EFFICIENT SWARM OPTIMIZED DATA AGGREGATION OF IOT DEVICES AND ITS APPLICATION IN AGRICULTURE

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Abstract
The Internet of Things (IoT) can be identified as a new paradigm that has recently been gaining ground to a tremendous extent. The Wireless Sensor Network (WSN) forms a main constituent of the IoT. Aggregation of data has also been identified as having a vital role to play in enhancing network efficiency. The primary goal of the scheme of aggregation is the collection and aggregation of data packets efficiently to bring down the consumption of power, congestion of traffic and to increase the lifetime of the network bringing accuracy. Swarm Intelligence (SI), on the other hand, analyses the systems and their collective behaviour of various individuals for local interaction with one another. The SI-based systems further offer self-organized and decentralized set of robust systems along with considering the framework of coordination. In this work, a study of the collective behaviour of various systems and this consisted of various individuals that interacted locally with one another is adapted to improve the data aggregation in IoT. This was along with an environment that had decentralized and control that was self-organized for achieving several complex tasks. In this work, algorithms based on Teaching-Learning Based Optimization (TLBO) with the Tabu Search (TS), the Particle Swarm Optimization were employed for improving the performance of WSN. In the proposed Coaching Swarm Learning based Optimization algorithm, the teacher had improved the performance of its mean grade for the entire class along with the student performance. This algorithm had been duly evaluated based on certain benchmark functions after which their results were compared with the other algorithms.

Keywords: Teaching-Learning Based Optimization (TLBO) Algorithm, Particle Swarm Optimization (PSO) Algorithm and Tabu Search (TS) Algorithm.

INTRODUCTION

Internet of Things (IoT) has proved to be an evolving paradigm in information collection, processing and application growing rapidly in different fields which include surveillance of environment, healthcare, transportation, manufacture and so on. The primary idea of such computing and networking paradigm is its obvious presence in devices such as tags, mobile devices, actuators, and sensors. WSNs have become an important aspect of the IoT for the purpose of collection and transmission of data and thus they have a major impact on the IoT and also on its performance. Thus, the WSN optimization has a very vital role in forming the IoT with good performance [1].

For the purpose of designing the large scale WSN backing the IoT system there are several issues faced. These have been triggered by the limitation of resources in the WSNs that include memory space, its capacity of computing and battery lifetime. Also, owing to the presence of a wider range of these applications that is implemented by the IoT in the future, the WSN tends to face certain design goals with each other. These can be in the form of lower end to end delay, higher packet delivery, minimum energy consumption, and even low cost.

Agricultural informatics is also known as e-agriculture. This is a simple combination of the advances that are made in agricultural information, the development of agriculture and entrepreneurship providing information delivery by means of Information, as well as Communication Technologies (ICTs) and also the internet, dissemination and enhanced technology. E-agriculture has its focus on the enhancement of both agricultural, as well as rural development and this is through improved processes of communication. It includes conceptualization, evaluation, application, design, and development using innovative methods of using ICTs in the rural domain. The ICT proves to be an umbrella term to include anything like satellite technology, mobile phones, electronic money transfers or radio.

There has been a growing interest in the IoT technologies to support the alleviation of poverty and the uplifting of the standard of living of rural people [2].

In the case of smart farming based on the IoT, systems are developed to monitor the crop fields making use of sensors (such as moisture of the soil, humidity, and light). The farmers can observe the conditions of the field from anywhere and anytime. This IoT-based smart farming was found to be very efficient on being compared to the conventional approaches. The IoT applications of smart farming will not just target the farming operations of a large scale, but also the new levers for uplifting of the other common trends in organic farming or family farming. This includes either small or complex spaces, cattle, cultures and the preservation of certain varieties of high quality. This can help enhance farming. For the environmental issues, the IoT based smart farming will be able to provide major benefits like the efficiency of water usage, optimization of treatments and inputs [3]. Aggregation of data is defined as a process that integrates and further summarizes data from its sensor nodes in the WSN using functions of aggregation like the COUNT, AVG, MIN, MAX and the SUM. The primary aim of the aggregation of data was the removal of redundant data transmission and further improve the lifetime of the network. For making the aggregation of data even more effective, all associated data packets that were sensed by various sensors need to be aggregated with one another. This shows how the data are collected with packet routing throughout the network [4].

In the earlier years, the problems of optimization were solved using pure mathematical methods like the traditional ones, random searches, planning algorithms, gradient methods, and dynamic programming. But most of these methods will not be able to efficiently identify optimal solutions within a reasonable time taken for computation [5]. Furthermore, designing a particular algorithm may be very challenging in case the original
issue is found to be complex. Recently, there has been an increase in the number of researchers showing interest in various algorithms of stochastic optimization that are normally based on population. Such classical and stochastic algorithms contain the Genetic Algorithm (GA), TABU Search Algorithm (TS), Artificial Bee Colony, Particle Swarm Optimization (PSO) and so on. For example, the GA can be a simulation of the process of biological evolution and the Ant Colony Optimization (ACO), ABC, and PSO can be enlightened by means of collective intelligence of certain creatures [6]. There are some well-designed algorithms showing good performance on different problems of optimization in different walks of life. Since it is simple and effective, the stochastic algorithms have been developed by the researchers recently. These include the Ant Colony Optimizer (ACO), Teaching Learning Based Optimization Scheme with Global Small World (TOSG) based on service selection based on the ACO. Finally, the method proposed was able to improve the rate of recall and the precision rate. This has a better level efficiency to solve the problems of service selection.

**RELATED WORKS**

Reddy and Babu [7] had developed the Self Adaptive Whale Optimization Algorithm (SAWOA) in order to accomplish an energy-aware selection of cluster heads and their clustering protocols under the WSN-based IoT. Considering the parameters like sensor node delay, distance, and energy, simulation further takes into consideration both the temperature and the IoT device. These modules the simulation is complete, it will carry out a performance that is valuable for the analysis of the efficiency of network and energy load that is normalized. The analysis of performance will compare the effectiveness of the SAWOA over the others like the Whale Optimization Algorithm (WOA), Adaptive GSA (AGSA), Gravitational Search Algorithm (GSA). The actual outcome of simulation proves a successful SAWOA performance in the selection of Cluster heads for prolonging the lifetime of the network.

Ezhalbisie et al., [8] had made a proposal of a new approach to employ the PSO and the GA for the purpose of determining near-optimal solutions in order to schedule the loadable components found in the application and this was with the intent of bringing about a reduction in the time taken for execution and energy consumption of smart devices. By using yet another new inertial weight-based equation, there was the Adaptive GA – PSO (AGA-PSO) that was proposed along with the GA and it’s also also ability to explore the ability of the PSO especially in terms of ofolloading the optimization without violation to the constraints of deadline of the application.

Hasan and Al-Rizzo [9] had further proposed another new bio-inspired metaheuristic called the Canonical Particle Multi-Swarm Optimization (CPMSO) algorithm that was able to investigate a new pattern of optimal deployment for the sensors in improving connectivity in the Industrial IoT. This algorithm further guarantees efficient deployment which is by constructing the k-connected network for tolerating and at the same time satisfying the Quality of Service (QoS) which is in terms of delay, throughput, and energy consumption. The work also proved the effectiveness of CPMSO which is done by deploying the multiple topologies that satisfy the QoS and the results were compared with the conventional Canonical PSO and the Fully Particle Multi-Swarm Optimization (FPMSO). The CPMSO along with the FPMSO will improve throughput by about 95.23% simultaneously minimizing consumption of energy by about 87.5%, and delay by 95.00% when compared to the CPSO.

To improve the privacy aspect of healthcare data among the individuals and for this, there was a model of share generation that was implemented by Rani et al., [10]. After this, there was a model for share creation such as the Chinese Remainder Theorem (CRT) had been developed for generating a copy of each cipher text that is based on the chosen users and the data was duly shared among their optimal users. The choice of users of the Internet of Healthcare Things (IoHT) had been made by a metaheuristic algorithm known as Hybrid TLBO. The authors further presented some providers of healthcare services to give a complete scope of the medical services to the people registered in the IoHT. The actual performance of secure data was duly endorsed by means of simulations such as time of computation and cost of energy. This was for the purpose of demonstrating secure data which is efficient to apply for the chances of security in the health care systems based on the IoT.

Zhang et al., [11] had further proposed a novel multi-objective service selection algorithm that was based on the ACO that was for the restrictions of Quality of Experience (QoE). The method proposed was able to obtain a feasible solution efficiently by means of using a speed of fast convergence of the ACO. In particular, this QoE model has been formed using all relevant constraints along with quantitative methods. Next was a model based on service selection based on the ACO. Finally, the method proposed was duly verified by means of simulations. The results proved that on being compared to the method based on the GA where the proposed method was able to improve the rate of recall and the precision rate. This has a better level efficiency to solve the problems of service selection.

Qiu et al., [12] had proposed a method based on Topology Optimization Scheme with Global Small World (TOSG) based on ACO for the lIoT. Firstly, in accordance with the number that appears on the short paths that were obtained by the ACO, there was a definition of each node and its importance was given. The node that had the greatest significance in the range of communication defined to be an important one. This was able to identify all important nodes found in the network which are used to build shortcuts between them in building a model. The results of the experiments had proved that the TOSG model will have an average shortest routes and a length that was higher compared to the Greedy Model.

**METHODOLOGY**

The results of this experiment had depicted that the SL-PSO was able to increase the rate of convergence and also decrease the average localization error when compared to the PSO. The primary idea of this was to ensure and embed both reasoning and capabilities of intelligence in each of these or also for imitating SI [13] based systems. This was conducted by modelling the system in the form of a collection of individuals that are simpler and interacting. This takes into consideration all simple individuals that have limited capabilities of computation, efficient and indirect tools of communication. Recently, there was an increase in the interest observed in research of swarm-based approaches that identified the effectiveness of the approaches while dealing with Non-Deterministic Polynomial (NP)-hard problems. Here, the TLBO-TS, PSO and the TLBO along with the proposed method of Coaching Swarm Learning were used.

**Teaching-Learning Based Optimization (TLBO) Algorithm**

The TLBO is a very powerful algorithm that is employed for solving different problems of engineering. This was introduced by Rao et al. [14] and was based on the phenomena of teaching-learning. For the TLBO algorithm, all potential solutions were taken into consideration from the class itself. It had some traits such as the simplicity of computation. This was a very popular approach identified in the evolutionary techniques owing to the
rate of convergence. The main purpose of the algorithm was the determination of the best learner by means of cooperation aside from sharing information. The TLBO has a working behaviour that is dependent on sophisticated beginners and are able to generate good results that concern grades or marks. A group of learners is known as a class and they learn by means of a neighbour learning phenomena [15]. The ith learner's position has been presented in (1):

$$A_{i,k} = \{A_{i,1}, A_{i,2}, \ldots, A_{i,D}\}$$  

(1)

Wherein, $S_k$ refers to the lower boundary and $B_k$ is the upper boundary belonging to dimension D within its search space $A_{i,k} \in [S_k, B_k]$. Learner A will be initialized in a completely random manner within the capabilities of the search space and the evolution of $A_{i,k}$ duly generated randomly as below (2).

$$A_{i,k} = S_k + r_3 \ast (B_k - S_k)$$  

(2)

Wherein, $i = 1, 2, 3 \ldots; k = 1, 2, 3 \ldots D; r_3$ denote the random variables. There are two steps in the TLBO algorithm which refers to the teacher and the learner step. An optimum learner is acquired from a teacher step by making use of the knowledge learning from neighbours and a learner stage for the purpose of identifying the best learner by means of interaction.

The teacher stage: Here the learners will obtain proper awareness by means of the best learner, the teacher who further improves knowledge for emanating messages through its class to enhance the grade mean. A teacher will be the measurement gaining optimum results obtained until now. Since a good teacher upgrades knowledge using the knowledge of the learner, the mean result for the class pertaining to a particular value dependent on the capacity of the entire class may be employed. If $Z_{i,k} = (1/P)\sum A_{i,k}$ denotes the mean value for the subject of $k = 1, 2 \ldots D$. Updating the equation of process as per (3).

$$A_{i,k}^{\text{new}} = A_{i,k}^{\text{old}} + r_4 \ast (A_{\text{teacher},k} - T_f \ast Z_{i,k} & T_f$$  

(3)

Wherein, $A_{\text{teacher},k}$ denotes the actual best learning for the population that is adopted in that of the current iteration. $r_4$ refers to random numbers; $T_f$ is treated as the teaching factor.

For each iteration, $A_{i,k}^{\text{new}}$ will be updated with the value of $A_{i,k}^{\text{old}}$. $A_{i,k}^{\text{new}}$ and $A_{i,k}^{\text{old}}$ are the kth learners elected before updating by the teacher. To maintain balance between exploration and exploitation ability of search it is important to continue this for the entire execution.

Learner stage: Here there is an rise in the knowledge of learners employing two techniques one is the way in which the input from a teacher is obtained and the next will be an idea via shared interaction among themselves. The aim for every such learner gets interacted in a random manner to the peer learners and further enhance the grade of communication. For choosing the ith learner to be the $A_{i}$ and one more random learner is $A_q$ ($P \neq Q$) by means of shared interaction with other learners. This new solution vector is depicted in the equations below (4 and 5).

Randomly select two different learners $A_p$ and $A_q$

In case ($f(A_q) < f(A_p)$)

$$newA_i = oldA_i + r_5 \ast (A_p - A_q)$$  

(4)

Else

$$newA_i = oldA_i + r_6 \ast (A_q - A_p)$$  

(5)

Wherein, $r_5$ and $r_6$ denote the random values uniformly distributed, $f(A_p)$ and $f(A_q)$ denote the best solution of learners $A_p$ and $A_q$ respectively. Taking the actual size of its learner group as $P$, the learner will be able to communicate from a good learner for the purpose of acquiring knowledge.

Particle Swarm Optimization (PSO) Algorithm

PSO has attracted the attention of different researchers as it is conceptually simple and easy to implement. In addition to this, the PSO was used for solving problems of optimization that were large and complex. These did not need any rigorous foundation in mathematics or any prior knowledge like machine learning, medical systems, aerospace aviation, signal processing, and vehicle scheduling. Every particle will represent a new candidate solution to exhibit two properties which were velocity and position. Velocity for each such particle will be modified for every iteration on the basis of its inertial weight ($w$), its best position (pbest), and its current global best position (gbest) [16]. There is also an assumption that the actual swarm size corresponds to N and the velocity $v_i$ and the position $x_i$ for the jth dimension of its ith particle as updated in $t + 1$ iteration in (6) and (7):

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1r_1(p_{\text{best},i,j} - x_{i,j}(t))$$  

$$+ c_2r_2(g_{\text{best},j} - x_{i,j}(t))$$  

(6)

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1)$$  

(7)

Wherein, $i = 1, 2, \ldots, N; j = 1, 2, \ldots, D$. $w \in [0; 1]$ is the inertial weight along with $c_1$ and $c_2$ and the acceleration coefficients for controlling the effects of social and their cognitive components. Normally, $c_1, c_2 \in [0, 2]$ and $r_1$ and $r_2$ will denote the uniformly distributed variables found in the interval $[0, 1]$, i.e., $r \sim U[0, 1]$.

**TLBO Algorithm with Tabu Search (TLBO-TS)**

A powerful algorithm for local search that was developed in the year 1986 by Glover that is used successfully in various problems of combinatorial optimization that includes project scheduling is the TS algorithm. This algorithm has strong capabilities of search that prevent early convergence. The solutions encoded for TS will be similar to the one for the TLBO. The neighbourhood solutions are created by means of a random change to the start time of the projects found in the solution and the new one automatically fall within the vicinity of its current solution. The change to the start time was applied respecting the constraints of resource and time. The TABU list size will be the function of the problem's size and this is when it is able to offer better solutions until now taken to be the criteria of aspiration [17].

The TLBO is an algorithm that is population-based and has a good level of exploration although it lacks in exploiting. For improving the capability of exploitation of the TLBO algorithm that has a good ability of local search, TS is hybridized with TLBO.
creating a hybrid TLBO-TS. It begins with a new initial student population and the TLBO was applied as per the discussion in section 3.1. The best solution can be identified with the TLBO algorithm as its new teacher. This algorithm gets iterated for a certain number of times. Figure 1 shows the steps in the hybrid TLBO-TS.

![Figure 1 Flowchart for Hybrid TLBO-TS Algorithm](image)

**Proposed Coaching Swarm Learning Based Optimization Algorithm**

The proposed Coaching Swarm Learning Based Optimization Algorithm is obtained by hybridizing the TLBO and PSO. As reviewed earlier, the primary concept of the TLBO was to imitate the process of teaching and learning. According to eqn (3) the teacher will improve the students’ grades by making use of a mean grade for the class. In TLBO, the actual distance between the teacher and students will not be considered in a teacher stage. Whereas in PSO, the actual difference between pbest and the particle will help in improving the individual [18]. Based on this concept, the PSO is hybridized with the TLBO for improving the efficacy of learning. The primary change for the TLBO is characterised by modifying the updating process as in equation (8):

\[
A_{i,\text{new}} = A_{i,\text{old}} + r_1(A_{\text{teacher}} - T_{p}Z_{i,k}) + r_2(A_{\text{teacher}} - A_{i,\text{old}})
\]

(8)

Wherein, \(r_1\) and \(r_2\) will be the random numbers that fall within the range \([0, 1]\). Using this modification, the TLBO and its performance are enhanced.

**The Steps of Proposed Coaching Swarm Learning Based Optimization Algorithm**

Step 1. Set the maximum \(A_{\text{max}}\) and minimum \(A_{\text{min}}\) for position and the highest evolution generation which is \(gen_{\text{max}}\), its population size \(\text{popsize}\), and finally the size of the dimension of this task. Now initial population \(\text{pop}\) is created as below:

\[
\text{pop} = A_{\text{min}} + r^\ast(A_{\text{max}} - A_{\text{min}})
\]

(9)

Step 2. Now estimate this individual, choose the best individual \(A_{\text{teacher}}\) to be the teacher, and finally compute a mean solution \(Z_{i,k}\) for the population.

Step 3. For every such individual, update position in accordance with (8). In case \(A_{i,\text{new}}\) is found to be better than \(A_{i,\text{old}}\) in that case \(A_{i,\text{old}} = A_{i,\text{new}}\).

Step 4. For every individual, there is a need to make a random choice of one more individual and update its position in accordance with (4) and (5), and then select a solution that is better from \(A_{i,\text{old}}\) and \(A_{i,\text{new}}\) to be the new individual position in this.

Step 5. If maximum iteration is not met, the algorithm goes back to Step 2 and if not completed.

**RESULTS AND DISCUSSION**

In this section, the TLBO-TS and coaching swarm learning based optimization methods are evaluated. For simulation, network sized 200 to 1000 number of nodes is used. The average end to
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end delay, average Packet Delivery Ratio (PDR) and lifetime computation as shown in tables 1 to 3 and figures 2 to 4.

### Table 1 Average End to End Delay for Coaching Swarm Learning Based Optimization

| Number of nodes | TLBO-TS | Coaching Swarm Learning Based Optimization |
|-----------------|---------|-------------------------------------------|
| 200             | 0.0018  | 0.0017                                    |
| 400             | 0.0018  | 0.0017                                    |
| 600             | 0.0184  | 0.0176                                    |
| 800             | 0.0294  | 0.0282                                    |
| 1000            | 0.0658  | 0.0634                                    |

From the figure 2, it can be observed that the coaching swarm learning based optimization has lower average end to end delay by 5.71% for 200 number of nodes, by 5.71% for 400 number of nodes, by 4.44% for 600 number of nodes, by 4.16% for 800 number of nodes and by 3.71% for 1000 number of nodes when compared with TLBO-TS method.

### Table 2 Average Packet Delivery Ratio for Coaching Swarm Learning Based Optimization

| Number of nodes | TLBO-TS | Coaching Swarm Learning Based Optimization |
|-----------------|---------|-------------------------------------------|
| 200             | 0.8531  | 0.8725                                    |
| 400             | 0.8466  | 0.8691                                    |
| 600             | 0.8905  | 0.9138                                    |
| 800             | 0.7993  | 0.8166                                    |
| 1000            | 0.7619  | 0.7836                                    |
From the figure 3, it can be observed that the coaching swarm learning based optimization has higher average PDR by 2.24% for 200 number of nodes, by 2.58% for 600 number of nodes, by 2.62% for 400 number of nodes, by 2.58% for 600 number of nodes, by 2.14% for 800 number of nodes and by 2.81% for 1000 number of nodes when compared with TLBO-TS method.

![Figure 3 Average Packet Delivery Ratio for Coaching Swarm Learning Based Optimization](image)

**Table 3 Lifetime Computation for Coaching Swarm Learning Based Optimization**

| Number of rounds | TLBO-TS | Coaching Swarm Learning Based Optimization |
|------------------|---------|--------------------------------------------|
| 0                | 100     | 100                                        |
| 100              | 96      | 96                                         |
| 200              | 91      | 92                                         |
| 300              | 84      | 87                                         |
| 400              | 49      | 63                                         |
| 500              | 31      | 47                                         |
| 600              | 19      | 32                                         |
| 700              | 11      | 18                                         |
| 800              | 5       | 7                                          |
From the figure 4, it can be observed that the coaching swarm learning based optimization has higher lifetime computation by 1.09% for 200 number of rounds, by 3.51% for 300 number of rounds, by 25% for 400 number of rounds, by 41.02% for 500 number of rounds, by 50.98% for 600 number of rounds, by 48.27% for 700 number of rounds and by 33.33% for 800 number of rounds when compared with TLBO-TS method.

CONCLUSION
The IoT has been attracting plenty of attention recently. This involves problems of high dimension along with plenty of data. The SI-based algorithms are the best when duly applied to dynamic, large-scale and complex issues of the IoT. The TLBO method was based on the effect of the actual effect of a teacher based on the learner output in a certain class. The PSO was an optimization technique that was based on population development from nature and various evolutionary computations. The TS also has a memory that is adaptive for exploring the search space and this further makes use of memory in order to forbid returning to the solutions that were visited recently. In the proposed Coaching Swarm Learning-based Optimization algorithm, the TLBO teacher stage of the TLBO will be changed; yet another new individual position was determined by means of the old position, its mean position, and the current generation’s best position. The results have proved that the Coaching Swarm Learning-based Optimization had a higher average PDR by about 2.24% for the 200 number of nodes, by about 2.62% for the 400 number of nodes, by about 2.58% for the 600 number of nodes, by about 2.14% for the 800 number of nodes and finally, by about 2.81% for the 1000 number of nodes on being compared to the TLBO-TS method.

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