How managerial perspectives affect the optimal fleet size and mix model: a multi-objective approach

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Accepted: 8 September 2022 / Published online: 11 November 2022 © The Author(s), under exclusive licence to Operational Research Society of India 2022

Abstract

We examine the interplay between the business and logistical aspects of a heterogeneous vehicle mix and fleet size problem using inputs from a dairy cooperative in India. Five objective functions have been modelled and simultaneously solved using a mixed-integer linear fuzzy goal programming method. These include net profit as a maximization function, and transportation cost, transportation time, lost sales due to non-service, and in-transit damage or loss as minimization functions. Our paper contributes to the literature by evaluating critical business objectives such as net profits, lost sales due to non-service, and in-transit loss in conjunction with the typical heterogeneous fleet size and mix optimization decisions. The paper proposes two different solution methods: the Competing and the Compensatory method, which may be viewed as two extreme ends of the solution spectrum. Under the Competing method, all five objectives are assumed to be equally important, while the Compensating method allows the optimal solution to endogenously attach priorities to the different objectives. The two provide very different solutions since the Compensatory method considers the synergies between the objectives while the Competing method ignores them. The sensitivity analysis in the paper will also aid to managerial decision-making by evaluating different priorities for the multiple objectives during different periods. Given the impreciseness in the goal definitions and incomplete information available to a decision-maker, our paper strengthens vehicle fleet size and mix decision modelling problems by adding other managerial perspectives.

Keywords Managerial decision modeling · Fleet size and mix · Multi-objective optimization · Fuzzy sets · Sensitivity analysis · Goal programming
1 Introduction and background

Transportation optimization and its many variations have long formed an active research line with the operations research community. Starting with the classical Vehicle Routing Problem (VRP), researchers have examined the heterogeneous fleet problem [1, 2], multiple trip routing problems [3, 4], the time window based delivery problem [5, 6], as well as other variants comprehensively discussed in surveys by Baldacci et al. [7], Hoff et al. [8], Pantuso et al. [9], and Cattaruzza et al. [10]. Outside observers have criticized these models by arguing that they are reductionist in nature and lack applicability to real-world situations, clearly reflecting research gaps and scarcity of documented research to several practical problems [10–13]. However, model-building is inherently an art that requires Occam’s razor’s application—providing maximal insights with the simplest possible (reductionist) structure, which is the case with many of these papers [14–16]. On the other hand, operations research (OR) models can be easily extended to incorporate missing real-world elements [17]. In fact, in many situations, the transportation problem’s logistical aspects lead to several real-world issues that should be incorporated into the OR model to provide an ideal solution [18]. Our research objective in this paper is to illustrate how to tackle this more significant problem, i.e., how to address practical issues faced by logistics practitioners in a specific context.

The focus of our research is to develop a multi-objective multi-criteria (MOMC) decision model for heterogeneous fleet size and vehicle mix problem based on stakeholder input in the downstream milk distribution from the dairy plants to the Point of Sale (POS) which considers critical managerial issues. The specific research questions addressed in the study are:

i. To test and propose a multi-objective decision model considering net profit, lost sales due to non-service, in-transit loss, transportation cost, and total transportation time simultaneously.

ii. Aid the decision-maker to plan the optimal heterogeneous fleet size and mix depending on changing priorities and uncertainty of the decision-maker.

iii. Model and test three objective functions for the first time that have not been studied in the extant literature, namely, net profit maximization, in-transit loss minimization, and minimization of lost sales due to non-service.

From a research rationale perspective, the research questions addressed in the study are critical for practically any distribution intensive industry (e.g., consumer durables, food and beverages, cement, pharmaceuticals, perishables etc.). Often this last aspect of delivery is not given adequate attention and “the beat” may be based on gut feelings or on simple heuristics maximizing one objective and not on making an optimal choice that addresses multiple concerns. For instance, in the perishables industry, transportation time could be of utmost importance, while for consumer durables transportation cost may be of higher priority. We focus our study in a complex industry with several challenges faced by the decision maker (i.e., dairy industry). In fact, as climate change becomes a bigger issues and countries want to reduce
their dependence on fossil fuels, one could imagine a future where both concerns could be equally important. Moreover, in the perishable goods industry, the over-time one can imagine that climate change as well as the rapid urbanization and road congestion will make these multiple objectives important and while different decision-makers will assign different weights to them, they will all become important.

Discussing the research questions further, while net profit accounts for the firm’s profit (net of costs) based on total milk sales, lost sales due to non-service includes the stock returns daily due to delay in service as delivery must be achieved within a fixed time window. In-transit loss is on account of damage caused during transportation and handling of the milk packets, while transportation cost and transportation time are related to vehicle mix—i.e., carrying capacity, cycle time, fuel efficiency, and average speed of commuting. In fact, it should be easy to see that an optimal solution to these problems is just as important as minimizing production costs for profitability.

It is worth emphasizing that three of the objective functions, namely, net profit maximization, in-transit loss minimization, and minimization of lost sales due to non-service for the perishable product of milk (that allow us to focus more on the business side than on the logistics side) have never been jointly studied previously in the context of vehicle fleet size and mix problems. Hence this research adds a more robust real-world component to a traditional OR problem.

From the solution perspective, the fuzzy Mixed Integer Goal Programming (f-MIGP) approach has been used to address the lack of complete information for the payoffs and outcomes of all the possible alternative solutions that are unknown (Simon, 1955). Since the decision-maker is driven by multiple conflicting objectives characterized by bounded rationality, it becomes difficult to define precise goals for the different objective functions leading to imprecise fuzzy goals [19–21]. Our model is related to but does not fall under the category of VRP problems. In our model, vehicle routes are unalterable due to the fixed delivery time and preset demand. Moreover, our model is different from Dairy Transportation Problems (DTPs) since our focus is not on determining optimal routes for collecting milk from farms and delivering it to processing plants.

We develop an approach for simultaneously tackling the logistical aspects of the optimal Fleet Size and Mix (FSM) problem and its business or real-world application side (incorporating the different perspectives of a firm’s decision-makers) facing several industries in their transportation optimization problem. Although theory development in the field has often neglected other market-based decision variables [11] that are realistic and address managerial issues, our paper addresses this issue and intersects with several strands of the literature. For instance, the paper has implications for other FSM problems like multi-compartment [25], open routes [26], green routing [27, 28], single and double container loads [29], and collection depot [30] variants that wish to incorporate managerial perspectives. In these papers, the focus has remained on arriving at the optimal route design focusing on the cost

1 We show below that the business problem arises from the transportation problem and therefore must be solved simultaneously.
2 See also Derigs and Vogel [22], Miranda et al. [23], and Alcaraz et al. [24] for more discussion on this.
or the time aspect. In contrast, simultaneous consideration of multiple real-world objective functions has remained unexplored. The is the primary motivation underlying our research.

Similarly, multi-objective multi-criteria OR decision models have focused on objectives as distance travelled, cost of transportation, and tardiness time as minimization functions, and customer service satisfaction as the maximization function [31–34], [35]. Note also that these papers use a two-step partitioning approach as in Grandinetti et al. [36] or bi-objective minimization as in Velasco et al. [37] and Dridi et al. [38]. Moreover, with a few exceptions that model customer satisfaction using a maximization function [31–33], [39, 35, 34], to the best of our knowledge the literature on MOMC is restricted to models with two or three minimization functions, which are non-conflicting. While fuzzy goal programming (FGP) has been used in a bi-level multi-objective linear fractional programming problem in the published work of Lachhwani [40], this paper’s gap is identified, i.e., the simultaneous solution of multiple real-world objectives in the FSM context remains unaddressed so far.

In the study, we rely on stakeholders at a cooperative milk marketing federation for managerial inputs to optimize their operations in a large city with over 1.1 million population in the state of Odisha, in India. We study downstream milk distribution from the dairy plant to the retail points in a given territory. The task has some pre-specified existing features: (i) Choosing a heterogeneous mix of vehicle types with varying capacities and associated operating costs for delivering to line haul customers. (ii) The demand for milk at different retail points varies at different periods and is pre-informed to the plant. (iii) The vehicle fleet is characterized by other specifications for pick-up and delivery cycle time based on average speed, vehicle load capacity for delivery, lost sales due to non-service, and loss in transit due to damage of milk packets. Observe that this is an information-rich environment with many different time-varying information that the firm needs to process. Observe that the decision-maker has to choose vehicle mix and fleet size, balancing different objectives simultaneously, such as transportation cost, net profit, lost sales, loss in transit, and transportation time. Our research, which involved detailed conversations with the firm’s senior and middle management, revealed exciting features. First, we found no consensus in the management to agree on the objectives mentioned above, although they all considered these things to be important. Second, it was not even clear if one could prioritize these objectives in any systematic manner. Third, given the information available to the management, we found some ambiguity when discussing information with different managers. These unalterable characteristics of the problem and stylized facts present some interesting modeling challenges. Senior management must make several possible conflicting business decisions in an environment where many parameters are not well defined. To ensure that the optimal heterogeneous vehicle mix, and fleet size also addresses the managerial concerns, we propose a multi-objective decision model (MODM) using linear fuzzy goal programming. Goal programming models are used in decision problems where the alternatives cannot be compared based on a single performance criterion and are formulated with precise goals and constraints [41]. But real-world problems are characterized by volatility, uncertainty, complexity, and ambiguity. Decisions
need to be made in an imprecise environment. Hence, we propose using fuzzy sub-
sets to formulate the problem as a fuzzy goal-programming model [42] and solve it
by linear-programming methods. We first provide the optimal solution using two dif-
ferent methods to incorporate the senior management’s different perspectives. Both
techniques demonstrate how to optimize five different objective functions simul-
taneously, some of which require minimization while others solve a maximization
problem. Then we perform sensitivity analysis and explain how such analysis can
be extended to other types of counterfactual simulation that might aid decision-mak-
ing. The paper addresses a broader concern in downstream distribution by solving a
real-world managerial dilemma carrying out any downstream distribution from the
production centers to the multiple stocking points and then to the retail sales points.
While we develop and test the model for a complex category (i.e., milk) that is per-
ishable and has a fixed time window for distribution, the results are generalizable to
the downstream distribution of various consumer products (e.g., beverages, tooth-
paste, shampoo, soap, detergent).

The remainder of the paper is structured as follows. The model is developed in
Sect. 2, and the solution method is discussed in Sect. 3. Computational results and
sensitivity analysis are presented in Sect. 4, followed by concluding remarks in
Sect. 5.

2 Model building

India happens to be the largest milk producer globally, with 22 percent of the global
milk production. Growth in the industry has been phenomenal, registering a 6.2
percent increase in production between 2016–2017 and 2017–2018, against a world
average growth of 1.5 percent (FAO, 2018). Despite the disruptions in the market
due to the COVID-19 pandemic in 2020–2021, India has registered a 4.5 percent
increase in 2019 and is forecasted to grow by 2.6 percent in 2020 (FAO, 2020). The
organized dairy industry at the retail level in India is estimated to be at ₹1,200,000
million4 (Das, 2016), growing at 15 percent per annum. The demand for milk in
India has some well-established features. There is a fixed time window, mainly in
the morning between 6 and 9 AM and in the evening between 5 and 7 PM. If the
product is unavailable at the point of sale during the demand windows, it is a lost
sale. Also, milk is typically bought daily, and non-availability leads to switching to a
competing brand.

The vehicles delivering the milk start from a dairy plant with drop shipment of
loads at pre-defined POS outlets based on preset orders and sequence and then return
to the plant. Given these characteristics, the firm selling milk has to make multiple
complex decisions in determining the vehicle allocation mix for downstream milk
distribution from the dairy plants to the POS outlets for finalizing the lease contract
for the given time period. These include determination of the right vehicle mix and

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3 http://www.fao.org/dairy-production-products/production/en/ (accessed on 21 August 2021).
4 The ₹ to US Dollar conversion rate is 73.8457₹= 1 USD as on 24th October’ 2020. https://www.xe.
    com/currencyconverter/convert/?Amount=1&From=USD&To=INR
fleet size based on demand pattern, managing the fixed window constraint (i.e., the cycle time of delivery starting from the dairy plants and returning), and selection of vehicle type based on the traffic and road conditions based on the defined cycle time for delivery of milk from the dairy plant to all POS on a specific route. These numbers can vary for different routes. For instance, one route may have 50 POS with a load not exceeding 0.5 Metric Tons (MT) and a cycle time of 180 min to complete the delivery. Vehicles are assigned to these routes based on the solution to the MODM problem.

The relevant data for this study were collected over 6 months through interviews with senior management and other employees in the firm, including the Head of Marketing, Sales Officers, Plant Head (Bhubaneswar), Logistics In-Charge, and Drivers of the vans, at the site of the dairy cooperative plant and offices in the city of Bhubaneswar (in the state of Odisha, India). Interviews of multiple individuals over an extended period allowed us to verify facts using numerous observations. The cycle time for different routes is based on past data, road conditions, and traffic conditions. Based on the actual data across delivery schedules, we develop, test, and validate our model so that it closely replicates the real-world problem for optimizing the fleet size and mix and captures the complexity of dealing with multiple objective functions simultaneously and the uncertainty of parameter values due to limited information available. Thus, we assume a multi-objective decision model (MODM) with imprecise goals for the decision-maker.

Note that while this research was carried out for a dairy cooperative firm, the situation bears similarities to the problem of downstream distribution of bottled beverages by firms such as Coke and Pepsi, and consumer product group items distributed by Unilever, P&G, Nestle, and ITC Ltd., to name a few. Although milk is a perishable good whose buyers have specific purchase patterns, the similarity with the products mentioned above lies in the uncertainty faced by the decision-maker while addressing the routine distribution beat plans from distributor stocking point to the retail outlets [1] considering the prioritization of different objectives as modeled in the paper [30]. In other words, the precise objectives may be different from the ones we use. Still, our approach would certainly apply to the problem since our paper shows how to address practical managerial issues in this context.

The firm’s objective is to solve a heterogeneous fleet size and vehicle mix problem for downstream milk delivery from its dairy plants to the POS in a given territory with multiple objectives where the fixed delivery time window and pre-defined demand are the exogenously given constraints. This has some clear implications for the model. First, because of the fixed delivery time and preset demand, the vehicle routes are unalterable. Second, the vehicles rented by the firm are heterogeneous with different load-carrying capacities, delivery cycle time, in-transit damage/loss, and cost of transportation. Third, since the problem focuses on pick-up from the dairy plants, delivery to the POS outlets, and return to the pick-up location within a fixed time window, each vehicle makes a single round trip in
a delivery schedule.\textsuperscript{5} This setup allows us to go beyond the transportation/logistics issues related to milk delivery and focus more on the firm’s business operations, as captured by the objectives mentioned below. Note that the constraint values for the model are based on historical data provided by the firm. Based on senior managers’ input (including Chief Managing Director, Head of Marketing, Head of Finance, Head of Logistics, and a representation of middle-level managers) at the dairy federation, we assume that the firm has five objectives.\textsuperscript{6} This set of objectives have been derived based on discussions with senior management. Our paper provides a methodology for studying such multi-objective problems to focus on the business aspects of the problem. The same method can be easily adapted to include additional or different objectives [14, 31, 40].

\textsuperscript{5} Note that single trip assumption is a description of reality and not an attempt to simplify the problem. As will be clear from the model formulation, this can be relaxed in many different ways and the complexity will increase depending on what we assume about vehicle use/.

\textsuperscript{6} Later we also followed up with the senior management who approved our final choice of five objectives.
Our notation is presented in Table 1. The model solves the number of different vehicle types \( (X_i) \), differing in their maximum weight carrying capacity. Each vehicle type has a fixed cost of transportation and cycle time in hours (see Table 2). To compute the overall travel time by the chosen vehicle mix, cycle time (in hours) is given by vehicle type \( i \). The overall net profit computation is based on profit per unit delivered. Lost sales \( (\sigma_i) \) occur when the vehicle cannot deliver the load at the pre-defined point \( q \) due to traffic congestion, lack of time, and other similar issues, and this quantity is returned to the plant unsold. Loss in transit \( (\delta_i) \) arises from the damage of the packaged milk product during transportation and handling. The parameters for the averages in-transit loss and lost sales by vehicle type are based on qualitative inputs from the dairy federation managers.

The model’s objective functions are listed below, followed by the formulation of the equations (numbered from 1 to 10).

**Objective 1**—Minimize \( T \): Total Cost of Transportation (in Rupees, ₹).

**Objective 2**—Maximize \( P \): Total Net Profit (in Rupees, ₹).

**Objective 3**—Minimize \( M \): Total Transportation Time, i.e., Pick-up and delivery (Hours).

**Objective 4**—Minimize \( LS \): Total Loss in Sales due to Non-Service (in Rupees, ₹).

**Objective 5**—Minimize \( L \): Total Loss/ Damage during Transit (in Rupees, ₹).

Equation (1) below defines the total transportation cost, \( T \) for the chosen vehicle mix, and the delivery conditions. The total distance travelled by the vehicle type \( i \) selected for the route \( r \) connecting \( q \) points is denoted by \( p_{rqi} \). Also, \( \alpha_i \) denotes the cost per unit distance travelled for vehicle type \( i \) and from plant \( u \). In the dairy cooperative case, there was one plant to supply to the area under study. However, we have introduced \( u \) to factor for the generic model where there could be a set of manufacturing units/ stocking points for pick up and distribution serving the given territory. Equation 2 pertains to overall net profit based on the volume of milk sold and per-unit profit generated from each litre of milk. Equation 3 relates to the total transportation time for one round trip by vehicle based on the distance travelled and the vehicle’s average speed (depending on the type of vehicle, \( i \)). The following two Eqs. (4 and 5) capture lost sales and loss in transit due to product damage, respectively. Equations (6) to (10) are the model’s boundary conditions that must be satisfied for any chosen vehicle mix. Equation (6) defines the firm’s total transportation budget constraint for a period (set at the beginning of the financial year). Equations (7) and (8) are the constraint sets for minimum permissible demand to be served and net profit to be earned for the given period. Equation (9) is the constraint set for maximum lost sales permissible due to non-service of certain outlets, and Eq. (10) lists the maximum permissible loss in transit due to damage or pilferage in the given period for the chosen vehicle mix and fleet size.
Min $T = \sum_{r=1}^{R} \sum_{q=1}^{Q} \sum_{i=1}^{I} \beta_{rqi} \alpha_i X_i$, where, $i = 1, 2, 3, 4, \ldots, I$. \hspace{1cm} (1)

Max $P = \sum_{f=1}^{F} \sum_{i=1}^{I} X_i \eta_f$ \hspace{1cm} (2)

Min $M = \sum_{f=1}^{F} X_i \left\{ \left( \sum_{r=1}^{R} \sum_{q=1}^{Q} \sum_{i=1}^{I} \beta_{rqi} \right) / \sum_{f=1}^{F} \mu_i \right\}$ \hspace{1cm} (3)

Min $LS = \sum_{i=1}^{I} X_i \sigma_i$ \hspace{1cm} (4)

Min $L = \sum_{i=1}^{I} X_i \delta_i$ \hspace{1cm} (5)

S.T.

\[ \sum_{r=1}^{R} \sum_{q=1}^{Q} \sum_{i=1}^{I} \beta_{rqi} \alpha_i X_i \leq V \] \hspace{1cm} (6)

where $V \in \mathbb{R}$ and is the maximum transportation budget available for the period

\[ \sum_{i=1}^{I} X_i \geq D_{qf}, \] \hspace{1cm} (7)

where $D_{qf} \in \mathbb{R}$ and is the minimum demand to be met for the period

\[ M = \sum_{f=1}^{F} X_i \left\{ \left( \sum_{r=1}^{R} \sum_{q=1}^{Q} \sum_{i=1}^{I} \beta_{rqi} \right) / \sum_{f=1}^{F} \mu_i \right\} \geq M', \] \hspace{1cm} (8)

where $M' \in \mathbb{R}$ and is the minimum net profit to be earned for the period

\[ LS = \sum_{i=1}^{I} X_i \sigma_i \leq LS', \] \hspace{1cm} (9)

where $LS' \in \mathbb{R}$ and is the maximum lost sales permissible for the period

\[ L = \sum_{i=1}^{I} X_i \delta_i \leq L' \] \hspace{1cm} (10)
| Origin                             | To                      | Vehicle type \((i)\) (MT) | Average speed of vehicle \((\mu_i)\) (Kms/Hr) | To & Fro distance \((\beta_{rqi})\) (Kms) | Cycle time To & Fro \((\gamma_{rqi})\) (\(\leq\) Mins) | Lost sales due to non-service \((\sigma_i)\) (\(\₹\)/Trip) | Loss in transit due to damage \((\delta_i)\) (\(\₹\)/Trip) |
|-----------------------------------|-------------------------|-----------------------------|-----------------------------------------------|---------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|
| Bhubaneswar dairy                 | Bhubaneswar intra city distribution | 0.5                         | 30                                            | 50                                          | 180                                                           | 300                                                           | 200                                                           |
|                                   |                         | 1.0                         | 35                                            | 75                                          | 150                                                           | 250                                                           | 150                                                           |
|                                   |                         | 1.5                         | 35                                            | 100                                         | 140                                                           | 200                                                           | 150                                                           |
|                                   |                         | 4.0                         | 40                                            | 130                                         | 120                                                           | 100                                                           | 100                                                           |

\(MT\) Metric Tonne; \(Kms/Hr\) Kilometres per Hour; \(Kms\) Kilometers; \(Mins\) Minutes; \(\₹/Trip\) Rupees per round trip

Source: Internal discussions and federation website
| Constraint | Goods Auto (0.5MT) (x₁) | TATA Ace (1MT) (x₂) | Maxx Pick-up (1.5MT) (x₃) | TATA 407 (4MT) (x₄) |
|------------|--------------------------|---------------------|---------------------------|----------------------|
| Cost of transportation, αᵢ (Rupees/ Kilometre) | 6 | 8 | 10 | 13 |
| Max capacity by vehicle type (≤) (Litres) | 300 | 800 | 1500 | 4000 |
| Minimum demand to be met in a day, Dᵣᵢ (Litres) | 10,000 | | | |
| Net Profit per litre of milk (Rupees, ₹) | 0.25 | | | |
| Daily maximum permissible transportation budget for a region, V (Rupees, ₹) | 100,000 | | | |
| Maximum lost sales due to non-service permissible per day in a region, LS' (Rupees, ₹) | 30,000 | | | |
| Maximum loss in transit permissible per day in a region, L' (Rupees, ₹) | 25,000 | | | |

*MT* Metric Tonne

*Source: Internal discussions and federation website*
where \( L' \in \mathbb{R} \) and is the maximum permissible loss in-transit for the given period \\

\[
X_i, N_i, \beta_{rqi}, \gamma_{rqi}, \sigma_i, \delta_i, \eta_f \geq 0
\]

These equations are formulated using the information provided in Tables 2 and 3. For example, Eq. (1, which is the total transportation cost minimization function, is arrived at by considering the product of to and fro distance from Table 2 (\( \beta_{rqi} \)) for each vehicle type \( i \) and cost of transportation from Table 3 (\( \alpha_i \)) with the number of vehicles of each type (\( X_1, X_2, X_3, \) and \( X_4 \)) which are the variables solved in the model giving the allocation mix. The rest of the Eqs. (2 to 5) have been formulated similarly. The developed model was solved using TORA software (Version 2.00). The trip details and parameter values by vehicle type used in the model are provided in Tables 2 and 3.

The multiple criteria for the model for the corresponding daily constraints are as follows. (i) The maximum permissible daily transportation budget for distribution from the plant to the POS is ₹100,000/-. (ii) The minimum milk demand to be met per day for the study location of Bhubaneswar is 10,000 L. (iii) Further, the maximum permissible daily lost sale towards non-service is ₹30,000/-, and the maximum permissible loss in transit on a per-day basis is ₹25,000/-. (iv) The minimum profit earned by the federation per litre of milk sold is ₹0.25, with the minimum profit made on a per-day basis being ₹2500/-. Although constraints on minimum milk demand and minimum net profit to be earned by the federation are linked, the model considers the managerial dilemma of meeting the minimum demand constraint and raising net profit. To cite an example, the boundary condition for maximum permissible transportation budget as fixed by the firm is arrived at by applying the upper limit of ₹100,000 in a day for the chosen vehicle mix of \( X_1, X_2, X_3, \) and \( X_4 \). The model factors the situation wherein the manager has to increase profit and sales, leading to higher transportation costs such that the daily budget does not exceed the upper constraint. The nature of the problem is a departure from a typical logistical problem since it encompasses associated business dimensions, namely, profits, sales, lost sales, in-transit damage, to name a few.

Similarly, the boundary condition for maximum possible lost sales per day is formulated by considering the daily lost sales data by vehicle type from Table 2 (i.e., ₹300, ₹250, ₹200 and ₹100 for \( X_1, X_2, X_3, \) and \( X_4 \) respectively) and the upper boundary at ₹30,000 (see Table 3). The rest of the equations have been formulated similarly.

### 3 Solution method

We start with multiple objectives provided by a set of senior managers. Hence to deal with this linguistic variation, these objectives are fuzzified with aspiration levels defined for the different goals. The solution is obtained for the heterogeneous vehicle fleet size and mix (\( X_1, X_2, X_3, \) and \( X_4 \)). We use fuzzy goal programming and rely on two different methods to solve the problem. We also
explore combining these methods to examine if we can improve the solution. Our two proposed methods have very different objectives, and as we will see, provide different solutions. This two-method approach has some obvious advantages over using one method. First, it can provide us with two different solutions, and the associated range may be helpful to the decision-maker for planning purposes. Second, potential drawbacks like an inefficient solution or a lack of computational efficiency cannot be ruled out (Li et al. 2006). Thus our methodology also suggests the different ways in which a manager can test out their various objectives. In that sense our solution method clearly befits the research rationale we set out with.

The proposed solution method of fuzzy multi-integer goal programming (f-MIGP) is superior to other comparable methods used to assist managerial decision-making in the absence of precise information and uncertainties about the future [43]. Operating in a dynamic environment as the goals keep changing for the decision-maker, the need is to work with impreciseness [32, 44]. Given the dynamics of the problem, the proposed method, therefore, is superior to the optimization techniques based on natural analogies such as social organisms, genetic evolution [37, 38], stochastic mixed-integer programming [45], heuristics methods such as the neighborhood search method [46] or simulated annealing [47]. It explains our choice of the technique, which has also been adopted for similar managerial issues addressed in extant literature (see for instance [44, 48].

Before we introduce the two solution methods, we first demonstrate how we obtain the membership function \( \mu_{Zk}(X_i) \) for the \( k \)th fuzzy goal in the f-MIGP formulation. It may be noted that linear fuzzy membership functions [49] have been used to solve the model. Recall that we have multiple objective outlines in Eqs. (1)–(5), one of which involves maximization (2) and all the others minimization [Eqs. (1), (3), (4), and (5)]. For illustrative purposes, let us first consider a maximization objective function (i.e., Max \( P = \sum_{f=1}^{F} \eta_f \sum_{i=1}^{I} X_i \) in Eq. 2) Then using standard fuzzy set theory techniques, this is rewritten as,

\[
\text{Max } \mu_{\{Z_k(X_i)\}} = \left[ Z_k(X_i) - Z_k^{\min} \right] / \left[ Z_k^{\max} - Z_k^{\min} \right], \text{ where } Z_k^{\min} \leq Z_k(X_i) \leq Z_k^{\max}
\]

(11)

A typical minimization objective function like Min \( T = \sum_{r=1}^{R} \sum_{q=1}^{Q} \sum_{i=1}^{I} \beta_{rq} \alpha_i X_i \) in (1) can be written as,

\[
\text{Min } \mu_{\{Z_k(X_i)\}} = \left[ Z_k(X_i) - Z_k^{\min} \right] / \left[ Z_k^{\max} - Z_k^{\min} \right], \text{ where } Z_k^{\min} \leq Z_k(X_i) \leq Z_k^{\max}
\]

(12)

In these equations \( Z_k^{\min} \) represents the relative aspirational minimum constraint and \( Z_k^{\max} \) represents the relative aspirational maximum constraint between which the satisfaction of membership function \( \mu_{\{Z_k(X_i)\}} \) lies. In our case, these have been obtained from data provided by the firm managers and \( Z_k(X_i) \) the variable of interest.

Our first solution method is called the Competing Method. Here the objective functions are all assumed to compete with each other and hence equally
important. This method simultaneously raises the overall system satisfaction level by considering the intersection of the fuzzy sets, as shown in Eq. (13).

\[
\text{Max } \lambda = \bigcap_{i=1}^{5} \mu_{A_i}(X) = \min_{i=1,...,5} \{ \mu_{A_i}(X) \} \tag{13}
\]

Note that maximizing \( \lambda \) amounts to maximizing the overall system satisfaction, since \( \mu_{A_i}(X) \) represents membership functions for the five different objective functions. To explain in simple terms, they include the objective functions Net Profit (P), Cost of Transportation (T), Transportation Time (M), Loss in Transit (L), and Loss in Sales due to Non-service (LS). Operationally, this amounts to ensuring that \( \lambda \leq \{ \mu_{A_1}(X), \mu_{A_2}(X), \mu_{A_3}(X), \mu_{A_4}(X), \mu_{A_5}(X) \} \) when solving the problem. This method’s solution provides us five values: optimal \( \lambda \) (or maximized value of the membership function) and the vehicle mix with exact numbers for each of the four types of vehicles. Note that in this solution method, the goal has been to treat all objective functions with equal importance without sacrificing resources from one objective in favour of another.

Our second method is called the **Compensatory Method**, where one or more of the objective functions may be more important than others. Thus, we consider the additive operator of the union of the membership function. The set-theoretic operation is represented in Eq. 14 below.

\[
\text{Max } Z = \mu_{A_1}(X) \cup \mu_{A_2}(X) \cup \mu_{A_3}(X) \cup \mu_{A_4}(X) \cup \mu_{A_5}(X) = \max_{i=1,...,5} \{ \mu_{A_i}(X) \} \tag{14}
\]

Operationally, this amounts to maximizing \( \sum_{i=1}^{5} \mu_{A_i}(X) \). Thus, each of the fuzzy membership functions raises its satisfaction levels at the cost of others. The solution provides nine different values—the optimal value of each of the five membership functions (Eqs. (1)–(5)) and the optimal vehicle number for each of the four vehicle types. It is therefore critical in this situation that the decision maker choose the higher priority objective functions beforehand. From a managerial perspective, both methods have their significance based on the business situation. The competing method is appropriate for business scenarios with no pressing need to focus on a specific objective function. For example, during the first quarter of the financial year or in the first month of a new quarter with no special needs, a firm may use the competing method as the solution technique. However, when there are pressing issues facing the decision-maker wherein one has to minimize lost sales due to the channel partners’ complaints or improve the net profit, this method may not be appropriate. Under such a situation, the Compensatory method is more relevant, and the decision-maker iteratively arrives at the best fit solution by adjusting the goals of the different objective functions. Subsequently, a sensitivity analysis is also carried out to understand the interplay between the two methods. For instance, we consider situations where the decision-maker may enhance the satisfaction levels of specific objective functions iteratively at others’ cost, keeping the overall system satisfaction level unchanged. To summarize, the proposed solution methodology is designed keeping in mind the research objective and the research rationale.
4 Computational results

The equations, as formulated in Sect. 2, are solved using the methods discussed in Sect. 3. The results of the Competing Method and Compensatory Method are discussed in Sects. 4.1 and 4.2, respectively. In Sect. 4.3, we explore how to combine these two methods. Section 4.4 details the managerial implications of this study.

4.1 The competing method

This method aims to have the highest overall satisfaction level $\lambda$ common to all the objective functions. The optimal value given by $\lambda^*$ is such that no single objective function has a lower value. Observe that in the absence of this lower bound restriction, one or more objective functions could have had a higher satisfaction level or a lower value for the individual objective if necessary. The optimal overall system satisfaction is estimated to be at $\lambda^*=0.4974$ with the vehicle mix consisting of 21 of type 0.5MT, 41 of 1.0MT, and 26 of 4MT (refer to Table 4 below). It essentially states that when the decision maker does not have a specific preference for any particular objective function and treats all of them equally, this solution method is chosen. To summarize it implies that if all the five objectives are equally important for the logistics company delivering milk from the factory to the POS outlets and given the constraints of the business problem addressed, the company needs to deploy a

| Table 4 | Computational results: competing method and compensatory method |
|-----------------|--------------------------------------------------|
| Competing method: Iteration 31 gives the following results |
| $\lambda = 0.4974$ (overall system satisfaction in the Competing Method) |
| Vehicle Allocation Mix (Numbers), $X_1 = 21$, $X_2 = 41$, $X_3 = 0$, $X_4 = 26$ |
| The values of objective functions are (at a system satisfaction level of 0.4974): |
| Total Transportation Cost, $T = \text{₹} 52,640/-$ |
| Total Transportation Time, $M = 128.13$ Hours |
| Total Loss or Damage during Transit, $L = \text{₹} 7400/-$ |
| Total Loss of Sales due to Non Service, $LS = \text{₹} 9,900/-$ |
| Total Net Profit, $P = \text{₹} 28,375/-$ |

Compensatory Method: Iteration 45 gives the following results

Satisfaction Levels of the different fuzzy membership functions are,

- Total Transportation Cost, $\mu_1 = 0.9979$;
- Total Transportation Time, $\mu_2 = 0.9990$;
- Total Loss or Damage during Transit, $\mu_3 = 1.0$;
- Total Loss due to Non Service, $\mu_4 = 0.9945$; and
- Total Net Profit, $\mu_5 = 0.0015$

Vehicle Allocation Mix (Numbers), $X_1 = 0$, $X_2 = 3$, $X_3 = 0$, $X_4 = 2$

The values of objective functions are:

- Total Transportation Cost, $T = \text{₹} 5180/-$ (Satisfaction of 0.9979)
- Total Transportation Time, $M = 12.92$ Hours (Satisfaction of 0.9990)
- Total Loss or Damage during Transit, $L = \text{₹} 650/-$ (Satisfaction of 1.0)
- Total Loss of Sales due to Non Service, $LS = \text{₹} 950/-$ (Satisfaction of 0.9945)
- Total Net Profit, $P = \text{₹} 3600/-$ (Satisfaction of 0.0015)
total of eighty-eight vehicles of which 21 of type 0.5MT, 41 of 1.0MT, and 26 of 4MT.

### 4.2 The compensatory method

This solution method is appropriate when the decision-maker has to prioritize among their specific objectives. This represents a business scenario when the decision-maker has greater clarity on the priorities regarding the objective functions. For instance, if the firm faces in-transit severe damage that needs to be reduced, this method may be more appropriate. This amounts to solving the following maximization problem: 

\[
\sum_{i=1}^{5} \mu_i(X_i) \]

Given that we maximize the sum of the membership functions, it would not be surprising to have different optimal values. The optimal solution for the compensatory method is presented in Table 4 above. Observe a significantly reduced fleet size for the vehicle allocation mix consisting of three vehicles (i.e., 1 of 1MT and 2 of 4MT). However, this comes at a high cost: the satisfaction levels are more significant than 0.9 for each objective function except for total net profit, \( P(0.0015) \), which may not be an acceptable outcome. Observe that this is starkly different from the solution obtained by the competing method. In a sense, these two methods can provide a range within which the decision-maker may explore alternative solutions. In what follows, we explore how robust our results are to changes in the managerial objectives. To summarize, it may be stated that except for the objective function on Total Net Profit \( P \), all the other objectives have a satisfaction level greater than 0.99 (with Total Loss during Transit has a value of 1.0). Thus if the transportation involves high value products (i.e., decorative flowers or liquid injectables or lobsters—all for exports), this solution is optimal with a mix of three vehicles.

A comparison of the two methods is needed before we proceed to the sensitivity analysis section simply because the outcomes achieved by the two methods are so stark. While the Competing method requires 88 vehicles, the Compensatory method only needs five vehicles. These can be seen as the two extreme ends of the spectrum of possible solutions in some ways. While the difference in magnitude is surprising, that we expect different solutions is not. The Competing method assigns no priorities—everything is equally important. Therefore, a solution cannot exploit any of the benefits or synergies between the objectives. This leads to a vast number of vehicles.

On the other hand, the Compensatory method allows the system to trade-off between the objectives and endogenously determines the solution that maximizes the objective function’s sum. In other words, it fully exploits all possible trade-offs in the system, resulting in a very low number of vehicles. It should be clear from this that the management of a firm should find out the answers suggested by both these methods before making any decisions.

The above exercise is vital for another reason. It demonstrates that while not having priorities may not be a good idea, allowing the system to set priorities may not be the best approach. We find that while the number of vehicles under the Compensatory method is low, this has been achieved at the cost of Net Profit, which has a satisfaction level of 0.0015. This is a crucial lesson since many problems that focus
on logistics, like routing, completely ignore such business decisions. These solutions highlight that the fleet mix problems need to combine both the logistical and business aspects to find reasonable solutions. In practice, a decision-maker can use this methodology to assign their priorities and determine optimal solutions, which will lie between them and choose what seems acceptable. Once again note that our solution method justifies the rationale for the study.

4.3 Sensitivity analysis

The sensitivity analysis approach can be called the interactive method since it is based on both methods’ results. In the first sensitivity test, we evaluate our solution’s robustness by sacrificing loss in transit (L), which achieved a solution value of ₹650 at a satisfaction level of \( \mu_j = 1.0 \) (refer to Table 4). For analysis, the upper boundary of L was raised to ₹800, i.e., ₹150 was sacrificed towards one of the other objective functions among Net Profit (P), Cost of Transportation (T), Transportation Time (M), and Loss in Sales due to Non-service (LS). Recall that P had a meager value, and hence we hoped that by relaxing the constraint on L, we might be able to improve P. However, as reported in Table 4, the findings did not change the overall system satisfaction level or the vehicle allocation mix. This indicates that the overall system satisfaction does not improve by sacrificing the objective function L by ₹150. The computation of the values of the objective functions also did not indicate any improvement in the solution. This suggests that our initial solution is relatively robust to changes in L. It may be noted that the decision-maker may wish to attribute the amount ₹150 to another objective function based on the business scenario.

Next, we investigated an alternative approach where the overall system satisfaction level was first fixed at the one obtained from the competing method (0.4974). The model was then solved using the compensatory method to raise individual objective functions’ satisfaction levels. This is equivalent to solving \[ \max \sum_{i=1}^{5} \mu_i(X_i) \] subject to \( \mu_i(X_i) \geq 0.4974 \), for \( i = 1, \ldots, 5 \). Since no feasible solution was obtained even after 139 iterations, we did not explore this approach further. Again, this suggests that the Competing Method’s original solution is quite robust (see Table 5 below for a summary of results). Note that while the sensitivity analysis was done by sacrificing resources from the objective function L, such a sensitivity analysis can also be performed using other objective functions.

4.4 Managerial implications

Based on the decision environment, the decision-maker could use these approaches to explore alternative solutions that may provide alternate heterogeneous vehicle mix solutions. For instance, a firm may set a minimum satisfaction level for a specific objective like P (Total Net Profit) and then examine how the optimal solution changes. Such counterfactual simulations can be a handy tool for the decision-maker. Vehicle contracts are typically at least annual and cannot be altered in the short run. Conducting such simulations can help the firm determine how much variance in the
Table 5  Overall results summary

| Description                          | Competing method | Compensatory method | Sensitivity analysis (Superimposition) | Sensitivity analysis (Interactive) |
|--------------------------------------|------------------|---------------------|----------------------------------------|------------------------------------|
| System satisfaction ($\lambda$)      | ₹0.4974          | T = 0.9979, M = 0.999, L = 1.0, LS = 0.9945, P = 0.0015 | No feasible solution                | No change                          |
| Fleet mix & size                     | *0.5MT = 21, 1.0MT = 41, 1.5MT = 0, 4.0MT = 26 | 0.5MT = 0, 1.0MT = 3, 1.5MT = 0, 4.0MT = 2 | No feasible solution                | No change                          |

Objective Functions

| Objective Function                       | Competing method | Compensatory method | Sensitivity analysis (Superimposition) | Sensitivity analysis (Interactive) |
|-----------------------------------------|------------------|---------------------|----------------------------------------|------------------------------------|
| Total cost of transportation (T)        | ₹52,640/-        | ₹5180/-             | No feasible solution                   | No change                          |
| Total transportation time (M)           | 128.13 Hours     | 12.92 Hours         | No feasible solution                   | No change                          |
| Total loss/damage during transit (L)   | ₹7400/-          | ₹650/-              | No feasible solution                   | ₹800/- Upper boundary raise by ₹150/- |
| Total loss in sales due to non-service (LS) | ₹9900/-        | ₹950/-              | No feasible solution                   | No change                          |
| Total Net Profit (P)                    | ₹28,375/-        | ₹3600/-             | No feasible solution                   | No change                          |
This can be a helpful tool that can enable the decision-maker to be nimble and cope with changing business environments. The proposed model and the suggested method can address various managerial concerns for downstream distribution—be it from the stocking points to the POS or from the manufacturing plants/processing centers to the multiple stocking points/POS. At the height of e-commerce, when brick and mortar stores are building Omni-channels and going hyperlocal with last-mile delivery models, our findings provide a robust decision support approach addressing the decision-maker’s real-world problem. Starting with a perishable category like milk and milk products, the proposed model can be applied to other consumer product group companies, i.e., Coke, Pepsi, Unilever, Nestle, P&G, and Reckitt Benckiser, in their downstream distribution from stocking centers to POS. The model can incorporate a mix of perishable and non-perishable products with different vehicle types (refrigerated vs. non-refrigerated) to solve the downstream distribution problem for a large class of products. While the cooperative dairy has a greater complexity of fixed delivery time window due to the demand patterns, the other firm mentioned above is governed by similar challenges of transportation cost, net profit as a function of sales, loss in sales due to non-service, in-transit damage, in addition to transportation time as stocks need to be delivered at the different POS as per a pre-defined beat plan. Our study addresses this gap by focusing on the logistics aspect of the problem and considering the business perspective bringing in greater practice orientation rather than just a complex mathematical formulation with limited application.

5 Conclusion

This paper contributes to the body of literature on heterogeneous vehicle mix problems by proposing a solution that factors the dynamic business environment and the impreciseness and uncertainty in defining the goals for the different objective functions. Making it a better alternative to solve similar managerial decision problems. It adds to the existing knowledge on the domain that include generic pick-up and delivery problems (PDP) or fleet size mix (FSM) or MODM on FSM which ignore the impreciseness and uncertainty element in defining goals for the multiple objectives. Some of the research papers that have dealt with similar decision models but have ignored the critical gap addressed in this study include Huang et al. (2018) studying the dairy transportation problem in Indonesia using a stochastic integer programming model factoring route duration, travel time and external cooling facility; Staab et al. [50] studying route design and pipeline inventory cost optimization in the dairy industry, and Derbel et al. [51] proposing a heterogeneous fleet VRP using a neighbourhood search method with a threshold accepting mechanism. None of the studies highlighted above address the business reality of uncertainty and impreciseness in the decision-maker’s mind.

Second, our model includes three critical business objectives simultaneously for the first time (a combination of maximization and minimization functions): net profits, lost sales due to non-service, and in-transit loss into heterogeneous fleet size and
mix optimization decisions. From 2009 onwards there has been conscious effort by OR researchers to pursue the field of multi objective multi criteria (MOMC) decision models. But the choice of objectives is limited to distance travelled, cost of transportation, and tardiness time as minimization functions, and customer service satisfaction as the maximization function [31–35]. For example, Grandinetti et al. [36] consider three minimization objective functions (i.e., number of vehicles, total travel cost and longest travel cost) using a two-step partitioning approach optimizing one criterion at a time. Multi-item multi-stage transportation problem has been studied minimizing transportation cost using fuzzy set [48]. Velasco et al. [37] and Dridi et al. [38] propose bi-objective minimization functions for total transportation cost and total tardiness time by using a genetic algorithm based on non-dominated sorting algorithm. Guerriero et al. [52] focused on bi-objective multi criteria dial-a-ride public transportation problem using tabu embedded simulated annealing algorithm. Further, the sensitivity analysis in the paper with two solution approaches contributes to managerial decision-making based on priorities for different objectives during different periods. The study thus strengthens the domain of heterogeneous fleet size and mix decision models.

5.1 Limitations and future research directions

The study has several limitations that form the future research directions in the domain. We propose extending the research area in the future by testing other decision objectives, such as product returns, delivery and payment collection effectiveness, and different specific dimensions on last-mile delivery in hyperlocal distribution, given the greater dependency on e-commerce post-pandemic. Second, the model can be tested in other industry sectors having different complexities such as low density and high-volume categories (e.g., large plastic containers and storage containers, synthetic packaging material, etc.) constrained by traffic congestion with intra-city distribution, a firm with a broader assortment of products with differing transportation requirements, to name a few. Third, it may be worthwhile to compare the results of the proposed approach with another method (ignoring the fuzzy sets). These remain the new areas of research to extend the body of knowledge on the domain.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12597-022-00603-2.

Acknowledgements We would like to thank Sunita Sarangi, Shivani Sarangi, Abhishek Chakraborty, Eric Bahel, Matt Kovach, Mallikarjuna Rao, and Kostas Triantis for their thoughtful suggestions.

Authors’ contributions All three authors have contributed equally to all aspects of the paper. 1. Subrat Sarangi. 2. Sudipta Sarangi. 3. Nasim S. Sabounchi.

Funding The research has not been supported by external funding and was carried out independently by the authors.

Availability of data and materials Data used for analysis has been provided in the manuscript, and any additional information desired will be made available by the authors on request.
Declarations

Competing interests There is no conflict of interest or competing interests whatsoever in the preparation of the manuscript and conducting the study.

Ethics approval and consent to participate Not applicable: No human subject data.

Consent for publication Not applicable.

References

1. Penna, P.H.V., Subramanian, A., Ochi, L.S., Vidal, T., Prins, C.: A hybrid heuristic for a broad class of vehicle routing problems with heterogeneous fleet. Ann. Oper. Res. 273(1–2), 5–74 (2019)
2. Taillard, É.D.: A heuristic column generation method for the heterogeneous fleet VRP. RAIRO-Operations Research 33(1), 1–14 (1999)
3. Olivera, A., Viera, O.: Adaptive memory programming for the vehicle routing problem with multiple trips. Comput. Oper. Res. 34(1), 28–47 (2007)
4. Battarra, M., Monaci, M., Vigo, D.: An adaptive guidance approach for the heuristic solution of a minimum multiple trip vehicle routing problem. Comput. Oper. Res. 36(11), 3041–3050 (2009)
5. Vidal, T., Crainic, T.G., Gendreau, M., Prins, C.: A hybrid genetic algorithm with adaptive diversity management for a large class of vehicle routing problems with time-windows. Comput. Oper. Res. 40(1), 475–489 (2013)
6. Vidal, T., Crainic, T.G., Gendreau, M., Prins, C.: Time-window relaxations in vehicle routing heuristics. J. Heuristics 21(3), 329–358 (2015)
7. Baldacci, R., Battarra, M., & Vigo, D. (2008). The vehicle routing problem: Latest advances and new challenges. Chap. Routing a heterogeneous fleet of vehicles (pp. 11–35). Berlin: Springer.
8. Hoff, A., Andersson, H., Christiansen, M., Hasle, G., Løkketangen, A.: Industrial aspects and literature survey: Fleet composition and routing. Comput. Oper. Res. 37, 2041–2061 (2010)
9. Pantuso, G., Fagerholt, K., Hvattum, L.M.: A survey on maritime fleet size and mix problems. Eur. J. Oper. Res. 235(2), 341–349 (2014)
10. Cattaruzza, D., Absi, N., Feillet, D.: Vehicle routing problems with multiple trips. Ann. Oper. Res. 271(1), 127–159 (2018)
11. Irnich, S.: A unified modelling and solution framework for vehicle routing and local search-based metaheuristics. INFORMS J. Comput. 20, 270–287 (2008)
12. Schmid, V., Doerner, K.F., Laporte, G.: Rich routing problems arising in supply chain management. Eur. J. Oper. Res. 224(3), 435–448 (2013)
13. Song, X., Jones, D., Asgari, N., Pigden, T.: Multi-objective vehicle routing and loading with time window constraints: a real-life application. Ann. Oper. Res. 291(1), 799–825 (2020)
14. Liang, T.F.: Fuzzy multi-objective project management decisions using two-phase fuzzy goal programming approach. Comput. Ind. Eng. 57(4), 1407–1416 (2009)
15. Mahapatra, N.K., Maiti, M.: A fuzzy-stochastic approach to multi-objective inventory model of deteriorating items with various types of demand and time dependent holding cost. Opsearch 43, 117–131 (2006). https://doi.org/10.1007/BF03398769
16. Selim, H., Araz, C., Ozkarahan, I.: Collaborative production–distribution planning in supply chain: a fuzzy goal programming approach. Transport. Res. Part E: Logis. Transport. Rev. 44(3), 396–419 (2008)
17. Parsaei Motamed, M., Bamdad, S.: A multi-objective optimization approach for selecting risk response actions: considering environmental and secondary risks. Opsearch (2021). https://doi.org/10.1007/s12597-021-00541-5
18. Allahdadi, M., & Batamiz, A. (2021). Generation of some methods for solving interval multi-objective linear programming models. OPSEARCH, 1–39.
19. Yager, R.R., Basson, D.: Decision making with fuzzy sets. Decis. Sci. 6(3), 590–600 (1975)
20. Zimmermann, H.J.: Fuzzy programming and linear programming with several objective functions. Fuzzy Sets Syst. 1(1), 45–55 (1978)
21. Zimmermann, H.J.: Fuzzy set theory and its applications, 2nd Edn. Boston: Allied Publishers Limited, In association with Kluwer Academic Publishers. http://www.fao.org/dairy-production-products/production/en/. Accessed on 21 August 2021. (1996)

22. Derigs, U., Vogel, U.: Experience with a framework for developing heuristics for solving rich vehicle routing problems. J. Heuristics 20(1), 75–106 (2014)

23. Miranda, P. L., Morabito, R., & Ferreira, D.: Mixed integer formulations for a coupled lot-scheduling and vehicle routing problem in furniture settings. INFOR: Information Syst. Oper. Res., 57(4), 563–596 (2019).

24. Alcaraz, J.J., Caballero-Arnalodos, L., Vales-Alonso, J.: Rich vehicle routing problem with last-mile outsourcing decisions. Transport. Res. Part E: Logis. Transport. Rev. 129, 263–286 (2019)

25. Wang, Z., Liang, W., Hu, X.: A metaheuristic based on a pool of routes for the vehicle routing problem with multiple trips and time windows. J. Oper. Res. Soc. 65(1), 37–48 (2014)

26. Li, X., Leung, S.C., Tian, P.: A multi start adaptive memory-based tabu search algorithm for the heterogeneous fixed fleet open vehicle routing problem. Expert Syst. Appl. 39, 365–374 (2012)

27. Juan, A.A., Goentzel, J., Bektaş, T.: Routing fleets with multiple driving ranges: Is it possible to use greener fleet configurations? Appl. Soft Comput. 21, 84–94 (2014)

28. Koç, Ç., Bektaş, T., Jabali, O., Laporte, G.: The fleet size and mix pollution-routing problem. Transport. Res. B: Methodol. 70, 239–254 (2014)

29. Lai, M., Crainic, T.G., Di Francesco, M., Zuddas, P.: An heuristic search for the routing of heterogeneous trucks with single and double container loads. Transport. Res. Part E: Logis. Transport. Rev. 56, 108–118 (2013)

30. Yao, B., Yu, B., Hu, P., Gao, J., Zhang, M.: An improved particle swarm optimization for carton heterogeneous vehicle routing problem with a collection depot. Ann. Oper. Res. 242(2), 303–320 (2016)

31. Ghannadpour, S.F., Noori, S., Tavakkoli-Moghaddam, R., Ghoseiri, K.: A multi-objective dynamic vehicle routing problem with fuzzy time windows: Model, solution and application. Appl. Soft Comput. 14, 504–527 (2014)

32. Gupta, R., Singh, B., Pandey, D.: Multi-objective fuzzy vehicle routing problem: A case study. Int. J. Contemp. Math. Sci. 5(29), 1439–1454 (2010)

33. Tang, J., Pan, Z., Fung, R.Y., Lau, H.: Vehicle routing problem with fuzzy time windows. Fuzzy Sets Syst. 160(5), 683–695 (2009)

34. Xu, J., Yan, F., Li, S.: Vehicle routing optimization with soft time windows in a fuzzy random environment. Transport. Res. Part E: Logist. Transport. Rev. 47(6), 1075–1091 (2011)

35. Lopez-Castro, L. F., & Montoya-Torres, J. R.: Vehicle routing with fuzzy time windows using a genetic algorithm. In: Computational Intelligence In Production And Logistics Systems (CIPLS). New York: IEEE, pp 1–8 (2011).

36. Grandinetti, L., Guerriero, F., Pezzella, F., Piscane, O.: The multi-objective multi-vehicle pickup and delivery problem with time windows. Proc. Soc. Behav. Sci. 111, 203–212 (2014)

37. Velasco, N., Dejaz, P., Guéret, C., Prins, C.: A non-dominated sorting genetic algorithm for a bi-objective pickup and delivery problem. Eng. Optim. 44(3), 305–325 (2012)

38. Dridi, I.H., Kammarti, R., Ksouri, M., Borne, P.: Multi-objective optimization for the m-PDPTW: aggregation method with use of genetic algorithm and lower bounds. Int. J. Comp. Commun. Control 6(2), 246–257 (2011)

39. Ghoseiri, K., Ghannadpour, S.F.: Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. Appl. Soft Comput. 10(4), 1096–1107 (2010)

40. Lachhwani, K.C.: On fuzzy goal programming procedure to bi-level multi-objective linear fractional programming problems. Int. J. Oper Res. 28(3), 348–366 (2017)

41. Narasimhan, R.: Goal programming in a fuzzy environment. Decis. Sci. 11(2), 325–336 (1980)

42. Petrovic, D., Roy, R., Petrovic, R.: Modelling and simulation of a supply chain in an uncertain environment. Eur. J. Oper. Res. 109(2), 299–309 (1998)

43. McNally, R.C., Durmusoglu, S.S., Calantone, R.J., Harmanacioglu, N.: Exploring new product portfolio management decisions: The role of managers’ dispositional traits. Ind. Mark. Manage. 38(1), 127–143 (2009)

44. Cole, B.M., Bradshaw, S., Potgieter, H.: An optimisation methodology for a supply chain operating under any pertinent conditions of uncertainty-an application with two forms operational uncertainty, multi-objectivity, and fuzziness. Int. J. Oper. Res. 23(2), 200–228 (2015)

45. Huang, K., Wu, K.F., Ardiansyah, M.N.: A stochastic dairy transportation problem considering collection and delivery phases. Transport. Res. Part E: Logis. Transport. Rev. 129, 325–338 (2019)
46. Kritzinger, S., Tricoire, F., Doerner, K.F., Hartl, R.F., Stützle, T.: A unified framework for routing problems with a fixed fleet size. Int. J. Metaheuristics 6(3), 160–209 (2017)

47. Afshar-Nadjafi, B., Afshar-Nadjafi, A.: Multi-depot time dependent vehicle routing problem with heterogeneous fleet and time windows. Int. J. Oper. Res. 26(1), 88–103 (2016)

48. Baidya, A., Bera, U.K., Maiti, M.: Multi-item multi-stage transportation problem with breakability. Int. J. Oper. Res. 31(4), 510–544 (2018)

49. Fan, M., Zhang, Z., & Wang, C.: Mathematical Models and Algorithms for Power System Optimization: Modeling Technology for Practical Engineering Problems pp. 49–80. New York: Academic Press (2019).

50. Staab, T., Klenk, E., Galka, S., Günthner, W.A.: Efficiency in in-plant milk-run systems—the influence of routing strategies on system utilization and process stability. J. Simulation 10(2), 137–143 (2016)

51. Derbel, H., Jarboui, B., Bhiri, R.: A skewed general variable neighborhood search algorithm with fixed threshold for the heterogeneous fleet vehicle routing problem. Ann. Oper. Res. 272(1–2), 243–272 (2019)

52. Guerriero, F., Pezzella, F., Pisacane, O., Trollini, L.: Multi-objective optimization in dial-a-ride public transportation. Transport. Res. Proc. 3, 299–308 (2014)

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