Topology Control of Mobile Robot Networks for Optimal Coverage and Connectivity using Irregular Hexagonalization

Karthik Mahesh Varadarajan, Markus Vincze
ACIN, TU Vienna
Vienna, Austria
{kv,mv}@acin.tuwien.ac.at

***Abstract*— A number of multi-robot networks (operating both indoors and outdoors) such as security and surveillance systems, industrial manufacturing, mobile defense robotic systems, mobile distributed monitoring systems as well as other cooperative robotic network systems like robotic soccer require multiple robots to provide maximal coverage and connectivity while being able to rapidly adapt to changes in environmental and channel conditions. Variation in link quality in the transition region is often a major concern in wireless multi-robot sensor networks. The quality of the wireless link varies temporally as well as spatially. Traditional algorithms attempt at solving this issue through a combination of deployment schemes and power control, leading to various topology control mechanisms. In the case of mobile robot networks, it is possible to resolve this issue using the additional degree of freedom rendered by the mobility of the robots. In this paper we introduce a novel robot node deployment scheme and topology control mechanism that aims at maximizing coverage, connectivity while providing reliable communication under varying network conditions. The topology control is achieved by modeling the inverse signal loss, multi-path fading and other effects and combining them to control the topology of the network in an irregular hexagonal static/ mobile multi-robot deployment scheme. Experimental data, together with simulation results demonstrate connectivity enhancement under signal loss with mobility based topology control.**

Keywords- Multi-robot Networks, Topology Control, Outage, Fading Models, Hexagon, Deployment, Rayleigh, Log-Normal, Dynamic Network Topology, Mobile, Sensors

I. INTRODUCTION

Efficient deployment of nodes in a multi-robot wireless sensor network is necessary to achieve good connectivity and reliability over time. A number of multi-robot networks such as security and surveillance systems, industrial manufacturing, mobile defense robotic systems, mobile distributed monitoring systems as well as other cooperative robotic network systems like robotic soccer require multiple robots to provide maximal coverage and connectivity while being able to rapidly adapt to changes in environmental and channel conditions. Numerous deployment strategies and topology control schemes have been developed for wireless sensor nodes over the last few years [23, 24, 25]. Schemes that involve both static and mobile nodes have been developed. These are directly applicable to mobile robot networks. Topology of multi-robot networks can also affected by the tasks assigned to the individual robots [27]. In addition, localization of mobile robots can be implicitly solved using the wireless sensor network framework [26]. Topological coverage management for mobile robots (especially with individual robots and cell divisions) [28] also contributes to the understanding of the problem of topology control for multi-robot networks.

The main criteria on which deployment schemes are currently developed are connectivity and coverage. In this paper, we focus on topology control of a mobile robot node network for 3-connectivity with blanket coverage. Terminology and algorithms from the domain of wireless sensor networks have been borrowed to this end.

The degradation of signal strength with the distance from the source node follows a logarithmic power law. The variation in the power level across time, in the case of a static wireless sensor network is largely dependent on changes in the environment parameters that determine the multipath fading effects. In the case of mobile networks, this also depends on other factors such as velocity of nodes, relative velocity of objects in the surrounding environment etc. The paper brings these effects into the modeling of the topology and hence the deployment scheme, thus improving the reliability and connectivity of the network. The base topology for the proposed deployment model is a hexagonal grid structure. The structure is designed by the superposition of static and mobile diamond topologies. Logarithmic models and various fading models have been combined for simulations. The metric for performance measurement is the '*Outage probability*' defined on the signal level falling below a threshold.

The central theme of this paper revolves around the development of a dynamic topology that is not just efficient in terms of reliability, connectivity and coverage but also has the capacity to alter its state in the case of an event (critical/non-critical) to obtain a new optimal state. The dynamic nature of signal strength variability in mobile robot networks is largely due to environmental changes, as these networks are deployed in areas where there is high channel variability and over which the user has little control. One such example setting is the equatorial rain forest, where it rains heavily in the afternoons and is extremely hot and sunny in the mornings. As a result, the fading model (rain fading [21]) of the environment changes largely, from time to time. These effects assume great significance in the case of surveillance, monitoring and defense robot networks. The fading models are important as they contribute to significant changes in the power level of the signal received by the nodes over short periods of time. The variation in the received signal at any point in the network depends on a number of factors like reflections, scattering etc. causing variations in the signal level in nano-sec to milli-sec range, a fraction of which is the time for measurement of the signal. Hence, it becomes necessary to adapt the network to the non-linearities in nature. One possible method would be to use power control. Another method would be to create a dynamic topology that adapts itself to changes in the environment.

Besides these non-linearities, there are numerous other effects that result in variation in the signal level received at a point in the network [12]. These include the fact that (1) the world is not flat but curved, (2) radio transmission areas are not circular, i.e. radios are not isotropic, (3) different radios have different ranges, (4) bi-direction links are not perfectly symmetric, (5) the quality of a link varies with time, (6) signal strength varies with distance in a complex way, (7) there are considerable fading effects and variations in fading effects. The goal of this paper is to design a dynamic topology that would enable to overcome these issues thereby creating a reliably connected network. While it is not possible to model each of these parameters individually, it should be possible to capture the group behavior approximately by fitting probability distributions.

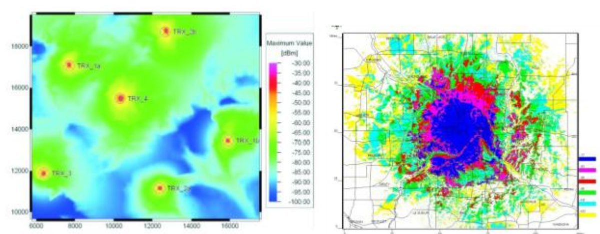

Figure 1. Typical radio power level contours with color representing the signal quality (Source: University of Stuttgart, Midwest Radio Association and [12]).

II. Related Work

Node Deployments can be largely classified as structured and randomized. Using power control various network topologies have been achieved (MFCN, COMPOW, CRTC) [3]. Lifetime oriented, connectivity oriented and hybrid development schemes have also been analyzed [4]. While most of the sensor placement schemes are deterministic, stochastic node placement schemes are also being developed. One important node placement scheme uses the Power-Law placement [2] in which the degree of the nodes follows a power law. In the case of mobile nodes, schemes such as DSSA [5] and Incremental Self-Deployment algorithm [6] have been developed. An approach using the concept of potential fields repelling each other and stationary objects has been used in sensor node deployments [7] and for multi-robot networks using virtual angle forces for bi-connection in [29]. However, not all such approaches are feasible in an arbitrary environment. Few approaches utilize the power of mobile nodes in augmenting the quality of the network of static nodes. The theory developed in this paper corresponds to mobile nodes that have limited or constrained mobility (constraints could be task driven). The primary function of these nodes is to reposition themselves on the deployment grid in such a way that optimal link connectivity is obtained. Hexagonal node deployments have been expounded in [8, 9]. Efficiency of dynamic self-organizing networks has been demonstrated in [10].

Considerable work has been done in communication theory on the study of non-linearities in nature affecting radio propagation. While considerable amount of the theory from wireless communication has been borrowed into studying the radio propagation mechanisms of mobile wireless sensor networks, there are several differences. These stem from the fact that the sensors in general do not possess directional antennas and also the range of radios used on sensor networks is of the order of a few tens of meters to the maximum. Hence it is not possible to apply models such as the Clarke's model directly without adaptation to wireless nodes. The variation of power level with distance, time and position (due to fading effects) has been observed to fit a log-normal distribution (Fig. 1). This is especially true in the case of indoor environments [14]. Furthermore, the arrival time of the multipath has been found to be Poisson and the log-mean value of amplitude decreases with increasing excess delay. Also, the path loss varies linearly with the delay spread [15]. A possible model for simulating the power values at adjacent points uses a superposition of bivariate Gaussians. Also another simulation model for urban radio propagation was obtained by Suzuki, called the Suzuki Distribution [16]. In the case of nodes in motion, the relative velocity causes a Doppler shift in frequency. This could also cause fading effects. However, this effect is excluded from analysis in the model developed in this paper. Mobile node localization based on this Doppler shift frequency is studied in [13].

III. Dynamic Topology Design

This paper concentrates on the developing a topology that captures the seven dynamic effects (referenced from [12]), which cause variation in the signal level received. The primary focus is on modeling the variation of the signal level with distance and in short intervals of time, characterized by fading models. These multipath effects also vary with the position of the receiver. Along with the other effects, the fading effects are captured implicitly and used to optimize node locations in the deployment scheme. The topology developed can be described in terms of the following structural topology features.

A. Hexagonal Base Topology

There are several advantages of using a hexagonal grid structure. Hexagonal structures offer the largest area coverage for a given number of points with the requirement of exact packing. Of all possible topologies, the least amount of energy is required for a random arrangement to be isomorphed into a hexagonal structure. Hence hexagonal topology is taken as the base topology for the network deployment scheme developed in this paper. Also, a hexagonal scheme covers the minimum overall perimeter for a given area, since it approximates a circle and at the same time allows for perfect packing. Hence links in a hexagonal network are closer to each other than in other schemes. This enables enhanced connectivity. Other advantages include: the lack of a blind spot, ease of

 ISBN: 978-1-61208-134-2

deployment, adaptability to cell based sleep scheduling, ease in control of power level, ability to turn off transfer nodes to enable power savings, lack of network congestion due to simplicity of structure and simplicity of routing mechanisms [9]. Further, hexagonal networks give optimal performance in terms of minimal requirement of number of nodes [8].

B. *Complementary Static-Mobile Nodes*

Topology control is traditionally established using power control. However, the combination of mobile and static nodes provides a very powerful alternate deployment scheme. While it may be useful to have the entire network to be composed of mobile robot nodes, there are several practical considerations (task constraints) which prevent such a possibility for a non-critical network. Based on task constraints and desired work space of each robot, it can be expected that the mobile nodes do not move over a long range or continuously. Instead these mobile nodes are to alter their position in the grid only at periodic intervals.

C. *Dynamic Hex Network*

While a mobile robot network with full degree of freedom in mobility is highly adaptable to various topology requirements, the optimization is computationally extremely intensive for continuous real-time change in requirements and can lead to sub-optimal solutions with respect to connectivity of the network graph. Hence, a dynamic hex network which is completely connected (on an average) is employed as the underlying topology. However, due to time variation of fading and other effects, it is possible that the network becomes disconnected. It is this probability that the algorithm developed in the paper tries to minimize. This is called the outage probability. In other words, the no-outage probability (i.e. 1 - outage probability) is to be maximized.

Such a dynamic hex network formed by superimposing a diamond topology of static nodes on a diamond topology of mobile nodes is depicted in Fig. 3. Fig. 2 illustrates the constraints on the optimization of position of a mobile node. It can be seen that the position of a mobile node can vary within a triangular area bounded by the neighboring nodes. For simplicity, the position of the nodes is assumed to vary linearly from or to the neighboring nodes in this triangular region.

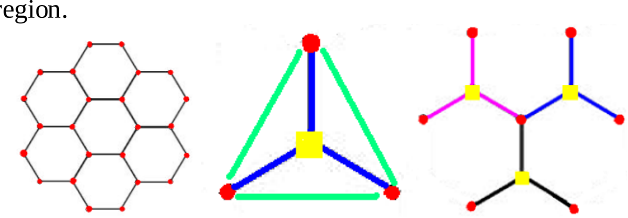

Figure 2. Left: Hexagonal grid topology, Center: Each mobile node is connected to three other nodes in a triangular area of constrained motion. Right: Unique colors represent the link minimization criteria for each node. Clearly, the optimization of one node does not affect the other nodes.

Such a topology preserves the static power relationships. Thus, it can be seen that each node can optimize its position dynamically, without regard to the other nodes. Typically the time interval for optimizing can be set based on the frequency of occurrence of the natural event. The optimization process can occur by decentralized processing. Also, all mobile nodes can reposition themselves simultaneously. Since the static nodes do not require to reposition themselves or identify the position of the mobile nodes, they can be devoid of memory and information about the network topology. On the other hand, the mobile nodes require knowledge of the position of the static nodes and also should be capable of localizing themselves so that they move and relocate to an optimal position.

D. *Non-Ideal Environment Modeling*

If the network is ideal, then all the links between the nodes will have equal weight, i.e., the radio range will be isotropic. For the ideal case the power topology is composed of regular hexagons when the deployment topology is made of regular hexagons (Fig. 3).

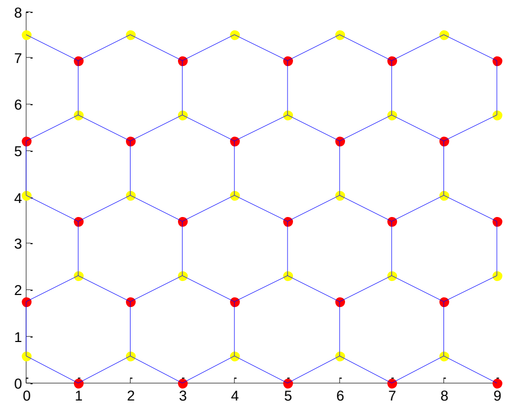

Figure 3. Array of superimposed static (red) and mobile (yellow) diamond topologies forming the Hexagonal Dynamic Topology. It can be seen that the mobile and the static nodes fall on alternate layers. The blue segment represent ideal links

In a practical scenario, the major large scale path loss in the signal received from a radio can be attributed to reflections, scattering and diffraction. The effect of these factors can be modeled individually. An alternate method would be to model the path loss in a single term as log-normal. A Gaussian factor is included in the log-normal model to indicate the variation in the values of the received power at different points at the same distance from the transmitter [17].

$$PL(d) = \overline{PL\ (d_0)} + 10nlog\frac{d}{d_0} + X_\sigma$$

All the power values in the above equation are represented in terms of dB. $PL(d)$ is the Path Loss at a distance d from the transmitter. X_σ is the zero-mean Gaussian distributed random variable (in dB) with σ (also in dB) as variance. n is the Path Loss exponent and $\overline{PL\ (d_0)}$ represents the average power level at a reference distance d_0 from the transmitter. The received power is related to the power loss as below.

$$P_r(d) = P_t(d) - PL(d)$$

Here, $P_r(d)$ *and* $P_t(d)$ are given dBm and PL (d) is given in dB. The value of the path-loss exponent varies typically from 1 to 6 depending on the availability of a line of sight path. It is higher for the case of larger spaces or spaces with more obstructions and in places where there is

 ISBN: 978-1-61208-134-2

no line of sight. A good way to represent numerically the probability that the signal level will exceed a particular threshold is given by the Q function (z is the random variable representing the power level)[17].

$$Q(z) = \frac{1}{\sqrt{2\pi}}\int_{z}^{\infty} \exp(-\frac{x^2}{2})dx$$
$$= \frac{1}{2}(1 - \mathrm{erf}\left(\frac{z}{\sqrt{2}}\right))$$

where $Q(z) = 1 - Q(-z)$

The probability that the received signal (in dB power units) will exceed a certain value γ can be calculated from the cumulative density function of the log-normal distribution as

$$\Pr[P_r(d) > \gamma] = Q(\frac{\gamma - \overline{\overline{P_r(d)}}}{\sigma})$$

Thus values from the Cumulative Distribution Function (CDF) of the function gives the probability that the signal power level is above a certain threshold. This is the metric used in this paper for the optimization. This metric is directly related to the outage probability (which uses the signal amplitude value instead of the power value) and hence increase in the probability of the above function is equivalent to increasing the no-outage probability.

Propagation models for outdoor and indoor wireless communication include the Longley Rice Model, Durkin's Model, Okumura Model, Hata Model, Lee Model, Walfisch and Bertoni Model, Attenuation Factor Model and the Partition Losses Model [17]. Further, there are small scale fading and multipath effects causing variations in the received signal level. In the case at hand, the multipath fading occurs only due to rapid changes in the signal strength over a small travel distance and time dispersion caused by multipath propagation delays. The spatial variations can be essentially modeled as variations across time as the mobile robot has to change its position through time in order to reach its new position. Multipath propagation effects are largely due to the reflections of the signal by the environmental features resulting in multiple paths for the signal arrival at a point and these are delayed or phase shifted. This phenomenon is called Multipath time delay spread. Thus, fading due to shadowing and other location specific properties is called 'Slow Fading', whereas that due to multipath forms 'Fast Fading' (Fig. 4). Here two possible cases arise. One possibility is that the frequency response of the channel is constant or flat and the other possibility is that it varies with the frequency. Correspondingly we have Flat Fading and Frequency Selective Fading. Besides, small scale fading based on Doppler spread can also create fading effects. Again we have Fast and Slow fading corresponding to Doppler Spread based fading. The only fading of concern in this paper is the flat fading based on the Multipath time delay spread. This is because the system feature response can be assumed to be flat and doesn't change with the frequency. Also, since the mobile robots are not required to measure power when in motion, Doppler effects are not of concern. The time range of concern is of the order of a few milliseconds.

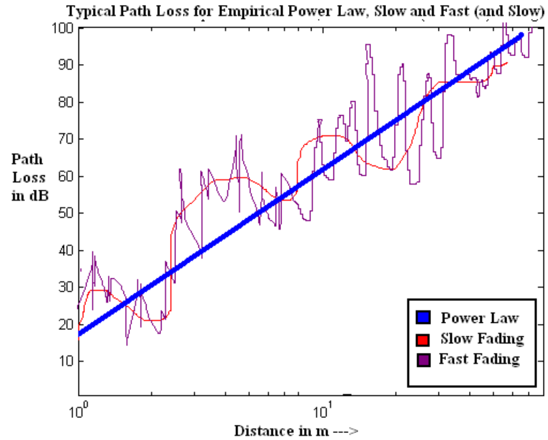

Figure. 4. Typical Path Loss with Power Law, Slow Fading added and Fast Fading added.

While the power loss in the case of slow fading (flat) is represented conveniently by the log-normal distribution, the total power received (after the power loss) in the case of fast fading can be represented in the form of other statistical distributions [20, 22] such as the Rayleigh, Rician, Nakagami-m, Weibull, Lognormal, Suzuki, Gauss-Markov or HMM distributions. In this paper, the slow flat fading using log-normal distribution and fast flat fading using Rayleigh have been used. By fitting measured data, it is possible to calculate the parameters of the distributions. Once the parameters are calculated, it is relatively easy to calculate the integral of the Cumulative Distribution Function above a certain threshold. This gives the probability that the signal power was above a certain threshold.

Rayleigh Distribution:

$$p(r) = \left\{\frac{r}{\sigma^2}\exp\left(-\frac{r^2}{2\sigma^2}\right)\right\} \; 0 \le r \le \infty$$
$$p(r) = 0 \;\; r < 0$$

where σ is the RMS value of the received signal voltage and r is the envelope of the signal.

Rician Distribution:

$$p(r) = \left\{\frac{r}{\sigma^2}\exp\left(-\frac{r^2 + A^2}{2\sigma^2}\right) I_0(\frac{Ar}{\sigma^2})\right\} \; A \ge 0 \; r \ge 0$$
$$p(r) = 0 \;\; r < 0$$

'A' refers to the mean component adding to the signal. Rayleigh distribution is used where most components are scattering or multipath components. Rician distribution is used when there is a strong Line of Sight (LoS) component.

Another method of optimizing the position of the mobile robots would be to obtain the PRR (Packet Reception Rate) and use it as the metric for comparison. This is natural to use as it would take into account the modulation effects and hence the frequency selectiveness of the fading, irrespective of whether it is narrowband or wideband. However, since the PRR variation is very steep in the sigmoidal region (the transition region) it is difficult to use it as a metric. Further, the PRR depends on the digital modulation scheme employed [18]. In order to simplify the working of the algorithm, the power levels are considered directly, yielding the outage probability. A further simplification would be to use the RSSI values directly instead of calculating the RF power levels in dB. This is acceptable as the relationship between the RSSI and the RF power levels is a linear shift, and this can be modeled by an equivalent shift in the log domain [19].

E. Algorithm

Given the constraints on the mobile robot nodes, the following heuristic algorithm is proposed in order to optimize the positioning of the mobile node.

Training Mode

i) The hexagonal deployment of the mobile and static nodes is carried out.
ii) An efficient hill climbing approach can be implemented to relocate the mobile node in each triangular cell at its optimal position. But, this is computationally demanding on the mobile node. An easier approach is to create power level bins and estimate the optimal position by a brute force approach. For the case of pure slow fading (log-normal shadowing), an estimate of the optimal position can be computed.
iii) The mobile nodes walk through a triangular region bounded by the static nodes gathering data on the power levels from nearby nodes at preassigned bin locations.
iv) A Maximum Likelihood Estimation (MLE) is performed on data obtained to estimate the distribution parameters.
v) The outage probability is estimated from the distribution model.

Redeployment Strategy

i) An initial value of desired outage probability is chosen.
ii) The mobile robots, based on the data collected during the training mode calculate the position where the no-outage probability from each static node is satisfied.
iii) If the mobile node is successful in finding a bin/point, the value of the desired no-outage probability is increased and step ii repeated.
iv) The process is terminated when the mobile node does not find a bin satisfying the no-outage probability criterion for all three nodes.
v) The mobile node moves to the last successful position identified.

IV. EXPERIMENTS, SIMULATIONS AND RESULTS

Experiments were conducted to measure the power levels at various distances (power bins). The chosen distances were 1m, 5m, 10m, 20m and 25m. The RSSI values obtained were used in the fitting of distributions. The setting of the experimental process was in a parking lot, an environment with both fast and slow fading effects. Multiple measurements in short time intervals yield the multipath fading components. In our testing, we simulate the environment for multiple mobile node using parameters obtained from the experimentation on a few nodes. Parameters of the distributions were obtained for Log-Normal, Weibull and Rayleigh distributions.

TABLE I

Distance	RSSI in –dB for 25 positions				
1	38.1140	37.6980	37.5220	33.7150	31.9310
	31.6930	31.6880	31.6250	31.3300	31.1170
	30.6310	30.6100	30.5630	30.5120	30.5120
	30.2220	29.9970	29.5960	29.2120	29.2100
5	44.7210	44.6730	44.5830	44.3890	44.3600
	44.1220	44.1000	43.6280	42.2310	41.7800
	41.6220	41.2120	41.0000	40.9180	40.8820
	40.5100	39.6210	39.2420	38.1510	37.2830
10	46.2310	46.2060	45.2330	44.6670	44.5460
	44.5410	44.5320	44.4440	44.4270	44.2120
	44.1970	44.1660	43.2220	42.7700	42.4960
	41.5350	41.5260	41.1230	41.1130	40.3230
20	49.8330	49.6580	49.3610	49.3580	49.1380
	49.1110	48.9440	48.1450	47.4750	47.3630
	47.3450	47.2530	47.2330	47.1550	47.1230
	47.0030	46.9430	46.7350	46.6330	46.3330
25	50.1720	49.7220	49.5570	49.4880	49.2880
	49.2220	48.9200	48.8480	48.5330	48.2580
	47.3900	46.7520	46.2370	46.0020	45.7370
	45.5870	45.4790	45.2570	45.2360	45.2290

Table 1. Distance in meters and Average RSSI values in –dB for 25 positions.

A Linear Regression fit for the experimental data yielded values of n and X_σ (for the Log-Normal Fading model) as 1.1419 and 4.085. Correspondingly, the following approximate parametric values were obtained for the log-normal fading Param1 (μ) = [3 2 1 0.6 0.5] over the r distance bins and Param2 (σ) = [1 0.7 0.5 0.25 0.2]. For Rayleigh, values obtained were (σ) = [25 12 8 2 1] and that for Weibull (μ) = [30 10 4 2 1.5] and (ω) = [2 2 2 6 4]

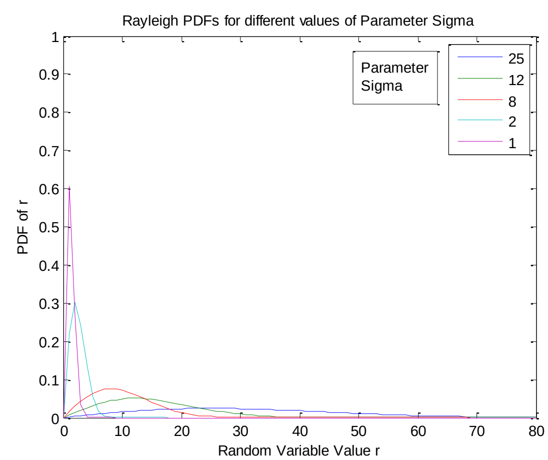

Figure. 5. Rayleigh distributions for different values of parameters in inset.

The random variable 'r' represents the values the distribution can take. It is directly related to the power values measured. In Fig. 5, the different curves indicate the Rayleigh distributions for different values of parameters. The parameters are obtained at different distances of the mobile node from the static node. The higher the distance, the larger is the value of the Rayleigh parameter. It is seen that curves corresponding to larger distances are flatter. Thus, it can be seen that towards larger values of r, the area under the curve beyond r (and hence the no-outage probability) is larger than for smaller parametric values or shorter inter-node distances. Since this variation is non-linear and differs from one static node to the other, it is possible to find an optimal position for the mobile node by brute force.

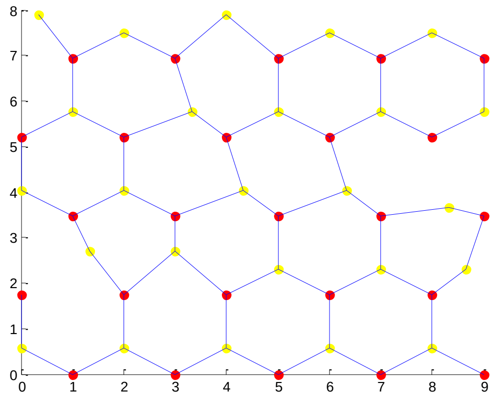

Figure. 6. Graph showing connectivity pattern after the node repositioning (based on the connectivity of the original regular hexagonal topology)

Using the heuristic node repositioning algorithm operating on the experimental data in Table 1, the overall average outage probability of the simulated network, using the Rayleigh distribution was increased from 0.60 to 0.80 (assuming 15m as the initial hypothetical location of each mobile node from the other three static nodes). Since the network is designed to choose dynamically thresholds in order to increase the no-outage probability, the result is on expected lines. Also, in order to keep the algorithm fast, only few bins were used (5*5*5 bins one each at 25, 20, 10, 5 and 1 meter from the static nodes). The thresholds were increased in coarse steps of 0.05. The results can be enhanced by proper choice of step size and distribution based on the environment at hand.

V. Conclusion And Future Work

In this paper, we have presented a novel mobility based topology control scheme for mobile robot networks. The method presented uses a combination of static and mobile nodes in an irregular hexagonal framework combined with dynamic topology management to enhance reliability and connectivity. Experiments and simulations demonstrate reduced outage probability.

The current algorithm uses a brute force optimization approach. Investigation of alternate approaches to identify the optimal location form future work. While localization using the Log-Normal fading model is easy, it does not take into account the fast fading effects. These can be modeled using Rayleigh or Rician fading, but with increased computational requirements. One way of achieving this would be to use a recursively updating procedure to find the optimal location. It could be designed such that at each step of the process, the node improves its positioning and the process converges in a limited number of steps. Further, the radio model and effects of the modulation scheme can be included in the modeling as well. However, in this case, it is necessary to alter the fading model as well. This is because, if the implementation is not narrowband but instead uses a wideband channel, then the effects of frequency selective fading come into play. Alternate schemes that enable a mobile node to find the optimal position by moving towards it will necessitate changes to the fading model by introducing effects of Doppler spread. Also, a PRR based measure will be the most suitable for optimization. Future work will involve incorporating the above in the modeling.

References

[1] G. Hoblos, M. Staroswiecki, and A. Aitouche, "Optimal Design of Fault Tolerant Sensor Networks," ICCA, Sept. 2000, pp. 462–472.
[2] M. Ishizuka, M. Aida, "Achieving Power-law Placement in Wireless Sensor Networks", ISADS 2005.
[3] Bhaskar Krishnamchari, "Networking Wireless Sensor Networks", Edition 1, Cambridge 2005.
[4] K. Xu, H. Hassanein, G. Takahara, Q. Wang, "Relay Node Deployment Strategies in Heterogeneous Wireless Sensor Networks: Single-Hop Communication Case", IEEE GlobeCom 2005.
[5] N. Heo, Varshney, P.K., "An intelligent deployment and clustering algorithm for a distributed mobile sensor network", IEEE International Conference on Systems, Man and Cybernetics, 2003.
[6] A. Howard, M. J. Mataric, G. Sukhatme, "An incremental self-deployment algorithm for mobile nets", J. Autonomous Robots, 2003.
[7] A. Howard, M. J. Mataric, G. Sukhatme, "Mobile Sensor Network Deployment using Potential Fields: A Distributed, Scalable Solution to the Area Coverage Problem", DARS, 2002.
[8] M. M. Iqbal, I. Gondal, L. Dooley, "Dynamic Symmetrical Topology Models for Pervasive Sensor Networks", INMIC 2004.
[9] H. Tian, H. Shen, "An Optimal Coverage Scheme for Wireless Sensor Network", ICN 2005.
[10] S. S. Doumit, D. P. Agrawal, "Self-Organized Criticality & Stochastic Learning Based Intrusion Detection System for Wireless Sensor Networks", Military Communications Conference, 2003.
[11] D.W. Gage. "Command control for many-robot systems", AUVS-92.
[12] D. Kotz, C. Newport, C. Elliott, "The mistaken axioms of wireless-network research", Dartmouth College Computer Science Technical Report TR2003-467, July 18, 2003.
[13] A. Lakhzouri, E. S. Lohan, R. Hamila, M. Renfors, "Extended Kalman Filter Channel Estimation for Line-of-Sight Detection in WCDMA Mobile Positioning", EURASIP 2003.
[14] H. Hashemi, "Impulse Response Modeling of Indoor Radio Propagation Channels", IEEE J. on Comm. 1993, Vol.11, pp.967-978.
[15] H. Nikookar, H. Hashemi, "Statistical Modeling Of Signal Amplitude Fading Of Indoor Radio Propagation Channels", IEEE UPC 1993.
[16] H. Suzwi, "A Statistical Model for Urban Radio Propagation", IEEE Trans. on Communications 1977, Vol. 25, pp. 673 - 680.
[17] T. S. Rappaport, "Wireless Communications: Principles and Practice", Edition 1, Prentice Hall, 1996.
[18] M. Zuniga, B. Krishnamachari, "Analyzing the Transitional Region in Low Power Wireless Links", IEEE SECON 2004.
[19] TMOTE SKY Manual.
[20] JPL's Wireless Communication Reference Website: http://wireless.per.nl/reference/about.htm (accessed 15 Jan 2011)
[21] "Uncorrelated Rain Fading and its Impact on Frequency Re-Use and Antenna" RPE, Specifications, IEEE 802.16 BWAG.
[22] Joel T. Johnson, "Computer Simulations of Rough Surface Scattering", Nanostructure science and technology, 2007, pp.181-210.
[23] Iino, Y., Hatanaka, T., Fujita, M., "Dynamic topology optimization for dependable sensor networks", IEEE CCA 2010.
[24] J.M. Hong, Q. Zhang, L.M.Ni, "Energy-efficient opportunistic topology control in wireless sensor networks", MobiOpp 2007.
[25] J. Pan, Y.T. Hou, L. Cai, Y. Shi, S.X. Shen, "Topology control for wireless sensor networks", IEEE MobiCom 2003.
[26] Maxim A. Batalin, Gaurav S. Sukhatme, Myron Hattig, "Mobile Robot Navigation using a Sensor Network", IEEE ICRA 2004.
[27] Ceng Xian-yi, Li Shu-qin, & Xia De-shen, "Study of Self-Organization Model of Multiple Mobile Robot", IJARS 2005.
[28] Sylvia C. Wong, Bruce A. MacDonald, "A topological coverage algorithm for mobile robots", IEEE IROS 2003.
[29] Casteigts, A., et al., "Biconnecting a Network of Mobile Robots Using Virtual Angular Forces", IEEE VTC, 2010.