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Design a Robust Logistics Network with an Artificial Physarum Swarm Algorithm

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Abstract: The robust optimization of logistics networks can improve the ability to provide sustainable service and business sustainability after uncertain disruptions. The existing works on the robust design of logistics networks insisted that it is very difficult to build a robust network topology, and this kind of optimization problem is an NP-hard problem that cannot be easily solved. In nature, Physarum often needs to build a robust and efficient topological network to complete the foraging process. Recently, some researchers used Physarum to build a robust transportation network in professional biological laboratories and received a good performance. Inspired by the foraging behavior of natural Physarum, we proposed a novel artificial Physarum swarm system to optimize the logistics network robustness just on a personal computer. In our study, first, the robustness optimization problem of a logistics network is described as a topology optimization model based on graph theory, and four robustness indicators are proposed to build a multi-objective robustness function of logistics network topology, including the relative robustness, the betweenness robustness, the edge robustness and the closeness robustness. Second, an artificial Physarum swarm system is developed to simulate the foraging behavior of a natural Physarum swarm to solve this kind of complex robust optimization problem. The proposed artificial Physarum swarm system can search for optimal solutions by expansion and contraction operations and the exchange of information with each other through a self-learning experience and neighbor-learning experiences. The plasmodium of Physarum forms the edges, and the external food sources simulate the logistics nodes. Third, an experimental example is designed on the basis of Mexico City to verify the proposed method, and the results reveal that the artificial Physarum swarm system can help us effectively improve the logistics network robustness under disruptions and receive a better performance than natural Physarum. The article may be helpful for both theory and practice to explore the robust optimization in logistics operation and provide engineers with an opportunity to resist logistics disruptions and risk loss by a novel artificial intelligence tool.

Keywords: logistics network; robustness; disruption; artificial intelligence optimization; artificial Physarum swarm

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1. Introduction

Sustainable economic and social development is vulnerable to natural disasters, wars and severe infectious diseases, posing a serious challenge to the robustness of the logistics network [1]. It is hoped that the logistics network can resist unexpected disruptions and achieve an optimal operation [2]. Aloui et al. [3] designed a resilient and sustainable logistics network under epidemic disruptions and demand uncertainty, and Xu et al. [4] employed a robust modeling and the planning of a radio-frequency identification in logistics networks under uncertainties. If the key node of a logistics network is congested or disrupted, many other network nodes or edges will soon be easily propagated to be congested, resulting in a cascading failure for network topology and the rapid reduction in the efficiency of the logistics network [5]. The robustness of the road network plays an important role in the robustness of the logistics network, where the evaluation indexes include the road capacity expansion degree, the simplified connectivity between the origin and the destination, the path betweenness and the logistics instability variation coefficient. Dehshiri et al. [6] presented a novel robust stochastic, possibilistic and flexible approach for the design of a multi-objective closed-loop supply chain network. This kind of stochastic disruption will destroy the network topology and be propagated to more logistics nodes or logistics flows, even resulting in more impacts on the whole logistics network's robustness.

Hence, logistics business sustainability should be studied in case of a topology robustness, such as disjoint paths and survivable networks, or greatly increased efforts will be put into topology management, contingency planning, traffic optimization and so on. Kulkarni et al. [7] proposed a hyperconnected parcel delivery network design under the disruption risks, while Maneengam et al. [8] considered the impacts of the cross-chain collaboration center model on the transportation performance and made a case study of a bulk transportation network in Thailand. The robustness of the logistics network will decrease the lack of reliability and bring an additional cost for users. The more important the network node is, the more severe the damage would be if a robust failure takes place in it. To identify which links or nodes would impair the network's performance the most, Suchat et al. [9] used a series of indexes to measure the road network's robustness toward flood-resilient transportation systems. Yang et al. [10] explored a nonlinear load-capacity model to evaluate the controllability robustness against a cascading failure for complex logistics networks. Therefore, the substance of the robustness optimization on the logistics network is to improve the connectivity of the network's nodes and edges.

Additionally, the robust optimization and sustainable scheduling of the logistics networks are challenging and costly. Now, many artificial intelligence methods are applied in this area, i.e., fuzzy AHP and fuzzy VIKOR methods [11,12] and particle swarm optimization (PSO) [13]. In the past ten years, a strange living thing has extended our minds to solve the network robustness problems. In nature, Physarum often needs to build a robust and sustainable topological network to complete the foraging process. Hence, some researchers used Physarum to build a robust transportation network in professional biological laboratories and received a good performance. In 2010, Science published a paper applying the Physarum to solve the traffic planning problem of the Tokyo railway [14] and gained a great attention. After that, Andrew et al. [15] constructed approximating Mexican highways with slime mold. Inspired by the smart Physarum swarm without a brain or a neuron, Cai et al. [16] design an artificial intelligence algorithm on a personal computer to help solve the robust optimization problem of transportation networks by simulating the behavior of true slime mold. In fact, the slime molds have swarm intelligence. If we improve the artificial slime mold algorithm by the swarm intelligence, it is hopeful that we will receive a novel artificial swarm intelligence method for the optimization of the logistics network, instead of doing it in a professional biological laboratory.

The contributions in this paper are as follows. First, according to the characteristics of random disruptions and business sustainability, we employ a relative robustness, betweenness robustness, edge robustness and closeness robustness to build the multi-objective robustness function of the logistics network. The robustness optimization problem is modeled as a topology optimization problem based on graph theory. That is, a higher robustness value means a stronger connectivity for the logistics network to resist disruptions. Second, a novel artificial Physarum swarm (APS) system is specially designed to simulate the foraging behavior of a natural Physarum swarm and to help us to solve this kind of complex robust topology optimization problem. The proposed artificial Physarum swarm model includes external food sources, plasmodium, nucleus and nutrients flowing in its body. The Physarum plasmodium constructs the edges, and the external food sources form the nodes of the logistics network. The proposed artificial Physarum swarm system can search for optimal solutions by expansion and contraction operations and through the exchange of information with each other through a self-learning experience and neighbor-learning experiences. Third, an experimental example is designed to verify the proposed method, and the results demonstrate that the artificial Physarum swarm system can help us solve the NP-hard problem and improve the logistics network's robustness through its heuristic searching capability.

The rest of this paper is organized as follows. Section 2 reviews the relevant works on the robust logistics network design problem. Section 3 describes the robust design problem of the logistics network's topology and the multi-objective function. Section 4 presents the solving methodology based on an artificial Physarum swarm system. The experimental results are analyzed and compared in Section 5. Finally, Section 6 concludes our work and indicates some limitations and future research directions.

2. Literature Review

Many existing methods for evaluating the robustness and sustainability of logistics networks are based on the topology indexes in graph theory. Hence, the robustness of a logistics network can be measured by the space dimension and time dimension. In the space dimension, graph theory has been widely used to describe the interactions and interdependencies between topology nodes and edges, which can directly evaluate the importance of nodes or edges and is useful to measure the logistics network's robustness [1–11].

Among them, the degree method is used early on for an important index to measure the connectivity of a node, such as the degree of the node's connection [7] and the degree heterogeneity on the structural robustness under a cascading failure [5,10]. Based on this model, the expected traffic loss originating from a disruption can be calculated by the network's links and be used to depict the network's vulnerability cost. Most of the logistics network is a centralized network around one or more central nodes, so the degree method can help us find the vulnerable nodes quickly [8]. Furthermore, the logistics connectivity and the network's complexity will be increased in reverse logistics, which is ubiquitous in the steel industry [17], plastic wastes recycling [18], end-of-life vehicles [19] and electronic products [20].

However, some logistics networks are regular democratic graphs, thus the degree method may not be suitable. Joo et al. [21] used the betweenness and coronary calcium to measure the association and accessibility of the network under different risks. The betweenness method used betweenness centrality to measure the node importance, such as the shortest pair of disjoint paths problem. That is, the more the shortest paths pass through a node, the more significant the node is. To measure the robustness or vulnerability of a network, the pair-wise nodes' connectivity and the disruption should be both taken into account. The material recycling [22] and remanufacturing business [23] may affect the betweenness centrality and it will also decrease the robustness of the logistics network.

Nevertheless, the node degree and betweenness are mainly dependent on the whole network topology, where the closeness can be applied to evaluate the local topology and relative relationship between the nodes. Zarghami et al. [24] adopted three prototypical examples of centrality indices including the betweenness, closeness and eigenvector centrality to evaluate the supply vulnerability. The closeness is suitable to evaluate the robustness of a decentralized blockchain network [25,26], where all blocks are often linked to the nearest blockchain nodes to reduce the branching. In addition, due to its particularity, food logistics often require a nearby transportation to improve the quality of the service (QoS) and the robustness of the network's response [27].

In the time dimension, the robustness of a logistics network can be evaluated by the time response of the logistics system [28], which is the maximum possible damage according to the residual connectivity after a disruption [29]. A good robustness should have a good time response performance in multiple products [30], collaborative distribution [31] and malicious attacks [32]. A robust logistics network may diminish the loss of disruptions or the number of disruption nodes [33]. This kind of fast recovery performance is often called resilience [3,7,9,13,19,22]. Furthermore, Evangelos et al. [34] made a literature review on the quantitative modeling of resilient 3PL supply chain network designs, and Maryam et al. [35] surveyed the strategic alliance for resilience in the supply chain.

Due to the difficulty of solving the robustness problem of the logistics network, many researchers applied a lot of artificial intelligence algorithms to improve the network's robustness, such as the fuzzy set [11,12], ant colony optimization (ACO) [36], artificial neural network (ANN) [37,38], particle swarm optimization (PSO) [13,39,40], genetic algorithm (GA) [39] and deep learning (DL) approach [41]. In 2010, a novel Physarum method was used for the optimization of a traffic network [14]. In the same year, Adamatzky et al. [42] also stated a road planning with Physarum, where the nature Physarum were used to build motorways to route the M6/M74 through Newcastle. Then, Andrew et al. [15] again applied Physarum to get an approximation of Mexican highways. After that, more and more researchers were involved in the area. Zhang et al. [43] described an improved Physarum polycephalum algorithm for the shortest path problem, and then designed an efficient Physarum algorithm to solve the bicriteria traffic assignment problem [44]. Different from other living things with a head or many neurons, the Physarum is only a single-cell structure without any head or neuron. Although there are some advantages in solving the network planning problem by real Physarum [14,15,42,43], there are also many shortcomings, such as a low precision, a long solution period (i.e., 26 h in [14], 70 h in [15] and 96 h in [43]) and professional biological laboratories. However, until now, research on the artificial intelligence and swarm learning mechanism in Physarum swarm's foraging behavior is still very lacking.

The contributions of this paper are of not only theoretical but also practical importance for the logistics network's sustainability and artificial intelligence. The artificial Physarum swarm described in our paper is not natural Physarum in [14,15,42,43], but an artificial intelligence algorithm that can solve network optimization problems on a personal computer by simulating the swarm behavior of a real Physarum swarm.

3. Problem Description

3.1. The Robustness Measurement of Logistics Network

The logistics network formed by nodes and edges is to complete all kinds of sustainable transportation tasks between the nodes, where the logistics nodes form the facility network, and the logistics flow form the path network. Accordingly, the problem of the logistics network's robustness and sustainability includes a node-based disruption and an edge-based disruption, where the nodes and edges may be a failure.

In graph theory, to enhance the topology robustness, it is applicable to improve the residual closeness of the local structure. Therefore, we try to evaluate the robustness of a logistics network by the redundancy of nodes and edges.

In the graph model of a logistics network, the whole solution space can be expressed as a directed graph $G = (N, V)$, with n logistics nodes and several logistics flows. The node matrix $N = [(x_i, y_i)]_n$ includes n logistics nodes, and the flow relationship between the nodes constitutes an edge matrix $V = \{v_{ij} |\ i, j \in N\}$. The logistics network is a time-varying structure, and at time t, the topology of G can be symbolized by an $n \times n$ matrix $\mu = [\mu_{ij}(t)]_{n\times n}$, where

$$\mu_{ij} = \begin{cases} 1, \text{if there is a direct edge from node } i \text{ to } j \\ 0, \text{if there is no direct edge from node } i \text{ to } j \end{cases} \tag{1}$$

The flow on every edge v_{ij} is continuously changing and forms an $n \times n$ weight matrix $w = [w_{ij}(t)]_{n\times n}$, where w_{ij} describes the volume of the logistics flows from the logistics nodes i to j at time t. Assuming that the relationships of all the logistics nodes are known, the distance matrix between logistics nodes can be given as:

$$D = [d_{ij}]_{n\times n} = [|v_{ij}|]_{n\times n} = [\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}]_{n\times n} \tag{2}$$

where d_{ij} is the length of the edge v_{ij}, that is $d_{ij} = |v_{ij}|$. The node degree can directly give us a reference for the node connectivity, and the definition is as follows [5,7,8,10].

$$Dg_i(t) = \sum_j \mu_{ij}(t) \tag{3}$$

Then, the total degree of n nodes is $Dg_\Sigma = \sum_i Dg_i(t)$. Now, that the average redundancy rate of the whole network can be defined, also referred to as the average degree of the logistics network, there is:

$$R_\Sigma(t) = \frac{Dg_\Sigma}{n} = \frac{1}{n}\sum_i Dg_i(t) \tag{4}$$

Although it is different from the traditional degree index in [5,7,8,10], it can help us evaluate the network's robustness. The higher the redundancy rate $R_\Sigma(t)$ is, the stronger the connectivity of the logistics network is, meaning more connections between different nodes and a stronger robustness. To compare the robustness relationship of different network nodes, the relative robustness of the node i can be defined here, which can express the relative strength of the node's connectivity.

$$Rel\_rob_i(t) = \frac{R_\Sigma(t)}{Dg_i(t)} \tag{5}$$

Therefore, the lower the relative robustness $Rel\_rob_i(t)$ is, the stronger the connectivity of the node i is, meaning a stronger robustness. In a network disruption, the failure on the nodes with a higher connectivity will result in less influence in the logistics network.

To reflect the robustness of the node's betweenness, $\theta_{jk}(t)$ is assumed to be the number of the shortest paths connecting to a node i at time t, which points from the logistics nodes j to k. The betweenness index $Bt_i(t)$ [21] of the logistics node i can be given as:

$$Bt_i(t) = \sum_{j=1}^{n}\sum_{k=1}^{n} \theta_{jk}(t) \tag{6}$$

Similarly, the betweenness robustness of the node i can be defined here, which can express the relative strength of the logistics node's betweenness.

$$Bet\_rob_i(t) = \frac{R_\Sigma(t)}{Bt_i(t)} \tag{7}$$

The lower the betweenness robustness $Bet\_rob_i(t)$ is, the stronger the connectivity of the node i is, meaning a stronger robustness.

Hence, the redundancy rate can help us measure the relative robustness and betweenness robustness of the nodes, and it can also help us to evaluate the robustness of edges, which is also important in a logistics network. If a failure takes place on an edge, both nodes on the same edge will have to search other routes for a logistics transportation. So, a higher redundancy rate can help the nodes search for more backup routes. The shorter the distance of the backup route is, the more robust the logistics network is and the less vulnerable the edge is. There is:

$$Edg\_rob_{ij}(t) = \frac{\min\{\sum_{k=1}^{j} d_{ik}(t)\}}{d_{ij}(t)} \tag{8}$$

Now, $\min\{\sum_{k=1}^{j} d_{ik}(t)\}$ in the edge robustness $Edg\_rob_{ij}(t)$ is strongly correlated with the number of backup routes, namely the total redundancy rate $R_\Sigma(t)$.

Furthermore, by the closeness indexes, the network edges can be endowed with corresponding weights to describe the flow or functional features of the edges [24]. It is assumed that $fl_{ij}(t)$ is the flow volume of the logistics node i, presenting the load of the logistics network. Accordingly, the node flow comprises all the flows from the other nodes through it, that is:

$$Fl_i(t) = \sum_{j=1}^{n} fl_{ij}(t) \tag{9}$$

where $fl_{ij}(t)$ includes the flow volume of arriving traffic and departing traffic of the edge v_{ij}.

Similarly, the closeness robustness of the node i can be defined here, which can express the relative strength of the nodes' closeness.

$$Col\_rob_i(t) = \frac{R_\Sigma(t)}{Fl_i(t)} \tag{10}$$

The lower the closeness robustness of $Col\_rob_i(t)$ is, the stronger the connectivity of the node i is, meaning a stronger robustness. It is reasonable to consider that a logistics node with a higher robustness has a relatively low vulnerability, but a high redundancy rate also increases the connection number for the logistics transportation.

3.2. How to Improve the Robustness of Logistics Network

Here, the robustness evaluation system can help us improve the robustness and sustainability of logistics networks under random disruption, including a node-based disruption and an edge-based disruption. The heterogeneous structures of the logistics networks result in a different robustness and a different network connectivity.

For node-based disruptions, the robustness of the logistics nodes depends on their connectivity and redundant connections, that is, increasing the redundant connections will enhance the robustness and decrease the vulnerability of the logistics topology. The larger the number of paths passing through the node i, the stronger the connectivity of the node i is. According to the topological features, the logistics flows or edges play a significant role in the network's robustness. The more traffic volume that passes through the node i, the more robust the topology is [5,7,8,10].

For an edge-based disruption, since the degree index, betweenness index and closeness index can help us depict the robustness of a network, a disruption on the edges will decrease the network's robustness on both the logistics network's nodes and edges. The core problem to decrease the vulnerability of the logistics network is to increase the number of edges and enhance the redundancy rate. According to graph theory, the vulnerability of a logistics network can be diminished by more redundant connections between the nodes and edges.

However, it is not simple to improve the robustness. The higher the redundancy rate is, the higher the cost is, because the total length of the redundant logistics routes may increase accordingly [45–47].

The operation of a logistics network can be described as a process in which m logistics flows traverse all the external logistics nodes or edges from the beginning to the end. Each logistics flow does not need to traverse all the nodes or edges, but only needs to visit the nodes or edges closest to itself, so different logistics flows can pass through a series of different nodes or edges. Supposing $i_1 \sim i_{n-1}$ are the traveled logistics nodes, i_n is the present node and the $k(\leq m)$th logistics flow has traveled the c_k nodes, the edge set forming its route L_k can be obtained as:

$$L_k = \{v_{12}^k, v_{23}^k, \ldots, v_{l-1,l}^k, \ldots, v_{c_k-1,c_k}^k\} \tag{11}$$

where L_k is an arrangement of a subset of the edges $V = \{v_{ij}|\ i,j \in N\}$, and the last node i_{c_k} is the last node that the logistics flow arrived at. The whole travel length of the logistics flow $k(\leq m)$ can be described as the total length of all the edges passed by the $k(\leq m)$th logistics flow.

$$D_k = \sum_{l=2}^{c_k} d_{l-1,l}^k = \sum_{l=2}^{c_k} \left|v_{l-1,l}^k\right| = \sum_{l=2}^{n} \sqrt{(x_{l-1}^k - x_l^k)^2 + (y_{l-1}^k - y_l^k)^2} \tag{12}$$

The distance in Equation (12) can directly describe the traffic cost of the $k(\leq m)$th logistics flow. The total number m of the logistics flows determines the total volume of the logistics network that is sequentially calculated in the order of the node number $1 \leq k \leq m$, where every node will be solved at each time. The total logistics cost can be derived from the total length of all the travel routes in the whole logistics network. That is:

$$L(t) = [L_k(t)]_m \tag{13}$$

Then, the total logistics cost can be summed up by the whole route of the logistics network where the total logistics length of all the m logistics flows subtracts the length of the overlapping paths of the logistics flows at the same time.

$$D_{\Sigma m} = \sum_{k=1}^{m} D_k - \sum_{i,j=1}^{n} d_{ij}\big|_{overlap} \tag{14}$$

Therefore, the optimization objective function of the logistics network's robustness is to both improve the total robustness and decrease the total cost or total length, that is, to find the most connections with the shortest routes. In this context, the relative robustness $Rel\_rob_i(t)$ in Equation (5), the betweenness robustness $Bet\_rob_i(t)$ in Equation (7), the edge robustness $Edg\_rob_{ij}(t)$ in Equation (8) and the closeness robustness $Col\_rob_i(t)$ in Equation (10) are suitable to measure the logistics network robustness, and the total length $D_{\Sigma m}$ can be used to evaluate the total logistics cost [45,47]. Then, the optimization function can be defined as a multi-objective function to depict the topological characteristics of a logistics network. There is:

$$\begin{array}{l} obj : \min\{Rel\_rob_i(t), Bet\_rob_i(t), Edg\_rob_{ij}(t), Col\_rob_i(t), D_{\Sigma m}\} \\ st : i, j \in (1, n), k \in (1, m), L \in [0, L_{\max}] \end{array} \tag{15}$$

As noted in the discussion above, the logistics network robustness is strongly related to the redundancy rate $R_\Sigma(t)$, and other robustness indicators have a strong relationship with it. The redundant connections will provide more alternative routes when node-based disruptions or edge-based disruptions cause any failures to break off the logistics flowing. The redundancy rate $R_\Sigma(t)$ is positively related to the numerators and denominators in Equations (5), (7), (8) and (10). Then, the optimization function in Equation (15) can be rewritten as a bi-objective optimization function.

$$\begin{array}{l} obj : \{\max\{R_\Sigma(t)\}, \min\{D_{\Sigma m}\}\} \\ st : i, j \in (1, n), k \in (1, m), L \in [0, L_{\max}] \end{array} \tag{16}$$

where the maximum redundancy rate $R_\Sigma(t)$ is in conflict with the minimum total length $D_{\Sigma m}$. The increase in the redundancy rate $R_\Sigma(t)$ will also decrease the relative robustness $Rel\_rob_i(t)$ in Equation (5), the betweenness robustness $Bet\_rob_i(t)$ in Equation (7), the edge robustness $Edg\_rob_{ij}(t)$ in Equation (8) and the closeness robustness $Col\_rob_i(t)$ in Equation (10). In both optimization objective Functions (15) and (16), it searches the optimal route L^* with a high redundancy rate and less cost. In a logistics network with an optimal robustness, there are more resilient topologies for the selection and m logistics flows, and it can also obtain the shortest routes traversing all of the nodes.

$$L^* = [L_k^*]_m = \left[\{v_{12}^k, v_{23}^k, \ldots, v_{l-1,l}^k, \ldots, v_{c_k-1,c_k}^k\}\right]_m \tag{17}$$

After the optimal route L^* is obtained, the optimization objective function of the logistics network's robustness can find a feasible solution though it is a multi-objective function with conflicting objectives and constraints. Unlike the traditional robust optimization problems with a single degree index [1–24], the objective function uses multi objectives to search the optimal logistics topology and shortest routes traversing all of the nodes. When a disruption takes place on any node or edge, even on the most important nodes or edges, less impact will be propagated to the other areas and the logistics network will be more robust and reliable. For the optimal route L^*, a corresponding route selection matrix will be created.

$$\mu = [\mu_k]_m = [[\mu_{ij}^k(t)]_{n \times n}]_m \tag{18}$$

After the optimization, there will not exist an apparent vulnerability in the optimized logistics network when a node or edge fails, and there is less impact on the functional operation of the logistics network. The more robust the logistics network is, the stronger the ability is to resist uncertain disruptions and the less loss there is.

4. Methodology

4.1. The Structure of Artificial Physarum Swarm System

Here, an artificial Physarum swarm system is proposed to solve the robustness optimization problem of a logistics network by simulating the swarm behavior of a true Physarum swarm, which has to search for more food sources with an optimal network structure all day and all night. According to the structure of real Physarum [14,15,42,43], an artificial Physarum swarm system includes external food sources, plasmodium, nucleus and nutrients, as shown in Figure 1. The Physarum plasmodium is the main part of problem-solving and forms a travel route of logistics flows. The external food sources are the search goals of logistics network nodes, and the nucleus is the center of a logistics network. The nutrients play important roles in the transmission of information for algorithm learning.

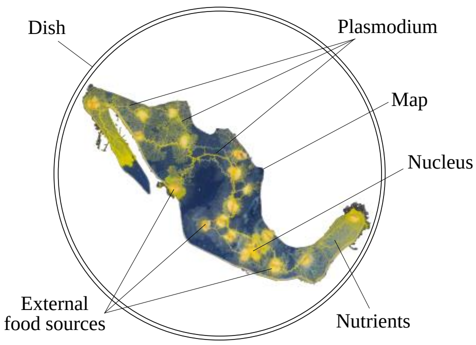

Figure 1. Artificial Physarum swarm system [15].

The external food sources around the artificial Physarum swarm can provide the nutrients to support the survival of a Physarum swarm. The Physarum swarm will search all the external food sources and digest them into nutrients in the body. The external food sources act as network nodes in logistics networks.

The plasmodium is a multinucleated single-cell organism with no fixed size or shape and it can freely move on food surfaces to continually search and obtain external food sources by a lot of silk-like plasmodium.

The nucleus is the center of an artificial Physarum swarm system, and a Physarum swarm cannot survive without the nucleus. Hence, they can only move or forage or feed around the nucleus' center. The nucleus is often acting as the beginning logistics node of a route or the most important node in a logistics network.

The Physarum is a kind of tentacle-shaped, deformed structure of the plasmodium, and a Physarum swarm can collaboratively search the external food sources. The external food sources will be digested and transported into its body by different Physarum according to a parallel probability searching algorithm. Larger and more Physarum individuals can find more food sources with a greater probability and transporting capacity, but will consume more energy and nutrients; on the contrary, smaller and less Physarum individuals find less and consume less. The Physarum plasmodium acts as the route in a logistics network.

The nutrients throughout the Physarum swarm's body are absorbed from the external food sources by its foraging and can provide a significant energy and material basis for its survival. Almost all the life-sustaining activities of a Physarum swarm will consume energy and nutrients in the body, including food searching, foraging and digesting activities, the expansion and contraction of a Physarum swarm, moving, and so on. The nutrients act as the information learning media for its parallel probabilistic searching.

The artificial Physarum swarm system has a strong learning capability to search multiple different external food sources at the same time and transport the nutrients from the found external food sources into its body simultaneously. The artificial Physarum swarm will deform its plasmodium according to the absorbed nutrients, that is, the Physarum swarm will contract the plasmodium into an optimal network structure according to the nutrient concentration. After several iterations of learning for the expansion and contraction, the artificial Physarum swarm can find the optimal solution of the foraging network with a high efficiency and robustness, namely a feasible solution to the optimization problem of the logistics network's robustness.

There are two ways to adjust the nutrient concentration for its learning mechanism, and the concentration matrix of the nutrients transported on the edge $V = \{v_{ij}|\ i, j \in N\}$ at time t is:

$$\tau(t) = [\tau_{ij}(t)]_{n\times n} \tag{19}$$

One way is the enhancing operation, that is, the nutrient density on a route will be enhanced by the food's absorption and nutrient's transportation while foraging, where the nutrient concentration $\tau_{ij}(t)$ in the corresponding route v_{ij} will also be enhanced by $+\Delta_{ij}(t)$. For example, when multiple Physarum share a mutual nutrient transport route, then the nutrient concentration $\tau_{ij}(t)$ on the transportation route will be higher. There is:

$$\tau_{ij}(t) = \tau_{ij}(t-1) + \Delta_{ij}(t), \Delta_{ij}(t) \geq 0 \tag{20}$$

The other is the decreasing operation, that is, the nutrient concentration on a route will be reduced by a ratio $-\sigma_{ij}(t)$, which simulates the nutrient consumption and energy expenditure of the natural Physarum swarm in life-sustaining activities. There is:

$$\tau_{ij}(t) = \tau_{ij}(t-1) - \sigma_{ij}(t), \sigma_{ij}(t) \geq 0 \tag{21}$$

Therefore, the logistics routes can be scored by a Physarum swarm based on the values of the nutrient concentration on the routes.

4.2. The Expansion Operation

The whole solving process of an artificial Physarum swarm for the logistics network's robustness includes two stages, namely the expansion operation and the contraction operation. The expansion operation is the first step for the computing of our algorithm. The Physarum in the expansion operation is continuously expanding around the nucleus, and the expanding behavior cannot perform too far away from the nucleus. Further, the Physarum swarm can sense external node information by the Physarum expanding in the surrounding environment, where the biochemical reactions between the Physarum and the environment will help it identify external food sources or non-food sources.

Further, the expansion operation of the Physarum swarm comprises three sub-steps:

Sub-step 1–1: initialization. It is to initialize the iterative counter of the bionic algorithm, and the directed graph $G = (N, V)$ as the logistics network is to be solved. It is to set all the external food source nodes as logistics network nodes in a position matrix with the n nodes, and set the distance matrix $D = \{|v_{ij}||\ i, j \in N\}$ between these nodes. When the foraging starts at time $t = 0$, the node sets passed by m Physarum are set to be empty, there is $L = [L_k]_m = [\{\}]_m$, and the length of each Physarum is set to be $D_k = 0$. Hence, the initial value of the nutrient's concentration is set to $\tau_{ij}(0) = 0$, that is, all the routes have no nutrient in the transporting at the start.

Assuming that $\xi_i \geq 0$ is an affinity parameter of the food source node i, the affinity matrix for each external food sources is initialized to be $\xi = [\xi_i]_n$. The more nutrients the food source node i has, the larger the ξ_i is; on the contrary, the ξ_i is smaller in the food source node i with less nutrients and $\xi_i = 0$ is in non-food sources. In a logistics network, the ξ_i can be seen as the logistics capacity of a logistics node.

Furthermore, assuming that $\zeta_{ij} \geq 0$ is a parameter related to the consumption-ability of the route v_{ij} on the nutrients, and the matrix of the nutrient consumption rate for the plasmodium is initialized as $\zeta = [\zeta_{ij}]_{n\times n}$. The greater the nutrient consumption of the Physarum is, or the greater the nutrient consumption on the transportation route v_{ij} is, the larger the ζ_{ij} is, otherwise, the smaller the ζ_{ij} is. In a logistics network, the ξ_i can be seen as the transporting volume of logistics flows in a logistics node.

In this stage, the velocities of the expanding and contracting of the Physarum are set as e^+ and e^-, respectively. The $e^+ \geq e^-$ when the Physarum expands, and $e^+ < e^-$ when the Physarum contracts.

Sub-step 1–2: Physarum foraging. When $e^+ \geq e^-$, the Physarum will continuously expand to search the external food sources, simulating the logistics flows to travel in all logistics nodes. Additionally, the expansion operation of the plasmodium is constrained by the capacity of the nutrients and energy in its body.

At time t, if a Physarum selects a node into its route, that is, $L_k(t) = \{v_{12}^k(t), v_{23}^k(t), \ldots, v_{l-1,l}^k(t), \ldots, v_{c_k-1,c_k}^k(t)\}$, then the selection parameter can be set as $\mu_{ij}^k(t) = 1$, meaning that the edge $v_{ij} \in V$ is selected by the Physarum L_k; if not, the selection parameter can be set as $\mu_{ij}^k(t) = 0$, meaning that the edge $v_{ij} \in V$ is not selected by the Physarum L_k. Then, the selecting matrix of the Physarum L_k is $\mu_k = [\mu_{ij}^k(t)]_{n\times n}$.

When $\mu_{ij}^k(t) = 1$, the nutrient concentration on the newly added edge $v_{ij} \in V$ of the Physarum k will be increased at a speed $\Delta_{ij}^k(t) > 0$ according to Equation (20), meaning more nutrients flowing on the edge v_{ij}. On the contrary, no matter $\mu_{ij}^k(t) = 1$ or $\mu_{ij}^k(t) = 0$, the nutrients will be continuously consumed at a speed $\sigma_{ij}^k(t)$, according to Equation (21), where there is often $\sigma_{ij}^k(t) \leq \Delta_{ij}^k(t)$. Then, the nutrient concentration can be updated as:

$$\tau_{ij}(t) = \tau_{ij}(t-1) + \sum_{k=1}^{m} \mu_{ij}^k(t)\Delta_{ij}^k(t) - \sum_{k=1}^{m} \sigma_{ij}^k(t) \tag{22}$$

Now, m Physarum will transport nutrients from the external food sources into its body, and the transport route shared by multiple Physarum will repeatedly enhance the nutrient concentration $\Delta_{ij}^k(t) - \sigma_{ij}^k(t) \geq 0$ in the body. Different Physarum can learn the nutrient concentration information and add the connection probability of shared edge v_{ij}, by which the connections between these nodes will be strengthened.

Sub-step 1–3: Updating parameters. During the expansion operation of the Physarum, the artificial Physarum swarm may find food sources and mark their positions to prepare for the next contraction operation. Alternatively, the Physarum may not find a food source or encounter a non-food source, and they will leave and move to other areas where the position will be marked to avoid entering again.

After several iterations, all external food sources may be confirmed by the Physarum swarm. If the end condition of the expansion operation is satisfied, all the results of external food sources or non-food nodes will be output. Now, a foraging network will be formed, and the total degree of all nodes can be given as:

$$Dg(t) = \sum_i Dg_i(t) \tag{23}$$

Then, some useful new indexed can be obtained, that is, the redundancy rate index $R_\Sigma(t)$ by Equation (4), the length D_k by Equation (12) and the total length $D_{\Sigma m}$ of all the Physarum by Equation (14). The robustness indexes, i.e., the relative robustness $Rel\_rob_i(t)$ in Equation (5), the betweenness robustness $Bet\_rob_i(t)$ in Equation (7), the edge robustness

$Edg\_rob_{ij}(t)$ in Equation (8) and the closeness robustness $Col\_rob_i(t)$ in Equation (10) can all be computed.

In this stage, the robustness of the logistics network is not optimized, but the found food sources will be randomly connected. The topology result in this step may not be optimal. The robustness indicators will be compared and optimized by an artificial Physarum swarm in the next contraction operation.

4.3. The Contraction Operation

The contraction operation is the second stage of the artificial Physarum swarm algorithm. In this stage, the external food sources will be digested into the nutrients and utilized by the artificial Physarum swarm. The Physarum swarm will contract its body to efficiently transport the nutrients absorbed from the external food sources and the plasmodium will form an optimized logistics network by a probability search algorithm and parallel learning mechanism. After finding a feasible solution to the logistics network, the artificial Physarum swarm will continuously evaluate the solution until it reaches the predefined end conditions.

Further, the contraction operation also comprises three sub-steps.

Sub-step 2–1: Physarum feeding. In this sub-step, the total number m of Physarum constitutes a calculating loop in the middle layer, which is calculated in the order of Physarum number $1 \leq k \leq m$ and every Physarum will be solved at each time. As the analysis above, the Physarum also need to consume the nutrients $\tau_{ij}(t)$ in life-sustaining activities no matter whether the food sources are found or not. Hence, in this sub-step, m Physarum begins to contract into an optimal foraging network to transport nutrients from the external food sources into the body, and it is a reverse operation different from the expansion operation. The nutrient concentration of Physarum will be lower when the Physarum need to consume nutrients and energy in life-sustaining activities by Equation (21). However, nutrient concentrations on the transporting routes will be higher when the Physarum transport the external food sources into its body by Equation (20).

Generally, $\Delta_{ij}^k(t)$ and $\sigma_{ij}^k(t)$ are positively correlated with the affinity ξ_i of the food sources, and negatively correlated with the distance d_{ij} between the nodes. That is, the richer the food source affinity ξ_i is, and the shorter the distance d_{ij} on the edge v_{ij} is, the greater the nutrient concentration τ_{ij} is. Additionally, the increase in the nutrient concentration on each edge can also be obtained, which is decided by the affinity parameter $\xi_i \geq 0$ of the food source node i and the distance d_{ij} of the edge v_{ij}. There is:

$$\begin{cases} \Delta_{ij}(t) = \sum\limits_{k=1}^{m} \mu_{ij}^k(t)\Delta_{ij}^k(t) = \sum\limits_{k=1}^{m} [\mu_{ij}^k(t)\frac{\xi_i}{d_{ij}}] \\ \sigma_{ij}(t) = d_{ij}/\sum_{i,j} d_{ij} \end{cases} \tag{24}$$

The contraction of the Physarum swarm uses a kind of swarm learning mechanism. On one hand, a Physarum individual must select the current nodes or routes according to its own experience by a certain probability $a_{ij}^k(t) \in [0,1]$, that is, the self-learning experience of its own. Therefore, the Physarum individual will transit to new nodes or routes found by itself according to a predefined probability. On the other hand, it is needed to learn the information of the Physarum neighbor to select the optimal neighbor nodes or routes by another probability $b_{ij}^k(t) \in [0,1]$, that is, the neighbor-learning experience of others. Hence, the Physarum will shift to the new nodes or routes found by its neighbors.

Sub-step 2–2: solution evaluation and comparison. In this sub-step, the solution will be evaluated and compared to select the optimal one. The nutrient concentrations of those routes with a low performance in transporting nutrients will be less and less, and the Physarum have no choice but to contract and delete these routes for the lacking nutrients. Conversely, the nutrient concentrations on those routes with a high performance will be higher and higher. Hence, the logistics network will continue to be optimized according to the solution evaluation and comparison. After several iterations in the whole solution space, each Physarum learns and contracts by the two probabilities $a_{ij}^{k}(t) \in [0,1]$ and $b_{ij}^{k}(t) \in [0,1]$, and then reciprocates according to the solution evaluation. The matrix of the nutrient concentration can be calculated as Equations (20) and (21). The evaluation function can select a multi-objective optimization function in Equation (15) or (16).

After the comparison, the Physarum swarm will build a global optimal route to transport the nutrients where there is $L^* = [L_k^*]_m = \left[\{v_{12}^k, v_{23}^k, \ldots, v_{l-1,l}^k, \ldots, v_{c_k-1,c_k}^k\}\right]_m$. The next transiting probability $p_{ij}^{k}(t) \in [0,1]$ of each Physarum k consists of two parts. There is,

$$a_{ij}^{k}(t) \in [0,1] \tag{25}$$

$$b_{ij}^{k}(t) = \tau_{ij}^{k}(t) / \sum_{i,j=1}^{n} \tau_{ij}(t) \tag{26}$$

where $b_{ij}^{k}(t)$ is related to the nutrient concentration $\tau_{ij}^{k}(t)$, so it will be easier to select the routes with higher nutrient concentrations, but $a_{ij}^{k}(t)$ is used to avoid a premature trapping in the local optimal solutions and to improve the algorithm's global searching ability.

Sub-step 2–3: optimal solution output. In this sub-step, each foraging is taken as a calculating iteration for an outer loop, and a calculation error can also be set as an end condition for the foraging process. Now, the Physarum surround their found food sources and then convert these food sources into the nutrients to support the life-sustaining activities of a Physarum swarm.

According to the newly obtained $\tau(t)$, the optimal routes L^* of all the Physarum individuals will be output to connect all the nodes with the corresponding optimal robustness and cost. The objective function value calculated this time is compared with the one calculated last time. If the objective function error between the two calculations is less than the preset threshold value, the calculation is completed, and the optimal solution obtained this time is the output as the result. Otherwise, the finished conditions will be judged whether the number of iterations has arrived. If not, the algorithm will return to repeat sub-step 1–2 for the expansion and the sub-steps 2–1, 2–2 and 2–3 for the next contraction computing. In the next iterative computation, the Physarum k ($1 \leq k \leq m$) will again start to form a route from the external food source node i_1 to the nucleus to transport the nutrients, and all the Physarum individuals will learn from each other to form a new logistics network $L(t) = [L_k(t)]_m$.

After a lot of iterative computing from sub-step 1–2 to sub-step 2–3, the nutrients in the non-optimal routes will be gradually decreasing until it disappears, and an optimal nutrient transport network is left in the artificial Physarum swarm which can connect all the outside food sources with the optimal performance. Finally, the whole nutrient transport network can be output as a feasible solution to a global-optimized logistics network.

4.4. Algorithm Flow of Artificial Physarum Swarm

The algorithm flow of the artificial Physarum swarm system includes two main steps and a total of six sub-steps to solve the problem of the logistics network's robustness, where the first main step is the expansion, and the second main step is the contraction. The Physarum can randomly search in the expansion operation and connect as many as possible of the logistics nodes. Then, the Physarum will be continuously contracting to optimize the logistics network by the objective function in the contraction operation. The optimization algorithm flow is shown in Figure 2.

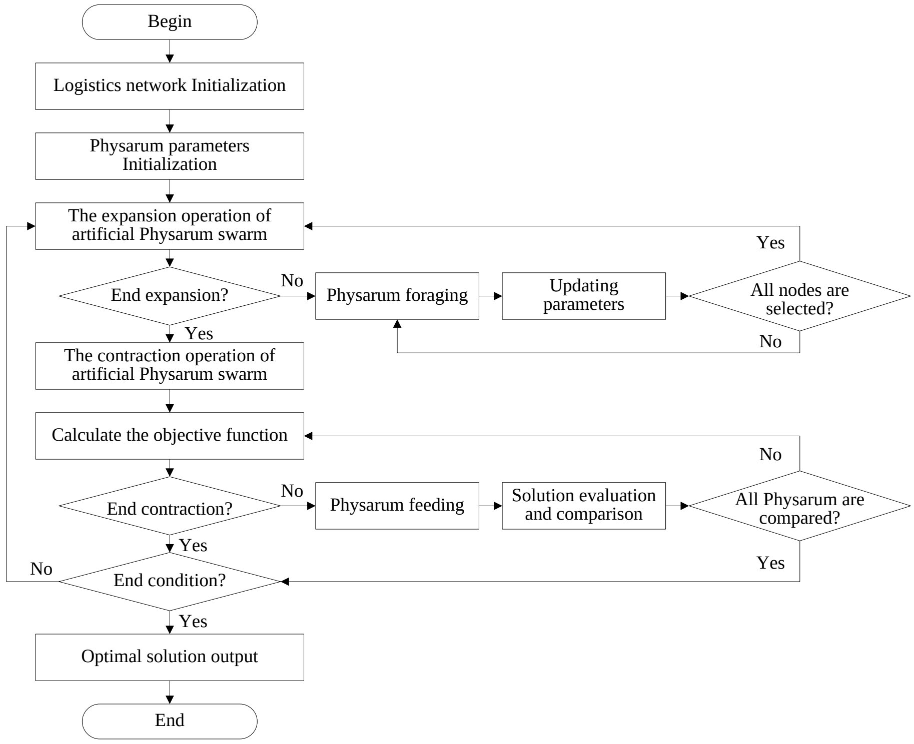

Figure 2. The algorithm flow of the artificial Physarum swarm system.

The algorithm uses parallel and probabilistic searching to solve the problem of the logistics network's robustness, and each Physarum will calculate the solution in each iteration before the end condition is fit. When the error between the late results is less than a predefined threshold, the optimal solution will be the output to stop the algorithm calculation. Alternatively, the algorithm will continue calculating until the number of iterations reaches a predefined value.

The algorithm has the following characteristics.

First, the initialization includes two main parts, namely the logistics network initialization and the Physarum parameters initialization. As a single-cell living thing, there is no head and not even a neuron in the body of a Physarum swarm to transmit information. If an external food source is found, the Physarum swarm will digest it and convert it into nutrients for transportation, and the other Physarum can share the information of the nutrient concentration to learn about the food distribution and logistics network.

Second, the expansion operation of the artificial Physarum swarm is to search the solution space. The process of the Physarum swarm to find food is by a probable expansion, and the foraging process of the Physarum swarm is also by probable searching to form a nutrient transportation network. The Physarum will continue to expand and update the parameters in the unexplored areas by a heuristic searching to look for more logistics nodes.

Third, the contraction operation of an artificial Physarum swarm is to compare all the feasible solutions and select the optimal one. Multiple Physarum can select the optimal nodes or routes according to its own experience or neighbor experiences. If there is no food being found in expanding areas, it will only contract because the nutrients and energy will be consumed.

Fourth, the end condition includes the predefined error threshold and the maximum number of iterations. The Physarum will continuously expand to find external food sources and continuously contract into different transporting routes to digest and absorb the external food sources. After many iterations of expanding and contracting, the error will be greater and greater, and it is possible to form an optimal logistics network topology.

5. Experiment Analysis

5.1. Experimental Results

To verify the proposed artificial Physarum swarm, an experiment is designed and the experimental data are an extension of reference [15]. In 2011, Adamatzky et al. [15] used 19 oat flakes to simulate 19 geographical locations of Mexican highways, then placed a piece of Physarum plasmodium in the dish. In this experiment, they photographed the Physarum's foraging process and its foraging network for the nutrient transportation, as shown in Figure 1. Surprisingly, the Physarum can successfully build approximating Mexican highways without the help of any brain or nerve. Although the Physarum is so primitive, it only took 70 h (Figure 1) [15] to solve the network optimization problem and got similar results to a true traffic network.

In our experiment, 30 cities are selected, 11 nodes more than the experiment in [15], where the node No.1 is Mexico City, as shown in Figure 3. Mexico covers an area of 1,964,375 square kilometers and has a population of more than 100 million, composed of 31 states and one Federal District for the government center. Each city in Mexico has a fast route linking the main highways to Mexico City. With more Physarum, our artificial Physarum swarm system spends less time in getting the same optimal solution in about 10 s, as shown in Figures 4–6 in Section 5.1.

Furthermore, the trialed error results of our proposed method are summarized and compared with other related algorithms in references, as shown in Section 5.2. The engineering application suggestions are shown in Section 5.3.

Some assumptions are made to simplify the experimental difficulty. (i) It is assumed that the positions and parameters of the Mexican highway nodes are fixed and meet the values in reference [15]. (ii) There was no consideration of the political and military factors; it was assumed that the Mexican highway nodes are the external food source nodes of an artificial Physarum swarm system; and (iii) there was no consideration of the influence of other factors on the behavior of an artificial Physarum swarm. The Physarum swarm optimizes the logistics network through expansion and contraction operations, according to the nutrient concentration in network routes throughout the Mexican highways system. Additionally, (iv) to evaluate and output an optimal topology solution, this was done by the objective function in Equation (16); (v) the Physarum can discover environmental information by the self-learning possibility of 0.2 and the neighbor-learning possibility of 0.4; and (vi) the Physarum swarm can compute no more than 100 iterations.

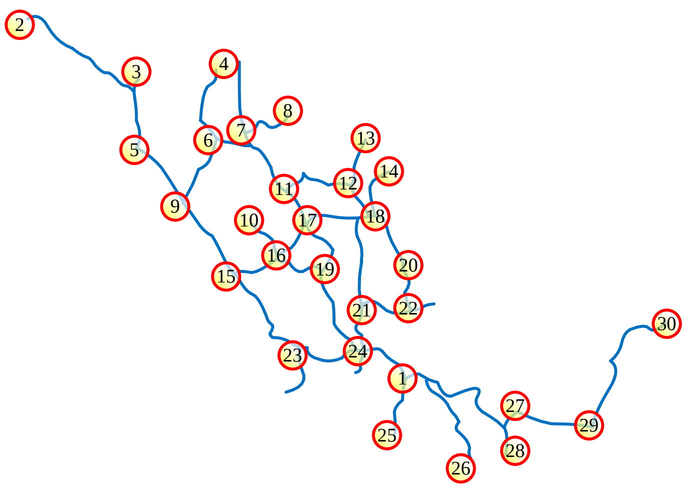

Figure 3. The Mexican highways [15]. The number in the figure corresponds to the important logistics nodes in Mexico City.

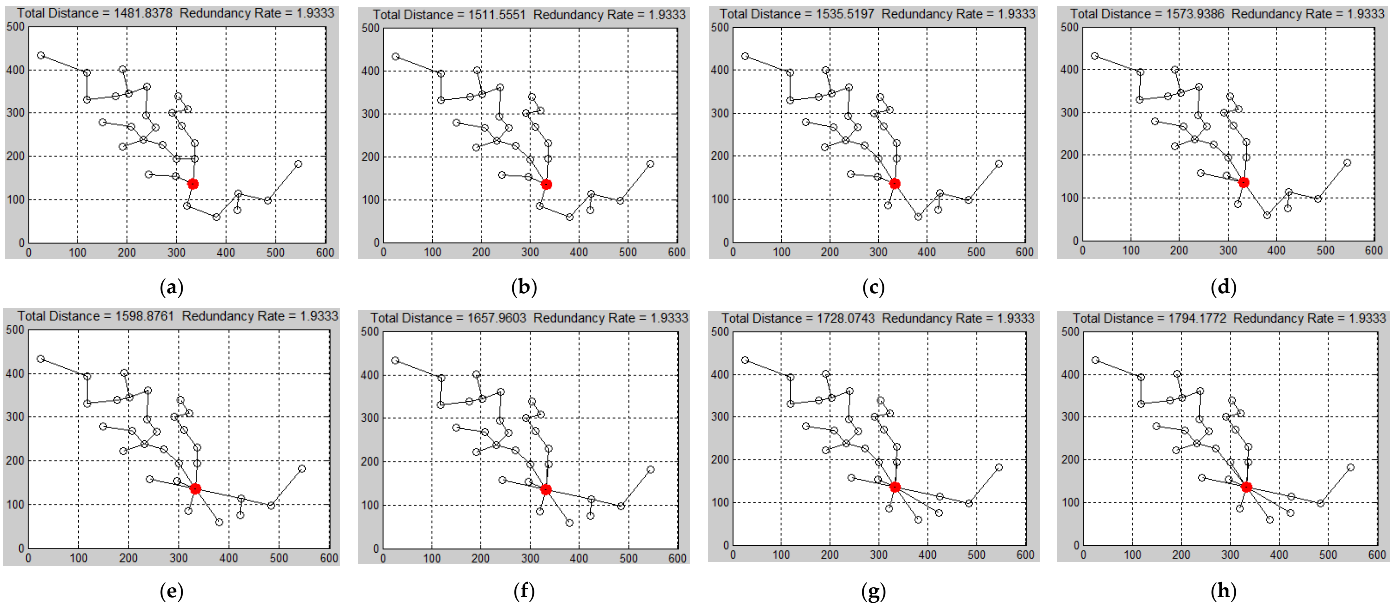

Figure 4. Simulated Mexican highways with low robustness. (**a**) The number of Physarum = 3; (**b**)the number of Physarum = 4; (**c**) the number of Physarum = 5; (**d**) the number of Physarum = 6; (**e**) the number of Physarum = 7; (**f**) the number of Physarum = 8; (**g**) the number of Physarum =9; and (**h**) the number of Physarum = 10.

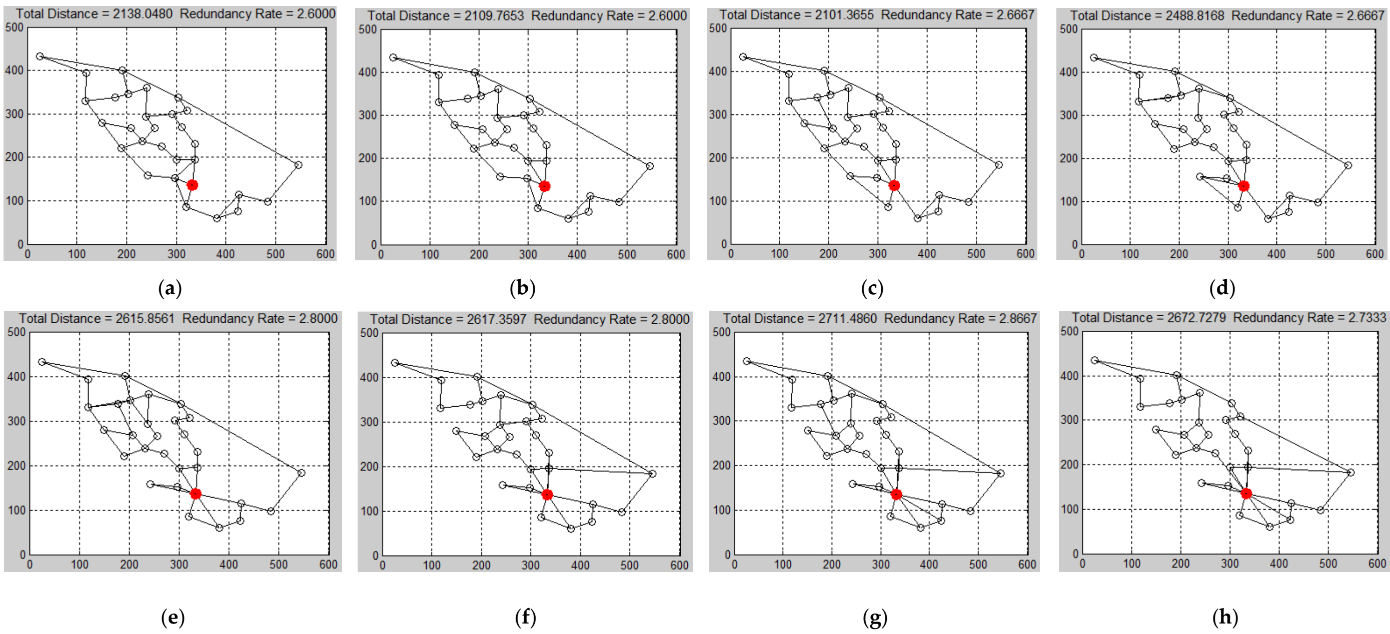

Figure 5. Improved robustness with different Physarum. (**a**) The number of Physarum = 3; (**b**) the number of Physarum = 4; (**c**) the number of Physarum =5; (**d**) the number of Physarum = 6; (**e**) the number of Physarum = 7; (**f**) the number of Physarum = 8; (**g**) the number of Physarum = 9; and (**h**) the number of Physarum = 10.

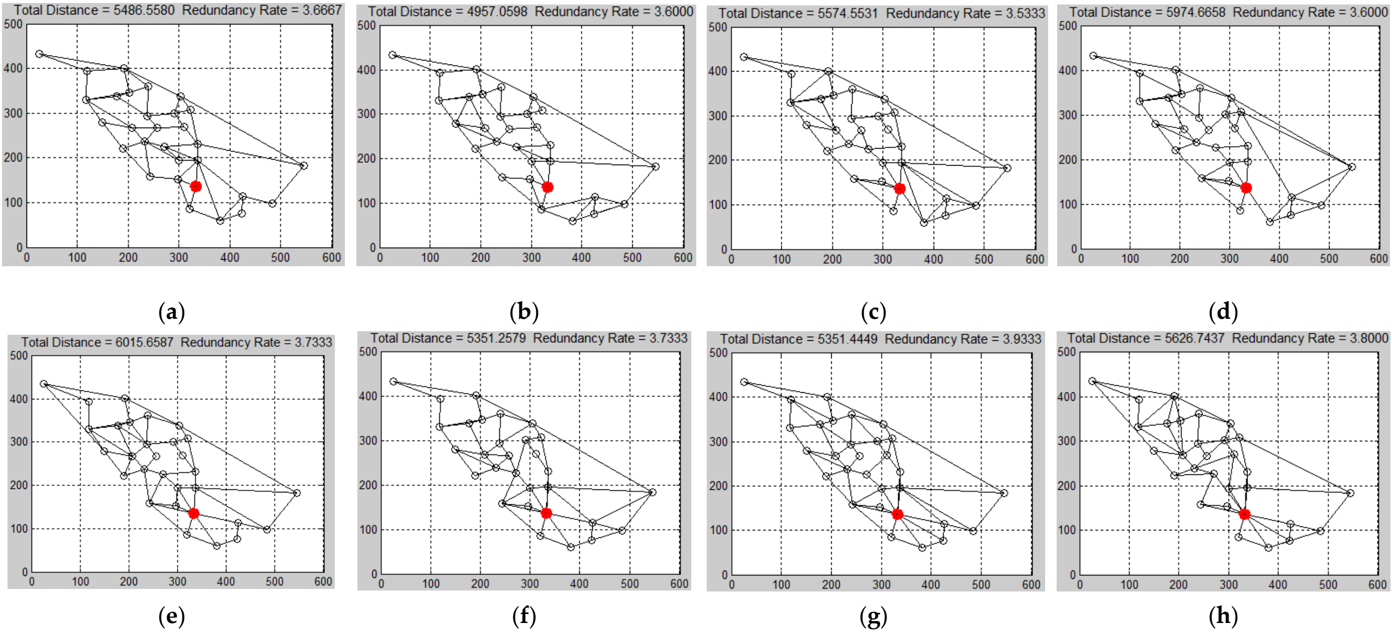

Figure 6. Higher robustness with different Physarum. (**a**) The number of Physarum = 3; (**b**) the number of Physarum = 4; (**c**) the number of Physarum = 5; (**d**) the number of Physarum = 6; (**e**) the number of Physarum = 7; (**f**) the number of Physarum = 8; (**g**) the number of Physarum = 9; and (**h**) the number of Physarum =10.

The simulated Mexican highways with a low robustness are shown in Figure 4. Compared with the solutions generated by the nature Physarum in [15] (Figure 1) and the real traffic network (Figure 3) formed by human beings after decades of trial and error, our results in Figure 4 used the most concise way to build the Mexican highways. Although the nature Physarum's results (Figure 1) and man-made results (Figure 3) are similar to our results, three kinds of results can connect all the nodes to build a Mexican traffic network in different ways. Above all, our solutions present the shortest routes connecting all the logistics nodes (Figure 4) and are vulnerable and subject to a network disturbance. In Figure 4a–h, our proposed artificial Physarum swarm system demonstrated strong capabilities of trial and error and developed different topology schemes. Our simulation results in Figure 4 were obtained by the cooperative behavior of an artificial Physarum swarm running on a personal computer where every individual is based on the basic principle of the nature Physarum's foraging behavior [14,15,42,43]. Our algorithm has the solving advantage that the previous nature Physarum's method (Figure 1) and the man-made method (Figure 3) cannot match. These experimental results can help us make optimal decisions in logistics network problems and extend our minds to try more topology schemes. The results in Figure 4 verified the effectiveness of the proposed artificial algorithm, and the calculating precision and time consumption of our experiment are better than the nature Physarum's method [14,15,42,43] and man-made method (Figure 3). Based on the results in reference [15] and our results in Figure 4, more simulated Mexican highway maps can be tried to improve the logistics network robustness and the trial–error results with more Physarum, and this is shown in Figure 4a–h.

Our method has stronger capabilities to find the optimal solutions for topology robustness problems than nature Physarum's method [14,15,42,43] and man-made method (Figure 3). As we can see from Figure 4a–h, the proposed artificial system successfully improves the robustness of the core node (No.1) by more Physarum. The artificial Physarum swarm in this paper can expand from central Mexico City by multiple Physarum, ranging from three Physarum in Figure 4a to ten Physarum in Figure 4h. Then, the proposed algorithm can imitate the feeding behavior of a true Physarum swarm to contract to an optimal logistics network around the largest point marked as No.1 for Mexico City in the center of the highway system, and the rest can be connected in different ways. All the results can pass through all Mexican highway nodes with the same redundancy rate of 1.9333, but the shortest total distance is 1481.8378 (Figure 4a) and the longest total distance is 1794.1772 (Figure 4h).

In engineering applications, the results in Figure 4 can help us construct the backbone of a logistics network with the least cost. Although different numbers of Physarum can receive optimal solutions with the different shortest distance and the same lowest redundancy rate 1.9333, there is no redundant route for the whole logistics network against the robustness disruption. Every node in Figure 4 has few connections to other nodes (except the No.1), so a disruption on any one of the nodes or edges can easily break the logistics network into separated parts. However, the cost advantage of Figure 4 is so great that most countries adopt these schemes to construct their logistics networks at first. Nevertheless, we can still improve the robustness of the core node because more Physarum will help us to connect Mexico City (No.1) to other nodes with a better connectivity (Figure 4b–h). If a disruption takes place in Mexico City (No.1), more connections will decrease the negative effects to other areas of the logistics network. Then, Figure 4a is the optimal scheme with the lowest cost of 1481.8378, and Figure 4h is another optimal scheme with the highest cost of 1794.1772 but also the optimal robustness for the core node No.1.

Our algorithm can further improve the robustness of the other nodes and the whole logistics topology. Facing this challenging task, the artificial Physarum swarm system demonstrated a strong solving ability only on a personal computer, which is not available by nature Physarum's method [14,15,42,43] and man-made method (Figure 3). More trial–error results with different Physarum are shown in Figure 5a–h, where the redundancy rate is increasing to above two and the number of Physarum is increasing from three to ten. The number of Physarum around Mexico City is continuously increasing and more Physarum can help us find more network topologies with a higher robustness.

In this experiment, the proposed artificial Physarum swarm can feed itself around the No.1 node in Figure 5, which is Mexico City in the center of the logistics map, and form stronger topology connections with a higher robustness than those of Figure 4. After an iterative computing, the highway network in Figure 5 increases more connections besides the shortest routes in Figure 4. At the same time, the total distance of the highway network increases from 2101.3655 to 2711.4860 and the redundancy rate of the Mexican highway network ranges from 2.6000 to 2.8667. Among them, Figure 5c is the optimal scheme with the lowest cost of 2101.3655, and Figure 5g is another optimal scheme with the highest redundancy rate of 2.8667, but with the highest cost of 2711.4860. It can be seen that based on the shortest routes in Figure 4, all the marked highway nodes in Figure 3 can be connected with a higher robustness. Now, the disruption on any one of the nodes or edges cannot break off the logistics network, meaning that the logistics network's robustness has been improved by a higher redundancy rate index.

The experiment in Figure 5 verifies the strong solving ability on the topology robustness problem which is not available by nature Physarum's method [14,15,42,43] and man-made method (Figure 3). The improved highway networks generated in Figure 5 still include the corresponding shortest routes in Figure 4 for a fast logistics flow transportation. After the continuous learning and optimization of the Physarum, it is enough for the proposed artificial swarm system to connect all the nodes in the Mexican highway system, with a shorter calculating time of just only a few seconds. Our calculating results are more accurate, with less computing time than the real Physarum in [15] (70 h to get a solution result) and the man-made method (decades to get a solution).

In further experiments, the proposed method shows a higher solution accuracy, as shown in Figure 6a–h, where the redundancy rate increases above three and the number of Physarum increases from three to ten. The results in Figure 6 still include the corresponding shortest routes in Figure 4, but they increase more connections besides the routes in Figures 4 and 5. The total length of the highway network increases from 4957.0598 to 6015.6587 and the redundancy rate of the Mexican highway network ranges from 3.5333 to

3.9333. Among them, Figure 6b is the optimal scheme with the lowest cost of 4957.0598, and Figure 6g is another optimal scheme with the highest redundancy rate of 3.9333, but also with the highest cost of 5351.4449. Compared with the shortest routes in Figure 4, all the logistics nodes in Figure 6 can be connected with more links through an expansion and contraction to resist more serious disruptions. The disruption on any nodes or edges may not break them off the logistics network, meaning that the logistics network's robustness of Mexico's highways has been further improved by a higher redundancy rate index.

Summing up the results in Figures 4–6, the different parameters are compared in Table 1. The analysis and discussion in Table 1 consider different numbers of Physarum individuals, the robustness indicator or redundancy rate and the cost or the total length, as shown in Figures 4–6.

Table 1. Parameter comparison of APS.

Number of Physarum	Total Length/Cost			Redundancy Rate		
	Lowest	**Medium**	**Highest**	**Lowest**	**Medium**	**Highest**
3	1481.8378	2138.0480	5486.5580	1.9333	2.6000	3.6667
4	1511.5551	2109.7653	4957.0598	1.9333	2.6000	3.6000
5	1535.5197	2101.3655	5574.5531	1.9333	2.6667	3.5333
6	1573.9386	2488.8168	5974.6658	1.9333	2.6667	3.6000
7	1598.8761	2615.8561	6015.6587	1.9333	2.8000	3.7333
8	1657.9603	2617.3597	5351.2579	1.9333	2.8000	3.7333
9	1728.0743	2711.4860	5351.4449	1.9333	2.8667	3.9333
10	1794.1772	2672.7279	5626.7437	1.9333	2.7333	3.8000

From Figures 4–6 and Table 1, the artificial Physarum swarm system can help us save considerable costs and improve the robustness of a logistics network. The traditional optimization methods for transportation networks often make people spend a lot of time on repetitive planning, construction, reconstruction, demolition and optimization. For example, the traditional optimization method in Figures 4–6 is time-consuming, laborious and easy to result in an enormous amount of waste. The reconstruction of a logistics network is subject to much interference with people's livelihoods and even mass incidents. However, the proposed artificial Physarum swarm can easily try many different logistics topologies and obtain the optimal solution in a short time.

First, Figure 4 can be selected as a cost-optimal scheme with the lowest redundancy rate and the worst robustness. Figure 4a has the advantage of the shortest total length of 1481.8378, and Figure 4h has the advantage of both the shortest total length of 1794.1772 and the optimal robustness for the core node No.1.

Second, Figure 6 can be selected as a robustness-optimal scheme with the highest redundancy rate and containing the shortest routes in Figure 4. The topologies can easily resist the robustness disruption on any nodes or edges. Figure 6g has the advantage of the highest redundancy rate 3.9333.

Third, Figure 5 can be selected as a comprise scheme with both a low total cost and a high redundancy rate. The topologies can easily resist the robustness disruption on any one node or edge at a low cost. Figure 5c is the cost-optimal scheme with a total length of 2101.3655, and Figure 5g is a robustness-optimal scheme with the highest redundancy rate of 2.8667.

Fourth, more connections will improve the robustness of the important node (such as the core node No.1), but at a higher cost. Four Physarum individuals in Figure 5c or five Physarum individuals in Figure 6b may be the optimal number to get a low total cost with a high robustness for the important node.

5.2. Comparison and Discussion

In this section, we compared the proposed APS with other algorithms. The comparison between our proposed APS and the true Physarum [14,15,42,43] is shown in Table 2, and the proposed method is more convenient and can solve a more complex problem. The artificial Physarum swarm system has some advantages over the nature Physarum [15] in computation performance with a shorter computing time and a higher accuracy, and it is easier for the APS to adjust the experimental parameters only on a personal computer to obtain more feasible solutions. The proposed method of this paper will help us greatly improve the solving efficiency of the logistics network robustness problems with a higher accuracy than true Physarum [14,15,42,43]. More importantly, the problem-solving process of our proposed artificial system is greatly simplified, where the complex biological instruments and professional biological operations [14,15,42,43] have all disappeared in our method, such as the Physarum cultivation, environmental control, experimental design, biosafety and data analysis.

Table 2. Comparison of APS and the true Physarum swarm.

Items	Proposed APS	Nature Physarum [14,15,42,43]
Solving tool	Algorithm software	True Physarum
Solving platform	A personal computer	Biological instruments
Laboratory	Computer laboratory	Professional biological laboratory
Biosafety equipment	No requirement	Mandatory requirement
Solving process	Software running	Professional biological operations
Consumption	Electric power	Biological materials
Operational requirements	General	Professional
Solving speed	Second level	Hour level
Solving accuracy	High	Low
Parameter adjustment	Software	Professional biological operations
Parallelism	Iterative computing	True parallelism

Now, the related artificial intelligence algorithms are listed here for a comparison to solve the traffic planning problem of Mexican highways, including the ant colony optimization (ACO) [36], artificial neural network (ANN) [37,38], particle swarm optimization (PSO) [13,39,40], genetic algorithm (GA) [39] and deep learning (DL) approach [41]. The related results are shown in Figure 7a–d, where the number of network nodes is extended from 30, 60, 90 to 120. The parameters of the ACO method [36] are set at a pheromone importance of 1.0, the importance of heuristic factors 5.0 and 20 ants. The parameters of the ANN [37,38] are set as a three-layer BP neural network with three nodes in the input layer, two nodes in the immediate layer and three output nodes in the output layer. The PSO [13,39,40] sets the population size as N = 40, location limitation as 50, speed limitation as [−0.5, 0.5], self-learning factor as c1 = 0.5 and social learning factor as c2 = 0.5. The GA [39] sets the population size Nind = 40, chromosome length Lind = 20, crossover probability px = 0.7 and mutation probability pm = 0.01. The DL approach [41] is set as a convolutional neural network with eight nodes in the input layer, eight nodes in every immediate layer and eight output nodes in the output layer.

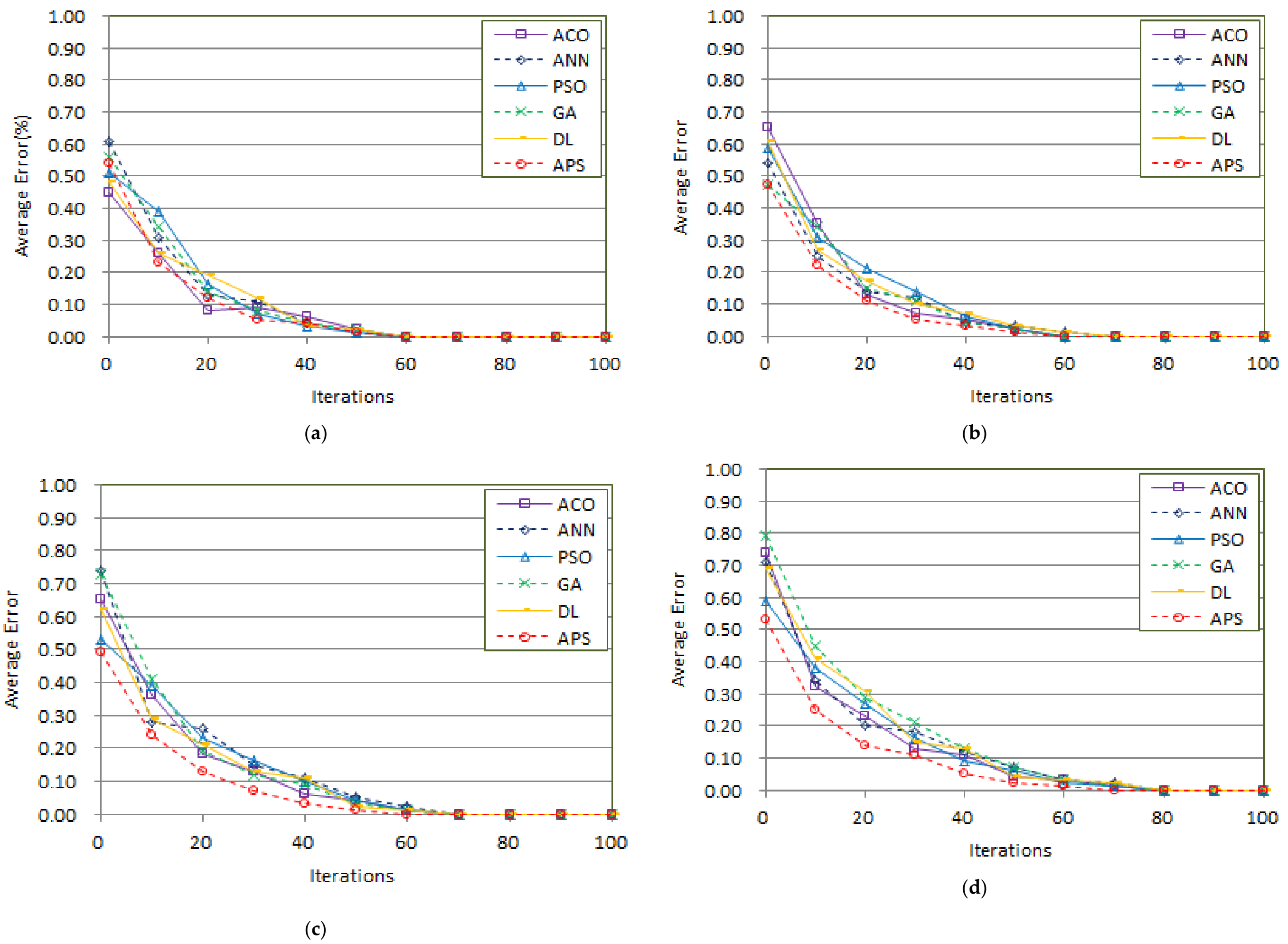

Figure 7. Performance comparisons of different artificial intelligence algorithms. (**a**) The number of network nodes = 30; (**b**) the number of network nodes = 60; (**c**) the number of network nodes = 90; and (**d**) the number of network nodes = 120.

As we can see from Figure 7, in solving the logistics network robustness problem, the proposed APS system can obtain a solving performance similar to those of artificial intelligence algorithms, such as the ACO [36], ANN [37,38], PSO [13,39,40], GA [39] and DL [41]. When the number of logistics nodes is small, such as 30 nodes in Figure 7a and 60 nodes in Figure 7b, these artificial intelligence algorithms can obtain a similar performance, where the proposed APS can obtain satisfying computing errors. When the number of logistics nodes is increasing, such as 90 nodes in Figure 7c and 120 nodes in Figure 7d, the proposed APS begins to have advantages over those artificial intelligence algorithms in the computing errors. The proposed APS algorithm uses Physarum swarm to share the information of all the logistics nodes and routes by a self-learning experience and neighbor-learning experience and it has great advantages on the topology exploration.

The results in Figure 7 verify that the proposed method can also be used as traditional artificial intelligence algorithms. Among the other artificial intelligence algorithms, the ACO [36] and GA [39] can get the closest performance to the proposed APS system, which may mean that they have a similar swarm learning mechanism. Hence, the proposed APS system can be used not only to the solve logistics network's robustness problems but also to solve the complex traveling salesman problem (TSP), multi-objective optimization problems, computer networks and routing problems.

The results in Figure 7 also confirm that the proposed method has a good scalability. From Figure 7a–d, all the artificial intelligence methods suffer from the increasing number of logistics nodes, and higher errors will be easily generated with the increasing scale of the logistics network. Compared with the traditional artificial intelligence algorithms, such as the ACO [36], ANN [37,38], PSO [13,39,40], GA [39] and DL [41], the proposed APS system can obtain a better performance with lower computational errors when the scale of the logistics network is greater.

5.3. Engineering Application Suggestions

(i) Logistics facility location. This application can provide the logistics managers and decision makers with a new perspective on logistics facility sustainability and help us build a more robust logistics network to improve the transportation safety and real-time delivery performance. The location of the logistics facility plays a significant role in the logistics' efficiency and supply chain's sustainability. In application, a swarm of artificial Physarum can be used to encode any feasible solutions, but a true Physarum is just corresponding to a feasible solution. The learning factors of our proposed artificial Physarum swarm can be fixed or adjustable on a personal computer.

(ii) Vehicle routing. This application aims at finding optimal routes for a lot of vehicles to travel a set of buyers and has a great impact in the logistics and supply chain sustainability. The logistics managers and decision makers can apply our results to optimize a true vehicle routing network which considers the 3D geographic factors, such as mountains, valleys, rivers, seas, etc. In application, the possibilities of a self-learning experience and neighbor-learning experiences can be fixed or adjustable. The self-learning experience will decide the convergence ability, but the neighbor-learning experiences will determine the global searching ability.

(iii) Energy saving. The logistics managers and decision makers can use our method to guide energy analysis from the view of the network's topology and apply the analysis results to optimize the energy's sustainability. In the real world, the logistics volume and connections are time-varying, that is, the energy consumption is dynamic. The nutrient consumption speed can be used to simulate the energy consumption and energy sustainability. A fast consumption speed may speed up the searching process by the positive feedback mechanism of the nutrients and it may be easily trapped into a locally optimal solution. The food sources will be consumed by real Physarum before the optimal solution is obtained but it will not by an artificial Physarum swarm on a personal computer.

(iv) Carbon reduction. Achieving the dual carbon goal and carbon reduction sustainability has affected all sectors and all levels of society. With real-time data, the logistics managers and decision makers can utilize the artificial Physarum swarm to optimize the transportation routes to avoid traffic congestion and decrease carbon emissions. The logistics capability and carbon emissions in the real world are dynamic, and the proposed method should also be adjusted to fit the requirements. The number of Physarum is decided by the real problem scale, and the main structures of the Physarum swarm's foraging system can be adjustable, i.e., the number of external food sources, plasmodium, nutrients, etc.

6. Conclusions and Limitations

It is very important to design a robust and sustainable topology for a logistics network, but it is not an easy thing to achieve. In this paper, we build the robustness mathematics model for the logistics network sustainability, and a novel artificial Physarum swarm system based on the foraging behavior of Physarum [14,15,42,43] was proposed to solve the multi-objective robustness problem. It may help us understand the learning intelligence of single-cell living things and provide us with a novel artificial intelligence tool to solve complex NP-hard problems.

First, this article builds a robust model of the logistics network by rigorous graph theory. Four robustness indicators are proposed to build a multi-objective robustness function of the logistics topology network, including the relative robustness, betweenness robustness, edge robustness and closeness robustness.

Second, in this paper, a complete mathematical model of the foraging behavior for an artificial Physarum swarm system is built, and the artificial system in this paper is completely different from the traditional artificial intelligence algorithms or machine learning theories (ACO [36], ANN [37,38], PSO [13,39,40], GA [39] and DL [41]). The calculating mechanism of the artificial Physarum swarm is parallel, probabilistic, iterative and distributed.

Third, the proposed method is verified by an experiment. In the real world, the logistics managers and decision makers can firstly select the topologies in Figure 4 with the lowest total costs. In future development, the decision makers can secondly select the comprise schemes in Figure 5 with a low total cost and a high redundancy rate. After that, Figure 6 can be further selected as a robustness-optimal scheme for a sustainable operation. Furthermore, the logistics managers and decision makers can apply our method to solve other engineering problems in the real world, such as the logistics facility location, vehicle routing, energy saving and carbon reduction.

There are still some limitations in our work. Above all, the optimization process of the foraging networks of natural Physarum protoplasm is truly parallel computing, while the algorithm proposed in this paper is to simulate foraging behavior through iterative computing on a personal computer, which is not particularly parallel in nature. In addition, to simplify the methodology and experiment, we also omitted some factors which may play an important role in the Physarum foraging behavior or network optimization.

Several research directions in the future may enrich this promising area. First of all, how it may be possible to improve the parallelism of the proposed algorithm, so that it can be applied to solve the larger logistics network problem. Therefore, improving its performance to solve large-scale problems is an important direction. Second, the environmental and social sustainability of a logistics network can also be assessed as a goal in the robustness function. The sustainability goals may therefore provide a more comprehensive robustness assessment. Third, the forward flow and reverse recovery in logistics, as well as the time constraints of products, are also important research topics in the future. Fourth, it is also promising to integrate other artificial algorithms or strategies. For example, it may also be a very interesting direction to combine fuzzy mathematics with uncertainty operators and deep learning methods to improve the learning ability of the proposed algorithm.

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