Research Article

ANN-Based Control of a Multiboot Group for the Deployment of an Underwater Sensor Network

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Received 23 April 2014; Revised 14 June 2014; Accepted 16 June 2014; Published 6 July 2014

1. Introduction

Most of the Earth’s surface is covered by water. Sensing and monitoring of aquatic environments are used in several potential applications including oceanographic data collection for fish and mussels growth observation, pollution detection, oil monitoring, seismic and volcanic prediction, coastal surveillance, and different objectives such as exploration, protection, and commercial exploitation [1]. A low-cost approach for all these applications is the use of underwater sensor networks (USNs). In USNs, nodes can be equipped with sensors for the measurement of different parameters such as depth, conductivity, oxygen, pH, turbidity, temperature, and salinity. In USNs, the transmission of information can be realized in the form of acoustic, electromagnetic, or optical waves. All the wireless communication techniques, acoustic, optical, and electromagnetic communications, have pros and cons [2].

Due to the nature of aquatic environments, a number of key constraints like the low-bandwidth capacity, large propagation latency, high bit-error rate, and short-distance radio communications must be taken into account [3]. These key constraints call for the deployment of a large number of sensor nodes for a successful USN. Its key advantage, the low attenuation of acoustic waves in water, makes acoustic communication the most widely used technique in USNs. Although the deployment of USNs can be realized using a number of different approaches, it remains a significant challenge due to the inherent difficulties posed by the underwater
Section 2 presents a detailed literature survey on underwater sensor networks, while it also presents an overview of the artificial neural network designed to control a multiboat group. Before a deployment mission, a map of the deployment zone and optimal locations of USN nodes, provided by the USN deployment module, are fed into the onboard computers of the boats. The boats process the data and determine the paths that they are going to follow in order to deploy the USN nodes at the predetermined optimal locations. As proven by the simulation studies presented in this study, the use of ANNs reduces the path errors considerably compared to the traditional control approaches. We also investigate the tradeoffs between energy consumption, end-to-end delay, and number of hops for the case of USN. Although similar problems were investigated in previous works [4–6], the obtained results are not sufficient for the particular scenario examined in this paper. Numerical results in this study demonstrate the theoretical derivations.

The remainder of the paper is organized as follows. Section 2 presents a detailed literature survey on underwater sensor network deployment approaches. Section 3 presents a novel strategy for the deployment of USNs and gives the results obtained from a set of simulation studies, which were carried out for the evaluation of this approach. Section 4 provides a detailed description for the implementation of an artificial neural network designed to control a multiboat group that is responsible for the deployment of underwater sensor networks, while it also presents an overview of the performance evaluation results. Finally, Section 5 concludes the paper.

2. Related Work

In recent years, USNs (e.g., cf. Figure 1) have considerably drawn attention of the research communities. Although they offer numerous advantages in several different application scenarios, they come with many issues that need to be addressed. Therefore, factors associated with the success or failure regarding the implementation of USNs should be identified and subsequently handled in an appropriate way. As it has been shown by both simulation studies and field tests, one of the most important phases of all the sensor network implementations is the deployment phase which can be realized in an attended or unattended manner [7, 8]. Since USN implementations are much harder than other sensor network implementations and they are associated with several performance related factors, the attended deployment approaches offer considerable advantages over the unattended ones, including cost-effectiveness.

The most important objectives of an efficient USN deployment are (i) to provide full-connectivity coverage and (ii) to optimize the USN lifetime. However, the performance of USNs is greatly limited by the low-bandwidth and high propagation delay of underwater acoustic communications [9, 10]. In this regard, several network-related factors such as the packet reception rate and the delay and throughput, as well as node related factors, such as the transceiver power, the battery, and the CPU power, should be taken into consideration [11]. In [9], Felamban et al. define an optimal node placement strategy for USNs in order to obtain maximum coverage and connectivity with minimum transmission loss. By taking the characteristics of underwater acoustic channels, the authors formulated this problem as a nonlinear programming model. The authors proved that the number of USN nodes required to cover a definite volume depends on the operating frequency. When it is increased, more nodes are required with short internode distances in order to maintain a transmission loss threshold. Due to the abovementioned limitations of USNs, most studies have been focused on specific techniques to enhance USN performance metrics. Ibrahim et al. propose the use of multiple surface-level gateways to improve end-to-end delay and reduce energy consumption by distributing traffic loads [10, 12]. The authors show the significant advantages of their approach.

USN deployments can be realized using different manned or unmanned vehicles including boats and aerial vehicles. Before deployment, the deployment locations of sensor nodes and a map of the deployment site are loaded to the onboard computer of the vehicle or are provided to the human operator. This can be realized online during deployment, too. To realize USN deployments, unmanned autonomous vehicles need an accurate navigation system. In [13], Erckens et al. present a special navigation system that plans an optimal navigation course and efficiently controls an unmanned boat vessel called “Avalon boat” on this course. The navigation system is based on a novel path planner that generates the fastest path to a given destination and is able to avoid both static and dynamic obstacles [13]. While a boat moves on the sea or ocean, it is exposed to several uncontrollable factors that may affect its direction. For unmanned autonomous boats, it is difficult to obtain an accurate model and it requires a lot of sensors to feed a proper controller [14, 15].
A simple boat model which relates the most important variables and concentrates on data that can be provided by low-cost sensors is proposed in [14]. As proven in many field tests, autonomous boat navigation systems cannot easily replace human operators due to uncontrollable factors such as wind and waves [16, 17]. On the other hand, knowledge of sailing experts can be transformed into a fuzzy interference system in order to steer sails and rudder according to weather conditions and target [16].

However, all the aforementioned deployment algorithms are either driven by the deployment cost or performance related factors like the network lifetime. Furthermore, they do not focus on the navigation accuracy of the vehicles that deploy the sensor nodes. Our approach differs from the related studies since it combines a performance-driven deployment scheme with an ANN-based path-following system used for the realization of an USN deployment.

3. Efficient Node Placement for Balanced Energy Consumption and End-to-End Delay of a Multiple-Hop USN

In the following, we present a simulation study to reveal the communication related tradeoffs arising for an acoustic wave USN deployed in a model dam. The USN consists of two entities: the relay nodes and the surface gateway. A sufficient number of nodes are deployed to cover a certain underwater volume, in this case the volume of an orthogonal shallow dam model. The surface of this dam is 3.391 km², while the depth is 26.3 m. Each node can be deployed in any position, while the location of the gateway node is known. Since the sensor nodes communicate with each other using acoustic links, the path loss is caused by two phenomena: the energy (geometric) spreading and the wave absorption. The energy spreading mainly depends on the transmission range of the acoustic waves [19], while the wave absorption is frequency-dependent; that is, high frequency signals are more vulnerable to absorption loss due to the conversion of acoustic energy to heat. The nodes in the USN are powered by batteries and hence they should be properly placed to reduce path loss and energy consumption. Then, these nodes will maintain their location using various means of location and depth adjustments.

Two-dimensional (2D) shallow-water acoustic communications were considered, since the depth is set to 26.3 m. In this case, the acoustic signals propagate within a cylinder bounded by the surface and the sea floor; that is, cylindrical spreading applies and the signal spreads horizontally due to low depth [20]. We assume that all nodes are equipped with homogenous transceivers and have a cylindrical based communication with a radius of $d$, where $d$ is assumed to be constant for all nodes. Two nodes are connected if the node interdistance is less than or equal to $d_{\text{max}}$. The number of nodes is inversely proportional to the volume covered by the nodes. We further assume that all nodes in the network transmit with a uniform transmission power. Let the node $N$ be located at a distance of $D$ from gateway. In general, this node sends its data packets to the gateway over a multiple-hop path, denoted by $h_1, h_2, h_3, \ldots h_n$ [6].

Underwater sound propagation is described using the Sonar equations [19]. The source signal level (which is related to the transmission power intensity and hence to the transmission power $P_t$ of the transceiver) of an emitted underwater acoustic signal can be expressed by the following passive sonar equation [20]:

$$SL = TL + NL + SNR - DI,$$  

where $TL$ is the transmission loss, $NL$ is the ambient noise level, $SNR$ is the signal-to-noise ratio at the receiver, and $DI$ is the directivity index. In general, $NL$ decreases with increasing frequency and also decreases at great depths, since most noise sources are at the surface. Thus, it is greater in shallow water than in deep water, since noise is trapped between water floor and surface. Factors contributing to the ambient noise level in shallow water networks include waves, shipping traffic, wind level, biological noise, seaquakes, and volcanic activity. The impact of each of these factors on the ambient noise level depends on the particular setting. In this paper, we consider an average value for the ambient noise level to be 50 dB as a representative shallow water case, based on several studies of shallow water noise measurements [19, 21] and our particular scenario. By assuming omnidirectional hydrophones, the directivity index is set to zero. Through the above assumptions, we can express the source level $SL$ intensity as a function of $TL$ and $SNR$ only:

$$SL = TL + SNR + 50.$$  

Since cylindrical spreading applies for shallow waters, the transmission loss in dB is approximated as [19]

$$TL = 10 \log d + ad \times 10^{-3} + A,$$  

where $d$ accounts for the distance between source and receiver in meters and $a$ is the frequency-dependent medium absorption coefficient. Note that $A$ denotes the transmission anomaly, which results from degradation of the acoustic intensity caused by multiple path propagation, refraction, diffraction, and scattering of sound. This value is usually between 5 and 10 dB and is higher for shallow-water horizontal links, where multipath effects are higher. Furthermore, $SL$ is related to the transmitted signal intensity at 1 m from the source according to the following expression:

$$SL = 10 \log \frac{I_s}{1 \mu Pa},$$  

where the intensity $I_s$ of an underwater signal is in $\mu Pa$.

Solving for $I_s$ yields

$$I_s = 10^{SL/10} \times 0.67 \times 10^{-18},$$  

in Watts/m², where the constant converts $\mu Pa$ into Watts/m². The transmission power $P_t$ needed to achieve an intensity $I_s$ at a distance of 1 m from the source in the direction of the receiver is expressed as [19]

$$P_t = 2\pi \times 1 \text{ m} \times H \times I_s,$$  

in Watts, where $H$ is the water depth in m.
We assume 16-quadrature amplitude modulation (QAM) and orthogonal frequency division multiplexing (OFDM) encoding method. Then, the bit error rate (BER) is derived as [22]

\[ P_b^{16\text{QAM}} = \frac{3}{2k} \text{erfc} \left( \sqrt{\frac{k E_b}{10 N_0}} \right), \]  

(7)

where \( k \) is \( \log_{16} \) and \( E_b/N_0 = \text{SNR}(B_N/R) \) is the energy per-bit-to-noise power spectral density ratio, \( B_N \) is the noise bandwidth in Hz, and \( R \) is the data rate in bps.

The propagation time in seconds for a distance \( d \) in meters is

\[ t_{\text{prop}} = \frac{d}{c_{\text{acw}}}, \]

(8)

where \( c_{\text{acw}} \) is the propagation velocity of the acoustic waves in water and depends on environmental parameters, such as water temperature, salinity, and depth. Contention-based medium access control (MAC) protocols, for example, aloha and carrier sense multiple access (CSMA), unsatisfactorily perform in USNs [23]. Hence, the time division multiple access (TDMA) MAC protocol is considered [5], in order to evaluate the end-to-end delay in the string USN. This protocol allocates to each node an exclusive time-slot for communication and guarantees collision-free media access. This behavior allows for the reduction of the transceiver state switches and preamble transmissions to save more energy. The end-to-end delay of multiple-hop string network is given by [5]

\[ \text{Delay} = n (t_{\text{prop}(i,i+1)} + t_{\text{pkt}}), \]

(9)

where \( t_{\text{prop}(i,i+1)} \) is the propagation time between nodes \( i \) and \( i+1 \), \( n \) is the number of hops, and

\[ t_{\text{pkt}} = \frac{\text{Packet length}}{\text{Data rate}} \]

(10)

is the time required to transmit data packet.

3.1. USN Simulation Results. In this subsection, we investigate the influence of placing middle nodes to convey information from a source to a destination on the energy consumption and the end-to-end delay. Based on the measurements of medium absorption in shallow water conducted at temperatures between 4°C and 20°C [24] and considering that \( f = 40 \text{KHz} \), the value of the average medium absorption \( a \) is set to 8.96 dB/km. The mean depth of the orthogonal dam is \( H = 26.3 \text{m} \) and the transmission anomaly \( A \) was set to 5 dB. Moreover, the propagation velocity \( c_{\text{acw}} \) of acoustic waves in water can be empirically estimated using the formula in [25]. In particular, the mean water temperature is set to 15°C and the propagation velocity is equal to 1466 m/s. In addition, the packet length, the data rate for each node, and the noise bandwidth are set to 512 bit, 1 Kbps (this bit rate is well within the bit rates of current hydrophones [26]), and 1 kHz, respectively.

Figure 2 demonstrates the total energy consumption (normalized transmission power \( P_t \)) of the USN, when sending a single packet. In order to obtain the required transmission power \( P_t \) for signal transmissions at a given distance \( d \) and frequency \( f \), one can initially compute the transmission loss TL in (3). Then, using (2) and (5), the source level SL and the intensity \( I_t \) of an underwater signal can be computed, respectively. Using (6), the corresponding transmission power \( P_t \) needed to achieve intensity \( I_t \) can be computed. The normalized transmission power is obtained by dividing all the values of \( P_t \) by the maximum value of \( P_t \). Since the surface of the orthogonal dam is 3.391 km², it is assumed that the sides of the orthogonal surface are \( a = 1 \text{km} \) and \( b = 3.391 \text{km} \). Hence, reasonable distances between nodes of 50 m, 100 m, 200 m, and 400 m are considered at depth of 26.3 m, while the BER is set to 10⁻⁹. The number of nodes within the dam required for full coverage is related to the distance between the nodes. For instance, considering that this distance is constant and equal to 400 m, 2 nodes can be placed alongside \( a \), while 8 nodes can be placed alongside \( b \). Thus, overall 16 nodes are required. The results indicate that the total energy consumption is reduced, as the number of hops increases. In particular, the total energy consumption reduces by approximately 10%, 15%, 30%, and 50% for links with distances of 50 m, 100 m, 200 m, and 400 m, respectively. These results also show that the total energy consumption insignificantly changes, when the number of hops is greater than 10.

Using (8)–(10), Figure 3 depicts the normalized end-to-end delay in string USN as a function of the number of hops for distances between nodes of 50 m, 100 m, 200 m, and 400 m at depth of 26.3 m. The normalization is obtained by dividing all the values of the delay by its maximum value. One observes that the end-to-end delay almost linearly increases with the augmentation of hops. However, the distance between nodes slightly affects the end-to-end delay. Thus, the number of hops should be carefully determined to compromise energy consumption and end-to-end delay.

4. Artificial Neural Network-Based Control of a Multiboat Group

An ANN is essentially a parallel distributed processor made up of simple processing units that has an inherent trend for storing empirical knowledge and making it available for
use [27]. Multilayer feed-forward neural networks (NNs) are widely used, while their training is based on the minimization of an error function. Specifically, backpropagation (BP) is a well-known training method that is used in the case of multilayer feed-forward NNs. BP learning uses the gradient descent procedure to determine the connection weights [28].

The multilayer feed-forward NNs consist of one input layer, one or more hidden layers, and one output layer. Each layer is composed of neurons which are connected to the neurons of the neighboring layers. Each connection link is characterized by a weight. The evolution of the online supervised training of multilayer perceptrons has been further raised by the development of the BP algorithm. The following equations summarize the main steps of the BP algorithm. Consider

\[ o_j = f \left( \text{net}_j \right) = f \left( x \right) \text{ then net}_j = \sum_i w_{ji} o_i + \theta_j \]  
\[ E_p = \frac{1}{2} \sum_{j \in \text{out.}} \left( t_{pj} - o_{pj} \right)^2 \]  
\[ \delta_{pj} = \left( t_{pj} - o_{pj} \right) \]  
\[ \Delta_p w_{ji} = -\varepsilon \left( \frac{\partial E_p}{\partial w_{ji}} \right) \]  
\[ \Delta_p \theta_j = -\varepsilon \left( \frac{\partial E_p}{\partial \theta_j} \right) \]  

where \( j \) is the layer number and \( i \) is the neuron number; \( o_j \) is the output, net \( j \) is the weighted sum, and \( \theta_j \) is the bias, respectively, while \( w_{ji} \) is the weight characterizing the connection; \( \varepsilon \) is the learning rate, \( \delta_{pj} \) represents the error value in layer \( j \), \( t_{pj} \) is the target output, and \( o_{pj} \) is the actual output. Equation (12) is used to estimate the total error in the output layer for the \( p \)th sample pattern, the error that is eventually minimized by changing the weights and biases using gradient descent (13).

The optimization method known as Levenberg-Marquardt algorithm [29] was used for the development of the proposed NN. This technique, due to Levenberg [30] and Marquardt [31], is a combination of the following two methods [32, 33]:

(i) the Gauss-Newton’s method approaches rapidly near to a global or local minimum but sometimes may deviate;

(ii) the Gradient descent method certainly approaches through a proper selection of step size parameter but does slowly.

Figures 4 and 5 illustrate the block diagrams and the architecture of the developed ANN.

4.1. Performance Evaluation of the Proposed ANN Model. As already mentioned, this study proposes the use of an ANN model for the determination of the path trajectories of multiboat groups used for the deployment of USNs. Lake Buyukcekmece, Istanbul, Turkey, was selected as the application area. It is the major water resource of Istanbul, Turkey, and is located in the Architect Sinan District of Istanbul, on the coast of the Marmara Sea. The lake is 7 kilometers long, 2 kilometers wide, with an average depth of 8.6 meters. It covers an area of 28.47 km\(^2\). The Buyukcekmece Dam was built on the sea side of the lake. Besides that, the lake is available for fishing, energy generation, tourism, and irrigation.

In this simulation study, three autonomous boats belonging to a multiboat group in the Lake Buyukcekmece were initially considered at three different static points, while a static target point was also considered. The main objective of this study was that these boats should track a predefined path through which each boat arrives at the target point and then the second and the third boats track the same path to the opposite direction in order to go back to their original positions, while the first boat tracks a different path to go to a new static target point.

The simulated results were obtained using MATLAB Neural Network Toolbox [18] and they were compared to
their corresponding actual datasets. Eloquent figures showing both actual and estimated trajectories, marking the coordinates during the progressive movement of the boats, are given for the evaluation of the effectiveness of the proposed method. The data used to develop the NN model were based on a virtual x-y plane coordinate system, where "X" and "Y" were the input variables, while "X", (standing for X of target) and "Y", (standing for Y of target) were the output variables. The paths of the boats on the virtual x-y plane are shown in Figure 6. The length unit of the virtual plain grid corresponds to 120 meters in either direction.

Boat 1 was initially located at the virtual x-y plane position (10, 76), Boat 2 at (24, 50), and Boat 3 at (44, 21). There was a target point which was located at the static position (27, 34). All three boats followed a specific, predefined path to reach the target point. Then, the second and the third ones went back to their original positions, (10, 76) and (44, 21), respectively, while the first one tracked a different path to go to a new target point located at (34, 34). The full dataset used in this study is given in Table 1 and comprises 164 sets of input-output variables values.

The developed ANN model is a 1-input layer, 2 hidden layers (comprising 24 and 22 nodes, resp.), and 1-output layer. As already mentioned, the Levenberg-Marquardt optimization algorithm was used since it presents certain advantages against the simple BP [34]. Table 2 shows the test dataset, while Table 3 shows the corresponding ANN results for the test data. The comparison of the training dataset with the corresponding ANN results for Boat 1, Boat 2, and Boat 3 is given in Figures 7, 8, and 9, respectively. Figure 10 shows a combined view of the training datasets and ANN obtained positions for all three boats.

Before entering the ANN model, the input dataset was normalized for more reliable results and then rescaled to the original dataset. The activation functions used for the neurons of the proposed ANN model were tangent-sigmoid functions for the 2 hidden layers and linear transfer functions for the output layer. In addition, specific algorithms such as the one proposed in [35] can be implemented in order to speed up the convergence of ANN training phase.

The performance of the NN model and regression between target and NN output are shown in Figures 11 and 12, respectively.
Table 1: Dataset used for the ANN model. The column label "Step" refers to the sequential progressive movement of each boat, while \( B_j \), \( j = 1, 2, 3 \), corresponds to the movement from the original location of each boat (indicated by \( j \)) to the first target, at \((27, 34)\), while \( B_j \text{back} \), \( j = 1, 2, 3 \), corresponds to the next mission, that is, return to original locations for Boat 2 and Boat 3, while movement to a new target, at \((34, 34)\), for Boat 1.

| Step | Boat | X | Y | X' | Y' |
|------|------|---|---|----|----|
| 1    | 10   | 76| 10| 75 |    |
| 2    | 10   | 75| 10| 74 |    |
| 3    | 10   | 74| 10| 73 |    |
| 4    | 10   | 73| 10| 72 |    |
| 5    | 10   | 72| 10| 71 |    |
| 6    | 10   | 71| 10| 70 |    |
| 7    | 10   | 70| 10| 69 |    |
| 8    | 10   | 69| 10| 68 |    |
| 9    | 10   | 68| 10| 67 |    |
| 10   | 10   | 67| 10| 66 |    |
| 11   | 10   | 66| 10| 65 |    |
| 12   | 10   | 65| 10| 64 |    |
| 13   | 10   | 64| 10| 63 |    |
| 14   | 10   | 63| 10| 62 |    |
| 15   | 10   | 62| 10| 61 |    |
| 16   | 10   | 61| 10| 60 |    |
| 17   | 10   | 60| 10| 59 |    |
| 18   | 10   | 59| 10| 58 |    |
| 19   | 10   | 58| 10| 57 |    |
| 20   | 10   | 57| 10| 56 |    |
| 21   | 10   | 56| 10| 55 |    |
| 22   | 10   | 55| 10| 54 |    |
| 23   | 10   | 54| 10| 53 |    |
| 24   | 10   | 53| 10| 52 |    |
| 25   | 10   | 52| 10| 51 |    |
| 26   | 10   | 51| 10| 50 |    |
| 27   | 10   | 50| 10| 49 |    |
| 28   | 10   | 49| 10| 48 |    |
| 29   | 10   | 48| 10| 47 |    |
| 30   | 10   | 47| 10| 46 |    |
| 31   | 10   | 46| 10| 46 |    |
| 32   | 11   | 46| 12| 46 |    |
| 33   | 12   | 46| 13| 46 |    |
| 34   | 13   | 46| 14| 46 |    |
| 35   | 14   | 46| 15| 46 |    |
| 36   | 15   | 46| 16| 46 |    |
| 37   | 16   | 46| 17| 46 |    |
| 38   | 17   | 46| 18| 46 |    |
| 39   | 18   | 46| 19| 46 |    |
| 40   | 19   | 46| 19| 45 |    |
| 41   | 19   | 45| 19| 44 |    |
| 42   | 19   | 44| 19| 43 |    |
| 43   | 19   | 43| 19| 42 |    |
| 44   | 19   | 42| 19| 41 |    |
| 45   | 19   | 41| 19| 40 |    |
| 46   | 19   | 40| 19| 39 |    |
| 47   | 19   | 39| 19| 38 |    |
| 48   | 19   | 38| 19| 37 |    |
Table 1: Continued.

| Step | Boat | X | Y | X_i | Y_i |
|------|------|---|---|-----|-----|
| 49   | 19   | 37 | 19 | 36  |
| 50   | 19   | 36 | 19 | 35  |
| 51   | 19   | 35 | 19 | 34  |
| 52   | 19   | 34 | 20 | 34  |
| 53   | 20   | 34 | 21 | 34  |
| 54   | 21   | 34 | 22 | 34  |
| 55   | 22   | 34 | 23 | 34  |
| 56   | 23   | 34 | 24 | 34  |
| 57   | 24   | 34 | 25 | 34  |
| 58   | 25   | 34 | 26 | 34  |
| 59   | 26   | 34 | 27 | 34  |
| 60   | 24   | 50 | 24 | 49  |
| 61   | 24   | 49 | 24 | 48  |
| 62   | 24   | 48 | 24 | 47  |
| 63   | 24   | 47 | 24 | 46  |
| 64   | 24   | 46 | 24 | 45  |
| 65   | 24   | 45 | 25 | 45  |
| 66   | 25   | 45 | 26 | 45  |
| 67   | 26   | 45 | 27 | 45  |
| 68   | 27   | 45 | 27 | 44  |
| 69   | 27   | 44 | 27 | 43  |
| 70   | 27   | 43 | 27 | 42  |
| 71   | 27   | 42 | 27 | 41  |
| 72   | 27   | 41 | 27 | 40  |
| 73   | 27   | 40 | 27 | 39  |
| 74   | 27   | 39 | 27 | 38  |
| 75   | 27   | 38 | 27 | 37  |
| 76   | 27   | 37 | 27 | 36  |
| 77   | 27   | 36 | 27 | 35  |
| 78   | 27   | 35 | 27 | 34  |
| 79   | 44   | 21 | 43 | 21  |
| 80   | 43   | 21 | 42 | 21  |
| 81   | 42   | 21 | 41 | 21  |
| 82   | 41   | 21 | 40 | 21  |
| 83   | 40   | 21 | 39 | 21  |
| 84   | 39   | 21 | 38 | 21  |
| 85   | 38   | 21 | 37 | 21  |
| 86   | 37   | 21 | 36 | 21  |
| 87   | 36   | 21 | 35 | 21  |
| 88   | 35   | 21 | 34 | 21  |
| 89   | 34   | 21 | 33 | 21  |
| 90   | 33   | 21 | 32 | 21  |
| 91   | 32   | 21 | 31 | 21  |
| 92   | 31   | 21 | 30 | 21  |
| 93   | 30   | 21 | 29 | 21  |
| 94   | 29   | 21 | 28 | 21  |
| 95   | 28   | 21 | 27 | 21  |
| 96   | 27   | 21 | 27 | 22  |
| 97   | 27   | 22 | 27 | 23  |
| 98   | 27   | 23 | 27 | 24  |
| 99   | 27   | 24 | 27 | 25  |
### Table 1: Continued.

| Step | Boat | $X$ | $Y$ | $X_t$ | $Y_t$ |
|------|------|-----|-----|-------|-------|
| 100  |      | 27  | 25  | 27    | 26    |
| 101  |      | 27  | 26  | 27    | 27    |
| 102  |      | 27  | 27  | 27    | 28    |
| 103  |      | 27  | 28  | 27    | 29    |
| 104  |      | 27  | 29  | 27    | 30    |
| 105  |      | 27  | 30  | 27    | 31    |
| 106  |      | 27  | 31  | 27    | 32    |
| 107  |      | 27  | 32  | 27    | 33    |
| 108  |      | 27  | 33  | 27    | 34    |
| 109  |      | 27  | 34  | 28    | 34    |
| 110  |      | 28  | 34  | 29    | 34    |
| 111  |      | 29  | 34  | 30    | 34    |
| 112  |      | 30  | 34  | 31    | 34    |
| 113  |      | 31  | 34  | 32    | 34    |
| 114  |      | 32  | 34  | 33    | 34    |
| 115  |      | 33  | 34  | 34    | 34    |
| 116  |      | 27  | 34  | 27    | 35    |
| 117  |      | 27  | 35  | 27    | 36    |
| 118  |      | 27  | 36  | 27    | 37    |
| 119  |      | 27  | 37  | 27    | 38    |
| 120  |      | 27  | 38  | 27    | 39    |
| 121  |      | 27  | 39  | 27    | 40    |
| 122  |      | 27  | 40  | 27    | 41    |
| 123  |      | 27  | 41  | 27    | 42    |
| 124  |      | 27  | 42  | 27    | 43    |
| 125  |      | 27  | 43  | 27    | 44    |
| 126  |      | 27  | 44  | 27    | 45    |
| 127  |      | 27  | 45  | 27    | 45    |
| 128  |      | 26  | 45  | 25    | 45    |
| 129  |      | 25  | 45  | 24    | 45    |
| 130  |      | 24  | 45  | 24    | 46    |
| 131  |      | 24  | 46  | 24    | 47    |
| 132  |      | 24  | 47  | 24    | 48    |
| 133  |      | 24  | 48  | 24    | 49    |
| 134  |      | 24  | 49  | 24    | 50    |
| 135  |      | 27  | 34  | 27    | 33    |
| 136  |      | 27  | 33  | 27    | 32    |
| 137  |      | 27  | 32  | 27    | 31    |
| 138  |      | 27  | 31  | 27    | 30    |
| 139  |      | 27  | 30  | 27    | 29    |
| 140  |      | 27  | 29  | 27    | 28    |
| 141  |      | 27  | 28  | 27    | 27    |
| 142  |      | 27  | 27  | 27    | 26    |
| 143  |      | 27  | 26  | 27    | 25    |
| 144  |      | 27  | 25  | 27    | 24    |
| 145  |      | 27  | 24  | 27    | 23    |
| 146  |      | 27  | 23  | 27    | 22    |
| 147  |      | 27  | 22  | 27    | 21    |
| 148  |      | 27  | 21  | 28    | 21    |
| 149  |      | 28  | 21  | 29    | 21    |
| 150  |      | 29  | 21  | 30    | 21    |
**Table 1: Continued.**

| Step | Boat | X | Y | X’ | Y’ |
|------|------|---|---|----|----|
| 151  | 30   | 21| 31 | 21 |
| 152  | 31   | 21| 32 | 21 |
| 153  | 32   | 21| 33 | 21 |
| 154  | 33   | 21| 34 | 21 |
| 155  | 34   | 21| 35 | 21 |
| 156  | 35   | 21| 36 | 21 |
| 157  | 36   | 21| 37 | 21 |
| 158  | 37   | 21| 38 | 21 |
| 159  | 38   | 21| 39 | 21 |
| 160  | 39   | 21| 40 | 21 |
| 161  | 40   | 21| 41 | 21 |
| 162  | 41   | 21| 42 | 21 |
| 163  | 42   | 21| 43 | 21 |
| 164  | 43   | 21| 44 | 21 |

**Table 2: Dataset for test.**

| X | Y |
|---|---|
| 10 | 47 |
| 11 | 46 |
| 18 | 46 |
| 19 | 45 |
| 19 | 35 |
| 20 | 34 |
| 24 | 47 |
| 27 | 45 |
| 36 | 21 |
| 28 | 21 |
| 27 | 22 |
| 27 | 29 |
| 30 | 34 |
| 27 | 43 |
| 24 | 45 |
| 27 | 29 |
| 27 | 22 |
| 28 | 21 |
| 36 | 21 |

**Table 3: ANNs results.**

| X | Y |
|---|---|
| 10.265003 | 46.587496 |
| 11.908684 | 46.203325 |
| 18.681534 | 45.940821 |
| 19.034220 | 44.207650 |
| 19.310665 | 34.966706 |
| 20.778849 | 34.432972 |
| 23.709556 | 47.529866 |
| 25.610589 | 45.114751 |
| 36.037393 | 21.191301 |
| 28.188850 | 21.252901 |
| 27.281613 | 22.342490 |
| 27.129286 | 29.131046 |
| 30.808445 | 33.931133 |
| 26.750776 | 42.699318 |
| 24.745857 | 45.002582 |
| 27.129286 | 29.131046 |
| 27.281613 | 22.342490 |
| 28.188850 | 21.252901 |
| 36.037393 | 21.191301 |

**5. Conclusion**

In this paper, an unattended deployment approach for underwater sensor networks has been proposed. The proposed approach combines an efficient node placement strategy with an artificial neural network- (ANN-) based control system in order to drive an autonomous multiboat for deploying underwater sensor network (USN) nodes. The node placement strategy provides balanced energy consumption and reduces end-to-end delay of the USN nodes.

Performance results in this paper have shown that the proposed ANN-based control system can drive an autonomous multiboat group to enable them to follow a predefined path set successfully in order to deploy USN.
nodes. In addition, a set of performance evaluations has been performed to show the efficiency of the proposed node placement strategy. The tradeoffs between energy consumption, end-to-end delay, and number of hops in string network have been also investigated. The results revealed that increasing the hops in the acoustic link almost linearly increases end-to-end delay but reduces the total network energy consumption. These results can be used to determine the number of hops that satisfy the energy consumption and end-to-end delay requirements.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgment

This research has been supported by Yildiz Technical University Scientific Research Projects Coordination Department, Project no. 2013-04-04-KAP02.

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