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SUSTAINABLE FIXED-CHARGE FUZZY MULTI-OBJECTIVE 5D SHORTEST PATH PROBLEM USING ASPIRATION LEVEL-BASED NSGAS: APPLICATION TO AQUATIC FISH HAUL SYSTEM

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Abstract. Sustainability encompasses the interaction between environmental, economic, and social systems at various levels. In transportation systems, vehicles rely on different fuels to meet energy demands. However, these fuels contribute to environmental pollution by releasing greenhouse gases. Considering this context, the present study investigates a sustainable fixed-charge multi-objective multi-driver multi-route multi-conveyance shortest path problem (FCMOMDMRMCSPP). The primary intent is to identify the most efficient route that minimizes cost, time, risk, carbon emissions, and distance while traveling between sources and destinations. Real-world scenarios often involve uncertainties, making it difficult to precisely define the parameters of FCMOMDMRMCSPP. Triangular fuzzy numbers are introduced in the proposed model to address this ambiguity. The possibilistic programming approach is employed to transform the fuzzy problem into a deterministic one. The resulting deterministic model is then solved using two multi-objective genetic algorithms (MOGAs): aspiration level (AL)-based non-dominated sorting genetic algorithm (NSGA)-II and NSGA-III. An aquatic fish haul system problem has been examined as an application within the framework of the proposed model. For $\alpha = 0$ and 0.1, the AL-based NSGA-II and III generate 6, 11, and 4 solutions that satisfy the decision-maker's (DM's) ALs in cases I, II, and III of the AL and shape parameter combination, respectively. Similarly, for $\alpha = 0.5$, these methods yield 5, 11, and 4 solutions, while for $\alpha = 0.9$, they provide 6, 11, and 4 solutions for the same cases. A comparative analysis is conducted between the compromise solutions obtained from the proposed techniques and those derived from the hybrid genetic algorithm, NSGA-II and NSGA-III. A sensitivity analysis of the objective functions concerning the shape parameter and AL is also performed. Finally, the coverage performance measure is computed to assess the effectiveness of the proposed methods.

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1. Introduction

Meta-heuristic algorithms have emerged as powerful tools for solving complex optimization problems due to their flexibility and effectiveness. Among these, population-based meta-heuristics, especially evolutionary

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algorithms, have drawn considerable interest. These algorithms are capable of generating multiple potential solutions in a single execution by emulating the principles of natural evolution. A prominent example in this category is the genetic algorithm (GA), which has been widely applied to diverse and challenging optimization tasks. Originally conceptualized by John Holland in the 1960s, the GA is rooted in Darwinian evolutionary theory, specifically the idea of "survival of the fittest". It begins with an initial population of candidate solutions and iteratively refines them using genetic operators such as selection, crossover, and mutation to evolve toward optimal or near-optimal outcomes.

In multi-objective optimization, it is common to encounter several trade-off solutions referred to as non-dominated or Pareto-optimal solutions. To address such problems, Schaffer [1] modified the genetic algorithm by splitting the population into subgroups, with each subgroup evaluated using a different objective function. This method allowed the algorithm to converge toward a particular region of the Pareto front, demonstrating the importance of customizing GAs to fit specific problem domains. Following this advancement, researchers proposed various MOGAs. Notable among these are the MOGA introduced by Fonseca and Fleming [2], and the weighted-sum based GA proposed by Hajela *et al.* [3]. A major milestone in the evolution of MOGAs was Goldberg's incorporation of the dominance principle into multi-objective evolutionary algorithms in 1989. Building on this concept, Srinivas and Deb [4] developed the NSGA, which explicitly implemented non-dominated sorting. However, the initial version of NSGA had several shortcomings, such as the lack of elitism, dependence on user-specified parameters, and significant computational burden. To overcome these drawbacks, Deb *et al.* [5] introduced an improved version known as NSGA-II, which incorporated a better diversity maintenance mechanism and eliminated the need for external parameters. NSGA-II has since been widely applied to numerous practical optimization problems, including the two layer supply chain problem [6], closed loop supply chain network problem [7] and the uncertain shortest path problem [8]. Later, Deb and Jain [9] developed NSGA-III, which uses a reference-point-based approach. This method enables decision-makers to focus on solutions in proximity to their preferred reference points, and also addresses the high computational complexity associated with the crowding distance mechanism in NSGA-II. NSGA-III has found applications in diverse domains; for instance, Bhesdadiya *et al.* [10] applied it to solve economic and environmental dispatch problems, Ji *et al.* [11] used it for tuning MMC controller parameters, and Agnihotri and Dhodiya [12] employed it for multi-objective solid transportation problems. Despite the progress in MOGAs, one key limitation persisted: the lack of priority consideration based on the preferences of the DM. To overcome this issue, Todkar and Dhodiya [13–15] introduced AL-based NSGA-II and III. These improved methods integrate DM's ALs into the evolutionary process, ensuring the generated Pareto-optimal solutions are aligned with the DM's preferences.

MOGAs and their various enhancements have proven to be powerful tools for solving intricate optimization problems that involve multiple, often conflicting, objectives. A prominent example of such a problem is the shortest path problem (SPP), which frequently arises in the context of supply chain management, where goods or services must be transported efficiently from a source to a destination. The classical SPP is a foundational problem in graph theory and network optimization, typically defined by three key constraints: the starting point (source), the ending point (destination), and the conditions governing the intermediate nodes. The objective of the traditional SPP is to determine the most efficient route between the source and destination by minimizing the cumulative weights assigned to the edges of the graph. This optimization problem is critical in numerous domains such as transportation and logistics, telecommunication networks, data routing, supply chain operations, and even in robotics and autonomous navigation systems. Pioneering researchers such as Dijkstra [16], Bellman [17], Floyd [18], and Dreyfus [19] made significant contributions to the development of algorithms for solving SPPs during the 1950s and 1960s.

In real-world transportation scenarios, movement between two locations often requires the use of different modes or types of vehicles, commonly referred to as multiple conveyances. To accommodate this complexity, the conventional 2D SPP is extended into a 3D framework, known as the multi-conveyance SPP (MCSPP). In transportation terminology, this extended version is often referred to as the solid transportation problem (STP). Notably, researchers such as Ghosh *et al.* [20–22] have made significant contributions in this domain, addressing various aspects of the STP under different operational and environmental constraints. However, in the context of SPP, no research has yet addressed this scenario involving multiple conveyances. Modern travel routes connecting sources and destinations typically offer a range of paths. Some of these may be well-maintained and smooth, while others could be damaged, congested, or irregular. In such situations, even a route that is shorter in distance may require more time to travel if its condition is poor. Furthermore, travel expenses tend to increase on rougher routes due to wear and inefficiency. Hence, both the physical condition and length of a route become critical factors in minimizing total cost and travel time. Given the availability of multiple direct paths between points, it is rational to consider route options in addition to conveyance types. When both route selection and vehicle type are taken into account, the problem transitions from a 3D to a 4D SPP, termed the multi-route MCSPP (MRMCSPP). In transportation, many researchers, such as Giri and Das [23] and Kakran and Dhodiya [24], have explored 4D transportation problems, highlighting the importance and complexity of incorporating multiple routes and vehicle types in transportation models. Their work has significantly contributed to advancing the field of 4D transportation, demonstrating its relevance in optimizing real-world transportation networks. Another major factor that influences travel efficiency is vehicle speed, which is largely determined by the driver's behavior and driving style. These behavioral attributes can be affected by road quality and traffic conditions, further influencing travel time and cost. Skilled drivers typically optimize speed and reduce cost more effectively than less experienced ones. Moreover, for long-distance routes, it is often impractical for a single driver to manage the entire journey, necessitating the inclusion of multiple drivers in planning. Despite its practical importance, the scenario involving multiple drivers, multiple routes, and multiple conveyances has not been adequately addressed in existing shortest path models. This leads to the evolution of the 4D SPP into a 5D SPP, more precisely referred to as the multi-driver MRMCSPP (MRMCMDSPP).

In practical applications, optimizing a single criterion such as distance or travel time, is often not sufficient. Stakeholders frequently seek to balance multiple goals, including reducing fuel consumption, choosing safer (less risky) routes, and achieving overall efficiency across several parameters. This complexity necessitates a transition from the SPP to a multi-objective SPP (MOSPP). Accordingly, the previously discussed 5DSPP is extended into a multi-objective 5DSPP (MO5DSPP). The foundational work in this area was initiated by Hansen [25], who first addressed the MOSPP framework. Following his contribution, a wide body of literature emerged, with significant advancements by researchers such as Papadimitriou and Yannakakis [26], Gandibleux *et al.* [27], and Sedeño-Noda *et al.* [28], whose studies have played pivotal roles in advancing the theory and applications of multi-objective shortest path models in network optimization. Numerous techniques have been proposed to address the SPP under the assumption of deterministic edge weights. However, in practical settings, the parameters are usually imprecise due to a wide range of uncertainties, including floods, uneven roads, strikes, road accidents, traffic congestion, poor visibility in the winter, or poor health while traveling. In order to address this impreciseness, fuzzy set theory is one of the tools. This leads to the transformation of the MO5DSPP into fuzzy MO5DSPP (FMO5DSPP). Dubois [29] introduced SPP in a fuzzy environment. Mukherjee [30] tackled fuzzy SPP using a methodology known as the fuzzy programming technique. Ebrahimnejad *et al.* approached fuzzy SPP with the particle swarm optimization algorithm [31] and the artificial bee colony algorithm [32]. Lin *et al.* [33] employed a genetic algorithm to solve fuzzy SPP, while Di *et al.* [34] utilized an ant colony optimization algorithm. Rani and Reddy [35] explored the fuzzy MOSPP, which is a bi-objective optimization problem involving both crisp and trapezoidal fuzzy values. Using a data envelopment analysis approach, Bagheri *et al.* [36] addressed fuzzy MOSPP. Majumder *et al.* [8] modeled and solved the MOSPP under uncertain environment utilizing classical global criterion method, and two MOGAs. Todkar and Dhodiya solved fuzzy MOSPP with triangular fuzzy number [13] and trapezoidal fuzzy number [14] using AL-based NSGA-II & III. Todkar and Dhodiya [37] modeled and solved the uncertain multi-objective SPP by AL-based NSGA-II & III. Several remarkable recent SPP studies are given in Table 1.

Nowadays, an additional charge known as a fixed charge, is sometimes imposed on various travel routes from source to destination along that route. The fixed charge could be permit fees, road tolls, festive occasion subscription expenses, etc. The modified structure of FMO5DSPP with a fixed charge is known as fixed-charge FMO5DSPP (FCFMO5DSPP). In the transportation domain, Ghosh and Das [38] have applied the concept of a fixed charge to enhance the modeling of transportation systems, considering its impact on routing and cost optimization. Additionally, greenhouse gas (GHG) emissions are currently a major environmental concern. The transportation system is significantly responsible for releasing CO2 and other GHGs due to the internal combustion engines of vehicles. It is estimated that 50 percent of greenhouse gases are emitted by light-duty vehicles such as passenger cars and minibusses, while 50 percent come from heavy-duty vehicles like trucks, ships, and freight trucks. Consequently, GHG emissions are a significant threat to the environment and air pollution. Several factors affect carbon emissions, including engine type, gasoline type, traffic laws, road conditions, driving experience, driving restrictions, and so forth. Proper vehicle selection is necessary while traveling from source to destination in an SPP system in order to minimize carbon emissions.

Research gaps

The existing literature on the SPP, as summarized in Table 1, continues to underexplore several important aspects despite significant advancements in the field.

- Existing SPP models do not simultaneously address multi-driver, multi-route, and multi-conveyance scenarios, although they are common in practice.
- Carbon emissions, a critical environmental factor, have not been explicitly considered as an optimization objective in MOSPPs.
- The concept of fixed charges (*e.g.*, tolls, permits, subscription fees) has not been integrated into shortest path formulations.
- Only a few studies employ advanced MOGAs with decision-maker preference incorporation (aspiration levels) in fuzzy MOSPPs.

These unresolved issues highlight the need for developing more realistic and comprehensive shortest path models.

Motivation

In light of these gaps, the motivation of this study stems from the growing requirement for optimization models that reflect the true complexities of transportation systems and support sustainable decision-making. Specifically:

- Real-world transportation systems demand solutions that are cost-effective, time-efficient, and environmentally sustainable.
- Practical networks involve multiple routes, conveyances, drivers, and fixed charges, all of which significantly affect travel time, cost, and risk.
- Simultaneously optimizing cost, time, distance, risk, and carbon emissions under uncertain conditions remains an open challenge.

Contributions

To address the above motivations, the present study makes the following key contributions:

- Propose a fixed-charge fuzzy multi-objective multi-driver multi-route multi-conveyance shortest path problem.
- Formulate the problem in a fuzzy environment using triangular fuzzy numbers to model uncertainty.
- Solve the proposed model using five meta-heuristic algorithms: HGA, NSGA-II, NSGA-III, AL-based NSGA-II, and AL-based NSGA-III.
- Demonstrate applicability through a real-world case study on aquatic fish haul systems.

Novelty

The novelty of the study lies in several unique aspects that distinguish it from existing works:

- First study to integrate fixed charges and carbon emissions into a fuzzy MOSPP framework.
- Simultaneous consideration of multi-driver, multi-route, and multi-conveyance dimensions in shortest path modeling.

TABLE 1. Several remarkable recent SPP studies.

Article	Objective	Additional cost	Carbon emission	Environment
Mukherjee [30]	Single	No	No	Fuzzy
Ebrahimnejad *et al.* [31]	Single	No	No	Fuzzy
Ebrahimnejad *et al.* [32]	Single	No	No	Fuzzy
Sedeno-Noda and Colebrook [39]	Bi-objective	No	No	crisp
De las cases *et al.* [40]	Multi	No	No	crisp
Ebrahimnejad *et al.* [41]	Single	No	No	fuzzy
Lin *et al.* [33]	Single	No	No	Fuzzy
Bagheri *et al.* [36]	Multi	No	No	Fuzzy
Majumder *et al.* [8]	Multi	No	No	Uncertain
Todkar and Dhodiya [13,14]	Multi	No	No	Fuzzy
Todkar and Dhodiya [15]	Multi	No	No	Uncertain
Present study	Multi	Fixed-charge	Yes	Fuzzy

– Use of aspiration-level based NSGA-II and NSGA-III to align solutions with decision-maker preferences.
– Introduction of an unexplored application domain (aquatic fish haul systems) for validating the proposed model.

The article is organized as follows: Section 2 outlines the study's preliminary aspects. The mathematical model and problem statement are detailed in Section 3. In Section 4, the formulation of the 0–1 programming model is discussed. Section 5 describes the solution methodologies applied to solve the deterministic model of FCFMO5DSPP. The application of FCFMO5DSPP to solve aquatic fish haul system problems, along with results, discussion, and sensitivity analysis, is covered in Section 6. Sections 7–9 address various aspects including comparisons, performance measures, and provide the conclusion and future scope.

2. Preliminaries

2.1. Triangular fuzzy number

A triangular fuzzy number (TFN) $\tilde{A}$ is represented by a triplet (a_1, a_2, a_3), where $a_1 \leq a_2 \leq a_3$. The membership function $\mu_{\tilde{A}}(x)$ of $\tilde{A}$ is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1 \\ \frac{x-a_1}{a_2-a_1}, & a_1 \leq x \leq a_2 \\ \frac{a_3-x}{a_3-a_2}, & a_2 \leq x \leq a_3 \\ 0, & x > a_3. \end{cases}$$

Here, a_1 is the lower limit, a_2 is the most likely value (modal value), and a_3 is the upper limit of the fuzzy number.

Arithmetic operations of TFNs *via* membership functions

Let $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ be two TFNs with their respective membership functions $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{B}}(y)$. According to Zadeh's extension principle, the membership function of a fuzzy number $\tilde{C} = \tilde{A} \circ \tilde{B}$, where $\circ$ denotes a binary operation (*e.g.*, $+$, $-$, $\times$), is given by:

$$\mu_{\tilde{C}}(z) = \sup_{\substack{x,y \in \mathbb{R} \\ x \circ y = z}} \min\{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)\}.$$

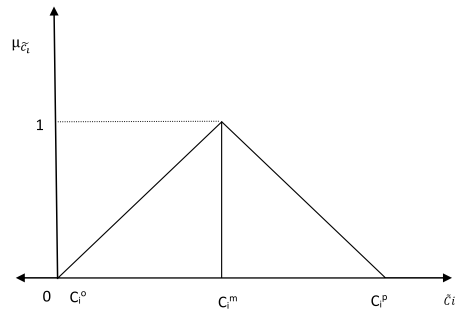

FIGURE 1. TPD of $\tilde{c}_i$.

This formulation defines the resulting membership function based on the minimum of the membership grades of all (x, y) pairs that satisfy $x \circ y = z$. While exact evaluation using this principle is computationally intensive, in practice, TFN operations are approximated using the following closed-form expressions, which preserve the triangular membership shape:

- **Addition:**
$$\tilde{A} + \tilde{B} = (a_1 + b_1,\ a_2 + b_2,\ a_3 + b_3).$$
- **Subtraction:**
$$\tilde{A} - \tilde{B} = (a_1 - b_3,\ a_2 - b_2,\ a_3 - b_1).$$
- **Multiplication (for $a_i, b_i > 0$):**
$$\tilde{A} \cdot \tilde{B} = (a_1 b_1,\ a_2 b_2,\ a_3 b_3).$$
- **Scalar Multiplication (for scalar $\lambda \geq 0$):**
$$\lambda \cdot \tilde{A} = (\lambda a_1,\ \lambda a_2,\ \lambda a_3).$$

2.2. Possibilistic programming approach

Generally, there is some risk involved with collecting data on real-world scenarios. Many types of data are non-specific by nature; hence, fuzzy numbers are used to represent them. These fuzzy numbers are modeled using a possibility distribution [42]. With several significant applications, fuzzy advancement models with uncertain coefficients in the objective function have been solved using the probabilistic distribution. A crisp multi-objective optimization model was created from the fuzzy multi-objective optimization model using the possibilistic technique [43].

2.3. Triangular possibilistic distribution

As uncertain parameters are not precisely defined, triangular possibilistic distribution (TPD) is commonly utilized since it is easy to use and provides good computational viability. The TPD can be constructed under sensitive conditions using the most optimistic (o) (possibility degree = 0), most likely (m) (possibility degree = 1), and most pessimistic (p) values, all of which are usually denoted by (c_i^o), (c_i^m), and (c_i^p), respectively. Figure 1 illustrates the objective function cost at three points $(c_i^o, 0)$, $(c_i^m, 1)$, and $(c_i^p, 0)$. By moving the three points of TPD to the left, the objective function cost is minimized.

2.4. α-level set

Zadeh [44] formulated the α-level set, considered as the basis for the relationship between traditional and fuzzy set theories. The α-level (confidence level) reflects the DM's confidence in his fuzzy judgement. The smallest

α-value reflects a substantial degree of pessimism and uncertainty, leading to a wide-ranging interval judgment that offers considerable savings. Conversely, the highest α-value yields a more optimistic judgment, with lower and upper bounds having greater level of membership in the original fuzzy set. In order to address the fuzzy optimization problems, many researchers like Todkar and Dhodiya [13]; Tailor and Dhodiya [45] utilized this α-level concept. This same concept is used in the present article to determine the DM's confidence in fuzzy judgment.

2.5. Exponential membership function

In order to normalize the data corresponding to the given problem, the exponential membership function can be utilized. If z_p^{NIS} and z_p^{PIS} represent negative ideal solution (*i.e.*, greatest value of the objective function) and the positive ideal solution (lowest value of the objective function), respectively, for objective z_p, then the $\mu_{z_p}(x)$ is expressed as follows,

$$\mu_{z_p}(x) = \begin{cases} 1, & \text{if } z_p \leq z_p^{\text{PIS}}, \\ \frac{e^{-s_p \psi_p(x)} - e^{-s_p}}{1 - e^{-s_p}}, & \text{if } z_p^{\text{PIS}} < z_p < z_p^{\text{NIS}}, \\ 0, & \text{if } z_p \geq z_p^{\text{NIS}} \end{cases} \tag{1}$$

where, $\psi_p(x) = \frac{z_p - z_p^{\text{PIS}}}{z_p^{\text{NIS}} - z_p^{\text{PIS}}}$, $0 \leq \mu_{z_p}(x) \leq 1$ and the DM's shape parameter $s_p \neq 0$. The membership function in $[z_p^{\text{PIS}}, z_p^{\text{NIS}}]$ will be convex or concave, depending on $s_p < 0$ and $s_p > 0$.

3. Mathematical model and problem statement

3.1. Notations

The multi-objective 5-dimensional shortest path model is constructed using the following notations:

(i) $G = (\mathcal{V}, \mathcal{E})$ be a network.
(ii) $\mathcal{V}$ = set of vertices of network G.
(iii) $\mathcal{E}$ = set of edges of network G.
(iv) n = number of vertices.
(v) m = number of edges.
(vi) I = number of conveyances (distinct modes of transit).
(vii) J = number of direct routes.
(viii) K = number of drivers.
(ix) $\tilde{Z}_p$ = pth objective function with triangular fuzzy numbers.
(x) x_{baijk} = flow from the bth vertex to ath vertex using ith conveyance *via* jth route with the kth driver.
(xi) $\tilde{c}_{baijk}$ = total cost of travelling from the bth vertex to ath vertex using ith conveyance *via* jth route with the kth driver.
(xii) $f_{baij=}$ fixed charge (toll tax) of travelling from the bth vertex to ath vertex using ith conveyance *via* jth route.
(xiii) $\tilde{t}_{baijk}$ = total time of travelling from the bth vertex to ath vertex using ith conveyance *via* jth route with the kth driver.
(xiv) $\tilde{r}_{baijk}$ = total risk of travelling from the bth vertex to ath vertex using ith conveyance *via* jth route with the kth driver.
(xv) $\tilde{e}_{baijk}$ = total carbon emission of travelling from the bth vertex to ath vertex using ith conveyance *via* jth route with the kth driver.
(xvi) $d_{baj=}$ distance between the bth vertex to ath vertex *via* jth route.

3.2. Assumptions

The proposed model considers the following assumptions:

– Fixed charge is associated with toll tax.
– Cost, time, risk, and carbon emission are considered in the form of trianglar fuzzy numbers.
– Distance is considered in the form of crisp.

3.3. Formulation

The proposed model aims to minimize the cost and distance while travelling from source to destination by selecting the shortest path among different available paths with the best route, conveyance, and driver. Additionally, the problem focuses on minimizing time while reducing risk and carbon emissions caused by the route, conveyance, and driver. It is crucial to choose the route, the conveyance, and the driver precisely in order to minimize all of these objectives, as they all highly depend on them.

Objective functions

The formulation of objective functions of the proposed problem is as follows using the notations provided in Section 3.1:

$$\min \tilde{z_1} = \sum_{b=1}^{n} \sum_{a=1,a\neq b}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\tilde{c}_{baijk} x_{baijk} + f_{baij}), \tag{2}$$

$$\min \tilde{z_2} = \sum_{b=1}^{n} \sum_{a=1,a\neq b}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \tilde{t}_{baijk} x_{baijk}, \tag{3}$$

$$\min \tilde{z_3} = \sum_{b=1}^{n} \sum_{a=1,a\neq b}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \tilde{r}_{baijk} x_{baijk}, \tag{4}$$

$$\min \tilde{z_4} = \sum_{b=1}^{n} \sum_{a=1,a\neq b}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \tilde{e}_{baijk} x_{baijk}, \tag{5}$$

$$\min z_5 = \sum_{b=1}^{n} \sum_{a=1,a\neq b}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} d_{baijk} x_{baijk} \tag{6}$$

where, f_{baij} denotes the fixed charge in equation (2). The equations (2)–(6) aims to minimize the cost, time, risk, carbon emission, and distance respectively.

Constraints

$$\text{For source vertex: } \sum_{a=2}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} x_{1aijk} = 1, \tag{7}$$

For other than source and destination vertices:

$$\sum_{a=1,a\neq b}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} x_{baijk} - \sum_{u=1,u\neq b}^{n} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} x_{ubijk} = 0, \qquad b \neq 1 \;\&\; n, \tag{8}$$

$$\text{For destination vertex: } \sum_{b=1}^{n-1} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} x_{bnijk} = 1, \tag{9}$$

Non-negativity constraints:

$$x_{baijk} = \begin{cases} 1, & \text{if the path travel from } b\text{th to } a\text{th vertex using } i\text{th conveyance} \\ & \textit{via } j\text{th route with the } k\text{th driver,} \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

Decision problem

Thus, with regard to the problem having objectives of minimizing cost, time, risk, carbon emissions, and distance, and the relevant constraints, the mathematical model can be written as follows:

Model 1

$$\left.\begin{aligned} &\min(\tilde{z}_1, \tilde{z}_2, \tilde{z}_3, \tilde{z}_4, z_5) = \min\left(\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\tilde{c}_{baijk}x_{baijk} + f_{baij}),\right. \\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\tilde{t}_{baijk}x_{baijk}, \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\tilde{r}_{baijk}x_{baijk}, \\ &\left.\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\tilde{e}_{baijk}x_{baijk}, \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}d_{baijk}x_{baijk}\right), \\ &\text{subject to the constraints (7)–(10)} \end{aligned}\right\} \quad (11)$$

where, $\tilde{c}_{baijk} = (c^o_{baijk}, c^m_{baijk}, c^p_{baijk})$, $\tilde{t}_{baijk} = (t^o_{baijk}, t^m_{baijk}, t^p_{baijk})$, $\tilde{r}_{baijk} = (r^o_{baijk}, r^m_{baijk}, r^p_{baijk})$, $\tilde{e}_{baijk} = (e^o_{baijk}, e^m_{baijk}, e^p_{baijk})$ denote the TFN for cost, time, risk, and carbon emission respectively.

4. Formulation of 0–1 programming model

A crisp MOMDMRMC optimization model of Model 1 is constructed using the TPD technique to handle fuzzy objectives. The objective function of cost is represented as follows:

$$\begin{aligned} \min \tilde{z}_1 = \min(z_1^o, z_1^m, z_1^p) &= \min\left(\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\tilde{c}_{baijk}x_{baijk} + f_{baij})\right) \\ &= \min\left(\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(c^o_{baijk}x_{baijk} + f_{baij}), \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\right. \\ &\qquad \left.(c^m_{baijk}x_{baijk} + f_{baij}), \quad \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(c^p_{baijk}x_{baijk} + f_{baij}\right)\right) \end{aligned} \quad (12)$$

where $\tilde{c}_{baijk} = (c^o_{baijk}, c^m_{baijk}, c^p_{baijk})$. The above equation can be also written as,

$$\begin{aligned} (\min z_{11}, \min z_{12}, \min z_{13}) = \min&\left(\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(c^o_{baijk}x_{baijk} + f_{baij}),\right. \\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(c^m_{baijk}x_{baijk} + f_{baij}), \\ &\left.\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(c^p_{baijk}x_{baijk} + f_{baij}\right)\right). \end{aligned} \quad (13)$$

The equations (12) and (13) describes the optimistic, most likely, and pessimistic scenario. Using the α-level set, each $\tilde{c}_{baijk}$ can be written as $(\tilde{c}_{baijk})_\alpha = ((c_{baijk})^o_\alpha, (c_{baijk})^m_\alpha, (c_{baijk})^p_\alpha)$, where $(c_{baijk})^o_\alpha = (c_{baijk})^o + \alpha((c_{baijk})^m - (c_{baijk})^o)$, $(c_{baijk})^m_\alpha = (c_{baijk})^m$, and $(c_{baijk})^p_\alpha = (c_{baijk})^p - \alpha((c_{baijk})^p - (c_{baijk})^m)$.

Hence, equation (13) becomes,

$$\begin{aligned}(\min z_{11}, \min z_{12}, \min z_{13}) = \min\Bigg(&\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big((c_{baijk})^o_\alpha x_{baijk} + f_{baij}\big),\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big((c_{baijk})^m_\alpha x_{baijk} + f_{baij}\big),\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big((c_{baijk})^p_\alpha x_{baijk} + f_{baij}\big)\Bigg). \end{aligned} \tag{14}$$

Similarly, the objective functions of time, risk, and carbon emission can be represented in the form of equation (14). Thus, the crisp MOMDMRMC optimization model of Model 1 is represented as follows:

Model 2

$$\left.\begin{aligned}&\min(z_{11}, z_{12}, z_{13}, z_{21}, z_{22}, z_{23}, z_{31}, z_{32}, z_{33}, z_{41}, z_{42}, z_{43}, z_5)\\ &= \min\Bigg(\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big((c_{baijk})^o_\alpha x_{baijk} + f_{baij}\big),\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big((c_{baijk})^m_\alpha x_{baijk} + f_{baij}\big),\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big((c_{baijk})^p_\alpha x_{baijk} + f_{baij}\big),\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(t_{baijk})^o_\alpha x_{baijk}, \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(t_{baijk})^m_\alpha x_{baijk},\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(t_{baijk})^p_\alpha x_{baijk}, \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(r_{baijk})^o_\alpha x_{baijk},\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(r_{baijk})^m_\alpha x_{baijk}, \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(r_{baijk})^p_\alpha x_{baijk},\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(e_{baijk})^o_\alpha x_{baijk}, \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(e_{baijk})^m_\alpha x_{baijk},\\ &\sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(e_{baijk})^p_\alpha x_{baijk}, \sum_{b=1}^{n}\sum_{a=1,a\neq b}^{n}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}d_{baijk}x_{baijk}\Bigg)\end{aligned}\right\} \tag{15}$$

subject to the constraints (7)–(10).

5. Solution methodologies

This section provides an overview of the two AL-based MOGAs, namely AL-based NSGA-II & III, utilized to tackle the FCFMO5DSPP. These evolutionary algorithms utilize a population of feasible solutions that progressively evolve over successive generations to approach optimal solutions. Consequently, the representation of chromosomes and the configuration of the population plays a crucial role in these methodologies.

Chromosome encoding

A chromosome represents the route between the starting and the ending vertex, serving as a feasible solution that may be optimal. In this study, binary encoding is used to create the chromosomes, indicating the presence or absence of an arc in a feasible path. Consider, x_{baijk} represents an arc from bth vertex to ath using ith conveyance *via* jth route with the kth driver. Construct a row vector that lists all the arcs of the network in sequential order (excluding the conveyance option, direct route option, and driver option). If an arc x_{baijk} is part of the feasible path, the corresponding entry is 1; otherwise, it is 0.

Initial population

This paper generates the initial population randomly. Using MATLAB, we create a random row vector of size $1\times$(total number of arcs, *i.e.*, connections excluding the conveyance option, direct route option, and driver option) with entries of 0 or 1, repeating this process a predefined number P of times. Scrutinize these randomly generated vectors for feasibility. The unique feasible vectors identified in this process are directly included in the initial population. If the number of feasible vectors exceeds the desired population size, a random selection is made to match the population size. If the number of feasible vectors is insufficient, the selection process is repeated until the population size requirement is met.

5.1. AL-based NSGA-II

Deb *et al.* [5] introduced an innovative NSGA-II approach to generate a Pareto frontier, which may result in some solutions falling below the DM's AL. To address this issue, Todkar and Dhodiya [13–15] adapted NSGA-II to meet the DM's aspiration level by incorporating a constraint $\mu_z(y) - \overline{\mu_z}(y) \geq 0$, where $\overline{\mu_z}(y)$ represents the given AL for the objective function z and y is a solution. This modified version of NSGA-II is referred to as AL-based NSGA-II.

For clarity, we have defined several terms, including feasibility test and population update, as detailed below. Additionally, the crowded distance assignment and the procedure of the aforementioned method are discussed in this section.

Feasibility test: This test determines whether the solution is feasible or not to a given problem.

Population update: Consider the population P of size N, and y_1 is any member of P. If y_1 satisfies the AL-based constraint $\mu_z(y_1) - \overline{\mu_z}(y_1) \geq 0$, where $\overline{\mu_z}(y_1)$ is given aspiration level corresponding to objective function z and $\mu_z(y_1)$ is exponential membership function value corresponding to solution y_1, it is directly incorporated in updated P and denoted by $\overline{P}$. If the population size of $\overline{P}$ is not equal to N, then fulfil the remaining size by adding constraints satisfying y_i repeatedly.

Crowded distance assignment: A solution p wins a competition against another solution q if one of the below conditions are valid:

(1) If a solution p has a superior rank.
(2) If they have a similar rank however solution p has a superior crowding distance than solution q.

Crowded distance assignment procedure:

(1) Call $l = Cardinality(F)$ for the number of solutions in F. For every p in the set initially allot crowding distance $d_p = 0$.
(2) In worse order of F_r sort the set for every objective function $r = 1, 2, \cdots, R$.

(3) For $r = 1, 2, \cdots, R$ assign a high distance to the border solutions, then for all remaining solutions from $q = 2$ to $l - 1$, assign

$$d_{(I_q^r)} = d_{(I_q^r)} + \frac{f_r^{(I_{q+1}^r)} - f_r^{(I_{q-1}^r)}}{f_r^{\max} - f_r^{\min}}. \tag{16}$$

The index I_q represents the solution index of the qth item of the sorted list.

AL-based NSGA-II procedure

The technique begins with generating the random population P_0 of size N. Update P_0 as $\overline{P_0}$ using population update. At generation t, parent population is $\overline{P_t}$ and offspring population is Q_t which is generated using the genetic operators (selection, crossover, and mutation) on $\overline{P_t}$. Check the feasibility test for Q_t. The individuals of Q_t satisfying the feasibility test remain present in Q_t; others are removed. Update Q_t as $\overline{Q_t}$ using population update. Now, at generation t, the merge set $M_t = \overline{P_t} \cup \overline{Q_t}$ of size $2N$. Among them, the fitter N individuals are picked utilizing the crowding comparison operator for the subsequent generation. The operator has two metrics: (1) non-domination level/rank (j_{rank}) and (2) crowding distance (j_{distance}).

Divide M_t into distinct non-dominance fronts $F_1, F_2, \ldots$, and so on. The individuals belonging to front F_1 have j_{rank} equals 1, the individuals belonging to front F_2 have j_{rank} equals 2, and so on. Lower j_{rank} individuals are favored over those with higher j_{rank}. For the subsequent iteration P_{t+1}, the individuals with $j_{\text{rank}} = 1$ are favored over the individuals with $j_{\text{rank}} = 2$, and so on. Add fronts $F_1, F_2, \ldots$, and so on in P_{t+1} until the size of P_{t+1} equals or exceeds N for the first time. Assuming that F_k is the final front inserted in P_{t+1}, and all fronts from F_{k+1} are rejected. If P_{t+1} has precise size N then P_{t+1} equals $F_1 \cup F_2 \cup \ldots \cup F_k$. If the size of P_{t+1} exceeds, solutions should be chosen according to their crowding distance criteria (say, j_{distance}) since j_{rank} is the same for all individuals in F_k.

$N - |F_1 \cup F_2 \cup \ldots \cup F_{k-1}|$ numbers of individuals from the front F_k are now required. If c and d are individuals of F_k and $c_{\text{rank}} = d_{\text{rank}}$ but $c_{\text{distance}} > d_{\text{distance}}$, then c is favoured above d in P_{t+1}. To put it another way, individuals with the greatest crowding distance are eventually picked from F_k to occupy the remaining vacant positions in P_{t+1}. Finally, the members of P_t are replaced with those of P_{t+1} for the next generation. Repeat this technique until the stopping criteria are reached.

Algorithm

The AL-based NSGA-II algorithm for solving Model 2 is as follows in Algorithm 1:

5.2. AL-based NSGA-III

When crowding comparison is used to limit the population size, the NSGA-II approach by Deb *et al.* [5] may struggle with convergence. This method preserves all members of the first non-dominated set when its size is smaller than the population size. However, suppose more than N individuals belong to the first non-dominant set in the next generation. In that case, some densely packed Pareto-optimal solutions might be replaced by neither dominant nor Pareto-optimal solutions. These latter solutions can eventually be surpassed by other Pareto-optimal solutions in subsequent generations. The process may cycle through generating Pareto-optimal and non-Pareto-optimal solutions until it converges to a well-distributed set of Pareto-optimal solutions. To address this issue, Deb and Jain [9] developed NSGA-III, a heuristic that maintains population diversity using a reference-point strategy, ultimately providing the Pareto front. Consequently, DM receives solutions that fall below their ALs. As a result, Todkar and Dhodiya [13–15] introduces the AL-based NSGA-III, which incorporates the DM's AL to address this issue.

Definition 1. A Reference Point (RP) in objective space is a point where the DM specifies their ALs for the objective functions.

Algorithm 1. AL-based NSGA-II.

Require: Objective function, Aspiration level ($\overline{\mu}$), Shape parameter, Population size
Ensure: $\min Z_i$, X (Values of decision variables)
Read: Model 2
Begin: Iteration=0; Construct random initial population P_0
Update P_0 as $\overline{P_0}$ using population update
while Termination condition not met **do**
  Iteration $\leftarrow$ Iteration+1;
  Begin
  Set $f \leftarrow$ By applying selection procedure of NSGA-II on P_0
  for $d_1, d_2 \in f$ **do**
    $d_1', d_2' \leftarrow$ new offsprings employing crossover on d_1 & d_2
    $Q_0' = \cup d_x'$ where d_x' is new offsprings from above step
  end for
  for $g_1 \in f$ **do**
    $g_1' \leftarrow$ new offsprings employing mutation on g_1
    $Q_0'' = \cup g_y'$ where g_y' is new offsprings from above step
  end for
  Update $Q_0 \leftarrow Q_0' \cup Q_0''$
  $Q_0 \leftarrow$ Check feasibilty test of Q_0, infeasible individuals are discarded. Update Q_0 as $\overline{Q_0}$ using population update
  End (Begin)
  At generation t, $\overline{P_t} \leftarrow$ parent population and $\overline{Q_t} \leftarrow$ offspring population. Merge set $M_t \leftarrow \overline{P_t} \cup \overline{Q_t}$
  Do non-dominated sorting on M_t as same as in NSGA-II
  $P_{t+1} \leftarrow$ to choose N fitter solutions use crowding distance criteria on M_t
end while
End (Begin)

AL-based NSGA-III procedure

The technique start with randomly generated population P_0 of size N and a collection of widely dispersed M-dimensional RPs H on a hyperplane spanning the entire RM^+ area. Consider at generation t, the parent population $\overline{P_t}$ and updated offspring population $\overline{Q_t}$, where the process of creating $\overline{P_t}$ and $\overline{Q_t}$ is same as discussed in AL-based NSGA-II. The merge set $M_t = \overline{P_t} \cup \overline{Q_t}$ of size $2N$. The main objective of this approach is to select N better members from M_t for the next generation.

Perform Pareto-based non-dominating sorting on M_t to obtain non-dominating levels $F_1, F_2, \ldots, \&$ so on. At this stage, an empty population S_t is established, and members from non-domination levels are gradually added to S_t, beginning with F_1, until the size of S_t approaches or exceeds N. Consider that F_l is a most recently included level to S_t, and all the fronts starting from $(l+1)$th are rejected. The final level allowed is lth, which is only partially acceptable in some circumstances. The individuals of the S_t/F_l population have been included in the new population P_{t+1}, and the diversity maintenance operator chooses the remaining individuals from F_l. The normalization operator should be used to make the environment selection while maintaining the RP and objective points within the same unit range. The zero vector, which after normalization reflects the population's ideal point S_t, is where defined RPs are located. According to a calculation of each individual's perpendicular distance in S_t from each RP line (connecting the RP with the origin), individuals are connected to RPs with a minimum perpendicular distance. A niche preservation approach is used to choose individuals from F_l. The niche count for the jth RP is ρ_j, which is defined as the number of people connected to the jth RP from the S_t/F_l. Determine the lowest value of ρ_j in the RPs set $J_{\min} = \{j : \arg\min_j \rho_j\}$. If $|J_{\min}| > 1$ then randomly choose $j^- \in J$.

The following two scenarios are then implemented:

– If some members in F_l are related to the jth RP, there are two possibilities:

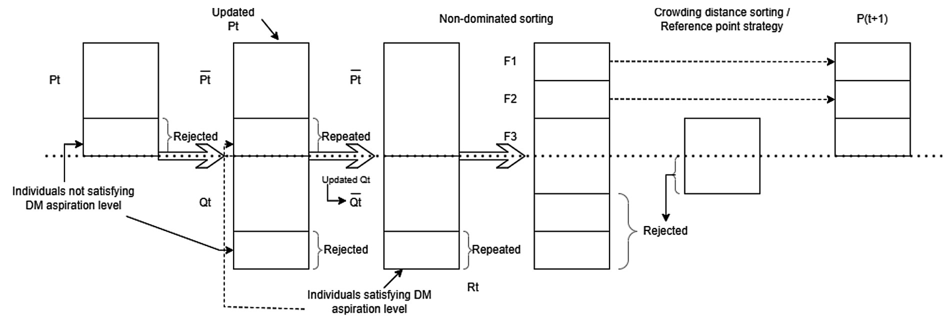

FIGURE 2. Schematic of AL-based methods procedure.

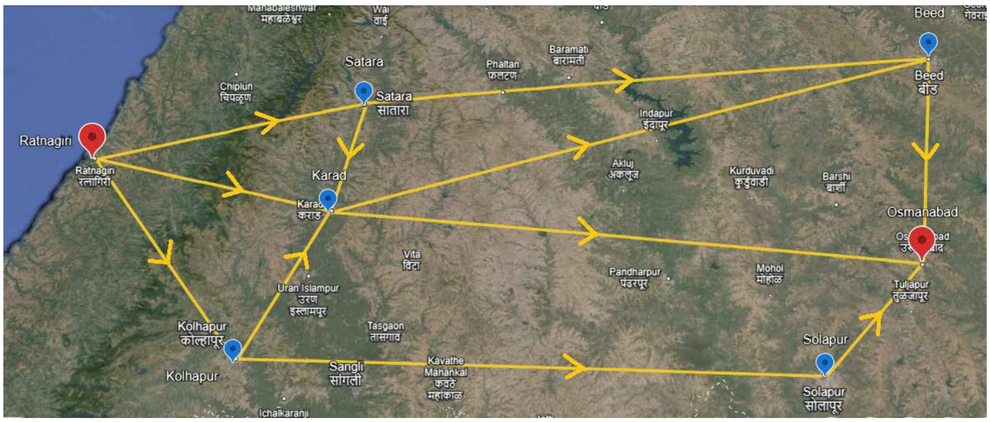

FIGURE 3. Designed network diagram from Google earth for AFHS problem.

(1) If $\rho_j = 0$, the member of F_l with the least perpendicular distance from the jth reference line adds up to P_{t+1}. The ρ_j count is then increased by one.
(2) If $\rho_j > 0$, select one member at random from F_l who is associated with jth RP and add up to P_{t+1}. The ρ_j count is then increased by one.

– If no members in F_l are associated with the jth RP, the current RP is ignored for the present generation, for the moment $J_{\min}$ is recalculated, and j^- is selected again.

Repeat this process until all of the remaining P_{t+1} individuals have been filled up. This will result in better solutions evolving over consecutive generations until the stopping condition is met.

Algorithm

The algorithm for AL-based NSGA-III for solving Model 2 is the same as AL-based NSGA-II; the only difference is that the selection procedure occurs in steps 20 and 21 of the AL-based NSGA-II algorithm. AL-based NSGA-III uses NSGA-III selection procedure. A Schematic of the solution procedure of AL-based techniques is shown in Figure 2.

6. Application to aquatic fish haul system

In this section, the real-life aquatic fish haul system (AFHS) problem has been considered as an application in the framework of FCFMO5DSPP. The AFHS problem aims to minimize the cost, time, risk, carbon emission,

Table 2. Data coordinates of 7 cities from Maharastra state, India.

Vertex number	City name	Latitude	Longitude
1	Ratnagiri	16.99180	73.31341
2	Kolhapur	16.70779	74.23818
3	Satara	17.68173	74.01586
4	Karad	17.28447	74.18060
5	Solapur	17.66211	75.90557
6	Beed	18.99078	75.75326
7	Osmanabad	18.18694	76.03808

Table 3. Aggregated fuzzy value of cost objective with three direct routes, two conveyances, and two drivers.

Cost in Rs.

Arcs	Route 1											
	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	756	779	795	840	857	883	177	182	186	196	200	206
1–3	1341	1382	1410	1490	1520	1566	313	323	329	348	355	366
1–4	813	838	855	903	922	949	190	196	200	211	216	222
2–4	412	425	434	458	468	482	96	99	101	107	109	112
2–5	1361	1403	1431	1512	1543	1590	317	327	334	353	360	370
3–4	298	307	313	331	338	348	70	72	73	78	79	82
3–6	1879	1937	1976	2088	2131	2195	438	452	461	487	497	512
4–6	2320	2392	2440	2579	2631	2710	541	558	569	602	614	632
4–7	1677	1729	1764	1864	1902	1959	391	403	411	434	443	457
5–7	384	396	404	427	436	449	89	92	94	99	101	104
6–7	663	684	698	737	752	775	155	160	163	172	176	181

Arcs	Route 2											
	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	1016	1047	1068	1129	1152	1186	237	244	249	263	268	276
1–3	1081	1114	1136	1201	1225	1262	259	267	272	288	294	303
1–4	813	838	855	903	922	949	190	196	200	211	216	222
2–4	491	506	516	545	557	573	114	118	120	127	130	134
2–5	1417	1461	1490	1575	1607	1655	331	341	348	368	375	386
3–4	405	418	426	451	460	474	94	97	99	105	107	110
3–6	1538	1586	1618	1710	1745	1797	381	393	401	424	432	445
4–6	2051	2114	2156	2279	2325	2395	478	493	503	531	542	559
4–7	1776	1831	1868	1974	2014	2075	414	427	436	460	470	484
5–7	398	410	418	442	451	465	93	96	98	103	106	109
6–7	792	816	832	880	898	925	184	190	194	205	209	215

Arcs	Route 3											
	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	874	901	919	971	991	1021	204	210	214	226	231	238
1–3	1110	1144	1167	1233	1258	1296	259	267	272	288	294	303
1–4	1045	1077	1099	1161	1185	1220	243	251	256	271	276	284
2–4	534	551	562	594	606	624	125	129	132	139	142	146
2–5	1441	1486	1516	1602	1635	1684	337	347	354	374	382	393
3–4	403	415	423	447	457	470	94	97	99	105	107	110
3–6	1599	1648	1681	1777	1813	1867	373	385	393	415	424	436
4–6	1922	1981	2021	2136	2179	2244	448	462	471	498	508	523
4–7	1733	1787	1823	1926	1966	2025	404	417	425	450	459	472
5–7	562	579	591	624	637	656	131	135	138	146	149	153
6–7	1072	1105	1127	1191	1216	1252	250	258	263	278	284	292

and distance for a refrigerated truck traveling between the source and the destination. As a result, we can provide the most efficient routes for moving fishes by refrigerated trucks within a short period with minimal costs, risks, carbon emissions, and the shortest distance. In order to achieve this, we must determine the efficient route for a refrigerated truck, considering the cost, time, risk, carbon emission, and distance. This process considers imprecise parameters due to many factors; therefore, cost, time, risk, and carbon emission are fuzzy, while distance is a crisp quantity.

In this study, the FCFMO5DSPP has been used as a tool to solve the AFHS problem. The below network diagram G shown in Figure 3 has been made on Google Earth. It includes 7 cities of Maharastra state, India, as vertices and 11 connections between them, each with three direct routes. In order to systematically analyze the data, we have shown data coordinates of considered cities and assigned numerical identifiers to each city in Table 2. For AFHS problem, we have considered two conveyances namely diesel refrigerated truck (DRT) and electric refrigerated truck (ERT), three direct routes in each connection, and two drivers. Therefore, the decision variable x_{baijk} represents amount of flow from bth vertex to ath vertex using ith conveyance *via* jth route with the kth driver. Each x_{baijk} is associated with five non-negative weights: (1) fuzzy cost ($\tilde{c}_{baijk}$), (2) fuzzy time ($\tilde{t}_{baijk}$), (3) fuzzy risk ($\tilde{r}_{baijk}$), (4) fuzzy carbon emission ($\tilde{e}_{baijk}$), and (5) crisp distance (d_{baijk}). The time and distance objective data is directly collected from the Mappls MapmyIndia app for the considered conveyances. For cost data, we have assumed the conveyance DRT has a fuel efficiency of 16 km/L and conveyance ERT has 8 km/unit. The cost data is also collected from the Mappls app using these assumptions. The risk data is collected from Google Maps using road condition events, safety events, and traffic events. The weightage for these three events is 0.25, 0.5, and 0.25, respectively. Moreover, the data for carbon emission is collected from the Indian government site https://e-amrit.niti.gov.in/. The units for objectives are cost in rupees, time in minutes, risk on a scale of 0 to 1 (with 0 being low risk and 1 being high risk), carbon emission in CO2, and distance in km. Tables 3, 4, 5, 6, and 7 show the data for ($\tilde{c}_{baijk}$), ($\tilde{t}_{baijk}$), ($\tilde{r}_{baijk}$), ($\tilde{e}_{baijk}$), and (d_{baijk}) respectively. These fuzzy data are in the form of triangular fuzzy number. The fixed-charge data associated with arcs is presented in Table 8.

In this study, we focused on the model (2), a crisp version of the model (1), to address the FCFMO5DSPP problem. Given that model (2) represents a multi-objective optimization problem, we employed evolutionary

Table 4. Aggregated fuzzy value of time objective with three direct routes- two conveyances, and two drivers.

Time in minutes — Route 1

Arcs	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	199	207	217	181	190	198	246	257	270	224	236	246
1–3	308	321	337	281	295	307	382	398	418	348	366	381
1–4	208	217	228	190	200	208	258	269	283	235	248	257
2–4	86	90	95	79	83	86	107	112	117	98	103	107
2–5	247	257	270	225	236	246	306	319	335	279	293	305
3–4	57	59	62	52	54	56	70	73	77	64	67	70
3–6	399	416	437	364	383	398	495	516	542	451	475	494
4–6	433	451	474	394	415	432	537	559	587	489	515	535
4–7	321	334	351	292	307	320	398	414	435	362	381	396
5–7	71	74	78	65	68	71	88	92	96	80	84	88
6–7	125	130	137	114	120	124	155	161	169	141	148	154

Time in minutes — Route 2

Arcs	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	270	281	295	246	259	269	335	348	366	305	321	333
1–3	268	279	293	244	257	267	332	346	363	302	318	331
1–4	232	242	254	212	223	232	288	300	315	262	276	287
2–4	123	128	134	112	118	122	152	159	167	139	146	152
2–5	307	320	336	280	294	306	381	397	417	347	365	380
3–4	108	112	118	98	103	107	133	139	146	121	128	133
3–6	386	402	422	351	370	385	479	498	523	436	459	477
4–6	408	425	446	371	391	407	506	527	553	461	485	504
4–7	353	368	386	322	339	352	438	456	479	399	420	437
5–7	82	85	89	74	78	81	101	105	111	92	97	101
6–7	156	163	171	142	150	156	194	202	212	177	186	193

Time in minutes — Route 3

Arcs	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	228	237	249	207	218	227	282	294	309	257	270	281
1–3	285	297	312	260	273	284	354	368	387	322	339	352
1–4	249	259	272	226	238	248	308	321	337	281	295	307
2–4	176	183	192	160	168	175	218	227	238	198	209	217
2–5	286	298	313	260	274	285	355	370	388	323	340	354
3–4	100	104	109	91	96	100	124	129	135	113	119	123
3–6	413	430	452	376	396	411	512	533	560	466	491	510
4–6	399	416	437	364	383	398	495	516	542	451	475	494
4–7	362	377	396	329	347	361	449	467	491	409	430	447
5–7	124	129	135	113	119	123	154	160	168	140	147	153
6–7	269	280	294	245	258	268	333	347	365	303	319	332

Table 5. Aggregated fuzzy value of risk objective with three direct routes, two conveyances, and two drivers.

Risk in scale — Route 1

Arcs	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	0.43	0.45	0.47	0.46	0.48	0.50	0.50	0.52	0.55	0.52	0.55	0.57
1–3	0.78	0.81	0.85	0.82	0.86	0.90	0.90	0.93	0.98	0.94	0.99	1.03
1–4	0.52	0.55	0.57	0.55	0.58	0.60	0.60	0.63	0.66	0.63	0.67	0.69
2–4	0.18	0.19	0.20	0.19	0.20	0.21	0.21	0.22	0.23	0.22	0.24	0.25
2–5	0.26	0.27	0.29	0.28	0.29	0.30	0.30	0.32	0.33	0.32	0.33	0.35
3–4	0.19	0.20	0.21	0.20	0.22	0.23	0.22	0.23	0.25	0.24	0.25	0.26
3–6	0.25	0.26	0.27	0.26	0.27	0.28	0.28	0.30	0.31	0.30	0.31	0.33
4–6	0.40	0.41	0.43	0.42	0.44	0.46	0.46	0.48	0.50	0.48	0.50	0.52
4–7	0.27	0.28	0.30	0.29	0.30	0.31	0.31	0.33	0.34	0.33	0.35	0.36
5–7	0.05	0.06	0.07	0.06	0.07	0.08	0.06	0.07	0.08	0.07	0.08	0.09
6–7	0.12	0.13	0.14	0.13	0.14	0.15	0.14	0.15	0.16	0.15	0.16	0.16

Risk in scale — Route 2

Arcs	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	0.51	0.54	0.56	0.54	0.57	0.59	0.59	0.62	0.65	0.62	0.65	0.68
1–3	0.78	0.81	0.85	0.82	0.86	0.90	0.90	0.93	0.98	0.94	0.99	1.03
1–4	0.63	0.66	0.69	0.66	0.70	0.73	0.73	0.76	0.80	0.76	0.80	0.84
2–4	0.15	0.16	0.17	0.16	0.17	0.18	0.18	0.19	0.20	0.19	0.20	0.21
2–5	0.29	0.31	0.32	0.31	0.32	0.34	0.34	0.35	0.37	0.35	0.37	0.39
3–4	0.07	0.08	0.09	0.07	0.08	0.09	0.08	0.09	0.10	0.09	0.10	0.11
3–6	0.27	0.28	0.30	0.29	0.30	0.31	0.31	0.33	0.34	0.33	0.35	0.36
4–6	0.33	0.34	0.36	0.35	0.36	0.38	0.38	0.39	0.41	0.40	0.42	0.43
4–7	0.32	0.33	0.35	0.33	0.35	0.37	0.37	0.38	0.40	0.39	0.41	0.42
5–7	0.09	0.10	0.11	0.10	0.11	0.12	0.11	0.12	0.13	0.11	0.12	0.13
6–7	0.07	0.08	0.09	0.07	0.08	0.09	0.08	0.09	0.10	0.08	0.09	0.10

Risk in scale — Route 3

Arcs	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	0.45	0.46	0.49	0.47	0.49	0.51	0.51	0.53	0.56	0.54	0.57	0.59
1–3	0.58	0.61	0.64	0.61	0.64	0.67	0.67	0.70	0.73	0.70	0.74	0.77
1–4	0.60	0.62	0.65	0.62	0.66	0.68	0.69	0.71	0.75	0.72	0.76	0.79
2–4	0.19	0.20	0.21	0.20	0.21	0.22	0.22	0.23	0.24	0.23	0.25	0.26
2–5	0.25	0.26	0.27	0.26	0.27	0.28	0.28	0.30	0.31	0.30	0.31	0.33
3–4	0.18	0.19	0.20	0.19	0.20	0.21	0.21	0.22	0.23	0.22	0.23	0.24
3–6	0.22	0.23	0.24	0.23	0.24	0.25	0.25	0.26	0.27	0.26	0.27	0.29
4–6	0.44	0.46	0.48	0.46	0.48	0.50	0.50	0.52	0.55	0.53	0.56	0.58
4–7	0.19	0.20	0.21	0.20	0.21	0.22	0.22	0.23	0.24	0.23	0.24	0.25
5–7	0.07	0.08	0.09	0.08	0.09	0.10	0.09	0.10	0.11	0.09	0.10	0.11
6–7	0.06	0.07	0.08	0.07	0.08	0.09	0.08	0.09	0.10	0.09	0.10	0.11

methods for its solution. Specifically, we explored various MOGAs, including the HGA, NSGA-II, NSGA-III, AL-based NSGA-III, and AL-based NSGA-III. These algorithms were utilized to generate a set of diverse non-dominated solutions for G. The parameter settings for the MOGAs are detailed in Table 9. Table 10 lists the NIS and PIS values for the objectives at various α levels. The NIS and PIS values of cost objective is presented with fixed-charge. Table 11 outlines the different cases of shape parameters and AL. This research was performed on an HP laptop equipped with an Intel (R) Core i5 10th generation processor operating at 2.60 GHz and 8 GB of RAM. The model was solved using MATLAB (R2015a, Runtime version 8.5, and Windows 64-bit). The subsequent Sections 6.1 and 6.2 discuss the outcomes of applying the five MOGAs to the given G and sensitivity analysis of objective functions with respect to shape parameter and ALs.

6.1. Results and discussion

We solved Model (2) of the network G using multiple MOGAs, including HGA, NSGA-II, NSGA-III, AL-based NSGA-II, and AL-based NSGA-III, as explained below. To keep things simple, we designed the route's nomenclature and associated objective values at $\alpha = 0$, as Table 12 illustrates.

HGA

HGA always generates a unique solution. As a result, we get a unique efficient route for the AFHS problem to travel between Ratnagiri and Osmanabad. The solution for the case-I of Table 11 at $\alpha = 0$ is φ_{16} of Table 12. Their corresponding objective values are $\tilde{z}_1 = (669, 688, 700)$, $\tilde{z}_2 = (707, 736, 774)$, $\tilde{z}_3 = (0.82, 0.86, 0.9)$, $\tilde{z}_4 = (20.55, 21.4, 22.47)$, and $z_5 = 445$. For the case-II and case-III of Table 11 at $\alpha = 0$, HGA provides φ_{13} and φ_5 of Table 12 respectively. Simillarly, at $\alpha = 0.1,\ 0.5$, and, 0.9, we get similar solutions as $\alpha = 0$.

TABLE 6. Aggregated fuzzy value of carbon emission objective with three direct routes, two conveyances, and two drivers.

Arcs	Carbon emission: Route 1											
	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	9.19	9.57	10.05	10.18	10.72	11.15	7.20	7.50	7.88	7.98	8.40	8.74
1–3	11.67	12.16	12.77	12.94	13.62	14.16	9.15	9.53	10.01	10.14	10.67	11.10
1–4	8.64	9.00	9.45	9.58	10.08	10.48	6.77	7.05	7.40	7.50	7.90	8.21
2–4	4.38	4.56	4.79	4.85	5.11	5.31	3.43	3.57	3.75	3.80	4.00	4.16
2–5	14.48	15.08	15.83	16.05	16.89	17.57	11.34	11.81	12.40	12.57	13.23	13.76
3–4	4.07	4.24	4.45	4.51	4.75	4.94	3.20	3.33	3.50	3.54	3.73	3.88
3–6	17.16	17.87	18.76	19.01	20.01	20.81	13.44	14.00	14.70	14.90	15.68	16.31
4–6	19.95	20.78	21.82	22.11	23.27	24.20	15.63	16.28	17.09	17.32	18.23	18.96
4–7	18.25	19.01	19.96	20.23	21.29	22.14	14.29	14.89	15.63	15.84	16.68	17.34
5–7	4.35	4.53	4.76	4.82	5.07	5.28	3.29	3.43	3.60	3.65	3.84	4.00
6–7	6.93	7.22	7.58	7.68	8.09	8.41	5.43	5.66	5.94	6.02	6.34	6.59

Arcs	Carbon emission: Route 2											
	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	8.03	8.36	8.78	8.90	9.36	9.74	6.29	6.55	6.88	6.97	7.34	7.63
1–3	12.59	13.11	13.77	13.95	14.68	15.27	9.87	10.28	10.79	10.94	11.51	11.97
1–4	9.67	10.07	10.57	10.71	11.28	11.73	7.57	7.89	8.28	8.39	8.84	9.19
2–4	4.87	5.07	5.32	5.39	5.68	5.91	3.81	3.97	4.17	4.22	4.45	4.62
2–5	15.02	15.65	16.43	16.65	17.53	18.23	11.77	12.26	12.87	13.04	13.73	14.28
3–4	3.97	4.14	4.35	4.40	4.64	4.82	3.00	3.13	3.29	3.33	3.51	3.65
3–6	18.00	18.75	19.69	19.95	21.00	21.84	14.10	14.69	15.42	15.63	16.45	17.11
4–6	24.33	25.34	26.61	26.96	28.38	29.52	19.09	19.89	20.88	21.16	22.28	23.17
4–7	17.40	18.12	19.03	19.28	20.29	21.11	13.63	14.20	14.91	15.11	15.90	16.54
5–7	4.01	4.18	4.39	4.45	4.68	4.87	3.15	3.28	3.44	3.49	3.67	3.82
6–7	7.06	7.35	7.72	7.82	8.23	8.56	5.53	5.76	6.05	6.13	6.45	6.71

Arcs	Carbon emission: Route 3											
	DRT						ERT					
	Driver 1			Driver 2			Driver 1			Driver 2		
1–2	10.34	10.77	11.31	11.46	12.06	12.54	8.10	8.44	8.86	8.98	9.45	9.83
1–3	12.84	13.37	14.04	14.23	14.97	15.57	10.05	10.47	10.99	11.14	11.73	12.20
1–4	11.13	11.59	12.17	12.33	12.98	13.50	8.72	9.08	9.53	9.66	10.17	10.58
2–4	5.29	5.51	5.79	5.86	6.17	6.42	4.15	4.32	4.54	4.60	4.84	5.03
2–5	15.15	15.78	16.57	16.79	17.67	18.38	11.87	12.36	12.98	13.15	13.84	14.40
3–4	3.10	3.23	3.39	3.44	3.62	3.76	2.43	2.53	2.66	2.69	2.83	2.95
3–6	17.03	17.74	18.63	18.88	19.87	20.66	13.34	13.90	14.60	14.79	15.57	16.19
4–6	20.62	21.48	22.55	22.85	24.06	25.02	16.16	16.83	17.67	17.91	18.85	19.60
4–7	17.58	18.31	19.23	19.48	20.51	21.33	13.78	14.35	15.07	15.27	16.07	16.71
5–7	4.79	4.99	5.24	5.31	5.59	5.81	3.62	3.77	3.96	4.01	4.22	4.39
6–7	7.91	8.24	8.65	8.77	9.23	9.60	6.19	6.45	6.77	6.86	7.22	7.51

Table 7. Values of distance objective with three direct routes.

Arcs	Distance in km.		
	Route 1	Route 2	Route 3
1–2	132	178	153
1–3	235	194	210
1–4	142	160	183
2–4	72	86	94
2–5	238	248	252
3–4	52	71	70
3–6	329	286	280
4–6	406	359	336
4–7	293	310	303
5–7	67	70	98
6–7	116	139	187

Table 8. Values of fixed-charge (toll tax) for considered conveyances with three direct routes.

Arcs	Fixed-charge in Rs.		
	Route 1	Route 2	Route 3
1–2	0	230	0
1–3	480	250	0
1–4	0	0	230
2–4	230	0	0
2–5	1035	655	980
3–4	75	75	75
3–6	80	0	0
4–6	430	80	75
4–7	275	145	75
5–7	75	75	60
6–7	115	75	75

Table 9. Parameter settings for MOGAs.

Parameters	Settings for considered MOGAs
Number of iteration	1000
Population size	200
Selection	Binary-tournament
Crossover probability	0.5
Crossover	Double point
Mutation probability	0.5
Muation	Bit

TABLE 10. NIS & PIS values of fuzzy objectives.

Objectives	$\alpha=0$		$\alpha=0.1$		$\alpha=0.5$		$\alpha=0.9$	
	NIS	PIS	NIS	PIS	NIS	PIS	NIS	PIS
z_{11}	6771	669	6782.6	670.9	6829	678.5	6875.4	686.1
z_{12}	6887	688	6887	688	6887	688	6887	688
z_{13}	7062	700	7044.5	698.8	6974.5	694	6904.5	689.2
z_{21}	1423	471	1428.8	473.3	1452	482.5	1475.2	491.7
z_{22}	1481	494	1481	494	1481	494	1481	494
z_{23}	1556	515	1548.5	512.9	1518.5	504.5	1488.5	496.1
z_{31}	1.86	0.71	1.87	0.71	1.93	0.74	1.96	0.75
z_{32}	1.96	0.75	1.96	0.75	1.96	0.75	1.96	0.75
z_{33}	2.03	0.78	2.03	0.78	2	0.77	1.96	0.75
z_{41}	54.47	20.4	54.75	20.49	55.9	20.83	57.05	21.16
z_{42}	57.33	21.25	57.33	21.25	57.33	21.25	57.33	21.25
z_{43}	59.63	22.31	59.4	22.21	58.49	21.79	57.56	21.36
z_5	899	435	899	435	899	435	899	435

TABLE 11. Cases of shape parameter and AL.

Case	Shape parameter $(K_1, K_2, K_3, K_4, K_5)$	AL $(\tilde{\mu}_{z_1}(x), \tilde{\mu}_{z_2}(x), \tilde{\mu}_{z_3}(x), \tilde{\mu}_{z_4}(x), \tilde{\mu}_{z_5}(x))$
I	$(-0.1, -0.1, -0.1, -0.1, -0.1)$	$(0.8, 0.7, 0.9, 0.8, 0.9)$
II	$(-0.5, -0.5, -0.5, -0.5, -0.5)$	$(0.7, 0.8, 0.8, 0.95, 0.95)$
III	$(-0.9, -0.9, -0.9, -0.9, -0.9)$	$(0.9, 0.9, 0.9, 0.9, 0.9)$

NSGA-II & III

For the given network G, NSGA-II and NSGA-III generate the Pareto front. These methods do not require the shape parameter or the AL, and consequently, their results remain unaffected by the cases presented in Table 11. The outcomes of these methods at $\alpha = 0$, 0.1, 0.5, and, 0.9 are presented in Table 13. The Table 13 shows that NSGA-II & III generate the Pareto front of 80 solutions. Thus, the DM gets many compromise solutions to move fishes from Ratnagiri to Osmanabad.

AL-based NSGA-II & III

For the given network G, Table 14 shows the results of the AL-based NSGA-II and III for all the cases of Table 11; this method yields a Pareto front that satisfies the DM's AL. Therefore, DM recieves the compromise solutions that satisfies their AL for moving fishes from Ratnagiri to Osmanabad. Figures 4 and 5 illustrate the convergence behavior of the AL-based NSGA-II & III methods, respectively, in terms of the number of convergent solutions of the Pareto front that satisfy the DM's AL with respect to population size and the number of iterations for the case-I of Table 11 at $\alpha = 0$. Figure 4 demonstrates that the AL-based NSGA-II method reaches convergence with fewer iterations compared to the AL-based NSGA-III method, as depicted in Figure 5. This implies that the AL-based NSGA-II method is more efficient regarding the number of iterations and population size required for convergence. Figure 6 illustrate the variance in cost objective prompted by various shape parameter choices for model 2 at $\alpha = 0$. Moreover, this figure presents the value of corresponding membership function for the solution φ_4.

TABLE 12. Nomenclature of routes with corresponding objective values at $\alpha = 0$.

Notation	Route	Cost	Time	Risk	Carbon emission	Distance
φ_1	$x_{14111} - x_{47131}$	(2621, 2700, 2753)	(570, 594, 624)	(0.71, 0.75, 0.78)	(26.22, 27.31, 28.68)	445
φ_2	$x_{14111} - x_{47212}$	(1522, 1556, 1587)	(570, 598, 624)	(0.85, 0.9, 0.93)	(24.48, 25.68, 26.79)	435
φ_3	$x_{14112} - x_{47211}$	(1569, 1600, 1635)	(588, 614, 643)	(0.86, 0.91, 0.94)	(23.87, 24.97, 26.11)	435
φ_4	$x_{14112} - x_{47232}$	(1428, 1456, 1496)	(599, 630, 655)	(0.78, 0.82, 0.85)	(24.85, 26.15, 27.19)	445
φ_5	$x_{14111} - x_{47211}$	(1479, 1516, 1541)	(606, 631, 663)	(0.83, 0.88, 0.91)	(22.93, 23.89, 25.08)	435
φ_6	$x_{14111} - x_{47232}$	(1338, 1372, 1402)	(617, 647, 675)	(0.75, 0.79, 0.82)	(23.91, 25.07, 26.16)	445
φ_7	$x_{14212} - x_{47211}$	(877, 894, 908)	(633, 662, 692)	(0.94, 1, 1.03)	(21.79, 22.79, 23.84)	435
φ_8	$x_{14112} - x_{47231}$	(1382, 1414, 1449)	(639, 667, 699)	(0.77, 0.81, 0.84)	(23.36, 24.43, 25.55)	445
φ_9	$x_{14111} - x_{47221}$	(1372, 1410, 1436)	(646, 673, 707)	(0.89, 0.93, 0.97)	(22.27, 23.2, 24.36)	452
φ_{10}	$x_{14211} - x_{47211}$	(856, 874, 886)	(656, 683, 718)	(0.91, 0.96, 1)	(21.06, 21.94, 23.03)	435
φ_{11}	$x_{14111} - x_{47231}$	(1292, 1330, 1355)	(657, 684, 719)	(0.74, 0.78, 0.81)	(22.42, 23.35, 24.52)	445
φ_{12}	$x_{14211} - x_{47222}$	(795, 811, 829)	(657, 689, 720)	(0.99, 1.04, 1.08)	(21.88, 22.95, 23.94)	452
φ_{13}	$x_{14211} - x_{47232}$	(715, 730, 747)	(667, 699, 730)	(0.83, 0.87, 0.91)	(22.04, 23.12, 24.11)	445
φ_{14}	$x_{14212} - x_{47231}$	(690, 708, 722)	(684, 715, 748)	(0.85, 0.9, 0.93)	(21.28, 22.25, 23.28)	445
φ_{15}	$x_{14211} - x_{47221}$	(749, 768, 781)	(696, 725, 762)	(0.97, 1.01, 1.06)	(20.4, 21.25, 22.31)	452
φ_{16}	$x_{14211} - x_{47231}$	(669, 688, 700)	(707, 736, 774)	(0.82, 0.86, 0.9)	(20.55, 21.4, 22.47)	445
φ_{17}	$x_{14211} - x_{47132}$	(2191, 2237, 2300)	(587, 616, 644)	(0.8, 0.84, 0.88)	(26.25, 27.56, 28.73)	445
φ_{18}	$x_{14211} - x_{47131}$	(1998, 2058, 2098)	(620, 646, 679)	(0.79, 0.83, 0.87)	(24.35, 25.36, 26.63)	445
φ_{19}	$x_{14212} - x_{47232}$	(736, 750, 769)	(644, 678, 704)	(0.86, 0.91, 0.94)	(22.77, 23.97, 24.92)	445
φ_{20}	$x_{14212} - x_{47222}$	(816, 831, 851)	(634, 668, 694)	(1.02, 1.08, 1.11)	(22.61, 23.8, 24.75)	452
...	...	...	...	...	...	...
...	...	...	...	...	...	...
φ_{38}	...	...	...	...	...	...
ϱ_1	$x_{12112} - x_{25112} - x_{57112}$	(3889, 3946, 4032)	(471, 494, 515)	(0.8, 0.84, 0.88)	(31.05, 32.68, 34)	437
ϱ_2	$x_{12211} - x_{25211} - x_{57212}$	(1703, 1720, 1734)	(632, 660, 693)	(0.87, 0.92, 0.97)	(22.19, 23.15, 24.28)	437
ϱ_3	$x_{12211} - x_{25211} - x_{57211}$	(1693, 1711, 1724)	(640, 668, 701)	(0.86, 0.91, 0.96)	(21.83, 22.74, 23.88)	437
ϱ_4	$x_{12211} - x_{25211} - x_{57221}$	(1697, 1715, 1728)	(653, 681, 716)	(0.91, 0.96, 1.01)	(21.69, 22.59, 23.72)	440
...	...	...	...	...	...	...
...	...	...	...	...	...	...
ϱ_{42}	...	...	...	...	...	...

TABLE 13. Pareto front by NSGA-II & III.

α-level	Cases	NSGA-II & III
0, 0.1, 0.5, and 0.9	I, II, and III	φ_1, φ_2, $\varphi_3, \dots, \varphi_{38}$, ϱ_1, ϱ_2, $\varrho_3, \dots, \varrho_{42}$

TABLE 14. Pareto front that satisfies DM's AL by AL-based NSGA-II & III.

α-level	Cases	AL-based NSGA-II & III
0 & 0.1	I	φ_4, φ_6, φ_8, φ_{11}, φ_{13}, φ_{16}
	II	φ_7, φ_9, φ_{10}, φ_{11}, φ_{12}, φ_{13}, φ_{14}, φ_{15}, ϱ_2, ϱ_3, ϱ_4
	III	φ_2, φ_3, φ_4, φ_5
0.5	I	φ_4, φ_6, φ_8, φ_{11}, φ_{16}
	II	φ_7, φ_{10}, φ_{11}, φ_{12}, φ_{13}, φ_{14}, φ_{15}, φ_{19}, ϱ_2, ϱ_3, ϱ_4
	III	φ_2, φ_4, φ_5, φ_{17}
0.9	I	φ_4, φ_{11}, φ_{13}, φ_{16}, φ_{18}, φ_{20}
	II	φ_7, φ_{10}, φ_{11}, φ_{12}, φ_{13}, φ_{14}, φ_{15}, φ_{19}, ϱ_2, ϱ_3, ϱ_4
	III	φ_2, φ_4, φ_5, φ_{17}

6.2. Sensitivity analysis

Sensitivity analysis is an effective tool for examining how different variables influence objective function outcomes. This research utilized AL-based NSGA-II and III algorithms with various shape parameters and ALs to analyze the sensitivity of the objective functions. In this section, we have considered the same cases of shape parameters and ALs as mentioned in Table 11 for given G at $\alpha = 0, 0.1, 0.5$, and 0.9. At $\alpha = 0$ and case-I of Table 11, the AL-based techniques generate the six compromise solutions for DM to move the fishes from origin to destination, which shown in Table 14. Moreover, for the case-II and case-III, these methods obtain the eleven and four compromise solutions respectively, that are shown in Table 14. The solutions for $\alpha = 0.1$, 0.5, and 0.9 are also presented in Table 14.

Table 14 illustrates that the results for a given G using AL-based methods fluctuated based on the shape parameter and AL combinations. This suggests that the shape parameter and AL have a significant effect on the outcomes of the objective functions.

7. Comparison

Since this study introduces the FCFMO5DSPP for the first time, a direct comparison with previous research is impossible. However, to evaluate the effectiveness of different solution approaches, Table 15 presents a comparative analysis of HGA, NSGA-II, NSGA-III, AL-based NSGA-II, and AL-based NSGA-III for a given G at $\alpha = 0$, 0.1, 0.5, and 0.9. In Section 6.1, we reviewed the results for these five methods with various combinations of shape parameters and ALs. Hence, this section focuses specifically on Case I from Table 11 at $\alpha = 0$ for a concise discussion.

For this case, Table 15 highlights distinct differences in the solution sets produced by each method. HGA generates a single solution φ_{16}, whereas NSGA-II and NSGA-III provide an Pareto front consisting of solutions $\varphi_1, \varphi_2, \varphi_3, \dots, \varphi_{38}, \varrho_1, \varrho_2, \varrho_3, \dots, \varrho_{42}$. Every other individual is dominated by at least one member of the Pareto front. In contrast, AL-based NSGA-II and III refine the solution set by filtering out non-preferred solutions, ultimately selecting φ_4, φ_6, φ_8, φ_{11}, φ_{13}, and φ_{16} that align with the DM's AL. By eliminating 74 non-preferred solutions, these AL-based methods significantly reduce the complexity of decision-making.

Computational efficiency is another crucial factor in evaluating these methods. The time required to generate solutions for the AFHS problem varies across approaches. HGA takes 504 s, while NSGA-II and NSGA-III require 413 and 482 s, respectively. The AL-based NSGA-II and III demonstrate superior efficiency, taking only 361 and 414 s, respectively. These results indicate that the proposed AL-based methods require less computational time compared to their conventional counterparts, making them a more efficient choice for solving FCFMO5DSPP.

From a comparative perspective, the results in Table 15 show that AL-based methods offer greater flexibility, allowing the DM to adjust the shape parameter and AL to better align with their objectives. Unlike conventional approaches, which present large Pareto fronts requiring additional filtering, AL-based methods directly provide a refined set of solutions modified to DM's preferences. This not only enhances the effectiveness of decision-making but also reduces computational overhead, making them a more practical and efficient solution approach for complex multi-objective optimization problems.

8. Performance measure

The coverage performance metric can be utilized to assess the effectiveness of multi-objective optimization algorithms.

TABLE 15. Comparison of proposed methods with existing MOGAs.

α-level	Cases	HGA	NSGA-II & III	AL-based NSGA-II & III
0 & 0.1	I	φ_{16}	$\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_{38}, \varrho_1, \varrho_2, \varrho_3, \ldots, \varrho_{42}$	$\varphi_4,\ \varphi_6,\ \varphi_8,\ \varphi_{11},\ \varphi_{13},\ \varphi_{16}$
	II	φ_{13}		$\varphi_7,\ \varphi_9,\ \varphi_{10},\ \varphi_{11},\ \varphi_{12},\ \varphi_{13},\ \varphi_{14},\ \varphi_{15},\ \varrho_2,\ \varrho_3,\ \varrho_4$
	III	φ_5		$\varphi_2,\ \varphi_3,\ \varphi_4,\ \varphi_5$
0.5	I	φ_{16}	$\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_{38}, \varrho_1, \varrho_2, \varrho_3, \ldots, \varrho_{42}$	$\varphi_4,\ \varphi_6,\ \varphi_8,\ \varphi_{11},\ \varphi_{16}$
	II	φ_{13}		$\varphi_7,\ \varphi_{10},\ \varphi_{11},\ \varphi_{12},\ \varphi_{13},\ \varphi_{14},\ \varphi_{15},\ \varphi_{19},\ \varrho_2,\ \varrho_3,\ \varrho_4$
	III	φ_5		$\varphi_2,\ \varphi_4,\ \varphi_5,\ \varphi_{17}$
0.9	I	φ_{16}	$\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_{38}, \varrho_1, \varrho_2, \varrho_3, \ldots, \varrho_{42}$	$\varphi_4,\ \varphi_{11},\ \varphi_{13},\ \varphi_{16},\ \varphi_{18},\ \varphi_{20}$
	II	φ_{13}		$\varphi_7,\ \varphi_{10},\ \varphi_{11},\ \varphi_{12},\ \varphi_{13},\ \varphi_{14},\ \varphi_{15},\ \varphi_{19},\ \varrho_2,\ \varrho_3,\ \varrho_4$
	III	φ_5		$\varphi_2,\ \varphi_4,\ \varphi_5,\ \varphi_{17}$

Coverage

In order to compute coverage, we compare two sets of non-dominated solutions, R and S, and determine the percentage of one set that is dominated by the other. Rao [46] defined the coverage as follows:

$$\mathrm{Cov}(R,S) = \frac{\mid \{s \in S/\ \exists\ r \in R : r \prec= s\} \mid}{\mid S \mid}$$

where, R and S denote the two sets of non-dominated solutions and $r \prec= s$ indicates that r dominates or is equal to s.

For understanding, coverage for the above-solved G has been calculated by considering the case-I of Table 11 at $\alpha = 0$. If R holds the solution set of HGA, and S contains the solution set of NSGA-II, NSGA-III, AL-based NSGA-II, and AL-based NSGA-III techniques one by one, then $\mathrm{Cov}(R,S) = \frac{1}{80}$, $\frac{1}{80}$, $\frac{1}{6}$, and $\frac{1}{6}$ respectively and $\mathrm{Cov}(S,R) = 1, \forall S$. These outcomes lead us to conclude that NSGA-II, NSGA-III, AL-based NSGA-II, and AL-based NSGA-III all perform better than HGA. The coverage between solutions of NSGA-II and NSGA-III is $\mathrm{Cov}(R,S) = \mathrm{Cov}(S,R) = 1$. These obtained results indicate that NSGA-II and NSGA-III techniques perform equally.

Lastly, in the case of AL-based NSGA-II and AL-based NSGA-III, the coverage is $\mathrm{Cov}(R,S) = \mathrm{Cov}(S,R) = 1$. As a result, these two methods have the same efficacy. Similarly, we can evaluate performance measure coverage for all cases of Table 11 for given G at $\alpha = 0$, 0.1, 0.5, and 0.9.

9. Conclusion and future scope

This research focuses on the formulation and analysis of a multi-objective 5D SPP involving fixed charges and triangular fuzzy numbers. The proposed model, FCFMO5DSPP, aims to find the shortest path between origin and destination vertices in a network G while minimizing total fuzzy cost, time, risk, carbon emissions, and crisp distance. To illustrate the application, the FCFMO5DSPP is employed to solve aquatic fish haul system problems, encompassing 7 cities and 11 connections, with each connection offering 3 direct routes, 2 conveyances, and 2 drivers. A deterministic model for the AFHS problem is developed and solved using five MOGAs: HGA, NSGA-II, NSGA-III, AL-based NSGA-II, and AL-based NSGA-III.

The outcomes of the analysis reveal that HGA generates a single solution, while NSGA-II and NSGA-III produce a Pareto front of optimal solutions. The AL-based approaches yield a Pareto front that aligns with the AL specified by the DM. From a numerical perspective, the AL-based NSGA-II and III methods outperformed the other algorithms in terms of fulfilling the DM's AL requirements. Additionally, the AL-based techniques provide increased flexibility for the DM, enabling them to adjust the shape parameter and AL, thus facilitating a more customized selection of optimal solutions. This demonstrates the effectiveness and practical value of the proposed methodology.

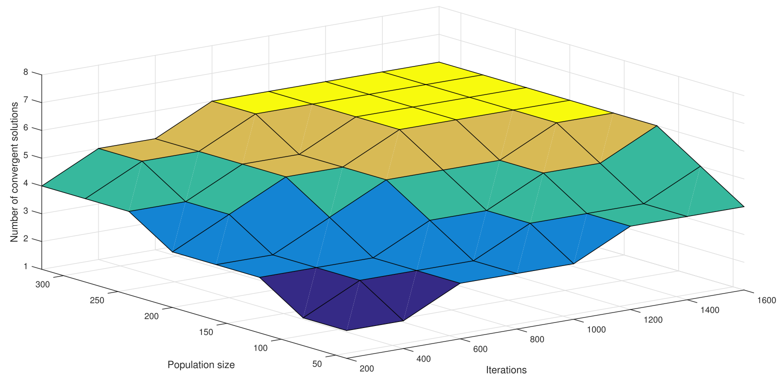

FIGURE 4. Convergence of AL-based NSGA-II concerning number of solutions.

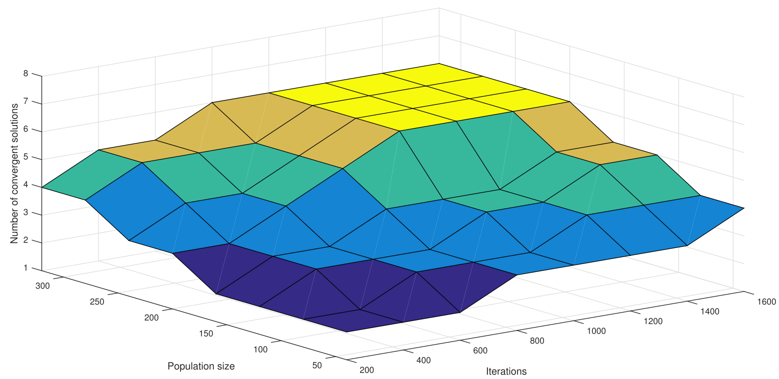

FIGURE 5. Convergence of AL-based NSGA-III concerning number of solutions.

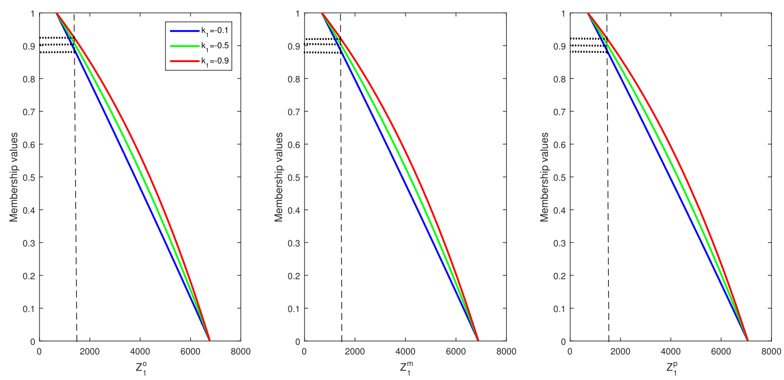

FIGURE 6. Degree of satisfaction of Cost objective for $\alpha = 0$.

Advantages of the proposed approach: The FCFMO5DSPP model offers several key advantages:

- **Comprehensive multi-dimensional optimization:** The model addresses multiple objectives, such as cost, time, risk, emissions, and distance, providing the compromise solutions to real-world optimization problems.
- **Fuzzy representation:** By using TFNs, the model accounts for uncertainties and imprecision in data, allowing for more realistic problem representation.
- **Scalability and generalizability:** Although the aquatic fish haul system is used as a representative case study, the proposed FCFMO5DSPP model is generalizable and can be effectively applied to a wide range of logistics and supply chain problems involving multiple routes, drivers, and conveyances under uncertainty. Its structure and objectives are well-suited for scenarios such as perishable goods transport, cold-chain logistics, and multi-modal freight systems.
- **Flexibility in decision-making:** The application of multi-objective optimization and genetic algorithms produces a Pareto front, giving DMs a range of compromise solutions to choose from based on their preferences.
- **AL customization:** The AL-based methods allow DMs to specify ALs of objective functions, thus tailoring the model's solutions to meet specific needs and preferences.

Limitations of the proposed Approach: While the proposed approach has significant benefits, it also has some limitations:

- **Dependency on algorithm-specific parameters:** The AL-based techniques rely on specific parameters, such as the shape parameter, crossover, mutation, and selection.
- **Computational intensity:** The solution process for the multi-objective optimization problem with numerous objectives and variables can be computationally demanding, especially in large-scale problems with many routes and drivers.

Managerial implications: The findings from this research offer several implications for managerial decision-making:

- **Enhanced flexibility in decision-making:** The availability of a Pareto front which satisfies DM's AL provides DMs with multiple compromise solutions, allowing them to select the best trade-offs between competing objectives such as cost, time, risk, emissions, and distance.
- **Optimization of resources:** Managers in transportation and logistics can apply this model to optimize routes, conveyances, and drivers, thereby reducing operational costs, carbon emissions, and risks, while improving overall efficiency.
- **Adaptability to specific needs:** The ability to adjust the ALs of objectives allow DMs to tailor the model to meet their specific operational or financial objectives.
- **Broad application potential:** The methodology can be extended to a wide range of real-world problems beyond transportation, such as supply chain management, environmental logistics, and other multi-objective optimization scenarios in uncertain environments.

Future research directions: While the focus of this study is on the FCFMO5DSPP, there are opportunities for future research to explore different variants of the MO5DSPP under intuitionistic fuzzy [47], type-2 fuzzy [48], gaussian type-2 fuzzy [49], type-2 neutrosophic [50], uncertain, and two-fold uncertain conditions. The AL-based techniques have the potential to address fuzziness in several other areas, such as transportation systems, traveling salesman problems, and assignment problems. However, a limitation of these techniques is their dependency on algorithm-specific parameters, including crossover, mutation, and, selection. These factors substantially affect the convergence speed, solution quality, and diversity of the obtained Pareto front, often require manual tuning based on trial-and-error or domain knowledge. This sensitivity may reduce the robustness and replicability of the results across different problem instances or applications. As such, future work should aim to eliminate or adaptively tune these parameters by developing self-adaptive, parameter-free, or automated control strategies within the evolutionary framework. Such advancements would enhance the adaptability, usability, and generalizability of AL-based methods, making them more accessible to practitioners and effective across a wider range of fuzzy optimization problems.

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Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Data availability statement

The data supporting this study's findings are available upon request from the corresponding author.

Author contribution statement

Dr. Jayesh Dhodiya has developed methods for FCFMO5DSPP. ***Aniket Todkar*** developed the algorithm of the AL-based methods to solve FCFMO5DSPP and wrote the paper.

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