BOUNDARY DETECTION USING CONTINUOUS OBJECT TRACKING IN IOT ENABLED WIRELESS SENSOR NETWORKS

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Candidate of **Master of Science in Computer Science (MSCS)** at the National University of Modern Languages do hereby declare that the thesis **Boundary Detection using Continuous Object Tracking in IoT Enabled Wireless Sensor Networks** submitted by me in partial fulfillment of MSCS degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be cancelled and the degree revoked.

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ABSTRACT

Title: Boundary Detection using Continuous Object Tracking in IoT Enabled Wireless Sensor Networks

Internet of Things (IoT) has attained implausible consideration in today's era because of their enormous applications in different fields such as environmental perception, military observing, predictive maintenance and industrial applications. IoT approach, provide numerous considerable advantages to various application domains. IoT acquired radiant consideration throughout the ongoing years on account of arise sort of applications that allows tracking and monitoring. The most transcendent applications offer confinement and detection of continuous objects for example wild fire, toxic gas, mud stream, oil spills, wild fire and so forth. Continuous objects are detected to investigate the boundary of hazardous area and alert the staff for safety. Existing studies lacks accurate, energy efficient and delay minimized boundary detection mechanism for continuous objects. In emergency situation detecting accurate boundary of continuous objects has become note worthy challenge, where reducing the delay and minimizing energy consumption are well thought out as first-class citizens. This work proposes a novel mechanism for detecting the accurate boundary of continuous objects in a fog oriented environment using IoT enabled devices to tackle delay related issues and also maximizing energy efficiency. To avoid high latency rate in communication with cloud computing, a grid based scheme is applied for detecting accurate boundary region of continuous objects. To reduce the energy and latency rate our technique requests only grid's cluster head for making decisions and fog node estimate the diffusing region of object. The propose work implement through simulation in NS-2. Experiment results show that we get better boundary detection while reducing the transmission delay and energy consumption by comparing to state of the art strategies.

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LIST OF ABBREVIATIONS

ACO	-	Ant Colony Optimization
AN	-	Active Node
AONN	-	Abnormal One Hop Neighbor Nodes
BA	-	Boundary Accuracy
BL	-	Boundary Line
BDCO	-	Boundary Detection of Continuous Objects
BRDCO	-	Boundary Recognition and Tracking of Continuous Objects
BRTCO	-	Boundary Recognition and Tracking Algorithm for Continuous Objects
BTS-COT	-	Boundary Tracking of Continuous Objects Based on Binary Tree Structured SVM
CDCAPC	-	Consistent Data Collection and Assortment in the Progression of Continuous Objects in IoT
CHS	-	Convex Hull Algorithm
CM-IOTSN	-	Cloud Monitoring IoT Sensing Network
CODA	-	Continuous Object Detection
CODAT	-	Continuous Object Detection And Tracking
COT	-	Continuous Object Tracking
COZ	-	Comparing on Zero
CVN	-	Changed value node
DC	-	Dynmic Cluster
DCSODT	-	Dynamic cluster structure for object detection and tracking
DCTC	-	Dynamic convoy tree-based collaboration
DDATG	-	Detecting the Dangerous Area of Toxic Gases
DEMOCO	-	Energy-efficient detection and monitoring for continuous objects
EEAOC	-	Energy-Efficient Adaptive Overlapping Clustering
EEATDC	-	Energy Efficient and Accurate Tracking and Detection of Continuous Objects
EEBDCO-IoTSN	-	Energy-Efficient Boundary Detection of Continuous Objects in IoT Sensing Networks
HGI	-	Hierarchical Grid Index
IoT	-	Internet of Things
IDW	-	Inverse Distance Weighting
NSS	-	Node Self Scheduling

QPI		Quadratic polynomial interpolation
OPS	-	Optimal path selection.
PA & QPI	-	A data aggregation scheme for boundary detection and tracking of continuous objects
PDR	-	Packet Delivery Ratio
PCCS	-	Preliminary Congestion Control Stage
PG	-	Proximity Graphs
RBNIC	-	Representative Boundary Nodes Identification And Congestion Control
SIM	-	Spatial Interpolation Methods
TFSDC	-	Twofold Sink Based Data Collection for Continuous Object Tracking
SHDB	-	A Mechanism Filling Sensing Holes for Detecting the Boundary of Continuous Objects
WSN	-	Wireless Sensor Network

LIST OF SYMBOLS

CH	-	Cluster Head
SN_{id}	-	Sensor Nodes ID
$SN_{(lang.\& \ latit.)}$	-	Sensor Nodes location with coordinates
SN_{status}	-	Sensor Nodes status Active/Sleep
TS	-	Time Stamp
N_i	-	Nonce value
D_i	-	Distance of nodes
H	-	Hash Function
DN	-	Detection Node
AN	-	Abnormal Node
BN	-	Boundary Node
HC	-	Hybrid Clustering

ACKNOWLEDGMENT

First of all, I wish to express my gratitude and deep appreciation to Almighty Allah, who made this study possible and successful. This study would not be accomplished unless the honest espousal that was extended from several sources for which I would like to express my sincere thankfulness and gratitude. Yet, there were significant contributors for my attained success and I cannot forget their input, especially my research supervisors, Associate Prof. Dr. Ata Ullah, who did not leave any stone unturned to guide me during my research journey.

I shall also acknowledge the extended assistance from the administrations of Department of Computer Sciences who supported me all through my research experience and simplified the challenges I faced. For all whom I did not mention but I shall not neglect their significant contribution, thanks for everything.

DEDICATION

This thesis work is dedicated to my parents and my teachers throughout my education career who have not only loved me unconditionally but whose good examples have taught me to work hard for the things that I aspire to achieve.

CHAPTER 1

INTRODUCTION

1.1 Overview

Wireless Sensor Network (WSNs) is architecture of interconnecting few to thousands tiny sensor nodes by using wireless communication to monitor, sense, collect and process data about the environmental conditions (i.e. temperature, pressure, vibration or movement) [1].With the progression of micro-electronics, wireless communications and multi-functional low cost sensor nodes have made promising the evolution of WSN [2]. WSNs comprises enormous amount of low powered, spatially distributed self-directed and multi-functional sensor nodes with limited resources which are capable for sensing and exchanging data with neighbors and sink node. These nodes are extremely dependent on storage, data computation, data size, battery power and available bandwidth, therefore they transfer small amount of sensing data with minimum power consumption [3][4]. Generally, sensor nodes are deployed in a specific way in target regions and also fixed a single node in a distant or inaccessible place to monitor and track the object [5]. Distantly regions which are not yet explored because of its unsafe nature and unavailable spots, wireless sensor network is observed to be most adequate answer and make it possible to implemented and examined effectively in real-time scenario [6].The term “IoT” is illustrated as internet connection oriented objects that are capable of collecting and transmitting sense data over a wireless telecommunication network without human interference.

Emerging new innovation of information technology, IoT (Internet of Things) [7] devices develop cost effectual wireless sensor nodes within internet connection that participate in sensing and monitoring procedure. The basic idea of IoT technology is the pervasive presence of different kinds of things or objects around us, such as sensors, tags, Radio-Frequency (RFID), mobile phones, etc [8]. These devices are playing a vital role in

WSNs such as distant monitoring and perception [9]. Internet of Things (IoT) consist of a large number of smart intelligent devices that collaborate, cooperate and exchange information with each other and establish a large scale self-organizing IoT sensing networks [10]. It has the ability to stores real world sensing data and monitors the real world parameters as well also makes decisions on the sensed data and responsible for data computation, management, and decision-making. So, IoT has become new sensation, fast growing and the most significant technology of today's era. The WSNs are acting as the eyes and ears of IoT-based network and makes a connection between the real world and the digital world [11] thus, it considered as the essential part of (IoT). The mix up of WSN and IoT leads towards edge technology [12]. By the advantage of providing lightweight, inexpensive and feasible solutions for early warnings, data aggregation and analysis IoT assisted WSN have been paid deep interest in many research area, mainly in physical sensing and monitoring fields [13].

The rapid and progressive proliferation of information technological development and IoT enabled WSN are broadly appropriate in many fields like environmental protection, agriculture sector, healthcare, industrial monitoring, smart buildings, battlefield surveillance, forest fire detection, weather forecasting, habitat, seismic sensing, disaster discovery, volcanoes, predictive maintenance and automated system etc [14].

One of the significant research areas in IoT enabled WSNs is object tracking. Object tracking is a process of positioning a moving object in time using smart sensing network with heterogeneous sensor nodes. Generally, Process of tracking objects can be categories into individual and continuous object tracking. Individual object might be a single object like an enemy tank or one vehicle which has regular shape and size. Contrary to individual objects, continuous objects have irregular shape, dynamic in nature and flexible. Extensive research works have been conducted on individual object tracking and monitoring but small efforts were paid on continuous object tracking. The continuous object is continuously disperses in the large geographic area i.e., forest fire[15], toxic gas leakage, oil spill and agricultural infections in industrial applications[16][17][18].These objects change their form and size dynamically, which results in severe harm to the atmosphere and human life. Object tracking mechanism consist of two levels, at initial level it detects and estimates object location and at second level it monitors the object [19].

Object monitoring and tracking both have significant importance, basically, static objects are only concerned with the monitoring but in case of mobile objects, sensors and actuators are utilized for monitoring and tracking[20][21] as shown in Figure 1.1. Therefore, application of object monitoring and tracking communicates with the devices while exchanging report messages to track and monitor objects. Tracking and detection of continuous objects boundary is a main concern in the application scenario of IoT enabled WSNs because of its speedy movement, change in shape, expansion in size, and split into various minor continuous objects [22], [23]. In spite of the fact that, boundary detection of objects is an effective method to send information to BS contrast to formal detection procedure. In this process lots of detecting nodes transmit information to the BS and enhance the energy efficiency and minimize the communication overhead. Though, boundary estimation depends upon the reliability of data and boundary nodes failure leads to decreases the reliability and boundary accuracy [24][25].

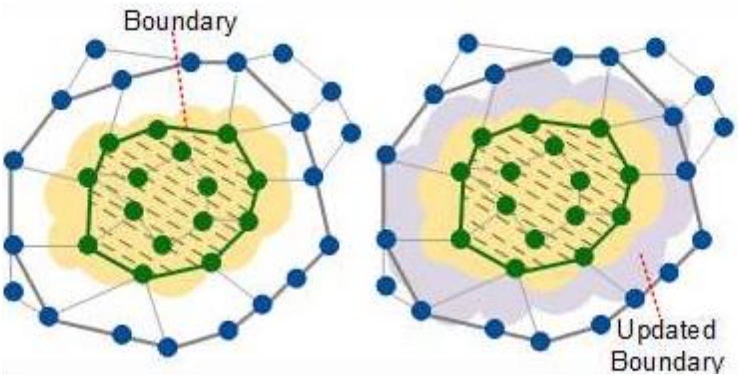


Figure1.1: Boundary detection of continuous objects

1.2 Motivation

Continuous objects are extensively spread in broad area with diverse scattering of speed that brings about severe air pollution and damages. Tracking and detecting the accurate boundary of such objects have become a significant problem due to its fast development, increasing size, diffusion, changing forms or splitting into multiple smaller objects and invisibility of the phenomena. Generally, these objects frequently need multiple features for describing and they cannot be showed by a single point. All sensor nodes that are used to track these objects (i.e. fire or pollution) have various sensing modalities and they construct a

Heterogeneous Sensor Network. However, when emergency event occurs, to timely and accurately detecting the target object, high data reporting rate is needed. As a result, a large quantity of message exchanged between sensor nodes and sinks which lead towards communication overhead and transmission delay. This delay is not affordable in emergency situations. Also, increasing the number of sensing nodes and activation of large amount of nodes for boundary detection of contaminated areas consumes more energy. To reimburse the gap in the field of continuous object tracking and boundary detection, our main concern is to construct an energy efficient network architecture that should be able to track and detect the boundary of continuous object with minimal delay and errors.

1.3 Architecture of IoT enabled Wireless Sensor Network

IoT assisted wireless nodes are installed in a object region for examining the target object and these devices are linked by wireless media [26].These smart sensing devices are capable of sense the object, process data and exchange the sensing data with neighbors(s), they also responsible for transmitting the sensed data back to base station (BS). Sink node has the ability to remotely compute the data and share with outside for example PC. Recently, deployment of IoT sensor nodes plays significant roles in environmental monitoring, health care, traffic control, battlefield surveillance, intruder tracking, emergency response and gas leakage detection[27].

As shown in Figure 1.2, three tier architecture of IoT enabled WSNs is demonstrated that include first tier of IoT enabled wireless sensor network. IoT nodes are deployed in target region for monitoring and tracking the physical objects or environmental situation, (for example temperature, vibration, sound, pressure and movement). These nodes are responsible for detecting and refine the boundary of continuous object.

Typically, sensor nodes are made up five parts (battery, processor, transceiver memory and a sensor). All the parts have limited resources. Sensing the target event incurs large energy costs and collection of huge data for object tracking tends to reduction in memory, processing efficiencies and battery powers incurring delays. Whereas, reporting excessive amounts of data by the transceiver leads to high energy consumption[28]. These scarcity issues of the resources have a great influence on many applications of event tracking and network's longevity[29]. Second tier includes network transport layer which is composed of backbone and fog node.

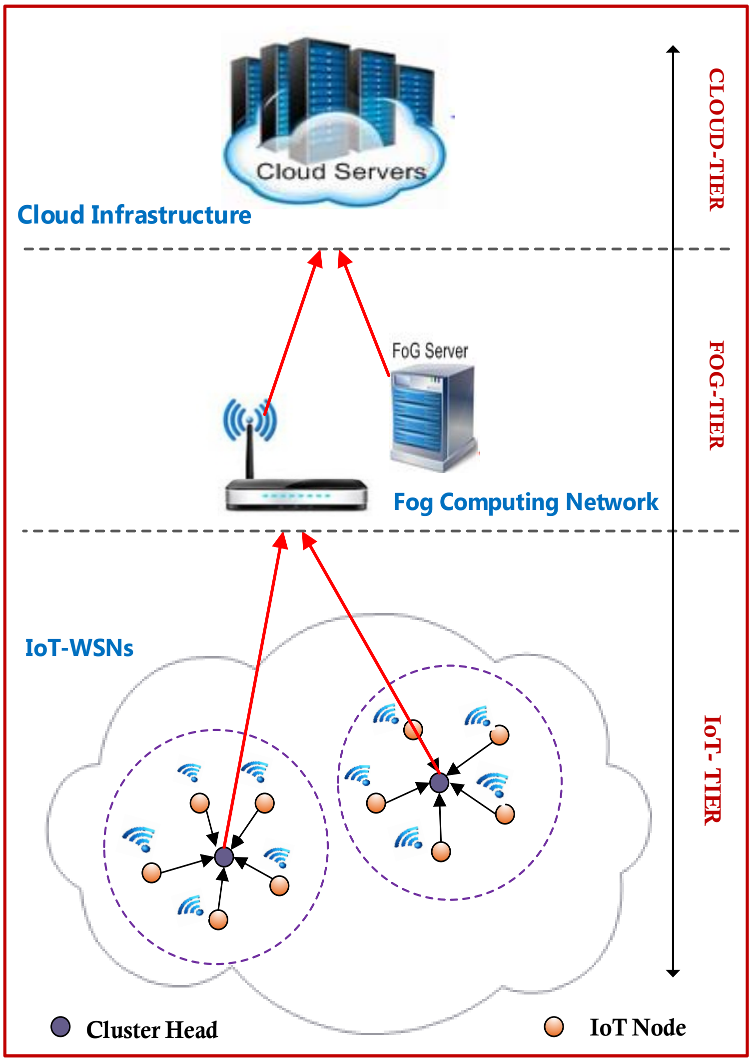


Figure 1.2: Computing paradigm in IoT enabled WSNs

For reducing the delays in data transmission towards sink and for advance alerts and decision making in emergency situation, fog node deployment at the edge is essential. In fog computing framework, sensory data of sensor nodes are routed to the edge node for further processing. Fog nodes are also responsible for analyzing the sensory data and routed it to the cloud. Fog nodes required high computational capacity to handle these sensory data and to analyzing these data in well-organized manner [30]. Thus, it very challenging task to achieved the accurate boundary area of continuous objects by minimizing the transmission overhead in real-time fashion [31]. Whereas, third tier includes data centers with high processing computers i.e. cloud that is responsible for reducing the communication overhead between nodes.

1.4 Applications of IoT enabled Wireless Sensor Network

IoT empowered applications are generally put upon to make more well-off the catastrophe tracking and monitoring i.e. toxic gas, oil spills and fire detection that would cause harmful to the overall environment as well as physical body. These continuous objects are extensively spread in broad area with diverse scattering of speed according to the climate conditions and because of the fast development, increasing size, diffusion and forms changing nature tracking and detecting the precise boundary for these continuous objects have become a noteworthy issue.

1.5 Constraints in Boundary Detection of Continuous Objects

In the following section, different constraints are discussed including energy consumption, sensing range, accuracy of boundary detection, transmission overhead, boundary face area localization, Data congestion, boundary nodes reduction and expanding and shrinking phenomenon.

1.5.1 *Energy Consumption:*

Accurate tracking of continuous object is a big challenge. Energy utilization of sensors has a great impact on extending the lifetime of networks [32]. For tracking the continuous object simple techniques are used in which all the sensor nodes sense the object, exchange information among neighbors and report their sensory data back to the base station [33]. In this process, energy of the sensor nodes consumed quickly [34]. Generally, all the sensors used battery power that results in draining the batteries quickly. Sensor nodes exchange huge amount of messages in between nodes as a result communication overhead occurs also exhausted high energy. This communication overhead cannot be affordable by the sensors nodes because they have limited bandwidth, minor storage and computation capacity [35][36].More energy is essential when transmitting the data to BS which also lessens the life time of network [37]. Energy efficiency can be acquired by minimizing the sensing and communication cost, but compromising the data accuracy. Thus, an efficient boundary detection method needs a robust mechanism to get the accurate detection information while consuming the low energy. It is very challenging aspect that how the energy efficiency can be achieved to get better performance and accurate boundary detection in continuous objects tracking [38].

1.5.2 Sensing Range:

Sensing range is very important factor that affects network performance and energy efficiency while tracking the continuous object. There are lots of sensor nodes that use their sensing power for continuous object detection and for communicating with other nodes [39][40]. Simplest approach is used earlier in which the boundary nodes transmit sensed data to the backbone node for tracking the continuous object. Sensing range is important factor for accurate boundary detection and better performance of network because sensor nodes used their sensing power for sending the report back to the BS and interaction with each other [41]. So, it is challenging task to select long and short sensing range. Short and long sensing range affects the network performance in sparse and dense network. When small numbers of nodes report back to sink in sparse network, then it would involve in long transmission ranges for communication [42]. Whereas short sensing range is need to consider for overlapped sensing region in dense network. Long sensing range reduces communication cost and packet drop ratios by utilizing high energy for each packet transmission which affects the performance. This issue should be managed efficiently to enhance network lifetime [43]. Sensor node should adjust appropriate sensing range for energy utilization and monitoring the object for longer time [44].

1.5.3 Accuracy of Boundary Detection:

Due to the diverse nature of continuous objects, accurate boundary detection of these objects is noteworthy issue [45][46] which needs proper order of node deployment [47]. Continuous object like toxic gas, wild fire and oil spills have a tendency to spread under the wind pressure with different scattering speed as well as change forms, thus, finding out the accurate boundary of such infected areas become a noteworthy problem[48]. Toxic gas leakage and dispersion are complicated procedures that grounds severe loss. Accurately and timely detection of the source and its diffusion direction is quite critical [49]. IoT enabled applications have been extensively used to make easier the catastrophe tracking and monitoring i.e. toxic gas leakage [50][51]fire detection and oil spills. It requires the precise boundary detection for reliable solutions [52].

1.5.4 Transmission Overhead:

In continuous objects tracking and detection, communication during the neighbor nodes and the sink node is a challenging task [53]. These objects dynamically changed their shapes, size and locations and constantly move in the network [54]. For tracking and monitoring such objects static sensors nodes generate massive data and report the sink node which causes traffic overhead [55]. In emergency scenarios, data transmission is considered as a most challenging factor to identify the object boundary and well use of network link capacity. It needs massive communication for exchanging detection information between neighbors and sink node. And generate transmission overhead when multiple sensing nodes report the detected data to sink, which results in delays, collision and data loss. It is a challenging task to acquire the accurate boundary while ensuring minimum transmission overhead and communication cost in real-time situation[56].

1.5.5 Congestion and Data Loss:

The continuous objects are blowout over a large area such as toxic gas leakage infrequently. To tackle this situation in WSNs few sensor nodes are recommended to be active and monitoring the incidence of phenomenon functionally. It is critical issue in dense environment, there will be congestion [57] if all sensor nodes reporting to the sink in long boundary. Consequently, the data size will be increase and will consume more energy which grounds data loss. In normal situation, prior the event occurrence sensor nodes detected it and report back to the sink in lower data transfer rate. On the other hand, in case of emergency events i.e. toxic gasses, fire detection and oil spills must detect the event precisely and timely and it extremely required higher data rate to report to sink. In this situation, sensor nodes report back to the sink at the same time can cause congestion and the massive data produced which outstrips the capacity of the network. This reduction of data injecting rate is not affordable during the crisis. It is very challenging aspect in emergency that how to control the congestion employ the network capacity, resource utilization and reduce the packet drop ratio in an efficient manner.

1.5.6 Decreasing Active Nodes:

Continuous objects are generally in greater size and for detecting such greater size objects more event nodes are required which implies difficulty to detect and monitor these objects. Massive traffic load is produced when all the event nodes report their data and location information to sink node. For accurate boundary detection it is essential to decrease the amount of BNs that send the data to the base station [58]. Thus, reducing the amount of reporters for continuous object tracking is the key issue. Forgetting the energy efficiency, reducing the size of report message is the main concern. It is difficult process to identify the accurate boundary when nodes are deployed in a sparse network. Boundary accuracy must ensure by the trustworthy solutions that involve least number of active nodes [59].Usually, energy consumption is minimized by lessen the number of BN and size of reporting message.

1.5.7 Expanded and Shrinking Phenomenon:

Continuous objects spread in huge geographical area such as diffused harmful gases, chemical liquids and wild fires. These objects gradually change their shapes when a phenomenon is shrinking or expanding or splitting into different phenomenon and different phenomena merge with each other to making single phenomenon as a result, holes may come into sight or fade away in phenomenon. This nature of continuous object has a great influence and cause severe damage. Monitoring and developing a possible situation for such spatial phenomena is become noteworthy issue. Therefore,[60] provide less energy consumption in order to few nodes selection for reporting data among huge amount of predefined boundary nodes.

1.6 Problem Background

IoT proliferation has become the infrastructure to make possible the real-time monitoring and boundary detection of continuous objects. Many existing research works have conducted lots of solution in the field of WSN’s application continuous object tracking and boundary detection and have gained extensive attention. However, this investigation is incessantly taking place. For detecting the boundary of accident-prone areas different strategies are adopted by the researchers that includes clustering approach to detect the event, different sensing ranges, mobile nodes deployment, detecting boundary face detection by planarization algorithms, gas diffusion methods, boundary predication methods and mobile sink approach. The severity levels of real time emergency data transmission in energy efficient manner with low latency rate are rarely focused by the researchers.

Due to the fact that leakage and diffusion of continuous object cover huge area and greater in size, for detecting the boundary of these objects a number of sensor nodes activates for transmitting the data to sink. This activation method entail large amount of exchanged messages between nodes in real time. Hence, long-distance data transmission produces large delay and consumed more energy.

The main problem is that emerging IoT enabled WSNs applications support report the data to cloud for boundary prediction or estimation by IoT nodes which result in delays in this long transmission and leads to data loss in emergency conditions. Also repetitive activation procedure of neighbor nodes for boundary accuracy consumes high energy. Any delays in time sensitive data transmission can be tragic and results severe destruction of physical and environmental health of society. There is a need of effective computing framework for processing and analyzing the data at the edge. Moreover, IoT intelligent network architecture should be able to track and detect the object boundary in energy efficient manner with consistent emergency-controlled functionalities, high service ratio and with minimum delay. To compensate this gap, IoT enabled WSNs based boundary detection of continuous object scheme is presented that can track the continuous object in an adequate level of accuracy and estimate the accurate boundary in energy efficient duty cycle mechanism.

1.7 Problem Statement

Transferring information to cloud for boundary prediction and then reporting outcomes to IoT devices takes time which produces delay and increases communication overhead in emergency situation [61]. Delay grounds severe damages in time sensitive applications (e.g., Toxic gas, forest fire, and Earthquakes). Activating more neighbor nodes for detecting the boundary of continuous object consumes excessive amount of energy [62].

1.8 Research Questions

The study addresses the following research questions.

i. How to reduce transmission delays for sending emergency messages from sensor nodes to cloud?
ii. How to reduce the active sensor nodes during emergency reporting for reducing the energy consumption?

1.9 Aim of the Research

In IoT-based system, continuous objects i.e., forest fire, toxic gas leakage and mud flow were detected to find out the boundary of dangerous area and to let somebody know for rescue efforts in advance. Transmission delay affects the performance of time sensitive sensing and monitoring applications while exchanging emergency messages. For detecting the boundary of hazardous region these applications need high reliability and low delay. An uneven delivery of these significant and time sensitive data packets can be tragic that leads to severe loss. The aim of this research work is to accurately track and detect the boundary of continuous object in IoT enabled WSNs that ensure low latency and reliable communication without compromising any significant data from critical region. Network performance will be improved by minimizing the activating nodes and reducing delays during data transmission. Boundary detection data will be transmitted and estimated in energy efficient and timely manner using fog computing as a result transmission delays will be minimized and will achieve boundary accuracy.

1.10 Research Objectives

The following objectives are defined to track and detect the boundary of continuous object in IoT enabled WSNs.

i. To investigate the boundary of continuous objects by reducing the delays and communication overhead.
ii. To develop proficient network architecture in order to minimize the number of sensor nodes for tracking continuous object in energy efficient manner.

1.11 Thesis Organization

The thesis is organized as follows:

Chapter 2 will render a comprehensive state of the art schemes and algorithms for tracking and boundary detection of continuous objects in IoT enabled WSNs that are presented in current research. It includes detailed overview of all the existing work and describes how this study distinguishes itself with the existing schemes. Also, contains the categorical discussion, detailed comparative analysis of state of the art schemes and their research limitations that lead towards new research direction.

Chapter 3 will present methodology and description of plans that how will solve the identified problem. The methodology comprised of operational framework, research design and simulation framework. Sampling mechanism has also been discussed which is developed to further conserve energy. Simulation framework is presented for the performance evaluation of BDCO-IoT scheme and it also considered the performance metrics of simulation. Extensive simulation is put into practice using NS-2 to get the accurate and effective results.

Chapter 4 presents detailed operational frame work and verification of proposed algorithm. It introduces the novel boundary detection mechanism of continuous objects in IoT enabled WSNs (BDCO-IoT). This prototype provides delay minimized and energy efficient real time data transmission for remotely tracking and detecting the boundary of continuous objects. Also, discusses and analyzes the four phases of BDCO-IoT mechanism to detect and track the event boundary in real time scenario i.e. (i) Initial Deployment of Network, (ii). Abnormal Nodes Detection, (iii). Object boundary detection and (iv). Reporting Mechanism of detected Data.

Chapter 5 will provide experimental evaluation to prove the validity of Boundary Detection of Continuous objects in IoT (BDCO-IoT) scheme in detail. It discusses the results of the experiments and presents the comparative analysis of these results with other schemes. It explains the results that will be presented in the form of multiple graphs that will produce from the simulator and log files.

Chapter 6 will sum up the contributions of this research work. It also discusses the gaps of the proposed prototype which lead toward further directions for future work and attract the innovative researchers to take benefit from this work.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

In this chapter a comprehensive overview of state of the art schemes have been highlighted for continuous object tracking and boundary detection in IoT environment. Also, a taxonomy of object detection and boundary detection schemes is presented. Accurate tracking of continuous object is a big challenge i.e. forest fire or oil spill. Among these studies some techniques are discussed the proposed algorithms for continuous object tracking while other techniques are discussed the boundary detection and energy efficient mechanisms of continuous object tracking. Moreover, the basic idea, limitations and advantages of the schemes are analyzed in literature. Finally, a number of research challenges are explored.

2.2 Object Tracking Schemes

For tracking the continuous object simple techniques [39], [52], [63]–[65] are used in which all the sensor nodes sense the object and send their sensory data back to the base station. Latest techniques [34], [40], [51], [55], [59], [66], [67] mostly used to resolve the challenges of accurate boundary detection, energy consumption, communication overhead, energy efficient sensor deployment, boundary node reduction, analyzing and processing data capabilities in continuous object's boundary detection process used in IoT environment. To realize the problem of continuous objects tracking and boundary detection a lot of works have been done recently in different literature review and survey articles [19], [21], [25], [27]–[29], [60], [68]–[71]. Figure 2.1 explores the taxonomy for the schemes in literature.

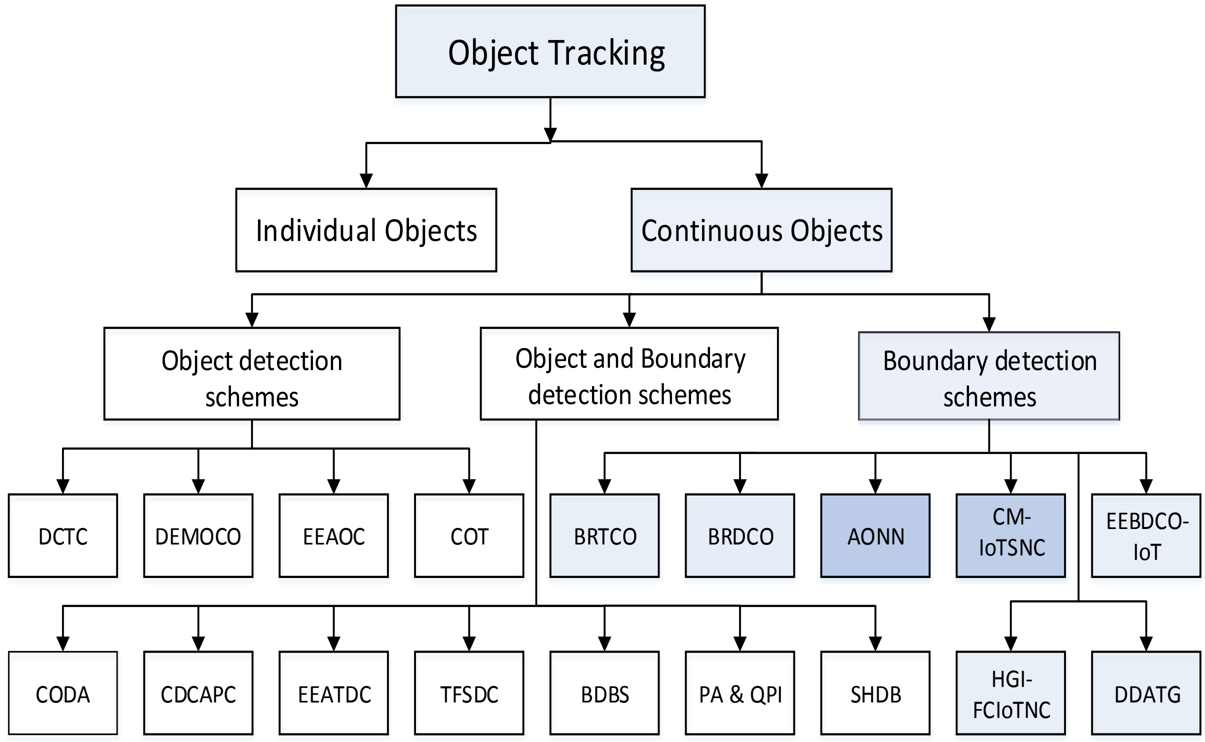


Figure 2.1: Taxonomy for Object Tracking

2.2.1 Continuous Object Tracking Schemes

In the following category multiple schemes have been presented for continuous object tracking. In which sensing information accuracy, sensing power, network architecture, data communication, energy utilization and object modes are considered as significant factors. For continuous object tracking sensor nodes provide detected information within its sensing area and transmit it to the base station. Both sensor nodes and sink node maintain the tracking information and update the object tracking information when needed.

A dynamic convoy tree-based collaboration (DCTC) scheme is presented by W.S. Zhang and G. Cao for detection and tracking of mobile target. In this method introduce a dynamic tree base construction (convoy tree) for optimal solution that grounds minimum energy consumption and long tree coverage. Sensor nodes are deployed within mobile target region. At first when the targets object is detected, initial convoy tree is dynamically constructed. Sensors nodes that detected the event collaborate with other nodes for selection of root node. Root node of the convey tree gathers sensory data from others nodes and relying on that information it attains accurate target information by using some algorithms. As the target moves, covey tree has the ability to reconfigures itself in energy efficient manner. DCTC try to balance the trade-off between energy consumption and target tracking accuracy [42], [72]. It pays high cost for cluster construction. Cluster overhead increases when the number of nodes and their neighbors nodes increase which will results in death of clusters and low network life. Mostly this scheme explicitly focuses on single object tracking i.e. animals, humans and vehicles [73]. Keeping all nodes active in the network tends to maximizing energy consumption[64].

In [27] M. Akhter et al. offered energy efficient clustering scheme for localization and tracking methods in WSNs to prolong the life of network. Also, designed a GAR (Gaussian adaptive resonance) system at boundary outline to aggregates the clusters and sensor nodes patterns that based on sensing ranges. For tracking the change in object movements, it dynamically forms and updates the cluster at boundary region and makes available the accurate position of dynamic objects by utilizing trilateration mechanism. It does maintain the network accuracy and constancy in a big network. To detects and tracks the continuous object that is dynamic in nature J. H. Kim et al. planned a scheme (DEMOCO) by electing a subset of BNs. For detecting the object's boundary it elects small number of boundary nodes [30]. These lessen BNs helps in reducing the message size to transfer the sensory data from BNs to the sink. It also selects RNs (representative nodes) among boundary nodes for data transmission and relieves traffic load between BNs and sink nodes. If a node found dissimilar reading from earlier then it becomes "(CVN) changed value node" and broadcasts comparing one zero (COZ) message to its nearby nodes. Receiving node that has the similar reading, ignore it and only those nodes becomes BNs that have the different reading. For selecting the RNs among BNs only those nodes becomes RNs that have higher number of COZ messages with different status and shorter back-off time. Moreover, to lessen the quantity of uploaded messages, RNs only transfer the closest node's ID to BS that has dissimilar current reading. However, for BNs identification DEMOCO exchanges much messages. In practical scenario, it overlooked the continuous objects which lead towards decision making error [49].

Tracking and detection of shrinking and expanding phenomenon in critical situation is noteworthy issue. To tackle with this condition an algorithm named CODAT is designed by T. R. Sheltami et al. that identify and track the continuous object expansion and shrinking condition. CODAT is hybrid of both schemes COBOM [37] and DEMOCO [49] algorithms. It monitors holes within the object area. It provides boundary accuracy by selecting small number of BNs and RNs also use average reporting size for transmitting sensory data to sink to decreases the overall communication cost and energy consumption. In sparse network, it is not good to reduce the number of nodes that detects event and sensing hole [63].

To ensure the better performance of object tracking process Chengyue et al. designed a hybrid (static/mobile) sink based architecture. For boundary node partition between mobile nodes and sink centroid algorithm is presented that optimally calculate the mobile node position all the way through static node and collaboration of hybrid sinks facilitates with boundary node detection, information collection and falling message overhead. Additionally, these approaches accurately track the object location by mitigating the energy limitation and transmission overhead and also prolongs the network life [60], [68].

According to the dynamic nature of continuous objects, clusters should be organized energetically for proficient data aggregation in continuous monitoring mechanism. EEAOC dynamic clustering approach, Y. Hu et al. proposed an adaptive overlapping clustering scheme for monitoring the continuous objects. This scheme gets used to event fluctuation, by using 2-logical overlapping organization of clusters and makes sure that object detection data gathered by nearby nodes can be used to same cluster head for transmission and data aggregation process. For effective configuration of clusters and for balancing the energy consumption of intra-cluster, CH re-adjustment and cluster relocation method is used with less communication overhead. A hybrid data communication method is adapted to enhance the network life and event detection precision in energy efficient manner. Swapping network topology information among neighboring nodes for cluster maintenance consumes more energy [74].

For taking out the redundancy of space domain and adaptive sampling approach (time domain) Woon et al. planned a technique for proficiently tracking of continuous object using virtual grid in static clustering based WSNs. It visualizes sensing area into cells just like pixels on TV and estimates the sampling and transmission time according to pixels density. For getting the diffusing object boundary information in space domain it uses boundary traverse algorithm BTA (pictured image) to lessen the redundant boundary Information [75].

M. A. Alqarni presents a study for tracking the continuous objects in WSNs by considering different sensing range of sensor nodes for detecting the continuous object of different speed (fast and slow) in different networks(sparse and dense). Sensing power is most significant factor which affects energy efficiency and network performance. Different sensing ranges (long and short) are used by sensor nodes for detecting the object and for communincating with base station and other nodes. These sensing powers also affects the performance in dense and sparse environment of network. By the Simulation experiments, it is observed that how the sensing range, deployment and speed of the object make affect the tracking accuracy and network performance. For the purpose of energy saving and accurately monitoring of object for the long time sensor node must regulate its sensing power according to the specific environments. In high dense environment short sensing range is utilized for tracking fast objects and there are more chances of getting detected boundary that is more close to real boundary. As a result, sensor nodes transmit precise boundary information to sink and consume less energy. On other hand long sensing range can minimize packet droping issues and also diminish communication overhead in some caseswhen tracking a slow object in sparse deployment for accurate boundary line but it cost more energy [76].

2.2.2 Continuous Object Tracking and Boundary Detection Schemes

In this category various protocols have been presented for tracking and detection of continuous object boundary. Unlike an individual object, continuous object is typically an area of interests and the procedure of tracking such area is called boundary detection. For tracking and detecting the boundary of continuous object different cluster based tracking schemes (i.e. static, dynamic and hybrid clustering schemes) have been proposed. In these schemes network is organized into different clusters for aggregating and analyzing the sensory data also provided the two-way communication between sensor nodes and cluster head.

Chang WR et al. developed a hybrid cluster (static/dynamic) target tracking scheme CODA. Hybrid (static/dynamic) clustering mechanism is used for continuous objects tracking and detection like oil spill, toxic gas and wild fire. In this method within sensing range, every sensor node examines and tracks the dynamic boundary of continuous objects. Initially, network is configured with static clusters and also deployed sensors nodes into these clusters.

When any sensors within static cluster detecting the target object they transmit their sensory data to CH by the help of 1 hop selection method. CH simulates the boundary estimation method for structuring the BNs around the object boundary that lies within cluster and makes the dynamic cluster, also shared this information with designated sink. After that designated sink execute this boundary data for determining the whole boundary of the object. It incurs lower overhead costs by dynamic cluster construction at static CH level. In this technique, high energy consumes by cluster structuring and maintenance overhead[65]. In crisis, it does not sustain by the overloaded sensory data at sink. For transmitting the boundary information to CH one hop selection process grounds in high energy consumption. This method is not appropriate for estimating precise boundary when the object is in concave polygon shape [48].

A dynamic cluster based structure DCSODT is presented for detecting and tracking the movements of continuous object boundaries. Boundary nodes are organized dynamically in each cluster and CH collects boundary detection information from other BNs of cluster and forward to the sink. When object boundary moves, every CH of cluster inform its members. Energy limitation and communication overhead occurs when every BN and CH directly transmit the data to BS [77].

Massive data communication requires for continuous object detection and tracking which may results in congestion, packet loss and exhaust high energy. To tackle these problems, Taj Rehman, et al. introduces a consistent data collection and transmission scheme in IoT named CDCAPC. This mechanism handles congestion related problems, reduces data transmission rate and throughput maximization issues by utilizing different assortment of link capacity, residual energy of nodes and congested BNs selection. A hotspot is created during the event detection for consistent data collection and transmission at the massive data generated nodes. For mitigating the congestion and buffered packet drop ratio PCCS algorithm is utilized that chooses the PN (parent node) and from multiple data flows it provides only one data flow. A node that has minimum data transfer rate and maximum priority is selected as child node by parent node. If the buffer overflow still exist, RBNIC algorithm carryout for choosing the uncongested parent node and some RNs are used for transferring data to parent node.

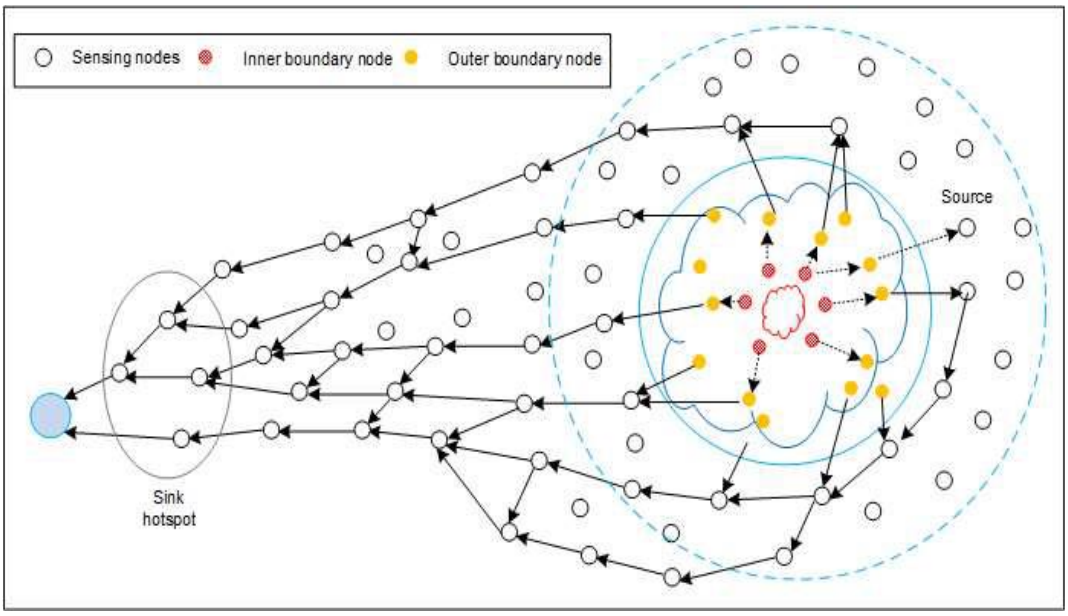


Figure2.2: Network connectivity in congestion control mechanism

It is obvious that it's not necessary for congested nodes to transfer data to parent node and neighboring with other nodes. Later than, removed the hotspot and every node ensured the next hop and calculate link capacity in the sending procedure [56].

For getting the exact tracking and detection of continuous objects in energy efficient manner, T. Rehman et al. presented a two-stage boundary face detection and localization scheme (EEATDC) in dense duty-cycled WSNs. To attain the energy efficiency, few nodes are active in duty cycle environment for detecting the object whereas others are inactive which also decrease the data traffic load. When an object is detected by active nodes, different planarization algorithms are used to construct boundary faces and for determining the object's coarse boundary [34]. For boundary face refinement procedure it is compulsory to activate the dormant nodes for routing their data to sink. For this purpose, four types of SIMs (spatial interpolation methods) are used to estimate the sensory data of inactive nodes within boundary faces and awaked only most suitable nodes among them to report the sensing data to sink. Follow the iteration of this process until the last dormant node checked in the boundary face. Therefore, fine boundary faces are completed that gives accurate boundary area in energy proficient manner. A self-scheduling scheme is also proposed to ensure the network connectivity, cover the long sensing range and fault-tolerance requirements. Granularity of the planarization constantly becomes a dilemma [38].

For tracking the continuous objects C. Sajjid et al, proposed a twofold-sink based data collection to find the best optimal path and saving residual energy of network nodes. It comprises mobile and static sink nodes. These sink nodes gather information mutually from BNs. Mobile sink give a hand to the static node in clustering. Clusters are formed by using centroid algorithm. Boundary nodes are uniformly distributed into clusters and both sink nodes are placed in the centric points of their relevant clusters. That is, makes minimum distance from each BN to the sink nodes. Sink nodes gather sensory data about BNs then put together distribution of energy consumption among nodes as much as possible to prolonging the network lifetime. In the case of static sink node located outside the event, mobile sink node assisted the static sink node by moving to the object position. It obtains the object's centric position by gathering the BNs information and broadcast the message. After receiving the message each node compare its distance from the both sink nodes and choose the nearest sink node for transmit the data. K-means algorithm is used to find the optimal sensing location for mobile sink movement within network. It helps to lessen the overall hop count and traffic load of data packets on the intermediate nodes that resides in-between static nodes and regular network nodes by the mobility and optimal path calculations [55].

Accurate detection, tracking and monitoring of continuous objects become a challenging task in WSNs because of their uneven attributes of contraction and expansion. For detecting such objects extensive amount of sensors nodes are used that sense the object, aggregate data and communicate with other devices as well. Sink node analyzes received data from nodes to detect the precise object boundary. Accuracy of boundary detection is dependent on the collected data from sensor nodes so, there is need to be carefully chosen boundary nodes. Failure of BNs affects the event detection information which results in imprecise boundary estimation. To overcome the issue of node failure, Sajida et al. proposes a scheme BDBS for failure-prone object detection and recovery that uses voronoi graph based clustering technique to detects and improve the failure arise at the BNs. Also utilize the temporal and spatial features of sensor nodes for detecting the status. When a node detected abnormal during change in phenomena, its one hop and two hop neighbors are detected to decide whether the node is BN or not. If a BN failure status is detected, the suitable node is activated in place of failure node. For getting optimality some leader nodes are selected on the basis of high residual energy of nodes among BNs that transmit data towards sink node. Mainly this scheme makes a reasonable use of sleeping method of sensors for reducing the energy consumption in a network [78].

Hyun et al. introduces a proficient algorithm to monitor the mobile object with the aid of subset selection of monitoring data of BNs. At first, a data aggregation method is presented for reducing the amount of data packets among nodes and for energy conservation in the network. After that, a Quadratic polynomial interpolation mechanism is applied to enhance the boundary accuracy by interpolating the object's boundary lines among RNs. Conversely, this scheme does not consider the fact about predicted boundary whether it is correct or not [79].

To overcome the long term maintenance cost for WSNs and inaccuracy of continuous object detection in sparse network Jianming et al. presented a method of detecting sensing holes and selecting optimum path positions for mobile nodes. Sensing holes detected by the help of Voronoi diagram prior to the network initialization [80], [81] and provide location weight of the perceptual holes following the static nodes detecting the value in toxic air. For optimum path selection mobile sensors can fill up perception holes and detect the variation points for object boundary detection. Therefore, sensing holes, which elected by data variation and spatial factors are recorded in the list of target node for mobile node. To conclude, an optimal path is set by considering distance between points and priority of the mobile nodes cooperatively. In this method dynamic nodes are used for probing that is not a suitable choice in all scenarios [82].

2.2.3 Continuous Object Boundary Detection Schemes

Recently, important research work has been taken place to continuous objects tracking [39],[49],[64] using sensor networks. Many of those researches [51], [55], [59], [67] intended not only to track the continuous objects that have dynamic nature and constantly move in the target field but also to determine the accurate boundaries of the tracked objects. The following category recommends latest techniques for boundary detection of continuous object in IoT enabled WSNs. Also presents their effectiveness based on network distribution, detected data collection and computation, boundary node selection, BN reduction, duty cycle mechanism, energy conservation, managing traffic between nodes and object boundary accuracy.

Y. Zhang et al. presented a method for boundary region detection of continuous objects named BRDCO in which mobile sensors nodes are used in order to remove the sensing holes in sparse network and effectively determine the accurate object boundary information. Static nodes are installed in the associate region and send out their sensing data to sink node. Based on this data, predicated boundary is generated. Mobile nodes are passed through BL points to get new boundary line. Widely use of mobile sensors is cost oriented method and not a suitable option for using these sensors in special environments[30].

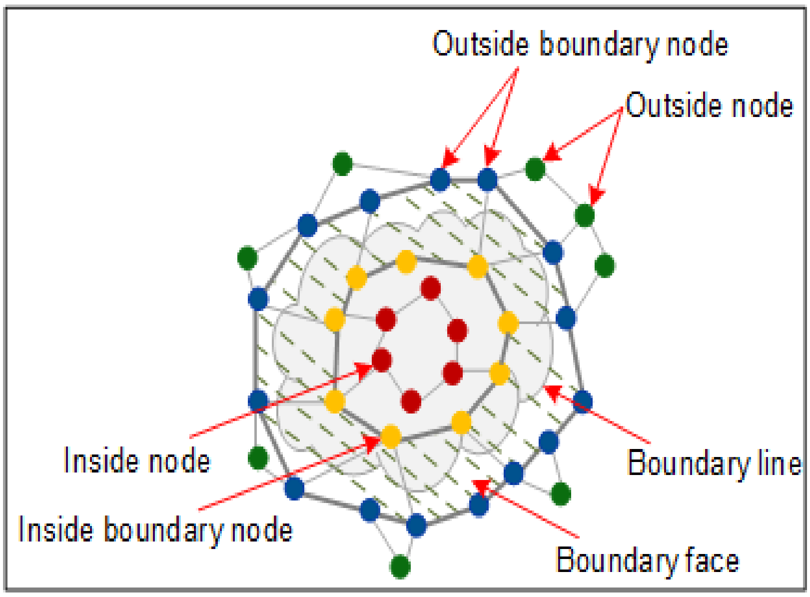


Figure 2.3: Boundary detection object model

In [40] clustering and predication concepts are fused together to enhance the object tracking accuracy. Constant gain Kalman filter mechanism helps the BS to predict the next location of continuous object. After predicting, BS sends predicted result to CH that is nearest to the object boundary. CH activates three sleeping nodes that are closest to the target. As the diffusion rate of continuous object becomes high, large numbers of boundary nodes are required to estimate the accurate outline of object and it also involve in massive data communication and data uploading which produces transmission overhead and energy consumption. It has significant impact on the detection of object boundary to tackle with this critical condition.

Guangjie et al. planned a technique (BRTCO), boundary recognition and tracking algorithm for continuous objects to promise the effectiveness of objects outline extraction. This technique involves in two steps, first is collaborative filtering scheme and second is data reporting process. In first step, a coarse-to-fine filtering method is introduces to filters the unnecessary BNs that have no benefit to track and detect the object without reducing tracking accuracy. Through this a number of BNs can be significantly diminished in a dense network and acquire energy efficiency. In the data reporting step, a clustering approach is introduced to lessen the communication overhead and energy consumption. Based on CH competition a report node selection method is considered to avoid potential interference [41].

For efficiently detection of faulty nodes with lessen searching space of boundary tracking nodes L. Liu et al. presented a binary tree structure based continuous object boundary detection and tracking protocol BTS-COT structure. Partition the network in the binary tree structure within the object area to obtain the coarse boundary area mapping. It takes potential of both collective intelligence and machine learning in the sensor nodes for decision boundaries [59].

F. Lei et al, presented (CM-IoTSNC) cloud model-IoT sensing network collaborative technique for detecting and predicting the boundary of continuous objects[61]. Lei et al. proposed a mechanism of (AONN) activating one hop neighbor nodes for accurately detecting the boundary of continuous objects[62].

To outperform the boundary accuracy, H. Ping et al. introduces a two step boundary face detection approach EEBDDC in duty cycled WSNs. At first, active nodes sense the event and detected the object boundary faces. After this detection process, few nodes remain in sleeping state that cause in coarse boundary faces. For removing this coarseness, SIMs algorithms are applied for data estimation and based on this estimated sensory data suitable (candidate) boundary nodes are selected. Hence, boundary face sizes are reduced [66].

In [67], Diao et al. introduces an energy proficient scheme EEBDCO-IoTSN. Boundary information is calculated by using convex hull algorithm [83]. An optimized greedy algorithm is modified to activate a few neighboring nodes in the sub area of network. This scheme can mitigate the energy consumption and get the refine boundary.

To get better detection efficiency of continuous object boundary J. Tang et al, propose a novel approach of HGI-tree in collaborative fog-cloud IoT networks. This scheme used edge devices for detecting the hazardous area and initially builds a spatial index tree of multiple layers and divide grid. To minimize the energy consumption and issue of exchanging large messages a novel method probability density function is proposed. Uneven nodes distribution in grid cell causes failure of boundary grid detection [23].

Due to the diverse nature of continuous object diffusion, it is complicated task to detect and visualize such objects i.e. toxic gases. For accurate detection and visualization of hazardous area of toxic gasses Lei et al. proposed a method DDATG, in which five planarization algorithms are adopted for planarize purpose of a monitoring network. Divide the dangerous area into inner and outer boundary zone for detection of leakage. Planarization of monitoring network attains different topologies and also calculated and analyzed the boundary area of toxic gas diffusion to delimitate the hazardous area. Based on the detection accuracy of leakage area this study briefly analyzed and discussed the effect of these 5 algorithms. However, these planarization algorithms are difficult to resolve the planarization granularities[84].

2.4 Comparison of Continuous Object Tracking based Schemes

This section presents a comparative analysis of different schemes based on the taxonomy depicted in Figure 2 and further provides detailed analytical review of these schemes in tabular form that represented in Table 2. This table illustrates the comparative analysis of multiple schemes based on their basic idea, method, pros and cons. Also, Table 2 contains different schemes of continuous object tracking and boundary detection. These schemes further classified into three categories based on the proposed taxonomy.

Category-I, elaborates four schemes [64][49][74][76] that put special assumptions on continuous object tracking. These schemes offer a solution of energy utilization and increasing accuracy by structuring cluster mechanism for continuous object tracking and some schemes [64][49][74] help in prolonging the network life by minimizing the communication overhead. In [49] subset of boundary nodes are chosen to mitigate the uploaded messages quantity that tends to less transmission overhead. In [64][74] similar work of configuring network in clusters is adapted in static and dynamic clustering mechanism, [64] also uses an well-organized method of tree based approach for object tracking. [76]considers different sensing ranges for getting better performance for object tracking in different networks.

Category-II, analyzes seven schemes [38][48][55][56][78][79][82] for continuous object tracking and boundary detection. These schemes[38][48][55]efficiently decrease the redundant communication cost and high data traffic also improve system life whereas [38] facilitates boundary face detection mechanism and uses a duty cycle method to ensure the energy efficiency. [78][79][82] efficiently detect the precise object boundary [78][82] present fault detection and recovery method. For proficient data collection from BNs [55] uses a hybrid sink mechanism to tracks the continuous objects also utilizes the residual energy of tracking nodes. For congestion avoidance, [56] employs a mechanism of transmitting data by computing assortment of link capacity and lessen the packet drop ratio.

In category-III, seven schemes [41][30][62][61][[23][67][84] are analyzed for continuous object boundary detection.[41][30][61][67]facilitate energy efficiency by reducing number of activating boundary node neighbors and effectively detect accurate boundary of continuous object.[62][61][23] present grid based network structure for detecting the object boundary in energy efficient manner and decreasing communication cost. For efficient data computation and boundary predication, cloud and IoT devices are used by[23][61] whereas [23] also provides the special functionality of fog devices for diminishing the data transmission cost and give low latency.

To detect and visualize the continuous object diffusion [84] analyzed the impact of 5 planarization algorithms on boundary detection accuracy of hazardous area and give way to tolerate the fault. Analysis put special recommendations that if we require object tracking and boundary detection in energy proficient manner then we have to devise an effective system that give minimum communication cost, latency rate and packet drop ratio. Furthermore, accuracy is important factor for target boundary detection that should not be neglected in crisis.

Table2.1: Analysis of Continuous Object Tracking based Schemes

Scheme	Basic Idea	Mechanism	Pros	Cons
Continuous Object Tracking Schemes				
DCTC [64]	Clustering scheme DCT presented for tracking the mobile target. Reduces the number of BNs that transmit the data to SN.	Energy efficient boundary detection algorithm. Simulation is implemented in NS2.	Energy saving. Prediction method helps in reporting high data rate.	Clustering overhead. Disconnection of networks. Single object tracking.
DEMOCO [49]	This technique selects few BNs and RNs for energy utilization. It bane other BNs to become RNs by passing control message.	An algorithm is used to detect and track the boundaries of dynamic nature objects.	Few BNs and RNs. Energy saving. Reduces traffic overhead and communication cost.	Inaccurate boundary shape. Energy consumption.
EEAOC [74]	Energy efficient organization of clusters to attain efficient data collection and communication.	Uses EEAOC algorithm for clusters construction, data fusion and movement. Uses simulation in MATLAB.	Energy efficient. Lower communication overhead.	Cluster maintenance may induce high energy.
COT [76]	Discusses different sensing range for boundary accuracy in different deployments and speed of the CO.	Modification of DEMOCO [49] algorithm. Uses simulation in JAVA.	Better performance and accurate tracking of CO. Lower cluster maintenance.	More energy consumption using long sensing range.
Continuous Object Tracking and Boundary Detection Schemes				
CODA [48]	Uses hybrid clustering method for detecting and tracking the dynamic boundary of CO.	Give HC algorithm for reporting fewer messages and CHA for boundary detection. Uses Qualnet simulator.	Prolongs network life. Dynamic clusters reduce the cost of communication overhead.	Consumes high energy. Does not handle missing track recovery.
CDCAPC [56]	Provides CDCAPC algorithm for	Employs PCCS and RBNIC algorithms	Reduces congestion and data	Massive data load may cause high

	consistent data assortment, congestion reduction and data transmission with different link capacities.	for reporting fewer messages. Uses simulation in JAVA.	transmission. Transmits high priority data packets in severe condition.	energy and communication cost.
EEATDC [38]	Uses two-level boundary detection and localization procedure in duty-cycled environment to attain the BA.	Gives PG and four SI algorithms for exact boundary estimation. Uses simulation in JAVA.	Energy efficient. Reduces data traffic by using small numbers of ANs.	Supposition of PAs is not applicable to all cases. Planarization granularity issue.
TFSDC [55]	Twofold sink based data collection for finding the best optimal path in CO tracking.	Gives K-means algorithm to locate optimal positions and CA for clusters formation. Uses simulation in JAVA.	Energy saving. Transmission overhead reduces through best OPS.	Boundary accuracy is not considered. Cluster formation and maintenance overhead.
BDBS [78]	An efficient failure prone method for detecting and recovering the failure of nodes without affecting the BA.	It uses voronoi graph based clustering technique and temporal and spatial features of SNs.	Energy efficient. Provides optimality and boundary accuracy.	Inconsistent data aggregation and high communication cost.
PA & QPI [79]	A subset selection of reporting data of BNs for monitoring the boundary of moving objects.	Uses data aggregation algorithm for data exchanging at RNs and QPI for accurate boundary detection.	Energy efficient. Lower transmission overhead. Improve boundary accuracy.	RNs selection method and correctness of predicated boundary does not consider.
SHDB [82]	A method of detecting sensing holes and selecting optimum path positions for mobile nodes.	Uses three algorithms, one for primary candidate selection of filling the sensing holes and others for selecting the target.	Efficient sensing holes detection. Energy saving. Provides optimality.	Cost overhead. Mobile nodes have not practical use in inaccessible areas.
Continuous Object Tracking and Boundary Detection Schemes				
BRTCO [41]	A two-way filtering and data reporting	Uses collaborative filtering method to	Energy efficient. Lower transmission	Consumes energy during detection

	mechanism for boundary recognition and tracking of CO.	lessen the BNs and clustering technique for data reporting. Performs simulation in MATLAB.	overhead.	procedure. Cluster's maintenance issue.
BRDCO [30]	Determines the accurate boundary of CO by using mobile sensors nodes that remove the sensing holes in sparse network.	Uses SI, Gabriel graph and RNG planar algorithms for detecting the accurate boundary of CO.	Energy efficient. Boundary accuracy. Mobile sensors give obstinacy of sensing holes.	Cost overhead. Mobile nodes are not feasible in special environment.
AONN [62]	A mechanism of activating one hop neighbor nodes for accurately detecting the boundary of CO.	Reprocesses the interpolation methods for extracting BNs at sink. Simulation in java and MATLAB.	Provides optimality and boundary accuracy.	Transmission overhead. Consumes high Energy.
CM-IoTSNC [61]	A dynamic diffusion method that detects and track the boundary of gas leakage area by the help of cloud computing power.	Uses a grid based network and dynamic diffusion model for tracking the CO. Simulation in Java program.	Small numbers of active devices consume less energy.	Transmission delay. Energy consumption.
EEBDO-IoTSN [67]	A method of boundary detection of CO in which only relay nodes are activated to sense the event.	Uses convex hull algorithm for detecting the coarse boundary of object.	Energy efficient. Precise boundary detection.	Partitioning of boundary area and nodes checking is still a problem.
HGI-FCIoTNC [23]	HGI is build by using the combination of edge devices and cloud.	Uses probability density function for boundary points detection.	This approach serves as low latency and saves more energy.	Performance degradation occurs.
DDATG [84]	A method of dividing the hazardous region into different boundary areas for accurate detection	Uses five PAs for precisely detecting and visualizing the hazardous zone of gas diffusion in	Energy efficient. Precise detection of tiny objects. Fault tolerant.	Partitioning granularities problem. Transmission delay.

	and visualization of toxic gas leakage.	WSNs.		

2.5 Research Gap and Directions

We have inspected different existing research work on continuous objects tracking and boundary detection in literature. Based on the analysis of state-of-the-art literatures we have observed some deficiencies that have not focused. The main deficiencies are investigated as follows;

- Recently, existing approaches highly focus on continuous object detection and tracking, whereas little attention is paid on boundary detection of these objects.
- Cluster based approach is most suitable for deploying the sensors in energy efficient network, where only cluster head transmit the data to base station but cluster maintenance overhead occurs by increasing sensor nodes in the network field and also provoke high energy when network topology information exchange among neighbors.
- Massive data load at base station may incur high energy consumption and communication cost.
- Considering long sensing range for detecting slow speed continuous object in sparse network, large number of representative nodes will require that resulting in high energy loss.
- In some research works planarization algorithms are adopted for making boundary faces defined by BNs for detecting accurate boundary. Because of real networks complications, making assumptions of these algorithms may not supported to all cases. In some works network partitioning granularities problem is not focused for selecting BNs.
- Repetitive activation procedure of all 1 hop neighbors resulting high energy loss.
- Communication for simulating the gas diffusion prediction in between IoT devices and cloud takes time which produces delay and consumed high energy.
- In existing methods, boundary prediction accuracy is not considered.

- Some researchers used mobile sensors with the collaboration of static nodes to acquire the better detection of object boundary. Mobile nodes sense and collect target information in more effective way. But use of mobile nodes may cause in high cost overhead and consume more energy when they continuously move, sense and gather sensing data. Moreover, use of mobile in harsh places and mountains is inadaptable.

Many schemes have been proposed for continuous object tracking where accuracy of sensing information, sensing power, network architecture, data communication, energy utilization and object modes are considered as significant factors in the design of continuous object tracking and detection. Most of these reaserch works have considered traking and boundary detection models that track and detect the boundary of continuous objects over a period of time and use this tracking information for furture predictions. Also presents effectiveness of these techniques that depend upon the multiple features such as data collection and processing, network distribution, BN selection, boundary node reduction, duty cycle mechanism, traffic management between nodes,energy conservation and boundary accuracy. When we talk about boundary detection of continuous object that data transmission delay is not only focused but excessive amount of boundary node's selection causes high energy consumption and hence cannot be considered as boundary accuracy factor.

Based on the above findings, this research work is directed towards proposing a continuous object tracking and boundary detection method which should be competent to efficiently track the continuous object to an adequate level of accuracy and estimate the precise object boundary while maintaining energy efficiency in duty cycle mechanism. Also, should facilitate low latency rate when a large amount of object detection information arrives in real time.

2.6 Summary

In this chapter, different continuous object boundary tracking and detection schemes have been discussed. The comparative analysis of these schemes is presented in terms of energy efficiency, number of nodes uses, transmission delay, boundary accuracy, boundary predication, complexities of planarization algorithms, uses of mobile nodes and clustering techniques. Basic idea, mechanism, pros and cons of different schemes have been discussed in Table 2 and highlighted the research gap in literature that leads towards new research direction. According to this research direction, a method proposes for boundary detection of continuous object in IoT enabled WSNs that facilitate low latency rate when large amount of object detection information arrives in real time. It also activates least number of nodes to improve energy efficiency and network life.

CHAPTER 3

PROPOSED SOLUTION-BOUNDARY DETECTION OF CONTINUOUS OBJECTS IN IOT(BDCO-IOT)

3.1 Overview

In this chapter, a novel mechanism is proposed for detecting the boundary of continuous objects BDCO-IOT. This technique is intended for developing boundary detection and tracking mechanism of continuous object which should be capable to track continuous object within a certain threshold of adequate accuracy that maintains low latency contact for exchanging information in real time scenario while extending energy efficiency by activating small number of nodes to keep the network scalable. The main goal is to build a grid based mechanism for detecting hazardous boundary area with the aid of fog computing to reduce the delay of transmitting information between cloud and IoT nodes by making the head node a powerful node that make decisions for whole region. It also generates plan to alert the teams for rescue efforts in advance. Main objective of this research work is to reduce transmission delay, energy consumption, number of nodes, packet loss ratio and improves detection accuracy.

3.2 Operational Framework

BDCO-IoT is proposed for boundary detection of continuous object in IoT enabled wireless sensor network. This technique is promoted to address these shortcomings and facilitates low latency by using fog computing with IoT sensing network. Fog intelligent networks are used to replace sink nodes with powerful fog nodes or edge devices that have higher capability of storage and processing than normal IoT nodes.

Also extend the network life by using the duty cycle method of activating some nodes which ensures low energy cost. This strategy can generally make up for the shortcomings of latest monitoring technology and empowers efficient monitoring. The operational frame work consists of four phases. Operational framework is as shown in figure 3.1.

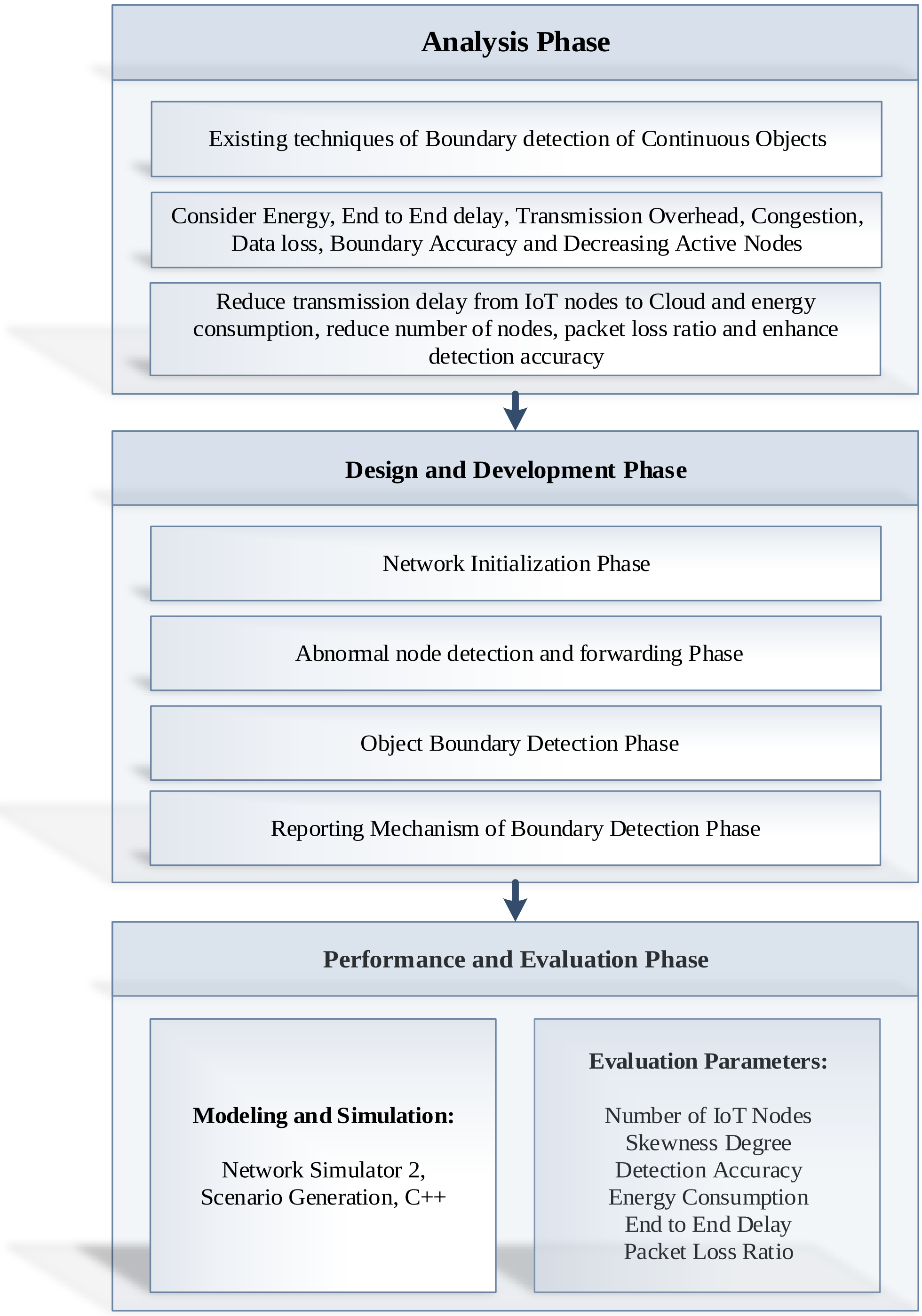


Figure 3.1: Operational Frame work

First phase is about network initialization (i.e. making grid clusters) and deployment of nodes in clusters grids. In second phase, sensor nodes detect the event and transmit the abnormal node detection information to the CH in ANL. In third phase, CH detects the initial boundary nodes by calculating the distance between ANs and centric point of event. After that, it sends the detected information to the fog server in IBNL. Fog server simulates the convex hull algorithm for detecting the exact boundary nodes and informs the CHs to activate the exact boundary nodes in their respected cluster grids. In fourth phase, reporting mechanism of detected information is shown.

3.3 Research Design and Development

CM-IoTSNC[61] cloud model- IoT sensing network technique detects and predicts the boundary of continuous objects. In Figure 3.2, head node detects the event periodically. When the target event such as gas leakage is detected it reports detected data to backbone node (black arrow shows the reporting path). For finding the precise location of leakage source it activates 1 hop neighbor nodes of abnormal nodes as represented by green circles. Backbone node receives this leakage source information from head node and uploads it to the cloud for toxic gas diffusion’s prediction. Cloud simulates the climatic diffusion of gas in preferred and complicated environments. After that cloud transfers the prediction outcomes of continuous object boundary to the backbone node (indicating by red arrow). Subsequently backbone node sends this information to IoT sensors for activating corresponding boundary nodes (orange arrows show this flow). Based on this information abnormal nodes activate their 1 hop neighbor nodes (i.e. blue circles) to establish the accurate continuous object boundary area. Transferring sensing information by backbone node to cloud for prediction, processing information at cloud and then reporting outcomes back to the IoT devices takes time which produces delay and increases communication overhead in emergency situation. Activation of 1 hop neighbor nodes for boundary detection consumed energy. How to reduce this transmission delay and energy consumption is the main concern of this research.

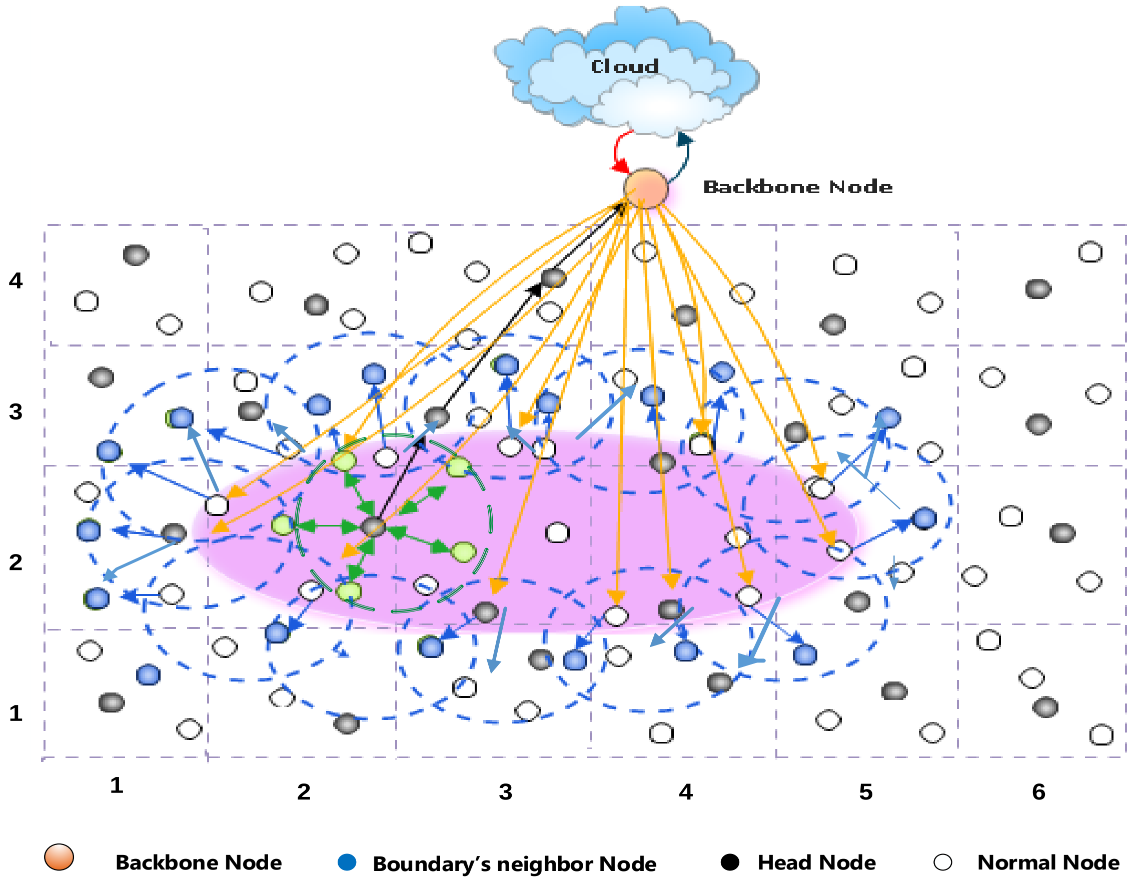


Figure 3.2: Boundary detection producing delay

Solution of identified issues are presented, which consist of four phases:

3.3.1 Network Initialization

At first, network initialize by making clusters of grid cells. IoT nodes deploy in these cluster grids with skewness degree which helps in reducing number of nodes for data transmission to cloud. Also, introduce the fog node server as a powerful node that is place in between the IoT nodes and cloud for data transmission. It simulates the boundary information after getting the detection information from CH and reduces the long transmission delays between IoT nodes and cloud.

3.3.2 Event detection by abnormal nodes

At SN, sensor nodes detect the event and add to the DNL whereas rests of the nodes are in sleep state. In DNL, if a node detects its concentration value is greater than the threshold value then it will be active and added to the ANL as AN. Each abnormal node detects the event within its cluster grid and forwards the detection information to CH in ANL. It helps in minimizing the communication overhead, transmission delay and energy consumption as only active nodes in ANL transmit the detected information to CH.

3.3.3 Boundary nodes detection

At CH level, CH calculates the distance of ANs by the distance formula and inserts the ANs in IBNL if the ANs are far from the centric point of event. This also helps in reducing energy consumption by activating small amount of nodes.CH transmit this information to the fog server in IBNL. Fog server simulates the boundary by convex hull algorithm and adds BNs toBNL. It shares BNL to the CH. CH activates the corresponding BNs in its respected clusters without activating the BNs neighbor nodes and get the exact boundary of continuous object with minimum energy consumption. After that, fog server stores the results in cloud without the interference of sensor nodes which reduce the transmission delay.

3.3.4 Delay minimized transmission of detected information from IoT to Cloud

In this process, reporting mechanism of detected information between CH and fog server is introduces. Fog server reduces the transmission delay between the IoT nodes and cloud as the CH transmits the detected information to the fog server for boundary estimation not to the cloud. Fog server also transmits the results to cloud for storage so that user can access these results in emergency situation without any delay.

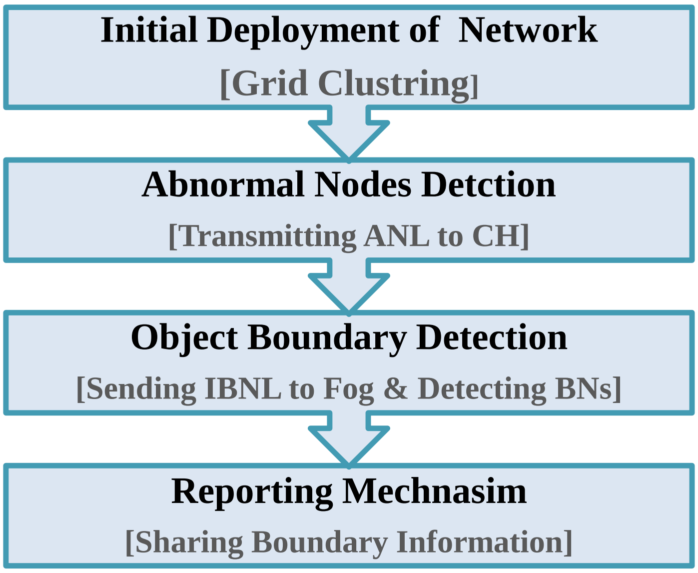


Figure 3.3: Proposed system steps

3.4 Simulation Framework

The performance of BDCO-IoT algorithm is evaluated using extensive experiments. Simulation was conducted in combination with the stated boundary detection mechanism in IoT enabled WSNs, and the results were evaluated. To simulate data transmission and communication between IoT nodes and the fog node for efficient boundary detection NS-2.35 simulator is operated. Table 3.1shows the Parameters and environmental setting for BDCO-IoT. In simulation setup, network field is set to 500x500m for the deployment of IoT sensor nodes. Maximum numbers of IoT sensor nodes are 1500 to 3500. In which 200 CHs are stayed in the active mode to monitor the network and these are located at the center point of four grid cells. Set the side length of cluster grid as √2 with radius of 100m. Different numbers of IoT nodes 1500 to 3500 are deployed in the network with skewness degree sd = 10% to 50%. Skewness degree shows the uneven distribution of IoT nodes in the region. It can be calculated by formula in Equation 3.

$$\boldsymbol{sd = (d - s)/sum} \qquad \boldsymbol{sum = d + s} \qquad (3)$$

Simulation begins after setting up all of the simulation parameters in order to test the proposed work. To evaluate the performance of BDCO-IoT is compared with existing boundary detection schemes in continuous objects such as CM-IoTSN, AONN and WSM.

3.4.1 Performance Metrics

In order to evaluate the effectiveness and robustness of BDCO-IoT and the sampling method consider the following evaluation metrics: Average End to End Delay, Energy Consumption, Number of IoT Nodes, Skewness Degree, Detection Accuracy of continuous objects and Packet Loss Ratio.

Table 3.1: Simulation Parameters for BDCO- IoT.

Parameter Descriptions	Values
Network Field	500x500 m
Number of Nodes	1500-3500
Communication Radius	100 m
Skewness degree	10% to 40%
Number of bits in 1 packets is transmitted (k)	1
Threshold value (thd)	70mg/m^2
Time interval of SNs detection	10 sec.
Initial energy	1000 nJ
Energy consumption to transmit or receive for per bit Eelec	50 nJ/ bit
Energy consumption transmitting amplifier $\in_{amp}$	0.1 nJ/ (bit x m^2)
Attenuation Index (n) for transmission	2
Channel Type	Wireless
Time slot	0.1-1s
Number of packets	500

3.4.2 Assumptions and Limitations

Following assumptions are considered for BDCO-IoT.

i. The IoT-WSNs consists of thousands of smart intelligent devices (IoT) and powerful edge node (fog node).
ii. At the start all IoT nodes have the same radio, memory, battery, and processing capabilities. CH of each cluster grid is selected on the basis of residual energy of nodes in the network.
iii. Each CH is aware of its location and its corresponding IoT nodes' locations in the respected cluster grid.
iv. The communication links between IoT nodes are omni-directional.
v. IoT devices are capable of multi-hop communication to transmit data.
vi. IoT nodes are not affected by environmental elements i.e. water, fire, humidity, air temperature, direct sunlight, etc.
vii. For object boundary detection, inner condition of the object area is important. So, the inner condition of an object can be roughly detected.

3.5 Objectives of this work

Main objectives of this research work are to reduce transmission delay, energy consumption, number of nodes, packet loss ratio and improve detection accuracy.

3.5.1 Transmission Delay from IoT nodes to cloud

For reducing the transmission delay, unlike the CM-IoTSNC in this scenario fog node is placed between the IoT nodes and cloud that simulates the boundary of dangerous area. Also uses the cluster grid architecture in the network for reducing the communication overhead between nodes.

3.5.2 Reduce number of nodes for data transmission

As CH calculates the distance of ANs from centric point of event and transmits the detection information of only activated nodes those are in IBNL to fog node. By using this information fog node simulates the boundary of dangerous area and report back to CH of exact boundary nodes. In this method there is no need to activate the neighbor nodes of BNs for boundary detection. So, it utilizes the duty cycle mechanism of activating least amount of sensor nodes which guarantee low energy cost.

3.5.3 Improves detection accuracy of continuous objects

As the number of active nodes increases in the grid architecture CH receives the detected information from all the active SNs and forward it to the fog server for processing. More IoT nodes deploy in the network that result in more detection accuracy.

3.6 Proposed Scheme (Boundary Detection of Continuous objects in IoT (BDCO-IoT)

The BDCO-IoT mechanism has been presented to overcome the shortcomings of boundary detection and tracking mechanism of continuous objects such as timely data collection, high communication and energy costs. The proposed system model is able to serve the demands of delay-sensitive real-time IoT-enabled continuous object detection application. The strategy employs the communication between IoT nodes to cloud by utilizing the computing power of fog nodes to timely locate the boundary of hazardous region. The strategy consists of four phases: i) Initial Deployment of Network, ii) Abnormal Node Detection, iii) Object Boundary Detection, iv) Reporting Mechanism.

3.6.1 Initial Deployment of Network

At the deployment stage, evenly divide the whole region into grid cells. Grid cell is in the shape of perfect square and IoT nodes deploy in these grid cells with skewness degree. This phase introduces cluster architecture of grids that equally form clusters by joining the four grid cells in each cluster. The side length of each cluster grid is √2 r, where r shows the communication radius of IoT nodes. Figure 3.4 shows an example of cluster architecture of grids in which clusters are denoted by brown lines and grid cells are denoted by black dashed lines. Cluster grid names are represented by C1, C2, C3, C4, C5 etc.

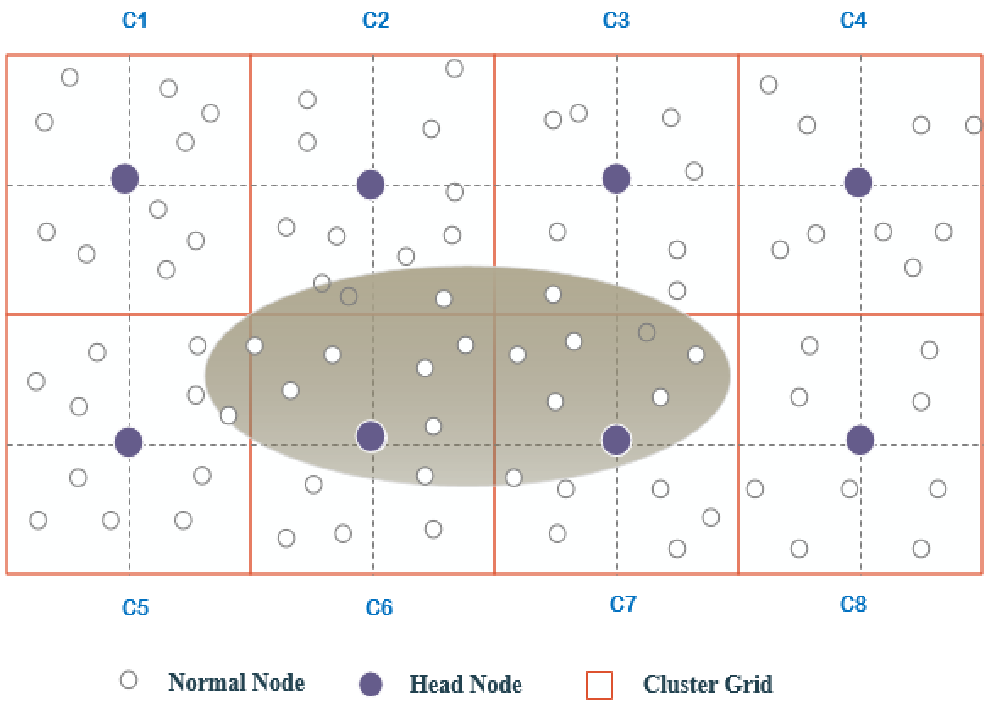


Figure 3.4: Network architecture of BDCO-IOT

The white circles represent the sensor nodes (SN), gray shaded area represents the leakage area and the black circles refer to the cluster head (CH). Also, set the cluster head as a powerful node that locates at the centre of the four grid cells or in other words, CH locates at the centre point of cluster grid. Each cluster grid has its own powerful head node that act as controller. It detects the initial boundary of continuous object after getting the object detection information from abnormal nodes. Each CH has the id and location information and it can also know the state information within its cluster grid.

3.6.2. Abnormal Node Detection

This phase introduces the algorithm about abnormal node detection at SN in which SNs detect and transmit the detected information to the CH. Algorithm 3.1 details the process of abnormal node detection. In this context, each SN detects the event within a specific grid cell and reports immediately to its CH. SNs detect concentrations and insert them into DNL detection node list (line 1-3) while, rest of nodes will remain in sleep state in order to consume less battery power and extend the network life. For each SN in detection node list DNL (line 5), when one SN detects its current concentration (*cv*) value is greater than threshold (*cth*) value (line 6), the SN will be inserted to the ANs list (ANL) that reflects the object's inner condition (line 7) and activates the SN (line 8). It calls abnormal node AN. Each abnormal node detects the event within its cluster grid and sends the abnormal information in ANL to CH (line 9). Equation (3.1) explains the abnormal node detection information sent from SN to CH where $\mathrm{SN_{id}}$ shows the ID of sensor nodes, $\mathrm{SN}_{\mathrm{lang}\,\&\,latit}$ shows the location of sensor nodes, $\mathrm{SN_{status}}$ shows the status (active/sleep) and $\mathrm{TN_{SNi}}$ represented as timestamp which is essential to guarantee the message freshness. $\mathrm{N_i}$ as nonce value ensures protective communication in order to make sure that these code values are not reused. In equation (3.2), M1 represents the message send to CH whose hash H (M1) ensures the message integrity at CH side. But if SN does not detect its current concentration value (*cv*) greater than the threshold value (*cth*) it turns into sleep mode and it will be deleted from DNL (line 11). In figure 3.6 yellow circles show the abnormal nodes (ANs) in object area. To find out the precise location of leakage source ANs detect the event and transmit the sensory data to its CH (such as black circle) within cluster grid. If the event detected in another cluster grid it will be detected by the subsequent CH. For example, in C2, C3, C5, C6, C7 cluster grids, ANs transmit their sensory data to their corresponding CH.

$$\mathrm{ANL}\ \{\mathbf{SN_{id}}, \mathbf{SN}_{\mathbf{lang}\,\&\,latit}, \mathbf{SN_{status}}, \mathbf{TN_{SNi}}, \mathbf{N_i}, \{\mathrm{ANL}\}, \mathrm{H\ (M1)}\} \qquad (3.1)$$

$$\mathrm{M1} = \mathrm{ANL}\ (\mathbf{SN_{id}} \| \mathbf{SN}_{\mathbf{lang}\,\&\,latit} \| \mathbf{SN_{status}} \| \mathbf{TN_{SNi}} \| \mathbf{N_i}) \qquad (3.2)$$

Table 3. 1: Notations and their Descriptions

Symbol	Description
cth	concentration threshold
cv	concentration value of node
CH	Cluster Head
SN	Sensor Node
AN	Abnormal Node
DN	Detection Node
BN	Boundary Node
SN_{id}	Sensor Nodes ID
$SN_{lang\,\&\,latit}$	Sensor Nodes location with coordinates
SN_{status}	Sensor Nodes status Active/Sleep
TS	Time Stamp
N_i	Nonce value
D_i	Distance of nodes
H	Hash Function
C_{Di}	Distance of centric point of event
AN_{Di}	Abnormal Node Distance
DNL	Detection Node List
ANL	Abnormal Node List
BNL	Boundary Node List
IBNL	Initial Boundary Node List

Algorithm 3.1: Abnormal Node Detection

```
for all SN do
   SN detect c
      DNL. insert(SN)
  End for
   for each SN in DNL do
      if  SN (cv >cth) then
         ANL. insert(SN)
         activates SN in DNL
         M1 = ANL (SN_id || SN_lang & latit || SN_status || TN_SNi || N_i)
   Else
         SN is sleep and DNL.delete (SN)
   End if
   End for
```

Figure 3.5: Algorithm of Abnormal Node Detection

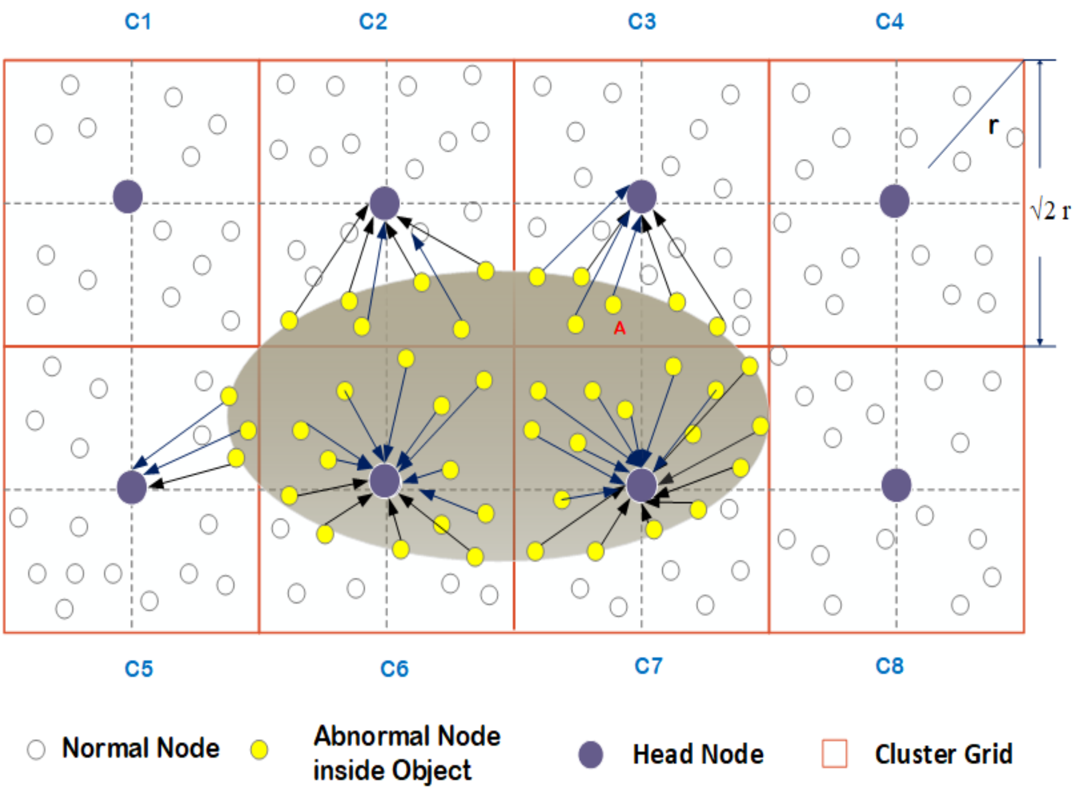


Figure 3.6: Abnormal node detection process

3.6.3. Object boundary detection

In this phase, object boundary detection algorithm is used at the CH to detect the initial boundary of the object. It further detects the exact boundary nodes at fog server. In algorithm 3.1 CH receives abnormal detection information of event RCH (message) from SNs. It includes SN_{id}, $SN_{lang\,\&\,latit}$,SN_{status}, TS_{SNi}, N_i and hash H(M1) of message. To ensure the message freshness CH checks timestamps difference between TS_{CHi} and TS_{SNi}. CH calculates the distance of ANs in abnormal node list ANL (line 1-3) by the distance formula as shown in Equation (3.3).

$$D = \sqrt{(\mathbf{x2}-\mathbf{x1})^2 + (\mathbf{y2}-\mathbf{y1})^2} \tag{3.3}$$

If the distance of abnormal nodes (AN_i) is greater than the distance of centric point of event then these nodes will be inserted to the (IBNL) iinitial boundary node list (line 4-5).

Algorithm 3. 2: Object Boundary Detection

CH: Receive message *RCH*={SN_{id}, $SN_{lang\,\&\,latit}$,SN_{status},TS_{SNi}, N_i, {ANL}, H (M1)} from SNs

1: Calculate D_i of SN_i

2: **for** each AN_i in **ANL do**

3" Extract the AN_{Di} of each AN_i

4: **if** (AN_{Di} > C_{Di}) **then**

5: Insert AN_i into IBNL as IBN

6: M2 = IBNL (CH_{id} || $CH_{lang\,\&\,latit}$ ||SN_{Di} || AN_{Di} || TS_{CHi} || N_i || IBN {ANL })

7: **Else**

8: **ANL**.add (AN_i)

9: **End if**

10: Applying Convex Hull algorithm to extract the BN **then**

11: Add BN in the BNL

12: **End for**

Figure 3.7: Algorithm of Boundary Detection

For estimating the exact boundary, CH transmits the IBNL (as shown in Equation (3.4)) and accurate position of leakage source to fog node (line 6). Otherwise abnormal nodes (AN_i) remain in abnormal node list ANL (line 8). Equation (3.5) explains the initial boundary node list sent from CH to Fog node. Fog node receives this information and start to simulate the boundary by convex hull algorithm that is deployed on the fog node (line 10). After that detected boundary nodes BNs will be added to BNL (line 11). The outcomes of convex hull algorithm as BNL are transmitted back to the CH and the corresponding boundary nodes BNs are activated in the respected clusters. In figure 3.8 blue circles represent the boundary nodes.

$$\mathbf{IBNL}\ \{\mathbf{CH_{id}}, \mathbf{CH}_{\mathbf{lang}\,\&\,\boldsymbol{latit}}, \mathbf{SN_{Di}}, \mathbf{AN_{Di}}, \mathbf{TS_{CHi}}, \mathbf{N_i}\ , \mathbf{ANL},\ \mathrm{H(M_2)}\} \qquad (3.4)$$

$$\mathrm{M2} = (\mathbf{CH_{id}} \,\|\, \mathbf{CH}_{\mathbf{lang}\,\&\,\boldsymbol{latit}} \,\|\mathbf{SN_{Di}} \,\|\, \mathbf{AN_{Di}} \,\|\, \mathbf{TS_{CHi}} \,\|\, \mathbf{N_i} \,\|\, \mathbf{IBN}\ \{\mathbf{ANL}\ \}) \qquad (3.5)$$

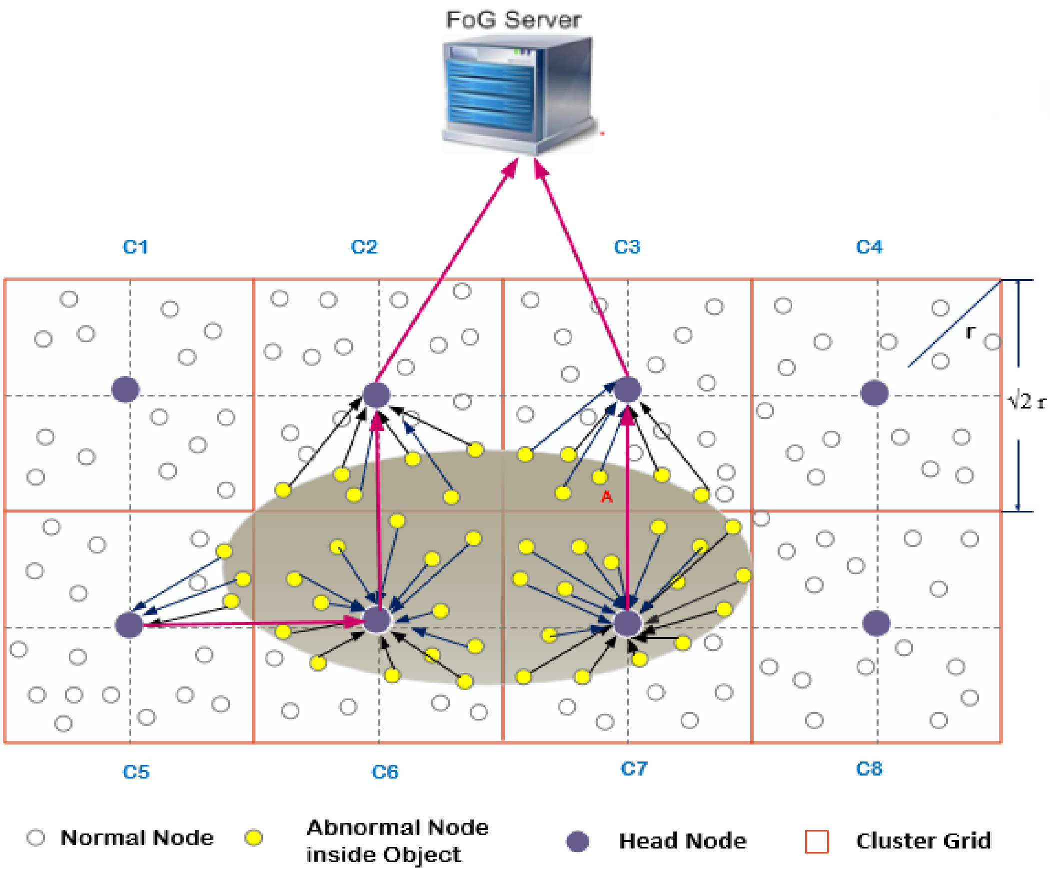


Figure 3.8: Process of Boundary Detection

3.6.4. Reporting Mechanism

Each CH transmits information of initial object boundary to fog server. It also shares information of its respected IBNs with their id and loc. In figure 3.9 CH of cluster grid C5 transmits information to CH of cluster grid C6 then it sends this information to CH of C2 which is closest to these cluster grids. Similarly, CH of C7 transmits the detected boundary information to C3. After that, C2 and C3 transmit the information to fog server. Fog server as acting node compute the boundary information and transmit it to cloud without any delay.

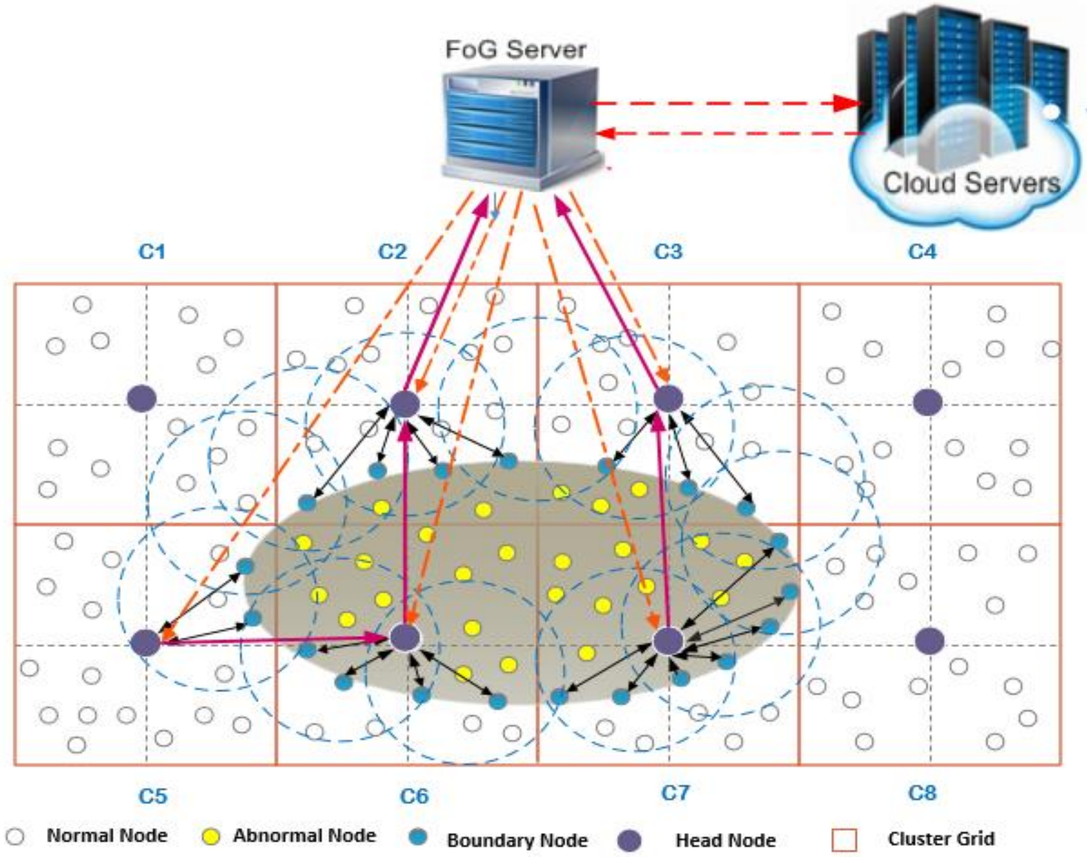


Figure 3. 9: Reporting Mechanism

3.7 Summary

This chapter gives information about the problem, and then discussed that how to resolved an identified problem. Operational frame work has considered that leads to proposed work. It explores the sampling design for the propose scheme. Different phases of proposed solution are examined and different parameters are considered for implementation. Proposed work is divided into four phases Initial Deployment of Network, Abnormal Node Detection, Object Boundary Detection and Reporting Mechanism. Also phases are shown in a pictorial form. It also shows that the propose scheme prolongs the network life by minimizing the transmission delays and energy consumption while detecting the boundary of continuous object. Moreover, objectives of this work are explained, that are: transmission delay from IoT nodes to cloud, reduce number of nodes for data transmission and improve detection accuracy of continuous objects.

CHAPTER 4

PERFORMANCE EVALUATION

4.1 Overview

In this chapter, we implement the BDCO-IoT algorithm for the given simulation system in terms of different performance evaluation metrics. Comparative analysis of existing schemes has been offered in the following section.

4.2 Results and Analysis

In order to evaluate the effectiveness and robustness of BDCO-IoT and the sampling method considered the following evaluation metrics: Average End to End Delay, Number of messages, Energy Consumption, Number of IoT Nodes, Skewness Degree, Detection Accuracy of continuous objects, and Packet Loss Ratio. We calculate the results for these metrics and a comparative analysis performed with the CM-IoTSNC, AONN and WSM methods. Results are presented in the form of multiple graphs. These results produce from the simulator and log files that maintained for each metric.

Wireless technology is utilize to exchange data packets in IoT enabled WSNs. In BDCO-IoT, SNs use Wi-Fi technology to communicate with CH because SNs are available within the range of CH. They are directly connected with each others. In simulation, we implement the data communication between nodes as transmission of detected data packets.

In the simulation environment, SN detect the event when its threshold value exceed the limit and generate data message that is received at its corresponding CH. CH calculate the distance of SN and forward it along with detected data packet to the fog node for further processing of boundary detection. The statistical data for stated performance metrics has been calculated and examined.

4.3 Performance Comparison with Benchmark Schemes

The proposed BDCO-IoT scheme is compared with earlier schemes such as CM-IoTSNC, AONN and WSM. The comparison of BDCO-IoT with benchmark methods have been defined as follows:

4.3.1 Average End to End Delay

This performance metric has a significant role in time sensitive applications and shows the efficiency of algorithm. To enhance the algorithm performance shorter the end-to-end delay. Data transmission between large numbers of IoT nodes and cloud takes time because the distance between these nodes and cloud server is long. BDCO-IoT minimized the long transmission distance which ultimately results in minimum average end to-end delay. Others schemes activate large amount of nodes and their neighbors for data transmission to backbone node or cloud server. Long distance produces large delay in data transmission. As shown in Figure 4.1 BDCO-IoT presents the minimum delay while other schemes produce large delay. At 20th pakects/sec, BDCO-IoT has least average end-to-end delay while other schemes CM-IoTSNC, AONN and WSM have represent maximum average end to end delay. But when 50 pakets/sec transfer, average end to end delay of BDCO-IoT, CM-IoTSNC, AONN and WSM increase to 6.5ms, 25ms, 11.5ms and 18.5ms respectively.

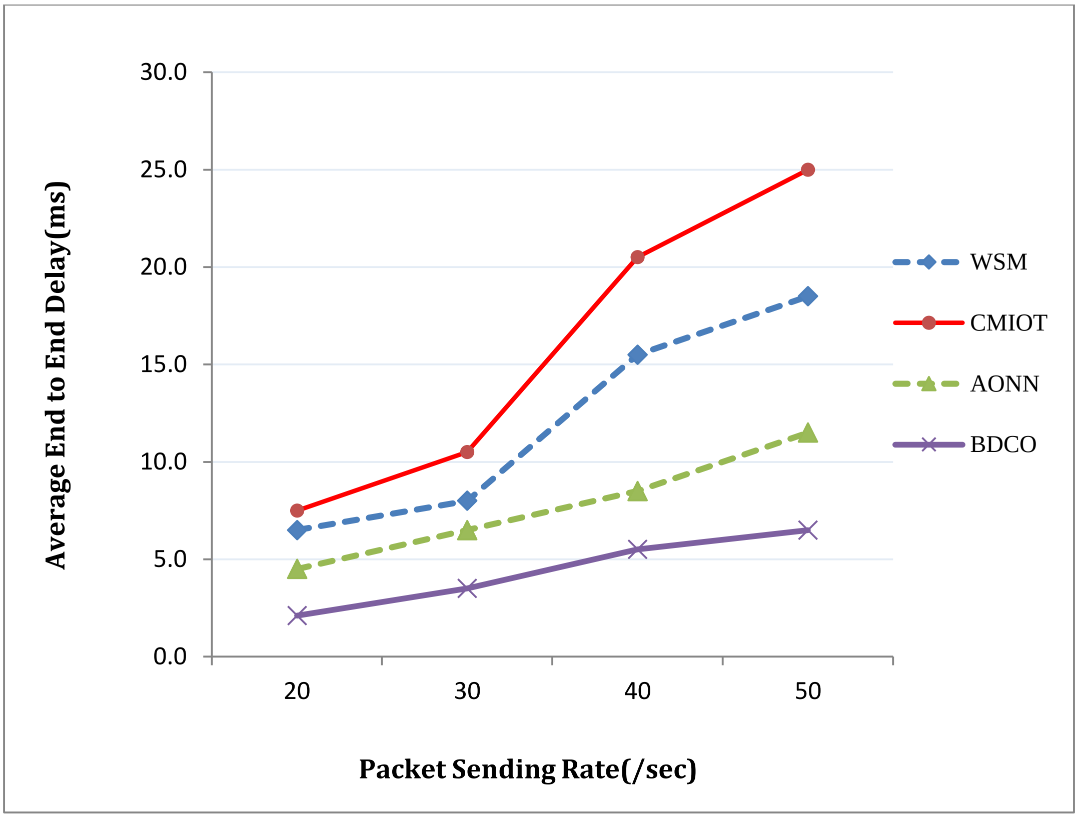


Figure 4.1: Average End To End Delay

4.3.2. Effect of number of messages transmitted by nodes on skewness

Transmissions of data packets by nodes have a great impact on the results. Mostly, large amount of messages transmission enhances the communication cost. Figure 4.2 illuminates the communication cost of different schemes by using different number of messages and skewness degree. BDCO-IoT reduces the transmission of messages where only CH sends the messages of four grid cells. CM-IoTSN sends messages of active nodes by every grid head to sink; AONN sends messages of active nodes and their one hop neighbor nodes by every grid head to sink. In WSM nodes send all the messages directly to sink. At 20% skewness, BDCO-IoT transmits 2 messages while other schemes CM-IoTSNC, AONN and WSM transmit 8messages,16messages and 32 messages respectively. This shows that only BDCO-IoT transmits minimum number of messages which results in low communication cost.

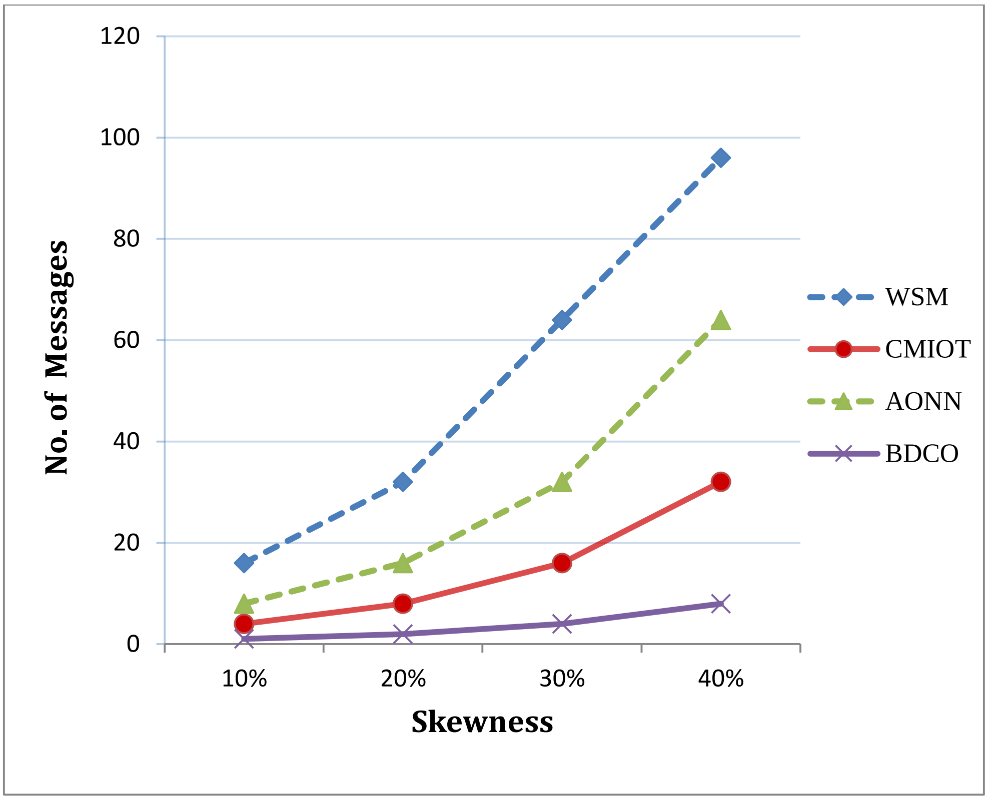
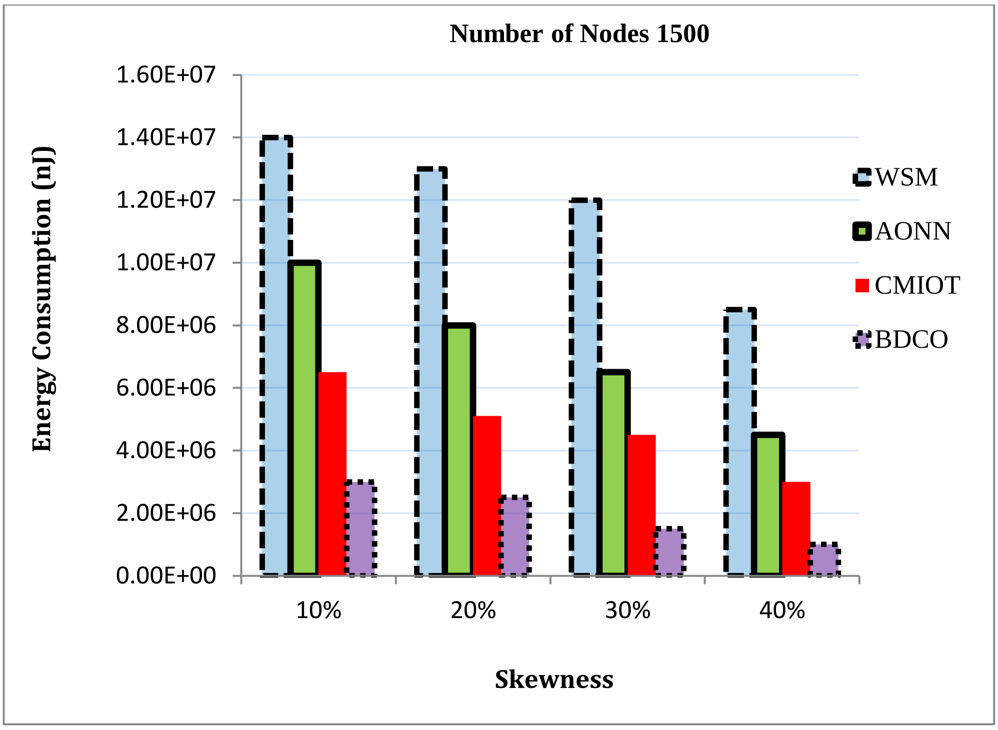


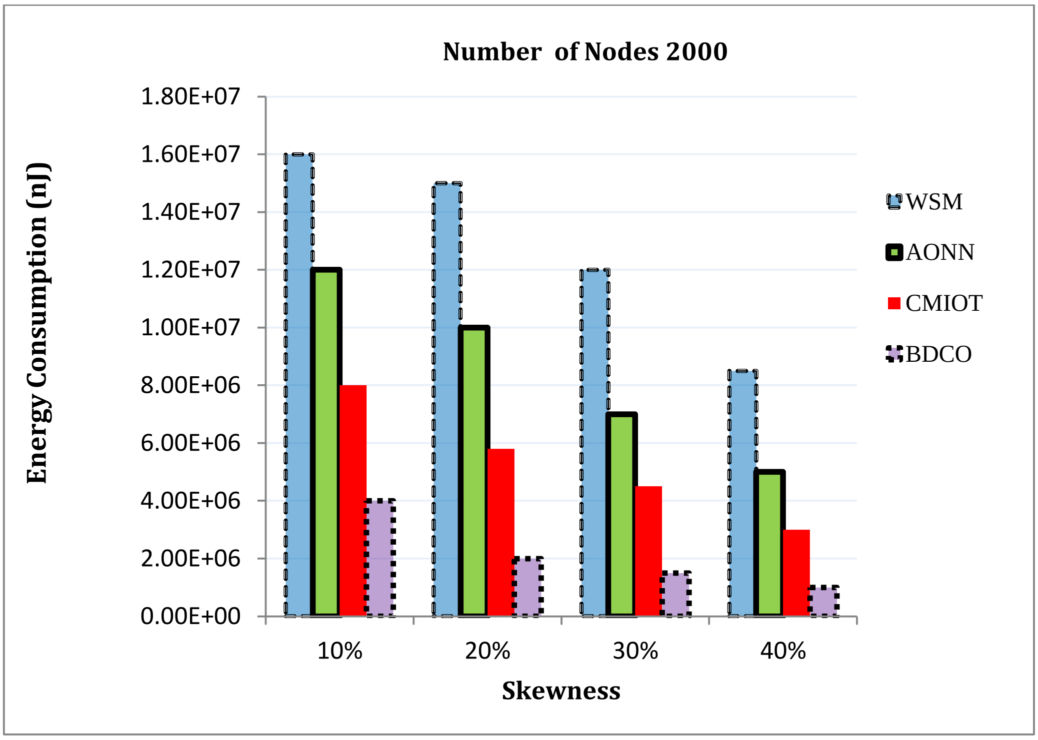
Figure 4. 2: Effect of no. messages transmitted by nodes on skewness

4.3.3 Energy consumption of IoT nodes at different skewness degree

IoT nodes density and the skewness degree for nodes distributions in the network have a great impact on the results. In figure 4.3, we compare propose scheme BDCO-IoT with CM-IoTSNC, AONN and WSM and examine the effect of energy consumption under the corresponding number of IoT nodes and different skewness degree. Figure 4.3(a) represents the energy consumption at the 1500 IoT nodes with skewness degree of 10%,20%,30% and 40%. Figure 4.3(b) represents the energy consumption at the 2000 IoT nodes with skewness degree of 10%,20%,30% and 40%. The bar graph shows that in the whole process BDCO-IoT consumes least amount of energy and gets better detection results.



(a)



(b)

Figure 4.3: Comparison of energy consumption with different skewness degree of IoT nodes.

4.3.4 Effect of different IoT nodes on detection accuracy

In BDCO-IoT method we use IoT sensor nodes in network field for detecting the boundary of continuous object. As the number of nodes increases in the grid architecture CH received the detected information from all the active increased SNs and forward it to the fog server for processing. In figure 4.4, as number of IoT nodes increase 1500,2000,2500,3500 detection accuracy of BDCO-IoT become high. Maximum detection accuracy of BDCO-IoT is higher than other schemes at the number of 1500 to 3500 IoT nodes. Whereas others methods CM-IoTSNC, AONN and WSM have maximum detection accuracy but less than the BDCO-IOT.

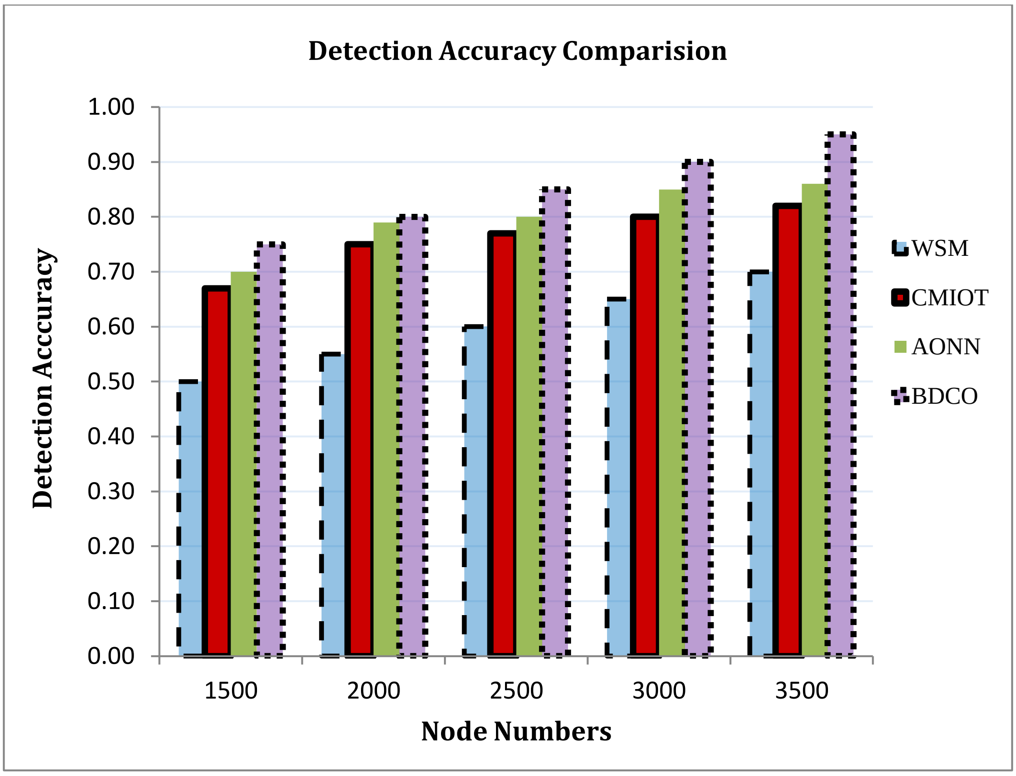


Figure 4.4: Effect of different IoT nodes on detection accuracy

4.3.5 Effect of number IoT nodes on service delay

In comparison to existing schemes, service delay of the proposed scheme BDCO-IoT fluctuates between 10-33 mili seconds which is significantly less than other schemes. In

Figure 4.5, the service delay for BDCO-IoT, CM-IoTSNC, AONN and WSM is displayed respectively when IoT nodes are 1500 to 3500. BDCO-IOT shows minimum service delay in mili seconds. Our propose BDCO-IoT scheme outperforms by minimizing it to 10ms.Others schemes CM-IOTSNC, AONN and WSM show maximum service delay respectively.

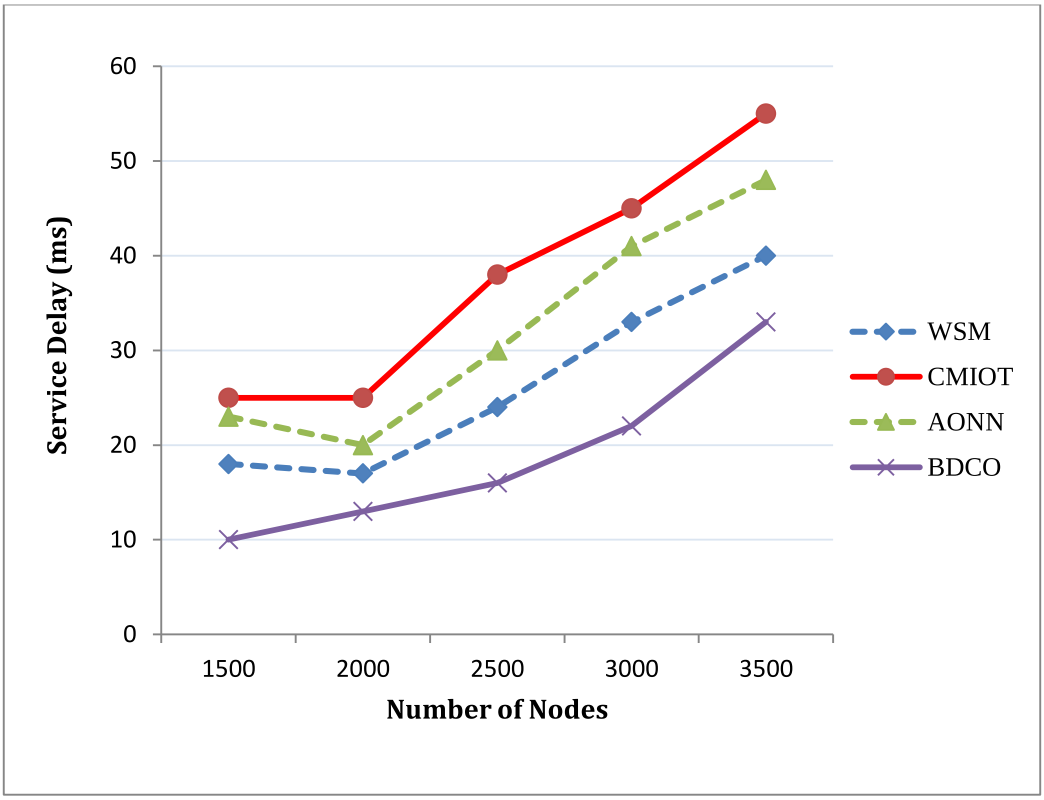


Figure 4.5: Effect of number IoT nodes on service delay (ms)

4.3.6 Packet Loss Ratio

In emergency situation, successful delivery of boundary detection information is very important. It affects the detection results and generates errors. In propose scheme BDCO-IoT, long transmission distance is reduces by utilizing edge node in order to mitigate the packet loss ratio. Figure 4.6 shows packet loss ratio of BDCO-IoT, CM-IoTSNC, AONN and WSM schemes respectively. The comparative analysis indicates that the proposed scheme BDCO-IoT dominates by minimum packet loss ratio with the increasing data packet rate from 20pkts/sec to *120* pkts/sec also make sures the successful data delivery to receiving node.

CM-IoTSNC, AONN and WSM schemes show higher packet loss ratio at the data rate of 20pkts/sec to 120 pkts/sec.

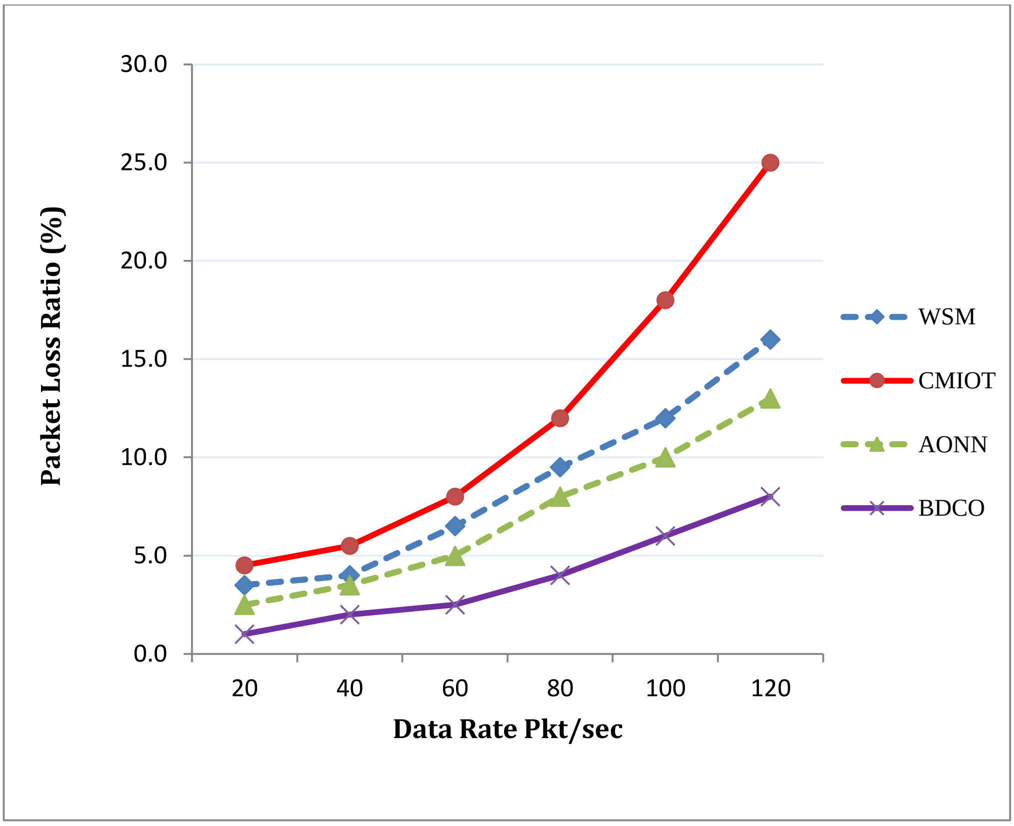


Figure 4.6: Packet loss ratio

4.4 Summary

A boundary detection mechanism of continuous object has been proposed to intend a reliable boundary detection mechanism. The main objective of stated scheme is to reduce the transmission delay and energy consumption in the boundary detection process to meet the requirements of delay-sensitive real time applications. NS-2 simulation model is used to evaluate the performance of our proposed algorithm. Comparative analysis for the performance metrics has been conducted, it is concluded that our proposed BDCO-IoT scheme is able to accurately detect the object boundary with minimum transmission delay and least amount of energy.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Overview

The performance of the prototype BDCO-IoT is evaluated by NS-2 simulations in terms of different performance metrics such as average end to end delay, communication cost, energy consumption, number of IoT nodes, skewness degree, detection accuracy of continuous objects and packet loss ratio. The proposed BDCO-IoT scheme is compared with earlier schemes such as CM-IoTSNC, AONN and WSM. It improves data transmission rate and reliability of the boundary detection.

5.2 Conclusion

A continuous object are extensively spread in broad area with diverse scattering speed and because of the fast development, increasing size, diffusion and forms changing nature tracking and detecting the precise boundary of these continuous objects has become a noteworthy issue. Although different state of the art schemes present several solutions for continuous object boundary detection and for efficient data transmission. However, current research works facing several problems in terms of energy efficiency, boundary accuracy, transmission delay and active nodes reduction. Therefore, energy efficient and delay minimized boundary detection mechanism of continuous objects (BDCO-IoT) is proposed. The whole network is divided into grid cells and constructed the cluster grid by joining four grid cells. A distance calculation mechanism for initial boundary detection is deployed at CH. For detecting the exact boundary convex hull algorithm is employed at fog server.

SNs transmit detected data to cluster head and the CH estimates the location information of abnormal nodes. Based on the location information it selects the initial boundary nodes and forward the data to fog server for further processing. Fog server simulates the exact boundary using convex hull algorithm and activates the exact boundary nodes. It reduces the long transmission distance between IoT nodes to cloud which result in minimum delay and conserve energy. Moreover, the performance of proposed algorithm is evaluated using extensive simulation in NS-2. BDCO-IoT evaluation is compared with the CM-IoTSNC, AONN and WSM schemes in terms of average delay, number of messages, number of IoT Nodes, skewness Degree, detection Accuracy, energy consumption and packet loss ratio.

5.3 Future Work

In the future work, a more proficient real time boundary detection mechanism will be employed to further enhance the boundary accuracy and communication architecture of our proposed method.

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