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An Energy-Aware Load Balancing Method for IoT-Based Smart Recycling Machines Using an Artificial Chemical Reaction Optimization Algorithm

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Abstract: Recycling is very important for a sustainable and clean environment. Developed and developing countries are both facing the problem of waste management and recycling issues. On the other hand, the Internet of Things (IoT) is a famous and applicable infrastructure used to provide connection between physical devices. It is an important technology that has been researched and implemented in recent years that promises to positively influence several industries, including recycling and trash management. The impact of the IoT on recycling and waste management is examined using standard operating practices in recycling. Recycling facilities, for instance, can use IoT to manage and keep an eye on the recycling situation in various places while allocating the logistics for transportation and distribution processes to minimize recycling costs and lead times. So, companies can use historical patterns to track usage trends in their service regions, assess their accessibility to gather resources, and arrange their activities accordingly. Additionally, energy is a significant aspect of the IoT since several devices will be linked to the internet, and the devices, sensors, nodes, and objects are all energy-restricted. Because the devices are constrained by their nature, the load-balancing protocol is crucial in an IoT ecosystem. Due to the importance of this issue, this study presents an energy-aware load-balancing method for IoT-based smart recycling machines using an artificial chemical reaction optimization algorithm. The experimental results indicated that the proposed solution could achieve excellent performance. According to the obtained results, the imbalance degree (5.44%), energy consumption (11.38%), and delay time (9.05%) were reduced using the proposed method.

Keywords: algorithm; internet of things (IoT); load balancing; energy consumption; smart recycling machines; artificial chemical reaction optimization algorithm

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1. Introduction

Lately, increased greenhouse gas emissions have contributed to global warming and climate change. Carbon reduction and long-term development have become hot topics globally. Recycling resources can help to minimize the use of virgin natural resources [1,2]. The rapid increase of the world's population and the contemporary lifestyle has resulted in a sharp rise in urban garbage. The only way to create a sustainable ecosystem is to recycle. Recycling necessitates separating waste materials, which is time-consuming [3,4]. Waste and recycling containers that employ radio-frequency identification technology to allow haulers to track environmental assets are already examples of Internet of Things (IoT) initiatives [5]. They prevents garbage and recycling containers from going missing [6,7].

The smart recycling machine concept, which is based on IoT, is being used to create a full supply-chain system. This system consists of a single machine that collects, cuts, and stores discarded personal protective equipment (PPE) while also incorporating IoT functionalities to interface with various machinery in public and centralized recycling centers at the same time [8,9].

Short-run study results also show that forestry output, agricultural production, population increase, animal production, rainfall, and temperature all positively influence carbon dioxide emissions; energy usage has a negative effect [10,11]. The load-balancing approach distributes the load by assigning a set of demands to a resource set [12,13]. This approach is used to decrease resource use, which reduces energy consumption and carbon emissions, a critical requirement of IoT. It is a method that equally distributes the dynamic local workload among all nodes in the resource, preventing situations where some nodes are severely loaded. In contrast, others are idle or perform minimal work. It aids in achieving a high level of satisfaction and resource usage, enhancing the system's overall performance and resource utilization. Nevertheless, with effective load balancing, resource usage may be maintained at a minimum, lowering expenses and making businesses more environmentally friendly [14].

One of the viable alternatives for consolidating the collecting and sterilizing techniques before shifting the following recycling stages from the public area to the manufacturing recycling facility is to use a smart recycling machine. The objects are connected with different capacities in a heterogeneous network, and the purpose is node cooperation to perform tasks. Load balancing among task allocations in smart recycling is an NP-hard problem. Because deterministic approaches for addressing it are ineffective, non-deterministic methods are proposed to address it in the polynomial time interval [12]. This study considers the load balancing problem as an optimization issue to reduce power consumption, reduce energy consumption, assign tasks to appropriate nodes, decrease the imbalance degree, and improve utilization. Mostly, some objects do the same tasks. As a result, a task group may be described as a collection of objects that execute comparable and interchangeable activities. Most IoT applications will have many task groups. Numerous items with varying abilities may be found in the network. Virtual objects are items that have been chosen from each task group to be displayed. They divide tasks among members of their group and assign the task of processing requests to these physical objects. Some workgroups may be overloaded when assigned. So, tasks are removed from that workgroup and assigned to another node of a suitable workgroup based on energy consumption and execution time using the chemical reaction optimization algorithm. Load balancing, as the main issue for reducing the power consumption, is known as an NP-complete problem. Therefore, this paper proposes an artificial chemical reaction optimization algorithm for effective and efficient load balancing in IoT. The artificial chemical reaction optimization algorithm is a novel computational method inspired by chemical reactions. The artificial chemical reaction optimization algorithm is applied successfully to solve optimization problems and classification rules. The artificial chemical reaction optimization algorithm is an adaptive technique based on the process of chemical reactions [15]. Hence, this article employs this algorithm for load balancing and increasing energy usage via a fitness function in each workgroup. Briefly, the contributions of this research are as follows:

- Applying an artificial chemical reaction optimization for the load balancing of IoT-based smart recycling machines;
- Improving the imbalance degree improvement in IoT-based smart recycling machines;
- Reducing the energy consumption and delay time in IoT-based smart recycling machines.

The remainder of the article focuses on the sections below. Section 2 discusses the associated work. The system model and definitions of problems are presented in Section 3. In Section 4, the proposed method is described. The findings of the tests conducted to assess the efficacy of the proposed method are demonstrated in Section 5. Eventually, in Section 6, the conclusions and future works are presented.

2. Related Works

Our everyday routines have undergone several transformations due to rapid advancements in IoT and wireless communication technology [16]. This section analyzes and summarizes some of the modern approaches in the IoT-based smart recycling domain.

Javadpour and Sangaiah [17] proposed a dynamic voltage and frequency scaling (DVFS) -based algorithm that prioritized the tasks regarding their execution deadline. Additionally, they categorized the physical machines considering their configuration status. Henceforth, the proposed method assigned the jobs to the physical machines with the same priority class close to the user. The proposed method migrated the jobs to maintain the workload balance according to their scores. The proposed method was evaluated and validated in the CloudSim library. The results showed that the proposed method optimized energy consumption by 12% and power consumption by 20%.

In the first study, Suddul and Soobhen [18] proposed an energy-efficient method employing a power-down mode on the Arduino microcontroller applied to a recycling bin. It was achieved with an automated wake-up bit technique, which followed an on-demand approach rather than a time-interval one. It eliminated the unnecessary wake-up of the microcontroller, decreasing its energy consumption. The battery life of the autonomous device was increased, which contributed to reducing maintenance downtime, increasing the confidence level of the users, and reducing electronic waste. Additionally, the quick response (QR) code was introduced as an alternative to RFID tags to identify the material type. Both techniques contributed towards a more environmentally friendly waste disposal system. This study did not consider the imbalance degree and utilization.

Harjoseputro and Julianto [19] suggested an IoT-based smart waste recycling container that allowed customers to convert organic home garbage into fertilizer. The technology employed two microcontrollers to regulate sensors put in the bin to detect movements and garbage levels. Moreover, via a WiFi connection, the microcontrollers enabled the procedure to be watched and managed through mobile apps. It could be a prototype for a household gadget that motivates people to participate more in garbage disposal. In particular, this smart recycling container required human interaction to guarantee that liquid fertilizer was created and available to utilize after seven days. Hence, combining the bin with additional sensors that monitor and detect temperature, humidity, and pH would fully automate the system. Additionally, since the focus was primarily on the functional and technical elements, this investigation did not consider power usage as part of the research debate.

A novel IoT-based smart recycling machine suggested in [8] is a viable option for consolidating collecting and sterilizing techniques before moving on to the following recycling phases from the public to the manufacturing recycling facility. They generated a complete supply-chain system that included gathering, cutting, and storing discarded PPE in a single machine. This machine was incorporated with IoT functions to communicate with multiple machines in a centralized and public recycling center at the same time. The machinery technician must be able to monitor several key data both within (for example, electrical power and temperature) and outside the machine (for instance, humidity, and outdoor temperature). Hence, the recycling center might designate a logistic path for gathering trash in various places and performing preventative machinery maintenance.

Additionally, a unique concept of an agent-based IoT platform was developed by González Briones and Chamoso [20] to encourage public engagement in recycling tasks via gamification mechanisms. The gathering of data from the inhabitants of a vicinity might provide obstacles to raising the quantity of garbage to recycle. Therefore, gamification was portrayed as a significant component in this sort of IoT platform. In each container, as with any IoT platform, the infrastructure was required to deliver information on the subscriber's engagement with the gamification model. Information regarding which user has recycled, the amount of rubbish introduced, the container in which waste has been put, or the container's occupation status, among other things, can be referred to as examples. This data supplies the platform with the required knowledge for executing the gamification model and defining optimum trash collection routes based on the occupation state of the containers and the nearest waste treatment facility, allowing for effective and efficient waste management. Subscribers' behavior was reconstructed using data from their interactions with their city's recycling procedure. The evaluation outcomes of the suggested platform have confirmed the proposal's effectiveness. Additionally, public engagement has grown by 32.2%, while trash volume has climbed by 17.2%. Similarly, the number of garbage collection journeys has decreased by 53.4%.

An IoT-based smart fish farm in [21] was created, analyzed, and implemented, including a water recycling technology to reduce water waste. Sensors are critical for increasing water quality in an intelligent fish farm with an automated management system. A proportional integrator-derivative controller, dissolved oxygen concentration, water temperature, water-level ultrasonic, and pH sensors manage the water flow procedure in this aquatic system. Sensor data are gathered and saved as big data on the lab server. These sensors provide feedback to the PID controller, which allows the fish farm to function inside the defined range of operational circumstances.

An IoT-based algorithm was suggested in [22]. This article developed a genetic algorithm-based IoT control platform for a straw recycling system, consisting of the IoT's fundamental architecture and the control terminal. The system's energy usage is successfully lowered by improving the energy usage of the core architecture of the IoT. The straw recovery platform's heat energy conversion rate is optimized using a genetic algorithm, and the architecture's original goal is well-achieved. The findings demonstrate that the platform consumes little energy, and the thermal energy conversion rate of the straw recovery system may be significantly increased. The architecture and implementation of this system allow IoT technology to be used in a novel agricultural production mode, which can provide more opportunities and economic advantages for agricultural growth.

A weight-based smart recycling system using a single-board computer was developed by Ramasamy, Thiagarajah [23]. Arduino Uno R3, plastic bins, and load cells were used to design the hardware incorporated with a Wi-Fi module to send the data to the IoT platform, which serves as the cloud storage. A seven-day trial run was conducted at a residential area in Puchong, Malaysia to prove the concept. The output of the test was used to predict the waste yield if the I-Bin system was deployed in other similar residential areas. The average amount of recyclable garbage collected per household was 0.0966 kg. It is estimated that the IBin system would be able to gather 483 kg of trash from ten residential locations. The collection of the bin was done almost immediately once the bins met their threshold value. It increases the efficiency of collection, saves time, and reduces the operating costs for recycling companies.

Table 1 compares the existing techniques for the IoT-based smart recycling machines, approaches, benefits and disadvantages. We have observed that there is no absolute way to act reasonably in all load-balancing metrics. For example, some methods check the cost, energy consumption, and utilization, while others disregard these metrics. However, it seems that some parameters are mutually exclusive. Nevertheless, only a few investigations have looked into these two issues. Carbon releases are considered a wellness and ecological threat, whereas energy usage is supposed to be a cost-cutting measure. The present investigation recommended a strategy based on the chemical reaction optimization algorithm for efficient load-balancing, which aims to consider the imbalance degree, optimize energy-efficient, and increase utilization.

Table 1. Side-by-side comparison of the discussed studies.

Paper	Approach	Benefits	Disadvantages
Javadpour, Sangaiah [17]	Using DVFS computing in cloud data centers for an energy-optimized embedded load balancing	▪ Improving response times ▪ Minimizing energy consumption ▪ Migrating the jobs to maintain the workload balance	▪ Increasing delay in the system
Suddul and Soobhen [18]	Applying an energy-efficient technique, using power-down mode on the Arduino microcontroller	▪ Reducing energy consumption ▪ Increasing battery life ▪ Reducing cost	▪ Lack of synchronizing ▪ Without considering utilization
Harjoseputro, Julianto [19]	Proposing a smart waste recycling bin based on IoT	▪ Increasing performance ▪ Constructing the smart bin	▪ Without considering energy consumption
Li, Mak [8]	Implementing a creative IoT-based smart recycling machine	▪ Providing feasible solutions to consolidate the collection and sterilization ▪ Increasing utilization	▪ Without considering energy consumption ▪ Without considering the imbalance degree
González Briones, Chamoso [20]	Using a unique concept of an agent-based IoT platform to stimulate citizen engagement in recycling activities via gamification techniques	▪ Reducing the number of journeys for waste collection ▪ Allowing optimal and efficient management of urban waste.	▪ Increasing complexity
Angani, Lee [21]	Applying intelligent fish farm with a water recycling system	▪ Automatic controlling and real-time monitoring ▪ Improving performance	▪ Without considering optimal growth conditions
Mao, Jiang [22]	Applying genetic algorithm	▪ Reducing energy consumption ▪ Improving the thermal energy conversion rate of the straw recovery system	▪ Increasing complexity
Ramasamy, Thiagarajah [23]	Developing a weight-based smart recycling system using a single-board computer	▪ Reducing cost ▪ Increasing the efficiency ▪ Saving time	▪ Increasing energy consumption

3. System Model and Problem Definition

This section describes the system model, and then the problems' definitions are presented. Modern consumer product recycling can only be optimized by thoroughly comprehending the whole recycling system as a dynamic feedback mechanism [24]. Governments and businesses invest tens of thousands of dollars in waste management each year, but they never reach 100% efficiency. Sometimes the collection schedules and frequency are not well thought out, or the bins are placed in the incorrect locations. Smart bins, which include the IoT, sensors, and eco-friendly technology to enhance city garbage management systems, have been developed to address this issue. Due to significant ecological concerns, academics have been paying close attention to emission reduction, carbon labeling, energy conservation, trade, and footprint. Leveraging, architecture, and enabling technology are the three ideas that make up Green IoT. Architectural technologies, to begin with, pertain to energy-efficient device designs, network structures, communication protocols, and linkages. Additionally, leverage technologies pertain to reducing carbon emissions and increasing energy efficiency, enabling technologies to assist the IoT to become more efficient by lowering energy usage, resource usage, hazardous emissions, and pollution. Therefore, Green IoT contributes to preserving natural resources, reducing costs, and reducing technology's influence on the ecosystem and human wellness. So, Green IoT focuses on green production, green design, green usage, and green disposal [25]. The most common IoT architectural model comprises three levels, as shown in Figure 1, including network, application, and perception layers. The first layer of the three-layer architectural model is the objects or perception layer, which refers to IoT devices and physical sensors responsible for gathering and processing data and having sensors to detect and obtain info about their surroundings. It recognizes other intelligent objects nearby or picks up on specific physical characteristics. Connecting to other network devices, smart objects, and servers is the responsibility of the network layer. Its capabilities are also utilized in the transmission and processing of sensor data. This layer has two sublayers: a routing layer that manages packet transmission from source to destination, and an encapsulation layer that creates packets. The application layer is responsible for delivering the services that subscribers demand. It describes numerous IoT applications, such as smart cities, homes, recycling, and health [26–28].

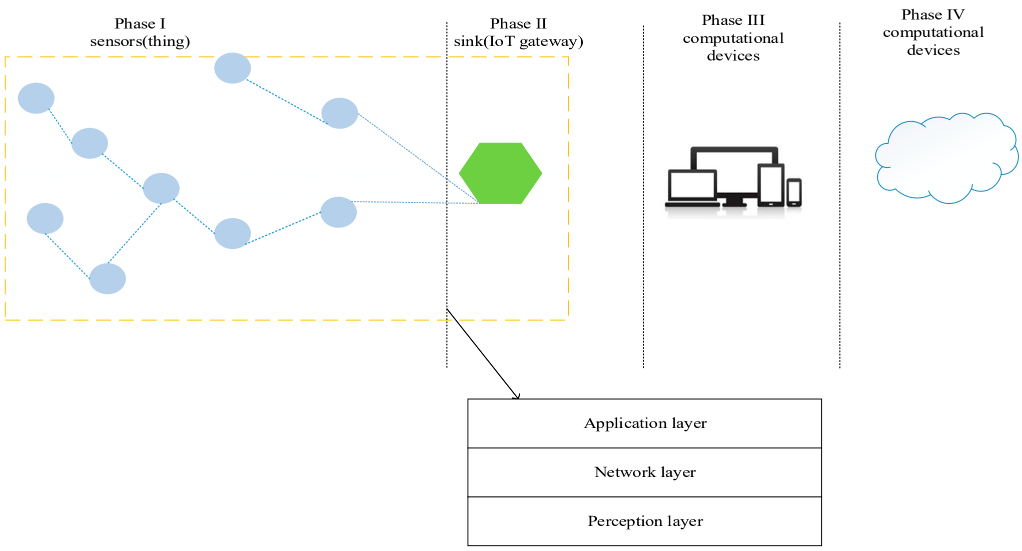

Figure 1. The IoT architecture: three-layer.

In the considered scenario, the user equipment (UE) sent service requests to the controller, and controller allocated the recycling service (RS) to provide the service path. Therefore, the set of services, Set_RS $= \{\mathrm{rs}_1 \cdot rs_2 \ldots .\mathrm{rs}_k\}$, the set of function, Set_$SF = \{sf_1 \cdot sf_2. \ldots .sf_n\}$, and the set of equipment, Set_UE $= \{\mathrm{ue}_1 \cdot ue_2 \ldots .\mathrm{ue}_m\}$, are defined. Where k is the total number of RSs, n is the total number of SFs and m is the total number of UEs. The rs_i represented ith RS, sf_j meat jth SF, and ue_q is qth UE. Each sf_j has its own capacity (SF_Cap$_\mathrm{j}$). For the definition of rs_i, see Equation (1) [29].

$$RS_i = \begin{bmatrix} \left(sf\_s_{(1.1)}.sf\_o_{(1.1)}\right) & \cdots & \left(sf\_s_{(1.j)} \cdot sf\_s_{(1.j)}\right) \\ \vdots & \ddots & \vdots \\ \left(sf\_s_{(i.1)}.sf\_o_{(i.1)}\right) & \cdots & \left(sf\_s_{(i.j)} \cdot sf\_o_{(i.j)}\right) \end{bmatrix} \tag{1}$$

Each RS will be stored in a matrix. The SF_s is a Boolean value, and it represents the used status of $sf_j \cdot rs_i \cdot$ $sf_s = 1$ means that sf_j will be used in rs_i and vice versa. The sf_o means the sequence of sf_j that will be used by rs_i. This study defined some restrictions as follows. Firstly, there should be at least one type of SF service, such as a recycling can, recycling machine, or recycling staff. Secondly, users could only make requests for the services within the scope of SF categories so that the supplier and the demander can match with each other. Finally, the overload of SF was obtained by calculating the service load. The minimum overload of SF should be zero and should not be negative. In other words, the overload of SF should not be lower than zero.

4. Methodology

The suggested approach is a cognitive/intelligent load-balancing algorithm, including an artificial chemical reaction optimization technique.

The first module, Task Pre-Processor (TPP), operates within the IoT gateway and performs preprocessing of specific activities depending on user queries. The primary function of an IoT gateway is to generate task groups and assign virtual items to lead them. TPP is utilized for task preprocessing, which is required to build task groups. TPP is in charge of breaking down user requests into numerous tasks and determining which sensors are needed to complete each task. In total, IoT devices must process two types of tasks [11]: spatial and temporal tasks. Tasks that require information from a particular place or expressly reference a location are classed as spatial activities; tasks that are time-sensitive and prioritize completion time are categorized as temporal tasks. Because time is the most important restriction in temporal activities, they are never negotiable. However, the spatial tasks may be negotiable. Tasks that are not negotiable cannot be postponed when tasks at the IoT gateway are spatial, temporal, non-negotiable, or negotiable. Non-negotiable tasks can be allocated to sensor nodes for instant implementation; however, negotiable tasks can have a maximum delay before execution. Thus, load balancing is required when ordering them. They are kept in a task pool and then categorized according to their placement. The virtual leader node is in charge of leading the workgroup. As a result, it contains the details of all nodes that have joined that task group. Hence, the virtual leader is responsible for choosing the way to send task packets across task groups to finish the work (Figure 2). Non-negotiable activities will already be sent to TPS, while negotiable tasks will be split into groups, with only the leader tasks from each group being assigned to TPS. TPS schedules tasks according to the delay. The task with the least time latency will be scheduled first in the implementation queue, followed by tasks with a longer delay. They presented a load-balancing approach for greater performance since one node may be needed to execute many activities, leading to overloading.

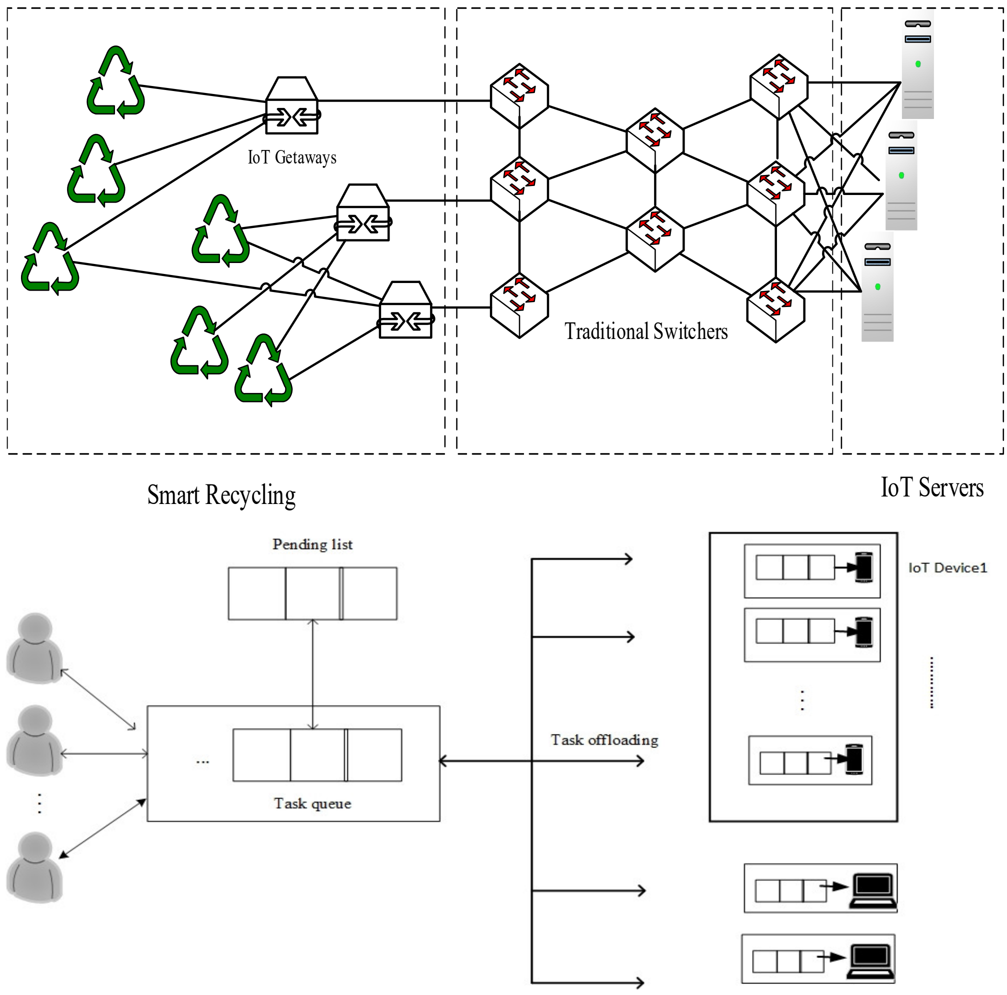

Figure 2. Task allocation in IoT.

4.1. Proposed Method

This section proposes the load balancing technique using IoT's chemical reaction optimization algorithm. Section 4.1.1 describes the basic concept of the chemical reaction optimization algorithm. Section 4.1.2 proposes the structure of the chemical reaction optimization algorithm. Finally, the load balancing method is described and proposed in Section 4.1.3.

4.1.1. The Basic Concept of the Chemical Reaction Optimization Algorithm

Lam and Li proposed artificial chemical reaction optimization in 2010 [30]. It attempts to quantify the energy released throughout the reaction procedure by simulating what occurs to molecules in a chemical reaction system [31]. The molecules symbolize the answer to the issue at hand, each of which has its own set of characteristics. The atom type, angle, bond length, and torsion describe a molecule made up of many atoms. Any alteration in atom type, angle, bond length, or torsion will cause the molecules to be distinct from one another [30].

4.1.2. Chemical Reaction Optimization Algorithm

A chemical reaction is a process by which a set of chemicals is converted into another. These responses happen at a variety of rates, ranging from quite slow to extremely quick. Multiple stages in chemical reactions are quite frequent [32]. Chemical reactions are generally described by a chemical alteration followed by the formation of one or more products with characteristics that vary from the reactants. N various sorts of molecules or chemical species are engaged in chemical reactions. These molecules might be involved in any of M different chemical processes. Under normal physiological circumstances, reactions that are neither substantially endergonic (requiring energy) nor significantly exergonic (releasing energy) are generally spontaneous backward and forward. Numerous reactions are reversible, which means they may go either way. A rate forward reaction equals a rate reverse reaction at the chemical equilibrium point. When a chemical system reaches equilibrium, all members' apparent characteristics and concentrations are constant. One reaction's output might react with the products of other reactions [33]. Figure 3 depicts a schematic illustration of chemical processes [34].

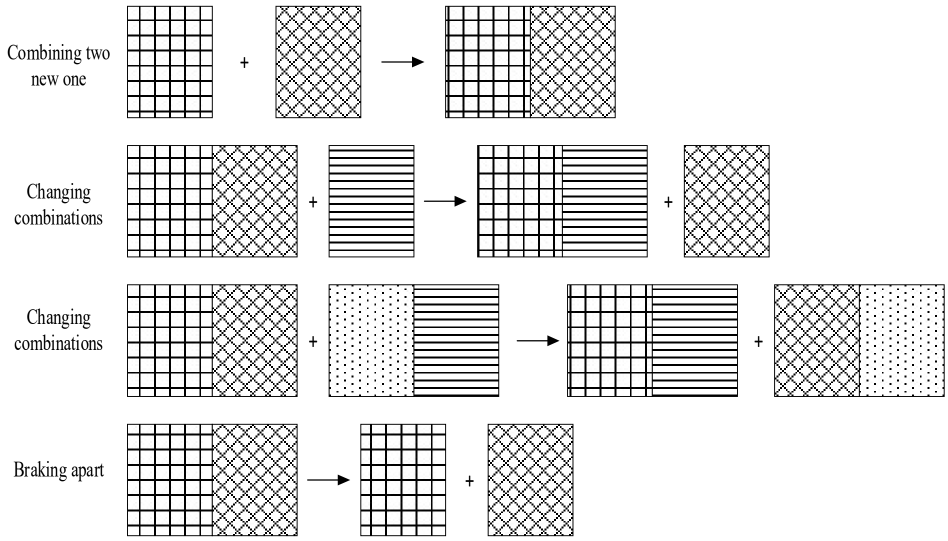

Figure 3. Chemical reaction sorts depicted in schematic form.

Atoms and molecules constantly move and clash in a viscous fluid that fills a two-dimensional cell space. Atoms are subatomic particles with mass, radius, charge, direction, location, and velocity. A molecule is a collection of atoms held together by bonds. The mapping of discrete cell configurations to the application of parameters to atoms is a chemical reaction operation. Actions allow bonding and non-bonding to build and break down molecules, create and destroy atoms, orient, change type, and drift. Time proceeds in discrete steps. In short, reactions are obtained by the fractionation of atoms. The encoding technique of our load-balancing approach for depicting search nodes as molecules is presented in this section. Any molecule should be able to select a timetable independently. Furthermore, the original molecular population's quality is increased to improve the chances of obtaining a globally optimum solution. Eventually, the first molecular population algorithm is given. A solution T of the executive order is encoded as an integer queue, where an integer depicts a recycling task ID, i.e., $T = \{t_1, t_2, \ldots, t_i, \ldots, t_n\}$, as shown in Figure 4.

t_0	t_1	t_2	Molecular Structure	t_n

Figure 4. The demonstration of molecular structure.

The interaction between one or two reactants is defined by the rules of reaction, leading to producing a novel reactant. It starts with a set of primary reactants in a solution to optimize the synthetic chemical reaction [35]. Eventually, the reactants are produced through chemical reactions. It should be noted that the termination of the algorithm occurs when no other reaction can be performed (inert solution). The choice of reactants for the reactions is probably based on their concentration and potential. Furthermore, competitive and sequential reactions are the two basic sorts of reactions. Chemical reactions are sequentially linked in the sequential kind, such as $A + B + C \rightarrow AB + C \leftrightarrow ABC \rightarrow A + BC$.

It is feasible for distinct goods to arise depending on particular parameters in the competing type. One reaction's product might be used as a reactant in another. A variety of things influence how people react. The artificial chemical reaction optimization method introduces the notion of equality for bimolecular or monomolecular processes and their kinds. In the following, the five steps of the proposed method are mentioned:

Step 1: Initialization of algorithm and problem parameters.
Step 2: Evaluation and regulation of primary reactants.
Step 3: Applying chemical reactions.
Step 4: Reactants update.
Step 5: Check the terms and criteria of termination.

A. Initialization of algorithm and problem parameters

The following is a description of the optimization issue: Minimize $f(T)$, where $f(T)$ is an objective function, N is the number of decision variables, t is the collection of each decision variable t_j, and t_j is the collection of the feasible range of values for every decision variable, i.e., T_j^{min} and T_j^{max} are the bottom and top bounds of the j'th decision parameter for real-values encoding, respectively. Various methods of encoding, such as binary, permutation, real, etc., might be needed to solve the issue. This stage additionally specifies the algorithm parameter *ReacNum*.

B. Evaluation and regulation of primary reactants

The major reactants are uniformly initialized in the search space at this step of the method. Initial reactants can be created using the uniform population approach for the initial population generation. In general, the linear composition of the components of the base set can provide all vectors in space. If one or more items are missing from the base set, the dimension associated with that element may be lost. Thus, the primary reactants must include the reactants required to hold each member of the base set. The condition of the rule and the base set is used to ensure the regularity of the principal reactants and the preservation of the base set. The recommended approach in this study meets both instances. Producing beginning reactants using the divide and general concept is one approach to creating high-quality reactants.

Initially, two reactants R_0, R_1 are set where $R_0 = \{u_1, u_2, \ldots, u_n\}$, $R_1 = \{l_1, l_2, \ldots, l_n\}$, n is the length of reactant and this case is considered as $k = 1$ (Figure 5.a). Then, a dividing factor, k, is determined. Firstly, $k = 2$ and two extra R_2, R_3 reactants are derived from R_0 and R_1 (Figure 5b).

$$\mathrm{R}_2 = \left\{ \mathrm{r} * \mathrm{u}_1, \mathrm{r} * \mathrm{u}_2, \ldots, \mathrm{r} * \mathrm{u}\frac{n}{2}, \mathrm{r} * \mathrm{l}\frac{n}{2+1}, \ldots, \mathrm{r} * \mathrm{l}_\mathrm{n} \right\}$$

$$\mathrm{R}_3 = \left\{ \mathrm{r} * \mathrm{l}_1, \mathrm{r} * \mathrm{l}_2, \ldots, \mathrm{r} * \mathrm{l}\frac{n}{2}, \mathrm{r} * \mathrm{u}\frac{n}{2+1}, \ldots, \mathrm{r} * \mathrm{u}_\mathrm{n} \right\}$$

where r is a random integer between $0 \leq r < 1$. We take into account the size of population P as $|P|$ and the number of elements in the created reactants R as $|R|$, respectively. Since R_0 and R_1 are separated into three sections, if $|R| < |P|$, the value of k is raised by 1, and $2^3 - 2 = 8 - 2 = 6$ reactants may be extracted from R_0 and R_1, which are not in R. The following is a list of these reactants (Figure 6).

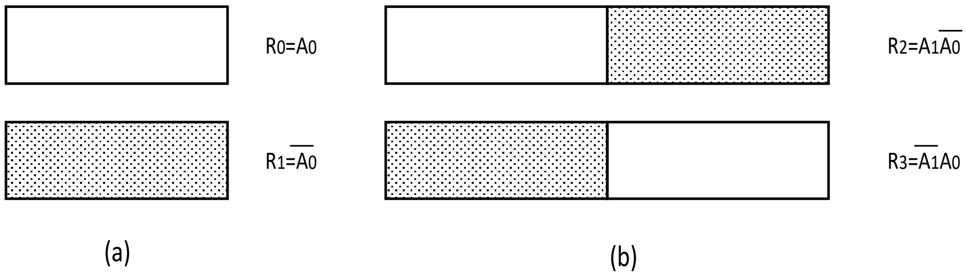

Figure 5. (**a**,**b**) New reactants with k = 2.

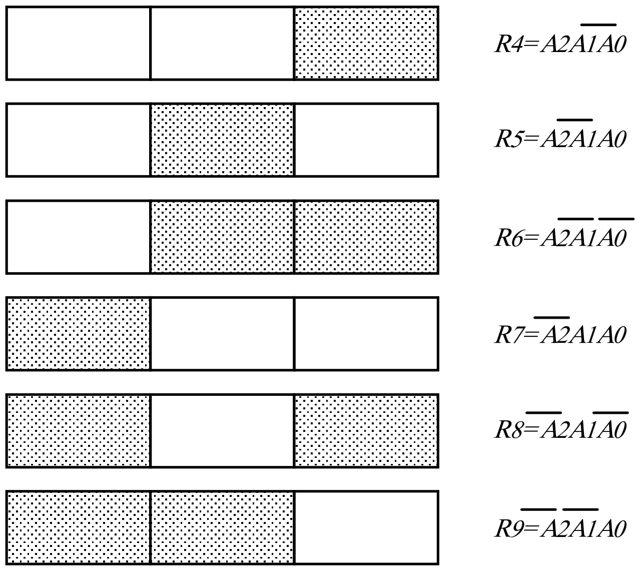

Figure 6. New reactants with k = 3.

C. Applying chemical reactions

The population of solutions is subjected to four different sorts of responses. The algorithm may occasionally keep fewer or more solutions overall depending on how many molecules are added or removed from the reaction pool by the decomposition and synthesis operators, respectively. This section talks about how these reactions were implemented computationally.

➢ *Bimolecular reactions:* In a bimolecular reaction, the reactants *R1* and *R2* are engaged. The sorts of bimolecular reaction processes employed in the synthetic chemistry algorithm are discussed in the subsequent sections. For reaction actions, string encoding is equivalent to binary encoding. The artificial chemical reaction optimization technique uses mutation and crossover types.
➢ *Synthesis reaction:* A new reactant is showed as $R = (r_1, \ldots, r_i, \ldots, r_n)$, where $\boldsymbol{r_1} = \boldsymbol{ri} + \boldsymbol{\alpha_i}(r_i^2 - r_i^1)$, where $\boldsymbol{\alpha_i}$ is a randomly selected number in $[-0.25, 1.25]$. It is comparable to the planned expanded line crossover operator in [36]. Figure 7 illustrates this procedure.

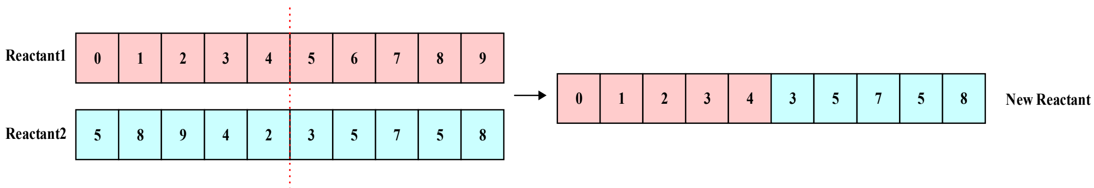

Figure 7. Synthesis reaction operation representation.

➢ Displacement reaction: Two new reactants are shown as $\boldsymbol{R_k} = \{r_1^k \ldots . r_i^k \ldots . r_n^k\}.\ \boldsymbol{k} = \mathbf{1.2}$, where

$$r_i^1 = \alpha_{td} r_i^1 + \left(1 - \alpha_{td} r_i^2\right)$$

$$r_i^2 = \alpha_{td} r_i^2 + \left(1 - \alpha_{td} r_i^1\right)$$

when this reaction is conducted, $\alpha_{td} \in [0.1]$, and $\alpha_{td+1} = 2.3 * (\alpha_{td})^{2\sin(\pi\alpha_{td})}$ td is elevated by 1 (see Figure 8).

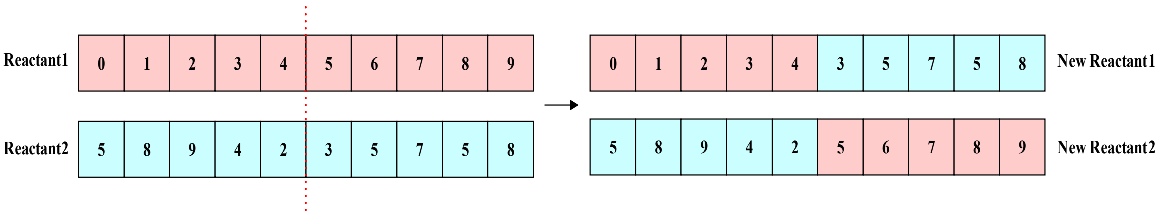

Figure 8. Displacement reaction operation representation.

➢ Redox2 reaction: If R_1 is the reactant with a better objective function then, $r_i = \alpha_{tr}(r_i^1 - r_i^2) + r_i^1$ where $\alpha_{tr} \in [0.1]$. $\alpha_{tr} = \begin{cases} 0\ .\alpha_{tr} = 0 \\ \frac{1}{\alpha_{tr}}\ Mod\ 1\ .\ \alpha_{tr} \in [0.1] \end{cases}$

D. Monomolecular reactions

➢ *Decomposition reaction:* $R = (r_1, \ldots, r_i, \ldots, r_n)$ illustrated the reactant and $r_i \in [l_i, u_i]$ is an atom or an attribute that will act as a part of a monomolecular reaction. This molecule's novel atom or a distinct attribute $r_i{}'$ is a random value from the domain $[l_i, u_i]$ (see Figure 9).

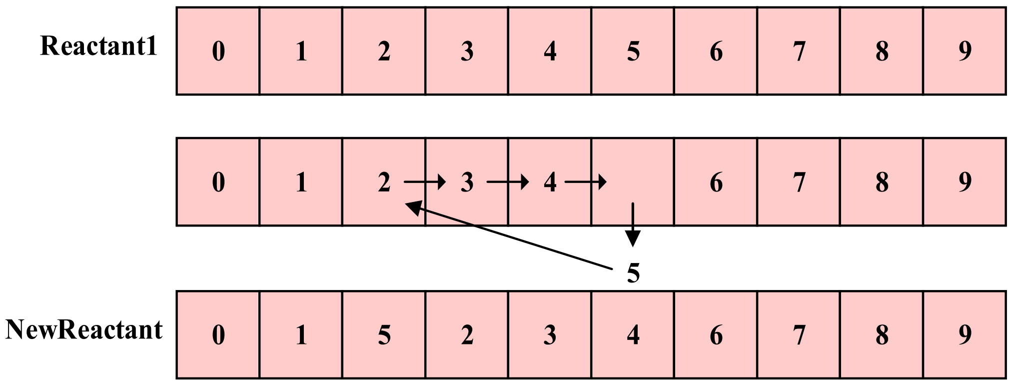

Figure 9. Displacement reaction operation representation.

➢ *Redox1 Reaction:* $\boldsymbol{r_i'} = \boldsymbol{l_i} + \boldsymbol{\alpha_t}(\boldsymbol{u_i} - \boldsymbol{l_i})$ where $\boldsymbol{\alpha_t} \in [\mathbf{0.1}]$ under the conditions that the initial $\boldsymbol{\alpha_0} \in [\mathbf{0.1}]$ and that $\boldsymbol{\alpha_0} \notin \{0.0, 0.25, 0.5, 0.75, 1.0\}$ and $\boldsymbol{\alpha_{t+1}} = \mathbf{4}\boldsymbol{\alpha_t}(\mathbf{1} - \boldsymbol{\alpha_t})$. t is elevated by 1 when this reaction is carried out.

➢ *Reactants update:* The chemical equilibrium test is carried out at this point. If the newly generated reactants' function values are better, new reactants are added to the set, and the worse reactants, similar to reversible reactions, are removed.

4.1.3. Load Balance

While forwarding data packets, each node picks the next-hop node in the inner layer with the least network loading to achieve load balancing. Each node publishes its network loading value to let its outer-layer nodes obtain its network loading in its beacon message. When a node in the inner layer sends a data packet, it picks the next hop with the least network loading from among its neighbors. Load balancing is based on the design layer service because each data packet is sent to the node with the least network loading.

Nodes often modify their next-hops if network loading is assessed based on the current network loading over a short period. It can result in a significant increase in network traffic and associated bottlenecks. As a result, load balancing assesses network loading using an exponential weighted moving average algorithm. Recent data have a stronger weighting and a greater effect on the subsequent estimation value. In contrast, the impact of data declines exponentially with time. Hence, the projected loading can represent long-term network loading, allowing nodes to swap the next hops seamlessly.

Given a time slot i, the current sample network loading (SNL) is denoted as $\mathrm{SNL_i}$, and the estimated network loading (ENL) is denoted as $\mathrm{ENL_i}$. If $\mathrm{SNL_i}$ is not 0, $\mathrm{ELN_i}$ is calculated as $(1 - w) * ENL_{i-1} + w * SNL_i$ and determines the effect of the current traffic load to estimate long-term traffic by considering the weight w for the SNL.

The SNL weight is calculated to determine the effect of the current traffic load for estimating long-term traffic if it is not 0. In order to prevent ENLi from being 0 when $\mathrm{SLN_i}$ is 0 even though w is 1, *ENLi* is set to $1/2$ ENL_{i-1}. ENL_0 is first set to SNL_0. If w is small, the ENL will change slowly; if w is large, the ENL will change rapidly due to the large effect of the SNL on the ENL. Traffic is dynamically routed through nodes with the lowest long-term traffic loading utilizing load balance on the design layer. Hence, it achieves load balancing through dependable multipath layered routing.

5. Results for Evaluating the Proposed Method

This section compares the suggested technique's simulation to other methods. In particular, Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) algorithms have become popular for the optimization of IoT-based systems. These algorithms offer higher accuracy for problems with a wide range of solutions and can obtain results faster than traditional mathematical solutions [37]. Therefore, these three algorithms were selected to compare with the proposed method in this paper. The simulation tool is provided in Section 5.1. Section 5.2 lists the simulation parameters. Eventually, Section 5.3 discusses the examination of the simulation findings.

5.1. Simulation Tool

The suggested approach is analyzed and evaluated by using V2016 MATLAB software. MATLAB is one of the most extensively utilized IoT simulators. The MATLAB 2017b R software environment may be used to simulate and evaluate a variety of applications. The MATLAB simulator was selected because of its significant development and support for IoT solutions.

5.2. Simulation Parameters

The simulation settings should be appropriately established in order to successfully simulate and generate precise and dependable outcomes. Table 2 lists the most relevant and important factors.

Table 2. Simulation parameters.

Parameter	**Amount**
Number of IoT nodes	10–300
Number of servers in each IoT node	1–5
Number of tasks	50–500
Data Size	10–15 Mb
Computing intensity	300 cycle/bit
Cost	1–10$
Energy	1–10 mj
Processing time	1–10 s
Parameters of the proposed algorithm	
Iteration	100
popSize	50
KELossRate	0.85
MoleColl	0.50
InitialKE	0
alpha	1
beta	10
buffer	0
GA parameters	
Number of chromosomes (solutions)	100
Selection operator	Roulette wheel
Cutting operator	Single point
Probability of crossover	0.8
Mutation rate	0.1
Maximum number of generations	100
PSO parameters	
Number of particles (solutions)	100
Inertial weight	First 0.9 then decrease to 0.4
C1	Rand $*$ 2
C2 (C1 + C2 $\leq$ 4)	Rand $*$ 1.5
Maximum speed	Number of Rand tasks
Maximum number of generations	100
ABC Parameters	
Number of bees (solutions)	Three times higher the number of IoT nodes
Maximum number of generations	100
Onlooker	50
Scout bee	1
Employed bees	50

5.3. Experiment Results

The methodology outcomes are compared to the ABC, GA, and PSO algorithms and suggested method in this section. The relative performance for the varied number of iterations is evaluated by computing the objective function and how it functions to optimize the method, as illustrated in Figure 10. The fitness of 100 generations is evaluated in this simulation. The fitness function grows as the generations grow. The fitness quantity among the 30th and 100th generations has fallen to its minimum point, 0.48, as can be observed.

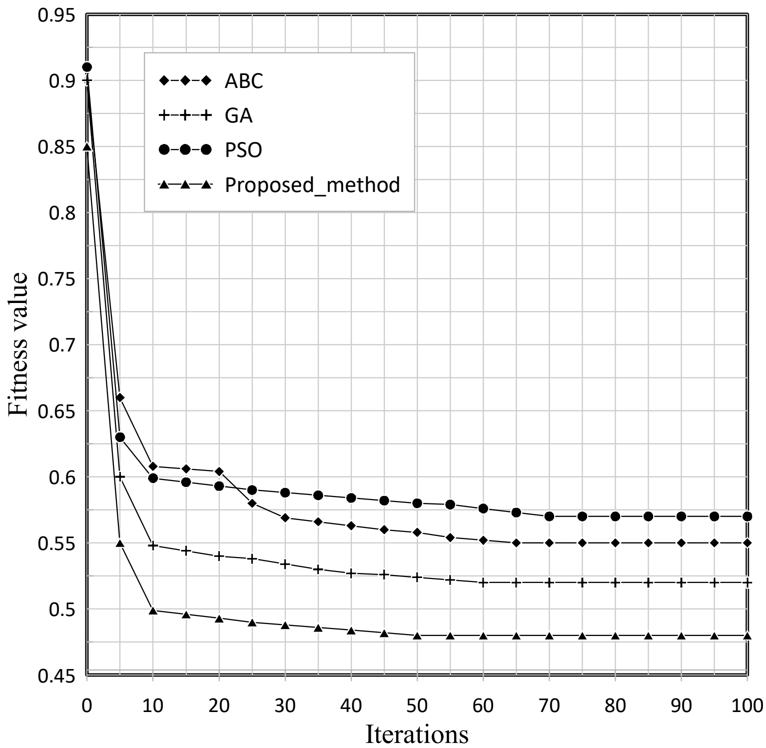

Figure 10. The result for fitness in 100 iterations.

The rest of this section describes the analysis of the simulation results and shows simulation diagrams of the load balance degree, energy consumption, and delay time.

- ***Load Balance Degree***

In the investigation, the nodes in layer 1 have easy accessibility to the IoT gateway, while the nodes from other levels communicate data to the nodes in layer 1 through Zigbee links. Hence, the data traffic at layer 1 is significantly higher than at other levels. Therefore, load balancing at layer 1 is important.

We propose a load balance degree (LBD) derived using the standard deviation (SD) of the traffic load and the load average (LA) across all nodes in a layer to assess the load balancing performance according to Equation (2):

$$\text{LBD}Y = [1 - (\text{SD}Y\ \text{LA})] \times 100\% \tag{2}$$

where LBD, SD, and LA are illustrated with LBDY, SDY, and LAY in layer Y. SDY = 0 indicates that all nodes in layer Y possess identical traffic loads. The load balance performance is the best in this situation, and LBDY is 100%. When LBDY is 0, that means SDY equals LDY. It means that because the variance of traffic load in layer Y equals the average load, this layer's load balancing is inadequate. If LBDY is negative, the load balancing is considerably worse since it means that certain nodes' traffic loads are much higher than the average plus SD.

The comparison of the results of the imbalance degree of the state-of-the-art to the proposed method is shown in Figure 11.

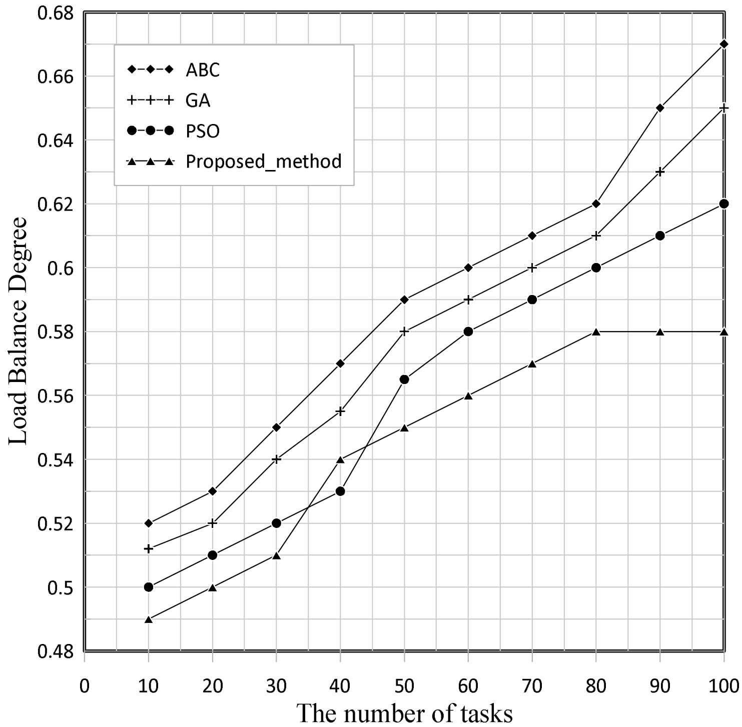

Figure 11. Comparison of the results of the load balance degree.

- ***Energy consumption***

Each mobile contains its own set of CPU cores ($PL_j = \{pl_{j,1}, pl_{j,2}, ..., pl_{j,n}\}$). Equation (3) calculates the energy usage of each core depending on the total CPU cycles (C_{ci}), voltage supply ($V_{local,j,k}$), operating frequency ($f_{local,j,k}$), and effective commutative capacitance ($C_{local,j,k}$). Equation (3) calculates the IoT device's local dynamic energy consumption throughout each task.

$$E_{i,local} = P_{i,local} * T_{i,local} \tag{3}$$

where

$$T_{i,local} = \frac{C_{cti}}{f_{local,j.k}} \tag{4}$$

$$P_{i,local} = C_{local,j,k} * V^2{}_{local,j,k} * f_{local,j,k} \tag{5}$$

A device D_j should evaluate if it is more suitable to execute the job locally or remotely, taking the battery level and latency into account as model restrictions. As the battery level is such an important component in the decision, the system will welcome a strategy that decreases energy usage. Equation (6) expresses the local expense of one task i.

$$Cost_{i,local} = u_{localT} * T_{i,local,total} + u_{localE} * E_{i,local} \tag{6}$$

The coefficients $u_{localE} \in [0, 1]$ and $u_{localT} \in [0, 1]$ are weightings, where $u_{localT} + u_{localE} = 1$.

According to Wangetal, these variables reflect a trade-off between implementation time and energy usage, reducing costs. In the best- and worst-case situations, the DVFS-related overhead rate is between 0.02% and 2% [38]. The suggested technique's energy consumption analysis is shown in Figure 12 compared to the ABC, GA, and PSO algorithms. The obtained results show that energy consumption has significantly decreased compared to the previous methods.

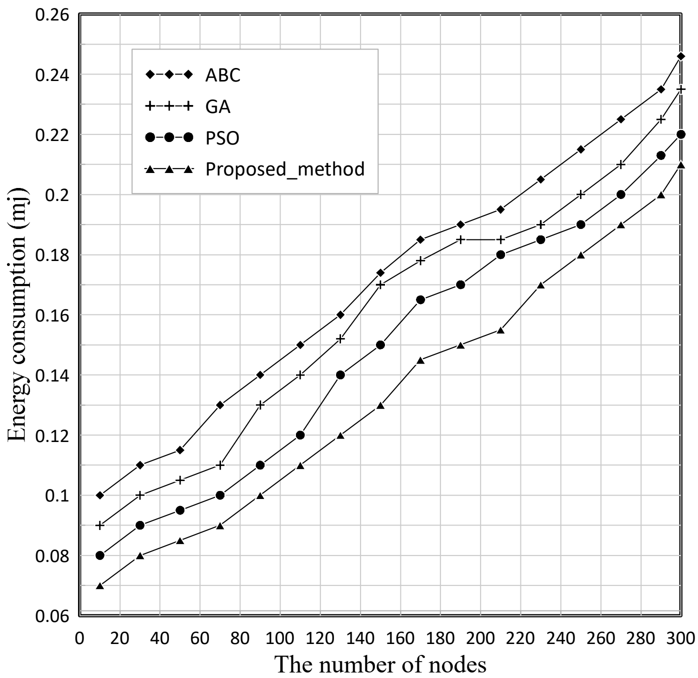

Figure 12. Comparison of ABC, GA, PSO, and the proposed method in energy consumption.

- ***Delay time***

The delay time is one of the most significant metrics for assessing the network performance. The suggested technique's delay analysis is shown in Figure 13 compared to the ABC, GA, and PSO algorithms. The obtained results show that the delay time has significantly decreased compared to the previous methods.

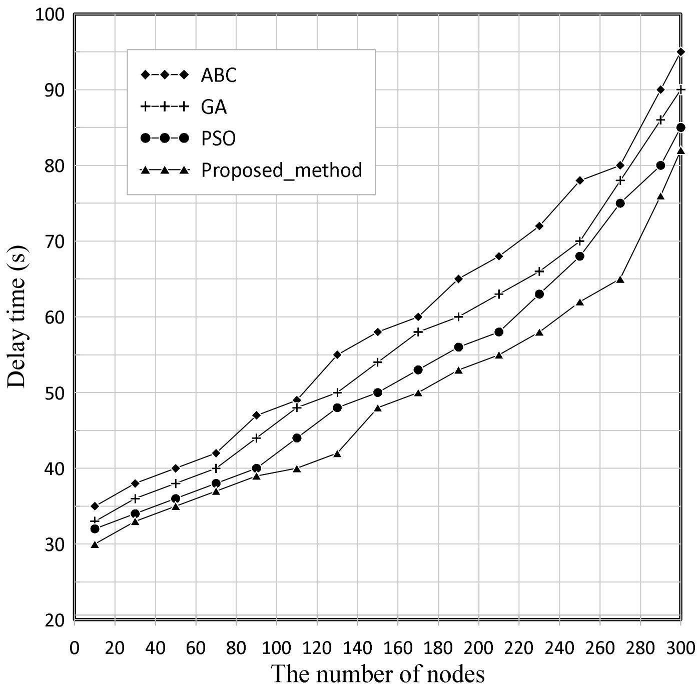

Figure 13. Comparison of ABC, GA, PSO, and the proposed method in delay time.

6. Conclusions and Future Work

The IoT-based smart recycling system delivers real-time information, improves collection routes, and lowers expenses. The smart recycling solution contains a transponder and gauges attached to the lid of the recycling containers, using ultrasound to measure the level in the container. The information is transferred to cloud servers through the mobile network, where it is reported and made accessible to the emptying contractors. Emptying containers are thus planned and optimized in real-time in this way. Recycling solutions illustrate how new linked technologies can significantly impact and help a more sustainable society. Leading organizations that see the benefits of the IoT will be able to obtain competitive advantages by implementing this technology. This research work focuses on the load balancing of IoT tasks in the field of smart recycling. We present an energy-efficient and low-cost prototype system for a recycling bin based on an artificial chemical reaction optimization algorithm. Simulation-oriented comparative performance evaluation attests to the proposed framework's load balance degree and delay time compared to the state-of-the-art techniques. It is also observed that the proposed method has a lower energy consumption rate than the state-of-the-art techniques. The next step of this research is to experiment with federated learning techniques and investigate how they could increase our system's performance. Additionally, the research team will further investigate innovative recycling machinery to achieve the recycling process in the future.

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