Optimization of Logistics and Industrial Wastewater Treatment System Using Grey Wolf Optimization Algorithm

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Abstract

Industrial wastewater collection involves the systematic gathering, transportation, and disposal of waste generated by industrial activities. This process is crucial for maintaining environmental health and safety, as industrial wastewater may contain hazardous materials that require special management. Effective waste collection strategies not only help reduce pollution but also contribute to the recycling and reuse of materials, thereby conserving resources. Advanced technologies and adherence to regulations play key roles in ensuring the efficient and sustainable management of industrial wastewater. Considering the role of closed-loop supply chains in industrial wastewater collection, this paper presents a bi-objective mathematical model aimed at minimizing both the costs associated with surface wastewater collection and the environmental pollution from waste discharge. The model is solved using the multi-objective Grey Wolf Optimization algorithm. The results show that the model extends the network by including more vehicles and increasing the distances between locations. This optimal collection model ensures that wastewater is gathered from candidate sites by the vehicles within the network. Additionally, sensitivity analysis reveals that the most influential parameters on the model's objectives are the transportation cost per unit distance, the penalty for vehicle usage, and the revenue per kilogram of treated wastewater.

Keywords: *industrial wastewater collection, closed-loop supply chain, sustainability requirements, Grey Wolf Optimization algorithm.*

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1. Introduction

One of the most significant topics in recent decades has been sustainable supply chains, as the environment has increasingly become polluted due to the operations of companies and factories. The destruction of the environment is growing day by day due to carbon emissions and products produced by factories. The adoption of green supply chains is often driven by two common variables: the reduction of pollutants and the cost of a sustainable supply chain [1]. With the intensification and expansion of the competitive landscape in today's world, supply chain management has become one of the key challenges for business enterprises, influencing all organizational activities aimed at product production, quality improvement, cost reduction, and the provision of customer services. On the other hand, environmental issues have previously received attention in developed countries, and government regulations, along with customer pressure to comply with them and consider environmentally friendly products, have increased. Supply chain design models have generally worked to minimize costs without considering the level of carbon emissions. However, recent studies have focused on environmentally friendly production, considering carbon emissions and optimizing the overall cost [2-5]. Across the supply chain, the process of considering environmental criteria and considerations involves greening the supply chain. The integration of supply chain management with environmental requirements across all product design processes, selection and procurement of raw materials, manufacturing, distribution and transportation processes, delivery to customers, and ultimately, post-consumption recycling and reuse management, aims to improve energy and resource consumption efficiency while enhancing overall supply chain performance [6].

Closed-loop supply chains (CLSC) represent an alternative logistics approach for addressing environmental degradation and resource shortages. In CLSC systems, materials are controlled, greenhouse gas emissions and waste are reduced, and production processes become cost-effective [7]. Closed-loop supply chain management (CLSC) integrates forward and reverse logistics to create a sustainable and efficient system. This approach aims to reduce waste and maximize resource use by incorporating processes such as recycling, remanufacturing, and reuse of materials. Recent studies have highlighted the importance of CLSC in addressing environmental and economic challenges [8]. For instance, a comprehensive review of CLSC literature underscores the role of optimization techniques in enhancing sustainability and resource efficiency. Researchers have identified key trends and challenges, such as the need for better integration of recovery options and the development of stronger models to manage the complexities of CLSC networks [9]. Another important aspect of CLSC is its contribution to the circular economy. By closing the loop, companies can reduce their environmental impact and improve their economic performance. Studies have shown that effective CLSC management can lead to significant cost savings and improved competitiveness. Analyzing CLSC models indicates that integrating forward and reverse supply chains can optimize both economic and environmental outcomes. This dual focus on sustainability and profitability makes CLSC a vital strategy for modern supply chain management [10].

The components of reverse supply chains include customers, collection centers, and recycling or disposal facilities for used products. Returned products are collected, inspected, and sent to the appropriate centers for recycling or disposal. Key decisions in this network include the location of recycling and disposal centers and the flow of returned materials. Integration in CLSC design involves simultaneous decision-making for both strategic and operational decisions for forward and reverse supply chains [11]. On the other hand, a critical issue for many companies is the management of industrial waste, including its treatment, recycling, or disposal. Effective water and wastewater management is essential for public health and economic development, but it remains a significant challenge in many low- and middle-income countries [12]. Consequently, in many countries, the focus on implementing sustainable development requirements within the supply chain has led to significant attention to the allocation and capacity-building of industrial wastewater recycling centers to optimize resource use and increase sustainability. By strategically locating these centers, industries can significantly reduce transportation costs and related carbon emissions. This approach ensures that wastewater is treated near its source, minimizing the need for long-distance transportation. Furthermore, by maximizing the capacity of these centers, industries can increase the volume of recycled and reused water, thereby reducing their dependence on fresh water resources. This not only helps in water conservation but also assists companies in complying with regulations and achieving sustainability goals [13]. Therefore, this paper aims to propose an optimized model for industrial waste recycling centers in reverse supply chains of industrial companies, using metaheuristic algorithms to solve the multi-objective and NP-hard problem. Thus, the main contributions of this paper are as follows:

- Reduction in industrial wastewater transportation
- Increased production of usable water from recycling
- Enhanced recycling rates of industrial wastewater pollutants into organic and mineral materials required in industries and agriculture.

2. Methodology

This research presents an intelligent model for the closed-loop supply chain of industrial wastewater collection and recycling, based on the work of Kabir et al. (2021). Kabir and colleagues proposed a mixed-integer linear programming model for a multi-stage, multi-product, and multi-period reverse supply chain network, aiming to maximize profit and optimize logistics. They introduced two models: the first minimizes the travel distance and water collection vehicle costs, while the second maximizes the profit from urban water collection, deducting the costs of the first model [14]. The present study adapts the second model for the routing of industrial wastewater collection vehicles, pursuing two simultaneous objectives: maximizing profit and minimizing pollution. This problem involves optimizing the collection of industrial wastewater using a set of n potential locations, v homogeneous vehicles, and one depot. The system is modeled as an undirected complete graph with (n+1) nodes, where each node represents a wastewater location with a maximum capacity of (E_i). The vehicle transportation cost per unit distance is denoted by C, and the revenue generated from wastewater collection is represented by R. Each vehicle has a fixed capacity Q in kilograms. Filling sensors at each location send the wastewater volume to the collection center, which is converted to kilograms based on the wastewater density B in kilograms per cubic meter. The proposed method aims to maximize profit from wastewater collection while minimizing pollution, considering road gradient and truck load.

The wastewater locations along with the waste collection center (node indices): $i, j \in I$

Vehicle index: $v \in F$

The number of wastewater locations is n, along with the actual industrial wastewater collection center (where vehicles start) and a virtual surface wastewater collection center, forming the nodes of the model. The actual surface wastewater collection center is node 0, and the virtual surface wastewater collection center is node n+1. After reaching the virtual wastewater collection center, wastewater collection vehicles follow the same route back to the actual depot.

- Transportation cost per unit distance (USD): C
- Revenue per kilogram of treated wastewater collected (USD): R
- Penalty for vehicle usage (USD): P
- Capacity of wastewater collection vehicles (kg): Q
- Wastewater density (kg/m³): B
- Distance between two nodes i and j: d_{ij}
- Amount of wastewater at location i in kilograms (calculated from sensor data in cubic meters and wastewater density): S_i
- Forecasted daily accumulation rate of wastewater at location i: a_i
- Wastewater location capacity i: E_i
- Total wastewater considered, based on the collected wastewater and the forecasted rate exceeding capacity at location i, $S_i + a_i > E_i$: H

Considering the service level provided, the percentage of wastewater tanks that can overflow: θ
Maximum allowed overflow threshold: T_max
Effect of road gradient: G
Effect of truck load: L
Road gradient on the edge between two nodes i and j: θ_{ij}
Pollution produced per unit distance traveled by the vehicle: Pol

- 3.3 Decision Variables
- Binary variable (0 or 1) indicating whether vehicle v visits the edge (i, j): x_{ij}^v
- Binary variable indicating whether waste bin i is visited: g_i
- Amount of load carried by vehicle v when visiting node j: y^{vj}
- Integer variable for the number of vehicles used: k

In the model proposed by Kabir et al. (2021), after routing the vehicles, it is not specified which routes each industrial wastewater collection vehicle has taken [14]. In fact, there is no record of the routes traveled by the wastewater collection vehicles. In the present study, by modifying the decision variables, this issue has been addressed. The decision variable x_{ij}^v is defined as a three-dimensional variable, whereas in the work of Kabir et al., it was defined as a two-dimensional variable. This modification indicates whether a vehicle passed from node i to node j, and in our research, the vehicle index has been added to specify which collection vehicle passed from node i to node j. Additionally, a constraint has been applied that only one vehicle should pass from node i to node j for wastewater collection. Our proposed model is formulated as follows.

1)

$$Max\, P = R \sum_{i \in I \backslash \{0,n+1\}} S_i g_i - (C \sum_{v \in F} \sum_{i \in I} \sum_{j \in I,(j \neq i)} x_{ijv} d_{ij} + k\Omega)$$

2)

$$Min \;\; \text{pollution} = \sum_{v \in F} \sum_{i \in I} \sum_{j \in I,(j \neq i)} x_{ijv}.d_{ij}.Pol.(1+\theta h_{ij}).\beta y_{vj}$$

3)

$$\sum_{i \in I \backslash \{0,n+1\}:\, S_i + a_i \geq E_i} g_i \leq H - n\delta$$

4)

$$g_i = 1, \;\; \forall i \in I \backslash \{0,n+1\} : S_i \geq \psi E_i$$

5)

$$\sum_{v \in F} \sum_{i \in I,(i \neq j)} x_{ijv} = g_j, \forall j \in I \backslash \{0,n+1\}$$

6)

$$\sum_{i \in I} \sum_{j \in I,(i \neq j)} x_{ijv}.s_j < Q \quad \forall v \in F$$

7)

$$x_{ijv} \in \{0,1\} \quad \forall i,j \in I, i \neq j, v \in F$$

8)

$$g_i \in \{0,1\} \quad \forall i \in I \backslash \{0,n+1\}$$

9)

$$\mathrm{k} \in N$$

Equation (1) represents the first objective function of the model, where the profit from collecting industrial wastewater is maximized. This objective function is derived from the revenue minus transportation costs. Equation (2) represents the second objective function of the model, where the pollution produced by the collection vehicles is minimized. In this objective, the distance traveled by vehicles is multiplied by the road gradient, the current load of the wastewater collection vehicle, and the pollution rate per unit distance. The road gradient is a numerical value between 0 and 1 and is adjusted based on the impact factor. The vehicle load is also adjusted by multiplying with the load impact factor to reflect the effect of vehicle load on the level of pollution.

Constraint (3) allows a percentage of the total wastewater locations to overflow based on the service level. Constraint (4) indicates that if a location exceeds the permissible overflow threshold, it must be collected by the designated vehicles. Constraint (5) specifies that the total number of incoming edges to a wastewater location is 1 if the location is collected, and 0 if not. Constraint (6) ensures that the total load collected by each vehicle does not exceed its capacity. Constraint (7) refers to the binary nature of the decision variables. Constraint (8) ensures that a specific decision variable is binary. Constraint (9) enforces the use of integer variables.

3. Findings and Results

This algorithm, like the single-objective Grey Wolf Optimizer (GWO), begins with an initial population P that is randomly generated. In the next step, the produced population is evaluated based on the defined objective functions. In the proposed model, there is one minimization objective and one maximization objective. After dividing the population into different categories using the Non-Dominated Sorting process, a control parameter called the "wolf position" is calculated to identify the location of the prey. This parameter is calculated for each member in every group and reflects the proximity of alpha, beta, and gamma wolves to the target prey. A larger value of this parameter leads to divergence and a broader range in the population set. In this algorithm, a number of solutions from each wolf population P_E are selected randomly using vector c. In the random selection method, solutions are chosen randomly from the population, and then a comparison is made between these two solutions. The better one is ultimately selected. The selection criteria in the MOGWO algorithm primarily depend on the distance between the wolves for prey hunting, and secondarily on the distance of the prey. The smaller the distance between the wolves for hunting and the lesser the prey distance, the more optimal the solution is. By repeating the random selection operator on each group of wolves, a set of wolves for hunting is chosen from the population. It should be noted that none of the solutions on the Pareto front are considered superior to others, and depending on the situation, each can be regarded as an optimal decision. The general approach of this algorithm is shown in Figure 1 below.

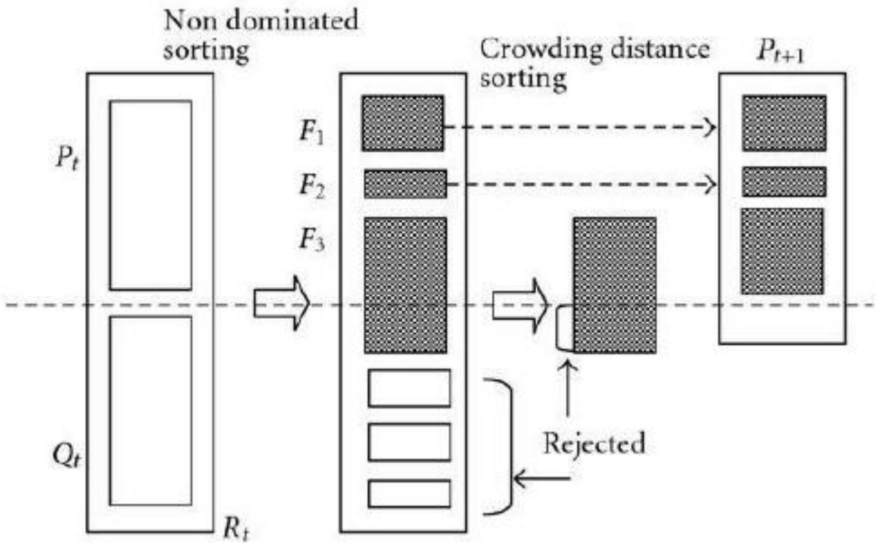

Figure 1. Mechanism of the MOGWO algorithm

To implement the MOGWO algorithm with the goal of finding the best solutions, the optimal input parameters are searched. To achieve this, the Taguchi method is applied. In this section, the Taguchi method is fully presented to adjust the parameters of the MOGWO algorithm. The Taguchi method is the most well-known parameter optimization method using experimental design and response surface methodology. When the number of parameters is large, numerous experiments must be conducted to find the optimal solution, and due to the need for many experiments, methods such as Taguchi or trial and error are used. The Taguchi method provides a systematic, simple, and efficient approach to optimize the parameters of any algorithm using a limited set of experiments. The results of these experiments are valid for the entire experimental region created by the factors and their levels. Table 1 shows the main parameters of the MOGWO algorithm, which are determined using the Taguchi method at three levels.

Table 1. MOGWO Parameters Adjusted According to Taguchi Levels

Level 3	Level 2	Level 1	Parameter
2	1	0.5	Scale Factor (SF)
50	40	30	Population Size (np)
150	100	70	Number of Iterations (niter)

In Table 2, the Taguchi experiments for determining the optimal parameters of MOGWO are shown.

Table 2. Taguchi Parameter Settings for MOGWO

R5	R4	R3	R2	R1	niter	np	SF	Test Number
0.741	0.748	0.698	0.635	0.658	70	30	0.5	1
0.635	0.815	0.704	1.01	0.968	100	40	0.5	2
0.787	0.810	0.801	1.487	1.748	150	50	0.5	3
0.718	0.719	0.684	0.898	0.748	70	30	1	4
0.710	0.801	0.810	1.315	1.42	100	40	1	5
0.698	0.863	0.862	1.101	1.102	150	50	1	6
0.653	0.687	0.635	1.035	1.245	70	30	2	7
0.635	0.631	0.674	0.814	0.947	100	40	2	8
0.721	0.719	0.749	1.169	1.25	150	50	2	9

Finally, Table 3 presents the average response levels for the parameters of the MOGWO algorithm.

Table 3. Taguchi Response Levels for MOGWO Parameter Adjustment

niter	np	SF	Level
0.8649	0.8759	1.2635	1
1.0787	1.1215	1.1069	2
1.3165	1.4635	1.0469	3

The results show that the optimal value for SF is at level 3 (2), the optimal value for np is at level 1 (30), and the optimal value for niter is at level 1 (70). Now, using these initial values, the proposed model will be solved using the MOGWO algorithm.

Now, with the wolf population set to 10 and the number of iterations set to 300, we present the results obtained for both objective functions. On the other hand, since the proposed model has different levels based on 7 potential wastewater sites and 6 wastewater collection vehicles, the wastewater collection flow is determined based on the number of discharge and collection locations. Table 4 presents the demand levels for each of the five customers.

Table 4. Customer Demand Levels

Candidate Wastewater Location	1	2	3	4	5	6	7
Wastewater Production Capacity (kg/m³)	150	180	365	410	95	263	315

According to Table 4, it is clear that the first wastewater location has a production capacity of 150 kg/m³, the second location has a production capacity of 180 kg/m³, and so on. It is also important to note that the maximum time allowed for transferring wastewater from each candidate location, which does not cause dissatisfaction, is considered to be 100 hours. Another point to consider is that since the initial values of the model are randomly assigned in solving the problem, it may result in an infeasible solution, but the algorithm will immediately act to overcome this and reach a feasible solution. This process is considered during 300 iterations of the algorithm.

Based on this, Table 5 presents the results obtained from solving the problem with the MOGWO algorithm for both defined objectives.

Table 5. Results from Solving the Problem with the MOGWO Algorithm

Objective Function	Cost Objective (Toman)	Pollutant Emission Objective (PPM)
Value	12,141,035	12,524

As shown in Table 5, for the proposed model with the given numerical example, the optimal results have been achieved.

Table 6 shows the wastewater transfer values by the wastewater trucks from the candidate wastewater locations to the treatment facility.

Table 6. Industrial Wastewater Transfer by Trucks from Candidate Locations to Treatment Facility

Truck 1	Truck 2	Truck 3	Truck 4	Truck 5	Truck 6
25	0	80	0	45	0
0	65	46	4	50	15
0	0	50	65	224	26
150	89	0	71	100	0
16	11	10	5	49	5
197	50	13	0	3	0
150	109	41		5	0

From Table 6, it is evident that Truck 1 receives all 150 kg/m^3 of its wastewater from Trucks 1, 3, and 5, or that the fifth candidate location used all the trucks for transferring 95 kg/m^3 of its wastewater. The total of each row in this table corresponds to the collection capacity of wastewater from the candidate wastewater locations, all of which are transferred by the wastewater trucks.

One of the topics that can provide valuable insights for solving problems is sensitivity analysis of the model's parameters. In other words, sensitivity analysis determines how much a dependent variable will change when the value of an independent variable is altered, assuming all other variables remain constant in a specific, defined situation. In this problem, we modify the parameters of the model to observe how increasing or decreasing each parameter impacts the cost and the final pollutant emission of the model. The results of the sensitivity analysis for each parameter are presented in the tables below.

Table 7. Sensitivity Analysis on Vehicle Transportation Cost

Row	Vehicle Transportation Cost (C)	Cost (USD)	Pollutant Emission (PPM)
1	18000	11,095,253	15,296
2	20000	12,536,658	29,854
3	100000	152,652,541	162,352
4	200000	349,455,260	452,533

Table 8. Sensitivity Analysis on Revenue per Kilogram of Treated Wastewater Collected

Row	Revenue per Kilogram of Collected Treated Wastewater (R)	Cost (USD)	Pollutant Emission (PPM)
1	80,000	115,823,252	18,665
2	100,000	152,644,287	35,692
3	800,000	253,310,249	212,749
4	170,000	405,331,207	603,521

Table 9. Sensitivity Analysis on Penalty for Vehicle Usage

Row	Penalty for Vehicle Usage (Ω)	Cost (USD)	Pollutant Emission (PPM)
1	28,000	118,212,748	19,224
2	45,000	154,821,049	39,326
3	360,000	254,526,411	236,359
4	750,000	421,244,512	652,415

Table 10. Sensitivity Analysis on the Capacity of Wastewater Collection Trucks

Row	Capacity of Wastewater Collection Trucks (Q)	Cost (USD)	Pollutant Emission (PPM)
1	7,500	11,025,315	15,216
2	24,000	11,233,657	21,042
3	190,000	119,524,102	182,523
4	380,000	210,425,573	223,024

Table 11. Sensitivity Analysis on Wastewater Density

Row	Wastewater Density (B)	Cost (USD)	Pollutant Emission (PPM)
1	210	11,036,985	12,963
2	400	11,454,255	15,342
3	2,000	121,004,635	115,241
4	4,000	229,305,421	186,352

Table 12. Sensitivity Analysis on the Number of Candidate Wastewater Locations

Row	Distance Between Two Nodes (dij)	Cost (USD)	Pollutant Emission (PPM)
1	6	10,998,524	12,052
2	8	11,031,524	13,635
3	25	154,215,259	98,254
4	50	197,487,754	123,635

Table 13. Sensitivity Analysis on the Amount of Wastewater at the Specified Location

Row	Amount of Wastewater at the Specified Location (Si)	Cost (USD)	Pollutant Emission (PPM)
1	5	11,563,598	11,896
2	10	12,541,457	12,086
3	50	16,052,418	101,256
4	100	20,053,625	153,628

4. Discussion and Conclusion

This paper presents an intelligent model for the planning and investment of urban infrastructure for the collection of surface wastewater and its impact on pollutant emissions. Based on this, after reviewing the literature and presenting the research background, a bi-objective model was proposed that includes investment costs and pollutant emissions. In this study, after collecting data for modeling and considering the assumptions of the problem, we were able to determine the reduction in costs for surface wastewater collection and the decrease in pollutant emissions to the environment by identifying the optimal routes for wastewater collection vehicles. Additionally, due to the NP-Hard nature of the problem, a multi-objective Grey Wolf Optimization (MOGWO) algorithm was used to minimize both objectives under various scenarios and conditions. The results showed that the proposed model can effectively address the problem from different perspectives, including increasing the number of wastewater collection vehicles, the number of candidate collection locations, the accumulation of wastewater at the locations, the number of vehicles in the network, and the distances between candidate wastewater locations, ensuring that all accumulated wastewater at candidate locations is collected by the network's vehicles. Furthermore, sensitivity analysis on the main model parameters revealed that among all the parameters, the cost of vehicle transportation per unit of distance traveled, the penalty for using vehicles, and the revenue per kilogram of treated wastewater collected have the most significant impact on the objective functions.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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