristics, which is an innovative approach.

It does not imply that we cannot combine the two methods of tackling the issue of routing in IoT devices. Using a combination of the previously mentioned two methodologies for IoT devices, we can always get an answer. When the issue is complex or the current techniques are ineffective, both approaches are commonly used together [15]. There are two types of heuristics: one is an algorithm that provides a rapid approximation solution for more complex issues, and the other is a greedy method that produces the optimal solution by using assumptions.

a) Proposition based on Particle Swarm Optimization (PSO)

One of the most well-known population-based optimization algorithms, PSO can resolve optimization problems that traditional algorithms may have trouble with via an iterative process of checking and modifying the location of the particles. It was PSO's inspiration to study the swarming behavior and schooling nature of animals and other species. Numerous research papers on different optimization techniques have been published in the last several years using PSO [16] as a means of optimization.

This approach employs an orthogonal learning technique to provide fast route recovery when the path to the sink node fails due to sink node displacement, as well as an alternative path for efficient path repair, as described in [17] by its developers. Results show that the method lowers communication costs and increases the longevity of the network.

According to [18], PSO was used by the authors to test different transmission power levels for the sensor cluster's individual nodes without causing any disconnected sections to form. The end results show that adopting PSO saved more sensor energy compared to common nodes placed with a single transmission power. As the selection of cluster heads has a considerable influence on network performance, energy efficiency is an important consideration in cluster-based capillary networks.

It was suggested by Wen et al. [19] to improve PSO (IPSO) by applying weight factors collected from experimental simulations. These findings show that this strategy incorporates issues affecting weight, information source reliability, information redundancy, and hierarchical structure consolidation into its design.

b) Proposition based on GA (Genetic Algorithm)

Genetic Algorithm uses Mark Baldwin's theory of natural election and the tactics of evolution of the species to find the best solution to a given issue. Contained and unconstrained challenges may both benefit from the usage of GA.

By combining the well-known k-means clustering algorithm with the GA, Amol et al. introduced a novel technique in [20]. The k-means clustering approach is used to find the best cluster head and the best clusters, and the GA method is used to find the best route. Because GA is dependent on the cluster-energy head's level and the length of the route, the resulting path will be more reliable, quicker, and have a longer lifespan.

[22] proposed a heuristic-based evolutionary strategy to identifying the most efficient nodes in the network for sensor data interpretation.

Using a variety of parameters, the top candidates are narrowed down to those with the largest storage capacity and energy output.

(c) **Propositions based on Non-dominated Sorting Genetic Algorithm II.**

NSGA II is a member of a family of algorithms in which numerous goals must be addressed. Using the term "multi-objective" implies that we are aiming for more than one goal at the same time. Multiple goals are common in IoT device energy optimization/minimization problems. For example, we may want to decrease energy consumption while simultaneously ensuring that data packets follow the shortest route possible, requiring the fewest number of intermediary nodes. Considering that our communication technology has a hard limit on the number of intermediary nodes it can support, we may also be restricted by range and data rate constraints. As a result, using a multi-objective optimization strategy might be beneficial. Authors in [23] suggested a multi-objective evolutionary technique to optimize the distributed sensor network, consequently reducing energy usage, in this area of study.

Our primary focus is on meta-heuristic scheduling; thus, we are just going to talk about other scheduling approaches like heuristics and other statistical methods here.

Numerous meta-heuristic ideas for effective scheduling techniques may also be found, such as applications based on ACO (Ant Colony Optimization), (DE) Differential Evolution, Grey Wolf Optimization (GWO), and Ant Colony Optimization (ACO) [23][24].

3. Proposed Environmental Adaptation Method

We have chosen Environmental Adaptation Method (EAM) [25] as a base for the optimization of our routing protocol. The improvement is basically focused on its application on our objective of energy minimization while routing huge number of IoT devices across a specific region. Since we have well defined boundaries of regions, hence we can add adaption parameters based on the region to which it is routed. The name comes from this tuning of environmental parameters as Improved Environmental Adaptation Method, and hence we achieve a better routing protocol which not only minimizes the energy consumption as well as throughput of the routing mechanism.

One of the evolutionary techniques for tackling single objective optimization issues is the Environmental Adaption Method (EAM) [26]. Following EAM's initial proposal, several versions were proposed and we designed it specifically for our use in routing protocol for IoT devices. The Environmental factor that we have considered comes from the humidity and temperature, as these factors of humidity and temperature greatly effects the energy consumption of IoT devices. These environmental conditions or rather we can say noise is added as a tuning parameter to the adaptation operator of the EAM.

EAM is one of the various evolutionary approaches proposed in the past. EAM uses adaptive learning approach that helps in faster convergence to the optimal solution. IoT devices' performance relies on quicker response time, hence a faster convergence is most sought. We have used binary version of EAM because in routing we already have binary values which need not to be converted to real and vice-versa, hence computational complexity involved in this process is also decreased.

The results when compared with similar metaheuristic algorithms are very promising than the other proposed state-of-the-art algorithms in this metaheuristic domain, which are discussed later in the results and discussion section.

The operators of EAM have been shown in equation 1:

$$P_{i+1} = \left[round \left(\alpha(g) * (P_i)^{\frac{F_n(P_{in})}{F_{avg}}} + \beta(g) \right) \right] \% \, 2^L \quad (1)$$

Where, α(g) and β(g) are random numbers L represents the total number of bits in an individual, F_*avg*is the average fitness value of the current population. Then alteration operator and selection operator change the unfit solution and selects the best solution respectively. The modified optimization algorithm proposed in this paper which determines the optimal routing path can be shown as in algorithm 1.

Algorithm 1: Modified Environmental Adaptation Method for energy minimization in IoT

Input: dimension, SL, SH, max_eval

Output: Solutions participated in optimal path

Begin:

*1. Fix population size in a linearly increasing way as per the dimension using equation initial_population = 50*dimension,* *2. Generate the population randomly from within the search boundary of [SL, SH]*

3. Calculate the throughput values of all the possible paths between the given 2 nodes.

4. Initialize counter i as 0

do

create temp_population using equation 1

change population using selection operators in algorithm2

increment counter i

while (i<Max_evaluations);

End

The selection process of EAM is done by selection operator whose algorithm can be depicted as in algorithm 2.

Algorithm 2: Selection operator of Modified Environmental Adaptation Method for energy minimization in IoT

Input: previous_population, current_population

Output: population for adaptationoperator

Begin:

1. Combine previous_population and current_population

2. Calculate all possible paths between any given 2 nodes.

3. Select only the better half paths/particles/individuals from the merged population.

End

After getting an optimal routing path among the nodes/IoT devices, the communication protocol Long Range (LoRa) is used. This communication protocol is specially designed for IoT devices since its deployment to large scale IoT devices is very cost effective in terms of battery life of small IoT devices. Moreover, it can establish the desired long-range broadcasts of up to 10 Kms when obstructions to the communication path is minimal as seen in villages. For lighting systems LoRa has already been proven to decrease the energy by 40% [11]. For all other use case scenarios as expected in cities it has been proven to decrease the energy consumption by about 20% as the reference [12] suggests. The LoRa devices that we have used is depicted in Figure 1(a), 1(b), 1(c) and 1(d).

1(a) LoRaWan Gateway

1(b) LoRa Gateway

1(c) A LoRa Module

1(d) LoRa Terminal

Fig 1: (a) LoRaWan Gateway we have used for connectivity with the Wide-Area-Network. (b) LoRa Gateway for communication with the internet (c) and (d)are LoRa modules and LoRa based raspberry pi used as terminals.

4. Results and Discussions

The results are simulated in MATLAB in which we were routing in between any 2 selected nodes with 5000 IoT devices. The hardware and software configuration of our experiment module setup are described in Table 1 & 2 respectively.

Table 1 Hardware requirements

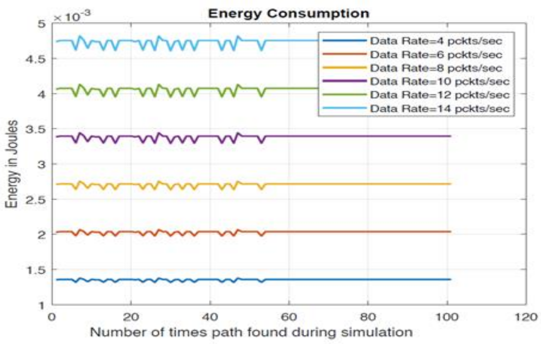
CPU	intel core i7 7700K with speed 4.2Ghz
RAM	2100 Mhz with size as 16GB
Graphics	1080 Ti with size as 11 GB running at 1708 Mhz
Storage	m.2 SSD with 240 GB

Table 2 Software requirements

Java	JDK 17.0
Compilers	MATLAB Compiler, MinGw Compiler
Software Package	MATLAB 2022a (Evaluation Version)
Simulator	MATLAB based IoT Routing Sim.

LoRa Nodes that we have used are depicted in figure 2.

Fig 2 LoRa Nodes



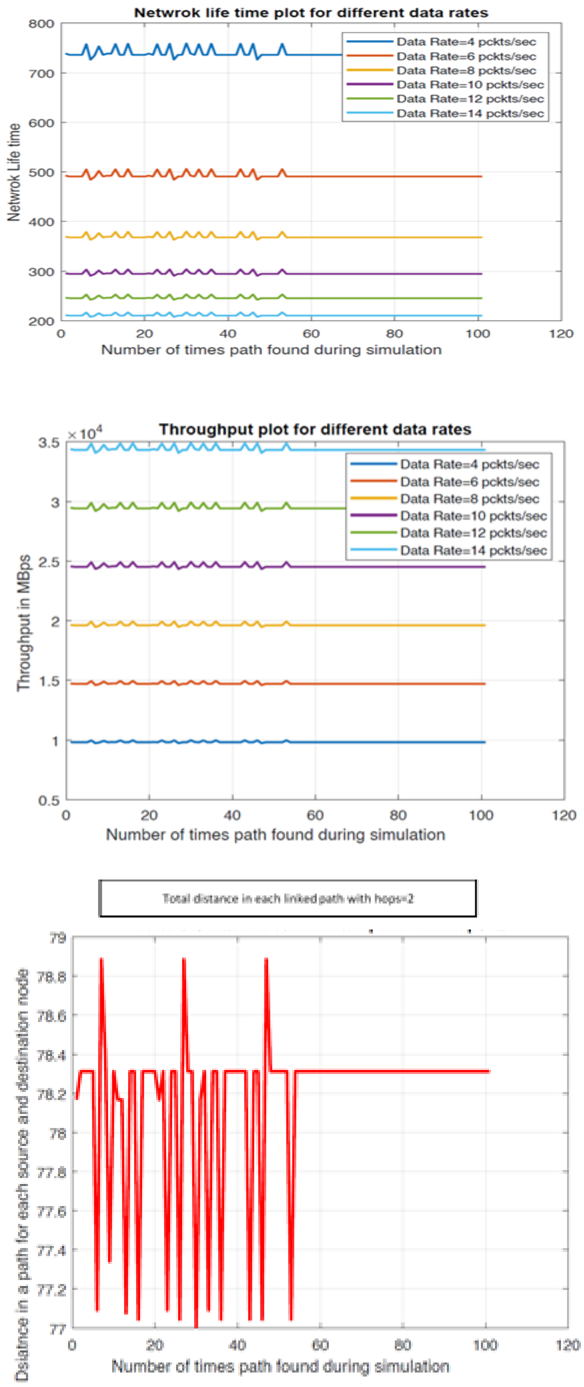
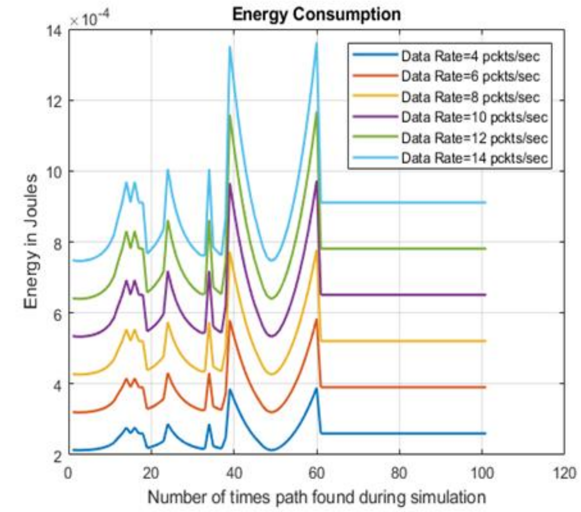
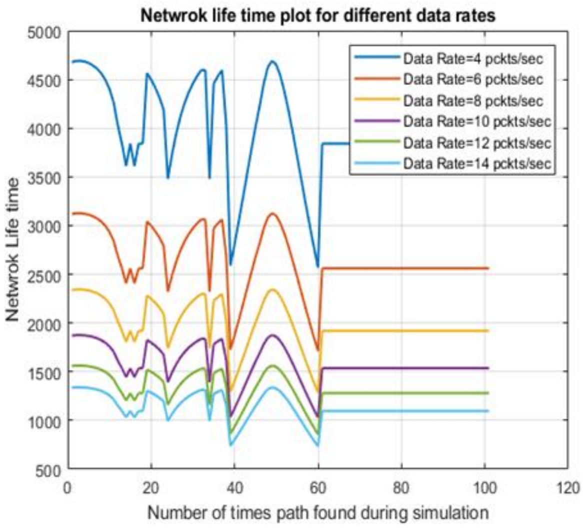
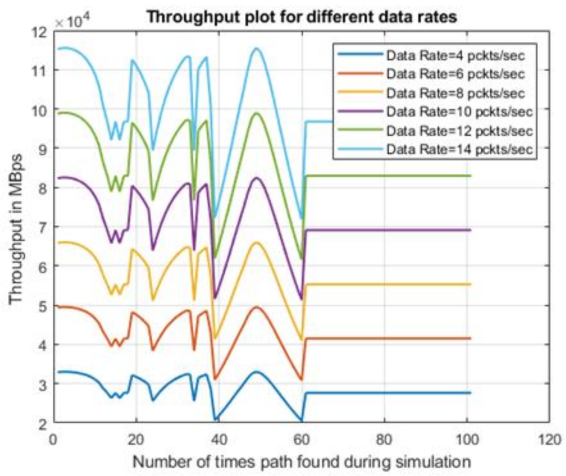


Fig 2 Results of Energy Consumption, Network Life-time, Throughput and Distance when routing between randomly selected 2 devices in a cluster of 5000 devices.


Energy Consumption
Energy in Joules
Number of times path found during simulation
Data Rate=4 pckts/sec
Data Rate=6 pckts/sec
Data Rate=8 pckts/sec
Data Rate=10 pckts/sec
Data Rate=12 pckts/sec
Data Rate=14 pckts/sec


Netwrok life time plot for different data rates
Netwrok Life time
Number of times path found during simulation
Data Rate=4 pckts/sec
Data Rate=6 pckts/sec
Data Rate=8 pckts/sec
Data Rate=10 pckts/sec
Data Rate=12 pckts/sec
Data Rate=14 pckts/sec


Throughput plot for different data rates
Throughput in MBps
Number of times path found during simulation
Data Rate=4 pckts/sec
Data Rate=6 pckts/sec
Data Rate=8 pckts/sec
Data Rate=10 pckts/sec
Data Rate=12 pckts/sec
Data Rate=14 pckts/sec

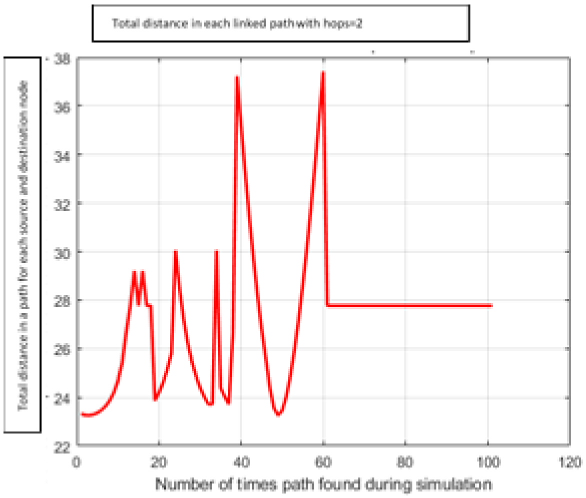


Fig 4 Results of Energy Consumption, Network Life-time, Throughput and Distance when routing between randomly selected 2 devices in a cluster of 300 devices.

The response time involved in scheduling of the job also determines the energy consumption of the IoT devices. The shorter the response time the less an IoT device would have to wait for the job execution. We see in figure 4, the response time of our IoT device routing algorithm has outperformed the famous heuristic and meta-heuristic algorithms.

The result for the average response time in tabular as well as graphical format has been shown as Table 3 and figure 4 respectively.

Table 3 Average response time of other algorithms as compared with IEAM.

Nodes	**ACO**	**GA**	**K-Means**	**PSO**	**DE**	**IEAM**
10	0.0193	0.0194	0.0265	0.0215	0.0208	**0.0147**
20	0.0507	0.0432	0.0585	0.054	0.0471	**0.0349**
30	0.0590	0.0583	0.0805	0.0649	0.0625	**0.0445**
40	0.0863	0.0789	0.1138	0.0886	0.0871	**0.0705**
50	0.1105	0.1026	0.1479	0.1117	0.1138	**0.0875**
60	0.1218	0.1179	0.1605	0.1455	0.1413	**0.1017**
70	0.1447	0.1406	0.2015	0.1585	0.1632	**0.1157**
80	0.1578	0.1705	0.2307	0.1856	0.1698	**0.1329**
90	0.1863	0.18	0.2439	0.2043	0.2034	**0.1449**

100	0.212	0.2111	0.2726	0.2245	0.2175	**0.1622**

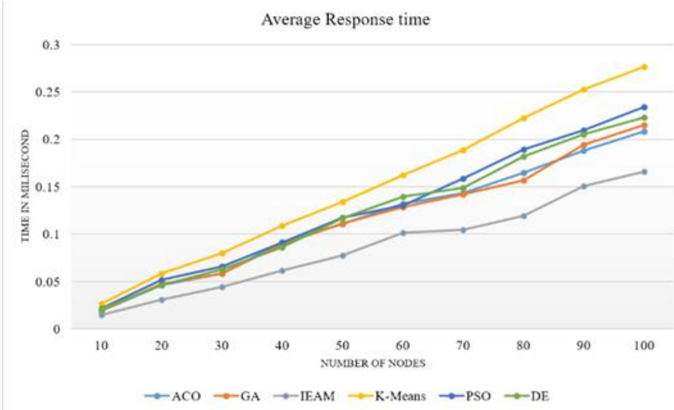


Fig 4 Response time of IoT devices when used with Ant Colony Optimization (ACO), Genetic Algorithm (GA), Improved Environmental Adaptation Method (IEAM), K-Means, Particle Swarm Optimization (PSO) and Differential Evolution (DE).

5. Conclusion and Future Work

This study presents a method for scheduling and determining the shortest path between nodes and IoT devices that employs a metaheuristic approach. We employed LoRa as a communication protocol to further reduce power usage after finding an appropriate path in the node cluster. We could have also used other communication approach between the nodes such as satellite communication, Bluetooth, Wifi(2.4Ghz/5Ghz) and others, but the minimized consumption of energy that we get after scheduling it with IEAM will be shadowed by modes of communication other than LoRa. As metaheuristic approaches offers a mathematical proof of the propositions which are well established by the benchmark functions. The energy usage and throughput of the routing mechanism are both reduced by our proposed solution. When compared to other current metaheuristic approaches such as ACO, GA, K-Means, PSO, and DE, the average response time of the proposed method is 0.09095, whereas those of ACO, GA, K-Means, PSO, and DE are 0.11484, 11225, 0.15364, 0.12591, and 0.12265, respectively.

We can do more improvements in the proposed approach while combining the improved versions with other spectrum too. We will be extending our work within the domain of effect of environmental conditions on the energy consumption of the IoT devices and incorporate other factors which are responsible for energy consumption.

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