

Link Utilization for IOT Quality of Service using Hybrid swarm in Wireless Sensor Networks

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Abstract – The wireless sensor networks (WSN) that find its use in various applications of internet of things(IOT) have been regarded as the norm of today’s world. The wireless sensor networks (WSN) as its name suggests have nodes or sensory nodes that have limited energy for operation, because of their limited battery life and their use in certain unreachable places and hence they have been termed as energy-constrained devices. In order to overcome such restrictions it is need of hour to develop such approach whose focus must be on power optimization by using cross-layer coding and also in turn maintaining the quality of service in data trafficking. The data communication with a high level of accuracy in a wireless sensor network has been required, in order to achieve it, it is a necessary condition to have optimal coding which helps us in achieving a maximum level of intelligence with minimum computation. In order to achieve this we have developed a technique based on particle swarm optimization (PSO), which helps in bettering the link parameters that consists of bit error rate (BER), loss, energy and signal to noise ratio (SNR) and side by side restrains, the utilization of energy by wireless nodes. The infrastructure which has been obtained by this, will consist of a low number of sensors, have low cost, can be deployed fastly, having long lifetime, along with low maintenance, and also have high quality of service (QOS). The method used by us has been tested on two channels like additive white gaussian noise channel (AWGN) and rayleigh channel, that shows better quality of service and hence also improves the utilization of link up to a great extent.

Keywords – WSN, IOT, BER, SNR, PSO.

I. INTRODUCTION

With the increase in WiFi and 4G-LTE wireless Internet access, an evolution towards ubiquitous information and communication networks has already been evident. However, for the Internet of Things the vision of a successful emerging computing paradigm must go beyond traditional mobile computing scenarios that use smartphones and portables, and in turn evolve into connecting everyday existing objects and embedding intelligence into our environment. For technology disappearing from the consciousness of the user, the Internet of Things demands: (1) a shared understanding of the situation of its users and their appliances, (2) software architectures and ubiquitous communication networks to process and convey the contextual information to where it is relevant, and (3) the analytical tools in the Internet of Things that aims for autonomous and smart behavior [1]. The wireless sensor network (WSN) forms part and parcel of (IoT) for different applications as discussed above and therefore can be widely utilized in various application scenarios of the Internet of Things (IoT) in modern societies, such as smart intelligent agriculture, environmental monitoring, intelligent medical treatment, early warning of natural disasters, etc. The WSN is an important implementation of IoT and the architecture of

such a network based on WSN usually comprises various dynamic nodes and base station (BS), which cooperates to perform different works as data acquisition, data processing, and transmission tasks. Each node in a network is mainly composed of a sensor unit, wireless transmitting module, power module, data processing, and storage unit. Usually, the nodes are embedded micro-devices with limited processing, storage, and communication capabilities along with limited power for operation, which is the most critical challenge in other terms referred to as energy limitation. Simultaneously, it is difficult to replenish the extra energy demand of the deployed nodes. Hence, the exhaustion of energy means the “death” of those nodes [2]. Apart from power components and communications, IoT systems are mainly consisting of sensors and actuators. Sensors are known as the system's sensory organs that sense the particular physical condition such as temperature, pressure, or simply used for video/audio recording in this particular case senses the changes in the environment. The actuators are also called as the action or response organs that are responsible for reacting to these changes. Wireless sensor networks (WSN) are defined as a wireless network that consists of spatially distributed embedded sensors that operate cooperatively as data sources because of their ability of sensing and collecting data about the physical and environmental conditions, that includes temperature,

light, pressure, motion, or pollutants of the particular area which has been under study. After collecting the information they convert this information into digital data and lastly pass the collected data via the network to a head sink point. A new enhanced algorithm has been developed which is called “multi-verse optimizer with overlapping detection phase (DMVO)” in order to solve area coverage problems, which is done by finding the best spatial distribution of WSN. A computational intelligence algorithm (multi-verse optimizer (MVO) has been considered as hybridized with Generalized Opposition-Based Learning (GOBL) method to perform editing spatial locations of sensors. In addition to these applications, DMVO has been used for deploying WSN in the IoT ecosystem of the East Oweinat area which is located in the southwest, Egypt[3]. The problem of wireless signal quality for the requirement of applications that can be fulfilled if communication is done through a reliable network, this was done based on the functional design and implementation of a complete WSN platform that would have been used for a long term environmental monitoring which is further based on IoT applications. The infrastructure so designed was low cost, having low number of sensors with fast deployment as well as long lifetime requires low maintenance, and having high quality of service allowed for required specifications and design of the platform and of all its components. Low-effort platform's use was also considered while starting from the specification and at all design levels for a wide range of related monitoring applications. The motivation for this study was established by a very important concept of data which is important because if the data bits received have an error it can corrupt the forecast as in mentioned particular application. The analysis of two important parameters have been done as BER over different channels as Longley-Rice, LOS, NLOS, Hata Ikegammi fading channels etc, and determining of optimal values for IEEE 802.15.4 standard for improving BER performance [4]. Another application is wireless video sensor networks that has fascinated the researchers in order to gain the interest in improvising real issues occurring in streamlining of framework and control of the framework execution in transfer of speed requirements. Rate-twisting (R-D) speculations is normally connection in order to break down the framework compartment inside capacity of transmission confinements. The rate-twisting qualities of a framework have been utilized so that the issue of finding the base number of bits which have been transmitted for accomplishing a given level of twisting. A remote video sensor organization is a framework that contains spatially circulated remote video sensor networks (WVSNs) [5]. In order to maximize the fault tolerance and minimize communication delay for VNE(virtual network embedding) in WSN environments that focus on IoT services. The reactive optimization of fault tolerance and delay in communication for service-oriented heterogeneous virtual networks in IoT have been used.

Explicitly, the main components of the framework have been listed as: The fault tolerance optimization problem which is a mathematical formulation mainly concerned with fault tolerance and communication delay as the two conflicting objectives in WSNs environments. An adaptive non-dominating sorting which is based on a genetic algorithm (A-NSGA) was developed in order to solve the optimization problem. The solution framework consists of representation of chromosomes, tolerance of fault, computational delay, mutation and crossover and non-dominance based sorting. Simulations thus performed in order to analyze the performance of A-NSGA in optimizing fault tolerance for virtualization in WSNs are done [6].

II. THEORETICAL FRAMEWORK

The primary objective of such an approach is to develop a methodology for power optimization using cross-layer coding and maintain the quality of service in data trafficking. Wireless sensor nodes are inherently energy-constrained devices. Furthermore, most of the time, these devices are deployed in hard to reach areas where recharge or replacement of batteries is not possible. Therefore, energy conservation through efficient utilization of available energy helps to prolong the operation of the network. Wherein data communication in a wireless sensor network is required with a high level of accuracy, it is necessary to have optimal coding to achieve a maximum level of skill with minimum computation. Complex coding is present to overcome the interference effect in wireless sensor networks; the coding demands a high level of resources to perform the calculation. Hence, requiring massive power consumption minimizing the node life. In such a system, power could be optimized during coding, forwarding, or receiving. Wireless signal quality because applications can fulfill their requirement if communication through the reliable operation, this was done based on the functional design and implementation of a complete WSN platform that can be used for a range of long term environmental monitoring IoT applications. The infrastructure was low cost, low number of sensors, fast deployment, long lifetime, low maintenance, and high quality of service was allowed for in specification and design of the platform and all its components.

The main object of this research is based on the followings principles of the wireless sensor networks used in internet of things(IoT) applications as discussed below in the following points:

To improve the quality of service of wireless communication in a different type of noise channel like AWGN, Rayleigh.

Additive white Gaussian noise (AWGN) is a basic noise model that is used in information theory to mimic the effect of many of the random processes that occur in nature. The modifiers denote specific characteristics:

Additive because it is used to add any noise that might be intrinsic to the information system.

White It refers to the idea that it has a uniform power across the frequency band for the information system. It is homologous to the white color because it has uniform emissions at all frequencies in the visible spectrum.

Gaussian As it has a normal distribution in the time domain having an average time domain value of zero.

The AWGN channel has been represented by a series of outputs which is at a discrete time event index . is considered as the sum of the input and noise , where has been independent and identically distributed and has been drawn from a zero-mean normal distribution with variance (the noise). The has been further assumed as not be correlated with the .

$$(1) \quad (2)$$

The capacity of the channel has been considered as infinite unless the noise is nonzero, and the has been sufficiently constrained. The most common constraint on the input is "power" constraint, that requires a codeword which would be transmitted through the channel, we have:

$$(3)$$

where can represent the maximum channel power. Therefore, the channel capacity for the power-constrained channel has been given by:

$$(4)$$

Where is the distribution of . Expand which is writing it terms of the differential entropy:

$$(5)$$

But X and Z are independent, therefore

$$= \quad (6)$$

Evaluating the differential entropy of a Gaussian gives:

$$= \quad (7)$$

Because and are independent and their sum gives

From this bound, we can infer from a property of the differential entropy that

$$(8)$$

Therefore, the channel capacity can be given by the value of highest achievable bound on the mutual information:

$$(9)$$

Where is maximized when:

$$(10)$$

Thus the channel capacity for the AWGN channel is given by:

$$= (1+ \quad) \quad (11)$$

Rayleigh fading It is a statistical model which shows the effect of a propagation environment on a radio signal, such as that used by wireless devices.

Rayleigh fading has been viewed as a reasonable model for tropospheric and ionospheric signal propagation as well it shows the effect of heavily built-up urban environments on radio signals. Rayleigh fading is much suitable when there is no dominant propagation along a line of sight between the transmitter and receiver. If there is a dominant line of sight, Rician fading may be more applicable. Rayleigh fading has been viewed as a special case of two-wave with diffuse power (TWDP) fading.

The multipath fading results because of the fluctuations of the signal amplitude and the addition of signals that arrive with different phases. This phase difference has been caused because the signals have traveled different distances by traveling along different paths. Since the phases of the arriving paths have been changing rapidly, the received signal amplitude thereby undergoes rapid fluctuation that is often being modeled as a random variable with a particular distribution.

The most commonly used distribution for multipath fast fading is the Rayleigh distribution, whose probability density function (pdf) is given by : (12)

Here, it has been assumed that all signals suffer nearly the same attenuation, but they arrive with different phases. The random variable which corresponds to the signal amplitude is r. Here is the variance of the in-phase and quadrature components. It has been considered theoretically that the sum of such signals will result in such an amplitude which has the Rayleigh distribution of the above equation . This can be also supported by measurements at various frequencies. The phase of the complex envelope of these received signals has been normally assumed to be uniformly distributed in $[0, 2\pi]$.

When strong LOS signal components also exist, the distribution is found to be Rician, the pdf of such function is given by: (13)

Where is regarded as the variance of the in-phase and quadrature components. A is considered as the amplitude of the signal of the dominant path and is the zero-order modified Bessel function of the first kind. Normally this dominant path has been seen to significantly reduce the depth of fading, and in terms of bit error rate (BER) Ricean fading provides superior performance to Rayleigh fading. The probability of having line-of-sight (LOS) components is dependent on the size of the cell. The smaller the cell the higher its probability of having LOS path. If there is a situation of having no dominant path then the Rician pdf reduces to Rayleigh pdf. When A is large as compared with σ , the distribution is then approximated to Gaussian. Thus, since Ricean distribution covers also Gaussian and Rayleigh distribution, thus mathematically the Ricean fading channel can be considered to be a general case.

To propose an approach for reduction of power consumption. Energy in Wireless Sensor networks

(WSNs) represents an essential aspect in areas such as designing, controlling and operating the sensor networks. Minimizing the consumed energy in WSNs applications has been regarded as a crucial issue for the network effectiveness and efficiency in terms of lifetime, cost and operation. Number of algorithms and protocols have been proposed and implemented to decrease energy consumption. WSNs operate with battery powered sensors. Sensor batteries are not easily rechargeable because of their places of use, even though they have restricted power. It has been seen that network failure occurs due to the sensor's energy insufficiency. MAC protocols in WSNs have achieved low duty-cycle by employing periodic sleep and wakeup.

To improve Loss and Bit Error Rate by swarm intelligence approach. It has been done by joint antenna combination and symbol detection. More specifically, this new approach simultaneously determines the transformation weighting for antenna combination to lower the RF chains which are called for and to design the minimum bit error rate (MBER) detector which is used to effectively mitigate the impairment caused due to interference. The joint decision statistics is highly nonlinear and the particle swarm optimization (PSO) algorithm has been employed to reduce the computational overhead.

To analyze the comparison of proposed and existing approaches using QAM modulation. Quadrature Amplitude Modulation or QAM is a form of modulation that has been widely used for modulating data signals onto a carrier and then used for radio communications. QAM, when used for digital transmission in radio communications applications, it has been seen that it was able to carry higher data rates than ordinary amplitude modulated schemes and phase modulated schemes. This approach can be analyzed with the following parameters as:

- BER In digital transmission, the number of error bits has been given as the number of received bits of a data stream in a communication channel that have been altered due to various factors such as noise, interference, distortion or bit synchronization errors. The bit error rate (BER) is the number of errors bits per unit time. The bit error ratio (also BER) is defined as the number of error bits divided by the total number of transferred bits in a particular time interval. Bit error ratio is a unitless performance measure, which can be often expressed as a percentage. For example, in the case of QPSK modulation and AWGN channel, the BER as function of the E_b/N_0 is given as:

$$BER = () \quad (15)$$

- LOSS Path loss, or path attenuation, has been defined as the reduction in power density (attenuation) of an

electromagnetic wave as it propagates through space. This term has been commonly used in wireless communications and signal propagation. Path loss may be caused due to a number of effects, which include free-space loss, refraction, diffraction, reflection, aperture-medium coupling loss, and absorption. Path loss is also affected by terrain contours, environment (urban or rural, vegetation and foliage), propagation medium (dry or moist air), the distance between the transmitter and the receiver, and the height and location of antennas.

- SNR Signal-to-noise ratio (SNR or S/N) is defined as a measure that compares the level of a desired signal to the level of background noise. SNR can be further explained as the ratio of signal power to the noise power, often expressed in decibels. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. Signal-to-noise ratio is defined as the ratio of the power of a signal (required input) to the power of background noise (unwanted input): $SNR = (16)$ where P is average power. Both signal and noise power must be measured at the same points in a system, and within the same system bandwidth. Depending on whether the signal is a constant (s) or a random variable (S), the signal-to-noise ratio for random noise N becomes: $SNR = (17)$ where E refers to the expected value, i.e. in this case the mean square of N and can be expressed as: $SNR = (18)$
- Energy Reduction Duty cycling schemes is the most compatible technique for energy saving and others are the data-driven approaches that can be used to improve energy efficiency. Further communication protocols are also used to save energy for sensor networks.

III. PROPOSED ARCHITECTURE

1. Working Principle

The profound advances that take place in micro-electro-mechanical-system (MEMS) and wireless communication technology that helps in enabling the development of wireless sensor networks (WSNs). WSNs have thus attracted enormous attention for their potential applications which are in diverse areas such as disaster warning systems, environment monitoring, health care, safety, surveillance, intruder detection, etc. A WSN is believed to consist of a large number of tiny, low power and inexpensive sensor nodes, which has been deployed randomly or manually over an unattended target area. These sensor nodes have been equipped with sensing, processing and communication components along with a power unit.

These sensor nodes are used to periodically collect local information of the targets, process the data and

finally send it to a remote base station (called sink). The data is received at the sink which is further connected to the Internet for the public notice of the phenomena. The main drawback of a WSN is the limited and irreplaceable power source of the sensor nodes. Moreover, in many of the applications, it has been seen as almost impossible to replace the sensor nodes when their energy is completely exhausted. Therefore, the factor of energy consumption for the sensor nodes is regarded as the most challenging issue for the long run operation of WSNs. This drawback can be overcome by using low-power radio communication hardware, energy-aware medium access control (MAC) layer protocols, etc.

However, another technique based on clustering is regarded as the most effective technique for energy saving of the sensor nodes. This cluster based architecture divides sensor nodes into several groups called clusters. Each of the clusters has a leader known as cluster head (CH). All the sensor nodes are used to sense local data and then send them to their corresponding cluster head. The CHs then accumulated the local data and finally sent it to the base station directly or via other CHs.

2. Initialize swarm optimization

particle swarm optimization (PSO) is known as a computational method that is used to optimize a problem by iteratively and trying to improve a candidate solution with regard to a given measure of quality. It is used to solve a problem by having a population of candidate solutions, here designated as particles, and then moving these particles around in a search-space which depends on a simple mathematical formulae over the particle's position and velocity. Each particle's movement has been influenced by its local best known position, but has also been guided towards the best known positions in the search-space, which are regularly updated when better positions are found by other particles. This is then expected to move the swarm toward the best solutions.

PSO has originally been attributed towards Kennedy, Eberhart and Shi and was first designed for simulating social behaviour, as a stylized representation which shows the movement of organisms in a bird flock or fish school. The algorithm was then simplified and it has been observed to perform optimization. Also, PSO does not intend to use the gradient of the problem being optimized, that means PSO does not require that the optimization problem should be differentiable as has been required by classic optimization methods such as gradient descent and quasi-newton methods.

The block diagram below shows the working principle of particle swarm optimization(PSO) which is the basis of our methodology of optimization

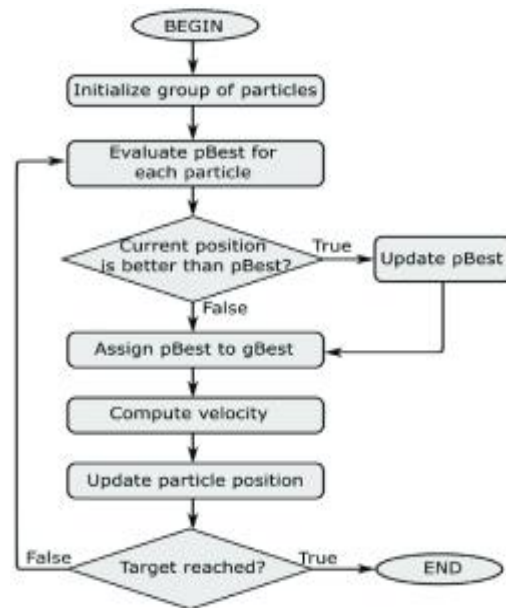


Fig.3.1. Block diagram representation of PSO.

3. Brief introduction of PSO

Particle swarm optimization has been inspired by the behaviour of different social organisms in groups, such as bird and fish learning or ant colonies. This type of algorithm imitates the interaction between members in order to share information. Particle swarm optimisation has been applied to a large number of areas in optimisation and also in combination with other existing algorithms. This method is believed to perform the search of the optimal solution through agents, which are also referred to as particles, whose trajectories have been adjusted by a stochastic and a deterministic component. Each particle is seen to be influenced by its 'best' achieved position and the groups 'best' position, but tends to move randomly. Here a particle i is defined by its position vector, x_i , and its velocity vector, v_i . On every iteration, each particle changes its position according to the new velocity and is given below as:

$$v_i = \omega v_i + \phi_1 (p_{best} - x_i) + \phi_2 (g_{best} - x_i) \quad (19)$$

$$x_i = x_i + v_i \quad (20)$$

where x_{best} and g_{best} are used to denote the best particle position and best group position and the parameters ω , ϕ_1 and ϕ_2 are respectively inertia weight, along with two positive constants and two random parameters within [0, 1]. In the baseline particle swarm optimisation algorithm ω has been selected as a unit, but an improvement of the algorithm can be found in its inertial implementation using $\omega = [0.5 \ 0.9]$. Usually Maximum and minimum velocity values have been also defined and at initial stages the particles are distributed randomly in order to encourage the search in all possible locations.

One of the advantages of particle swarm optimization over other derivative-free methods has been found as the

reduced number of parameters in order to tune and constraints acceptance. Fig. 3.3 emphasizes a two-dimensional representation of one particle 'i's movement between two positions. It has been observed that the particle best positions, pBest, and the groups best position, gBest, alter the velocity of the particle at the next iteration. Nevertheless, the stochastic properties of the algorithm can allow for solution variability in order to guarantee the solution space exploitation.

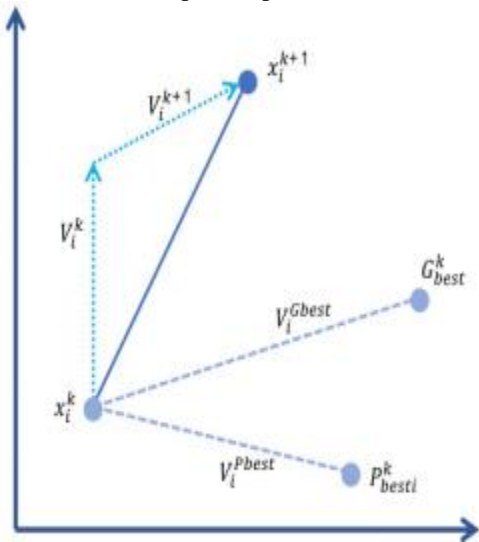


Fig.3.2. Illustration of a two-dimensional representation of one particle 'i's movement between two positions.

Basically the implementation has been done by following the steps given below as:

4. Deployment of wireless sensor network with IOT specification

A node in a wireless sensor network is capable of performing some processing, gathering sensory information and communicating with other connected nodes in the network. Each node has a function to participate in routing by forwarding data to other nodes, so that the determination of which nodes forward data has been made dynamically on the basis of network connectivity and the particular routing algorithm in use. One of the methods for deployment of node includes key predistribution onto nodes before deployment. In this particular scheme, secret keys are generated and are placed in sensor nodes, and each sensor node then searches the area in its communication range in order to find another node for communication. A secure link is then established after two nodes discover one or more common keys (this differs in each scheme), and communication took place on that link between those two nodes. Afterwards, paths are established for connecting these links and to create a connected graph. The result thus obtained is a wireless communication network functioning in its own way, according to the key predistribution scheme used in creation. After deployment the network can be connected to the internet or to other industrial applications hence paving the way to IOT.

5. Apply QAM modulation on data

After deployment of nodes, the data gathered by sensory nodes has to be modulated in order to send them wirelessly to other nodes and hence for this particular purpose QAM is used. It is a modulation scheme used for digital telecommunication systems, such as in 802.11 Wi-Fi standards. Approximately high spectral efficiencies have been achieved with the use of QAM and by setting a suitable constellation size, which are limited only by the noise level and linearity of the communications channel. QAM has been used in optical fiber systems because of higher bit rates; QAM16 and QAM64 can be optically emulated with a 3-path interferometer.

6. Apply gradient descent

After modulation is done on data we apply the first order algorithm to find the local minimum of a function for the purpose of optimization by PSO. In order to find a local minimum of a function by using gradient descent approach it must take steps proportional to the negative of the gradient (or approximate gradient) of the function at the current point. If, for instance, one takes steps which are proportional to the positive of the gradient, in order to find a local maximum of that function; the procedure is then called a gradient ascent. Gradient descent was originally proposed by Cauchy in 1847.

Analyze energy reduction: After applying the gradient descent approach there occurs an immediate effect in the form of an energy reduction due to the finding of a local minimum of a function which enables the system to use limited energy now.

7. Initialize swarm optimization

particle swarm optimization (PSO) is known as a computational method that is used to optimize a problem by iteratively and trying to improve a candidate solution with regard to a given measure of quality. It is used to solve a problem by having a population of candidate solutions, here designated as particles, and then moving these particles around in a search-space which depends on a simple mathematical formulae over the particle's position and velocity. Each particle's movement has been influenced by its local best known position, but has also been guided towards the best known positions in the search-space, which are regularly updated when better positions are found by other particles. This is then expected to move the swarm toward the best solutions.

Algorithm: A basic alternative of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are then moved around in the search-space in accordance with a few simple formulae. The movements of such particles are then guided by their own best known position in the search-space and in accordance with the entire swarm's best known position. When improved positions have been discovered these particles will then

come to guide the movements of the swarm. The process is then repeated and by doing so, it has been hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

Formally, let $f: \mathbb{R} \rightarrow \mathbb{R}$ represents the cost function which must be minimized. The function then takes a candidate solution as an argument which is in the form of a vector of real numbers and then produces a real number as an output which indicates the objective function value of the given candidate solution. The gradient of f is not known. The goal is to find a solution (a) for which $f(a) \leq f(b)$ for all (b) in the search-space, which would mean (a) is the global minimum.

Let (S) be the number of particles contained in the swarm, each of which has a position ($x_i \in \mathbb{R}$) in the search-space and a velocity ($v_i \in \mathbb{R}$). Let p_i be the best known position of particle(i) and let (g) be the best known position of the entire swarm. A basic PSO algorithm is then
Also PSO requires certain parameters to work on which has been described with in this section as:

Update fitness function: The fitness function or we can say position and velocity of each particle is updated to its best value on each iteration.

8. Check objective function

The objective function of an algorithm remains unchanged as it is predetermined as in our case predetermined by channel specifications. As the functions velocity and position is updated regularly on every iteration and our objective is that position and velocity of the function must merge to the objective function which in more technically referred to the functions global best in terms of velocity and position so we had to check the algorithm regularly after certain set of iterations to see whether our objective is achieved or not. If not then we will continue by only changing number of iterations.

9. Optimize

Optimization is referred to as a selection of a best element (having some criterion) from some set of available alternatives. An optimization problem is considered to consist of the maximum or minimum of a real function by systematically choosing input values from the allowed set and then computing the value of the function. In general optimization theory and techniques in other formulations constitute a vast area of applied mathematics and more generally, optimization includes finding "best available" values of some objective function given within a defined domain (or input), also including a variety of different types of objective functions and different types of domains.

A counter is applied which counts the number of iterations in optimizing algorithms and in our case is particle swarm optimization (PSO). The counter is set such

that when the number of iteration count reaches to zero the algorithm then converges and is forcefully stopped. But if the count does not reach zero then PSO runs again and its fitness function is updated and the objective function is checked again and again until the count reaches zero.

10. Analyzing BER, SNR and loss of a link:

After all these processes the last objective of our is to analysis the bit error rate, signal to noise ratio and loss of a link and then comparing these parameters to the previous ones we can reach to the conclusion that there is greater reduction in error bits received and much more improvement in signal to noise ratio which overall reduces the losses of a link.

IV. IMPLEMENTATION AND RESULTS

1. Index properties

The properties which have been discussed in methodology section of the file are further discussed below along with their results and also comparing these results with the previous method used to improve the link utilization and hence at the end of this section we came to the conclusion that our method improves the quality much better than the existing one. The properties which we discuss would include bit error rate (BER), Loss of a link, Energy consumption, signal to noise ratio (SNR), which in our case is kept fixed and we analyse other properties based on it. The signal to noise ratio will be given different fixed values and by obtaining the other parameters with respect to it, we then compare the results obtained with the existing method on the same set of values for signal to noise ratio on which the other parameters have been obtained previously. On comparing the results we came to know that our method shows much better results than the previous existing one as:

2. Parameter results

Results of Bit Error Rate: Bit error rate (BER) is one of the important parameters in improving the link in wireless communication networks because it shows how much data which have been received at the receiver is error free that means how many bits have been transmitted from the transmitter reaches to the receiver without error, hence affecting the overall performance of the system.

The symbol error rate (SER) for a rectangular M-QAM, here M stands for how many bits are transmitted in QAM like (16-QAM, 64-QAM, 256-QAM etc) with size $L =$ can be calculated by considering two M-PAM on in-phase and quadrature components. The error probability of QAM symbol has been obtained by the error probability of each branch (M-PAM) and is given by: (21)

If the use of a nearest neighbor approximation has been considered for an M-QAM rectangular constellation, then

there are 4 nearest neighbors with distance . So the SER for high SNR can be approximated by:

$$c \quad (22)$$

And if we had to calculate the mean energy per transmitted symbol, it can be calculated as:

$$(23)$$

Using the fact that and for $i = 1, \dots, L$. After some simple calculations we obtain:

$$(24)$$

For example for 16-QAM and $\alpha = 2$ the $\beta = 10$. For 64-QAM and $\alpha = 2$ the $\beta = 21$.

A fading channel can also be considered as an AWGN with a variable gain. The gain itself is considered as a RV with a given pdf. So the average BER can then be calculated by averaging BER for instantaneous SNR over the distribution of SNR:

$$(25)$$

The BER is expressed by a Q-function as

$$(26)$$

Where $g = 1$ for the case of coherent BPSK.

The figure below shows the result of Bit error rate (BER) obtained by using the particle swarm optimization(PSO) used in our case and also comparing the result found by us with the existing method in both additive white gaussian noise channel(AWGN) and Rayleigh channel.

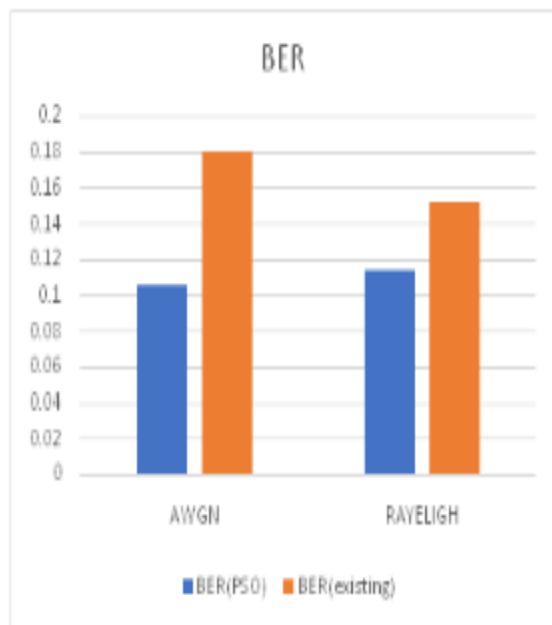


Fig.4.1. Comparison of BER.

Result of LOSS: Path loss is closely related to the environment where the transmitter and receiver are located. Path loss models have been developed using a combination of numerical methods and empirical approximations of measured data collected in channel sounding experiments. In general, propagation path loss can increase with both frequency and distance:

$$= 10(\alpha) \quad (27)$$

where 'p' is the average propagation path loss, 'd' is the distance between the transmitter and receiver, 'n' is the path loss exponent which can vary between 2 for free space and 6 for obstruction during building propagation and 'λ' is the free space wavelength which can be defined as the ratio of the speed of light in meters per second to the carrier frequency in Hz.

$$= = \quad (28)$$

The maximum range between two transceivers can be defined as the distance where the two nodes can communicate with an acceptable BER.

The figure below shows the comparison between the losses in AWGN and Rayleigh channels for both the optimization methods used i.e between particle swarm optimization and existing methods. Here we can see that there is much less loss in PSO method as compared to the existing methods as:

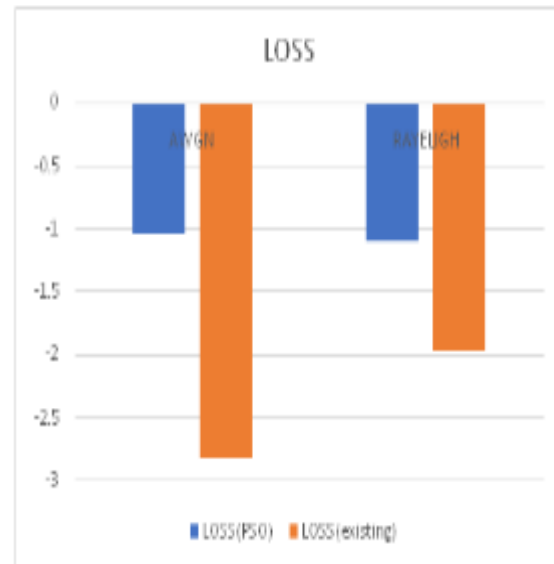


Fig.4.2. Comparison of LOSS.

Result of Energy: A wireless sensor network consisting of a large number of sensor nodes which have been deployed over a vast area to perform local computations which are based on gathering of information from the surroundings. Each node in such a network consists of a battery, but it has been very difficult to change or recharge batteries. Thus the techniques used for energy conservation in sensor networks are much more important which include duty cycling scheme, data driven approaches, mobility-based schemes, energy efficient MAC protocols and node self scheduling scheme. These schemes help in improving the energy efficiency of the wireless sensor network so that the network can be used to work with greater efficiency and high battery lifetime. The Particle Swarm Optimization (PSO) approach can be applied for producing energy-aware clusters having optimal selection of cluster head. The PSO then ultimately reduces the cost of locating optimal positions

for the cluster head nodes. The PSO implementation can be performed within the cluster rather than base station, which helps it in making a semi-distributed approach. The selection criteria of the objective function has been based on the residual energy, also on minimum average distance from the member nodes and head count of the probable head nodes.

The figure below shows the comparison of energy utilization in PSO and Existing approach in both AWGN and Rayleigh channels as:

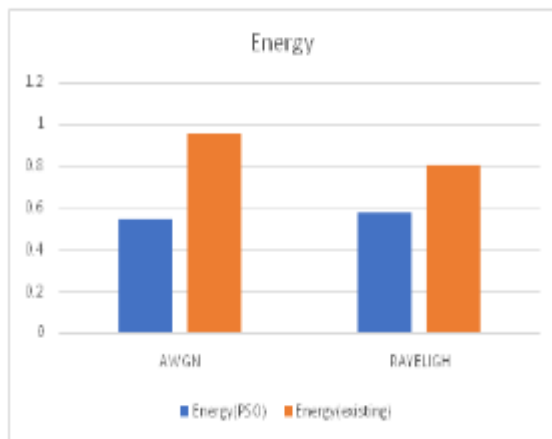


Fig .4.3 . Comparison of energy.

Result of SNR: All real measurements which take place are disturbed by noise. This can include electronic noise, but can also include external events that mostly affect the measured phenomenon like wind, vibrations, gravitational attraction of the moon, variations of temperature, variations of humidity, etc, depending on what has been measured and due to the sensitivity of the device. It has been regarded as often possible to reduce such noises by controlling the environment. The figure below shows the comparative study of SNR in AWGN and Rayleigh channels using both particle swarm optimization and existing technique as:

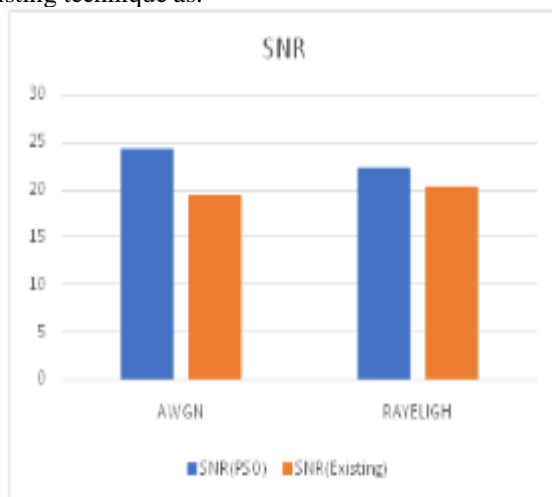


Fig. 4.4 .Comparison of SNR.

3. Performance Evolution

The table below shows all the parameters in AWGN and Rayleigh channel which further explains the different parameter values side by side along with the values of the existing method parameters which enables us to compare and hence come to the conclusion that the PSO optimization method proves to be much more effective and efficient as compared to the previous existing one as shown below

Table -4.1:Table of comparison of BER

Channels	SNR (PSO)	SNR (Existing)
AWGN	24.3182	19.3182
Rayleigh	22.3182	20.382

Table -4.2: Table of comparison of LOSS

Channels	LOSS (PSO)	LOSS (Existing)
AWGN	-1.0399	-2.819
Rayleigh	-1.094	-1.959

Table -4.3:Table of comparison of LOSS

Channels	LOSS (PSO)	LOSS (Existing)
AWGN	-1.0399	-2.819
Rayleigh	-1.094	-1.959

Table 4.4: Table of comparison of SNR

Channels	SNR (PSO)	SNR (Existing)
AWGN	24.3182	19.3182
Rayleigh	22.3182	20.382

V. CONCLUSION

As it been seen already in result section that different parameters which have been considered in the topic like BER, LOSS, Energy, SNR in both AWGN and Rayleigh channels have been seen to prove more effective or we can say the values obtained by our method are much better than the values obtained previously. Our method which is based on particle swarm optimization technique have effectively improved the link between transceiver nodes in wireless sensor networks which is particularly used for internet of things applications in our case.

REFERENCES

- [1]. Jayavardhana Gubbi, Rajkumar Buyya, Slaven Marusic, Marimuthu Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions", Elsevier 2013
- [2]. Qi Wang, Wei Liu, Hualong Yu, Shang Zheng¹, Shang Gao and Fabrizio Granelli, "CPAC: Energy-Efficient Algorithm for IoT Sensor Networks Based on Enhanced Hybrid Intelligent Swarm", CMES 2019
- [3]. Mihai T. Lazarescu, "Design of a WSN Platform for Long-Term Environmental Monitoring for IoT Applications", IEEE 2013.
- [4]. Mohamed Abdel-Basset, Laila A. Shawky, Khalid Eldrandaly, "Grid quorum-based spatial coverage for IoT smart agriculture monitoring using enhanced multi-verse optimizer", Springer 2018.
- [5]. S. Ramesh, C. Yaashuwanth, "QoS and QoE Enhanced Resource Allocation for Wireless Video Sensor Networks Using Hybrid Optimization Algorithm", Springer 2018
- [6]. Omprakash Kaiwartya, Abdul Hanan Abdullah, Jaime Lloret, Sushil Kumar, Rajiv Ratn Shah, Mukesh Prasad, Shiv Prakash, "Virtualization in Wireless Sensor Networks: Fault Tolerant Embedding for Internet of Things", IEEE 2016.
- [7]. Yinggao Yue, Li Cao, Bo Hang¹, Zhongqiang Luo² "A Swarm Intelligence algorithm for Routing Recovery Strategy in Wireless Sensor Networks with Mobile Sink", IEEE 2017.
- [8]. Mohsen Akbari, Mohsen Riahi Manesh, Ayman A. El-Saleh, and Ahmed Wasif Reza "Receiver Diversity Combining Using Evolutionary Algorithms in Rayleigh Fading Channel", The Scientific World Journal 2014.
- [9]. Gurbinder Singh Brar, Shalli Rani, Vinay Chopra, Rahul Malhotra, Houbing Song, Syed Hassan Ahmed "Energy Efficient Direction Based PDORP Routing Protocol For WSN", IEEE 2016.
- [10]. Tarunpreet Kaur, Dilip Kumar "A survey on QoS mechanisms in WSN for computational intelligence based routing protocols", Springer 2019.
- [11]. Mihai T. Lazarescu, "Design of a WSN Platform for Long-Term Environmental Monitoring for IoT Applications", IEEE 2013
- [12]. Suárez Carlos, Gaona Paulo, Montenegro Carlos, Parra Jaime, "IOT quality of service based in link channel optimization in Wireless Sensor Networks", IEEE 2018.
- [13]. Wen-Tsai Sung & Yen-Chun Chiang, "Improved Particle Swarm Optimization Algorithm for Android Medical Care IOT using Modified Parameters", Springer 2012.
- [14]. Runan Yao, Wei Wang, Mahdi Farrok-Baroughi, Honggang Wang, YiQian, "Quality-Driven Energy-Neutralized Power and Relay Selection for Smart Grid Wireless Multimedia Sensor Based IoTs", IEEE 2013.
- [15]. K. Sakthidasan Sankaran, N. Vasudevan, Ashok Verghese, "ACIAR: application-centric information-aware routing technique for IOT platform assisted by wireless sensor networks" Springer 2020.
- [16]. Waleed Ejaz, Mehak Basharat, Salman Saadat, Asad Masood Khattak, Muhammad Naeem, and Alagan Anpalagan, "Learning Paradigms for Communication and Computing Technologies in IoT Systems" Elsevier B.V 2020.