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An artificial neural network approach to the problem of wireless sensors network localization

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ABSTRACT

One of the imperative problems in the realm of wireless sensor networks is the problem of wireless sensors localization. Despite the fact that much research has been conducted in this area, many of the proposed approaches produce unsatisfactory results when exposed to the harsh, uncertain, noisy conditions of a manufacturing environment. In this study, we develop an artificial neural network approach to moderate the effect of the miscellaneous noise sources and harsh factory conditions on the localization of the wireless sensors. Special attention is given to investigate the effect of blockage and ambient conditions on the accuracy of mobile node localization. A simulator, simulating the noisy and dynamic shop conditions of manufacturing environments, is employed to examine the neural network proposed. The neural network performance is also validated through some actual experiments in real-world environment prone to different sources of noise and signal attenuation. The simulation and experimental results demonstrate the effectiveness and accuracy of the proposed methodology.

1. Introduction

Localization of wireless mobile nodes in wireless sensor networks (WSN) has been widely used in different applications including but not limited to tracking AGVs (automated guided vehicle), robot navigating and large scale metrology [1] among others. Besides the direct applications of localization in wireless mobile sensors, they play a crucial role in the fundamental protocols of wireless sensor networks such as sensor network quality of coverage using the location of active nodes, controlling wireless network topology based on geometric techniques, geographic routing of messages among wireless sensor nodes based on the location of the current node, its neighbor nodes, and the destination node and location information of certain events captured by wireless sensors [2]. Localization refers to the problem of determining the location or position of wireless sensors in the wireless sensor network filed [3].

In this study, we attempt to find the location of mobile sensor nodes in the harsh, uncertain, dynamic, and noisy conditions of manufacturing environments using some beacon nodes called simply beacons or anchor nodes. The locations of the anchor nodes, with respect to a global frame of reference, are known a priori. Among all factors which appear to have significant impact on the performance of the wireless sensor nodes localization in manufacturing environments, we take into consideration noise sources, physical obstructions and ambient conditions for further investigation.

Signal attenuation constitutes numerous phenomena, each of which impact strength of signals in a way. The distance between transducers, the misalignment angle between transmitter and receiver transducer (in case of ultrasonic signals), ambient conditions (especially for acoustic signals), and multipath are among the phenomena that impact the signal attenuation. Path loss model is also affected by the environment. The presence of a plethora of obstacles in indoor environments in general, and manufacturing environments in particular, makes the signal propagation model and path loss model different from open field environments. Obstacles can reflect and diffract signals toward a different direction or even worse scatter them in many directions. The aforementioned phenomena can have both a destructive and a constructive effect on the propagation of the signals. They can cause interference – hence having deteriorative effect – or they can propagate the signals toward areas where there is no clear line of sight. Moreover, the destructive effect of noise sources in a manufacturing environment, including but not limited to vibration sources and diverse electrical and electronic systems, can deteriorate the signal attenuation to an even higher extent. These noise sources eventually beget some measurement errors when the localization of wireless sensor nodes is undertaken.

As discussed, one group of factors which affect the performance of the wireless sensor nodes localization are the ambient

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conditions. The level of humidity, temperature and the medium pressure are three main factors that are particularly important when it comes to sonic and ultrasonic waves.

Finally, among all aforementioned factors, perhaps the most destructive impact on the performance of wireless sensor networks belongs to obstruction. In a typical manufacturing environment, there exist tens or hundreds of machines, workers, conveyors, vehicles and forklift trucks among other solid bodies each of which can be accounted as an obstruction for the carrier waves. The carrier waves which encounter a solid body either go through the new medium and become refracted and attenuated, or return to the originated medium and become deflected, diffracted, and scattered; finally, they propagate in the medium in different directions. In either case, the signal waves may become so much attenuated that they may no longer be perceived by any other wireless sensor nodes.

The novelty of this study lies in investigating the impact of different interfering factors on the localization of wireless sensor networks in indoor environments in general and in manufacturing environments in particular. Subsequently, we present a neural based technique to reduce the impact of the interfering factors on the localization of wireless sensor networks. A simulation study following with statistical analysis is devised to examine the proposed technique's performance in comparison with a conventional trilateration technique. Finally, actual experiments are conducted to validate the performance of the proposed technique in indoor environments. The commonly used cricket devices developed by MIT and produced by Crossbow [4] are employed to perform the experiments.

The remainder of the paper is organized as follows. Section 2 presents some background and literature review on wireless sensor networks in general, localization of wireless sensor nodes, and some industrial applications of wireless sensor nodes localization. The third section sheds light on the problem at hand in more detail. Section 4 elucidates the undertaken approaches and methodologies. Subsequently, the fifth and sixth sections illustrate the simulation study and experimental results respectively. Finally, the last section presents our conclusions and future work.

2. Background

2.1. Wireless sensor networks

The wireless sensors in wireless sensor networks can be categorized based on their ability to move. With this regard, a wireless sensor can be mobile, hence having the capability of changing its position from time to time and as needs arises, or it can be static, thus having always the same location through its life-cycle in the network [2].

In the former scenario, the necessity of localization of wireless sensors is self-evident. The mobile wireless sensors move from place to place collecting data and interacting with the physical environment, and whenever they are within the range of other mobile or static nodes (sink nods for instance) they can communicate the collected data. In general, mobile wireless sensors have all the abilities of a static one, such as sensing and monitoring, communication, and processing, yet they are equipped with the extra potential for changing position. A mobile wireless sensor can either be self-propelled and be in control of its trajectory such as AGVs (automated guided vehicles) or mobile robots, or it can monitor the physical property of interest while being mounted on mobile vehicles or even animals, hence not having any control on the path it is on. In either case, localization plays an imperative role on many wireless sensor network applications and protocols. As a case in point, once an event is monitored by a mobile wireless sensor, the location of the reported event can become of paramount importance.

However, the localization can be even of the same importance in case of static wireless sensor networks. In some application of static wireless sensor networks – especially in large scale outdoor applications such as environment monitoring – the wireless sensor may be deployed on an ad hoc fashion: for instance, they can be spread out in the environment on a random basis without any prior knowledge about their employed locations. In this case, although static, the location of the wireless nodes becomes also important.

2.2. Sensor node localization

Global positioning system (GPS) has been long used for positioning especially in outdoor environments. However, when it comes to indoor applications or outdoor applications with large-scale obstructions, such as dense foliage areas or metropolitan areas with high-rise structures, the GPS system reaches its limits [3,5]. Ref. [2] extensively studies different positioning systems designed particularly for wireless sensor networks. According to the WSN localization technique taxonomy introduced by Ref. [2], the localization techniques are either range-based or range-free. In case of range-based localization methods, the precise distance from the wireless sensor node of interest to other wireless sensor nodes in general and to reference nodes in particular is estimated and then employed to find the location of the wireless sensor node of interest. The reference nodes whose locations are known a priori and have the capacity to send/receive beacon messages to/from other nodes are referred as anchor nodes or sometimes beacons. On the other hand, in the range-free methods, only a coarse approximation of the distance between nodes is used to estimate the whereabouts of a wireless sensor node. The latter techniques are usually more cost efficient and require less complex hardware [2].

The range-based techniques can be further classified into two categories, namely methods with anchor nodes and methods without anchor nodes. The former, refers to the methods employing anchor nodes, the position of which is known a priori, and are able to find the absolute location of the wireless sensors with respect to a global frame of reference. On the contrary, in the latter approach, the anchor nodes are not used. Thus, the relative locations of the wireless sensors with respect to a local frame of reference are of interest. For further information about range-based techniques, one may refer to reference [2].

The range-free techniques can be also categorized into two main classes: hop-count-based methods and area-based methods. It is noteworthy that methods in this category can estimate a rough approximation of location of wireless sensors. The former technique is especially suitable for multiple-hops networks. That is, if the network field is too large for the wireless sensors to communicate directly with the anchor nodes, some other sensors can relay the messages from the wireless sensor in the origin to the anchor nodes. The hop-count-based techniques count the number of hops it takes to relay the message from a wireless sensor to an anchor node and then multiply it by the average size of one hop to the anchor node (in terms of distance) to calculate the approximate distance from a particular wireless sensor to an anchor bode. Although producing approximate location of the wireless sensor nodes, this class of techniques is cost efficient and does not require complex hardware [2].

The second class of range-free techniques is area-based methods. In this class of methods, instead of providing the location coordinates of a wireless sensor, the area/region in which the wireless sensor is deployed is given. The logic behind these techniques is that in many applications, there is no need to determine the exact coordinates of a wireless sensor, instead only the area that the wireless sensor node lies would suffice. Thus, only area information of the wireless sensors is determined in this class of localization techniques [2].

One fundamental step in localization of wireless sensor nodes through range-based techniques is measuring the distance or the angle between the node of interest and the reference nodes (anchor nodes) or its neighboring nodes (in case of multiple hops connections to anchor nodes). At least five main techniques for measuring distance or angle between the nodes are discussed in the literature: namely time of arrival (ToA), time difference of arrival (TDoA), received signal strength (RSS), angle of arrival (AoA), and frequency difference of arrival (FDoA) [2].

To estimate the distance between every two neighboring nodes by the ToA method, the time that the signal takes to travel from one node to another is measured. If the propagation velocity of the signal is known, then the distance between two nodes can be estimated by multiplying the travel time by the propagation velocity of the signal. As the distance between two nodes can be in the order of, at most, a couple of hundred meters for many wireless sensor networks applications (especially indoor applications), the signals employed in this technique is preferred to have rather slow propagation speed. In fact, the limited resolution of timers is the main reason why sonic and ultrasonic signals are usually used with this technique [6].

In order for the ToA to work properly, time synchronization is required on all communicating nodes. One way to circumvent the time synchronization is by applying a ping–pong style round trip message passing. Further information about this method can be found in Ref. [2]. Another more effective approach to avoid explicit time synchronization is through employing two kinds of signals traveling at different speed such as ultrasound and RF signals. This method leads to another technique for measuring the distance between nodes: time difference of arrival or briefly TDoF. In this method, two kinds of signal are transmitted from the transmitting wireless node. The signals are later received by the receiver wireless node. Given the propagation speed of both signals and the time delay between receiving two signals one after another, one can estimate the distance between the transmitting node and the receiver.

A completely different approach involves estimating the distance between two wireless nodes using the strength of the received signal. The fundamental theory behind the RSS technique is based on the fact that signals strength attenuates as the signals are being propagated into the media. Hence, given the path loss model of a particular medium, the transmission signal strength at the transmitter, and the received signal strength at the receiver, the distance between the transmitter and the receiver can be computed. As an advantage, this technique does not require any additional hardware; yet, as it depends heavily on the precision of the pass loss model, this model may incur erroneous estimations especially when deployed in congested environments of indoor applications, where the pass loss model may be very complex.

Angle-of-arrival (AoA) is another approach used by WSNs localization techniques. However, unlike the last three aforementioned techniques, with this method the angle between sensor nodes or orientation of received signals is of interest. By measuring the angle bearings of incoming signals from at least three reference nodes and by employing triangulation, the surface coordinates of a particular wireless node can be estimated. One potential problem of this approach is the expense of equipment to obtain precise angle estimates [7].

Lastly, frequency difference of arrival (FDoA) is another distance measurement technique in WSNs that measures the difference between received frequencies, transmitted from a single transmitter, at two receivers. Recently more interest is shown in this method. Further information about this method can be found in Ref. [2].

There has been a considerable amount of recent research on the performance of physical WSN nodes using these localization techniques. For example, Priyantha [4] studies cricket WSN nodes for indoor localization. A TDoA technique employing RF and ultrasonic signals is used to measure the distance between the transmitters and listeners. In his studies, he investigates the indoor RF and ultrasound propagation properties. The conducted experiments confirm that the distance between nodes and misalignment between transmitters and receivers have the strongest impact on the accuracy of the cricket indoor localization.

Priyantha et al. [8] propose a hybrid technique based on Kalman filter method to track the mobile devices with cricket location system in indoor environments. In their approach they employ a passive tracking system to localize a mobile node using a constellation of beacons the locations of which are known in advance. The experimental results confirm the better performance of the hybrid Kalman filter technique over the other methods.

Franceschini et al. [9] introduce application of ultrasound transducers for large-scale metrology. In their studies, they deploy cricket motes developed by MIT and Crossbow technology to localize a portable probe: i.e., a probe that is in contact with surface of an object, through a constellation of cricket motes. As cricket motes employ RF and ultrasound signals to measure the distance between nodes through time of flight (ToF) method, the study then follows by investigating the key factors impacting the time of flight. The experimental results again reveal that the distance between transmitter and receiver, and the misalignment between the transducer surface of the transmitter and that of the receiver have the most significant impact on the ToF. They also investigate the impact of node battery level using the ToF approach. The experimental results show that battery level can be important only at the very last stage of battery life, when the battery is about to die. Otherwise, it does not show any significant impact on ToF accuracy.

Localization of a WSN in the presence of different noise sources has attracted considerable attention in the recent years. Moore et al. [10] presented a distributed localization algorithm for location estimation based on the use of a robust quadrilateral. A robust quadrilateral is a fully-connected quadrilateral whose four sub-triangles are robust. By using robust quadrilateral, this method can be adjusted to support noisy measurements, so that it can increase the likelihood of localizing wireless nodes correctly.

Besides the analytical approach taken by some researchers to tackle the noise interference in wireless sensors localization, other researchers have attempted to diminish noise effects by employing artificial intelligence (AI) approaches such as artificial neural network (ANN) and fuzzy logic system (FLS).

Yun et al. [11] proposed two intelligent localization schemes for wireless sensor networks. Both schemes proposed in their study can be fully characterize as range-free localization technique. However, received signal strength is used as input to the intelligent techniques to localize the wireless sensors. The first scheme employs a fuzzy logic system is used to find the position of nodes through the combined sum of the edge weight of each anchor node. A genetic algorithm is used to find the optimal edge weights. The second scheme uses a neural network approach that takes the received signal strength as input and computes the approximate location of wireless nodes. The proposed schemes then are compared against some previous work.

Localization of wireless sensor networks in the presence of obstacles is the subject of the work done by Chen et al. [12]. To address the limitations of static WSNs in node localization, they propose a cooperative localization algorithm that makes use of mobile anchor nodes. Being in cooperation with static anchors, the mobile anchors move to improve the localization performance. Moreover, to improve localization accuracy and coverage, a novel convex position estimation algorithm is also proposed.

The algorithm is particularly effective when infeasible points occur because of the effects of radio irregularity and obstacles. Simulation results demonstrate the effectiveness of this algorithm.

Irfan et al. [13] discuss that received signal strength alone is not enough to localize the wireless sensors accurately. However, they claim that a combination of received signal strength and link quality indicator can be used to improve the localization accuracy. An artificial neural network trained with Bayesian regularization and gradient descent is used to position the wireless nodes.

Ogawa et al. [14] also propose an artificial neural network trained with LVQ (learning vector quantization) to address the problem of indoor wireless sensors location detection. Received signal strength is used as input to the artificial neural network. However, in the output the neural network produces the location area where the wireless node lies in, as opposed to the exact coordinate of the node. The method results in more accurate estimations in areas far from the base points.

Stella et al. [15] developed an indoor WSNs positioning system based on location fingerprinting and artificial neural network. The positioning system benefits from received signal strength as a substitute to distance to localize the wireless nodes. A neural network is employed to establish the relations between different levels of received signal strength and the location of wireless sensors in an indoor environment. A promising result of 1.79 m of mean accuracy error has been reported.

One important problem that needs to be addressed in designing a WSN to track the mobile nodes is the problem of optimal beacon sensor positioning. Galetto and Pralio [16] study the problem of optimal sensor positioning for large-scale metrology applications. Through experimental results, they show that the location of beacons and the position of beacons with respect to each other (the beacons configuration) have significant impact on the accuracy of localization process, as well as the coverage capabilities of the sensor configuration. Consequently, they propose a genetic algorithm to simultaneously maximize the accuracy of localization, maximize the coverage capabilities of sensor configurations, and minimize the cost.

The application of WSNs localization has also been reported in factory logistics and warehousing. One such research has been conducted by Intel Corporation [6,17]. Moving just alongside the corridors, automated mobile forklifts need their own location in order to locate the goods in the shelves. Forklifts and shelves can be equipped with ultrasound transceivers that communicate with each other, with the purpose of evaluating mutual distances using ToA technique [6,17]. Localization of forklifts with WSNs can have a plethora of applications in factory logistics and warehousing. To name a few, indoor navigation of forklifts and traffic monitoring are among the applications reported by different studies [6–18].

3. Problem description

3.1. Wireless sensors localization using ToA

Localization of mobile wireless sensors in a manufacturing environment is the prime objective in this study. Manufacturing environments are by nature harsh, uncertain and dynamic. Besides, in these environments, there are many noise sources which malignantly impact on the performance and the efficiency of a wireless sensor network. The very commonplace noise sources in a manufacturing environment include, but are not limited to, vibration sources and many electrical and electronic systems. Therefore, localization of wireless sensor nodes in such dynamic and noisy environments requires more advanced methodologies that can tackle the coarse, volatile, and uncertain conditions of manufacturing environments.

Among the factors that impact distance measurement, hence localization accuracy, are ambient conditions (such as the medium temperature, humidity and pressure), obstruction and signal attenuation. Signal attenuation is composed of several phenomena. As the signals propagate in the media, the signal strength attenuates. If there are obstacles in the environment, reflection, diffraction and scattering can further attenuate the signals. Besides, in case of ultrasonic/sonic signals, depending on the type of the transducers, misalignment between transmitter transducer surface and that of receiver can also attenuate the signals.

The distance between the transmitter and receiver along with the misalignment between the transmitter transducer surface and that of receiver (in case of ultrasonic/sonic signals) has significant impact on the accuracy of distance estimations, hence the localization accuracy. Refs. [4,9,16] have studied the effect of these phenomena especially on cricket wireless nodes comprehensively (we use the same wireless sensors in this study). Hence, in order to not duplicate their studies in this research, mentioning the results would suffice here. One may refer to [4,9,16] for further information.

According to the results reported in [4,9,16], the cricket ultrasonic sensor has a range of almost 6–8 m, and as the communication is also confined by "cone of vision", the sensors can communicate with an opening angle of about 170° toward the direction that the transducer is facing. Outside the cone of vision, the signal strength drops to 1% of the maximum value [9]. For the cricket motes, the signal strength diminishes along the directions that are away from the normal of the transmitter surface. Misalignment between transmitter and receiver can be even more limiting when the angle of misalignment passes 50°. At directions around 50° away from normal of the transmitter surface, the signal strength drops to 10% of maximum signal strength. These facts demonstrate how much the distance estimation accuracy is affected by the range and misalignment between transmitter and receiver when it comes to cricket ultrasonic wireless sensors.

The rest of this section focuses primarily on the ambient conditions, the signal attenuation due to existence of obstacles in the environment (reflection and refraction) and their effects on the distance measurement accuracy. In the next section, factors affecting WSNs localization are explored; then, based on the assumed significant factors, we propose a model for the problem at hand.

Both ToA and RSS methods can be used to estimate the distance between two wireless nodes. In general, RSS is an easier parameter to implement, yet ToA may achieve a higher accuracy [6]. As ToA method can realize higher precision, compared to RSS method, and since the ToA has been successfully applied in many industrial and metrological systems, such as the work reported in [6,9], we also employ ToA method to estimate the distance between two mobile wireless sensor nodes. Nevertheless, the methodologies proposed to localize the mobile wireless sensors are general and can be employed for both ToA and RSS methods.

Due to the relatively lower propagation speed of ultrasound (as opposed to RF signals), sonic/ultrasonic signals are usually employed when ToA method is in use. Estimating the distance between two wireless sensor nodes using ultrasound can be interfered by many factors including ambient conditions, such as temperature and humidity, signal attenuation, and the measurement error due to different noise sources. With this regard, the estimated distance between the sensor nodes can be modeled for manufacturing environments as follow:

$$D = \hat{t} \times \nu(T,H,B) \tag{1}$$

where D is the distance between two wireless sensors. $\hat{t}$ is the measured time of flight. ν represents the velocity of the signal carrier. T is the ambient temperature. H is the ambient humidity. B represents the propagation loss (especially signal blockage).

Since $\hat{t}$ is subject to measurement errors invoked by noise, we define $\hat{t}$ as follows:

$$\hat{t} = t \times (1 + randn \times nf) \tag{2}$$

where t is the time distance irrespective of measurement errors. nf is the noise factor and is considered to be 10% in this study. $randn$ is a normally distributed random number.

In order to understand the behavior of the ultrasonic sensors in manufacturing environments, we need to have a better comprehension of the characteristics of ultrasonic waves and their behavior especially in manufacturing environments.

3.2. Ultrasound characteristics and its behavior in manufacturing environments

3.2.1. Velocity of ultrasound

The speed of sound is not constant, and depending on properties of the medium through which it is traveling, it varies considerably. It is also a function of various ambient factors, such as temperature and humidity among others. In this section, we explore the impact of the ambient temperature and humidity on the speed of ultrasonic waves.

The speed of ultrasound is defined as the distance traversed during a unit of time by an ultrasonic wave propagating through an elastic medium. In many physical circumstances, the speed of ultrasound weakly depends on its frequency, yet it is independent of the frequency when the wave is propagating in ideal gases. Indeed, being a dispersive medium, the small amount of CO_2 in air introduces dispersion to air at ultrasonic frequencies; therefore, the speed of ultrasound is weakly affected by its frequency when it is propagating in the air. The velocity of ultrasound is a function of the square root of temperature, but it is almost independent of pressure or density for a given gas. Indeed, in case of a single given gas, meaning that molecular weight does not change, and over a small temperature range, indicating that heat capacity is relatively constant, the speed of ultrasound solely depends on the gas temperature [19].

Another factor impacting the speed of ultrasound is Humidity. It causes the speed of ultrasound to increase by about 0.1%–0.6%. The reason for this increase lies under the fact that oxygen and nitrogen molecules of air are replaced by the lighter molecules of water. Nevertheless, the effect of humidity on the speed of ultrasound although measureable is infinitesimal and can be disregarded [19].

In a particular direction, the velocity of ultrasound (m s^{-1}) in dry air where the humidity is 0% can be approximated at different temperatures using the following equation [19]:

$$v_{dryair}(T) = 331.3\ \text{m s}^{-1} \times \sqrt{1 + \frac{T}{273.15\ ^\circ\text{C}}} \tag{3}$$

where T is the temperature in degrees Celsius (°C) and υ is the velocity of sound.

The aforementioned equation can be applied for a wide range of temperatures; nonetheless, the formula produces a considerable amount of errors at very high temperatures in that it is presumed that the approximation of heat capacity ratio is independent of temperature. On the other hand, the equation particularly makes very satisfactory predictions in relatively dry, cold, low pressure conditions, typical of Earth stratosphere.

3.2.2. Ultrasound behavior

The application of ultrasonic sensors in congested and dynamic indoor environments such as manufacturing environments, in which there exist tens or hundreds of machines, conveyers, workers, and vehicles and plenty of raw materials, work in process, and final products, is substantially different from that of outdoor environments where the space is typically not as confined. In the presence of many obstructions in the manufacturing environment, it is quite likely that an ultrasonic wave encounters an obstacle, hence becoming reflected, refracted, and attenuated. As a result, the signal wave may become so much diminished that the receiving sensor may not be able to perceive it correctly, or the signal becomes so weak that the sensor node at the destination cannot receive it at all.

With this regard, it is imperative to have a distinct understanding about the behavior of ultrasound in the confined environments where there exist a plethora of obstructions. Particularly, we take an avid interest in the effects of reflection and refraction phenomena; consequently, we can grasp a better understanding about attenuation of ultrasounds when the ultrasonic waves encounter obstructions.

Reflection refers to a sudden change in direction of a wavefront at an interface between two different media so that the wavefront returns into the medium from which it originated [20]. In other words, at boundaries where the acoustic impedances (Z) of the materials on each side differ, the ultrasonic waves are reflected. The greater the impedance mismatch, the greater the percentage of energy that will be reflected at the interface or boundary between one medium and another [21].

The characteristic impedance (Z) of a material is defined as the product of its density (ρ) and acoustic velocity (ν) [21].

$$Z = \rho \times \nu$$

The reflection coefficient can be obtained as follow [21]:

$$R = \left(\frac{Z_2 - Z_1}{Z_2 + Z_1}\right)^2$$

Multiplying the reflection coefficient by 100 yields the amount of energy reflected as a percentage of the original energy [21]. As a case in point, suppose we are interested to calculate the amount of energy reflected when an ultrasonic wave traveling in air encounters an obstruction made of mild steel. With this concern, the percentage of energy reflected can be calculated as follow [21]:

$$Z_1 = \rho \times \nu = 1.204\ \text{kg/m}^3 \times 343.2\ m/s = 413.2128\ \text{kg/m}^2\ \text{s}$$

$$Z_2 = \rho \times \nu = 7860\ \text{kg}/m^3 \times 5960\ m/s = 46{,}845{,}600\ \text{kg/m}^2\ \text{s}$$

$$R = \left(\frac{46845600 - 413.2128}{46845600 + 413.2128}\right)^2 = 0.9999647177 = 99.99647177\%$$

As a result, 99.99647177% of the original wave energy is reflected when an ultrasonic wave traveling in air encounters an obstruction of mild steel.

Refraction refers to the change in direction of a wavefront at an interface between two dissimilar media, but instead of returning to the medium where it originated, the wavefront enters the new medium [20]. This phenomenon can be commonly observed when waves bend while passing from one medium to another. When an ultrasonic wave interfaces with a new medium, a fraction of the original wave will be transmitted into it [21]. This fraction in percentage can be calculated as follow [21]:

$$Refracted\ energy\% = (1 - R) \times 100$$

The amount of ultrasound energy, for instance, that is transmitted into a mild steel equals $(1-R) \times 100 = 0.00352823\%$.

Finally, as an ultrasonic wave propagates through a medium, its strength diminishes with distance. In idealized materials, ultrasound amplitude is only diminished by the act of propagation. On the other hand, natural materials cause different effects, each of which further weakens the ultrasound. This aggravated weakening stems from scattering and absorption. Scattering refers to reradiating of the ultrasound in directions other than its original direction of propagation [20]. Absorption phenomenon happens when the ultrasound energy is converted to other forms of energy. Overall, attenuation is defined as the combined effect of scattering and absorption. In other words, attenuation of ultrasound refers to the decay rate of the wave as it propagates through material [22]. Accounting for attenuation effects in ultrasound is imperative, for the attenuated signal may not be detected by the receiver transducer [9].

To sum up, ultrasonic waves undergo various phenomena when they travel in congested mise-en-scene of manufacturing environments. Three main phenomena taking place when an ultrasound propagates into an environment are reflection, refraction and attenuation. However, as demonstrated in the mild steel example, reflection and attenuation seem to have more significant impact on the behavior of ultrasounds. In view of the fact that manufacturing environments are very congested with machines, vehicles and workers, ultrasonic waves may become reflected, refracted and attenuated numerous times before reaching the receiving antenna, hence producing multipath phenomena. The effects of multipath include both constructive and destructive interference in the signal. Inasmuch as investigating the effects of multipath on ultrasonic sensors in manufacturing environment is beyond the objective of this research, in this study it is assumed that the reflected and refracted signals become so attenuated that they can be hardly perceived by the receiving wireless sensors antennas. That is, it is assumed that in case an ultrasonic wave encounters an obstacle, the signal becomes blocked. Hence, the wireless sensors obstructed by the obstacle are not able to receive the signal.

With this concern, we modify the proposed model to estimate the distance between the sensor nodes in manufacturing environments. By merging Eqs. (2) and (3) into Eq. (1) and introducing variable α, we obtain the following equation:

$$D = t \times (1 + randn \times nf) \times 331.3\ \mathrm{m\,s^{-1}} \times \sqrt{1 + \frac{T}{273.15\ ^{\circ}\mathrm{C}}} \times \alpha \qquad (4)$$

where $\alpha = 0$ indicates that the signal carrier is obstructed by at least one obstacle. $\alpha = 1$ signifies that the signal carrier is not blocked by any obstacles.

Herein, $D = 0$ implies that we do not have any clear-cut information about the distance between two nodes.

4. Undertaken approaches and methodologies

4.1. Classical techniques for positioning

After estimating the distance between the mobile wireless sensors and the anchor nodes, some techniques are required to position the mobile wireless sensors. Notwithstanding researchers have taken different methodologies to employ the distance data to localize the wireless sensors, the backbone of many localization techniques is mainly one of the two common approaches called trilateration and triangulation. The former is also applied in this study to compare our proposed approach with.

Trilateration is the most basic, general positioning technique that has been used for centuries [23]. It can be used to accurately localize an object when the distances to at least three already positioned reference objects are known in advance. For our purposes, the basic idea is as follows. To find the location of a node, say *d*, we need to have at least three reference nodes, say *a*, *b*, and *c*, the position of which are known a priori. Suppose (X_a, Y_a), (X_b, Y_b) and (X_c, Y_c) are the positions of the reference nodes *a*, *b*, and *c* respectively, and we are interested to find (X_d, Y_d), the location of node *d*

$$|ad|^2 = (X_d - X_a)^2 + (Y_d - Y_a)^2$$

$$|bd|^2 = (X_d - X_b)^2 + (Y_d - Y_b)^2$$

$$|cd|^2 = (X_d - X_c)^2 + (Y_d - Y_c)^2$$

By solving the above set of equations, we can obtain the location of node *d*. The only constraint is that the reference nodes *a*, *b*, *c* cannot be on a straight line. In case we need to localize a node in a three-dimensional network, another reference node will be required.

However, the trilateration precision is highly dependent on the accuracy of measured distances to the reference nodes. Hence, the trilateration technique is prone to error when it is exposed to harsh, uncertain, and noisy circumstances of manufacturing environments. In view of many noise sources and obstacles in such environments, every distance measurement may be somewhat deviated from the actual distance. Overall, trilateration is an impeccable technique to localize a node when the accurate distances from the node to at least three reference nodes are known in advance; however, the technique is prone to grave errors when used in noisy environments.

4.2. Artificial neural network approach

In order to moderate the effects of noise sources on localization of wireless sensors, we propose using artificial neural networks. Application of artificial neural networks (ANN) has been successfully reported in the general area of signal processing. The ability of ANNs to suppress noise is of great interest for many researchers. For instance, adaptive noise cancellation on a telephone line with the help of an ADALINE neural network has been reported [24]. In the discussion that follows, we explain an application of artificial neural network to suppress noise for the localization of a wireless sensor in the noisy conditions of manufacturing environments.

4.2.1. Artificial neural network in general

Inspired by biological neural networks, an artificial neural network is an information processing system, which has been developed as generalization of mathematical models of human cognition or neural biology.

Concisely, every artificial neural network has the following features in common. Information processing takes place at many simple elements called neurons. When a neuron fires, it transmits signals to other neurons over connection links. Each connection link has an associated weight. The weight multiplies the signal transmitted, and the resulted signal stimulates the neuron at the other end of the connection link. In case the net stimulation (sum of weighted input signals) for a neuron is greater than a threshold, the neuron applies an activation function to its net input to determine its output signal and fires [24].

An artificial neural network is characterized by the pattern of connection between the neurons (also called the neural network architecture), the method of determining the weights on the connections (also called the training method or learning algorithm), and the neurons' activation functions [24].

4.2.2. An artificial neural network to the localization of a wireless sensor

In this section, we propose an artificial neural network approach to localize wireless sensor nodes. Depending on the application, the neural network can be implemented on each wireless sensor node so that the node can localize itself, or it can be on a central controller, say a computer, to keep track of wireless sensor nodes' positions. Owing to the fact that in many industrial applications, we are interested to keep track of wireless sensor nodes' positions, we consider the latter case and assume that we have a central controller, which needs to be equipped with a localization module. Herein, we assume that each anchor node is connected (either wirelessly or conventionally with wire) to a central controller through a sink node.

Thus, the anchor nodes provide raw data to the sink node. Then the central controller, equipped with an artificial neural network module, calculates the location of each wireless sensor node. However, it needs to be mentioned that the proposed methodologies and algorithms are general and can be applied with very minor revisions for the case that the neural network is implemented on each wireless sensor node.

In the discussion that follows, first the network architecture is explained, which is followed by more details about network elements, such as neurons' activation functions and connection links. Then the training algorithm is elucidated. In addition, we elaborate some details about the initialization of the neural network link weights and some methods to faster convergence of the neural network training algorithm.

In order to design a proper neural network for positioning wireless sensors, first we need to clarify what inputs can be provided for the network and what outputs we need to obtain. Our wireless sensors are equipped with ultrasonic transducers, and they use ToA technique to measure the time distance between the sender and receiver sensor. Thus, the data each anchor node can provide for the neural network is the time elapsed for the signal to travel from the sender wireless node to the receiver anchor node. Obviously, the location of wireless sensors in a two dimensional plane is the desired output. Fig. 1 illustrates a neural network to localize wireless sensors in a two-dimensional plane when there are five anchor nodes to feed the network with ToA data. As demonstrated in Fig. 1, the network has five input neurons corresponding to five anchor nodes and two output neurons corresponding to x and y coordinates in a two-dimensional plane.

A multilayer perceptron (MLP) is a multilayer feed-forward neural network that is capable of mapping a given set of inputs to a specified set of target outputs. Multilayer perceptrons use supervised learning, and algorithms such as backpropagation and Bayesian regularization can be used to train them. Multilayer perceptrons are very popular networks and have been used in many studies including localization [13,15], pattern recognition, and signal processing among others. Even though a single layer perceptron is very limited in the mappings that it can learn, a multilayer perceptron can learn any continuous nonlinear mappings to any arbitrary accuracy [24]. Thus, two multilayer perceptrons, one with one hidden layer (ANN1) and the other with two hidden layers (ANN2), are designed to address the problem of localization of the wireless sensor nodes. Fig. 2 shows the proposed architectures.

A backpropagation algorithm is used to train the neural networks. Training a network by backpropagation technique involves three stages: the feedforward of input training pattern, the backpropagation of the associated error, and the adjustment of weights.

During feedforward, each input neuron receives an input signal and broadcasts the signal to the neurons in the hidden layer. Each neuron in the hidden layer applies its activation function on its net input and then broadcasts the signal to the neurons in the output layer. Each neuron in the output layer applies its activation function on its net input to form the response of the network for the given input pattern. Neurons compute their activations using following formulas:

$$y_{in_j} = v_{0,j} + \sum_i x_i v_{ij}$$

$$Y_j = f\left(y_{in_j}\right)$$

where v_{ij}s are the connection link weights; $v_{0,j}$ s signify the bias terms on neuron j. y_{inj} and Y_j denote the net input to and the output of neuron j, respectively. x_is represent the input signals.

During training, each output neuron compares its computed output with its target value to determine the associated error and then propagates this error back to the neurons in the previous layers (both hidden layer(s) and input layer). This distributed error later is used to update the weights between neurons.

The last stage is the adjustment of the weights. With this regard, the algorithm utilizes the back-propagated errors to adjust each weight in proportion to the weight impact on making the errors. The backpropagation algorithm is a gradient descent technique which changes the weights in a direction that is proportionate to the current

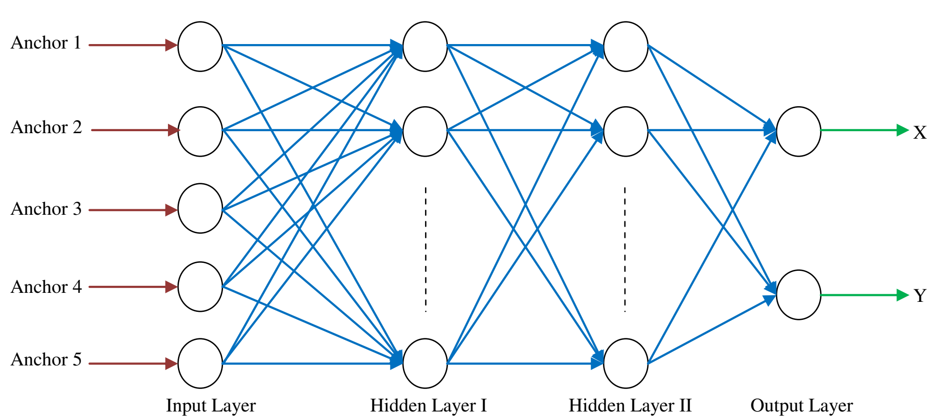

Fig. 1. The architecture of the neural network to localize the wireless nodes in two-dimensional.

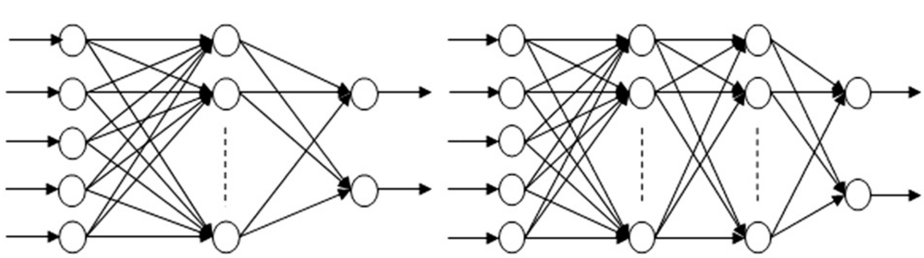

Fig. 2. ANN1 (at the left) and ANN2 (at the right).

gradient. When the training patterns are relatively similar, the back-propagation technique works well. On the other hand, when there are some drastic changes among the training patterns, unless the learning rate is set to a very small value, the outcome would be very poor. Hence, there is a trade-off between how well a network can learn any arbitrary set of patterns with any degrees of agitation among patterns and how rapid the network can learn the set of patterns. In order to tackle this problem, we employ an alternative weight update procedure called backpropagation with momentum [24].

In back propagation with momentum, the weights are updated in a direction that is a combination of the current gradient and the previous gradient. The advantage of this approach arises chiefly

0. Initialize weights.
1. While termination conditions are not met do:
   a. For each training pair do:

Feedforward

i. Each input unit ($X_i, i = 1,2,\ldots,n$) receive input signal x_i and broadcasts this signal to all units in the layer above (the hidden units).

ii. Each hidden unit $(Z_j, j = 1,2,\ldots,p)$ sums its weighted input signals,

$$z_{in_j} = v_{0j} + \sum_{i=1}^{n} x_i v_{ij},$$

applies its activation function to compute its output signal,

$$z_j = f\left(z_{in_j}\right),$$

and sends this signal to all units in the layer above (output units).

iii. Each output unit ($Y_k, k = 1,2,\ldots,m$) sums its weighted input signals,

$$y_{in_k} = w_{0k} + \sum_{j=1}^{p} z_j w_{jk}$$

and applies its activation function to compute its output signal,

$$y_k = f(y_{in_k}).$$

Backpropagation of error

iv. Each output unit ($Y_k, k = 1,2,\ldots,m$) receives a target pattern, computes its error information term,

$$\delta_k = (t_k - y_k) f'(y_{in_k}),$$

calculates its weight correction term (used to update w_{jk} later),

$$\Delta w_{jk}^{t+1} = \alpha \delta_k z_j + \mu \Delta w_{jk}^{t},$$

calculates its bias correction term (used to update w_{0k} later),

$$\Delta w_{0k}^{t+1} = \alpha \delta_k + \mu \Delta w_{0k}^{t},$$

and sends δ_k to units in the layer below.

v. Each hidden unit $(Z_j, j = 1,2,\ldots,p)$ sums its delta inputs (from units in the layer above),

$$\delta_{in_j} = \sum_{k=1}^{m} \delta_k w_{jk},$$

multiplies by the derivative of its activation function to calculate its error information term,

$$\delta_j = \delta_{in_j} f'\left(z_{in_j}\right),$$

calculates its weight correction term (used to update v_{ij} later),

$$\Delta v_{ij}^{t+1} = \alpha \delta_j x_i + \mu \Delta v_{ij}^{t},$$

and calculates its bias correction term (used to update v_{0j} later),

$$\Delta v_{0j}^{t+1} = \alpha \delta_j + \mu \Delta v_{0j}^{t}.$$

Update weights and biases

vi. Each output unit ($Y_k, k = 1,2,\ldots,m$) updates its bias and weights:

$$w_{jk}^{new} = w_{jk}^{old} + \Delta w_{jk}.$$

vii. Each hidden unit $(Z_j, j = 1,2,\ldots,p)$ updates its bias and weights:

$$v_{ij}^{new} = v_{ij}^{old} + \Delta v_{ij}.$$

   b. Evaluate termination conditions.

Fig. 3. The backpropagation algorithm with momentum.

when we use a diminutive learning rate to avoid a major disruption of the direction of learning due to a very unusual pair of training patterns, yet it is desirable to maintain training at a fairly rapid pace provided that the training data are somewhat similar. Adding momentum terms to weight update formulas may sometimes cause a faster convergence. Fig. 3 demonstrates the modified backpropagation algorithm for a multilayer perceptron with single hidden layer (ANN1) in more details. The nomenclature used in the training algorithm is delineated in Tabel A1 in the appendix. The modified backpropagation algorithm for a multilayer perceptron with two hidden layers (ANN2) is just a simple extension of that of single hidden layer MLP.

An activation function for neurons in a multilayer perceptron should have several fundamental characteristics. It should be continuous, differentiable, and monotonically non-decreasing. Besides, the function is expected to saturate. That is to say, it approaches finite maximum and minimum values asymptotically [24]. In this study, we have used several activation functions many of which comply with the foregoing characteristics. For the first neural network (multilayer perceptron with single hidden layer), we have employed the identity function for the input and output layers and the bipolar sigmoid function for the hidden layer. Moreover, for the second neural network (multilayer perceptron with two hidden layer), we have employed the identity function for the input and output layers, the bipolar sigmoid function for the first hidden layer, and the binary sigmoid function for the second hidden layer. These functions are chosen empirically. The identity function is the only non-saturated function used. Hecht-Nielson [25] proposes the identity function as the activation function on output neurons, especially if the target values are continuous rather than bipolar or binary.

The choice of initial weights has a significant impact on the speed of convergence of neural networks learning process. Moreover, it can influence whether the network converges on a global or a local minimum of the total error. The update of the weight between two neurons depends on both the derivative of the upper unit's activation function and the activation function of the lower unit. On one hand, it is of crucial importance to avoid choices of initial weights that would lead to the points that either activations or their derivatives are zero. On the other hand, the initial weights must not be too large or too small. In case the initial weights are too large, the initial input signals to hidden or output layer neurons will be likely to fall into the saturation region where the derivative of the sigmoid function has very small values, hence causing extremely slow learning. On the contrary, if the initial weights are too small, the net input to a hidden or an output unit will be too close to zero, which also leads to slow convergence of the network. In this study, we initialize the weights and biases for ANN1 to random values from -0.25 to $+0.25$ and for ANN2 to random values from -0.5 to $+0.5$. These values are selected empirically, and in order to help prevent difficulties caused by very small activations or derivatives [24].

The next issue that needs to be addressed regarding designing an artificial neural network is how long to train the network and how many training pairs there should be. Regarding how long to train, there exists a balance between memorization and generalization. In other words, we need to achieve a balance between correct responses to the training patterns and acceptable responses to the new input patterns. Therefore, it is not necessarily advantageous to continue training until the total squared error actually reaches a minimum. With this regard, we continue training the network up until the mean error associated with the input patterns reaches 0.05 and simultaneously the difference between mean errors of two consecutive epochs is less than 1×10^{-9}. Concerning the number of training pairs, we select 200 input patterns to train both ANN1 and ANN2. This number has been selected empirically.

Concerning the data representation, the input patterns are portrayed using n-tuples (n is the number of anchors). As a case in point, if there are five anchors to help localize the mobile wireless sensors, the input patterns would be represented using five-tuples. Indeed, each locus in a five-tuple represents the time the signal takes to travel from the mobile sensor node to an anchor node.

As it was mentioned earlier, we employ two multilayer perceptrons one with one hidden layer denoted as ANN1 and the other one with two hidden layers denoted as ANN2. The former has 400 neurons in the hidden layer, and the latter has 200 neurons in each of the hidden layers. Due to the fact that we are interested to find the location of mobile wireless sensors in a two-dimensional plane, we have two output neurons in each of the neural networks as well.

5. Simulation study and experimental results

5.1. Simulation study

In this section we devise a simulator to investigate the performance of the proposed neural networks under the noisy, harsh, and uncertain conditions of manufacturing environments. According to the model, discussed in Section 4, to localize mobile wireless sensors in real-world manufacturing environments, noise sources, temperature, and signal attenuation due to the signal obstructions are three main factors influencing mobile wireless sensors localization.

To examine the proposed approach, we developed a simulator which can properly simulate the propagation of signals in a manufacturing environment where there exist obstacles attenuating and blocking the signals, noise sources effectuating the measurement errors, and signal propagation speed change owing to the temperature fluctuations. The simulator contains the flowing components:

1. A component to simulate the behaviour of mobile wireless sensors.
2. A component to simulate the behaviour of anchor nodes.
3. Another component called future event list (FEL) to list the future events, to schedule them, and finally to plan their occurrence sequence.
4. A component to simulate the propagation of signals in the medium, and the destructive behaviour of attenuation and blocking phenomena.
5. A sink node which is connected to a computation unite, say a central controller or a computer, to calculate the location of mobile wireless sensors.
6. Another component to model the physical objects in a manufacturing environment.
7. And finally, a timer to advance the simulation clock and to synchronize all the events with that clock.

These components interact and cooperate together in an object-oriented design to simulate the localization of mobile wireless sensors in a manufacturing environment. Further details about the components are explained below.

The mobile wireless sensor class is designed to address the behavior of mobile wireless sensor nodes. It contains procedures to plan for the mobile sensor trajectory and to transmit and receive ultrasonic waves.

The anchor node class represents anchor nodes which are designed to send or receive beacon signals (depending on whether each mobile node is meant to find its own location, or a central controller is intended to localize the mobile nodes) to help in finding the time distance between a mobile node and anchor nodes. In case of a central controller, this class contains procedures to estimate the distance between a mobile node and an anchor node, to send the signals to the central controller, and to receive signals coming through the medium. The anchor node class also includes another procedure which simulates measurement errors caused by noise sources by introducing Gaussian noise to every receiving signal.

The FEL is a class that manages future events. Events that can be triggered by FEL include but not limited to sending signals by mobile nodes, propagating signals through medium, and receiving signals by anchor nodes. The FEL encompasses the following procedures. One procedure handles the upcoming events. This procedure sorts the event list chronologically, and once triggered by a procedure in the timer class, it explores all the events that are due to trigger. The next two procedures are to add new events and to remove outdated events to and from the event list, respectively. There is another procedure the function of which is to trigger the mobile node to send signals. Likewise, another procedure is to trigger the medium to propagate the signal sent by the mobile sensor. Finally, a procedure is responsible to monitor the whole system. Once a signal has been delivered successfully, it calls the relevant procedure to remove the performed event from the event list and to schedule for the future events.

After an ultrasonic wave is sent by a mobile sensor, the wave is propagated through a medium the properties of which affect the carrier wave. The medium class is designed to simulate the ultrasound propagation through a medium. The medium class embraces several procedures to propagate signals from mobile nodes to anchor nodes and to attenuate and block the ultrasonic waves once encountering the obstacles.

In the simulation model, we contemplate a central controller to calculate the location of mobile sensors given the data provided by anchors. The sink node class is designed to address the need for such controller. Another approach could be embedding this module inside each mobile node so that each mobile node can localize itself given the beacon signals provided by anchor nodes. Although these two approaches are totally different architecturally (the former leads to a centralized control design whereas the latter results in a distributed control design), they would end up the same result in that depending on the application, the localization algorithm can be implemented in each mobile node instead of a central controller. The sink node class includes following procedures. It has a procedure to receive messages from anchor nodes. The messages contain the time distance each anchor node has with a mobile node. In order to find the position of a mobile node given the data provided by the anchor nodes, a sub-class implementing the neural network is provided. Therefore, the sink node instantiates an object of the neural network class to help localize the mobile node. In case of exploiting the trilateration technique, the sink node class can also employ another procedure to find the location of the mobile nodes using the trilateration algorithm. The sink node class is also equipped with some procedures to interface with the user.

When anchor nodes are sending the messages regarding the distance each of them has with a mobile node, these messages may be received by the sink node at different times depending on the time distance each anchor node has with the mobile node. Besides, the sink node may receive data regarding different mobile nodes. Hence, a stack has been designed to store the messages, and once there are enough data concerning a mobile node (the time distance from five anchor nodes in case of employing a neural network approach and the physical distance from at least three anchor nodes in case of employing a trilateration technique), the sink node utilizes the data to localize the mobile node; then it removes the data from the stack.

The next class, which has a strong interaction with the medium class, is the environment class. The environment class provides the simulator with the information about the manufacturing environment in which the wireless sensor network operates. The number and location of obstacles, the shape and the size of obstacles, the surrounding temperature, and other ambient conditions are among the information provided by the environment class.

Finally, the last but not the least is the timer class. This class is to advance the simulation clock and to synchronize the events with the simulation clock. Through a procedure, the timer class, moreover, triggers the FEL to handle the events.

5.2. Simulation results

To examine the proposed artificial neural network approach and to compare its performance with that of the conventional trilateration technique, we devise some experiments according which we run the foregoing simulator under different scenarios. In the experiments, we consider a hypothetical manufacturing environment in which there exist two machines that are massive enough that can block the ultrasonic waves completely. The surrounding temperature is set to 20 °C, yet it is possible to set the temperature to any arbitrary degrees, hence changing the ultrasound velocity. As it has been discussed in Section 3, we assume that the noise is generated from a normally distributed population with mean zero and standard deviation 0.05. The noise impacts on every distance measurements taken by wireless nodes. In fact, the normally distributed noise portrays the effect of miscellaneous noise sources, typical to manufacturing environments, upon measurement errors.

To dissect the effects of noise sources, obstructions and ambient conditions upon localization of a mobile wireless sensor, we propose a paradigm under which all three algorithms are analyzed. In the paradigm, a mobile sensor traverses a serpentine trajectory among the obstructions in the aforementioned environment (Fig. 4).

The wireless mobile node has been localized while traveling in the abovementioned path using all three algorithms (ANN1, ANN2, and the trilateration). For each trip, the mobile node has been positioned 200 times at different points. Due to the stochastic nature of measurement errors, each algorithm has been replicated 25 times for the same path. Thus, we run the total of 75 experiments each contains 200 instances of positioning the mobile node. The estimated location of the mobile node in every point is compared against the actual location of the mobile node in the respective point, and the absolute errors and the relative errors obtained are calculated. Besides, in order to have a clear-cut understanding about how well different algorithms localize the mobile node, another criterion based on the Euclidean distance between the estimated

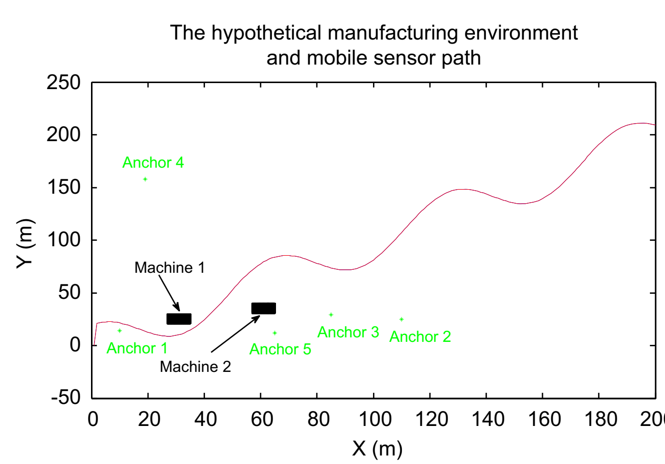

Fig. 4. The hypothetical manufacturing environment and mobile node path.

Table 1
The experimental results.

Technique	Total relative error	Mean relative error	SD of relative errors	Average distance	SD of distance
Trilateration	15.70453527	0.039261338	0.128268375	4.108054725	5.049970227
ANN1	10.21118941	0.025527974	0.059964062	3.15401017	3.814507619
ANN2	7.405563495	0.018513909	0.049669624	2.273879291	3.306204622

Table 2
The confidence intervals.

Technique	Relative error		Euclidean distance	
	Lower limit	Upper limit	Lower limit	Upper limit
Trilateration	0.037537225	0.040985451	4.007336142	4.208773307
ANN1	0.024293266	0.026762681	3.065041224	3.242979115
ANN2	0.017551353	0.019476465	2.180821324	2.366937257

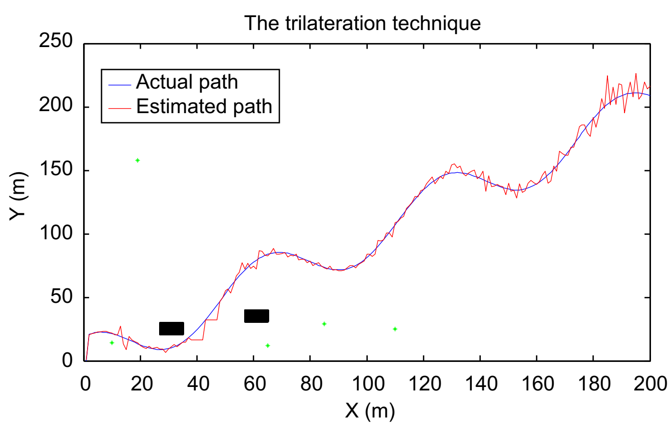

Fig. 5. Localization of a mobile wireless sensor node using trilateration technique.

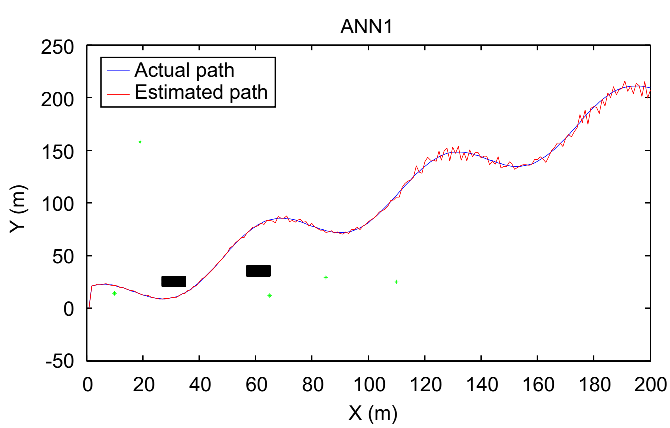

Fig. 6. Localization of a mobile wireless sensor node using ANN1.

location and the actual location is taken to calculate the measurement errors. The results obtained are demonstrated in Table 1.

Table 2 presents the 95 percent confidence intervals for the mean relative errors and the mean Euclidean distance based errors. It is conspicuous from Table 2 that the ANN2 by far outperforms other algorithms. Figs. 5–7 illustrate examples of how the trilateration technique, ANN1, and ANN2 respectively perform with respect to the path that the mobile node actually traverses.

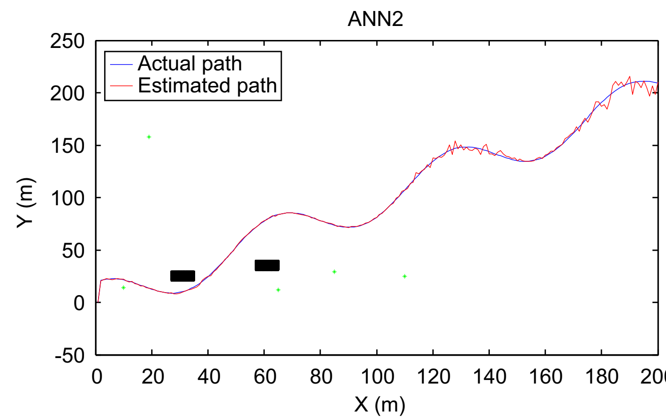

Fig. 7. Localization of a mobile wireless sensor node using ANN2.

6. Model validation

6.1. The underlying platform and testbed

To evaluate the performance and the efficiency of the undertaken technique (the multilayer perceptron with two hidden layers), a testbed based on the MCS410CA cricket mote, which is a MICA2 based cricket mote platform and is developed by MEMSIC Inc., is deployed. The cricket motes employ a 433 MHz processor and a radio module besides an ultrasound transmitter and receiver. In fact, the cricket motes include all the standard MICA2 hardware along with an ultrasound transceiver. The addition of this ultrasound transceiver to existing RF devices allows the cricket mote to derive linear range estimates by establishing differential time of arrival between these two signals. The cricket motes also employ TinyOS operation system and platform to manage the operations required by the networked sensors.

The cricket motes can be configured as either a listener or a beacon. As a beacon, the cricket mote transmits concurrent RF and ultrasound pulses that are then received by other cricket motes configured as listeners. An individual listener obtains distance estimates for a specific beacon by running algorithms that compare RF and ultrasound samples to establish the best correlation. Listeners are attached to mobile devices and listen for RF signals. Upon receipt of the beacon RF signal, the listener then listens for the corresponding ultrasonic pulse. When this pulse arrives, the listener obtains a distance estimate for the corresponding beacon by taking advantage of the difference in propagation speed between RF and ultrasound (speed of sound). The listener runs algorithms that correlate RF and ultrasound samples to pick the best correlation. Even in the presence of several competing beacon transmissions, the cricket mote rapidly achieves impressive precision and accuracy.

In our experiments, we deploy six cricket motes, such that five motes are the beacons and one mote, which is a mobile node, is the listener. The listener receives the RF and ultrasound signals to obtain the distance estimates for the corresponding beacons, hence estimating its own location.

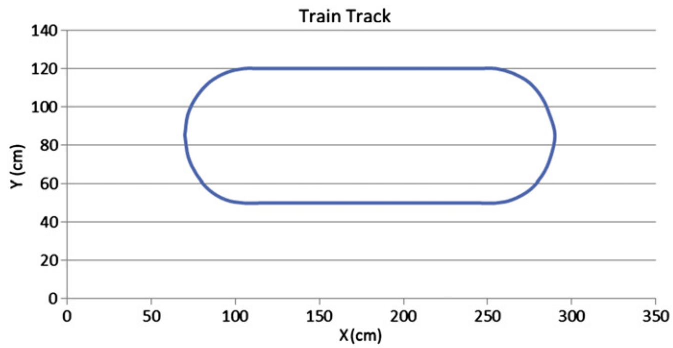

Fig. 8. Model train trajectory.

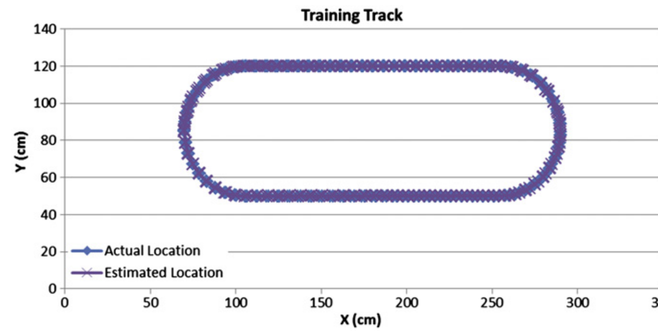

Fig. 9. Points in the track used to train the ANN2.

The mobile mote is mounted on a model train traversing an elliptical trajectory with a constant speed of 6.5 cm s^{-1}. The track is 519.8 cm in length. Five beacons are attached to the ceiling right above the model railway trajectory. The beacons are installed in their positions to form a cross-shape constellation, with one beacon on the either end of the model railway and three beacons in the middle. Fig. 8 demonstrates the model train trajectory. The model train setup is used in this study to approximate the motion of AGVs (automated guided vehicle) in industrial environments. Besides, the employment of model train setups are frequently reported in many studies undertaking mobile node tracking, such as [4,8].

Before delineating the experiments and demonstrating the results, it should be noted that the environment where the experiments are conducted is not a noise free environment. The experiments are performed in a congested office environment, where the probability of occurring multipath phenomena is rather high, and path loss model is quite complex. Besides, due to the presence of electrical and electronic noise sources in the environment, such as fluorescent lights and electronic equipment, the measurements are prone to error [4].

6.2. Experimental results

As noted, we study the situation in which a wireless sensor node, mounted on a train, moves with a constant speed of 6.5 cm s^{-1} on an elliptical track of 519.8 cm in length. The cricket mote mounted on the train updates its location at the intervals of one second using the distance estimates it has been obtained in that interval. Hence, the number of distance estimates in each interval may vary from one to five depending on the number of beacons the cricket mote has obtained the distance for.

To validate the results obtained in the simulation study, we examine the performance of the proposed ANN in real physical experiments. Herein, we expect that by training the ANN in these noisy circumstances, a robust technique to different sources of variability can be accomplished. To train the ANN, we let the train traverse the track for a number of laps. During each lap, the distance estimates for the available Beacons are obtained at each of one-second intervals. To provide the ANN with different scenarios of availability and sequence of the distance estimates for the beacons at each point, the ANN is trained with three different sets of data obtained from three trips of train. Then, to evaluate the performance of the ANN, the mote is equipped with the ANN localization algorithm and let the ANN algorithm track the mobile wireless sensor.

Fig. 9 illustrates the training track used to train the ANN2. As demonstrated in this figure, the ANN has learnt the track with high precession. Table 3 also present the absolute, relative and an Euclidian distance based error associated with ANN training. As exhibited in the table, the ANN has learnt the track with an average Euclidian distance error of 0.1 cm and an average relative error of less than 0.058%.

Table 3
The ANN training error results.

Error	Absolute error		Relative error		Euclidean distance (cm)
	X	Y	X	Y	
Max error	3.94468	5.01830	1.422%	4.902%	6.38224
Min error	0.00001	0.00000	0.000%	0.000%	0.00015
Average error	0.07614	0.05373	0.033%	0.058%	0.10073

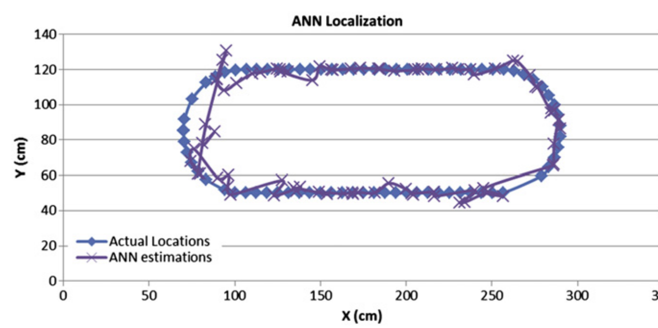

Fig. 10. Performance of the ANN localization technique against the actual location of the train (example 1).

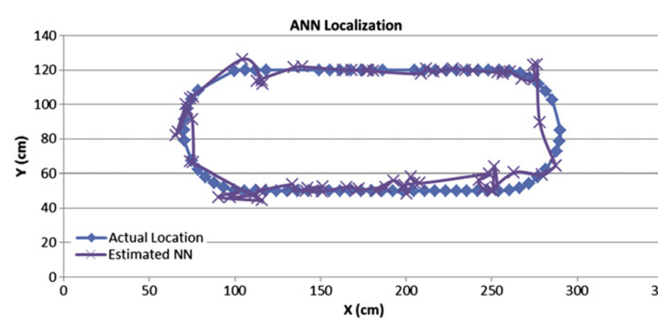

Fig. 11. Performance of the ANN localization technique against the actual location of the train (example 2).

After training the ANN, now we can equip the cricket motes with the neural network algorithm, and have the ANN localize the mobile cricket mote. Herein, we run the experiments again and recorded the localization data. Figs. 10 and 11 exhibit the results of ANN localization of mobile nodes in two completely different runs. Tables 4 and 5 give the statistical results of the experiments.

Table 4
The statistical results of the ANN performance in example 1.

Error	Absolute error		Relative error%		Euclidean distance based error
	X	Y	X	Y	
Max error	18.3867	21.9142	25.849	22.545	28.2301
Min error	0.0538	0.0420	0.032	0.035	0.3901
Average error	5.9476	3.5902	4.468	4.643	7.8962

Table 5
The statistical results of the ANN performance in example 2.

Error	Absolute error		Relative error%		Euclidean distance (cm)
	X	Y	X	Y	
Max error	30.56995	20.63875	36.921	26.987	32.91340
Min error	0.01714	0.00720	0.009	0.014	0.27277
Average error	6.33778	4.25083	4.257	6.014	8.52058

As depicted the average relative errors are less than 5% and the average Euclidian distance error is almost 8.21 cm.

As portrayed by the figures, the ANN shows some inaccuracy at the two ends of the track. To analyze this behavior, we can enumerate at least two sources of error that can justify the localization perturbations at these two regions. First is the presence of obstacles around the track at these spots that may have affected the path loss model hence aggravating the signal attenuation. The other source of error can be due to the radiation pattern of the cricket US transducers. As the radiation pattern of the cricket US transducer is a function of the transmitter angle with respect to the receiver, any misalignment angle between the transmitter and receiver can cause the signal strength to drop along the direction that is away from the normal direction to the transducer surface [4,9]. As the anchor nodes are located right above the train track in a crossed-shape constellation, with one anchor node at the end of each arm and one anchor node at the center, the transducer of the anchor node at the either end of the crossed-shape constellation is misaligned with the transducer of the mobile cricket mote when it is travelling on the other end of the track. This phenomenon can be another reason why we have more error at the two ends of the track [4,9]. Other than that, the ANN localizes the mobile mote with high precession at other points.

7. Conclusions and future work

In this paper, we studied the localization of wireless mobile sensors in the harsh, uncertain, and noisy conditions of manufacturing environments. Two algorithms based on artificial neural network are presented, and the results obtained are compared with that of a trilateration based technique. The simulation results corroborate the superiority of the multilayer perceptron with two hidden layers over the other techniques. Finally, the physical experiments deploying the cricket motes are employed to validate the proposed neural technique.

There are potentially unlimited opportunities for research in localization of wireless sensor networks. In this paper, we have addressed only a few areas. Future studies can focus on more precise algorithms to localize the wireless sensors under the real-world conditions. Fuzzy control systems may be applied to diminish the noise and obtain a better positioning. The optimum location of the anchor nodes may help the anchor nodes to be placed into the areas that have lower chance of becoming obstructed by obstacles. Hence, a technique to find the optimum positions of the anchor nodes may be devised for a future study.

Table A1
The nomenclature used in the modified backpropagation algorithm.

Symbol	Definition
x	Input training vector: $x=(x_1,\ldots,x_i,\ldots,x_n)$
t	Output target vector: $t=(t_1,\ldots,t_k,\ldots,t_m)$
δ_k	Portion of error correction weight adjustment for w_{jk} that is due to an error at output unit Y_k; also, the information about the error at unit Y_k that is propagated back to the hidden units that feed into units Y_k
δ_j	Portion of error correction weight adjustment for v_{ij} that is due to the backpropagation of error information from the output layer to the hidden units Z_j
v_{ij}	The weight between input unit i and hidden unit j
w_{jk}	The weight between hidden unit j and output unit k
α	Learning rate
X_i	Input unit i: for an input unit, the input signal and output signal are the same, namely x_i
v_{0j}	Bias on hidden unit j
Z_j	Hidden unit j
w_{0k}	Bias on output unit k
Y_k	Output unit k
μ	Momentum parameter

Appendix A

See Table A1 for the nomenclature used.

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