Current Applied Science and Technology Vol. 22 No. 1 (January-February 2022)

Research article

Energy Optimization Algorithm for Path Selection in Wireless Body Sensor Networks

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Received: 16 December 2020, Revised: 16 March 2021, Accepted: 5 July 2021

DOI: 10.55003/cast.2022.01.22.014

Keywords

wireless networks;
body sensors;
mobile nodes;
algorithm;
optimization

Abstract

Recent advancement in technologies for wireless sensor networks has led to the emergence of wireless body sensor networks (WBSN). These networks are composed of various sensor nodes that are placed on the human body and have the ability to constantly detect, process and transmit any sensed vital signs of patients to physicians without confining the patients to their hospital beds or restraining their movement. In common with a good number of other sensor network applications, the sensors are constrained by not having sufficient energy for them to function, a situation which often leads to unexpected failures in the network. However, recent research has shown that the use of mobile nodes for data transfer can significantly reduce energy consumption of the network. Hence, in this paper, an energy efficient hybrid algorithm using particle swarm optimization (PSO) algorithm and teaching-learning-based optimization (TLBO) algorithm is presented. The proposed algorithm takes into consideration the residual energy and the distance of each node from the base station to select routes from the sensing nodes to the base station. The hybridization is performed by the incorporation of the teaching and learning factors of TLBO algorithm into the velocity equation of PSO algorithm in order to improve the convergence of the algorithm into global optimum. The performance of the new hybrid algorithm is compared to similar optimization algorithms. Extensive simulation results show the potential of the proposed algorithm to optimize the energy of wireless body sensor networks.

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1. Introduction

The rising demand for an improved remote and continuous health monitoring system has encouraged the use of wireless sensor network (WSN) in medical applications. WSN applied in health care are mostly classified under wireless body sensor network (WBSN), a new term that was recently invented [1]. A wireless body sensor network is made up of wireless sensor nodes that can evaluate various physical occurrences in the human body. WBSN can be used to monitor electrocardiography (ECG), blood oxygen, electroencephalography (EEG), central venous pressure (CVP), electromyogram (EMG), pulmonary arterial pressure (PAP), and respiratory impedance, among other variables. From a historical perspective, the body sensor is a technology that has been in existence for more than a century [2]. This wearable technology is more proactive and less expensive [3]. A notable landmark was the discovery of the clinical thermometer, meant to measure body temperature, in the year 1867. As the years rolled by, body sensors of diverse types with different capacities and functions were developed and utilized. Quite a number of physiological sensors can now communicate directly with compatible and available devices, which makes the unlimited monitoring of patients in hospitals, and care for the old or handicapped in their respective homes, possible. WBSN provides drastic improvement in the quality of health care over a relatively broad range of contexts for various in-need sectors of the population. The technology is able to detect some early clinical conditions by monitoring the patients in a hospital environment in real time [4, 5].

Clinical parameters are monitored basically for the purpose of observing changes in the physiological state of each patient. The most common physiological vital signs in humans which can help express a normal or an abnormal health status are pulse rate, blood pressure, respiration rate, and body temperature [6]. The vital signs of sound health are few and relatively constant although often dependent upon environmental conditions, age and special conditions such as pregnancy and other health issues like diabetes. Continuous monitoring of patient vital signs manually at regular intervals can be very laborious and stressful for the health practitioners. However, with WBSN, the monitoring of patients can be done with ease through the remote use of these body sensors via wireless communication.

As is the case with other sensor network applications, energy is an important resource that is needed for the smooth operation of WBSN [7]. These body sensors are made as small as possible so that the users can feel relaxed and comfortable when wearing them or having them implanted in their bodies. This reduction in size limits the battery size due to the fact that the capacity of a battery is equivalent to its size. Hence, the energy available for the wireless body sensor becomes very limited thereby reducing the lifespan of the sensor network. Moreover, it would be inconvenient and unpleasant and sometimes impossible for the users to recharge or change the battery. It is believed that the cost of communicating a single bit of information and that which is required to run a thousand operations are the same [8]. In reality, the transmission of data often consumes higher energy than sensing and processing of data.

A number of researchers have proposed mobility as a solution to the problem of energy consumption where mobile elements traversing the network and collecting data from sensor nodes when they come near them [9, 10]. This naturally avoids multi-hop and removes the relaying overhead of nodes near the base station. Recent work shows that data collection from sensor nodes using mobile sinks minimizes multi-hop data transmission and improves energy efficiency. Although the use of mobile nodes reduces energy consumption, it also increases delay in delivering sensed data to the base station. Hence, there is a great need for energy efficient algorithms to optimize the energy of the WBSN using mobile nodes in good time.

Several optimization algorithms that have proven to be efficient and reliable in obtaining close to global optimum solutions have been employed to maximize the energy of sensor networks.

Most of these algorithms also require several common control parameters like population size, number of generations and elite size. Moreover, different algorithms require their own algorithm-specific parameters aside from the common control parameters. Thus, it is advisable to develop an algorithm that requires fewer algorithm-specific parameters and higher optimization ability like the teaching-learning-based optimization (TLBO) and particle swarm optimization algorithm (PSO). The calculation in PSO is very simple and can be completed easily while TLBO algorithm is reliable, accurate and robust. The total computational time is less and the consistency is high [11]. Hence, this research developed an algorithm that requires few algorithm-specific parameters and involves the use of PSO and TLBO algorithms to optimize the energy of wireless body sensor networks.

Over the last few decades, various strategies have been deployed to reduce energy consumption in wireless body sensor networks. Some researchers have tried to work on the hardware components of the nodes by making use of energy harvesting technologies as a method of prolonging the lifetime of wireless body sensor networks. The use of energy harvesting technologies is a good method of prolonging the lifetime of wireless sensor networks. A gateway selection algorithm (GSA) was employed with energy scavenger which was inbuilt in the sensor nodes on the patient's body to select the fittest node that served as a gateway to the base station [12]. This algorithm considered the residual energy of each node and the rate of energy harvesting from the human body in order to determine the gateway node in WBSN. The data routing topology was dynamically regulated so that the node with the highest residual energy became the gateway that linked the network to the physician in charge. Although the energy scavenging technologies were expensive, the simulation results revealed an increase in network lifetime with the gateway selection algorithm.

Some researchers tried to achieve data transmission by setting up a topology in which the sensor nodes agreed to send their data to a predetermined sink without considering the residual energy of the nodes [13, 14]. Another technique involved the development of MAC protocols that took advantage of the capacity of wireless body sensor networks to optimize the energy at the link and physical layers of the network. Others proposed duty cycling where nodes that were needed at a particular time were awake while others were asleep [15].

Other works attempted to reduce energy consumption at the communication layer, which was known to consume more energy than the sensing and processing of data, by devising new routing protocols that exploited the unique features of WBSN. Ayatollahitafti *et al*. [16] presented an efficient next hop selection algorithm for WBSN which made use of the least hop count to the base station together with a link cost function to determine the best next hop. The cost function of the link factored in the residual energy, the size of the queue, and the reliability of the link to neighboring nodes. Evaluation of this protocol revealed a lower energy consumption, end to end delay, and higher packet delivery ratio than other protocols; however, it was discovered that the position of the sink node on the body determined the success of the protocol.

Moreover, research has proved that the use of multi-hop routing is more efficient than single-hop communication in WBSN. A muiti-hop routing protocol selects a forwarder node using a cost function which considers the residual energy of the node and the distance of each node from the base station [17]. The residual energy is important to balance the consumption of energy of each node in the network while the distance is necessary to ensure the packets are successfully delivered to the base station. The protocol enhances the stability of the network and delivery of packets to the base station but it is not the best for cases of medical emergencies because it experiences some delays. Another multi-hop protocol was designed for swallowable body sensor networks in which sensor nodes followed a schedule computed by a coordinator node to send data through multiple routes to the base station [18]. Although the protocol put more pressure on the coordinator node, it was found to be energy efficient and avoided idle listening and overhearing associated with scheduling algorithms.

A routing algorithm in which all sensed data of all nodes were transmitted to the destination node that was the base station employed for WBSN [19]. Although the algorithm exhausted energy on transmitting redundant data, the parameters applied helped in achieving the maximum network lifetime of the WBAN among existing algorithms. A steady high throughput wireless body area network protocol was also proposed [20], which transmitted data to a sink node through intermediate nodes. A cost function was characterized to choose a forwarder node which was a node with high residual energy and least separation from the sink. The simulation results demonstrated that the proposed protocol was able to maximize the packets received at the sink node.

Contrary to existing techniques of optimizing the energy of only sensor nodes, the energy of base stations can also be optimized. A mobile phone can be used for data collection. This step can relieve the base station of having to receive all the data, thereby optimizing the energy of both sensor nodes and base station [21]. The architecture provides sensor options through the mobile phones or access points by which the sensed data can get to the required destinations. This approach increases sensor lifetime but incurs additional cost.

Unlike these approaches, this research employs an alternative to multi-hop routing by using mobile elements for data collection and transmission in WBSN. The paths of the mobile elements are determined by the proposed PSO-TLBO algorithm, which takes into consideration the energy of each static node and the distance of each node from the base station. Previously, various algorithms that made use of several parameters were adopted. These parameters had to be properly tuned in order to avert being stuck in a solution that was optimal within a local set of solutions and to reduce efforts applied in computation. However, this research developed an algorithm that requires few algorithm-specific parameters with the use of PSO and TLBO algorithms to optimize the energy of wireless sensor networks.

2. Materials and Methods

In this research, a wireless body sensor network is regarded as a combination of stationary sensors distributed around the body with a mobile node (Data MULE) for data collection. The sensor nodes have fixed locations at which they are deployed and each is allowed to monitor a region of interest, as shown in Figure 1. Each sensor produces a data packet at a time and has the capacity to communicate the sensed event to the base station through the mobile node. Since signals are transmitted within the operating region (sensing radius), a data mule can receive data from a sensor within the sensing radius. In common with other WSN applications, there is a finite and non-rechargeable battery in each sensor node, and the greater portion of the energy is used by the sensor node for receiving and transmitting data.

A mathematical model for WBSN was designed with consideration of the limited energy resources available. This research only considered the energy employed in data communication since it is believed to be far greater than the energy used in sensing and data processing. The research adopted the energy model used in the work of Heinzelman *et al.* [22], as shown in equations 1-5. The distance between the nodes and the energy of each sensor node were considered important because of the small amount of energy available.

According to the model, the transmitter, amplifier and the receiver consume more energy than the other parts of the system. The difference between the transmitter and receiver determines the channel that will be adopted by the model. 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;

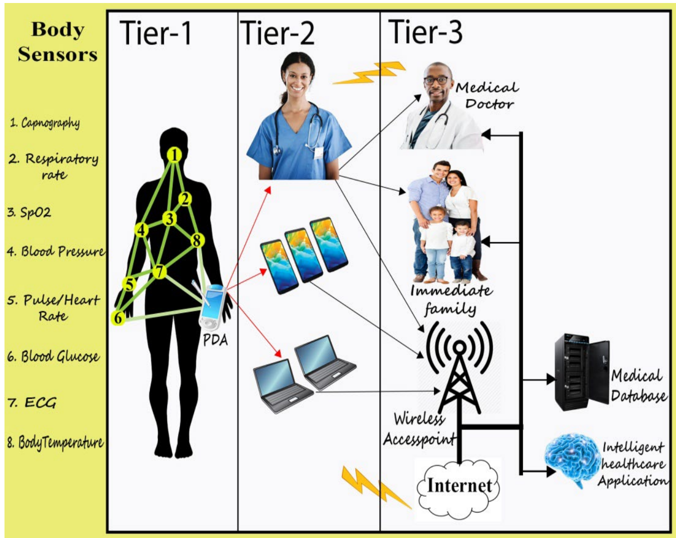

Figure 1. Architecture of the Vital Sign Monitoring System

otherwise, it is proportional to $d^{4.}$ The energy required for transmitting a k-bit message for a distance, d is given as;

$$E_{Tx}(k,d) = E_{Tx-elect}(k) + E_{Tx-amp}(k,d) = E_{elect} * k + E_{amp} * k * d^2 \qquad (1)$$

Equation 1 defines the energy spent in transmission of the message. The energy spent to receive this message is expressed as equation 2.

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

Where E_{Tx} is the energy consumed by the transmitter, E_{Rx} is the energy consumed by the receiver, E_{amp} is the energy consumed by the amplifier, E_{elect} is the energy consumed by a sensor node to transmit or receive 1-bit data, k is the number of bits transmitted and d is the distance from source to destination.

The objective is to minimize the energy consumed E_c : expressed in equation 3.

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

Subject to equation 4:

$$\sum_{i \in N} d_{Tx} \le d_0 \ \ all\ Tx \in N, \qquad (4)$$

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 next node.

The remaining energy of the sensor node (E_{rem}) can be evaluated from the initial energy ($E_{initial}$) and the energy consumed (E_c) as shown in equation 5:

$$E_{rem} = E_{initial} - E_c \tag{5}$$

The function in equation 1 is used to estimate the energy consumed by the nodes while transmitting. Equation 2 is used to estimate energy consumed by the receiving node. Equation 3 is a minimization function which minimizes the total energy consumed by the nodes while equation 4 puts a restriction on the maximum transmission distance between the nodes and represents the energy capacity constraint on sensor nodes. Equation 5 evaluates the energy remaining on each node.

2.1 The proposed PSO - TLBO algorithm for data transmission

This research proposes an efficient hybrid PSO-TLBO algorithm to reduce the energy consumption during data transmission by using a mobile data collector. The PSO and TLBO algorithms are optimization techniques that have attracted growing interest due to their outstanding features, such as a small number of parameters, and simplicity with few mathematical requirements.

2.2 Hybrid PSO-TLBO algorithm

The idea behind PSO-TLBO is the combination of the strengths of PSO with those of TLBO to make a better algorithm. The benefit of PSO is its exploitation power; it is very efficient and can deliver outcomes rapidly. The PSO algorithm also has memory, so all the particles can understand and retain good solutions. Despite these good qualities, it still suffers from premature convergence, which is a result of the rate at which information flows in between particles thereby leading to the production of particles that are similar. With this, the possibility of being trapped in local optima is high due to the lack of diversity. A lot of efforts have been put into enhancing the original PSO algorithm through hybridization and other means.

TLBO is efficient as it can achieve extraordinary precise solutions and also has good exploration potential. One of the essential characteristics of this metaheuristic is reduced number of parameters as the complexity of known metaheuristics is determined by the number of parameters used. After locating the global optimal region, 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 equations 6 and 7. A bigger velocity will facilitate global exploration; hence, the incorporation of the TLBO equation into the velocity and position equations of PSO.

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

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

where:

Vij is 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 are 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 hybridize the two algorithms, the velocity of each particle in PSO was updated with the learning phase of the TLBO algorithm, as seen in equation 8. Update of velocity of particles;

$$\begin{aligned}\vec{v}_{ij}(t+1) = \omega\vec{v}_{ij}(t) + \; & c_1r_1\left(P_b - \vec{X}_{bj}(t) + \; r_i(X_{bjp} - X_{bjq})\right) \\ & + c_2r_2\left(P_b - \vec{X}_{bj}(t) + \; r_i(X_{bjp} - X_{bjg})\right) \\ & + c_3r_3\left(G_b - \vec{X}_{bj}(t) + \; r_i\left(X_{bjp} - X_{bjg}\right)\right)\end{aligned} \tag{8}$$

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 9:

$$\vec{x}_{ij}(t+1) = \vec{x}_{ij}(t) + \; r_i(x_{j,kbest,i} - T_F M_{j,i}) + \vec{v}_{ij}(t+1) \tag{9}$$

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, which is referred to as the number of particles. Then, the 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 sets of particles. After obtaining the best fitness value, the velocity of each path is 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. PSO-TLBO balances the energy of the network by evaluating the remaining energy on each node and the distance before sending data to a node using the fitness function.

The procedures involved in the algorithm are given below:

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
   $f = \sqrt{\sum_i^N (E_{initial} - E_{consumed}) \,.\, d}$
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

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

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

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

j) Update $Gbest$ of population
If $F_{bj}(t+1) < F_{bj}(t)$ then $G_{bj}(t+1) = P_{bj}(t+1)$ and set $b = b_1$ else
$$G_{bj}(t+1) = G_j(t)$$

k) If $k < Max\_no$ then $k = k+1$ and go to step f else go to step l

l) Output optimum solution as $G_{best}(t)$.

2.3 Simulation of the developed algorithm PSO-TLBO algorithm

The developed PSO-TLBO algorithm was implemented using Matrix Development Kit MATLAB R2013. This was done in an environment using window ten based PC with 2.94 GHz, Intel processor (i7) and 4 Gigabytes RAM. In the network, the number of nodes was varied between 10 to 100 nodes arranged in random style with 100 m × 100 m area where the base station was located in network region. Also, there was a wireless mobile node (data MULE) which was responsible for relaying the data sensed by the detecting nodes and forwarding them to the base station from where data were disseminated to the appropriate channel. Different parameters were initialized based on each of the algorithms to be implemented: PSO, TLBO, and PSO-TLBO. For PSO, the parameters employed were 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 = 100. For TLBO, the following the parameters were used: 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.

3. Results and Discussion

3.1 Performance evaluatıon of the proposed PSO-TLBO algorıthm

To validate the performance of the developed PSO-TLBO algorithm, energy consumption, run time analysis, and 23 benchmark test functions were employed as metrics of evaluation to determine its efficiency over PSO and TLBO algorithms.

3.2 Energy consumption analysis

The result of the analysis of energy consumed by each of the algorithms, PSO, TLBO and PSO-TLBO with varying number of nodes, is presented in Figure 2. The average energy consumed by PSO-TLBO was 7650.34J, which was far from that of PSO and TLBO which were 31168.08J and 32065.18J, respectively. The result implied that the PSO-TLBO technique consumed lesser energy than the TLBO and PSO technique.

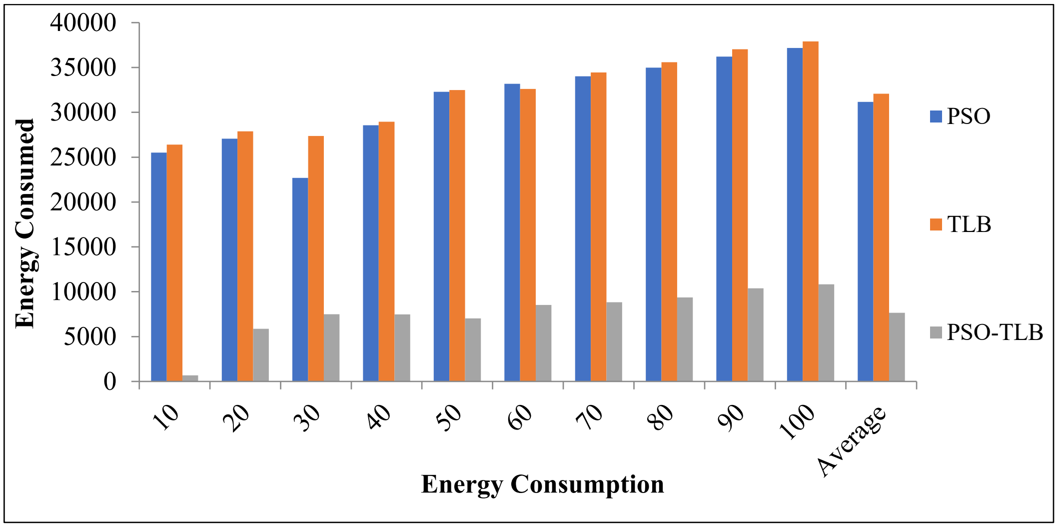

Figure 2. Energy consumed by the simulated algorithms

The relationship between the energy consumed (E_c) and the number of nodes (N_n) is found to be a polynomial of order 3 with a high correlation coefficient for the PSO-TLBO, TLBO and PSO techniques, as shown in equations 4.1, 4.2 and 4.3, respectively.

$$E_c = 0.046{N_n}^3 - 8.592{N_n}^2 + 543.52N_n - 3089.9R^2 = 0.93 \tag{10}$$

Where R^2 is the coefficient of determination, which is applicable to any statistical relationship and gives the percentage of variation. The relations in equation 10 can be used for further prediction of energy consumed using number of nodes.

3.3 Simulation time analysis

The result of the runtime by taking each algorithm to run through the network and getting to the base station, is shown in Figure 3. TLBO was very fast resulting in an average simulation time of 28.1365s. PSO took a longer time with some delays, achieving this feat in an average of 30.6295s. The developed hybrid PSO - TLBO performed better than both algorithms and obtained a simulation average of 26.9349s. The graph shows that PSO-TLBO has a better simulation time than TLBO and PSO, which implied that the speed of mobility in PSO-TLBO was higher than that of PSO and TLBO.

The relationship between the simulation time (S_t) and the number of nodes (N_n) is found to be linear with a high correlation coefficient for PSO-TLBO, TLBO and PSO techniques as shown in equations 11,12 and 13, respectively. The relations in equations 11, 12 and 13 can be used for further prediction of the speed of the algorithm with respect to the number of nodes.

$$S_t = 0.096N_n + 21.62R^2 = 0.9679 \tag{11}$$

$$S_t = 0.177N_n + 20.151R^2 = 0.9689 \tag{12}$$

$$S_t = 0.1165N_n + 24.144R^2 = 0.9679 \tag{13}$$

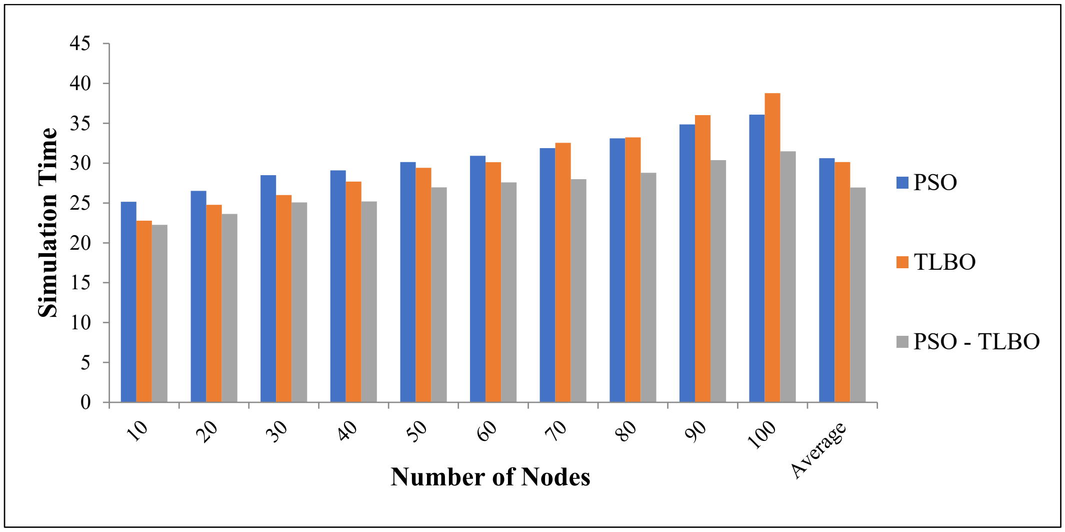

Figure 3. Average simulation time of each algorithm at varying number of nodes

3.4 Benchmark functions

The benchmark functions employed consist of both unimodal and multimodal functions. A function is said to be unimodal if it contains only one optimum, and it is said to be multimodal if it contains many local optima but only one global optimum. The experimental results of the 23 benchmark functions and their run times are shown in Table 1. The averages of the results over 30 simulation runs are presented, and the results closest to the global minimum value are indicated in bold type.

Sphere (F_1) is a continuous, separable, unimodal, scalable and differentiable function that has zero as its analytical minimization value. The result in F1 indicated that PSO-TLBO obtained the closest value to the global optimum value, with average of 1.17E+08, which was followed by TLBO and PSO with 2.16E+08 and 2.44E+08, respectively. In step function (F_2), a scalable, unimodal, discontinuous, non-differentiable function, the best minimization performance was not achieved by any of the algorithms; however, PSO-TLBO was still closer to the global minimum of zero than the others, with a value of 15124. PSO was the second best with 31515.4. The third best was TLBO, which managed to achieve 32890.1.

The Schwefel 1.2 function (F_3) is a continuous, differentiable, non-separable, scalable and unimodal function. The nearest result to the analytical ideal value of zero was achieved by PSO-TLBO with 6.66E-19, and TLBO followed with 1.19E-16. PSO achieved better minimization performance compared to TLBO and PSO-TLBO when applied to the Schwefel 2.21 (F_4) function. PSO-TLBO was the most outstanding method applied to the Rosenbrock function, having 3.18E-09 as its average value, and right after it came TLBO, whose average value was 4.77E-08. In Step 2 (F_6) function, PSO-TLBO, PSO and TLBO recorded an average value of -1.01E+00, which indicated a good performance by all the algorithms. Aside from TLBO with 5.88E+17 as its average value, the other two algorithms achieved the maxima value with the quadratic function.

PSO managed to perform better than other algorithms by achieving -586322 mean value, which was the closest to the theoretical optimum value on the F8 function. PSO-TLBO and TLBO were the best algorithms on F_9 with the mean value of 1.29E+08, while PSO-TLBO did better in F_{10} with a mean value of 10.7171. In F_{11}, TLBO obtained the optimal value of 31934, which exceeded the values of the other two algorithms. PSO-TLBO came next having the average value of 47028.1.

Table 1. Results of simulation time and average best of the 23 Benchmark functions

	PSO		TLBO		PSO-TLBO	
Benchmark Functions	**Simulation time**	**Avg Best**	**Simulation time**	**Avg Best**	**Simulation time**	**Avg Best**
F_1	51.3959	2.44E+08	38.0222	2.16E+08	36.026	**1.17E+08**
F_2	51.5906	31515.4	38.0477	32890.1	36.1374	**15124**
F_3	51.6058	2.83E-04	38.1961	1.19E-16	36.1482	**6.66E-19**
F_4	48.1839	**7800.6**	38.2939	14456.5	36.1522	14025.5
F_5	49.1839	5.50E-03	38.1399	4.77E-08	36.11595	**3.18E-09**
F_6	49.4183	**1.01E+00**	45.2427	**-1.01E+00**	51.0118	**-1.01E+00**
F_7	49.6496	5.11E+17	36.9747	5.88E+17	34.9659	**3.60E+17**
F_8	49.7732	**-586322**	36.9426	-28494.9	34.9682	-14362.9
F_9	49.7471	2.00E+08	36.9869	**1.29E+08**	34.9762	**1.29E+08**
F_{10}	49.7022	20.1432	36.9533	21.4343	35.0869	**10.7171**
F_{11}	50.2516	59366.1	37.2099	**31934**	35.3411	47028.1
F_{12}	50.04564545	**409.936**	38.38501667	734.566	37.72501667	**409.936**

Table 1. Results of simulation time and average best of the 23 Benchmark functions (Continued)

	PSO		TLBO		PSO-TLBO	
Benchmark Functions	**Simulation time**	**Avg Best**	**Simulation time**	**Avg Best**	**Simulation time**	**Avg Best**
F_{13}	50.04564545	4.38E-07	37.38377917	1.47E-02	35.78230417	**3.37E-10**
F_{14}	50.04564545	500	39.5589	500	37.7599	**250**
F_{15}	50.04564545	4.96E+00	38.13439896	1.67E-16	37.72501667	**7.40E-19**
F_{16}	49.67436515	2.60E-01	38.3655237	4.58E-01	37.6599	**5.09E-02**
F_{17}	49.95282538	**-12213.7**	38.68627422	-2437.52	35.6599	5909.47
F_{18}	61.942	201.665	38.1231	56.2952	35.712	**35.0076**
F_{19}	63.5188	**0**	37.8715	**0**	36.813	**0**
F_{20}	56.0597	**0**	42.5536	**0**	40.4771	**0**
F_{21}	55.9597	-5.39E-08	43.2068	**-8.50E-09**	40.6321	-2.57E-09
F_{22}	57.609	1.96E+08	60.0074	**-8.30E-09**	41.6157	-4.31E-09
F_{23}	56.2454	1.28E+08	41.2283	-1.07E-08	39.3091	**-3.44E-09**

For function F_{12}, PSO-TLBO and PSO obtained a theoretical value of 409.93,6 which was the best performance achieved on that function. The best performance for F13, F_{14} and F_{15} was achieved by PSO-TLBO followed by PSO and TLBO, respectively. In the function F_{16}, with theoretical value of 5.09E-02, PSO-TLBO obtained the closest mean value followed by TLBO. In F_{17}, PSO applied all effort to perform better than other algorithms with an average of -12213.

In F_{18}, PSO-TLBO acquired the theoretical value of -35.0076, which made it the best of the three algorithms. The results in Hartmann 3 (F_{19}) and Hartmann 6 (F_{20}) functions showed that PSO-TLBO, PSO and TLBO all obtained the maxima value (0.0), which implied the three algorithms were on the same level for that function. In F_{21} and F_{22}, TLBO recorded an average of -8.50E-09 in both functions, achieving the best results. For the last function considered F_{23}, PSO-TLBO obtained a mean value of -3.44E-09 to achieve the best result.

Analytically, the results of the 23 benchmark functions revealed that for the average of the results over 30 simulation runs, PSO-TLBO obtained the best values (which were the closest to the global minimum values) on 17 functions, PSO obtained the best values on six functions, and TLBO was also best on six functions. Therefore, it can be deduced that the number of functions for which the PSO-TLBO displayed better performance was higher than that of PSO and TLBO combined. This can be used to justify that the new PSO-TLBO achieved better results than standard PSO and TLBO in their rate of convergence.

For the average of 30 simulation runs, it was revealed that PSO-TLBO obtained the global optimal value in the majority of the benchmark functions except for F_4, F_8, F_{11}, F_{17}, F_{21} and F_{22}. Function F_4 is a noticeable problem that is common with the convergence patterns of all the three algorithms. The functions F_6, F_{19}, and F_{20} reflect an equal ability of PSO-TLBO, PSO and TLBO to achieve the global optima value in an average of 30 simulation runs. For functions (F_1 to F_{13}), which have high dimension, PSO-TLBO found it difficult to obtain the global minima values only for F_4 and F_8, thus, this can be used to argue that PSO-TLBO performs well on functions with high-dimension.

Furthermore, PSO-TLBO algorithm possesses another important strength for the use of fewer control parameters than most other hybrid algorithms. The performances of these algorithms are affected and determined by the use of many complex algorithm-specific control parameters like population size, mutation rate, elite size and others. Thus, PSO-TLBO is simple and adapts for optimization easily than other algorithms.

4. Conclusions

In this research, an efficient and effective methods for energy optimization in wireless body sensor networks was developed. The developed algorithm evolved from the hybridization of PSO with teaching-learning-based optimization algorithm (TLBO) to synergistically simplify difficult optimization problems. The hybridization was achieved by the incorporation of the teaching and learning factors of TLBO equation into the velocity equation of PSO in order to improve the velocity equation by expanding its scope. The hybrid takes into consideration the residual energy and the distance of each node from the base station to determine the path of transmission of the sensed data to the end point.

The performances of the algorithms were estimated based on 23 benchmark functions derived from the literature. The results obtained clearly revealed that the proposed hybrid PSO-TLBO was better in performance than the original PSO and TLBO in terms of energy consumption and simulation. The results also show that PSO-TLBO outperformed both PSO and TLBO in seventeen (17) out of the twenty-three (23) benchmark functions. The different performance metrics employed were thoroughly evaluated to confirm the efficacy of the developed algorithm.

It is also important to note that this research work only considered a single mobile node for data collection. However, the deployment of several mobile nodes for the collection of data in WBSN should be looked into in the future. In addition, a robust test bed for real life implementation of the algorithm would also need to be considered and the result should be compared with that obtained from the simulation experiment.

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