Integrating Priority Structures into NSGA-II for Interval Data-based Multi-Objective Nonlinear Fixed-Cost Transportation Problem

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***Abstract*—In this study, we propose a new approach for solving the interval data-based multi-objective non-linear fixed-cost transportation problem (MO-FCTP) with different means of transport by integrating priority structures into the framework of the NSGA-II. We analyzed different ways of calculating the crowding distance corresponding to a solution of the investigated problem and proposed new genetic operators specifically designed to handle different means of transport. Computational experiments conducted on benchmark instances from the literature demonstrate that our approach is suitable and efficient for solving the considered MO-FCTP.**

***Index Terms*—interval data-based multi-objective fixed cost transportation problem with multiple modes of transportation, genetic algorithms, priority-based encoding, NSGA-II**

I. Introduction

The Fixed Cost Transportation Problem (FCTP) was originally introduced by Balinski [1]. In real-world applications, the uncertainty of demand often requires an extension of the classical single-stage transportation problem to a two-stage framework, which incorporates nodes corresponding to distribution centers (DCs) in addition to the source and destination nodes [2]–[7]. Several researchers considered the integration of various fuzzy numbers in FCTPs, for example Srivastava and Bisht [8] investigated an interval data based transportation problem. For a detailed overview of FCTPs and solution approaches, see the comprehensive presentation by Kacher and Singh [9].

In practical transportation settings, decision-makers frequently encounter multiple objectives that are either conflicting or non-commensurable. When these objectives are optimized simultaneously, the problem is formulated as a Multi-Objective Transportation Problem (MOTP). Formulating an MOTP within a mathematical programming framework aims to optimize several objectives simultaneously while satisfying a set of constraints. Typically, a multi-objective transportation model focuses on minimizing total transportation costs as a primary objective, while additional objectives may include reducing delivery time, minimizing product degradation, ensuring secure delivery, and other performance criteria.

The key distinction between single-objective and multi-objective transportation problems lies in the nature of their solutions. While single-objective optimization seeks a unique optimal solution, multi-objective optimization (MOO) identifies a set of solutions that reflect the best trade-offs among the objectives. This set, known as the Pareto front, consists of solutions for which no objective can be enhanced without deteriorating at least one other objective.

Evolutionary algorithms are particularly well suited for MOO, as they can be adapted to incorporate selection mechanisms that account for multiple criteria. Such adaptations often employ techniques such as non-dominated sorting and crowding distance measures to preserve diversity and ensure a well-distributed set of solutions along the Pareto front. Among the most widely used evolutionary multi-objective algorithms, Non-dominated Sorting Genetic Algorithm II (NSGA-II), developed by Deb et al. [10], stands out for its simplicity, effectiveness, and robustness. NSGA-II is particularly valued for its efficiency, diversity-preserving capability, and versatility across a wide range of application domains.

In this work, we focus on the non-linear MO-FCTP involving different means of transport with given capacities. The problem simultaneously optimizes two conflicting objectives, namely the minimization of overall transportation cost and the minimization of total delivery time. In addition, we assume that both variable cost and transport time are represented as interval numbers. This variant of MOTP was introduced by Biswas et al. [11].

The existing literature on this subject is relatively limited. Biswas et al. [11] considered the non-linear MO-FCTP with different means of transport in crisp and interval environments and provided a solution approach based on NSGA-II, using a matrix representation of the chromosomes and adapted genetic operators that can handle different means of transport. Biswas and Pal in [12] studied a MO-FCTP that considers different means of transport with given capacities. For this MO-FCTP, they provided a modified NSGA-II using a matrix representation of the chromosomes and adapted crossover and mutation genetic operators for the investigated problem. Biswas et al.

in [13] investigated a MO-FCTP with multiple items, with different means of transport. They developed two versions of the multi-item MO-FCTP, modeling item demands either as crisp values or as interval numbers. Each model was tested on four instances and solved using two MOEAs: NSGA-II and SPEA2. Haque et al. [14] investigated a non-linear solid MO-FCTP with budget constraints, modeling uncertainty through closed intervals. The authors proposed an efficient solution using interval analysis based on a parametric view of intervals and converting the problem into a deterministic non-linear MO programming formulation. More recently, Pop et al. [15], [16] introduced new solution methodologies for MO-FCTP, using modified NSGA-II that relies on a priority-based representation, respectively Prüfer-based encoding. The computational experiments conducted on a collection of existing benchmark instances showed that their approach outperformed current state-of-the-art algorithms, yielding improved Pareto fronts.

In this paper, we present a new solution approach for interval data-based non-linear MO-FCTP with different means of transport with given capacities. Our approach is based on a modified NSGA-II that uses a priority-based representation, ranking route allocations by priority levels instead of transportation quantities, together with an adapted priority-based decoding procedure and newly developed genetic operators integrated into the algorithm.

The rest of our paper is organized as follows. In Section II, we define the investigated interval data-based MO-FCTP with different means of transport with fixed capacities. Section III presents the non-linear mixed integer formulation and an example of the problem. In Section IV, we detail our novel approach achieved by integrating priority structures into NSGA-II. We analyze different ways of calculating the crowding distance corresponding to a solution of the investigated problem and proposed new genetic operators specifically designed to handle different means of transport. Section VI reports the results of the computational experiments performed on a set of existing benchmark instances, and finally, Section VI concludes the paper and outlines some future research directions.

II. Definition of the Problem

In this section, we describe the non-linear MO-FCTP with different means of transport, as introduced by Biswas et al. [11]. The key features of this MO-FCTP are:

- $\{S_1, S_2, ..., S_m\}$ is the set of sources, and s_i are the quantities available at each source S_i, $i \in \{1, ..., m\}$;
- $\{D_1, D_2, ..., D_n\}$ is the set of destinations, and d_j are the demands at each destination D_j, $j \in \{1, ..., n\}$;
- $\{M_1, M_2, ..., M_l\}$ is the set of available means of transport, and e_k is the number of units of the product that can be transported by transport mode M_k, $k \in \{1, ..., l\}$;
- We assume that the TP is balanced, i.e. $\sum_{i=1}^{m} s_i = \sum_{j=1}^{n} d_j$;
- f_{ijk} are the fixed costs associated with the M_k mode of transportation's route from source S_i to destination D_j;
- Due to uncertainty in the environment, $[c^L_{ijk}, c^R_{ijk}]$ and $[t^L_{ijk}, t^R_{ijk}]$ are the variable interval transportation cost, respectively transportation time, per square unit of the commodity transported from the source S_i to the destination D_j by means of transport M_k.

The aim of the interval data-based non-linear MO-FCTP with different means of transport with fixed capacities is to determine the quantities to be shipped and the mode of transport used on each route so as to satisfy the demand at each destination, remain within the supply limits at the sources, and respect all capacity constraints, while simultaneously optimizing two objectives: minimizing total transportation cost and minimizing total distribution time.

In Fig. 1, we illustrate graphically our investigated problem: the interval data-based non-linear MO-FCTP with different means of transport with fixed capacities.

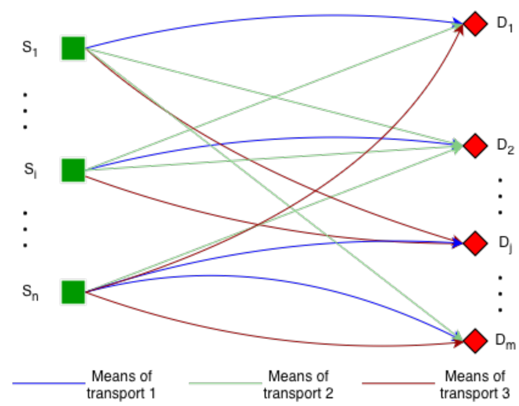

Fig. 1. Illustration of the interval data-based non-linear MO-FCTP with different means of transport with fixed capacities

III. The Formulation of the Interval Data-Based Non-Linear MO-FCTP

The investigated non-linear FCTP considers two distinct cost components. The first component is a variable transportation cost that depends on the squared quantity of goods shipped between a source and a destination using a specific transportation mode, while the second component is a fixed cost incurred when a particular route is utilized. Since the objectives of minimizing total transportation cost and minimizing total distribution time are inherently conflicting, the problem is naturally formulated as a non-linear MO-FCTP.

Due to uncertainty in the environment, for example fluctuations in fuel prices, weather conditions, etc., the variable transportation costs and times are not always fixed. To properly reflect the inherent uncertainties in transportation cost and time, both are modeled as interval numbers.

Let $A = [a^L, a^R]$ be an interval number, where a^L and a^R are the left and right bounds of the interval, then binary operations of addition, subtraction, multiplication, and division can be defined straightforwardly for interval numbers; see, for example, [17]. The interval number A can also be represented as $A = \langle a^c, a^w \rangle$, where a^c and a^w are the center and radius of the interval A with $a^c = \dfrac{a^L + a^R}{2}$ and $a^w = \dfrac{a^R - a^L}{2}$.

Different partial order relations have been introduced on the set of interval numbers [17], the one used in our paper to compare the interval numbers $A = \langle a^c, a^w \rangle$ and $B = \langle b^c, b^w \rangle$, is defined as follows: $A \preceq B$ iff $a^c < b^c$ and $a^w \geq b^w$ if $a^c = b^c$, and $A \prec B$ if and only if $A \preceq B$ and $A \neq B$.

The non-linear MO-FCTP with different means of transport in interval environments is formulated as follows:

$$\min[Z_1^L, Z_1^R] = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{l} \{[c_{ijk}^L, c_{ijk}^R] \times (x_{ijk})^2 + f_{ijk} y_{ijk}\}$$

$$\min[Z_2^L, Z_2^R] = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{l} [t_{ijk}^L, t_{ijk}^R] \times y_{ijk}$$

$$s.t. \sum_{j=1}^{n} \sum_{k=1}^{l} x_{ijk} = s_i,\ i = \overline{1,m} \qquad (1)$$

$$\sum_{i=1}^{m} \sum_{k=1}^{l} x_{ijk} = d_j,\ j = \overline{1,n} \qquad (2)$$

$$x_{ijk} \leq e_k,\ i = \overline{1,m},\ j = \overline{1,n},\ k = \overline{1,l} \qquad (3)$$

$$x_{ijk} \geq 0,\ i = \overline{1,m},\ j = \overline{1,n},\ k = \overline{1,l}$$

$$y_{ijk} \in \{0,1\},\ i = \overline{1,m},\ j = \overline{1,n},\ k = \overline{1,l}$$

Our investigated problem has two conflicting objectives: the first objective is non-linear and its goal is to minimize the total transportation cost, which consists of unit transportation costs defined as interval numbers and fixed costs associated to the source-destination routes, while the second objective aims to minimize the total transportation time defined as interval number. Restrictions (1) establish that the quantity transported from each source is equal to its capacity, while restrictions (2) guaranty that demand at each destination is satisfied. Restrictions (3) guaranty that the quantity transported by a specific means of transport cannot exceed its capacity. Finally, the last restrictions define the decision variables.

Example. We present a feasible solution (Fig. 2) and the corresponding values of the objective functions in the case of the 4×5 instance introduced by Biswas et al. [11]. The characteristics of this instance are: 4 sources with available quantities $\{35, 27, 45, 37\}$; 5 destinations with the requested demands $\{33, 27, 22, 28, 34\}$; 3 different means of transport with the capacities $\{15, 18, 20\}$, and the variable costs and transportation times parameters are interval numbers, while the fixed costs parameters are real numbers.

$$[Z_1^L, Z_1^R] = ([74, 80] \times 7 \times 7 + [136, 136]) + ... + \\ + ([72, 76] \times 7 \times 7 + [114, 114]) = [139946, 148684]$$

$$[Z_2^L, Z_2^R] = [176, 178] + ... + [179, 186] = [2284, 2340]$$

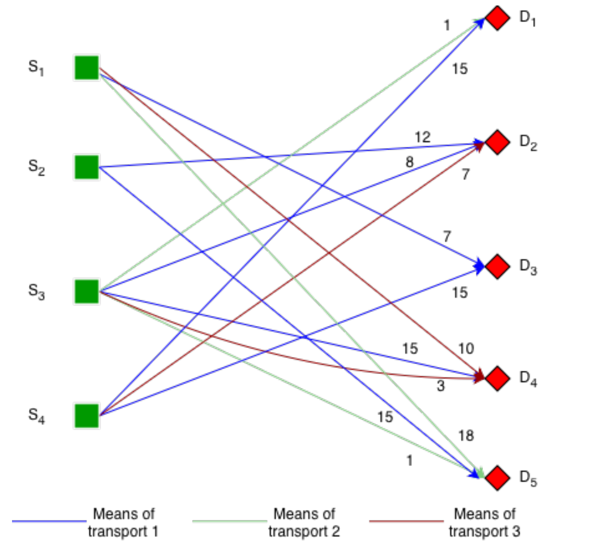

Fig. 2. Illustration of a solution for the 4x5 test example for the interval data-based non-linear MO-FCTP with different means of transport

IV. Our solution approach

This section outlines the modified NSGA-II obtained by integrating priority structures by prioritizing the routes according to assigned priority levels, the adapted priority based decoding procedure and the specifically tailored genetic operators for the interval data-based non-linear MO-FCTP.

Chromosome representation. In this paper, we integrate priority structures within NSGA-II, using the representation introduced by Gen and Chen [18], originally applied to the shortest path and project scheduling problems. Previous studies, such as Gen et al. [5], have shown that the priority-based representation can be successfully employed for linear and nonlinear FCTP. Each chromosome in our approach has a compact encoding that captures the priorities of sources and destinations to build a feasible solution to the problem, having a fixed length, i.e. $m + n$.

Unlike matrix or spanning-tree representations, integrating priority structures into NSGA-II avoids the need for repair mechanisms when implementing the proposed genetic operators for interval data-based MO-FCTP.

To match the structure and specific characteristics of the non-linear MO-FCTP based on interval data with different means of transportation, we adjusted the decoding process of the priority-based representation developed by Lotfi [6].

Initial population. Chromosomes are initialized using a random permutation of integers in the range $[1, m+n]$. Then, the priorities are assigned to the sources and destinations, starting from the highest value $m+n$ and sequentially decreasing until all sources and destinations receive a priority.

Fitness function. In the context of multi-objective optimization, the evaluation of a solution is not reduced to a single scalar value but is instead based on multiple, potentially conflicting criteria. In the investigated problem, each solution is assessed with respect to two objectives: minimizing the overall transportation cost and minimizing the total distribution time. The comparison between solutions is performed using Pareto dominance, complemented by an additional diversity-preserving measure known as the crowding distance.

The **crowding distance** of a solution reflects how densely other solutions are distributed around it. To calculate this value, the population is initially sorted in ascending order according to each objective. The extreme solutions are assigned an infinite distance value, whereas for all remaining solutions the crowding distance associated with the q-th objective is determined using two alternative formulations:

- one using the interval center of the q-th objective function, as in the case of crisp objectives:

$$dI_r^q = \frac{Z_q^{c(I_{r+1}^q)} - Z_q^{c(I_{r-1}^q)}}{\max Z_q^c - \min Z_q^c}$$

- the other one using the interval boundaries of the q-th objective:

$$\begin{aligned}[dI^L, dI^R]_r^q &= \frac{[Z_q^L, Z_q^R]^{(I_{r+1}^q)} - [Z_q^L, Z_q^R]^{(I_{r-1}^q)}}{\max [Z_q^L, Z_q^R] - \min [Z_q^L, Z_q^R]} \\ &= \frac{\left[Z_q^{L(I_{r+1}^q)} - Z_q^{R(I_{r-1}^q)},\ Z_q^{R(I_{r+1}^q)} - Z_q^{L(I_{r-1}^q)}\right]}{\left[\max Z_q^L - \min Z_q^R,\ \max Z_q^R - \min Z_q^L\right]} \\ &= \left[\frac{Z_q^{L(I_{r+1}^q)} - Z_q^{R(I_{r-1}^q)}}{\max Z_q^R - \min Z_q^L}, \frac{Z_q^{R(I_{r+1}^q)} - Z_q^{L(I_{r-1}^q)}}{\max Z_q^L - \min Z_q^R}\right]\end{aligned}$$

where $q = 1, 2$, $r = 2, 3, ..., p-1$, p is the total number of solutions, I_r^q is the index of the r-th solution in the sorted list, while $[I^L]_r^q$ and $[I^R]_r^q$ are indexes corresponding to the solutions with the lowest and highest values of the objective function, Z_q^c, Z_q^L and Z_q^R is the center, respectively, the left and right bounds of the interval $[Z_q^L, Z_q^R]$ and $\max Z_q$ and $\min Z_q$ are the maximum and minimum population values of the q-th objective function.

We used a **crowded tournament selection** that chooses between two individuals based on: Pareto rank (non-domination level) and crowding distance. In this way, we selected solutions that are better and more diverse.

The **crossover operator** employed in the proposed approach is a one-point crossover specifically adapted to the priority-based chromosome representation. Given two parent chromosomes, a crossover point is first randomly selected along the length of the chromosome. The genes located before this point are directly inherited by each offspring from the corresponding parent, while the genes located after the crossover point are exchanged between the two parents. Since this operation may generate duplicate priority values in the offspring, an additional correction step is applied as follows: duplicate values are replaced by missing priorities in such a way that each offspring remains a valid permutation of the priority set. This guaranties the feasibility of the resulting chromosomes without the need for repair mechanisms and preserves the relative ordering information encoded by the priorities.

Mutation operator is implemented as a *swap* mutation. Two distinct positions in the chromosome are randomly selected, and the priority values at these positions are exchanged. This operator introduces controlled perturbations into the population while maintaining the permutation structure of the chromosome. By swapping priorities rather than altering values arbitrarily, the mutation preserves feasibility and enables local exploration of the search space, contributing to diversity without disrupting the underlying priority-based encoding.

Genetic parameters. To ensure a fair comparison, we adopted the same parameter settings for our modified NSGA-II as those used by Biswas et al. [11]

V. Computational experiments and comparisons

In this section, we present the results of the computational study conducted to evaluate the performance of the NSGA-II integrating priority structures for solving the interval data-based non-linear MO-FCTP with different means of transport. A comparison of our developed approach with the only existing algorithm from the literature for this problem is provided.

Our modified NSGA-II based on priority structures was coded in Java 17 and has been evaluated on a PC with Intel Core i5 1.6 GHz, 16 GB RAM, and Windows 10 Pro operating system. Our programs and results will be made available on our GitHub website once this paper is accepted.

We tested our approach in the five existing instances of increasing size introduced by Biswas et al. [11]. To evaluate the performance of our modified NSGA-II, we compared it with the existing algorithms the modified NSGA-II using matrix representation and developed by Biswas et al. [11].

In Table I, we report our achieved computational results. The first column gives the index of the test example, the second column provides the anchor points achieved by Biswas et al. [11]. The last four columns contain the anchor points obtained by our modified NSGA-II integrating priority structures and three quality measures: the cardinality of the achieved Pareto fronts and the set-based metrics spacing and spreading.

From Biswas et al. [11] results, we observe that the cost-minimizing anchors exhibit the lowest cost values but are associated with very large time cost values, while the time-minimizing anchors achieve low times at the expense of substantially increased costs. In contrast, our proposed priority-based NSGA-II does not aim to reproduce these single-objective extremes, it simply converges toward the intermediate and practically relevant region of the Pareto front. For example, in the 4×5 instance, Biswas et al. [11] obtained a cost-optimal solution with a total cost of 93958 and a total time of 4558, and a time-optimal solution with a time value of 1227 at a cost value of 240089, whereas the proposed approach yields anchor points such as 135606.5 at 2305.5 and 156749.5 at 1875, simultaneously improving one objective without excessively degrading the other. Similar behavior is observed across all larger instances, where the proposed method consistently fills the gap between the two anchor points reported by Biswas et al. [11], achieving lower costs than the time-optimal anchors and lower times than the cost-optimal anchors. This demonstrates improved convergence toward balanced Pareto-efficient trade-offs rather than a focus on extreme single-objective optima under interval uncertainty.

Figures 3–7 illustrate the interval Pareto fronts obtained for the five instances. In all figures, each non-dominated

TABLE I
ACHIEVED COMPUTATIONAL RESULTS AND QUALITY MEASURES

Test	Biswas et al. [11]	Our computational results			
	Anchor points	Anchor points	Cardinality	Spacing	Spreading
1	Cost: <93958, 2066 >, Time: <4558, 57 > Cost: <240089, 8311 >, Time: <1227, 14 >	Cost: <135606.5, 2665.5 >, Time: <2305.5, 32.5 > Cost: <156749.5, 4181.5 >, Time: <1875, 28 >	10	1554.761	0.688
2	Cost: <130212, 2795 >, Time: <5937, 87 > Cost: <262779, 7628 >, Time: <2133, 28 >	Cost: <193743, 4469 >, Time: <3107, 40 > Cost: <263269, 6343 >, Time: <2318, 35 >	21	2687.146	0.684
3	Cost: <119093, 2308 >, Time: <6652, 82 > Cost: <263906, 7155 >, Time: <2330, 30 >	Cost: <136643, 3801 >, Time: <5245.5, 72.5 > Cost: <157874.5, 4390.5 >, Time: <4137.5, 55.5 >	21	958.674	0.634
4	Cost: <217921, 4302 >, Time: <12057, 147> Cost: <418071, 14362 >, Time: <4211, 59 >	Cost: <305421.5, 7111.5 >, Time: <5703, 75 > Cost: <374025, 9982 >, Time: <4304, 61 >	46	1452.874	0.750
5	Cost: <328267, 6883 >, Time: <20012, 253> Cost: <657549, 21444 >, Time: <7399, 89 >	Cost: <423960.5, 12403.5 >, Time: <10007, 137 > Cost: <523815.5, 15597.5 >, Time: <7781.5, 104.5>	47	2581.088	0.777

solution is represented in the objective space defined by total transportation time and total transportation cost, where both objectives are modeled as interval numbers and interpreted according to the center–radius solution representation.

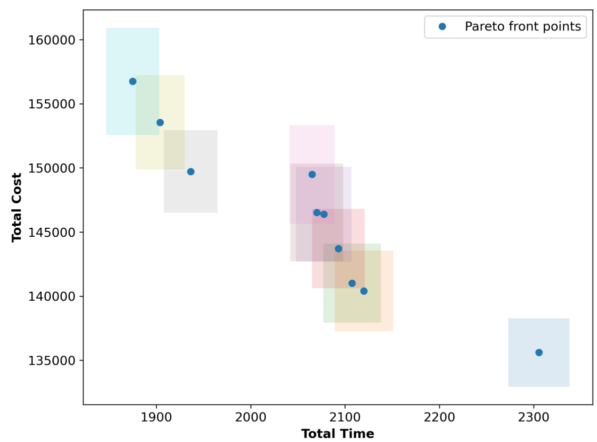

Fig. 3. The interval Pareto front in the case of 4×5 instance

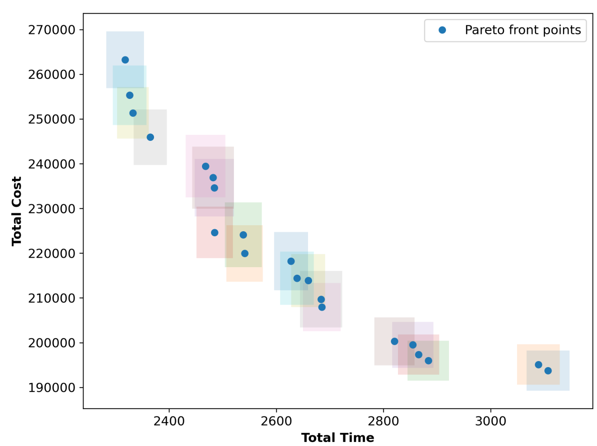

Fig. 4. The interval Pareto front in the case of 5×10 instance

The center–radius representation provides a clear and intuitive visualization of both performance and uncertainty. As problem size increases, the Pareto fronts expand and the interval radii grow (see results from Table I), reflecting higher uncertainty in transportation cost and time. These figures highlight that the proposed approach does not merely generate Pareto-optimal solutions in terms of expected values (centers), but also captures the variability inherent in interval data, offering richer decision support for real-world transportation

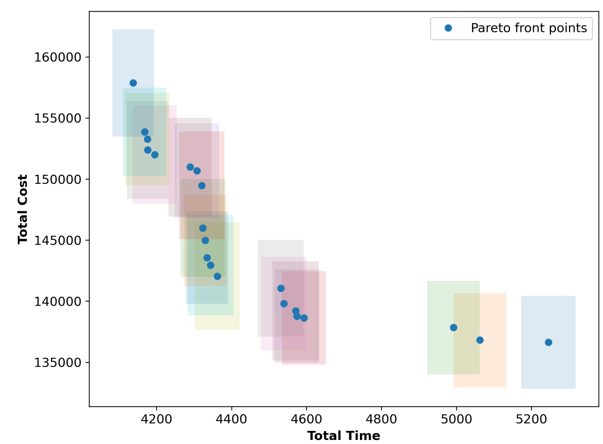

Fig. 5. The interval Pareto front in the case of 10×10 instance

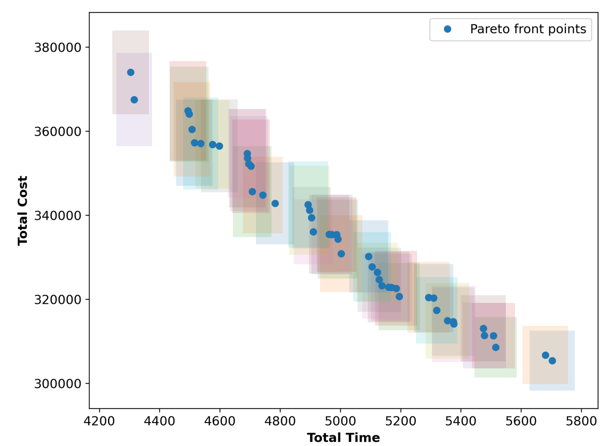

Fig. 6. The interval Pareto front in the case of 10×20 instance

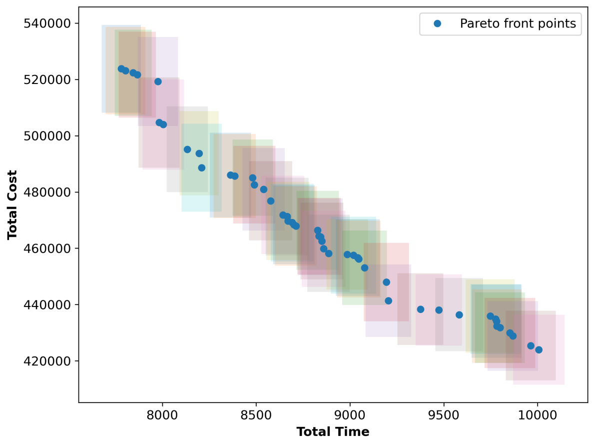

Fig. 7. The interval Pareto front in the case of 20 × 30 instance

problems under uncertainty.

Figure 8 compares the interval Pareto front obtained by the proposed priority-based NSGA-II with the Pareto front reported by Biswas et al. [11] for the largest test instance (20 × 30). The comparison is carried out in the objective space defined by total transportation time and total transportation cost, where both objectives are modeled as interval numbers and interpreted through their centers.

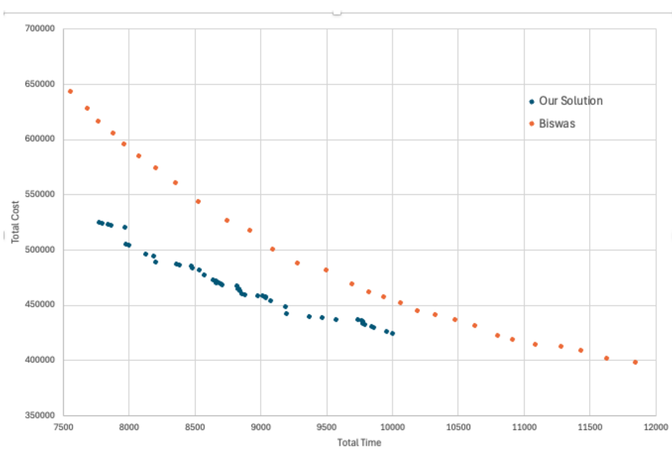

Fig. 8. Comparison of interval Pareto fronts in the case of 20 × 30 instance

Analyzing Figure 8, we observe that the Pareto front generated by our approach is systematically shifted toward lower cost values for comparable levels of total transportation time. When considering the centers of the interval objectives, this shift indicates that the proposed method achieves better expected transportation costs without degrading expected time performance. In other words, for most trade-off levels, our solutions dominate those of Biswas et al. [11] in terms of nominal objective values.

VI. Conclusions and further research directions

In our paper, we proposed a novel solution approach for solving the interval data-based MO-FCTP with different means of transport by integrating priority structures into the framework of the NSGA-II. The developed solution approach demonstrates high efficiency and competitiveness in solving the investigated MO-FCTP.

Future research will explore alternative encoding methods and genetic operators and assess the flexibility, scalability, and robustness of our approach in larger problem instances.

References

[1] M. L. Balinski, "Fixed-cost transportation problems," *Naval Research Logistics Quarterly*, vol. 8, no. 1, pp. 41–54, 1961.

[2] O. Cosma, P. C. Pop, and D. Danciulescu, "A novel matheuristic approach for a two-stage transportation problem with fixed costs associated to the routes," *Computers & Operations Research*, vol. 118, 2020.

[3] O. Cosma, P. C. Pop, and D. Dănciulescu, "A parallel algorithm for solving a two-stage fixed-charge transportation problem," *Informatica*, vol. 31, no. 4, pp. 681–706, 2020.

[4] O. Cosma, P. C. Pop, and C. Sabo, "An efficient hybrid genetic approach for solving the two-stage supply chain network design problem with fixed costs," *Mathematics*, vol. 8, no. 5, 2020.

[5] M. Gen, F. Altiparmak, and L. Lin, "A genetic algorithm for two-stage transportation problem using priority-based encoding," *OR Spectrum*, vol. 28, pp. 337–354, 2006.

[6] M. M. Lotfi and R. Tavakkoli-Moghaddam, "A genetic algorithm using priority-based encoding with new operators for fixed charge transportation problems," *Applied Soft Computing*, vol. 13, no. 5, pp. 2711–2726, 2013.

[7] P. C. Pop, C. Sabo, B. Biesinger, B. Hu, and G. R. Raidl, "Solving the two-stage fixed-charge transportation problem with a hybrid genetic algorithm," *Carpathian Journal of Mathematics*, vol. 33, no. 3, pp. 365–371, 2017.

[8] P. K. Srivastava and D. C. Bisht, "Dichotomized incenter fuzzy triangular ranking approach to optimize interval data based transportation problem," *Cybernetics and Information Technologies*, vol. 18, no. 4, pp. 111–119, 2018.

[9] Y. Kacher and P. Singh, "A comprehensive literature review on transportation problems," *International Journal of Applied and Computational Mathematics*, vol. 7, pp. 1–49, 2021.

[10] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: Nsga-ii," *IEEE transactions on evolutionary computation*, vol. 6, no. 2, pp. 182–197, 2002.

[11] A. Biswas, A. A. Shaikh, and S. T. A. Niaki, "Multi-objective non-linear fixed charge transportation problem with multiple modes of transportation in crisp and interval environments," *Applied Soft Computing*, vol. 80, pp. 628–649, 2019.

[12] A. Biswas and T. Pal, "A comparison between metaheuristics for solving a capacitated fixed charge transportation problem with multiple objectives," *Expert Systems with Applications*, vol. 170, 2021.

[13] A. Biswas, L. E. Cárdenas-Barrón, A. A. Shaikh, A. Duary, and A. Céspedes-Mota, "A study of multi-objective restricted multi-item fixed charge transportation problem considering different types of demands," *Applied Soft Computing*, vol. 118, 2022.

[14] S. Haque, A. Bhurjee, and P. Kumar, "Multi-objective non-linear solid transportation problem with fixed charge, budget constraints under uncertain environments," *Systems Science & Control Engineering*, vol. 10, no. 1, pp. 899–909, 2022.

[15] C. Pop, P. C. Pop, and A. Petrovan, "An improved pareto front for the non-linear multi-objective fixed cost transportation problem," in *2025 IEEE Congress on Evolutionary Computation (CEC)*, 2025, pp. 1–4.

[16] ——, "A prüfer-based genetic algorithm for solving a non-linear multi-objective fixed-charge transportation problem," in *IEEE International Conference on Systems, Man, and Cybernetics*, 2025, pp. 468–473.

[17] A. K. Bhunia and S. S. Samanta, "A study of interval metric and its application in multi-objective optimization with interval objectives," *Computers & Industrial Engineering*, vol. 74, pp. 169–178, 2014.

[18] M. Gen and R. Cheng, *Genetic algorithms and engineering optimization*. John Wiley & Sons, 1997.