Investigation of multi-objective optimisation techniques to minimise the localisation error in wireless sensor networks

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Abstract: Wireless Sensor Networks (WSN) have a major role in remote sensing environments. In recent trends sensors are used in various wireless technologies due to their smaller size, cheaper rates and ability to communicate with each other to create a network. The sensor network is the convergent technology of micro-electronics and electro-mechanical technologies. The localisation process can determine the location of each node in the network. Mobility-assisted localisation is an effective technique for node localisation using mobility anchor. The mobile anchor is also used to optimise the path planning for the location-aware mobile nodes. In this proposed system, a multi-objective method has been proposed to minimise the distance between the source and the target node using the Dijkstra algorithm with obstacle avoidance. The Grasshopper Optimisation Algorithm (GOA), and Butterfly Optimisation Algorithm (BOA) based multi-objective models have been implemented along with obstacle avoidance and path planning. The proposed system maximises the localisation accuracy. Also it minimises the localisation error and the computation time when comparing with existing systems.

Keywords: localisation models; grasshopper optimisation; butterfly optimisation; Dijkstra; path planning.

Reference to this paper should be made as follows: Puvitha, H., Palani, S., Vijayakumar, V., Ravi, L. and Subramaniyaswamy, V. (2021) 'Investigation of multi-objective optimisation techniques to minimise the localisation error in wireless sensor networks', *Int. J. Grid and Utility Computing*, Vol. 12, No. 1, pp.33–42.

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1 Introduction

Wireless Sensor Network (WSN) is a network of featured transducers which communicate about the infrastructure to monitor and record the conditions of the various locations. There are some advantages in WSN because of its inexpensive cost, limited issue, sensible sensor nodes. It is deployed in many areas to control and monitor the daily activities and also activated in dangerous and dense areas (Akyildiz et al., 2002). A communicational ability is essential to sense an event and store the data driven by the battery (Chen and Varshney, 2004). The various uses of WSN involve different design, implementation, and performance issues in WSN. Therefore, single – hop communications consume more power when compared with multi-hop communication system in a network. Long-range communication networks can face signal propagation issues, and multi-hop communications can solve it. The power sources for sensor nodes are very limited, and mostly they are irreplaceable (Borges et al., 2014).

To measure certain incidents many nodes are deployed in an area. Anchors are also called a beacon node which has awareness about their true location and ranges through single or multi-hop communication. The unknown nodes which are not location aware receive information from anchor to estimate the locations. The mobile anchor is deployed in the network where it reduces the nodes and location is shared to the neighbour nodes (Han et al., 2016). Multi-objective optimisation algorithm finds multiple solutions in one run, and this solution challenges the minimisation of path distance (Zille et al., 2018). Multi-objective optimisation techniques are useful in various domains including computer engineering (Omar et al., 2017), environmental engineering (Wu and Wan, 2018), marine engineering (Fox et al., 2019). Many network optimisation problems are solved using multi-objective genetic algorithms (Gen et al., 2008).

In this proposed system, a multi-objective optimisation using Grasshopper Optimisation Algorithm (GOA) and Butterfly Optimisation Algorithm (BOA) has been proposed. Path planning is made using Grasshopper Optimisation Path Planning (GOPP), and Butterfly Optimisation Path Planning (BOPP) and the Dijkstra's algorithm is used to evaluate the minimal distance. The research contributions of this work are as follows.

1. Investigating the existing optimisation techniques for localisation process wireless sensor nodes.
2. Designing the multi-objective optimisation technique-based localisation system for wireless sensor network communication using Optimisation Algorithm (GOA) and Butterfly Optimisation Algorithm (BOA).
3. Investigating the proposed method for path planning with obstacle avoidance.
4. Comparing the performance of the proposed optimised localisation model with existing model.

This paper has the following sub-divisions: Section 2 delivers a survey about the work done. Section 3 tells about multi-objective optimisation WSNs in brief, and the two distinct optimisation methods are used. Section 4 discusses the system model assumptions. Our proposed models are introduced in Section 5, which gives details about GOPP and BOPP, and finally describes the localisation process. Section 6 discusses both models based on their accuracy and ratio and Section 7 concludes the proposed work.

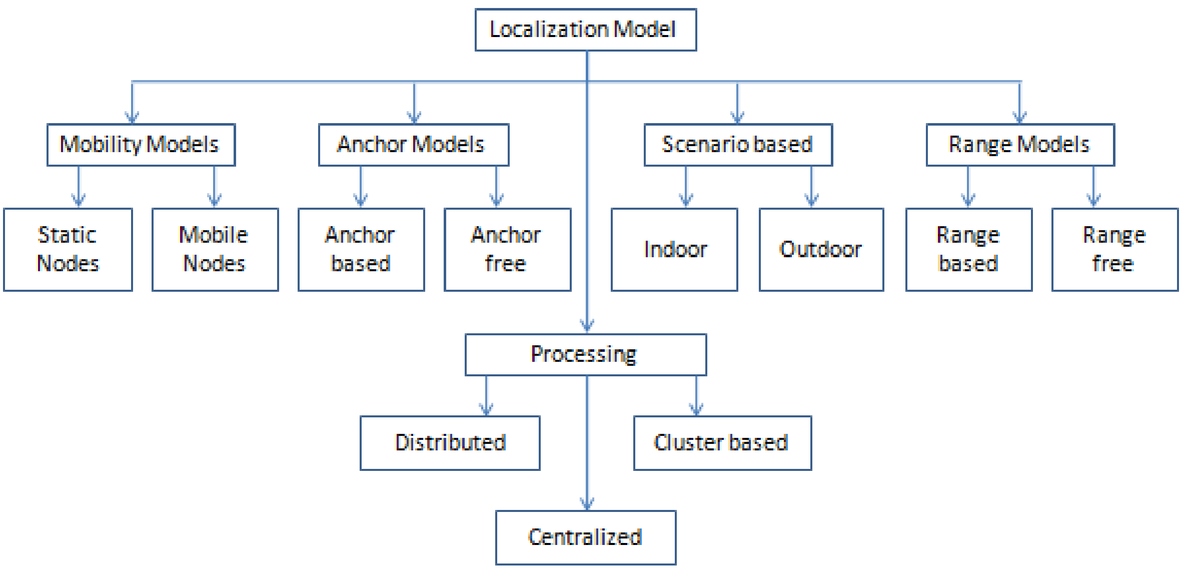
2 Related work

Localisation is used to find the true location of nodes and information may be useless if the nodes do not know their current positions. Global Positioning System (GPS) is used to localise the node in a simple method, but it is more costly if a large number of sensor nodes are deployed in a specific region (Alrajeh et al., 2013). To solve the issues in localisation many algorithms have been proposed (Coluccia and Fascista, 2019). If the anchor node propagates wrong information, then this error propagates through the entire network (Suzhe and Yong, 2012). The distance between the Unknown Nodes (UN) and guide points is used to find the true location of the nodes (Cheng et al., 2012). The implementation of this algorithm faces two challenges, at first, the indoor wireless environment and outdoor wireless environment with irregular objects and distance calculation is very difficult with Received Signal Strength (RSS) Secondly, determining the model parameter is also very difficult. To solve those problems, a profiling measurement technique is used which estimates the sensor location from RSS and improves the accuracy.

The actual propagation loss is calculated based on the known transmit power received from the Received Signal Strength Indicator (RSSI) which is used to calculate the power of the signal (Sivasakthiselvan and Nagarajan, 2018). This method is mainly used for radio frequency signals. All sensor nodes have radios and RSSI is cheap and does not use any additional devices.

Mobile anchor node assisted localisation algorithm is to focus the movement of the mobile anchor and move in an assumed region to enhance the performance of the localisation (Han et al., 2016; Cui et al., 2018).There are three stages of this type of algorithms. Mobile anchor nodes move around the area broadcasting the beacon packets which contains their current positions, unknown nodes within the shortest range receives the packet from beacon nodes and estimate the distance to the anchor node once needed, and finally UNs calculate their positions if they are within the ranges with minimum three non-collinear (non-coplanar) anchor nodes (Fei et al., 2017). Figure 1 describes the classification of various localisation systems.

Figure 1 WSN based localisation systems



3 Multi-objective localisation using swarm intelligence

The optimisation objective is chosen as the most significant performance in conventional WSN. The remaining metrics are treated as the limitations of the optimisation problem (Deb, 2011). The maximum energy efficiency and the residual energy among the above ideas are simultaneously satisfied with multiple objectives by more realistic optimisation (Sun et al., 2015).

The Multi-Objective Optimisation (MOO) is adopted naturally to solve the above problem, as it is more consistent with the realistic scenario. The number of objective functions included by a multi-objective optimisation is either minimised or maximised. Figure 2 shows the flow chart of proposed methodology. The proposed system starts with the initial placement of nodes. Distance Vector hop (DV-Hop) algorithm is used to place the sensor in the appropriate location. This algorithm is simple and has high coverage. However, its major drawback is that the setting of the accuracy is low. A DV-Hop method is improved and has been projected to enhance the accuracy of the localisation.

3.1 Grasshopper optimisation algorithm

Grasshoppers are the biggest swarm of all creatures and a nightmare for farmers (Saremi et al., 2017). The swarming behaviour is found by birth in nymph, and it is a unique character. Grasshoppers eat all the prey in their path, and they form a group in the air when they become adult (Rogers et al., 2003). They migrate over a long distance. The swarm moves gently in small steps; these are the main features of the swarm in the immature phase. In the adult stage, it moves fast and covers a long distance. Searching the prey is another characteristic of grasshoppers. The methods used in the searching process are exploration and exploitation. In exploration, the search agents move a short distance whereas the search agents move locally during exploitation.

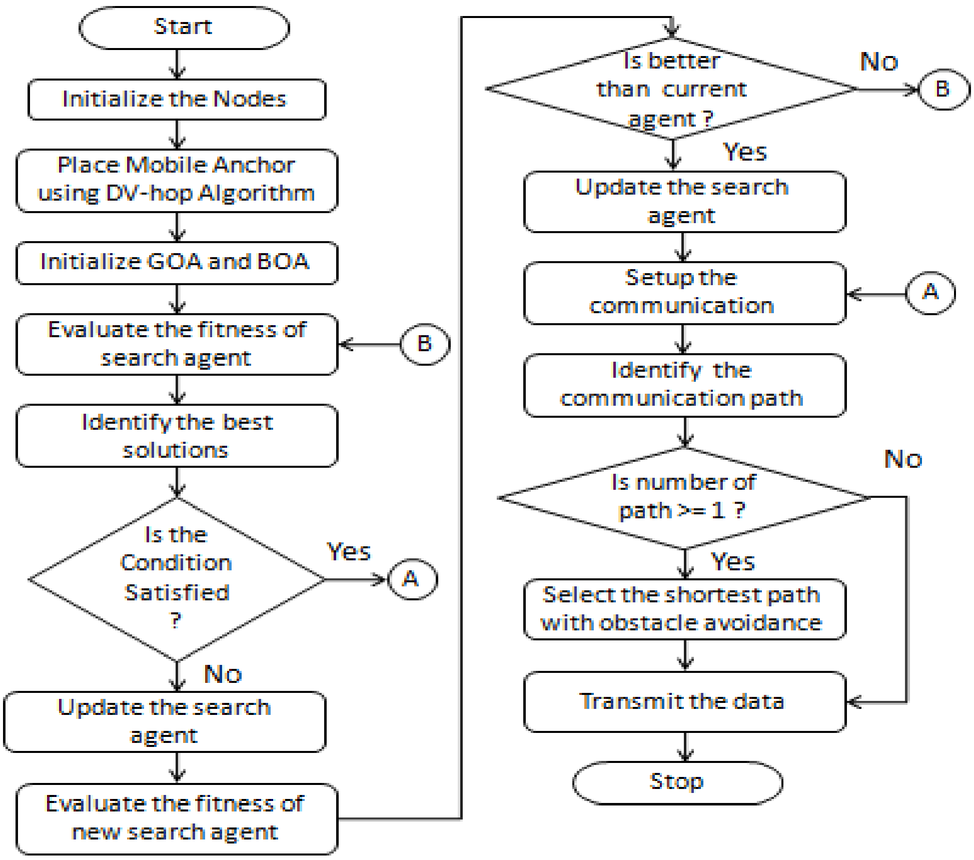
The swarming behaviour of pest is represented as,

$$Y_i = P_i + M_i + A_i \tag{1}$$

where Y_i refers to the location of the i-th pest, P_i is the public interface; M_i is the magnitude force on the i-th pest, and A_i is the wind advection. The equation is rewritten with random numbers r_1, r_2, and r_3 to meet the random behaviours. Then,

$$Y_i = r_1 P_i + r_2 M_i + r_3 A_i \tag{2}$$

Figure 2 Flow chart for the proposed multi-objective optimisation in WSN



So,

$$P_i = \sum_{\substack{k=1 \\ k \neq i}}^{N} P\left(d_{ij}\right) \hat{d}_{ik} \tag{3}$$

where d_{ik} is the distance among the grasshopper of *i* and *k,* and it is calculated as $d_{ik} = \left|Y_k - Y_i\right|$, the power of the social forces is represented as *s* and the unit vector $\hat{d}_{ij} = \frac{y_{k-}y_i}{d_{ik}}$. Then, the social forces are

$$\mathrm{s}\left(r\right) = fe^{\frac{-r}{t}} - e^{-r} \tag{4}$$

where *f* is the intensity of attraction with the length scale *l.* Hence, strong forces cannot be applied to the long space between grasshoppers. The distance of grasshoppers is placed in the interval of [1, 5] to overcome this type of issues, M_i in equation (1) is calculated as

$$M_i = -g\hat{e}_g \tag{5}$$

Here, the constant value of gravitation is *g* and a unity vector represented as $\hat{e}_g$. In equation (1) A_i is calculated as,

$$A_i = u\hat{e}_v \tag{6}$$

where $\hat{e}_v$ is the unit vector and *u* is a constant. Using (4), (5) and (6),

$$Y_i = \sum_{\substack{k=1 \\ k \neq i}}^{N} P\left(\left|y_k - y_i\right|\right) \frac{y_k - y_i}{d_{ik}} - g\hat{e}_g + u\hat{e}_v \tag{7}$$

where $\mathrm{s}\left(r\right) = fe^{\frac{-r}{t}} - e^{-r}$ and *N* refers to the number of grasshoppers. To balance the exploration, the parameter *t* is required to decrease. This method stimulates the exploration as the number of iteration increases. It is calculated as,

$$t = t\max - l\frac{t\max - t\min}{L} \tag{8}$$

$t\max$ is the maximum value, $t\min$ refers to minimum value, current iteration *I*, and *L* refers to the number of iterations. By default 1 and 0.0001 is used for $t\max$ and $t\min$.

3.2 Butterfly optimisation algorithm

Butterfly Optimisation Algorithm (BOA) is encouraged by the intellectual behaviour of the butterflies while searching for a food source. The butterflies find the correct direction by sensing and analysing the smell of the food (Arora and Singh, 2018). To find the optimal solution in the hyper search space BOA mimics this behaviour. Chemoreceptors are known as sensory receptors, scattered over the butterfly's body parts to sense the fragrance of the food. The butterfly produces a fragrance and it is associated with the fitness value. Its fitness value changes concerning the movement of the butterfly from one place to another place. There are two types of searching methods they are local search and global search method. If the butterfly senses the fragrance of the food, then it is called a global search method and it takes random positions when they didn't find the prey this stage is called local search method.

The strength of BOA is to modulate its strength. Many of butterflies emit fragrance at same time, where sensory modality allows butterflies to sense and segregate these fragrances from one another. Stimulus intensity represents the degree of the actual stimulus and it is associated with the highest fitness value. The constraint *b* permits the stimulus intensity to gets stronger so that the pest becomes less sensitive when stimulus intensity varies accordingly. The sensation depends on the parameters variant of *current iteration I*, and definition of *f*, the intensity of attraction. In our proposed system the objective function is associated with *I* and *f* is considered as a relative function. The fragrance of the physical intensity is calculated as follows.

$$fk = cI^b \tag{9}$$

where *fk* refers to the superficial degree of fragrance, sensory modality is referred to as *c*, and *b* is power exponent.

3.2.1 Movement of butterfly

The above discussions can be validated and the characteristics of butterfly are summarised as follows, they are

1. Butterflies attract each other when they emit fragrance.
2. Every butterfly swarms towards the best butterfly which emits more fragrance.
3. The landscape of the objective function determines the stimulus intensity of the butterfly.

Initialisation, iteration, and final are the three stages in BOA. The initialisation stage is executed at first; then after iterative searching is done and then the final stage, the algorithm gets terminated once the finest solution is known. These stages are processed with each run of BOA. The constraints used in BOA are selected. Once the values are allotted, an initial population of butterflies for optimisation is created. To store the information memory size is allotted where the memory size is fixed and the butterfly remains unchanged. The positions are generated in random search space.

The next segment is the iteration phase. The fitness value and the positions are evaluated, and then all the solutions in the butterfly space move to the new positions in each iteration. Butterflies produce fragrance at their positions using equation (9). Global search method and local search method are the two types of search methods in BOA; the butterflies move towards the fittest solution vector *h**in global search space and it is represented as

$$y_i^{t+1} = y_i^t + \left(r^2 \times h* - y_i^t\right) \times fi \tag{10}$$

where y_i^t is the solution vector of *i*-th butterfly in the iteration. f_i is referred to the fragrance of *i*-th butterfly and random number *r* is taken as [0, 1]. The local search method is represented as

$$y_i^{t+1} = y_i^t + \left(r^2 \times yj^t - yk^t\right) \times fi \tag{11}$$

where y_j^t and y_k^t are butterflies from j and k in the solution space. If y_j^t and y_k^t are from the same swarm and random number r is [0, 1] then equation (11) converts to a local random search.

4 Implementation of multi-objective localisation

It is a two-dimensional network in a square shape region. All nodes are assumed as mobile nodes which are movable, and these nodes are represented as *N*. Initially all nodes are assumed as unknown nodes which do not have any prior knowledge about their location. For this anchor, nodes are introduced where it knows the prior knowledge about the current location and communicates with the neighbour unknown nodes about the location. The network area has a set of the obstacle. The obstacle given in the network is represented as *O* and it is defined in a circular shape. A mobile anchor moves freely in the network area except in the place of the obstacle. The mobile anchor is placed to reduce the number of nodes for communication. *M* refers to a number of Mobile Anchor (MA) in the network region. The MA can sense any obstacles in its direction using the obstacle detection method. MA cannot go beyond the value; if it goes beyond the range then it stops providing the current position to the nodes. If the locations between the MA and UNs are not within the communication range, they do not communicate with each other. Once the UN receives the information of their current location, it turns to a QN where QN is a reference node. The location of the UN can be estimated if QNs share their present location to the other nodes.

4.1 Optimisation-based path planning with obstacle avoidance

The movement is made only after MA obtains the data from the network region. MA moves randomly with three random movements. This tends the MA to get additional information about its source. MA provides the current location to the neighbouring nodes in every move. When three random movements are achieved MA selects the path to satisfy the colinearity condition and avoids the obstacle.

The localisation error rate is minimised by the fitness function, it is denoted as

$$error_{total} = \sum_{k=1}^{N} error_{(k)} \tag{12}$$

The localisation error of node i is error (*k*) and it is given as

$$error_{(k)} = \sqrt{\left(x_k - u_k\right)^2 + \left(y_k - v_k\right)^2} \tag{13}$$

where $\left(x_k, y_k\right)$ are the coordinates of the node *k*, and $\left(u_k, v_k\right)$ are the value of the identical node *k*. The nodes are estimated by MA within its region, the GOA and BOA method is compiled and the point is chosen based on the fitness value. The Grasshopper Optimisation Path Planning (GOPP) is proposed with GOA and Butterfly Optimisation Path Planning (BOPP) is proposed with BOA. Algorithm 1 describes the steps in GOA and Algorithm 2 depicts the pseudo code for BOA.

Algorithm 1: Pseudo code for GOA in GOPP

$t_{\min} = 0$
$t_{\max} = 0.001$
$T = Y_1$
while $\left(I < t_{\max}\right)$
  $t = t\max - l\left(\left(t\max - t\min\right)/L\right)$
  $d_{ik} = \left|Y_k - Y_i\right|$,
  $Y_i = \sum_{\substack{k=1 \\ k\neq i}}^{N} P\left(\left|y_k - y_i\right|\right)\frac{y_k - y_i}{d_{ik}} - g\hat{e}_g + u\hat{e}_v$
  If $\left(Y_i < Y_1\right)$
    $T = Y_i$
end while
return *T*

Algorithm2: Pseudo code for BOA in BOPP

Initialise *n*
Initial population $a_i = \left(i = 1, 2, ..., k\right)$
$I_i = f(b_i)$
Initialise c, a, p
While stop at the certain point where the criteria do not meet.
  for each butterfly
    fk = pow (*cI, b)*
  end for
  Find the finest *fk*
  for each *bf* taken from population of the butterfly **do**
    r = random (0, 1)
    if $r < p$ **then**
      $y_i^{t+1} = y_i^{\,t} + \left(r^2 \times h^* - y_i^{\,t}\right) \times fi$
    else
      $y_i^{t+1} = y_i^{\,t} + \left(r^2 \times yj^t - yk^t\right) \times fi$
    end if
  end for
  Update the value of sensor modularity(a)
end while
Print the best solution

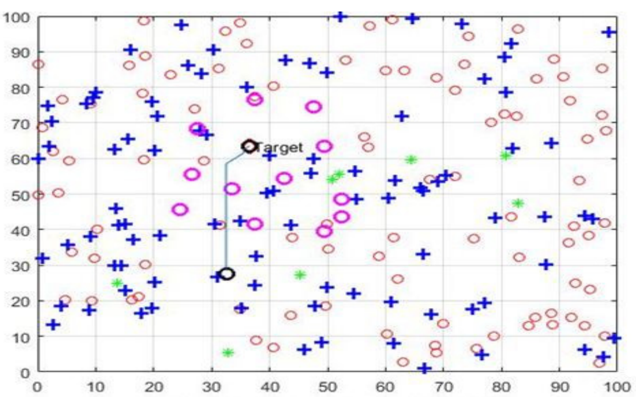
5 Shortest path planning with obstacle avoidance

To increase the functionality between nodes intelligent path planning is being incorporated. Some components need to be considered in intelligent path planning. The first component is the algorithm that calculates the shortest path to have an efficient path planning. There are many varieties of the algorithms that can be used (Yang and Miao, 2017). One of them is Dijkstra's algorithm. Dijkstra's algorithm is used to calculate the shortest path between. There are a lot of different variants of Dijkstra's algorithm that exist. It is also used in a wireless sensor network where it transfers the information between two nodes. Most of these variants use fixed nodes as their source in finding the shortest path and produce the shortest path between the source and destination. Dijkstra's algorithm finds the shortest distance while considering the lowest cost of the distance between the source node and the target node (Zhang and Zhao, 2014). Nodes save the cost of the distance which is low and then excludes the path which has the highest cost of distance and updates the lowest cost. The path through a neighbour node is considered as the temporary distance. If the distance calculated by the nodes is less than the current distance, then the smaller distance is updated as the shortest distance between the source and the destination (Li and Liu, 2004).

6 Result analysis

The efficiency of the planned models is tested and evaluated. The result constraints have been tested. Localisation accuracy, localisation ratio and computation time for two algorithms, GOPP and BOPP is evaluated. Figure 3 shows the path planning with obstacle avoidance using GOPP and BOPP.

Figure 3 Path planning with obstacle avoidance using GOPP and BOPP



6.1 Localisation accuracy

To calculate the behaviour of the future model it is compared with other models. Performance is made with 100 UN nodes. Table 1 shows the implementation parameters and their values. Localisation accuracy is important in path planning. It is compared with other algorithms to make higher accuracy. It is calculated using the localisation error. Lower localisation error gives higher accuracy. We evaluate the localisation accuracy through the mean localisation error of all nodes in a given network region.

Table 1 Parameters and values used

Parameter	*Symbol*	*Value*
Size of the network area	A	100 × 100 sq.m
Nodes	N	100
Movement distance	d_{max}	35 m, 70 m, 105 m, 140 m, 175 m
Maximum no of iteration	t	50–300
Resolution	R	1

In equation (12) the localisation error, $error_k$ describes the distance between the nodes and its original position. The mean localisation error, $error_{avg}$, consider all sets of unknown nodes N, It is estimated as,

$$error_{avg} = \left(\sum_{k=1}^{N} error_{(k)} \right) / RN \tag{14}$$

Here, $error_k$ is the localisation error and k is evaluated using equation (12) Reference Node (QN) are called as localised nodes. The standard error is calculated as,

$$error_{std} = \frac{\sqrt{\sum_{k=1}^{N} \left(error_{(k)} - error_{avg} \right)^2}}{QN} \tag{15}$$

N refers to the number of localised nodes, $error_k$ is the localisation error of k node and $error_{avg}$ is the mean localisation error.

6.1.1 The influence of maximum movement distance

For all movement models, the mean localisation error is applied with different maximum distances $(d_{\max})$. Altered values of $d_{\max}$ from 35 to 175 m are used for better results. The network region consists of 100 UNs with any number of obstacles. By default, each resolution value (R) is assumed as 1. The mean localisation error is calculated with five different values of $d_{\max}$ are 35 m, 75 m, 105 m, 140m, 175 m. Proposed optimised path models GOPP and BOPP give higher accuracy. The localisation error decreases when the value of $d_{\max}$ increases. As a result, BOPP shows better performance when compared with GOPP. Figure 4 describes the mean localisation error with respect to maximum movement.

6.2 Localisation ratio

The localisation ratio is defined as the number of Reference Nodes (QN) to the total number of nodes. Localisation with higher value gives the best path planning. Localisation ratio is evaluated as,

$$L_{avg} = \frac{QN}{N} \tag{16}$$

A network with 100 nodes is used with different $d_{\max}$ and R value is set to 1 by default. Since MA has a less coverage property so that it is hard to cover the entire network. BOPP and GOPP show the higher localisation ratio when compared to the other two models Grey Wolf Path Planning (GWPP) and Whale Optimisation Path Planning (WOPP). Localisation ratio for all the models is low when $d_{\max}$ is short with 40 m. The ratio improves when $d_{\max}$ increases.

6.3 Computation time

Computation time is calculated by the time taken to execute the algorithms. This model is executed in a system which has the configuration of Windows 8.1 and a system type is × 64-based processor. A maximum number of iterations is taken for both models with 50 runs. The parameters used are 100 UNs, $d_{\max}$ =140, R value is taken as 1 as a default value, and the other values are taken from Table 1. As a result, BOPP shows less computation time when compared with GOPP. When $t_{\max}$ increases the computation time also increases. Figure 5 shows the computation time taken by both the models, GOPP and BOPP.

Figure 4 Mean localisation error versus maximum movement for GWPP, WOPP, GOPP and BOPP

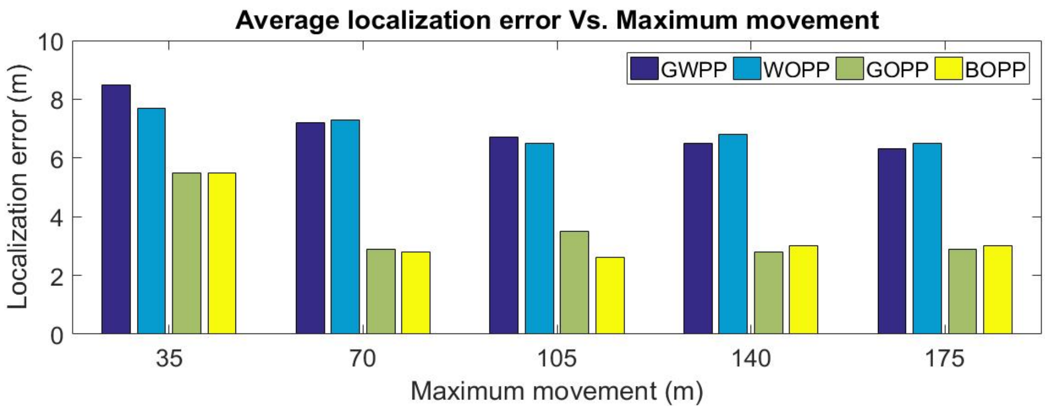
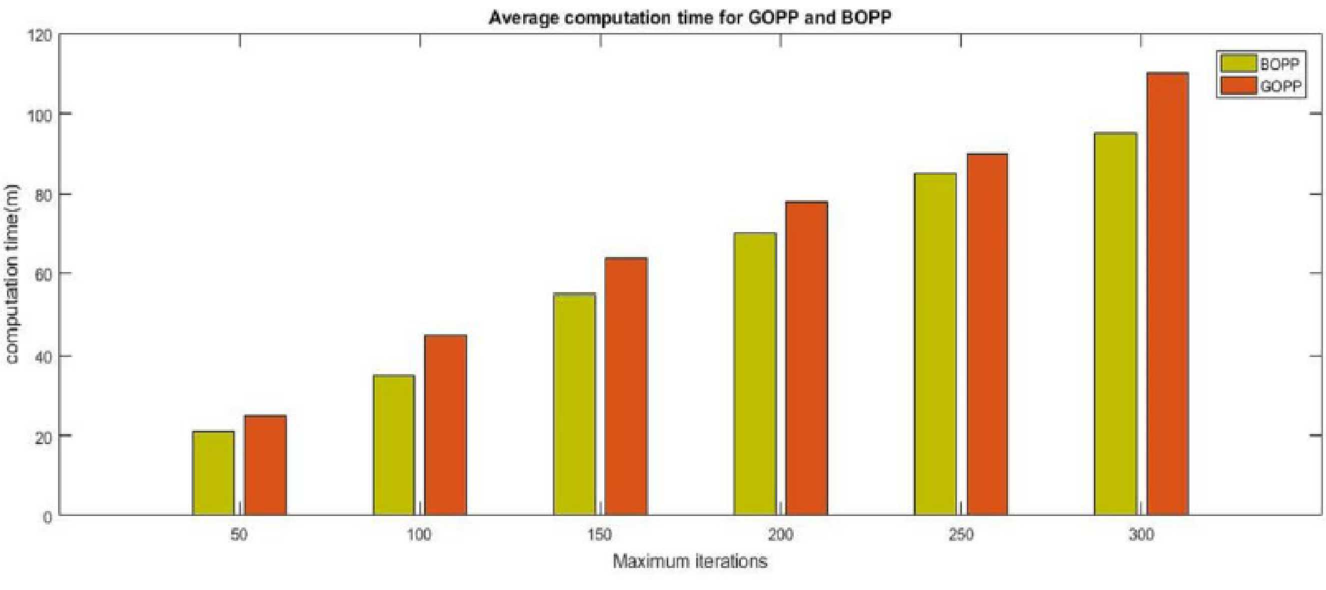


Figure 5 Average computation time for GOPP and BOPP



7 Conclusion and future work

The proposed system is aimed to improve localisation process in a wireless sensor network. A multi-objective model has been proposed to reduce the localisation error. Two dynamic obstacle avoidance path planning models called GOPP and BOPP have been proposed for mobile anchor-assisted localisation. The proposed model has optimised the path based on the current information received from the region and path planning is made with the shortest distance using Dijkstra's algorithm. The two optimisation methods not only avoid the obstacle located in the path of MA but also plan an optimised path between source and target. The effectiveness of the proposed models is compared with the other two models, GWO and WOA, with obstacle-avoidance methods. The ultimate results show that our proposed models, GOPP and BOPP, have a higher localisation efficiency with respect to accuracy, computation time and localisation ratio. But the proposed model is limited to optimise the localisation only with the fixed obstacles. In future, we planned to investigate the system with movable obstacles which allows the MA to control its movement and three-dimensional movement patterns.

Acknowledgements

The authors are grateful to Indian Council of Social Science Research (ICSSR), New Delhi, under IMPRESS scheme for the financial support (No. IMPRESS/P580/278/2018-19/ICSSR). Authors express their gratitude to SASTRA Deemed University, Thanjavur, for providing the infrastructural facilities to carry out this research work.

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