HETROGENEOUS MULTI-DEPLOYMENT STRATEGY EFFECT ON MAXIMIZING THE LIFETIME ROUTING IN WIRELESS SENSOR NETWORK

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COMMITTEE DECISION

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DEDICATION

To my inspiring in life, the symbol of challenge and hard working…
To my dear father.

To the resource of peace and sympathy...

To the one who granted the love without tiredness…

To my ever beloved mother.

To the rosy part of my life, my brother Abd El-Aziz

and my darling sisters, Areej, and Afra, who always supported me

with their love and compassion…

To my fiancé for his kind help, patience, and encouragement…

To those who lived the experience with me...

Who were always there, with support and love… To my dear friends,

Samya, Eman, Amna, Noraz, Malak, Wala'a, and Selma.

To all, I dedicate this work.

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I am thankful to all my friends over here and back in Sudan for their love, support, criticism and encouragement.

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LIST OF ABBREVIAVIONS OR SYMBOLS

Abbreviation	Meaning
WSN	Wireless Sensor Networks
OML	Online Maximum Lifetime Heuristics
MRPC	Maximum Residual Packet Capacity
CMAX	Capacity Maximization
DAG	Directed Acyclic Graph
UC	Uniform_Chi-square Distribution
UP	Uniform_Poisson Distribution
UN	Uniform_Normal Distribution
CP	Chi-squre_Poisson Distribution
CN	Chi-squre_Normal Distribution
NP	Normal_Poisson Distribution
PCNU	Poisson_Chi-square_Normal_Uniform Distribution
CPUN	Chi-square_Poisson_Uniform_Normal Distribution
NPCU	Normal Poisson_Chi-square_Uniform Distribution
PCUN	Poisson_Chi-square_Uniform_Normal Distribution

CNPU	**Chi-square_Normal_Poisson_Uniform Distribution**
CPNU	**Chi-square_Poisson_Normal_Uniform Distribution**
λ **c**	**Algorithm Parameter for CMAX and OML Heuristics for giving cost for the edges.**
re(u)	**Residual Energy**
minRE	**Minimum Residual Energy**
eMin(u)	**energy needed by sensor u to transmit a message to its nearest neighbor in G″**
ρ **(u,v)**	**OML heuristic Parameter**

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ABSTRACT

In the last few years, a significant increasing interest in the Wireless Sensor Networks (WSN) is noticed. A great challenge in WSN is the limitation of power in sensor nodes batteries, hence developing energy efficient solutions is a key issue for providing as long as possible lifetime for these networks.

Data transmission is thought of to be the main reason for consuming power in sensor nodes. That is why many power efficient routing heuristics have been proposed to maximize sensor networks lifetime such as capacity maximization (CMAX) and Online Maximum Lifetime heuristics (OML).

In order to evaluate these two heuristics, intensive researches has been conducted. One research was based on the Uniform distribution. Another research took the same concerns using Poisson distribution. These two researches worked on 1D space. A recent research was proposed to evaluate the OML and CMAX heuristics in 3D space. All of these researches agreed on the superiority of OML over CMAX heuristic.

The type of distribution for sensor nodes gives us detailed information about the nature of application requirements. In other words, the accuracy of experimental results will be defected if the distribution was wrongly chosen. While trying to make fair comparison between routing protocols, major attention should be paid to the deployment strategy effect. This leads us to concentrate on the way that sensor network's deployment is simulated which is the major achievement in this thesis work.

In this thesis, in order to better represent real life terrains, four different types of single distributions were studied. In three-dimensional (3D) space, those distributions (Uniform, Poisson, Normal, and Chi-square) were used to generate a Directed Acyclic Graph (DAG) to simulate the connectivity of random deployed WSN.

Furthermore, we considered the multi-tone terrain changes and study its effect on the existing routing heuristics (namely OML and CMAX) in 3D space. For simulating Heterogeneous environments, 2-Hetro- and 4-Hetro-Distributions, were implemented.

Our experimental results showed that the average lifetimes provided by OML and CMAX change as we change the deployment strategy. Using 2-Hetro-Distributions, Noraml_Poisson (NP) distribution was the best case for both OML and CMAX heuristics, the average lifetime for OML and CMAX were about 64209 and 2251 respectively. In 4-Hetro-Distributions, the best case for applying OML heuristic is when using the Normal_Poisson_Chi-square_Uniform (NPCU) distribution with average lifetime more than 487418, and CMAX showed the best average lifetime when based on Chi-square_Normal_Poisson_Uniform (CNPU) distribution with more than 1038 average lifetime.

Results of 2-Hetro-Distributions revealed the superiority of OML over CMAX heuristic in most of the cases. But unlike previous researches, slight improvement was shown by CMAX over OML when Chi-square_Normal (CN) distribution is used, with improvement ratio more than 7%. Also, improvement in the average lifetime equals to 38.63% is provided by CMAX when sensor nodes were deployed in a Chi-square_Poisson (CP) terrain. In 4-Hetro-Distributions, the best case for applying OML heuristic is when using the Normal_Poisson_Chi-square_Uniform distribution (NPCU) with improvement ratio up to 99.82% over CMAX. Results of Chi-square_Poisson_Normal_Uniform (CPNU) distribution pointed out that CMAX heuristic is providing better average lifetime than OML heuristic, with unexpected improvement ratio up to 65.48%. As evident by the results of this work, it is proven that Heterogeneity of real life terrains (i.e. multi-tone terrain changes) has a major effect on the lifetime routing in Wireless Sensor Networks (WSN).

INTRODUCTION

Introduction

1. Wireless Sensor Networks Overview

Low cost, low-power, small-sized multifunctional sensor nodes has been recently developed as a result of advances in digital electronics, wireless communication, and micro-electromechanical systems (MEMS). These tiny sensor nodes, which consist of sensing, data processing, and communicating components, leverage the idea of sensor networks based on collaborative effort of a large number of nodes, (I.F. Akyildiz, 2002).

Sensor nodes are capable to sense, process data, and communicate with each other via one or more CPUs, microcontrollers or DSP chips using a RF signals. Power is applied to sensor nodes in different forms such as batteries and solar cells or using sensors actuators, (M. Ilyas and I. Mahgoub, 2004).

Sensor networks are improving traditional sensors by achieving the goal of having large number of nodes that cooperate together; this feature gives the advantage of having some sensors that can perform only sensing. In addition to that, we can deploy sensors far from the actual phenomenon -called sense perception- where complex techniques used by large sensors to distinguish the targets from environmental noise.

1.1. Applications of Sensor Networks

Many different types of sensors may be deployed in Wireless Sensor Networks (WSNs) such as thermal, seismic, low sampling rate, magnetic, visual, infrared, acoustic, and radar. Sensor networks are used for monitoring in several domains such as: temperature, vehicular movement, the presence or absence of certain kinds of objects, mechanical stress levels on attached objects, soil makeup, lightning condition, and noise levels.

Having the advantage of wireless connection, along with the ability of micro-sensing, sensor nodes promise many new application areas, (I.F. Akyildiz, 2002). Applications for sensor networks can be categorized into military, environment, health, home and other commercial areas. More categories can be classified as space exploration, chemical processing and disaster relief. There are some specific applications that deploy wireless sensor networks such as: object tracking, habitat monitoring, traffic monitoring, monitoring medical and environmental events, nuclear reactor controlling, and fire detection.

1.2. Technical Challenges

Sensor networks are classified under ad hoc wireless networks. Conserving energy of un-rechargeable batteries is considered as the most challenging issue in sensor networks, (I.F. Akyildiz, 2002). Mainly, there are three purposes that consume power in sensor networks those are: hardware operation, signal processing, and data transmission. Therefore, many studies focused on improving the energy efficiency in order to deal with that issue.

Although many protocols and algorithms have been proposed for traditional wireless ad hoc networks, they do not well suit the unique features of sensor networks. This is due to the fact that the number of sensor nodes in an ad hoc network can be several orders of magnitude lower than the nodes in a sensor network. Another characteristic that is not present in general ad hoc networks is the densely deployed sensor nodes which are prone to failures.

In addition, the topology of a sensor network changes very frequently, because sensor nodes are limited in power, computational capacities, and memory. Furthermore, Sensor nodes mainly use broadcast communication paradigm whereas most ad hoc networks are based on point-to-point communications.

1.3. Power Aware Routing in WSN

In wireless sensor networks, large number of sensor nodes is densely deployed. As a result, neighbor nodes may be very close to each other. That is why, low levels of transmission power is achieved by multihop communication. In addition to short-range broadcast communication and multihop routing, sensor networks have frequently changing topology due to fading and node failures, limitations in energy, memory, transmit and computing power, (I.F. Akyildiz, 2002).

A sensor network is designed to monitor a wide variety of ambient conditions (such as detecting pressure, heat, or humidity in wild life). Then, after collecting and processing data, sensors transmit sensed information to concerned users, (I.F. Akyildiz, 2002).

According to WSN's application, sensor nodes can be deployed in deterministic manner or randomly. In disaster relief operations or inaccessible terrains, random deployment is needed; this means that the position of sensor nodes can not be pre-defined which leads to the fact that protocols in sensor networks must be self-organized*. Also, sensor networks provide the ability for sensors to transmit a partially locally processed data instead of sending the raw data to the fusion-responsible nodes.

Power consumption is thought of to be one of the most important requirements in wireless sensor networks, (Anastasi et al., 2009). If no power management schemes are used, two AA batteries provide only few days lifetime for very active nodes. In most of the systems, this is considered to be very far from the required lifetime needed for sensors.

In addition to the functional requirements to be considered and met, significant researches has been undertaken to increase lifetime. Lifetime is defined as the successfully routed messages before the first failed message route. The main issue is that message routing in wireless sensor networks is done through battery operated sensors, this makes the critical applications assume that batteries are either recharged or replaced, (Sahni, 2006).

Recently, some heuristics which try to delay the early depletion of sensors energy were proposed, such as the Online Maximum Lifetime (OML), Maximum Residual Packet Capacity (MRPC), and Capacity Maximization (CMAX) heuristic were designed to maximize the lifetime of sensors in WSN, (Misra 2002), (K. Kar, 2003), (Sahni, 2006).

* Self-organizing sensors are sensor nodes that can spontaneously create impromptu network, assemble the network themselves, dynamically adapt to device failure and degradation, manage movement of sensor nodes, and react to changes in task and network requirements.

In our study, we will consider two routing heuristics, those are: CMAX and OML. Using admission control, CMAX rejects some routes that are possible. As a modification for CMAX, OML heuristic was proposed. OML recommends to delay as much as possible the depletion of a sensor's energy to a level below that needed to transmit to its closest neighbour. This is achieved by employing two shortest path computations to route each message, (Sahni, 2006).

The deployment of sensors on which the characteristics (lifetime) of the aforementioned routing protocols is based on a uniform environment. A comparison between MRPC, OML, and CMAX heuristics indicates that deployment strategy affects their characteristics, (Al-Sharaeh et al., 2009). The results of the study showed that the OML heuristic has superiority over the CMAX and the MRPC heuristics in terms of average lifetime, and network capacity.

In this thesis, we will study the deployment strategy effect on the WSN routing protocol metrics. Our work will include four well known distributions namely: Uniform, Poisson, Normal, and Chi-square distribution.

In addition to single distributions, our strategy takes in consideration real life environment such as multi-tone terrain changes (Heterogeneous Environment). In order to better represent real life environment, Two-Hetro-Distributions and Four-Hetro-Distributions were used. Basically, WSN were deployed in three-dimensional environment.

The study also includes the dimension effect (1D and 3D) on the lifetime performance metric.

2. Thesis Objectives

This study is conducted to achieve the following:

- Implementing and analyzing the existing heuristics using single distributions including Uniform, Poisson, Normal, and Chi-square distribution.
- Implementing and analyzing the existing heuristics using 2-Hetro-Distributions.
- Implementing and analyzing the existing heuristics using 4-Hetro-Distributions.
- Comparing the results of one-dimensional and three-dimensional environment and studying the dimension effect.
- Comparing the results of single distributions, 2-Hetro-Distributions, 4-Hetro-Distributions and studying the effect of average lifetime, and effect of distribution route on lifetime maximization.

3. Thesis Overview

This thesis is organized as follows. In Chapter One, a problem overview, types of applications, technical challenges that face sensor networks system, power aware routing methods, and finally, the main objectives for the proposed system are discussed. In Chapter Two, other existing heuristics and studies in the literature for maximizing lifetime routing using 1D single distribution are reviewed. The description of maximizing lifetime routing using Uniform, Poisson, Normal, and Chi-square distribution and their effect on the connectivity of sensors and the required energy to transfer packets from one sensor to another using search methods will be illustrated in maximizing lifetime routing heuristics in Chapter Three. Experiments and the evaluation of the results for the new heuristic using different types of distribution in single, 2-Hetro, and 4-Hetro distributions are given in Chapter Four. Chapter Five includes thesis conclusion and suggested future studies.

LITERATURE REVIEW

Literature Review

1. Overview

Over the past few decades, due to the fact that power limitation in wireless sensor networks (WSN) is a great challenge, most of the researches were proposed to maximize network lifetime. For this purpose, energy-efficient algorithms have been studied and many techniques were presented to either maximize the capacity like (K. Kar 2003), or the lifetime of the network, (Sahni, 2006). Some of these researches will be discussed in the next section.

Many researchers used balancing formulations for maximizing the lifetime of sensor networks for example, (Chang and Tassiulas 2000), (Toh 2001) and (Wu 2002). Some researchers achieved lifetime maximization for sensor networks using energy-efficient routing algorithms such as, (Misra and Banerjee, 2002).

Other researchers assumed that, the distribution type is a key issue to maximize lifetime for wireless sensor networks. In order to better fit real life terrains they used Poisson distribution, like (Al-Sharaeh et al., 1996) and (Al-Sharaeh et al., 2009)

2. Related Works

In Al-Sharaeh(Al-Sharaeh et al., 1996) paper, researchers discussed the use of Poisson distribution in order to solve the scheduling problem and determine which heuristic better fits the real-world systems. According to their study, they found that Poisson distribution give a better description for real environment when compared to the task graph of shuttle space main engine.

Singh et al. (Singh, 1998) proposed five metrics that maybe used in selecting the routing path for energy efficient routing. The first metric is to use a minimum-energy path from source node s to destination node t (i.e. the sum of the edge weights is minimum), which can be computed using a shortest path algorithm. But using a minimum-energy path for the current route request may result in routing failure in future transmissions.

The other four metrics are, maximize time to network partition, minimize variance in node energy levels, minimize the node cost of each transmission[†], and minimize maximum node cost. The first (minimum-energy path) and the fourth (minimize node cost), raise concerns about the difficulty of implementing the remaining three metrics in a routing protocol.

In Heinzelman (Heinzelman 2000), they proposed clustering-based algorithm (LEACH) for sensor networks, which is a protocol to utilize randomized rotation of cluster-

[†] The cost of a node is some function of the amount of energy used so far by that node

heads in order to distribute the energy load among the sensor network. Localized coordination is used to enable robustness and scalability for dynamic networks. To reduce the amount of information that must be transmitted to the base station, LEACH incorporates data fusion into the routing protocol. As it is able to distribute energy dissipation evenly throughout the sensors, LEACH algorithm could increase the useful system lifetime for the network to the double.

Meanwhile, in Chang (Chang and Tassiulas 2000), linear programming formulation for maximizing lifetime was developed. The rate of each node to generate messages is needed for the formulation. The assumption states that the single important resource is the limited battery energy. Hence, instead of routing to minimize the absolute consumed power, the traffic is routed in a way to balance the energy consumption among the nodes in proportion to their energy reserves.

After that, Toh (Toh 2001) developed two online algorithms to select a source-to-destination path, the MMBCR (min-max battery cost routing) and CMMBCR (conditional MMBCR). To maximize lifetime MMBCR need to achieve some balance between the maximum residual energy at the nodes along the chosen path P, and the energy consumed by a route. CMMBCR (conditional MMBCR) looks for source-to-destination path with minimum energy, in which every sensor has a residual energy more than Y (Y is a threshold that represents energy units). Otherwise, if there is no path from source to destination that satisfies this property, then MMBCR is used instead.

One year later, A. Misra (A. Misra et al., 2002) proposed the MRPC (maximum residual packet capacity), a power-aware routing algorithm for maximizing lifetime. MRPC is an energy-efficient routing algorithm that increases the operational lifetime of multi-hop wireless network. MRPC uses two aspects to identify node's capacity these are, node's residual battery energy and the expected energy spent in reliably forwarding a packet over a specific link. This captures scenarios where link transmission costs depend on link error rates and physical distances between nodes. MRPC algorithm uses min-max formulation to select the path that has the largest packet capacity at 'critical' node (the node with the smallest residual packet transmission capacity) in the selected path.

Contemporarily, (Wu, 2002) have investigated routing based on the selection of the connected dominating sets to maximize network lifetime. Selection of the dominating sets is based on the node degree and energy level of each host. The goal is to provide a selection scheme that balances the overall energy consumption in the network, and generate a relatively small connected dominating set at the same time.

CMAX (capacity maximization) is an online capacity-competitive algorithm, proposed in (K. Kar 2003). They defined capacity as, the number of messages routed over some time period. To achieve a logarithmic competitive ratio, the algorithm CMAX does admission control. That is, some possible routes are rejected.

Consequently, Aslam (Aslam 2003) mentioned that for lifetime maximization problem, there is no on-line algorithm with a constant competitive ratio O(n)[‡] to the optimal off-line algorithm. In large wireless ad-hoc networks for applications where the message sequence is unknown, Aslam discussed the online power-aware routing; the author has shown that it is impossible to design an on-line algorithm that has a constant competitive ratio to the optimal on-line algorithm.

After that, (Stojmenovic and Lin, 2004) developed localized algorithms to maximize lifetime, they combined both nodes lifetime and distance based power metrics to give out a new power cost metric. Researchers also investigated some properties of power adjusted transmission and showed that, if additional nodes can be placed at desired locations between two nodes at distance d, the transmission power can be made linear in that distance d. Their investigation provides basis for cost, power, and power-cost localized routing algorithms. Location of node's neighbours and destination are the two bases for each node to make routing decisions solely.

In Y. Hou (Y. Hou et al., 2005) studied the network lifetime by considering Lexicographic Max-Min (LMM) node lifetime problem. LMM concerns about not only maximizing the time until the first node fails, but also maximizing the lifetimes for all nodes in the network. Two contributions are considered, first to develop a polynomial-time algorithm to determine LMM-optimal node lifetime vector. Second, to present another polynomial-time algorithm to calculate the flow routing schedule such that the MML-

[‡] The competitive ratio of an online algorithm is the ratio between the performance of that algorithm and the optimal online algorithm that has access to the entire execution sequence prior to making any decisions.

optimal node lifetime vector can be achieved. This paper provides an improvement to the state-of-the-art algorithmic design for network-wide node lifetime problem.

After that, (J. Park and S. Sahni, 2006) proposed OML (Online Heuristic for Maximum Lifetime Routing) heuristic, in which future route is not needed to be indicated in order to send a message. To determine the effect of transmission radius on the performance of OML heuristic, they used ten networks each is randomly obtaining sensors in 25*25 grid, considering that for each network there will be 10 route requests to be generated. The objective of OML heuristic is to maximize network lifetime which is accomplished using a two-step algorithm to find the path for each routing request. Results show that OML heuristic is superior on the capacity metric. Additionally, it results in greater lifetime and its performance is less sensitive to the selection of heuristic parameters.

Two years later, (Al-Sharaeh et al., 2008) introduced a Multi-Dimensional Poisson Distribution Heuristic to better evaluate the routing heuristics; by taking in consideration earth's terrain and the multi-dimensional concept. This is done by the way they generate the placement of the sensors as well as the interconnection between sensor nodes. A major effect on the performance of different routing heuristics was gained. Mainly, though OML has superiority over CMAX, CMAX shows resilience to terrain changes.

Recently, (Al-Sharaeh et al., 2009) investigated the performance of three heuristics: (OML, MRPC, and CMAX), in order to study the effect of Poisson distribution on maximizing wireless sensor networks lifetime. Their simulation results show that the OML heuristic has superiority over the CMAX and the MRPC heuristics in terms of average lifetime and network capacity. The experiments indicate that the average lifetime when using Poisson distribution is less than the average lifetime when using Uniform distribution, due to the clustering of nodes around the mean.

MAXIMIZING LIFETIME ROUTING HEURISTICS IN WIRELESS SENSOR NETWORKS

Maximizing Lifetime Routing Heuristics in Wireless Sensor Networks

Sensor network model in the perspective of programming, the use of three-dimensional, different types of statistical distribution, maximum lifetime routing heuristics, and implementation of power aware routing heuristics will be studied in this chapter.

1. Sensor Network Model

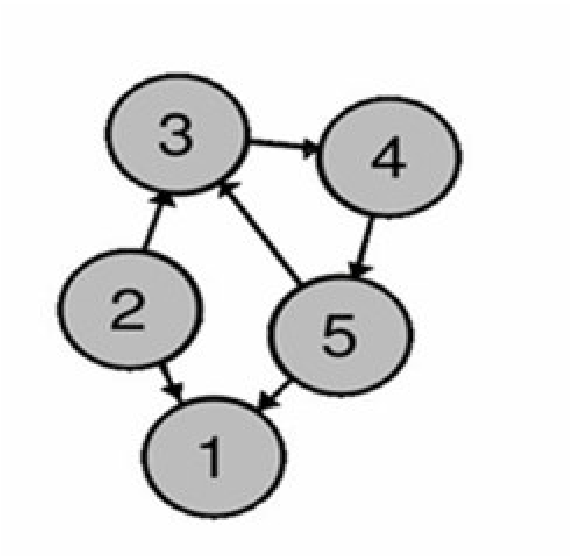
Using a directed graph *G= (V, E),* a wireless sensor network is described, where *V* is the set of nodes, and *E* is the set of edges between these nodes. For modeling Wireless Sensor Networks (WSN), a directed edge from node v to node u exists, if a single-hop transmission form node *v* to node *u* is possible. The current energy in transmitter sensor u is $c_e(u)$, for each edge in the graph (v, u)∈E. In case of single hop transmission from sensor *u* to sensor *v*, $c_e(u)$ is represented by Equation (3.1) (Sahni, 2006).

$$c_e(u) = c_e(u) - w(u,v) \tag{3.1}$$

Where v is the destination sensor node, and $w(u,v)$ is the energy required to make a single hop transmission from sensor u to sensor v, such that $w(u,v) > 0$, and $c_{e(u)} \geq w(u,v) > 0$. The current energy in sensor v is unaffected by the transmission from (*u*) to (*v*), because in (Sahni, 2006) paper they assume that no energy is consumed during message reception.

An adjacency matrix can be used to represent directed graphs of WSN (Sahni, 2006; Al-Sharaeh, et al., 2008; Al-Sharaeh, et al., 2009). The adjacency matrix of a finite directed graph *G* on n vertices (where n is the number of vertices in *G*), is the $n \times n$ matrix such that, the diagonal entry a(i, i) is assigned by zeros, because here we assume that there is no internal loops in the WSN. The existence of an edge from sensor i to sensor j is represented by a non-diagonal entry a(i, j)= 1, otherwise a(i, j)=0.

In our experiments, directed graph was used to represent sensor network, For example, Figure 3.1(a) shows a simple representation for sensor network N. As, can be seen from the figure, the nodes are representing sensors, and the edges represent the existence of single-hop communication between the sensor nodes. The adjacency matrix of the sensor network N is shown in Figure 3.1(b).



	1	2	3	4	5
1	0	0	0	0	0
2	1	0	1	0	0
3	0	0	0	1	0
4	0	0	0	0	1
5	1	0	1	0	0

(a): Simple graph network representation (b): Corresponding adjacency matrix

Figure 3.1: Representation of Wireless Sensor Network (N)

We can notice from Figure 3.1(b) that the network N has been implemented using 1D (one dimension) to represent locations for sensor nodes. In (Al-Sharaeh, et al., 2009), such representation for sensors has been used. But in this work, basically we represent sensors using 3D (three dimension) space; each sensor is represented using three dimensions: X, Y, and Z, in order to get more realistic results (Al-Sharaeh, et al., 2008).

2. Use of Three-Dimensional:

In the literature, the known method is to use one dimension for representing sensor nodes. A better description for real environment can be gotten by using 3D instead of 1D to represent the position for each sensor in the network, (Al-Sharaeh, et al., 2009).

In this work, we explored the use of 3D in representing sensor nodes positions, in order to better represent real life terrains. Furthermore, to get even better description for real environment, we investigated different distribution types, those are: Uniform, Poisson, Normal, and Chi-square distributions. Each of these distributions will be investigated separately in 1D, 2D, and 3D.

To implement the 3D representation for sensor nodes locations, three dimensions X, Y, and Z will be used. Connectivity between sensors in 3D space is implemented, such that; the sensor node (s) is considered to be connected to sensor (t) only if the cell in the adjacency matrix for the cross point of row (s) and column (t) holds the value 1. In 3D space, the existence of value 1 in the adjacency matrix's cell, using Poisson distribution for example, depends on satisfying the condition that; each of X, Y, and Z axis should be greater than or equals to the corresponding mean value of Poisson distribution.

3. Statistical Distributions

Several types of statistical distribution procedures exist according to the purpose of analysis. Furthermore, almost every real life system contains such resources of randomness. The accuracy of experimental results will be defected if the distribution was wrongly chosen, (M.Law & Kelton, 2000). The type of sensor nodes distribution gives us detailed information about the nature of application requirement. It also indicates how each source sensor node communicates with destination sensor nodes.

In this work, all subsequent formulas of the statistical functions are given for the standard form, since the general form of probability functions can be expressed in terms of the standard distribution[§]. Four types of distribution, Uniform, Poisson, Normal, and Chi-square distribution, are studied in the following sections. These distributions are implemented using 3D (three dimension) space to represent the positions for sensor nodes.

[§] All statistical distributions were referenced from: *NIST/SEMATECH e-Handbook of Statistical Methods*, http://www.itl.nist.gov/div898/handbook/, June-2009.

3.1. Uniform Distribution

Most of the performed simulations in literature are based on distributing the sensor nodes randomly using uniform distribution, (Kar 2003) and (Sahni 2006). Uniform distribution of sensors best fits the symmetric environment where the lands are flat and there are no geographical differences in terrains. Equation (3.2) expresses the general formula for the probability density function of the uniform distribution.

$$f(x) = \begin{cases} \dfrac{1}{b-a} & \text{for } b \leq x \leq a \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

With a <b, where (*a* and *b*) are real numbers, (a) is the location parameter and (b-a) is the scale parameter. Standard Uniform distribution, as expressed by Equation (3.3), is defined where a=0 and b=1. Figure 3.2 illustrates the probability distribution for Uniform distribution.

$$f(x) = 1 \qquad \text{for } 0 \leq x \leq 1 \tag{3.3}$$

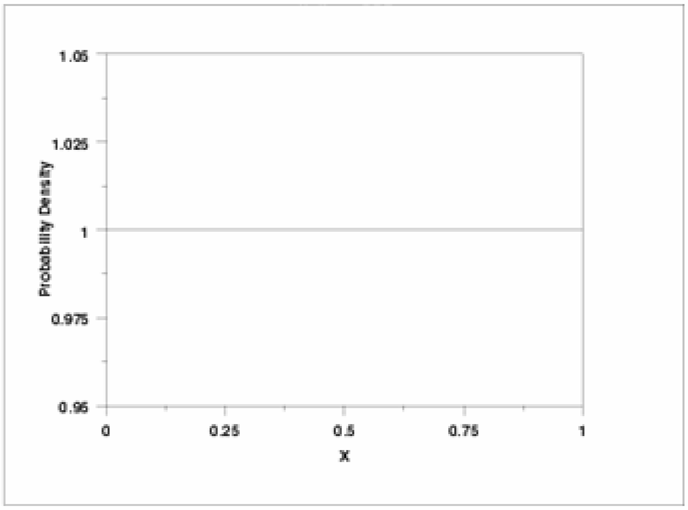


Figure 3.2: Probability Distribution Function for Uniform Distribution

As described by Figure 3.2, Uniform is a distribution that has constant probability, which means that sensor nodes are evenly distributed. This is shown in Figure 3.3.

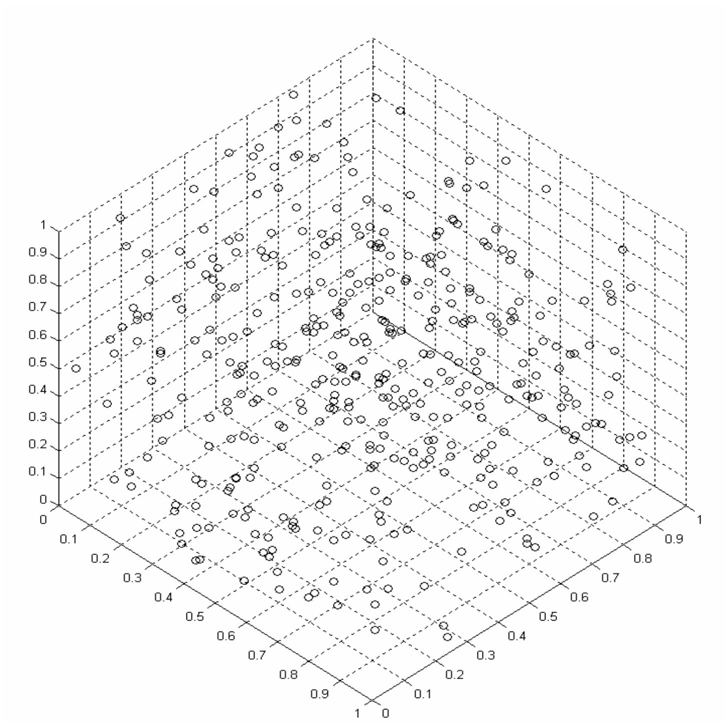


Figure 3.3: 3D Sensor Nodes Distribution Based on Uniform Distribution

3.2. Poisson Distribution

Real environment is characterized by terrain changes, which is hard to be handled using Uniform distribution. That is due to the fact that the use of Uniform distribution causes sensor nodes to be evenly distributed. In order to represent the train changes, Poisson distribution is used, as it has the nature of best fitting the asymmetric environment (Al-Sharaeh, et al., 2008; Al-Sharaeh, et al., 2009). The Poisson distribution is used to model the number of events occurring within a given time interval. The Poisson distribution function is given by Equation (3.4), and Figure 3.4 expresses the Poisson probability distribution function for four values of the shape parameter λ.

$$p(x,\lambda) = \frac{e^{-\lambda}\lambda^{x}}{x!} \qquad \text{for } x = 0,1,2,\ldots \tag{3.4}$$

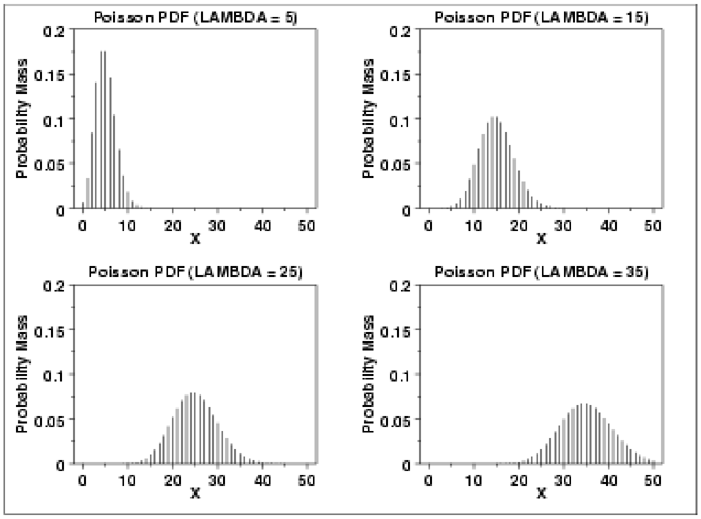


Figure 3.4: Probability Distribution Function for Poisson Distribution

Where λ is the shape parameter which indicates the average number of events in the given time interval. Poisson distribution is appropriate for applications that involve counting the number of times a random event occurs in a given amount of time, distance, or area, etc. Therefore, Poisson distribution is used in some environmental applications, such as: detecting earthquakes, battlefields, and volcanoes detection application. Figure 3.5 shows sensor nodes distribution based on Poisson distribution, it is clear that sensors are concentrated around the mean. This kind of deployment fits the case where sensors are deployed via airplane in a terrain that is close to valleys.

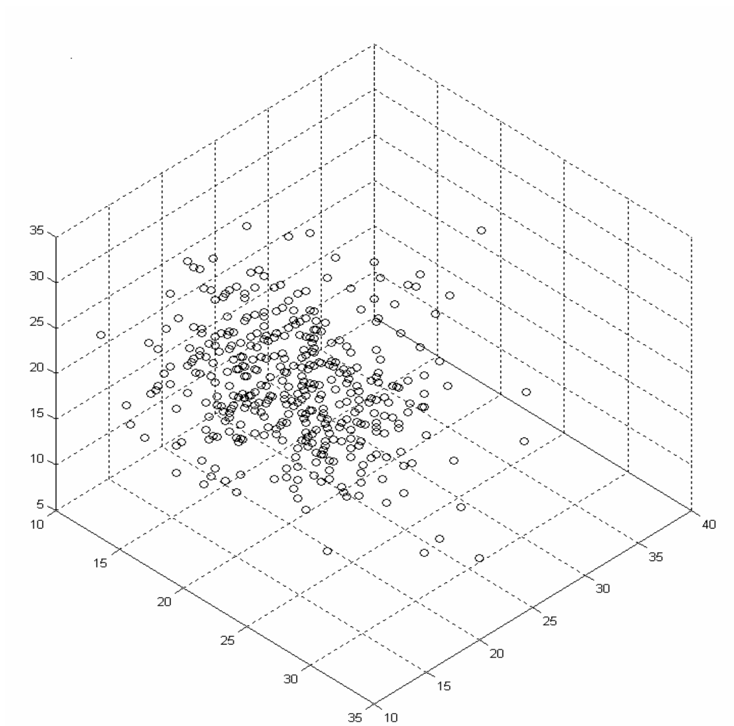


Figure 3.5: 3D Sensor Nodes Distribution Based on Poisson Distribution

3.3. Normal Distribution

Another alternative way of deploying sensor nodes is the Normal distribution. Normal distribution better represents geographical differences in terrains. Unlike Poisson distribution, Normal distribution of sensors best fits the environment where the lands are not flat but there are some symmetric geographical differences in terrains. Equation (3.5) expresses the probability distribution function of the Normal distribution.

$$f(x) = \frac{e^{-(x-\mu)^2/(2\sigma^2)}}{\sigma\sqrt{2\pi}} \tag{3.5}$$

Where μ is the location parameter and σ is the scale parameter. The case where $\mu = 0$ and $\sigma = 1$ is called the standard normal distribution. The standard normal distribution is expressed by Equation (3.6). Normal probability distribution function is illustrated in Figure 3.6.

$$f(x) = \frac{e^{-x^2/2}}{\sqrt{2\pi}} \tag{3.6}$$

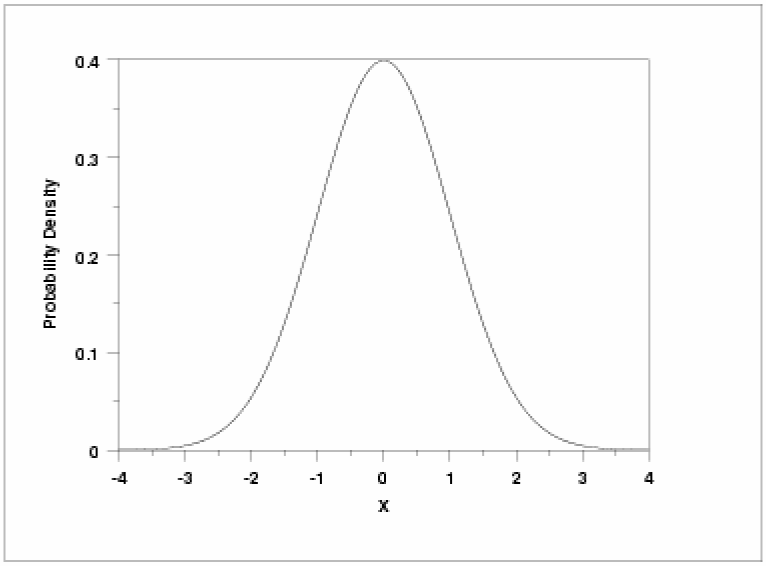


Figure 3.6: Probability Distribution Function for Normal distribution

Figure 3.7 shows sensor nodes distribution in three dimensional space based on Normal distribution. From the figure, it can be noticed that sensors locations are concentrated but in symmetric form.

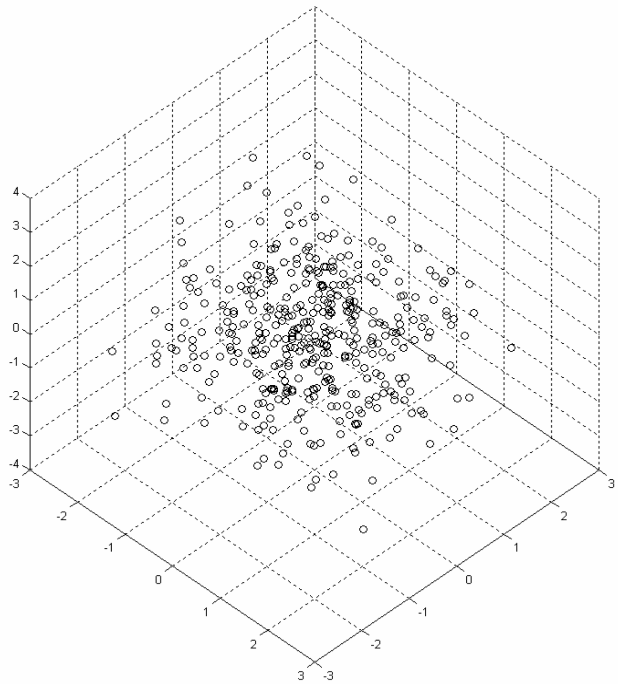


Figure 3.7: 3D Sensor Nodes Distribution Based on Normal Distribution

3.4. Chi-square Distribution

The fourth distribution we used in this thesis work is the Chi-square distribution. Using Chi-square distribution, sensor nodes are scattered in random manner, with concentration in some places while having few number of sensors in other places. Chi-square distribution results when ν independent variables with standard normal distributions are squared and summed. The formula for the probability distribution function of the chi-square distribution is shown by Equation (3.7). Where ν is the shape parameter and Γ is the gamma function.

$$f(x) = \frac{e^{\frac{-x}{2}} x^{\frac{\nu}{2}-1}}{2^{\frac{\nu}{2}}\Gamma(\frac{\nu}{2})} \qquad \text{for } x \geq 0 \tag{3.7}$$

Where the gamma function is expressed by Equation (3.8)

$$\Gamma(a) = \int_0^\infty t^{a-1} e^{-t} dt \tag{3.8}$$

Figure 3.8 shows the Chi-square probability distribution function for 4 different values of the shape parameter.

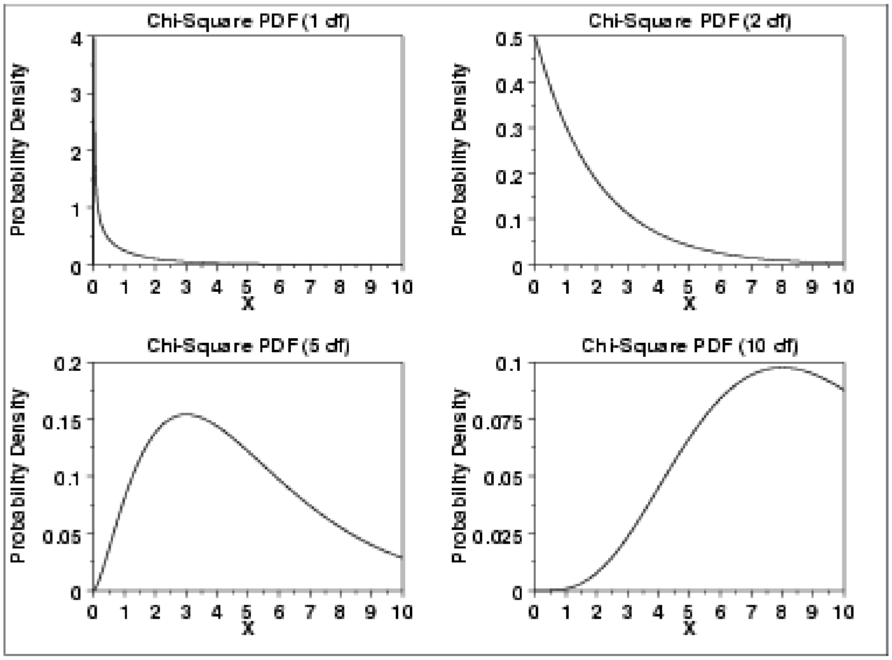


Figure 3.8: Probability Distribution Function for Chi-square Distribution

Like Poisson distribution, Chi-square distribution represents hard terrain environments that have geographical changes. A major difference between Chi-square distribution and Poisson distribution is that in Chi-square distribution sensors are more concentrated in the left side of the mean. This leads to the fact that Chi-square distribution is used for representing an environment with terrains harder than that represented by Poisson distribution, as shown in Figure 3.9.

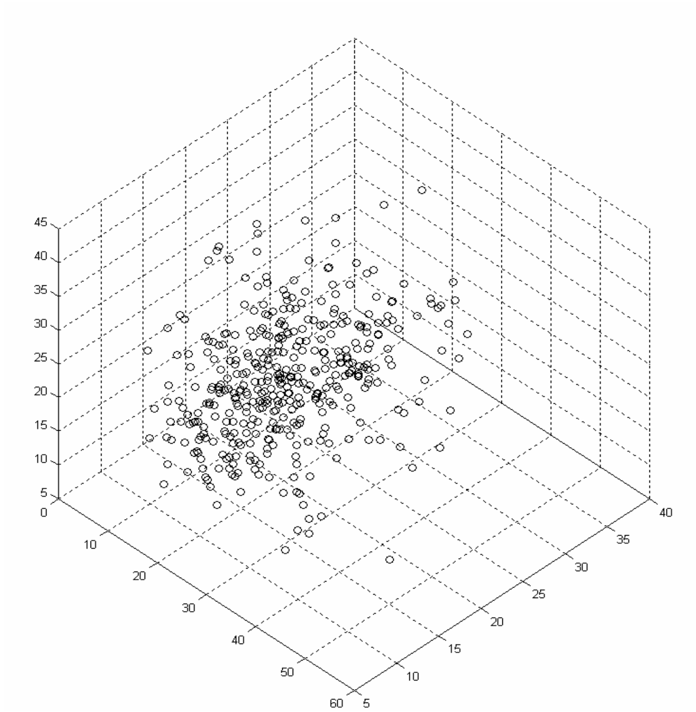


Figure 3.9: 3D Sensor Nodes Distribution Based on Chi-square Distribution

3.5. Example of Wireless Sensor Network Application:

Nowadays, sensor deployment applications are widely used, one of these applications is Tsunami Warning System (TWS). Tsunamis defined as a series of very long waves generated by any rapid, large-scale disturbance of the sea. Most are generated by sea floor displacements caused by undersea earthquakes, volcanic eruptions and other underwater explosions. Thus, great destruction and loss of lives within minutes on shores near the source may be caused by Tsunamis. The basic design for Tsunami Warning System consisted of four components: (1) a bottom pressure recorder (BPR), (2) an acoustic link (3) a surface buoy equipped with (4) a satellite telecommunications capability (Yilmaz M., 2004), as shown in Figure 3.10.

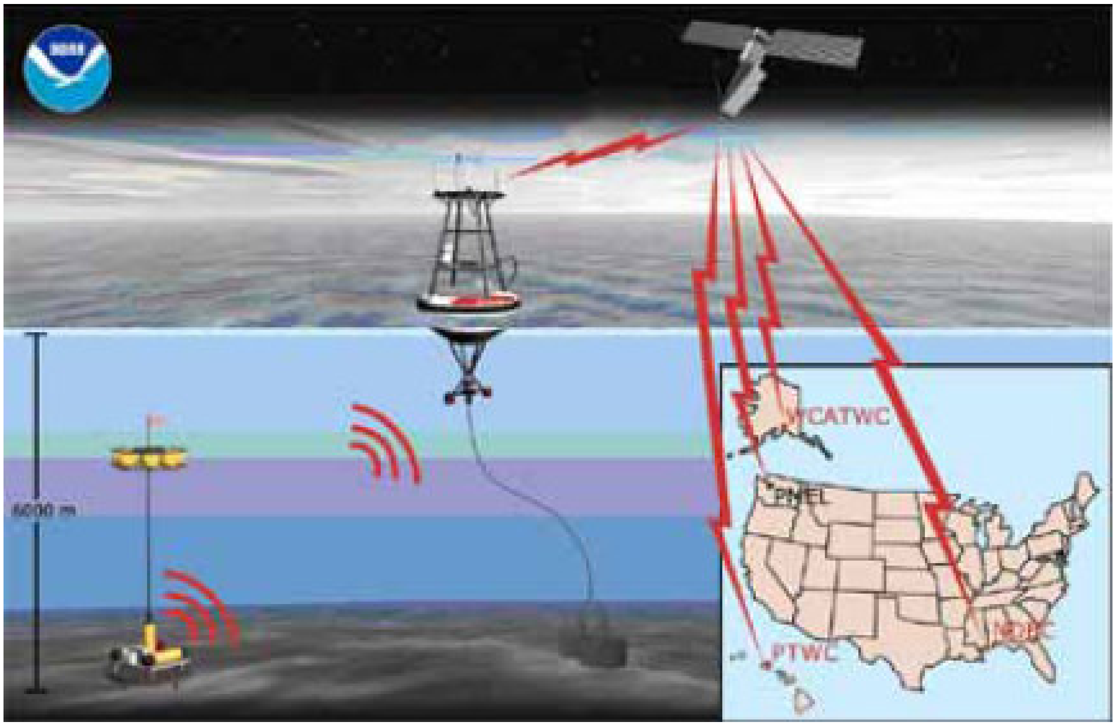


Figure 3.10: Tsunameter For Pacific Network, (Yilmaz M., 2004).

The bottom pressure recorder is the main sensing element. Continuously, this sensor monitors pressure, once the pressure reading changes above a specified threshold, the tsunameter automatically transmits data to a surface buoy. Then the surface buoy makes a satellite connection to Tsunami warning centers to evaluate the threat and issue a tsunami warning. In this application, positions of sensor nodes are previously engineered and not randomly deployed.

3.6. Example of Heterogeneous Terrains Application:

Another application for wireless sensor networks is avalanching predictions. This application requires random distribution for sensor nodes. In order to make full coverage, all the challenges that may face sensor network deployment are portrayed by mountainous terrains. Therefore, when considering the fact that real life environment is featured with terrain changes; deployment strategy should have a major effect on evaluating a routing heuristic. In this thesis work, we study the deployment strategy effect on the WSN routing protocol metrics. Our strategy takes in consideration real life environment such as multi-tone terrain changes (Heterogeneous Environment). Figure 3.11 shows the landscape of typical environment that ranges from flat land, hilltop, cliffs, valleys, to mountains top.

Figure 3.11: Mountains Terrains for Avalanche Detection WSN Application.

It is obvious from the figure that the space to be covered by sensor nodes is heterogeneous. As we are trying to make fair comparison between the two routing protocols (OML and CMAX), major attention should be paid to the deployment strategy. To achieve this goal, we concentrate on the way that sensors network deployment is simulated. For that, the random graph that both simulate the position as well as the connectivity between sensor nodes is generated in a form that fits multi-tone terrain changes.

3.7. Implementation of Heterogeneous Terrains:

In order to get more realistic description for real environment, we investigate heterogeneous environment, by having more than single distribution in the deployment graph. A second goal to be achieved in this work is to point out if the deployment route (i.e. the order of distributions) does affect maximizing lifetime routing heuristics. For that, we investigated non-single distributions for wireless sensor networks. Heterogeneous distributions in this work are divided to two types, 2-Hero-distribution, and 4-Hetro-distribution.

In 2-Hetro-distribution, the space of deployment for sensors is divided to two equal halves each with different type of distribution. Distributions to be discussed here include: Uniform, Poisson, Normal, and Chi-square distribution. To match these four distributions into a 2-Hetro distribution, we will have 6 types of distributions which are: Uniform_Chi-square(UC), Uniform_Poisson(UP), Uniform_Normal(UN), Chi-squre_Poisson(CP), Chi-squre_Normal(CN), and Normal_Poisson(NP). Implementation for the Uniform_Chi-square(UC) distribution for example, will be by having Uniform distribution in the top of the graph with Chi-square distribution in the bottom.

In 4-Hetro-distribution, the space of deployment is divided into four quarters; each quarter has different type of distribution for network deployment. As a result for implementing each quarter with non-repeated distribution, we will have (4*3*2*1) that is 24 cases. This thesis will discuss six types of 4-Hetro-distributions, listed as: Poisson_Chi-square_Normal_Uniform(PCNU),Chi-square_Poisson_Uniform_Normal(CPUN), Normal Poisson_Chi-square_Uniform(NPCU),Poisson_Chi-square_Uniform_Normal (PCUN),Chi-square_Normal_Poisson_Uniform(CNPU), and Chi-square_Poisson_Normal_Uniform (CPNU).

For example the order of the Four-Hetro-distribution NPCU, is meant to be: Normal distribution is implemented in the top-left quarter, with Poisson distribution in the top-right, along with Chi-square distribution implemented in the bottom-left quarter, and finally the Uniform distribution position will be in the bottom-right quarter, as shown in Figure 3.12.

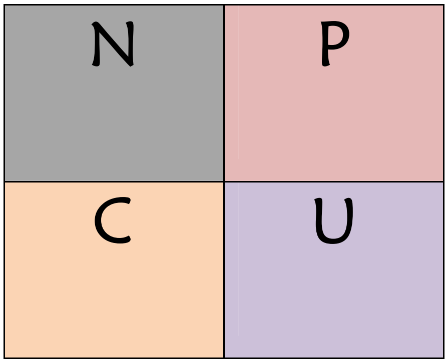


Figure 3.12: Normal_Poisson_Chi-square_Uniform Distribution

4. Maximum Lifetime Routing Heuristics

Data transmission in wireless sensor networks is battery operated. In addition, signal processing and hardware operation are thought of to be consuming energy. This is considered to be the most challenging issue, as the battery is neither replaceable nor rechargeable (Sahni, 2006). This is due to the fact that, most of the sensor networks are unreachable to be recharged or replaced after deployment, for example, deploying sensor networks in forests or battlefield. In our study, a very important metric to maximize lifetime in wireless sensor networks is energy conservation. Energy is conserved using multi-hop routing in wireless sensor networks, (Sahni, 2006). Hence, the sensor nodes between source (s) and destination (t) are used as relays. In order to consider real life environment such as multi-tone terrain changes, we have used two well known heuristics those are OML and CMAX heuristics.

4.1. CMAX Heuristic

The first heuristic used CMAX (capacity maximization) heuristic which makes admission control. That is, it rejects some routes that are possible (Kar, 2003). CMAX heuristic provides a single path for each message (i.e. no multiple paths are used), and all messages are assumed to be routed directly after the route is requested. Using CMAX (capacity maximization) heuristic, each link in the network is represented by a corresponding weight. When a message is routed through a link, the weight of that link is increased by the energy consumed to pass through that link; it is also increased by the energy spent by the transmitting node. The specification of the shortest path in CMAX heuristic is done with respect to the links weights. Using admission control, the CMAX heuristic can occasionally reject messages if they are considered to be too detrimental to the network's residual capacity.

Let a(u) be the percentage of the initial energy that has already been spent at the sensor node in the wireless sensor network. It can be calculated using Equation (3.9) as follows:

$$a(u) = 1 - c_e(u) / i_e(u) \tag{3.9}$$

While the weight of every edge (u,v) is renewed, as Equation (3.10) shows:

$$w(u,v) = w(u,v) * (\lambda c^{a(u)} - 1) \tag{3.10}$$

Where λ_c is an algorithm parameter and $(\lambda c^{a(u)} - 1)$ is the cost function for giving the edge weight. Then, in the resulting graph, the shortest path (p) from source to destination is determined. Figure 3.13 illustrates the CMAX Heuristic.

Heuristic 1: CMAX Heuristic

Step 1: [Initialize]

(a) Eliminate from G every edge (u, v) for which:

$$ce(u) < w(u,v)$$

(b) Change the weight of every remaining edge (u, v) to:

$$w(u,v) = w(u,v) * (\lambda_c{}^{a(u)} - 1)$$

Where λ_c is a heuristic parameter , a(u) is the percentage of the initial energy that has already been spent at the sensor node .

Step 2: [Shortest Path]

Let P be the shortest source-to-destination path in the modified Graph.

Step 3: [Wrap Up]

If no path is found in Step 2, the route is not possible. Use P for route if its length is less than σ.

Figure 3.13: CMAX Heuristic

To implement heterogeneous terrains, some modifications were done on CMAX heuristic. For example, CMAX based on the Four-Hetro-distribution Normal_Poisson_Chi-square_Uniform Distribution (NPCU) is illustrated in Figure 3.14.

Heuristic 2: CMAX Heuristic based on NPCU Distribution

Assumption: The graph in which sensor nodes are deployed is divided to four quarters.

In 1st quarter: sensors are distributed using Normal distribution.

In 2nd quarter: sensors are distributed using Poisson distribution.

In 3rd quarter: sensors are distributed using Chi-square distribution.

In 4th quarter: sensors are distributed using Uniform distribution.

For each routing request $r_i = (s_i, t_i)$ two steps are done:

Step 1: [Initialize]

(a) Eliminate from G every edge (u, v) for which:

$$ce(u) < w(u,v)$$

(b) Change the weight of every remaining edge (u, v) to:

$$w(u,v) = w(u,v) * (\lambda_c^{a(u)} - 1)$$

Where λ_c is a heuristic parameter , a(u) is the percentage of the initial energy that has already been spent at the sensor node .

Step 2: [Shortest Path]

Let P be the shortest source-to-destination path in the modified Graph.

Step 3: [Wrap Up]

If no path is found in Step 2, the route is not possible. Use P for route if its length is less than σ.

Figure 3.14: CMAX Heuristic Based on NPCU Distribution

4.2. OML Heuristic

The other heuristic is OML (Online Maximum Lifetime). With OML heuristic, in order to route each message, two shortest path computations must be employed. To maximize lifetime, it is recommended to delay as much as possible the depletion of a sensor's energy to a level below that needed to transmit a message to its closest neighbour (Sahni, 2006). OML heuristic is an enhancement of the CMAX heuristic that uses a two-step approach where they remove those edges with low energy from the graph. Then, run Dijkstra's to find the shortest path on a graph where the edge weights have been modified in such a way that the paths found usually use nodes with high energy levels and edges with low energy costs.

To maximize lifetime, OML accomplishes two steps to find a path for each routing request $r_i = (s_i, t_i)$. In the first step, all edges with current energy, such that $c_e(u) < w(u, v)$ are removed from (G). That's because, these transmission requires more energy than available for the edges. Let the resulting graph be G = (V, E). Next, use shortest path algorithm to determine the minimum energy path $P`_i$ from $(s)_i$ to $(t)_i$ in graph G`. If there is no path for (s) to (t), then the routing request fails. But if routing request exists, then minimum energy path P` is used to compute the residual energy, Equation (3.11) illustrates how to compute it.

$$re(u) = ce(u) - w(u,v) \tag{3.11}$$

Equation (3.12) shows how the minimum residual energy minRE is calculated.

$$minRE = \min\{re(u) \mid u \text{ in } P\} \tag{3.12}$$

Let G`` = (V, E``) be a graph that is obtained from G` by removing all edges (u,v) in E` with ce(u) – w(u,v) < minRE. Which means that all the edges with residual energy below (minRE) will pruned from the graph. This means, we prevent the reduction of energy from sensors with low energy.

Now, find the path to be used to route the request (r), by assigning weights for the obtained graph G``. As expressed in Equation (3.13), let eMin be the energy needed by sensor (u) to transmit a message to its nearest neighbor in G‘. This is done to satisfy the desired targets to minimize total energy consumption and to prevent the depletion of a sensor s energy.

$$eMin(u) = \min \{ w(u,v) \mid (u,v) \text{ in } E`` \} \qquad (3.13)$$

Now, let ρ (u,v) be defined using Equation (3.14).

$$\rho(u,v) = \begin{cases} 0 \text{ if } ce(u) - w(u,v) > eMin(u) \\ c \quad \text{otherwise} \end{cases} \qquad (3.14)$$

Where (c) is an algorithm parameter (that is non-negative constant). Sensor's residual energy becomes low as a result of updating the weights through ρ , in which we assign high weights to the edges used in routing path. For each (u) in V, a(u) is defined as we can see in Equation (3.15) **.

$$a(u) = minRE / ce(u) \qquad (3.15)$$

The new weight w``(u,v) assigned to edge (u,v) in E``is defined as in Equation(3.16), Where λ_c is another non-negative constant and an algorithm parameter.

** All equations for CMAX and OML heuristics are implemented by referring to (Sahni, 2006) paper.

$$w``(u,v) = (w(u,v) + \rho(u,v))\,(\lambda_c^{a(u)} - 1) \tag{3.16}$$

Because of the (λ_c) term, all edges starting from a sensor whose current energy is small relative to (minRE) are assigned a high weight. Figure 3.15 illustrates the OML Heuristic.

Heuristic 3: OML Heuristic

Step 1: [Compute G″]

(a) G′ = (V, E′), where $E' = E - \{(u,v) | ce(u) < w(u,v)\}$.

(b) Let P_i be a shortest s_i to t_i path in G′.
If there is no such P_i, the route request fails, then stop.

(c) Compute the minimum residual energy minRE for sensors other than t_i on P_i as :
$minRE$ = min $\{r_e(u) | in\ P\}$

$$r_e(u) = ce(u) - w(u,v)$$

(d) Let G″ = (V,E″) where E″= $E' - \{(u,v)\ \text{ if }\ ce(u) - w(u,v) < minRE\}$.

Step 2: [Find route path]

(a) Compute the weight w″(u, v) for each edge of E″ as :
$\mathbf{w``(u,v) = (w(u,v) + \rho(u,v))(\lambda_c{}^{a(u)} - 1)}$ **, Where:**

$$\rho(u,v) = \begin{cases} 0 \text{ if } ce(u) - w(u,v) > eMin(u) \\ c \quad \text{otherwise} \end{cases}$$

c symbol is a non-negative constant and it is a heuristic parameter.

eMin is the energy needed by sensor u to transmit a message to its nearest neighbor in G``

eMin(u) = min { w(u, v) | (u, v) Є E``}

$a(u) = minRE / ce(u)$

(b) Let $P``_i$ be a shortest from $s_i$ to $t_i$ path in G``.
(c) Use $P``_i$ to route from s_i to t_i.

Figure 3.15: OML Heuristic

As we can see, edges whose use on a routing path will result in failure of a future route are unlikely to be selected by the weighting function. In addition, two shortest path algorithms are used. This is done to allow us to do one level look ahead without increasing complexity too much and in the same time to gain more lifetime.

As done with CMAX heuristic, OML is also modified to implement each of the heterogeneous distributions discussed in this work. In order to implement OML heuristic based on NPCU distribution, for example, we used the heuristic illustrated in Figure 3.16.

Heuristic 4: OML Heuristic based on NPCU Distribution

Assumption: The graph in which sensor nodes are deployed is divided to four quarters.

In 1st quarter: sensors are distributed using Normal distribution.

In 2nd quarter: sensors are distributed using Poisson distribution.

In 3rd quarter: sensors are distributed using Chi-square distribution.

In 4th quarter: sensors are distributed using Uniform distribution.

For each routing request $r_i = (s_i, t_i)$ two steps are done:

Step 1: [Compute G″]

(a) G′ = (V, E′), where $E' = E - \{(u,v)|ce(u) < w(u,v)\}$.

(b) Let P_i be a shortest s_i to t_i path in G′.
If there is no such P_i, the route request fails, then stop.

(c) Compute the minimum residual energy minRE for sensors other than t_i on P_i as :
$minRE = \min \{r_e(u)| in\ P\}$

$$r_e(u) = ce(u) - w(u,v)$$

(d) Let G″ = (V,E″) where E″= $E' - \{(u,v) \text{ if } ce(u) - w(u,v) < minRE\}$.

Step 2: [Find route path]

(a) Compute the weight w″(u, v) for each edge of E″ as :
$\mathbf{w``(u,v) = (w(u,v) + \rho(u,v))(\lambda_c{}^{a(u)} - 1)}$ **, Where:**

$$\rho(u,v) = \begin{cases} 0 \text{ if } ce(u) - w(u,v) > eMin(u) \\ c \quad \text{otherwise} \end{cases}$$

c symbol is a non-negative constant and it is a heuristic parameter.

eMin is the energy needed by sensor u to transmit a message to its nearest neighbor in G``

eMin(u) = min { w(u, v) | (u, v) Є E``}

$a(u) = minRE / ce(u)$

(b) Let $P``_i$ be a shortest from $s_i$ to $t_i$ path in G``.
(c) Use $P``_i$ to route from s_i to t_i.

Figure 3.16: OML Heuristic Based on NPCU Distribution

EXPERIMENTAL RESULTS AND DISCUSSION

Experimental Results and Discussion

Evaluation of single distributions, 2-Hetro-distributions, and 4-Herto-distributions for maximizing lifetime routing, using Uniform, Poisson, Normal and Chi-square distribution is presented in this section. Depending on the assumptions, the performed experiments, result analysis, performance measurement and a comparison of the results for single distributions, 2-Hetro-distributions, and 4-Herto-distributions are presented.

1. Implementation of Power Aware Routing Heuristics

The Uniform, Poisson, Normal and Chi-square distributions were implemented in this thesis using single distributions, 2-Hetro-distributions and 4-Hetro-disrtributions. In order to get better description for real environment, 3D space is used in the implementation of sensor networks. According to these distributions, while meeting better description for real environment, we calculate the network lifetime to determine if the deployment strategy has an effect on the routing heuristics.

2. Assumptions

First, we implement our experiments using Uniform and Poisson distributions to investigate the effect of 1D, 2D, and 3D using CMAX and OML heuristics. Then, experiments on non-single distributions were done using Uniform, Poisson, Normal, and Chi-square distributions. With 2-Hetro-distributions and 4-Hetro-distributions, OML and

CMAX heuristics were evaluated. These two heuristics has shown superiority over other lifetime routing heuristics, that is why they were chosen. In the simulation, the energy required by a single-hop transmission between two sensors is ($0.001 * d^3$), where d is the Euclidean distance between the two sensors. For this purpose 20 sensors were randomly populated in each network of 10 networks (Sahni, 2006).

All the experiments were tested on 2.27 GHz, 3.00 GB of RAM laptop running under Windows Vista Home. The simulation for those lifetimes routing heuristics were implemented using MATLAB 7.0.

3. Performance Evaluation

First, two routing heuristics that use energy-aware routing metrics has been introduced. Finding a scheme for evaluating and comparing the performance of the various heuristics is considered to be the next step. As mathematical analysis method is possible to be performed in only very few and simple cases, we perform simulations. As requirements differ from one application to another, the criterion which suited for some purposes might be useless for others. The most popular criterion in the literature is lifetime[††].

4. Selecting OML and CMAX Parameters

OML and CMAX heuristics were implemented in a single distribution, 2-Hetro-distripution, and 4-Hetro-distripution using Normal, Poisson, Uniform, and Chi-square

[††] Lifetime is defined as the successfully routed messages before the first failed message route.

distributions. Ten sensor networks, each with 20 randomly populated sensors were implemented. The transmission radius r_T is set to 5. In the definition of ρ , the heuristic parameter c was set as = $0.001r_T^3$, where r_T is the transmission radius. The network lifetime was determined for $\lambda_c = 2^i$, where i = 2. Each single-hop transmission between two sensors was assumed to require $0.001 * d^3$. Finally, the initial energy is set to 90 for each sensor. (Sahni, 2006)

5. Results and Discussion

This section describes the experiment results using single distributions, 2-hetro-distributions and 4-hetro-distribution. For each case of distribution ten experiments were performed to give out ten lifetimes. In our study, as we consider random distributions we use the average of these ten lifetimes to calculate the average-lifetime for a single network. This is done for ten networks. Different metrics are studied, and three dimensions are investigated, based on distributing sensor nodes randomly using Uniform, Poisson, Normal, and Chi-square distributions.

5.1. Dimension Effect (Comparing 1D, 2D and 3D):

In order to represent a directed graph for sensor network, there exists a unique adjacency matrix, (Al-Sharaeh, et al., 2008). In literature, Uniform distribution is used to give random positions for sensor nodes as well as the existence of connection between sensors in that network. Uniform distribution is used to represent graphs in one dimension

(1D). Using 3D better describes real environment than using 1D space to represent the position for each sensor in the network.

In order to show the dimension effect, in this section we discuss the results of using 2D and 3D along with 1D in representing sensor nodes' positions.

5.1.1 Results for Dimension Effect:

Table 4.1 shows the change in the average number of edges, using Uniform distribution, when the first failure on sending a message in the network occurs. Table 4.2 demonstrates the change in the average number of edges, using Poisson distribution. As shown in Table 4.1 and Table 4.2, it is clear that the number of edges is decreased when we used 3D for representing sensor nodes.

Table 4.1: Average Number of Edges Using Uniform Distribution

Dimension	8 Nodes	16 Nodes	32 Nodes	64 Nodes	128Nodes
1D	20.9	90.4	369.1	1511	6094.1
2D	12.4	55.4	220.1	883.2	3561.1
3D	6.7	30.1	111	470.9	1911.2

Table 4.2: Average Number of Edges Using Poisson Distribution

Dimension	8 Nodes	16 Nodes	32 Nodes	64 Nodes	128Nodes
1D	20.6	84.8	371.3	1432.3	5816.4
2D	11.9	47.9	204.8	819.9	3358.8
3D	5.6	24.1	119.5	419.9	1629.2

Using Formula 4.1, Table 4.3 shows the percentage of average number of edges using Poisson to the average number of edges using Uniform distribution. Note that, if the result is more than 100% then it means that average number of edges is higher when using Poisson distribution; otherwise, it is higher when using Uniform distribution. In a network with 128 nodes, the average number of edges using Poisson distribution is 85.24% of edges using Uniform distribution.

$$\% \text{ Percentage} = (Avg.Poisson\_Edges) / (Avg.Uniform\_Edges) * 100\% \quad (4.1)$$

Energy is conserved using multi-hop routing in wireless sensor networks, (Sahni, 2006). Hence, the sensor nodes between source (s) and destination (t) are used as relays. As we have less number of edges, and less choices of paths for each route, therefore we will have less power reservation. For example to travel from source node s to destination node t, a lifetime maximization heuristic will give better lifetime for the network if the it is provided more alternatives of paths to use for a single route. This leads to the fact that, when using 3D we get more power consumption (i.e. less lifetime).

Table 4.3: Average Number of Edges (Percentage of Poisson to Uniform Distribution)

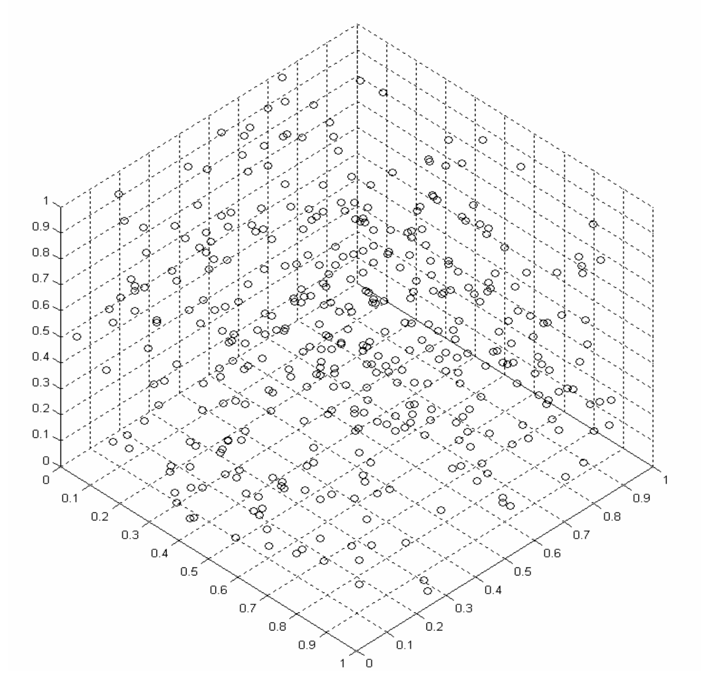
Dimension	8 Nodes	16 Nodes	32 Nodes	64 Nodes	128Nodes
1D Percentage	98.56%	93.81%	100.60%	94.79%	95.44%
2D Percentage	95.97%	86.46%	93.05%	92.83%	94.31%
3D Percentage	83.58%	80.07%	107.66%	89.17%	85.24%

According to our experiments, the four distributions are classified into two groups. The first group includes Chi-square and Poisson distributions, while the second group includes Uniform and Normal distributions. This classification is based on the relationship between number of edges and network lifetime. The first group (Chi-square, Poisson) is featured by having less average lifetime when changing the representation for sensors from 1D to 3D, which agrees with the previous works indicating that the less number of edges we have the less lifetime we get. But, unlike the first group, second group (Uniform, Normal) gives the opposite, that means when we change from 1D to 3D (knowing that the number of edges still decreases) the average lifetime is increased.

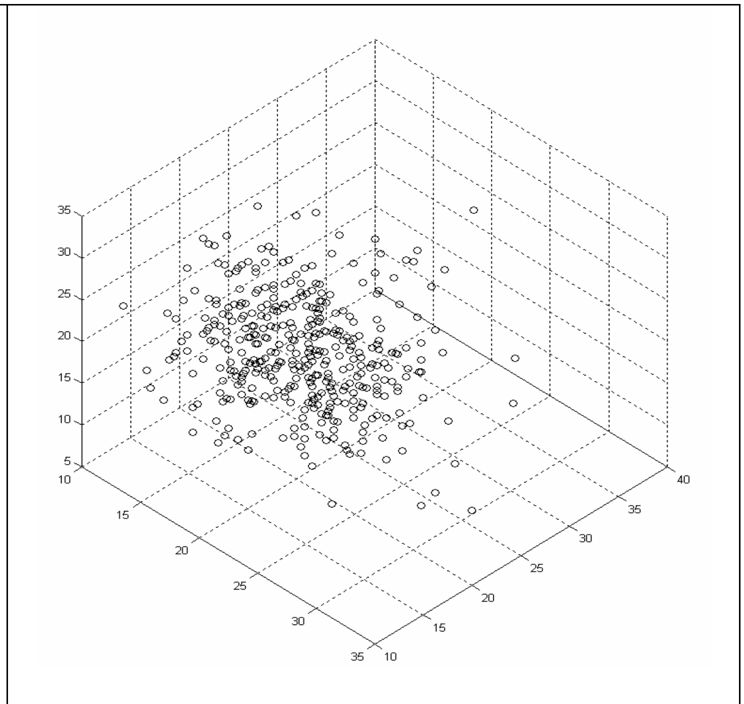
We believe that the reason for such results is caused by the aspects of these distributions; in the second group, the Uniform and Normal distributions are featured by the symmetric nature. That is, they are both representing symmetric environments. But in the first group, the two distributions Poisson and Chi-square are having an asymmetric nature; this is due to the fact that they both have a shape parameter (that gives the ability of simulating different asymmetric environments with a single distribution).

5.2 Single-Distribution Effect on Maximizing Lifetime

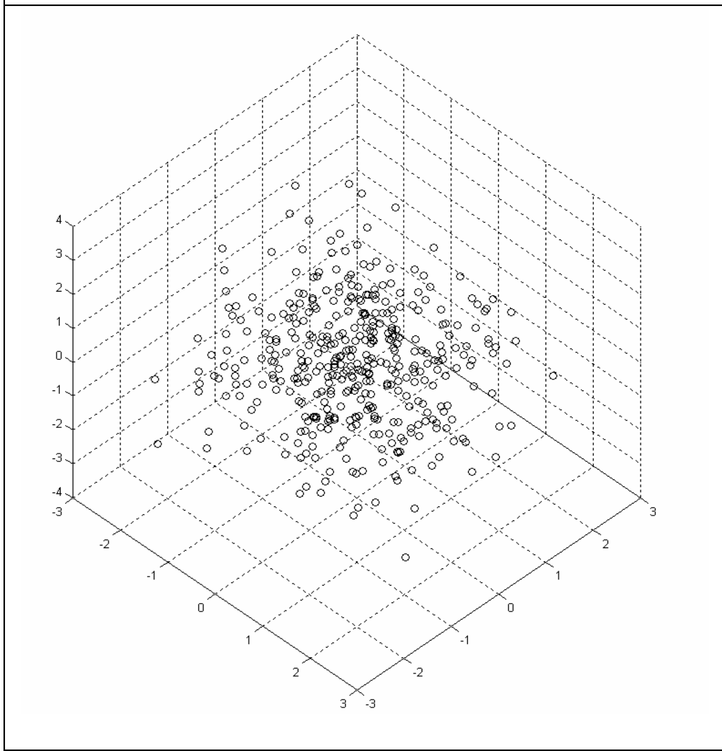
Figure 4.1 shows the Uniform, Poisson, Normal, and Chi-square distributions in 3D space. As can be seen from Figure 4.1(a), sensor nodes are uniformly distributed by Uniform distribution, which can be used to describe the flat terrain environment. Unlike Uniform, Poisson distribution gives more concentration of sensor nodes around the mean, as we can see in Figure 4.1(b).Thus; Poisson distribution can well describe the hard terrain environment. Figure 4.1(c) shows a 3D Normal distribution, which describes the symmetric lightly hard terrains. Never the less, the distribution of sensors using 3D Chi-square is shown in Figure 4.1(d), as can be noticed, Chi-square is somehow looks like Poisson distribution, but with more concentration to the left of the mean (mean = 20). This leads to the fact that Chi-square distribution is used for describing harder terrains in real environment.



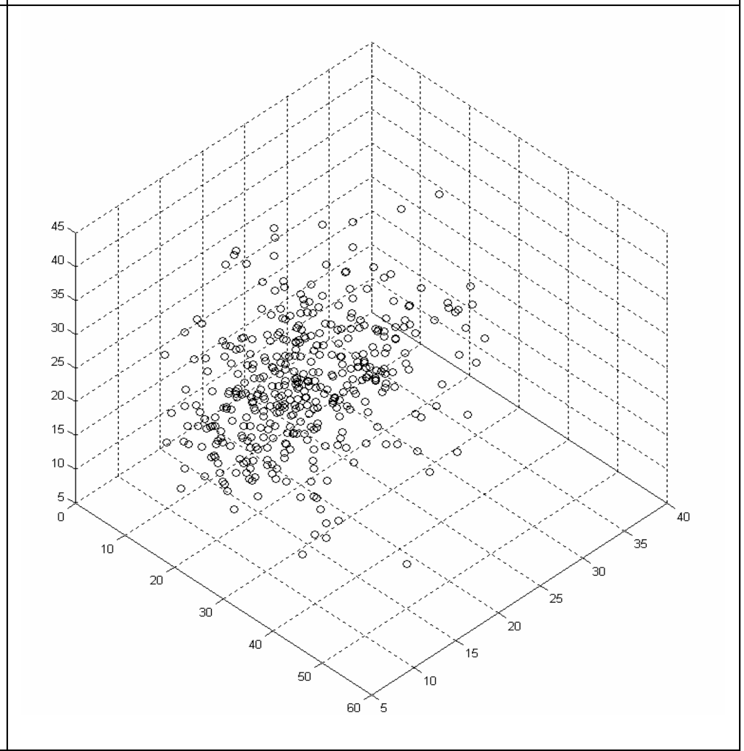
(a) Uniform distribution



(b) Poisson distribution



(c) Normal distribution



(d) Chi-square distribution

Figure 4.1: Different Types of Distributions in 3D Space.

Using Uniform, Poisson, Normal and Chi-square distributions give a fair description of the real environment, as we will consider different types of surfaces starting from the plan area expressed by Uniform distribution, through the symmetric lightly hard terrains shown by Normal distribution, and then Poisson distribution is used to express the hard terrains, until the extremely hard terrains which is expressed by Chi-square distribution.

Table 4.4 describes the average lifetime for OML and CMAX heuristics using these four types of distributions. Figure 4.2 illustrates the effect of different types of distribution in maximizing lifetime for the OML. Figure 4.3 shows the effect of different types of distribution in maximizing lifetime for the CMAX. Due to the random distribution, it can be noticed that the average lifetime for each network is not the same for the ten networks.

Table 4.4: Average Lifetime Statistics Using Different Types of Distributions in 3D Space

	Network 1				**Network t 2**				**Network 3**			
	Uni	**Poi**	**Chi**	**Norm**	**Uni**	**Poi**	**Chi**	**Norm**	**Uni**	**Poi**	**Chi**	**Norm**
Average Lifetime using OML	8481	2713	765	2324 3	0	2522	330	38640	25826	380	1234	13450
Average Lifetime using CMAX	704	354	230	2032	623	654	225	1160	676	480	339	1846
	Network t 4				**Network 5**				**Network 6**			
	Uni	**Poi**	**Chi**	**Norm**	**Uni**	**Poi**	**Chi**	**Norm**	**Uni**	**Poi**	**Chi**	**Norm**
Average Lifetime using OML	666	4013	1139	20611	12002	553	860	32379	726	2515	747	24778
Average Lifetime using CMAX	1527	608	371	1175	924	440	430	928	854	281	363	1063
	Network 7				**Network 8**				**Network 9**			
	Uni	**Poi**	**Chi**	**Norm**	**Uni**	**Poi**	**Chi**	**Norm**	**Uni**	**Poi**	**Chi**	**Norm**
Average Lifetime using OML	978	1495	380	40609	0	1698	1258	27728	1026	4183	1001	12069
Average Lifetime using CMAX	785	882	273	1080	808	723	244	1163	561	707	432	1155

	Network 10			
	Uniform	**Poisson**	**Chi-square**	**Normal**
Average Lifetime OML	23874	564	708	42786
Average Lifetime using CMAX	865	926	137	1017

As we can see from Figure 4.2, the best average lifetime provided by OML is based on Normal distribution, which is about 27629. We believe that the reason for such results is caused by the symmetric nature of Normal distribution. The average lifetime of OML based on Uniform, Poisson and Chi-square distribution is about 7357, 2063, 842 respectively. It can be noticed that the lowest average lifetime is provided by Chi-square distribution.

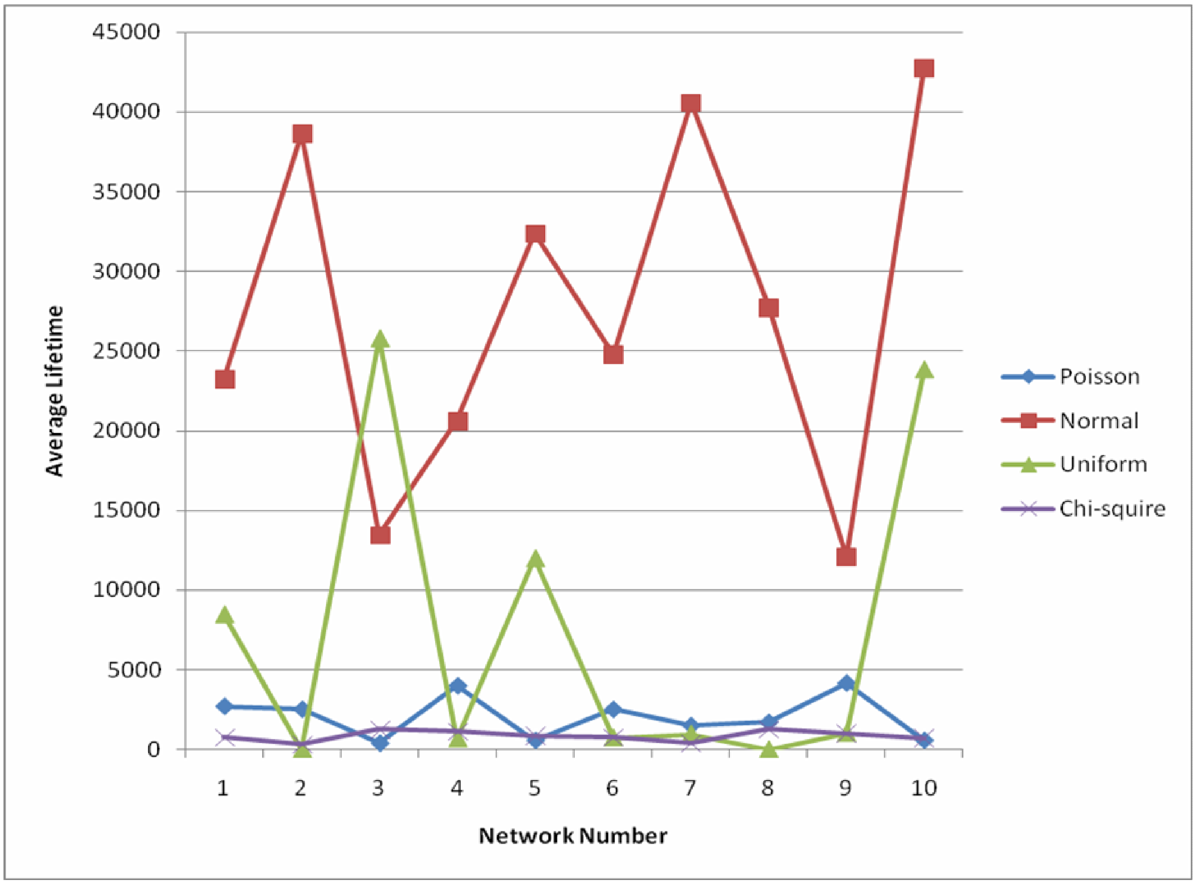


Figure 4.2: Average Lifetime Using Single Distributions in 3D for OML Heuristic

As shown in Figure 4.3, the average lifetime provided by OML is about 1261.9 based on Normal distribution, which is the best case for CMAX in single distributions. We believe that having this distribution with the best lifetime, as seen with OML heuristic is caused by the symmetric nature of Normal distribution. The average lifetime of OML based on Uniform, Poisson and Chi-square distribution is about 832, 605, 842, and 304 respectively. It can be noticed that the descending order of the average lifetime provided by the four distributions (i.e. Normal, Uniform, Poisson, then Chi-square) is still the same with CMAX heuristic, but with lower band. We believe that the reason for such results is caused by the superiority of OML over CMAX heuristic.

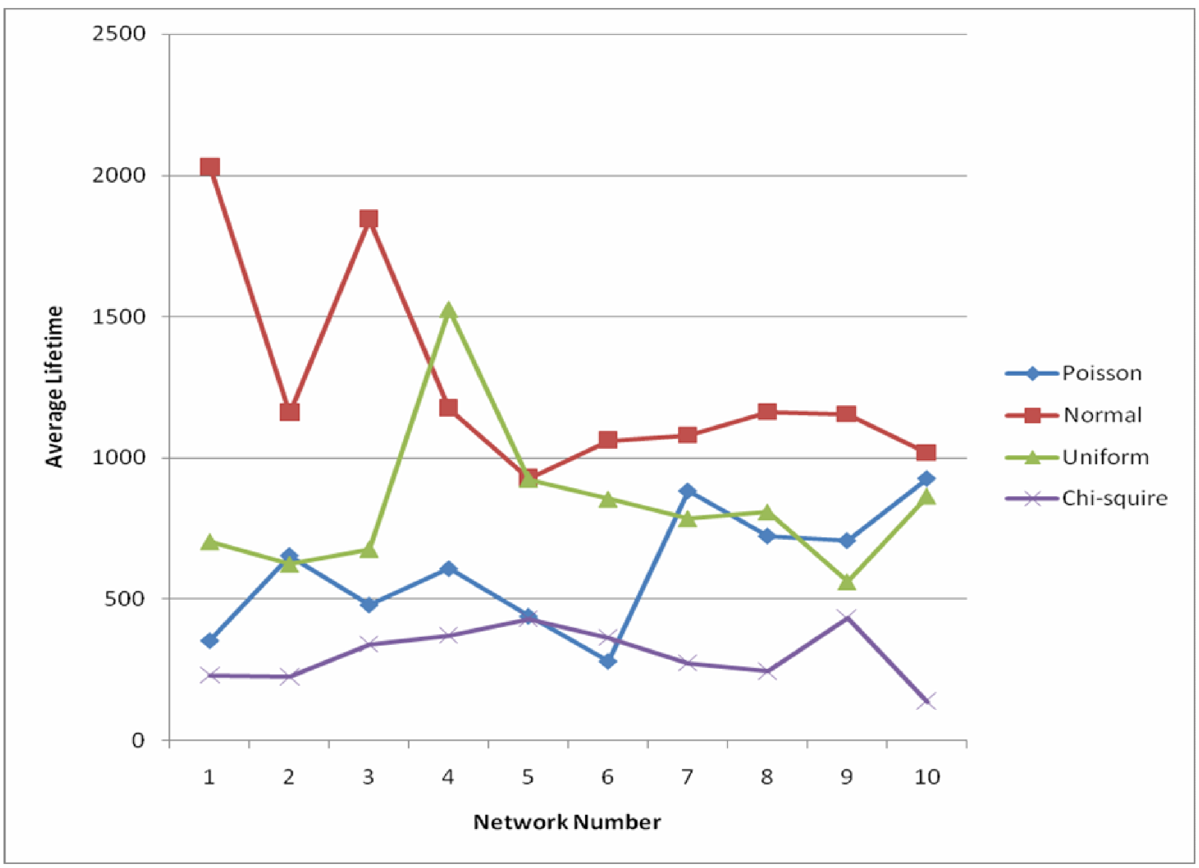


Figure 4.3: Average Lifetime Using Single Distributions in 3D for CMAX Heuristic.

5.3 Average Lifetime Routing Using Non-single Distributions

By having more than single distribution in the graph of deployment, we investigate multi-tone terrains. In this work also, we investigate the deployment route effect on maximizing lifetime routing heuristics. For that, we investigated non-single distributions for wireless sensor networks were implemented, including 2-Hero-distributions, and 4-Hetro-distributions.

In 2-Hetro-distribution, we will have 6 types of distributions which are: Uniform_Chi-square(UC), Uniform_Poisson(UP), Uniform_Normal(UN), Chi-squre_Poisson(CP), Chi-squre_Normal(CN), and Normal_Poisson(NP). Implementation for the Uniform_Chi-square(UC) distribution for example, will be by having Uniform distribution in the top of the graph with Chi-square distribution in the bottom.

In 4-Hetro-distribution, the space of deployment is divided into four quarters; each quarter has different type of distribution for network deployment. In this thesis work, we will discuss six types of 4-Hetro-distributions, listed as: Poisson_Chi-square_Normal_Uniform(PCNU),Chi-square_Poisson_Uniform_Normal(CPUN), Normal Poisson_Chi-square_Uniform(NPCU),Poisson_Chi-square_Uniform_Normal (PCUN),Chi-square_Normal_Poisson_Uniform(CNPU), and Chi-square_Poisson_Normal_Uniform (CPNU). For example, the four-hetro-distribution (NPCU) is shown in Figure 4.4.

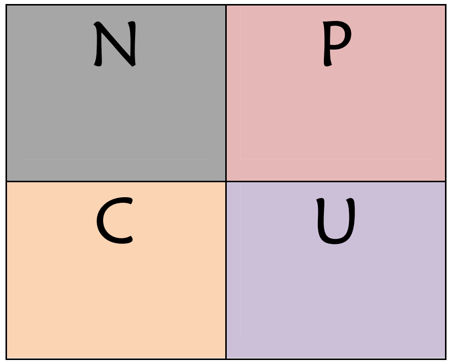


Figure 4.4: Normal_Poisson_Chi-square_Uniform Distribution

The reason for having only six types of 4-Hetro-distributions is that we consider the unrepeated distribution for deployment cases, which means that every type of distribution will appear only once in each 4-Hetro-distribution. These six types of distributions are chosen as a result of making some random sequence of modifications performed by sapping distributions' positions, made on the first chosen distribution.

5.4 Results Using 2-Hetro Distributions

Changing the type of the distribution of sensor nodes to non-single distributions will give us better description for real environment. As we consider the multi-tone terrains with many different combination of Hetro-distributions. A 20 sensor networks are deployed to be randomly distributed using 2-Hetro-distributions in 3D space.

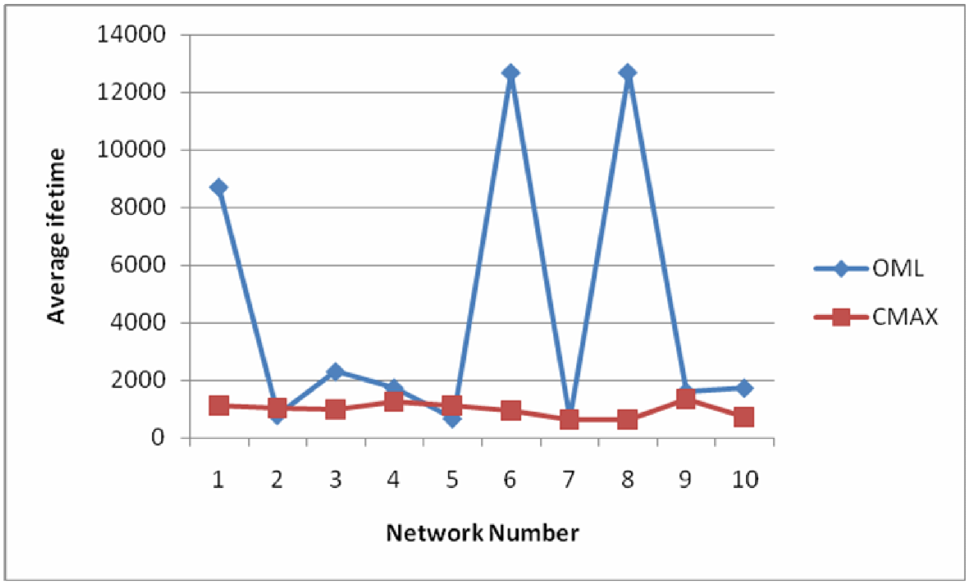


Figure 4.5: Average Lifetime Using Uniform_Chi-square Distribution in 3D Space

Figure 4.5 shows the average lifetime for 10 sensor networks with 20 sensors in each network. Using 3 dimensions, Uniform distribution is positioned above the Chi-square distribution. From the figure, the average lifetime for the OML is 77% better than the CMAX. Where the percentage difference is calculated as follows: First, we consider which heuristic provides greater lifetime in that specific case of distribution. Then, if the average lifetime for example the CMAX is greater than that of the OML, then the percentage difference is equal to the OML average lifetime, subtracted from the CMAX average lifetime, divided by the CMAX average lifetime, all multiplied by 100%, as shown in Equation (4.2):

$$\% Difference = \frac{Avg.CMAX \text{ - Avg.OML}}{Avg.CMAX} * 100\% \tag{4.2}$$

If the average lifetime of CMAX less than the average lifetime of OML, the equation would be as illustrated in Equation (4.3):

$$\%Difference = \frac{Avg.OML - \text{Avg.CMAX}}{Avg.OML} * 100\% \qquad (4.3)$$

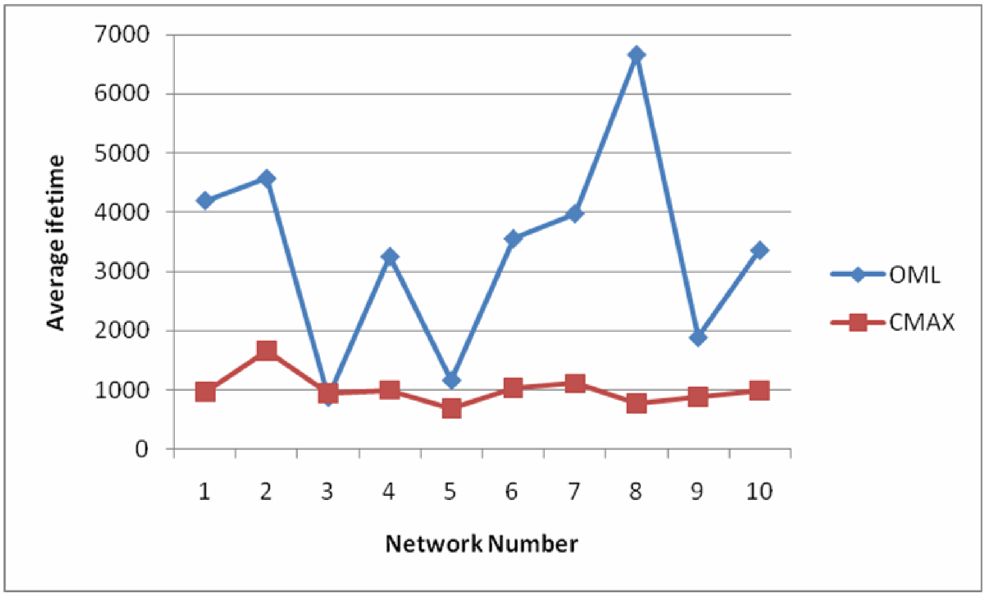


Figure 4.6: Average Lifetime Using Uniform_Normal Distribution in 3D Space

Figure 4.6 demonstrates that after we changed the 2-Hetro-distribution to Uniform_Normal distribution in 3D space, we found that the performance of OML heuristic is still better than the performance of CMAX heuristic. The improvement ratio is 70%. As can be seen, the band of average lifetime provided when using Uniform_Normal distribution is lower than the band of average lifetime given by Uniform_Chisquire distribution in Figure 4.5, especially for OML heuristic.

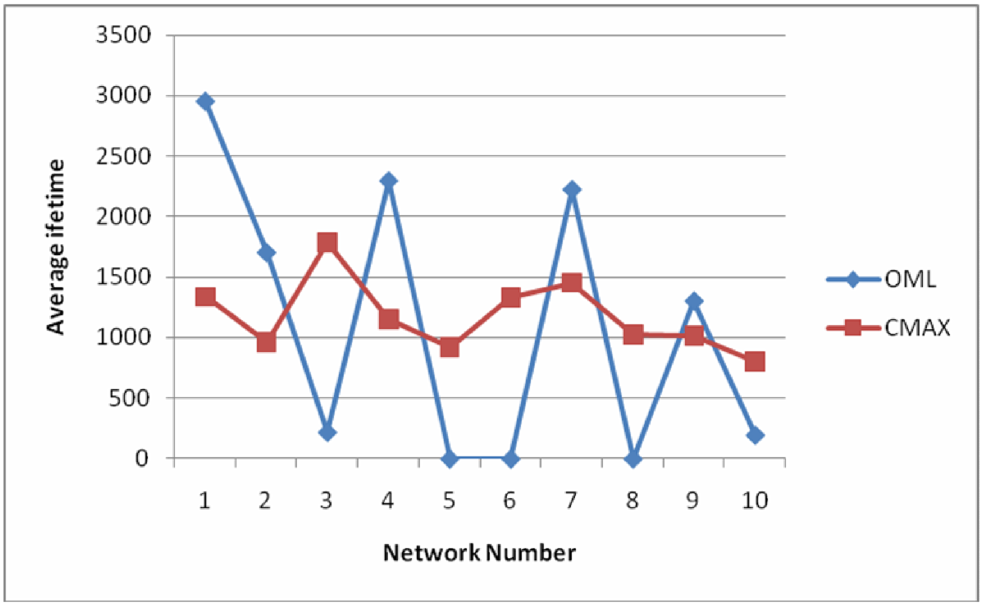


Figure 4.7: Average Lifetime Using Chi-square_Normal Distribution in 3D Space

As we can see from Figure 4.7, unlike previous cases, the performance of CMAX heuristic is slightly better than the performance of the OML heuristic with improvement ratio equals 7%. Since the type of distribution has been changed to Chi-square_Normal, and still representing sensors in three dimension space, we believe that the reason for having larger average lifetime provided by CMAX is because of using Chi-square distribution at the top of the deployment area with Normal distribution at the bottom. Also, it is noticed that OML heuristic is showing higher deviation compared to CMAX heuristic.

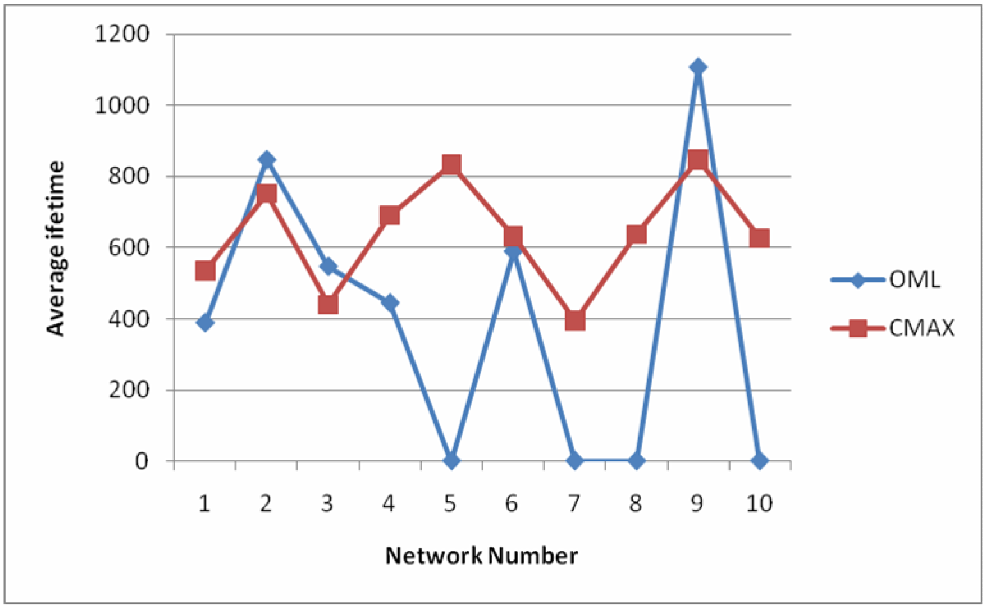


Figure 4.8: Average Lifetime Using Chi-square_Poisson Distribution in 3D Space

Figure 4.8 demonstrates the performance of OML vs. CMAX heuristic when the distribution is Chi-square_Poisson using three dimensions for representing the position of each sensor. From the figure, the average lifetime of CMAX is 38% better than the average lifetime of OML. As can be noticed, in some cases when using the 2-Heto-distributions, CMAX is showing superiority over OML. We believe that having such results is caused by the effect of the deployment strategy. In addition, the band of the lifetime provided by Chi-square_Poisson experiments is very low when compared with other 2-Hetro-distributions for both OML and CMAX heuristics. We believe that this difference in band of average lifetime between this case and other 2-Hetro-ditributions is caused by the effect of distribution type. This means, when the Chi-square and Poisson distributions are founded in the same area to be covered by sensors, with Poisson distribution below the Chi-square distribution, then CMAX is preferred, with expectation for having low band of lifetime provided by both OML and CMAX.

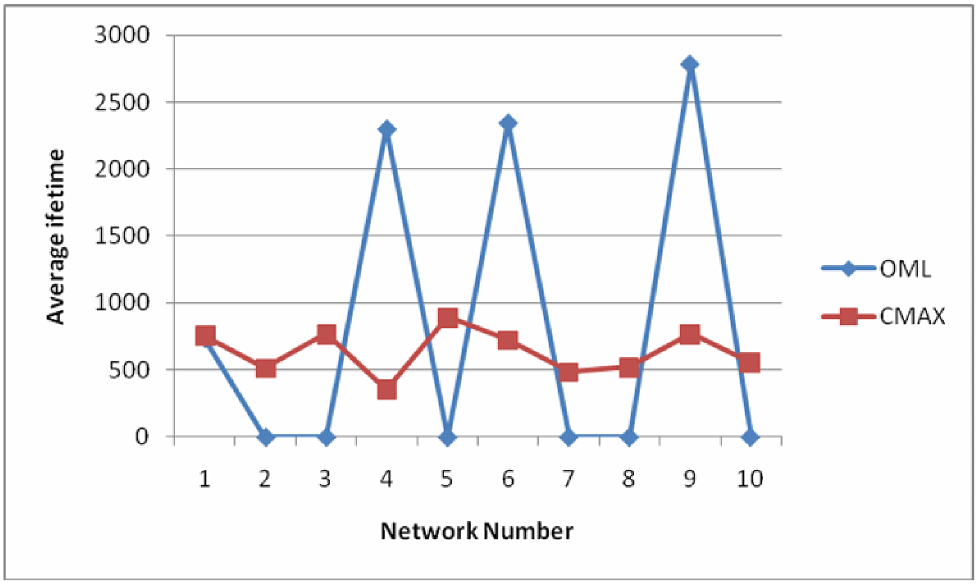


Figure 4.9: Average Lifetime Using Uniform_Poisson Distribution in 3D Space

Figure 4.9 exposes the 2-Hetro-distribution when changed to Uniform_Poisson using three dimensions to represent sensors' positions. As can be seen, the deviation is decreased when using CMAX heuristic compared to OML, But OML heuristic is still providing much more average lifetime. The OML improvement ratio over CMAX is 22.7%.

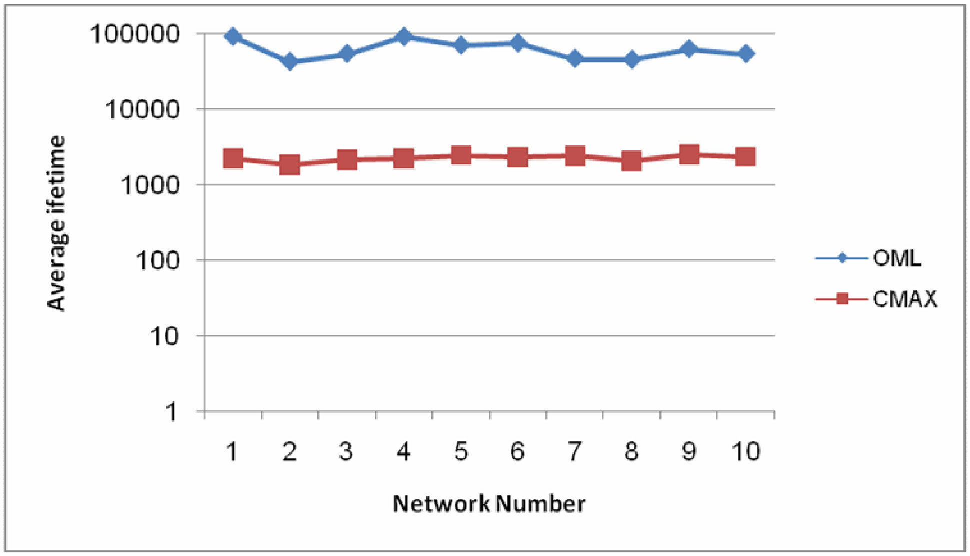


Figure 4.10: Average Lifetime Using Normal_Poisson Distribution in 3D Space

Figure 4.10 shows that after we modified the 2-Hetro-distribution by having Normal distribution positioned above the Poisson distribution (Normal_Poisson distribution). The average lifetime for the OML and CMAX were about 64209.6, and 2251.6 respectively. Among all the cases we considered in 2-Hetro_Distributions, the figure points out that OML heuristic records the highest band of average lifetime. With improvement ratio equals to 96.49% over CMAX.

It is worthy to be mentioned here that, while running the case of Normal_Poisson distribution with OML heuristic (NP_OML heuristic), it was noticed that the runs took an extremely long time (more than 48 hours) compared to other cases. We believe that, this is due to the high values for average lifetime obtained by NP_OML. Table 4.5 shows the average lifetime statistics for OML and CMAX using 2-Hetro-Distributions in 3D space, (*****) indicates the higher lifetime.

Table 4.5: Average Lifetime Statistics Using 2-Hetro-Distributions in 3D Space

2-Hetro-Distribution	CMAX	OML	Difference %
NP	2251.6	64209.6*	96.49%
CP	639.1*	392.2	38.63%
CN	1178.2*	1090.7	7.43%
UN	997.6	3349.9*	70.22%
UC	971.6	4351.88*	77.67%
UP	631.7	817.6*	22.74%

5.5 Effect of Distribution Route on Lifetime Maximization:

The Deployment Route Effect is considered in our research, as we believe that the position of the distribution does make difference, even if it is neighbored with the same type of distribution in the left, right, or diagonal positions, but with different quarter positions. This means, we care about the order of distributions, and the position we start implementing these distributions.

For example, if an airplane is ordered to deploy sensors in a space having the NPCU 4-Hetro-distribution as shown in Figure 4.4. If that airplane was coming from the north, then we will use the same implementation for that space if the airplane came from the south, east or west direction. Let's go again to Figure 4.4, if we turned that figure to have C at the top-left quarter, N at the top-right, U at the bottom-left and P at the bottom right. As we can see, the NPCU 4-Hetro-distribution is still there, we just turned the whole figure (i.e.: the airplane is coming from the western side of the same space).

But, the turned figure we just mentioned can not be read as CNUP 4-Hetro-distribution. This is due to the fact that each of the two 4-Hetro-distributions expresses different terrains. Simply, in the first case we had the NPCU 4-Hetro-distribution, with Chi-square distribution positioned in the 3rd quarter having Normal distribution above, and Uniform distribution at the right side. But in CNUP, the Chi-square distribution is positioned at the 1st corner with Uniform distribution below, and Normal distribution at the right side. Clearly, these two 4-Hetro-distributions are expressing two different terrains.

Also, it is worthy to be mentioned here that within the single quarter that holds the Chi-square distribution, in the first case that is shown in Figure 4.4, the concentration of sensors in Chi-square distribution will be in the left side (i.e: to the west direction of the figure). But in the case of CNUP distribution, the concentration of sensors deployed by Chi-square will be in the left side, which is the South direction of the NPCU distribution.

5.6 Results Using 4-Hetro Distributions

After seeing the effect of 2-Hetro-distributions on the performance of OML and CMAX, in order to get even more realistic description for multi-tone terrains, we used 4-Hetro-distributions to distribute sensor nodes. Every network is got the average lifetime by deploying ten networks and calculating the mean of their lifetimes. Each network consists of 20 sensors that are deployed to be randomly distributed in 3D space using 4-Hedtro-distributions.

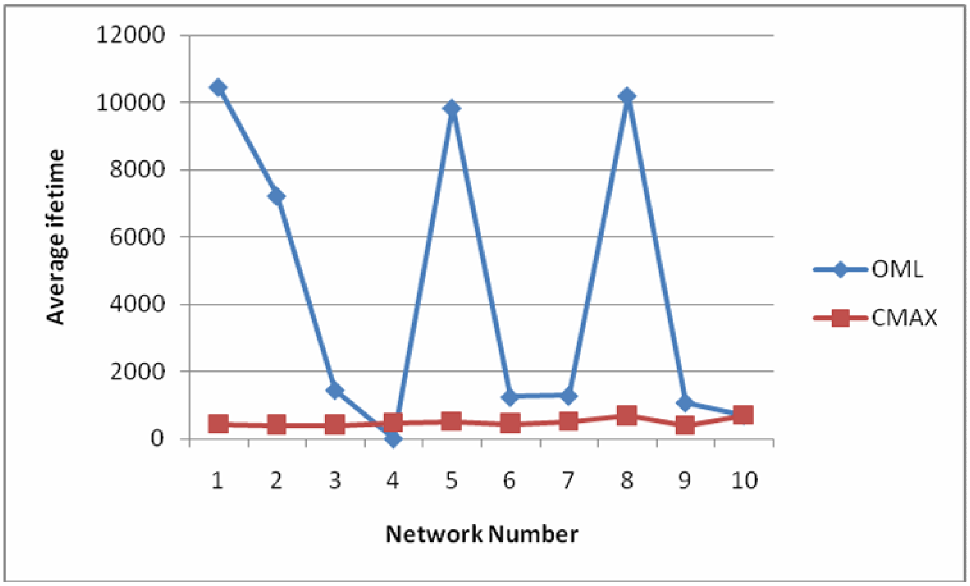


Figure 4.11: Average Lifetime Using Poi_Chi_Norm_Uni Distribution in 3D Space

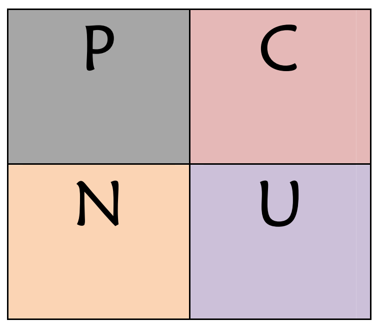


Figure 4.12: Poisson_Chi-square_Normal_Uniform Distribution

Figure 4.11 illustrates the difference between OML heuristic and CMAX heuristic in three dimensional representations for sensors, when distribution type is altered to be Poi_Chi_Norm_Uni (PCNU) 4-Hetro-distribution. As the figure shows, the average lifetime of OML is 4347.7, while CMAX average lifetime is 500.2. The improvement ratio on average lifetime obtained by using OML is 88%. Even after changing the distribution type from 2-Hetro-distribution to 4-Hetro-distribution, it is still noticed that OML is showing higher deviation compared to CMAX, and CMAX is providing lower average lifetime when compared to OML.

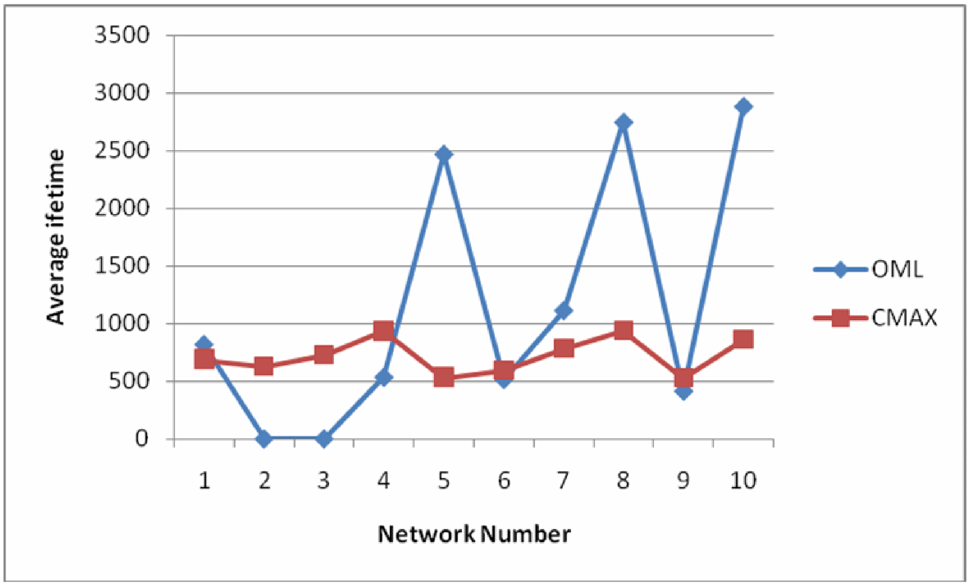


Figure 4.13: Average Lifetime Using Chi_Poi_Uni_Norm Distribution in 3D Space

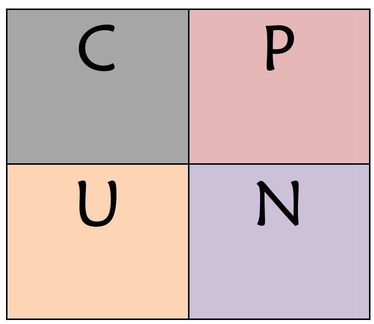


Figure 4.14: Chi-square_Poisson_Uniform_Normal Distribution

After seeing the effect of (PCNU) shown in Figure 4.11, we will make some changes in the order of that 4-Hetro-distribution to get a new different distribution to be tested. By switching the two columns of Figure 4.12, we will get the distribution Chi_Poi_Uni_Norm (CPUN), as shown in Figure 4.14. Figure 4.13 disposes the result of experiments on OML and CMAX done by deploying 10 networks using Chi_Poi_Uni_Norm (CPUN) distribution in 3D. The average lifetime obtained by OML is 1147.8, and the average lifetime obtained by CMAX is 721.6. Although, in networks 2, 3 and 4, OML lifetime is lower than CMAX, the average lifetime of OML is 37% better than CMAX.

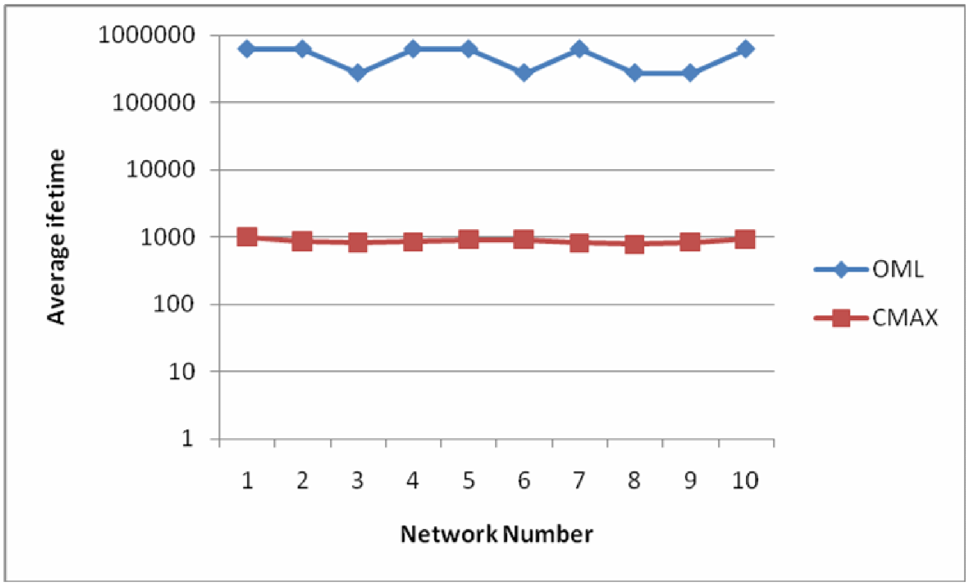


Figure 4.15: Average Lifetime Using Norm_Poi_Chi_Uni Distribution in 3D Space

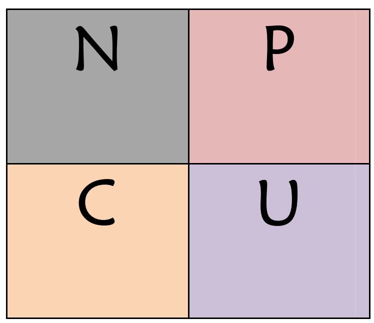


Figure 4.16: Normal_Poisson_Chi-square_Uniform Distribution

To get a new different 4-Hetro-distribution, we will alter the previous distribution shown in Figure 4.14. This time, the modification process will include two steps. First, exchange the 1st and the 4th quarters of Figure 4.14, to get NPUC. Then, exchange the 3rd and the 4th quarters, to finally have the distribution Norm_Poi_Chi_Uni (NPCU).

Figure 4.15 points out that OML heuristic gives an extremely high average lifetime when used with NPCU 4-Hetro-distribution. Clearly, if implemented with NPCU distribution, OML will give the largest band of lifetime, compared with all experiments included in this work. As shown in the figure, the average lifetime of OML is 487418.6, while CMAX average lifetime is only 873. In the case of NPCU, OML has shown an improvement up to 99.8% over CMAX. In Figure 4.15, the average lifetime given by OML ranges between 300,000 and 600,000.

Now, two swaps will be needed to generate the new 4-Hitro-distribuion. First, swap the two columns of (NPCU) shown in Figure 4.16, then swap the second and the fourth quarters. The distribution will be Poi_Chi_Uni_Norm (PCUN) as in Figure 4.18. In this case, the average lifetime for OML and CMAX were 4343.43, and 842.2 respectively.

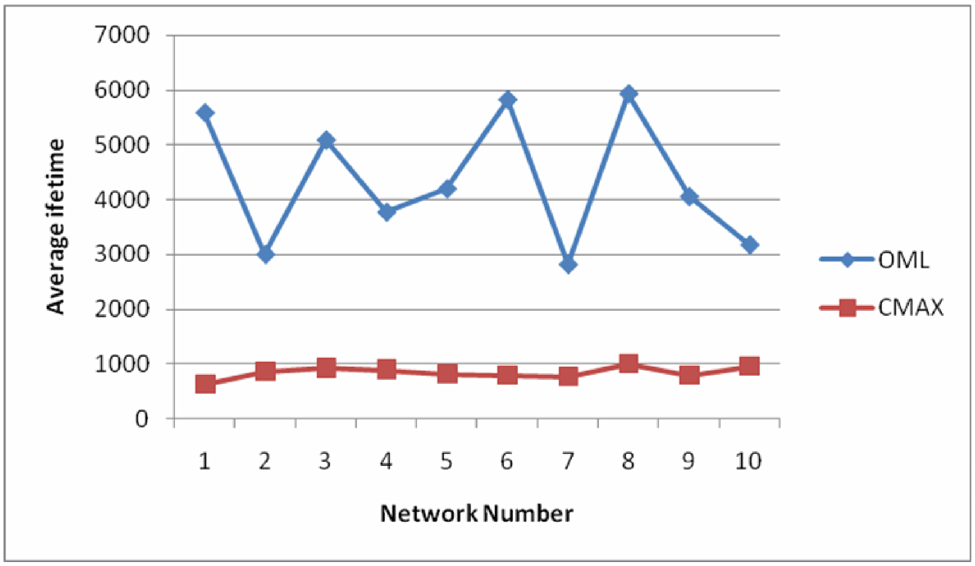


Figure 4.17: Average Lifetime Using Poi_Chi_Uni_Norm Distribution in 3D Space

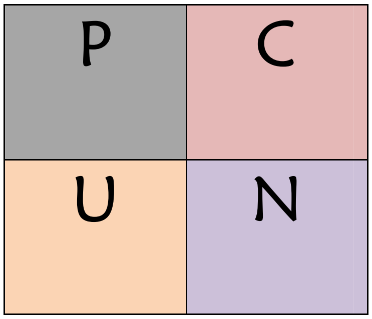


Figure 4.18: Poisson_Chi-square_Uniform_Normal Distribution

As shown in Figure 4.17, when the type of distribution is modified to be PCUN in 3D, the OML still provides better average lifetime than CMAX. Improvement achieved by OML is more than 80 %. But as we can see, the band of OML average lifetime is relatively low compared with NPCU in Figure 4.15.

So far, the current distribution is PCUN, three modifications will be included to form the new 4-Hetro-distribution. First modification is to swap the first and third distributions positions; this will form UCPN distribution, as a temporal situation to be altered by next modification. Second modification, which will affect the UCPN, is to swap the first and second quarters' positions, giving out the CUPN distribution. Then, exchange the second and the fourth quarters. This will finally form the Chi_Norm_Poi_Uni (CNPU) distribution, as Figure 4.20 shows.

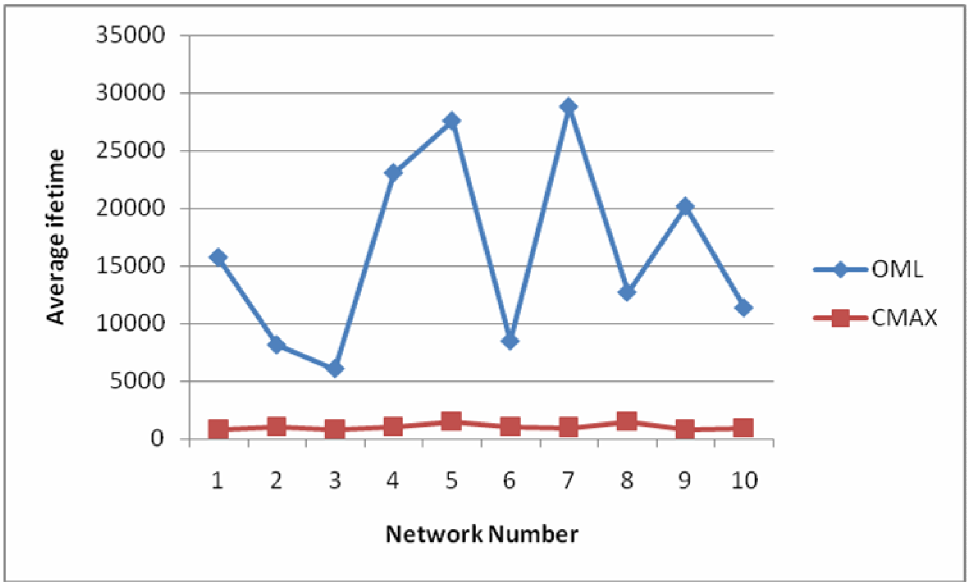


Figure 4.19: Average Lifetime Using Chi_Norm_Poi_Uni Distribution in 3D Space

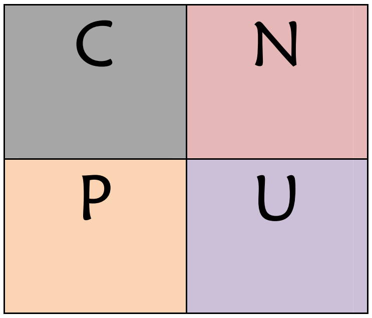


Figure 4.20: Chi-square_Normal_Poisson_Uniform Distribution

Figure 4.19 demonstrates that when the distribution is CNPU, the average lifetime of OML was 93% better than CMAX. The average lifetime for the OML and CMAX were about 16218.7, and 1038.7 respectively. Three dimensions were used for representing the distribution of sensors, and the band of lifetime given by OML ranges between five thousands to thirty thousands, which is higher than the band of PCUN shown in Figure 4.17.

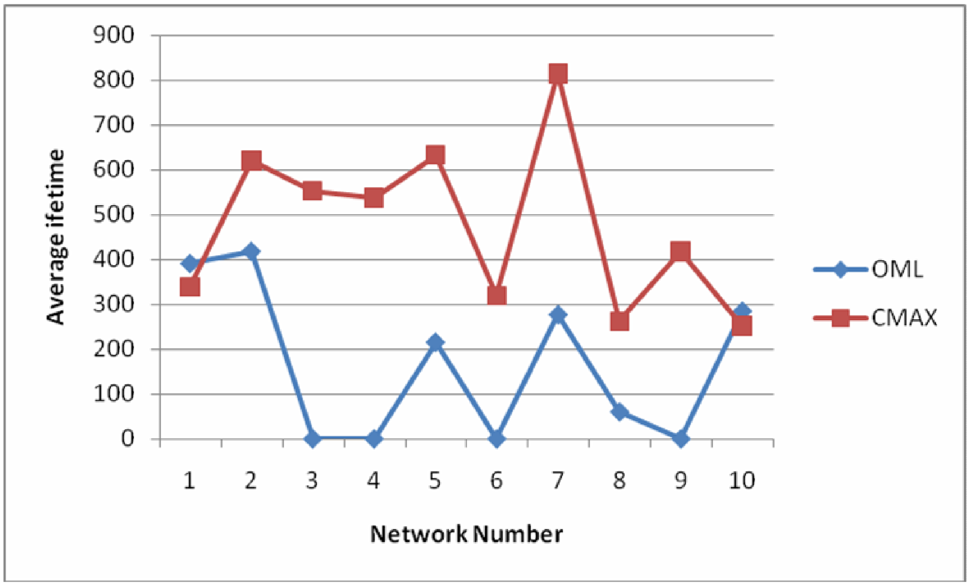


Figure 4.21: Average Lifetime Using Chi_Poi_Norm_Uni Distribution in 3D Space

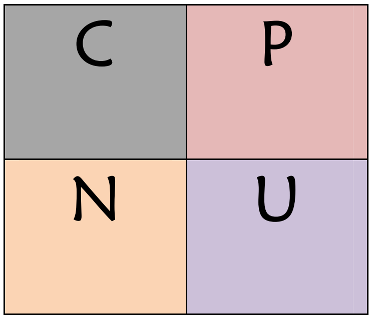


Figure 4.22: Chi_Poi_Norm_Uni Distribution

Figure 4.22 illustrates the way our 4-Hiro-distribution will look like after swapping the 2nd and 3rd quarters. This single modification will lead us to have Chi_Poi_Norm_Uni (CPNU). Figure 4.21 points out that, in 3D space when the 4-Hetro-distribution CPNU is used in the experiments to compare between OML and CMAX, unexpected results will show that CMAX is better than OML. Putting in consideration that the average lifetime given by OML is 164.2, and the average lifetime given by CMAX is up to 475.8. It is true that band of lifetime is very low for both OML and CMAX, but the improvement achieved by CMAX over OML is 65.48%.

It is worthy to be mentioned here that, the CPNU distribution is extracted by single modification on CNPU distribution. Even though, Figure 4.19 and Figure 4.21 are giving very different information about OML and CMAX heuristics. Figure 4.19 illustrates that OML is better than CMAX, with high band for the average of lifetime, while Figure 4.21 demonstrates that with CPNU distribution, OML provides an extremely low average lifetime compared to other experiments. Also, CMAX gives low band of lifetime, but it is better than OML. We believe that the reason for having such conflict is the single switching process, which was made on CNPU to get CPNU distribution. This will lead to the fact that; Deployment Route Path does affect the lifetime maximization. Table 4.6 shows the average lifetime statistics for OML and CMAX using 4-Hetro-Distributions in 3D space**,** (*****) indicates the higher lifetime.

Table 4.6: Average Lifetime Statistics Using 4-Hetro-Distributions in 3D Space

4-Hetro-Distribution	CMAX	OML	Difference %
PCNU	500.2	4347.7*	88.50%
PCUN	842.2	4343.43*	80.61%
CPUN	721.6	1147.8*	37.13%
CPNU	475.8*	164.23	65.48%
NPCU	873	487418.6*	99.82%
CNPU	1038.7	16218.7*	93.60%

CONCLUSION AND FUTURE WORK

Conclusion and Future Work

1. Conclusion

This study shows that changing the deployment strategy on Wireless Sensor Network (WSN) does affect the performance of maximizing lifetime routing heuristics. To meet real environment requirements, we used four different types of well known statistical techniques to distribute sensor nodes. Two heuristics OML, and CMAX were implemented in 3D space. Because of its behavior of assigning high weights to the used edges in the current route so that these routes will not be selected next time (one level look ahead), OML heuristic showed superiority over CMAX in most of distribution cases. On the other hand, CMAX heuristic showed stability when changing the type of Hetro-distribution. In addition, some cases of Hetro-distributions that CMAX was providing better average lifetime than OML heuristic.

As the accuracy of experimental results will be defected if the distribution was wrongly chosen, we fairly evaluate heuristics for the real-world systems using non-single distributions. Our work shows that the deployment strategy has an effect in the behavior of wireless sensor networks. Using 2-Hetro-Distributions, Noraml_Poisson (NP) distribution was the best case for both OML and CMAX heuristics, the average lifetime for OML was about 64209 and the average lifetime for CMAX was about 2251. In 4-Hetro-Distributions, OML showed the best average lifetime when based on Normal_Poisson_Chi-square_Uniform (NPCU) distribution with average lifetime more than 487418, and the 4-

Hetro-Distribution Chi-square_Normal_Poisson_Uniform (CNPU) distribution was the best case for CMAX with more than 1038 average lifetime.

Our experiment study, using 2-Hetro-distributions, shows the superiority of OML over CMAX in four deployment types those are UN distribution by 70.22%, UP distribution by 22.74%, UC distribution by 77.67%, and the best case for OML was when the Poisson distribution positioned below Normal distribution (that is NP distribution) with improvement ratio up to 96.49%. Furthermore, unlike previous researches, CMAX heuristic showed superiority over OML in two cases. In the first case, slight improvement was shown by CMAX over OML when Chi-square distribution was positioned above Normal (CN) distribution, with improvement ratio more than 7%. Another 2-Hetro-Distribution case that shows the superiority of CMAX over OML is the Chi-square_Poisson (CP) distribution, with improvement in average lifetime equals to 38.63%. The best average lifetime provided by OML was 64209.6 shown in NP distribution. Also, CMAX heuristic obtained the best average lifetime when investigated with NP distribution, with average lifetime more than 2251.

Our extensive runs show that applying 4-Hetro-Distribution results in up to 99.82% improvement ratio when using OML instead of CMAX with the NPCU distribution, which is the best 4-Hetro-Distribution case for implementing OML heuristic. In CNPU, CPUN, PCUN, and PCNU, OML heuristic provided better average lifetime than CMAX, with improvement ratio equals to 93.60%, 37.13%, 80.61%, and 88.50% respectively. The last 4-Hetro-Distribution case, when the deployment strategy is changed to CPNU, unexpected results revealed that using CMAX heuristic shows superiority over OML heuristic, with improvement ratio up to 65.48%.

All previous researches, with the use of single (Uniform, and Poisson) distributions in 1D space, agree on the superiority of OML over CMAX. Although, our results show that in some cases, using 2-Hero- and 4-Hetro-Distributions in 3D space, CMAX heuristic can provide superiority over OML heuristic. This leads to the fact that, Heterogeneity of real life terrains (i.e. multi-tone terrain changes) has a major effect on the performance of different routing heuristics.

2. Future Work

The goal of this study was to construct a model that simulates a wireless sensor network on reality using the 2-Hetro- and 4-Hetro-distributions. This model was tested on three dimension (3D) space to evaluate two different heuristics, CMAX and OML. Since conserving battery energy in sensor network is a very important metric that affects the performance of the whole sensor network, it is recommended to apply new methods that maximize lifetime routing in our model, and study the effect of other types of Heterogeneous distributions on maximizing lifetime routing like 6-Hetro and 8-Hetro-Distributions.

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Appendix A

To insure that our networks were correctly implemented, we give an example to show the probability of Uniform and Chi-square distribution for sensor nodes in 3D space.

Uniform_3D:

The adjacency matrix was as follows:

Uniform_3D-- adjacency matrix																				#Edges
0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	**3**
0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	**3**
0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	**4**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**1**
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**1**
0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	1	**4**
0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	**3**
0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	**2**
1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**2**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	**1**
0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	**2**
0	0	1	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	**4**
0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	**3**
0	1	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	**4**
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	0	0	0	**4**
0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	**3**

From the above adjacency matrix, we found the frequency for each number_of_edges in single node (i.e. node degree), as shown in the following table :

Node Degree	Frequency
4	5
3	5
2	5
1	5
Total	**50**

We note that the frequency is equal in the four possible node degrees provided in that network. This means, Uniform distribution is providing equal probability for each node degree (i.e. nodes are uniformly distributed), as seen in Figure 1.

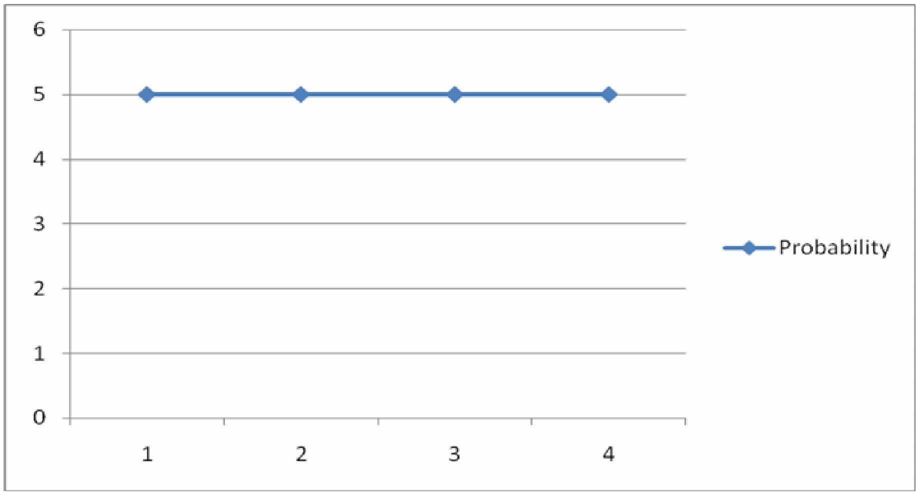

Figure 1: Probability Function for Uniform Distribution

Chi-square _3D:

The adjacency matrix for Chi-square distribution was as follows:

Chi-square_3D-- adjacency matrix																				#Edges
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	**1**
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	**2**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	**1**
0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	**3**
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	**1**
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	**1**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**3**
0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	**3**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	**2**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	**1**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	**1**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**2**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**2**

From the above adjacency matrix, we found the frequency for each number_of_edges in single node (i.e. node degree), as shown in the following table :

Node Degree	Frequency
0	2
1	10
2	5
3	3
Total	**29**

We note that the frequency varies in the four possible node degrees provided in that network. This means, Chi-square distribution is providing different probability for each node degree, as can be seen in Figure 2.

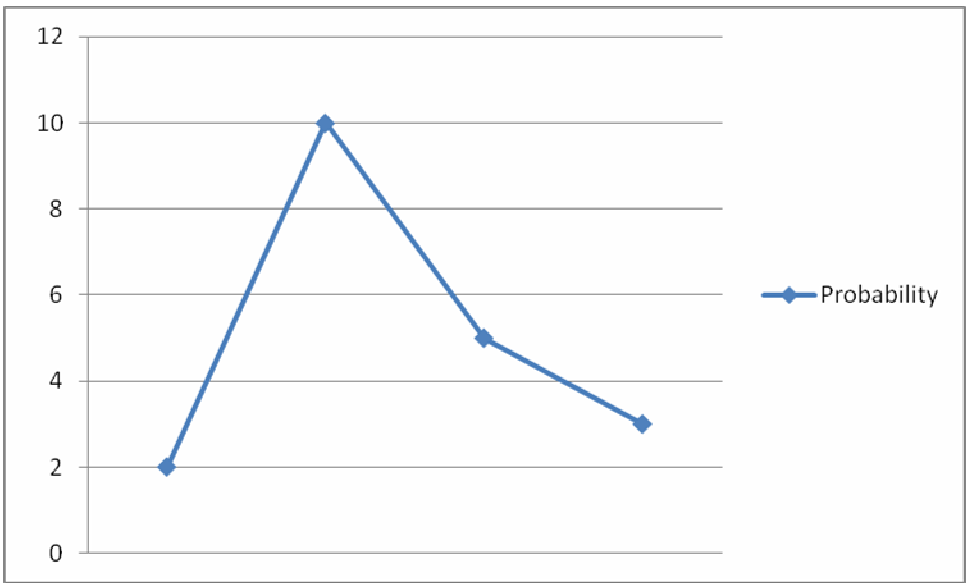

Figure 2: Probability Function for Chi-square Distribution

تأثير إستراتيجية متعدِد الانتشار المتباين على إطالة العمر في شبكات الاستشعار اللاسلكية

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الملخص

أصبحت شبكات الاستشعار اللاسلكية تحظى بأهتمام ملحوظ في السنوات القليلة الماضية. واحدة من القضايا الرئيسية في هذه الشبكات هي محدودية قدرة البطارية. لذلك فانه من المهم تطوير حلول فعالة لإطالة عمرالشبكة قدر المستطاع.

يعتبر نقل البيانات السبب الرئيسي لأنفاق الطاقة في شبكات الاستشعار اللاسلكية، لذلك نجد العديد من تقنيات التوجيه المقترحة لاطالة عمر الشبكة مثل فرضية إطالة العمر المباشرة (OML) و فرضية إطالة السعه (CMAX).

أجريت العديد من البحوث بهدف تقييم هذين التقنيتين أحداها كان يستند توظيف التوزيع العشوائي المتماثل (Uniform) والأخر إعتمد توزيع (Poisson). كلا البحثين استخدما البعد الواحد(1D). هناك بحث تم تقديمه موخرا إعتمد الأبعاد الثلاثة (3D) في بناء OML وCMAX. كل هذه البحوث إتفقت على تفوق OML على CMAX.

تعطي طريقة توزيع العقد معلومات مفصلة حول متطلبات النظام المحدد. بمعنى آخر، دقة نتائج التجارب ستتأثر سلباً إذا تم اختيار طريقة توزيع خاطئة. لإجراء مقارنة عادلة بين تقنيات التوجيه يجب الإنتباه إلى تأثير إستراتيجية الإنتشار، الأمر الذي يقودنا إلى التركيز على كيفية محاكاة توزيع شبكات الإستشعار، وهذا هو محور العمل في هذه الرسالة.

في هذا البحث نستعرض أربعة أنواع مختلفة من التوزيعات العشوائية الاحادية لتحسين تمثيل البيئة الحقيقية. هذه التوزيعات هى (Uniform, Poisson, Normal, Chi-square)، وقد تم تمثيلها بإستخدام ثلاثة ابعاد لبناء الرسم البياني المُوَجَّه الغير دوري (DAG) لمحاكاة الاتصال في شبكات الاستشعار اللاسلكية العشوائية.

علاوة على ذلك، هذه الرسالة تشمل المناطق متعددة التضاريس و تأثيرها على كل من CMAX وOML. لمحاكاة المناطق متعددة التضاريس تم استخدام التوزيعات ثنائية التباين و التوزيعات رباعية التباين.

نتائج التجارب أظهرت أن معدَل إطالة العمر في كلٍ من OML و CMAX يتغير عند تغير استراتيجية الإنتشار. بالتوزيعات ثنائية التباين ,(Normal_Poisson) مثلت أفضل حالة لكلٍ من OML و CMAX وقد وصل معدل إطالة العمر إلى 64209 و 2251 على التوالي. بالتوزيعات رباعية التباين، أفضل حالة لتقنية OML تم تسجيلها عند التوزيع (Normal_Poisson_Chi-square_Uniform)، بمعدل إطالة العمر تجاوز 487418. عند استخدام التوزيع (Chi-square_Normal_Poisson_Uniform) أظهر CMAX أفضل معدل لإطالة العمر و الذي فاق 1038.

نتائج التجارب بالتوزيعات ثنائة التباين كشفت عن تفوق تقنية OML على CMAX بمعظم الحالات. لكن على خلاف البحوث السابقة، تقنية CMAX احزرت تقدماً طفيفاً على OML عند التوزيع (Chi-square_Normal) بنسبة تقدم تجاوزت 7% . أيضا أحرز CMAX تقدما بمعدل إطالة العمرعلى نظيره OML بنسبة تساوي 38.63 %. بالتوزيعات رباعية التباين، افضل حالة لتقنية OML تم تسجيلها عند التوزيع (Normal_Poisson_Chi-square_Uniform)، بمعدل إطالة العمر تجاوز 487418 و نسبة تفوق على (CMAX) تصل إلى 99.82%. عند تمثيل التوزيع الرباعي (Chi_square_Poisson_Normal_Uniform) قدم CMAX معدل إطالة لعمرالشبكة أكثر من OML بنسبة تقدم غير متوقعة تصل إلى 65.48%. من نتائج هذا العمل نستنتج أنه قد ثبت ان إستراتيجية متعددة الإنتشار المتباين ذات تاثير رئيسي في إطالة العمر في شبكات الإستشعار اللاسلكية.