M-IWD ALGORITHM WITH HEURISTIC FUNCTION FOR MEB IN WIRELESS SENSOR NETWORKS

A THESIS

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N. MOHAMED YASIN

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BONAFIDE CERTIFICATE

Certified that this thesis entitled **"M-IWD ALGORITHM WITH HEURISTIC FUNCTION FOR MEB IN WIRELESS SENSOR NETWORKS**" submitted for the award of the degree of **DOCTOR OF PHILOSOPHY** in COMPUTER SCIENCE AND ENGINEERING is a record of original research work done by **Mr. N. MOHAMED YASIN** who carried out the research under my supervision. Certified further that to the best of my knowledge, the work reported here in does not form part of any other thesis or dissertation based on which a degree or award was conferred on an earlier occasion of this or any other candidate.

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ABSTRACT

Minimum Energy Broadcasting (MEB) is a well-known optimization problem in Wireless Sensor Network (WSN) which holds the major issue of energy consumption for data transmission from the sensor node to sink node. This problem comes under the category of ‘combinatorial optimization problem’ with very large search space, since the number of solutions for data transfer is high in number. The traditional methods for solving MEB instances takes more computation time (in terms of years) to evolve the best solution. After the emergence of Evolutionary Algorithms (EA), the computational complexity gets reduced in a remarkable manner. But, the quality of solution seems to be a low achievement factor since the global solutions are not attained within the given number of iterations. This research intends to modify a Swarm Intelligence(SI) Algorithm, namely Intelligent Water Drops(IWD) Algorithm, in terms of three different versions to improve the ability to evolve an optimal solution. The core of this research-work is to design and develop a Modified Intelligent Water Drops Algorithm (M-IWD) with enhanced divergence and enriched convergence factors. This research work was motivated by the inherent shortfalls in the existing models and lack of divergence and convergence in the Version-I of the proposed model.

The proposed Divergence and convergence factors are used to improve the performance in terms of computation time, convergence rate, average convergence rate, excess rate and distribution of individuals.

The first goal is to explain and formulate the IWD Algorithm for solving MEB instances of WSN. The aim of the second goal is to design an effective divergence function for improving the exploration capability of the proposed algorithms during the run. The third goal is to derive a convergence factor for balancing exploration and exploitation phases throughout the run in M-IWD Algorithm. All these goals are measurable and, of course, proved with an appropriate set of experiments.

The proposed M-IWD Algorithm with all three versions is validated by comparing them with the corresponding recent and best techniques existing in the appropriate literature both in the independent and hybrid fashion. The promising experimental results demonstrate the impact of the proposed models in terms of computation time, convergence rate, average convergence rate, excess rate and distribution of individuals. The constructive and encouraging results justify the significance and necessity of the proposed line of research and it motivates future researchers to further enhanced investigation in the identified area of research.

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ACRONYMS	ABBREVIATIONS
ABR	Ant-Based Routing
ACO	Ant Colony Optimization
ACS	Ant Colony System
AODVR	Ad-hoc On Demand Distance Vector Routing
BIP	Broadcast Incremental Power
BIP-VND	Broadcast Incremental Power -Variable Neighborhood Descent Algorithm
CBTS	Class Based Tunnel Selection
CDMA	Code Division Multiple Access
CH	Cluster Head
CoCMA	Coverage control in Cluster-based WSN using a Memetic Algorithm
CR	Convergence Rate
DARPA	Defense Advanced Research Projects Agency
DSN	Distributed Sensor Network
EA	Evolutionary Algorithms
EC	Energy Consumed
EEABR	Energy-Efficient Ant-Based Routing Algorithm
EGDG	Efficient Grid-based Data Gathering
EO	Optimal Energy consumed by the network
ER	Excess Rate

ACRONYMS	ABBREVIATIONS
FRMOO	Fuzzy Random and Multi-Objective Optimization
GA	Genetic Algorithm
HUD	Heuristic function
IoT	Internet of Things
IWD	Intelligent Water Drops
JADE	Joint Application Development Environment
LB	Lower Bound
LEACH	Low Energy Adaptive Clustering Hierarchy
LMAC	Lower Medium Access Control
MAC	Medium Access Control
MANET	Mobile Ad-hoc Network
MEB	Minimum Energy Broadcasting
MEB-WSN	Minimum Energy Broadcasting - Wireless Sensor Networks
MEMS	Micro-Electro-Mechanical Systems
M-IWD	Modified Intelligent Water Drops
$\text{M-IWD}_{\text{Con}}$	M-IWD with Convergence function
$\text{M-IWD}_{\text{Div}}$	M-IWD with Diversification function
$\text{M-IWD}_{\text{HUD}}$	M-IWD with Heuristics function
$\text{M-IWD}_{\text{HUD}}^{\text{Div}}$	Modified Intelligent Water Drop with Heuristic function and Diversification
$\text{M-IWD}_{\text{HUD}}^{\text{Div-Con}}$	Modified Intelligent Water Drop(M-IWD) with Heuristic, Diversification and Convergence

ACRONYMS	ABBREVIATIONS
NSGA	Non-Dominated Sorting Genetic Algorithm
PADP	Power Assignment Deployment Problem
P-BIP	Pruned Broadcast Incremental Power
P-MST	Pruned Minimum Spanning Tree
PSO	Particle Swarm Optimization
P-SPT	Pruned-Shortest Path Tree
QELAR	A machine learning based energy-efficient and lifetime-aware adaptive routing protocol
R	Total number of Runs
RMOO	Random Multi Objective Optimization
S-MAC	Sensor-Medium Access Control
SBX	Simulated Binary Crossover
SN	Sensor Node
SOSUS	Sound Surveillance System
TDMA	Time Division Multiple Access
TEEN	Threshold sensitive Energy Efficient sensor Network protocol
TSP	Travelling Salesman Problem
UB	Upper Bound
VFP	Vector based Forwarding Protocol
w	Inertial weight factor
WSN	Wireless Sensor Networks

CHAPTER 1

INTRODUCTION

1.1 AN OVERVIEW OF WSN

A Wireless Sensor Networks (WSN) can be defined as a self-regulated network which is wireless in nature for monitoring the physical and environmental changes such as weather, wind, clouds, natural calamities, etc. These networks do not have a static connection between nodes, and this network can be coined as infrastructure-less network. The collected data is forwarded to the sink node where, all the data will get aggregated and analyzed. In WSN, a sink node will act as a mediator between the deployed network and the users who access it. The data from sensor nodes are interpreted with the help of sink nodes. Each WSN holds hundreds and thousands of sensor nodes, and a sink node to store the data from sensor nodes. Besides, the communication among sensor nodes and sink nodes, all the sensor nodes are gets connected with other nodes with the help of radio signals.

Each sensor node consists of the following components within its structure:

1. Sensor
2. Microcontroller
3. Transceiver
4. Memory
5. Power Source
6. ADC converter

1.2 Significance of Wireless Sensor Network

WSN is one of the most-distinguished form of ad-hoc network type that is used to manipulate a wireless infrastructure. This special kind of ad-hoc network is used to observe and respond to a phenomenon in the natural environment. This infrastructure can communicate with itself for data transmission. This type of network is widely used in multidisciplinary stream for efficient monitoring, and thus reduces the human resources. Some of the popular domains are described below:

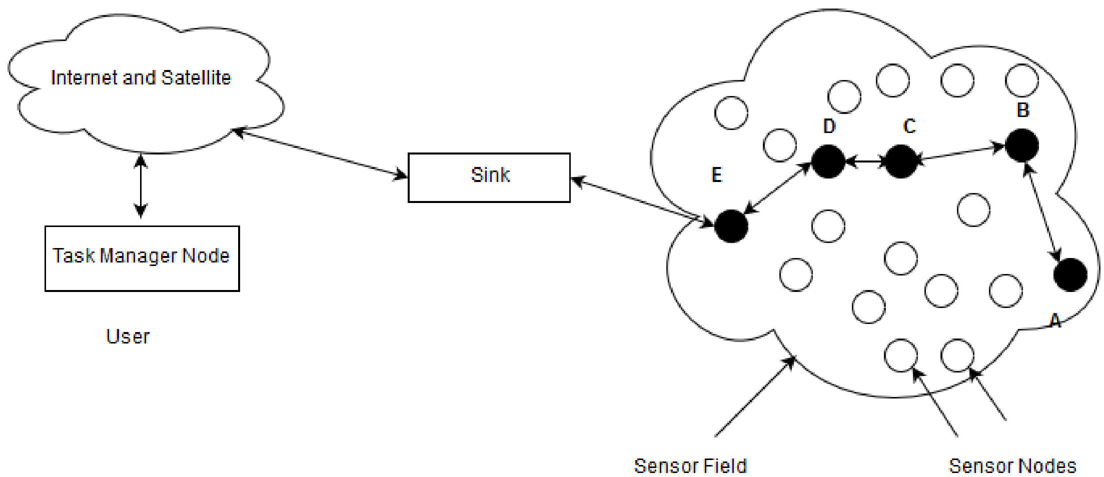


Figure 1.1 An Overview of WSN

Military applications:

WSN in the military serves as an artificial intelligence network. It monitors the battlefield for communication purposes, for controlling process, reconnaissance and for targeting the systems.

Transportation:

Many of the transportation are now made of selfless drivers. In this stream, the sensors collect the information from all sides of a vehicle, and report it to the sink node for decision-making.

Health care applications:

One of the major streams which hold the contribution of WSN is in healthcare applications. These applications include a patient’s physical and conditional monitoring, medicine administration, in drug manufacturing factories and an interface for disabled people.

Internet of Things (IoT):

Yet another automated approach in the fast feed of computation. The sensors in this disciplinary monitors the environment and alerts the user if there is any precaution mentioned in the system. Some of the example include water level monitoring in water tanks, automated washing machines, and much more.

Environmental Sensing:

For the contribution of earth science research, WSN has been termed as Environmental Sensor Networks. This environmental sensor network monitors the changes in volcanoes, forests, seas, etc.

Agricultural sector:

With the combined approach of data mining along with WSN maintenance of field crops, enhancement of future crop cultivation has become an automated process with the help of WSN. Automation of irrigation in this field has made a phenomenal change in minimal water consumption.

These significances made researchers work in the WSN domain where more utilization of computation increased with reduced man-power on the other side.

1.3 Evolution of WSN

WSN has become one of the top research oriented domains owing to its variety of applications and the importance of precision in it. For improving reliability and robustness of the network, many researchers worked on different aspects of WSN such as radio communication characteristics, sensor node deployment, localization of sensor nodes, synchronization of sensor nodes and much more.

Evolution of WSN to this new era has been started in the year 1950 by the US military which was named as Sound Surveillance System (SOSUS) for detecting submarines. This is the first-ever wireless network-based application of that decade. This network used hydrophones and acoustic sensors. This technology is still in use for monitoring the activities of volcanoes under the oceans.

In late 1960's and early 1970's, huge investments were made in developing wireless networks for monitoring purpose in different aspects and Defense Advanced Research Projects Agency (DARPA) initiated Distributed Sensor Network (DSN) in the year 1980 [1]. In the late 1980's, some other universities united together with DARPA to address all the issues which arise while implementing WSN and finally WSN settled in the home of academia and civilian scientific research. In recent decades, the use of WSN by the government has increased in an enormous amount which includes air pollution tracking, forest fire detection and prevention from natural calamities. From the commercial point of view, IBM and Bell Labs have initiated in building industry-based products such as power distribution, water waste management, etc.

Evolution of WSN technology has been contributed mainly by academia and other industries. In 1993, Wireless Integrated Network Sensors has been contributed by academia. Later, in the year 1999, Pico Radio was developed. In the year 2001 and 2002, NASA Sensor Labs and ZigBee Alliance were initiated. Later, in 2002, Embedded Network Sensing center was developed.

Apart from the basic components in a sensor, there are some other components which have also emerged in these many years. Micro Electro Mechanical Systems (MEMS), a new sensor type, has emerged in the last decade. Components inside MEMS include magnetometers, pressure sensors, gyroscopes, accelerometers, pyroelectric effect sensors and acoustic sensors. Later, CMOS-based sensors were developed, which includes some other new range of accessibilities. These sensors sense the temperature, humidity, capacitive proximity, chemical composition by themselves without a third-party command. These sensors have been widely used in physical environment where few play a critical role on it. LED sensors are yet another new approach in sensor design, which includes proximity sensing, chemical composition, ambient light sensing.

1.4 Issues in WSN

The recent technologies in WSN provide more precise results even in uneven situations or climates. But there exist some performance issues in WSN which degrades the design and robustness of WSN.

1.4.1 Issues on Hardware and Operating System in WSN

WSN consists of thousands of sensor nodes in a single network for efficient tracking or monitoring of temporal changes in the environment. A sensor node consists of a mote which holds all the components to process the sensed data by the sensors. Motes are commonly called as Smart Dust.

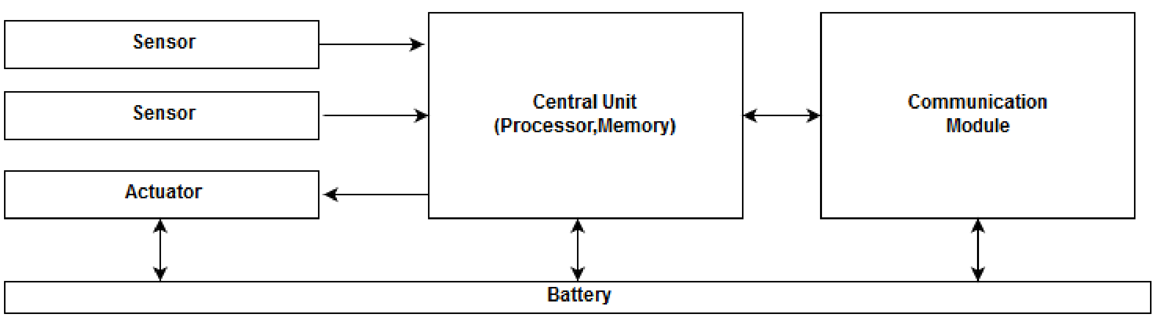


Figure 1.2 Architecture of sensor node

There are some constraints which exist for using the sensor nodes in WSN and those include [2] the following:

1. The radio range is limited in sensor nodes. This range plays a major role to transmit the sensed data to the sink node. A strong and high radio range should be ensured in order to make a reliable network and for collecting the data from the monitored environment.

2. The use of memory chips inside the sensor nodes is supposed to be non-volatile. For a particular instance, if the node fails to communicate in a network, the monitored data are supposed to be stored in the mote for further accessing. The memory chip should be inexpensive preferably.

3. Power/ Energy consumption plays yet another critical role in hardware design. In using high energy consumption for data transmission or data sensing, it lets the battery power to drain sooner which leads to the failure of the sensor node.
4. CPU processing in mote is another issue in hardware issue. Since the sensor node is of power-restricted, the sensed data is supposed to be processed, manipulated, filtered, and the required data is given to the sink node from the monitored environment. If all monitored data are processed to sink node, the network might face bottleneck problems.

5. The operating system in the microcontroller is supposed to be application-specific which processes only the needed data from raw collected data for efficient data transfer with reduced energy consumption.

6. Since mote cannot be charged owing to low-cost budgeted sensor nodes, the OS in microcontroller should be designed in such a way to process all the data with respect to energy consumption.

Hardware and software issues are the ones which are supposed to be handled at first, since that plays a major role in WSN.

1.4.2 Issues on Medium Access Schemes

In WSN, high energy is consumed by sensor nodes while transmitting the collected data to sink node, either directly or in a multi-hop manner. MAC protocols are used in WSN for controlling radio signals in sensor nodes. The design of MAC protocol should utilize minimum energy consumption and this also increases the lifetime of network.

Some of the design issues [3-7] in MAC protocols are given below:

1. MAC layer gives a control strategy to the transceivers regarding ON and OFF of radio for efficient energy saving scheme in sensor nodes. In case it is continuously ON, the energy will be consumed for continuous sensing of radio signals from all nodes which might reduce the lifetime of the network.

2. The design of MAC protocol should consist of collision avoidance from other neighbor nodes, over-emitting of radio signals, overhearing of other node signals and avoidance of idle listening.

3. Design of MAC protocols should hold the property of adaptability, scalability and decentralized in nature. Adaptability is the property of enhancing the protocol to handle the communication even when the network size gets increased.

4. Low latency in WSN is achieved on tuning MAC protocols. This shows the consistency of a network. Higher throughput will be required in some cases when the network is not stable.

5. On transmitting the collected data towards sink nodes, sometimes multi-hop communication is preferable. MAC protocols should be aware of the route it chooses for transmission of data. This process is called as Information Asymmetry.

These issues in MAC protocols of WSN can highly affect the performance of WSN over a practical situation. Addressing these issues, many researchers worked on this theme for achieving betterment of WSN lifetime.

1.4.3 Issues in Network Layer

Routing is the process of sending data from one place to another. In WSN, this routing plays a critical role in sending data between sensor nodes and sink nodes. Routing in WSN is a challenging issue since the transmission of data relies on other nodes in case of multi-hop communication. Before routing process, the respective node should be aware of the awakened nodes in the network.

The challenges in the network layer of WSN are listed below.

1. Energy efficient paths are highly preferable in WSN for data transfer to avoid the failure of the network due to node failure. A number of different methods are required to determine more efficient routes for transmission of data among sensor nodes and sink nodes.

2. Designing more than one optimal path is another strategy that the network layer should handle if the primary path fails to transmit the data.

3. Fault tolerance in case of path collision or path damage while transmitting data is preferable in WSN. Routing protocols in network layer should have the tendency of choosing another route if the given route by the protocol gets collided or damaged during the runtime of data transmission.

4. On handling routing and data management by sensor nodes, the burden of sink node can be reduced since WSN is a data centric network. All the data are collected by the sink node to be processed further. In handling routing process, a reliable platform is needed for WSN.

5. Handling heterogeneous nodes avoids the latency in WSN. When each node seems to be different either by its communication or computation, a predefined method is preferable by routing protocols to handle these scenarios.

Some of the routing protocols in WSN are LEECH, TEAN, GEAR, SAR, SPIN, etc.

1.4.4 Security issues in WSN

A secure network should possess the capability of protecting the message from a hacker or attacker. Confidentiality is the process of avoiding an attacker from intruding into the network for stealing a message. Integrity is the process of making a secure way to transmit the data without any damage to the message. The freshness of data refers that the user or network receives information which has been recently sent with low latency. In order to fulfill all these capabilities, WSN provides a layer based approach for improving the robustness of WSN.

1. **Application Layer:**

   In application layer, the reliability of data is being handled. In [8], the author proposed a scheme for cluster based network to ensure the reliability of network with the help of resilient aggregation. Since this is applicable for cluster-based networks, there exists a practical constraint in it. This actually acts as an aggregation node in which all the data from other sensor nodes gets accumulated here and further processing will be done. So, apparently, this node should be in a range of where it should be reached by all other nodes. The accumulated data's validity can be proved by cluster heads using cryptographic techniques.

2. **Network Layer:**

   Property of Network layer in WSN is to ensure the message transmission from node to node, messages from cluster head to nodes, message transfer between cluster heads, cluster heads to sink nodes and vice versa.

3. **Data link Layer:**

   Data link layer possesses the potentiality of error detection, error correction, encoding and decoding of data. Jamming and DoS attacks are more frequent attacks in data link layer. Researcher worked on this layer using encryption technique for secure processing of data. In [9], the author proposed LMAC which holds anti-jamming properties which seem to be a better proposal as far as this layer is concerned.

4. **Physical Layer:**

   Use of physical properties for transmitting data from one node to other is encountered at this layer. This layer holds the media to propagate the messages to the concern node or cluster head or to sink node. In this layer, the following processes will take place: Data rate at which the data is getting transmitted, strength of the signal that the node possesses and the type of frequency that the node holds can be retrieved.

Security issues in WSN are concerned with the attacks of the above listed layer. On attacking these layers, attackers or hackers can breach into the network.

1.4.5 Issues in node deployment

Deployment of sensors refer to the actual location of sensor placement in the real world scenarios. Deployment of sensors can be done either by planting it one after the other or it can be randomly plotted by dropping it from the plane. Issues on deploying sensor nodes are as follows:

1. In case of node death: either by energy depletion caused by frequent transmission or monitoring of data due to short-circuit which results in improper observation results.

2. Random deployment of sensor nodes leads to network congestion or collision of data between nodes. Sometimes repeated observations of same location can be made owing to neighborhood conflict of sensors.

3. Due to environmental challenges, sometimes neighbor sensor nodes also cannot be able to communicate with each other. This may be because of bad weather conditions, formation of mist, etc. These issues are in need to be addressed before deploying sensors in real the world scenarios.

4. There are two different radio ranges will be available in each and every node in the network. One will be called as sensing range and the other one as coverage range. This coverage range will be used to monitor real world locations and the sensing range is used to transmit the data from one node to another. Some of the nodes due to bad weather conditions, the gathered information will not be completely delivered to sink nodes.

   Self-regulation of sensor nodes is one possible method for random deployment of sensor nodes in WSN.

1.5 Energy consumption issues in WSN

In WSN, one of the most important factors is energy consumption, since the lifetime of the whole network depends on restricted battery power. Energy consumption plays a major role in WSN because of its limited power for sensor nodes, the design of network in terms of routing of data transmission is supposed to be optimized. Optimizing energy consumption become a tedious task in WSN, since optimizing route not only depends on the energy of the sensor node but also on the lifetime of the entire network model.

The basics of energy requirements by sensor nodes in WSN are categorized into four subsystems.

1. **Computing Subsystem:**

   The microprocessor in mote uses power from battery for controlling the sensors and protocols used in sensors. For the purpose of power management, these microprocessors in motes operated in different modes. When this processor operates at different modes, energy consumption by these processors varies and this should be considered when solving energy consumption issue.

2. **Communication subsystem:**

   A short-range radio is usually used for the communication purpose between nodes in WSN. This also consumes a considerable amount of battery power for communication purpose. It is advisable to shut down the antenna instead of making it to be in idle mode since idle mode also consumes power.

3. **Sensing subsystem:**

   A sensing system consists of a considerable number of sensors and actuators which are used to communicate with the outside environment. In this subsystem, by using low power consumption components can be used to reduce energy consumption.

4. **Power supply subsystem:**

   This is the actual power supply system which supplies the power to all other components in the sensor node. For efficient handling of power supply subsystem, it should be turned off when there is no use of it. This can be done by automating the scenario.

Many protocols and algorithms have been derived for efficient handling of power consumption. This enhances the lifetime of the network if the operating system in microprocessor, application layer protocols and network protocols are built with energy awareness phenomena.

1.6 Motivation

WSN and MANET (Mobile Ad-hoc Network) are similar in terms of multi-hop communication process. Both resemble same in terms of their behavior. Both the networks transmit data to the mobile nodes which are dynamic in terms of location. This does not impose that both use the same protocols for message transfer. MANET uses mobile devices which have the tendency of required charging in frequent intervals of time by the user. In WSN, the sensor nodes use battery power which is initialized only at the time of deployment. There will not be the charging process for sensor node batteries as like MANET mobile devices. Managing energy resources utilized by sensor nodes are to be built efficiently for enhancing the lifetime of the network.

This energy consumption is not a single objective problem since it enhances the lifetime of the network. A multi-objective is supposed to be imposed on an energy efficient network for avoiding the loss of network connectivity, mitigating the number of failures of sensor nodes, avoidance of redundancy in monitoring which has to be taken into account for designing an efficient protocol to handle energy consumption issue.

MEB is one such approach where the data will be transmitted to all the nodes which are in its sensing range with minimal energy consumption. This message will then be collected either by a cluster head or by other nodes which are near the sink node, and message transfer process will be carried on. The objective is to find a minimal path for efficient data transmission from the sensor node to sink node. Many strategies have been derived to handle this MEB instances. On successful transmission of messages, utilization of energy by each sensor will be added and the total energy consumed by the network on that transmission will be tabulated. The theme of MEB is to minimize the energy consumption consumed by WSN nodes. These above challenges in this interested domain have motivated the research work reported in this thesis.

1.7 Research Objectives

As discussed earlier, the construction of Minimum Energy Broadcasting (MEB) Tree for minimal energy consumption which illustrates a perilous role to conclude the lifetime of the network. Besides that, even though numerous problems in WSN are proposed to enhance the potentiality of data transfer without loss, efficient coverage region, etc., MEB plays a major role since it determines the lifetime of the network. This is because of the limited power source provided to the nodes of WSN.

In this perspective, an M-IWD Algorithm is proposed for solving MEB instances with enhanced diversification and precise convergence scheme. The experimental assessment schemes, which were designed to validate the impacts of the proposed model with respect to the existing best working models of MEB.

To accomplish the above technique, this experimental research model has been constructed into numerous stages with the following points that are listed out to cover major contributions of this research:

a) A comprehensive survey has been made with the recent related existing works, and it has been concluded with the obligation for achieving an enhanced model for solving MEB instances in both forms of generic and evolutionary based algorithms.

b) Proposed a Modified Intelligent Water Drops Algorithm (M-IWDs) with a new Heuristic Function, with features of choosing the best node to participate in data transmission to sink node and constructive based feasible solutions.

c) Enhanced the proposed model by imposing random based diversification function with Modified IWD for enhanced search space exploration.

d) Derived an improved model of Modified IWD by combining diversification function along with dynamic soil updating parameter for balancing between exploration and exploitation throughout the run.

e) Several performance measures are listed out and applied for the evaluation of the final outcomes achieved by the experimentation step in response to validate the results of the research presented in this thesis.

1.8 Organization of the thesis

The remainder of this thesis work is organized as the following:

a) Chapter 2 describes a detailed view on recent advancements contributed for solving MEB instances. It is organized into two sections; discussion in the first section is focused on generic solutions for solving MEB in WSN, whereas the next section is focused on Evolutionary based solution models for solving MEB in WSN.

b) Chapter 3 defines the system design of this research and explains the contributions made in the proposed work as it is discussed in research objectives. This chapter also defines the mapping process of MEB with IWD algorithm.

c) Chapter 4 enlightens the formulation of Modified IWD algorithm with all its three versions. A complete description of modifications and the use of proposed versions are given.

d) Chapter 5 describes the performance measures used for analyzing the performance of Modified IWD's proposed versions. Also, the evaluated results of proposed algorithms are tabulated for small, medium and large scale instances.

e) Chapter 6 comprises the comparison between proposed work and existing algorithms such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). The results of these algorithms are compared, based on the performance measures and graphs which are derived from the tabulated results for effective representation.

f) Chapter 7 delivers the ultimate observations and final decisions of the work presented in this thesis and the future research, enhancements of the proposed line of research.

1.9 SUMMARY

This chapter starts with the overview of the WSN domain, along with its significance and applications. In section 1.3, the evolution of WSN from its origin has been clearly explained, along with references. In section 1.4, the issues of WSN including hardware and operating system issues, Medium Access Control scheme issues, issues in network layer, issues in transport layer of WSN, issues due to high energy consumption are described in detail. In section 1.6, the motivational factors that are to be considered for the development of this thesis are given in a clear organized manner. In section 1.7, the research objectives are mentioned. In section 1.8, the organization of the thesis is clearly explained, which states the description of the following chapters in an abstract format. This chapter provides an overall introduction about the research proposal of the thesis.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

Construction of the MEB tree is one of the emerging problems in WSN, which has the tendency of keeping the network alive. This MEB tree has been constructed previously with the use of precise algorithms, and some heuristic algorithms for minimum energy consumption. After bio-inspired algorithms come into the limelight for solving combinatorial optimization problems, MEB grasps a number of researchers for solving it. This part of interest leads these researchers to produce many algorithms for solving MEB, along with hybrid models for an efficient local search procedure.

In this chapter, a survey of MEB-solved methods using generic solutions and bio-inspired algorithms are provided. Literature survey based on evolutionary algorithms provides the author, title of the paper, year of publication, issues described, constraints considered, mapping of MEB with the proposed method, algorithm used for solving MEB, modifications taken over original algorithm, need for the modification, performance measures, parameters used, algorithms compared with the proposed method are provided. Along with this, some of the papers hold the advantages and disadvantages of the proposed model.

2.2 GENERIC SOLUTIONS

In the year 2000 and 2002 [10, 11], author Jeffrey E. Wieselthier, et al proposed a method for efficient handling of multicast /broadcast routing using Broadcast Incremental Power (BIP) algorithm. The design process of proposed BIP algorithm includes efficient handling of data transmission by choosing which nodes should be used for data transmission, and the power level they use for the transmission of data.

In the year 2003 [12], author Arindam K. Das, et al proposed a heuristic procedure for solving MEB instances in WSN. After initializing the broadcast tree in WSN, r-shrink heuristic search procedure is used to alter the path for minimizing the energy consumption. This algorithm devised a better path by tuning the initial path. r-shrink procedure works well for smaller instances of MEB. But for large scale datasets, computational time for tuning gets increased exponentially.

In the year 2003, author Maggie X.Cheng, et al [13] proposed Minimum Longest Edge method based on Minimum Spanning Tree. The proposed method solves larger instances of MEB in the wireless ad-hoc network. The strategy it followed includes an equal amount of energy among all nodes in the network which shares the energy and data distribution.

Author I. Kang, et al [14] proposed an algorithm, namely Greedy Perimeter Broadcast Efficiency, for efficient allocation of power based on the density of nodes distributed. It enables the choice of choosing multiple nodes for data transmission at the same time on which each node uses the minimum amount of power. This leads the nodes to use less power in each transmission and use residual power for further processes. This paper has addressed the problem of network lifetime of sensor nodes.

In the year 2001, J. E. Wieselthier, et al [15] proposed a new set of algorithms for handling multicast routing in the ad-hoc network. The proposed algorithms were evaluated under several modes by selecting appropriate relay nodes based on their transmission level for message transfer.

O. Egecioglu, et al [17] suggested an approximation algorithm for solving multicast energy consumption by assuming that each node in the network is possible to communicate with all other nodes.

In the year 2004, P. J. Wan, et al [16] proposed two different algorithms for an efficient multicasting, namely the shortest path first algorithm and minimum incremental path first algorithm for efficient data transfer. This is the first paper to produce a proof on three different pruned algorithms, namely "Pruned-Shortest Path Tree (P-SPT), Pruned Minimum Spanning Tree (P-MST) and Pruned Broadcast Incremental Power (P-BIP)" have lower bounds in it.

In the year 2002, M. Cagalj, et al [18] intended "new heuristic based algorithm" for MEB tree construction. Since no performance measure was stated in the proposed paper, this algorithm fails to come into the picture while other algorithms are used for comparison state. Another heuristic algorithm proposed by W. Liang [19] is based on "directed Steiner tree". The efficiency of the intended algorithm has the potentiality of solving MEB instances with 's' timestamp of n^{ε}, where 'n' is the quantity of nodes in WSN and $'\varepsilon'$ is known as constant value between the ranges (0,1).

In the year 2006, W. Liang [20] proposed another algorithm for solving multicast tree problem in WSN, which is based on approximation. This algorithm is proposed for solving symmetric wireless ad-hoc network where the transmission power of the node will be the same irrespective of the environmental conditions. This algorithm solves MEB with minimal time complexity from the algorithms given above with $4\ln_{k}$.

In the year 2010, P. Kamboj, et al [22] proposed "An energy efficient routing protocol for Mobile Ad-hoc Networks" with minimum control overhead during data transfer. In 2011, D. Li, et al [21] proposed approximation algorithms for solving multicast energy routing problem in WSN.

In the year 2004, D. Li, et al [23] proposed three different broadcast routing algorithms for solving asymmetric wireless ad-hoc network with the assumption that every node in the network has fixed amount of power. Among these three proposed approximation algorithms, one has the solving ratio of 1+2ln (n−1).

In the year 2007, D. Li, et al [24] proposed three different multicast routing algorithms for solving asymmetric wireless ad-hoc network with the assumption that each node of the network consists of fixed volume of power.

2.3 EVOLUTIONARY ALGORITHM BASED SOLUTION MODELS

The exact methods for solving MEB problem seems to be a time-consuming process in which all the possible solutions are supposed to be calculated and the best solution would be found among them. After the emergence of Bio-Inspired Algorithms for solving NP-hard problems, MEB instances grasped many researchers' interest for solving MEB using Bio-Inspired Algorithms. Some of the algorithms which are used for solving MEB are stated below.

2.3.1 Solution Models Using Genetic Algorithm

In the year 2008, Steffen Wolf, et al [26] proposed "An evolutionary Local Search algorithm for the MEB Problem" which holds the objective of finding a broadcast scheme for MEB instances for efficient data transfer in wireless ad-hoc network. Evolutionary algorithm used in this paper is Genetic Algorithm. The proposed algorithms are mapped into the problem as follows: Each gene is represented as a node in WSN. Each solution represents a complete solution for data transfer between sensor node and sink node, or vice versa. The modifications handled in this proposed local search mechanisms are: two different representation of solution are combined together and used with the Genetic Algorithm, namely tree representation and range assignment representation for each node. Tree representation is used for retrieving receiver range of node and assignment range representation is used to calculate the maximum possible range up to which it can communicate with another node. r-shrink is an another procedure used in this algorithm. r-shrink is used for efficient local search in Genetic Algorithm. These proposed algorithms are compared with the existing algorithms for efficient data transmission like Nested Partitioning, iterated local optimization, broadcast incremental power-shrink. The performance factors that are used to compare the proposed algorithms with existing algorithms are excess rate, number of times minimal solutions found, and time taken for achieving the minimum value.

In the year 2008, Wolf, Steffen, et al [44] proposed “An evolutionary local search for the MEB problem”. The objective of this paper is to propose a hybrid evolutionary algorithm which comprises effective local search. Conventional Genetic algorithm and r-shrink procedure are used for solving MEB problem. The algorithm is mapped with the problem as follows: Every node exist in the sensor network is represented as a gene in Genetic Algorithm. A complete chromosome is represented as a path for data transmission in WSN. r-shrink procedure is imposed in Genetic Algorithm to incorporate effective local search after the mutation process terminated from conventional Genetic Algorithm. Its performance is compared with Iterative local search and BIP^+ r-shrink. The performance measures include excess rate, number of times minimal solutions found, and time taken for achieving the minimum value.

In the year 2011, Singh, et al [46] recommended a paper entitled “Hybrid genetic algorithm for the MEB problem in wireless ad hoc networks”. The aim of the suggested algorithm is to reduce the energy consumption in WSN. The proposed method comprises an evolutionary algorithm named Genetic Algorithm and 2 other local search heuristic algorithms, namely 1-shrink and 2-shrink local search. These proposed algorithms are mapped with the given problem as follows: Permutation encoding is used for solution initialization. The solution is represented in an array format which comprises the sensor nodes in WSN. During permutation encoding, not all solutions start with the source node, since it is random in nature. Cyclic crossover is used for efficient adaptation of Genetic Algorithm towards MEB problem. A decoder of arborescence is used for fixing the first node as source node. The performance of proposed algorithms has been compared with Evolutionary local search, iterative local search, and Nested partitioning. The performance measure includes excess rate, number of times minimal solutions are found, and the time taken for achieving the minimum value.

2.3.2 Solution Models Using Multi-Objective Evolutionary Algorithm

In the year 2010, Konstantinidis, et al [43] presented a paper entitled “A multi-objective evolutionary algorithm for the deployment and power assignment problem in WSN”. The Power Assignment Deployment Problem (PADP) for minimizing energy consumption is the objective presented here. “A multi-objective evolutionary algorithm based on decomposition” is proposed in this paper which solves more deployment and power consumption issues in WSN. The problem is represented and solved using proposed algorithms as follows: The PADP is decomposed into a set of sub-modules where each sub-module is considered as an individual to solve, using an evolutionary algorithm. A new M-tournament selection operator is used for choosing the parents to participate in the crossover. It comprises mutation restriction over a normal selection tournament operator. Window crossover is designed for efficient handling over sub problems of PADP. An adaptive mutation operator also proposed for mutation purposes, which induces global search capability in evolutionary algorithm. The modification over existing selection operators and crossover operators are due to the adaptability of evolutionary algorithm on PADP and for efficient convergence towards the global optimal solution. The proposed multi-objective based evolutionary algorithm is solved and the results are compared against NSGA-II. Performance metrics taken into account are as follows: Δ metric, computational time and non-dominated solutions.

In the year 2011, Enan A. Khalil, et al [32] proposed a paper named “Energy-aware evolutionary routing protocol for dynamic clustering of WSN” for achieving network stability, optimal energy consumption with a long-lasting lifetime of the network. Energy aware Evolutionary routing protocol is the protocol defined in this proposed methodology to carry out minimum energy consumption process. The proposed protocol is mapped with the existing problem as follows: Each node in EA will be considered as a node in the sensor network. 0 and 1 are used to represent the cluster head node. If 1, then that particular node has been elected as cluster head and if 0, then that particular node has not been elected as cluster head. EA is used to choose the cluster head from the available nodes using a centralized evolutionary algorithm, and this process is executed in the sink node. For identifying the stability period of the network, it runs the algorithm until the first node dies in the network. To check the long lasting capability (longevity), the proposed algorithms runs until last node dies. The modification is carried out for enhancing the stability of the network when one node fails by acting as a cluster head. The proposed protocol is checked with the results of existing protocols such as LEACH, stable election protocol, hierarchical clustering-algorithm-based genetic algorithm. The performance measures used for evaluation purpose are stability period, network lifetime, energy consumption, throughput and computational time.

Soumyadip Sengupta, et al [34] in the year 2012 proposed a paper on “Energy-Efficient Differentiated Coverage of Dynamic Objects using an Improved Evolutionary Multi-objective optimization Algorithm with Fuzzy-Dominance”. The proposal composed of objectives such as tracking of sensor nodes, which are dynamic in nature with static coverage range. The given algorithm is imposed for minimum energy consumption of data transfer for dynamic nodes. Evolutionary algorithm used in these proposed algorithms are “a multi-objective evolutionary algorithm”. The algorithm is mapped with the problem as follows: Each gene in a chromosome is represented as a node and a complete chromosome is considered as a complete path for routing. An efficient energy optimization technique, namely energy efficient sensor manager, is employed. A new concept for tracking is used for all kinds of information with a single ping. A dynamic differentiated coverage procedure is incorporated for efficient tracking of dynamic nodes. The parameters used in the proposed algorithms for efficient computation of MEB are radius of sensing, confidence, range of communication, maintenance node energy, transmission node energy, reception node energy, activation node energy and non-connectivity penalty parameter. The performance measures include rate of energy consumption, total number of non-dominated solutions, and distribution of non-dominant solutions in the populations.

In the year 2013, S Sengupta, et al [38] proposed a paper entitled “Multi-objective node deployment in WSNs”. The objectives of the proposed algorithms are listed as follows: least quantity of sensor node deployment so as to reduce the deployment cost, minimum energy consumption by the deployed nodes for improving the lifetime of the node, enhance the lifetime of WSN and provide maximum coverage by the nodes' deployment to reduce the total number of nodes. The constraint in the proposed methodology is that there should be at least one path for communication between sink node and sensor node. An optimization based evolutionary multi-objective algorithm is used in the proposed method. The algorithm is mapped with the problem as follows: Each node is represented as a parameter in a solution, and a whole solution is represented as a complete individual. The proposed algorithms are compared with existing algorithms, such as Particle Swarm Optimization (PSO), Comprehensive learning PSO, Differential evolution, NSGA-II and JADE. The parameters taken into consideration include radius of sensing, confidence, range of communication, maintenance node energy, transmission node energy, reception node energy, activation node energy and non-connectivity penalty parameter. The performance measures used to evaluate and compare the proposed algorithms are coverage, spacing metric, minimum energy, minimum lifetime and maximum lifetime.

In the year 2014, J. Lu, et al [39] proposed a paper on "fuzzy random multi-objective optimization based routing for WSN". The main purpose of the proposed algorithm is to enhance the network lifetime by minimizing the latency delay, reliability, jitter, balanced energy distribution, communication interference energy. A new optimization algorithm was introduced in this paper, namely "Fuzzy Random and Multi-Objective Optimization (FRMOO) algorithm for efficient routing in WSN". The proposed algorithms are mapped with the problem in WSN as follows: The random variables of the fuzzy algorithm are link delay, reliability and node residual energy. The proposed algorithms use fuzzy random's expected value for building a routing model. For obtaining the optimal solution from the available feasible solutions, the fuzzy random simulation has been made. The performance of proposed algorithms has been compared with the existing technique called RMOO (Random Multi Objective Optimization). The performance metrics used for the evaluation of proposed algorithms includes average delay, average reliability, average jitter, average interference, average energy, and average residual energy. This paper holds a number of objectives, but it fails in one perspective. A multipath solution is given, but the optimal path used for the simulation to generate the results is not mentioned.

2.3.3 Solution Models Using Memetic Algorithm

In the year 2013, Arivudainambi, D, et al [47] proposed a research paper entitled "Memetic algorithm for MEB problem in wireless ad hoc networks". The main goal of this research paper is to identify the minimum energy broadcasting tree. The proposed methodology uses a memetic algorithm and r-shrink procedure. The proposed algorithms are mapped with the MEB problem as follows: Permutation encoding is used for solution initialization. The solution is represented in an array format which comprises the sensor nodes in WSN. During permutation encoding, not all solutions start with the source node, since it is random in nature. Cycle crossover and swap mutation is used for solution generation for participating in the next iteration. The proposed algorithms are compared with Evolutionary local search, iterative local search and Nested partitioning. The performance measures include excess rate, number of times the minimal solutions are found, and the time taken for achieving the minimum value.

In the year 2009, Jiang, Joe-Air, et al. [49] proposed a paper entitled "CoCMA: Energy-Efficient coverage control in cluster-based WSN using a Memetic algorithm". The objective of the proposed algorithm is to design an energy-efficient coverage control by an evolutionary memetic algorithm. The algorithm has been mapped with MEB problem as follows: Binary representation of solution is used in the proposed algorithms. When '0' is used, that particular sensor node is inactivated and it is not among one of those transmission nodes which are used for data transmission, and vice versa. Tournament selection strategy is used for choosing the parents to participate in crossover process. For the wake-up procedure, TDMA (Time Division Multiple Access) is used. The proposed algorithms are compared with "LEACH, LEACH-Coverage-U, PEGASIS, and EGDG in terms of Convergence time, network lifetime prolongation and coverage preservation".

2.3.4 Solution Models Using Ant Colony Optimization

In the year 2002, Das, Arindam K., et al [45] proposed a paper titled "The minimum power broadcast problem in wireless networks: an ant colony system approach for minimizing power consumption in WSN". Using the ant colony system, the broadcast tree is built in such a way as by considering each node as a vertex in ACS. Now, when the ant moves across the graph through the edges to the food source, that path is considered as a broadcasting path and the vertices which have been chosen for travelling is considered as the node by which the data can be transferred. The proposed algorithms has been evaluated and compared with the existing algorithms like Broadcast Increment Process (BIP) and BIP sweep.

In the year 2012, Hugo Hernandez, et al [33] proposed a paper on "Distributed ant colony optimization for minimum energy broadcasting in sensor networks with realistic antennas". The focus point of this paper is to minimize power consumption in a distributed environment. The constraint imposed with the goal is to reduce the power consumption with respect to the number of newly added nodes (i.e. it should not expand the use of energy consumption by which the network lifetime can be improved). The proposed algorithms are a hybrid of two algorithms, namely Ant Colony Optimization (ACO) and Broadcast Increment Process (BIP). The algorithm is mapped with the problem as follows: Each node in ACO is considered as a sensor node in WSN. The modifications in the proposed methodology are given below. Instead of considering the increment of transmission power level in the proposed work, a newly added node power consumption level was considered in the BIP greedy function. This modification has been carried out for adapting the algorithm in a distributed environment. The proposed algorithms are compared with existing BIP+ and Centralized ACO. The performance measures, which are considered while computing and comparing simulation result, are Best, Average, Deviation rate and the Number of iterations.

In the year 2011, Hugo Hernández, et al [31] proposed a paper on "Minimum energy broadcasting in WSN: An Ant Colony Optimization approach for a realistic antenna mode". The objective of this paper includes adapting realistic antenna for MEB problem in the wireless ad-hoc network. The constraint followed in this proposed methodology is to minimize energy consumption with respect to defined antenna range. ACO is the metaheuristic evolutionary algorithm used in this proposed methodology. This algorithm had been inspired owing to the foraging behavior of ants. The algorithm has been mapped with the WSN problem as follows: Each node in WSN is represented as a vertex in ACO. A complete solution from source to destination is defined as a foraging path from nest to the food source in ACO. The modifications done with the existing ACO includes: A realistic antenna model, which has a finite set of transmission range, is applied for depicting the real world scenario. The need for the proposed procedure is as follows: SWEEP procedure and variable neighborhood descent algorithm are used for local search. SWEEP procedure is used to identify the nodes which reduce transmission power level of network and resolve it. Variable Neighborhood Descent algorithm is further used to improve the quality of the solution. It consists of r-shrink procedure in it. The proposed methodology has been compared with the existing algorithms like Broadcast Incremental Power (BIP) and BIP-Variable Neighborhood Descent algorithm (BIP-VND). The parameters carried out in the whole process is r-max (defines the rate of shrink used in r-shrink procedure). The performance measures used to carry out the comparison process includes deviation rate, Best energy consumption, average energy consumption and computational time.

In the year 2006, T. Camilo, et al [27] proposed a paper on "Energy-efficient ant-based routing algorithm for WSN”. This paper is composed with the objectives of improving the efficiency of power consumed by WSN, and improvising network lifetime. The metaheuristic bio-inspired algorithm used in this proposed work is ACO. This problem has been mapped with the proposed algorithms as follows: Each sensor node is represented as a node in ACO. The source and sink nodes are fixed. The problem is to find out the intermediate nodes that are used to transmit the data. The proposed algorithms alters conventional ACO algorithm as follows: The changes are made while updating pheromone trail. There are two types of ants used in this algorithm. The forward ant chooses which node to participate in the solution. The backward ant is used to update the pheromone trail. In this algorithm, both the path length and energy consumed to transmit data are considered while updating pheromone trial. These changes are made in order to achieve energy efficiency and maximize the network lifetime. For performance comparison, the proposed algorithm has been compared with the existing algorithms like Basic Ant-Based Routing (ABR), Improved ABR and Energy-efficient ABR. The performance of the proposed algorithms has been qualified with the performance measures such as average energy consumed by network, minimum energy, standard deviation and transmitting energy efficiently by the network.

In the year 2010, J. Yang, et al [29] proposed a paper on “Multipath Routing Protocol Based on Clustering and Ant Colony Optimization for WSN”. The objective is to provide a multipath routing scheme from the source node to sink node with minimum consumption of power and improved lifetime of the network. Multipath is one such scenario where there will be more than one path available in all the nodes to reach the sink node. This multipath scheme will be effective when the highly preferable path has collided, or some interruption occurs which cannot be further available for remission usage. There are three different phases for secure and effective data transmission in this proposed work. The three phases are dynamic clustering, multipath construction, and data transmission. The metaheuristic algorithm used in this proposed work is ACO for multipath construction. The proposed algorithm has been mapped with the problem as follows: Each vertex in ACO is considered as a cluster-head in sensor node. A complete path driven by ACO is considered as a path from sink node to source node, or vice versa. The modification of existing ACO algorithm has been done in probability calculation for choosing the next node in order to participate in the data dissemination process. The modification over existing ACO was made for balancing the load in the path and for maximum network lifetime. The proposed algorithm has been compared with existing algorithms such as Energy-Efficient Multipath Routing, Multipath Routing Based on Ant Colony System and TEEN. The parameters used for simulation are packet size, broadcasting packet size, location coordinates of sink node, event radius for communication. For evaluation purpose, the performance metrics used for comparison are average energy consumed by the network, minimum energy, standard deviation and energy efficiency by the network.

In the year 2009, S. Okdem, et al [28] proposed a paper on “Routing in WSN using an Ant Colony Optimization (ACO) router chip”. This paper holds the real-time implementation of ACO in a router chip in order to implement in the real world applications. The objective is to achieve reliable communication which handles only the path length. ACO algorithm is one of the major discrete-cum-probabilistic algorithm in evolutionary computing. The problem has been mapped with the proposed algorithms as follows: Each node in the path of transmission is considered as a vertex in ACO. The choice of next node to be transmitted is based on the newly designed probabilistic decision rule. The modifications in the proposed algorithms includes change in probability calculation in ACO. The performance measure used in this algorithm for evaluation purpose is response time. The advantages of this algorithm over other evolutionary algorithm is that the packets that are to be forwarded to the sink nodes are not needed to be retained by the transmission nodes, which further reduces the packet head and thus saving energy. While pheromone trail updates, energy levels of the nodes are suppressed and reduces the lifetime of WSN.

M. Sousa, et al [35] in 2012, proposed a paper on “Cognitive LF-ant: A novel protocol for healthcare Wireless Sensor Network in order to provide an inter-cluster based routing protocol between the sink and sensor node”. ACO algorithm is altered with the help of Saharan Desert ant behavior, which mimics a safety-based inter cluster routing mechanism. The modifications are in the calculation to change in pheromone rate and probability calculation. This modification helps to form a cluster when cognitive LF-Ant scheme is combined with ACO. For scheduling, based on the priority of emergency, an intra-cluster emergency reporting protocol has been designed. An inter-cluster cooperative modulation has been decided for reducing the packet loss rate, etc. the performance measures that are used to compare the existing algorithm with the proposed are average delay time, average SNR and packet loss rate.

E. Amiri, et al [40] in the year 2014 proposed a paper entitled “Energy efficient routing in WSN based on fuzzy ant colony optimization”. The objective is to decrease the power consumption by WSN and thus enhance the lifetime of the network. ACO algorithm is used in this paper for solving energy-based routing, along with fuzzy logic. The proposed algorithm works as follows: The forward ants build the solution for data transmission based on the pheromone table. The backward ants are used to update the pheromone table based on the path that is chosen on that iteration. This updated level of pheromone will be used in next generation for choosing the best nodes. The modifications of proposed algorithms over conventional ACO are made in updating the changes in pheromone trail. A fuzzy rule is incorporated for an efficient choice of next node participation in data transmission. The devised algorithm which is associated with the existing algorithm known as "Ad-hoc On demand Distance Vector Routing (AODVR)". The performance measures include "routing setup time, number of routing request packets, energy consumption, delay and network lifetime".

2.3.5 Solutions Models Using Particle Swarm Optimization (PSO)

M. Liu, et al [36] in the year 2012, proposed an "Agent-assisted QoS-based routing algorithm for wireless sensor network". The objective of the proposed algorithm is to improve the performance of the network by improving QoS based services, such as packet loss, bandwidth and delay. A widespread evolutionary algorithm is used for efficient routing called as PSO. This PSO algorithm mimics the foraging behavior of birds. This algorithm works with the personal best and global best concept. Two different parameters are used in PSO namely cognitive and social parameter. A new intelligent software agent is imposed to monitor the topology of network and nodes transition state. The proposed PSO-based routing is mapped with the existing problem as follows: two different types of agents are used namely forward and backward agent. The forward agent is used to give options to find next node to be transmitted. The backward agent actually travels in a route which is chosen by the forward agent. PSO algorithm has been carried out with some modifications for maintaining network routing and maintenance. These proposed algorithms are related with "Ad hoc On-Demand Distance Vector Routing (AODVR) and Energy-Efficient Ant-Based Routing Algorithm (EEABR)". The performance measures calculated during simulations are; "end-to-end delay, packet loss and synthetic QoS".

In the year 2011, Molina, et al [42] proposed a paper entitled "Location discovery in WSN using metaheuristics". The objective is to provide an efficient procedure to mitigate distance estimation errors which result in node positioning errors during location discovery. The proposed methodology uses three algorithms include simulated annealing, Genetic Algorithm (GA) and PSO. The given problem is mapped with the algorithms are as follows: The solution representation is in the form of location coordinates. Each solution consists of twice the length of the number of sensor nodes. Each sensor node is represented in the form of '*x'* and '*y'* coordinates. For GA, the ranking method is followed for choosing the parents and rephrasing the selection phase with elastic replacement. A set of 10 configurations are simulated and the performance is measured. The performance measures include minimum error obtained and average error obtained while locating the sensors for evaluation and comparison purposes with existing algorithm.

2.3.6 Other Evolutionary Algorithm based Solution Models

T. Hu, et al [30] suggested a protocol known as "QELAR, a machine learning based adaptive routing protocol for energy-efficient underwater sensor networks". The target of the protocol is to develop a network with minimum power consumption and better network lifetime. A novel algorithm is proposed in this paper, namely QELAR, which is inspired by a machine learning technique. A WSN is mapped into machine learning process as follows: The current state is defined as 's', the action to be taken for transmission to next state is defined as 'a' and the policy for transition is defined as π. For adaptation of machine learning technique to WSN, QELAR introduced Q-learning technique for balancing loads among the nodes so as to extend the lifespan of the entire network. A new learning based technology is imposed for achieving the adaptation capability of proposed protocol for dynamic network environment. The proposed algorithms are compared with Vector based Forwarding Protocol (VFP). The performance measures taken into account for comparison of the existing method with the proposed work are delivery rate, latency, energy consumption and residual energy.

M. Saleem, et al [37] in the year 2012 proposed a paper entitled on "Bee Sensor: an energy-efficient and scalable routing protocol for WSN". The objective is to provide an efficient routing protocol for path maintenance and multiple route discovery between the sink and the source node. The proposed methodology has been inspired by the behavior of honeybees. The proposed algorithms consist of 4 important phases of bees, which are listed below. Packer bees allocate the forager bees to packets which are received from the upper layer. Next, scout bees are further divided into forward and backward scouts. The forward scout bee builds the path between the sink and the source node. The backward scout bee reports the fitness of given path. Third, the forager bees transmit the packets from source to destination in the defined path by scout bees. Finally, the collection of foragers is called swarm. This swarm helps to get back to its own source nodes with the help of embedded route in the payload. The proposed algorithms are compared with the existing algorithms like EEABR, FP-Ant, FF-Ant and SC-Ant and AODVR. The performance measures taken into account for comparison and evaluation purpose include loss ratio, control overhead, packet delivery ratio, latency and energy efficiency and lifetime of the network.

In the year 2013, Hsiao et al [48] proposed a paper entitled "Static and dynamic MEB problem in wireless ad-hoc networks: A PSO-based approach and analysis". The objective is to minimize the consumption of energy by the nodes of WSN. The suggested algorithm comprises PSO algorithm and intensified r-shrink procedure for efficient local search. The algorithm has been mapped with the problem as follows: A power degree encoding is used for solution re-orientation. After the acceleration process, the solution comes to a landing phase. During this phase, the particles are divided into three different modules include no change in power degree, increase in power degree and decrease in power degree. For solution feasibility, the intensified r-shrink procedure is carried out. For conversion of static to dynamic MEB, the author proposed a new repairing scheme to avoid instability over the network and a simple conditional incremental power heuristic function is imposed. The proposed algorithms are compared with the evolutionary local search, BIP, ACO and hybrid GA in terms of excess rate, number of times minimal solutions found, time taken for achieving the minimum value, average energy consumed by the population of a single cycle and standard deviation of an entire population.

In the year 2016, Zeng, et al [41] proposed an “improved harmony search based energy-efficient routing algorithm for WSN”. The major role of the experimental algorithm is to maximize lifetime of the network. The constraint followed in the proposed algorithm is to follow a restricted length of the path. The conventional Harmony Search algorithm is used in this proposed methodology. The algorithm is mapped into the proposed algorithms as follows: A set of nodes are placed in an individual in harmony search and set of node which connects from source to destination is called as a complete path for data transmission. The modifications taken place for adaptation of proposed method with existing problem included as follows: Initialization process of the randomly permuted solution has been replaced with harmony memory based initialization. An adaptive parameter is introduced for adapting the protocol with current scenario. The modifications carried out for faster convergence towards an optimal solution. The proposed algorithms are compared with existing algorithms such as “Energy-Efficient Ant-Based Routing algorithm (EEABR)” and Routing in WSN by ACO algorithm. The performance metrics are residual energy and network lifetime.

In the year 2007, Shah-Hosseini. H, et al [25] proposed a paper entitled “Problem solving by Intelligent Water Drops (IWD)”. The objective of the proposed algorithm is to find problem-solving algorithm in which the responses of river systems and the exploitation that water drops perform in the rivers are dealt with. The concepts are based on the reality of natural water drops and those notions are applied in response to construct artificial water drops. This kind of water drops are further applied for solving the TSP problems. A water drop in a river has some amount of velocity in it. Normally, this carries some amount of soil. Some quantity of soil can be loaded from the riverbed source, usually from the fast flowing areas, and unloaded in slower areas of the riverbed. This IWD consist of two important properties in it: 1) The quantity of soil it carries now, referred as Soil (IWD) and 2) The velocity of the soil while moving in the riverbed, called as Velocity (IWD). The algorithm is mapped into the proposed algorithms as follows: For the TSP, the cities are often modeled by the nodes of a graph and the link graph represents the path joining cities. Each link has some amount of soil. An IWD can travel between cities through the link and can change amount of their soil. For each IWD moving between the cities, the proposed algorithm updates its velocity.

In the year 2017, Gopal Chand Gautam, et al [51] proposed a paper titled "A Novel Cluster Based Time Synchronization Technique for WSN". The idea behind the proposed research of this author was to construct time synchronization technique that assists to coordinate the Sensor Nodes (SN) efficiently in response to energy consumption. The author projected "A novel cluster-based time synchronization technique" for WSN to hold all the sensor nodes' local clock that being synchronized with a global clock. The performance of CBTS estimated by simulation technique. The performance metrics include the SNs primary energy, number of nodes in the WSN and convergence time. The result of simulation which is based on the analysis of energy with the proposed model validates that the proposed technique of CBTS reduces the energy consumption of node and also the errors occurred during synchronization process are compared with the other existing models. The synchronization processes were performed using top-down approach. The Cluster Heads (CH) synchronizes with the sink while SNs synchronizes with their associated CHs.

In the year 2002, Wei Ye, et al [5] proposed a paper entitled "An Energy-Efficient MAC Protocol for WSN". This research paper devised a new version of MAC protocol which referred as Sensor Medium Access Control (S-MAC), which is designed for WSN. The initial job of the MAC protocol is to overcome collision of node through avoiding the transmission of data among two or more interfering nodes that participate at the same time. Some of the distinctive examples include "Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA)". The two important attributes of MAC protocols were energy efficiency and scalability. The main sources of wastage of energy are control packet overhead, collision and overhearing.

The main goal of the MAC protocol design is to minimize the consumption of energy while achieving collision avoidance and good scalability. The intended protocol attempts to minimize the energy consumption from all the sources that were identified to cause energy wastage, *i.e.*, collision, idle listening, control overhead and overhearing. To attain this design goal, the researcher established a model which known as S-MAC which has 3 essential components: "message passing, periodic listen and sleep, collision and overhearing avoidance".

2.4 Research Gap:

The research gap that led to the research problems of the thesis were identified after applying various level of literature review process. The following points that are listed out to determine major drawbacks which is found in the existing model:

a) A comprehensive survey has not been made with the recent related existing works, and it has not been concluded with the obligation for achieving an enhanced model for solving MEB instances in both forms of generic and evolutionary based algorithms.

b) In the existing algorithms, it is very difficult to choose the best node to participate in data transmission to sink node and constructive based feasible solutions.

c) There was no enhanced existing model by imposing random based diversification function with enhanced search space exploration.

d) No improved model of IWD Algorithm exists by combining diversification function along with dynamic soil updating parameter for balancing between exploration and exploitation throughout the run in the existing model.

e) Several performance measures are not listed out in the existing model for the evaluation of the final outcomes achieved by the experimentation step in response to validate the results of the research presented in this thesis.

2.5 SUMMARY

In this chapter, a meticulous review of literature on MEB problem and its solution methods are given. Section 2.1 elaborates the introduction of this chapter and its organization. Section 2.2 describes the generic solutions represented for solving MEB instances in overall wireless domains. Then, in section 2.3, the evolutionary based solution instances for solving MEB are given in a detailed manner. The details emphasized include mapping of MEB with evolutionary algorithms, its modifications, need for modifications, performance measures that are encompassed with it for comparison purposes.

CHAPTER 3

SYSTEM DESIGN

3.1 INTRODUCTION

Among various phases of WSN such as node deployment, efficient routing, collision avoidance, fault tolerance, node recovery, node coverage and network establishment, the search space exploration comes under the concept of efficient routing. In our context, the efficiency in WSN is based on the amount of energy required to transmit the packets between nodes. This energy has been considered as one of the major issues in WSN; so, the energy of a particular node will be only allocated to a fixed amount of energy in order to handle the network transmission. If node spends more energy in order to transmit a packet, its energy will be obviously reduced. As a result, the node will exhaust the battery and the node will die.

An efficient strategy will make the network more reliable and the availability of the node will be consistent. For achieving these objectives, finding the finest way of transmission to deliver the packet between nodes with minimal energy consumption is required, many approaches were being made. Our work deals with search space exploration in the network that explores more paths to find optimal routes between node or nodes and the base station.

Many techniques were being proposed in order to minimize the energy consumption. Exhaustive algorithms known as ‘Branch and Bound’, ‘Dynamic Programming’ and ‘Greedy Method’ are some of the techniques which were being applied to the MEB problem in WSN. This method achieves the best solutions when the problem size is small; but when the size of network increases with several number of nodes, the search space also increases. It becomes a tedious task for accomplishing the finding out the best path for packet transmission.

3.2 Minimum Energy Broadcasting (MEB)

MEB is one among the well-known techniques and recent trends in "wireless ad-hoc networks" for efficient packet transmission. Broadcasting is a method in which it allows all the nodes in a network to share data efficiently with all other nodes.

3.2.1 Wireless Sensor Networks (WSN)

WSN and "wireless ad-hoc networks" which are used for monitoring certain events. The message transfer will be from the sensor nodes to base station or vice versa. Multi-hop communication is also enabled in WSN for energy conservation. Since the sensor nodes are wireless, their lifetime will obviously be limited, and it has been limited in terms of batteries. In such a lifetime, limited conditions using the available source, transferring data between nodes seem to be a challenging issue.

WSN do not possess a wired backbone infrastructure in order to transfer the information to the base station. The communication has been done only via a single-hop communication in case the nodes are close enough to transmit the data, or through intermediate nodes to transfer the data. The sensor nodes in these wireless networks use omni-directional antenna for transferring data. Using this omnidirectional antenna, a single transmission of data is enough to cover or transfer the data to other nodes within its coverage range. This feature plays a major role in broadcasting or multicasting communications.

WSN recently grasp a vast range of attention due to its potentiality of revolutionary changeover in many segments like environmental monitoring and conservation, in the field of manufacturing etc. The core technology inside WSN holds multi-disciplinary approaches. It includes design, implementation and the operations that actually wireless network do. The multi-disciplinary domain includes embedded systems for its operation, signal processing for communication purpose, networking and protocols for efficient packet routing, information management and distributed algorithms for handling the received data from a sensor node. The deployment of such wireless sensor nodes often takes place in resource-constrained regions along with a battery for obtaining energy. These constraints promote WSN towards the researchers for efficient energy management.

3.2.2 Minimum Energy Broadcast (MEB) Problem

One of the recent debates towards WSN is efficient routing between sensor to the sink node and vice versa. Since the sensor nodes are limited in terms of lifetime (battery- based power), efficient management of power consumption seems to be an emerging concept in WSN. For example, if all the sensor node of a network communicates to sink node, the power of the nodes will be consumed more which causes the battery power to get reduced much sooner after a communication chain has been made. On the other side, if the nodes communicate in the form of peer to peer or as a unicast network, the power consumption will be reduced when compared to direct communication of sink node, but it leads to unwanted delay.

Since the energy resources for wireless networks are limited, energy efficiency is the major theme which has to be concentrated in these types of networks.

Considering a set of nodes $N\ where\ N = \{n1, n2, \dots\dots.., n_n\}$,'$n$' is a single node and one node 'n' among N is assigned as a source node. The MEB problem is to reduce the total consumption of power when the nodes are connected to each other, and they communicate with other remaining nodes in the network. In "wireless ad-hoc networks", all the nodes are suitable for regulating the energy required for transmission. Since each node assigns its own transmission range, other nodes which come under its range are capable of receiving the messages from this node. The aim of MEB is to assign ranges to the nodes where minimum energy can be consumed to cover all the nodes in the network.

In graphical form, the MEB can be stated as G = (N, E), where 'G' represents the complete graph which has been built by the 'N' nodes, and 'E' represents the edges which connect each node. The energy required to communicate with other nodes can be represented as P_{ij}, where 'i' referred as source node and 'j' known as destination node which receives the message from the node 'j', $(i, j) \in E$.

The property of broadcast states that a node 'x' can transmit data to node 'y'; all the other nodes with the range of P_{xy} can receive the data without any excess power consumption. That is, node 'i' can receive the transmitted data from the node 'x', if $P_{ix} \leq P_{xy}$. The theme of MEB problem is to find out a broadcast tree in which all the nodes could be covered for transmitting the data with minimum power consumption. The data transmission process has been initiated using 'single hop' communication process if the network size is small, or else using multi-hop communication when the size of the network is large.

In "wireless ad-hoc networks", the start node is responsible for relaying the message to the terminal node of the same edge. The power required to transmit the message by a node 'x' to its farthest child node can be determined by:

$$Transmission\ Power\ TP_i = \max d(i, j) \tag{3.1}$$

In "wireless ad-hoc networks", the leaf nodes transmission power is zero since it does not transmit the data to any other node. The total transmission power required for message broadcasting can be calculated as the sum of power required by each parent node in the broadcast tree.

$$Total\ Transmission\ Power\ \ TTP_{Sol_i} = \sum_{p \in (i,j) \in E_{sol_i}} \max\ \ d(i, j)^{\alpha} \tag{3.2}$$

where TTP is the total transmission power of solution (sol_i) and 'α' refers to a path loss constant. The 'α' range is between the interval 2 and 4.

The power consumption from the node 'i' to node 'j', at the time of message transmission $d(i, j)$ will be determined by the derivation as given below:

$$d(i,j)^{\alpha} = \left(\left[(x_i - x_{j)})^2 + (y_i - y_{j)})^2\right]^{1/2}\right)^{\alpha} \tag{3.3}$$

$d(i,j)^{\alpha}$ is defined as the Euclidian distance from node 'i' to node 'j'. '(x_i, y_i)' represents the coordinates of node 'i' and '(x_j, y_j)' represents the coordinates of node 'j'. The optimal and near optimal solutions will be found based upon the minimum value of TTP_{Sol_i}.

In ad-hoc networks, there exists no sink node which gathers the data from all the nodes of the network and accumulates it and stores it in the sink node for processing. But in WSN, the data are supposed to reach the sink node for further processing. So, the path for broadcasting is supposed to support the transformation of messages to the sink node also.

3.3 MEB in WSN

Nodes in WSN can interact with the sink node either in "single-hop or multi-hop" communication process. The sensor node collects the data from the environment and transfers it to the sink node. During the transmission process, the power consumption will be high since it needs to spend some amount of energy for the communication process. And also the data transmission should be towards the sink node for energy saving process. There will not be any guaranteed solution of energy saving will be given out using any algorithm of "wireless ad-hoc networks" applied to WSN. Because the data transmission of "wireless ad-hoc networks" have not been converged towards any particular node as in WSN. So, some specific methodology is needed which consumes less power during data transmission in WSN to solve MEB problem.

Considering the set of nodes SN = {sn_1, sn_2, ……., sn_n} in WSN where 'sn' denotes the Sensor Node and 'i' denotes the total capacity of nodes in the network, the energy consumption of node 'i' in a communication session can be determined as follows:

$$T(N_i) = \sum d(i,k) \tag{3.4}$$

where 'k'is a series of nodes which satisfies the condition

$$k \in \{N | d(i,k) \leq d(i,j)\} \quad (3.5)$$

where 'j' is a node which is chosen to be the farthest node to which node 'i' can transmit the data.

The total energy consumption of complete broadcast tree can be determined using Total Transmission Power:

$$TTP(t) = \sum T(N_i) \quad (3.6)$$

where 't' represents the iteration number and N_i represents the cluster head that participates in the data transfer of current IWD.

3.4 INTELLIGENT WATER DROPS ALGORITHM

3.4.1 Behavior of Natural Water Drops

In rivers, flowing of water drops will be observed in the huge form of swarms. The path of the river is created by the water drops that flow in it. The environment has a dramatic effect over these water drops in which case it can move smoothly on soft soils, and hard soil resists the movement of these water drops. Still, the water drops move towards the center of earth because of gravitational pull. One of the salient features of water drops is that it moves based on their velocity. It is observed that the water drops also holds some amount of soil with it. So, the water drops can also carry soil along with it. As the soft soils get removed by the water, the depth of the soft soil regions gets deeper and attracts more water drops into it. The water drops, which consist of those removed soils from the riverbed, can move faster than before and these soil get unloaded in the hard soil regions. In this scenario, there are three changes which were made to the environment as well as to the water drops.

- Water drop velocity is subjected to change
- Water drop soil is subjected to change
- Soil between the two points of river adopts some modifications

3.4.2 Intelligent Water Drops

Intelligent water drops model is one of the well-known motivational techniques that was imitated from the natural behavior of water drops which holds predominant features of it. The two important properties are as follows:

- Soil (IWD) - the soil that the water drop carries
- Velocity (IWD) – the velocity of the water drop

From the perspective of engineering, the environment is considered as the representation of problem which is in need to be solved. The swarm of IWD's is the one that searches for the optimal solution from the given environment.

In IWD algorithm, when the IWD moves from the node 'i' to node 'j', the velocity of the IWD gets changed based on the soil between those two nodes, and it is indirectly proportional:

$$\Delta velocity(IWD) \propto^{NL} \frac{1}{soil\,(i,j)} \tag{3.7}$$

Where, $\Delta velocity(IWD)$ represents the change in the velocity of IWD.
Soil (i, j) represents the soil that presents between the node 'i' and 'j', $\propto^{NL}$ represents that the velocity of IWD is nonlinearly proportional.

The IWD make some changes over the soil that it carries with them when it travels from the node 'i' to node 'j' and it can be represented in the form of $\Delta soil(IWD)$.

$$\Delta soil(IWD) = \Delta soil(i,j) \propto^{NL} \frac{1}{time\,(i,j;IWD)} \tag{3.8}$$

Where, $\Delta soil(IWD)$ represents the change in the amount of soil that has been carried by IWD. "$\Delta soil(i,j)$" represents the change it has made in the edge between node 'i' and node 'j'. $time(i,j;IWD)$ represents the time that the IWD takes to travel between node 'i'

and node 'j' with its velocity, $\propto^{NL}$ represents that the equation is nonlinearly proportional. The sooner it travels from the node 'i' to node 'j', the more amount of soil it carries which, in turn, increases its speed.

The time spent to travel from the node 'i' to node 'j' by IWD can be calculated in mathematical form as follows:

$$time(i,j;IWD) \propto^{L} \frac{1}{Velocity\ (IWD)} \tag{3.9}$$

where, $\propto^{L}$ represents that the equation between the time spent to travel for IWD between node 'i' and node 'j' along is linearly comparative to the velocity of IWD.

During the transfer from node 'i' to node 'j', the amount of soil removed from the edge between node 'i' and node 'j' can be represented as follows:

$$soil(i,j) = \rho_o.soil(i,j) - \rho_n.\Delta soil(i,j) \tag{3.10}$$

where, ρ_o and ρ_n are the positive values between the range 0 and 1.

At the time of removal of soil in the edges of node 'i' and 'j', the soil is supposed to be added to the existing soil of IWD and it can be represented as follows:

$$soil^{IWD} = soil^{IWD} + \Delta soil(i,j) \tag{3.11}$$

3.5 MAPPING BETWEEN MEB-IWD

MEB in WSN consists of sensor nodes that collects the information from its allocated environment and forwards the data to the sink node. During the transmission of messages, the choice of choosing a hop to forward the packet to the sink node is the preliminary thing that should be noted in MEB-WSN. The packet forwarding to the sink node can be made either via single hop or multi-hop communication structure when the total amount of nodes or the size of the network is large.

The constraints of MEB-WSN are given below:

1. The data or information from/to the sensor node should be collected / delivered to all the nodes present in the network.
2. During multi-hop communication, the information should be relied on the other node in the network for efficient energy minimization.
3. If multi-hop communication has been chosen, then the sensor nodes transfer the data to the cluster head of the current iteration.
4. The cluster head will be found using the Heuristic function (HUD).
5. While choosing the cluster head for energy saving during the transmission of information, three preliminary things are supposed to be followed.
    a. The chosen node should be able to a cover maximum number of nodes within its range.
    b. The chosen head should be near to the sink node when compared to the other nodes of that cluster.
    c. The cluster head chosen should not belong to the cluster that is already built during the current iteration.

WSN holds 'N' nodes which can be represented as follows:

$$N = \{n1, n2, \dots \dots .., n_n\} \tag{3.12}$$

where, 'N' is the set of sensor nodes and 'n' represents the total number of nodes in the network

$$n = |N| \tag{3.13}$$

Let the power consumption of network for transferring the data from the node 'i' to node ' j' be represented as $d(i, j)$.

The energy consumption will be determined using the following formula:

The energy consumption of node 'i' in a communication session can be determined as follows:

$$d(i,j)^{\alpha} = \left(\left[(x_i - x_{j)}{}^2 + (y_i - y_{j)}{}^2\right]^{1/2}\right)^{\alpha} \tag{3.14}$$

$$T(N_i) = \sum_{k\in\{d(i,k)\leq d(i,j)\}} d(i,k) \qquad (3.15)$$

The total energy consumption of complete broadcast tree can be determined using Total Transmission Power as follows:

$$TTP(t) = \sum_{N_i\in Cluster\ head} T(N_i) \qquad (3.16)$$

For some extent to use IWD algorithm in the MEB-WSN problem, the MEB-WSN problem as stated above could be considered as a complete undirected graph G = (N, E). Every edge in the graph 'G' contains expected quantity of soil in it. An IWD visits the nodes in the graph via those 'E' edges. The IWD has the ability to change the amount of soil in the edges.

Moreover, the sensor nodes in the MEB-WSN are mentioned by the nodes in the graph which obviously holds the physical position of sensor nodes. An IWD starts its process by choosing a random node as its starting node, and finds another node to which it can relay the data for completing the process of transfer of data to sink node. This process will be made until the complete solution is found (i.e. until the IWD visits the sink node). The IWD modifies the amount of soil that exist in the edge that it travels during the construction of the solution. In order to fulfill the constraint in MEB-WSN, the cluster head should not belong to the previously built cluster in the current iteration. A chosen nodes' list C_N (IWD) should be maintained for each IWD for every iteration. C_N represents the chosen nodes at the current iteration. This list adds the nodes that are already chosen as either a cluster head or as a leaf node of a certain cluster into it. So, the next cluster head can be chosen for IWD from the nodes that are not exist in the C_N.

3.6 MODIFIED IWD MODEL FOR MEB PROBLEM

Based on the above mentioned MEB problem, it is considered as a 'combinatorial NP-hard problem' where, the time complexity of the problem-solving increases exponentially as the problem size increases. IWD algorithm is one such algorithm which divides the water drops are considered as vertices and the flow of water is considered as edges which is suitable to discover new path. When this scenario is applied for solving MEB instances, each node is represented as the divider in IWD and the edges are considered as the combination of those nodes to communicate with each other. This procedure is used to map IWD with MEB and further process has been done on iteration basis.

Solving MEB using IWD requires certain kind of modifications which include the probabilistic calculation for choosing a node to participate in data transfer, for maintaining diversification throughout the run and for convergence of algorithm towards an optimal solution. These natures are combined with original IWD for solving MEB instances which in turn comes out as Modified Intelligent Water Drops algorithm (Modified IWD).

In our proposed Modified IWD, a probabilistic heuristic function is proposed which effectively chooses next optimal node to participate in multi-hop based broadcast messages. The key concepts of modified IWD are given as follows.

3.6.1 Probabilistic Heuristic Function Phase

The original IWD algorithm consists of a phase called probability calculation, where it allows the user to choose their heuristic function based on the problem it applies. In MEB problem, choosing the transmission by which the data can be transmitted and reach the sink node is one of the major parts in solving MEB instances.

In our Modified IWD algorithm, an efficient strategy for choosing the next visiting node by IWD is done by choosing the maximum probabilistic value that a node holds. The calculation of probability can be defined as follows:

For the transmission of data towards the sink node, this mathematical equation needs to be altered in such a way:

$$HUD_{MEB-WSN} = \min \mathrm{d}(\text{sink node}, \max d(i,j)) \quad (3.17)$$

where, $d(i,j)$ is the energy consumed when data transferred from the node 'i' to the node 'j', sink node is the node where all the data of sensor nodes are to be converged. The difference of MEB in "wireless ad-hoc networks" and WSN is the directional way of transmission of data. In "wireless ad-hoc networks", the message will be broadcast to all the nodes and the process ends with that. But in WSN, the data are in need to be directed towards the sink node for further processing the analysis, etc.

- Each IWD is considered to be a feasible solution in MEB-WSN, which comprises cluster heads.
- Iteration Best solution (T^{IB}) of IWD is the best solution to the current population in MEB-WSN.

3.6.2 Enriched Diversification Phase

After claiming the probability heuristic functions in an efficient manner, the population diversification faces a major problem of premature convergence which in turn returns optimal results which are saturated in half of the total iterations. This is due to the guidance of complete probabilistic value on choosing next transmitting node for data transmission. An effective mechanism which avoids premature convergence in bio-inspired algorithms is randomness. A random walk in optimization algorithm approves exploration instead of exploitation.

On choosing the next node for data transmission instead of choosing maximum probability consisted node, a random walk has been introduced. This can be defined in the mathematical formulation as follows:

V_N can be chosen based on this form

$$p(N_{Chosen}) = \begin{cases} rand(\max(prob), rand()) & if \quad rand() > \max(prob) \\ \max(prob) & else \end{cases} \quad (3.18)$$

The probability value can be chosen by equation 3.17 states that it can return the maximum probability-holding node when the random value is less than the maximum probability for all nodes. Normally the random value lies in the range of (0, 1). A node can be chosen in a random manner among the available nodes, i.e. if the generated random number is greater than maximum probabilistic value.

$$Chosen\ Node = N_{IWD}(p(N_{Chosen})) \tag{3.19}$$

Equation 3.19 returns the node which belongs to the probability of value returned by equation 3.18.

This kind of node selection method leads to Modified IWD to carry diversified population throughout the algorithm by which premature convergence is highly balanced when compared with Modified IWD with Heuristic function.

3.6.3 Balanced Exploration and Exploitation Phase

After invoking diversification factor in Modified IWD, the resultant factor shows an incredible deviation in standard deviation. Since the diversification factor impacts throughout the run, this problem arises when the algorithm moves towards exploration till the run ends.

In order to balance between exploration and exploitation, a PSO-inspired inertial weight factor is introduced in the proposed Modified IWD. This proposed inertial factor in Modified IWD replaces the local soil updating parameter which, in turn, reduces the concentration as the iteration number increases. On reducing the updating value of soil between the edges, the probability value will remain unchanged which, in turn, lets the maximum probability value to be chosen, and thus improve the convergence over optimal solution at the end of iteration.

Initialize the local soil updating parameter value with the following equation:

$$\rho_n = \mathrm{LB} + (\mathrm{UB} - \mathrm{LB}) \frac{t}{Max\_It} \tag{3.20}$$

where, LB is Lower Bound =0.4 and UB is Upper Bound=0.9, 't' is the current iteration number and 'Max_It' indicates the maximum number of iterations.

3.7 SUMMARY

This chapter describes the system design of MEB using IWD Algorithm on WSN. The topic covers an introduction to WSN, characteristics of MEB, and the adoption made on MEB tree when it is applied to WSN. Also, an introduction about Intelligent IWD algorithm has been described in a detailed manner along with the systematic flow of IWD is maintained. Finally, the mapping process of IWD algorithm over the problem of MEB in WSN has been mapped, so that it can be solved with IWD algorithm. MEB has been represented in the form of a graph in order to solve it using IWD.

CHAPTER 4

ALGORITHM FORMULATION

4.1 INTRODUCTION

Intelligent Water Drops (IWD) consist of two important features by which they solve the optimization problems:

- A graph which comprises the distributed memory will keep track of the changes made in the soil of its edges.
- Moving capability of IWD over the edges of the given graph.

IWD finds the optimal solutions with the help of the soil that it assigns at the initial phase of algorithm and the changes that it makes on that soil's matrix. The path which holds the low density soil will be attracted by the IWD's and thus will find the optimal solution.

For every iteration in the IWD algorithm, each IWD explores and makes changes in the environment. IWD constructs the solution in the constructive phase where each solution will be built from the partial solutions by adding a node one by one to the IWDs. The swarm of IWD flows on the given graph (i.e. the environment) with the help of a heuristic function which guides the IWD to find optimal solutions.

The flow of IWD algorithm, which has been stated in the previous chapter, shows that the IWD algorithm can solve any complex optimization problem which is nonlinear in nature. Examples of these are "Travelling Salesman Problem (TSP)", "N queen problem", "Multi-dimensional knapsack problem" and "automatic multilevel thresholding", etc. [50].

However, the IWD algorithm still lacks in better performance when it is applied to any large-scale optimization problem. In IWD, the solutions are getting trapped into local optima because of the lack of divergence parameters in it. Since the parameters are embedded with other parameters of convergence, the diversification process gets very negligible impact on IWD, in which certain conditions give up the diversification and move towards the convergence of the algorithm.

Based on the problem stated above in the novel IWD algorithm, our proposed Modified IWD algorithm solves the problem of lack of divergence. This is done by finding the optimal solutions by electing the nodes to construct a feasible solution with the help of randomness and guidance through an efficient heuristic function. The proposed heuristic function is well suited for building MEB tree in WSN. The proposed heuristic function considers not only the nodes that participate in relaying the messages but also the sink node, which is the destination. With the help of proposed heuristics, the optimal solutions for MEB in WSN can be built without any transmission gap in message passing.

This diversification leads to the lack of convergence in the Modified IWD since the diversification process continues until the end of the cycle. In order to maintain the convergence rate in the modified IWD, a formula for updating local soil parameter has been proposed. This equation has been inspired from PSO algorithm's inertial weight factor (w). In PSO, the inertial weight factor controls the previous velocity which influences over the current particle to achieve the convergence. This inertial factor will have high impact in the 3rd and 4th quarter of iterations.

The propositions of proposed Modified IWD algorithm are as follows:

Proposition 4.1 After $'t'$ iterations, the soil gets deposited on the edges of graph (N, E) will be in between the interval$[soil(edge_{min}), soil(edge_{max})]$.

$$soil(edge_{max}) = ((\rho_s \rho_o)^m IS_o) \tag{4.1}$$

where, IS_o represents the initial soil that is fixed at the initial phase of the algorithm.

$soil(edge_{min})$ can be calculated using the formula:

$$soil(edge_{min}) = \left(m(\rho_{IWD} - \rho_n N_{IWD}) \left(\frac{a_s}{b_s}\right) \right) \tag{4.2}$$

The probability of finding the feasible and optimal node to participate in the IWD_i, where, 'i' is the current population number at 'm' iteration is given as follows:

$$p(N_{Chosen}) = \begin{cases} rand(\max(prob), rand()) & if \quad rand() > \max(prob) \\ \max(prob) & else \end{cases} \tag{4.3}$$

$$P(IWD_i; m) = N_{IWD}(p(N_{Chosen})) \tag{4.4}$$

4.2 MODIFIED INTELLIGENT WATER DROPS (M-IWD) ALGORITHM

4.2.1 Nomenclature

$G\ (N, E)$	Graph G consists of N nodes connected with E edges
N_C	Number of nodes in WSN
T^{TB}	Best solution throughout the iteration
T^{IB}	Best solution of current iteration
$q(.)$	Fitness function
$iter_{max}$	Maximum number of iterations
$iter_{count}$	Current iteration number
N_{IWD}	Number of Water drops
a_v, b_v, c_v	Velocity updating parameters
a_s, b_s, c_s	Soil updating parameters
ρ_n	Local Soil updating parameter
ρ_{IWD}	Global Soil Updating parameter
Ini_Soil	Initial soil assigned at the edges
Ini_Vel	Velocity of IWD
V_N	Visited Nodes
$p(j)$	Probability of Node j
ε_s	Positive Constant
Vel^{IWD}	Velocity of IWD
$\Delta soil(i, j)$	Change of soil between the edge of nodes i and j
$Soil^{IWD}$	Soil the IWD carries
HUD	Heuristic function
ΔVel^{IWD}	Change in the velocity carried out by IWD

Initialization of static parameters:

- The graph (N, E) of the problem is given to the algorithm which contains N_c nodes.
- The quality of the total-best solution T^B is initially set to the worst value: $q(T^B) = -\infty$.
- The maximum number of iterations $iter_{max}$ is specified by the user and the algorithm stops when it reaches $iter_{max}$.
- The iteration count $iter_{count}$, which counts the number of iterations, is set to zero.
- The number of water drops N_{IWD} is set to a positive integer value. This number should at least be equal to two. However, N_{IWD} is usually set to the number of nodes N_c of the graph.
- Velocity updating parameters are a_v, c_v =1 and b_v =0.01.
- Soil updating parameters are a_s, c_s=1 and b_s =0.01.
- The global soil updating parameter, ρ_{IWD}= 0. 9.
- The initial soil on each edge of the graph is denoted by the constant InitSoil such that the soil of the edge between every two nodes 'i' and 'j' is set by soil(i,j) = InitSoil . Here, InitSoil = 10000.
- The initial velocity of each IWD is set to InitVel. Here, InitVel = 200.

Initialization of dynamic parameters:

- Every IWD has a visited node list V_c(IWD), which is initially empty: V_c(IWD) = {}.
- Each IWD's velocity is set to InitVel.
- All IWDs are set to have zero amount of soil.
- Initialize ρ_n.

The procedure of Modified IWD is given as follows:

Spread the IWDs randomly on the nodes of the graph as their first visited nodes.

Repeat (until termination conditions satisfied)

Initialize the local updating parameter value with the following equation:

$$\rho_n = \mathrm{LB} + (\mathrm{UB} - \mathrm{LB}) \frac{t}{MAx\ It} \tag{4.5}$$

where LB =0.4 and UB =0.9

Update the visited node list of each IWD to include the nodes just visited.

Repeat steps 4.1 to 4.4 for those IWDs with partial solutions.

Step 4.1: For the IWD residing in node 'i', choose the next node 'j', which doesn't violate any constraints of the problem and is not in the visited node list V_c (IWD) of the IWD, using the following probability P_i^{IWD} (j):

$$P_i^{IWD}(j) = \frac{f(soil\,(i,j))}{\sum_{k \notin vc\,(IWD)} f(soil\,(i,k))} \tag{4.6}$$

Such that:

$$f(soil(i,j)) = \frac{1}{\mathcal{E}_s + g(soil\,(i,j))} \tag{4.7}$$

and

$$g\big(soil(i,j)\big) = \begin{cases} soil(i,j)\ if\ min_{l \notin vc(IWD)}\big(soil(i,l)\big) \geq 0 \\ soil(i,j) - \ min_{l \notin vc(IWD)}\big(soil(i,l)\big)\ else \end{cases} \tag{4.8}$$

Add the newly visited node to Vc(IWD).

V_N can be chosen based on this form:

$$p(N_{Chosen}) = \begin{cases} rand(\max(prob), rand()) & if \quad rand() > \max(prob) \\ \max(prob) & else \end{cases} \tag{4.9}$$

$$Chosen\ Node = N_{IWD}(p(N_{Chosen})) \tag{4.10}$$

Step 4.2: For each IWD moving from node 'i' to node 'j', update its velocity vel^{IWD}(t) by:

$$vel^{IWD}(t+1) = vel^{IWD}(t) + \frac{a_v}{b_v + c_v . soil^2(i,j)} \quad (4.11)$$

where $vel^{IWD}(t+1)$ is updated velocity of the IWD.

Step 4.3: For the IWD moving on the path from node 'i' to node 'j', compute the soil $\Delta soil(i,j)$ that the IWD loads from the path by:

$$\Delta soil(i,j) = \frac{a_s}{b_s + c_s . time^2(i,j; vel^{IWD}(t+1))} \quad (4.12)$$

Such that:

$$Time\left(i,j; vel^{IWD}(t+1)\right) = HUD(j)/vel^{IWD}(t+1) \quad (4.13)$$

where the heuristic desirability HUD(j) is defined appropriately for the given problem.

Step 4.4: Update the soil $soil(i,j)$of the path from node 'i' to node 'j' traversed by IWD, and also IWD update the soil that the IWD carries $soil^{IWD}$ by soil.

$$soil(i,j) = (1 - \rho_n). soil(i,j) - \rho_n . \Delta soil(i,j) \quad (4.14)$$

$$soil^{IWD} = soil^{IWD} + \Delta soil(i,j) \quad (4.15)$$

Find the iteration-best solution T^{IB} from all the solutions T^{IWD} using:

$$T^{IB} = \arg max_{\forall T^{IWD}}\, q(T^{IWD}) \quad (4.16)$$

Update the soils on the paths that form the current iteration-best solution T^{IB} by:

$$soil(i,j) = (1 + \rho_{IWD}). soil(i,j) - \rho_{IWD} . \frac{1}{(N_{IB}-1)} . soil_{IB}^{IWD} \quad \forall (i,j) \epsilon T^{IB} \quad (4.17)$$

where N_{IB} is the number of nodes in solution T^{IB}.

Update the total best solution T^{TB} by the current iteration-best solution T^{IB} using:

$$T^{TB} = \begin{cases} T^{TB} & if\ q(T^{TB}) > -q(T^{IB}) \\ T^{IB} & otherwise \end{cases} \quad (4.18)$$

Increment the iteration number by $Iter_{count} = Iter_{count} + 1$.

Then, go to step 4.2, if $Iter_{count} < Iter_{max}$.

The algorithm stops here with the total-best solution T^{TB}.

4.2.2 Modified Intelligent Water Drops (M-IWD) Algorithm with Heuristic Function (M-IWD$_{HUD}$)

Heuristic function in IWD is used to find out the probability of a node to construct the IWD in a constructive manner. This heuristic function is a problem-dependent process. Since MEB in WSN is not applied on IWD algorithm, there is no existing heuristic method to solve this problem using IWD.

Constructing heuristic function imposes a lot of constraints. Some of them are:

- The heuristic function should not violate the MEB tree construction rules.
- The chosen node from any heuristic function should not depend on other clusters which have been built already in the same iteration.

An IWD starts its travel through the graph by choosing a random node. It finds the next node to transfer the data in response to meet the final phase of reaching the sink node. Each IWD starts with a random node and completes its travel by choosing the nodes one-by-one until it reaches the sink node. The soil on each edge that the IWD travels is subjected to change in IWD algorithm.

Heuristic function for MEB-WSN should be imposed so as to use IWD algorithm with this problem.

For the transmission of data towards the sink node, this mathematical equation needs to be altered in such a way:

$$HUD_{MEB-WSN} = \min \mathrm{d}(\text{sink node},\ \max d(i,j)) \tag{4.19}$$

where, $d(i,j)$ is the energy consumed when the data is transferred from node 'i' to node 'j'. The sink node is the node where all the data of sensor nodes are to be converged. The difference of MEB between wireless ad-hoc networks and wireless sensor networks is the directional way of transfer of data. In wireless ad-hoc networks, the message will be broadcast to all the nodes, and the process ends with that stage. In wireless sensor network, the data are in need to be directed towards the sink node for further analysis, etc.

The Modified IWD algorithm, which imposes the heuristic function, is as follows:

M-IWD algorithm with $\boldsymbol{HUD_{MEB-WSN}}$

Initialize the static and Dynamic Parameters
Calculate the Energy consumption Table $d(i,j)$
Generate ***Pop***
while *(*$iter_{count} \le iter_{max}$*)* ***do***
  for *(each IWD)*
    Update V_N
    for *(each Node in IWD* $\notin V_N$*)*
      Calculate $\boldsymbol{p_i^{IWD}(j)}$ *using eq(4.6)*
      Choose the node with max(p)
    end for
    for *(each Node in IWD* $\in V_N$*)*
      Update $\boldsymbol{Vel^{IWD}}$*using eq(4.11)*
      Calculate ***HUD*** *using eq(4.19)*
      Calculate $time(i,j;Vel)$*using eq(4.13)*
      Compute $\Delta soil(i,j)$ *using eq(4.12)*
      update the soil at each edge using eq(4.14)
      Update $\boldsymbol{Soil^{IWD}}$*using eq(4.15)*
    end for
    end for
    Update $\boldsymbol{T^{IB}}$*using eq(4.14)*
    Update the soil path of T^{IB}*using eq(4.16)*
    Update $\boldsymbol{T^{TB}}$*using eq(4.18)*
    Update $soil(edge_{min})$ *using eq (4.2)*
    Update $soil(edge_{max})$ *using eq(4.1)*
    $iter_{count}++$
end while
Project $\boldsymbol{T^{TB}}$

Figure 4.1: Algorithm for M-IWD with Heuristic Function

4.2.3 Modified Intelligent Water Drops (M-IWD) Algorithm with Heuristic function and Diversification (M-IWD$_{HUD}^{Div}$)

Diversification is the process of exploring the search space in order to escape from the local optimal solutions for finding the global optimal solutions. In original IWD algorithm, the choice of choosing the next visiting node in order to travel to the next node is based on the maximum probability of that particular node. This method provides good results in low dimensional problems; but as the problem size increases, choosing the nodes which have the maximum probability leads to local optima since on choosing only the nodes with maximum probability leaves the chance for other nodes to participate in the race.

Considering the above stated lack of exploration in original IWD algorithm, the Modified IWD algorithm comes with the diversification equation as follows:

$$p(N_{Chosen}) = \begin{cases} rand(\max(prob), rand()) & if \quad rand() > \max(prob) \\ \max(prob) & else \end{cases} \tag{4.20}$$

$$Chosen\ Node = N_{IWD}(p(N_{Chosen})) \tag{4.21}$$

where $p()$ refers to the probability of the chosen node.

With this equation, the Modified IWD with Heuristic function (HUD) can be stated as follows:

MIWD-HUD algorithm with Diversification

1: Initialize the static and Dynamic Parameters

2: Calculate the Energy consumption Table $d(i, j)$

*3: Generate **Pop***

*4: **while** ($iter_{count} \leq iter_{max}$) **do***

*5: **for** (each IWD)*

6: Update V_N

*7: **for** (each Node in IWD $\notin V_N$)*

8: Calculate $\boldsymbol{p_i^{IWD}(j)}$ using eq(4.9)

9: Choose the node based on eq(4.10)

*10: **end for***

for *(each Node in IWD* $\in V_N$*)*

Update $\boldsymbol{Vel^{IWD}}$ *using eq(4.11)*

Calculate ***HUD*** *using eq(4.19)*

Calculate $time(i, j; Vel)$ *using eq(4.13)*

Compute $\Delta soil(i, j)$ *using eq(4.12)*

update the soil at each edge using eq(4.14)

Update $\boldsymbol{Soil^{IWD}}$ *using eq(4.15)*

end for

end for

Update $\boldsymbol{T^{IB}}$ *using eq(4.14)*

Update the soil path of T^{IB} *using eq(4.16)*

Update $\boldsymbol{T^{TB}}$ *using eq(4.18)*

Update $soil(edge_{min})$ *using eq(4.2)*

Update $soil(edge_{max})$ *using eq(4.1)*

$iter_{count} + +$

end while

Project $\boldsymbol{T^{TB}}$

Figure 4.2: Algorithm for M-IWD with Heuristics function and Diversification

4.2.4 Modified Intelligent Water Drops (M-IWD) Algorithm with Heuristic, Diversification and Convergence (M-IWD$_{HUD}^{Div\text{-}Con}$)

Convergence is the process of allowing an algorithm at the end of the cycle to collect near optimal solution which, in turn, exploits more around the existing solution. In original IWD algorithm, this has been handled very well when compared to the Modified IWD with Heuristic function and Diversification. Since Modified IWD adopts the new diversification process, the results indicate that there is a lack of convergence at the end of the cycle. The standard deviation found in Modified IWD along with heuristic function and diversification seems to be higher in range when compared to Modified IWD with heuristic function.

With reference to the above statement for achieving the convergence, the local soil updating parameter ρ_n has been converted from static parameter to dynamic parameter, and it is as follows:

$$\rho_n = \mathrm{LB} + (\mathrm{UB} - \mathrm{LB})\ \frac{t}{Max\_It} \qquad (4.22)$$

where LB =0.4 and UB =0.9.

This equation is inspired from PSO algorithm. With the help of this scenario, there will be minimal values promoted to the probability function of choosing nodes which in turn, increase the convergence property in Modified IWD.

MIWD-HUD DIV with convergence

Initialize the static and Dynamic Parameters

Calculate the Energy consumption Table $d(i,j)$

Generate ***Pop***

while *(*$iter_{count} \leq iter_{max}$*)* ***do***

update ρ_n *using eq(4.22)*

for *(each IWD)*

  Update V_N

  for *(each Node in IWD* $\notin V_N$*)*

    Calculate$\boldsymbol{p_i^{IWD}}(\boldsymbol{j})$ *using eq(4.9)*

    Choose the node based on eq(4.10)

  end for

for *(each Node in IWD* $\in V_N$*)*

  Update $\boldsymbol{Vel^{IWD}}$*using eq(4.11)*

  Calculate ***HUD*** *using eq(4.19)*

  Calculate $time(i,j;Vel)$*using eq(4.13)*

  Compute $\Delta soil(i,j)$ *using eq(4.12)*

  update the soil at each edge using eq(4.14)

  Update $\boldsymbol{Soil^{IWD}}$*using eq(4.15)*

end for

end for

  Update $\boldsymbol{T^{IB}}$*using eq(4.14)*

22: Update the soil path of T^{IB} using eq(4.16)

23: Update $\boldsymbol{T^{TB}}$ using eq(4.18)

24: Update $soil(edge_{min})$ using eq(4.2)

25: Update $soil(edge_{max})$ using eq(4.1)

26: $iter_{count} + +$

*27: **end while***

28: Project $\boldsymbol{T^{TB}}$

Figure 4.3: Algorithm for M-IWD$_{\mathbf{HUD}}$$^{\mathbf{Div\text{-}Con}}$

The algorithm for solving the MEB problem using Modified IWD algorithm along with divergence and convergence function is stated above. The previously proposed divergence functions over Modified IWD is tabulated as the result in chapter 5. On comparing the results with Modified IWD with heuristic function, there is a lack of convergence which has been noted. This problem is owing to the missing parameter of convergence at the end of the cycle.

Since the divergence function works throughout the entire cycle of Modified IWD, there is a lack of convergence, and this has been noted based on the difference between the best solution and the worst solution found in the same cycle. To mitigate this problem of a lack of divergence, a new formula for updating the local soil parameter has been proposed. This has been inspired from the PSO algorithm's inertial weight factor. This mathematical equation reduces the process of updating the probability function with a higher range of values. It allows the proposed algorithms to converge the results at the end of the iteration. The result of Modified IWD with divergence and convergence function is tabulated in chapter 5.

4.3 SUMMARY

This chapter explains the formulation of Modified IWD algorithm in a detailed manner. It starts with the introduction of the problems stated in the original IWD algorithm. The problems stated are lack of divergence in the original IWD. Also, the heuristic function that is needed by IWD for solving MEB problem of WSN has been discussed. In Modified IWD algorithm, the lack of divergence was being handled by imposing the randomness along with the guidance of heuristic function which is proposed in this chapter. With the help of proposed heuristics function, the optimal solutions for MEB problem in WSN can be built without any transmission-gap in message passing. Due to the diversification, there was a problem raised in the convergence rate. In order to mitigate that issue, a new type of soil updating parameter function has been proposed. This proposed soil updating parameter has been inspired by the PSO algorithm. The next chapter deals with the experimental results of the proposed Modified IWD (M-IWD) algorithm.

CHAPTER 5

EXPERIMENTATION AND RESULTS

5.1 INTRODUCTION

In Chapter 4, Modified IWD Algorithm was designed in order to achieve the divergence to find out an optimal MEB tree in WSN. The Modified IWD algorithm is incorporated with the proposed heuristic function in order to enhance the characteristics of randomness and individual diversity. It is employed to minimize the total energy required to broadcast the data from each sensor node towards sink node in a network. The proposed variant has been evaluated and compared with respect to contemporary Evolutionary techniques using appropriate performance criteria. In this perspective, a suitable experimental setup has been designed, and experiments are performed on different classes of MEB instance tables obtained from standard MEB library [Comopt 2012] in order to validate the proposed Modified IWD.

5.2 EXPERIMENTAL SETUP

5.2.1 Test bed Design

The performance of different approaches over Heuristics, Divergence and Convergence of Modified IWD has been revealed by evaluating their concert MEB instances of WSN. Experiments have been demonstrated on different Evolutionary Algorithms like Genetic Algorithm, PSO and Memetic Algorithms under similar environmental conditions to evaluate the performance.

The Evolutionary Algorithms such as Genetic Algorithm, PSO algorithm, Memetic Algorithms and Modified IWD algorithm has been represented below.

For experiments, Genetic Algorithm [1] is proposed on a hybrid genetic algorithm for the MEB problem in WSN working model. PSO Algorithm [2] is proposed on a PSO for the MEB problem in WSN working model. Memetic Algorithm [3] is proposed on a

Memetic algorithm for MEB problem in WSN working models were being demonstrated, and compared with our proposed approach. The main reasons for selecting these algorithms for comparison are:

- Out of algorithms proposed in the previous sets, the Memetic Algorithm shows promising results.
- Since Genetic Algorithm is the ever first proposed evolutionary algorithm, and it is also being applied in a wide range of problems, it has been chosen for the comparison with our proposed algorithms.

5.2.2 Assessment Criteria

There are eight most preliminary and predominant performance factors that are in need to be considered for comparing the result of our proposed algorithms with the existing algorithms for MEB problems in WSN.

1. Computation Time:

The computation time is the time taken to evaluate the algorithm which finds the solution. The computation time is defined as the total time taken for finding out the solution. It computes the time from the starting of initial population computation till the completion of iteration. For other algorithms, the computation time has been taken from the references [1, 2, 3].

2. Best Case:

Best case represents the optimum amount of energy consumed by MEB Tree using Modified IWD algorithm during the simulation over MEB data instances. This Best value is used to calculate the Excess value. This is the best optimal energy consumed by Modified IWD over 30 runs.

3. Worst Case:

Worst case represents the maximum amount of energy consumed by MEB Tree using Modified IWD Algorithm during the simulation over MEB data instances. This Worst energy consumption value comes over the simulation of Modified IWD over 30 runs.

4. Average Case:

Average case represents the average amount of energy consumed by MEB Tree using Modified IWD Algorithm during the simulation over MEB data instances. The average energy consumption value can be found by taking the average of the entire population of which the best energy optimal value has been found.

5. Convergence Rate:

Rate of convergence measures how fast the solution convergence towards the optimal solution with respect to time, and it can be formulated as:

$$Convergence\ Rate\ (\%) = \frac{Total\ Number\ of\ Generations - i}{Total\ number\ of\ generations} \times 100 \qquad (5.1)$$

6. Average Convergence Rate:

The Average Convergence Rate will be derived from the complete energy consumed during all the trials for the given instances. It has been calculated by finding the average of all energies consumed among 30 trial runs, and the value is passed on in the following equation:

$$Average\ Convergence\ (\%) = \frac{Total\ Number\ of\ Generations - Average\ number\ of\ iteration}{Total\ number\ of\ generations} \times 100 \qquad (5.2)$$

7. Found:

Found is defined as the number of times the best result has been found on the aggregate number of runs.

8. Excess rate:

Excess rate has been evaluated as the ratio between the Best and the Worst results found in a particular cycle which produced an optimum result of the maximum number of trials.

$$Excess = \left[\frac{Best}{Optimal\ result} - 1\right] X\ 100 \qquad (5.3)$$

5.3 ANALYSIS OF EXPERIMENTS AND RESULTS

The following tables from table 5.1 to table 5.9 which refers to the results of Modified IWD are under three proposed objectives. They are IWD algorithm with proposed Heuristic function, Modified IWD with Divergence and Modified IWD with Divergence and Convergence. There are totally three sets of data available in OR library. It consists of 20 nodes' dataset with 30 instances, 50 nodes' dataset with 30 instances and 100 nodes' dataset with 30 instances.

The performance metrics, which are used to compare the performance, are as follows: Best Energy Consumed, Average Energy Consumed, Worst energy consumed, Computation Time, Minimum Generation number on which the best energy consumption value was found, Convergence Rate, Average Convergence Rate, Found and Excess rate. The discussed results have been cited in the Section 5.2.2.

5.3.1 MIWD-HUD

The proposed Modified IWD Algorithm has been imposed with a heuristic function which is designed for solving MEB problem in WSN. Since this heuristic function is problem-dependent, it is designed to solve the MEB with a concept of finding a node to rely the message based on its location from the sink node.

In order to transmit the information to sink node, the mathematical formulation has been devised as follows:

$$HUD_{MEB-WSN} = \min \mathrm{d}(\text{sink node}, \max d(i,j)) \qquad (5.4)$$

Where, $d(i,j)$ is the energy consumed when data was transferred between node $'i'$ and node $'j'$, and sink node is the node where all the data of sensor nodes are to be converged. The result of the proposed Modified IWD along with its heuristic function has been tabulated below. The table below indicates the energy consumed on MEB instances of Modified IWD for 20, 50 and 100 nodes.

The tables 5.1, 5.2 and 5.3 show the performance of Modified IWD with heuristic function on MEB instances of WSN for 20 nodes, 50 nodes and 100 nodes respectively. The results in the table interpret the Modified IWD with the performance measures listed in section 5.2.2.

Table 5.1 indicates that there is no deviation or excess rate with the results when Modified IWD are applied on MEB instances of 20 nodes. All the 30 instances report that there is no deviation captured when using M-IWD over MEB instance of 20 nodes. The convergence rate reports that the M-IWD results are there on an average of 65%. Table 5.2 shows the deviation rate as 0%. The results indicate that M-IWD finds out the MEB tree in a nominal manner. The performance measures of M-IWD on 100 node instance of MEB shows that there is some deviation in the best values, and in the optimal results in energy consumed by the broadcast tree. However, the excess rate has not been recorded with any integer values, and it shows that the optimal values have been exploited by M-IWD even in high dimensional instances.

5.3.2 IWD-HUD with Divergence

Exploration of more solution spaces in a search space for finding global optimal solutions by boycotting the barrier of local optimal solutions is called as divergence. In original IWD algorithm, next node to be visited for completing the tour was followed by a choice of choosing the nodes which hold maximum probability value. And this process gets into local optima.

Considering the above stated lack of exploration in original IWD algorithm, Modified IWD algorithm comes with the diversification equation as follows:

$$p(N_{Chosen}) = \begin{cases} rand(\max(prob), rand()) & if \quad rand() > \max(prob) \\ \max(prob) & else \end{cases} \quad (5.5)$$

$$Chosen\ Node = N_{IWD}(p(N_{Chosen}))$$

Where, $p()$ refers to the probability of the chosen node.

Table 5.1 Results of M-IWD-HUD on 20 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p20.00	407250.81	407250.81	407250.81	407250.81	100.00%	100.00%	30/30	2.47	0
p20.01	446905.52	446905.52	446905.52	446905.52	100.00%	100.00%	30/30	3.28	0
p20.02	335102.42	335102.42	335102.42	335102.42	100.00%	100.00%	30/30	2.35	0
p20.03	488344.90	488344.90	488344.90	488344.90	100.00%	100.00%	30/30	3.69	0
p20.04	516117.75	516117.75	516117.75	516117.75	100.00%	100.00%	30/30	2.97	0
p20.05	300869.14	300869.14	300869.14	300869.14	100.00%	100.00%	30/30	1.65	0
p20.06	250553.15	250553.15	250553.15	250553.15	100.00%	100.00%	30/30	3.65	0
p20.07	347454.08	347454.08	347454.08	347454.08	100.00%	100.00%	30/30	1.87	0
p20.08	390795.34	390795.34	390795.34	390795.34	100.00%	100.00%	30/30	2.50	0
p20.09	447659.11	447659.11	447659.11	447659.11	100.00%	100.00%	30/30	2.49	0
p20.10	316734.39	316734.39	316734.39	316734.39	100.00%	100.00%	30/30	2.00	0
p20.11	289200.92	289200.92	289200.92	289200.92	100.00%	100.00%	30/30	3.86	0
p20.12	314511.98	314511.98	314511.98	314511.98	100.00%	100.00%	30/30	2.38	0
p20.13	346234.51	346234.51	346234.51	346234.51	100.00%	100.00%	30/30	2.33	0
p20.14	301426.68	301426.68	301426.68	301426.68	100.00%	100.00%	30/30	3.23	0
p20.15	457467.93	457467.93	457467.93	457467.93	100.00%	100.00%	30/30	3.34	0
p20.16	484437.68	484437.68	484437.68	484437.68	100.00%	100.00%	30/30	2.20	0
p20.17	380175.41	380175.41	380175.41	380175.41	100.00%	100.00%	30/30	1.62	0
p20.18	320300.23	320300.23	320300.23	320300.23	100.00%	100.00%	30/30	1.68	0
p20.19	461267.52	461267.52	461267.52	461267.52	100.00%	100.00%	30/30	2.25	0
p20.20	403582.74	403582.74	403582.74	403582.74	100.00%	100.00%	30/30	3.15	0
p20.21	271958.28	271958.28	271958.28	271958.28	100.00%	100.00%	30/30	3.97	0
p20.22	328659.78	328659.78	328659.78	328659.78	100.00%	100.00%	30/30	1.65	0
p20.23	326654.08	326654.08	326654.08	326654.08	100.00%	100.00%	30/30	3.43	0
p20.24	395859.67	395859.67	395859.67	395859.67	100.00%	100.00%	30/30	2.38	0
p20.25	453517.28	453517.28	453517.28	453517.28	100.00%	100.00%	30/30	3.03	0
p20.26	461547.18	461547.18	461547.18	461547.18	100.00%	100.00%	30/30	2.81	0
p20.27	389057.00	389057.00	389057.00	389057.00	100.00%	100.00%	30/30	2.25	0
p20.28	279251.95	279251.95	279251.95	279251.95	100.00%	100.00%	30/30	3.06	0
p20.29	299586.76	299586.76	299586.76	299586.76	100.00%	100.00%	30/30	1.12	0

Table 5.2 Results of M-IWD-HUD on 50 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p50.00	399074.64	439711.56	447797.36	444638.06	89.82%	88.58%	30/30	4.00	0.10
p50.01	373565.15	402442.67	406870.49	404397.01	92.27%	91.75%	30/30	6.22	0.08
p50.02	393641.09	415102.96	421109.51	418458.38	94.55%	93.70%	30/30	5.57	0.05
p50.03	316801.09	335777.49	342648.38	339172.16	94.01%	92.94%	30/30	6.51	0.06
p50.04	325774.22	346214.51	353870.11	349849.69	93.73%	92.61%	30/30	4.29	0.06
p50.05	382235.90	429640.22	434581.99	432215.67	87.60%	86.92%	30/30	4.41	0.12
p50.06	384438.46	406387.30	412006.87	409186.61	94.29%	93.56%	30/30	5.12	0.06
p50.07	401836.85	422740.74	428326.48	425748.77	94.80%	94.05%	30/30	4.08	0.05
p50.08	334418.45	355293.47	364128.08	359849.15	93.76%	92.40%	30/30	6.06	0.06
p50.09	346732.05	365008.55	370418.00	368310.62	94.73%	93.78%	30/30	7.87	0.05
p50.10	416783.45	466003.05	470711.93	468409.27	88.19%	87.61%	30/30	5.01	0.12
p50.11	369869.41	393543.95	398207.23	395677.64	93.60%	93.02%	30/30	5.89	0.06
p50.12	392326.01	407960.80	412074.43	410159.61	96.01%	95.45%	30/30	7.22	0.04
p50.13	400563.83	424766.67	432147.15	428615.19	93.96%	93.00%	30/30	7.61	0.06
p50.14	388714.91	420126.53	428250.44	424214.40	91.92%	90.87%	30/30	5.59	0.08
p50.15	371694.65	386985.62	391784.13	389834.49	95.89%	95.12%	30/30	8.47	0.04
p50.16	414587.42	457384.38	464000.65	460975.40	89.68%	88.81%	30/30	6.42	0.10
p50.17	355937.07	389682.99	396783.91	393521.40	90.52%	89.44%	30/30	6.18	0.09
p50.18	376617.33	415145.29	419360.78	417605.40	89.77%	89.12%	30/30	4.78	0.10
p50.19	335059.72	377899.86	382342.82	380209.56	87.21%	86.52%	30/30	5.49	0.13
p50.20	414768.96	462615.28	469217.00	466118.04	88.46%	87.62%	30/30	5.70	0.12
p50.21	361354.27	378277.73	386401.76	382765.48	95.32%	94.07%	30/30	5.38	0.05
p50.22	329043.51	356303.41	360367.98	358578.38	91.72%	91.02%	30/30	5.71	0.08
p50.23	383321.04	414600.03	418627.82	416658.16	91.84%	91.30%	30/30	4.27	0.08
p50.24	404855.92	449183.11	456974.23	453270.18	89.05%	88.04%	30/30	4.66	0.11
p50.25	363200.32	403531.85	411072.95	407756.06	88.90%	87.73%	30/30	5.82	0.11
p50.26	406631.51	435445.57	441727.26	438670.76	92.91%	92.12%	30/30	7.15	0.07
p50.27	451059.62	487971.82	492400.31	490234.47	91.82%	91.31%	30/30	7.84	0.08
p50.28	415832.44	435571.99	444108.98	440407.53	95.25%	94.09%	30/30	4.30	0.05
p50.29	380492.77	407938.62	412260.16	410162.73	92.79%	92.20%	30/30	6.03	0.07

Table 5.3 Results of M-IWD-HUD on 100 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg.Conv	Found	Time(s)	Excess
p100.00	340869.27	456214.94	518955.23	483411.14	66.16%	58.18%	14/30	17.90	0.34
p100.01	355284.77	466942.85	508442.72	487958.25	68.57%	62.66%	12/30	18.22	0.31
p100.02	377145.59	513697.92	560780.80	537760.36	63.79%	57.41%	30/30	15.34	0.36
p100.03	356942.53	525297.37	581897.23	554753.19	52.83%	44.58%	15/30	15.53	0.47
p100.04	384446.36	528998.56	598879.56	565476.54	62.40%	52.91%	9/30	20.18	0.38
p100.05	416758.58	484146.79	546971.64	515840.75	83.83%	76.23%	5/30	19.95	0.16
p100.06	376408.49	460902.03	512782.53	487021.32	77.55%	70.61%	10/30	15.87	0.22
p100.07	343798.46	481859.52	540347.06	511402.22	59.84%	51.25%	12/30	18.92	0.40
p100.08	372254.06	479833.07	538240.59	509688.96	71.10%	63.08%	5/30	17.89	0.29
p100.09	366993.89	531866.56	599895.16	564420.02	55.07%	46.20%	16/30	17.86	0.45
p100.10	334579.00	484110.91	546549.22	517368.70	55.31%	45.37%	16/30	17.30	0.45
p100.11	356219.14	501523.89	559231.98	531503.36	59.21%	50.79%	19/30	15.21	0.41
p100.12	393854.17	494204.86	534691.97	512335.53	74.52%	69.92%	14/30	19.66	0.25
p100.13	331270.37	501071.96	571049.90	537415.43	48.74%	37.77%	20/30	17.29	0.51
p100.14	344175.57	458902.04	519864.32	489718.98	66.67%	57.71%	14/30	16.81	0.33
p100.15	352884.55	537596.02	587933.29	563387.88	47.66%	40.35%	12/30	16.73	0.52
p100.16	338713.69	506399.00	553803.35	532226.78	50.49%	42.87%	21/30	17.65	0.50
p100.17	374059.25	497531.80	552562.91	529801.36	66.99%	58.36%	13/30	15.94	0.33
p100.18	331926.13	472548.88	517590.49	492083.25	57.63%	51.75%	19/30	15.36	0.42
p100.19	365078.37	457558.31	497823.28	481771.65	74.67%	68.04%	25/30	19.25	0.25
p100.20	355078.27	483403.95	533084.19	512885.87	63.86%	55.56%	15/30	19.11	0.36
p100.21	362204.29	501011.88	546070.82	527139.26	61.68%	54.46%	14/30	18.99	0.38
p100.22	366125.96	493242.61	551850.16	525134.56	65.28%	56.57%	19/30	14.82	0.35
p100.23	409062.55	532084.98	572126.51	551769.02	69.93%	65.11%	18/30	14.10	0.30
p100.24	357772.11	509577.30	564232.69	535407.33	57.57%	50.35%	18/30	18.78	0.42
p100.25	357191.63	531832.04	594903.41	563844.61	51.11%	42.15%	4/30	18.13	0.49
p100.26	352148.02	529248.43	579975.99	558585.78	49.71%	41.38%	5/30	19.25	0.50
p100.27	370033.07	468509.56	519935.15	491991.02	73.39%	67.04%	10/30	19.41	0.27
p100.28	348889.36	507708.99	576807.80	540363.46	54.48%	45.12%	6/30	16.66	0.46
p100.29	357595.04	518630.01	581532.43	544058.48	54.97%	47.86%	17/30	17.52	0.45

Table 5.4 Results of M-IWD-HUD with Divergence on 20 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p20.00	407250.81	407250.81	407250.81	407250.81	100.00%	100.00%	30/30	5.11	0
p20.01	446905.52	446905.52	446905.52	446905.52	100.00%	100.00%	30/30	5.46	0
p20.02	335102.42	335102.42	335102.42	335102.42	100.00%	100.00%	30/30	6.97	0
p20.03	488344.90	488344.90	488344.90	488344.90	100.00%	100.00%	30/30	4.01	0
p20.04	516117.75	516117.75	516117.75	516117.75	100.00%	100.00%	30/30	5.91	0
p20.05	300869.14	300869.14	300869.14	300869.14	100.00%	100.00%	30/30	3.15	0
p20.06	250553.15	250553.15	250553.15	250553.15	100.00%	100.00%	30/30	4.48	0
p20.07	347454.08	347454.08	347454.08	347454.08	100.00%	100.00%	30/30	7.66	0
p20.08	390795.34	390795.34	390795.34	390795.34	100.00%	100.00%	30/30	3.03	0
p20.09	447659.11	447659.11	447659.11	447659.11	100.00%	100.00%	30/30	4.26	0
p20.10	316734.39	316734.39	316734.39	316734.39	100.00%	100.00%	30/30	4.42	0
p20.11	289200.92	289200.92	289200.92	289200.92	100.00%	100.00%	30/30	6.82	0
p20.12	314511.98	314511.98	314511.98	314511.98	100.00%	100.00%	30/30	5.06	0
p20.13	346234.51	346234.51	346234.51	346234.51	100.00%	100.00%	30/30	4.36	0
p20.14	301426.68	301426.68	301426.68	301426.68	100.00%	100.00%	30/30	7.47	0
p20.15	457467.93	457467.93	457467.93	457467.93	100.00%	100.00%	30/30	5.70	0
p20.16	484437.68	484437.68	484437.68	484437.68	100.00%	100.00%	30/30	6.05	0
p20.17	380175.41	380175.41	380175.41	380175.41	100.00%	100.00%	30/30	5.26	0
p20.18	320300.23	320300.23	320300.23	320300.23	100.00%	100.00%	30/30	5.59	0
p20.19	461267.52	461267.52	461267.52	461267.52	100.00%	100.00%	30/30	5.98	0
p20.20	403582.74	403582.74	403582.74	403582.74	100.00%	100.00%	30/30	7.28	0
p20.21	271958.28	271958.28	271958.28	271958.28	100.00%	100.00%	30/30	5.02	0
p20.22	328659.78	328659.78	328659.78	328659.78	100.00%	100.00%	30/30	5.19	0
p20.23	326654.08	326654.08	326654.08	326654.08	100.00%	100.00%	30/30	3.26	0
p20.24	395859.67	395859.67	395859.67	395859.67	100.00%	100.00%	30/30	6.83	0
p20.25	453517.28	453517.28	453517.28	453517.28	100.00%	100.00%	30/30	7.76	0
p20.26	461547.18	461547.18	461547.18	461547.18	100.00%	100.00%	30/30	5.08	0
p20.27	389057.00	389057.00	389057.00	389057.00	100.00%	100.00%	30/30	7.77	0
p20.28	279251.95	279251.95	279251.95	279251.95	100.00%	100.00%	30/30	6.22	0
p20.29	299586.76	299586.76	299586.76	299586.76	100.00%	100.00%	30/30	3.92	0

Table 5.5 Results of M-IWD-HUD with Divergence on 50 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p50.00	399074.64	399074.64	399074.64	399074.64	100.00%	100%	30/30	6.93	0
p50.01	373565.15	373565.15	373565.15	373565.15	100.00%	100%	30/30	10.53	0
p50.02	393641.09	393641.09	393641.09	393641.09	100.00%	100%	30/30	5.29	0
p50.03	316801.09	316801.09	316801.09	316801.09	100.00%	100%	30/30	10.03	0
p50.04	325774.22	325774.22	325774.22	325774.22	100.00%	100%	30/30	9.23	0
p50.05	382235.90	382235.90	382235.90	382235.90	100.00%	100%	30/30	5.24	0
p50.06	384438.46	384438.46	384438.46	384438.46	100.00%	100%	30/30	10.69	0
p50.07	401836.85	401836.85	401836.85	401836.85	100.00%	100%	30/30	5.51	0
p50.08	334418.45	334418.45	334418.45	334418.45	100.00%	100%	30/30	6.89	0
p50.09	346732.05	346732.05	346732.05	346732.05	100.00%	100%	30/30	5.99	0
p50.10	416783.45	416783.45	416783.45	416783.45	100.00%	100%	30/30	8.43	0
p50.11	369869.41	369869.41	369869.41	369869.41	100.00%	100%	30/30	5.35	0
p50.12	392326.01	392326.01	392326.01	392326.01	100.00%	100%	30/30	10.33	0
p50.13	400563.83	400563.83	400563.83	400563.83	100.00%	100%	30/30	6.14	0
p50.14	388714.91	388714.91	388714.91	388714.91	100.00%	100%	30/30	7.28	0
p50.15	371694.65	371694.65	371694.65	371694.65	100.00%	100%	30/30	10.03	0
p50.16	414587.42	414587.42	414587.42	414587.42	100.00%	100%	30/30	6.62	0
p50.17	355937.07	355937.07	355937.07	355937.07	100.00%	100%	30/30	7.56	0
p50.18	376617.33	376617.33	376617.33	376617.33	100.00%	100%	30/30	10.24	0
p50.19	335059.72	335059.72	335059.72	335059.72	100.00%	100%	30/30	8.90	0
p50.20	414768.96	414768.96	414768.96	414768.96	100.00%	100%	30/30	7.89	0
p50.21	361354.27	361354.27	361354.27	361354.27	100.00%	100%	30/30	7.48	0
p50.22	329043.51	329043.51	329043.51	329043.51	100.00%	100%	30/30	8.60	0
p50.23	383321.04	383321.04	383321.04	383321.04	100.00%	100%	30/30	5.57	0
p50.24	404855.92	404855.92	404855.92	404855.92	100.00%	100%	30/30	10.14	0
p50.25	363200.32	363200.32	363200.32	363200.32	100.00%	100%	30/30	5.59	0
p50.26	406631.51	406631.51	406631.51	406631.51	100.00%	100%	30/30	10.25	0
p50.27	451059.62	451059.62	451059.62	451059.62	100.00%	100%	30/30	6.78	0
p50.28	415832.44	415832.44	415832.44	415832.44	100.00%	100%	30/30	10.92	0
p50.29	380492.77	380492.77	380492.77	380492.77	100.00%	100%	30/30	5.20	0

Table 5.6 Results of M-IWD-HUD with Divergence on 100 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p100.00	340869.27	462291.30	504869.95	480192.41	64.38%	59.13%	16/30	22.78	0.36
p100.01	355284.77	475574.20	517192.53	493756.09	66.14%	61.03%	18/30	20.41	0.34
p100.02	377145.59	434607.09	491068.08	467220.37	84.76%	76.12%	16/30	18.82	0.15
p100.03	356942.53	466977.03	510288.46	488810.65	69.17%	63.06%	14/30	20.04	0.31
p100.04	384446.36	493656.95	551733.51	522844.25	71.59%	64.00%	15/30	23.20	0.28
p100.05	416758.58	427855.73	453124.17	428719.86	102.14%	97.13%	12/30	21.37	0.03
p100.06	376408.49	470408.50	527368.75	504000.54	75.03%	66.10%	22/30	18.14	0.25
p100.07	343798.46	445262.75	494510.77	474803.92	70.49%	61.89%	10/30	18.73	0.30
p100.08	372254.06	425518.70	488778.60	454747.44	85.69%	77.84%	14/30	22.55	0.14
p100.09	366993.89	458158.09	520606.90	491305.73	75.16%	66.13%	11/30	20.49	0.25
p100.10	334579.00	438491.67	484357.51	459535.47	68.94%	62.65%	11/30	20.89	0.31
p100.11	356219.14	456200.70	503503.97	478874.99	71.93%	65.57%	10/30	17.47	0.28
p100.12	393854.17	412553.86	476541.41	441696.24	95.25%	87.85%	27/30	17.52	0.05
p100.13	331270.37	481742.86	547151.77	513843.32	54.58%	44.89%	12/30	19.71	0.45
p100.14	344175.57	448984.28	511364.22	484738.55	69.55%	59.16%	14/30	20.30	0.30
p100.15	352884.55	408088.89	459948.29	430570.54	84.36%	77.99%	26/30	22.26	0.16
p100.16	338713.69	404425.37	458390.81	428372.97	80.60%	73.53%	03/30	21.66	0.19
p100.17	374059.25	436459.88	497241.95	468143.86	83.32%	74.85%	10/30	19.53	0.17
p100.18	331926.13	467728.24	513161.06	495792.74	59.09%	50.63%	12/30	17.66	0.41
p100.19	365078.37	492621.72	556363.84	525642.35	65.06%	56.02%	17/30	18.52	0.35
p100.20	355078.27	448686.34	497725.11	474475.32	73.64%	66.37%	21/30	21.83	0.26
p100.21	362204.29	438356.94	485794.11	463556.77	78.98%	72.02%	25/30	21.56	0.21
p100.22	366125.96	417301.21	457634.07	440746.11	86.02%	79.62%	21/30	18.98	0.14
p100.23	409062.55	440364.80	498210.77	471296.62	92.35%	84.79%	24/30	19.36	0.08
p100.24	357772.11	429277.97	484626.06	451898.80	80.01%	73.69%	11/30	22.32	0.20
p100.25	357191.63	466143.20	534095.96	504853.57	69.50%	58.66%	9/30	23.52	0.31
p100.26	352148.02	487166.13	542074.93	514582.94	61.66%	53.87%	5/30	20.42	0.38
p100.27	370033.07	435100.81	485876.78	464182.79	82.42%	74.56%	21/30	21.55	0.18
p100.28	348889.36	409040.81	475475.52	440369.98	82.76%	73.78%	17/30	17.21	0.17
p100.29	357595.04	478841.01	533183.97	503842.10	66.09%	59.10%	16/30	17.12	0.34

The results which are tabulated above in tables 5.4, 5.5 and 5.6 project the performance of Modified IWD-HUD with divergence on MEB instances of WSN for 20 nodes, 50 nodes and 100 nodes respectively. The results in the tables interpret the Modified IWD with the performance measures listed in section 5.2.2.

Table 5.4 shows that the deviation between optimal values and the best found values are null. The broadcast tree has been built in such a manner that there is no energy loss when compared to the optimal results. Table 5.5 projects the time taken to solve 50 nodes' instance are a bit higher than the previous results tabulated in table 5.2 (i.e. computational time of 50 node instances solved with Modified IWD with Heuristic function). The high computational time on solving the instances have been recorded because of the divergence function. Performance measures of MIWD-HUD with divergence on 100 node instances of MEB shows that the differences between Best and Worst values of energy consumption is in higher range when compared to the table 5.3. In order to solve the divergence value results, convergence has been incorporated and the results are tabulated below.

5.3.3 IWD-HUD-DIV with Convergence

When compared to M-IWD with HUD and Diversification, original IWD algorithm performs better in terms of convergence. The diversification process of M-IWD results in lack of convergence at the end of iteration. This has been found in the results tabulated in tables 5.4, 5.5 and 5.6. The standard deviation found in M-IWD along with heuristics and Diversification seems to be higher when compared to M-IWD with heuristic function.

For better convergence in the proposed M-IWD algorithm, a variable in IWD has been changed from static parameter to dynamic parameter. Local soil updating parameter ρ_n has been converted from static parameter to dynamic parameter, and it is shown as follows:

$$\rho_n = \text{LB} + (\text{UB} - \text{LB}) \frac{t}{Max\ It} \qquad (5.6)$$

where LB =0.4 and UB =0.9.

Table 5.7 Results of IWD-HUD-DIV with Convergence on 20 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p20.00	407250.81	407250.81	407250.81	407250.81	100.00%	100.00%	30/30	8.58	0
p20.01	446905.52	446905.52	446905.52	446905.52	100.00%	100.00%	30/30	8.56	0
p20.02	335102.42	335102.42	335102.42	335102.42	100.00%	100.00%	30/30	8.14	0
p20.03	488344.90	488344.90	488344.90	488344.90	100.00%	100.00%	30/30	8.00	0
p20.04	516117.75	516117.75	516117.75	516117.75	100.00%	100.00%	30/30	9.95	0
p20.05	300869.14	300869.14	300869.14	300869.14	100.00%	100.00%	30/30	8.86	0
p20.06	250553.15	250553.15	250553.15	250553.15	100.00%	100.00%	30/30	9.26	0
p20.07	347454.08	347454.08	347454.08	347454.08	100.00%	100.00%	30/30	9.34	0
p20.08	390795.34	390795.34	390795.34	390795.34	100.00%	100.00%	30/30	5.48	0
p20.09	447659.11	447659.11	447659.11	447659.11	100.00%	100.00%	30/30	9.63	0
p20.10	316734.39	316734.39	316734.39	316734.39	100.00%	100.00%	30/30	5.29	0
p20.11	289200.92	289200.92	289200.92	289200.92	100.00%	100.00%	30/30	5.54	0
p20.12	314511.98	314511.98	314511.98	314511.98	100.00%	100.00%	30/30	7.94	0
p20.13	346234.51	346234.51	346234.51	346234.51	100.00%	100.00%	30/30	6.70	0
p20.14	301426.68	301426.68	301426.68	301426.68	100.00%	100.00%	30/30	7.39	0
p20.15	457467.93	457467.93	457467.93	457467.93	100.00%	100.00%	30/30	8.66	0
p20.16	484437.68	484437.68	484437.68	484437.68	100.00%	100.00%	30/30	7.54	0
p20.17	380175.41	380175.41	380175.41	380175.41	100.00%	100.00%	30/30	7.09	0
p20.18	320300.23	320300.23	320300.23	320300.23	100.00%	100.00%	30/30	7.06	0
p20.19	461267.52	461267.52	461267.52	461267.52	100.00%	100.00%	30/30	9.11	0
p20.20	403582.74	403582.74	403582.74	403582.74	100.00%	100.00%	30/30	5.87	0
p20.21	271958.28	271958.28	271958.28	271958.28	100.00%	100.00%	30/30	6.92	0
p20.22	328659.78	328659.78	328659.78	328659.78	100.00%	100.00%	30/30	8.91	0
p20.23	326654.08	326654.08	326654.08	326654.08	100.00%	100.00%	30/30	6.39	0
p20.24	395859.67	395859.67	395859.67	395859.67	100.00%	100.00%	30/30	7.38	0
p20.25	453517.28	453517.28	453517.28	453517.28	100.00%	100.00%	30/30	8.76	0
p20.26	461547.18	461547.18	461547.18	461547.18	100.00%	100.00%	30/30	9.65	0
p20.27	389057.00	389057.00	389057.00	389057.00	100.00%	100.00%	30/30	6.98	0
p20.28	279251.95	279251.95	279251.95	279251.95	100.00%	100.00%	30/30	9.63	0
p20.29	299586.76	299586.76	299586.76	299586.76	100.00%	100.00%	30/30	7.00	0

Table 5.8 Results of IWD-HUD-DIV with Convergence on 50 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p50.00	399074.64	399074.64	399074.64	399074.64	100.00%	100.00%	30/30	14.12	0
p50.01	373565.15	373565.15	373565.15	373565.15	100.00%	100.00%	30/30	12.68	0
p50.02	393641.09	393641.09	393641.09	393641.09	100.00%	100.00%	30/30	9.06	0
p50.03	316801.09	316801.09	316801.09	316801.09	100.00%	100.00%	30/30	9.26	0
p50.04	325774.22	325774.22	325774.22	325774.22	100.00%	100.00%	30/30	15.58	0
p50.05	382235.90	382235.90	382235.90	382235.90	100.00%	100.00%	30/30	11.71	0
p50.06	384438.46	384438.46	384438.46	384438.46	100.00%	100.00%	30/30	9.03	0
p50.07	401836.85	401836.85	401836.85	401836.85	100.00%	100.00%	30/30	15.43	0
p50.08	334418.45	334418.45	334418.45	334418.45	100.00%	100.00%	30/30	14.26	0
p50.09	346732.05	346732.05	346732.05	346732.05	100.00%	100.00%	30/30	12.20	0
p50.10	416783.45	416783.45	416783.45	416783.45	100.00%	100.00%	30/30	10.39	0
p50.11	369869.41	369869.41	369869.41	369869.41	100.00%	100.00%	30/30	10.16	0
p50.12	392326.01	392326.01	392326.01	392326.01	100.00%	100.00%	30/30	9.38	0
p50.13	400563.83	400563.83	400563.83	400563.83	100.00%	100.00%	30/30	11.01	0
p50.14	388714.91	388714.91	388714.91	388714.91	100.00%	100.00%	30/30	12.87	0
p50.15	371694.65	371694.65	371694.65	371694.65	100.00%	100.00%	30/30	13.88	0
p50.16	414587.42	414587.42	414587.42	414587.42	100.00%	100.00%	30/30	9.51	0
p50.17	355937.07	355937.07	355937.07	355937.07	100.00%	100.00%	30/30	8.05	0
p50.18	376617.33	376617.33	376617.33	376617.33	100.00%	100.00%	30/30	10.98	0
p50.19	335059.72	335059.72	335059.72	335059.72	100.00%	100.00%	30/30	11.70	0
p50.20	414768.96	414768.96	414768.96	414768.96	100.00%	100.00%	30/30	15.11	0
p50.21	361354.27	361354.27	361354.27	361354.27	100.00%	100.00%	30/30	15.27	0
p50.22	329043.51	329043.51	329043.51	329043.51	100.00%	100.00%	30/30	12.33	0
p50.23	383321.04	383321.04	383321.04	383321.04	100.00%	100.00%	30/30	12.32	0
p50.24	404855.92	404855.92	404855.92	404855.92	100.00%	100.00%	30/30	15.38	0
p50.25	363200.32	363200.32	363200.32	363200.32	100.00%	100.00%	30/30	15.99	0
p50.26	406631.51	406631.51	406631.51	406631.51	100.00%	100.00%	30/30	14.02	0
p50.27	451059.62	451059.62	451059.62	451059.62	100.00%	100.00%	30/30	15.30	0
p50.28	415832.44	415832.44	415832.44	415832.44	100.00%	100.00%	30/30	14.34	0
p50.29	380492.77	380492.77	380492.77	380492.77	100.00%	100.00%	30/30	10.41	0

Table 5.9 Results of IWD-HUD-DIV with Convergence on 100 nodes MEB for 30 instances

MEB Instances	Optimum	Best	Worst	Average	Conv. rate	Avg. Conv	Found	Time(s)	Excess
p100.00	340869.27	346085.73	398212.43	371929.07	98.47%	90.89%	30/30	21.95	0.02
p100.01	355284.77	364183.93	420866.31	394641.87	97.50%	88.92%	21/30	24.17	0.03
p100.02	377145.59	384501.22	445304.61	412270.69	98.05%	90.69%	30/30	20.78	0.02
p100.03	356942.53	365037.30	403998.99	385968.41	97.73%	91.87%	30/30	18.61	0.02
p100.04	384446.36	388855.16	440420.11	415529.21	98.85%	91.91%	25/30	23.87	0.01
p100.05	416758.58	422147.72	478714.63	454116.11	98.71%	91.04%	17/30	20.07	0.01
p100.06	376408.49	380825.84	439125.96	408427.43	98.83%	91.49%	12/30	20.33	0.01
p100.07	343798.46	348552.97	409357.68	378756.56	98.62%	89.83%	15/30	24.52	0.01
p100.08	372254.06	378150.25	438079.05	411411.44	98.42%	89.48%	30/30	22.46	0.02
p100.09	366993.89	375141.59	435137.48	407573.57	97.78%	88.94%	17/30	20.34	0.02
p100.10	334579.00	341081.96	385955.87	360081.46	98.06%	92.38%	25/30	25.77	0.02
p100.11	356219.14	361547.40	398569.41	380374.69	98.50%	93.22%	19/30	23.24	0.01
p100.12	393854.17	398640.80	463266.18	431081.27	98.78%	90.55%	30/30	23.05	0.01
p100.13	331270.37	338917.98	374394.00	355706.70	97.69%	92.62%	19/30	19.10	0.02
p100.14	344175.57	351643.84	403838.74	376680.12	97.83%	90.56%	16/30	20.93	0.02
p100.15	352884.55	357530.83	403698.21	379400.57	98.68%	92.49%	29/30	21.06	0.01
p100.16	338713.69	344343.02	387328.73	365708.53	98.34%	92.03%	20/30	24.61	0.02
p100.17	374059.25	381359.73	430828.72	405027.85	98.05%	91.72%	26/30	20.84	0.02
p100.18	331926.13	340115.48	382774.17	361220.42	97.53%	91.17%	28/30	22.55	0.02
p100.19	365078.37	373481.38	413590.25	394751.02	97.70%	91.87%	19/30	23.35	0.02
p100.20	355078.27	362407.41	406400.36	385511.86	97.94%	91.43%	30/30	25.42	0.02
p100.21	362204.29	370708.43	407929.79	388687.51	97.65%	92.69%	21/30	24.19	0.02
p100.22	366125.96	372154.48	424245.69	394551.11	98.35%	92.24%	30/30	23.03	0.02
p100.23	409062.55	413371.93	450699.27	434307.77	98.95%	93.83%	15/30	24.30	0.01
p100.24	357772.11	364974.69	408629.11	384106.99	97.99%	92.64%	12/30	21.54	0.02
p100.25	357191.63	364651.60	417428.02	392377.52	97.91%	90.15%	14/30	24.37	0.02
p100.26	352148.02	357549.75	405871.78	381732.55	98.47%	91.60%	30/30	22.84	0.02
p100.27	370033.07	376039.87	432835.42	405467.31	98.38%	90.42%	30/30	18.75	0.02
p100.28	348889.36	357624.21	391284.73	378556.10	97.50%	91.50%	16/30	19.22	0.03
p100.29	357595.04	365942.72	401952.52	383832.47	97.67%	92.66%	11/30	18.13	0.02

The results of the above tables 5.7, 5.8, 5.9 displays the performance metrics of Modified IWD-HUD with divergence and convergence on MEB instances of WSN for 20 nodes, 50 nodes and 100 nodes respectively. The results in the table interpret the Modified IWD algorithm with the performance measures listed in section 5.2.2.

Tables 5.7, 5.8, 5.9 tabulate the results of Modified IWD which incorporates proposed heuristic function with divergence for achieving better exploration, and finally with the convergence formula which is inspired from PSO algorithm. The results of these tables will be interpreted and compared with other algorithms like ACO and PSO, where PSO is the one which already solved this MEB instances on WSN. These algorithms were implemented on our test bed, and the results have been tabulated.

5.4 SUMMARY

This chapter explains the experimental results of the proposed Modified IWD model on MEB in WSN. Section 5.1 starts with the introduction on the proposed Modified IWD algorithm and its special features. Then, the dataset for MEB instances was referred followed by the experimental setup which consists of test bed design and assessment criteria as sub divisions. In the test bed design system requirements, simulation tool used and all other minimum requirements for simulating this Modified IWD was stated. In assessment criteria, eight performance metrics have been explained along with the equation of how it has been calculated. Then in section 5.3, a short note on experiments and result analysis is given. Then from tables 5.1 to 5.3, the results of Modified IWD with heuristic function have been tabulated. From tables 5.4 to 5.6, Modified IWD-Heuristic function with divergence have been tabulated. Finally, the tables 5.7, 5.8 and 5.9 show the tabulated information about simulation results of MEB for Modified IWD-Heuristics function with convergence and divergence.

CHAPTER 6

RESULT ANALYSIS

6.1 INTRODUCTION

In Chapter 5, the Modified IWD Algorithm has been proposed for the MEB problem in WSN. The proposed methodology incorporates a heuristic method for solving the MEB problem in the first phase. The potential technique considers the highly qualified nodes to participate in the cluster head formation. The participation of such potential nodes in the population can be solved within the stipulated time-slot.

The second phase imposes the diversification factor in the proposed Modified IWD Algorithm. The primary objective for proposing a diversification factor is the reason that without the diversification factor, the algorithm converges towards any local optimal solution. In such cases, the Modified IWD algorithm returns the local optimal values even after 'n' number of iterations, and over many cycles. In order to solve the exploration issues, a new diversification factor has been incorporated. Instead of choosing the maximum probability valued node, M-IWD_{Div} chooses a node based on the proposed equation which exhibits the nature of exploration in IWD.

In the third phase, a novel convergence factor has been derived and incorporated into the M-IWD_{Div}. The proposed convergence factor is inspired from PSO algorithm. In PSO, there is 'w', an inertial weight factor which exists to converge the algorithm towards the optimal solution as the iteration number increases. In M-IWD_{Div}, such factor has been incorporated with upper bound and lower bound values as 0.9 and 0.4 respectively. This variation in the values defines that there will be exploration at the initial phase of M-IWD_{Div}. But, as the iteration number increases, the exploration phase converges towards the exploitation.

The proposed phases of M-IWD_{Div}^{Con} has to be evaluated with the given MEB datasets, and the comparison of these three proposed objectives has to be compared with ACO and PSO Algorithms.

6.2 EXPERIMENTAL SETUP

6.2.1 Test bed Design

Experiments are carried out in three different sets of iterations. Since the MEB datasets are of 20, 50 and 100 nodes, the experimental design has been set as follows:

Table 6.0 M-IWD$_{Div}^{Con}$ configuration parameters for instances of MEB

S. No	Parameter	Value / Technique
1	Intelligent Water Drops	100
2	Maximum Iterations (20,50,100 nodes)	500, 1000, 2000
3	Initialization Technique	Random
4	Heuristic	Proposed Heuristic
5	Divergence Factor	Proposed Divergence
6	Convergence Factor	Proposed Convergence
7	Termination Condition	Maximum Iteration Number

For 20 node instances, the number of iterations is set to be 500. For 50 node instances, iteration number has been fixed at 1000. For 100 node instances, the maximum volume of iteration has been fixed at 2000.

6.3 ASSESSMENT CRITERIA

There are six assessment criteria that compare the proposed algorithms with the existing algorithms. They are:

[1] Best Energy Consumed by the network

[2] Average Energy Consumed by the network

[3] Computational time

[4] Convergence Rate with respect to minimum energy,

[5] Average Convergence Rate with respect to minimum energy

[6] Excess Rate.

Since the 20 node instances are being solved by all the algorithms within the stipulated number of iteration time, the comparison will be done only for 50 node instances and 100 node instances.

6.3.1 Minimum Energy Consumption by WSN

The minimum energy consumed by WSN has been found by calculating the amount of energy that each and every node spends to communicate with the other nodes in order to make the data reach the base station. The best value has been found by the trial of the MEB dataset of 50 and 100 node instances for 30 runs, with the similar specification of parameters except the total number of iterations. The minimum energy that the WSN spent has been considered here as the best energy consumption by WSN.

Energy consumed by the network in WSN can be calculated as follows:

$$Energy\ Consumed\ (EC) = \sum_{j=1}^{m} CH_{i,j} + \sum_{j=1}^{m} \sum_{i=1}^{n} SN_{i,j} \qquad (6.1)$$

where,'CH' represents the Cluster Head node, 'SN' represents the sensor nodes, 'm' represents the total number of 'CH' and 'n' represents the total number of nodes in each cluster.

Minimum Energy consumption by a network in WSN can be calculated by:

$$Minimum\ Energy\ Consumed = min\{EC_1, EC_2, \ldots, EC_{pop}\} \qquad (6.2)$$

where, 'EC' represents the energy consumed by a solution and 'pop' defines the aggregate population which exists in the algorithm.

Table 6.1 formulates the results of 30 instances of 50 node datasets. It compares the minimum energy consumed by the network out of 30 runs with the similar system specification and tabulated parameters. There were totally five methodologies given which includes two existing methodologies and three proposed methodologies to solve MEB problem in WSN.

Table 6.1: Experimental Results of Minimum Energy Consumption for 50 nodes of 30 instances

	Best Energy Consumption by 50 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWD$_{Div}$**	**M-IWD$_{Div}^{Con}$**
p50.00	526946.86	495096.83	439711.56	399074.64	399074.64
p50.01	463859.87	436249.40	402442.67	373565.15	373565.15
p50.02	489030.43	447446.85	415102.96	393641.09	393641.09
p50.03	446022.32	382923.93	335777.49	316801.09	316801.09
p50.04	462920.51	420367.45	346214.51	325774.22	325774.22
p50.05	501549.62	436524.60	429640.22	382235.90	382235.90
p50.06	482211.10	461279.41	406387.30	384438.46	384438.46
p50.07	540995.16	468234.06	422740.74	401836.85	401836.85
p50.08	415278.23	432781.98	355293.47	334418.45	334418.45
p50.09	489144.91	434809.34	365008.55	346732.05	346732.05
p50.10	566115.38	473322.66	466003.05	416783.45	416783.45
p50.11	508692.16	456899.86	393543.95	369869.41	369869.41
p50.12	513962.18	444317.62	407960.80	392326.01	392326.01
p50.13	511846.81	451800.92	424766.67	400563.83	400563.83
p50.14	494473.71	446564.69	420126.53	388714.91	388714.91
p50.15	467773.44	454844.64	386985.62	371694.65	371694.65
p50.16	505793.65	475624.82	457384.38	414587.42	414587.42
p50.17	487959.43	451479.67	389682.99	355937.07	355937.07
p50.18	460057.33	431004.58	415145.29	376617.33	376617.33
p50.19	475906.44	407453.15	377899.86	335059.72	335059.72
p50.20	530976.18	471420.99	462615.28	414768.96	414768.96
p50.21	473414.44	416859.23	378277.73	361354.27	361354.27
p50.22	412160.44	414417.23	356303.41	329043.51	329043.51
p50.23	526530.90	478939.76	414600.03	383321.04	383321.04
p50.24	533117.14	483688.93	449183.11	404855.92	404855.92
p50.25	495935.78	425876.15	403531.85	363200.32	363200.32
p50.26	539674.62	479716.70	435445.57	406631.51	406631.51
p50.27	572647.54	507547.97	487971.82	451059.62	451059.62
p50.28	510690.32	511936.66	435571.99	415832.44	415832.44
p50.29	509364.07	440999.02	407938.62	380492.77	380492.77

Table 6.1 formulates the results of minimum energy consumption of five algorithms including ACO, PSO algorithm and the other three proposed methodologies to solve MEB problem namely Modified IWD model, M-IWD model with Diversification and M-IWD$_{Div}$with Convergence. The table reveals that for 50 node instances, algorithms of M-IWD$_{Div}$ and M-IWD$_{Div}^{Con}$ contributes to the optimal values. For comparison state, the optimal results were taken from the official website. Figure 6.1 shows that the comparison results of the first 10 instances of 50 node datasets.

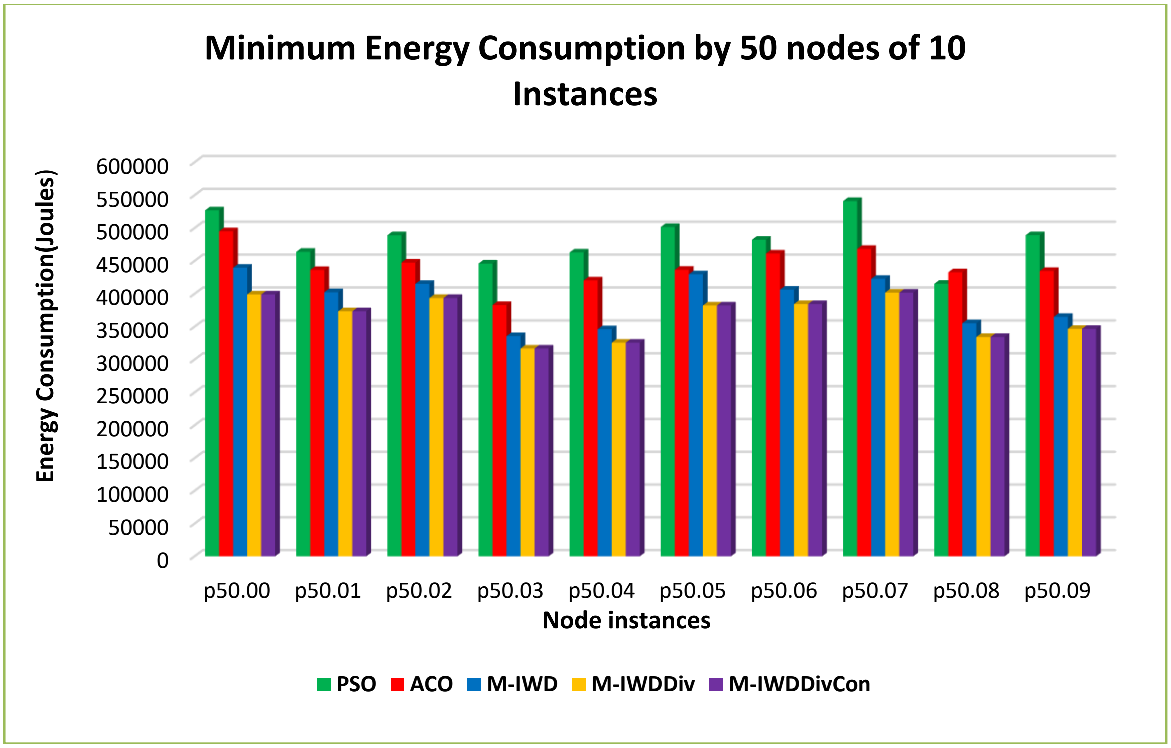


Figure 6.1: Performance of Energy Consumption of M-IWD vs other algorithms

The graph in Figure 6.1 is generated based on the results shown in table 6.1. This graph compare the results of first 10 instances of 50 node datasets. Comparatively, it was shown that the proposed algorithms find the path to consume the energy in minimal level for the given dataset of MEB.

Table 6.2 shows that the minimum energy consumption of five algorithms for 100 nodes of 30 instances. The following results were simulated by setting the maximum iteration number as 2000.

Table 6.2: Experimental Results of Minimum Energy Consumption for 100 nodes of 30 instances

	Best Energy Consumption by 100 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWD$_{Div}$**	**M-IWD$_{Div}^{Con}$**
p100.00	515654.25	505415.21	456214.94	462291.30	346085.73
p100.01	619082.11	603045.81	466942.85	475574.20	364183.93
p100.02	506333.78	585409.69	513697.92	434607.09	384501.22
p100.03	566861.33	601997.16	525297.37	466977.03	365037.30
p100.04	664357.10	641588.27	528998.56	493656.95	388855.16
p100.05	512638.21	487220.48	484146.79	407855.73	422147.72
p100.06	539579.99	540864.08	460902.03	470408.50	380825.84
p100.07	575184.18	601827.29	481859.52	445262.75	348552.97
p100.08	531324.52	546690.02	479833.07	425518.70	378150.25
p100.09	660466.14	478866.63	531866.56	458158.09	375141.59
p100.10	536623.48	517565.21	484110.91	438491.67	341081.96
p100.11	564502.33	626502.83	501523.89	456200.70	361547.40
p100.12	698575.65	642930.41	494204.86	412553.86	398640.80
p100.13	552993.03	581308.98	501071.96	481742.86	338917.98
p100.14	587781.19	623946.28	458902.04	448984.28	351643.84
p100.15	628675.08	458452.67	537596.02	408088.89	357530.83
p100.16	564601.71	606405.42	506399.00	404425.37	344343.02
p100.17	649825.36	621160.95	497531.80	436459.88	381359.73
p100.18	567616.32	484361.76	472548.88	467728.24	340115.48
p100.19	643392.26	472800.38	457558.31	492621.72	373481.38
p100.20	516761.17	541816.03	483403.95	448686.34	362407.41
p100.21	571061.41	585775.75	501011.88	438356.94	370708.43
p100.22	665084.96	494555.93	493242.61	417301.21	372154.48
p100.23	552923.37	584730.85	532084.98	440364.80	413371.93
p100.24	602900.60	511137.30	509577.30	429277.97	364974.69
p100.25	615838.15	500800.17	531832.04	466143.20	364651.60
p100.26	638353.50	519724.17	529248.43	487166.13	357549.75
p100.27	520184.28	629360.09	468509.56	435100.81	376039.87
p100.28	522494.76	550073.02	507708.99	409040.81	357624.21
p100.29	624641.32	617335.86	518630.01	478841.01	365942.72

Table 6.2 formulates the results of minimum energy consumption of five algorithms, including ACO, PSO algorithm and the other three proposed methodologies to solve MEB problem, namely Modified IWD model, M-IWD model with Diversification and M-IWD_{Div} with Convergence. The table reveals that for 100 node instances, M-IWD_{Div}^{Con} algorithm finds the optimal values. For comparison state, the optimal results were taken from the official website. Figure 6.2 shows that the comparison of first 10 instances of 100 node datasets.

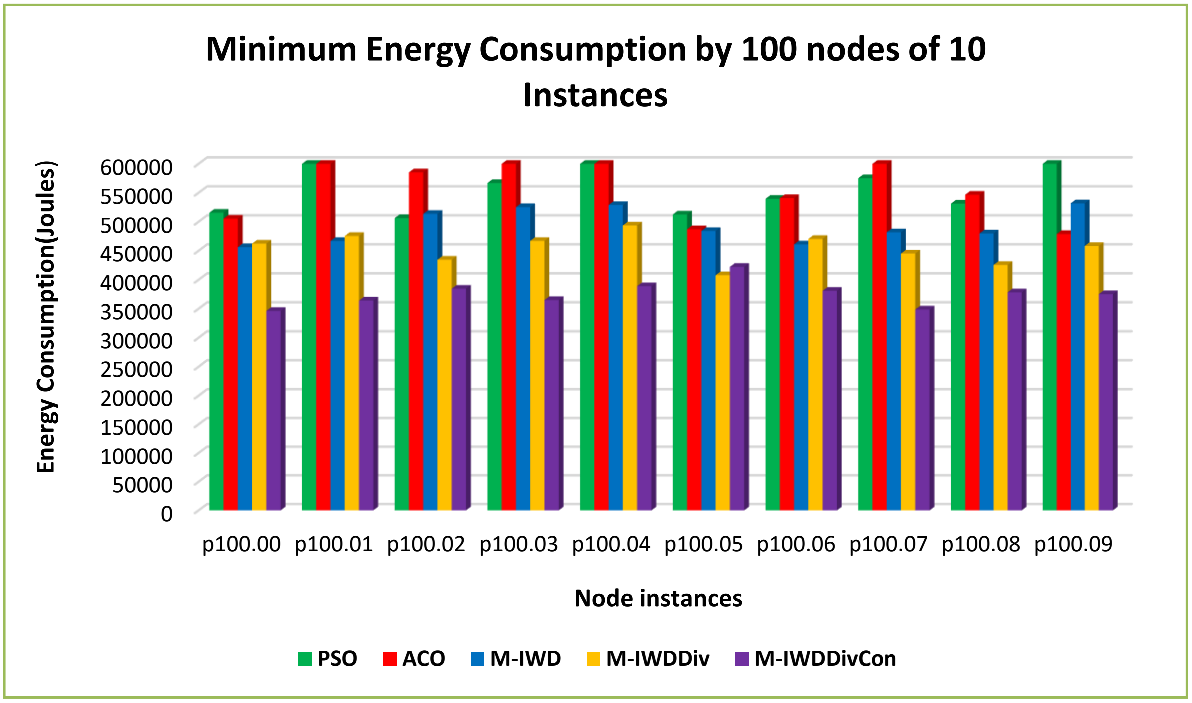


Figure 6.2: Performance of Energy Consumption of M-IWD vs other algorithms

The above graph is generated based on the results as shown in table 6.2. This graph compares the results of first 10 instances of 100 node datasets. Comparatively, it was shown that the proposed algorithms find the paths which consume the energy in minimal level for the given dataset of MEB.

6.3.2 Average Energy Consumption by WSN

The Average Energy consumed by WSN has been found out by taking the average of total amount of energy that the algorithm produced in each run. The best value has been found by doing a trial of the MEB dataset of 50 and 100 node instances for 30 runs with the same specification of parameters except the total number of iterations. The minimum energy that the WSN spent has been considered here as the Best Energy consumption by WSN.

Energy consumed by the network in WSN can be calculated as follows:

$$Energy\ Consumed\ (EC)\ = \sum_{j=1}^{m} CH_{i,j} + \sum_{j=1}^{m}\sum_{i=1}^{n} SN_{i,j} \tag{6.3}$$

Where, $'CH'$ represents the Cluster Head node, $'SN'$ represents Sensor Nodes, ‘m’ represents the total number of CH and ‘n’ represents the total number of nodes in each cluster.

Average Energy Consumption by a network in WSN can be calculated by:

$$Average\ Energy\ Consumed = \frac{\sum_{k=1}^{R} EC_k}{R} \tag{6.4}$$

where ‘EC’ represents the energy consumed by a solution and ‘R’ defines the total number of runs.

The following table 6.3 formulates the results of 30 instances of 50 node datasets. It compares the average energy consumed by the network for 30 runs with the same system specification and the tabulated parameters. In all, five methodologies were given, which includes two existing methodologies and three proposed methodologies to solve the MEB problem in WSN.

Table 6.3: Experimental Results of Average Energy Consumption for 50 nodes of 30 instances

Average Energy Consumption by 50 nodes of 30 instances					
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWDDiv**	**M-IWDDivCon**
p50.00	529116.96	498411.85	444638.06	399074.64	399074.64
p50.01	467985.64	439242.07	404397.01	373565.15	373565.15
p50.02	492862.63	452416.89	418458.38	393641.09	393641.09
p50.03	449922.30	385085.50	339172.16	316801.09	316801.09
p50.04	467220.13	424676.28	349849.69	325774.22	325774.22
p50.05	505472.82	440504.55	432215.67	382235.90	382235.90
p50.06	486504.93	465548.11	409186.61	384438.46	384438.46
p50.07	545258.77	472462.69	425748.77	401836.85	401836.85
p50.08	418424.00	437093.22	359849.15	334418.45	334418.45
p50.09	493635.83	439218.02	368310.62	346732.05	346732.05
p50.10	570153.92	476297.42	468409.27	416783.45	416783.45
p50.11	512869.66	460239.54	395677.64	369869.41	369869.41
p50.12	517828.59	448550.09	410159.61	392326.01	392326.01
p50.13	514247.75	456329.33	428615.19	400563.83	400563.83
p50.14	496682.88	449567.04	424214.40	388714.91	388714.91
p50.15	470563.33	459334.31	389834.49	371694.65	371694.65
p50.16	509710.68	479666.67	460975.40	414587.42	414587.42
p50.17	492511.22	454061.75	393521.40	355937.07	355937.07
p50.18	462648.85	434421.53	417605.40	376617.33	376617.33
p50.19	479633.65	411387.17	380209.56	335059.72	335059.72
p50.20	533660.44	474786.35	466118.04	414768.96	414768.96
p50.21	476436.34	419099.24	382765.48	361354.27	361354.27
p50.22	416266.00	419475.44	358578.38	329043.51	329043.51
p50.23	530621.87	483616.68	416658.16	383321.04	383321.04
p50.24	535425.76	488444.85	453270.18	404855.92	404855.92
p50.25	498117.39	429447.95	407756.06	363200.32	363200.32
p50.26	543248.14	482199.12	438670.76	406631.51	406631.51
p50.27	576906.98	510915.29	490234.47	451059.62	451059.62
p50.28	514289.86	514037.15	440407.53	415832.44	415832.44
p50.29	511916.42	444030.31	410162.73	380492.77	380492.77

Table 6.3 presents the results of average energy consumption of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem namely Modified IWD model, M-IWD model with Diversification and M-IWD$_{Div}$ with Convergence. The table reveals that for 50 node instances, algorithms of M-IWD$_{Div}$ and M-IWD$_{Div}^{Con}$ provide the optimal values. For comparison state, the optimal results were taken from the official website. Figure 6.3 shows that the comparison of the first 10 instances of 50 node datasets.

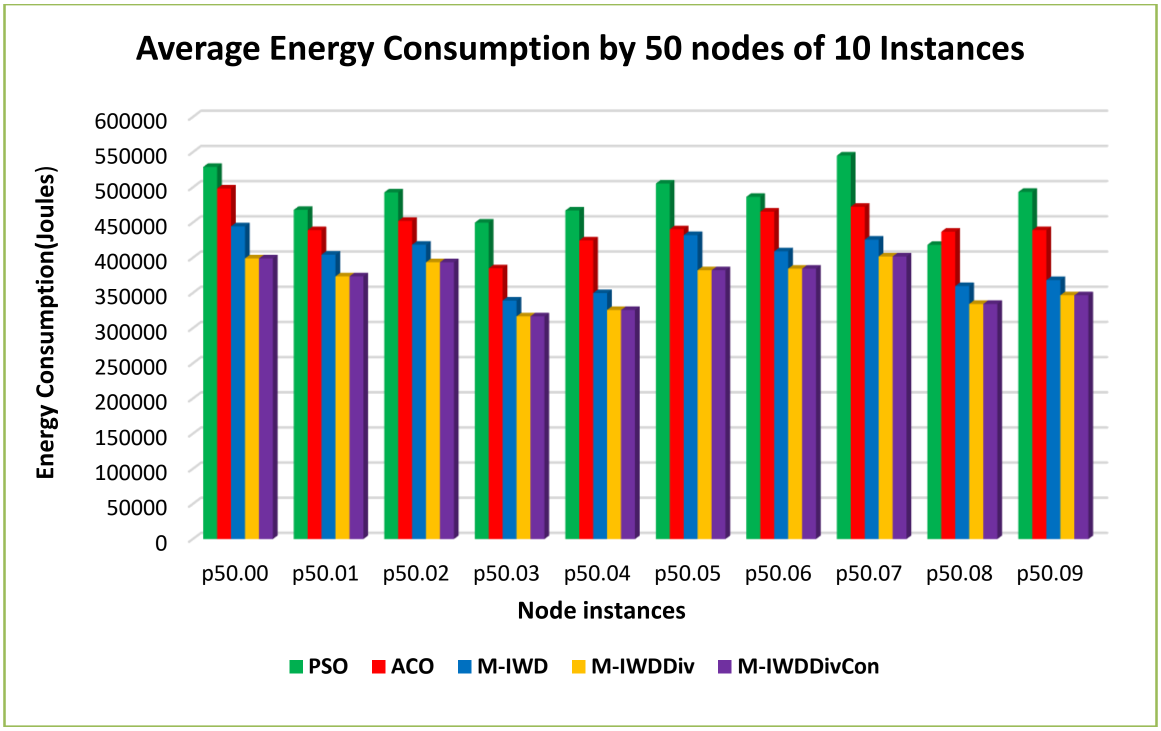


Figure 6.3: Performance of Average Energy Consumption of M-IWD vs other algorithms

The above graph is generated based on the results as shown in table 6.3. This graph compares the results of first 10 instances of 50 node datasets. Comparatively, it is shown that the proposed algorithms find the paths which consume the energy in average level for the given dataset of MEB.

The following table 6.4 shows that the average energy consumption by five algorithms for 100 nodes of 30 instances. The following results were simulated by setting 2000 as the maximum iteration number.

Table 6.4: Experimental Results of Average Energy Consumption for 100 nodes of 30 instances

	Average Energy Consumption by 100 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWD$_{Div}$**	**M-IWD$_{Div}^{Con}$**
p100.00	553479.81	529017.93	483411.14	480192.41	371929.07
p100.01	641791.27	626492.09	487958.25	493756.09	394641.87
p100.02	539534.18	609049.46	537760.36	467220.37	412270.69
p100.03	599009.60	627878.39	554753.19	488810.65	385968.41
p100.04	690127.32	678868.85	565476.54	522844.25	415529.21
p100.05	542506.81	523955.33	515840.75	428719.86	454116.11
p100.06	569184.19	572229.29	487021.32	504000.54	408427.43
p100.07	595797.60	625301.96	511402.22	474803.92	378756.56
p100.08	563859.15	581606.79	509688.96	454747.44	411411.44
p100.09	683733.77	511306.63	564420.02	491305.73	407573.57
p100.10	564488.48	541421.87	517368.70	459535.47	360081.46
p100.11	597798.55	662048.47	531503.36	478874.99	380374.69
p100.12	711652.27	678167.63	512335.53	441696.24	431081.27
p100.13	575482.05	608199.03	537415.43	513843.32	355706.70
p100.14	605100.32	644270.78	489718.98	484738.55	376680.12
p100.15	650975.23	493233.40	563387.88	430570.54	379400.57
p100.16	585166.75	632954.29	532226.78	428372.97	365708.53
p100.17	677980.28	643650.25	529801.36	468143.86	405027.85
p100.18	593136.10	518075.60	492083.25	495792.74	361220.42
p100.19	664244.94	497310.66	481771.65	525642.35	394751.02
p100.20	543239.54	567404.54	512885.87	474475.32	385511.86
p100.21	594658.43	604351.90	527139.26	463556.77	388687.51
p100.22	683445.45	524948.89	525134.56	440746.11	394551.11
p100.23	580889.50	612984.15	551769.02	471296.62	434307.77
p100.24	622216.41	539678.34	535407.33	451898.80	384106.99
p100.25	635703.36	529864.15	563844.61	504853.57	392377.52
p100.26	659725.08	552492.23	558585.78	514582.94	381732.55
p100.27	550908.46	657551.32	491991.02	464182.79	405467.31
p100.28	550883.70	577091.08	540363.46	440369.98	378556.10
p100.29	649231.21	642088.77	544058.48	503842.10	383832.47

The above table 6.4 presents the results of average energy consumption of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem namely Modified IWD model, M-IWD model with Diversification function and M-IWD$_{Div}$ with Convergence function. The table reveals that M-IWD$_{Div}^{Con}$ algorithm finds the optimal values for 100 node instances. For comparison state, the optimal results were taken from the official website. The following graph Figure 6.4 shows that the comparison of first 10 instances of 100 node datasets.

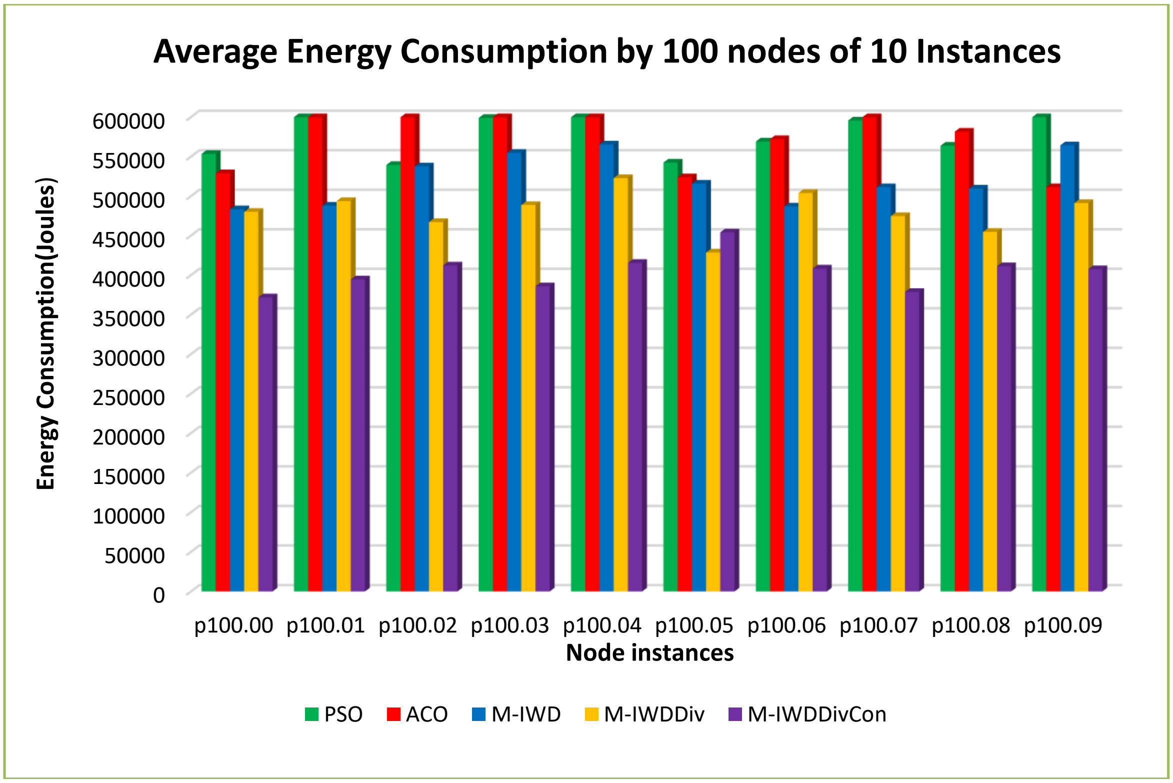


Figure 6.4: Performance of Average Energy Consumption of M-IWD vs other algorithms

The above graph is generated based on the results shown in table 6.4. This graph compares the results of first 10 instances of 100 node dataset. Comparatively, it was shown that the proposed algorithms find the path which consumes the energy in minimal level for the given dataset of MEB.

6.3.3 Convergence Rate

The convergence rate has been calculated by finding the minimum energy consumed among 30 run trials and the value is passed into the following equation. The best value has been found by making a trial of the MEB dataset of 50 and 100 node instances for 30 runs with the same specification of parameters, except the aggregate number of iterations. The convergence rate will be calculated based on the minimum energy that the WSN spent in the given instance.

Convergence rate towards the optimal solution can be calculated as follows:

$$Convergence\ Rate\ (CR) = \left[1 - \frac{\min(EC_1, EC_2, \ldots, EC_R) - OE}{OE}\right] X\ 100 \qquad (6.5)$$

where $'EC'$ represents the energy consumed by the network in each run, $'R'$ represents total number of runs and OE' represents the Optimal Energy consumed by the network as it was tabulated in the MEB site.

Table 6.5 formulates the results of 30 instances of 50 node datasets. It compares the convergence rate for 30 runs with the similar system specification and the tabulated parameters. Totally, five methodologies were given which includes two existing methodologies and three proposed methodologies to solve the MEB problem in WSN.

Table 6.5: Experimental Results of Convergence rate for 50 nodes of 30 instances

	Convergence Rate by 50 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**$M\text{-}IWD_{Div}$**	**$M\text{-}IWD_{Div}^{Con}$**
p50.00	67.96%	75.94%	89.82%	100.00%	100.00%
p50.01	75.83%	83.22%	92.27%	100.00%	100.00%
p50.02	75.77%	86.33%	94.55%	100.00%	100.00%
p50.03	59.21%	79.13%	94.01%	100.00%	100.00%
p50.04	57.90%	70.96%	93.73%	100.00%	100.00%
p50.05	68.79%	85.80%	87.60%	100.00%	100.00%
p50.06	74.57%	80.01%	94.29%	100.00%	100.00%
p50.07	65.37%	83.48%	94.80%	100.00%	100.00%
p50.08	75.82%	70.59%	93.76%	100.00%	100.00%
p50.09	58.93%	74.60%	94.73%	100.00%	100.00%
p50.10	64.17%	86.43%	88.19%	100.00%	100.00%
p50.11	62.47%	76.47%	93.60%	100.00%	100.00%
p50.12	69.00%	86.75%	96.01%	100.00%	100.00%
p50.13	72.22%	87.21%	93.96%	100.00%	100.00%
p50.14	72.79%	85.12%	91.92%	100.00%	100.00%
p50.15	74.15%	77.63%	95.89%	100.00%	100.00%
p50.16	78.00%	85.28%	89.68%	100.00%	100.00%
p50.17	62.91%	73.16%	90.52%	100.00%	100.00%
p50.18	77.84%	85.56%	89.77%	100.00%	100.00%
p50.19	57.96%	78.39%	87.21%	100.00%	100.00%
p50.20	71.98%	86.34%	88.46%	100.00%	100.00%
p50.21	68.99%	84.64%	95.32%	100.00%	100.00%
p50.22	74.74%	74.05%	91.72%	100.00%	100.00%
p50.23	62.64%	75.06%	91.84%	100.00%	100.00%
p50.24	68.32%	80.53%	89.05%	100.00%	100.00%
p50.25	63.45%	82.74%	88.90%	100.00%	100.00%
p50.26	67.28%	82.03%	92.91%	100.00%	100.00%
p50.27	73.04%	87.48%	91.82%	100.00%	100.00%
p50.28	77.19%	76.89%	95.25%	100.00%	100.00%
p50.29	66.13%	84.10%	92.79%	100.00%	100.00%

Table 6.5 formulates the results of convergence-rate of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem, namely Modified IWD model, M-IWD model with Diversification and M-IWD$_{Div}$ with Convergence. The table reveals that the algorithms M-IWD$_{Div}$ and M-IWD$_{Div}^{Con}$ shows the complete convergence towards the optimal solutions for 50 node instances. For comparison state, the optimal results were taken from the official website. The following Figure 6.5 shows the comparison of first 10 instances of 50 node dataset.

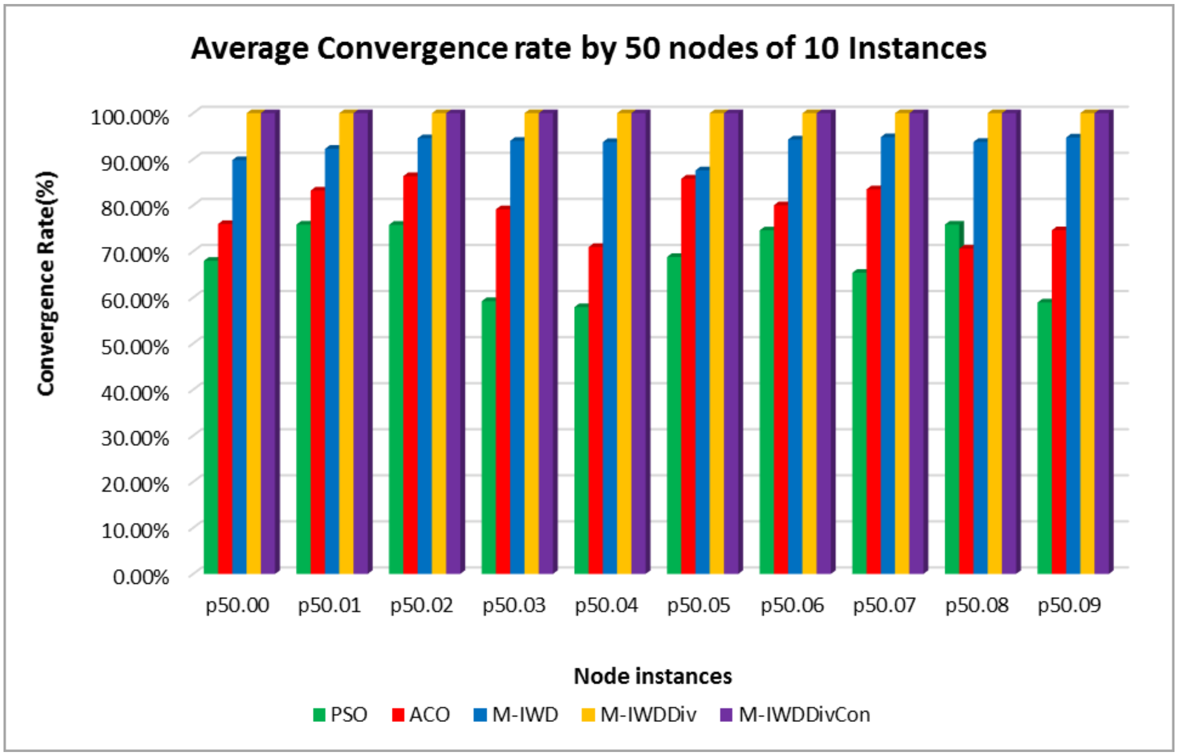


Figure 6.5: Performance of Convergence of M-IWD vs other algorithms

The above graph is generated based on the results shown in table 6.5. This graph compares the results of first 10 instances of 50 node datasets. Comparatively, it is shown that the proposed algorithm achieves complete convergence towards the optimal solution for the given dataset of MEB.

Table 6.6 shows the convergence rate of five algorithms for 100 nodes of 30 instances. The following results are simulated by setting 2000 as the maximum iteration number.

Table 6.6: Experimental Results of Convergence rate for 100 nodes of 30 instances

	Convergence Rate by 100 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**$M\text{-}IWD_{Div}$**	**$M\text{-}IWD_{Div}^{Con}$**
p100.00	48.72%	51.73%	66.16%	64.38%	98.47%
p100.01	25.75%	30.26%	68.57%	66.14%	97.50%
p100.02	65.75%	44.78%	63.79%	84.76%	98.05%
p100.03	41.19%	31.35%	52.83%	69.17%	97.73%
p100.04	27.19%	33.11%	62.40%	71.59%	98.85%
p100.05	76.99%	83.09%	83.83%	92.14%	98.71%
p100.06	56.65%	56.31%	77.55%	75.03%	98.83%
p100.07	32.70%	24.95%	59.84%	70.49%	98.62%
p100.08	57.27%	53.14%	71.10%	85.69%	98.42%
p100.09	20.03%	69.52%	55.07%	75.16%	97.78%
p100.10	39.61%	45.31%	55.31%	68.94%	98.06%
p100.11	41.53%	24.12%	59.21%	71.93%	98.50%
p100.12	22.63%	36.76%	74.52%	95.25%	98.78%
p100.13	33.07%	24.52%	48.74%	54.58%	97.69%
p100.14	29.22%	18.71%	66.67%	69.55%	97.83%
p100.15	21.85%	70.08%	47.66%	84.36%	98.68%
p100.16	33.31%	20.97%	50.49%	80.60%	98.34%
p100.17	26.28%	33.94%	66.99%	83.32%	98.05%
p100.18	28.99%	54.08%	57.63%	59.09%	97.53%
p100.19	23.77%	70.49%	74.67%	65.06%	97.70%
p100.20	54.47%	47.41%	63.86%	73.64%	97.94%
p100.21	42.34%	38.27%	61.68%	78.98%	97.65%
p100.22	18.35%	64.92%	65.28%	86.02%	98.35%
p100.23	64.83%	57.06%	69.93%	92.35%	98.95%
p100.24	31.48%	57.13%	57.57%	80.01%	97.99%
p100.25	27.59%	59.80%	51.11%	69.50%	97.91%
p100.26	18.73%	52.41%	49.71%	61.66%	98.47%
p100.27	59.42%	29.92%	73.39%	82.42%	98.38%
p100.28	50.24%	42.34%	54.48%	82.76%	97.50%
p100.29	25.32%	27.36%	54.97%	66.09%	97.67%

Table 6.6 formulates the results of the convergence rate of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem namely Modified IWD model, M-IWD model with Diversification and M-IWD$_{Div}$ with Convergence. The table reveals that for 100 node instances, M-IWD$_{Div}^{Con}$ algorithm effectively converges towards the optimal solution when compared to other algorithms. For comparison state, the optimal results were taken from the official website. The following Figure 6.6 shows that the comparison of first 10 instances of 100 node dataset.

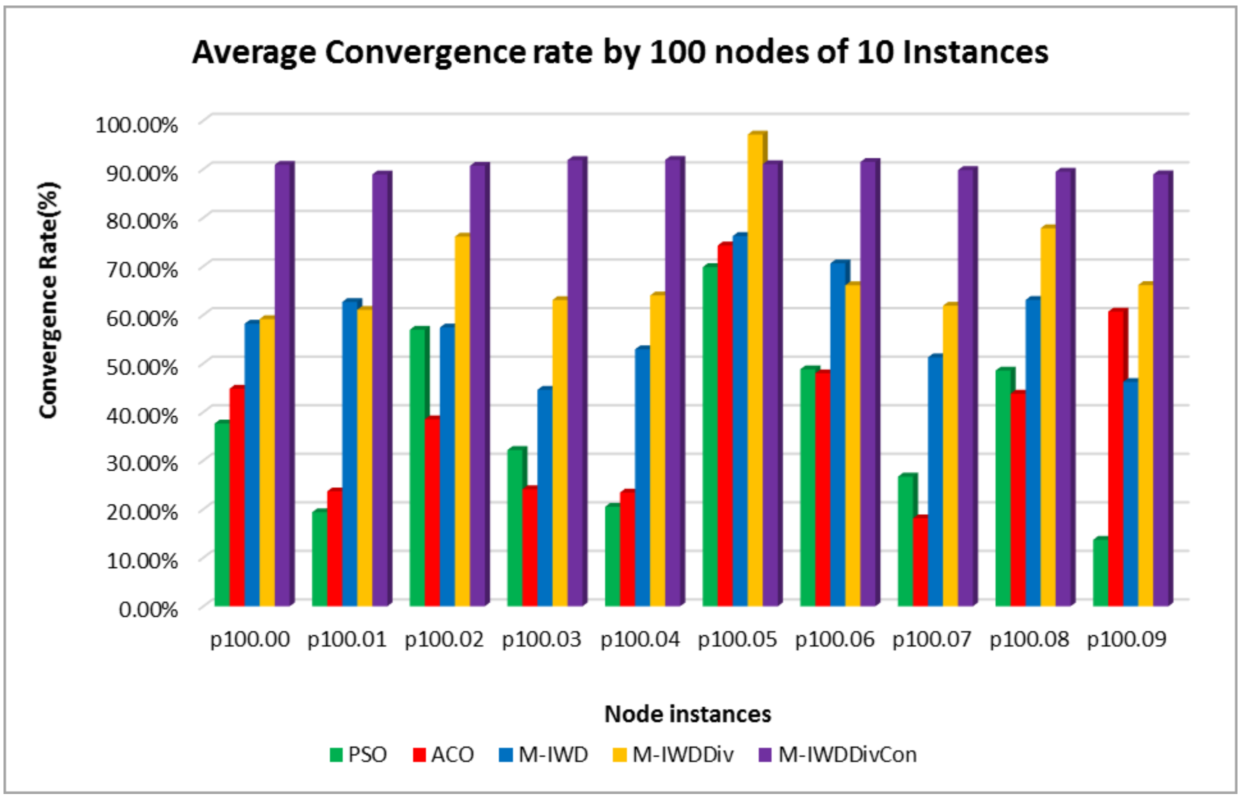


Figure 6.6: Performance of Convergence of M-IWD vs other algorithms

The above graph is generated based on the results shown in table 6.6. This graph compares the results of first 10 instances of 100 node datasets. Comparatively, it was shown that the proposed algorithms converge towards the optimal solution for the given dataset of MEB.

6.3.4 Average Convergence Rate

The average convergence rate has been calculated by finding the average of all energies consumed among 30 run trials, and the value is passed in the following equation. The average value has been found out by doing a trial of the MEB dataset of 50 and 100 node instances for 30 runs with the same specification of parameters except the total number of iterations. The Average Convergence Rate will be calculated based on the complete energy consumed during all the trials for the given instance.

Average Convergence Rate towards the optimal solution can be calculated as follows:

$$Average\ Convergence(\%) = \frac{\sum_{i=1}^{R} Energy\ Consumed_i}{R} \times 100 \qquad (6.6)$$

where ‘R’ represents the total number of runs and‘i’ ranges from 1 to 30.

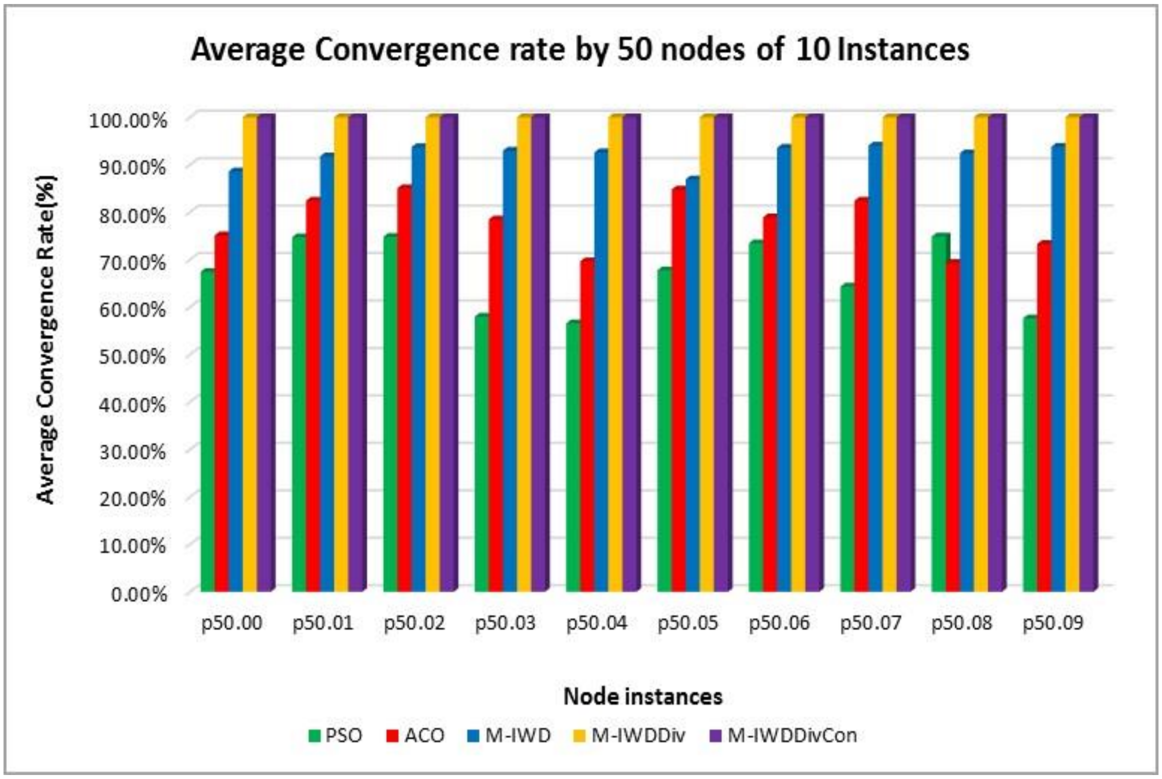
Table 6.7 formulates the results of 30 instances of 50 node datasets. It compares the average convergence rate from 30 runs with same system specification and the tabulated parameters. In all, five methodologies were given which includes two existing methodologies and three proposed methodologies to solve the MEB problem in WSN.

Table 6.7: Experimental Results of Average Convergence rate for 50 nodes of 30 instances

	Average Convergence Rate by 50 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWD$_{Div}$**	**M-IWD$_{Div}^{Con}$**
p50.00	67.41%	75.11%	88.58%	100%	100%
p50.01	74.72%	82.42%	91.75%	100%	100%
p50.02	74.79%	85.07%	93.70%	100%	100%
p50.03	57.98%	78.45%	92.94%	100%	100%
p50.04	56.58%	69.64%	92.61%	100%	100%
p50.05	67.76%	84.76%	86.92%	100%	100%
p50.06	73.45%	78.90%	93.56%	100%	100%
p50.07	64.31%	82.42%	94.05%	100%	100%
p50.08	74.88%	69.30%	92.40%	100%	100%
p50.09	57.63%	73.33%	93.78%	100%	100%
p50.10	63.20%	85.72%	87.61%	100%	100%
p50.11	61.34%	75.57%	93.02%	100%	100%
p50.12	68.01%	85.67%	95.45%	100%	100%
p50.13	71.62%	86.08%	93.00%	100%	100%
p50.14	72.22%	84.35%	90.87%	100%	100%
p50.15	73.40%	76.42%	95.12%	100%	100%
p50.16	77.06%	84.30%	88.81%	100%	100%
p50.17	61.63%	72.43%	89.44%	100%	100%
p50.18	77.16%	84.65%	89.12%	100%	100%
p50.19	56.85%	77.22%	86.52%	100%	100%
p50.20	71.34%	85.53%	87.62%	100%	100%
p50.21	68.15%	84.02%	94.07%	100%	100%
p50.22	73.49%	72.52%	91.02%	100%	100%
p50.23	61.57%	73.84%	91.30%	100%	100%
p50.24	67.75%	79.35%	88.04%	100%	100%
p50.25	62.85%	81.76%	87.73%	100%	100%
p50.26	66.40%	81.42%	92.12%	100%	100%
p50.27	72.10%	86.73%	91.31%	100%	100%
p50.28	76.32%	76.38%	94.09%	100%	100%
p50.29	65.46%	83.30%	92.20%	100%	100%

Table 6.7 formulates the results of average convergence rate of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem, namely Modified IWD, M-IWD model with Diversification and M-IWD$_{Div}$ with Convergence. The table reveals that for 50 node instances, M-IWD$_{Div}$ and M-IWD$_{Div}^{Con}$ algorithms shows the complete convergence towards the optimal solutions. For comparison state, the optimal results were taken from the official website. Figure 6.7 shows that the comparison of first 10 instances of 50 node datasets.

Figure 6.7: Performance of Average Convergence of M-IWD vs other algorithms



The above graph is generated based on the results shown in table 6.7. This graph compares the results of first 10 instances of 50 node datasets. Comparatively, it was shown that the proposed algorithm shows complete convergence towards the optimal solution for the given dataset of MEB.

The following table 6.8 shows the convergence rate of five algorithms for 100 nodes of 30 instances. The following results are simulated by setting the 2000 as the maximum iteration number.

Table 6.8: Experimental Results of Average Convergence rate for 100 nodes of 30 instances

	Average Convergence Rate by 100 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWD$_{Div}$**	**M-IWD$_{Div}^{Con}$**
p100.00	37.63%	44.80%	58.18%	59.13%	90.89%
p100.01	19.36%	23.66%	62.66%	61.03%	88.92%
p100.02	56.94%	38.51%	57.41%	76.12%	90.69%
p100.03	32.18%	24.10%	44.58%	63.06%	91.87%
p100.04	20.49%	23.42%	52.91%	64.00%	91.91%
p100.05	69.83%	74.28%	76.23%	97.13%	91.04%
p100.06	48.79%	47.98%	70.61%	66.10%	91.49%
p100.07	26.70%	18.12%	51.25%	61.89%	89.83%
p100.08	48.53%	43.76%	63.08%	77.84%	89.48%
p100.09	13.69%	60.68%	46.20%	66.13%	88.94%
p100.10	31.28%	38.18%	45.37%	62.65%	92.38%
p100.11	32.18%	14.15%	50.79%	65.57%	93.22%
p100.12	19.31%	27.81%	69.92%	87.85%	90.55%
p100.13	26.28%	16.40%	37.77%	44.89%	92.62%
p100.14	24.19%	12.81%	57.71%	59.16%	90.56%
p100.15	15.53%	60.23%	40.35%	77.99%	92.49%
p100.16	27.24%	13.13%	42.87%	73.53%	92.03%
p100.17	18.75%	27.93%	58.36%	74.85%	91.72%
p100.18	21.30%	43.92%	51.75%	50.63%	91.17%
p100.19	18.05%	63.78%	68.04%	56.02%	91.87%
p100.20	47.01%	40.20%	55.56%	66.37%	91.43%
p100.21	35.82%	33.15%	54.46%	72.02%	92.69%
p100.22	13.33%	56.62%	56.57%	79.62%	92.24%
p100.23	57.99%	50.15%	65.11%	84.79%	93.83%
p100.24	26.09%	49.16%	50.35%	73.69%	92.64%
p100.25	22.03%	51.66%	42.15%	58.66%	90.15%
p100.26	12.66%	43.11%	41.38%	53.87%	91.60%
p100.27	51.12%	22.30%	67.04%	74.56%	90.42%
p100.28	42.10%	34.59%	45.12%	73.78%	91.50%
p100.29	18.45%	20.44%	47.86%	59.10%	92.66%

Table 6.8 formulates the results of average convergence rate of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem namely Modified IWD model, M-IWD model with Diversification and M-IWD$_{Div}$ with Convergence. The table reveals that for 100 node instances, M-IWD$_{Div}^{Con}$ algorithm efficiently converges towards the optimal solution on an average when compared to other algorithms. For comparison state, the optimal results were taken from the official website. Figure 6.8 shows that the comparison of the first 10 instances of 100 node dataset.

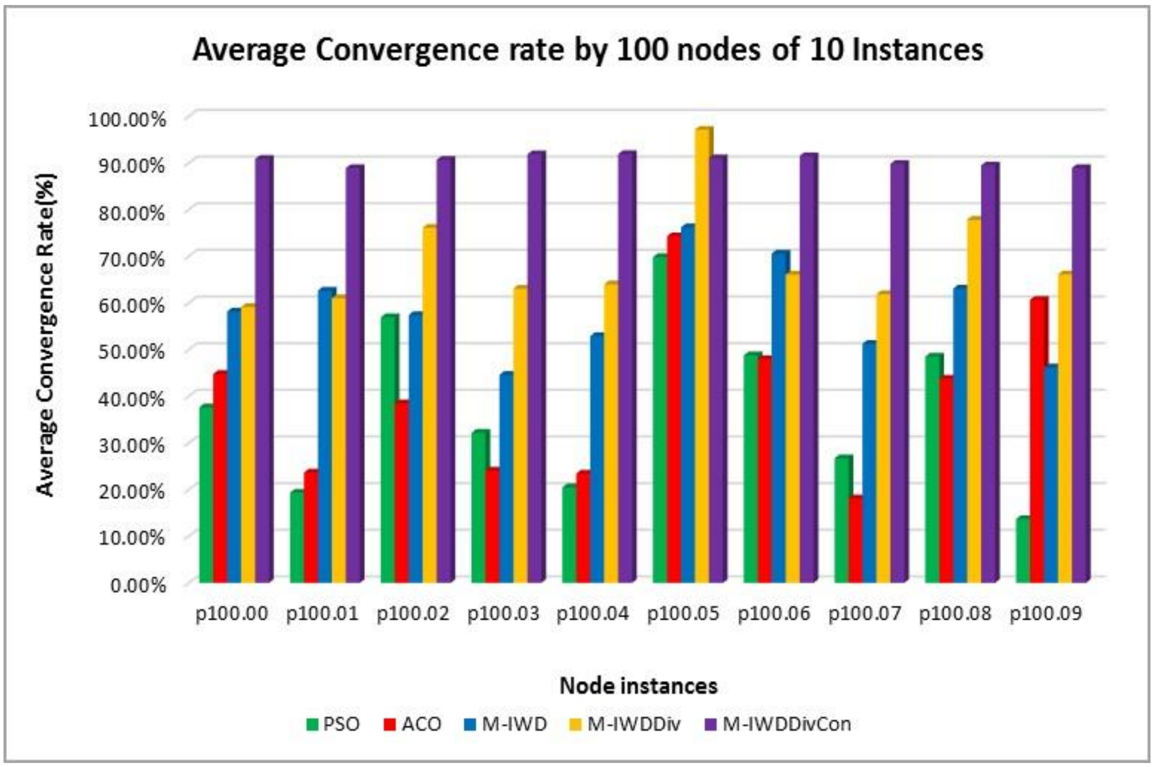


Figure 6.8: Performance of Average Convergence of M-IWD vs other algorithms

The above graph is generated based on the results shown in table 6.8. This graph compares the results of first 10 instances of 100 node datasets. Comparatively, it was shown that the proposed algorithms are converges towards the optimal solution on an average for the given dataset of MEB.

6.3.5 Excess Rate

Excess rate has been evaluated as the ratio between Best and Worst results found in a particular cycle, which produced optimum result of the maximum number of trials. The Excess rate can be calculated by doing a trial of the MEB dataset of 50 and 100 node instances for 30 runs with the same specification of parameters except the total number of iterations. The Excess rate will be calculated based on the complete minimal energy consumed among all the trials for the given instance.

Excess rate against optimal solution can be calculated as follows:

$$Excess\ Rate(ER) = \left[\frac{Best}{Optimal\ result} - 1\right] \tag{6.6}$$

Where, Best represents the minimal energy consumed out of 30 runs.

Table 6.9 formulates the results of 30 instances of 50 node datasets. It compares the excess rate for 30 runs with the same system specification and the tabulated parameters. In all, five methodologies were given which includes two existing methodologies and three proposed methodologies to solve MEB problem in WSN.

Table 6.9: Experimental Results of Excess rate for 50 nodes of 30 instances

	Excess Rate by 50 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWD$_{Div}$**	**M-IWD$_{Div}^{Con}$**
p50.00	0.32	0.24	0.10	0	0
p50.01	0.24	0.17	0.08	0	0
p50.02	0.24	0.14	0.05	0	0
p50.03	0.41	0.21	0.06	0	0
p50.04	0.42	0.29	0.06	0	0
p50.05	0.31	0.14	0.12	0	0
p50.06	0.25	0.20	0.06	0	0
p50.07	0.35	0.17	0.05	0	0
p50.08	0.24	0.29	0.06	0	0
p50.09	0.41	0.25	0.05	0	0
p50.10	0.36	0.14	0.12	0	0
p50.11	0.38	0.24	0.06	0	0
p50.12	0.31	0.13	0.04	0	0
p50.13	0.28	0.13	0.06	0	0
p50.14	0.27	0.15	0.08	0	0
p50.15	0.26	0.22	0.04	0	0
p50.16	0.22	0.15	0.10	0	0
p50.17	0.37	0.27	0.09	0	0
p50.18	0.22	0.14	0.10	0	0
p50.19	0.42	0.22	0.13	0	0
p50.20	0.28	0.14	0.12	0	0
p50.21	0.31	0.15	0.05	0	0
p50.22	0.25	0.26	0.08	0	0
p50.23	0.37	0.25	0.08	0	0
p50.24	0.32	0.19	0.11	0	0
p50.25	0.37	0.17	0.11	0	0
p50.26	0.33	0.18	0.07	0	0
p50.27	0.27	0.13	0.08	0	0
p50.28	0.23	0.23	0.05	0	0
p50.29	0.34	0.16	0.07	0	0

Table 6.9 formulates the results of excess rate of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem namely Modified IWD, M-IWD with Diversification and M-IWD$_{Div}$ with Convergence. The table reveals that for 50 node instances, M-IWD$_{Div}$ and M-IWD$_{Div}^{Con}$ algorithms shows excess rate against the null optimal solutions. For comparison state, the optimal results were taken from the official website. Figure 6.9 shows that the comparison of first 10 instances of 50 node datasets.

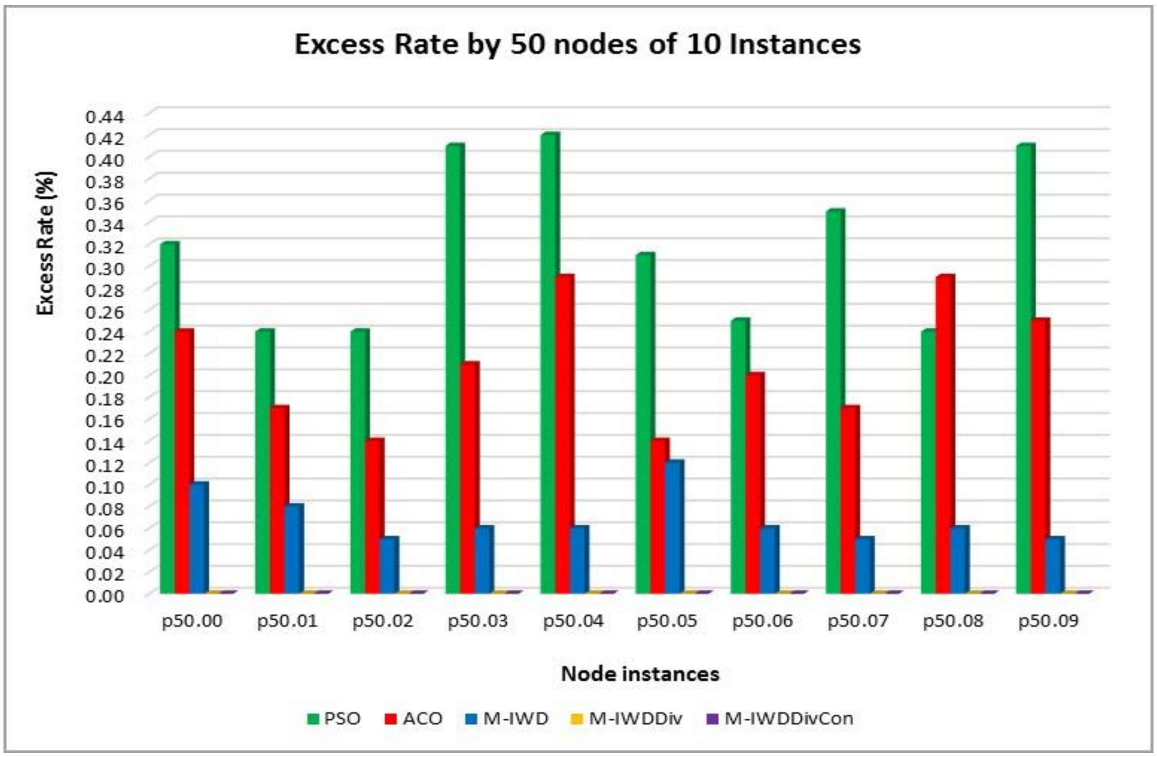


Figure 6.9: Performance of Excess rate of M-IWD vs other algorithms

The above graph 6.9 is generated based on the results shown in table 6.9. This graph compares the results of first 10 instances of 50 node datasets. Comparatively, it is shown that the proposed algorithms show excess rate against the optimal solutions which is null for the given dataset of MEB.

Table 6.10 shows the excess rate of five algorithms for 100 nodes of 30 instances. The following results are simulated by setting the 2000 as maximum iteration-number.

Table 6.10: Experimental Results of Excess rate for 100 nodes of 30 instances

	Excess Rate by 100 nodes of 30 instances				
Node Instances	**PSO**	**ACO**	**M-IWD**	**M-IWD$_{Div}$**	**M-IWD$_{Div}^{Con}$**
p100.00	0.51	0.48	0.34	0.36	0.02
p100.01	0.74	0.70	0.31	0.34	0.03
p100.02	0.34	0.55	0.36	0.15	0.02
p100.03	0.59	0.69	0.47	0.31	0.02
p100.04	0.73	0.67	0.38	0.28	0.01
p100.05	0.23	0.17	0.16	0.12	0.01
p100.06	0.43	0.44	0.22	0.25	0.01
p100.07	0.67	0.75	0.40	0.30	0.01
p100.08	0.43	0.47	0.29	0.14	0.02
p100.09	0.80	0.30	0.45	0.25	0.02
p100.10	0.60	0.55	0.45	0.31	0.02
p100.11	0.58	0.76	0.41	0.28	0.01
p100.12	0.77	0.63	0.25	0.05	0.01
p100.13	0.67	0.75	0.51	0.45	0.02
p100.14	0.71	0.81	0.33	0.30	0.02
p100.15	0.78	0.30	0.52	0.16	0.01
p100.16	0.67	0.79	0.50	0.19	0.02
p100.17	0.74	0.66	0.33	0.17	0.02
p100.18	0.71	0.46	0.42	0.41	0.02
p100.19	0.76	0.30	0.25	0.35	0.02
p100.20	0.46	0.53	0.36	0.26	0.02
p100.21	0.58	0.62	0.38	0.21	0.02
p100.22	0.82	0.35	0.35	0.14	0.02
p100.23	0.35	0.43	0.30	0.08	0.01
p100.24	0.69	0.43	0.42	0.20	0.02
p100.25	0.72	0.40	0.49	0.31	0.02
p100.26	0.81	0.48	0.50	0.38	0.02
p100.27	0.41	0.70	0.27	0.18	0.02
p100.28	0.50	0.58	0.46	0.17	0.03
p100.29	0.75	0.73	0.45	0.34	0.02

Table 6.10 formulates the results of excess rate of five algorithms including ACO, PSO and the other three proposed methodologies to solve MEB problem namely Modified IWD model, M-IWD with Diversification and M-IWD$_{Div}$ with Convergence. The table reveals that for 100 node instances, M-IWD$_{Div}^{Con}$ algorithm shows minimal excess rate when compared to the other algorithms. For comparison state, the optimal results were taken from the official website. The following Figure 6.10 shows the comparison of first 10 instances of 100 node dataset.

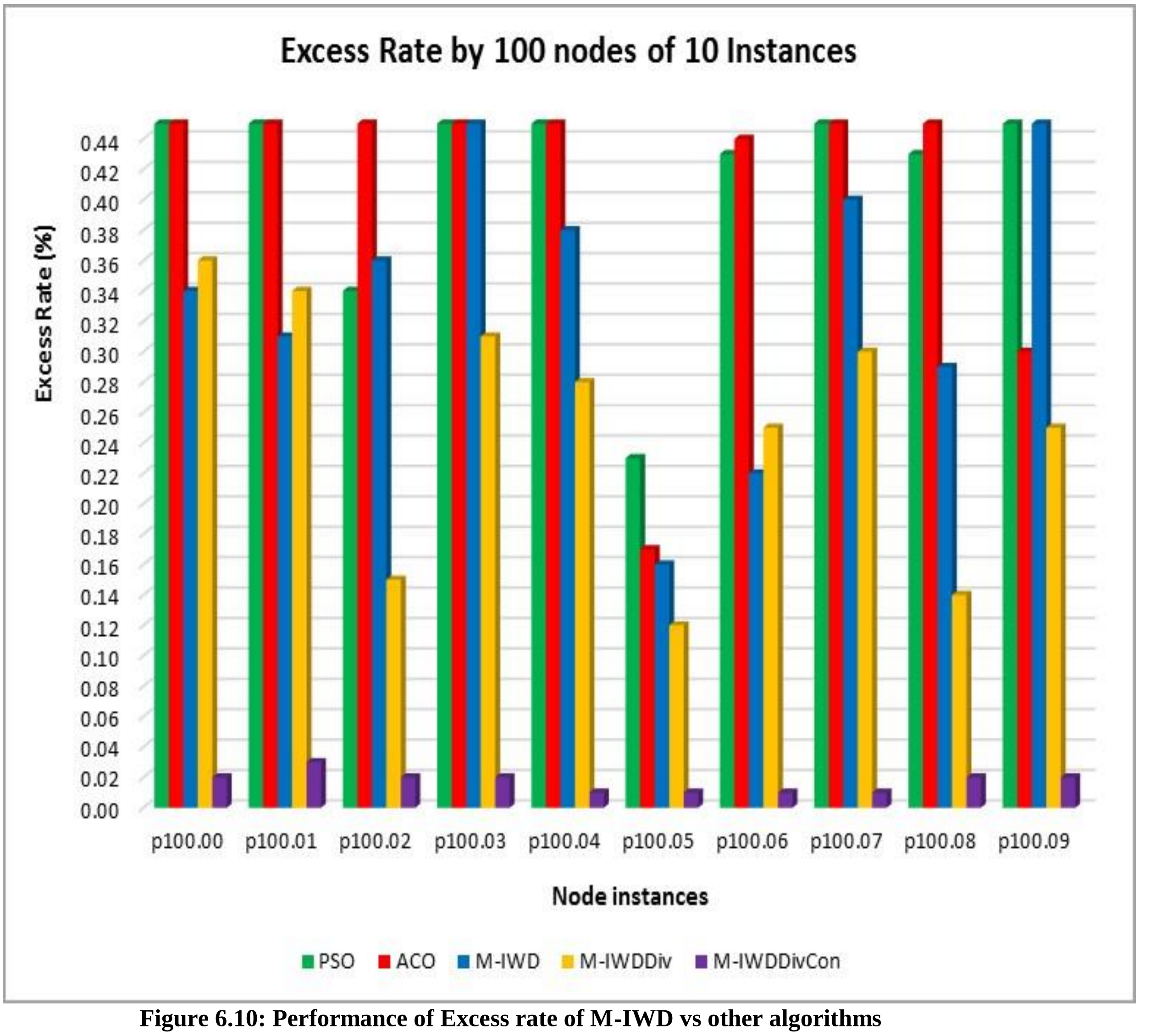


Figure 6.10: Performance of Excess rate of M-IWD vs other algorithms

The above graph is generated based on the results shown in table 6.10. This graph compares the results of first 10 instances of 100 node datasets. Comparatively, it was shown that the proposed algorithms shows minimal excess rate when compared to the other algorithms for the given dataset of MEB.

6.4 STATISTICAL TEST

6.4.1 TWO-WAY ANOVA TOOL

In this research, as a part of validation, Analysis of Variance (ANOVA) has been used as the statistical technique to test whether one or more samples means are significantly different from each other. In statistics, the two-way analysis of variance (ANOVA) is an extension of the one-way ANOVA that examines the influence of two different categorical independent variables on one continuous dependent variable. The two-way ANOVA not only aims at assessing the main effect of each independent variable but also if there is any interaction between them [52]. The ANOVA tests are performed for the significance level of 95% with the appropriate degree of freedom. If the sig value is less than the critical value (α) that is 0.05, null hypothesis *H0* is rejected and thereby the alternate hypothesis *H1* is accepted. Otherwise, the *H0* should be accepted by rejecting the *H1*.

For the table 6.10, Statistical test analysis has been carried out to justify the significance of the result. The statistical test result of two-way ANOVA is shown in below table 6.11:

Table:6.11 Two-way ANOVA: resp versus trt, Node Instances

Source	DF	SS	MS	F	P
trt	4	6.97133	1.74283	147.00	0.000
Node Instances	29	0.76979	0.02654	2.24	0.001
Error	116	1.37531	0.01186		
Total	149	9.11643			

S = 0.1089   R-Sq = 84.91%   R-Sq(adj) = 80.62%

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
trt              Mean  -+---------+---------+---------+--------
ACO          0.549333                             (-*-)
M-IWD        0.377667                      (-*-)
M-IWDDiv     0.248000               (-*-)
M-IWDDivCon  0.018000   (-*-)
PSO          0.618333                                 (-*-)
                       -+---------+---------+---------+--------
                        0.00      0.20      0.40      0.60
```

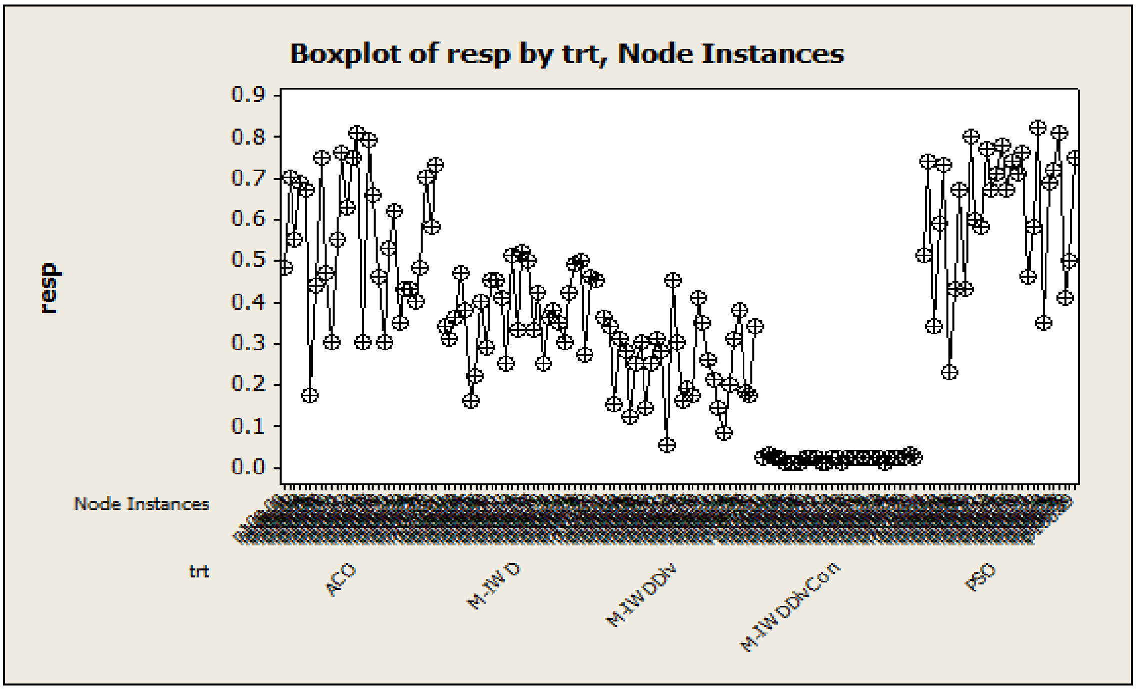


Figure 6.11: Statistical ANOVA Test Results for the proposed M-IWD algorithm

Observation:

From the result of the two-way ANOVA table 6.11, it has been observed that the proposed model of M-IWD with divergence and convergence shows an excellent performance result as compared with existing model of PSO and ACO, since proposed model's mean value is 0.018 which is less than 0.05.

6.5 SUMMARY

This chapter starts with an introduction to the analysis of results with an experimental comparison that was preceded with different methodologies to obtain the optimal results. In section 6.2, the parameters used in this experiment were clearly mentioned. In section 6.3, all the performance metrics of the proposed algorithms were compared with other existing algorithms such as PSO and ACO. The experimentation results were compared for 50 node instances and 100 node instances, since 20 node instances provide identical results for all algorithms. For each group of 50 and 100 nodes, the MEB dataset holds 30 instances with different location coordinates. On computing different instances for similar number of nodes, the reliability of algorithm over multiple scenarios can be projected efficiently. On comparing the results of the proposed Modified IWD versions with existing algorithms, the results and graphs show an incredible performance of Modified IWD model over existing algorithms.

CHAPTER 7

CONCLUSIONS AND FUTURE ENHANCEMENTS

7.1 CONCLUSIONS

The core of this research-work is to design and develop a Modified IWD Algorithm for solving MEB problem in WSN, which was motivated by the identified drawbacks of existing models. The goals of this research are derived in order to design a modified model of IWD Algorithm using improved Heuristic function, Enriched Divergence function, and composed Convergence function to improve the performance in terms of minimum energy consumed by WSN, average energy consumed, convergence rate, convergence diversity and computational time. Therefore, in principle, the goals of the proposed research are three-fold, as follows:

I. To formulate Modified Intelligent Water Drops Algorithm (M-IWD) with Heuristic function to adopt IWD for solving MEB problem in WSN.

II. To derive an Effective Divergence function to improve the exploration probability and to provide more solutions of population.

III. To enhance the proposed model with a convergence function for reducing exploration and to improve exploitation probability during the completion of run.

The first goal is defined to adopt the proposed M-IWD model with a proposed heuristic function for solving MEB of WSN with appropriate cluster head choice among the available nodes. The second goal is aimed at designing an effective divergence function for improving the exploration phases of M-IWD Algorithm. Finally, a convergence method is proposed for achieving multi-objective phase with improved exploitation and controlled exploration. All the goals are measurable and, of course, proved with appropriate sets of experiments.

A well-defined experimentation framework is designed for the research narrated in this thesis. Test bed layer defines the benchmark of MEB instances and the various performance assessment criteria. The proposed work is implemented in three different versions. In the first version of M-IWD model, a heuristic function is implemented for calculating the probability value in order to choose a node for transmitting the data. In the second version, a divergence function is imposed which covers the exploration process in the search space. In the final version, a complete regulation of M-IWD Algorithm along with convergence method of version II is proposed which comprises exploitation capability during the completion of run.

In order to validate the proposed version of the M-IWD model, several number of instances of MEB are being chosen as the test bed. Experiments were performed over small scale instances (20 nodes), medium scale instances (50 nodes) and large scale instances (100 nodes). The performance evaluation of the proposed research has been done for analysing the efficiency of the proposed work. In the experimental results' phase, all the results of proposed versions of M-IWD Algorithm with their performance metrics are clearly stated. In the experimental analysis phase, the results of existing Algorithms such as ACO and PSO for similar instances with the same experimental setup were performed and the optimal results were produced.

In the experimentation analysis chapter, the results of 20 node instances were not considered for comparison since the instance results of all the Algorithm states that there was an existence of similar results in terms of excess rate, convergence rate, average convergence rate and best energy consumption. Since it belongs to small scales instances with only 20 nodes per instance, all the compared and proposed algorithms provides similar results. On comparing the results of proposed versions with existing Algorithms (ACO, PSO), the 50 node and 100 node instances of M-IWD Algorithm were shown with remarkable results, since clustering process was included for efficient data transmission. The energy consumption phase is thus coming into control by using only the cluster head nodes for message transmission. From the experimental results, the M-IWD model with Divergence and Convergence factor outshines the other existing classical bio-inspired models identified in the literature.

7.2 FUTURE ENHANCEMENTS

The significance of this research work outlines the proposal of Modified IWD Algorithm for MEB problems. The optimal results obtained support the proposed model with enhanced divergence and enriched convergence for the relevant domain. It also contributes a pathway for continuing the research further in the direction of developing hybrid evolutionary solution models for the intended MEB problems. This may require a study of the related evolutionary solutions and to develop a common mapping model for connecting those related solutions with MEB problems. This research can further be extended to any real-time application with increased performance and for reducing computational time. This may bid a new track of research, which would attract extensive attention from many researchers and, of course, may offer enhanced set of solution models in the future.

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