# Improved GbLN-PSO Algorithm for Indoor Localization in Wireless Sensor Network

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Abstract ² Localization is one of the important matters for Wireless Sensor Networks (WSN) because various applications are depending on exact sensor nodes position. The problem in localization is the gained low accuracy in estimation process. Thus, this research is intended to increase the accuracy by overcome the problem in the Global best Local Neighborhood Particle Swarm Optimization (GbLN-PSO) to gain high accuracy. To compass this problem, an Improved Global best Local Neighborhood Particle Swarm Optimization (IGbLN-PSO) algorithm has been proposed. In IGbLN-PSO algorithm, there are consists of two phases: Exploration phase and Exploitation phase. The neighbor particles population that scattered around the main particles, help in the searching process to estimate the node location more accurately and gained lesser computational time. Simulation results demonstrated that the proposed algorithm have competence result compared to PSO, GbLN-PSO and TLBO algorithms in terms of localization accuracy at 0.02%, 0.01% and 59.16%. Computational time result shows the proposed algorithm less computational time at 80.07%, 17.73% and 0.3% compared others.

Index Terms² PSO, GbLN-PSO, IGbLN-PSO, TLBO, localization error, computation time.

## I. INTRODUCTION

Wireless Sensor Networks (WSN) is a group of sensor nodes that can sense their environment cooperatively and transfer the information to the base station [1]. WSN is widely used in the variety of application such as for hazardous detection for safety, enemy target tracking and surveillance for military purposed, health monitoring system, and home automation [2]. In most of these applications, location information of sensor nodes is critically important to support many other network services.

Localization aim is to achieve the high accuracy or lower localization error between the truth node location and estimated node location [3]. Knowing location sensor node for the outdoor environment is much easier than indoor environment because, for outdoor environment, a sensor node can install the special device into the node called as Global Positioning System (GPS) [4]. But, the weakness of the GPS is cannot be used inside the building because the signal from at least three satellites cannot penetrate the wall or the roof of the building. As a result, the wrong node location will achieve. Thus, indoor localization techniques are needed to replace the GPS.

The indoor localization process is subsisting into two phases: the first phase called as Ranging phase and the second phase called as Node Estimation phase [5]. The Ranging phase is used to measure the distances or angles between unknown nodes and anchor nodes where the popular technique in range based is called as Radio Signal Strength Indicator (RSSI) [6]-[8]. In Node Estimation phase, many researchers solved the localization problem by using a traditional algorithm such as trilateration, triangulation, or Maximum Likelihood Estimation [9]-[11]. The traditional technique shows can get the estimation location of a node, however the localization error still high [12]. To achieves lower localization error, recently, many researchers implement the meta-heuristic algorithm by formulating the localization problem as a optimization problem [13].

Wachowiak introduced an Adaptive Particle Swarm Optimization method to solve constrained Economic Load Dispatch (ELD) problems [14]. To expand the ability of PSO algorithm research, many researchers have enhanced the PSO algorithm [15]-[17] Stojkoska introduced Multidimensional Particle Swarm Optimization to avoid the premature convergence and speed up the convergence particle to the optimum global method by letting each swarm converge at a different optimum [18].

Different to Zhang also, proposed distributed iterative node localization in WSN using PSO algorithm. Three or more anchors are used to localize the unknown node in its communication range PSO technique is used to minimize the localization error [19]. However, the localization based on PSO algorithm requires complex computations which is cause relatively high computation energy because of longer time taken for localized the unknown nodes. Besides, the particle has found the fake target because of its weakness by trapping into local optimal.

To address the common problem of PSO, where the particle trapped into local optimal, variant PSO is introduced as well as Global best Local Neighborhood Particle Swarm Optimization (GbLN-PSO). GbLN-PSO

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algorithm proposed by Musa et al. [20] where it was applied in object tracking study. Then we have implemented it into localization in WSN [21]. Continue from previous study, we identified a problem in GbLN-PSO algorithm where the mechanism of exploitation process is not optimum searching yet where it is not utilized the ability of neighbor particles to keep searching the local search (exploitation) after particle move, make the particles still have probability to trapped into local optimal. Thus, this algorithm has the special mechanism of exploitation by distribute other particles around the main particles. The distributed particles are called as neighbor particles to keep doing local search by compared their fitness among them.

The main contribution of this paper is implementing an Improve Global best Local Neighborhood Particle Swarm Optimization (IGbLN-PSO) algorithm for indoor localization in WSN. This proposed algorithm is inspired by Teaching Learning Based Optimization (TLBO) in the term of exploitation and exploitation. The performance of the proposed algorithm is analyzed and compared with three (3) different algorithms: Particle Swarm Optimization (PSO), Global best Local Neighborhood Particle Swarm Optimization (GbLN-PSO), and Teaching Learning Based Optimization (TLBO). The results shown that the proposed algorithm is better than comparison algorithms in terms of computational time and percentage localization error.

The rest of this paper is organized as follows: a discussion PSO, GbLN-PSO and TLBO algorithms described in Section II. In Section III will be discussed the formulation of WSN Localization Problem, whereas Section IV discusses detailed the implementation of the IGbLN-PSO algorithm for WSN localization. Section V is the experimental setup, Section VI presents and investigates the simulation results. Finally, Section will present the conclusion and potential areas of improvement for future research.

## II. RELATED WORKS

### A. Particle Swarm Optimization

In the year 1995, J. Kennedy and R. Eberhart have proposed a population-based stochastic optimization technique called as PSO [22]. Variety of fields has been applied PSO algorithm such as object tracking [23] and Wireless Sensor Network (WSN) [24].

In the basic PSO algorithm, each of the particles has its GLVWDQFH IURP WKHLU WDUJHW ORFDWLRQ 7KH SDUWLFOHV¶ GLVWDQ formulated as the fitness or objective function to the optimization problem. The particles have li (local best), and a particle located near to the target location is called g (global best). The position of the particle is initialized based on (1):

$$x_i \sim r(0,1) * R \quad (1)$$

Here, $x_i$ represent the particle location, where $i = \{1,..,i\}$, while r is random number where $(0 < r < 1)$, and R is the size of search space. In PSO technique, a set of particles will move according to the lowest value objective function toward the direction of the particle.

The local best, l is determined by comparing the particle fitness value, fi and fitness value of local best. If the fitness value of the local best is smaller than the fitness value of a particle, $(f_{l_i} \; f_i)$, then the fitness value and the location of the particle will be appointed to the fitness value of local best, stated as $f_{l_i}$ ( $f_i$ and $l_i$ $x_i$ ). This will make the best particle always found to move near to the target.

When the new position is found by particle, it can be expressed by $(f_g \; f_{l_i})$, where the value of global best is smaller than local best, the fitness value and global best particle update such as ($f_g$ $f_{l_i}$ and $g$ $l_i$ ) respectively. Then, every iteration process will update the position an velocity of the particles to search for a new location, until the condition is satisfied. The particles are updating their location and velocity according to (2):

$$V_i \quad wV_i \quad c_1 r_1 (l_i \quad x_i) \quad c_2 r_2 (g \quad x_i) \quad (2)$$
$$x_i \quad V_i \quad x_i$$

In (2), Vi is the velocity calculation of the i particle and $x_i$ represent the new position of particle i. w is inertia weight used to accelerate the convergence speed of PSO. $c_1$ and $c_2$ are the acceleration constants that influence the velocity of the particle, while $r_1$ and $r_2$ are distributed random number $(0 < r < 1)$. The symbol li is the local best and g is the global best of the population.

### B. Global best Local Neigborhood Particle Swarm Optimization (GbLN-PSO)

One of the variant PSO algorithm called as Global best Local Neighborhood Particle Swarm Optimization (GbLN-PSO). GbLN-PSO algorithm was proposed by Musa [20] and [23] and implemented into the object detection in the tracking process where GbLN-PSO algorithm was combined with three different methods: particle filter, unscented Kalman Filter and Parzen Particle Filter. The ability of GbLN-PSO for the optimum searching value in a large space area (exploration) and the ability to search the best among the local search (exploitation) was solved to find the optimum solution. This is because this algorithm has been enhanced to avoid local optima trap by keep searching minimum value along with the particle movement. GbLN-PSO algorithm is shown to increase the capability of particles for a searching solution as well as to get the best quality result by recognizing the search space along with the movement. The GbLN-PSO result for object tracking study shows that model-based GbLN-PSO using particle filter achieved 25% better accuracy than other methods This algorithm has the ability to search for a large space area (exploitation) and the ability to search the best among the local search (exploration) particles in a space area. The particles are occasionally not able to solve the optimum solution but converge to a near-optimum peak. The GbLN-PSO has discuss detailed in our previous study in [21].

C. Teaching Learning Based Optimization

Another meta-heuristic algorithm that can solve the optimization problem is Teaching Learning Based Optimization (TLBO) algorithm. This algorithm is inspired by applying teaching and learning process occu in a classroom [25]. Most of the nature-inspired algorithms have limitation such as there need to contrc the tuning parameters. But, TLBO algorithm is parameters free algorithm which is no parameters ar required for running this algorithm [26]. Besides, TLBO performs stability with high performance when there is more iteration of the population in the searching process.

TLBO algorithm works according to the teaching and learning process. It is based on a teacher and learners i class. A teacher a highly educated person and the qual of a teacher will affect the results of the learners. In TLBO algorithm, a group of learners is a population. TLBO process is divided into two parts: which are Teacher Phase and Learner Phase. The first part consi of teacher phase in which learners learn from the teache The second part is learner phase in which learners lea from the interaction between themselves.

Teacher Phase: The learners gain knowledge from the teacher directly. A good teacher brings the learners t upgrade the level in terms of knowledge. But it depend on the quality of the teacher. The teacher makes an effc to gain the best value of the mean. The teacher can improve itself by shifting the mean value from $mean_1$ to $mean_2$ if the $mean_1$ value is worse than $mean_2$. Consider, $M_i$ denotes the mean of the knowledge of learners and $T_i$ denotes any teacher in the iteration. The teacher wants enhance the current mean knowledge of learners and the difference between the previous mean and new mean is given as shown in (3) below:

$$DifferentMean_i = r_i * (T_{mean} - T_f * M_i) \qquad (3)$$

where,

$$T_f = round(1 + rand(0,1)) \qquad (4)$$

In (3), $M_i$ and $T_{mean}$ represent the mean of the knowledge of learner and teacher in $i$th iteration, $T_f$ denotes the teaching factor as (4), and $r_i$ is a random number in the range of 0 and 1. The new mean of the knowledge is updated using (5) below.

$$X_{i,new} = X_{i,old} + DiffrentMean_i \qquad (5)$$

**Learner Phase:** Learner phase aims to enhance the knowledge of learner from others. So, to improve the learning ability, a learner can interact with other learners randomly. This learning capability of learners can be expressed as follows if $i$th learner wants to interact with the $j$th learner and the fitness of the $j$th learner is higher than $i$th learner ($j \neq i$), then the position of $i$th learner will be updated as shown in (6), otherwise, $i$th learner update the position as shown in (7). Figure 1 show the flowchart of TLBO Algorithm.

$$X_{i,new} = X_{i,old} + r_i * (X_j - X_i) \qquad (6)$$

$$X_{i,new} = X_{i,old} + r_i * (X_i - X_j) \qquad (7)$$

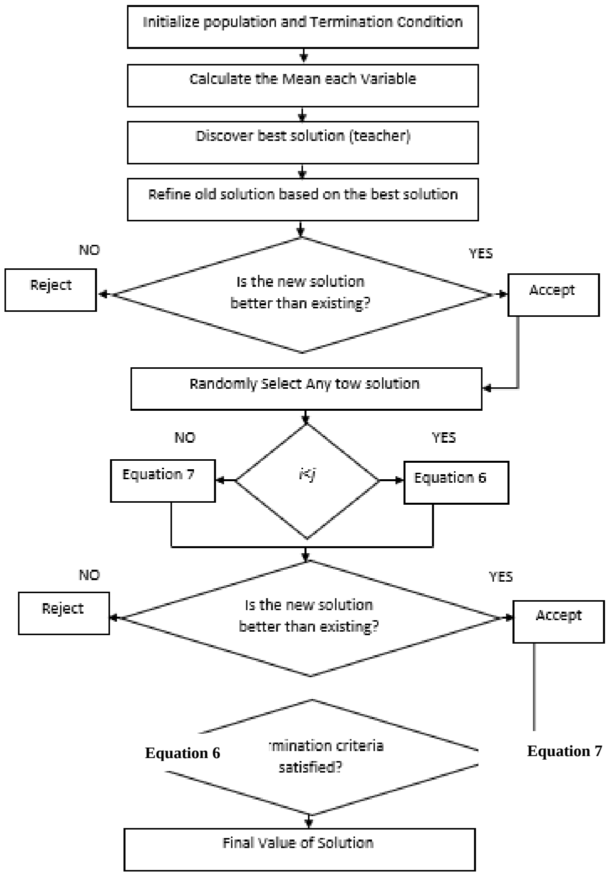


Fig. 1. Flowchart of TLBO algorithm

## III. Problem Formulation Localization in WSN

To show the localization as NP-problem, the sensor nodes randomly deployed in two-dimensional (2D). Each distributed sensor node has a transmission range $r$. The WSN can be defined as a graph $G = (V, E)$, where $V$ represents the group of sensor nodes $(i, j) \in E$, while the distance between the $i$th and the $j$th sensor node is $d$. Unknown target nodes are denoted as the set of N. Anchor nodes are defined as set M, with positions ($x_m$, $y_m$), for all $m \in M$. The goal of the localization is to find the positions unknown nodes ($x_n$, $y_n$) where $n \in N$. Then, to provide a solution for this problem, a function is being constructed and called as fitness function which is can provide the solution by minimizing the function of localization error of unknown node to find out the unknown node coordinate [15].

Thus, node localization problem is belonging to the group of NP-hard problem. Since deterministic algorithms (produce same result) could not solve NP-hard optimization problems within reasonable computational time, non-deterministic (stochastic), metaheuristics methods can be employed [27]. Metaheuristics methods can achieve an acceptable solution with in a suitable computational time [28]. Detailed the fitness function is discussed in [21].

## IV. IMPROVED GLOBAL BEST LOCAL NEIGBORHOOD PARTICLE SWARM OPTIMIZATION (IGBLN-PSO)

IGbLN-PSO is inspired by TLBO algorithm that applied teaching and learning process of the teacher and student. Teacher that has the qualification of teaching will transfer the knowledge to the student. This process called as an exploration process where the population will search the target far away over the search area. Then, after gained knowledge from a teacher, the student will learn among them to get more understanding. This process called as exploitation where the population will compare among their neighbor population to keep search the target position. Thus, from this idea, we enhance the GbLN-PSO algorithm, to have more efficient in the exploitation process by distributing the neighbor particles around the main particle. Fig. 3 illustrate the idea of IGbLN-PSO algorithm.

In IGbLN-PSO algorithm there are two processes of searching: 1) Exploration and 2) Exploitation. Like GbLN-PSO algorithm, the particle will undergo exploration process by updating the movement velocity ($v_i$) of the particle as shown in (2). The particle moves based on current global best ($g_k$), which lead to change from a location to another location and search for optimum value along the direction of current optimum value.

In the exploitation process, the neighbor particles will be distributed around the main particle in every iteration and calculate its fitness. The neighbor particles will compare their fitness to the main particle. If the fitness of the neighbor is better than the main particle, the neighbor particle will replace the main particle. The neighbor particles will help to prevent from being trapped into local optimal. Different to the GbLN-PSO, where the neighbor particle will be distributed along the movement of particle. While, exploitation in IGbLN-PSO algorithm, will added a subprocess, neighbor particles will generate a small population for its neighborhood around the main particles as shown in (8)

$$N \quad (x_n, y_n) \tag{8}$$

$$x_n \quad rand(x_a \quad , x_b \; Y) \qquad Y$$
$$y_n \quad rand(y_a \quad , y_b \; Y) \qquad Y \tag{9}$$

where

$$Y \quad \frac{\sqrt{(x_a \quad x_b) \quad (y_a \quad y_b)}}{2} \tag{10}$$

where, $n_i'$ is the random number that generates $x_i$ and $y_i$. The location ($x,y$) of neighbor particles are randomly selected as shown in (9), where $Y$ is distance calculation of the location before and after of the main particle move. Then the distance will divide by number two (2) to get the space of distribution neighbor particles. The distance calculated using Euclidean distance formula. Below is the illustration of creating the neighbor particles distribution space.

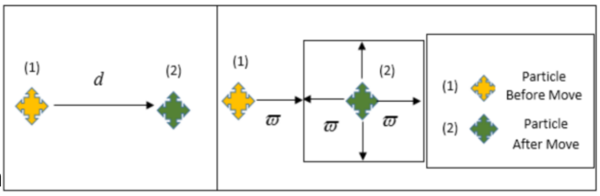


Fig. 2. Illustration the neighbor particles distribution space (Exploitation Phase)

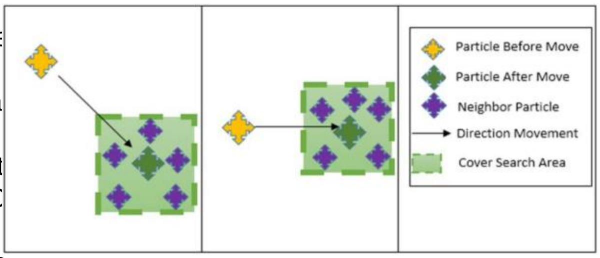


Fig. 3. Illustration distribution of neighbor particle on IGbLN-PSO algorithm (Exploitation Phase)

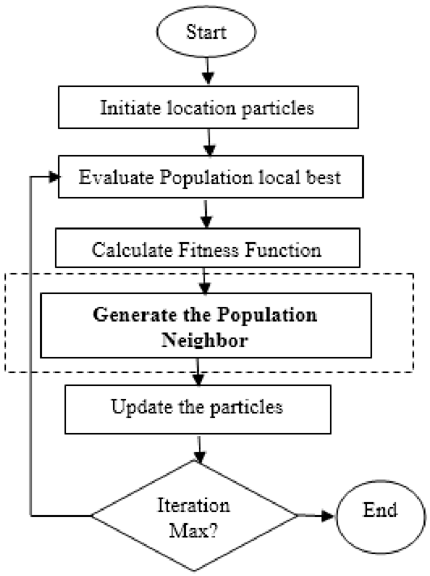


Fig. 4. Flowchart of IGbLN-PSO algorithm

Fig. 2 shows the illustration of the distribution space of the neighbor particles. The area of distribution space for neighbor particle such like the frame the be created from (10). Fig. 3, show on how particles in IGbLN-PSO algorithm move and distributed the neighbor particle around. In every movement, neighbor particles covered the around the main particle. Fig. 4 show the flowchart of the algorithm.

## V. EXPERIMENTAL RESULT

To evaluate the performance of the proposed algorithm in WSN, analysis was conducted using Matlab R2014a software. The parameters used for localization are listed in Table III and the parameters for algorithms listed in Table IV. In this experiment, the simulation has been run for 40 unknown nodes. The weight and coefficient have been selected after the tuning parameter process had been conducted at Table I and II.

TABLE I. SIMULATION PARAMETER FOR LOCALIZATION

| Parameters | Values |
|---|---|
| Network Size | 100 ×100 $m^2$ |
| Anchors Node | 3 |
| Unknown Nodes | 40 |

TABLE II. SIMULATION PARAMETER FOR COMPUTATIONAL TIME AND ACCURACY EXPERIMENT

| Parameters | Values |
|---|---|
| Maximum Iteration | 50 |
| Weight | 0.8 |
| Coefficient | 1.9 |
| Random Number | [0,1] |
| Number of Particle in PSO | 20 |
| Number of Particle in GbLN-PSO | 20 particles (5 particle with 3 neighbor each particle) |
| Number of Particle in TLBO | 20 |
| Number of Particle in IGbLN-PSO | 20 particles (5 particle with 3 neighbor each particle) |
| Particle Position | Xmin=0, Xmax=100 |

## VI. RESULT AND DISCUSSION

### A. Comparison of Particle Convergence

Fig. 5 shows the comparison between the iteration number of converging particle and minimum value. The PSO, TLBO algorithms have applied 20 particles, where GbLN-PSO and IGbLN-PSO algorithms also used 20 number of particles by applying five (5) particles and three (3) neighborhoods ((1 particle × 3 neighbors) + 5 particles = 20 particles), respectively.

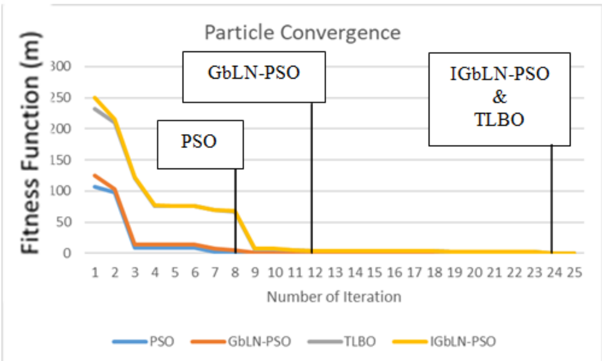


Fig. 5. Comparison converge rate on minimum value of unknown node

, Q  WKHRUHWLFDO  WKH  IDVWHU less exploitation of particle in the search area [28]. Fig. 5 shows the quickest convergence of the particle is PSO, followed by GbLN-PSO algorithms. TLBO and IGbLN-PSO have the slowest convergence at 24th iteration. PSO algorithm converged at the 8th iteration. As the traditional PSO algorithm, all the particles have a great exploration process. At the same time, every particle still has the exploitation process to avoid the trap into local optimal, but PSO have no mechanism to have great exploitation because the particle will move quickly jump into best solution. This will make the particle are ignoring the local search around them. It is different from GbLN-PSO algorithm that has converged at 12th iteration. The QHLJKERUV¶ SDUWLFOHV DUH XVHG W local optimal by doing the local search of each iteration. The ability of neighbor particle to scatter along with the movement leads to the GbLN-PSO algorithm to have vast particle diversity of exploitation process.

IGbLN-PSO algorithms have same number iteration with 7/%2 DOJRULWKP ZKHUH WKH SDUW at iteration 24th. IGbLN-PSO is inspired by TLBO algorithm, thus both algorithms have the same searching process. In the exploration process, the particles will randomly be scattered randomly over the search space. The best particle will excite other particles to move towards it. At the same time, the each of the moving particle will examine their fitness to their neighbors to have the local search. This process makes both algorithms have slower convergence, because there are two processes was running in a iteration. This will make both algorithms have more exploitation process compared to others.

### B. Comparison of Accuracy and Mean Error

To evaluate the performance of the proposed algorithm, the localization error and computation time was compared in the simulation for each algorithm. Localization error is gain by calculating error distance between the estimated location and truth location. Theoretically, the higher the accuracy, the lower the localization error result and vice versa [6].

TABLE III. COMPARISON OF LOCALIZATION ERROR AND MEAN ERROR OF ALGORITHMS

| Algorithms | Localization Error | Mean Error |
|---|---|---|
| PSO | 0.44928 | 0.5031 |
| GbLN-PSO | 0.44415 | 0.5273 |
| TLBO | 1.08450 | 0.9276 |
| IGbLN-PSO | **0.44283** | **0.3479** |

From Table III, we can see that PSO and TLBO algorithms have the highest localization error at 0.44928m and 1.08450m. Compared to GbLN-PSO and IGbLN-PSO, both gained the lowest localization error at 0.44415m and 0.44283m respectively. The result shows that IGbLN-PSO algorithm has the improve around 0.02%, 0.01% and 59.16% compared to PSO, GbLN-PSO and TLBO algorithms. The main advantage is GbLN-PSO can have more exploitation for particle to find the optimum value by keep scattered the neighbor particles to have the local search. IGbLN-PSO has a significant advantage in term of preventing the particle from converging early compared to others by distributed the neighbor particles around the main particle. This mechanism enhances the particle ability to search the optimum solution of unknown node location.

For mean localization error is the average of error localization for thirty-three (30) times running an experiment with the random location of unknown nodes and particles. Based on the mean error result in Table III, TLBO has the highest error at 0.9276m compared to PSO and GbLN-PSO at 0.5031m and 0.5273m respectively. This is because TLBO algorithm consumes more iteration to make the population more experience in searching process. The immature particle will cause the inaccurate location of the unknown node. In this experiment, IGbLN-PSO indicates the lowest localization error at 0.3479m. IGbLN-PSO can achieve lowest localization error to estimate the unknown node location with 30 times of running experiment. From this experiment, IGbLN-PSO algorithm has improved the accuracy slightly and best performance of computational time and lowest mean error in finding the target location.

### C. Comparison of Computational Time

The time taken by the node to be localized is important because the longer computation time means more energy consumption without loss of generality. Thus, the computational time is evaluated in this experiment by setting from the initialization of the localization process until the process the estimated unknown node location completed.

TABLE IV. COMPARISON OF COMPUTATIONAL TIME

| Algorithm | Computational Time |
|---|---|
| PSO | 118.9807 |
| GbLN-PSO | 28.8254 |
| TLBO | 24.5875 |
| IGbLN-PSO | **23.7126** |

In terms of computational time, IGbLN-PSO algorithm shows the best performance at 23.7126 second compared to PSO, GbLN-PSO, and TLBO algorithms. This result is improved significantly at 80.07%, 17.73% and 0.3% respectively. The ability of this algorithm is to increase the probability of finding the best optimum value around the main particle. In this experiment, five primary particles will have the exploration process, and three other particles are scattered around the main particle to have the exploitation process. This mechanism helps the particles to found the target with less computational time. This makes IGbLN-PSO have the fastest searching process and a more accurate result.

Different to others, TLBO algorithm shows a better result compared to PSO and GbLN-PSO. The result shows that TLBO algorithm takes 24.5875s to complete the process. TLBO algorithm has improved 79.33% and 14.7% compared to PSO and GbLN-PSO algorithms. It shows that TLBO algorithm can minimize the time taken by applying the teaching and learning in a iteration without adding subprocess to search the optimum value. The particles are exploring and can move towards the gBest (g) particle and the others will help to find the best value among them. This can make time taken to be short to finish the localization process. Whereas GbLN-PSO has improved 75.77% compared to PSO at 28.8254 second. This is because GbLN-PSO only distributed three (3) main particles to have the exploration process and it has the special mechanism by scattering the neighbor particles along the particle journey. The process of exploration and exploitation of neighbor particles occur in every iteration. This makes GbLN-PSO algorithm has the shorten time taken compared to PSO algorithm.

## VII. RESULT AND DISCUSSION

In this paper, we proposed to enhance Global best Local Neighborhood Particle Swarm Optimization (GbLN-PSO) called as Improve Global best Local Neighborhood Particle Swarm Optimization (IGbLN-PSO) to solve indoor localization in Wireless Sensor Network (WSN). The previous study, GbLN-PSO has been proposed to prevent the particle being trapped into local optimal, but still need other mechanism to have more exploitation process. Thus, IGbLN-PSO is proposed to enhance the ability of exploitation particle. Based on the result, IGbLN-PSO has proved can improved computational time at 80.07%, 17.73% and 0.3% compared to PSO, GbLN-PSO, and TLBO. At the same time IGbLN-PSO also increase the accuracy at the improve slightly around 0.02%, 0.01% and 59.16% respectively. For consistency result, IGbLN-PSO algorithm shows the inconsistency localization error but still hit the lowest localization error form others with the lowest mean error result. From all the running experiment, IGbLN-PSO algorithm proved can increase the accuracy and lower the computational time for node localization. For further research, the high accuracy of node localization needed by combining with the Case Based Reasoning (CBR) method and the proposed algorithm can be applying to the mobile node.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

In this paper, all the authors have the contributions. Shahkhir was the author that improved the recent algorithm from Zalili. Then the algorithm was verified by Zalili as the founder of GbLN-PSO algorithm. While, Rohani was the person that perform conceptual ideas and proof outline. Isni and Shahkhir was the person that conducted the experiment and verified. All authors had approved the final version.

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