A STATISTICAL EVALUATION APPROACH OF ROUTING TECHNIQUES THAT MAXIMIZE THE LIFETIME OF WIRELESS SENSOR NETWORK

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هذه النسخة من الرسالــة
التوقيع.........التاريخ...٢٠٠٧/٨/١٢

DEDICATION

I dedicate my work to my family for their love and understanding.

To my special partners in work and friends: Tamador, Hutaf, Shaden, Haitham, and Wasel.

To everyone at faculty and university hoping to add a value for my field of specialization.

To European Information Technology Center Family for their great help and understanding.

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LIST OF ABBREVIAVIONS OR SYMBOL

Abbreviation	Meaning
RF	Radio Frequency
OML	Online Maximum Lifetime Heuristics
MRPC	Maximum Residual Packet Capacity
CMAX	Capacity Maximization
R_T	Transmission Radius
MAC	Media Access Control
WSNs	Wireless Sensor Networks
G	Directed Experiment(Representation of Wireless Sensor Networks)
V	Set of Vertices in Experiment G
E	Set of Edges in Experiment G
W	Required Energy to transmit Packet from sensor s to sensor t
i_e	Initial Energy inside Sensor s in Experiment G
c_e	Current Energy inside Sensor s in Experiment G
N	Number of Vertices in Experiment G
a(u)	Percentage of the Initial Energy that Has Already Been Spent at the Node Used in OML and CMAX heuristics

P	**Shortest Path**
λ	**Poisson Distribution Parameter.**
λ **c**	**Algorithm Parameter for CMAX and OML Heuristics for giving cost for the edges.**
c(u,v)	**The number of unit-length messages that may be transmitted along (u, v) before node u runs out of energy.**
life (P)	**The minimum edge capacity on the path**
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**
R	**Routing Request**
PDF	**Probability Density Function**
CDF	**Cumulative Distribution Function**

LIST OF ALGORITHMS

A STATISTICAL EVALUATION APPROACH OF ROUTING TECHNIQUES THAT MAXIMIZE THE LIFETIME OF WIRELESS SENSOR NETWORK

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ABSTRACT

A sensor network is composed of a large number of sensor nodes. The researches indicate that most wireless sensors that were deployed in the real environment require much longer lifetime to send maximum number of packets to its destination. Accordingly, extensive research has been conducted to increase their lifetime. Furthermore, it is known that many heuristics were designed to maximize the lifetime of the wireless sensor network when sensors are distributed randomly using uniform distribution such as the Online Maximum Lifetime Heuristics (OML), Maximum Residual Packet Capacity (MRPC) and Capacity MAXimization (CMAX). These routing heuristics are used to enhance the sensors power and for maximizing lifetime. Researchers used these heuristics assuming that the sensor nodes are distributed uniformly. This means that probability of connectivity between

each sensor would be of the same probability, which is not always true in real life applications, where there are geographical differences in real life environment. Consequently, we investigate the lifetime assuming that the distribution of sensor nodes follows a Poisson distribution in order to meet the real life environment requirement and to have a fair comparison when discussing applications and the behavior of sensors in line with this type of distribution.

Three heuristics were implemented using the uniform and Poisson distribution. The first heuristic was the OML. It employs two shortest path computations to route each message. The second is the MRPC. It selects the path that has the largest packet capacity at the 'critical' node (i.e., the one with the smallest residual packet transmission capacity). The third heuristic is the CMAX. It makes admission control. (i.e., it rejects some routes that are possible). The uniform distribution of sensors is best fitted for symmetric environment with flat lands and no geographical differences in terrains. Deployment of sensors varies from deep oceans to high mounts which are close to the real life environment (asymmetric). Accordingly, this research proposes that Poisson distribution is best fitted for asymmetric environment.

The input for the heuristics was generated using Uniform and Poisson distribution. This simulation was made to maximize lifetime for each sensor for heuristic under study, where lifetime is defined as the number of successfully routed messages before the first route failure. Factors are studied in intensive simulation experiments, such as: number of sensors generated, connectivity between sensors, and distance between sensors. The responses were the average lifetime, and network capacity (the number of successful routes in a given time period). It was found that the average lifetime of all the three heuristics were decreased when moving to Poisson distribution. Our experiment Study, using Poisson distribution, show that the OML heuristic has superiority over the CMAX and the MRPC heuristics in terms of average lifetime and network capacity, and enhancing the required energy to transmit a packet. The percentage difference between each heuristic and the other was calculated by subtracting the average lifetime for the heuristic which has the lower lifetime from the one that has the lower average lifetime, and then divide the resulted value with the higher average lifetime, multiplied by 100%. We concluded that the average lifetime in the OML was 24% better than the CMAX and 47.2% better than the MRPC, while the average lifetime for the CMAX was 29% better than the MRPC heuristic. The average lifetime for the OML was about 767.4, and the average lifetime for the CMAX was about 577.833. Average lifetime for the MRPC was about 405, which is less than the average lifetime when using uniform distribution. The average lifetime using uniform distribution for the OML was 32% better than the CMAX and was 47.4% better than the MRPC, while the average lifetime for the CMAX was 22% better than the MRPC. The average lifetime for the OML was about 937.16, and 598.42 for the CMAX, while MRPC the average lifetime was about 464.

In conclusion, Poisson distribution is better fit for the real life environment because of its nature, and the OML has the superiority over the CMAX and MRPC heuristics.

INTRODUCTION

Introduction

1. Wireless Sensor Networks Overview

According to the development in wireless communications, the development of sensor nodes has received increasing consideration, (I.F. Akyildiz, 2002). These sensors have specific properties and varied by the type of sensors, which varies from simple one to more complex sensors. Such properties are: small size, the ability to sense, process data, and communicate with each other, typically over an RF (radio frequency) channel. A sensor network is designed for a specific event or phenomena such as detecting heat, humidity, wild life, collect and process data, and transmit sensed information to concerned users. Sensor networks have basic properties such as: self-organizing capabilities, short-range broadcast communication and multihop routing, dense deployment and cooperative effort of sensor nodes, frequently changing topology due to fading and node failures, limitations in energy, memory, transmit and computing power, (I.F. Akyildiz, 2002). Sensor nodes can be deployed in deterministic manner or randomly according to their application. Data in wireless sensor networks are routed using multihop routing through a sink to the end user. Figure 1 shows the communication operation.

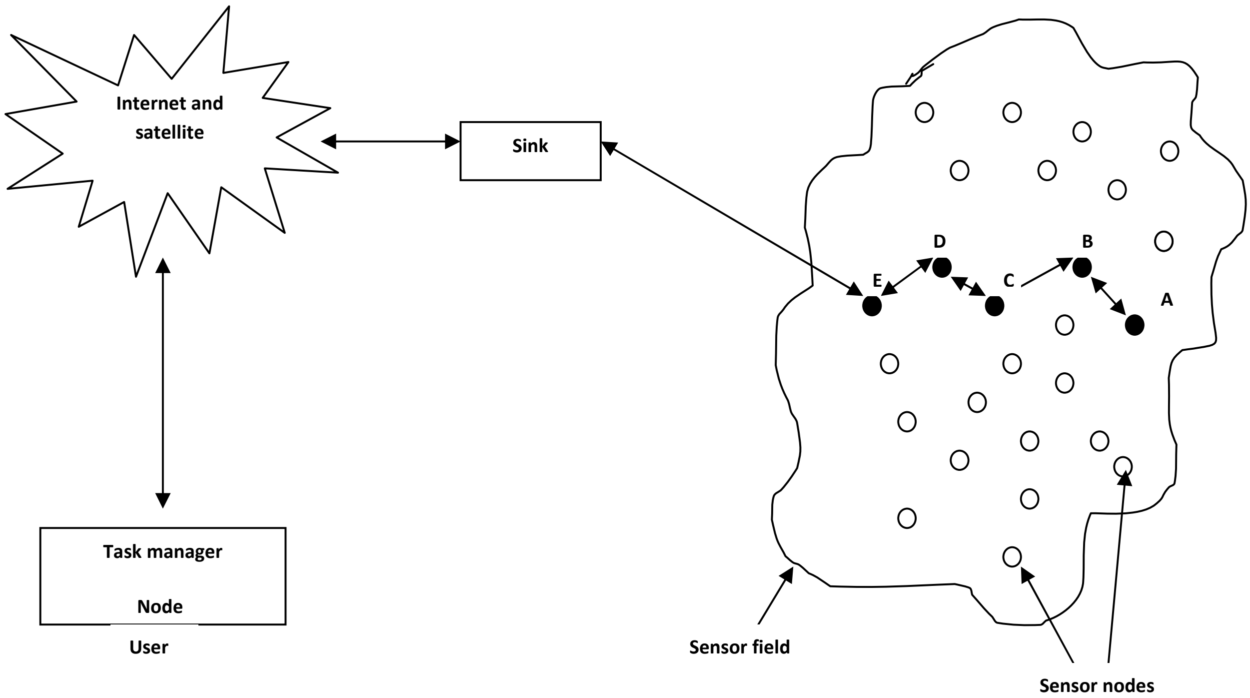

Figure1: Communications in Wireless Sensor Network (I.F. Akyildiz, 2002)

1.1.Sensor Node Structure

The sensor nodes are composed from four basic components, these components are: sensing unit, processing unit, transceiver unit, and power unit. There are additional components for sensor nodes which varies according to the application, such components are: location finding system, power generator, and mobilizer. Figure 2 shows the internal components for sensor node. We should take in consideration the limitation in power, memory, processing when designing sensor nodes, since these power units in sensor nodes can't be replaced nor charged. (I.F. Akyildiz, 2002).

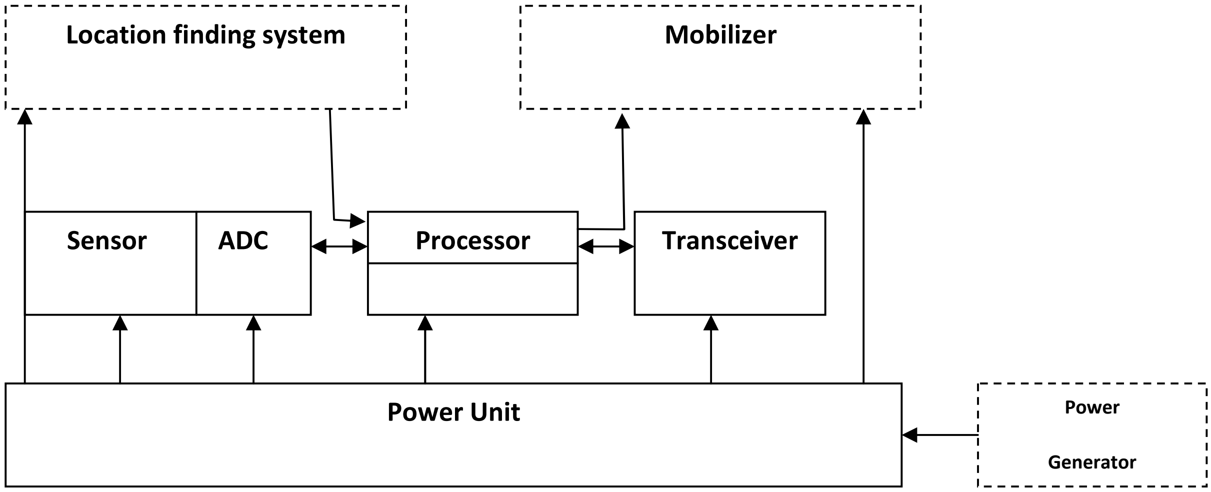

Figure 2: Internal Architecture for Sensor Node (I.F. Akyildiz, 2002)

1.2. Layers of Wireless Sensor Networks

The sensor network is usually designed for specific application. The organization and architecture of a sensor network should be designed for a special task, to optimize the system performance, and maximize the operation lifetime, so that many layers are collaborated to achieve this objective. Figure 3 shows the layers for wireless sensor network.

The physical layer is responsible for frequency selection, carrier frequency, signal detection, modulation and data encryption. Many researches should be done to develop physical layer in wireless sensor network. The data link layer in responsible for multiplexing of data streams, data frame detection, medium access and error control. We should take in consideration the design of power aware medium access control. Network layer is responsible for routing. The energy efficient routing techniques vary according to the chosen rout. The transport layer is accessed through the internet or other external networks. The application layer in potential applications in wireless sensor networks still unexplored. Power Management is a very important issue to optimize the above layer to fit various applications (I.F. Akyildiz, 2002).

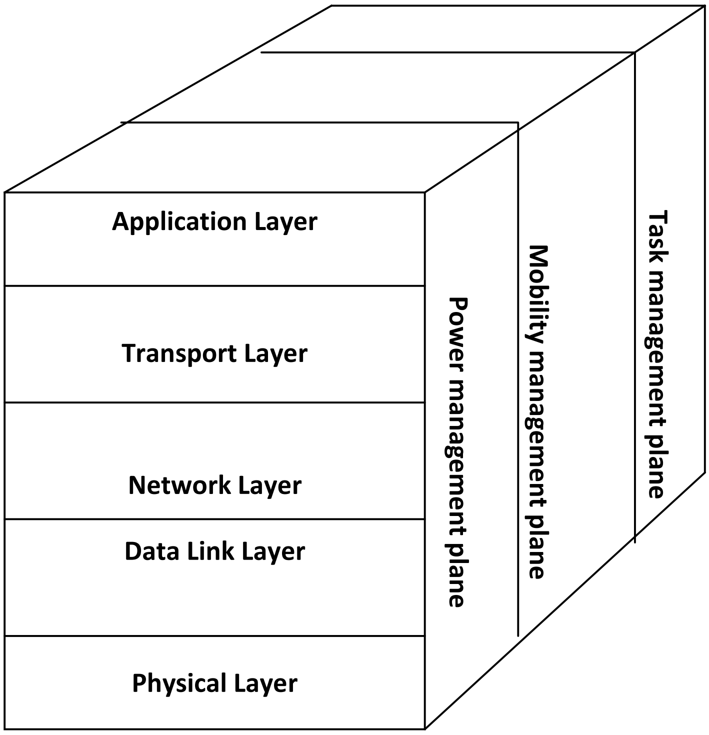

Figure 3: Sensor Networks Layers (I.F. Akyildiz, 2002)

1.3. Applications of Sensor Networks

There are various applications for Wireless Sensor Networks (WSNs). Sensor networks may be deployed to observe specific data. They could be deployed in wild life, for long time with monitoring some environmental variables without the need to recharge or replace their power supplies.

Examples of applications that deploys wireless sensor network are: monitoring, tracking, and controlling, where WSN is scattered in or near a phenomena to collect data through its sensor nodes. However, there are some specific applications such as: habitat monitoring, object tracking, nuclear reactor controlling, fire detection, traffic monitoring, and monitoring medical and environmental events.

1.4. Technical Challenges

Using networks of sensors requires a good understanding of techniques for connecting and managing sensor nodes with a communication network in an efficient ways. Sensor networks are related to a class of ad hoc networks, but they have specific characteristics that are not present in general ad hoc networks, sensor nodes are densely deployed, have frequent change in topology due to fading, limitation in power, computational capacities, and memory. And wireless sensor networks mainly use broadcast communications.

The most challenging issue in sensor networks is conserving energy of un-rechargeable batteries energy. Therefore, many studies aimed at improving the energy efficiency. In sensor networks, energy is consumed mainly for three purposes: data transmission, signal processing, and hardware operation. Thus, it would be desired to develop energy-efficient processing techniques that minimize power requirements, to solve that challenging issue.

1.5. Performance Metrics

Energy efficiency and maximizing lifetime for the whole network is one of the metrics which affects the performance of sensor networks. The most difficult constraints in the design of WSNs are those regarding the minimizing energy consumption, (Segall, 2006).

The growing interest in wireless sensor networks increased the work on multihop routing protocols. Unlike traditional routing protocols that minimize delay and due to the frequent failure of sensor nodes, many protocols attempt to minimize the energy required for communication since nodes in a sensor network depend on energy. However, minimizing the energy consumption for every route may lead to undesirable results. Some nodes will be dying out much earlier than others, resulting in lost sensing functionality. Many researchers have proposed ways to avoid this problem such as (I.F. Akyildiz, 2002), (Sahni, 2006), (Stojmenovic and Lin 2004), and (K. Kar 2003)).

Energy-aware routing tries to optimize network lifetime, Extending network lifetime translates to ensuring that energy use is fair across the network.

Many heuristics were designed to extend the lifetime of the network. Such as: the OML (Online Maximum Lifetime), which employs two shortest path computations to route each message. Another heuristic is the MRPC (maximum residual packet capacity), which selects the path that has the largest packet capacity at the 'critical' node (the one with the smallest residual packet transmission capacity). A third heuristic is the CMAX (capacity maximization) which makes admission control by rejecting some possible routes. The power aware routing heuristics were deployed randomly using uniform distribution. All conducted experiments prove the superiority of the OML heuristic over the two other heuristics the MRPC and the CMAX (Sahni, 2006), (Segall, 2006).

The Uniform distribution of sensors is best fitted for symmetric environment where the lands are flat and no geographical differences exist in terrains, however, this is not always true in real life environment. Deployment of sensors varies from deep oceans up to high mount which is complies with real life environment (asymmetric). Consequently, it is proposed that the nature of Poisson distribution is best fitted for asymmetric environment.

2. Thesis Objectives

This study is conducted to achieve the following:

- Implementing and analyzing the existing heuristics using uniform distribution.
- Implementing and analyzing the existing heuristics using Poisson distribution.
- Comparing the results from Poisson distribution with those from uniform distribution and studying the effect of average lifetime, network capacity, network density, and number of sensors.

3. Thesis Overview

This thesis is organized as follows. In this chapter, a problem overview, technical challenges, the performance metrics that affects the sensor networks system, power aware routing methods, the main objectives for the proposed system are discussed. In the next chapter, other existing heuristics and studies in the literature for maximizing lifetime routing using Uniform distribution are reviewed. The description of maximizing lifetime routing using Uniform and Poisson distribution and its 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 the third chapter, wireless sensor networks. Experiments and the analysis of the results for the new heuristic using different type of distribution are given in the discussion and analysis of results chapter. The final chapter include thesis conclusion and suggested future studies.

LITRATURE REVIEW

Literature Review

Several authors have developed power aware routing heuristics base in distributing the sensor nodes randomly using uniform distribution. The overall objective of these heuristics is to either maximize the lifetime (time at which a communication fails first) or to optimize the capacity of the network (number of successful communications over some fixed period of time in which the network continues to service route requests even after a communication failure). Many researchers have worked with Poisson distribution in fields other than wireless sensor networks. Following are some literatures on the issue concerned:

1. Maximizing Lifetime Routing

In Singh paper (Singh 1998) a five metrics that may be used in the selection of the routing path for energy efficient routing were developed. The first was to use a minimum-energy path from source node to target node. By that they minimize the total energy consumed over a sequence of routes. Among those five proposed metrics, only the first (minimum-energy path) and the fourth (minimize node cost) have been implemented by Singh. They raise concerns about the difficulty of implementing the remaining three in a routing protocol.

Two years later Change (Chang and Tassiulas 2000) developed a linear-programming formulation for lifetime maximization. Those researchers assumed that the limited battery energy is the most important resource, so their research problem was to maximize the battery lifetime of the system for a set of given information at the origin nodes. In order to do so, the traffic is routed in a way that the energy consumption is balanced among the nodes in proportion to their energy reserves, instead of routing to minimize the absolute consumed power.

While Heinzelman (Heinzelman 2000) developed in his paper a clustering-based routing heuristic protocol (LEACH) for sensor networks. He tries to distribute the energy load among the sensors in the network.

After that, Toh (Toh 2001) proposed the MMBCR (min-max battery cost routing) and CMMBCR (conditional MMBCR) online heuristics to select a source-to-destination path. The MMBCR heuristic selects a path (P) for which the minimum of the residual energies of the sensors on this path is maximum. Recognizing that to maximize lifetime we need to achieve some balance between the energy consumed by a route and the minimum residual energy at the nodes along the chosen route, Toh also propose a conditional MMBCR heuristic, CMMBCR. Through which a minimum energy source-to-destination path is searched for where no sensor has residual energy below a threshold γ. If there is no such path with this property, then the MMBCR path is used.

Another researcher, Wu (Wu 2002) developed a routing based on connected dominating sets to maximize network lifetime. In his paper, the connected dominating set is selected based on the node degree and the energy level of each host. There objective was to provide a selection scheme so that the overall energy consumption is balanced in network, and at the same time, a relatively small connected dominating set is generated.

Contemporarily, A.Misra (A. Misra and S. Banerjee 2002) proposed the MRPC (maximum residual packet capacity) for lifetime-maximization, which is a power-aware routing heuristic for energy-efficient routing that increases the operational lifetime of multi-hop wireless networks. This heuristic identifies the capacity of a node by the expected energy spent in forwarding a packet over a specific link. MRPC Heuristic selects the path that has the largest packet capacity at the 'critical' node (the one with the smallest residual packet transmission capacity). Misra also presented the CMRPC heuristic, which is a conditional variant of the MRPC that switches from minimum energy routing to MRPC only when the packet forwarding capacity of nodes falls below a threshold.

After that, Aslam (Aslam 2003) have shown that there is no online routing heuristic with O (n) competitive ratio for the lifetime maximization problem. In his paper, he discussed the online power-aware routing in large wireless ad-hoc networks for applications where the message sequence in not known. He seeks to optimize the lifetime of the network.

Consequently, Kar (K. Kar 2003) proposed an online capacity-competitive (the capacity is the number of messages routed over some time period) heuristic. The CMAX Heuristic (capacity maximization) with logarithmic competitive ratio. To achieve this logarithmic competitive ratio, the heuristic CMAX does admission control. That is, it rejects some routes that are possible.

Following that, Stojmenovic (Stojmenovic and Lin 2004) developed localized heuristics to maximize lifetime by defining a new power cost metric based on the combination of both nodes lifetime and distance-based power metrics. They 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), which provides basis for power, cost, and power-cost localized routing heuristics where nodes can make routing decisions solely on the bases of location of their neighbors and destination.

Following that, a group of researchers, Y. Thomas Hou (Y. THOMAS HOU and YI SHI and HANIF D. SHERALI 2005) studied the network lifetime problem by considering not only maximizing the lifetime until the first node fails, but also maximizing the lifetimes for all the nodes in the network, which is defined as the LexicoExperimentic Max-Min (LMM) node lifetime problem.

Recently, Joongseok (Joongseok Park and Sartaj Sahni 2006) proposed the OML heuristic where each message has to be routed without knowledge of future route requests. The goal of this heuristic was to maximize network lifetime, by performing two shortest path computations to route each message and maximize the lifetime.

2. Poisson Distribution

In Al-Sharaeh(Al-Sharaeh, S, Wells, B.E., 1996) paper they discuss the use of Poisson distribution in solving the scheduling problem and determine which heuristic is better fit the real-world systems. And they find according to their experiment that the result they get give a better description for real environment, which is mainly the base of our proposed idea using Poisson distribution.

After this presentation of some literature related to the thesis problem, it can be argued that all the previous researches deploy the sensors uniformly which is a good assumption for symmetric environment in wireless sensor networks, where lands are flat with no geographical differences in terrains. But as mentioned above this is not always the case in real life environment which is considered a logic reason for us to propose studying the effect of different distributions such as Poisson distribution, which is best fitted for asymmetric environment and uniform distribution on the performance of different heuristics on maximizing lifetime routing to be more comparable to real life environment.

MAXIMIZING LIFETIME ROUTING HEURISTICS IN WIRELESS SENSOR NETWORKS

Maximizing Lifetime Routing Heuristics in Wireless Sensor Networks

Sensor network model in the perspective of programming, different types of statistical distribution, maximum lifetime routing heuristics, implementation of power aware routing heuristics, and the time complexity analysis for the power aware routing heuristics were studied in this chapter.

1. Sensor Network Model

The sensor network is modeled using a directed graph in our Experiment, Figure 4 show simple representation for sensor network using directed Experiment.

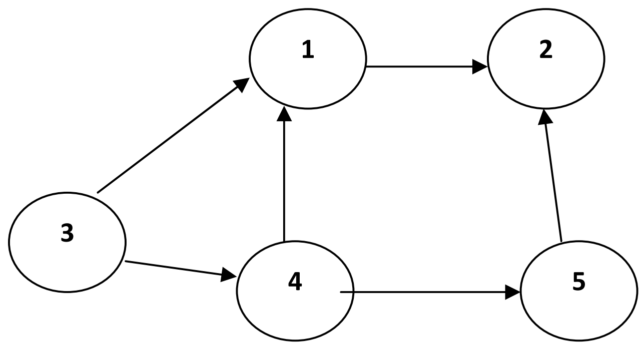

Figure 4: Simple Representation for Sensor Network Using Directed Experiment

Let the wireless sensor network modeled as illustrated in Relation 1:

$$G = (V, E) \qquad (1)$$

Where (V) is the set of sensors in the network, and (n) = |V| is the number of sensors. And E is the edge set (Sahni, 2006). If a single-hop transmission from u to v is possible then there will be a directed edge (u,v) ∈ E. let the initial energy in sensor(u) be defined as illustrated in Relation 2:

$$i_e(u)>0 \qquad (2)$$

The current energy in sensor u is defined as illustrated in Relation 3:

$$c_e(u) \geq 0 \qquad (3)$$

For each (u,v) ∈ E, define the energy required to make a single hop transmission from sensor u to sensor v in Relation 4:

$$w(u,v) > 0 \qquad (4)$$

Following a single-hop message transmission from *(u)* to *(v)*, the current energy in sensor *u* will be equal to Equation 1:

$$ce(u)= (c_e(u)-w(u,v) \qquad (1)$$

Note that this single hop transmission is possible only if $c_e(u) \geq w(u,v)$, and in (Sahni, 2006) paper they assume that no energy is consumed during message reception, so the current energy in sensor v is unaffected by a transmission from u to v.

In considering the sequence of routing requests represents by a pair of attributes (s,t), let R=r_1, $r_2 \ldots r_n$ be a finite sequence of routing requests. Noting that each r_i is a source–destination pair (s_i,t_i). The lifetime of a network for request sequence (R) is the maximum (i), so that routing request r_1,$r_2 \ldots$,r_i are successfully routed.

Wireless sensor network are represented using adjacency matrix, Figure 5 shows the adjacency matrix of the sensor network modeled in a directed Experiment as shown in Figure 4. An example of routing request based on Figure 4 from (3, 2) is the rout represented by (3, 1), (1, 2).

$$\left\{\begin{matrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \end{matrix}\right\}$$

Figure 5: Adjacency Matrix for the Network in Figure 4

2. Statistical Distributions

There are several types of statistical distribution procedures according to the purpose of analysis. Furthermore, the distribution of a variable is a description of the relative numbers of times that each possible outcome occurs in a number of trials, while probability function describes the occurrence of a given value, it is called also the probability density function (PDF). And the function which describes the cumulative probability of occurrence of a given value or any other smaller one than what occur value smaller than it will occur is called the distribution function (or cumulative distribution function (CDF), (StatisticalDistribution.html, 2007). Approximately all real life systems contain such resources of randomness. If we don't choose the correct distribution, the results accuracy will be defected. (M.Law & Kelton, 2000). After this statistical introduction, and since coverage and connectivity are basic requirements for sensor network, the way the sensor nodes are distributed gives us a detailed information about the nature of application requirement and how each source sensor node communicates with destination sensor nodes. Such properties are also considered in many sensor networks operations such as: clustering, synchronization, query and information discovery deployment and redeployment, (Liu, Oct. 1, 2006).

Some types of distribution are studied in the following sections:

2.1. Uniform Distribution

Uniform distribution of sensors is best fitted for symmetric environment where the lands are flat and there are no geographical differences in terrains. All simulations that are performed in literature based on distributing the sensor nodes randomly using uniform distribution, and then calculating the distance between each sensor and its neighbors Figure 6 describes the PDF of uniform distribution. Uniform distribution, sometimes also known as "rectangular distribution", is a distribution that has constant probability. As seen in Figure 6.

The PDF and CDF of a uniform distribution on the interval are expressed in Equation (2) and (3) respectively (M.Law & Kelton, 2000)*:

$$f(x) = \begin{cases} \dfrac{1}{b-a} & \text{for } b \le x \le a \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

$$F(x) = \begin{cases} 0 & \text{if } x < a \\ \dfrac{x - a}{b-a} & \text{if } a \le x \le b \\ 1 & \text{if } b < x \end{cases} \qquad (3)$$

Where (*a* and *b*) are real numbers with a <b, (a) is the location parameter and (b-a) is the scale parameter. Standard uniform distribution is defined where a=0 and b=1.

Uniform distribution is as important as a referential one because it defines equal probability over a given range for a continuous distribution. One of the most important applications of the uniform distribution is in the generation of random numbers, that is, almost all random number generators generate random numbers on the (0, 1) interval, as some transformations are applied to the uniform random numbers (Engineering Statistics HandBook, 2007).

* Chapter 6, page:292-318

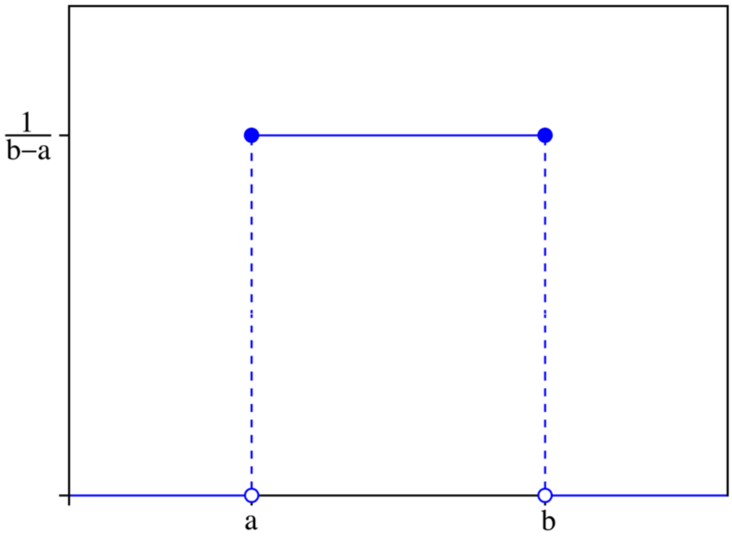

Figure 6: Uniform Distribution (Probability Density Function)

2.2. Poisson Distribution

This is another type of distribution that should be focused on as an alternate to the uniform distribution in our experiment. Poisson distribution plays a critical point in many real life applications. Alternatively, and due to the nature of Poisson distribution is best fitted for asymmetric environment, since it is appropriate for applications that involve counting the number of times a random event occurs in a given amount of time, distance, area, etc. Sample applications that involve Poisson distributions include, the number of people walking into a store in an hour, the number of flaws per 1000 feet of video tape (MathWorks, 2007), detecting volcanoes, earthquakes, battlefields, and many environmental applications. In these applications the distribution of sensor node would be scattered in random manner, and be clustered in some places where other places have a few number of sensor, and this would follow the PDF definition of Poisson distribution.

This distribution is a one-parameter discrete distribution that takes nonnegative integer values. Where the parameter (λ) is both the mean and the variance of the distribution, thus, there is a positive relationship between the size and the variability of numbers in a particular sample of Poisson random numbers (MathWorks, 2007). Figure 7 shows the PDF for Poisson distribution.

The Poisson PDF is given by Equation (4):

$$p(x, \lambda) = \frac{e^{-\lambda}\lambda^{x}}{x!} \qquad \text{for } x = 0,1,2,\ldots \quad (4)$$

While the Poisson CDF is given by Equation (5):

$$F(x, \lambda) = \sum_{i=0}^{x} \frac{e^{-\lambda}\lambda^{i}}{i!} \qquad (5)$$

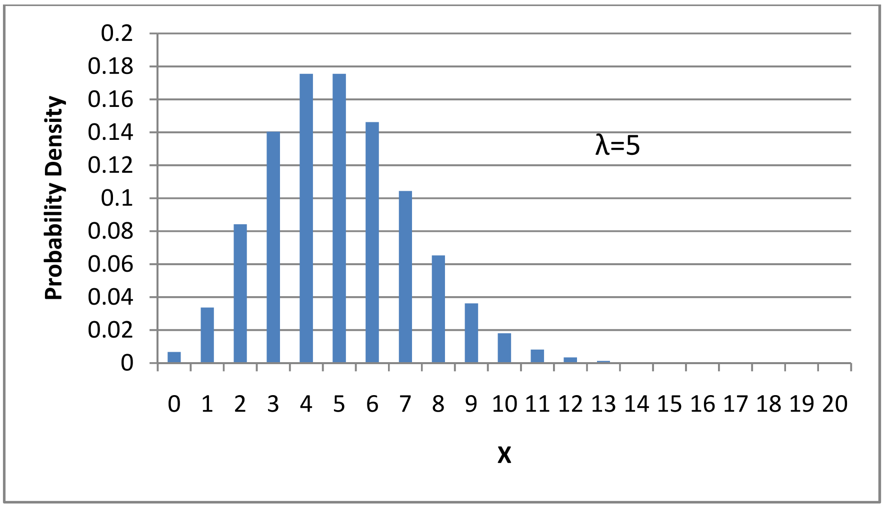

Figure 7: Poisson Distribution(Probability Density Function)

2.2.1 Generating Random Varieties for Poisson

The random generation for Poisson is done basing on the relationship between the Poisson (λ) and expo ($1/\lambda$) (M.Law & Kelton, 2000). Algorithm 1 illustrates the generation process:

Algorithm 1: Random Generation for Poisson **(M.Law & Kelton, 2000)**

Step 1:

let $a=e^{-\lambda}$, b =1, and i=0

Step 2:

Generate $U_{i+1} \sim U(0, 1)$ and replace b by bU_{i+1}. If $b < a$, return X=i. otherwise, go to step 3.

Step 3:

Replace I by i+1 and go back to step 2.

It is noted in the above algorithm that when increasing the value of λ, the algorithm become slow, because large value of λ means that $a=e^{-\lambda}$ is smaller, which requires more execution of step 2 to minimize the cumulative product of the U_{i+1} down under ***a*** (M.Law & Kelton, 2000).

2.2.2 Poisson Processes

In many applications, we need to generate a sequence of random points in time $0 = t_0 \leq t_1 \leq t_2 \leq$.., such that the i^{th} event of some kind occurs at time t_i (i=1.2…) and the distribution of the event time $\{t_i\}$ follows some specified form.

Let N (t) = max {i: $t_i \leq t$} be the number of events occur at or before time t for $t \geq 0$. This process {N (t), t≥0} is the arrival process (M.Law & Kelton, 2000).

The Poisson process has important properties, and should satisfy important requirements such as: customers arrive at one time, N (t + s) – N (t) (the number of arrival in the time interval (t, [t + s]) is independent of {N (u), $0 \leq u \leq t$}, the distribution of N (t + s) – N (t) is independent of t for all t, s≥0.

2.2.3 Nonstationary Poisson Processes

Let the arrival rate of customers to some system at time t denoted by $\lambda(t)$. If customers arrive at the system in accordance with Poisson process with constant rate λ, then λ (t) = λ for all $t \geq 0$. For many real life systems, $\lambda(t)$ is a function of t. For example the arrival rate of customers to a restaurant may varies according to the time of day. By that it is clear that the inter-arrival times A1, A2,.., are not identically distributed, so the process of Poisson is said to be nonstationary if the customers arrive one at a time, and N(t + s) – N(t) is independent of { $0 \leq u \leq t$}. (M.Law & Kelton, 2000).

3. Maximum Lifetime Routing Heuristics

Each message routing in wireless sensor networks is battery operated. However, there is a critical challenge in this concern as the battery is neither replaceable nor rechargeable (Sahni, 2006). Such as deploying sensor networks in forests, battlefield, or any place that is hard to reach. In this study, energy conservation is considered as a very important metric to maximize lifetime in wireless sensor networks. In general, the required energy for a sensor to transmit a unit length message a distance (r) is proportional to (r^d) for some (d) in the range. In wireless sensor networks, energy is conserved using multihop routing, (Sahni, 2006), so the sensor nodes between source and destination are used as relays. Following is an illustrative example for conserving energy using multihop routing

Example 1:

Let A, C: Sensors, B: a halfway sensor between A and C. d(A,C) =4, distance between Sensor A and C, d(A,B)=2, d(B,C)=2.

Energy required to transmit from A to C =16. While the energy required transmitting from A to B is 4 and from B to C is 4.

Consequently, totals Required Energy to Transmit from A to C using Multihop routing =8, as shown Figure 8.

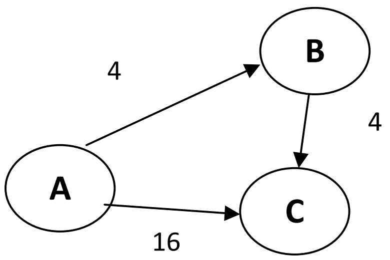

Figure 8: Sensor Network with Three Sensors

There are several energy-aware routing heuristics, that can be divided into four groups, according to their methods and rules which they used for calculating and comparing routing paths. The four groups are: minimum total cost routing, min-max cost routing, max-min cost routing and hybrid cost routing. Within each group, heuristics differ by the link cost function, while groups differ by the scheme for computing the cost of the entire path and by the method for comparing the quality of the path. Table 1 on Page 29 describes the summary of routing schemes for each of the four groups mentioned above.

The routing heuristics in general provides the best route from a source node (s) to a destination node (t) according to some criterion if such route can be found (Using one of the existing shortest path heuristics in the literature) or it rejects the packet if no feasible route exists. Any minimum cost routing heuristic minimizes the total cost of forwarding the packet along the entire route. In other words, among all possible routes from source node (S) to destination node (D), the minimum cost routing heuristic selects the rout with the minimum total cost, provided that the total cost is calculated as the sum of the link costs along the route. As for the second group, the Min-MAX cost routing heuristics are oriented to minimize the maximal cost of links in the path rather than its total path cost, where the selected route is the one whose maximal link cost is minimal.

Table 1: Energy Aware Routing Metrics **(Segall, 2006)**

Group	Heuristic Number	Name
Minimum total cost	(1)	Minimum Transmission Energy Routing
	(2)	Minimum Battery Cost Routing
	(3)	Minimum Residual Energy Path, "cap" means "capacity", "sum" means that the total cost of path is computed as a sum of link costs composing it) combines the two previous schemes and uses a metric, which is proportional to the transmission energy divided by the residual energy.
	(4)	Capacity Maximization heuristic
	(5)	Online Maximum Lifetime Heuristic
Min-max cost	(6)	Min-Max Battery Cost Routing heuristic
	(7)	Minimum Residual Energy Path, while "max" means that the total cost of path equals to maximal cost of links composing it) algorithm.
Max-min cost	(8)	Maximum Residual Packet Capacity heuristic
Hybrid cost	(9)	Conditional Min-Max Battery Capacity Routing heuristic
	(10)	Conditional Maximum Residual Packet Capacity heuristic

The third group of heuristics is max-min cost routing. These heuristics route packets along paths with maximum minimal link cost. The fourth and final group of heuristics is the hybrid (mixed) cost routing which is some combination of the three previous routing techniques. Each heuristic in this group applies its own methods and rules.

According to Table 1, many heuristics were related to the four categories. Experiments show the superiority of the CMAX Heuristic over other ones of its category, and the same for MRPC heuristic. However, experiments show superiority of OML heuristic over CMAX heuristic and MRPC heuristic (Sahni, 2006). For more clarification, CMAX, MRPC and OML heuristics are discussed in the next section.

3.1.CMAX Heuristic

The CMAX heuristic, (Segall, 2006), assigns weights to each link in the network. Where the weight of a link increases with the increase in energy expended in traversing that link as well as with the energy already spent by the transmitting node, then the shortest path, with respect to link weights, is selected. This heuristic as well requires that energy utilized by each node of the entire network.

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 (6)† as follows:

$$a(u) = 1 - c_e(u) / i_e(u) \qquad (6)$$

While the weight of every edge (u,v) is changed from w(u,v) to that in Equation (7):

$$w(u,v) = w(u,v) * (\lambda c^{a(u)} - 1) \qquad (7)$$

Where λ_c is an algorithm parameter and $(\lambda c^{a(u)} - 1)$ is the cost function for giving the edge weight, the shortest source to destination path (p) in the resulting Experiment then is determined. Algorithm 1 shows the sequences for the CMAX heuristic.

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

Algorithm 2: CMAX Heuristic **(Sahni, 2006)**

Step 1: [Initialize]

Eliminate from (G) every edge (u, v) for which ce(u) < w(u, v).

Change the weight of every remaining edge (u, v) to $w(u,v)*(\lambda c^{a(u)}-1)$

Step 2: [Shortest Path]

Let (P) be the shortest source-to-destination path in the modified Experiment.

Step 3: [Wrap Up]

If no path is found in Step 2, the route is not possible

3.2.MRPC Heuristic

In the MRPC lifetime-maximization heuristic (A. Misra and S. Banerjee 2002), the capacity function c(u,v) is defined as number of unit-length messages that may be transmitted along sensor nodes (u, v) before node (u) runs out of energy. The lifetime of path (P), life (P) is defined as the minimum edge capacity on the path, see Equation (8). Algorithm 2 shows the sequences for the MRPC heuristic.

$$\text{Life(P)} = \min(\text{u,v}) \text{ in P}\{\text{c(u,v)}\} \qquad (8)$$

In this heuristic, routing is performed along a path (P) with maximum lifetime, as shown Equation (9) below:

$$\text{P candidate} = \text{Max}\{\text{Life(P)}\} \qquad (9)$$

Algorithm 3: MRPC Heuristic **(Sahni, 2006)**

Step 1: [Initialize]

Eliminate from (G) every edge (u, v) for which ce(u) < w(u, v).

For every remaining edge (u, v) let c(u, v) = ce(u)/w(u, v).

Let (L) be the list of distinct c(u, v) values.

Step 2: [Binary Search]

Do a binary search in (L) to find the maximum value max for which there is a path P from source to destination that uses no edge with c(u, v) < value max.

For this, when testing a value (q) from (L), we perform a depth- or breadth-first search is performed, beginning at the source. The search is not permitted to use edges with c(u, v) < q.

Let P be the source-to-destination path with lifetime max.

Step 3: [Wrap Up]

If no path is found in Step 2, the route is not possible.

Otherwise, use (P) for the route.

3.3.OML Heuristic

To maximize lifetime, the reduction of sensor energy should be delayed as much as possible to a level below that needed to transmit to its closest neighbor. This is accomplished using a two-step heuristic to find a path for each routing request $r_i = (s_i, t_i)$. In the first step, all edge are removed from (G), such that $c_e(u) < w(u, v)$ as these edges require more energy than available for a transmit. Let the resulting Experiment be G = (V, E). Next, determine the minimum energy path $P`_i$ from $(s)_i$ to (ti) in Experiment G`. This is done using Dijkstra shortest path Algorithm. In case there is no path for (s) to (t), then the routing request fails, but if routing request exists, then P` used to compute the residual energy, Equation (10) illustrates how to compute it.

$$re(u) = ce(u) - w(u, v) \qquad (10)$$

Now, minimum residual energy minRE is calculated using Equation (11).

$$minRE = \min\{re(u) \mid u \text{ in } P\} \qquad (11)$$

Let G`` = (V,E``) be a Experiment 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 Experiment. By that, the reduction of energy from sensors that are low on energy could be prevented.

The second step in the procedure is, find the path to be used to route the request (r). By starting assign weight for the remaining Experiment. In order to satisfy the desired targets to minimize total energy consumption and to prevent the depletion of a sensor's energy, Let eMin as expressed in Equation (12) is the energy needed by sensor (u) to transmit a message to its nearest neighbor in G`.

$$eMin(u) = \min \{ w(u,v) \mid (u,v) \text{ in } E`` \} \qquad (12)$$

Now, let ρ (u,v) is defined using Equation (13).

$$\rho(u,v) = \begin{cases} 0 \text{ if } ce(u) - w(u,v) > eMin(u) \\ c \quad \text{otherwise} \end{cases} \qquad (13)$$

Where (c) in a non-negative constant and it is an algorithm parameter. By updating the weight function through ρ, assigns a high weight to edges whose use on a routing path causes a sensor residual energy to become low.

For each (u) in V, a(u) is defined as in Equation (14).

$$a(u) = minRE / ce(u) \qquad (14)$$

The weight w``(u,v) assigned to edge (u,v) in E`` is defined as in Equation (15), Where λ_c is another non-negative constant and an algorithm parameter.

$$w``(u,v) = (w(u,v) + \rho(u,v)) (\lambda_c^{a(u)} - 1) \qquad (15)$$

All edges starting from a sensor whose current energy is small relative to (minRE) are assigned a high weight because of the (λ_c) term. Weighting function discourages the use of edges whose use on a routing path is likely to result in the failure of a future route. Algorithm 3 describes the sequences of the OML Heuristic.

The goal of two shortest path algorithms is to allow us to do one level look ahead without increasing complexity too much and gaining more lifetimes.

Algorithm 4: OML Heuristic (**(Sahni, 2006)**

Step 1: [Compute G′′]

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

Let Pi be a shortest si to ti path in G'.

If there is no such P_i, the route request fails, stop.

Compute the minimum residual energy minRE for sensors other than ti on Pi .

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

Step 2: [Find route path]

Compute the weight $w''(u, v)$ for each edge of E''.

Let $P``_i$ be a shortest $s_i$ to $t_i$ path in G``.

Use $P``_i$ to route from s_i to t_i.

3.4. Comparing the performance of CMAX and OML

Both the CMAX and OML heuristics have a ($\lambda_c^{a(u)} - 1$) term in the edge weighting function. Where the two heuristics use a different a(u) function. In the case of CMAX, $a(u) = 1 - c_e(u) / i_e(u)$ is the fraction of u's initial energy that has been used so far. So, the CMAX heuristic discourages the use of sensors that have depleted a large fraction of their initial energy, as relays (even though such sensors may deplete a large amount of energy remaining). While in the OML heuristic, $a(u) = minRE/c_e(u)$. Hence, the OML heuristic discourages the use of sensors, as relays whose current energy is much less than minRE, (Sahni, 2006) .

4. Time Complexity Analysis

It is shown that there is no online routing heuristic with O (n) competitive ratio for the lifetime maximization problem (Aslam, Li and Rus 2001). While MRPC heuristic has O (m + nlog n) depth- or breadth-first searches per route request, which is the same for CMAX heuristic, where (m) is the number of edges and (n) is the number of nodes, but for OML heuristic it has $O(m + n^2)$.

DISCUSSION AND ANALYSIS OF RESULTS

Discussion and Analysis of Results

Evaluation of Uniform and Poisson distribution for maximizing lifetime routing is presented in this section. Depending on the assumptions that were taken in consideration, the performed experiments, result analysis, performance measurement and a comparison of the results for Poisson distribution with existing systems are presented.

1. Implementation of Power Aware Routing Heuristics

The uniform and Poisson distribution were implemented in this thesis. To meet real environment requirements, calculate the average lifetime according to this distribution and to determine the connectivity. Accordingly, the average lifetime change toward increasing, decreasing or remaining as it is studied to determine which heuristic performs best in this environment. Next, how to maximize lifetime routing when meeting real environment requirement using Poisson distribution is discussed.

2. Assumptions

First, we implement our experiment using Uniform distribution then compare the results with the existing experiments that are done in the literature for three heuristics (CMAX, OML, and MRPC). These heuristics were chosen because they show superiority over other heuristics.

For this purpose 20 sensors were randomly populated in each network of 10 networks[‡] (Sahni, 2006). 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.

The simulation for those lifetimes routing heuristics were implemented using MATLAB 2007a. All the experiments were tested on 1.73 GHZ, 1014 MB of RAM laptop running under Windows Vista Business.

3. Performance Evaluation

First, a number of routing heuristics that use energy-aware routing metrics have been introduced. The next issue is to find a good scheme to evaluate and compare the performance of the various heuristics. Only in very few and simple cases, it is possible to perform a mathematical analysis of the heuristics. Therefore, we have performed simulations that permit to give a proper answer to this problem have been performed serious. The other challenge is to select a good criterion for comparison of the heuristic performance. There is no universal criterion suitable for all possible applications (Segall, 2006). Different applications have quite different requirements, so the criterion which suited for some kind of missions might be useless for others. The most popular criterion in the literature is lifetime, which is defined as the time of the first node failure due to battery.

[‡] The value of 20 sensors were chosen arbitrary in the previous experiments, after that we deploy different number of sensors to see the effect of maximize lifetime.

4. Selecting OML and CMAX Parameters

To determine a suitable value for (λ_c), we used 10 random sensor networks. Each network had 20 sensors. The transmission radius and initial energy for each sensor were set to 5, 30 respectively. For the first experiment, c was set as = $0.001r_T^3$ in the definition of ρ . The network lifetime was determined for $\lambda_c = 2^i$, $1 \leq i \leq 12$. For each network and λ_c combination, the lifetime was measured. So, for each λ_c value, lifetime measurements were made, (Sahni, 2006).

5. Experimental Results

This section describes the experiment results using both Uniform distribution and Poisson distribution. Several experiments were performed and difference metrics were studied, based on distributing sensor nodes randomly using uniform distribution.

5.1 Results Using Uniform Distribution

Table 2 shows some collected statistics for deployed Sensor network in the study using uniform distribution for 10 sensor networks with 20 sensors in each network.

Table 2: Statistics for Wireless Sensor Network Using Uniform Distribution

Statistics / Network	Average Connectivity
1	0.3425
2	0.3375
3	0.3775
4	0.3625
5	0.34
6	0.3725
7	0.3575
8	0.355
9	0.355
10	0.3275

Figure (9) shows the average lifetime for 10 sensor networks with 20 sensors in each network. From the Figure, the average lifetime for the OML is of 32% better than the CMAX and of 47.4% better than the MRPC, while the average lifetime for the CMAX is 22% better than the MRPC heuristic. The average lifetime for the OML for different types of λ_c is about 937.16 and that of the CMAX is about 598.42. Finally, the average lifetime of MRPC is about 464. Where the percentage difference is calculated as follows: if the average lifetime for example the OML is greater than that of the CMAX, then the percentage difference is equal to the CMAX average lifetime, subtracted from the OML average lifetime, divided by the OML average lifetime, all multiplied by 100%, as shown in Equation 16:

$$\%Difference = \frac{Avg.OML - \mathrm{Avg.CMAX}}{Avg.OML} * 100\% \qquad (16)$$

If the average lifetime of OML less than the average lifetime of CMAX, the formula would be as illustrated in Equation 17:

$$\%Difference = \frac{Avg.CMAX - \mathrm{Avg.OML}}{Avg.CMAX} * 100\% \qquad (17)$$

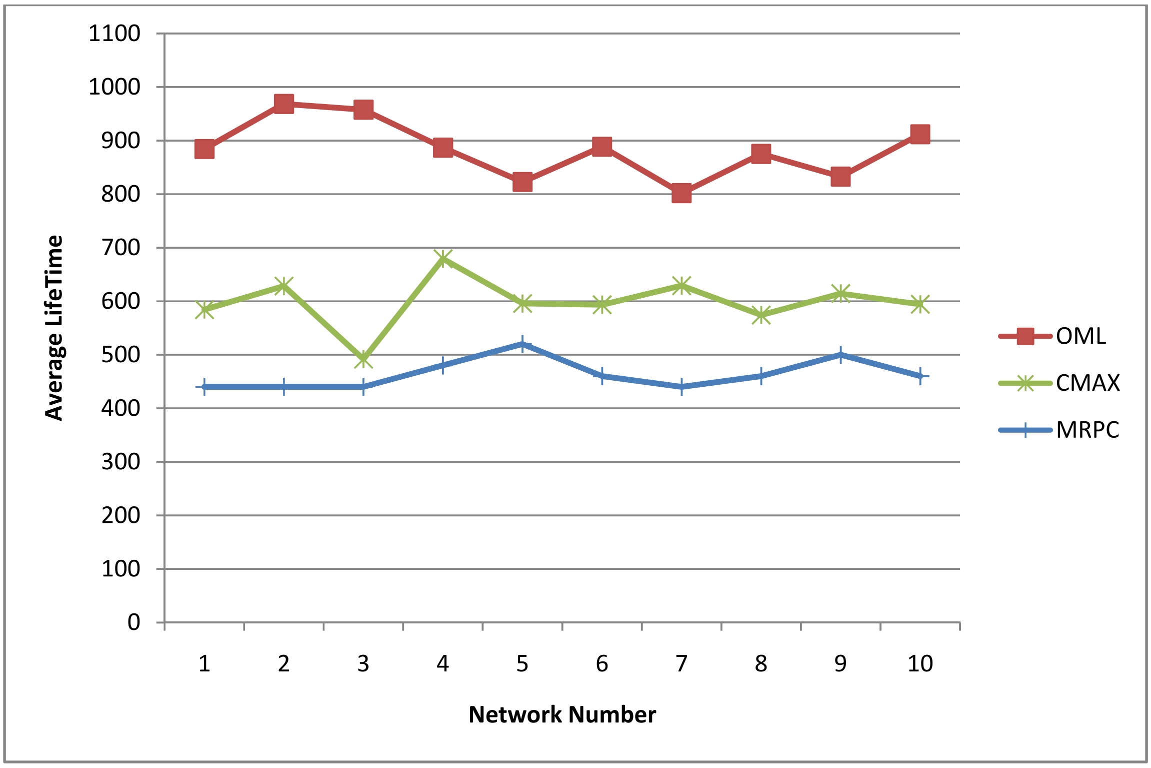

Figure 9: Average Lifetime Routing Using Uniform Distribution

5.1.1 Lifetime Change for OML and CMAX for different values of λ_c

After simulating the CMAX and the OML heuristic with the above assumptions, it is shown that OML heuristic has superiority over the CMAX. OML has high lifetime for values of λ_c between 1 and 3 because of the small values of λ_c. Figure 10 shows the average lifetime for the OML and the CMAX for different values of λ_c. Average lifetime and percentage difference between algorithms of OML and CMAX for 10 networks are shown in table 3 in Page 45.

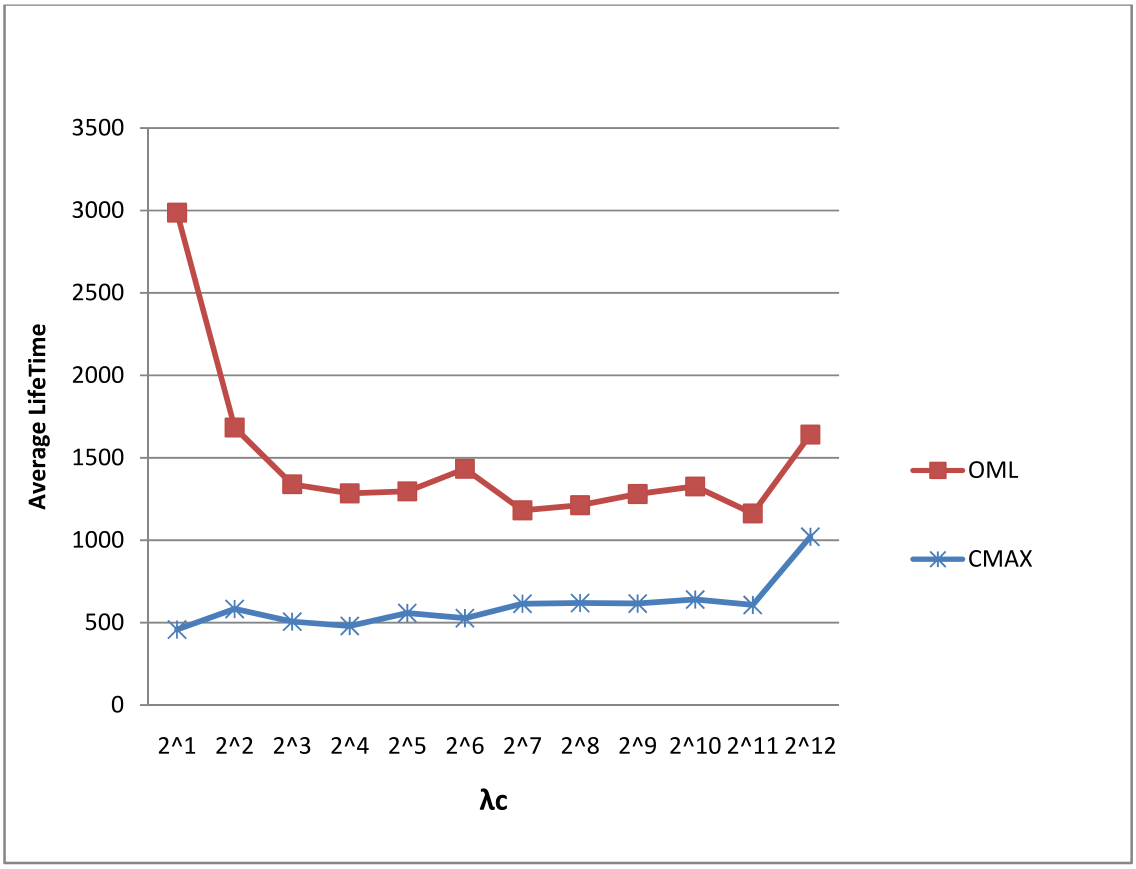

Figure 10: Average Lifetime for CMAX and OML Heuristic Using Uniform Distribution

Table 3: Lifetime Statistics for Different 10 Networks Using Uniform Distribution

	Experiment 1		Experiment 2		Experiment 3	
	CMAX	OML	CMAX	OML	CMAX	OML
Average	584.17	884.16	628.33	968.33	491.77	957.5
Percentage Difference	33.93%		35.11%		48.64%	
	Experiment 4		Experiment 5		Experiment 6	
	CMAX	OML	CMAX	OML	CMAX	OML
Average	679.17	886.66	595.83	822.5	593.33	888.3333
Percentage Difference	23.40%		27.56%		33.21%	
	Experiment 7		Experiment 8		Experiment 9	
	CMAX	OML	CMAX	OML	CMAX	OML
Average	594.17	832.5	629.17	801.66	574.17	875
Percentage Difference	21.52%		34.38%		26.23%	
	Experiment 10					
	CMAX			OML		
Average	614.17			911.6667		
Percentage Difference	34.83%					

5.2 Results Using Poisson Distribution

Changing the type of the distribution of sensor nodes to Poisson will give us better description for real environment. A 20 sensor networks are deployed to be randomly distributed using Poisson distribution. Table 4 shows some statistics that were collected for Deployed Sensor Network using Poisson distribution. We notice that the average connectivity for the 10 networks using Poisson distribution was higher than the average connectivity using uniform distribution. According to the resulted network, there is a clustering of the connected nodes in parts of network, where the other nodes are rarely connected along the network.

Table 4: Statistics for Wireless Sensor Network Using Poisson Distribution

Statistics / Network	Average Connectivity
1	0.47
2	0.4725
3	0.47
4	0.4725
5	0.47
6	0.47
7	0.475
8	0.475
9	0.475
10	0.4675

After distributing the sensor nodes using Poisson distribution, it was found that the OML has superiority over the CMAX in most cases and the MRPC. A decrease in the average lifetime for all heuristics was noticed because of the nature of Poisson distribution, the center nodes where become isolated first, leading to disconnection in the wireless sensor network. According to the study, it was found that the OML is 24% better than the CMAX and 47.2% better than the MRPC. The average lifetime for the CMAX is 29% better than the MRPC. The average lifetime for the OML for different values of λ is about 767.4 but that of CMAX is about 577.833, while for the MRPC, the average lifetime about 405. Figure 11 shows the average lifetime for the three heuristics in Poisson distribution.

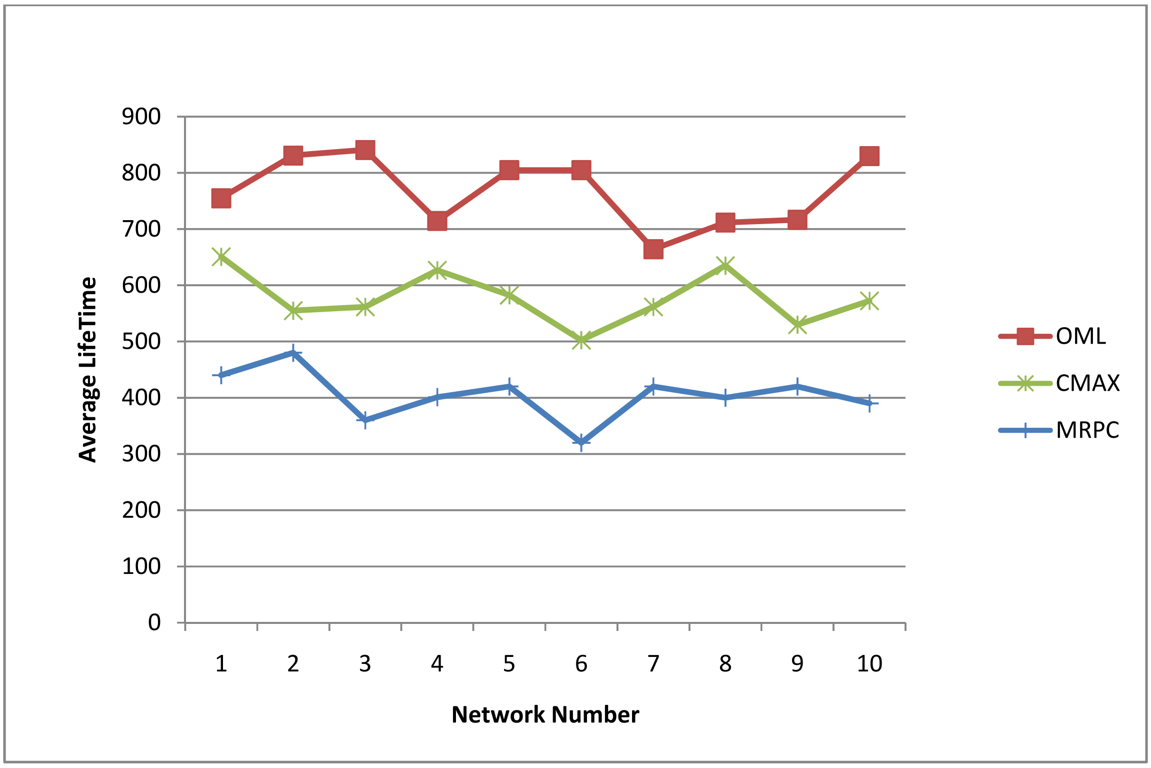

Figure 11: Average Lifetime Routing Using Poisson Distribution

5.2.1 Lifetime Change for OML and CMAX for different values of λ_c

After simulating the CMAX and the OML using Poisson distribution, the experiments indicate the superiority of the OML heuristic over the CMAX, and a minimization in the average lifetime values for both heuristics. Figure 12 shows the average lifetime changes according to the change in λ_c. For λ_c from 2^1 to 2^3, the average lifetime for the OML Heuristic was very high, and between 2^4 and 2^8 the average lifetime for OML approximately is lower than the average lifetime for CMAX algorithm between 2^9 and 2^{11}. The average lifetime for OML was approximately equals the average lifetime for CMAX algorithm.

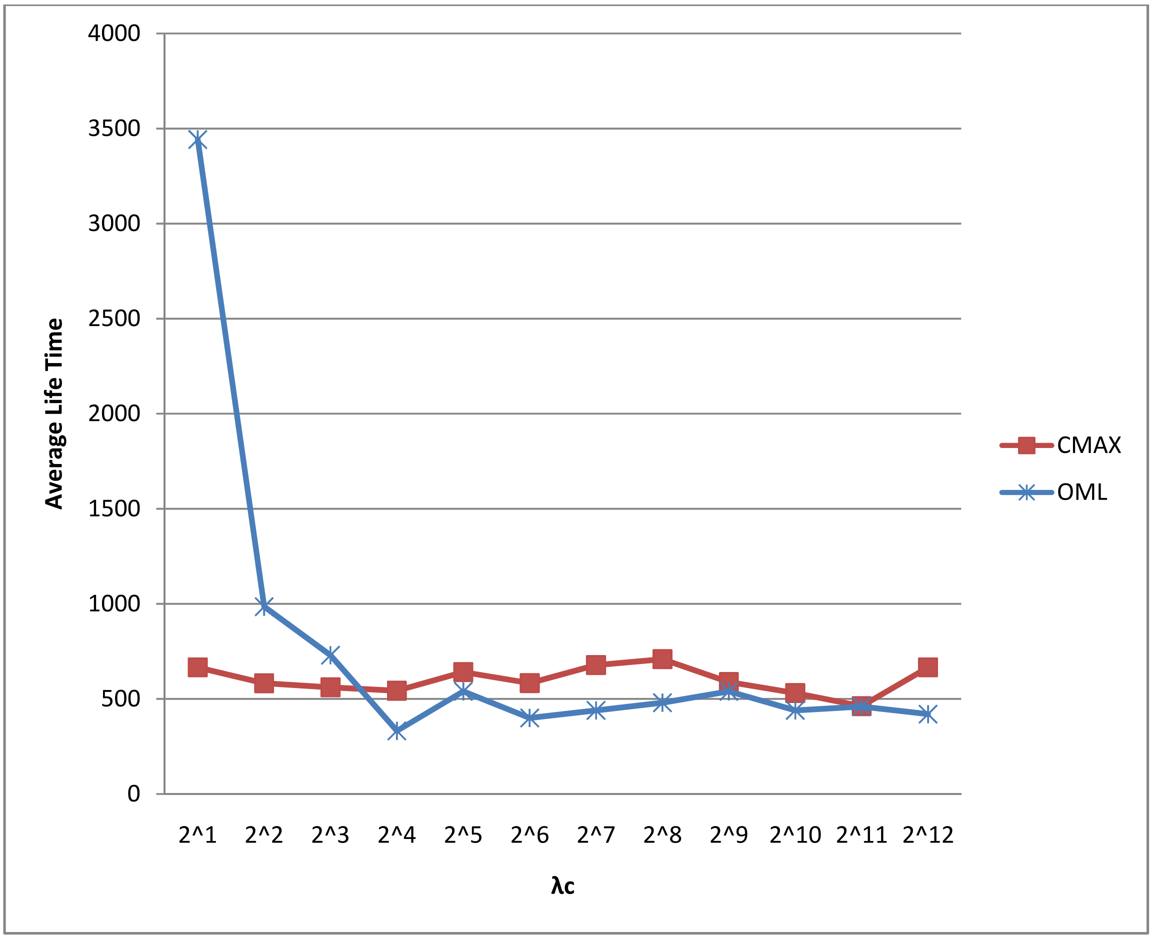

Figure 12: Average Lifetime for CMAX and OML Heuristic Using Poisson Distribution

Table 5 shows the average lifetime statistics for the 10 networks with different values of λ_c. In all cases, the average lifetime for OML heuristic was greater than that of CMAX heuristic, and the percentage difference between the two algorithms in each network.

Table 5: Lifetime Statistics for Different 10 Network Using Poisson Distribution

	Experiment 1		Experiment 2		Experiment 3	
	CMAX	OML	CMAX	OML	CMAX	OML
Average	650.83	755	555	830.83	561.66	840.83
Percentage Difference	26.49%		32.40%		25.47%	
	Experiment 4		**Experiment 5**		**Experiment 6**	
	CMAX	**OML**	**CMAX**	**OML**	**CMAX**	**OML**
Average	626.66	714.66	582.5	805	502.5	805
Percentage Difference	18.49%		37.58%		30.23%	
	Experiment 7		**Experiment 8**		**Experiment 9**	
	CMAX	**OML**	**CMAX**	**OML**	**CMAX**	**OML**
Average	561.66	664.33	635	711.66	530	716.66
Percentage Difference	4.42%		25.53%		20.12%	

	Experiment 10	
	CMAX	**OML**
Average	572.5	830
Percentage Difference	30.38%	

5.3 Distribution Effect on maximizing lifetime

Using Poisson distribution gives a fair description of the real environment, but it was noticed that the average lifetime is dropped by 13% in the OML heuristic, 12% in MRPC, and 3% in CMAX. This means that CMAX algorithm is a stable heuristic when changing the type of distribution. Table 6 describes the average lifetime for the three heuristic using the two types of distributions. Figure 1**3** shows the effect of different types of distribution in maximizing lifetime for the OML. Figure 14 shows the effect of different types of distribution in maximizing lifetime for the CMAX. Figure 15 shows the effect of different types of distribution in maximizing lifetime for the MRPC. We should notice that the average lifetime for each network isn’t the same for the 10 network, since we randomly distribute the network. The average lifetime is affected by the network density (number of edges in the network). When the number of edges increased, the average lifetime increased.

Table 6: Average lifetime Statistics Using Different Types of Distribution

	Experiment 1			Experiment 2			Experiment 3		
	MRPC	**CMAX**	**OML**	**MRPC**	**CMAX**	**OML**	**MRPC**	**CMAX**	**OML**
Average Lifetime using Uniform Distribution	440	584.17	884.17	440	628.33	968.33	440	491.77	957.50
Average Lifetime using Poisson Distribution	440	650.83	755.00	480	555.00	830.83	360	561.67	840.83
	Experiment 4			**Experiment 5**			**Experiment 6**		
	MRPC	**CMAX**	**OML**	**MRPC**	**CMAX**	**OML**	**MRPC**	**CMAX**	**OML**
Average Lifetime using Uniform Distribution	480	679.17	886.67	520	595.83	822.50	460	593.33	888.33
Average Lifetime using Poisson Distribution	401	626.67	714.67	420	582.50	805.00	320	502.50	805.00
	Experiment 7			**Experiment 8**			**Experiment 9**		
	MRPC	**CMAX**	**OML**	**MRPC**	**CMAX**	**OML**	**MRPC**	**CMAX**	**OML**
Average Lifetime using Uniform Distribution	440	629.17	801.67	460	574.17	875.00	500	614.17	832.50
Average Lifetime using Poisson Distribution	420	561.67	664.33	400	635.00	711.67	420	530.00	716.67
	Experiment 10								
	MRPC			**CMAX**			**OML**		
Average Lifetime using Uniform Distribution	460			594.17			911.67		
Average Lifetime using Poisson Distribution	390			572.50			830		

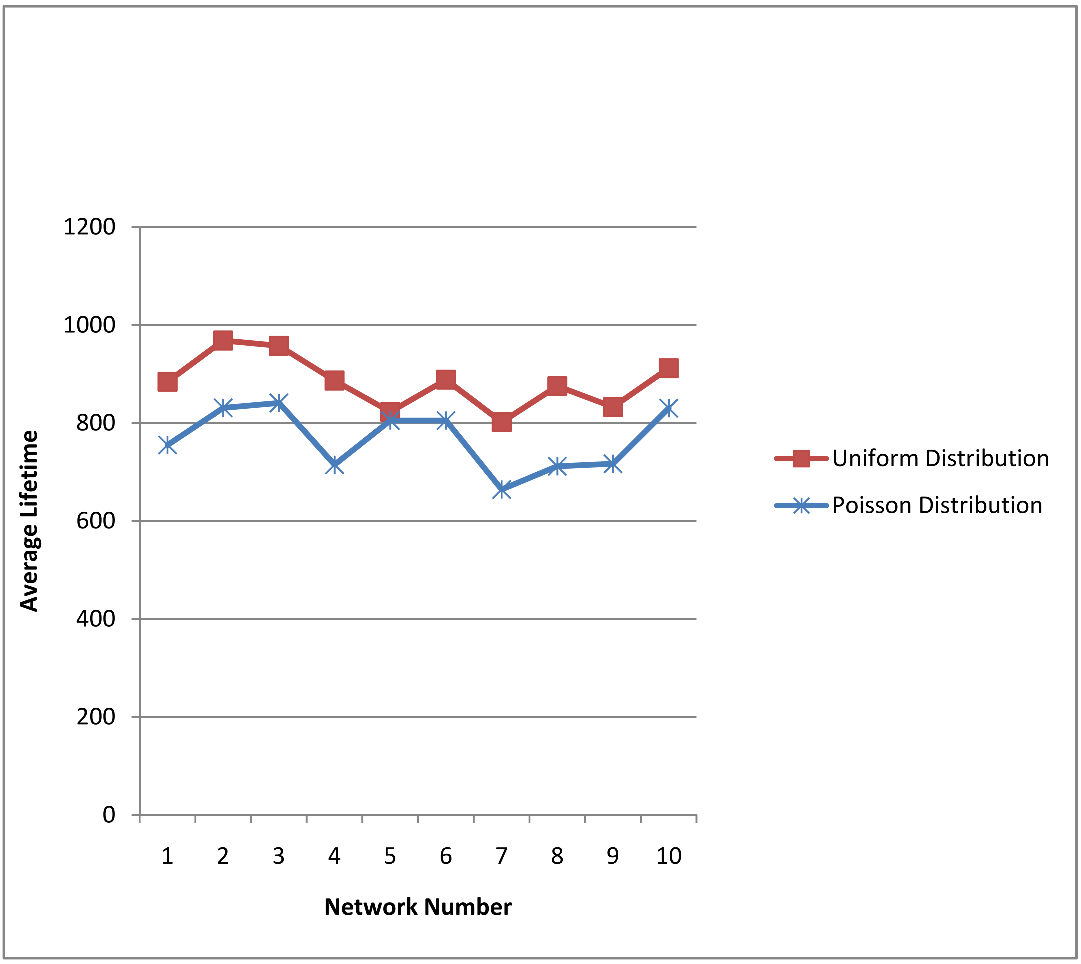

Figure 13: Average Lifetime Using Different Types of Distribution for OML Heuristic

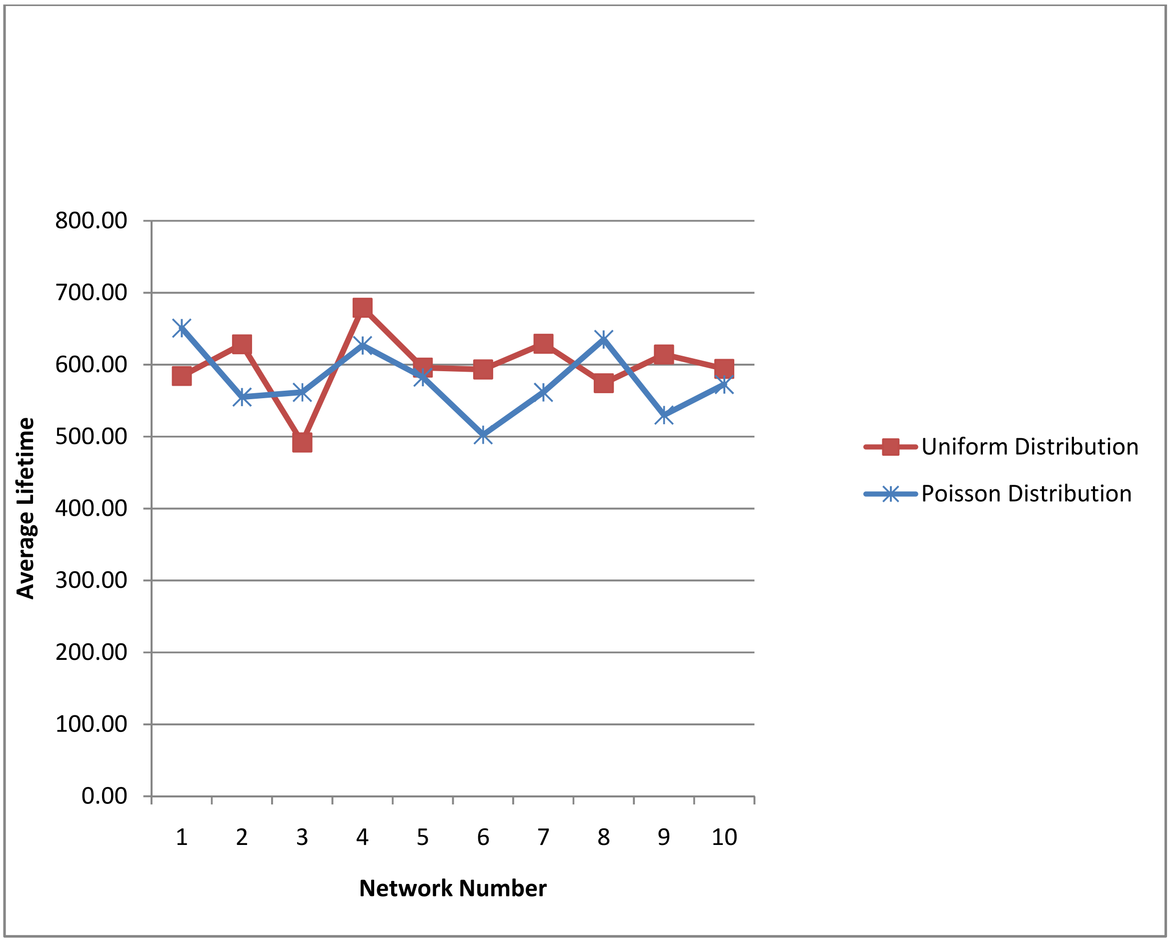

Figure 14: Average Lifetime Using Different Types of Distribution for CMAX Heuristic

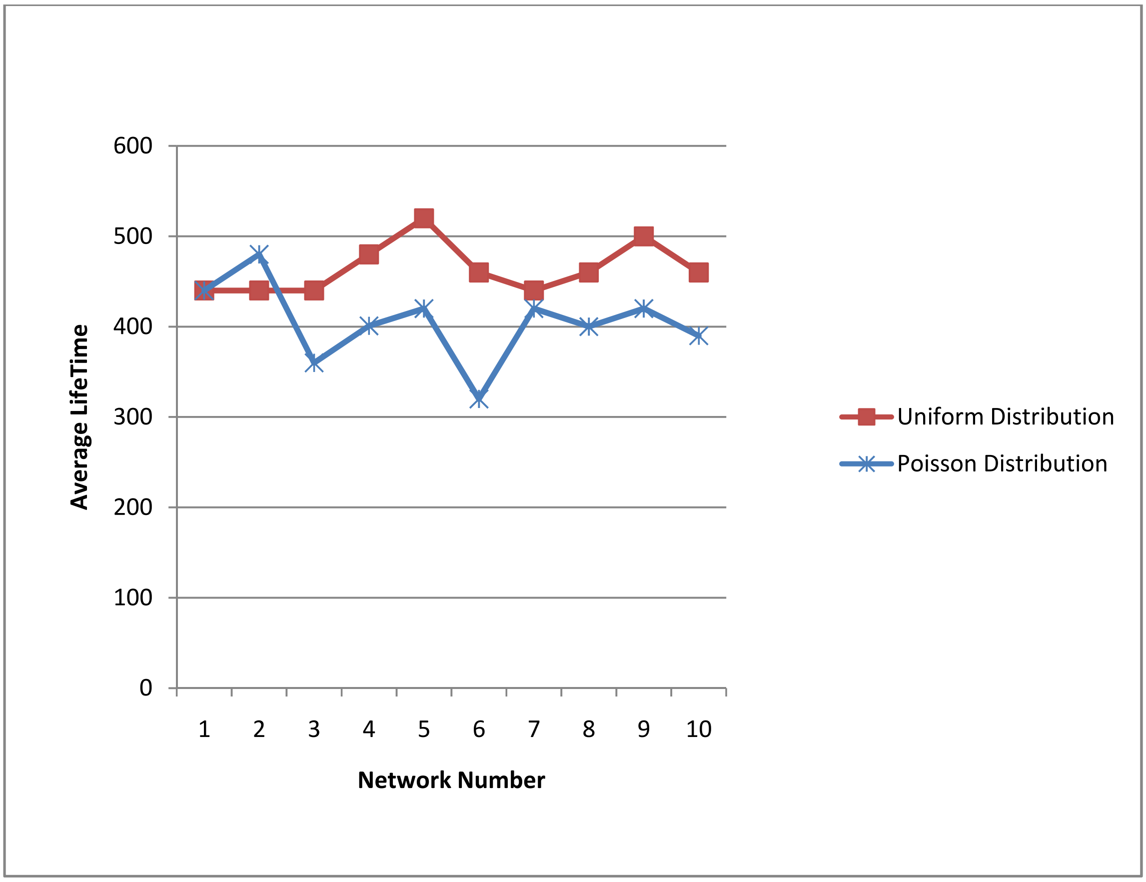

Figure 15 Average Lifetimes Using Different Types of Distribution for MRPC Heuristic

5.4 Effect of Network Capacity

Network capacity is defined as the Number of successful routes in a given time period. In our experiment study, the performance of the OML, the CMAX and the MRPC were compared using the capacity metric. In this study, 10 networks were generated by randomly placing 20 sensors. Each sensor started with 30 units of energy and r_T was set to 5. The remaining parameters were used in our earlier experiments. The network capacity was calculated by taking the average capacity of the 10 networks in specific periods of time for the three heuristics. Using uniform distribution, it is found that the network capacity using the OML is approximately 5.75% higher, on average, than when the CMAX is used. The capacity is about 38.93% higher using the OML rather than the MRPC and it is about 35.32% higher using the CMAX rather than the MRPC. Using Poisson distribution, it is found that network capacity using the OML is approximately 5.31% higher, on average, than when the CMAX is used. The capacity is about 39% higher using the OML rather than the MRPC. Also it is about 35.6% higher using the CMAX rather than the MRPC. Furthermore, it was noticed that the average network capacity decreased in the three heuristics using Poisson distribution by 16.68% in the MRPC, 16.30% in the CMAX, and 16.53% in the OML. Table 7 shows the average network capacity for uniform and Poisson distribution for the three heuristics mentioned above.

Table 7: Network Capacity Using Different Types of Distribution

Capacity / Algorithm	Using Uniform Distribution	Capacity Using Poisson Distribution
MRPC	916	763.2
CMAX	1416.4	1185.4
OML	1500	1252

5.5 Effect of Sensor Network Density

The network density in our study is defined as the number of edges in the wireless sensor networks. Figure 16 shows an example of the network with network density = 7. If the network is fully connected in wireless sensor network then the density formula for a directed graph is n (n- 1), where n is the number of vertices in the sensor network.

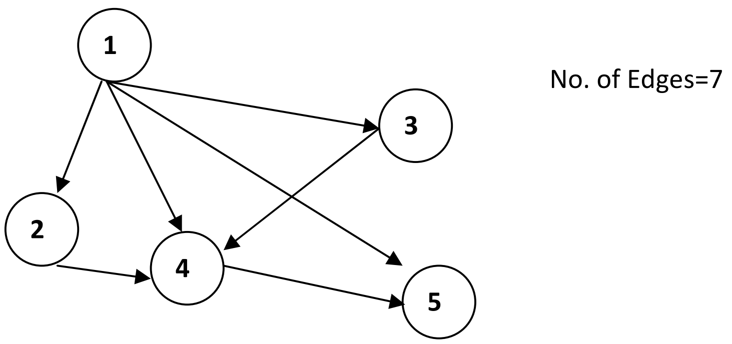

Figure 16: Sensor Network with Network Density of 7

In this study, we generated 10 networks by randomly placing 20 sensors. Each sensor started with 30 units of energy and r_T was set to 5 as previously mentioned. The network density varied from fully connected sensor network to a fully isolated sensor network. The effect of network density in both types of distributions uniform and Poisson was studied. Figure 17 shows the average lifetime of the three test heuristics using different network density using uniform distribution. Average lifetime using OML is approximately 45.35% higher, on average, than when CMAX is used and about 51.42% higher using OML rather than MRPC. The average lifetime is about 11.09% higher using CMAX rather than MRPC. Average lifetime of the three heuristics with different network density, but this time by using Poisson distribution is shown in figure 18. Average lifetime using OML is approximately 47.43% higher, on average, than when CMAX is used and about 11% higher using OML rather than MRPC. The average lifetime is about 40% higher using MRPC rather than CMAX.

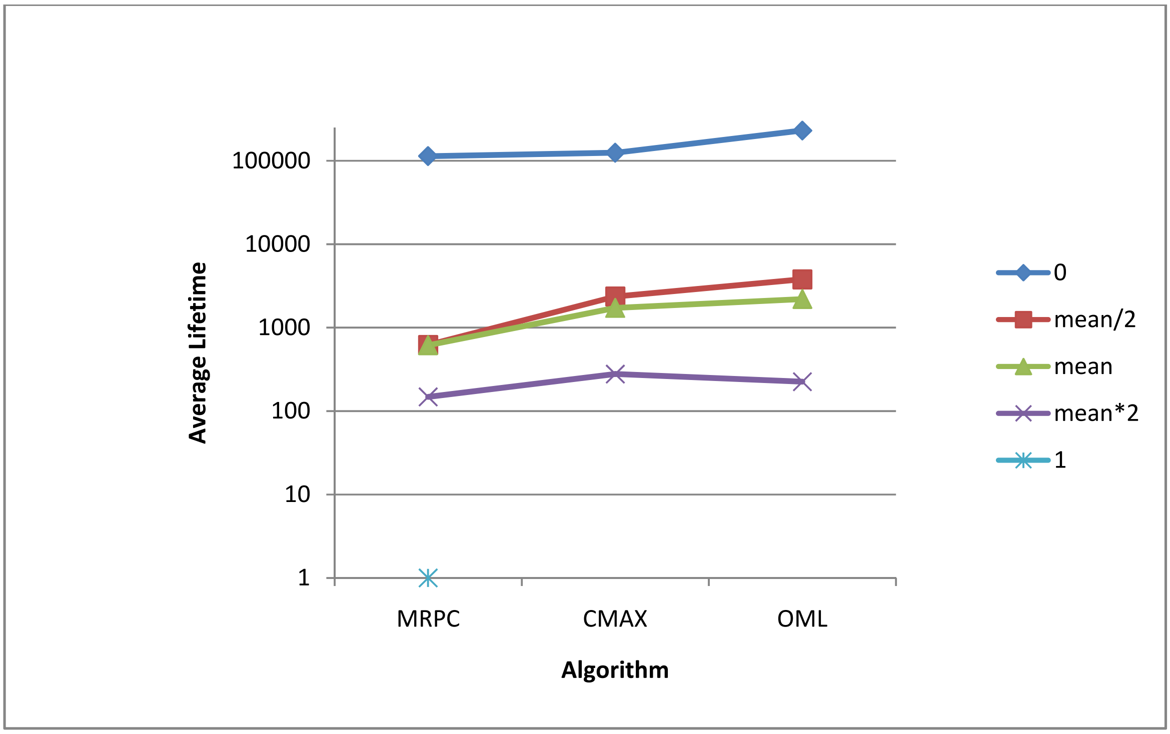

Figure 17: Average Lifetime Using Different Network Density Using Uniform Distribution.

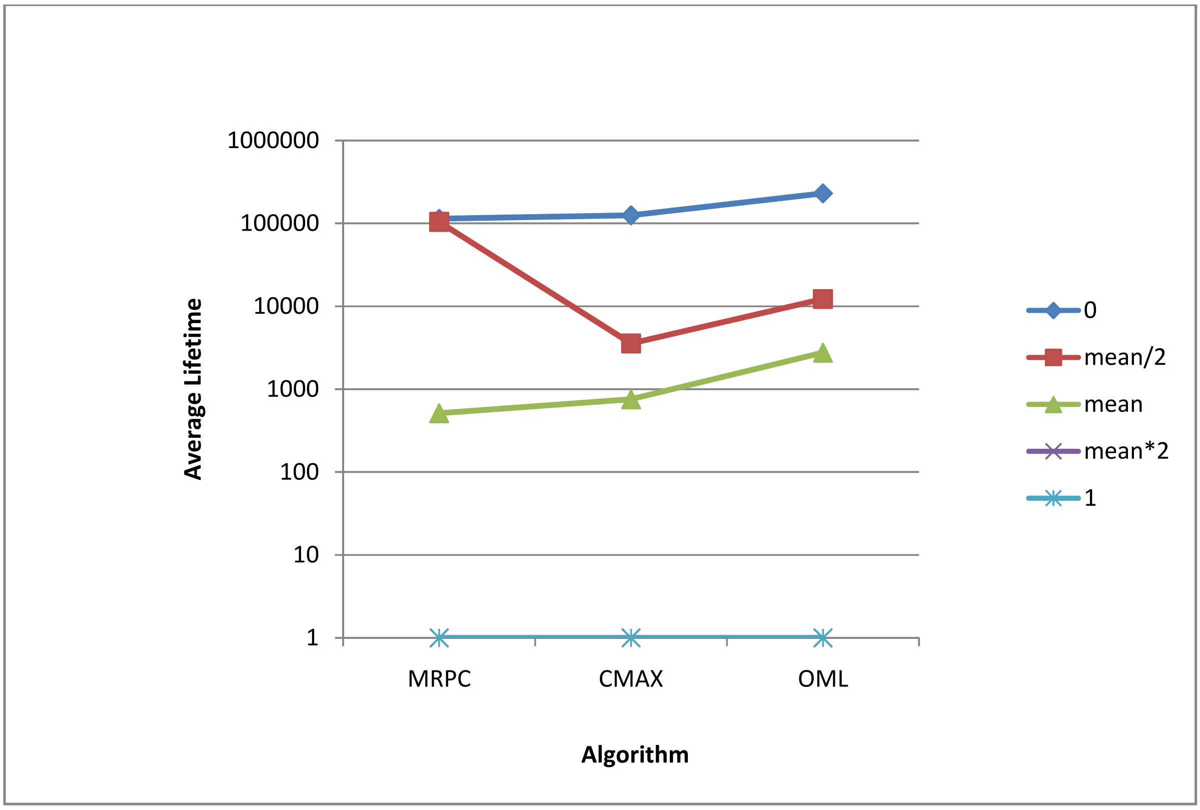

Figure 18: Average Lifetime Using Different Network Density Using Poisson Distribution.

5.6 Effect of Number of Sensor Nodes in the Sensor Network

In this section, the numbers of sensors on the average lifetime are discussed. For this study 10 networks were generated by randomly placing {30, 40, 50, 60, 70, 80, 90} sensors. Each sensor started with 30 units of energy and r_T was set to 5. Our experiments show that the average lifetime using the OML heuristic was greater than the CMAX heuristic under both distributions. MRPC heuristic has the lowest average lifetime using both distributions. Figure 19 and 20 show the effect of the number of sensor nodes in the sensor networks. It is clear also for all heuristics that when increasing the number of sensor nodes in WSN, the average lifetime increased accordingly.

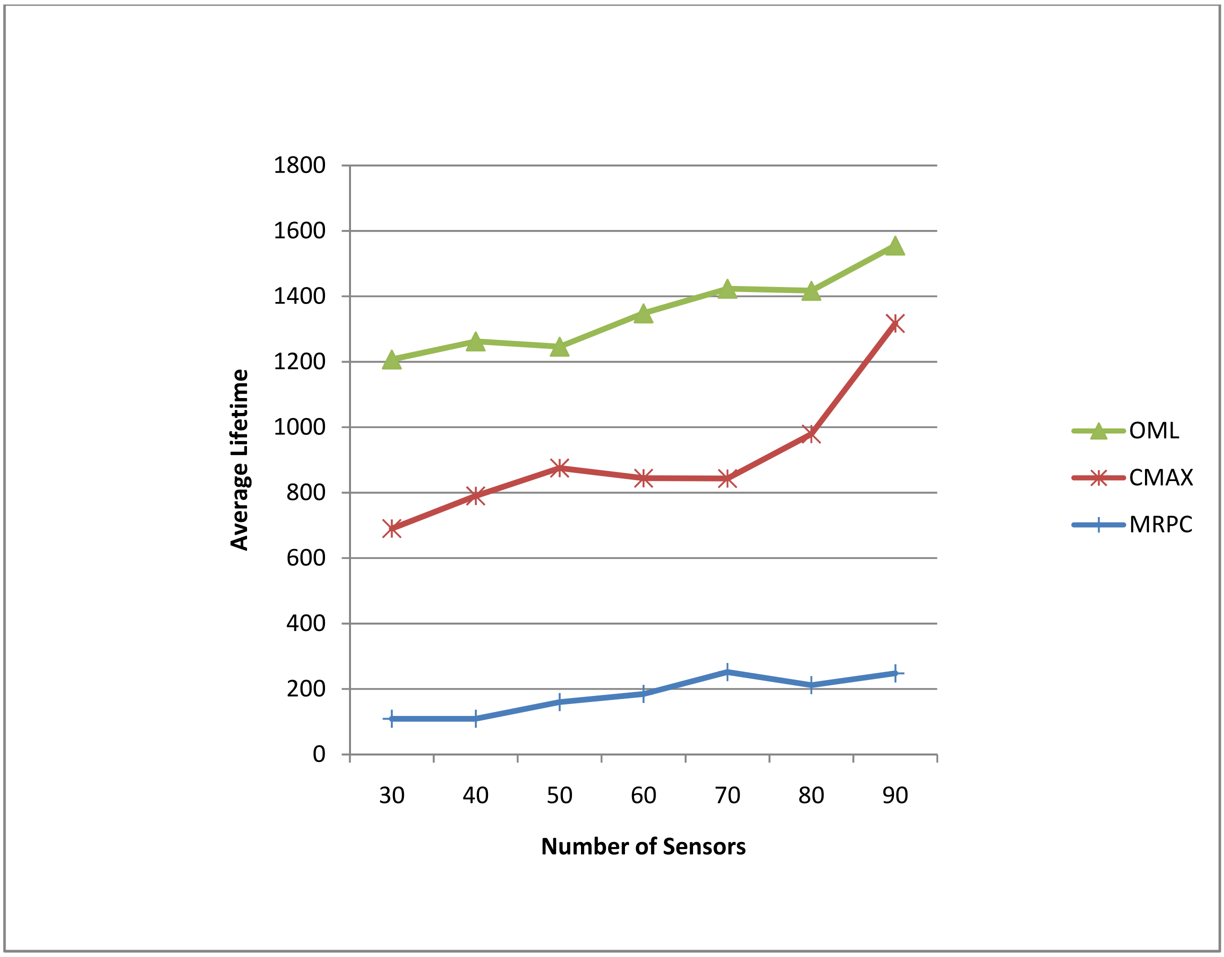

Figure 19: Average Lifetime with Different Number of Sensor Nodes Using Uniform Distribution

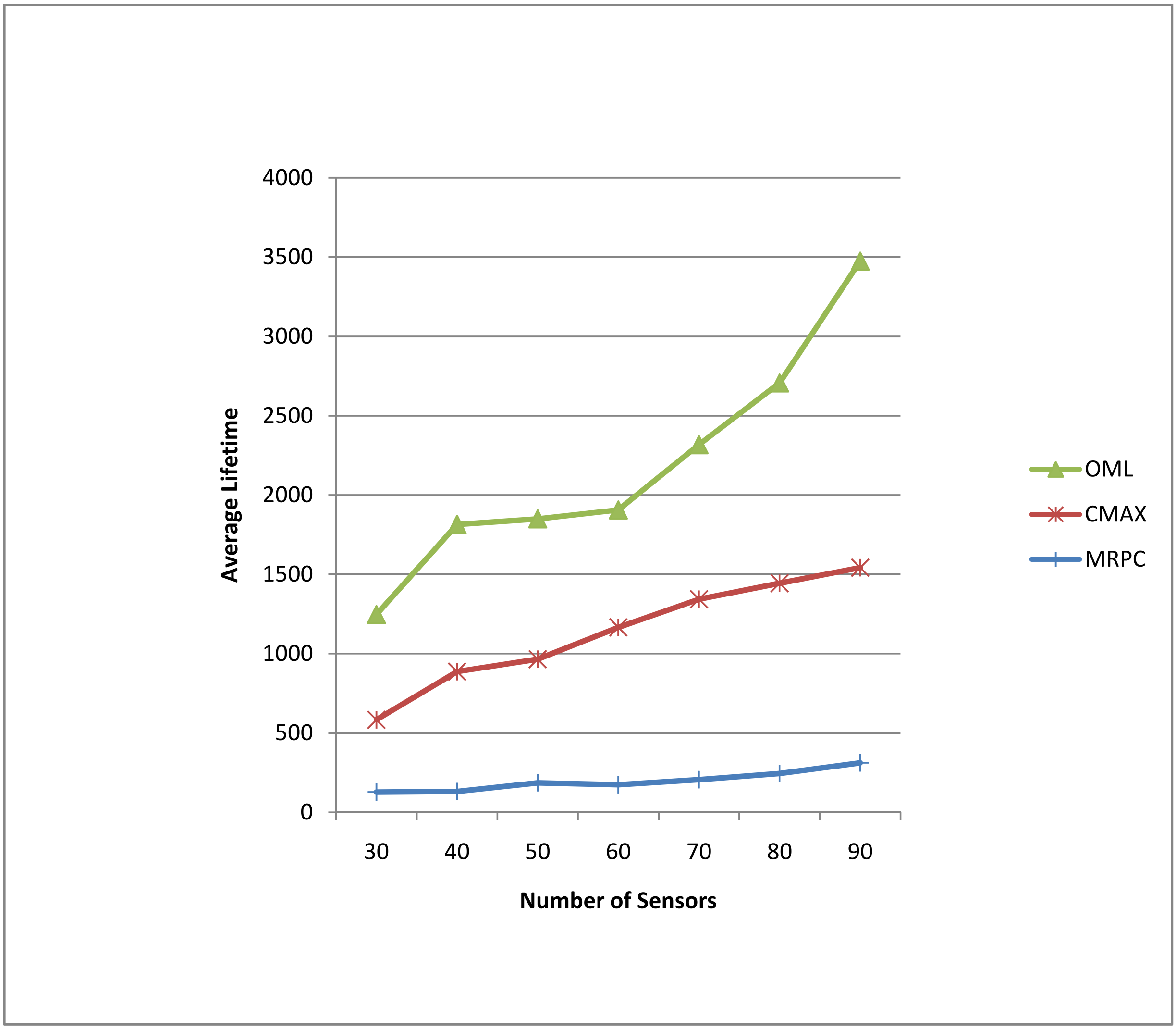

Figure 20: Average Lifetime with Different Number of Sensor Nodes Using Poisson Distribution

CONCLUSION AND FUTURE WORK

Conclusion and Future Work

1. Conclusion

This study shows that changing the statistical techniques of distribution to meet real environment requirements affect the performance of Maximizing lifetime routing heuristics. Three heuristics OML, MRPC, and CMAX were implemented. Results show the superiority of the OML heuristic over the others heuristics when using Poisson distribution, because of its behavior of assigning high weights to the used edge in rout so that next time the rout will not be selected, and also the stability of the CMAX heuristic when changing the type of distribution.

Our experiment study, using Poisson distribution, show that the results that were presented in the previous research did not directly apply to the real-world systems and doesn't take into consideration the effect of time of distribution in wireless sensor network behavior. Also, experiments that the OML heuristic has superiority over the CMAX and the MRPC heuristics in terms of average lifetime, network capacity and enhancing the required energy to transmit a packet. Average lifetime of all the previous heuristics was decreased when moving to Poisson distribution, because of Poisson distribution nature. It is shown by analysis that OML is 24% better than the CMAX and 47.2% better than the MRPC. The average lifetime for the CMAX is 29% better than the MRPC heuristic. The average lifetime for the OML, CMAX and MRPC were about 767.4, 577.833, and 405 respectively, which are less than the average lifetime when using uniform distribution. Using uniform distribution average lifetime for the

OML is 32% better than the CMAX and 47.4% better than the MRPC. While the average lifetime for the CMAX is 22% better than the MRPC. The average lifetime for the OML is about 937.16. Similarly average lifetime for CMAX and MRPC is about 598.42, 464 respectively. Using Poisson distribution gives fair description of the real environment, but it is noticed that there was a drop in the average lifetime by 13%, 12%, 3% in OML, MRPC, and CMAX heuristics, respectively. Which means that CMAX algorithm is stable algorithm when changing the type of distribution.

2. Future Work

The goal of this study was to construct a model that simulates a wireless sensor network on reality using the Poisson distribution. This model was tested on three different heuristics, CMAX, MRPC 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 distribution on maximizing life time routing.

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APPENDIX I

Appendix I

1. OML Pseudo-Code

```
Begin

 Build directed Experiment G with n node

 For each Experiment node  n loop

      Initialize node properties ( (ie), (ce),  (w))

 End for each n



    For each Experiment node u

       For each Experiment node v

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

                      Eliminate edge(u,v)

              End if

       End for each v

    End for each u
```

```
G`←G
Source si
Destination ti
[d dt] = digkstra ( G', si, ti )
If isempty(dt)
    Message ("Route Fails")
    Break;
else
  For each v in G'
     res(v)=ce(dt(i)) –w (dt(i),dt(i+1))
     End for each v in G'
  minRE←min(res)
 Exclude from G' every E` such that
 E′←E − {(u, v)|ce(u) − w(u, v) < minRE}
 G`←G``
```

```
For each node u in G``
   Compute a(u)← mine/ce(u)
     eMin(u) ← min { w(u,v) | (u,v) in E``}
End for each u in G``

For each node u in G``
      For each node v in G``
          If w(u,v)>eMin(u)
                  ρ(u,v) ←0
        Else
                ρ(u,v) ← C
      End if
     End for each v in G``
End for each u in G``
```

```
For each node u in G``
      For each node v in G``
     Compute the weight w``(u, v)← (w(u,v) + ρ (u,v)) (λ^a(u) -1)
     End for each v in G``
 End for each u in G``


[d dt]  = dijkstra (G'', si , ti )
  If isempty(dt)
    Message (" The route is not possible");
     else
   Use P``i to route from si to ti.
  End if
 End if
End
```

2. MRPC Pseudo-Code

```
BEGIN

    Build directed  Experiment G with n node

        For each Experiment node n

        Initialize node properties (ie(n), ce(n), w(ni,ni+1) )

        End for each n



        For each Experiment node u

         For each Experiment node v

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

                    Eliminate edge(u,v)

              End if

        End for each v

        End for each n
```

```
        For each Experiment node u

        For each Experiment node v

            If edge(u,v)==1

                c(u, v) = ce(u)/w(u, v)

            End if

      End for each v

   End for each n



  List L

  For each Experiment node u

     For each Experiment node v

                If c(u,v) not in L

                     Add c(u,v) to L

                End if

      End for each v

  End for each n
```

```
Source s
Destination d
List P[ ] = BFS (G,s, d)        // P is the shortest paths from source s to destination d
If is empty (P[ ] )
Message (" Path Not found")
else
Define max
X← max(P)
Do the route using x
End if
END
```

3. CMAX Pseudo-Code

```
BEGIN
 Build a directed Experiment G with n nodes
 For each Experiment node ni in n loop
         Initialize node properties ((ie), (ce), (w))
  End for each node ni
 For each Experiment node u in n loop
      For each Experiment node v in n loop
          If ce (u) < w (u,v)
                   Eliminate edge(u,v)
          End if
        Update the value of w(u,v)← w(u,v)*(λ^a(u) -1)
    End for each v
 End for each u
Source s
Destination d
 [d dt] = digkistra (G,s,d)
  If  isempty(dt)
    Messeage (' no path available")
 Else
  Do the route
END
```

APPENDIX II

Appendix II

1. Adjacency Matrix for the Derived Sensor Network Using Uniform Distribution

0	1	1	1	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0
0	0	0	0	1	1	0	1	0	0	0	1	1	0	1	0	1	1	0
0	0	0	1	1	0	0	1	0	0	0	0	1	1	1	1	1	1	0
0	1	0	0	1	1	1	1	1	1	1	1	0	1	0	0	0	1	1
1	0	0	0	0	0	0	0	1	1	1	0	0	1	1	1	1	0	0
0	0	1	0	1	0	1	0	0	1	1	0	1	0	0	1	1	1	0
0	0	1	0	1	0	0	1	1	1	1	0	1	0	1	1	1	1	1
1	0	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	0	1
0	0	0	0	0	1	0	0	0	1	0	1	0	0	1	0	0	0	0
0	1	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1
0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0
1	0	1	0	0	0	1	0	0	1	0	0	1	0	1	1	1	0	1
0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	1
0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0
0	0	0	1	0	1	0	0	0	0	0	0	1	1	0	0	0	1	0
1	1	0	0	0	0	0	0	1	1	0	0	1	0	1	0	0	1	0
0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	1	0	0	1
1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1
0	0	1	0	1	0	0	0	1	0	0	0	0	1	1	0	0	0	0
1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0

2. Adjacency Matrix for the Derived Sensor Network Using Poisson Distribution

0	0	1	1	0	1	0	0	0	1	0	1	1	1	0	1	0	1	1
1	0	1	1	0	1	0	1	1	0	1	1	0	1	1	1	1	1	1
0	0	0	0	0	0	1	0	1	0	1	0	1	0	1	1	1	1	0
0	0	0	0	1	1	1	0	1	0	1	1	0	1	1	1	1	1	1
1	1	1	0	0	1	1	1	1	1	1	0	0	1	1	0	1	1	1
0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
1	0	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
0	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	1	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1
0	1	0	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1
0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1
1	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	0	0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX III

Appendix III

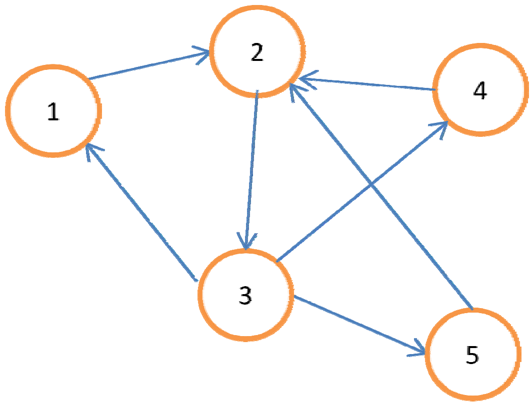

Figure 21: Wireless Sensor Network for 5 Nodes

In the following are examples for the three heuristics that we discuss, the examples are done based on figure 21.

Assumptions are:

- Source Sensor Node are: 1
- Destination Sensor Node are: 5
- Initial Energy in each Sensor is: 30.0.
- Current Energy in each Sensor is: 29.999.
- Required Energy to transmit are:

0.00	0.40	0.00	0.00	0.00
0.00	0.00	0.40	0.00	0.00
0.14	0.00	0.00	0.14	0.14
0.00	0.40	0.00	0.00	0.00
0.00	0.40	0.00	0.00	0.00

1. MRPC Algorithm Example

1. Remove from Experiment G all Edges such that ce(u)<w(u,v)
2. Calculate the value of c(u,v) = ce(u)/w(u,v):

0.00	75.00	0.00	0.00	0.00
0.00	0.00	75.00	0.00	0.00
212.12	0.00	0.00	212.12	212.12
0.00	75.00	0.00	0.00	0.00
0.00	75.00	0.00	0.00	0.00

3. Shortest paths are: {1, 2, 3, 5} only.

4. L is the list of Distinct values of c(u,v):

75.00
212.12

5. Life(p)= min c(u,v) in P{c(u,v)} = 75.00
6. Maximum value in P is 75.00 so routing will do through the path {1, 2, 3, 5}.
7. The route is done and the values of the current energy are updated and becomes:

29.599	29.599	29.858	29.999	29.999

2. CMAX Example

1. Let a(u) be the percentage of the initial energy that has already been spent at the sensor node in the wireless sensor network. $a(u) = 1 - c_e(u) / i_e(u)$:

3.333E-05	3.333E-05	3.333E-05	3.333E-05	3.333E-05

2. Calculate the new value of W with $\lambda = 2^{11}$:

0.000E+00	1.017E-04	0.000E+00	0.000E+00	0.000E+00
0.000E+00	0.000E+00	1.017E-04	0.000E+00	0.000E+00
3.595E-05	0.000E+00	0.000E+00	3.595E-05	3.595E-05
0.000E+00	1.017E-04	0.000E+00	0.000E+00	0.000E+00
0.000E+00	1.017E-04	0.000E+00	0.000E+00	0.000E+00

3. The shortest path is: {1, 2, 3, and 5}.

4. Do the route and update the nodes energy ce becomes:

29.99890	29.99890	29.99896	29.99900	29.99900

3. OML Example

1. Make the First Shortest Path: { 1, 2, 3, 5}
2. Residual energy for the path :

29.59900   29.59900   29.85758

3. Now, minimum residual energy minRE is : 29.5990.

4. Let G`` = (V,E``) be a Experiment 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 Experiment. By that, the reduction of energy from sensors that are low on energy could be prevented.
5. Calculate the minimum energy to transmit for each sensor:

0.40000   0.40000   0.14142   0.40000   0.40000

6. Now, calculate the value ρ (u,v) : the value for all matrix is equal to: 0.00.
7. Calculate the percentage energy spent at each sensor node:

0.98667   0.98667   0.98667   0.98667   0.98667

8. Now calculate the new value of w:

$$w``(u,v) = (w(u,v) + \rho(u,v)) (\lambda_a^{a(u)} - 1) \quad (14)$$

0.00000	0.39264	0.00000	0.00000	0.00000
0.000	0.000	0.393	0.000	0.000
0.139	0.000	0.000	0.139	0.139
0.000	0.393	0.000	0.000	0.000
0.000	0.393	0.000	0.000	0.000

9. Now make the second shortest path to make the rout: {1, 2, 3, 5}.

10. Update the values of the current energy ce:

29.60636 29.60636 29.86018 29.99900 29.99900

مدخل في التقييم الاحصائي لفرضيات إطالة العمر الإستدلالي في شبكات الإستشعار اللاسلكية

إعداد
رنا خليل إبراهيم أبو عليان

المشرف
الدكتور أحمد عبد العزيز الشرايعة

ملخص

تتكون شبكات الإستشعار اللاسلكية من عدد كبير من أجهزة الإستشعار ، حيث تم إعداد الكثير من الأبحاث لزيادة عمر البطارية في أجهزة الإستشعار وبنفس الوقت تمت المحافظة على المتطلبات الوظيفيه لهذه الأجهزه مع الأخذ بعين الإعتبار عمليه الإتصال بين كل جهاز إستشعار وآخر داخل الشبكة. ولقد تم تطوير العديد من الفرضيات لإطالة العمر الإستدلالي داخل شبكات الإستشعار اللاسلكية عند توزيع أجهزة الإستشعار بطريقه عشوائيه، منها فرضية إطالة العمر المباشرة (OML)، و فرضية أقصى قدره متبقيه داخل أجهزة الإستشعار (MRPC) ، و فرضية إطالة السعه (CMAX) .

إن المدخلات الخاصه بالبحث تم تحديدها بإستخدام أنواع مختلفه من التوزيع العشوائي (uniform, Poisson). أما العوامل المؤثره في النظام هي عدد أجهزة الإستشعار داخل الشبكه، و عملية الإتصال بين الأجهزه والمسافة بينها والعمر الإستدلالي لها وسعة الشبكه (وهي عبارة عن عدد المرات التي يتم فيها إرسال الرسالة بنجاح خلال فترة زمنية معينة). و في هذا البحث تم إجراء عملية مقارنه بين هذه الفرضيات التي تهدف الى إطالة العمر الإستدلالي لشبكات الإستشعار اللآسلكيه وتحديد الفرضيه الأفضل بإستخدام أنواع مختلفه من التوزيعات العشوائيه.

و في هذه الدراسه ، تم توظيف ثلاث فرضيات الأولى (OML) و التي تستخدم خوارزمية أقصر طريق مرتين لحساب الطريق لإرسال كل رسالة, و الفرضية الثانية هي (MRPC) والتي من خلالها يتم إختيار الطريق التي تملك أكبر قدرة , أما الخوارزميه الثالثه (CMAX) والتي تقوم بالسيطرة على عمليه إختيار الطريق الأفضل لإرسال الرساله من خلال رفضها لبعض عمليات نقل الرسالة بناءا على حاله معينه. و في الأبحاث السابقه لإطالة العمر الإستدلالي تم توظيف التوزيع العشوائي المتماثل، والذي يدل على أن إحتمالية وجود إتصال بين كل جهاز إستشعار وآخر متساويه، وهذه الحاله لا يمكن تعميمهاعلى جميع التطبيقات في حالة التغييرات الجغرافيه، لذا فإنه تم إقتراح تغيير نوعية التوزيع العشوائي بدلا من المتماثل إلى Poisson لأنه أقرب إلى البيئه الحقيقيه. و في هذا البحث، تم تطبيق إختبار لفرضيات مختلفه لإطالة العمر الإستدلالي بإستخدام التوزيع العشوائي المتماثل Uniform و Poisson. و من خلال تجربة إستخدام توزيع Poisson تم إثبات أن فرضية OML أفضل من الفرضيات الأخرى مثل CMAX (بمعدل 24% في حين أنه كان في حالة التوزيع المتماثل 32%) و MRPC(بمعدل 47.2% في حين كان في حالة التوزيع المتماثل 47.4 %). أما من حيث معدل العمر الإستدلالي للبطاريه فإن معدل العمر الإستدلالي في حالة OML كان 767.4 بينما في حالة التوزيع العشوائي المتماثل كان معدل العمر الإستدلالي 937.16 و في حالة CMAX فلقد كان 577.833 بينما في حالة التوزيع العشوائي المتماثل كان معدل العمر الإستدلالي 598.42 و في حالة MRPC كان 405 بينما كان في حالة التوزيع العشوائي المتماثل 464 ، كما تم إثبات أن جميع معدلات العمر الإستدلالي للفرضيات السابقه أقل في حالة التوزيع العشوائي Poisson من معدلات العمر الإستدلالي في حالة لتوزيع المتماثل .

نستنتج مما سبق أن التوزيع العشوائي باستخدام Poisson يعطي وصفا أفضل للأنظمه المطبقه في العالم الحقيقي، كما تم التوصل الى أن فرضية OML أفضل من الفرضيات الأخرى من حيث معدل إطالة العمر.