PSO-TLBO: A Hybrid Algorithm for Energy Optimization in Wireless Sensor Networks

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ABSTRACT

In recent times, energy optimization in wireless sensor network has become a major area of concern due to the high amount of energy expended in transmitting sensed data from the sensing node to the base station. These sensors are usually powered by a battery with limited energy to achieve its tasks which reduces the lifetime of the sensor network and hence the need for energy optimization. In this paper, a hybrid algorithm using Particle Swarm Optimization (PSO) algorithm and Teaching – Learning Based Optimization (TLBO) algorithm is proposed to selects routes from the sensing nodes to the base station. The proposed algorithm takes into consideration the residual energy and the distant of each node from the base station to determine the path of transmission of the sensed data to the end point. The performance of the PSO-TLBO algorithm was evaluated and compared with conventional PSO and TLBO algorithms based on energy consumption of the network, simulation time and statistical analysis. The results of evaluation revealed that the proposed PSO-TLBO algorithm performed better than the PSO and TLBO algorithms.

Key words: Algorithm, Energy optimization, Particle Swarm Optimization, Teaching Learning based Optimization, Wireless Sensor Networks

1. INTRODUCTION

In the field of wireless communications, wireless sensor technology is increasing rapidly and has the capability to prevail in the future as well. It is a modern network technology which makes use of micro electro-mechanics with low-power sensors and communication system (Ding and Xiao-Ming, 2010).A wireless sensor network is made up of sensor nodes which sense the physical phenomenon to be monitored, process the sensed data and transmit the data wirelessly through a transmission media (Alippi *et al.*, 2009). This network makes use of either stationary or mobile nodes that performs local computations based on information gathered from the surroundings where it is being deployed.

Wireless sensor network consists of several tiny sensing devices which are equipped with small batteries with little energy to power them up. These sensors are constrained by insufficient energy available for the remote sensors in the network to function which often reduce the lifetime of nodes and leads to unexpected failure in the network (Omodunbi *et al.*, 2013).In the architecture of the wireless sensor networks, the process of data communication is considered to consume more energy than the sensing and processing operations (Pottieand Kaiser, 2000). Moreover, if all data sensed by sensor nodes in Wireless Sensor Networks (WSNs) are transferred to the base of operation directly, the data will be too enormous and large amount of energy will be consumed during transmission.

A commonly used approach for routing in wireless sensor networks involve the use of mobile nodes such as data mules (Shah*et al.*, 2003), message ferry (Zhao*et al*., 2004) and Zebranet (Juang *et al.*, 2002) to collect data from sensors and deliver to the base station. Data Mobile Ubiquitous LAN Extensions (MULES) are mobile devices that can collect data from spatially dispersed stationary sensor nodes in a network field by moving near each sensor (Lai and Jiang, 2012)

With the use of these mobile devices, energy consumption of sensor nodes is reduced but there is an increase in data delivery delay (Mkhwanazi*et al.*,2012). In order to prevent unexpected failure and delay in the network, there is need to develop algorithms that can efficiently manage the communication subsystem during transmission of sensed data in the sensor network.

Several optimization algorithms have been employed to maximize the energy of sensor networks, which has proved to be efficient and reliable in obtaining a close to global optimum solution. However, the difficulty experienced in the process of tuning the required parameters for the algorithm is a main challenge. In order for the algorithm to obtain an optimum solution, the parameters must be carefully selected. The accuracy of the algorithm can be altered by a slight difference in the value of any of the required parameters; therefore, emergence of optimization algorithms with few number of parameters and distinct is important. In this paper, a Teaching–Learning-Based Optimization (TLBO) algorithm (Rao*et al.*,2012) which simulates the model of teaching and learning in a classroom to solve optimization problems with few parameters and significant efficiency is adopted and modified with Particle Swarm Optimization algorithm for optimization of energy in wireless sensor networks with less computational effort.

The rest of this paper is presented as follows: in section 2, several existing algorithms for solving energy optimization problem are discussed. In section 3, the description of the network and energy consumption model is presented. Section 4 described the proposed hybrid algorithm in detail. The experimental results obtained for the hybrid algorithm developed were comparatively evaluated with some other algorithms and presented in section 5 while conclusion is in section 6.

2. RELATED WORKS

Over the last decades, various heuristic evolutionary optimization algorithms have been developed to resolve routing in wireless sensor networks. A discovery protocol that puts together a learning-based system with a structure that is hierarchical in nature was proposed by (Kondepu*et al.*, 2012). It precisely tries to study the mobile processes of the mobile element (ME) and do well to predict the next time of arrival based on the history. It employs Q-Learning which is similar to reinforcement learning that does not need an environmental model. The duty cycle is adjusted based on the prediction of the sensor node. Hence, the sensor node is on passive mode, it is only active when the mobile element is about to arrive. Although, accurate prediction might not be made all the time, the hybrid algorithm tries to enhance its energy efficiency by exploiting a supplementary hierarchical scheme.

A genetic algorithm based solution was proposed to achieve two goals under one constraint by studying the data mule path planning optimization (DMPPO) problem (Lai and Jiang, 2012). The two important goals are to observe the path that is close to the sensor to collect data by the data mule which results in reduction of traversal time to the barest minimum and to modify the transmission range of the sensor node, so that the total energy consumed by the sensor node is reduced. The main problem is that the data mule must move close each sensor node at least once for data gathering. Therefore, in order to find optimal solution to this problem, a genetic algorithm using heuristics were suggested. The idea of the proposed algorithm would locate the set of non-dominated achievable solutions that are not dominated by any others.

An energy-efficient strategy was proposed to retrieve data from sensor nodes using mobile nodes (Brinis*et al*., 2012). It put into consideration the kinds of applications for data gathering where every event that occurs within the area being observed must be reported back to the sink. It is assumed that the intended applications can tolerate delay. The network cycle-life was defined as that particular time before the loss of coverage. The advantage of this strategy is that it doesn't require network connection. The movement of data to the sink, the proper scheduling of sensor nodes activities as well as replacement of energy constrained nodes are all coordinated by the data mules. The mules make use of energy harvesting produced from a power terminal to perform their roles.

Alnuaimi (2015) presented an algorithm for efficient data collection that made use of ferry node while observing the general ferry roundtrip travel time and the overall energy consumed by the network. Genetic Algorithm which makes use of weight metrics were employed to solve the Travelling Sales Man Problem (TSP) and decides on an optimum path for the ferry to collect data. An initially published Node Ranking Clustering Algorithm (NRCA) was applied in each virtual grid and in selecting the location for placing the ferry's checkpoints. The simulation for the proposed algorithm was done and the algorithm performance was observed to be efficient in terms of the network lifetime, total energy consumption and the total travel time.

Yadav and Kumar (2017) adopted a teaching learning-based optimization (TLBO) algorithm for locating the optimum number of Cluster Heads (CHs) in a sensor field. The aim of this algorithm is to manage and minimize power consumption and increase the network lifetime. The proposed algorithm is integrated with LEACH protocol, called LEACH-T and the residual energy was considered for selecting the CHS. In this algorithm, genetic crossover and mutation operators are integrated into the TLBO algorithm. The genetic mutation operator is applied in the teaching phase, whereas, genetic crossover operator is applied in the learning phase of the TLBO algorithm. The outcome of simulation shows that the algorithm enhances the network lifetime by managing excessive power consumption during packets transmission.

Zhang and Luo (2018) proposed a data fusion algorithm that is based on an extreme learning machine for a wireless sensor network in line with the temporal-spatial correlation in the data collection process. The technology behind data fusion is basically to process a large amount of raw data collected by the wireless sensor network nodes. Unneeded information can be subdued to reduce the excess pressure on wireless sensor networks with lesser energy, storage capacity, and limited network bandwidth. After the whole analyses of the principles, design ideas and implementation process of the extreme learning machine algorithm, the performance and results were compared with the traditional LEACH algorithm and Bacteria Foraging (BF) algorithm in the simulation environment.

Raisat et al (2018) developed an energy-efficient hybrid leach protocol comprises of Bacterial Foraging (BF) and Particle Swarm Optimization (PSO) algorithm with the aim of efficiently utilizing the energy of sensor networks while communicating with the base station (BS). The hybridization of BF with PSO is done at the chemotactic phase of bacteria foraging algorithm. The simulation results indicate that the proposed scheme BFPSO possesses a better performance when compared to the classical schemes in terms of energy efficiency.

Verma. and Gupta(2020) proposed an energy efficient multipath routing algorithm. The algorithm was used to increase the lifetime of wireless network by obtaining the optimum path which consumes less energy among all possible paths discovered in the network. A routing protocol, PSO-SIC with high throughput was employed to compute the available bandwidth of a given path. It uses SIC and energy of nodes as a parameter to obtain the best paths with the aid of Binary Particle Swarm

Optimization. The proposed algorithm was compared with multipath AODV routing protocol and the remaining energy of the network using the proposed algorithm was found to be more than the existing algorithms.

3 NETWORK DESCRIPTION AND ENERGY CONSUMPTION MODEL

The wireless sensor network can be regarded as a network comprising of fixed sensors and a mobile node (Data MULE) deployed around the region. In most WSN, sensor nodes have specified areas where they are implemented. The sensors are able to manage a region of interest of a specified base station. Individual sensor creates a data packet per time and are designed to communicate the sensed event to the base station. Since signals are passed across and picked up by each sensor within their region of operation (sensing radius), a mobile node can receive data from a sensor within the sensing radius. For most WSNs, they contain non-rechargeable and expendable battery in individual sensor node and a large portion of its energy goes to receiving and transmitting of data by the sensor node.

In consideration to the limited energy resources available, a mathematical model for WSN was designed. This was adopted from the work of Heinzelman *et al.*, (2000). Significant consideration is placed on the distance between the nodes and the energy of each sensor node because of the little amount of energy available. In any wireless sensor network, there must be a number of sensor nodes communicating with a base station. A mobile node was introduced for communication between the static nodes and the base station whose location was assumed to be constant during the process of data collection. The channel of the model to be adopted is dependent on the difference between the transmitter and receiver. When the distance of propagation is less than the threshold distance d_0, the rate at which each node consumes energy is directly proportional to d^2 otherwise, it is proportional to d^4. The energy required for transmitting a *k*-bit message for a distance, d is given as

;$E_{Tx}(k,d) = E_{Tx-elect}(k) + E_{Tx-amp}(k,d)$

$$E_{Tx}(k,d) = E_{elect} * k + E_{amp} * k * d^4 \quad (1)$$

The energy spent to receive this message is expressed as

$$E_{Rx}(k) = E_{Rx-elect}(k)$$

$$E_{Rx}(k) = E_{elect} * k \quad (2)$$

where E_{elect} is the energy consumed by a sensor node to transmit or receive 1-bit data, and E_{amp} is the amplifier coefficient of free-space model and multi-path fading model.

The objective is to minimize:

$$MIN \sum_{i \in N} E_c = \sum_{i \in N,} E_{Tx} + \sum_{i \in N} E_{Rx} \quad (3)$$

Subject to

$$\sum_{i \in N} d_{Tx}.d_{Rx} \leq d_0 allTx, Rx, \in N, \quad (4)$$

Where *N* is number of nodes, *i* is the index of each transmitting node, d_{Tx} is the distance from the node transmitting to the mobile node, d_{Rx} is the distance from the mobile node to the receiving node.

The function in equation 1 is use to estimate the energy consumed by the nodes while transmitting. Equation 2 is use to estimate energy consumed by the receiving node. Equation 3 is a minimization function which reduces the total energy consumed by the nodes while equation 4 puts a restriction on the distance between the nodes and represents the energy capacity constraint on sensor nodes.

4. THE PROPOSED PSO - TLBO ALGORITHM

PSO and TLBO algorithms are optimization techniques that have attracted growing interest due to their outstanding features, such as few number of parameters, simplicity with few mathematical requirements. Below is a brief description of both algorithms.

4.1 Standard Teaching-Learning Based Optimization (TLBO) Algorithm

The teaching-learning based optimization (TLBO) algorithm developed in 2012 is a nature inspired algorithm which is majorly inspired by the teacher's influence on the class and learners' interaction. The idea behind TLBO search algorithm imitates a tutor and the outcome of learning in a classroom (Rao *et al.*, 2012). In this optimization algorithm, a set of learners is regarded as population and diverse subjects offered to the learners are regarded as different design variables of the optimization problem. Moreover, the result of a learner is equivalent to the 'fitness' value of the optimization problem. The most outstanding solution in the entire population is regarded as the teacher. The parameters used in the objective function are the design variables of the given problem and the best value of the objective function is the most outstanding solution.

The algorithm defines two fundamental teaching methods: i) teaching with the aid of teacher (known as teacher stage) and (ii) teaching by communicating with other learners (known as learner stage) (Rao *et al.*,2012).

4.2 Standard Particle Swarm Optimization Algorithm

It is developed from swarm intelligence derived from research on bird and fish flock movement behaviour (Kennedy and Eberhart, 1995). While the birds make a critical search for a food place to place, there is always a bird that can smell the food very well, that is, the bird is perceptible of where food may be found, having the better food resource information. In swarm optimization algorithm, solution swam is compared to the bird swarm, the birds' in search of food is equal to the development of the solution swarm, good information is equal to the best solution, and the food resource is equal to the most optimist solution during the whole course.

In Particle Swarm Optimization algorithm, there are many candidate's(swarm) which are also called particles and the respective position of each particles in potential solution are represented in D-dimensional space (Kennedy and Eberhart, 1995). Each individual in PSO flies in space at a speed that is dynamically adapted to his or her own flying experience and the flying experience of its environs. Based on these values, the highest local values called *pbest* are achieved, from which the highest global value is derived, called *gbest*. Each particle is assessed using an objective function.

$$f = \sqrt{\sum_{i}^{N-1} \sum_{j}^{N} (x_i - x_j)^2 + (y_i - y_j)^2} \quad (5)$$

Each particle's positions are changed with the distance between *pbest* and the present position. This change can be depicted by the velocity. Velocity and each particle's position can be adjusted with the equations 6 and 7:

$$\vec{v}_{ij}(t+1) = \omega \vec{v}_{ij}(t) + c_1 r_1 \left(P_b - \vec{X}_{ij}(t)\right) + c_2 r_2 \left(P_b - \vec{X}_{ij}(t)\right) + c_3 r_3 \left(G_b - \vec{X}_{ij}(t)\right) \quad (6)$$

$$\vec{x}_{ij}(t+1) = \vec{x}_{ij}(t) + \vec{v}_{ij}(t+1) \quad (7)$$

where ω is the inertia factor that influences the local and global skills of the algorithm and regulates the impact of the past velocity on the new velocity, *Vij* is the velocity that is the rate at which the next position changes with regard to the present situation, and C_1 and $C_2$are the weights that affect both cognitive and social variables respectively.

4.3 Hybrid PSO-TLBO Algorithm

The concept behind PSO-TLBO is to merge the strength of PSO with that of TLBO to make a more effective algorithm. The advantage of PSO is its exploitation power that is the efficiency of delivering outcomes is rapid. The PSO algorithm also possess the ability to store data, so all the particles can understand and retain good solutions. The negative aspect of PSO is that it still suffers from premature convergence which is caused by the rate at which information flows in between particles thereby leading to the production of particles that are alike. With this, the probability of being trapped in local optima is high due to the lack of diversity. A lot of resources have been put into enhancing the original PSO algorithm through hybridization and other means.

The benefit of TLBO lies in its efficiency in achieving extraordinary precise solution and a good exploration potential. One of the essential features of this metaheuristic is the reduction in the number of parameter as the complexity of a known metaheuristics is determined by the number of parameters used. Once the global optimal region has been located, the TLBO algorithm starts to obtain higher probability at the later part of search process for maximizing the local search and exploiting high precision solution.

The maximum velocity of particles is used to control the global exploration capability of particle swarm as shown in equation 8 and 9. A bigger velocity will facilitate global exploration, hence, the incorporation of the TLBO equation into the velocity and position equations of PSO.

$$\vec{v}_{ij}(t+1) = \omega\vec{v}_{ij}(t) + c_1r_1\left(P_b - \vec{X}_{ij}(t)\right) + c_2r_2\left(P_b - \vec{X}_{ij}(t)\right) + c_3r_3\left(G_b - \vec{X}_{ij}(t)\right) \quad (8)$$

$$\vec{x}_{ij}(t+1) = \vec{x}_{ij}(t) + \vec{v}_{ij}(t+1) \quad (9)$$

where:

Vij : the velocity of particles at iteration t that is the rate at which the next position changes with regard to the present situation

ω : is the inertia weight that influences the local and global skills of the algorithm and regulates the impact of the past velocity on the new velocity,

C_1 and C_2 : is the acceleration coefficients that affect both cognitive and social variables respectively.

r_1, r_2 and r_3 : are random numbers between 0 and 1

P_{best} : is the best position of particle

G_{best} : is the best position which is the best solution so far among the entire group of particles

X_{ij} : is the current position of particle i at iteration t

In order to hybridise the two algorithms, the velocity of each particle in PSO was updated with the learning phase of the TLBO algorithm as seen in equation 10.

Update velocity of particles;

$$\vec{v}_{ij}(t+1) = \omega\vec{v}_{ij}(t) + c_1r_1(P_b - \vec{X}_{bj}(t) + r_i(X_{bjp} - X_{bjq})) + c_2r_2(P_b - \vec{X}_{bj}(t) + r_i(X_{bjp} - X_{bjg})) + c_3r_3\left(G_b - \vec{X}_{bj}(t) + r_i\left(X_{bjp} - X_{bjg}\right)\right) \quad (10)$$

where X_{bjp} and X_{bjg} are the updated values.
In each iteration, the particles' position was updated with the teaching phase of the TLBO algorithm as stated in equation 11:

$$\vec{x}_{ij}(t+1) = \vec{x}_{ij}(t) + r_i(x_{j,kbest,i} - T_F M_{j,i}) + \vec{v}_{ij}(t+1) \quad (11)$$

where, the teaching factor is T_f and $x_{j,kbest,i}$ is the estimated output of the best learner in subject j.

In PSO-TLBO, the algorithm initializes by setting up a number of paths linking all the nodes in the network, this is referred to as the number of particles. Then fitness of each path is obtained by calculating the fitness of each particle using the fitness function. The value obtained is used to determine the local best value among set of paths and the global best value among all set of particles. After obtaining the best fitness value, the velocity of each path are updated using the new velocity equation derived from both PSO and TLBO algorithms. Similarly, the position of each particle is also updated using the derived equation. This continues until the condition for termination is satisfied or maximum iteration is reached.

The procedures involved in the algorithm are given in Figure 1 and flowchart of PSO-TLBO is shown in Figure 2 as follows:

a) Set parameter ω_{min}, ω_{max}, c_1 and c_2 of PSO-TLBO
b) Initialize population of particles having positions x_j and velocities v_j
c) Set iteration k = 1
d) Calculate fitness of particles $F_{ij}(t)$and find the index of the best particle

$$f = \sqrt{\sum_{i}^{N} (E_i - E_c) \ \ .d}$$

e) Select $P_{bij}(t) = \vec{X}_{ij}(t)$ and $G_{bj}(t) = X_{bj}(t)$
f) $\omega = \omega_{max} - k \times (\omega_{max} - \omega_{min})/Max\_no$
g) Update velocity and position of particles

$$\vec{v}_{ij}(t+1) = \omega\vec{v}_{ij}(t) + c_1 r_1 \left(P_b - \vec{X}_{bj}(t) + r_i\left(X_{bjp} - X_{bjq}\right)\right) + c_2 r_2 \left(P_b - \vec{X}_{bj}(t) + r_i\left(X_{bjp} - X_{bjg}\right)\right) + c_3 r_3\left(G_b - \vec{X}_{bj}(t) + r_i(X_{bjp} - X_{bjg})\right)$$

$$\vec{x}_{ij}(t+1) = \vec{x}_{ij}(t) + r_i(x_{j,kbest,i} - T_F M_{j,i}) + \vec{v}_i(t+1)$$

Where,. the teaching factor is T_f and $x_{j,kbest,i}$ is the estimated output of the best learner in subject j.

Where X_{bjp} and X_{bjg} is the updated value.

h) Evaluate fitness $F_{ij}(t+1) = f(\vec{X}_{ij}(t+1))$ and find the index of the best particle b_1
i) Update $Pbest$ of population
   If $F_{ij}(t+1) < F_{ij}(t)$ then $P_{bij}(t+1) = \vec{X}_{ij}(t+1)$ else

$$P_{bij}(t+1) = P_{bij}(t)$$

Figure 1: Procedure of the Algorithm

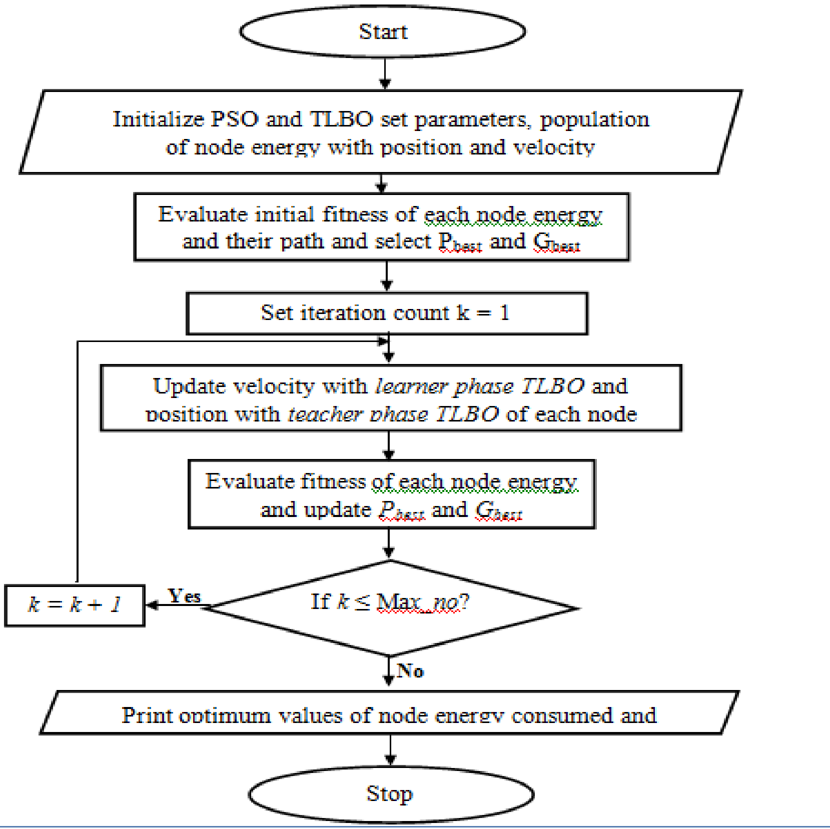

Figure 2: Flowchart of PSO-TLBO

4.4 Simulation of the Developed Algorithm PSO-TLBO Algorithm

Matrix Development Kit (MATLAB R2013) was used for the implementation of PSO-TLBO algorithm development. This was carried out in an environment using windows ten based PC with 2.94 GHz, Intel processor (i7) and 4 Gigabytes RAM. In the network, number of nodes were varied between 10 to 100 nodes arranged in random style with 100 m × 100 m area where base station is located within the network region. Also,a wireless mobile node is responsible for relaying the data sensed by the detecting nodes and forward them to the base station from where it will be disseminated to the appropriate channel. Based on each of the algorithm to be implemented, different parameters were employed: For PSO, the parameters applied are as follows: Population size=50, cognitive constant $c1$=0.4, social constant $c2$=0.2, inertia weight w= 0.99 with maximum number of iteration of 100. TLBO made use of the parameters: population size=50 and maximum number of iteration=100. PSO-TLBO employed a combination of each algorithm parameters as follows: Population size=50, cognitive constant $c1$=0.4, social constant $c2$=0.2, inertia weight w=0.99 and maximum iteration=100.

5. PERFORMANCE EVALUATION OF THE PROPOSED PSO-TLBO ALGORITHM

To validate the efficiency of the developed PSO-TLBO algorithm over PSO and TLBO algorithms, energy consumption, simulation/ run time and statistical analysis were applied as metrics of evaluation.

5.1 Energy Consumption Analysis

The result of the energy consumed by each of the algorithms, PSO, TLBO and PSO-TLBO with varying number of nodes is presented in Figure 4. The average energy consumed by PSO-TLBO as observed from the table was 7650.34J which is far from that of PSO and TLBO that were 31168.08J and 32065.18J, respectively. The result implies that the PSO-TLBO technique consumed lesser energy than the TLBO and PSO technique.

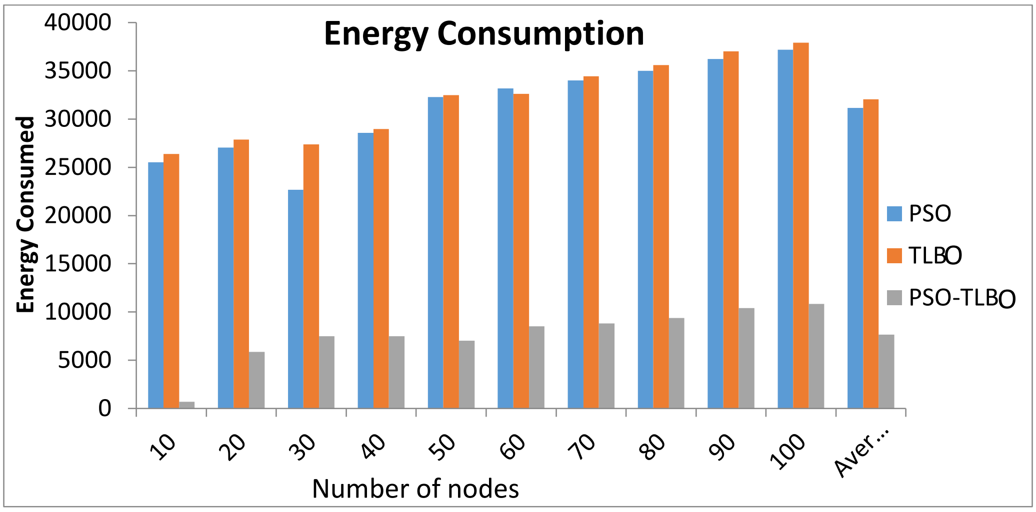

Figure 3: Energy consumed by the simulated algorithms

5.2 Simulation Time Analysis

The result of the runtime it takes each algorithm to run through the network and get to the base station is shown in Figure 4. TLBO was very fast resulting in an average simulation time of 28.1365s. PSO took longer time by achieving this feat in an average of 30.6295s. The developed hybrid PSO - TLBO performs better than both algorithms by obtaining an average of 26.9349s. The graph depicts that PSO-TLBO has a better simulation time than TLBO and PSO.

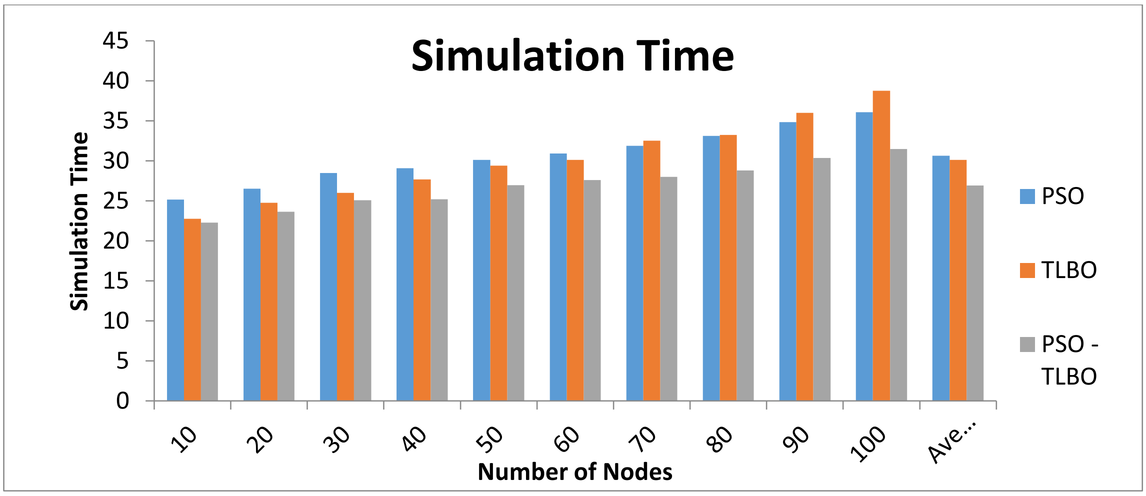

Figure 4: Average simulation time of each algorithm at varying number of nodes.

5.3 Statistical Analysis

Statistical analysis was performed on the result obtained in this study. Using the results for energy consumption and simulation time of each algorithm, a paired t-test value was measured between the energy consumed with regards to number of nodes of PSO-TLBO and TLBO as well as PSO-TLBO and PSO. The result of the paired t-test analysis conducted between the energy consumed with respect to number of nodes of PSO-TLBO combined with TLBO and PSO-TLBO with PSO were -24414.84 and -23517.74. The result confirmed that the PSO-TLBO was statistically significantat $P = 0.000$ and t value $= -23.81$. Furthermore, a paired t-test analysis conducted between the simulation time of PSO-TLBO combined with TLBO and between PSO-TLBO with PSO produced means difference of -3.199 and -3.690 respectively. The t-test result further validates the fact that PSO-TLBO performed better than both TLBO and PSO in terms of the energy consumed in relating to each number of nodes and the simulation time.

6. CONCLUSION

In order to optimize the energy of wireless sensor networks, an efficient and effective optimization algorithm was proposed. The developed algorithm evolved from the hybridization of PSO with Teaching Learning Based Optimization algorithm

(TLBO) to synergistically simplify difficult optimization problems. The hybridization is executed by the integration of the teaching and learning factors of TLBO equation into the velocity equation of PSO for the purpose of improving the velocity equation by expanding its scope. The residual energy and the distant of each node from the base station are taken into consideration by the algorithm to determine the path of transmission of the sensed data to the end point.

The evaluation of the performance of the algorithms is based on energy consumption, simulation time and statistical analysis. The results clearly revealed that the proposed hybrid PSO-TLBO is more efficient than the original PSO and TLBO in terms of energy consumption and simulation time. The different performance metrics employed were thoroughly evaluated to confirm the efficacy of the developed algorithm.

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Author's Brief Profile

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