International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8, Issue-1, May 2019

An Optimal Beacon Selection Technique for Time Synchronization in Underwater Acoustic Wireless Sensor Networks

M. Saranya Nair, K. Suganthi

Abstract*: Recently, Underwater Acoustic Sensor Networks (UASNs) have been developed as a significant research area since it is marked that a huge amount of unexploited resources lies under water which covers about 70% of the Earth. UASN is an effective combination of wireless, acoustic and sensor technology having the capabilities of smart sensing, intelligent computing and communication. In UASNs, the time associated with the sensed data is very critical for further data processing, which makes the time synchronization in UASNs as an essential requirement for many applications. Regrettably, GPS signaling cannot be used for underwater scenarios which pave the necessity to develop alternative synchronization approaches in UASNs. Beacon based synchronization approaches have been emerged as an efficient technique in UASNs, but in order to enhance the accuracy of such methods, the selection of an Optimal Beacon set is needed. In this paper, we are proposing an Optimal Beacon Selection Technique (OBST) for achieving accurate clock synchronization in UASNs. In our approach, a mobile AUV guided by a pre-defined trajectory will be used to generate a set of Virtual Beacons (VBs). The proposed beacon selection method addresses the physical, data link and network layer issues by selecting optimal beacon based on the Received Signal Strength (RSS) values from VBs, distance of separation from target node to be synchronized, residual energy and the received time stamps. An analytical model for optimal beacon selection was derived and analyzed based on the synchronization error and percentage of synchronization for dense and sparse networks. From the simulation results, it is found that the proposed optimal beacon selection technique outperforms the existing approaches in terms of synchronization accuracy, network cost and communication overhead.

Index Terms*: Optimal Beacon, Time Synchronization, Received Signal Strength, Timestamp.

I. INTRODUCTION

Underwater Acoustic Sensor Network offers a wide range of opportunities to variety of applications like monitoring, surveillance, archaeology, sports and so on [1]. Nevertheless, UASN faces severe challenges in communication due to acoustic channel bandwidth limitations and large propagation delays. The speed of acoustic signal, underwater environmental imperfections, mobility and energy are still challenges in underwater sensor network technologies [2]. However, the sensed data along with an accurate spatio-temporal mapping affords much information about underwater exploration [3].

Time synchronization is one of the major and challenging problems in UASNs because the underwater sensor nodes execute their clocks autonomously, the internal structure of the nodal clocks as well as the underwater operating conditions makes the network clocks drift over time. One possible solution for solving the synchronization problem in sensor networks is to equip the nodes with GPS, which cannot be implemented in UASNs since the signal cannot propagate through water [4]. Hence, alternative networking solutions are required to correct the clocks in UASNs.

Beacon based approaches are the eminent synchronization methods in UASNs in which few sensor nodes called as beacons will aid the network clock correction using their GPS reference. Employing static beacons throughout the network increases the network cost [5]. Also, the beacons will have no role after they have transmitted the required information to the sensor nodes. The problem of static beacon methods can be overcome by a mobile beacon which can move or fly through the sensor deployment region to complete the synchronization process.

In our synchronization approach, we are using a mobile AUV which will get the GPS information while floating on the water surface, then sink into the water and move along a pre-defined trajectory. While moving into the network, the AUV will transmit the GPS information required for synchronization as virtual beacons. The accuracy of synchronization is based on the optimal beacon selection.

The main objective of this paper is to provide an analytical modeling of the optimal beacon selection based on RSS, propagation distance, residual energy and timestamp metrics to address the synchronization issues in UASNs. The proposed model of beacon selection is analyzed for dense and sparse underwater network deployment scenarios. The results of analysis show that the proposed technique of beacon selection provides greater synchronization accuracy and percentage of synchronization with less computation overhead.

The rest of the paper is organized as follows. Related work is presented in Section II. Section III describes the network model with necessary assumptions followed by the proposed beacon selection technique. The analyses of results are presented in section IV. Section V provides the conclusion of the work.

Revised Manuscript Received on 30 May 2019.
* Correspondence Author
Prof. M. Saranya Nair*, Assistant Professor, School of Electronics Engineering, Vellore Institute of Technology, Chennai, India.
Dr. K. Suganthi, Assistant Professor (Sr), School of Electronics Engineering, Vellore Institute of Technology, Chennai, India.

II. RELATED WORK

Mobile Beacon based approaches are more suitable for UASN technologies due to the fact that it can eliminate the deployment of a large number of static beacon nodes which in turn helps in reducing the network cost. The services offered by many static beacons in UASN can be reliably provided by a single mobile beacon [6].

The Mobile Beacon (MB) learns the GPS information such as time and location, and while diving into the water, disseminate the information in the form of VBs using which the sensor nodes will correct their clocks. However, the selection of most-fit VB is still a challenge in UASNs which is addressed in few literatures [7]-[11].

In [7], a beacon selection algorithm is employed to improve the localization accuracy in ad-hoc networks. The algorithm selects a pivot beacon using 3-tuple combination from the neighbor set of the target node whose location is to be determined and then calculate the angle subtended by the pivot at the other beacons. The best beacon is selected based on the pivot angle. The method improves the accuracy but the computational complexity is O (n^3), which is sufficiently high when the value of n, i.e., the neighbor set is high.

In [8], the summation of Fisher Information Matrix (FIM) of beacon nodes is considered and Cramer Rao Bound (CRB) criterion is applied on the FIM values to select the best beacon whereas the CRB is applied on the average FIM values in [9] to select the optimum beacon. The beacon selection technique in [9] is still having a computational overhead of O (2^n), which in turn increases the localization time.

An online beacon selection method for real time localization in wireless networks is also proposed in [9], which reduces the search space of beacons thus improving the speed of localization.

Received Signal Strength based beacon selection approaches are proposed in [10] and [11], where the beacon node with highest level of RSS was considered as the optimum one. But, RSS values are prone to inaccuracies in UASNs due to the environmental imperfections. Selecting the best beacon on the consideration of only RSS will degrade the accuracy when being adopted for UASNs.

The proposed OBST aims at choosing the most-fit beacon set from the VBs transmitted by the AUV to assist for time synchronization in UASNs. The algorithm selects the optimum beacon based on the highest weighted value in terms of RSS, distance of separation, received timestamp and the residual energy. The various factors considered in the proposed beacon selection technique eliminate the errors caused by inaccuracies of RSS as in [10].

The proposed algorithm also considers an acute threshold value of residual energy associated with the AUV. The residual energy helps in finding the efficiency of the VBs emitted by the AUVs. The VBs with energy less than the critical energy value, E_c will not be included in the optimum beacon selection process which in turn improves the accuracy and also reduces the computational complexity of the proposed scheme.

III. PROPOSED OPTIMAL BEACON SELECTION TECHNIQUE (OBST)

The network considered in this paper is a 3-Dimensional Mobile UASN (3-D MUASN), in which the nodes are assumed to be classified into three types – sink nodes, virtual beacons and ordinary nodes. The sink node in our approach is a mobile AUV, which acts as a gateway between the sensor network under the water and the outside world. The sink node will be enabled with a GPS receiver, acquire information required for synchronization while floating on the water surface. It will plunge into the water and will be guided by a pre-defined trajectory. Undoubtedly, the trajectory design plays a vital role in achieving the network –wide coverage which is out of scope of this paper. While moving inside the water, the sink will transmit the GPS information in the form of Virtual Beacons (VBs). The ordinary nodes are the ones which will use the VB's information to correct their clocks. Fig.1 provides an illustration of the proposed network in which the black dots represent the ordinary nodes along with their ranges indicated by black circles whereas the VBs and their ranges are indicated by red dots and red circles respectively. The dashed line indicates the path of the sink node.

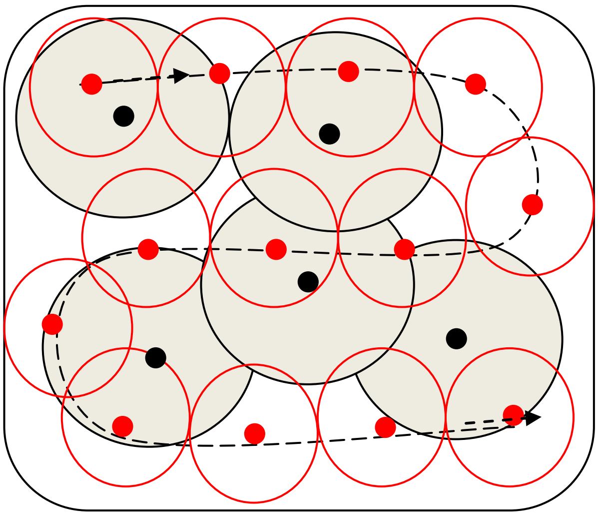


Figure 1: Proposed Network for the OBST

A. *Network Model*

Consider a 3-D MUASN, consisting of '*m*' ordinary nodes, '*k*' virtual beacons and *S* being the set of all nodes in the network such that $|S| = m + k$. The neighbor set, *N(u)* of a node '*u*' consists of all nodes in the transmission range of '*u*'. In our approach, the ordinary nodes are assumed to know their individual locations, through some localization approaches.

The sink node after acquiring the GPS information dive into the water, and travels along a set of VB points (VB_1, VB_2, ...,VB_k) where '*k*' is the number of VBs. The sink moves from VB_i to VB_{i+1} with velocity V_i, $V_{min} \le V_i \le V_{max}$ where V_{min} amd V_{max} are the minimum and maximum speed of the AUV. The speed and performance of the AUV is based on the residual energy associated with it.

The critical energy value, E_c assumed for our approach is 20% of the initial battery value which is required for the AUV to upsurge back to the water surface. The time t_{VB} for which the sink stays at every VB point is given by [5],

$$t_{VB} = t_m - d(VB_i, VB_{i+1}) / V_i \quad (1)$$

Where t_m is a constant for a given network and is given by

$$t_m \geq \max(d(VB_i, VB_j)) / V_{\min} \quad \forall VB_i, VB_j \tag{2}$$

$d(VB_i, VB_j)$ is the distance between two VBs VB_i and VB_j.

The network density, N_D of the proposed 3-D MUASN is defined as the total number of nodes present in unit volume of the deployment region. Mathematically,

$$N_D = \frac{m+k}{V} \tag{3}$$

Where V is the volume of the deployment region.

The set of virtual beacons from the sink node provide GPS information like time and location to the ordinary nodes. This information will assist to synchronize the clocks of ordinary nodes. It is obvious that a large number of VBs for a particular ordinary node in a synchronization cycle will increase the computational overhead whereas improving the synchronization accuracy.

The tradeoff between the accuracy and computational complexity can be resolved by selecting an optimal most-fit beacon among the VBs received by an ordinary node [12].

B. *Optimal Beacon Selection Technique (OBST)*

The ordinary nodes can extract different sensory data like RSS, Time of Arrival (ToA), beacon id, and the residual energy of the sink's battery from the received VBs. Existing literatures use only RSS as the main factor for selecting the most-fit beacon [10]. Since RSS is noisy and uncertain, we are considering in our approach distance of separation, time of arrival and residual energy along with RSS to select the optimal beacon.

The Optimal Beacon set, *OB* is carefully chosen based on highest weighted value in terms of Received Signal Strength (Link quality), Euclidean distance, Time-stamp of transmission and Residual energy.

The analytical expression for selecting the Optimal Beacon set *OB* for an ordinary node which receives '*p*' virtual beacons is given by,

$$OB = \begin{cases} OB_1 \cap OB_2 & if\ OB_1 \cap OB_2 \neq \varnothing \\ OB_1 & if\ OB_1 \cap OB_2 = \varnothing \end{cases} \tag{4}$$

Where

$$OB_1 = \left\{ \max\left(c_1 * RSS_{VBi} + c_2 * \left[\frac{E_{resVBi}}{E_{AUV}} \right] \right) \right\} [\bullet\bullet], 1 \leq i \leq p$$

$$OB_2 = \left\{ \min\left(c_3 * \frac{d_{VBi}}{d_{\max}} + c_4 * \left[\frac{t_{VBi}}{t_{\max}} \right] \right) \right\} [\bullet\bullet], 1 \leq i \leq p$$

c_1, c_2, c_3 and c_4 are the weights assigned to various sensory data such that $c_1 + c_2 + c_3 + c_4 = 1$ and $c_1 = 0.4, c_2 = 0.4, c_3 = 0.1, c_4 = 0.1$

$\max(*), \min(*)$ are the maximum and minimum values

RSS_{VBi} - Received Signal Strength of i[th] VB

E_{resVBi} - Residual Energy of i[th] VB

E_{AUV} - Initial Energy assigned to mobile AUV

d_{VBi} - Euclidian distance between ordinary node and i[th] VB

$d_{\max}$ -Maximum distance between ordinary node and received VBs

t_{VBi} -Timestamp of i[th] VB

$t_{\max}$ -Maximum Timestamp of received VBs

$[\bullet\bullet]$ - VBs with $E_{res} \geq E_c$ will be considered for OBST

C. *Modeling of OBST Metrics*

Consider the transmission range of ordinary node and VBs in the proposed 3-D MUASN as R0 and RB respectively. The signal strength received by ordinary nodes reflect the link quality between them and the VBs. If the RSS value is high, that implies a good transmission link and vice versa.

The RSS values of VBs can be modeled as follows,

$$RSS_{VBi} = \begin{cases} 1 & if \quad d_{VBi} \leq R_0 \\ \left[P_0 - P_{loss} + N_i \right]_0^1 & if \quad R_0 \leq d_{VBi} \leq 2R_0 \\ 0 & if \quad d_{VBi} \gg 2R_0 \end{cases} \tag{5}$$

Where P_0 is the reference power, P_{loss} is the loss in power based on different aquatic environments and N_i is a zero-mean Gaussian random variable that represents the log-normal shadowing effect.

The Euclidian distance d_{VBi} can be modeled as,

$$d_{VBi}{}^2 = (x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 \tag{6}$$

Where (x, y, z) and (x_i, y_i, z_i) are the 3-D co-ordinates of the ordinary node and the received VBs respectively.

IV. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

The proposed beacon selection technique is tested using simulation for a network model of random deployment in a 50 x 50 x 50 (cubic km) volume in a 3-D space. The number of sensor nodes varies from 25 to 250 respectively for sparse and dense deployments. The simulation time is set to 1000s and the sink nodes send VBs at 1s, 5s and 10s intervals. The ordinary nodes are assumed to have a communication range of 250m and the data rate is 50kbit/s.

We assume acoustic communication for physical layer, log-normal shadowing path loss model and CSMA for accessing the channel.

The simulated network model for 25 nodes is shown in Fig.2.

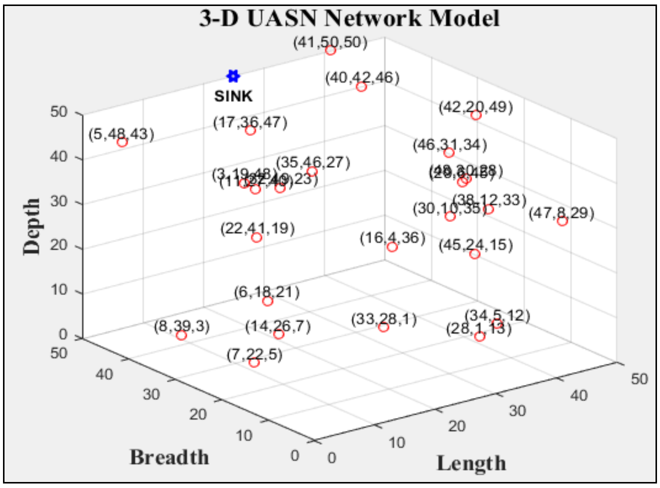


Figure 2: Network Model for OBST

We assume that the sink node moves with a maximum speed of 25m/s. The initial battery level of the sink node is assumed as 100 units and hence the critical battery value for our approach will be 20 units. The sink node spends 5 units of energy for each VB transmission. We investigate the performance of the proposed OBST for varying beacon percentage as 5, 10, 15, 20, 25 and 30. Here, we term the beacon percentage as the percentage of the VBs received by an ordinary node in a synchronization cycle.

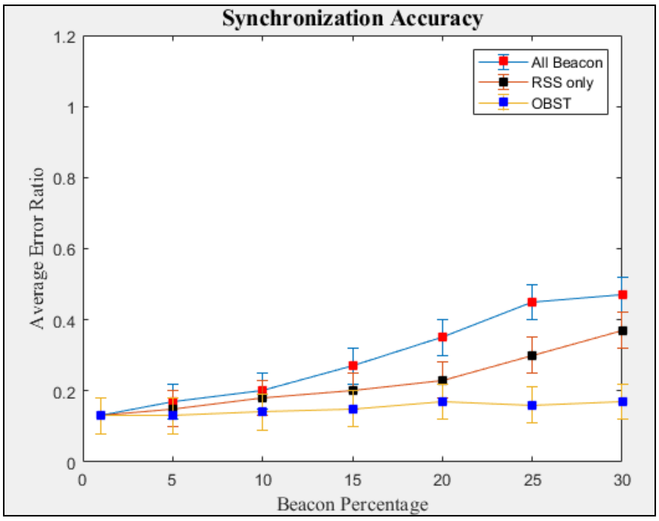


Figure 3: Accuracy Analysis of OBST

The simulation of OBST is tested for synchronization requirements and analyzed for three cases. The first case performs synchronization with all VBs received within the communication range of an ordinary node. The analysis is performed with mean values of results obtained from all VBs. The second case deals with the beacon selection based on RSS values of VBs [10]. The simulation is done with the beacon from which the RSS come across as a high value. The proposed OBST is simulated and tested as the third case. Performance of the proposed OBST is analyzed in terms of synchronization accuracy, computation cost and delay.

Synchronization accuracy is defined by the average error ratio. Average error is the mean value of the difference between the estimated and the actual clock value of a node for synchronization estimations. Average error is divided by transmission range to get the average error ratio [13]. Fig.3 shows the average error ratio of the three cases such as RSS Beacon, All Beacon and OBST. OBST achieves maximum

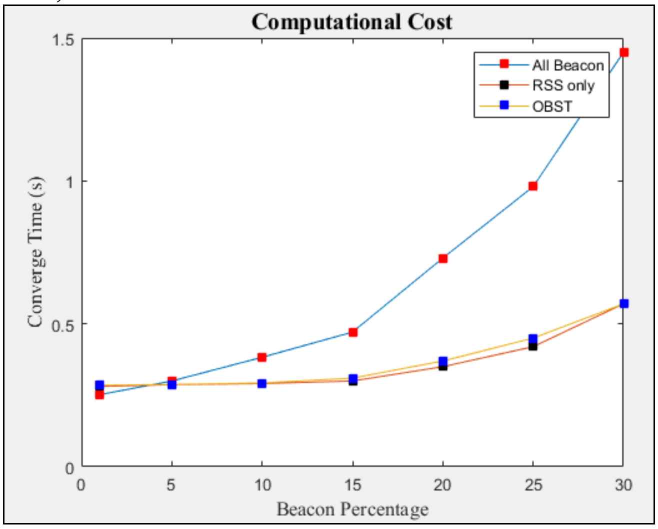
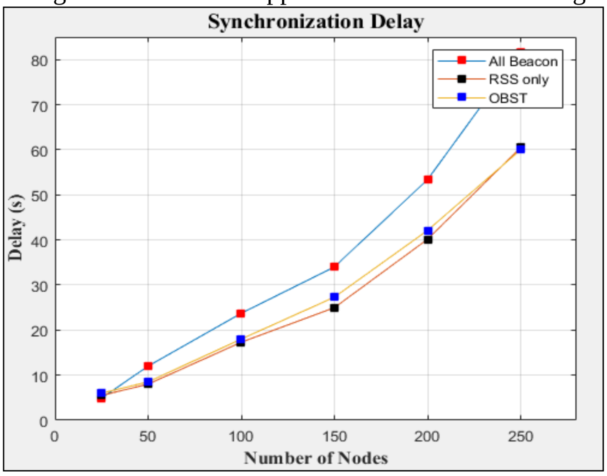


Figure 4: Complexity Analysis of OBST

accuracy among other methods. The error value seems high when compared to terrestrial sensor networks however; UASN applications may be lenient to less accuracy considering the scale of the ocean.

Computational cost/overhead is defined as the average number of instructions executed at a node to perform synchronization and it is realized from the synchronization converge time in our approach. While considering all



beacons, the ordinary nodes experience high computation cost for larger value of beacon percentage whereas RSS based

Figure 5: Delay Analysis of OBST

beacon and OBST methods shows reduction in computational overhead, but still OBST outperforms RSS beacon in terms of its accuracy. Therefore, from Fig. 4, it is evident that OBST shows better performance than other methods in terms of computational cost. In Fig. 5, it is shown that OBST experiences little more delay than RSS beacon approaches since it involves the comparison of more sensory data, whereas OBST have good convergence over All Beacons Approach. From simulation results, it is clear that more beacons are not assurance of more accurate nodal clock estimation. That is why our technique to find optimal beacon, from which results of synchronization will be the nearest to real.

V. CONCLUSION

In this paper, an optimal beacon selection technique based on highest weighted value of sensory measurements is proposed and investigated for mobile underwater sensor networks. Firstly, the network model for the proposed OBST is presented with necessary assumptions. The proposed network model is then considered for the implementation of the OBST. The proposed technique can assist different networking protocols pertaining to 3-D MUASNs to enhance the accuracy at a reduced computational complexity. The proposed beacon selection method was simulated and analyzed for dense and sparse underwater deployment scenarios. The performance of OBST against individual sensor data based beacon selection methods also studied. The results show that the proposed technique outperforms the existing schemes in terms of accuracy and computational overhead.

REFERENCES

1. E. Felemban, F. K. Shaikh, U. M. Qureshi, A. A. Sheikh, S. B. Qaisar, "Underwater sensor network applications: A comprehensive survey", *International J. of Distributed Sensor Networks*, vol. 11, no. 11, Nov. 2015, pp. 1-14. Available: https://doi.org/10.1155/2015/896832
2. K. M. Awan, P. A. Shah, K. Iqbal, S. Gillani, W. Ahmad, Y. Nam, "Underwater Wireless Sensor Networks: A Review of Recent Issues and Challenges", *Wireless Communications and Mobile Computing*, vol. 2019, 20 pages, Jan. 2019. Available: https://doi.org/10.1155/2019/6470359
3. P.-H. Tsai, R.-G. Tsai, S.-S. Wang, "Hybrid Localization Approach for Underwater Sensor Networks", *Journal of Sensors*, vol. 2017, 13 pages, Nov. 2017. Available: https://doi.org/10.1155/2017/5768651
4. G. Taraldsen, T. A. Reinen, T. Berg, "The underwater GPS problem", *OCEANS 2011 IEEE - Spain*, pp. 1-8, June. 2011. Available: https://doi.org/10.1109/Oceans-Spain.2011.6003649
5. T. V. Srinath, Anil Kumar Katti, V. S. Ananthanarayna, "Analysis of mobile beacon aided in-range localization scheme in ad hoc wireless sensor networks", *International Wireless Communications and Mobile Computing Conference*, pp. 1159–1164, July 2006. Available: https://doi.org/10.1145/1143549.1143782
6. S. Wang, H. Hu, "Wireless Sensor Networks for Underwater Localization: A Survey", *Technical Report: CES-521*, May 2012.
7. K. Sinha, A. D. Chowdhury, "A Beacon Selection Algorithm for Bounded Error Location Estimation in Ad Hoc Networks", *International Conference on Computing: Theory and Applications*, *2007*, pp. 87-93. Available: https://doi.org/10.1109/ICCTA.2007.1
8. D. Lieckfeldt, J. You, D. Timmermann, "An Algorithm for Distributed Beacon Selection", *Sixth Annual IEEE International Conference on Pervasive Computing and Communications*, 2008, pp. 318-323. Available: https://doi.org/10.1109/PERCOM.2008.78
9. R. Kim, H. Lim, D. Jung, K. Kim, "Beacon selection for localization in IEEE 802.11 wireless infrastructure", *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 14, no. 2, Sep. 2013, pp.135–143. Available: https://doi.org/10.1504/IJAHUC.2013.056448
10. M. Matula, J. Duha, "Optimalization of beacon selection for localization in wireless AD-HOC networks", *Advances in Electrical Electronic Engineering*, vol. 7, no. 1–2, pp. 62-65, 2008.
11. W. M. Y. W. Bejuri, M. M. Mohamad, R. Z. R. M. Radzi, "Offline Beacon Selection Based RSSI Fingerprinting for Location-Aware Shopping Assistance: A Preliminary Result", *New Trends in Intelligent Information and Database Systems, Studies in Computational Intelligence,* vol. 598, 2015, pp.303-312. Available: https://doi.org/10.1007/978-3-319-16211 -9_31
12. M.Erol, F. M. L. Vieira, M. Gerla, "Localization with Dive'N'Rise (DNR) beacons for underwater acoustic sensor networks", *Proceedings of the second workshop on Underwater networks*, Sep. 2007, pp. 97 – 100. Available: https://doi.org/10.1145/1287812.1287833
13. M. E. Kantarci, S. Oktug, L. Vieira, M. Gerla, "Performance evaluation of distributed localization techniques for mobile underwater acoustic sensor networks", *Ad-Hoc Networks*, vol.9, no.1, Jan 2011, pp. 61-72. Available: https://doi.org/10.1016/j.adhoc.2010.05.002

AUTHORS PROFILE

Prof.M.Saranya Nair received her Bachelor's degree in Electronics and Communication Engineering from Noorul Islam College of Engineering, Anna University in 2008. She obtained M.E. degree in Communication and Networking Engineering from Madras Institute of Technology, Anna University in 2010 and pursuing Ph.D in the area of Time Synchronization in Underwater Acoustic Sensor Networks in Vellore Institute of Technology, Chennai. She is currently working as an Assistant Professor in the School of Electronics Engineering at VIT University Chennai campus, India since 2013. Her research interests include Sensor Networks, Localization, Underwater sensor networks and Synchronization.

Dr. K. Suganthi received the B.E. degree in Computer Science and Engineering from Madras University in 2001, M.Tech degree in Systems Engineering and Operations Research and Ph.D in Wireless Sensor Network from the Anna University in 2006 and 2016 respectively. She is currently working as Assistant Professor(Senior) in the School of Electronics Engineering (SENSE) at VIT University Chennai campus, India since 2016. She is the author of about 10 scientific publications on journals and International conferences. Her research interests include Wireless Sensor Network, Internet of Things, Data Analytics and Network Security.