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Closed-Loop Supply Chain Network Design Optimization with a Multi-Objective Approach: Leveraging the Red Deer Metaheuristic Algorithm

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ABSTRACT

In an era marked by increasing global complexity, the strategic design of a sustainable supply chain has become imperative. Decision-makers are confronted with the challenge of reconciling economic objectives with environmental and social impacts. In this context, gaining a competitive edge hinge on two critical factors: reducing operational costs and elevating service levels. Achieving economic efficiency while adopting a sustainability-oriented approach is the central focus of this research within the closed-loop supply chain domain. This study introduces a comprehensive multi-objective model for supply chain optimization. Distinguishing itself from prior models, our mathematical framework incorporates the social dimension of sustainability into the total cost considerations and accounts for environmental factors. Furthermore, it comprehensively models both forward and reverse flows inherent to closed-loop supply chains. The complexities and diverse objectives within sustainable closed-loop supply chain network design necessitate innovative methodologies. To address this challenge, we introduce the novel Red Deer metaheuristic algorithm, alongside two other cutting-edge algorithms and two conventional ones. Comparative analysis of their performance across problems of varying sizes underscores the remarkable strength and efficacy of the Red Deer algorithm, making it a potent tool for solving complex closed-loop supply chain optimization challenges.

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1. Introduction

In light of the rapid pace of agricultural industrialization, several critical issues have gained paramount significance in agriculture and food products. These issues encompass the escalating global demand for food, apprehensions concerning food safety and quality, and the overarching principles of sustainability and supply chain management. The contemporary emphasis on sustainability performance underscores the imperative need to judiciously employ and manage natural resources, harmonizing ecological, economic, and societal dimensions within the agri-food industry. This heightened focus on sustainability management has introduced a novel imperative for business managers. It is particularly noteworthy that these managers often operate within narrow profit margins and are subject to exacting requirements imposed by influential and sizeable customers and retailers (Mangla, 2018).

Within the context of agri-food supply chains (AFSCs), which encompass the intricate network of organizations comprising raw material manufacturers, processors, distributors, and consumers, a confluence of factors has precipitated significant transformations. Notably, an upsurge in consumer awareness has elevated food safety to a central concern for consumers and producers. Furthermore, enhancing food quality has emerged as a pivotal objective in cooperative efforts within the food industry, with quality assurance taking on profound importance as a cornerstone of sustainable profitability (Hu, 2019).

In the present research article, we proffer a novel closed-loop sustainable model designed specifically for fruit supply chains. An explicit focus on managing returned goods assumes paramount importance in the contemporary market landscape. According to scholarly research, the adoption of this approach serves as a potent tool for the creation of added value across all facets of a supply chain. Additionally, the utilization of reverse logistics (RLs) is driven by another imperative, namely, the safeguarding of the environment.

In today's context, environmental degradation often takes precedence over the expenses associated with the retrieval of returned goods. As the terminology suggests, Reverse Logistics (RL) focuses on managing the reverse flow of goods, whereas Closed-Loop Supply Chains (CLSCs) encompass both forward and reverse logistics. Hence, these two concepts not only diverge in meaning but also establish a hierarchical relationship, with RL being a constituent of CLSC, which, in turn, forms a comprehensive network encompassing RL and forward logistics (Cheraghalipour, 2018).

The agricultural supply chain is characterized by a series of activities spanning from production to distribution, facilitating the journey of agricultural and horticultural products from farms to consumers' tables. However, agricultural supply chains stand apart from other supply chains due to their unique considerations, such as the critical importance of factors like food safety, quality, and variables influenced by climatic conditions (Tsolakis, 2014).

Each year, approximately 30% of all products face spoilage due to farmers' insufficient understanding of crop demand and a lack of well-structured harvest planning (Goli et al., 2021). Crops, like other agricultural products, are not exempt from these damages and associated costs. Consequently, this study aims to devise a supply chain network to ameliorate these unfavorable circumstances and reduce costs. The subsequent section will delve into a review of existing literature, while the third section will introduce the mathematical model of the problem. Furthermore, the fourth section will encompass an evaluation of the model's solution process, wherein a novel heuristic will be employed to analyze the data derived from the proposed model.

2. Literature Review

In recent years, there has been a significant increase in access to fresh fruits, fruit quality, food quality, and year-round availability. This surge in accessibility and quality has led to a substantial rise in demand for these products. Consequently, the agricultural industry has emerged as a pivotal sector for the future (Tsolakis, 2014). Supply chain dynamics have garnered attention across various domains, encompassing fields like blood management and distribution (Brodheim, 1975), food products (Osvald, 2008), and chemical compounds (Aelion, 2008).

Numerous studies have delved into diverse aspects of the food industry, including seafood products (Cai, 2008), dairy items, as well as fruits and vegetables. In this context, a primary investigation was undertaken, focusing on simulation models within agricultural supply chains (ASCs). This study encompassed a wide array of agricultural foods, especially those of a perishable and unpredictable nature, including vegetables (Ahumada, 2009).

Furthermore, we present an overview of studies conducted between 1991 and 2011, concentrating on fresh food products like fruits, vegetables, and flowers. These studies share a common theme of emphasizing perishable and fresh product categories (Shukla, 2013).

2.1. Reverse Logistics (RL)

Public Increased public awareness has brought greater attention to the existence of Reverse Logistics (RL) and Closed-Loop Supply Chain (CLSC) issues (Dowatshali, 2000). Furthermore, the growing significance of RL has prompted companies to adopt this strategic tool for both economic advantages and enhancing their social image (Kannan, 2012). Companies have come to recognize that gaining a deeper insight into returned goods and implementing effective RL practices can yield competitive advantages (Stock, 2009).

Numerous studies have explored the potential benefits of RL operations in various industries, including the publishing sector (Wu, 2006). For instance, Hong Love (2009) delved into the recognition of challenges within RL operations in the electronics industry. Additionally, research has proposed methodologies for selecting optimal alternatives within mobile phone manufacturing companies, employing graph and matrix theories (Agrawal, 2016; Goli and Malmir, 2020).

In a separate study, researchers scrutinized decisions related to electronic waste reverse logistics, employing the Strategic Options Development Analysis (SODA) methodology in Brazil (Guarnieri, 2016).

2.2. Sustainable Closed-loop Supply Chain

The concept of a "closed-loop," denoting the integration of reverse and forward supply chain activities, represents a key strategy to ensure supply chain stability. This subject has been thoroughly investigated, serving as the cornerstone for the development of Closed-Loop Supply Chains (CLSCs). Within such systems, unused items are safeguarded, and their inherent value is at least partially reclaimed. There are noteworthy instances of novel logistical structures that have harnessed the closed-loop concept, demonstrating its potential to significantly enhance resource utilization efficiency (Banasik, 2017).

Given the paramount importance of sustainability in contemporary research, a study has devised a multi-objective model that addresses uncertainty while incorporating a sustainability approach (Babazadeh, 2017). In another investigation, researchers have formulated a mixed-integer, non-linear model for the robust design of global supply chain networks under uncertain conditions, employing the memetic algorithm (Hasani & Khosrojerdi, 2016).

Furthermore, Soleimani and Kannan (2015) have proposed a hybrid approach combining Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to address sustainability challenges in CLSC design. Additionally, Zohal and Soleimani (2016) conducted an assessment of a green closed-loop Supply Chain Network Design (SCND) model to quantify carbon dioxide emissions within the gold industry.

For a comprehensive overview of supply chain-related literature, we present a summary of select articles in Table 1, aiming to provide a more extensive literature review and identify potential research gaps.

3. Problem Statement

In this study, we introduce a Closed-Loop Logistic Network (CLLN) for the design of fruit supply chains. The developed logistic network encompasses several key components, including producers, distribution centers, customers, reprocessing centers (compost centers), and compost customers (compost market). The forward flow of goods, from producer to customer and distribution centers within the supply network designed for forward-flowing fruits, occurs in only three periods. This limitation is since producers can engage in mass production for a maximum of three months. Furthermore, in this forward flow, customers receive goods from distribution centers to fulfill the demand generated by the producers. Distribution centers are capable of shipping goods within eight periods, aligning with the maximum storage period for products and fruit demand, which spans eight months. Additionally, the authenticity of customer locations is verified. In the reverse flow, returned goods are routed to vermicompost centers, where they undergo conversion into organic fertilizer before being delivered to compost customers. Notably, since producers (gardens) can also be customers for the fertilizer, the network can be classified as a Closed-Loop Supply Chain (CLSC), where producers share the same role as compost customers. It is worth mentioning that the network can easily accommodate fruit, fresh fruit, and vegetable supply chains with minimal modifications, mainly differing in the number of periods or types of distribution.

Table 1. Evaluation of supply chain-related literature.

Reference	**Supply Chain**			**Sustainability Dimensions**			**Model**		**Description**
	Direct	Reverse	Closed-loop	Economic	Green and environmental	Social	Single-objective	Multi-objective	
Hester and Kachu (2003)	-	-	-	-	-	-	-	-	Dynamic simulation model
Filho (2006)	√	-	-	-	-	-	-	-	Harvest schedule management
Ferrer et al. (2008)	-	-	-	-	-	-	√	-	Optimal operation planning
Nadal and Aragonés (2013)	√	-	-	-	-	-	√	-	Optimal transport planning to provide a logistics center
Wilichko (2014)	-	-	-	-	-	-	√	-	Integrated modeling of the distribution system
Boroudin et al. (2016)	√	-	-	-	-	-	-	-	Operational research methods to address uncertainty
Paydar et al. (2017)	-	-	√	-	√	-	-	√	Supply chain design considering collection risk
Orsilan et al. (2017)	-	-	√	-	√	√	-	-	Closed-loop supply chain network design in the Turkish automotive industry
Jenabzadeh et al. (2018)	√	-	-	√	√	√	-	√	Sustainable supply chain design
Talaeizadeh (2019)	√	-	-	√	√	√	-	√	Modeling and solving sustainable supply chain problems
Haji Aghaei and Fard (2019)	-	-	√	√	√	√	-	√	Sustainable supply chain network design with the assumption of discount
Bhutani et al. (2019)	√	-	-	√	√	-	-	√	Food supply chain design
Amiri et al. (2021)	-	-	√	-	-	-	-	√	Closed-loop supply chain design
Current study			√	√	√	√		√	Sustainable closed-loop supply chain design

Every year, millions of tons of biowaste are either disposed of or incinerated, leading to significant environmental issues and high costs associated with waste transportation, disposal, and incineration.

An effective method for managing organic waste is recycling waste into vermicompost, which not only contributes to environmental preservation but also benefits public health by producing valuable organic fertilizer known as vermicompost. In essence, vermicomposting involves the use of epigeic earthworms to process and transform organic waste and by-products into valuable biofertilizers (Kumari, 2011; Tambe, 2014).

In addition to incorporating both forward and reverse logistics networks, our study also introduces a closed-loop element. Furthermore, the model encompasses three conflicting objective functions: two minimization objectives for total cost and risk and a maximization function for supply chain demand. To address these multiple objectives, we employ multi-objective planning techniques. Additionally, we leverage various innovative algorithms, including the Red Deer Algorithm (RDA), a novel algorithm employed in this research, alongside established efficient algorithms such as Keshtel and Imperialist Competitive Algorithms. Lastly, we include traditional algorithms like Genetic Algorithm (GA) and Simulated Annealing (SA) for comprehensive comparison.

4. Mathematical Model

The model proposed in this article is based on the continuation of the work mentioned in the literature review. The premises of the proposed problem can be stated as follows:

- Customers' demands are pre-specified.
- The number of facilities in each category is equal to the number of potentially restricted locations with predefined values.
- There is no current between facilities and similar categories.
- The number of returned products delivered to the monitoring and inspection centers is based on an estimate of customer demand. In addition, the mentioned products are allocated to facilities based on their quality. The important points that distinguish this article from other works done in this field are as follows:
- There is an interaction between three sustainability pillars presented in three conflicting objective functions in the problem.
- Forward and reverse currents in the logistic network are unified, while a large number of closed-loop articles of supply chain network design have only generalized the forward currents. In this regard, coverage centers, as well as recycling centers for recycled products, are considered.
- Various environmental effects are caused by establishing facilities, production in factories, transportation of products from one facility to another, and environmental damages.
- Each technology available in factories for products has a certain cost. They also have different social effects when they lack some of the abilities.

4.1. Indices

I: Set of potential centers of producers; $i \in \{1,2, \dots, I\}$

J: Set of potential production centers; $j \in \{1,2, \dots, J\}$

K: Set of potential distribution centers; $k \in \{1,2, \dots, K\}$

L: Set of regions of customers; $l \in \{1,2, \dots, L\}$

M: Set of monitoring and inspection centers; $m \in \{1,2, \dots, M\}$

N: Set of production centers; $n \in \{1,2, \dots, N\}$

P: Set of potential reproduction centers; $p \in \{1,2, \dots, P\}$

R: Set of potential recycling centers; $r \in \{1,2, \dots, R\}$

S: Set of optional potential centers; $s \in \{1,2, \dots, S\}$

T: Set of product technology; $t \in \{1,2, \dots, T\}$

e, e': Set of categories; $e, e' \in \{i, j, k, l, m, n, p, r, s\}$

fe, *fe'*: Set of facilities in each category; *e*: $f_e, f'_e \in \{1, \dots, Fe\}$

4.2. Parameters

Pc_i: Cost of purchasing raw materials from the i-th supplier

fc_{fe}: Fixed cost of facility reopening $f_e | e \in \{k, m, n, p, r, s\}$

mc_{jt}: Production cost of each product in the j-th production center with t technology

vc_{fe}: The relocation unit cost in a facility $f_e | e \in \{k, m, n, p, r, s\}$

$tc_{ef'_{e'}}$: Cost of transportation from fe facility to $f'_{e'}$ facility, which depends on the $X_{f_e f' e'}$ variable.

ac_{kl}: Cost of customer allocation in l region to the k-th distribution center

cc_{lm}: Unit cost of product monitoring from customers in l region and purchasing from the m-th monitoring center

eo_{jt}: Environmental effects of the establishment of the j-th production center with t technology

eo_{fe}: Environmental effects of $f_e | e \in \{k, m, n, p, r, s\}$ facility establishment

em_{jt}: Unit cost of environmental effects on production at the j-th center and t technology

eh_{fe}: Unit cost of environmental effects on carrying products in $f_e | e \in \{k, m, n, p, r, s\}$ facility

$et_{fef'e'}$: Unit cost of environmental effects on purchasing materials from fe facility to f'e' facility, which depends on $X_{fef'e'}$, Z_{kl}, and Z_{lm} variables.

ed_s: Unit cost of environmental effects on optimal production in the s optional center

fj_{jt}: The number of job opportunities created by the establishment of the j-th production center with t technology

fj_{fe}: The number of fixed jobs created by establishment of the $f_e | e \in \{k, m, n, p, r, s\}$ facility

vj_{jt}: The number of variable jobs created by establishment of the j-th production center with t technology

vj_{fe}: The number of variable jobs created by the establishment of the facility $f_e | e \in \{k, m, n, p, r, s\}$

fl_{jt}: Cost of days lost during t technology establishment at the j-th production center

fl_f: Cost of days lost during the facility establishment period $f_e|e \in \{k,m,n,p,r,s\}$

vl_{jt}: Number of days lost by production damages in the j-th center with t technology

vl_{fe}: Number of days lost by damages caused by the transportation of products in the facility $f_e|e \in \{k,m,n,p,r,s\}$

p_{jt}: Production capacity of the j-th production center with t technology

p_{fe}: Facility capacity $f_e|e \in \{k,m,n,p,r,s\}$

max_e: Maximum number considered for facilities in each category $e \in \{k,m,n,p,r,s\}$

d_l: Customer demand in l region

dmg_{jt}: An estimation of faulty products that damage customers or production by t technology in the j-th production center

b_{jt}: An estimation of faulty products produced by t technology in the j-th production center

$\propto_l$: An estimation of used products that are returned by customers in l region

$\beta_m^n, \beta_m^p, \beta_m^r$ *and* β_m^s: An estimation of reused, recovered, and recycled products and expired products in the m-th monitoring center ($\beta_m^n + \beta_m^p + \beta_m^r + \beta_m^s = 1$)

γ_n, γ_p *and* γ_r: An estimation of products transferred to covering, reproducing and recycling centers for use in the sales market

sc_d, sc_m *and* sc_r: The value of the stored currency resulting from a covering, reproducing and recycling center.

sc_u: The unit selling price of each product in the reuse market.

se_d, se_m *and* se_r: Unit of environmental benefits of using coverages, reproducers, and recycling products

ω_{em} *and* ω_{dp}: Weights given to components of environmental impact on objective functions: (1) transport and reopening outputs and (2) product adjustment

ε_{jo} *and* ε_{ld}: Weights given to social factors in the objective functions: (1) creating job opportunities (2) Lost working days.

4.3. Variables

$X_{fef'e}$: Product current from fe facility to fe' facility

H_{jt}: The number of products produced by t technology in the j-th center

Y_{fe}: 1, if $f_e|e \in \{k,m,n,p,r,s\}$ facility is established; otherwise, 0.

Y_{jt}: 1, if the j-th production center is established with t technology; otherwise, 0.

Z_{kl}: 1, if customer of the l region is allocated to the k-th distribution center; otherwise, 0.

Z_{lm}: 1, if the customer of the l region is allocated to the m-th monitoring center

The proposed closed-loop supply chain problem is implemented, as follows:

$$\begin{aligned}\text{Min } OBJ1 = {} & \sum_{j}\sum_{t} fc_{jt}\, Y_{jt} + \sum_{e}\sum_{f_e} fc_{f_e}\, Y_{f_e} + \sum_{i}\sum_{j} pc_j\, X_{ij} + \sum_{j}\sum_{t} mc_{jt}\, H_{jt} \\ & + \sum_{e}\sum_{e'}\sum_{f_e}\sum_{f'e'} tc_{f_e f_e'\prime}\, X_{f_e f_e'\prime} + \sum_{k}\sum_{l} ac_{kl}\, d_1 Z_{kl} \\ & + \sum_{l}\sum_{m} (cc_{lm}\, vc_m) \propto_l d_1 Z_{lm} - sc_d\left(\sum_{n}\sum_{k} X_{nk}\right) - sc_m\left(\sum_{p}\sum_{j} X_{pj}\right) \\ & - sc_r\left(\sum_{r}\sum_{i} X_{ri}\right) - sc_u\left(\sum_{e}\sum_{f_e}\sum_{m} \gamma_e\, X_{m f_e}\right)\end{aligned} \tag{1}$$

Objective Function (1) is designed to minimize the entire cost structure of the network. To achieve this goal, the first and second clauses pertain to the fixed costs associated with facility reactivation. Subsequently, the following eight clauses encompass the comprehensive expenses associated with procurement, production, transportation, allocation, and monitoring. The concluding four clauses account for the costs linked to storing the outcomes of recycled products, production centers involved in coverage redistribution, reprocessed products, and the sale of products within the reuse market. Concurrently, the second objective function calculates the environmental impacts of the network.

$$\begin{aligned} Min\ OBJ2 = {} & \omega_{em}\left[\begin{array}{c} \sum_{j}\sum_{t} eo_{jt}\, Y_{jt} + \sum_{e}\sum_{f_e} eo_{f_e}\, Y_{f_e} + \sum_{j}\sum_{t} em_{jt}\, H_{jt} \\ + \sum_{e}\sum_{e'}\sum_{f_e}\sum_{f'e'} et_{f_e f_e'\prime}\, X_{f_e f_e'\prime} + \sum_{e}\sum_{e'}\sum_{f_e}\sum_{f'e'} eh_{f_e}\, X_{f_e'\prime f_e} \\ + \sum_{l}\sum_{m} (eh_m + et_{lm}) a_l d_1 Z_{lm} + \sum_{m}\sum_{s} ed_s\, X_{ms} \\ -se_d\left(\sum_{n}\sum_{k} X_{nk}\right) - se_m\left(\sum_{p}\sum_{j} X_{pj}\right) - se_r\left(\sum_{r}\sum_{j} X_{rj}\right) \end{array}\right] \\ & + \omega_{dp}[\sum_{j}\sum_{t} dmg_{jt}\, H_{jt}(1 - b_{jt})\end{aligned} \tag{2}$$

The environmental consequences stemming from facility reactivation are encompassed in the initial and secondary segments of the objective function. Within this framework, the third through seventh clauses within the objective function are founded upon the depiction of environmental impacts on production, transportation, and optional products. Furthermore, the eighth to tenth clauses elucidate the advantages derived from eco-friendly products, while the final clause outlines the drawbacks associated with certain products. As for the social aspects of the model, these are quantified in the third objective function.

$$\max OBJ3 = \varepsilon_{j0}\left[\sum_j\sum_t fj_{jt}\,Y_{jt} + \sum_e\sum_{fe} fj_{f_e}\,Y_{f_e} + \frac{\sum_j\sum_t vj_{jt}\,H_{jt}}{p_{jt}} + \sum_k\sum_j {vj_k X_{jk}}/{p_k} + \frac{\sum_m\sum_l vj_m\,Z_{lm}d_l\alpha_l}{p_m} + \sum_e \frac{\sum_{fe}\sum_m vj_{f_e}\,X_{mf_e}\beta_m^{fe}}{p_{f_e}}\right] \quad (3)$$

$$-\varepsilon_{ld}[\sum_e\sum_{fe} fl_{jt}\,Y_{jt} + \sum_e\sum_{fe} fl_{f_e}\,Y_{f_e} + \sum_k\sum_j {vl_k X_{jk}}/{p_k} + \sum_m\sum_l vl_m\,Z_{lm}d_l\alpha_l/p_m + \sum_e\sum_{fe}\sum_m vl_{f_e}\,X_{mf_e}\beta_m^{fe}/p_{f_e}]$$

The first and second terms within the equation represent the employment opportunities created by each facility. These opportunities encompass various roles, including management, which are essential for the capacity utilization of each facility. Alongside fixed positions, variable employment opportunities are contingent on the capacity utilization of each facility. The third through sixth terms elucidate the specific job categories associated with each facility. It is worth noting that when a facility is actively utilized, it necessitates an increased labor force, while it requires fewer workers when operating at full capacity. The seventh through twelfth terms within the mentioned objective function quantify labor losses incurred during facility establishment, as well as throughout the production and transportation phases of products. Below, we outline the constraints of the aforementioned model:

$$\sum_i X_{ij} = \sum_k X_{jk} \qquad \forall j \qquad (4)$$

$$\sum_j X_{jk} = \sum_l d_l Z_{kl} \qquad \forall k \qquad (5)$$

$$\sum_{fe} X_{mf_e} = \beta_m^e \sum_l \alpha_l d_l Z_{lm} \qquad \forall e \in \{n,p,r,s\} \qquad (6)$$

$$\sum_k X_{nk} = (1-\gamma_n)\sum_m X_{mn} \qquad \forall n \qquad (7)$$

$$\sum_j X_{pj} = \left(1-\gamma_p\right)\sum_m X_{mp} \qquad \forall p \qquad (8)$$

$$\sum_i X_{rj} = (1-\gamma_r)\sum_m X_{mr} \qquad \forall r \qquad (9)$$

The amount of goods produced in each of these centers is calculated by the following constraint:

$$\sum_t H_{jt} = \sum_i X_{ij} \qquad \forall j \qquad (10)$$

Only one technology will be established in each potential center for production:

$$\sum_{t} Y_{jt} \leq 1 \qquad \forall j \qquad (11)$$

The customer must be allocated to only one of the distribution, monitoring, or assessment centers in each region:

$$\sum_{k} Z_{kl} = \sum_{m} Z_{lm} = 1 \qquad \forall l \qquad (12)$$

The number of goods prepared by each supplier, constrained by its own capacity:

$$\sum_{j} X_{ij} \leq p_i \qquad (13)$$

A manufacturing center can produce only when it is open and its capacity has remained unused:

$$H_{jt} \leq p_{jt} Y_{jt} \qquad \forall j, t \qquad (14)$$

Product current only allows a facility to be operating and have sufficient capacity:

$$\sum_{j} X_{jk} \leq p_k Y_k \qquad \forall k \qquad (15)$$

$$\sum_{i} \propto_l d_l Z_{lm} \leq p_m Y_m \qquad \forall m \qquad (16)$$

$$\sum_{m} mf_e \leq p_{f_e} Y_{f_e} \qquad \forall e \in \{n, p, r, s\} \qquad (17)$$

The number of facilities in each row is constrained by predefined numbers:

$$\sum_{j} \sum_{t} Y_{jt} \leq max_j \qquad (18)$$

$$\sum_{fe} Y_{f_e} \leq max_e \qquad \forall e \in \{k, m, n, p, r, s\} \qquad (19)$$

In the end, binary and positive variables are guaranteed:

$$Y_{jt}, Y_{f_e}, Z_{kl}, Z_{lm} \in \{0,1\} \qquad (20)$$

$$X_{f_e f'_{e'}}, H_{jt} \geq 0 \qquad (21)$$

5. Solution Method

Various metaheuristic techniques have been employed to address the proposed closed-loop supply chain network design model. Traditional methods such as Genetic Algorithm (GA) and Simulated Annealing (SA) have been utilized alongside recently developed and innovative metaheuristic approaches, including Keshtel and Imperialist Competitive algorithms. Furthermore, a novel heuristic inspired by the Red Deer Algorithm (RDA) has been incorporated.

The study discusses the utilization of Keshtel and Imperialist Competitive algorithms, the Artificial Bee Colony algorithm, and the Firefly algorithm in the section devoted to standard functions. In each of these algorithms, the author has strategically harnessed the search phases, with the primary aim of promoting interaction between these phases. It is noteworthy that conventional methods like GA tend to explore metaheuristic phases in a random and less calculated manner, lacking the intelligent programming employed in recent metaheuristic developments. For instance, GA may employ mutation to focus its search and intersection to diversify it, but it does so without a systematic and calculated approach.

This approach stands in stark contrast to novel metaheuristics. In the Imperialist Competitive Algorithm, the primary aim of generating diverse empires is to foster a rich variety of solutions. Additionally, to sharpen the focus of the search and enhance solution quality, an assimilation policy is employed, which entails bringing weaker solutions closer to stronger ones while exploring adjacent areas. The implementation of a colonial competition policy intelligently promotes diversification and the formation of new solution groups. Furthermore, a "revolution" strategy is deployed within the colonies to break free from local optimality (Goli et al., 2018).

In the Keshtel algorithm, the author strives to achieve a distinct separation among solutions by categorizing the population into three different types. This approach leads to the formation of a more refined cohort of individuals, employing a clever rotational technique and promoting a concentrated search phase. These groups explore their surroundings by transitioning between potential points, and the final group introduces random diversity through stochastic production (Goli et al., 2020). Moreover, users have the flexibility to select one or both of the proposed operators.

The Artificial Bee Colony algorithm shares similarities with the Keshtel and Imperialist Competitive algorithms. By employing three distinct bee types and forming different colonies akin to empires, it effectively utilizes search phases, presenting an ingenious methodology **.**

In the Firefly algorithm, the concept of attracting individuals toward potential areas by creating light and facilitating mutual attraction results in a smart approach during the search focus phase. Furthermore, for all these algorithms, establishing search interactions and carefully selecting appropriate parameters are highly recommended**.**

In our study, we consider the search phases within the proposed Red Deer Algorithm (RDA). Focusing the search through roaring and combat and diversifying solutions through a range of parameters represents a sophisticated and beneficial approach. Furthermore, this algorithm incorporates a mechanism to break free from local optimization at the conclusion of each generation, employing an evolutionary strategy to select the next generation.

5.1. Parameter Production Method

This section is dedicated to elucidating the experimental design and parameter generation method. We have meticulously crafted an experimental design plan. The number of potential centers plays a pivotal role in shaping the problem's complexity. Consequently, we have categorized the problems into small, moderate, and large. Within each tier, we have devised eight distinct problem instances, resulting in a comprehensive set of 24 problems encompassing various complexity levels. The specifics of this work are comprehensively outlined in Table 2.

Table 2. Level, number, and size of problems.

Problem Level	Problem Number	Problem Size (I, J, T, K, L, M, N, P, R, S)
Small	P1	(7, 5, 2, 10, 9, 10, 2, 3, 2, 2)
	P2	(11, 7, 2, 10, 12, 10, 3, 5, 5, 3)
	P3	(15, 9, 2, 12, 15, 12, 4, 7, 6, 4)
	P4	(19, 11, 3, 14, 18, 14, 5, 9, 8, 5)
	P5	(23, 13, 3, 16, 21, 16, 6, 11, 10, 6)
	P6	(27, 15, 3, 18, 24, 18, 7, 13, 10, 7)
	P7	(31, 17, 4, 20, 27, 20, 8, 15, 12, 8)
	P8	(35, 19, 4, 22, 30, 22, 9, 17, 12, 9)
Moderate	P9	(55, 29, 7, 31, 51, 31, 14, 19, 18, 16)
	P10	(59, 31, 7, 33, 54, 33, 15, 21, 20, 17)
	P11	(63, 33, 7, 35, 57, 35, 16, 23, 20, 18)
	P12	(67, 35, 8, 37, 60, 37, 17, 25, 22, 19)
	P13	(71, 37, 8, 39, 63, 39, 18, 27, 22, 20)
	P14	(75, 39, 8, 41, 66, 41, 19, 29, 24, 21)
	P15	(79, 41, 9, 43, 69, 43, 20, 31, 24, 22,
	P16	(83, 43, 9, 45, 72, 45, 21, 33, 26, 23)
Large	P17	(103, 53, 11, 57, 107, 57, 27, 35, 34, 28)
	P18	(107, 55, 11, 59, 111, 59, 28, 36, 25, 29)
	P19	(111, 57, 11, 61, 115, 61, 29, 37, 37, 30)
	P20	(115, 59, 12, 63, 119, 63, 30, 38, 39, 31)
	P21	(119, 61, 12, 65, 123, 65, 31, 39, 40, 32)
	P22	(123, 63, 12, 67, 127, 67, 32, 40, 42, 33)
	P23	(127, 65, 13, 69, 131, 69, 33, 41, 42, 34)
	P24	(131, 67, 13, 71, 135, 71, 34, 42, 43, 35)

Table 3 presents the values of the parameters expressed in the experiments. We also introduced the gap parameter to evaluate the efficiency of the algorithms. This concept expresses the dispersion deviation of algorithms against the best solution. Eq. (22) has been proposed to define the gap mathematically.

$$GAP = \frac{II_{max} - II_{sol}}{II_{max} - II_{min}}, \tag{22}$$

where II_{sol} indicates the resonance parameter for each algorithm. In addition, II_{max} and II_{min} show the highest and lowest values of the resonance parameter in the algorithm, respectively. Table 4 presents the algorithm time calculation values and resonant and gap parameter values.

Table 3. Parameters and distribution method.

Parameters	Possible Distribution
VC_k, VC_m, VC_n, VC_r, VC_s	$\sim U(1,5)$
pc_i, mc_{jt}, vc_p	$\sim U(5,10)$
ac_{kl}	$\sim U(0.5,3)$
tc_{ff}, cc_{lm}	$\sim U(1,6)$
$et_{ff'}$	$\sim U(0.2,2)$
eh_k, eh_m, eh_n, her	$\sim U(1,10)$
em_{jt}, eh_p	$\sim U(10,30)$
ed_s	$\sim U(30,60)$
$\beta_m^n, \beta_m^p, \beta_m^r, \beta_m^s$	$\sim U(0,0.5) \mid \beta_m^n + \beta_m^p + \beta_m^r + \beta_m^s = 1$
b_{jt}	$\sim U(0.01,0.03)$
$\propto_l$	$\sim U(0.3,0.7)$
dmg_{jt}	$\sim U(0.001,0.003)$
fj_{jt}, fj_f	$\sim U(5,10)$
vj_{jt},vj_f	$\sim U(0.02,0.06)$
vl_{jt},vl_f	$\sim U(0.1,1)$
fl_{jt}, fl_f	$\sim U(10,1000)$
$\gamma_n, \gamma_p, \gamma_r$	$\sim U(0,0.3)$

Table 4. Results obtained from the comparison of different algorithms.

P_i	RDA			KA			ICA			GA			SA		
	II	CPU	GAP	II	CPU	GAP	II	CPU	GAP	II	CPU	GAP	II	CPU	GAP
P1	2.93	9.65	0.66	2.46	6.75	0.97	3.21	8.81	0.45	2.81	4.59	0.74	2.39	5.45	1.01
P2	3.25	8.94	0.53	2.89	7.56	0.83	3.13	9.36	0.64	2.94	5.65	0.77	2.68	5.88	1.01
P3	3.65	10.47	0.23	3.31	7.98	0.50	3.21	9.96	0.59	2.72	5.82	1.00	2.96	6.02	0.81
P4	3.95	11.12	0.00	3.35	8.52	0.32	2.96	10.44	0.57	2.30	6.14	1.00	2.75	6.53	0.72
P5	3.06	12.01	0.48	3.22	9.85	0.35	2.91	11.33	0.57	2.34	6.82	1.01	2.42	7.32	0.94
P6	3.05	11.92	0.42	3.12	10.36	0.38	3.10	12.79	0.40	1.85	8.26	1.00	1.84	8.27	1.00
P7	3.56	13.87	0.11	3.34	11.74	0.26	3.03	13.58	0.49	2.32	9.40	1.00	2.54	9.52	0.84
P8	3.29	15.08	0.47	3.10	13.03	0.51	3.09	15.04	0.52	2.45	10.53	0.93	2.81	10.40	0.71
P9	3.32	34.36	0.39	3.08	30.68	0.59	3.27	31.57	0.43	2.56	26.66	1.00	2.70	27.07	0.90
P10	3.49	37.44	0.31	3.09	32.73	0.68	3.20	33.70	0.60	2.95	28.10	0.82	2.89	25.78	0.88

Table 4. Results obtained from the comparison of different algorithms (continued).

P_i	RDA			KA			ICA			GA			SA		
	II	CPU	GAP	II	CPU	GAP	II	CPU	GAP	II	CPU	GAP	II	CPU	GAP
P11	3.34	38.85	0.38	3.20	34.83	0.48	3.34	35.96	0.39	3.25	29.51	0.44	2.42	29.59	1.00
P12	3.09	40.59	0.40	2.83	35.50	0.51	2.84	38.48	0.51	2.41	31.63	0.72	2.72	31.11	0.57
P13	3.09	42.52	0.39	3.52	37.65	0.13	3.24	40.24	0.31	2.26	33.60	0.88	2.05	33.46	1.01
P14	2.65	46.43	0.59	2.65	39.23	0.60	2.81	42.42	0.52	1.79	34.79	1.01	2.08	36.37	0.87
P15	3.24	46.01	0.45	3.07	41.65	0.57	3.42	44.76	0.30	2.50	36.65	1.01	2.89	38.65	0.75
P16	3.22	47.25	0.47	3.33	42.76	0.37	3.47	46.37	0.57	2.73	37.58	0.87	2.56	39.16	1.00
P17	3.29	78.44	0.35	2.87	64.47	0.63	2.97	72.75	0.58	2.68	58.63	0.78	2.36	59.52	1.01
P18	3.00	80.94	0.60	3.00	67.25	0.60	2.79	76.39	0.74	2.49	61.78	0.93	2.57	62.54	0.88
P19	3.33	84.14	0.21	3.05	70.69	0.41	3.07	79.13	0.42	2.34	63.68	1.01	2.39	65.49	0.95
P20	3.18	85.31	0.40	3.08	71.89	0.49	3.08	82.19	0.81	2.64	67.18	0.82	2.39	68.65	1.00
P21	3.53	86.67	0.21	3.56	74.58	0.19	3.25	83.94	0.45	3.17	69.64	0.53	2.60	69.77	1.01
P22	2.82	89.68	0.67	3.14	77.10	0.45	2.70	85.62	0.76	2.32	73.30	0.99	2.32	71.19	1.00
P23	3.28	92.81	0.47	3.35	79.81	0.41	2.97	87.55	0.71	2.74	75.08	0.89	2.81	73.27	0.84
P24	3.32	93.78	0.40	3.32	84.37	0.40	3.31	89.61	0.40	2.47	77.77	0.93	2.53	76.69	0.90

In addition, Figures 3 and 4 demonstrate the interaction between the growth of problem size and computational time and gap values in algorithms. According to these figures, while the red deer algorithm (RDA) requires more time, it has better efficiency in most problems with different sizes compared to other methods.

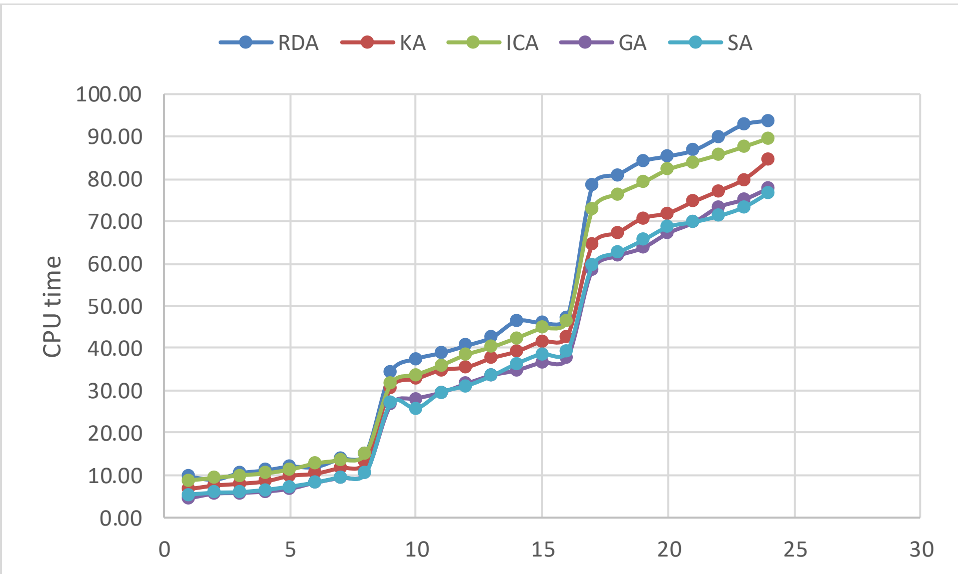

Fig. 3. Interaction between problem growth and computational time of algorithms.

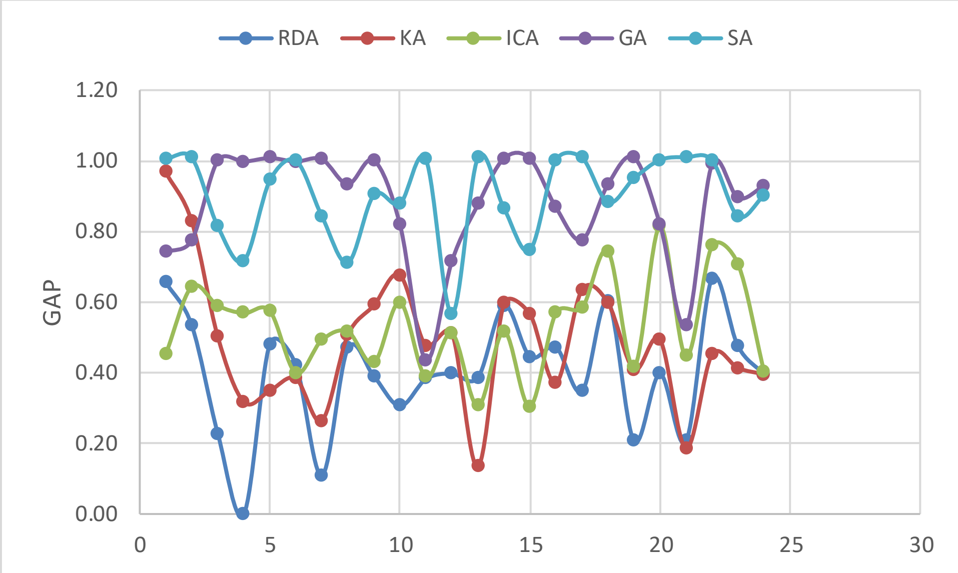

Fig. 4. Interaction between problem growth and the amount of gap in algorithms.

6. Conclusion and Recommendations

In this comprehensive research endeavor, we embarked on a journey to address the existing gaps within each algorithm concerning the intricacy of supply chain network design. Our investigation encompassed a rigorous model solution process, shedding light on critical insights.

The results of our study vividly highlight the remarkable prowess of the Red Deer Algorithm (RDA) when compared to its heuristic counterparts, particularly in dealing with problems of varying sizes. The RDA demonstrated a notable aptitude for optimizing supply chain network design across a spectrum of complexities. However, it is worth noting that, in the case of large-scale problems, the RDA did exhibit a relatively longer computational time when compared to other established metaheuristic techniques. This prompts us to underscore the importance of carefully considering problem size and computational resources when selecting the most suitable optimization approach.

As we look ahead, there is a plethora of opportunities for further exploration and innovation in the field of metaheuristic algorithms. We wholeheartedly recommend subjecting the novel algorithms we have presented here to rigorous testing across various optimization problem domains in future studies. This will allow us to better understand these algorithms' versatility and adaptability and identify areas for refinement and enhancement.

Moreover, we encourage researchers to explore alterations and refinements to algorithm structures with the overarching goal of improving their speed and efficiency. Developing novel algorithms grounded in well-defined search phases promises to be a promising avenue for future research endeavors, potentially yielding innovative and high-performing solutions to complex optimization challenges.

In conclusion, our research has contributed valuable insights into supply chain network design optimization and the potential of novel metaheuristic algorithms, with the Red Deer Algorithm at the forefront. As the field continues to evolve, we eagerly anticipate further advancements and innovations driven by the collective efforts of researchers and practitioners dedicated to the pursuit of optimized solutions in diverse problem domains.

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