# Collaborative Re-Localization Method in Mobile Wireless Sensor Network Based on Markov Decision Process

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**Abstract**

Localization in Mobile Wireless Sensor Networks (WSNs), particularly in areas like surveillance applications, necessitates triggering re-localization in different time periods in order to maintain accurate positioning. Further, the re-localization process should be designed for time and energy efficiency in these resource constrained networks. In this paper, an energy and time efficient algorithm is proposed to determine the optimum number of localized nodes that collaborate in the re-localization process. Four different movement methods (Random Waypoint Pattern, Modified Random Waypoint pattern, Brownian motion and Levy walk) are applied to model node movement. In order to perform re-localization, a server/head/anchor node activates the optimal number of localized nodes in each island/cluster. A Markov Decision Process (MDP) based algorithm is proposed to find the optimal policy to select those nodes in better condition to cooperate in the re-localization process. The simulation shows that the proposed MDP algorithm decreases the energy consumption in the WSN between 0.6% and 32%.

**Keywords:** Mobile Wireless Sensor Network, Markov Decision Process, Mobility Patterns, Time Bounded Essential Localization.

# 1. INTRODUCTION

A wireless sensor network includes several nodes in a cooperative network that each of them has a power source, processing capability and contains memory. Additionally, each node often has some sensors such as temperature, humidity or velocity sensors. Today, WSNs have become a significant technology for different types of smart devices for various applications including medical, transportation, military and environmental, and an intense research effort is currently proceeding to extend the application of wireless sensor networks [1]. Most of past research assumed that the system is wired, therefore, has an unlimited power supply, has determined resources and is location independent. But for wireless sensor networks, the system is real time and power limited. Sensors have changeable resources, especially for mobile nodes, which their location plays a significant role to choose appropriate resources.

Mobile wireless sensor networks (MWSNs) [2-4] are a particular class of WSN that has become an important area of research for the WSN community. MWSN deployments have considered several challenges that needed to be overcome, including energy consumption, connectivity, bandwidth, coverage, and real time functioning. When there is an uncertainty of the location of some fixed or mobile devices, localization also becomes an important issue. Localization algorithms can deploy obtainable information from the wireless sensor nodes to estimate the position of individual devices.

Sensor nodes may be positioned dynamically or change position during a given experiment time, therefore a method should be used to estimate the location of each node at any given time. For static WSNs, once the node locations have been determined, they are unlikely to change. On the other hand, mobile WSNs must repeatedly estimate their position which is time and energy consuming.

Moreover, all methods which are applicable for static networks and provide high accuracy are not useful for mobile networks due to their need for centralized processing, which is not applicable in a MWSN. At present, the most widely used method for localization is Global Positioning System (GPS). However, there are also several circumstances in which GPS will not work reliably. For instance, GPS requires line of sight to the satellites. As a result, MWSNs in indoor, urban, and underground environments will not be able to use GPS. Furthermore, GPS is relatively expensive, and therefore unattractive for many applications.

Recently, some localization techniques have been proposed to estimate a node's location using information transmitted by a set of nodes that know their own locations, called anchors (these nodes are able to find their location using some resources such as GPS). Additionally, to remove centralized computation, distributed localization methods are proposed in which each node relays the information gained through limited communication with nearby nodes in order to determine its location. These approaches exploit time of arrival (TOA), received signal strength (RSS), time difference of arrival of two different signals (TDOA), and angle of arrival (AOA) to estimate position [5-8].

In this paper, MWSN is studied which allows each node to be used for different purposes such as tracking targets. Principles of a new proposed localization algorithm, Time-Bounded Essential Localization (TBEL) [9], which is focused on achieving localization within a given time-bound through various means is applied to find each node’s location. Yet in the mobile network, nodes must repeatedly re-localize to keep their position information, accurate.

The other issues that arise in MWSN are power consumption and latency. In a large scale network containing mobile nodes it is not possible to recharge nodes whenever power has been drained. Therefore, it is valuable to decrease power consumption in order to increase the network lifetime [10]. One method to satisfy a power efficient network is the Markov Decision Process (MDP) [11] which is applicable to determine the limited number of nodes that contribute to perform localization. Moreover, it could be a method to decrease response time.

The remainder of the paper is organized as follows: A literature review is presented in section 2, Section 3 contains network model and assumptions, including localization method and movement patterns. MDP-Based algorithm is explained in section 4, results and discussion are included in Section 5, and Section 6 concludes the study.

## 2. LITERATURE REVIEW

Most of the existing research in localization area emphasizes static sensor networks. There are not many studies in Mobile WSN and few algorithms were proposed to work in both static and mobile networks to do localization in the situations which energy and delay are essential factors. There are some surveys that summarize different methods and algorithms for localization in WSN [1, 12]. Various techniques have been proposed to localize nodes in WSN which are based on distance between nodes [13-15]. The most important factors to measure distance are based on RSS, ToA, and AoA [5].

There are other methods which deploy the geometric condition of nodes such as the work in [16] that uses all possible triangles of nodes, so that the location of an unknown node is the center of the intersection of all triangles. In a Gradient Algorithm [17], nodes find the number of hops to all the seeds and apply multilateration technique to find their position. The mentioned algorithms are intended for static networks. For MWSNs, localization should be implemented periodically. In [18], the authors examined how often a localization algorithm should be run in a MWSN, considering the tradeoff between energy and accuracy. In some studies static mobile nodes are used to localize mobile nodes that are located in specific locations [19].

In a wireless sensor network, it is desirable to transmit data at a lower power level while ensuring error-free communication. To reduce power consumption, Transmit-Power Control (TPC) method is a way to save energy, reduce interference and increasing the security [20]. Many existing TPC methods have been proposed for different applications, and surveys of these schemes can be found in [21] and [22]. Energy efficient sensor networks can be improved by deploying localized communication among neighboring sensors and reducing long distance transmissions [23]. In this paper, an MDP based framework algorithm is applied to perform the re-localization process to avoid long distance communications to decrease response delay.

## 3. NETWORK MODEL AND ASSUMPTIONS

In this study, mobile nodes are moving in the scenario following one of the four particular mobility models which are discussed in section 3.1. Moreover, collaborative groups are formed to localize the mobile nodes. Localization of the mobile node is determined by combining sensed results from different localized sensors. In some random and dense wireless networks, nodes power refilling is not possible, therefore, network lifetime decreases. To overcome this problem, energy efficient methods are preferable. Additionally, applying a higher number of nodes in the localization process imposes a higher amount of information to the network which should be processed. Therefore, response delay and energy consumption increase.

In this work, the square area over which nodes are randomly spread is considered using a mixture of mobile and static nodes. The following assumptions are made regarding each node:

1. All nodes have the same communication range, which is denoted as a circle around the node;
2. Each node can estimate its power consumption to transmit and receive data to and from other nodes or servers that are within its communication range;
3. Each node or server can sense other nodes that are inside their communication range trough signal exchanging;
4. Anchor nodes are aware of their locations and can be either fixed or mobile;
5. Each node is capable of calculating its distance from neighboring nodes in its communication range through distance measurement techniques such as RSSI.

### 3.1 Movement Patterns

The movement patterns of sensor nodes have an important role in analysis of wireless communication network. It has seen that mobility affects radio communication networks therefore to improve the network performance [24], observing mobility patterns can be helpful.

Main realistic mobility patterns are classified as follows: pedestrians, vehicles, aerial, robots. Pedestrian mobility patterns can be the walking pattern of people or animals. Sensor nodes are attached to moving objects such as pets to track them or animals in herds to be observed by a biologist. The vehicular mobility is the movement pattern of cars, bicycles, trains and etc. Aerial movement pattern shows the flying pattern of birds or any flying objects. Mobility pattern of robots differs based on robot's applications. In some cases it is predictable and some other robots move erratic and unpredictable [24]. To model the realistic mobility patterns, different models are used which the important groups are; cellular mobility models and random trip models [24].

In cellular networks, handoff between cells is the main feature, not the movement details. Random trip mobility is the predominant mobility model for MANETs and is used in this research in simulation. It includes various models such as the Random Waypoint (RWP) pattern that is widely used to evaluate ad hoc network routing protocols. Also Brownian motion is a kind of Gauss-Markov mobility model which has a tuning parameter to change the randomness in movement pattern. Another applied movement pattern in this research is Levy walk pattern that is able to model different movement patterns from people in shopping centers to animals in wildlife [25, 26]. In Modified RWP (MRWP) method, nodes move in a specific direction to reach a target, which could be applicable in military purposes, moreover is practical for hardware implementation.

**Random Waypoint Pattern.** In this pattern, the sensors randomly move at various speeds in a zigzag pattern. At each point, every node pauses before it starts moving again. In Figure 1, nodes move under a RWP model. Here nodes move from waypoint $P_i$ to waypoint $P_{i+1}$ with speed $v_i$. Before moving toward the next waypoint, nodes pause at each waypoint [26].

The number of stops and speed changes in a predefined time depends on the node speed. A node can randomly move to any location within the network bounds, therefore, to update the node position, a random coefficient will be used which is between 0 and 1 according to Equation (1) where $X_L$ and $Y_L$ are the dimensions of a square network area. Also, the velocity is considered as a random value which is attainable by determining $MIN_{speed}$ and $MAX_{speed}$ (minimum and maximum speeds of nodes) according to Equation (2).

$$\begin{aligned} X_{waypoint} &= rand \times X_L \\ Y_{waypoint} &= rand \times Y_L \end{aligned} \tag{1}$$

$$V_i = MIN_{speed} + (MAX_{speed} - MIN_{speed}) \times rand \tag{2}$$

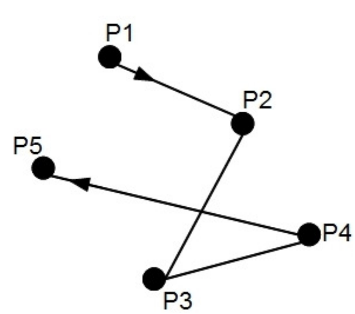


**FIGURE 1:** Random Waypoint Mobility Pattern for a node that moves from waypoint $P_1$ to $P_5$.

**Modified Random Waypoint Pattern.** In the proposed MWRP pattern, which is defined for nodes that have planned to reach a specific point, at each time step a random change is added to the last point. This is shown in Equation (3) where ω could be any value depending on the purpose of the movement. In this study, it is assumed that ω is 100 due to the environmental dimensions (500×500). This pattern continues until a node reaches a border, in which case the new position is calculated according to Equation (3).

$$\mathrm{X}_{\mathrm{waypoint}} = \mathrm{rand} \times \mathrm{X}_{\mathrm{L}} / \omega + X_{old}$$
$$\mathrm{Y}_{\mathrm{waypoint}} = \mathrm{rand} \times \mathrm{Y}_{\mathrm{L}} / \omega + Y_{old} \quad (3)$$

**Brownian Motion.** The random movement of particles suspended in a liquid or gas, caused by collisions with surrounding particles is called Brownian motion. In the simulation of a Brownian mobility model, time is divided into N time slots at a predefined interval T, in which a mobile node has a random move at each time slot and the endpoint after N time slots is the cumulative summation of all random moves [22]. Figure 2 shows an example of Brownian motion.

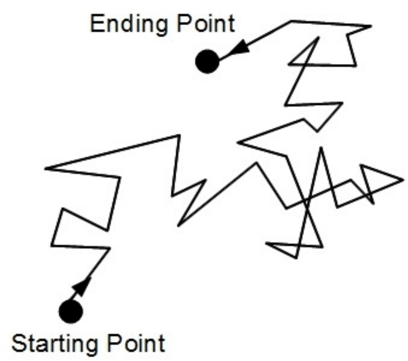


**FIGURE 2:** A movement example of Brownian Motion for a node.

**Levy Motion.** A Levy walk is a random walk in which the steps are defined in terms of step-lengths, which have a certain probability distribution, with the directions of the steps being random. As is shown in Figure 3, Levy walks consist of many short flights that are accompanied by long flights [26]. The distribution of the step sizes has a power like tail which is defined in (4) where the a value is between 1 and 3.

$$\Pr(D > d) = O(d^{-a}) \quad (4)$$

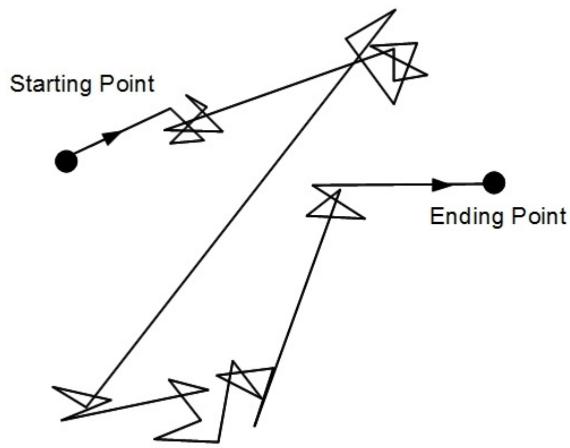


**FIGURE 3:** A movement example of Levy Walk.

### 3.2 Localization Method

Localization of sensors in a specific period of time is important in many applications such as battlefield, which message exchange is likely to be detected by enemies. Recently TBEL algorithm proposed a method to localize the network within a specific time bound by introducing k-rounds essential localization, time bounded relative localization and time bounded physical localization terms [9].

In TBEL algorithm, sensors ink rounds of essential localization, localize themselves under their local coordinate system (LCS), during *k* rounds of information flooding. Then sensor nodes relatively localized in *k* rounds of communications if local coordinate systems can be transformed into the same coordinate system for the whole network. Therefore sensor network is physically localizable if, for every pair of sensors, exists an anchor, with which, the pair of nodes are connected through a sequence of coordinate systems.

In this research the idea of TBEL is used to localize the system. Each node can localize itself if it is connected to at least 3 anchor/localized nodes. Then the node's condition would change from un-localized/blind to localized node and will be able to cooperate in the localization process of un-localized nodes. All the nodes in a sensor network transmit messages in predefined *k* rounds of communications, then they stop sending signal until the next re-localization process. The value of *k* depends on network conditions such as area, number of nodes and number of anchors. For example, for a smaller area with higher number of anchors, localization process would be done in a shorter time which means the smaller value of *k*.

In a network where whole nodes are connected, the network completely can be localized. But in cases with some isolated nodes, which are separated and have no connection to other nodes, they remain un-localized. This problem can be removed by providing more anchor nodes in such places.

### 3.3 Markov Decision Process

A Markov decision process (MDP) is defined by a set of states (S) and the set of actions (A), including transition function (T) and reward function (R) to do specific actions [27]. The transition function describes the probability distribution over the next states as a function of the current state and the agent's action. The reward function determines the reward received after deciding on a taking a certain action in a certain state. According to the Markov Property, the next state and the reward depend on the current state and the action, not on the previous states and actions. An agent or client in the MDP environment alternates between perception and action. The agent detects the state $s_t$ at time t, and selects an action $a_t$. The agent then receives the reward that is a function of state and action, $R(s_t, a_t)$, and observes the next state, $s_{t+1}$, with the probability specified by the transition function $T(s_{t+1}| s_t, a_t)$.

The main objective of an MDP is to find an optimal policy for a client. A policy $\pi: S \rightarrow A$ is a mapping function that defines an action in each state. An optimal policy for MDP maximizes some functions of the rewards received by fulfilling the policy.

The value of a policy π or the function value which starts at state 's', with a discount factor $\alpha \in [0, 1)$, is shown in Equation (5) where $E\{r^t|s^0 = s, \pi\}$ is the expected reward received at time t given the initial state 's'. Using this reward formulation, the goal for an agent is to find an optimal policy $\pi^*$ that maximizes the discounted future reward for all states. By defining the state transition function, T, and the reward function, R, the optimal policy can be calculated using a standard algorithm, e.g., value iteration and policy iteration [27, 28].

$$V^{\pi}(s) = \sum_{t=0}^{\infty} \alpha^t E\{r^t \mid s^0 = s, \pi\}, \tag{5}$$

# 4. PROPOSED METHOD

## 4.1 Method Description

Re-localization algorithms in which all neighboring localized nodes cooperate to re-localize un-localized mobile sensor nodes, are both energy and time consuming. The more information a node compiles the more energy and time it consumes. The best way to save energy in a node is by limiting the number of cooperating nodes and exploiting the best nodes to do localization. As a result, smaller amounts of information transfer between the nodes, leading to decreased energy consumption. In this method only the best nodes in the neighborhood are leveraged in the localization process and those nodes that are either too far away or have a low energy level are ignored.

In this study, the MDP method is used to handle the problem of choosing an optimal number of localized nodes, which are also in the best condition energy-wise to cooperate in performing localization for a mobile node. MDP can be used to obtain a tradeoff between energy efficiency and latency; therefore a cost function should be associated with the formulated MDP that is appropriate. This is shown in Equation (6) where P shows power efficiency and D shows delay in receiving signals which is in a direct relation with distance.

$$\mathrm{H} = \mathrm{a} \times \mathrm{P} + (1 - \mathrm{a}) \times 1/\mathrm{D} \tag{6}$$

Those nodes that contribute to the re-localization process should be the nodes that are within a mobile node's communication range (R). A server that could be an anchor takes part in choosing the optimized number of nodes to collaborate with, based on their conditions according to their distance to the mobile node and the power level. Shorter distances between nodes and anchor/server will lead to lower response delay.

Two states are defined to show the node's circumstances, 'active' and 'passive'. An active node collaborates to do localization, but a passive node remains inactive. The goal is to find the optimized solution for the number of active nodes – this is the policy that is being optimized. Commonly, for an accurate re-localization process, at least three localized nodes must be located within the mobile node's communication range [1]. For a more accurate re-localization process, one can use more than 3 anchors (multilateration localization), depending on the number of available localized nodes, although some nodes do not make any significant changes in accuracy. Additionally, the problem of power consumption arises; therefore it is valuable to consider an upper bound for the number of nodes that may be used in the localization process in order to decrease the required power consumption [11]. Therefore the localized nodes that are removed in one localization process for a specific node, can save their power to collaborate in the localization process for another node. In Equation (7) $N_l$ shows the number of collaborative nodes, which should be between 3 and $N_u$, as lower and upper bounds. $N_u$ depends on the number of nodes in the area, size of the area and node's communication range. Note that nodes are not uniformly distributed in the area, therefore some nodes are connected to the higher number of nodes rather than $N_u$.

$$\begin{aligned} &3 \le \mathrm{N_l} \le \mathrm{N_u} \\ &\mathrm{N_u} = \text{Node density} \times (\text{communication range})^2 \times \pi \end{aligned} \tag{7}$$

In the first phase of the proposed algorithm, the localization will be done for all nodes using the time bounded localization method [9]. The anchors and localized nodes will broadcast packets that contain their location information. They also will collect the information of other anchors. The other nodes will calculate their distances from the anchor, localized and un-localized nodes in their neighborhood and estimate their location according to TBEL algorithm. When an un-localized node changes to localized, it can broadcast its location and collaborate in localization as an active node.

All fixed or mobile localized nodes can be used to calculate the location of un-localized Mobile nodes. The position of mobile nodes can be calculated by collecting and combining the information from different localized nodes.To determine the number of active nodes to collaborate for each area or cluster in a network, a server or head can be used which could also be an anchor. According to the network condition, several servers can be assumed in different locations in which their density depends on the network that can be calculated statistically. The server will check if the mobile node is in its controlling area, by receiving acknowledgement signal from it. They exchange a signal containing; node ID, power level, localization condition- that can be '0' for un-localized node and '1' for localized node- and its location in localized node case. For un-localized node server will take the control of the localization process, including the calculation of the optimal number of active nodes which collaborate. If a mobile node leaves the server's environment, re-localization would be done by other server/anchor node.

A server or anchor will broadcast its decision to track a mobile node. The server should select collaborative localized nodes according to their distances to un-localized node and their energy level. Distances between all pairs of nodes are determined based on RSSI [3] at each node, and calculated distance information will be broadcasted. Therefore, all nodes and servers are aware of distances between nodes in their communication ranges and a server can determine closest nodes to un-localized nodes.

As mentioned before, MDP is used to find active nodes that are cooperating in localization. To choose the number of nodes, an energy consumption bound can be considered as shown in Equation (8) where "$E_i$" is the amount of energy that a node uses to transmit or receive a message and subscript "i" shows the index of a collaborative node. In this paper, $N_u$ is the maximum number of collaborating nodes and therefore the upper bound for energy ($E_{upperbound}$) can be expressed in term of $N_u$. In the other words $N_u \times E_i$ can define the $E_{upperbound}$ if another energy limitation is not considered.

$$\mathrm{E_{total}} = \sum_{i=1} E_i < \mathrm{E_{upperbound}} \tag{8}$$

To select some nodes among all possible options (if there are more choices available) a value function is introduced. Nodes with the higher values would be chosen as collaborative nodes according to:

$$V = a \times \frac{1}{d} + b \times (E - E_i)$$
$$b \approx 1 - a \tag{9}$$

Where "E" is the energy level of a node and "d" is the distance between the mobile and localized nodes. 'a' and 'b' are weight factors to define the importance of value function elements.

As mentioned before, in MDP, a transition probability value is considered in selecting a node as a collaborative node. In this paper, the probability of selecting a node to change its state as an active node depends on $E_i$ and its distance to the un-localized node:

$$P = \frac{1}{N} \times \frac{1}{d} \times \frac{1}{E_i} \tag{10}$$

where "N" is the number of active nodes in the communication range of the mobile node. But the problem is how to choose nodes with higher value functions. The upper bound is considered to determine the maximum number of nodes, however, it should be determined if all the nodes are in an appropriate condition to collaborate. Therefore, a condition is defined to evaluate the function value of the node. As mentioned before, at least 3 nodes should collaborate in the re-localization process. If more than 3 nodes are available, the decision on the number of active nodes would be made according to their function values. Nodes with function values comparable to the third node in the descending list of the node's function values, can act as active nodes. For this research, half of the third function value is used as the criteria. That means node with function values higher than criteria can be chosen as an active node. This is described in detail in the section 4.2 as Algorithm 1. But before investigating algorithm 1 which includes all information, Figure 4 shows an overview of whole re-localization process.

### 4.2 Algorithm Description

In this research, each server/anchor broadcasts a signal which all the nodes in its communication range that receive it, send an acknowledgment signal and their node ID would be saved in a list on server. Each node also broadcasts its information, including, ID, power level and its distances to other nodes. Therefore, each server knows all nodes in its neighborhood and also the other servers' locations. The list later can be used to find localized nodes in the mobile node communication range (potential active nodes). This list can include localized nodes both fixed and mobile or just fixed, that is explained in Algorithm 1 by Function 1. When a server/head/anchor recognizes a mobile node in its area, a message of sensing it would be broadcasted to other anchors and localized nodes in its zone. In the next step collaborative nodes are selected according to their power and their distance to the mobile node. Additionally, distance can be expressed as a delay factor. The optimal number of localized nodes to do re-localization is based on the MDP framework. The probability to choose a localized node to collaborate, which depends on its distance from the mobile node and its energy level, should be considered (10). Finally, the information would be collected to find the location of mobile nodes. The whole the process is described in a pseudo code format in Algorithm 1.

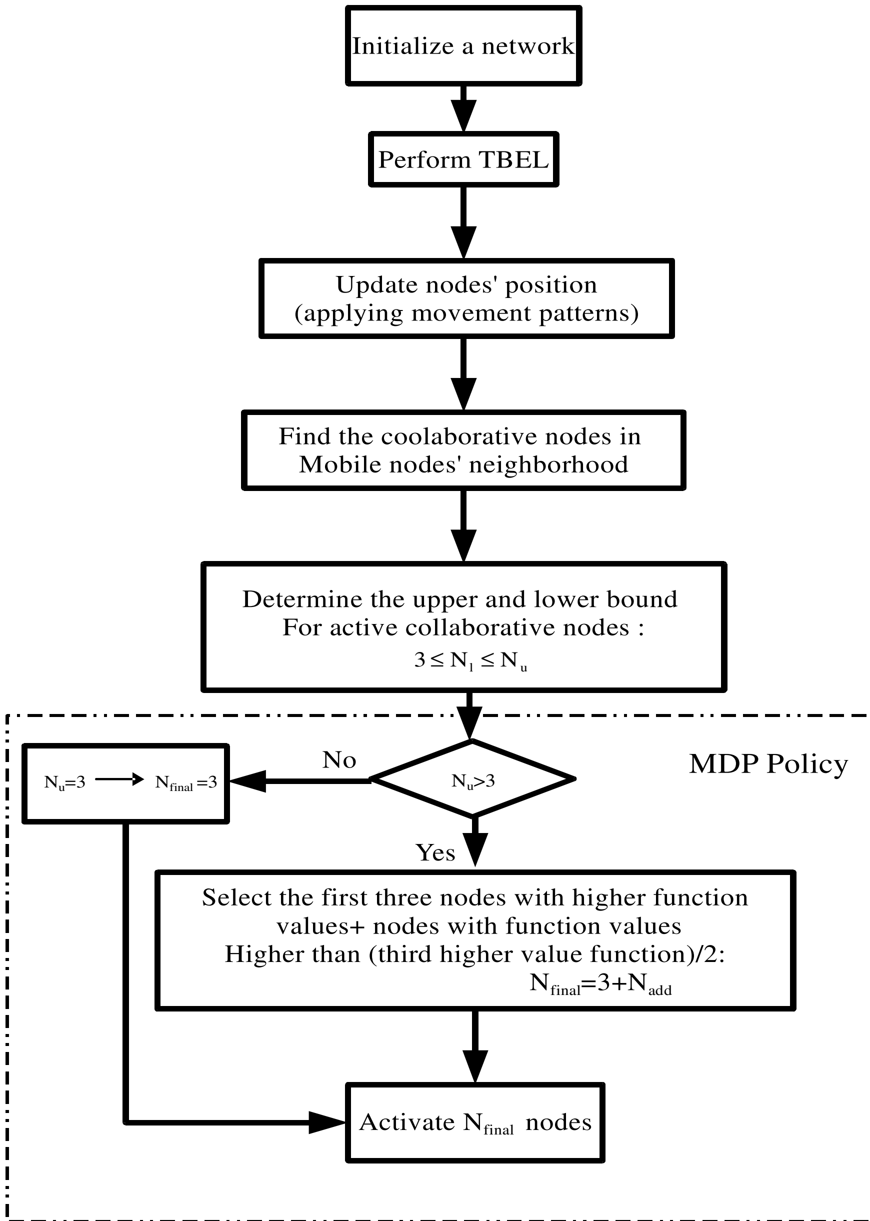


**FIGURE 4:** Flowchart of re-localization process.

**Algorithm. 1**

**Define** $E_i$, a, b
**Determine** the nodes by index
**Find** mobile nodes ($M_j$) distances from neighbor nodes
**Make** a list ($L_j$) of nodes in mobile node's communication range for each $M_j$
**If** mobile anchor nodes are allowed to collaborate in the localization process
  **Then**
    **Skip** Function 1

**Function 1**
  Remove mobile node indexes from $L_j$
**End Function 1**

**Sort** $L_j$ by distances from $M_j$ in an ascending manner
**Find** the length of $L_j$
**Determine** power values (E) of the nodes provided by $L_j$

**MDP function**
**Define** Transition probability matrix ($T_j$)
**Find** Value function for each node in $L_j$ %%%% including distances from $M_j$ and energy consumption
    $V_{ji}$= a × 1/distance$_{ji}$ + b × (E-$E_i$)
**Sort** $V_j$ in a descending manner
**Find** upper and lower bounds %%% to determine the no. of active nodes%%%
    Lower bound=3, upper bound=Nu

**Policy** %%% to select the best nodes to collaborate in the localization process%%%

**Select** the first 3 nodes with higher value functions
    Counter=3;
  **For** i=4: $N_u$
    If $V_j$(i)>$V_j$(3)/2
      Counter ++
  **End**

**Select** $V_j$(1)**:**$V_j$(counter) %%%The counter value determines the finalized number of active nodes%%%

  **If** length($V_j$)≤3
    Counter=length($V_j$)
  **End**

## 5. RESULTS

The simulations are run in Matlab in which an environment with dimensions of 500 (m) × 500 (m) is considered, including 120 nodes (containing 20 anchors) so that the number of mobile nodes changes from 12 to 60 (10%-50% of nodes). 8000 mw as a maximum power of a node, 0.5 mw for transferring each message that was shown by $E_i$ and a communication range of 60 meters for each node are assumed. These values were selected due to their use in real hardware applications. The MDP method was used to choose the optimal number of active localized nodes to cooperate in the localization process in order to decrease the power consumption and delay in response. The effect of power and response delay factors depends on their coefficients in (9), defined by 'a' and 'b' to show their weights, which are determined according to their importance. For the following results, a is chosen as 3/4. Algorithm 1 is applied for four different movement patterns (RWP, MRWP, Brownian and Levy) and the results in tables 1 and 2, which are the average of 10 runs of simulations show the energy reduction consumption- the difference between power consumption after and before applying algorithm 1, divided by the power consumption before applying MDP- which is calculated to evaluate the algorithm performance.

As mentioned before, localized mobile nodes can act as either active or passive nodes according to the network conditions. Therefore, two experimental conditions are considered. First, the mobile node is able to operate as an active localized node; therefore multiple localized nodes either mobile or fixed can contribute to estimate the location. Table 1 shows the percentage of power consumption reduction after applying algorithm 1 for four mentioned movement patterns. Power consumption reduction for RWP is almost the same for different numbers of mobile nodes because of node distribution after applying RWP movement. It can be then claimed that node density around the specific mobile nodes is almost fixed or comparable to the last position before applying movement pattern. In Modified RWP, increasing the number of mobile nodes leads to increase in the power consumption reduction and is due to the nature of this movement pattern. When the number of mobile nodes proliferates, more nodes move in a specific direction which causes more localized nodes in the neighborhood. However, saturation occurs because just a limited number of nodes are allowed to contribute in localization. Increasing the number of active nodes has no effect after passing the upper bound ($N_u$).

Brownian motion results are close for different percentages of nodes and it is due to the short movements of nodes around their last position. On a Levy walk with lower numbers of mobile nodes, nodes have sudden long flights which may put them in a place with lower number of localized nodes. When the number of mobile nodes increases, the probability of having more localized nodes in a neighborhood augments, and therefore the energy consumption reduction increases for environments with higher percentages of mobile nodes.

| | **Movement Pattern** | | | |
|---|---|---|---|---|
| **Percentage of mobile nodes** | **Random Waypoint** | **Modified RWP** | **Brownian Motion** | **Levy Walk** |
| 10% | 19.7 | 9.9 | 17.41 | 10.14 |
| 20% | 21.32 | 11 | 16.43 | 13.04 |
| 30% | 22.9 | 32 | 15.39 | 17.45 |
| 40% | 20.54 | 31.52 | 18.24 | 17.89 |
| 50% | 20.25 | 30.23 | 15.42 | 17.14 |

**TABLE 1:** The percentage of power consumption reduction for four movement patterns, considering both fixed and mobile nodes as active nodes.

In some conditions, it is not possible to exploit mobile nodes in the re - localization process due to different reasons such as saving energy for future activities. Therefore, in the second experiment, the mobile nodes are removed from the list of active nodes. That means they are not involved in the localization process, and the number of active nodes decreases. Results in table 2 for all movement patterns show the descending change versus additive number of mobile nodes. This behavior is due to the smaller number of active nodes. By increasing the number of mobile nodes, the number of potential active nodes decreases. Downward trend for all movement patterns is expected, which is endorsed by Table 2 results.

Figure 5 – which was applied for networks including 30-50% of mobile nodes – shows that after applying MDP, considering second experiment assumptions, for a random network topology without observing any special movement pattern, the number of collaborative nodes to do localization decreases which is the reason for lower energy consumption. Additionally, as mobile nodes are removed from active node lists, incrementing the number of mobile nodes decreases the number of active nodes. Therefore, as it is demonstrated in Figure 5, for a higher percentage of mobile nodes, the number of active nodes before and after MDP implementation is closer or almost the same.

In Figure 6 the tradeoff between energy consumption and response delay can be found. As mentioned before the response delay is in a direct relation to the distance of the mobile and active nodes. Figure 6 shows as the distance between nodes increases, value function decreases and there is no connection for distances more than 60. On the other hand, increasing the energy level increases the function value as well.

| Percentage of mobile nodes | Movement Pattern | | | |
|---|---|---|---|---|
| | Random Waypoint | Modified RWP | Brownian Motion | Levy Walk |
| 10% | 20.8 | 2.08 | 15.26 | 7.31 |
| 20% | 16.47 | 3.54 | 12.5 | 9.08 |
| 30% | 13.11 | 1.3 | 8.2 | 9.6 |
| 40% | 7.7 | 1.18 | 5.1 | 4.9 |
| 50% | 4.9 | 0.67 | 2.2 | 3.5 |

**TABLE 2:** The percentage of power consumption reduction for four movement patterns, considering fixed nodes as active nodes.

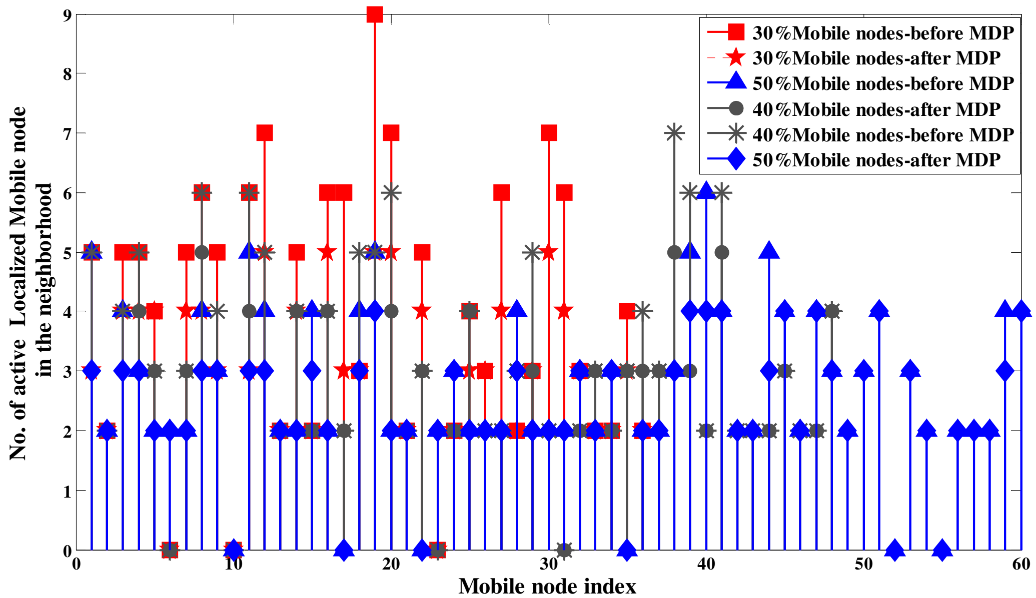


**FIGURE 5:** The effect of MDP algorithm on the number of active localized nodes for environment, including 30-50 percent of mobile nodes.

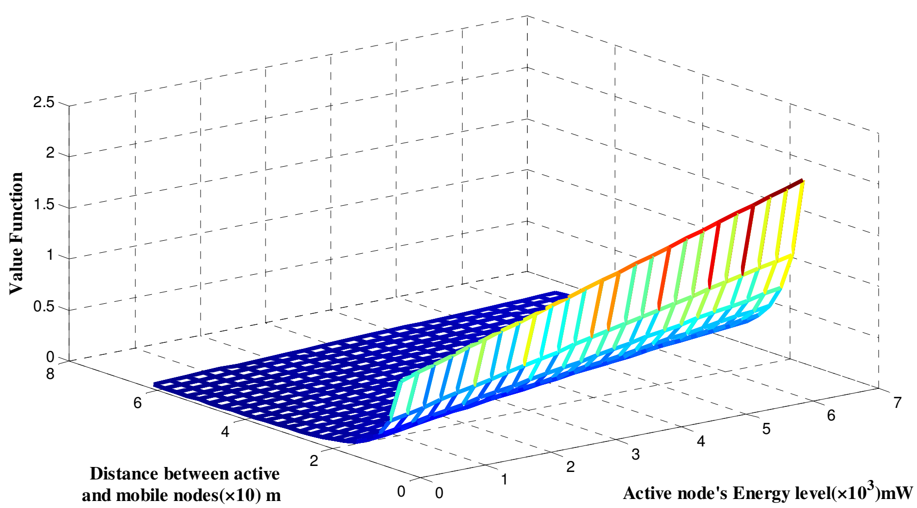


**FIGURE 6:** The tradeoff between energy levels and response delay to evaluate the value function.

## 6. CONCLUSION

In this work, a localization algorithm is proposed for energy constrained WSNs. The proposed scheme selectively activates nodes to collaborate in localization. The activation of nodes depends on the node value function coupled with an MDP approach. Results show that proposed algorithm is capable of reducing the total energy consumption of the network in the localization process. The algorithm was simulated observing four movement patterns (WRP, MWRP, Brownian motion and Levy walk) and varying the number of mobile nodes. In the proposed scheme, collaborative/active nodes are selected according to their instant power and their distance to the mobile nodes, in which distance can describe the delay factor. Based on the MDP framework, the optimal number of localized nodes to do re-localization was found and the MDP-based policy selects the best nodes among neighboring nodes. For the proposed algorithm, 0.6 to 32 percent, energy consumption reduction was obtained. As a future work the proposed algorithm will be simulated in Contiki software which can communicate with actual hardware. In the next phase of this research, the algorithm will be applied in a hardware platform, including several wireless Z1 Zolertia motes, to show the applicability of the proposed method.

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