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Building structural health monitoring using dense and sparse topology wireless sensor network

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Abstract. Wireless sensor technology has been opened up numerous opportunities to advanced health and maintenance monitoring of civil infrastructure. Compare to the traditional tactics, it offers a better way of providing relevant information regarding the condition of building structure health at a lower price. Numerous domestic buildings, especially longer-span buildings have a low frequency response and challenging to measure using deployed numbers of sensors. The way the sensor nodes are connected plays an important role in providing the signals with required strengths. Out of many topologies, the dense and sparse topologies wireless sensor network were extensively used in sensor network applications for collecting health information. However, it is still unclear which topology is better for obtaining health information in terms of greatest components, node's size and degree. Theoretical and computational issues arising in the selection of the optimum topology sensor network for estimating coverage area with sensor placement in building structural monitoring are addressed. This work is an attempt to fill this gap in high-rise building structural health monitoring application. The result shows that, the sparse topology sensor network provides better performance compared with the dense topology network and would be a good choice for monitoring high-rise building structural health damage.

Keywords: wireless sensor network; building structural health monitoring, dense network; sparse network; Optimum topology sensor network

1. Introduction

For more than a decade, wireless sensor systems have been growing in popularity in the research field. In recent years, structural health monitoring system (SHM) is an important area of the monitoring application that has received increasing research interest (Nikola *et al*. 2014). The field of wireless sensor networks (WSN) is an emerging area of research that is still under investigation. However, the problem of this emerging technology is the coverage area, or sensing

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area in structural health monitoring application (Kim *et al.* 2013, Casciati *et al.* 2011). Many studies of bridge structural health have been shown that the feasibility is the most important criteria in target applications. To measure the structural health response, usually three types of systems has been used: the sensor section, the communication section and the computing or analyzing section. In wireless communication data systems, the whole system should be designed and analyzed in properly; otherwise, the attenuation of the RF signal becomes worse. LOS (line-of-sight) is the another vital factor of the communication system that affects the performance of WSN (Kumar *et al.* 2011). When the structural dimensions become bigger, a huge amount of field information has been produced by the whole monitoring system. At that time, the whole monitoring system became difficult to maintain and control.

With the need to monitor the building structural health, WSNs become more popular in these application areas. The health of the building structure needs to be continuously monitored using sensor place at various locations on the structure (Casciati *et al.* 2014). Due to technology advancement, various kinds of sensing devices have already been developed to measure the structural health, such as ZigBee, Ultra Wideband (UWB), Global Positioning Systems (GPS) and so on (Almulla *et al.* 2013). Chang and Hung determined that, the 77.3 % of Taiwanese building structures are made of reinforced concrete (RC), and the majority of these should be supervised after a certain period of time. To determine the structural deterioration, temperature and humidity are the two key factors. Precipitation or the water content in the concrete structure defines how much the corrosion occurs and how its activity changes. Real-time and continuous monitoring of building structural health is still challenging, when they attempt to compute the exact damage and make administrative decisions (Chang *et al.* 2013). Among different kinds of wireless sensing devices, ZigBee provides the lowest power profile and most cost-effective system for various types of health monitoring applications in construction (Zhang *et al.* 2012). The lifetime of WSN network is gradually decreasing due to drawbacks such as strong earthquakes, corrosion, heavy traffic, etc. Interest in WSN has been growing due to their low power and low cost profile. In damage detection mechanisms, there is no need to deploy the fixed wire connections in monitoring network (Guo *et al*. 2014, Hackmann *et al*. 2014)). For monitoring structural health, the monitoring network should be efficient means transmission of data should be lossless and network should be scalable to cover the large monitoring area of interest of the structure (Yildirim *et al*. 2014). The problems of the SHM system do not completely satisfy by the existing WSN network. To address those issues, Wireless Intelligent Sensor and Actuator Network (WISAN) have been proposed as an alternative (Rohan *et al.* 2014). The goal of this work is to design and development of large area sparse and dense topology WSN using the Theory of Geometric Random Graph approach (TGRG). The performance related parameters of the dense and sparse topology sensor network monitoring system have studied to extend the monitoring system coverage area in building structural health. Three types of performance metrics are considered to measure the performance of the dense and sparse topology monitoring network and those performance metrics are: Maximum component (MC), connected topology (CT), average node degree (AND). The organization of the paper is as follows. The next Section describes research background. Section 3 contains the dense topology sensor network and its test result. Section 4 describes the principles of sparse topology sensor network and its analysis result. Section 5 provides a summary and conclusion of the simulation results for the proposed model.

2. Research background

The use of sensing technology is steadily increasing in buildings structural health monitoring. Usually, nodes with sensors has been used to collect the sensor data. Sensor nodes transmit their own sensed signal to the respective base station. Traditionally, the data collection system that connects the sensor nodes to the base station is a wired system. Wire-based data collection systems have the greatest monitoring system longevity. However, the wire-based data collection system has been lost popularity due to the several reasons such as a higher installation cost for a small period of usage. Noticeably, the wireless sensor systems for collecting sensor data still better performance compared with wired systems (Zhang *et al*. 2012). Hazard taxation has been designed to determine the structural risk due to the natural phenomena such as seismic activity, mudslides, etc. In the case of SHM systems, many sensors have been placed on the grave location in the service region. The most common technique has been used to fix the dynamic factors is the way to count the earthquakes inside buildings under constant surveillance, but such systems are expensive. Recently, the electromagnetic field (EMF) based sensing mechanisms become another kind of technique for monitoring structural health. The major benefit of the EMF method its high precision compared with the typical accelerometers method. This measurement technique based on microwave radar and can be applied in all weather conditions, and has been established as a dominant system to measure the different kinds of structural acceleration (Stabile *et al.* 2012). Durable SHM systems have been demonstrated in different countries, but the real-time measurement still facing many challenges shown by the author (Ko *et al.* 2005). The lifetime of a SHM system is gradually decreases due to its several drawbacks such as strong earthquakes, corrosion, heavy traffic, etc. According to the American Society of Civil Engineering, more than 26% of bridges experience a drop in efficiency over time. However, the wire-based sensor systems is more expensive and cannot be effectively used to monitor the large structures. WSNs allow a dense network to pinpoint the structural health problem based on fault tolerance.

Many researchers have been shown that various issues arise with WSNs among those interference and noise becoming a vital concern for sensor network communication systems (Boers *et al.* 2012). Setting up a health monitoring system for large-scale building structures, which require a large number of sensor nodes. The placement of these sensors is great significance for such distributed application of sensor node in the SHM system (Rao *et al.* 2007). To cover the large geographical civil infrastructure, scalability of the WSN is the most important issue. Sensor coverage area defines the complexity of the scalability to cover the whole service area. Scalability of the WSN provides the adjustment flexibility with infrastructure for monitoring structural health by adding a new sensor node in the network and also defines the higher precision of damage detection (Papadimitriou *et al.* 2004). A recent number of papers indicate that the artificial neural network has been considered for monitoring and detection of structural damage. The fault detection system consists of vector of the system as input and desired the fault classification as output. To bring the desired output, the internal structure of the neural network has been modified at presentation of the data level. When the neural network outputs have required properties over the whole training set, this iterative method has removed (Worden and Burrows *et al*. 2001). The authors believe that, to address the coverage area related problem, the application of the dense and sparse topology sensor network in high-rise building SHM overcomes the monitoring system coverage area related problem.

3. Dense topology sensor network

In a dense topology sensor network, the maximum number of sensor node to all other sensor nodes is near the total number of nodes used by the network. When each sensor node directly connected to all other nodes, the network is called a fully connected network. Fig. 1 shows the example of dense topology sensor network for N=9 number of sensor nodes.

TGRG approach (Nath *et al*. 2012) is used to provide an analytical solution to the communication range problem with high probability (w.h.p.) and produces a connected topology under some consideration. Consider, n is the number of sensor nodes are uniformly distributed in a square area L. The nodes organization is uniformly distributed means all the sensor nodes are equal distance in the monitoring area. The Penrose formula is used to determine the critical transmission range (CTR) value for the dense topology sensor network. Penrose formula is defined as follows

$$CTR_{dense} = \sqrt{\frac{\ln n + f(n)}{n\pi}}$$
$$\lim_{n \to \infty} f(n) = \infty \tag{1}$$

Where n is the total number of nodes and f (n) is the function of n. By increasing the value of n which lead the increasing value of the function f (n). The Penrose formula only applies to the dense topology sensor network. The accuracy of the Penrose formula is determined by the Giant Component (GC) test (Bollobás and Riordan *et al.* 2012). Table 1 shows the simulation setup for dense topology sensor network. The whole simulation result is obtained using update version of Atarraya simulator (Wightman and Labrador 2009). The number of nodes defines the density of the monitoring network. Initial CTR defines the initial value of the monitoring network. The CTR step defines the increasing value from the initial CTR. The number of topologies of monitoring network is predefined using topology parameter.

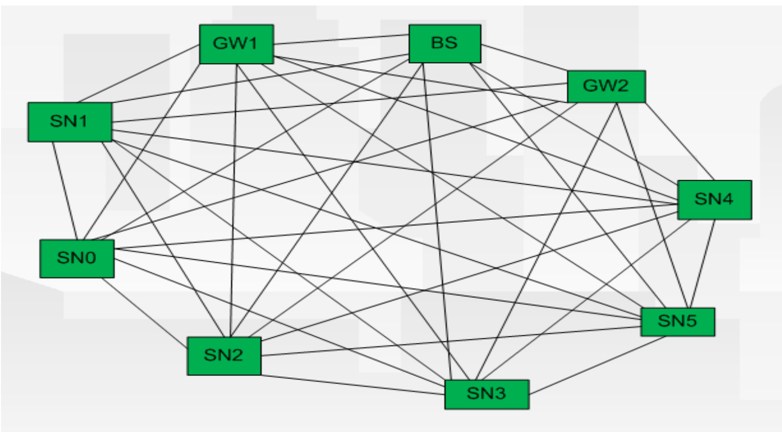

Fig. 1 Dense topology sensor network

Table 1 Simulation setup for dense network

Topology	Dense topology sensor network
Number of Nodes	10, 100, 200, 400
Initial CTR	0.01
CTR step	0.02
Number of topologies	100, 1000
Area	500 m x 500 m
Performance metrics	Maximum component, connected topology, average node degree

The area side of the monitoring network defines the deployment area of the dense network. The giant component is a very well known effect to compute the connectivity of the monitoring network. The maximum component, connected topology, average node degree is considered as a giant component of the SHM network. These performance metrics are calculated using a CTR function of the SHM network.

3.1 Dense topology test results

Fig. 2 shows the simulation results of dense topology sensor network maximum component curve, connected topology curve and average node degree using Eq. (1). The graph shows the result of dense topology sensor network where 200 nodes are uniformly distributed in the area of 500 m x 500 m and f(n)=log log (n) with 100 numbers of topologies.

The result shows that, the percentage value of the maximum component size increases with increasing values of communication radius. To have 100% maximum component size, a communication radius of 50-70 m is needed. When increase the value of communication radius, the maximum component value also increases. After 50 m communication radius, the network achieves the greatest component size and maximum at 145 m radius. In case of connected topology, the larger value of communication radius is required compared to the greatest component value. Before 75 m communication radius, there is no topology to connect the network. The topology connected is started from 75 m radius and the maximum connected value is obtained at 145 m radius. The average node degree of a network increases with increasing value of the communication radius and maximum value is obtained 40.83 degrees at 145 m radius. Table 2 shows the dense topology sensor network test result.

Fig. 3 shows the value of the greatest component size increases with the communication radius regardless of the network density for 10, 100, 200, 400 numbers sensor nodes. The density of the network nodes is uniformly distributed in the area of 500 m x 500 m with 1000 topology. Fig. 3 says that with increasing value of communication radius, the greater size component of dense network is increased. For larger number of dense topology network nodes, small radius of the network is required compared to a smaller number of sensor nodes. Therefore, for large sensor dense network, smaller amount of communication radius is required to achieve the largest connected set. Table 3 shows the computational result of the greatest component size for 10, 100, 200, 400 sensor node.

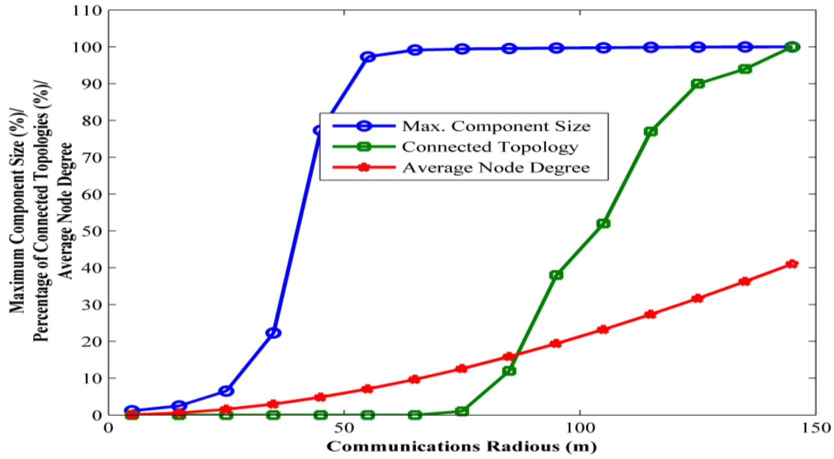

Fig. 2 Dense topology sensor network

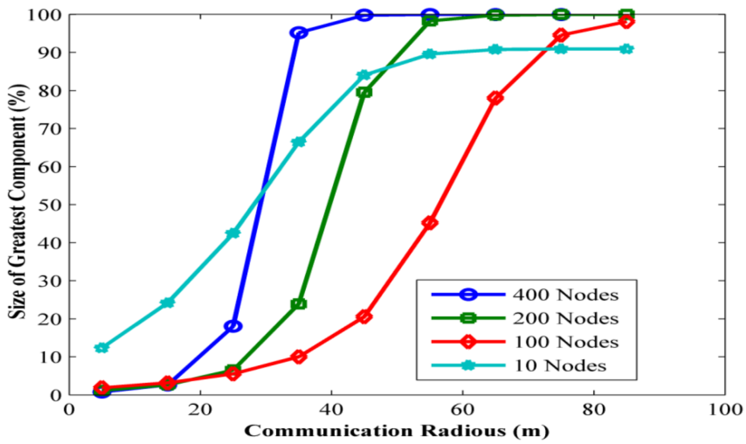

Fig. 3 Greatest component size

Fig. 4 shows the result of connected topology test result for the dense topology sensor network. The best result is obtained in a higher number of dense topology network compare to lower. Another way, it can be explained that the smaller communication radius is required with higher number of dense topology network nodes compared with lower number of dense topology network to achieve the same value of the connected network. Therefore, in case of 10 numbers of dense sensor nodes, the connected topology is zero. Because, at the given communication radius, the network is unable to connect the communication topology. The network can be connected the topology may be in larger communication radius. Table 4 report the ratio of connected topology test result.

Table 3 Greatest component size test result

Communication Radius (m)	Number of Nodes 10	100	200	400
5	12.33636364	1.866336634	1.139303483	0.779800499
15	24.18181818	3.161386139	2.610447761	2.623441397
25	42.44545455	5.518811881	6.528358209	18.040399
35	66.43636364	10.00891089	23.90547264	95.2159601
45	84.04545455	20.54554455	79.55970149	99.79625935
55	89.59090909	45.2039604	98.25373134	99.97805486
65	90.79090909	77.98910891	99.79402985	99.99800499
75	90.90909091	94.54653465	99.97512438	99.99950125
85	90.90909091	98.1019802	99.98955224	100

Table 4 Ratio of connected topology test result

Communication Radius (m)	Number of Nodes 10	100	200	400
5	0	0	0	0
15	0	0	0	0
25	0	0	0	0
35	0	0	0	1.9
45	0	0	0.1	69.8
55	0	0	35.9	95.4
65	0	0	81.5	99.6
75	0	0.1	96.5	99.9
85	0	5.4	98.7	100

Fig. 5 shows the average node degree of the dense topology sensor network. The result shows that the higher value of the communication radius provides the highest value of the average node degree. With increasing value of the network density lead the average node degree test result. However, some special result is found in the case of 10 numbers network node. Table 5 contains the average node degree computational result.

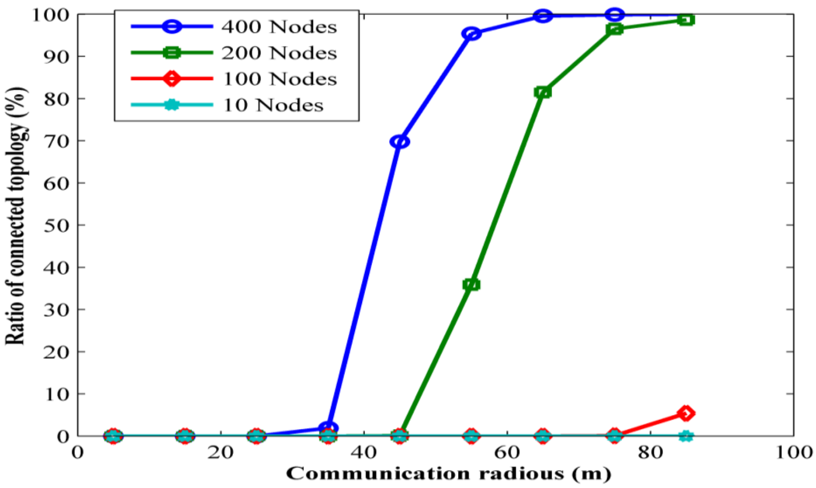

Fig. 4 Ratio of connected topology

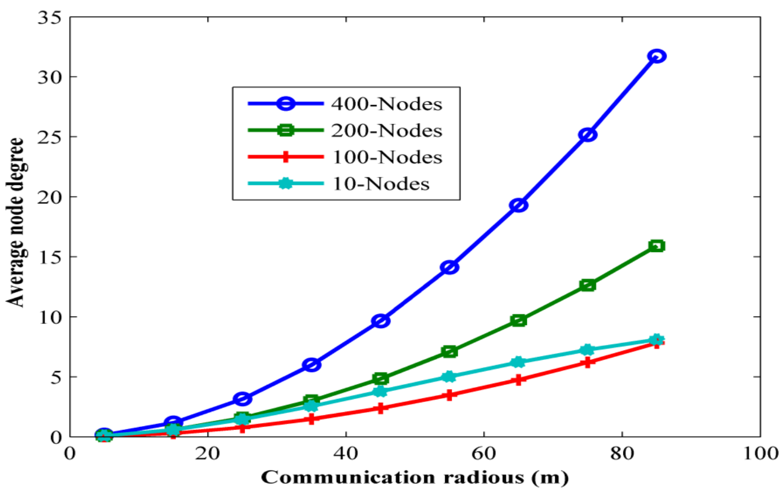

Fig. 5 Average node degree

The above result presented for 2-dimensional dense networks using a uniform distribution law.

4. Sparse topology sensor network

In a sparse topology sensor network, the minimum number of links is connected to form the topology of the monitoring network compared with the dense topology sensor network. This type of sensor network topology can be found in more difficult places to create the network links between nodes. For example, below Fig. 6 shows the sparse topology sensor network for N=9 number of sensor nodes.

Table 5 Average node degree test result

Communication Radius (m)	Number of Nodes 10	100	200	400
5	0.082030859	0.037530215	0.077717733	0.154577596
15	0.583860139	0.288156516	0.582874819	1.16969229
25	1.446843248	0.779963756	1.571877921	3.150499729
35	2.544316636	1.48229395	3.003053784	5.990973175
45	3.777099272	2.385613888	4.839994058	9.660872171
55	5.014347895	3.483309695	7.087267602	14.11879522
65	6.21891895	4.752152092	9.686523224	19.30628089
75	7.25664611	6.202177166	12.63150108	25.1675071
85	8.108962221	7.813264789	15.91689514	31.72295131

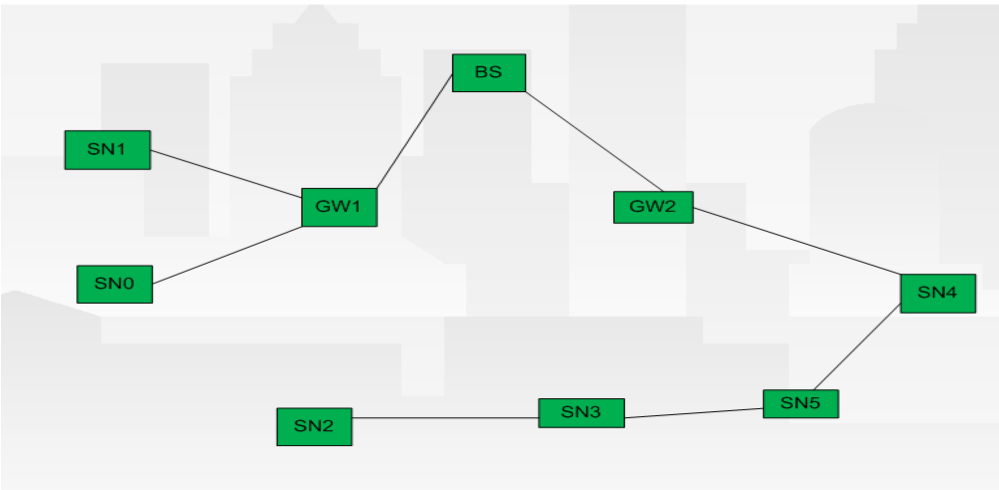

Fig. 6 Sparse topology sensor network

Using theorem from (Santi 2005), the CTR can be calculated for one dimensional sparse topology sensor network as follows

$$\mathrm{CTR} = k\frac{l \log l}{l} \tag{2}$$

Where the value of k is constant with $l \leq k \leq 2$ and l is the length of the uniformly distributed deployment area. The communication radius of the sparse topology sensor network is calculated using CTR formula.

Santi (Santi 2005) proposed a partial solution to find the CTR connectivity for d-dimensional sensor network as

$$\mathrm{CTR} = \mathrm{k}\frac{\mathrm{l^d \log l}}{\mathrm{n}} \tag{3}$$

Where, d= 2,3,……………. and $0 \le k \le 2^d d^{\frac{d}{2+l}}$.

The Eq. (3) is used for testing the greatest component (Labrador and Pedro 2009) in the sparse topology sensor network (Penrose 1999);

$$r_{com}=k.l^{3/4}.\sqrt{log_2 l} \text{ with } n=\sqrt{l}\,,\ 0.5 \le k \le l \text{ and } l = 2^{2i}, \text{ where } 4 \le i \le 10$$

Table 6 shows the definition of the simulation parameter for sparse topology sensor network. The K-factor define the connectivity of the monitoring network. The higher value of K defines the more connectivity than lower ones. The higher value indicates better performance of the monitoring network than lower. The area of the monitoring network is predefined by the area parameter.

Fig. 7 shows the greatest size component of the sparse topology sensor network with $0.5 \le \mathrm{k} \le 1$. It can be seen that with increasing value of k, the greatest size component of the sparse topology sensor network is also increasing and maximum value obtained at k=1. The greatest component size test result provides the percentage of the total number of nodes that are contained in the largest connected set in the sparse topology sensor network.

Table 7 shows the computational test result of greatest component size for the sparse topology sensor network.

The results in Fig. 8 show how equation 5 produces a giant component with $0.5 \le \mathrm{k} \le 1$. When the value of area side L=256, there is no topology connected. After that100% of the topologies connected is obtained at k=0.8 and L=1024. For k=0.8, 0.9 and 1, 100% topology connected is obtained for area side between L=1024 to L=1048576. In Fig. 8, while a value of k is equal to 0.5, than the greatest component (GC) produces maximum 95% and minimum 68% connectivity without considering L=256 area level. For k=0.6, 100% connectivity is obtained for L=65536. The slightly better result is found for k=0.7 compare to k=0.5, 0.6. However, for values of k=0.8, 0.9 and 1, the figures show that the CTR is given by equation 5 and produce an accurate result.

Table 6 Simulation setup for sparse network

Topology	Sparse topology sensor network
Number of Nodes	100
Initial K	0.5
Final K	1
Number of topologies	100
Area	500 m x 500 m
Parameters	Maximum component size, connected topology, average node degree

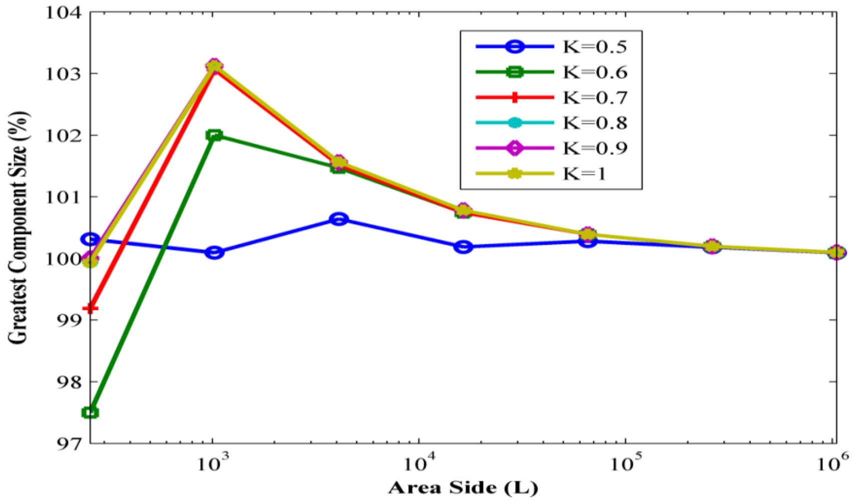

Fig. 7 Greatest component size

Table 7 Greatest component size test result

Area side	GC K=0.5	GC K=0.6	GC K=0.7	GC K=0.8	GC K=0.9	GC K=1
256	100.3125	97.5	99.1875	99.9375	100	99.9375
1024	100.09375	102	103.0625	103.125	103.125	103.125
4096	100.640625	101.4688	101.5156	101.5625	101.5625	101.5625
16384	100.1875	100.7422	100.7422	100.78125	100.78125	100.7813
65536	100.28125	100.3906	100.3906	100.390625	100.390625	100.3906
262144	100.1816406	100.1953	100.1953	100.1953125	100.1953125	100.1953
1048576	100.0917969	100.0977	100.0977	100.0976563	100.0976563	100.0977

Table 8 Ratio of connected topology test result

Area side	CT K=0.5	CT K=0.6	CT K=0.7	CT K=0.8	CT K=0.9	CT K=1
256	0	0	0	0	0	0
1024	68	93	99	100	100	100
4096	74	96	98	100	100	100
16384	77	96	98	100	100	100
65536	89	100	100	100	100	100
262144	96	100	100	100	100	100
1048576	95	100	100	100	100	100

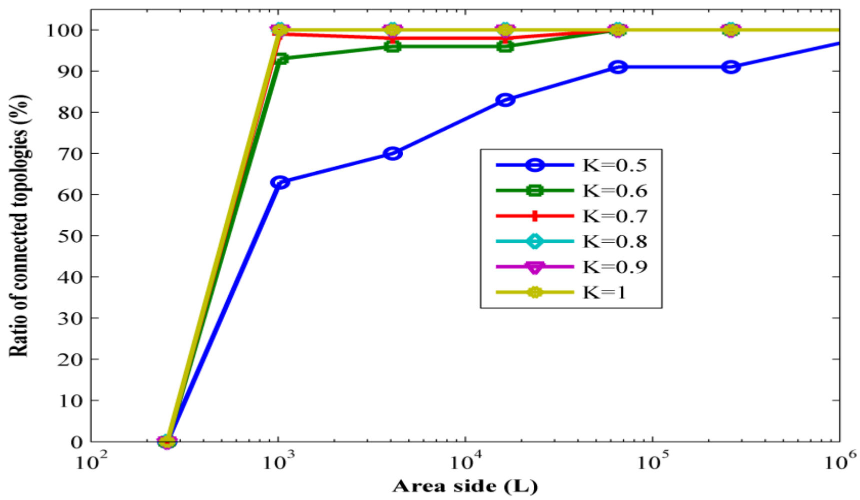

Fig. 8 Ratio of connected topology

Fig. 9 shows the results of the sparse topology sensor network average node degree. The figure shows also an increasing trend of average node degree with increasing value of network area side. Table 9 provides the computational result of the average node degree. It can be seen from Table 9 that in the case of l = 256 and n = 16, the average node degree goes from 4.357495743 for k = 0 .5 to11.30979 for k = 1. For the value of K=1 and L=1048576, the average node degree is 55.65%. However, with K=1, the average node degree is fairly high, but not equal to 100% that it setbacks the several goals of topology control mechanism.

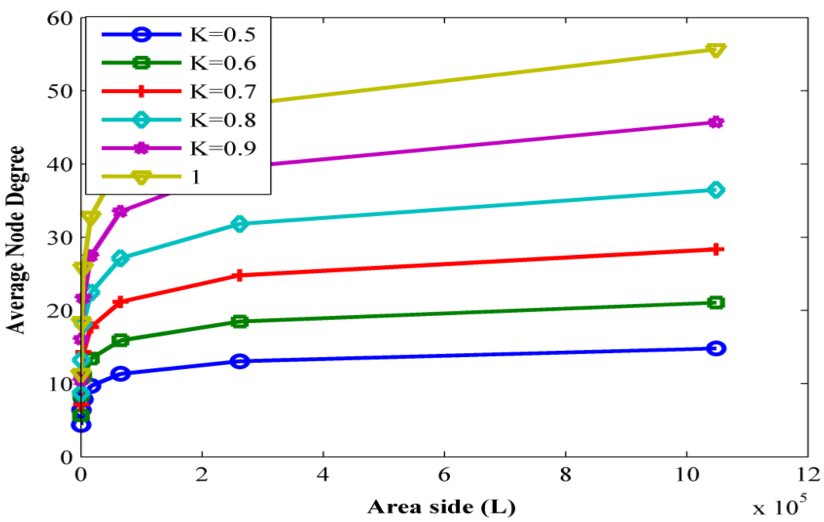

Fig. 9 Average node degree

Table 9 Average node degree test result

Area side	**n**	**K=0.5**	**K=0.6**	**K=0.7**	**K=0.8**	**K=0.9**	**K=1**
256	16	4.357495743	5.66009752	7.119964	8.738148	10.44959	11.30979
1024	32	6.397442066	8.387251456	10.99673	13.20993	16.09499	18.40403
4096	64	7.856924708	10.9474107	14.33147	18.18711	21.74619	25.82613
16384	128	9.678568029	13.40624257	17.71854	22.44261	27.43979	32.77554
65536	256	11.34351155	15.90505761	21.17893	27.12518	33.51502	40.1785
262144	512	13.07087837	18.49218076	24.79395	31.8139	39.57678	48.09278
1048576	1024	14.80764278	21.06518625	28.34052	36.472	45.71099	55.65807

5. Conclusions

In this study, Theory of Geometric Random Graphs approach has been proposed for monitoring building structural health. In this article, the critical transmitting range of connectivity has been investigated in dense and sparse topology sensor network for monitoring high-rise building structural health. From the dense topology sensor network, the greatest component size and connected topology has obtained 100% at 140 m communication radius with 40.83 degree average node degree. A dense comparison show that with 400 number of density nodes and 85 m communication radius fulfil the greatest component size and connected topology requirement. The average node degree in case of 400 number of nodes provides the larger value compared with 10, 100 and 200 number of nodes. In sparse topology sensor network, the better greatest size component is seen for k=0.5 and k=0.9. The highest connectivity value is obtained for k=0.8, 0.9 and 1. The average network node degree of the monitoring network indicates highly connected network, which optimize the network graph using maximum power graph theory. The average node degree is greater in sparse topology compared with the dense topology network. Although, the dense network sensor network is desirable in order to guarantee the redundancy of the measurements. But, the sparse network proved itself more redundant compared with dense network. Finally, it is seen that the sparse topology sensor network is selected as an optimum sensor topology for monitoring building structural health compared with the dense topology sensor network. The author believes that the results presented in this article provide a better understanding of performance comparison between dense and sparse topology sensor network in building structural health monitoring application.

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