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RESEARCH ARTICLE

A Multi-Objective Multi-Period Low-Carbon Location-Routing Problem: Improved NSGA-II Approach

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ABSTRACT In light of the escalating global concerns surrounding climate change, the significance of sustainable development in the realm of logistics cannot be overstated. This study undertakes the imperative task of devising strategies aimed at mitigating carbon emissions, reducing logistics costs, minimizing transportation time, and enhancing customer satisfaction. The research delves into the intricacies of an optimization model tailored for a specific iteration of the Location-Routing Problem (LRP), namely the Multi-Objective Multi-Period Low-Carbon Location-Routing Problem (MMLCLRP). This variant of the LRP takes into meticulous consideration several crucial parameters, such as the overall logistics cost, the arrival times of demand points, and carbon emissions. These factors are pivotal in determining both the optimal location for depots and the programming of routes within a multi-period planning horizon. The proposed model guarantees the long-term sustainability of logistics operations while flexibly adapting location routing decisions for each period in response to evolving market demands. To tackle the inherent complexity of this problem, an improved version of the Non-dominated Sorting Genetic Algorithm (NSGA-II) was employed. This approach integrates a pioneering similarity distance metric to quantify the resemblance between potential solutions. Additionally, a crowding clustering strategy was implemented to enhance the diversity within the NSGA-II. Empirical results illustrate the capability of the proposed optimization model in effectively harmonizing various objectives, encompassing economic, efficiency, and environmental aspects within the logistics domain. Additionally, the enhanced algorithm exhibits notable advantages in addressing the complexities inherent in the optimization model.

INDEX TERMS Improved NSGA-II, crowding clustering strategy, low-carbon location-routing problem, multi-objective optimization, multi-period.

I. INTRODUCTION

The Location-Routing Problem (LRP) holds significant practical importance in the logistics domain. Under the traditional circumstance of LRP, the decision makers determine the location of depots and the format of the distribution routes utilizing customer records [1], [2]. Supply chain management encounters various challenges, and among them, LRP stands out as a critical issue, particularly for logistics and e-commerce firms. It is important for these companies to select appropriate depot locations and allocate route programming over different periods for the location of the customers, which is usually not static. Considering the uncertain market environment, LRP is revealed as a weighty decision for logistics management to dynamically optimize depot locations and route programming under dynamic customer locations over several periods.

The increase in emissions of different pollutants is responsible for the occurrence of global warming, while gas emissions from freight transportation are generally recognized as

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one of the major factors of global climate change [3], [4]. In 2020, approximately 7.7 Gt CO_2, equivalent to around 8% of global greenhouse gas emissions, was attributed to freight transportation, but the figure increases to 11% when warehouses and ports are taken into consideration.[1] According to the EU greenhouse gas inventory report 2021 [5], approximately 27% of the EU's overall greenhouse gas emissions originated from road transportation. The economic expansions in Asia, Africa, and Latin America are likely to triple the need for freight services by the year 2050, resulting in a twofold increase in emissions [6]. There is thus a growing emergence for logistics management to pay regard to low-carbon logistics.

With the purpose of balancing economy, efficiency, and environmental issues of the logistics, an optimization model is proposed for a Multi-Objective Multi-Period Low-Carbon Location-Routing Problem (MMLCLRP), which features three objectives: the total cost, the service satisfaction, the carbon emissions. Further, in order to solve the Multi-Objective Problem (MOP), which requires optimizing several objectives simultaneously despite their inherent contradictions, Multi-Objective Evolutionary Algorithms (MOEAs) are utilized to discover a group of non-dominated solutions [7], [8].

During a planning horizon, the customers of each period stochastically evolve in the territory. Some customers left the territory during the previous period, and some new customers entered the territory. Nevertheless, prior to each period, the details regarding the number and whereabouts of customers are already known. Multiple potential depots are strategically positioned, and the primary challenges lie in determining the depot locations and adapting route scheduling over multiple periods.

The MMLCLRP problem can be depicted by an undirected graph $G = (V, E, P)$, where P indicates the group of all periods in the planning horizon, $V = D \cup V^1 \cup \cdots \cup V^t \cdots \cup V^T$ is the set of vertex, and D denotes the potential depot set, which is located at fixed positions. V^t is the customer set at period t ($t \in P$). The matrix E is symmetrical and represents the Euclidean distance, which is also equal to the distance traveled. The issue involves identifying multiple depots that are serviced in each period and programming routes for customers who belong to these depots in such a way that: (1) the depots' supply is sufficient; (2) a single vehicle with a carrying capacity of Q visits each customer only once; (3) when the vehicle goes through a section of road, it accumulates a service time denoted by s, and (4) the model's objectives including minimizing the total cost, minimizing all arrived time for demand points service, minimize the total emission of CO_2 of the transportation.

This article makes the following key contributions:

1) The focus of this study is to introduce an optimization model that addresses a multi-objective multi-period low-carbon problem that considers dynamic customer locations and CO_2 emissions.

2) A novel similarity distance is defined to measure the similarity between solutions.

3) An enhanced co-evolutionary algorithm built upon the NSGA-II is introduced in which a crowding clustering based on density and connectivity is applied to improve the performance of the algorithm.

The structure of the remaining sections of this article is as follows: A comprehensive review of related works is provided in section II. Section III provides a detailed explanation of the problem description and outlines the mathematical model. The improved NSGA-II algorithm is described in Section IV. The numerical experiments are conducted to validate the proposed works in Section V. Finally, In Section VI, the conclusions that have been reached from the study are presented.

II. LITERATURE REVIEW

A. THE LOCATION-ROUTING PROBLEM

The Location-Routing Problem (LRP) is a problem in combinatorial optimization that involves identifying the most optimal sites to position depots, as well as the most efficient routes for vehicles to take in serving customers. Over the past few years, there has been a significant increase in the search for efficient and effective algorithms designed to solve the LRP. Schneider and Drexl [9] treated the standard location-routing problem as a single-objective, static, deterministic, location-routing problem. There is a rich literature on the standard Location-Routing Problem (LRP). To reduce the level of complexity associated with various constraints and to minimize operational costs, Granada et al. [10] have proposed a mixed-integer programming model for the open location-routing problem. Lopes et al. [11] use a heuristic genetic algorithm that utilizes both variable neighborhood descent and biased random key techniques to minimize the total cost involved in the many-to-many hub location-routing problem. Fazayeli et al. [12] introduced an integer linear programming model for a location-routing problem that is based on a multimodal transportation network. The objective function is designed to minimize all associated costs, including those related to location-routing and multimodal transportation. Chen et al. [13] investigated the Location-Routing Problem With Full Truckloads (LRPFT) and developed a mathematical model that incorporates dual objectives for the many-to-many raw material supply network. A novel method that combines a multi-objective algorithm and heuristics has been introduced, along with a chromosome presentation built upon natural numbers. Rabbani et al. [14] have proposed an approach aimed at solving a mathematical model that incorporates multiple decisions related to industrial hazardous waste management. The approach takes into account location decisions, vehicle routing decisions, and inventory decisions. Given the uncertain nature of the waste management system, the problem is described as a multi-objective stochastic (MINLP) model, ensuring reliability. In order to address this

[1] IEA (2022), Transport, IEA, Paris https://www.iea.org/reports/transport. Accessed Sep 2022

problem, a new Sim heuristic approach has been developed by combining NSGA-II and Monte Carlo simulation.

The research on the Location-Routing Problem (LRP) has yielded fruitful results across various domains. However, there is not sufficient consideration of the comprehensive integration of sustainability metrics, including carbon emissions reduction, into the optimization models. Incorporating environmental considerations, such as carbon footprint reduction, adds complexity to the optimization models.

B. THE MULTI-OBJECTIVE LOCATION-ROUTING PROBLEM

Most of the above single-objective location-routing problems pursue economic indicators. In order to achieve the balance of economic, environmental, and societal issues of logistics, multi-objective location-routing models are getting more and more attention [15]. Samanlioglu [16] proposed a multi-objective location-routing model specialized for industrial hazardous waste management. Three criteria are incorporated in the model: minimizing the total cost, transportation risk, and site risk. Rabbani et al. [17] leveraged an NSGA-II along with a clustering method to solve a bi-objective location-routing problem, which consists of an economic objective and societal objective in the case of waste collection operations. Karimi and Setak [18] presented a hub location-routing problem that integrates flow shipment scheduling. The objective was to minimize overall costs while maximizing the volume of flow delivered within a predefined time frame. Bozorgi-Amiri and Khorsi [19] introduce a dynamic multi-objective location-routing model for relief logistics in the scenario that the needs of the affected areas, the total cost, and transportation time are assumed to be uncertain. Three objectives, the total travel time, the total post- and pre- disaster costs, and the maximum number of shortages are incorporated to decide the optimal number, the location, the optimal routes, and other relevant factors. Wang et al. [20] proposed a bi-objective model to address two-echelon location-routing problems regarding costs and customer satisfaction simultaneously. To simultaneously address the tasks of locating logistics facilities, optimizing the vehicle routing network, and allocating customers, a modified version of NSGA-II was introduced. The genetic operator utilized in this modified approach is the partial-mapped crossover.

Many stochastic location-routing problems are regarded as multi-period problems when taking into account the dynamic feature scenarios of a planning horizon [21], [22]. In many studies, the location of depots is set in the first period, and the routes are optimized in each period depending on the changing parameters [19], [21]. In a long planning horizon, if the depots are located first without considering the future route, low-quality solutions are acquired. There are few cases concerned with multi-objective programming with changing circumstances. Hassan-Pour et al. [23] presented a location-routing problem to minimize transportation costs and maximize customer delivery probability, where dynamic changes in facility and route availability were considered, and the problem was addressed using a mathematical algorithm for facility location and a hybridized simulated annealing algorithm with genetic operators for vehicle routing. Long et al. [24] proposed a multi-objective multi-period robust optimization model for the location-routing problem in the context of emergency logistics for epidemic relief distribution with an improved heuristic algorithm called PICEA-g-td implemented to solve the proposed optimization model. An enhanced genetic algorithm utilizing dynamic programming was suggested by Wang and Zu-Jun [25] for the multi-objective multi-period location-routing problem. Saffarian et al. [26] proposed a multi-objective location-routing model for relief chain management under uncertainty, considering three conflicting objectives: minimizing total costs, minimizing total delivery times, and maximizing fairness in distribution of commodities. However, due to the weight method treating the multi-objective model as a single-objective model, additional specifics regarding the problem exposed by the Pareto solution are not accessible.

The Location-Routing Problem (LRP) holds a fundamental position in logistics research. In contemporary studies, the LRP is often approached with consideration of multiple objective functions. Nonetheless, the majority of algorithms currently employed for addressing this multi-objective problem resort to conventional multi-objective techniques, which may result in suboptimal solutions. Therefore, it is necessary to develop algorithms that are tailored to the unique characteristics of location decision-making and path planning to achieve improved solution outcomes.

C. THE LOW-CARBON LOCATION-ROUTING PROBLEM

The Low-Carbon Location-Routing Problem (LCLRP) is a variant version of the Location-Routing Problem (LRP) that seeks to minimize both total costs and carbon emissions linked to the design of the supply chain network [13], [27], [28], [29]. It involves fuel consumption, vehicles, fixed costs of depots, and driver salaries [30], as well as time-dependent factors such as carbon emissions [31]. Martínezsalazar et al. [32] addressed a transportation location routing problem aimed at minimizing distribution costs while simultaneously achieving workload balance among drivers. A scatter tabu search procedure for the NSGA-II and non-linear multi-objective optimization were implemented to address the problem. Leng et al. [27] propose a multi-objective regional low-carbon LRP with three objectives: total costs, service duration, and client waiting time. A multi-objective hyper-heuristic approach consisting of both high-level and low-level heuristics was formulated by them. Leng et al. [33] explored a quantum-based approach combined with acceptance criteria for a regional low-carbon LRP with bi-objective. In order to improve clients' satisfaction with the logistics service and reduce cost, carbon emissions, and service cycles, Fatemeh et al. [34] proposed a bi-objective model to settle this problem, and a hybrid meta-heuristic algorithm combined genetic algorithms and simulated annealing algorithms for model optimization. To achieve economic and environmental optimization with the objective of minimizing total costs, including carbon emission costs, in the cold chain logistics low-carbon LRP model, Wang et al. [35] developed a hybrid genetic algorithm. A bi-objective mathematical programming model was introduced by Wang et al. [36] for optimizing the green logistics location-routing problem with eco-packages, which involves solving a two-echelon location-routing problem as well as the pickup and delivery problem with time windows. In order to address this problem, two metaheuristic algorithms, namely MOGWO and NSGA-II, were employed. A logistics system optimization model was presented by Biuki et al. [37] that incorporates location, routing, and inventory control planning, with a focus on minimizing costs and environmental impact from greenhouse gas emissions while maximizing job creation, taking into account economic, ecological, and social factors. A two-phase solution strategy was proposed to solve the problem, which involves supplier selection using a PROMETHEE method, followed by the use of two hybrid metaheuristics. Faraji et al. [34] devised a metaheuristic algorithm that merges the Genetic Algorithm (GA) with Simulated Annealing (SA) to address a green routing issue with multiple depots, hard and soft time windows, heterogeneous vehicles, multiple periods, and products. Tavana et al. [38] presented a bi-objective mixed-integer linear programming model for solving the location-inventory-routing problems in green supply chains with low-carbon emissions under uncertainty with consideration to supplier selection, order allocation, distribution center location, vehicle routing, inventory control, and backorder shortage.

Hence, reducing carbon emissions has emerged as a significant focus of contemporary logistics research in the realm of environmental protection. Nevertheless, a predominant proportion of studies equate carbon emissions solely with the distance covered by the vehicle. Nonetheless, it is noteworthy that carbon emissions are also contingent upon several additional factors, such as the vehicle's load and speed, which are not born in mind in many studies.

D. OPTIMIZATION ALGORITHM

As discussed above, the location-routing problem can typically be addressed using an evolution strategy algorithm, which is a classic NP-hard problem. However, when considering the Multi-objective location-routing problem, which is a variation of the standard LRP, the current state of multi-objective optimization research faces significant challenges. Over the past few decades, to obtain Pareto solutions for multi-objective problems (MOPs), a variety of Multi-Objective Evolutionary Algorithms (MOEAs) have been suggested [39]. Some well-known examples of classical MOEAs including NSGA-II [40], [41], Multi-Objective Particle Swarm Optimization (MOPSO) [41], [42], [43], MOSA et al. [44] and Multi-Objective Evolutionary Algorithm by Decomposition (MOEA/D) [45] are proved to offer advantages in gaining Pareto solutions.

The NSGA-II algorithm has been demonstrated to be a highly effective method for addressing multi-objective problems [46], [47], [48]. Nevertheless, there remains scope for enhancing the algorithm concerning varied mission-specified multi-objective problems [49]. In the context of location routing, a novel mathematical model has been proposed to address the waste collection problem based on specific assumptions [17]. It features two stages of collection and transfer and the use of vehicles with multiple compartments for diverse types of waste. The hybrid NSGA-II metaheuristic algorithm is employed to generate optimal solutions, which is augmented by clustering techniques to enhance the starting population. For stochastic combinatorial optimization, Rabbani et al. [14] have developed a new heuristic method that integrates NSGA-II and Monte Carlo simulation. A bi-objective mathematical programming model is proposed for open location-routing and two-echelon close problems to minimize costs and CO_2 emissions [50]. To tackle the problems, two metaheuristic algorithms, MOGWO and NSGA-II, are employed. An enhanced version of the NSGA-II is introduced to address a dynamic multi-objective location model with three objectives problem [51], which incorporates a tabu search algorithm into the elitism strategy. By combining the strengths of both local and global search methods, the evolutionary optimization algorithm proposed is expected to improve local search capability and retain global search ability. These enhancements are anticipated to increase the global optimal solution convergence and enhance solution accuracy.

However, most algorithms utilizing NSGA-II or its variants have primarily considered only two objectives. The inclusion of additional objectives tends to compromise algorithmic convergence performance due to conflicting goals. Simultaneously, the majority of studies have relied on generic approaches to address specific problems without delineating the similarity between solutions based on problem characteristics. This deficiency hinders the ability to enhance algorithm efficiency by better exploiting the information embedded within the relationships among solutions.

Inspired by the previous works, we improve the NSGA-II algorithm by combining an adaptive crowding clustering strategy to balance diversity and convergence to improve solving ability. Furthermore, by considering the similarity of the solution, this study provides a novel similarity distance to overcome fast convergence to a narrow solution of the multi-objective algorithm. As per our comprehension of the existing literature, the modification is novel.

III. MATHEMATICAL MODEL

A. THE PROBLEM DESCRIPTION

The model of the MMLCLRP can be described as a graph $G^t = (V^t, E^t)$ Where $t = 1, 2, \ldots, T$ is the planning period set. V^t is a vertex set and contains two subsets:

$M = \{1, 2, \ldots, m\}$ represents the set of eligible depots with a fixed cost F_i And adequate capacity. Besides, those candidate depots are fixed during the planning horizon. $N^t = \{m+1, m+2, \ldots, m+n^t\}$ is the set of demand points that is random in number and position in each period. In the context of MMLRP, the details regarding demand points, including their positions, the number of points $|N^t|$ the corresponding service time $s_j, j\in N^t$ are available at the outset of each period. Nonetheless, the actual customer demands are only disclosed once the initial location-routing decision has been made. $E = \{(g, h) : g, h\in V^t, g \neq h\}$ is the vehicle route set, $D = (d_{gh})$ is distance matrix which satisfies the triangle inequality. $K = \{1, 2, \ldots, k\}$ is the set of identical vehicles whose vehicles move with speed v. F_v is use-cost of a vehicle, c indicates the cost of each unit length of route for those vehicles, Q represents the loading capacity.

The key objective of this problem is to select established depots from a pool of candidate depots and devise the routing strategy for vehicles from the chosen depots to the demand points while taking into account the vehicle capacity. In addition, the depot location and the demand point allocation are adjusted based on the distribution of customers except for the first period. Notably, when addressing multi-period problem solving, it is crucial to consider the conditions from the previous period during each subsequent period. Decision-making regarding the location-routing problem significantly varies for each individual period.

The three objectives are incorporated in the MMLCLRP: (1) minimization of the total cost, which includes the establishment costs of depots, fixed vehicle expenses, and route travel costs; (2) minimization of the total traveling time for all of the demand points; (3) minimization the total emission of CO_2.

Objective 1 is to strive for economic value. Objective 2 is to seek effectiveness. Arriving earlier with vehicles allows for quicker assistance to be provided at the demand points. Objective 3 is to pursue the sustainability of the environment, which is an important goal of modern logistics.

B. THE OBJECTIVES OF THE MMLCLRP

We first propose the variables as follows:

$$y_i(t) = \begin{cases} 1, & \text{if depot i is chosen to usein period t;} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$x_{ij}(t) = \begin{cases} 1, & \text{if depot i is chosen in period t to} \\ & \quad \text{provide service for demand point j;} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$\mu_{ik}(t) = \begin{cases} 1, & \text{if vehicle k is assigned to} \\ & \quad \text{depot i in period t;} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$u_{jk}(t) = \begin{cases} 1, & \text{if demand point j is supplied} \\ & \quad \text{by vehiclek in period t;} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$\delta_{ghk}(t) = \begin{cases} 1, & \text{if vehicle k travels from vertex g} \\ & \quad \text{to vertex h during period t;} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The MMLCLRP has three fundamental objectives:

(1) The first objective is to minimize overall expenses and align rental expenses for TRCs and transport expenses within the planning horizon (the rental costs, the transportation costs, and the fixed cost of vehicles):

$$\min Z_1 = \sum_{t\in T}\sum_{i\in M} F_i y_i(t) + \sum_{t\in T}\sum_{i\in M}\sum_{k\in K} F_v \mu_{ik}(t) + \sum_{t\in T}\sum_{g\in(M\cup N^t)}\sum_{h\in(M\cup N^t)}\sum_{k\in K} c d_{gh}\delta_{ghk}(t) \tag{6}$$

(2) The second objective is to dispatch vehicles at the earliest possible time to demand depots in order to optimize the provision of aid to affected populations. We focus on the sum of time to each vehicle to ensure the time-effectiveness. $T_{jk}(t)$ represents the arrival time of demand point j served by vehicle k in period t.

$$\min Z_2 = \sum_{t\in T}\sum_{j\in N^t}\sum_{k\in K} T_{jk}(t) \tag{7}$$

(3) The third objective is the emission of CO_2: This study focuses on CO_2 emissions from transport to ensure the sustainability of the location-routing problem. The vehicle's fuel consumption is direct related with CO2 emissions. Burning fuels in engines produces carbon dioxide as a byproduct, with the carbon content in the fuel influencing emission levels. Therefore, we model the fuel consumption of vehicles to calculate the carbon dioxide emissions in this problem.

$$\min Z_3 = e\sum_{t\in T}\sum_{g\in(M\cup N^t)}\sum_{h\in(M\cup N^t)}\sum_{k\in K} \times\left(\rho^0 + \frac{\rho^* - \rho^0}{Q} q^t_{kgh}\right) d_{gh}\delta_{ghk}(t) \tag{8}$$

where q^t_{kgh} is the carrying amount of the vehicle from point g to point h at period t. The e is the CO_2 emissions originated by the vehicle's fuel consumption per unit. The ρ^0 and the ρ^* are the fuel consumption for the unit distance of an empty vehicle and the fuel consumption for the unit distance of a fully-loaded vehicle, respectively.

C. CONSTRAINTS OF THE MMLCLRP

$$y_i(t) \geq x_{ij}(t), \forall i \in M, j \in M, t \in T \tag{9}$$

$$y_i(t) \geq \mu_{ik}(t), \forall i \in M, k \in K, t \in T \tag{10}$$

$$\sum_{k\in K} \mu_{ik}(t) + \sum_{h\in(M\cup N^t)} \delta_{jhk}(t) - x_{ij}(t)$$

$$\leq 1,\ \forall i \in M, k \in K, t \in T \tag{11}$$

$$\mu_{ik}(t) \geq \sum_{j \in N^t} \delta_{ijk}(t), \forall i \in M, k \in K, t \in T \tag{12}$$

$$\sum_{i \in M}\sum_{j \in N^t} \delta_{ijk}(t) \leq 1, \forall k \in K, t \in T \tag{13}$$

$$\sum_{g \in (M \cup N^t)} \delta_{gjk}(t) = 1, \forall j \in N^t, k \in K, t \in T \tag{14}$$

$$\sum_{g \in (M \cup N^t)} \delta_{igk}(t) - \sum_{h \in (M \cup N^t)} \delta_{hik}(t) = 0, \forall i \in M, k \in K, t \in T \tag{15}$$

$$\sum_{g \in (M \cup N^t)} \delta_{gjk}(t) - \sum_{h \in (M \cup N^t)} \delta_{jhk}(t) = 0,\ \forall j \in N^t, k \in K, t \in T \tag{16}$$

$$T_{jk}(t) = T_{ik}(t) + s_i + \frac{d_{ij}}{v}\delta_{ijk}(t),\ \forall i \in M \cup N^t, j \in N^t, k \in K, t \in T \tag{17}$$

$$y_i(t) \in (0,1), \forall i \in M, t \in T \tag{18}$$

$$x_{ij}(t) \in (0,1), \forall i \in M, j \in N^t, t \in T \tag{19}$$

$$\mu_{ik}(t) \in (0,1), \forall i \in M, k \in K, t \in T \tag{20}$$

$$\delta_{ghk}(t) \in (0,1), \forall g \in (M \cup N^t),\ h \in (M \cup N^t), k \in K, t \in T \tag{21}$$

Constraints (9) and (10) serve to limit vehicle allocation and demand service provision to the selected depots. Constraint (11) mandates that vehicle k can only access demand point j if they are assigned to depot i in period t. Constraints (12) and (13) dictate that each route serviced by vehicle k must start at a single depot. Constraint (14) specifies that each demand point can only receive service from a single route in period t. Constraint (15) demands that each vehicle returns to the departure depot per period. Constraint (16) guarantees the continuity of each route. Formula (17) calculates the time required for vehicle k to reach demand point j in period t. Constraints (18) - (21) ensure that decision variables are non-negative and binary integers.

IV. AN IMPROVED NSGA-II ALGORITHM USING A CROWDING CLUSTERING STRATEGY

NSGA-II has become a widely adopted optimization algorithm, particularly in the field of multi-objective optimization. Renowned for its non-dominated sorting and crowding distance mechanisms, NSGA-II efficiently categorizes solutions into Pareto fronts, maintaining a diverse and well-distributed set of trade-off solutions. The inclusion of elitism ensures the preservation of high-quality solutions across generations, preventing premature convergence. NSGA-II is also adept at handling optimization problems with constraints, adding to its versatility. Researchers favor NSGA-II due to its effectiveness in finding a range of Pareto optimal solutions, its straightforward implementation, and its ability to address real-world problems, making it a popular choice in optimization studies and applications.

To efficiently get Pareto optimal solutions of the MML-CLRP (refer to Fig.1), we proposed an improved NSGA-II combining a clustering strategy, which performs well on many-objective problems [16], [52]. In order to enhance the quality and variety of the solutions, a strategy called crowding clustering is suggested, which has been incorporated into the evolutionary algorithm framework named NSGA-II-cc. The NSGA-II-cc algorithm, designed to enhance the overall solutions, introduces a subprocedure with a crowding clustering strategy that calculates distances between solutions to improve diversity and superiority. This modification is made without a substantial increase in computational complexity, as the crowding clustering strategy has a complexity of O(n), resulting in an overall algorithmic complexity of O(n^3) for NSGA-II-cc.

A. FRAMEWORK OF NSGA-II-CC

The NSGA-II-cc exists as an evolutionary algorithm, which is applied to solve the problem with multiple conflicting objectives. The NSGA-II-cc's general framework consists of encoding the population, crossover, and mutation operators, and selection operators based on solution fitness.

1) ENCODING SCHEME

Bulleted in MMLCLRP, a launched depot is allocated several customers, which are contiguity and around the depot. A solution is formed by a sequence of status numbers for the potential depots and an allocation of customers for the depots. The chromosome of the solutions is encoded in Fig. 2.

In Fig. 2, fifteen customers code from 1 to 15, and four potential depots in the triangle are distributed in the territory. Depots 1, 2, and 4 are opened. Each opened depot is arranged by several vehicles to service customers (such as depot 1) has two routes, and route 1 of depot 1 services customers 1, 2, 5, and 6.

The solution of the MMLRP is depicted by a natural number permutation encoding, which aids in identifying the potential depots to open and route planning for the demand points. In each solution Ch_g^τ at the period t, the depot selection, vehicle allocation, and demand point route planning are represented by three distinct vectors. $\tau \in NG$ is the number of generations and $g = 1, 2, \ldots, NP$. NP is the number of solutions in the population. The chromosome Ch_g^τ is encoded

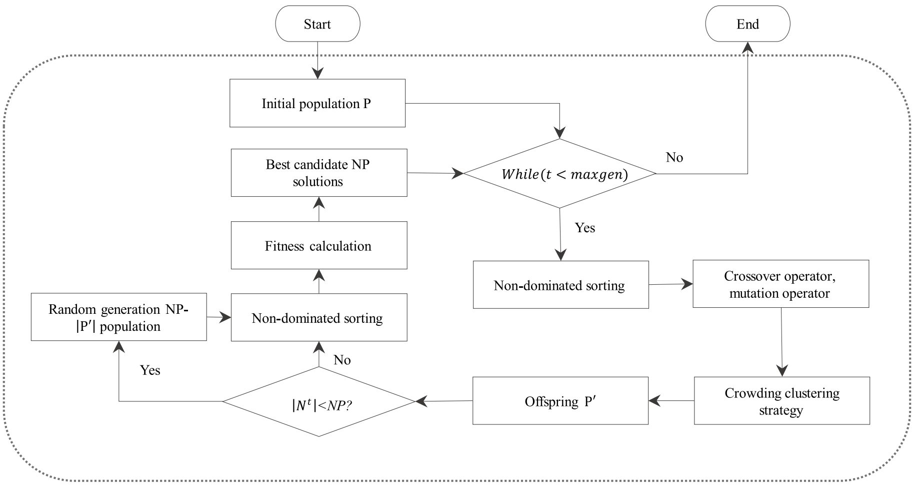

FIGURE 1. NSGA-II-cc framework.

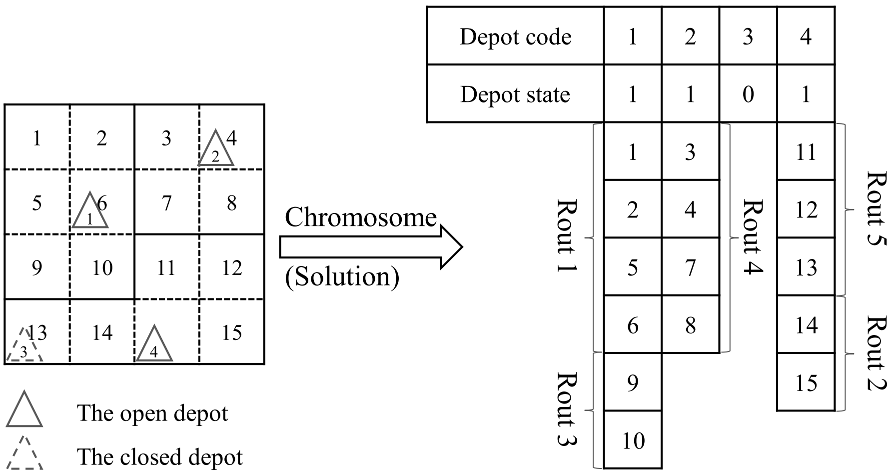

FIGURE 2. Example of solution.

as follows.

$$\mathrm{Ch}_g^\tau = \left\{ \begin{array}{c} \left(Ch_{g11}^{\tau 1}, Ch_{g12}^{\tau 1}, \ldots, Ch_{g1K}^{\tau 1}\right), \\ \left(Ch_{g21}^{\tau 1}, Ch_{g22}^{\tau 1}, \ldots, Ch_{g2K}^{\tau 1}\right), \\ \left(Ch_{g31}^{\tau 1}, Ch_{g32}^{\tau 1}, \ldots, Ch_{g3N^1}^{\tau 1}\right) \\ \vdots \\ \left(Ch_{g11}^{\tau t}, Ch_{g12}^{\tau t}, \ldots, Ch_{g1K}^{\tau t}\right), \\ \left(Ch_{g21}^{\tau t}, Ch_{g22}^{\tau t}, \ldots, Ch_{g2K}^{\tau t}\right), \\ \left(Ch_{g31}^{\tau t}, Ch_{g32}^{\tau t}, \ldots, Ch_{g3N^t}^{\tau t}\right) \\ \vdots \\ \left(Ch_{g11}^{\tau T}, Ch_{g12}^{\tau T}, \ldots, Ch_{g1K}^{\tau T}\right), \\ \left(Ch_{g21}^{\tau T}, Ch_{g22}^{\tau T}, \ldots, Ch_{g2K}^{\tau T}\right), \\ \left(Ch_{g31}^{\tau T}, Ch_{g32}^{\tau T}, \ldots, Ch_{g3N^T}^{\tau T}\right) \end{array} \right\} \tag{22}$$

The first vector $Ch_{g1}^{\tau t}$ is a permutation of K vehicles that allocates vehicles for candidate depots. The vector $Ch_{g2}^{\tau t}$ is an integer vector with K-dimension distributed from 0, 1 to |M| that determines which candidate depots are opened. A permutation of $\left|N^t\right|$ demand points $Ch_{g3}^{\tau t}$ determines routing sequences within each route for demand points. The assignments must comply with the loading capacity Q.

From the result of Fig. 3, as same as in Fig. 2, depots 1, 2, and 4 are open; vehicle1 and 3 start from depot 1; route 1 (Vehicle 1) caters to demand points 1, 2, 5, and 6 while route 3 attends to demand points 9 and 10 separately. Vehicle 4 departs from depot 2 and tends to demand points 3, 4, 7, and 8 prior to returning to depot 2. Due to the reality that three vectors of the chromosome differ, genetic operations of the improved NSGA-II algorithm respectively occur in $U_{g1}^{\tau t}$, $U_{g2}^{\tau t}$ and $U_{g3}^{\tau t}$.

2) CROSSOVER OPERATORS

In the given solution, the crossover operations are restricted to occur within a single period of the chromosome. The line vector $U_g^{\tau t}$ represents a particular location-routing planning period within the complete planning horizon, and it is chosen randomly for the crossover operation. The representation of

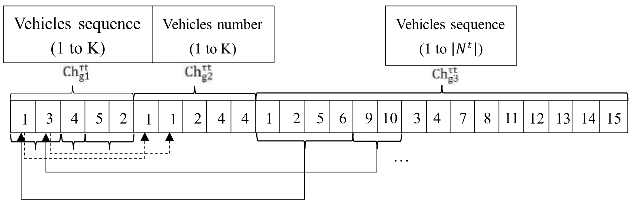

FIGURE 3. Encoding in the improved NSGA-II algorithm.

$U_g^{\tau t}$ is given by Eq. 42 as follows:

$$\mathrm{U}_{\mathrm{g}}^{\tau t} = \left\{ \begin{array}{l} \underbrace{\left(\mathrm{U}_{\mathrm{g}11}^{\tau t}, \mathrm{U}_{\mathrm{g}12}^{\tau t}, \ldots, \mathrm{U}_{\mathrm{g}1\mathrm{K}}^{\tau t}\right)}_{\mathrm{U}_{\mathrm{g}1}^{\tau t}}, \\ \underbrace{\left(\mathrm{U}_{\mathrm{g}21}^{\tau t}, \mathrm{U}_{\mathrm{g}22}^{\tau t}, \ldots, \mathrm{U}_{\mathrm{g}2\mathrm{K}}^{\tau t}\right)}_{\mathrm{U}_{\mathrm{g}2}^{\tau t}}, \\ \underbrace{\left(\mathrm{U}_{\mathrm{g}31}^{\tau t}, \mathrm{U}_{\mathrm{g}32}^{\tau t}, \ldots, \mathrm{U}_{\mathrm{g}3\mathrm{N}^t}^{\tau t}\right)}_{\mathrm{U}_{\mathrm{g}3}^{\tau t}} \end{array} \right\} \tag{23}$$

For the sub-vector $U_{g1}^{\tau t} U_{g2}^{\tau t}$ and $U_{g3}^{\tau t}$, offspring are generated using a two-point crossover as described below.

Firstly, two sub-vectors $U_{g1}^{\tau t}$ and $U_{g'1}^{\tau t}$ are picked by chance from the parent chromosome $U_g^{\tau t}$ and chromosome $U_{g'}^{\tau t}$ separately. Next, two crossover points are chosen haphazardly within vectors $U_{g1}^{\tau t}$ and $U_{g'1}^{\tau t}$.

$$U_{g1}^{\tau t} = [1\,2\,3\ |4\,5\,6\,7|\,8\,9\,10] \tag{24}$$
$$U_{g'1}^{\tau t} = [5\,1\,7\ |4\,2\,8\,10|\ 9\,3\,6] \tag{25}$$

Secondly, $U_{g1}^{\tau t}$ and $U_{g'1}^{\tau t}$ retain the numbers prior to the earliest crossover point and swap the numbers among the crossover points with one another, while ignoring the numbers beyond the second crossover point during this phase.

$$U_{g1}^{\tau t} = [\,1\,2\,3\ |4\,2\,8\,10|\,*\,**] \tag{26}$$
$$U_{g'1}^{\tau t} = [\,5\,1\,7\ |4\,5\,6\,7|\,*\,**] \tag{27}$$

Thirdly, if the quantity appears in the crossover vector, any amount beyond the initial crossover point will be removed.

$$U_{g1}^{\tau t} = [1\,3\ |4\,2\,8\,10|\,*\,*\,*\,*] \tag{28}$$
$$U_{g'1}^{\tau t} = [\,1\,|4\,5\,6\,7|\,*\,*\,*\,**] \tag{29}$$

Finally, after the second crossover point, the numbers that do not appear and the numbers behind the first crossover point in the parent chromosome will be retained based on the sequence.

$$U_{g'}^{\tau t} = [1\,3\ |4\,2\,8\,10|\ 5\,6\,7\,9] \tag{30}$$
$$U_{g'1}^{\tau t} = [1\,|4\,5\,6\,7|\,2\,8\,10\,9\,3] \tag{31}$$

3) MUTATION OPERATORS

After performing the crossover operations, mutation operations are applied to a randomly selected chromosome's line vector $\mathrm{V}_{\mathrm{g}}^{\tau t}$, which represents a section of location-routing planning throughout the planning horizon.

$$V_g^{\tau t} = \left\{ \begin{array}{l} \underbrace{\left(V_{g11}^{\tau t}, V_{g12}^{\tau t}, \ldots, V_{g1K}^{\tau t}\right)}_{V_{g1}^{\tau t}}, \\ \underbrace{\left(V_{g21}^{\tau t}, V_{g22}^{\tau t}, \ldots, V_{g2K}^{\tau t}\right)}_{V_{g2}^{\tau t}}, \\ \underbrace{\left(V_{g31}^{\tau t}, V_{g32}^{\tau t}, \ldots, V_{g3N^t}^{\tau t}\right)}_{V_{g3}^{\tau t}} \end{array} \right\} \tag{32}$$

A reverse sequence mutation is employed to generate offspring from sub-vectors of chromosomes. The mutation of $V_{g1}^{\tau t}$ is carried out as follows:

Firstly, two inversion points are haphazardly selected inside a sub-vector $V_{g1}^{\tau t}$.

$$V_{g1}^{\tau t} = [1\,2\,3\ |4\,5\,6\,7|\ 8\,9\,10\,] \tag{33}$$

Secondly, the inversion of the numbers between the two points of inversion results in the generation of offspring.

$$V_{g1}^{\tau t} = [\,1\,2\,3\ |7\,6\,5\,4|\ 8\,9\,10\,] \tag{34}$$

B. A CROWDING CLUSTERING STRATEGY FOR MULTI-OBJECTIVE NSGA-II-CC PROCEDURE

1) THE DEFINITION OF SIMILARITY DISTANCE

For multi-objective optimization, non-dominated objective vectors become exceptionally large with the increasing number of objectives. Fast convergence to a narrow solution space affects the multi-objective algorithm's efficiency [53]. It is important for a multi-objective optimization algorithm to keep the variety of solutions during the procedure of calculation. The crowding clustering strategy, as a niching technique, was widely used to improve the diversity of evolutionary algorithms [54], [55]. The crowding clustering algorithm is not influenced by parameters, and no prior knowledge of the objective function is required [56].

A similar distance is designed to assess the similarity among the solutions of the MMLRP. The similarity of solutions can be considered as the probability that two data belong to the same class in the clustering strategy. To resolve the quantification of the similarity between the solutions, we proposed a similarity calculation method considering the structure of the solutions, which are composed of depot selection and sequence of demand points on the routes. The similarity is obtained by averaging the similarity of each dimension of the solutions.

(1). The similarity of the depot location

Considering the depot's location of the solutions, the location similarity between the solution S^t and solution S'^t in the $l-th$ dimension is measured by the open state of the depot l. The similarity of the depot location is formulated as follows,

$$S_1\left(S^t, S'^t\right) = \sum_{l=1}^{|M|} \varphi_1\left(\alpha_{il}, \alpha_{jl}\right) \tag{35}$$

where α_{il} is the value of the set of open states α_i on the l $(l \in M)$ dimension, and α_{jl} is the value of the set of open states α_j on the l dimension. The similarity of different depot's positions can be transformed as follows,

$$\varphi_1\left(\alpha_{il}, \alpha_{jl}\right) = \begin{cases} 1, & if\, \alpha_{il} = \alpha_{jl} \\ 0, & otherwise \end{cases} \tag{36}$$

(2). The similarity of route planning

Due to the demand points in each route being different in solutions, the similarity of route planning between solution S^t and solution $S^{'t}$ in the $l-th$ dimension can be measured by the demand points served by the route l:

$$S_2\left(S^t, S^{'t}\right) = \sum_{v=1}^{|K|} \varphi_3\left(\gamma_{il}, \gamma_{jl}\right) \tag{37}$$

where γ_{ij} is a demand point set served by the route l, γ_{il} is the subset of the demand points of the allocation set γ_i on the $l-th$ dimension, and γ_{jl} is the subset of the demand points of the allocation set γ_j on the $l-th$ dimension.

$$\varphi_3\left(\gamma_{il}, \gamma_{jl}\right) = \begin{cases} \sum_r^{|\gamma_{il}|} \varepsilon\left(\gamma_{ilr}, \gamma_{jl}\right) / \left|\gamma_{jl}\right|, & \text{if } \left|\gamma_{jl}\right| > \left|\gamma_{il}\right| \\ \sum_r^{|\gamma_{jl}|} \varepsilon\left(\gamma_{jlr}, \gamma_{il}\right) / \left|\gamma_{il}\right|, & \text{if } \left|\gamma_{il}\right| \geq \left|\gamma_{jl}\right| \, and \, \left|\gamma_{il}\right| \neq 0 \\ 1, \, if \, \left|\gamma_{il}(t)\right| = \left|\gamma_{jl}\right| = 0 \end{cases} \tag{38}$$

where

$$\varepsilon(a, B) = \begin{cases} 1, & if\ a \in B \\ 0, & otherwise \\ ` \end{cases} \tag{39}$$

Considering that the similarity of the depot location and the similarity of route planning vary, the similar distance of solutions between the solution S^t and solution $S^{'t}$ is thus obtained by integrating three parts together:

$$SD\left(S^t, S^{'t}\right) = 1 - \sqrt{\frac{SD_1\left(S^t, S^{'t}\right) + SD_2\left(S^t, S^{'t}\right)}{2}} \tag{40}$$

2) THE PROCEDURE OF CROWDING CLUSTERING STRATEGY

In this study, a crowding clustering strategy is developed for the treatment of multi-objective optimization. The Crowding Factor (CF) is allocated to the population number (NP) to avoid substitution errors between the next-generation solutions and the previous-generation solutions. Each successive individual $C_i\,(i = 1, 2, \ldots, NP)$, chooses the nearest parent P_j according to the distance of the similarity in (40). For each parent $P_j\,(j = 1, 2, \ldots, NP)$, there is a set of successive individuals SS_j that compete with P_j, and the SS_j could be an empty set. A set $CS_j = \left\{P_j, SS_j\right\}, j = 1, 2, \ldots, NP$ is defined as a cluster in which individuals have a high degree of similarity. A cluster center CC_j is selected to survive and other individuals will have perished in the cluster CS_j. The crowding clustering strategy brings competition to avoid multiple clusters from converging to the same extremum and prevent individuals with high similarity from entering the evolutionary computation.

Considering that to address many-objective optimization problems, there are multiple Pareto solutions instead of only one optimal solution. Cluster center CC_j are determined as follows:

$$\min_{l \in NS_j} \sum_{k \in NS_j \backslash S_l} SD\left(S_k, S_l\right) \tag{41}$$

where $NS_j \in CS_j$ is a set of no-dominated solutions and $CR_j = max^{\alpha \in CS_j} SD\left(S_\alpha, S_j\right)$ is a no-dominated solution that has a maximum radius CR_j. The many-objective crowding clustering strategy is as algorithm 1.

Algorithm 1 A MANY-OBJECTIVE CROWDING CLUSTERING STRATEGY

Input: Candidate solution set S

Output: Update solution set S'

Step 1. Children set C is generated by the crossover operator and mutation operator.

Step 2. For each parent $\mathrm{P}_j \in S$, a set $\mathrm{OCS}_j \in \left\{\mathrm{P}_j, \mathrm{SS}_j\right\}$ is constructed as original cluster j, $(j = 1, 2, \ldots, NP)$. The original cluster radius OCS_j is calculated, and the original cluster center OCC_j is selected for each original cluster j. Using a non-dominated sorting approach, NP original clusters are sorted by the objectives of the original cluster center.

Step 3. First, a set $FC = \emptyset$ is initialized to save the final clusters, in which crowded and underperforming clusters have been removed.

Step 4. A final cluster center is randomly selected from the first Pareto layer, sorted by Step 2, and put into the FC. The cluster center and cluster radius of the final cluster l are FCC_l and FCR_1.

Step 5. Check for the cluster $j\,(j \notin FC)$ from the inner Pareto 1 front. If $SD\left(FCC_l, CC_j\right) > FCR_l$, the cluster j is put into FC and removed from the original cluster set. At the same time, the radius of cluster FC is updated to $min\left(SD\left(FCC_l, CC_j\right), CR_j\right), \forall l \in FC$.

Step 6. $|N_{FC}|$ is defined as the number of solutions in FC. If $|N_{FC}| < NP$, $NP - |N_{FC}|$, solutions are generated as the next generation of solutions together with the solutions in FC.

Step 7. Output S', if the run description criteria are met. Otherwise, return to step 2.

V. COMPUTATIONAL EXPERIMENTS AND DISCUSSIONS

All experiments presented in Section IV were conducted using Matlab2018 on a 4.60GHz Intel Core i7-11800CPU with 32GB of RAM and operating on Windows 10. The mutation and crossover rates for NSGA-II were set to pm = 0.7 and pc = 0.7, respectively. As the MMLRP is an NP-hard problem, obtaining the complete set of Pareto optimal solutions is not always feasible. Hence, we conducted ten runs on the test instance to obtain an approximate set of solutions.

TABLE 1. Parameters of test instances.

Number/Instance name	period	Candidate Depot	Demand point (each period)
R-3-5-20/30/25	3	5	20/30/25
R-3-8-40/50/35	3	8	40/50/35
R-3-10-90/100/80	3	10	90/100/80
R-5-5-20/30/40/35/25	5	5	20/30/40/35/25
R-5-10-70/90/100/80/75	5	10	70/90/100/80/75
RC-3-5-20/30/25	3	5	20/30/25
RC-3-8-40/50/35	3	8	40/50/35
RC-3-10-90/100/80	3	10	90/100/80
RC-5-5-20/30/40/35/25	5	5	20/30/40/35/25
RC-5-10-70/90/100/80/75	5	10	70/90/100/80/75
C1-3-5-20/30/25	3	5	20/30/25
C1-3-8-40/50/35	3	8	40/50/35
C1-3-10-90/100/80	3	10	90/100/80
C1-5-5-20/30/40/35/25	5	5	20/30/40/35/25
C1-5-10-70/90/100/80/75	5	10	70/90/100/80/75
C2-3-5-20/30/25	3	5	20/30/25
C2-3-8-40/50/35	3	8	40/50/35
C2-3-10-90/100/80	3	10	90/100/80
C2-5-5-20/30/40/35/25	5	5	20/30/40/35/25
C2-5-10-70/90/100/80/75	5	10	70/90/100/80/75

TABLE 2. Parameters of the vehicle.

Vehicle	Loading capacity Q	Velocity v	Cost per unit of length c	Use cost F_v
truck	70	40 km/h	1.7 km/Yuan	500 Yuan

A. TEST INSTANCES

There is currently no established benchmark dataset available for the evaluation of the multi-objective multi-period optimization problem addressed in this study, as far as we are aware. We have conducted a variant of standards LRP instances R, RC, C1, and C2 of Solomon designed to evaluate the capability of the improved NSGA-II as shown in Tab. 1 and Tab. 2 by the guidelines presented in reference [57]. In each test instance, all demand points and depots are located in a $100 \times 100\ km^2$ grid. Take the test instance R-3-5-20/30/25 which is a variant of standards LRP instances R as an example, we have divided the planning horizon into three periods and assumed that 5 potential depots satisfy 20 demand points in period 1, 30 demand points which increase 10 demand points relative to period 1 in period 2 and 25 demand points which lost 10 demand points and added 5 new demand points relative to period 2 in period 3.

To conduct a comparative analysis, the classical NSGA-II, PICEA-g, PICEA-G, MOPSO and MOEA/D are also employed to solve the test instances. The parameters of the algorithms are set as in Tab. 3 Note that PICEA-g is an outstanding optimization algorithm to cope with the multi-objective problem [58].

This study aims to identify potential depots to be opened and to establish the routes from these depots to the demand points while adhering to the vehicle capacity constraint. Furthermore, the variation in locations and also the number of demand points require readjusting decision making regarding the positioning of the depots as well as the vehicle's route scheduling.

Without loss of generality, the assumptions are made:

(1) During each period, a single vehicle services each demand point, and the demand at each point does not exceed the carrying capacity Q.

TABLE 3. Parameters of the algorithms.

Parameters	NSGA-II-cc	NSGA-II	PICEA-G	MOPSO	MOEA/D
Maximum generations maxGen	1000	1000	1000	1000	1000
Population size N	100	100	100	100	100
Number of goal vectors Ng	-	-	100	-	-
Number of weight vectors N_λ	-	-	-	-	100
Probability pc	0.7	0.7	0.7	0.7	0.7
Probability pm	0.7	0.7	0.7	0.7	0.7
Neighbourhood size T	-	-	-	-	20

TABLE 4. Computation results for test instances with algorithms (A: NSGA-II-CC, B: NSGA-II, C PICEA-G, D MOPSO AND E MOEA/D).

Instances	C (A, B)	C (B, A)	C (A, C)	C (C, A)	C (A, D)	C (D, A)	C (A, E)	C (E, A)
R-3-5-20/30/25	0.6296	0.0066	0.3000	0.2222	0.4853	0.3548	0.3855	0.2486
R-3-8-40/50/35	0.3928	0.2608	0.1786	0.4545	0.5436	0.0753	0.4866	0.3574
R-3-10-90/100/80	0.2069	0.0789	0.2727	0.1379	0.2546	0.2487	0.3127	0.1780
R-5-5-20/30/40/35/25	0.2173	0.2927	0.6000	0.0000	0.3274	0.1543	0.5471	0.3578
R-5-10-70/90/100/80/75	0.1333	0.074	0.6250	0.1111	0.5435	0.1475	0.4811	0.3227
RC-3-5-20/30/25	0.4062	0.1206	0.2352	0.2931	0.4578	0.2625	0.5974	0.2876
RC-3-8-40/50/35	0.4090	0.1320	0.1818	0.2241	0.3648	0.1825	0.4723	0.2264
RC-3-10-90/100/80	0.4838	0.0000	0.2500	0.0536	0.4820	0.3548	0.2358	0.1974
RC-5-5-20/30/40/35/25	0.2380	0.1785	0.4444	0.0357	0.1282	0.2675	0.4586	0.3877
RC-5-10-70/90/100/80/75	0.1176	0.0040	0.5714	0.0080	0.2859	0.3486	0.5468	0.3944
C1-3-5-20/30/25	0.6289	0.0138	0.2142	0.2093	0.4413	0.3507	0.4155	0.3574
C1-3-8-40/50/35	0.3836	0.0888	0.1538	0.2444	0.2577	0.3024	0.5444	0.3548
C1-3-10-90/100/80	0.3183	0.1071	0.1666	0.1071	0.3458	0.1844	0.2348	0.4822
C1-5-5-20/30/40/35/25	0.1315	0.2127	0.5555	0.0212	0.5460	0.2288	0.3027	0.3644
C1-5-10-70/90/100/80/75	0.2400	0.1304	0.8333	0.0000	0.2475	0.1376	0.4531	0.2548
C2-3-5-20/30/25	0.5319	0.0357	0.1333	0.2678	0.3621	0.2184	0.3114	0.4841
C2-3-8-40/50/35	0.4878	0.0682	0.0769	0.2727	0.2476	0.3745	0.3002	0.3524
C2-3-10-90/100/80	0.4137	0.1025	0.4284	0.0512	0.4786	0.1458	0.3665	0.1146
C2-5-5-20/30/40/35/25	0.2352	0.1600	0.6000	0.000	0.2467	0.1989	0.2846	0.2154
C2-5-10-70/90/100/80/75	0.1538	0.1034	0.4545	0.0344	0.2586	0.2278	0.2546	0.3465

(2) Candidate depots have adequate supply to satisfy the demand points, and the location of candidate depots is fixed during the planning horizon. The cost of location for each depot is 5000 Yuan.

(3) Vehicles that are considered to be homogeneous have the same speed and the same carrying capacity Q, as shown in Tab. 1. The number of vehicles is enough for transportation.

(4) Distance between traffic nodes can be assessed by Euclidean distance between points. In addition, the vehicle needs to return to the departure depot when the vehicle has serviced all the demand points on the route.

(5) To simplify the model, the MMLRP considers a single shipment of goods and does not take into account the situation of shortage.

(6) The empty loaded fuel consumption for unit distance ρ^0 is 0.165 km/L, and the thoroughly loaded fuel use for unit distance ρ^* is 0.377 km/L. Carbon emissions brought about unit fuel consumption e are 2.63L/kg.

B. COMPUTATIONAL RESULTS

All test instance parameters are set the same. The quantity of chromosomes amounts to 100, coupled with 2000 iterations. An assessment of the effectiveness of MMLCLRP algorithms is conducted utilizing a performance metric denoted as the C-metric, which enables a comparison of the quality of the Pareto approximation solution by the two algorithms. The $C(X, Y)$ indicator is the percentage of the solutions in the Pareto approximation solution Y dominated by any solution of Pareto approximation solution X [59].

$$\mathrm{C}\left(\mathrm{X},\mathrm{Y}\right)=\frac{|y\in Y|\exists x\in X:x\leq y|}{|Y|} \tag{42}$$

Note that the value of the $C(X, Y)$ is not essentially identical to $1 - C(Y, X)$. After 10 runs, the mean value of results solved by the NSGA-II-cc, NSGA-II, and PICEA-g are summarized in Tab. 4.

To compare the results, superior results are underlined in Tab. 4. NSGA-II-cc got superior results over NSGA-II for almost all the instances in R, RC, C1, C2 except for the Instance R-5-5-20/30/40/35/25 and C1-5-5-20/30/40/35/25. We observe that the capability of the NSGA-II-cc is superior to the PICEA-g, the MOPSO, and the MOEA/D for those instances with more nodes and 5 periods. The results show that the NSGA-II-cc algorithm has advantages for solving MMLCLRP with multiple points and periods. This work presents two novel techniques that have been incorporated into the NSGA-II-cc algorithm to enhance its performance. Firstly, customized designs were created for the similarity between depot location and vehicle routing, enabling the algorithm to elect neighborhoods more effectively and enhance convergence. Secondly, a crowding clustering strategy was implemented to augment the diversity of the NSGA-II-cc algorithm. This technique is particularly critical for addressing location-routing problems with complex solution structures. We analyze the optimal decision of the three objectives in the Pareto solution obtained using the Instance R-3-5-20/30/25, which comprises demand points for three periods: 1-20, 1-30, and 11-35, respectively. For the solution involving the minimum cost in the Pareto solution, the three objective values are 25387.36 Yuan, 111.11 hours, and 936.59 kilograms. In Fig.4, red points represent depots, and the black points represent demand points. The decision of the solution is as follows:

The solution selects only one depot in three periods to service all of the demand points because the use cost of the depot is 5000 Yuan, which is obviously higher than the vehicle uses cost and cost per unit of length. We can observe that Depot 1 is close to the central territory of the region, and the selection of this depot can minimize the distance to the routes. Compared with the first period, the amount of vehicles exploited in the second period and third period increases from 5 to 6 vehicles due to the increase in the demand points. Although the amount of vehicles exploited in the second period and the third period is as same as 6, we can also find that the route planning has been adjusted due to the change in demand points.

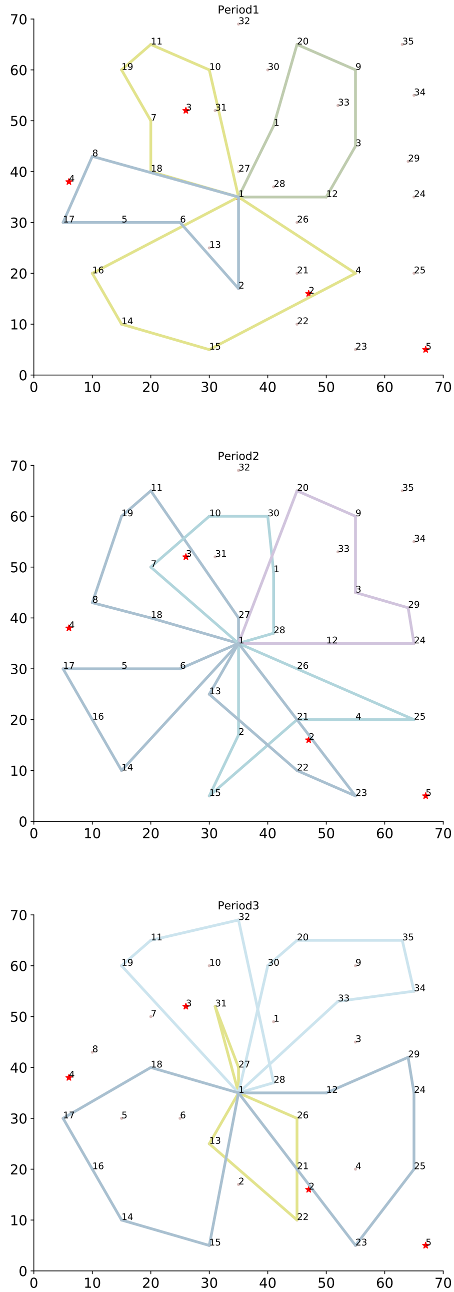

FIGURE 4. **Illustration of the solution of the instance R-3-5-20/30/25 (the optimal cost).**

For the optimal solution of objective 2 in the Pareto solution, the values of the three objectives are 40765.20 Yuan, 109.32 hours, and 862.11 kilograms. Fig.5 presents the decision of the solution.

Compared to Fig. 4, we can observe that more depots are used in Fig. 5. Multiple depot schemes can reduce the

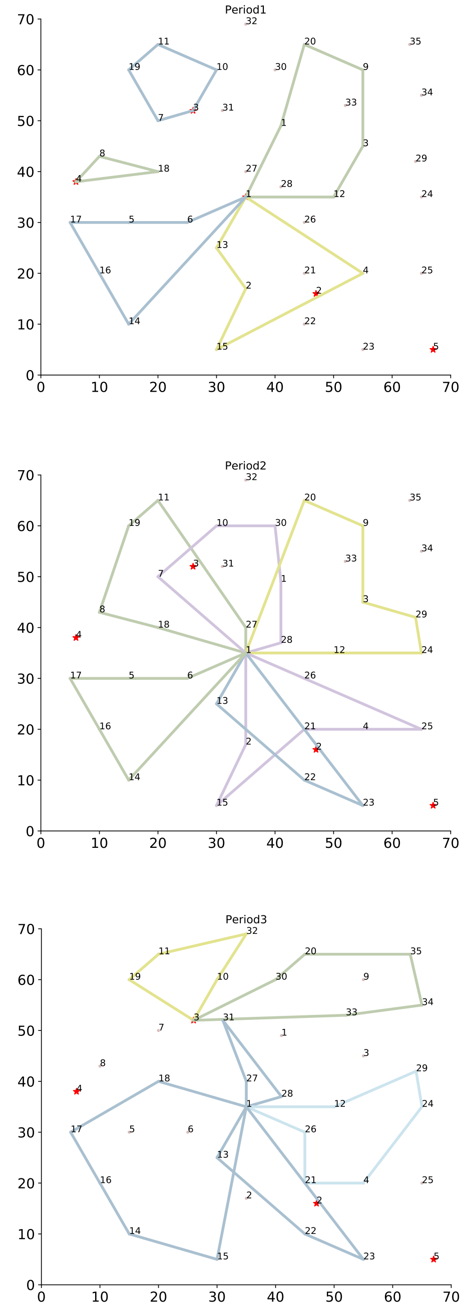

FIGURE 5. Illustration of the solution of the instance R-3-5-20/30/25 (the optimal service time).

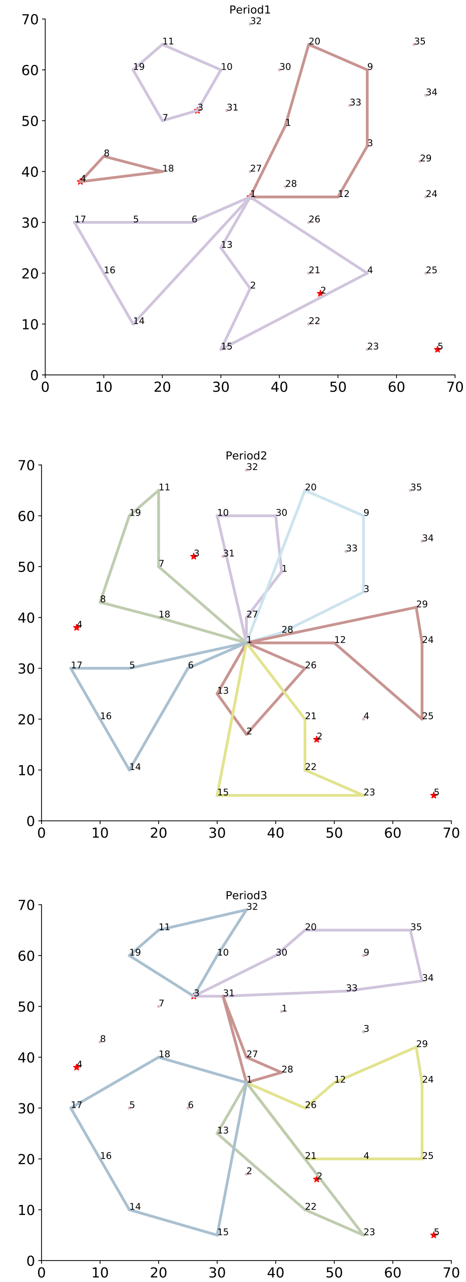

FIGURE 6. Of the solution of the Instance R-3-5-20/30/25 (the optimal carbon emission).

length of the routes. This results in a shorter total arrival time to reach the demand points but increases the total cost to 40765.20 Yuan. We observe that the second period in Fig. 4 and Fig. 5 adopts almost the same optimization strategy, and we believe this strategy has significant advantages for the optimization of the first and second objectives in the second period. In addition, a good strategy is included in different Pareto solutions, which indicates that the NSGA-II-cc algorithm has better stability. In addition, it is evident that each vehicle route typically complies with the TSP principle, affirming the rationality of the proposed algorithm for route creation. Consequently, based on the current circumstances, decision-makers can select the appropriate option from the multi-objective Pareto solutions.

In the option including the minimum CO_2 emission from the Pareto solutions, the values of three objectives are 41297.33 Yuan, 109.79 hours, and 847.65 kilograms. Fig.6 presents the decision of the solution.

From the solution illustrated in Fig. 6, minimizing CO_2 emission, we can see that 7 vehicles are used in the second period. Although the capacity of 6 vehicles is sufficient to serve all demand points, long-distance transportation increases vehicle carbon emissions. Compared with Fig.4 and Fig.5, the solution of Fig. 6 uses more depots and vehicles, which reduces carbon emissions but has the highest cost among the three solutions.

The findings reveal that the improved NSGA-II-cc is proficient in addressing the issue and has outperformed the other leading multi-objective evolutionary algorithms. In addition, the proposed MMLCLRP model can effectively deal with optimization with three objectives. We can provide logistics decision-makers with multiple solutions to achieve differentiated needs. For Instance, logistics decision-makers can reduce vehicle arrival time and carbon emissions by spending the corresponding cost when customers have strict service time requirements or government organizations have low carbonization requirements for logistics networks.

VI. CONCLUSION

This paper proposed an optimization model for a multi-objective multi-period low-carbon location-routing problem, the MMLCLRP, considering the total logistics cost, the arrival time of the demand points, and the carbon emissions to determine depot location, and route programming in a planning horizon with multi-period. The proposed model ensures the sustainability of the logistics and dynamically adjusts location routing decisions of each period to change market demand.

We have modified NSGA-II-cc to solve the MMLCLRP effectively. Through the customized design of the similarity between depot location and vehicle routing, the NSGA-II-cc algorithm was enabled to select more appropriate neighbors, thereby improving the rate of convergence. In addition, a crowding clustering technique was implemented to maximize the diversity of the NSGA-II-cc, which is essential to address location-routing problems with complex solution structures.

Experimental outcomes illustrate that the algorithm offers benefits in addressing the variable multi-objective LRP problem, and the MMLCLRP framework can effectively balance logistics-related concerns, including economy, efficiency, and the environment. Our future works will concentrate on solving the problem of multi-periods material distribution in a stochastic environment. In addition, emergency logistics, such as the relief supply for earthquakes, typhoons, and epidemics, will also be researched in the future.

COMPLIANCE WITH ETHICAL STANDARDS

Not applicable.

COMPETING INTERESTS

The authors declare no competing interests.

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

AUTHORS CONTRIBUTIONS

Binbin Chen was the primary contributor, responsible for formulating the idea, conducting the literature search and data analysis, and writing the original draft. Binbin Chen and Rui Zhang were responsible for resources and data collecting and generating. Shengjie Long was responsible for funding the acquisition. Rachsak Sakdanuphab provided supervision and contributed to formulating the discussion. All authors have read and approved the final manuscript.

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