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A reliability-extended simheuristic for the sustainable vehicle routing problem with stochastic travel times and demands

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Abstract

Real-life transport operations are often subject to uncertainties in travel time or customers' demands. Additionally, these uncertainties greatly impact the economic, environmental, and social costs of vehicle routing plans. Thus, analysing the sustainability costs of transportation activities and reliability in the presence of uncertainties is essential for decision makers. Accordingly, this paper addresses the Sustainable Vehicle Routing Problem with Stochastic Travel times and Demands. This paper proposes a novel weighted stochastic recourse model that models travel time and demand uncertainties. To solve this challenging problem, we propose an extended simheuristic that integrates reliability analysis to evaluate the reliability of the generated solutions in the presence of uncertainties. An extensive set of computational experiments is car-

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ried out to illustrate the potential of the proposed approach and analyse the influence of stochastic components on the different sustainability dimensions.

Keywords Transportation · Uncertainty modelling · Hybrid metaheuristics · Simheuristics · Vehicle routing problem · Reliability analysis

1 Introduction

The growing importance of sustainable logistics and transport (L&T) activities has become increasingly evident in recent years, driven by the rapid growth of online shopping and the increased demand for efficient, timely delivery across various sectors. This study is inspired by the challenges of depot-based distribution across multiple contexts: (i) urban retail distribution (e.g., e-commerce orders and small retail locations), (ii) regional delivery of essential goods (such as medical supplies to local clinics), and (iii) perishable goods supply chains (common in food and grocery distribution networks). These sectors often involve loading vehicles at a central depot and distributing goods to dispersed customer locations, with added complexities such as long travel distances, unpredictable travel times, and increased accident risk. A significant challenge in these contexts is the increased risk of accidents and delays, particularly during working hours and in residential areas. According to reports published by the European Commission (EU 2022) and the National Highway Traffic Safety Administration (NHTSA 2020), approximately 60% of traffic accidents occur during work hours, and around 55% occur in rural areas compared to urban areas, with 9% involving cargo vehicles. These statistics underscore the risks associated with transporting goods during peak periods. Furthermore, the increasing accident rate highlights the urgent need for better safety measures and regulatory interventions to address these risks effectively.

Consequently, this paper studies the Sustainable VRP with Stochastic Travel Times and Demands (SVRP-STD). Most existing vehicle routing problems (VRP) that deal with sustainability issues are concerned with reducing costs associated with carbon emissions and vehicle utilisation. However, consideration of social impacts is scarce (McKinnon et al. 2015; Mahdinia et al. 2018), particularly in VRP with stochastic travel times and demands. In a deterministic setting, Abdullahi et al. (2020) studied the VRP with operational costs including CO_2 emissions costs and safety costs in the form of risk of traffic accidents. Given the existence of government programmes aimed at taxing carbon emissions by freight transport in urban areas (Peters et al. 2022) and the impact of traffic accidents on victims, the model proposed in Abdullahi et al. (2020) provides a close representation of reality. However, to the best of our knowledge, previous VRP studies considering the three dimensions of sustainability mainly assume that customers' demands and travel times are fixed and known. Hence, in this paper, we propose the SVRP-STD, which considers economic, environmental, and social impacts with stochastic travel times and demands.

The SVRP-STD presents several challenges that must be addressed. Firstly, the challenge lies in quantifying the impact of distribution plans on social, environmental, and economic dimensions in an uncertain environment. Quantifying the social, environmental, and economic impact of transport activities is challenging, as these dimensions are often conflicting. Secondly, modelling of stochastic time and demand presents another challenge, and quantifying the effects of these stochastic components is crucial. Stochasticity of demands and travel times has social, environmental, and economic impacts and can lead to route failures requiring estimation of the reliability of solutions. The focus of this study is on developing corrective strategies to address route failures as they occur, rather than relying on preventive measures, which cannot fully guarantee the elimination of failures. An important but difficult aspect lies in the modeling of these corrective strategies and accurately quantifying the impact of failures on overall performance. Together, these challenges underscore the complexity of the SVRP-STD and highlight the need for a comprehensive approach to achieve efficient solutions in a short computational time.

To address these challenges, we propose an extended simheuristic approach (Juan et al. 2015) that combines Monte Carlo Simulation (MCS) with Biased Randomisation techniques (Grasas et al. 2017) and Iterated Greedy (Ruiz and Stützle 2008) with Local Search (Sim-BRIG-LS) to approximate the behaviour of travel times and demand patterns and provide computationally efficient solutions. Sim-BRIG-LS has the main advantage in that it does not assume that an algebraic description of the simulation is available (Amaran et al. 2016). Therefore, Sim-BRIG-LS solves the problem without having to solve a large number of constraints, which reduces computational time compared to traditional stochastic methods based on algebraic formulation. Simulation-optimisation represents a key advantage of our approach, as it provides an accurate and sustainable solution to the problem within a reasonable computational time. In addition, we also include risk and reliability analysis by employing the Kaplan–Meier estimator (KME) (Kaplan and Meier 1958). The KME is used primarily in survival analysis and medical research. However, we adapt and apply this in a novel way to measure and estimate the reliability of generated solutions.

Figure 1 illustrates a schema of the proposed methodology, which comprises a metaheuristic, simheuristic, sensitivity, and reliability analysis. The metaheuristic provides a set of solutions for the deterministic problem, and the simheuristic evaluates each deterministic solution in a stochastic environment using simulation. This process is repeated until a pool of elite solutions emerges, that is, stochastic solutions. Lastly, KME reliability analysis makes it possible to evaluate solutions holistically in stochastic scenarios by analysing various quartiles discovered during the simulation.

The main contributions of this paper are summarised as follows:

i. A weighted stochastic recourse model with uncertainties in travel times and demands, and that combines the economic, environmental, and social sustainability dimensions is proposed;
ii. An extended simheuristic approach with reliability analysis, in particular, the KME (Kaplan and Meier 1958) is developed;
iii. A comprehensive set of computational experiments is conducted to analyse the performance of the solutions and the trade-offs between the sustainability dimensions.

The rest of this paper is structured as follows: Sect. 2 presents a review of related literature, followed by a formal description of the problem addressed, including the

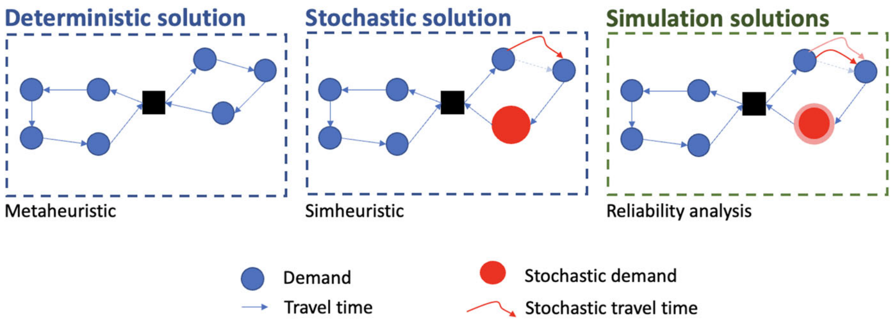

Fig. 1 A high-level schematic representation of our methodology

weighted recourse model in Sect. 3. The proposed solution approach is presented in Sect. 4. The computational results and their corresponding discussions are provided in Sect. 5. Finally, Sect. 6 presents the main conclusions and proposes future work.

2 Literature review

When random data is considered in VRP, the VRP is referred to as Stochastic VRP (SVRP). In general, stochasticity in the availability of data for the VRP occurs when some information may be uncertain or unclear before route planning (Gendreau et al. 1996). Compared to the deterministic VRP, the SVRP has been relatively less researched due to the additional complexity introduced by the randomness of information in the problem data (Goodson et al. 2012). The most studied SVRPs variants are: stochastic customers—where a customer needs to be serviced with a given probability (Bertsimas 1988; Waters 1989)—, stochastic travel times—where service or travel times are modelled as random variables (Laporte and Louveaux 1993; Kenyon and Morton 2003; Chen and Zhou 2010)—, and stochastic demands—where customers' demands are modelled using probability distributions (Laporte et al. 2002; Christiansen and Lysgaard 2007; Sun 2014), other studies deal with stochasticity by considering approaches that are based on estimations—such as crisp equivalents in uncertainty theory (Yang et al. 2021, 2022). A comprehensive description of the scientific literature on SVRP variants and their solution methods is provided in Gendreau et al. (2014), Oyola et al. (2016, 2017), Braekers et al. (2016).

Several researchers have applied different models and solution approaches to solve different variants of SVRPs. The two common modelling approaches are the Chance Constrained Problem (CCP) (Charnes and Cooper 1959; Miller and Wagner 1965) and the Stochastic Programming with Recourse (SPR). The CCP is based on the reliability of solutions by assigning some control (probability of success) to specific constraints to avoid violations, while the SPR is based on the concept of recourse/penalty. An example of a recourse action is when a route fails if the total realised travel time (hours) of a vehicle (route) exceeds the allowable driving duration (hours). The recourse action could be that the driver completes his tour and serves the remaining customers on the pre-planned route, if this does not violate the maximum allowed hours. This will incur a penalty cost in the form of overtime pay. In the case of uncertain demand, the recourse action requires that, if a pre-planned route fails (i.e., there is some unmet demand), then the vehicle must return to the depot for replenishment and resume the pre-planned route. These are generally known as “traditional corrective actions” (Dror and Trudeau 1986). Another commonly applied recourse action is preventive action, which is applied to reduce the risk of a route failure occurring. For instance, at certain predefined stages during the route execution, the current vehicle state is assessed to determine if a return trip to the depot is required to avoid a failure. Similarly, other recourse policies have been proposed in the literature (He et al. 2020). Summarily, a recourse model aims to find a solution containing routes that minimise expected costs. These are typically representative of the routes’ actual costs before failure and the penalty costs incurred due to route failure (Guimarans et al. 2018).

2.1 VRP with stochastic travel times and demands

The Vehicle Routing Problem with Stochastic Demands (VRPSD) is a well-known NP-hard problem characterised by some customers’ random requests to be served by a fleet of homogeneous vehicles with limited capacity (Bastian and Rinnooy Kan 1992). To model this variant of the VPR, some researchers proposed using recourse models (Tillman 1969; Tang and Wang 2006; Sungur et al. 2008; Marinakis et al. 2013; Juan et al. 2011). For instance, in Tillman (1969), penalties are incurred when a vehicle is over capacity. Bertsimas (1992) presented a deterministic visiting sequence to obtain the minimum expected distance and the expected value of demand that can be realised upon arrival at the customer. In Chang (2005) a two-stage recourse model contains the total cost of the aprioristic solution, while the second stage model computes the expected recourse costs.

The Vehicle Routing Problem with Stochastic Travel Times (VRPSTT) is perhaps one of the most challenging, but realistic variants of the VRP. Travel time between every pair of nodes assumes uncertainty in road (such as vehicle breakdowns or accidents) or weather conditions (Uchida and Kato 2017). Laporte et al. (1992) presented a VRPSTT and proposed a chance-constrained programming model and a recourse model to solve the problem, where the chance constraint model restricts the probability that a route can exceed a given threshold. Similarly, Guimarans et al. (2018) penalises the total cost of the route when the route duration exceeds a time threshold defined by the decision-maker. In the work of Tas et al. (2013) stochastic travel times were considered using soft time windows and solved using a three-stage solution method. The solution stages focused on defining an initial feasible solution with violation penalties, improving the quality of the initial feasible solution, and determining the best departure time for each vehicle at each node. Yang et al. (2021) study the consistent vehicle routing problem in travel, demand, and service times. The authors solve the problem using the Uncertain programming approach to minimise travel time, ensuring service consistency. Later, Yang et al. (2022) extended the problem to Yang et al. (2021) by considering a weighted objective function where the authors aim to minimise the weighted average of the total routing time and driver inconsistency.

The reliability of the solution in the VRPSTT has also been explored. Lecluyse et al. (2009) utilised the standard deviation of the travel times to select more reliable routes, while Yan et al. (2014) applied simulation techniques to assess the performance of the stochastic solution. Juan et al. (2023), Martin et al. (2023) optimised vehicle routes for the Time-Capacitated Arc Routing Problem (TCARP) amidst stochastic demands and travel times using a simheuristic approach focused on a singular problem-solving objective.

Table 10 provides a summary of recent studies that were considered in our paper, where we focus on scientific papers that explore the VRP with stochastic demand and travel times while also considering sustainability dimensions. The literature review indicates that hybrid algorithms that use metaheuristics combined with algebraic approaches are commonly used to solve stochastic problems. Furthermore, solution approaches tend to prioritise preventive strategies. Consequently, there is a growing interest in developing methodologies that accelerate the search for feasible solutions and incorporate corrective policies for possible disruptions caused by stochastic demands or travel times. Additionally, our analysis revealed a gap in the literature regarding the lack of robust criteria for evaluating the quality of solutions in terms of their environmental, economic, and social impacts in stochastic VRP studies.

2.2 Overview of simheuristics

Simheuristics are becoming increasingly popular methods for solving problems related to uncertain scenarios, where uncertainty can be modelled as a set of random variables following certain probability distributions (Panadero et al. 2020). Simheuristics involve the hybridisation of heuristics/metaheuristics with simulation techniques to handle high variability in stochastic Combinatorial Optimisation Problems (COPs) (Juan et al. 2015). Simheuristics are based on the hypothesis that by employing expected values of stochastic variables, deterministic problems can be solved using metaheuristic approaches. These methods have been implemented to tackle stochastic COPs in order to demonstrate their suitability. For example, Juan et al. (2011) proposed a simheuristic to solve the VRPSD, where the effect of safety stocks in routing under uncertainty is also investigated. They considered different safety stock levels to reduce the risk of route failure and computed expected costs by estimating expected demands using MCS. Similarly, González-Martin et al. (2015) proposed a simheuristic approach based on a RandSHARP algorithm presented in González-Martín et al. (2012) to solve the Arc Routing Problem with stochastic demands. The former was used to generate an initial solution, after which the latter was then implemented to estimate the total expected cost and solution reliability through the MCS technique.

Simheuristics have been applied to tackle other complex COPs such as Flow Shop Problems (Hatami et al. 2018; Juan et al. 2014; Villarinho et al. 2021), Orienteering Problem (Panadero et al. 2018), Facility Location Problem (De Armas et al. 2017), Inventory Routing Problems (Juan et al. 2014; Gruler et al. 2020; Raba et al. 2020) and Waste Collection Problem (Gruler et al. 2017).

3 The weighted stochastic recourse model

We propose a weighted stochastic recourse model for the SVRP-STD that extends the existing sustainable VRP model in Abdullahi et al. (2020) by considering the three sustainability dimensions, as well as stochastic travel times and demands. To generate an initial solution with route visit plans, the deterministic problem is first solved to reveal the expected values of demands and travel times using MCS. After determining the expected values, corrective actions are applied to failed routes and the reliability of the solution is assessed.

3.1 SVRP-STD recourse model

The SVRP-STD is formulated as a complete and undirected graph $G = (N, A)$, where N represents a set of nodes, including the depot. $A = (i, j)i, j \in N, i \neq j$ is a set of arcs connecting each pair of nodes and each node $i \in N_c$ has a non-negative demand $E[q_i]$. The homogeneous fleet of vehicles is denoted by $M = \{1, 2, \ldots, m\}$, with load capacity Q. Each route starts from and ends at the depot, and all customers' demands must be satisfied. d_{ij} and $E[t_{ij}]$ are the travel distance and the expected travel time between i and j. Each vehicle contributes a certain amount of CO_2, which has an associated cost C_e per kg. Furthermore, we assume that there is a risk related to traffic accidents. This risk represents the social impact propagated by the travel distance between i and j. We consider that the risk of traffic accidents has a correlation with driver fatigue, which could be related to the distance that the driver travels and the volume of loading and unloading while making deliveries (Torregroza-Vargas et al. 2014). Moreover, some other earlier studies found that fatigue due to longer driving distances and duration increases the risk of road accidents (Stevenson et al. 2010; Frith 1994; Cummings et al. 2001).

The SVRP-STD is formulated as a recourse model with a weighted objective function, where a vehicle's total travel time and customers' demands are assumed to be stochastic. We describe below the two-stage recourse model and provide the notations and parameters in Table 1 above.

The first-stage provides deterministic routing plans before the expected values of the stochastic variables are revealed. After the expected values have been revealed, a recourse/corrective action is applied if there are any route failures in the second stage model. We describe in details the failure types and recourse strategies in Sect. 3.1.2

3.1.1 First stage formulation of SVRP-STD

To represent the first stage model, we generate a deterministic route. We denote the sustainability dimensions as z_1, z_2, and z_3 which represent the economic, environmental, and social dimensions, respectively. These dimensions are calculated using the following expressions:

$$z_1 = \sum_{j \in N_c} \sum_{m \in M} FC \cdot x_{0jm} + \sum_{(i,j) \in A} \sum_{m \in M} C_d \cdot t_{ij} \cdot x_{ijm} + \sum_{(i,j) \in A} \sum_{m \in M} C_f \cdot f_{ijm} \cdot x_{ijm} \quad (1)$$

Table 1 Sets, parameters and variables

Sets and indices	
N	Set of all nodes
A	Set of arcs connecting nodes
N_c	Set of customers
M	Set of vehicles
i	Index of origin nodes
j	Index of destination nodes
m	Index of vehicles
s	Index of sustainability dimension

Parameters	
q_i	Demand of node i
d_{ij}	Distance between (i, j)
t_{ij}	Travel time from i to j
v_{ij}	Vehicle speed between i and j
Q	Vehicle capacity
C_d	Driver cost per time unit
FC	Vehicle fixed cost
kpl	Km/l fuel consumption rate
lph	l/h fuel consumption rate
C_f	Fuel price per liter
C_e	Carbon price per kilogram CO_2
a	Factor to monetise accident risk for a heavy vehicle
λ	Penalty cost per unit of overtime
γ	Conversion factor for fuel consumption to CO_2 (kg-CO_2/liter)
α_s	Weight of the indicator s

Variables	
x_{ijm}	Binary variable: 1 if arc (i, j) is traversed by vehicle m, 0 otherwise
y_{ijm}	Continuous variable: load on arc (i, j) when is traversed by vehicle m
f_{ijm}	Fuel consumption of vehicle m when travel from i to j
f_{jm}	Continuous variable: remaining tank fuel of vehicle m when it arrives at node j
U_{jm}	Auxiliary variable to eliminate sub-tours
z_s	Continuous variable. Value of indicator s

Equation 1 represents the *economic dimension*, where z_1 is the total cost which depends on: a fixed cost (FC)—including depreciation, repairing, and maintenance of vehicles; driver cost (C_d) which refers to driver wages; and f_{ijm}—representing the fuel consumption and fuel cost per unit of f_{ijm} is represented by (C_f).

$$f_{ijm} = lph_{ij} \cdot \frac{d_{ij}}{v_{ij}} \cdot \left(1 + p \cdot \frac{y_{ijm}}{H}\right) \quad \forall (i, j) \in A, \quad m \in M \tag{2}$$

Equation 2 computes fuel consumption f_{ijm} (Kuo 2010; Zhang et al. 2015), where lph_{ij} (Eq. 3) is fuel consumption per unit of time and kpl_{ij} calculates fuel consumption per distance unit (Muñoz-Villamizar et al. 2017).

$$lph_{ij} = \frac{v_{ij}}{kpl_{ij}} \quad \forall (i, j) \in A \tag{3}$$

To calculate the fuel consumption of a loaded vehicle m, when travelling from node i to j (f_{ijm}), we assume that an additional amount of load with weight H will increase fuel consumption by a ratio of p. Without loss of generality, we assume that $p = 0$ since the problem studied in this work does not consider pickups, then f_{ijm} can be up-bounded by f_{ij}.

$$z_2 = \sum_{(i,j)\in A} \sum_{m\in M} C_e \cdot f_{ijm} \cdot x_{ijm} \cdot \gamma \tag{4}$$

Equation 4 computes z_2, which represents the *environmental dimension*. This cost is associated with the CO_2 emissions generated per unit of fuel consumed (Kuo 2010; Zhang et al. 2015) and γ is an activity-based emission factor (Piecyk 2010). We monetise the emissions by a unit emission price C_e (World Bank 2015).

$$z_3 = \sum_{(i,j)\in A} \sum_{m\in M} a \cdot d_{ij} \cdot y_{ijm} \tag{5}$$

Lastly, Eq. 5 describes the *social dimension*, which is the cost attributed to the risk of accidents. The value attributed to this risk changes according to the travel distance and the vehicle's load when travelling from customer i to customer j (Eguia et al. 2013). To ensure the model accurately captures driver fatigue, Eq. 5 incorporates the accumulated distance travelled up to arc (i, j). This approach reflects the cumulative nature of fatigue, which increases with the total distance covered along the route. Additionally, as deliveries are made, the transported load decreases, while the cumulative volume of unloading increases, resulting in a proportional rise in driver fatigue associated with accident risk. This dynamic naturally integrates the effect of unloading into the calculation of social costs. In this study, we monetise the risk of accident by a factor a, which is a coefficient in USD/kg–km proposed in Delucchi and McCubbin (2011).

$$\text{Min } Z = \alpha_1 \cdot z_1 + \alpha_2 \cdot z_2 + \alpha_3 \cdot z_3 \tag{6}$$

subject to

$$\sum_{j\in N} \sum_{m\in M} x_{ijm} = 1 \qquad \forall\, i \in N_c \tag{7}$$

$$\sum_{i\in N} \sum_{m\in M} x_{ijm} = 1 \qquad \forall\, j \in N_c \tag{8}$$

$$\sum_{j\in N} x_{ijm} = \sum_{j\in N} x_{jim} \qquad \forall\, i \in N_c, \quad m \in M \tag{9}$$

$$y_{ijm} \leq Q \qquad \forall (i,j) \in A, \quad m \in M \tag{10}$$

$$f_{jm} \leq f_{im} - \frac{d_{ij}}{kpl} \cdot x_{ijm} + f_{0m} \cdot (1 - x_{ijm}) \qquad \forall i \in N, \quad j \in N_c, \quad m \in M \tag{11}$$

$$f_{jm} \geq \frac{d_{ij}}{kpl} \cdot x_{ijm} + \frac{d_{jo}}{kpl} \qquad \forall i \in N, \quad j \in N_c, \quad m \in M \tag{12}$$

$$\sum_{i \in N} y_{jim} = \sum_{i \in N} y_{ijm} - \sum_{i \in N} q_j \cdot x_{jim} \qquad \forall j \in N_c, \quad m \in M \tag{13}$$

$$y_{ijm} \leq (Q - q_i) \cdot x_{ijm} \qquad \forall (i,j) \in A, \quad m \in M \tag{14}$$

$$y_{ijm} \geq q_j \cdot x_{ijm} \qquad \forall (i,j) \in A, \quad m \in M \tag{15}$$

$$U_{im} - U_{jm} + |N_c| \cdot x_{ijm} \leq |N_c| - 1 \qquad \forall i, j \in N_c, \quad m \in M \tag{16}$$

$$x_{ijm} \in \{0, 1\} \qquad \forall (i,j) \in A, \quad m \in M \tag{17}$$

$$y_{ijm} \geq 0 \qquad \forall (i,j) \in A, \quad m \in M \tag{18}$$

$$f_{im} \geq 0 \qquad \forall i \in N, \quad m \in M \tag{19}$$

$$U_{im} \geq 0 \qquad \forall i \in N_c, \quad m \in M \tag{20}$$

The proposed weighted objective function Z in Eq. 6 is defined as a unified approach that combines the sustainability dimensions. α_s represents the weight or relative importance of a dimension s, where $0 \leq \alpha_s \leq 1$ and $\sum_{s=1}^{3} \alpha_s = 1$. This aggregates the objectives into a single objective with priority weights (Burke et al. 2014). This function aims to minimise the weighted cost associated with each dimension's negative impacts $z_s, \forall s \in \{1, 2, 3\}$.

Constraints in Eqs. 7 and 8 restrict that each customer is visited exactly once by one vehicle. The flow conservation, which ensures that the number of vehicles entering and leaving each customer node is equal, is outlined in Eq. 9. The constraint in Eq. 10 guarantees that the total vehicle load does not exceed its capacity. Equation 11 defines the state of fuel in a vehicle after visiting a customer j considering the fuel consumption and distance travelled. Equation 12 ensures that the fuel state of a vehicle is enough to return to the depot from any customer j location. Equation 13 determines that the load in the vehicle that reaches a customer j minus his demand must be equal to the load in the vehicle after the visit. Equations 14 and 15 bound the load of vehicle m when travelling between i and j. The sub-tour elimination constraint in Eq. 16 sets U_{jm} as an auxiliary variable and $|N_c|$ as the number of customers. This constraint prevents the formulation of smaller tours that do not include all customers. Equations 17–20 define variable domains that include binary variables for whether a vehicle travels between two nodes, non-negative variables for vehicle load and fuel state, and non-negative variable for U_{jm}.

3.1.2 Failure types and corrective strategies for the second stage model

When a restriction is violated, this is generally termed as a route failure and it is assigned a penalty. There are two types of route failure and their relevant corrective strategies, as described below.

1. Failure type 1: Insufficient remaining load—the remaining load of a vehicle is not sufficient to satisfy the demand of the customer being visited.
2. Failure type 2: Exceeding contracted working hours. Here, a driver has completed his contracted number of working hours and has to work overtime, but within the working time regulations.

Although other preventive strategies such as driver training and restricting transportation hours can also be applied (Asgari et al. 2017), it is important to note that the implementation of preventive strategies does not guarantee that a route will not fail. Therefore, we propose and implement two corrective strategies for the failure types considered in this study, as described below.

1. Corrective strategy 1: The total revealed demand in a route may exceed the capacity of the vehicle. This means that the remaining load of a vehicle is not sufficient to satisfy the demand of the customer being visited. In this case, the corrective strategy requires the vehicle to go back to the depot for reloading. For the purpose of this study, we assume that the availability of drivers is limited. This means that there are no additional drivers waiting at the depot. This strategy may impact the travel time and distance.
2. Corrective strategy 2: The actual travel time of a route may exceed the maximum allowed working hours. Here, a driver has been operating for the contracted 8 h (T_{max}), but he/she has not visited all the assigned customers: The corrective strategy applied in this case requires the driver to complete the route, which will incur penalties due to overtime pay. Without loss of generality, we assume that a driver can visit all assigned customers within a total maximum allowed working limit of 9 h (T_{limit}).

3.1.3 Second stage formulation of SVRP-STD

Following the first stage decisions, the second stage model considers stochastic demands and travel times as random variables following specific probability distributions, which could be theoretical or empirical. In practice, the actual travel time to a customer location is known upon arrival of the vehicle at the customer location. When a vehicle follows a deterministic plan and a route failure occurs, some recourse actions are taken, and the original plan is updated. The additional cost incurred for the recourse action (that is, the penalty cost due to the route failure) is equal to the travel cost of moving back and forth between the failure point and the depot. Thus, the objective of the SVRP-STD is to minimise the sum of the travel cost and the expected cost of a route failure. To compute the actual sustainability impacts in a stochastic environment, z_1^*, z_2^*, and z_3^* represent the expected economic, environmental, and social impacts, respectively. Equations 1, 4 and 5 are rewritten below.

$$z_1^* = \sum_{j \in N_c} \sum_{m \in M} FC \cdot x_{0jm} + z_{1_d} + z_{1_f} \tag{21}$$

$$z_{1_d} = \begin{cases} c_d \cdot T_{time} & \text{if} \quad T_{time} \leq T_{max} \\ T_{time} \cdot c_d + \lambda \left(T_{time} - T_{max}\right) & \text{otherwise} \end{cases} \tag{22}$$

where

$$T_{time} = \sum_{(i,j)\in A} \sum_{m\in M} t_{ij} \cdot x_{ijm} \tag{23}$$

In the second stage, the economic dimension is rewritten as in Eq. 21. If the total working hours of a route exceed the maximum allowed hours, penalties are incurred; see Eq. 22. The z_{1_d} component of the economic impact computes the total driver remuneration. When a deterministic route plan is generated, a MCS is run in order to observe the ‘real’ travel time t_{ij} between nodes i and j. If $T_{time} > T_{max}$, then, a penalty λ is incurred per unit of overtime. For this problem, we assume that T_{max} is the upper bound duration (contracted hours) a driver can work within a daily legal limit T_{limit} ($T_{time} \leq T_{max} \leq T_{limit}$), and T_{time} is the total travel time. Within the driver’s contracted hours T_{max}, a driver is paid c_d per time unit, and for any additional unit of time after T_{max}, a penalty cost of λ is incurred. This penalty cost corresponds to the overtime pay the driver receives (Tan et al. 2007). Additionally, we do not consider any break time, waiting time, or stopping time for the duration of the working time.

$$z_{1_f} = \begin{cases} c_f \cdot Fuel_c & \text{if} \quad T_{demand} \leq Q \\ c_f \cdot Fuel_c + Fuel_c^* & \text{otherwise} \end{cases} \tag{24}$$

where

$$Fuel_c = \sum_{(i,j)\in A} \sum_{m\in M} f_{ijm} \cdot x_{ijm} \tag{25}$$

Similarly, Eq. 24 computes the total fuel consumption, which is directly affected by the travelled distance. When the actual demand of a customer is revealed, and if the actual total revealed demand (T_{demand}) exceeds the vehicle capacity, a route failure occurs. In such a failure, a recourse action is taken, and the original plan is updated. The incurred extra cost for the recourse action (i.e., additional fuel consumption) is equal to the fuel cost of moving back and forth between the failure point and the depot. This additional cost is represented as the fuel cost of the additional distance travelled $Fuel_c^*$.

$$z_2^* = \begin{cases} c_e \cdot \mathrm{CO}_2 & \text{if} \quad T_{demand} \leq Q \\ c_e \cdot \mathrm{CO}_2 + \mathrm{CO}_2^* & \text{otherwise} \end{cases} \tag{26}$$

where

$$\mathrm{CO}_2 = \sum_{(i,j)\in A} \sum_{m\in M} f_{ijm} \cdot x_{ijm} \cdot \gamma \tag{27}$$

Equation 26 computes the expected emissions cost. CO_2 (Eq. 27) is the emissions generated before the realisation of the actual demand. However, upon the reveal of the actual demands and a customer’s demand cannot be met, the route fails. This means that the vehicle has to travel back to the depot to refill and fulfil unmet demands, generating additional emissions (CO_2^*).

$$z_3^* = \begin{cases} a \cdot w_{km} & \text{if} \quad T_{demand} \leq Q \\ a \cdot w_{km} + w_{km}^* & \text{otherwise} \end{cases} \tag{28}$$

where

$$w_{km} = \sum_{(i,j)\in A} \sum_{m \in M} d_{ij} \cdot y_{ijm} \tag{29}$$

Finally, Eq. 28 computes the accident risk impact, which is also referred to as the social impact of the objective function. w_{km} (Eq. 29) is the value attributed to travel distance and the vehicle's load when the revealed customers' demands if fully met. This means that route failure has not occurred. On the contrary, w^*_{km} is the additional load weight of a vehicle per kilometre in the case of unmet demand (route failure). Based on Eqs. 21–29, the objective of the recourse model for the SVRP-STD is to design a first-stage model that generates the expected values of the second-stage variables. The SVRP-STD second-stage stochastic recourse model is presented in Eq. 30.

$$\text{Min } Z^* = \alpha_1 \cdot z_1^* + \alpha_2 \cdot z_2^* + \alpha_3 \cdot z_3^* \tag{30}$$

Subject to:

$$T_{time} - T_{max} \geq 0 \tag{31}$$

$$T_{max} \leq T_{limit} \tag{32}$$

and Eqs. 7–19.

The total cost presented in Eq. 30 is the cost of the first-stage solution and the recourse cost of route failure.

4 The proposed Sim-BRIG-LS algorithm

Since uncertainty in routing information before route planning is nontrivial and may result in failure routes, violations such as maximum vehicle capacity need to be avoided or taken into account during route planning. Thus, solving a stochastic problem is complex, as it is not enough to simply obtain the solution with the best expected value; solutions that show reasonably good probabilistic behaviour need to be considered as well. This requires the development of an advanced simulation-optimisation approach. To solve the proposed SVRP-STD, we have developed a hybrid simheuristic integrating MCS and BRIG-LS metaheuristic, which we refer to as Sim-BRIG-LS (Fig. 2).

Simheuristics rely on a metaheuristic component, which searches for promising solutions. These solutions are found by solving a deterministic version of the problem, which is usually created by replacing the random variables by their expected values. The BRIG-LS is combined with MCS to assess the performance of promising solutions under stochastic demands and travel times. This solution is defined as the one with the lowest expected total cost or negative impacts for uncertain scenarios. The proposed approach comprises of three stages, as described below.

Stage I: This phase begins by generating an initial deterministic schedule for the vehicle (*baseSol*), which is then improved through a local search (Algorithm 1) and saved as (*bestSol*). This *bestSol* serves as the initial solution for the SVRP-STD, where expected values for travel times and demands are estimated using MCS (short

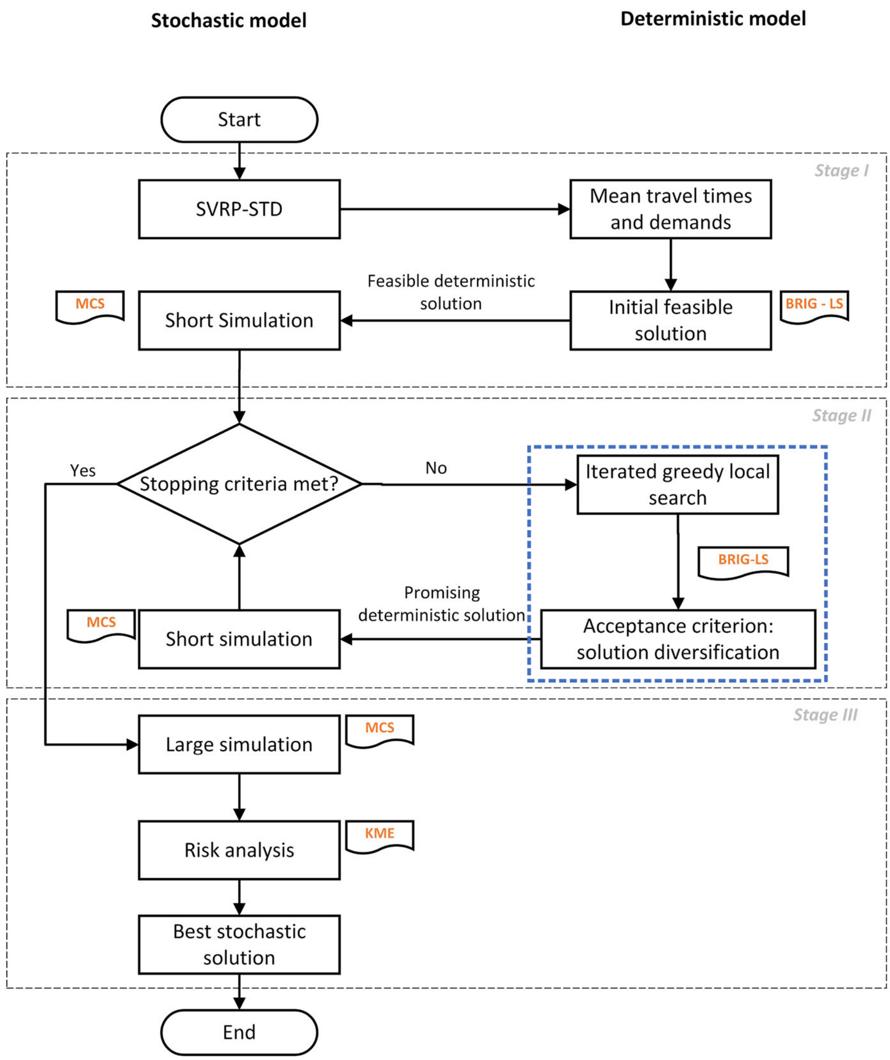

Fig. 2 Sim-BRIG-LS framework

simulation), typically with a few hundred simulation runs. If corrective actions are required, recourse costs are incurred, contributing to an updated expected total cost for the SVRP-STD. At this stage, $bestSol$ is stored as the temporary reference or 'base' solution ($baseSol$) and is added to a pool of elite stochastic solutions. This pool will be referenced continuously to assess and compare new solutions.

Stage II: An iterative process begins until the stopping condition is met:

- Starting with the current best stochastic solution from the pool, perform destruction, construction, and local search steps iteratively to generate a new candidate solution.

- Apply an acceptance criterion to evaluate the new candidate solution against the current best stochastic solution. If the new solution is accepted, it is added to the pool of elite stochastic solutions. To ensure that only the top-performing solutions are maintained, the pool size is restricted as the algorithm progresses.
- Update the best stochastic solution by comparing the expected cost of the new solution with that of the current best solution in the pool.

Stage III: Once the stopping condition is met, a detailed MCS (long simulation) is applied on all solutions in the pool of elite stochastic solutions to provide more accurate estimates of expected cost and reliability. Additionally, risk and reliability analysis is performed by applying the KME on the solutions in the pool to further assess robustness. The solution with the lowest expected cost and highest reliability from this analysis is then returned as the best stochastic solution found.

Algorithm 1 BRIG-LS for SVRP-STD

```
1: procedure BRIG- LS(inputs, weights, maxTime, β, p)
        ▷ inputs: geographical coordinates, demands, Q, impact parameters
        ▷ maxTime: max computing time allowed
        ▷ β: parameter for biased randomisation
        ▷ p: parameter of the destruction stage
2:    baseSol ← BRIG-LS(inputs, β)                              ▷ Based on 'rich' savings
3:    baseSol ←localSearch(baseSol)
4:    bestSol ← baseSol
5:    while (stopping criterion is not met) do                  ▷ Search for promising solutions
6:        newSol ← destructionConstruction(baseSol, p, inputs, β)
7:        newSol ← localSearch(newSol)
8:        rpd ← (cost(newSol) − cost(baseSol))/cost(baseSol) · 100
9:        if (rpd ≤ 0) then
10:           baseSol ← newSol
11:           if (cost(newSol) < cost(bestSol)) then
12:               bestSol ← newSol
13:           end if
14:       else                                                  ▷ Avoid local optimal
15:           u ← generateU()
16:           if (u < exp(−rpd)) then
17:               baseSol ← newSol
18:           end if
19:       end if
20:   end while
21:   return bestSol
22: end procedure
```

4.1 BRIG-LS procedure

In the BRIG-LS (Algorithm 1), an initial solution (*baseSol*) is generated based on the savings-based routing heuristics described in Dominguez et al. (2016) and an enhanced local search (Algorithm 2) is applied to improve the generated solution.

The best solution found (*bestSol*) is saved as the *baseSol*, and an iterative improvement process based on the Iterated Greedy method (Ruiz and Stützle 2008) is started until the stopping condition is met (lines 5–20). Within the iterative process, a new solution ($newSol$) is generated by partially deconstructing and re-constructing the $baseSol$. The local search—Algorithm 2 - is applied to the $newSol$. If this procedure generates a feasible solution, the relative percentage difference (rpd, line 8) between the costs of $newSol$ and $baseSol$ is computed. If this measure is negative (i.e., $newSol$ is better), $newSol$ replaces $baseSol$. Otherwise, $newSol$ may replace $baseSol$ with a probability of e^{-rpd} (lines 15–18) (Hatami et al. 2015).

4.2 Local search procedure

The proposed local search based on random swaps is described in Algorithm 2. This algorithm is iterated until two conditions are met: *(i)* the number of trials is greater than the number of routes, and *(ii)* the last swap did not lead to an improvement. For each iteration of the loop, a route (r) and two different nodes ($n1$, $n2$) of this route are randomly selected. Then, a potential swap is assessed. The solution introduces this change if the cost is improved.

Algorithm 2 Local Search Procedure

```
procedure LOCALSEARCH(sol)
    improvement ← TRUE
    nTrials ← 0
    while (improvement is TRUE or nTrials < nRoutes(sol)) do
        r ← getRandomRoute(sol)
        n1 ← getRandomNode(r)
        n2 ← getRandomNode(r)
        while (n1 is equal n2) do
            n2 ← getRandomNode(r)
        end while
        newR ← swap(r, n1, n2)
        if (cost(newR) < cost(r)) then
            improvement ← TRUE
            sol ← update(sol, newR, r)
        end if
        nTrials ← nTrials + 1
    end while
    return sol
end procedure
```

5 Computational experiments and analysis of results

In this section, a set of experiments to analyse the weighted recourse model's performance and the results of our simheuristic approach, and reliability analysis are presented. The aims of the experiments are as follows: *(i)* to evaluate the performance of the weighted recourse model and the Sim-BRIG-LS algorithm; *(ii)* to conduct a sensitivity analysis of different sustainability dimensions importance weights to assess the trade-offs between the parameters of the dimensions; *(iii)* to provide reliability analysis (e.g., the survival function analysis) as a novel tool to assess and understand the probabilistic behavior of the solutions provided by the Sim-BRIG-LS.

Table 2 Parameters of the algorithm

Parameter	Value
$maxTime$	100 s
Number of seeds	5
β	U(0.7, 0.8)
p	U(0, 100)
$nSim_s$, $nSim_l$	500, 5000

The proposed SVRP-STD and Sim-BRIG-LS have been coded in the Java programming language, and all tests were perfromed on a computer with a Core i5, 2.30 GHz processor and 4 GB of RAM.

5.1 Benchmark instances and experimental parameters

The Sim-BRIG-LS parameters used for the experiments are provided in Table 2 and the run-time limit has been set to 100 s for all instances. 10 runs (each with a different seed for the pseudo-random number generator) were executed. The distributions of β and p have been set after running a few experiments, based on the methodology described in Calvet et al. (2016). The remainder of this section describes the SVRP-STD instances, the assessment of the performance of the proposed Sim-BRIG-LS and the trade-off analysis among the impacts of different parameters of the sustainability dimensions.

To evaluate the performance of the proposed approach and perform a trade-off analysis between the sustainability dimensions, 43 deterministic test instances were adapted from Uchoa et al. (2017), which include instances ranging between 31 and 80 nodes. The test instances have been adapted by changing the deterministic demands and deterministic travel times into expected demands and travel times following log-normal probability distributions (Eqs. 33 and 34). Although identifying the best probability distribution can be challenging in practice, the log-normal distribution allows the approximation of real-world stochastic parameters effectively than the normal distribution (Juan et al. 2011).

Travel time between nodes and their demands are non-negative random variables that follow a Log-normal distribution. The Log-normal distribution has a location parameter $\mu_i j$ and a scalar parameter $\sigma_i j$, which are expressed below.

$$\mu(t_{ij}) = \ln(E[t_{ij}]) - \frac{1}{2} \cdot \ln\left(1 + \frac{Var[t_{ij}]}{E[t_{ij}]^2}\right) \tag{33}$$

$$\sigma(t_{ij}) = \left|\sqrt{\ln\left(1 + \frac{Var[t_{ij}]}{E[t_{ij}]^2}\right)}\right| \tag{34}$$

Given Eqs. (33) and (34), two uncertainty levels are presented in Table 3, that is, $Var[t_{ij}] = P \cdot t_{ij}$ for different values of the parameter P. The value of P determines the degree of uncertainty.

Table 3 Uncertainty levels

Levels	Degree of uncertainty	
	$E[t_{ij}]$	$E[q_i]$
1	$0.05 \cdot t_{ij}$	$0.10 \cdot q_i$
2	$0.85 \cdot t_{ij}$	$0.90 \cdot q_i$

Table 4 Parameters that quantify and monetise impacts

Input	Value	Converted to	Reference
kpl	0.052/km		Muñoz-Villamizar et al. (2017)
γ	0.75 kg of CO_2/l (rigid ≥ 7.5–17 t)		Piecyk (2010)
FC	59.90 £/day	66.58 €/day	
C_d	7.92 £/h	8.80 €/h	Koç et al. (2014)
C_f	1.4 £/l	1.56 €/l	
C_e	22 USD/ton of CO_2	0.02 €/kg of CO_2	World Bank (2015)
a	[0.1–2] USD/ton-mile	0.0005 €/kg–km	Delucchi and McCubbin (2011)
λ	20 USD/h	16.40 €/h	
T_{max}	8 h/day		Tan et al. (2007)
T_{limit}	9 h/day		Regulation (EC) no 561/2006

For example, if the customer's demand i follows a logarithmic normal probability with an expected value of q_i and a variance of $P \cdot q_i$ and the values of P, 0.05 and 0.90, are tested, representing a low and a high level of stochasticity, respectively. If $q_i = 20$, the smallest interval containing 90% of the generated values would be approximately $(18.42, 21.37)$ for $P = 0.05$ and $(13.83, 27.58)$ for $P = 0.90$. To fully describe these levels, *Level 1* $(0.05, 0.10)$ indicates more variability when, as indicated by the wider interval and less variability for *Level 2* $(0.85, 0.90)$. Lastly, the parameters for quantifying the impacts, including units and references, are provided in Table 4.

5.2 Experimental results to evaluate the quality of BRIG-LS

In Table 5, we evaluate the performance of BRIG-LS and compare our results to the benchmark deterministic instances in Uchoa et al. (2017). We report the following information: the best-known solution values (BKS), BRIG-LS solutions ($OurSol$), the %Gap (Eq. 35) from the BKS, and the CPU time of the proposed BRIG-LS.

$$\%Gap = \frac{OurSol - BKS}{OurSol} \cdot 100 \tag{35}$$

Results demonstrate that some of our solutions are slightly worse than BKS. On average, BRIG-LS achieves a gap of 0.69% compared to BKS and achieves the best solution in 36.47 s. To evaluate the stability of the BRIG-LS method, we provide in Table 11 statistical results or 10 experimental runs with random seeds. We found a mean standard deviation value of 1.41 indicating that small changes in input data of the algorithm (random seeds) do not result in large changes in the output. In other words, BRIG-LS produces consistent results even when there are minor variations in the input.

5.3 Experimental results for different uncertainty levels in Table 3

Here, the average objective function values for our Best Deterministic Solution (BDS), the best-found solution that minimises the total cost (assessed in a stochastic environment)—and our Best Stochastic Solutions (BSS), the best-found solution that minimises the expected total cost (considering recourse costs), are presented.

The uncertainty levels previously described are applied to all test instances. For the experiments, the following scenarios have been generated to represent the dimensions: The *economic scenario* represents the traditional objective, where the economic dimension is the main optimisation criterion. This scenario assigns 100% of importance to the economic dimension, while the remaining dimensions are assigned 0% importance. The *environmental scenario* represents the green dimension, where the environmental impact is the only important dimension with an importance weight of 100%. The *social scenario* represents the abstract scenario, where the social dimension is the main optimisation criterion. Lastly, in the *balanced scenario*, all three sustainability dimensions are assigned equal importance.

Tables 6 and 7 summarise the results found in the scenarios described above, with the uncertainty levels described in Table 3. The first column represents the instance name, and the next two columns present the BDS and BSS in terms of the expected value of the objective function for the balanced scenario. In columns 4–9, we present the gaps between the BDS and BSS economic, environmental, and social scenarios compared to the balanced scenario. To be specific, the percentage gap between solutions obtained in the balanced scenario (equally weighted dimensions) and the solutions when each dimension is assigned full importance is outlined. For evaluating solution quality, positive values (gaps) represent a cost increase, while negative gaps indicate a cost decrease. The %Gap in Eq. 36 compares the values of the BDS and BSS.

$$\%Gap = \frac{TC^* - TC^e}{TC^e} \cdot 100 \tag{36}$$

where TC^* is the average solution obtained when a dimension is given 100% importance, and TC^e is the solution value of the balanced scenario.

Analysing the solutions obtained for level 1 uncertainty in Table 6 it can be observed that, in comparison to the balanced scenario, the economic scenario is 0.38% and 0.35% more expensive in terms of the BDS and BSS, respectively. Additionally, comparing the BDS and BSS obtained when considering the social scenario, the social scenario is 12.47% and 12.39% more expensive than the balanced scenario.

Regarding the solutions obtained when considering level 2 uncertainty in Table 7, it can be observed that the gap between the average values of the BDS and the BSS for the economic scenario and the balanced scenario are 0.79% and 0.34% respectively. As expected, the BDS and BSS's gaps for the social scenario and the BDS and BSS gaps for the balanced scenario are 16.21% and 16.05%, respectively. The experimental results show that, in all tested instances, the stochastic solutions outper-

Table 5 Comparison of BRIG-LS against the BKS

Instance	BKS Uchoa et al. (2017) (km)	BRIG-LS (km)	Gap (%)	CPU time (s)
A-n32-k5	784	787.08	0.39	6.02
A-n33-k5	661	662.11	0.17	0.11
A-n33-k6	742	742.69	0.09	65.69
A-n34-k5	778	780.94	0.38	0.08
A-n36-k5	799	809.71	1.34	56.39
A-n37-k5	669	672.47	0.52	0.22
A-n37-k6	949	950.85	0.19	0.51
A-n38-k5	730	733.95	0.54	0.96
A-n39-k5	822	828.99	0.85	8.16
A-n39-k6	831	833.20	0.26	1.91
A-n44-k6	937	938.18	0.13	0.40
A-n45-k6	944	957.88	1.47	6.55
A-n45-k7	1146	1146.91	0.08	15.30
A-n46-k7	914	917.72	0.41	35.73
A-n48-k7	1073	1074.34	0.12	1.26
A-n53-k7	1010	1012.33	0.23	76.45
A-n54-k7	1167	1171.68	0.40	15.80
A-n55-k9	1073	1074.96	0.18	1.68
A-n60-k9	1354	1360.59	0.49	31.67
A-n61-k9	1034	1047.74	1.33	4.74
A-n62-k8	1288	1319.59	2.45	90.29

Table 5 continued

Instance	BKS Uchoa et al. (2017) (km)	BRIG-LS (km)	Gap (%)	CPU time (s)
A-n63-k9	1616	1622.14	0.38	99.99
A-n63-k10	1314	1319.93	0.45	76.60
A-n65-k9	1174	1190.52	1.41	3.74
A-n69-k9	1159	1179.76	1.79	86.61
B-n31-k5	672	676.09	0.61	2.36
B-n34-k5	788	789.84	0.23	5.06
B-n38-k6	805	807.88	0.36	38.35
B-n41-k6	829	833.66	0.56	26.54
B-n43-k6	742	746.98	0.67	0.10
B-n44-k7	909	914.96	0.66	21.71
B-n45-k5	751	753.96	0.39	0.43
B-n50-k7	741	744.23	0.44	0.25
B-n50-k8	1312	1324.61	0.96	99.59
B-n57-k9	1598	1609.26	0.70	98.65
B-n63-k10	1496	1507.59	0.77	95.06
B-n64-k9	861	869.08	0.94	6.04
B-n66-k9	1316	1329.21	1.00	98.79
B-n67-k10	1032	1044.46	1.21	85.40
B-n68-k9	1272	1298.70	2.10	93.52
	Average		0.69	36.47

Table 6 Level 1 uncertainty—gap (%) between the economic, environmental and social scenarios BDSs and BSSs and the BDSs and BSSs of balanced scenario

Instance	Balanced solution		Gap (%) with respect to the Balanced Solution					
			Economic solution		Environmental solution		Social solution	
	BDS	BSS	BDS	BSS	BDS	BSS	BDS	BSS
A-n32-k5	531.27	530.72	0.18	1.77	1.33	0.72	5.12	5.92
A-n33-k5	500.93	500.63	0.20	1.00	1.13	− 0.01	17.89	1.76
A-n33-k6	589.10	588.46	0.33	0.39	0.18	0.28	14.56	13.55
A-n34-k5	531.93	531.02	− 0.19	− 0.11	− 0.13	0.07	13.25	13.67
A-n36-k5	533.67	529.70	− 0.93	0.77	1.57	1.38	4.64	4.56
A-n37-k5	501.12	501.06	0.05	− 0.10	0.29	0.38	1.14	2.43
A-n37-k6	637.84	635.47	− 0.33	2.18	1.34	1.02	24.55	25.22
A-n38-k5	520.02	520.02	− 0.30	− 0.29	0.49	− 0.69	15.27	14.99
A-n39-k5	540.95	540.44	0.13	− 1.00	1.20	− 0.27	32.62	35.09
A-n39-k6	610.78	606.97	− 0.18	0.61	1.11	0.97	13.17	27.96
A-n44-k6	637.80	637.11	0.48	1.90	11.10	0.90	13.46	14.97
A-n45-k6	639.79	639.79	1.04	0.36	12.25	11.10	13.67	13.61
A-n45-k7	753.24	751.99	− 0.04	1.00	2.86	1.54	14.25	13.55
A-n46-k7	699.12	699.14	0.68	0.13	1.59	0.75	1.98	1.80
A-n48-k7	741.51	737.33	0.47	0.84	1.51	0.55	3.32	3.10
A-n53-k7	725.64	725.36	1.05	0.17	− 0.21	− 0.12	12.84	13.27
A-n54-k7	769.05	768.31	1.38	− 0.24	4.83	9.45	12.25	13.06
A-n55-k9	880.05	880.06	− 0.36	0.22	11.98	0.06	9.80	18.93
A-n60-k9	951.54	951.35	0.52	0.99	3.08	0.33	12.95	12.66
A-n61-k9	871.30	866.87	− 1.43	1.87	15.01	7.71	25.51	27.12
A-n62-k8	866.15	863.93	0.43	0.29	0.61	0.03	11.24	10.72
A-n63-k10	1015.06	1012.24	0.14	0.12	0.80	7.02	9.66	9.42
A-n63-k9	1031.08	1021.16	0.70	0.90	7.16	7.07	10.18	13.79

Table 6 continued

Instance	Balanced solution		Gap (%) with respect to the Balanced Solution					
			Economic solution		Environmental solution		Social solution	
	BDS	BSS	BDS	BSS	BDS	BSS	BDS	BSS
A-n64-k9	971.67	967.37	1.87	− 0.11	4.22	2.78	12.46	11.95
A-n65-k9	909.44	908.44	0.52	0.78	7.57	8.21	9.26	8.04
A-n69-k9	900.65	900.37	0.01	0.16	0.54	8.42	8.18	8.43
A-n80-k10	1137.43	1136.60	− 0.68	1.71	1.60	1.93	10.83	7.46
B-n31-k5	507.08	506.70	0.20	− 1.17	0.81	0.78	2.03	3.11
B-n34-k5	540.64	540.34	− 0.29	− 3.34	0.12	0.29	14.73	30.38
B-n38-k6	607.99	607.88	0.75	1.49	1.25	0.92	13.49	13.92
B-n41-k6	618.57	618.23	0.84	0.09	0.55	0.55	24.49	12.55
B-n43-k6	592.92	592.86	− 0.16	− 0.17	1.88	0.71	0.98	2.93
B-n44-k7	699.52	694.62	2.60	2.29	1.12	0.51	16.15	25.93
B-n45-k5	524.04	525.30	0.46	0.14	12.97	0.25	15.89	13.96
B-n45-k6	582.38	582.02	1.76	0.37	13.15	12.48	14.29	14.48
B-n50-k7	659.74	659.65	− 0.40	0.20	0.32	0.32	11.33	13.21
B-n50-k8	872.10	870.36	1.42	1.60	1.03	0.34	20.94	10.58
B-n57-k9	1029.54	1020.85	0.04	− 2.03	0.51	0.17	18.39	2.64
B-n63-k10	1079.62	1077.34	0.38	− 1.38	− 2.79	0.55	8.50	8.21
B-n64-k9	829.37	829.33	0.26	− 0.50	9.03	8.71	17.53	9.14
B-n66-k9	949.96	942.74	0.07	0.81	0.85	7.92	9.46	9.81
B-n67-k10	944.65	941.85	1.36	− 0.17	0.23	0.40	3.20	2.20
B-n68-k9	943.10	934.66	1.22	0.37	0.22	0.92	10.94	12.49
Average	743.71	741.78	0.38	0.35	3.17	2.50	12.47	12.39

Table 7 Level 2 uncertainty—gap (%) between the economic, environmental and social scenarios BDSs and BSSs and the BDSs and BSSs of balanced scenario

Instance	Balanced solution		Gap (%) with respect to the Balanced Solution					
			Economic solution		Environmental solution		Social solution	
	BDS	BSS	BDS	BSS	BDS	BSS	BDS	BSS
A-n32-k5	536.31	533.83	1.75	0.39	0.31	1.37	4.44	4.88
A-n33-k5	501.86	500.95	1.22	0.03	1.07	1.04	19.44	19.25
A-n33-k6	590.09	589.72	0.35	0.10	11.93	1.82	14.33	13.67
A-n34-k5	532.54	532.27	− 0.17	− 0.28	0.36	1.26	14.82	14.48
A-n36-k5	544.48	536.14	1.09	0.59	− 0.17	2.07	20.85	22.36
A-n37-k5	501.91	500.94	0.72	0.54	0.46	0.14	2.98	3.05
A-n37-k6	643.97	640.90	1.80	0.40	1.10	2.41	25.48	25.20
A-n38-k5	522.17	521.36	− 0.01	− 0.22	0.94	− 0.11	16.27	16.00
A-n39-k5	543.71	543.75	− 0.23	0.31	0.00	− 0.03	29.55	29.30
A-n39-k6	610.71	612.86	− 0.02	− 0.40	12.58	1.74	16.30	15.59
A-n44-k6	643.85	640.57	2.30	0.04	10.70	10.56	15.41	15.56
A-n45-k6	645.22	641.56	1.30	1.28	10.38	11.91	16.23	16.81
A-n45-k7	764.93	756.19	1.12	1.10	0.82	2.42	13.05	12.96
A-n46-k7	702.87	701.92	0.63	0.92	1.26	1.50	14.81	15.11
A-n48-k7	748.64	744.33	1.00	0.64	0.02	1.76	15.56	15.64
A-n53-k7	727.05	728.96	1.12	− 0.52	0.68	0.75	16.53	15.00
A-n54-k7	769.73	771.06	0.27	− 0.07	9.81	4.92	13.93	12.96
A-n55-k9	886.42	882.68	0.75	0.00	7.43	11.09	18.65	19.30
A-n60-k9	963.38	960.78	1.70	0.46	0.06	0.66	20.97	21.54
A-n61-k9	890.31	879.72	1.40	− 0.71	13.59	15.40	42.90	44.38
A-n62-k8	866.57	869.08	1.62	− 0.11	1.01	0.51	15.06	12.32
A-n63-k10	1016.09	1009.38	0.13	0.79	6.74	0.70	8.73	9.45

Table 7 continued

Instance	Balanced solution		Gap (%) with respect to the Balanced Solution					
			Economic solution		Environmental solution		Social solution	
	BDS	BSS	BDS	BSS	BDS	BSS	BDS	BSS
A-n63-k9	1031.20	1026.70	0.33	1.13	7.13	7.84	12.00	11.98
A-n64-k9	976.00	974.68	−0.22	−0.24	1.07	4.47	15.97	16.10
A-n65-k9	908.10	909.84	0.83	0.39	8.61	6.94	10.82	10.39
A-n69-k9	905.06	901.07	0.17	0.64	7.69	1.03	10.04	10.49
A-n80-k10	1160.76	1148.58	1.68	0.03	0.10	1.73	10.83	11.70
B-n31-k5	506.88	507.13	0.11	0.12	0.74	0.61	19.84	19.10
B-n34-k5	542.85	541.80	0.42	0.04	0.13	0.60	31.90	32.13
B-n38-k6	612.52	609.01	1.48	0.98	1.37	1.55	2.67	2.91
B-n41-k6	618.97	619.56	0.06	0.03	0.57	0.40	14.03	13.54
B-n43-k6	596.78	594.62	0.06	0.27	0.18	0.57	16.23	16.34
B-n44-k7	701.05	702.42	2.14	1.22	0.72	3.02	25.11	24.82
B-n45-k5	527.63	526.57	1.24	0.77	13.16	12.35	15.16	15.31
B-n45-k6	583.11	584.58	0.60	0.78	12.45	13.21	28.16	27.29
B-n50-k7	662.40	661.33	0.29	−0.16	0.22	0.92	14.80	13.72
B-n50-k8	874.62	874.95	1.59	0.62	0.65	2.23	22.54	22.41
B-n57-k9	1038.86	1034.92	1.14	0.33	0.01	0.89	11.45	10.19
B-n63-k10	1086.39	1078.01	1.33	1.15	−0.35	0.29	9.38	9.87
B-n64-k9	830.99	831.53	0.07	0.19	9.07	8.84	18.89	17.89
B-n66-k9	958.28	951.52	0.43	0.55	7.30	1.63	9.43	9.18
B-n67-k10	942.41	945.81	−0.03	0.37	2.05	−0.11	10.27	9.10
B-n68-k9	939.71	943.23	0.60	0.21	0.89	1.08	11.25	10.75
Average	747.85	745.74	0.79	0.34	3.83	3.35	16.21	16.05

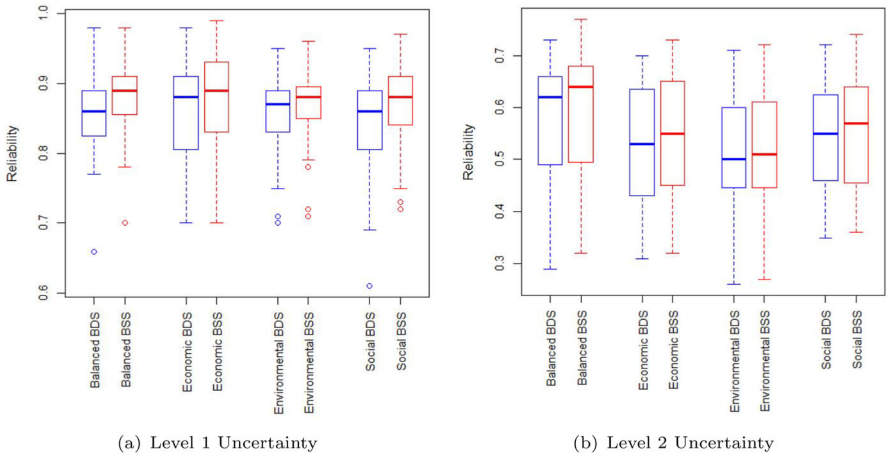

Fig. 3 Boxplot of reliability levels obtained for the BDSs and BSSs for the different solutions with *Level 1* and *Level 2* uncertainty

form the deterministic solutions. These results are expected since stochastic solutions minimise the objective value of the second-stage problem (Eq. 30) including recourse costs. This demonstrates the benefit of combining simulation with optimisation when solving stochastic optimisation problems.

5.3.1 Reliability levels of stochastic solutions versus the deterministic solutions

The reliability of a route in Eq. 37 is calculated as 1 minus the proportion of routes where, at least, a route failure occurs. $nSim$ is the number of simulations and $routeFailures$ is the total number of times a route fails.

$$R = \left(1 - \frac{\sum_{n=0}^{nSim} routeFailures}{nSim}\right) \tag{37}$$

The reliability level provides numerical insights into the probability that a solution may fail in the presence of uncertainty (Reyes-Rubiano et al. 2019). In the context of this work, this implies that solutions with higher reliability demonstrate better resilience against demand and travel-time variations. Therefore, the more reliable a solution is, the smaller the penalty cost it will incur. Thus, the route failure/cost decreases as the reliability increases. Figure 3 presents a boxplot of the BDS and BSS reliability obtained for the balanced, economic, environmental, and social scenarios.

As expected, the higher the uncertainty level, the lower the reliability level of the solution. This behaviour is consistent in all scenarios, as shown in Fig. 3. Consequently, the results of this experiment indicate that relying on deterministic solutions in a stochastic environment with high uncertainty may yield highly unreliable solutions. For instance, directly applying deterministic solutions in a high-uncertainty environment may not only result in a significantly higher cost in comparison to stochastic solutions but may also provide less reliable solutions.

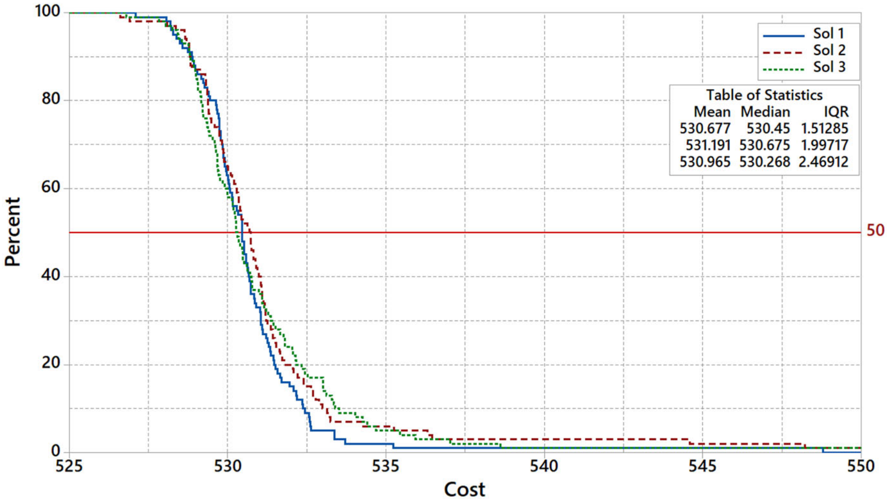

Fig. 4 Reliability functions to compare alternative solutions with a similar expected cost

5.4 Proposed new reliability functions to assess elite solutions

In addition to the reliability level comparison in 5.3.1, we have proposed the extension of the simheuristic algorithm by generating the reliability function associated with each of the elite solutions. In order to generate these reliability functions, we employ the well-known KME (Kaplan and Meier 1958). This is a non-parametric and flexible method typically applied in medical studies (Tolley et al. 2016; Vierra et al. 2023; Xu et al. 2022) that can be used in the presence of complete and censored data. Censored data might appear, for instance, if we utilise real-life observations associated with a proposed solution but are unable to accurately determine the survival rate (total cost).

For instance A-n32-k5, Fig. 4 shows three alternative solutions provided by the simheuristic approach. These three solutions offer similar expected costs. However, by analysing the reliability functions, one can notice that they also show a slightly different probabilistic pattern. Thus, it seems very rare (probability close to 0) to obtain cost values above 535 if Solution 1 is employed. In contrast, obtaining cost values above 535 has a non-negligible probability (around 0.05) for solutions 2 and 3. Similarly, while the probability of obtaining a cost above 532.5 is around 0.05 for Solution 1, this probability increases to 0.18% in the case of solution 3, and a similar probability can also be observed for solution 2 as well.

These results suggest that, while the expected cost of the three solutions is similar, Solution 1 may be 'reliable' in the sense that it will rarely generate a very high cost, something that cannot be said about Solutions 2 and 3. Hence, this reliability analysis using the KME provides valuable insights into the probabilistic patterns of the alternative solutions. Accordingly, it can be used to make informed decisions regarding the selection of the most reliable and cost-effective solution.

Table 8 Table of scenarios for sensitivity analysis

Scenarios	Importance weights		
	α_1	α_2	α_3
Economic	1	0	0
Environmental	0	1	0
Social	0	0	1
Balanced	0.33	0.33	0.33
S1	0.5	0.25	0.25
S2	0.25	0.5	0.25
S3	0.375	0.375	0.25
S4	0.25	0.375	0.375
S5	0.375	0.275	0.375
S6	0.42	0.29	0.29

5.5 Sensitivity analysis on sustainability dimensions

To conduct sensitivity analysis for different importance between the dimensions, scenarios has been generated based on the Revised Weight Sensitivity algorithm (Jones 2011). Particularly, for our experiments, a set S of scenarios represented as $S_i, i = \{1, 2, \ldots, 6\}$ has been generated and provided in Table 8. A combination of weights represents each scenario. The weights $(1, 0, 0)$, $(0, 1, 0)$, and $(0, 0, 1)$, are assigned in order to obtain the lower bounds for each dimension, while the balanced scenario assumes equal weights $(0.33, 0.33, 0.33)$ for the three dimensions. Finally, scenarios $S1$ to $S6$ represent other combination of weights assigned to the dimensions. The details of these scenarios can be found in Abdullahi et al. (2020).

This section looks at how low travel time and demand uncertainty impact the number of vehicles used, distance travelled, travel time, CO_2 emissions, failure cost, and the associated cost of accident risk. More precisely, the uncertainty levels have been set at $0.05 \cdot E[q_i]$ and $0.10 \cdot E[t_{ij}]$ for demand and travel time, respectively. The results are presented in Table 9.

5.5.1 Analysis of economic, environmental, and social impacts with recourse cost under scenarios with level 1 uncertainty

Table 9 shows the average results in the tested instances. The first column shows the tested scenarios. In columns 2–7, we show the mean distance, travel time, recourse cost, the number of vehicles ($|R|$), CO_2 emissions in kilograms kg and tonnes t. Lastly, column 8 presents accident risk costs.

From Table 9, observe the trade-off between the sustainability impacts. The scenario that reached the shortest route (travel time) is the economic scenario, while the least expensive recourse cost is realised in the social scenario. However, this solution with the least expensive recourse cost shows a trade-off with the mean number of vehicles used. This means that the social scenario requires one additional vehicle compared to the other scenarios. This implies that the social scenario will be more

Table 9 Number of vehicles, distance, travel time and recourse cost under different scenarios and *Level* 1 uncertainty

Scenario	Distance (km)	Time (h)	Recourse (€)	$\|R\|$	CO_2 (kg)	CO_2 (t)	Accident risk (€)
Economic	1052.6	**7.8**	17.8	7	760.9	0.76	24.4
Environmental	**1051.4**	8.4	18.3	7	**758.1**	**0.75**	24.1
Social	1169.7	9	**17.1**	8	858.0	0.86	**19.3**
Balanced	**1052.2**	**7.9**	**17.7**	**7**	**759.5**	**0.76**	**21.9**
S1	1063.2	8.4	18.1	7	824.9	0.82	22.3
S2	1058.4	8.5	17.9	7	792.5	0.79	22.1
S3	1064.9	8.1	18.1	7	809.9	0.81	22.5
S4	1057.1	8.1	17.9	7	774.9	0.77	22.1
S5	1059.3	8.9	17.9	7	795.2	0.80	22.1
S6	1060.8	9	18.1	7	805.2	0.81	22.3

Bold values highlight the best values for each evaluated sustainability criterion for a given scenario, thereby facilitating a comparative analysis of the trade-offs among economic, environmental, and social dimensions. This enables readers to quickly identify which scenario achieves the most favourable solution in terms of metrics such as travel time, travel distance, recourse cost, etc expensive in the global solution due to using more vehicles and paying more drivers. Although this scenario provides the highest number of vehicles, distance travelled, and CO_2 emissions, it reaches average solutions with fewer failures. This may be because this scenario uses more vehicles than the other scenarios, i.e., it may avoid overtime penalties.

Thus, as expected, each scenario that minimises only one dimension may present a lower impact in the considered dimension. However, when considering the balanced scenario, all the sustainability impacts show a certain equilibrium compared to the other scenarios. This could be connected with the logic that the routes are more balanced, thus minimising the sustainability impacts jointly while minimising the probability of route failures. Accordingly, it shows a balanced economic, environmentally friendly, and socially acceptable solution. This shows that sustainable solutions can be obtained with a minimal increase in the cost of any individual dimension. Overall, this experiment's results show that not accounting for stochasticity may yield highly unreliable and costly solutions.

6 Conclusions and future work

To the best of our knowledge, this is the first paper that addresses the problem of minimising the economic, environmental, and social sustainability impacts of a VRP under uncertain travel times and demands. We developed a weighted recourse model to integrate the three sustainability dimensions, implemented a simheuristic algorithm, and analysed trade-offs between the dimensions. In addition, the proposed approach has been extended to include reliability analysis techniques, which allow for a more accurate comparison of elite solutions in a scenario under uncertainty and yield numerous managerial insights. The trade-off analysis was conducted with different levels of uncertainty, and the results of the experiments showed that: *(i)* when maximum importance weight is assigned to only one dimension, solutions with the lowest impact in regards to that dimension are obtained; *(ii)* when all three dimensions are assigned equal importance weight, the probability of route failures is minimised and sustainable solutions with a marginal compromise can be obtained; *(iii)* ignoring uncertainty could have expensive consequences; and *(iv)* reliability analysis allows for the evaluation of the probability patterns of alternative solutions.

Several research lines can be established for future works: (i) the inclusion of additional social dimensions can be considered (e.g., fairness in driver working conditions); (ii) the use of chance constraint techniques to deal with travel time and demand uncertainty; (iii) using preference information from the decision-maker, goal programming approaches can be implemented with set achievement levels and (iv) incorporation of real-world, real-time data allowing dynamic changes during route execution to test the practical utility and scalability of our proposed methodology.

Appendix A Literature review summary

In this section, Table 10 focuses on scientific papers that solve the stochastic VRP with sustainability considerations.

Table 10 Summary of studies focused on travel time and stochastic demand with objectives related to sustainability dimensions

Study	Solution approach	D	TT	Eco	Env	Soc	Others
Tas et al. (2013)	Tabu Search algorithm		x	x			Soft time windows; objective: minimize expected delay and the expected earliness
Uchida and Kato (2017)	Link-based algorithm			x			Stochastic traffic flow; objective: minimizes expected path travel time variance
Eshtehadi et al. (2017)	Robust-stochastic optimization	x		x			Time windows
Guimarans et al. (2018)	Simheuristic algorithm: iterated local search and Monte Carlo simulation		x	x			Objectives: minimizes expected travel time
Shahmoradi-Moghadam et al. (2020)	Hybrid robust-stochastic optimization	x			x		Objective: minimize fuel consumption and noise emission simultaneously
Yang et al. (2021)	Uncertain programming	x	x	x			Objectives: minimizes total travel time of all vehicles over the planning horizon; multi-period
Yang et al. (2022)	Hybrid algorithm with large and Neighborhood search-simulated annealing	x	x	x		x	Soft time windows; objective: minimizes the weighted average of the total routing time and driver inconsistency driver consistency measure; multi-period
Messaoud (2023)	Chance constrained programming model, large neighborhood search (ILS) algorithm, and Monte Carlo Sampling		x	x			Objective: minimize travel time
Our paper	Simheuristic algorithm: biased randomised iterated greedy local search metaheuristic, and Monte Carlo simulation	x	x	x	x	x	Objective: minimise the weighted cost associated with economical, environmental, and social dimension; Corrective policy

D: Demand; TT: travel time; Eco: economic dimension; Env: environmental dimension; Soc: social dimension; Others: additional attributes

Appendix B Statistical analysis of BRIG-LS

In this section, we provide additional results from the experiments reported in Sect. 5.2 to analyse the stability of our proposed method. Table 11 shows the benchmark instance, the total distance per instance for each experiment run, the average distance and the standard deviation.

Table 11 Analysis of BRIG-LS stability

Instance	Run 1 (km)	Run 2 (km)	Run 3 (km)	Run 4 (km)	Run 5 (km)	Run 6 (km)	Run 7 (km)	Run 8 (km)	Run 9 (km)	Run 10 (km)	Average	STD
A-n32-k5	787.20	787.81	788.46	788.46	787.20	787.08	788.46	787.20	787.08	787.20	787.81	0.63
A-n33-k5	662.76	662.76	662.11	662.76	662.76	662.76	662.11	662.76	662.11	662.76	662.58	0.33
A-n33-k6	742.69	744.56	743.20	744.03	742.69	744.56	743.56	742.69	744.56	744.56	743.62	0.84
A-n34-k5	781.36	780.98	782.63	780.98	780.94	780.98	780.98	780.98	780.94	787.63	781.26	0.55
A-n36-k5	810.80	809.79	812.12	813.78	809.71	809.71	813.78	816.56	809.71	809.71	811.39	2.47
A-n37-k5	672.59	672.47	672.59	672.47	673.33	672.50	672.59	673.33	672.59	672.59	672.65	0.35
A-n37-k6	950.85	952.56	953.58	953.58	950.85	951.38	950.85	951.38	952.56	952.56	951.95	1.14
A-n38-k5	734.18	734.68	734.68	733.95	734.18	734.18	734.18	733.95	734.18	733.95	734.29	0.27
A-n39-k5	829.99	831.81	828.99	833.35	830.53	828.99	831.43	829.60	831.81	831.81	830.73	1.48
A-n39-k6	833.47	836.92	836.56	833.20	833.47	836.73	833.20	833.47	833.47	833.47	834.80	1.68
A-n44-k6	940.39	942.05	938.18	938.18	942.05	942.05	942.05	939.97	938.18	942.46	940.71	1.80
A-n45-k6	957.88	957.88	957.88	957.88	957.88	957.88	957.88	957.88	957.88	957.88	957.88	0.00
A-n45-k7	1148.67	1146.91	1146.91	1148.67	1148.67	1146.91	1150.08	1154.35	1151.38	1151.38	1148.12	2.46
A-n46-k7	917.72	920.28	918.68	917.72	918.68	918.68	920.28	917.90	918.50	917.72	918.86	0.98
A-n48-k7	1074.74	1074.34	1076.32	1075.56	1074.34	1074.74	1075.56	1074.74	1078.45	1078.45	1075.08	1.31
A-n53-k7	1014.70	1012.33	1014.70	1012.33	1014.70	1014.70	1012.33	1014.70	1014.70	1021.79	1013.69	1.19
A-n54-k7	1171.68	1171.68	1171.68	1177.37	1171.68	1171.68	1171.68	1177.51	1177.37	1171.68	1172.49	2.87
A-n55-k9	1074.96	1076.18	1074.96	1077.41	1079.41	1074.70	1077.04	1076.18	1076.82	1076.82	1076.38	1.49
A-n60-k9	1365.57	1360.85	1360.59	1365.51	1360.59	1360.59	1364.32	1360.59	1364.32	1360.59	1362.58	2.30
A-n61-k9	1052.83	1047.74	1050.45	1047.74	1050.56	1047.74	1050.62	1047.74	1054.14	1047.74	1049.67	2.41
A-n62-k8	1319.59	1321.30	1320.58	1320.49	1319.59	1319.59	1320.63	1319.59	1319.59	1320.49	1320.25	0.65
A-n63-k9	1622.88	1622.14	1622.96	1623.21	1623.59	1622.55	1627.98	1622.20	1623.59	1622.14	1623.62	1.78
A-n63-k10	1319.93	1320.68	1320.89	1324.68	1319.93	1322.90	1320.89	1320.52	1319.93	1320.89	1321.42	1.61
A-n65-k9	1190.76	1190.76	1190.52	1190.76	1190.52	1190.76	1190.52	1190.52	1190.76	1190.52	1190.66	0.13
A-n69-k9	1179.76	1179.76	1180.12	1179.84	1179.76	1179.76	1179.76	1179.84	1179.84	1181.40	1179.82	0.12

Table 11 continued

Instance	Run 1 (km)	Run 2 (km)	Run 3 (km)	Run 4 (km)	Run 5 (km)	Run 6 (km)	Run 7 (km)	Run 8 (km)	Run 9 (km)	Run 10 (km)	Average	STD
B-n31-k5	679.01	679.01	679.01	679.01	679.01	676.09	676.09	676.09	679.01	679.01	678.17	1.46
B-n34-k5	789.84	791.03	792.48	789.84	792.48	791.03	792.48	791.03	792.87	792.87	791.31	1.17
B-n38-k6	807.88	810.93	807.88	807.88	807.88	810.90	807.88	810.22	811.94	811.94	808.75	1.70
B-n41-k6	835.56	833.66	833.66	839.32	833.66	835.56	834.62	834.68	838.62	838.62	835.15	2.12
B-n43-k6	749.97	749.53	746.98	746.98	750.10	746.98	749.05	749.48	749.30	749.30	748.51	1.33
B-n44-k7	916.26	914.96	916.26	916.26	916.07	914.96	916.16	916.26	916.26	916.07	915.85	0.56
B-n45-k5	753.96	758.81	755.74	758.81	753.96	758.81	758.81	754.15	757.14	757.14	756.98	2.25
B-n50-k7	744.23	745.33	745.44	745.44	744.23	745.33	745.44	744.23	745.33	745.44	745.06	0.58
B-n50-k8	1324.61	1330.29	1329.36	1324.61	1330.29	1324.61	1329.36	1330.41	1330.29	1329.36	1327.59	2.72
B-n57-k9	1609.82	1609.26	1609.82	1609.26	1609.82	1609.26	1609.82	1609.82	1615.47	1615.47	1609.58	1.97
B-n63-k10	1507.59	1510.74	1510.74	1514.84	1510.74	1514.84	1514.84	1510.74	1507.59	1507.59	1512.05	2.88
B-n64-k9	871.31	869.08	869.08	872.98	869.08	872.49	870.64	872.49	871.65	872.16	870.67	1.58
B-n66-k9	1329.21	1333.06	1330.36	1329.21	1329.21	1331.40	1333.62	1330.36	1329.21	1341.94	1330.87	1.72
B-n67-k10	1044.46	1044.46	1047.61	1047.61	1047.61	1044.46	1047.61	1044.46	1044.46	1044.46	1046.26	1.66
B-n68-k9	1301.29	1299.22	1301.67	1298.70	1303.77	1302.25	1298.70	1298.70	1299.22	1298.70	1300.80	1.89
											Average	1.41

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Declarations

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