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Two Dimensional Gaussian Distribution for Dynamic Node Deployment in Wireless Sensor Network

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Abstract: The sensor node coverage plays a significant role in the design of Wireless Sensor Networks (WSN). In addition to coverage, shape and area is also important in wireless sensor network to limit the power consumption which is taken as the current research work for effective sensor network structure. Neighbor Position Verification (NPV) strategy with the help of fully distributed cooperative scheme enabled each node to acquire the neighbor locations but did not acquire data aggregation accuracy during node deployment. Decentralized estimation process using Decentralized Power Iteration (DPI) algorithm permitted every representative to track the algebraic sensor network connectivity but was not effective in deploying the sensor nodes with higher throughput ratio. In order to overcome such limitations, Two Dimensional Gaussian distribution based Dynamic Node Deployment (2D-GDDND) model is developed in this paper to deploy the sensor node in an efficient manner. The 2D-GDDND model initially identifies the directional position of sensor node based on the angle measurement (i.e.,) length and width of the sensor node position using the proposed 2-D Statistical Triangulation algorithm. The 2-D statistical triangulation algorithm focuses on entire sensor network area coverage to reduce the power consumption for the whole node deployment structure. Then, 2D-GDDND model is used Gaussian distribution model to efficiently deploy the dynamic sensor node in sensor network with the objective of improving the data aggregation accuracy and throughput level. In 2D-GDDND model, Gaussian distribution estimates angular difference between the sensor nodes and mobile robot. Then, 2D-GDDND model phase shift the sensor nodes according to their computed angular difference. Therefore, sensor nodes can easily gather and aggregates the data with another node in sensor network. For that reason the data aggregation accuracy and throughput level using 2D-GDDND model is improved in a significant manner. Experimental evaluation of 2D-GDDND model is done with the performance metrics such as power consumption, data aggregation accuracy, throughput level, dynamic node deployment time. Experimental analysis shows that the 2D-GDDND model is able to improve the data aggregation accuracy and also improves the throughput level of sensor nodes as compared to the state-of-the-art works.

Key words: Dynamic node deployment, statistical triangulation, wireless sensor network structure, two dimensional gaussian distribution, shift

INTRODUCTION

Dynamic node deployment has become an asset in WSN where the increasing range of protocols and applications require knowledge of the directional position of the participating sensor nodes. The information regarding routing in dynamic networks, data aggregation in sensor networks, movement coordination among sensor nodes, position-specific services for handheld mode of devices in WSN are all examples of dynamic node deployment mode that build on the availability of directional position information of the sensor nodes in the network coverage area. Therefore, the directional position information of sensor nodes is an important issue in WSN and it becomes particularly challenging when power consumption has to be addressed. In these scenarios, we need solutions that let sensor nodes correctly establish their directional position of the sensor nodes to reduce

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the power consumption and with the directional position to deploy the sensor nodes with higher data aggregation accuracy. NPV Strategy in (Fiore *et al*., 2013) addressed the problem by presenting fully-distributed cooperative solution that is highly robust whenever independent and adversary nodes in a colluding structure are involved. The NPV Strategy enabled each node to acquire the locations but the work was not extended to acquire the data aggregation accuracy during node deployment. The decentralization estimation process using DPI algorithm (Yang *et al*., 2010) has permitted tracking of algebraic sensor network connectivity. But the algorithm was not effective in deploying the sensor nodes with higher throughput ratio. Additionally, another new framework (Shang *et al*., 2014) was designed based on energy efficiency model that included fusion of collaborative signal and information for tracking acoustic. To reduce the spatial and time redundancy occurring, Gaussian particle filtering method was presented. But the major disadvantage of the model was noise variances which was assumed to prior designing that can't be in case of real scenario.

In order to enhance the efficiency of spectrum for the future generation wireless system, a model called as the Dynamic Spectrum Access (DSA) (Yen *et al*., 2009; Xu and Wang, 2009) has been considered. The sensor nodes deployment DSA technique in a sensing ground can assist public to check the cumulative information. Researchers also try to discover more resourceful ways of utilizing inadequate sensor node power to give longer WSN life span. Therefore, result a technique to decrease node information broadcast power utilization has become a very significant problem.

Secure walking GPS model (Mi *et al*., 2012) using location information was deployed in WSN to prevent certain attacks related to the denial of service. But the attacks detected with increasing number of nodes increased proportionately with time. To detect the attack in the early stage (Lee and Kwon, 2014) had designed a general deployment model that constructed a secure WSN using group placement phase and key management phase. Though security was improved but it was suitable for specific applications. A two-tier system was designed (Hailong *et al*., 2012) using two dimensional Gaussian distribution model to increase the lifetime of the network in a cost effective manner.

Meshed Emergent Firefly Synchronization (MEMFIS) (Wang and Bohacek, 2011) consisting of data packets and applied clocks, once the synchronization for nodes in the neighboring position was obtained. But synchronization for entire network coverage area remained an open issue. To address this issue, relay node placement problem with constrained versions were presented (Wang *et al*., 2012) in which the relay nodes were placed at specific locations. However, the problem of weaker connectivity for relay node placement was unaddressed.

Based on the a forementioned methods and techniques, this study proposed a new technique for addressing the problem related to dynamic node deployment using two dimensional Gaussian distribution model. The main objective of 2D-GDDND model is to improve the data aggregation accuracy and to increase the throughput level in sensor network. As data aggregation accuracy and throughput level are highly desirable for dynamic node deployment in sensor network the work 2D-GDDND model redesigned sensor network to consider both the measures. The novel model for applying power-saving techniques has also been developed so that node deployment efficiency can be exposed and better obtained.

Literature review: Most of the research works has been developed for dynamic node deployment in Wireless sensor network. For example, a novel framework was presented by Szczodrak *et al*. (2013) to dynamically rearrange the WSN and adjust its power consumption, transmission reliability and data throughput to the different requirements of the applications. Dynamic Sink Mobility equipped DBR (DSM) routing protocol was introduced by Khan *et al*. (2015) for Underwater Wireless Sensor Networks (UWSNs) to reduce the total energy usage by moving sink towards most dense region. A genetic algorithm was developed by Banimelhem *et al*. (2013) to discover an optimal solution to the coverage holes problem caused by random deployment of stationary sensor nodes in wireless sensor network.

Biogeography-based optimization was applied in (Ozturk *et al*., 2012) to the dynamic deployment of static and mobile sensor networks to attain better performance by means of increasing the coverage area of the network. In (Indhumathi and Venkatesan, 2015), the deployment of dynamic nodes was improved for obtaining the higher coverage deployment by using Genetic Algorithm. Energy Balanced-Dynamic Deployment (EB-DD) Optimization approach was introduced by Roselin and Latha (2013) to positions the self deployable mobile sensors towards CP according to its energy density. Topology control of DAWN was designed in (Guo *et al*., 2010) to facilitate MNs' communication by means of deploying a minimum number of RNs dynamically.

An artificial bee colony algorithm was developed by Celal and Beyza for dynamic deployment of mobile sensor networks to achieve better performance by means of increasing the coverage area of the network. A node deployment strategy was presented in (Halder and Ghosal, 2014) to energy balancing by means of customized gaussian distribution with discretizing the standard deviation. Proactive topology control algorithm called as PMD (Proactive Maintaining Algorithm) was introduced by Liu *et al.* (2013) for dynamic topology control and addressing the problem related to the network partitioning. The shortcomings of current solutions regarding the dynamic topology handling issues through QoS based transmissions and to enhance the performance of the network as a whole or for the individual nodes were examined by Tiwari and Kaur, 2015).

CDTRB based topology control mechanism was presented in (Tiwari and Kour, 2013) for satisfying the Quos requirement and dynamic topology control in Ad Hoc network. A movement pattern learning strategy system was developed by Duttaa *et al.* (2012) to track the node's movement by using adaptive fuzzy logic. Dynamic Sink Mobility equipped DBR (DSM) routing protocol was designed by Khan *et al.* (2015) for Underwater Wireless Sensor Networks (UWSNs) to increases the stability period, network lifetime and throughput of the UWSN.

Efficient autonomous deployment scheme called as Obstacle Avoidance Virtual Force Algorithm (OAVFA) was introduced by Rout and Roy (2016) for self-deployment of randomly scattered homogeneous and heterogeneous mobile sensor nodes over a squared sensing field to improve the network coverage and achieves the network connectivity in the presence of obstacles. The sensor node deployment task has been invented as a constrained Multi-Objective optimization (MO) problem in (Senguptaa *et al.*, 2013). Multi-Objective Evolutionary Algorithm (MOEA) was designed in this approach with the objective of discover a deployed sensor node arrangement to improve the area of coverage, reduce the net energy consumption, enhance the network lifetime and reduce the number of deployed sensor nodes while maintaining connectivity among each sensor node and the sink node for proper data transmission.

MATERIALS AND METHODS

Two dimensional gaussian distribution based dynamic node deployment model: In this study, an efficient two dimensional Gaussian distribution based dynamic node deployment model is presented to accurately deploy the nodes in the sensor network structure. The model is based on two folds. The first fold in this model identifies the directional position of nodes based on distance (i.e., length and width) which are deployed using the 2-D Statistical Triangulation algorithm to easily identify the directional position in sensor network. The second fold includes a two dimensional Gaussian distribution based dynamic node deployment model to easily deploy the sensor nodes and to increase the rate of data aggregation accuracy. The structural design of the gaussian distribution based dynamic node deployment for two dimensional sensor network structures are illustrated in Fig. 1.

From the Figure, sensors of different types are deployed in the network structure to accurately perform the data aggregation process on the deployed nodes. The initial work carried out in 2D-GDDND model is to identify the directional positioning of nodes. The directional position for the two dimensional structure is measured using the 2-D statistical triangulation algorithm that focuses on computing the distance of the positioned nodes.

With this angle of positioning in 2D-GDDND model is measured using the Statistical Triangulation algorithm. The triangular shape angle of positioning is used to easily identify the directional position of sensor nodes in 2D-GDDND model. The identified directional position is used to deploy the sensor nodes in the proposed work using the Gaussian Distribution Function. The positioned sensor node in 2D-GDDND model achieves the high data aggregation accuracy rate during the data aggregation process. As a result, the 2D-GDDND model covers larger connectivity area in the sensor network which in turn improves the throughput level.

2-D statistical triangulation process: In 2D-GDDND model to dynamically deploy the sensor nodes in wireless network, initially the directional position of nodes are identified using 2-D statistical triangulation. The directional position varies based on the measurement of the distance (i.e., length and width) between the sensor nodes deployed using 2D-GDDND model. Thus, 2-D statistical triangulation process uses the beacons present in the network structure to easily identify the specific position for deploying the sensor node. Let (x, y) represent the two dimensional space on the sensor network structure with the directional distance be D_1 between the sensor robot and beacon in the sensor network. To determine the position of the sensor nodes X_p, Y_p in the sensor network, the robot angle is measured

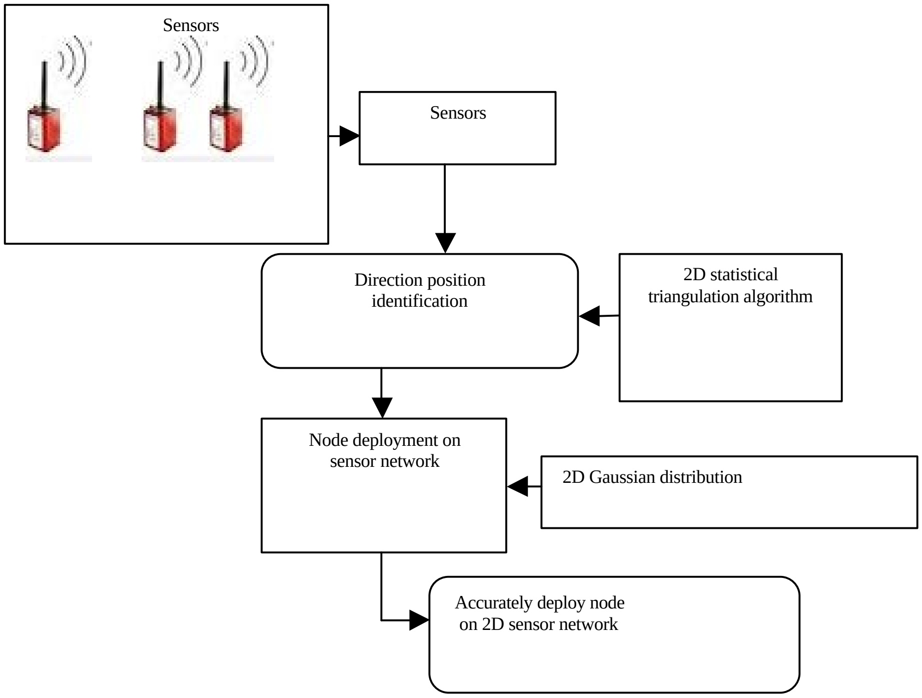

Fig. 1: Structural design of 2D-GDDND model

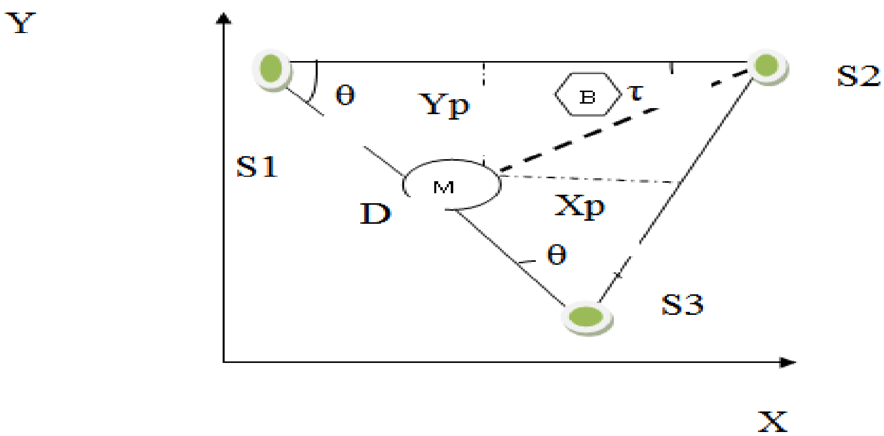

Fig. 2: Statisticalo triangulation representation for 2-dimensonal space (x_i, y_i)

and which is denoted as θ. The 2-D statistical triangulation process includes the three steps as follows.

- Label the beacon consecutively in the sensor network structure in the counter-clockwise direction
- The angle between the beacon and sensor node 1 $\theta(B, S_1)$ must be <180°
- The angle between the beacon and sensor node 2 $\theta(B, S_2)$ must also be <180°

//2-D statistical triangulation

Begin
Step 1: Place beacon based on Counter Clockwise Direction
Step 2: Compute Direction position on Triangular Form
Step 2.1: $\theta(S_1, S_3) = 360+(S_1, S_3)$
Step 2.2: $(S_1, S_2) = (S_2-S_1)$
Step 3: Let $\theta 1$ be angle between beacon to node point to measure the length (i.e.,) x-axis from two dimensional spaces
Step 4: Let $\theta 2$ be angle between beacon to node point to measure the width (i.e.,) y-axis from two dimensional spaces
Step 5: Compute angle of mobile robot γ = B-S where $S = S_1, S_2, S_3$
Step 6: $\tau = \tan^{-1}\mathrm{Sin}\ S_2(D_{12}\ \mathrm{Sin}\ S_3 - D_{13}\ \mathrm{Sin}y)/D_{13}\ \mathrm{Sin}\ S_2\ \mathrm{Cos}\gamma - D_{12}\ \mathrm{Cos}\ S_2\ \mathrm{Sin}S_3$
Step 7: If S_2<180 degree &τ<0 degree
  Step 7.1: Then $\tau = \tau 180$ degree
Step 8: If S_2>180degree &τ>0 degree
  Step 8.1: Then $\tau = \tau-180$ degree
Step 9: Direction position of $Xp = X_1-D_1\ \mathrm{Cos}(\theta+\tau)$
Step10: Direction position of $Y_p = y_1-D_1\ \mathrm{Sin}(\theta+\tau)$
End

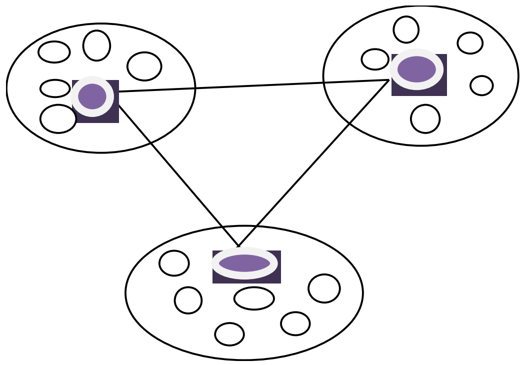

Fig. 3: Data aggregation proces using 2D-DDND model

2D statistical triangulation representation and Fig. 2, shown above clearly the parameters used for the directional positioning. The directional position of the x and y axis in the sensor network are denoted by X_p, y_p respectively. In Fig. 2, B is a beacon and τ indicates the angle between the mobile robot and sensor node 2 and S_1, S_2, S_3 are the different sensor nodes in WSN.

With the distances computation using the 2D statistical Triangulation algorithm, the 2D-GDDND model is efficiently identifies the directional position of nodes for providing higher data aggregation accuracy result in wireless sensor network. Besides, the 2-D statistical triangulation consumes the minimal power consumptions due to the beacon usage in the sensor network coverage.

Gaussian distribution: After identifying the directional position of nodes, the 2D-GDDND model in 2-dimensional network space (X_i, Y_i) use the Gaussian distribution to accurately deploy the dynamic sensor nodes in WSN. The implementation of Gaussian distribution with 'S' sensor nodes in sensor network structure is mathematically formularized as bel

$$GD(x,y) = \frac{1}{2\pi(\theta_{x,y})^2} e^{-\left[(x-X_i)^2 + \frac{(y-y_i)^2}{2\theta x,y^2}\right]} \quad (1)$$

From Eq. 1, GD denotes the Gaussian distribution function for the two dimensional space (x_i, y_i). The angular difference measured between the sensor node and the mobile robot in the sensor network is denoted byθ. The Gaussian distribution in 2D-GDDND model computes angular difference between the sensor node and mobile robot to accurately deploy the nodes in the sensor network which results in improved data aggregation accuracy. The node positioned (i.e.,) deployed point in the triangular field 'T' helps to easily observe the throughput level on the two dimensional space. The Gaussian distribution function on the triangular field is described as:

$$\text{GD on T} = \frac{1}{2\pi(\theta_{x,y})^2} e - (D_i T)^2 / 2\theta_{x,y}.dx.dy \quad (2)$$

From Eq. 2, Gaussian distribution on the triangular field T(x, y) identifies the throughput level attained on the dynamic node deployment with the distance D_i between the sensor nodes and the mobile robot in the wireless network structure. With this the value of D_i is combined with the Triangular field coverage point to easily identify the overall throughput level. The Gaussian distribution of sensor node in the dimensional space (x, y) with the statistical triangulation field is described as follows:

$$GD(L) = \int^T{}_0 f(D_i(x,y)) 2D\cos^{-1}\left(\frac{D^2+T^2}{2DT}\right)dx.dy \quad (3)$$

From Eq. 3, gaussian distribution computes the length 'L' for the easy deployment of x-axis position node in the sensor network with distance D_i evaluated using the distance of the mobile robot on the triangular sensor network coverage field. The Cosine function helps to identify the x-axis position on which the node to be deployed using 2D-GDDND model which in turn improves the data aggregation process in sensor network:

$$GD(W) = \int^T{}_0 f(D_i(x,y)) 2D\sin^{-1}\left(\frac{D^2-T^2}{2DT}\right)dx.dy \quad (4)$$

Equation 4, Gaussian distribution computes the width 'W' for easy deployment of the y-axis position node in the sensor network with distance evaluated using the distance of the mobile robot on the triangular sensor network coverage field. Sine function helps to identify the y-axis position where the node to be deployed using 2D-GDDND model which results in improved data aggregation process in sensor network. The data aggregation process using 2D-GDDND model is illustrated in Fig. 3.

The data aggregation process with the deployed nodes using the 2D-GDDND model is shown in Fig. 3. With this the identified directional position places the nodes in a dynamic manner using the Gaussian distribution model. The deployed nodes are correctly positioned (i.e.,) in terms of length and width to improve the success rate of the data aggregation process. The Gaussian distribution with the 2-D statistical triangulation algorithm reduces the power consumption on the whole node deployment structure.

Gaussian distribution is used in 2D-GDDND model to deploy the dynamic sensor nodes in WSN. With the help of identified directional position of sensor node the 2D-GDDND model evaluates the angular difference between the sensor node and mobile robot in sensor network. Then, 2D-GDDND model phase shift the sensor node in sensor network according to their angle difference. Hence, sensor nodes easily gather and aggregates the data with another node in sensor network data aggregation accuracy using 2D-GDDND model is improved in turn increased the throughput level.

Two dimensional-gd experimental work evaluation: The proposed 2D-GDDND model is implemented using NS-2 simulator. The sensor network is taken for the experiment performs the dynamic node deployment work on the aggregated data. The network range taken for the experimental work is about 900×900 m. The Random Waypoint model is developed to randomly group and move the sensed node location point to correctly deploy the sensor node. The RWM model shifts to an erratically chosen location to perform effective transmission on multiple sink nodes.

The 2D-GDDND model takes 25 milliseconds on each simulation and averagely 80 sensor nodes are taken for the experimental evaluation. The chosen nodes randomly move with a selected velocity and speed. The minimum moving speed of the sensor node is about 4.0 m sec^{-1} of each sensed node. The random movement of sensor nodes uses the Dynamic Source Routing (DSR) Protocol for performing the experimental evaluation. Simulation experiment of 2D-GDDND model is compared against with the existing NPV strategy and DPI process. The experiment is conducted on the factors such as node deployment efficiency, throughput level, data aggregation accuracy rate, power consumption and dynamic node deployment time. The node deployment efficiency measures the number of nodes involved in the model. When the node deployment efficiency is higher, the 2D-GDDND model obtained better result. The node deployment efficiency is measured in terms of percentage (%). The throughput level (T) using Gaussian distribution in 2D-GDDND is defined as the distance between the sensor nodes and mobile robot in the sensor network. The throughput level is usually measured in kilo bits per second (Kbit/s) in the simulation work. The aggregation in 2D-GDDNS is the aggregated output of the x axis position and the y axis position in the sensor network. When the data being aggregated is higher, the data aggregation accuracy is also increased in 2D-GDDNS model.

Power consumption (PC) in 2D-GDDNS measured in terms of joules (J) which obtained by dividing the energy consumed by all the sensor nodes in the network ($S_1+S_2+....+S_n$) by the network coverage area. For experimental purpose, we have considered the network coverage area as 900×900 m.

$$PC = \frac{Energy(S_1 + S_2 + ... + S_n)}{900 * 900m} \quad (5)$$

The Dynamic Node Deployment Time (DNDT) for 2D-GDDNS is obtained by dividing the time taken for each sensor node in the network to obtain the directional position based on the length and the width (X_p+y_p) by the network coverage area. The DNDT is measured in terms of milliseconds (ms). When lower the DNDT the efficiency of the 2D-GDDNS model is higher. The dynamic node deployment time is mathematically formularized as below:

$$DNDT = \frac{Time(x_p + y_p)}{900 \times 900m} \quad (6)$$

RESULTS AND DISCUSSION

The performance of the 2D-GDDND model in WSN has been compared with the existing NPV strategy and DPI process. The power consumption for each node has been tabulated in Table 1 with elaborate comparisons made with two other methods. Figure 4, show that the proposed 2D-GDDND model in WSN consumes lower power as compared with existing NPV strategy and DPI process. This is because of the application of 2-D Statistical Triangulation algorithm that easily identifies the specific position for deploying the sensor node in WSN which results in reduced the power consumption by 3-23% when compared to NPV strategy. In addition to that with the use of the beacon message in the sensor network coverage using the 2D-GDDND model reduced the power consumption by 4-19% than the DPI process.

The comparison of data aggregation accuracy is presented in Table 2 with respect to the number of sensor nodes in the range 5 and 35. With increase in the sensor nodes the data aggregation accuracy is also increased. To ascertain the performance of the data aggregation accuracy, comparison is made with two other existing NPV strategy and DPI process.

From the Fig. 5, the sensor Nodes (N) are varied between 5 and 35. From the figure it can be observed that the data aggregation accuracy is higher using the proposed 2D-GDDND model than when compared to the two other existing works. This is because with the application of Gaussian distribution on 2D sensor network spaces where the sensor nodes are accurately deployed with higher data aggregation accuracy by 5-12% when compared to NPV strategy. Furthermore by positioning the sensor nodes using triangular shape angle the directional position of the sensor nodes are easily identified in 2D-GDDND model which in turn improve the data aggregation accuracy by 10-17% than when compared to DPI process. The throughput level for 2D-GDDND model is

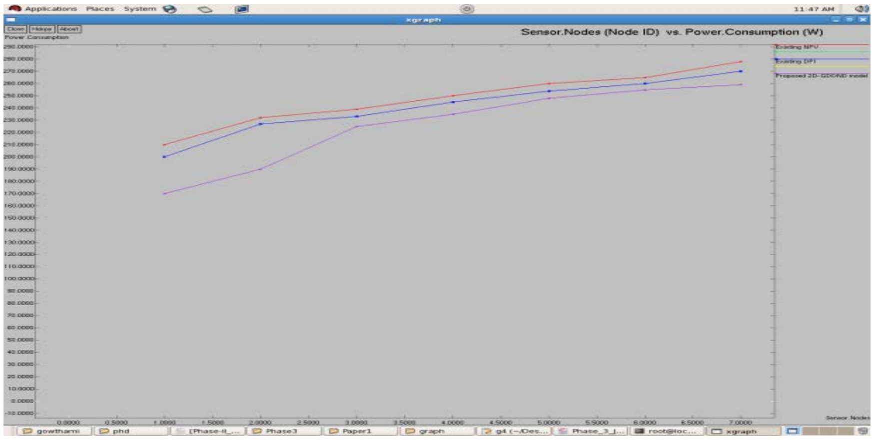

Fig. 4: Sensor nodes versus power consumption

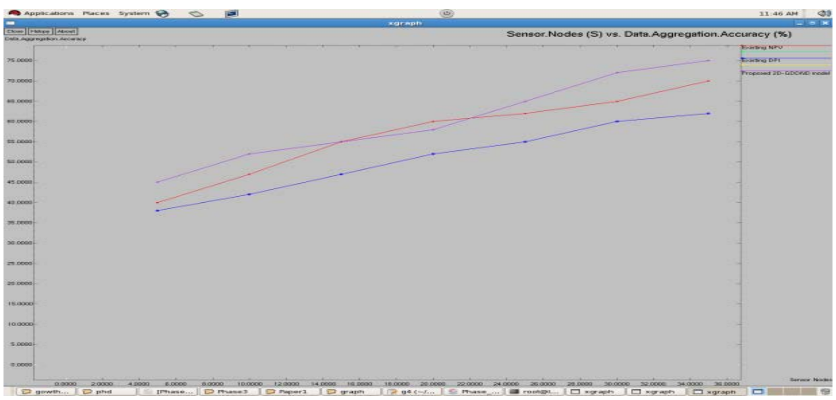

Fig. 5: Sensotr nodes versus data aggregation accuracy

Table 1: Tabulation for power consumption

Sensor nodes (Node ID)	Power consumption (W)		
	NPV strategy	DPI process	2D-GDDND model
S1	210	200	170
S2	232	227	190
S3	239	233	225
S4	250	245	235
S5	260	254	248
S6	265	260	255
S7	278	270	259

Table 2: Tabulation for data aggregation accuracy

Sensor Nodes (S)	Data aggregation accuracy (%)		
	NPV strategy	DPI process	2D-GDDND model
5	40	38	45
10	47	42	52
15	55	47	55
20	60	52	58
25	62	55	65
30	65	60	72
35	70	62	75

elaborated in Table 3. The throughput level attained by the sensor nodes of range 5-35 has been illustrated in Fig. 6. From the Figure 6, it has been observed that the

Table 3: Tabulation for throughput level

Sensor Nodes (S)	Throughput level (Kbits/sec)		
	NPV strategy	DPI process	2D-GDDND model
5	815	825	850
10	835	875	900
15	865	890	925
20	880	900	945
25	910	925	1000
30	915	940	1125
35	928	960	1230

throughput level achieved using the proposed 2D GDDND model is higher when compared to two other existing NPV strategy and DPI process. Besides we can also observe that by increasing the number of sensor nodes, the throughput is also increased using all the methods. But comparatively, it is higher in 2D-GDDND model because with the computation of distance (i.e., length and width) using the 2D statistical geometric algorithm. Therefore, 2D-GDDND model is achieved higher data aggregation accuracy which in turn increases the throughput level by 5-24 % than NPV strategy. It is also has been found that for higher number node, the proposed method provide very odd throughput level as

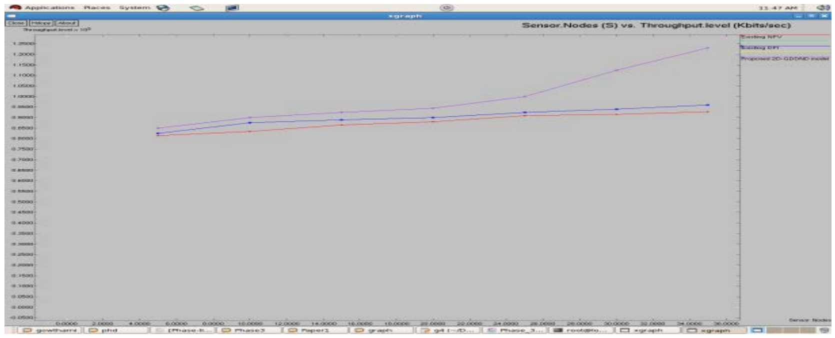

Fig. 6: Sensor nodes versus throuhgput level

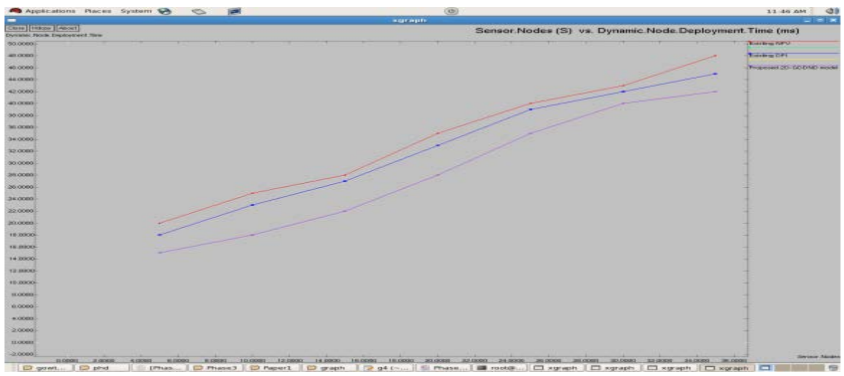

Fig. 7: Sensor nodes versus dynamic nodes deployment time

Table 4: Tabulation for dynamic node deployment time

	Dynamic node deployment time (m sec)		
Sensor nodes (S)	NPV strategy	DPI process	2D-GDDND model
5	20	18	15
10	25	23	18
15	28	27	22
20	35	33	28
25	40	39	35
30	43	42	40
35	48	45	42

compared with existing methods. In addition with the application of Gaussian distribution function and with the measured angle, the triangular field 'T' helps to easily observe the throughput level on the two dimensional space. As result, 2D-GDDND model is improved throughput level by 7-20% than compared DPI process.

Table 4 and Fig. 7 illustrates the dynamic node deployment time versus the sensor nodes S at different mobility in a network range of 900×900 m. From the figure we can note that the dynamic node deployment time is an increasing function but there is a significant gain using the proposed 2D-GDDND model. This is because, the sensor network identifies the directional position of nodes based on distance using 2-D statistical triangulation algorithm and reduced the dynamic node deployment time by 14-38% when compared to NPV strategy. Further using 2D-GDDND model, directional position easily identified in turn reduced the dynamic node deployment time by 5-27% when compared to DPI process.

CONCLUSION

In this study, two dimensional gaussian distribution based Dynamic Node Deployment (2D-GDDND) model has been developed for deploying the dynamic sensor nodes in wireless sensor network. Unlike the conventional methods, the proposed 2D-GDDND model exploits both the data aggregation accuracy and higher throughput ratio by deploying the nodes dynamically in the sensor network. 2D-GDDND model initially identifies the directional position based on the angle measurement of the sensor node position by using the 2-D statistical triangulation algorithm. The 2-D statistical triangulation algorithm has been proposed to reduce the power consumption for the entire node deployment structure as well as the Gaussian distribution model that accurately deploy the sensor nodes with higher data aggregation efficiency. In 2D-GDDND model, Gaussian distribution determines angular difference between the sensor node and mobile robot. Then, 2D-GDDND model phase shift the sensor nodes according to their computed angular difference. As a result, sensor nodes can easily gather and aggregates the data with another node in sensor network. For the reason that the data aggregation accuracy and throughput level using 2D-GDDND model is improved in an effective manner. Simulation results demonstrate that the proposed 2D-GDDND model outperforms the two existing ones and provides higher data aggregation accuracy and throughput level. The usage of 2D-GDDND model reduces the power consumption by 20% when compared to the State of-the-art works.

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