A Hybrid NSGA-II Approach to Solve a Bi-Objective Multi-Period Assembly Inventory Routing Problem

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Abstract

This study develops and solves a bi-objective optimization model for an inbound assembly inventory routing problem (IRP), considering carbon emission control, stochastic supply failure risks, and uncertainty in customer demand. An assembly plant needs three different components to assemble a product based on a particular bill of materials (BOM). These components are outsourced from various geographically dispersed suppliers. A depot provides light, medium, and heavy-duty vehicles to pick up product components from these suppliers during a particular period. The first objective function of the mixed-integer nonlinear model is to minimize the total IRP network cost. The second objective function is to reduce the total carbon emission. The model also considers constraints to achieve a minimum service level in each period and avert purchasing from high-risk suppliers. The best near-optimal Pareto fronts of problem instances are obtained using a hybrid non-dominated sorting genetic algorithm-II (HNSGA-II). The best near-optimal Pareto solution is determined using multi-criteria decision-making (MCDM) techniques. The impacts of different vehicle fleet types on the inbound IRP network's performance are also investigated. Finally, the sensitivities of important time-varying parameters are reported using a full factorial-designed experiment, and several insights and recommendations are provided.

Keywords
Inventory Routing Problem, Carbon Emission Control, Heterogenous Fleet, Risk and Uncertainty, Product Assembly

1. Introduction
The ability to better concentrate on core capabilities and cost savings are some benefits that drive manufacturing assembly plants to outsource product components from various suppliers. These suppliers may be subject to supply failure risks (SFR). A 'unique' supply failure event (e.g., workers' strike in a company, machine breakdown in a company's workshop, industrial fire) causes the failure of an individual supplier (Bagul and Mukherjee 2022). Geographically dispersed suppliers typically experience failure due to 'unique' events (Torabi et al. 2015). In addition, an assembly plant can face uncertainty in demand for assembled products. Thus, an assembly plant must consider risks and uncertainty while planning to satisfy customer demands. Supply chain coordination helps manage risk and uncertainty (Arshinder et al. 2008). Furthermore, an assembly plant also manages the transportation of product components. Therefore, an assembly plant may also need to control carbon emissions. Zissis et al. (2018) emphasized emission control through supply chain coordination.

A typical inbound assembly supply network comprises an assembly plant and multiple suppliers. In such an inbound supply network, joint decision-making for inventory management and vehicle routing [IRP; Coelho et al. 2014] can result in optimal vehicle routes, higher customer satisfaction, and a lower total network cost (TNC). A feasible solution in a specific period for a typical inbound assembly IRP is depicted in Figure 1. The assembly plant needs three types of components to assemble one product unit. Multiple geographically dispersed suppliers provide these components. The depot is situated close to the plant. In Figure 1, one light-duty vehicle (LDV), one medium-duty vehicle (MDV), and one heavy-duty vehicle (HDV) are provided by the depot to pick up necessary components from suppliers 2, 3, 4, 5, and S. The plant takes inventory and routing decisions (Chitsaz et al. 2020).

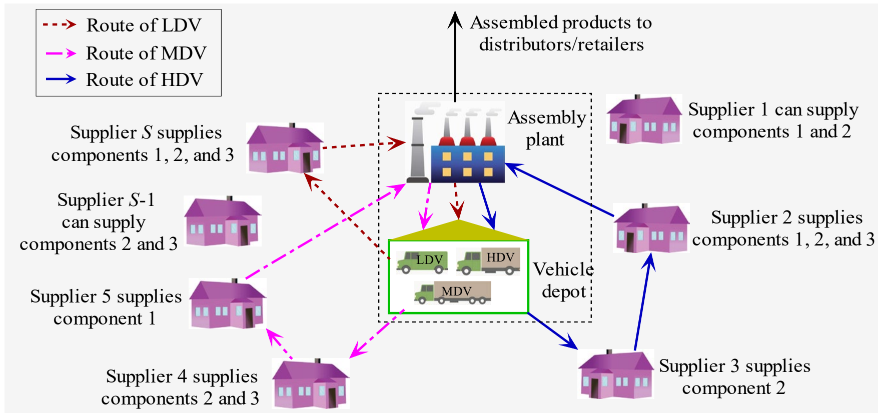

Figure 1. A feasible solution for a typical assembly IRP.

An assembly IRP model is solved to determine the outsourced quantities of components, optimal vehicle routes, and the assembled product quantity in each period. The assembled products are further supplied to distributors or retailers. However, a model for assembly IRP may additionally consider SFR, carbon emission control, and demand uncertainty. Soysal et al. (2019) reviewed the literature on IRPs with carbon emission control.

Mirzapour Al-e-hashem et al. (2019) formulated a bi-objective inbound IRP considering emission control, demand uncertainty, and a heterogeneous fleet. However, their model did not include SFR, service level constraint, or product assembly. Prakash and Mukherjee (2022) formulated a single-objective inbound IRP model considering demand uncertainty, product BOM, and SFR. However, they did not consider a heterogeneous fleet or emission control. Extending the work of Prakash and Mukherjee (2022), this study proposes a bi-objective assembly IRP model considering a heterogeneous fleet, product BOM, carbon emission control, SFR, demand uncertainty, and a minimum service level constraint. The proposed model considers TNC minimization as the first objective function and total carbon emission (TCE) minimization as the second objective function.

2. Literature Review

The literature on IRPs with multiple suppliers is the focus of this study.

2.1 The Many-to-One (Inbound) IRP

Al-e-Hashem and Rekik (2014) presented a single-objective model with a constraint for greenhouse gas (GHG) emissions within a given limit in each period. Cheng et al. (2016) proposed a single-objective model considering deterministic demand and carbon regulation policies. In order to control emissions, they used fuel consumption cost in place of vehicle travel cost in a single-objective TNC minimization function. The other cost components of TNC were inventory holding and fixed vehicle costs. They did not consider a heterogeneous fleet, supply capacity, SFR, or product assembly. Chitsaz et al. (2020) proposed a single-objective model considering BOM-based product assembly. However, their model did not consider demand uncertainty, SFR, carbon emission control, or a heterogeneous fleet. Al-e-hashem et al. (2019) formulated a bi-objective model fleet considering the minimization of TNC and GHG emissions. They considered emission minimization as a separate objective function. In summary, a few inbound IRP literature considered product assembly (Chitsaz et al. 2020) and demand uncertainty (Al-e-hashem et al. 2019). Moreover, SFR has not been addressed in the inbound IRP literature.

2.2 The Many-to-Many IRP

Micheli and Mantella (2018) considered fuel consumption cost in place of vehicle travel cost in a single-objective TNC minimization function. Tirkolaee et al. (2020) proposed a bi-objective model incorporating emission costs in the first objective function for TNC minimization. The second objective function was to maximize customer satisfaction. Kaviyani-Charati et al. (2022) formulated a multi-objective sustainable model including the minimization of TNC and TCE. Pratap et al. (2022) considered emission cost along with fuel cost in a single-objective TNC minimization function. In summary, none of the many-to-many IRP literature addressed SFR or product assembly.

Based on the literature review, the following research gaps are identified:

(i) There is no evidence of inbound IRP studies that simultaneously considered SFR, product assembly, carbon emission control, and demand uncertainty.
(ii) There is a lack of evidence in inbound IRP literature that investigated the impacts of different vehicle fleet types on the performance of the inbound IRP network.

2.3 Objectives

This study sets the following objectives to address the above-identified gaps:

(i) Formulate and resolve a bi-objective inbound IRP model, considering SFR, product assembly, carbon emission control, and demand uncertainty.
(ii) Study the impacts of different vehicle fleet types on the inbound IRP network's performance.
(iii) Study the influence of time-varying parameters on key performance indicators of the inbound IRP network.

3. Problem Discussion and Solution Approach

In order to develop a bi-objective assembly IRP model (Model Z), this study considers an inbound IRP network comprised of S geographically dispersed suppliers, an assembly plant, and a vehicle depot (refer to Figure 1). In each period, the depot provides several LDVs, MDVs, and HDVs to pick up necessary product components from various suppliers. After delivering the picked-up components to the plant, vehicles return to the depot. At the plant, a particular BOM (Figure 2) is used to assemble each product unit.

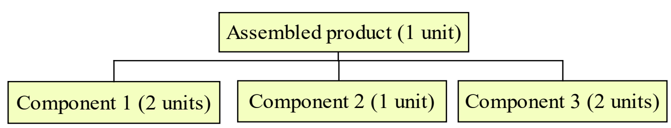

Figure 2. Bill of materials (BOM).

Model Z is developed based on the following assumptions:

(i) The demand for the assembled product is normally distributed in each period. The natural demand lies between three standard deviations from the mean.
(ii) Component holding costs are considered only at the assembly level.
(iii) In each period, the plant needs to achieve a minimum desired customer service level.
(iv) Suppliers experience stochastic SFR due to 'unique' events.
(v) In a particular period, a supplier can be visited by at most one vehicle.
(vi) A supplier can only provide a specific subset of the three product components (see Figure 2).
(vii) A minimum quantity of each available component must be collected from a selected (or visited) supplier.

The objectives of Model Z are to determine (i) component quantities outsourced from selected suppliers, (ii) the assembled product quantity, and (iii) routes for each vehicle type in each period, considering stochastic SFR, carbon emission control, and demand uncertainty. Input parameters and decision variables are listed in Table 1.

3.1 Model Development

An exponential distribution with a failure rate of λ_{sp} can be used to estimate the time between the failures of supplier s in period p (Tirkolaee et al. 2020). Thus, a supplier's supply failure probability can be derived as

$$fp_{sp} = \left(1 - e^{-\lambda_{sp} k}\right) \quad \forall s \in 1,..,S, \ \forall p \cdot \qquad (1)$$

Considering a low-risk supplier is more expensive than a high-risk supplier (Sawik 2013), the price of a component offered by a supplier is formulated as

$$CP_{csp} = BP_c \ \gamma_{cs} \left(1 - \lambda_{sp}\right) \quad \forall c,\ \forall s \in 1,..,S,\ \forall p. \tag{2}$$

Table 1. Parameters and variables.

Indices			
r,s	Depot $(r,s \in 0)$, Suppliers $(r,s \in 1,..,S)$, Assembly plant $(r,s \in S+1)$.	p	A period $(p \in 1,..,P)$.
v	A vehicle type $(v \in 1,..,V)$.	c	A component type $(c \in 1,..,C)$.
Input parameters			
wt_c	Weight of component c (in kg).	u_c	Unit(s) of component c in the product BOM.
BP_c	Base price of component c (in US$).	CP_{csp}	Price of component c available from supplier s in period p (in US$).
γ_{cs}	1, if supplier s can provide component c; 0, otherwise.	λ_{sp}	Supply failure rate of supplier s in period p.
fp_{sp}	Supply failure probability of supplier s in period p.	ψ^*	Cutoff probability for averting component purchases from high-risk suppliers.
$E[X]$	Expected value of X.	d_{rs}	Distance between nodes r and s (in km).
D_p	Demand for the assembled product in period p, normally distributed with mean $E[D_p]$ and standard deviation std_p.	RD_p	A demand that is randomly generated from the normal distribution in period p.
CV	Coefficient of variation of demand (assumed constant in each period).	W_{cs}	Supply capacity for component c at supplier s (assumed constant in each period).
IN_c	Initial inventory of component c at the assembly plant.	g	Minimum quantity to be collected for each component.
α	Ordering cost (in US$ per supplier per period).	β_c	Holding cost of component c (in US$ per unit per period).
θ	Product shortage cost (in US$ per unit).	a	Management cost (in US$ per supplier per period).
b	Reduced management cost (in US$ per supplier per period).	L_v	Load-carrying capacity of vehicle type v (in kg).
ce	Carbon emissions from the consumed fuel (in kg-CO_2/litre).	k	Length of each period (in 'number of weeks').
cr_v	Fuel consumption rate of an empty vehicle type v (in litre/km).	cr_v^*	Fuel consumption rate of a fully-loaded vehicle type v (in litre/km).
tc_v	Travel cost for vehicle type v (in US$/km).	ϕ_v	Fixed cost for vehicle type v (in US$ per trip).
SL	Minimum required service level in each period.	Z_{SL}	Standard normal variate for SL.
δ	Positive constant equal to 10^{-4}.	μ	Large integer equal to 10^5.
Decision variables			
x_{rsvp}	1, if a vehicle type v travels from node r to node s in period p; 0 otherwise.	y_{svp}	1, if a vehicle type v visits supplier s in period p; 0 otherwise.
m_{sp}	Management cost of supplier s in period p (in US$).	Q_{csp}	Quantity of component c provided by supplier s in period p.
I_{cp}	At the plant, inventory of component c at the end of period p.	B_{rsvp}	Carrying weight of vehicle type v between nodes r and s in period p.
EI_{cp}	Expected excess inventory of component c at the end of period p (at the plant).	MA_{cp}	Expected maximum assembled product quantity considering component c in period p.
A_p	Expected possible assembled product quantity in period p.	SA_p	Expected assembled product shortages in period p.

Objective functions

The first objective function of Model Z is expressed as

$$\begin{aligned} \textbf{\textit{Min TNC}} = &\sum_{p=1}^{P}\sum_{s=1}^{S} m_{sp} + \sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{s=1}^{S} \alpha\, y_{svp} + \sum_{p=1}^{P}\sum_{s=1}^{S}\sum_{c=1}^{C} CP_{csp} Q_{csp} + \sum_{p=1}^{P}\sum_{c=1}^{C} \beta_c EI_{cp} + \\ &\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{s=1}^{S} \phi_v x_{0svp} + \left(\sum_{p=1}^{P}\sum_{v=1}^{V} tc_v \left(\sum_{s=1}^{S+1}\sum_{r=0}^{S} d_{rs} x_{rsvp} + \sum_{s=1}^{S} d_{(S+1)0} x_{0svp}\right)\right). \end{aligned} \tag{3}$$

TNC is the sum of the supplier management cost (MC), the cost of placing orders (OC), the purchase cost of product components (PC), the holding cost (HC), the fixed vehicle cost (FC), and the variable travel cost (VTC), respectively. It is noteworthy that the product shortage cost (ShC) is not included in TNC.

According to Cheng et al. (2016), a specific vehicle's fuel consumption between two nodes can be formulated as

$$FC_{rsvp} = \left(cr_v + \left(\frac{cr_v * - cr_v}{L_v} \right) B_{rsvp} \right) d_{rs} \qquad \forall r,\ s \in 0,..,(S+1);\ r \neq s,\ \forall v,\ \forall p. \tag{4}$$

The second objective function of Model Z is expressed as

$$\boldsymbol{Min\ TCE} = ce\left(\sum_{p=1}^{P} \sum_{v=1}^{V} \left(\sum_{s=1}^{S+1} \sum_{r=0}^{S} \left(cr_v + \left(\frac{cr_v * - cr_v}{L_v} \right) B_{rsvp} \right) d_{rs} x_{rsvp} + \sum_{s=1}^{S} cr_v d_{(S+1)0} x_{0svp} \right) \right). \tag{5}$$

Constraints

At the end of a particular period, the expected component inventory at the plant is given as

$$E[I_{cp}] = IN_c + \sum_{e=1}^{p} \sum_{s=1}^{S} Q_{cse} - \sum_{e=1}^{p} u_c E[D_e] \qquad \forall c,\ \forall p. \tag{6}$$

The expected excess inventory of a component is derived from

$$EI_{cp} = \max\left(0,\ E[I_{cp}]\right) \qquad \forall c,\ \forall p. \tag{7}$$

The total quantity collected for a component must be within its maximum demand possible. It is expressed as

$$\sum_{p=1}^{P} \sum_{s=1}^{S} Q_{csp} \leq \sum_{p=1}^{P} u_c \left(E[D_p] + 3std_p \right) - IN_c \qquad \forall c \tag{8}$$

The customer service level achieved by the plant must be at least equal to the desired service level. It is expressed as

$$\frac{A_p - E[D_p]}{std_p} \geq Z_{SL} \qquad \forall p. \tag{9}$$

In Constraint (15), $std_p = CV \times E[D_p]$. A_p is obtained from Equations (10-11).

Considering a particular component, the expected maximum assembled product quantity in a period can be

$$MA_{cp} = \left\lfloor \frac{EI_{c(p\text{-}1)} + \sum_{s=1}^{S} Q_{csp}}{u_c} \right\rfloor \qquad \forall c,\ \forall p. \tag{10}$$

Thus, A_p can be computed as follows: $A_p = \min\limits_{c \in (1,..,C)} \left(MA_{cp} \right) \qquad \forall p.$ (11)

Suppliers may experience high or low SFR in different periods (Sodhi and Tang 2012). According to researchers (Sawik 2013), decision-makers avert making purchases from high-risk suppliers. In order to mitigate supply risks in each period, components are not purchased from high-risk suppliers $\left(fp_{sp} \geq \psi^*\right)$. It is formulated as

$$\sum_{v=1}^{V} y_{svp} \leq \max\left(0,\ \left\lceil \frac{\left(\psi * - fp_{sp}\right)}{\left|\psi * - fp_{sp} + \delta\right|} \right\rceil \right) \qquad \forall s \in 1,..,S,\ \forall p. \tag{12}$$

MC comprises negotiation, contract management, and quality monitoring costs (Meena and Sarmah 2013). An essential assumption is considered to calculate MC. MC includes all three of its components (a) in the first period of order placement. Whereas in other successive order placement periods, MC comprises only contract management and quality monitoring costs (b) . Readers may refer to Prakash and Mukherjee (2022) for more details.

$$m_{sp} \geq a\left(\sum_{v=1}^{V} y_{svp} - \sum_{v=1}^{V} y_{sv(p-1)}\right) + b\left(\sum_{v=1}^{V} y_{sv(p-1)}\right) \qquad \forall s \in 1,..,S,\ \forall p \tag{13}$$

$$m_{sp} \leq b\left(\sum_{v=1}^{V} y_{sv(p-1)}\right) + \mu\left(1 - \sum_{v=1}^{V} y_{sv(p-1)}\right) \qquad \forall s \in 1,..,S,\ \forall p \tag{14}$$

$$m_{sp} \leq a\left(\sum_{v=1}^{V} y_{svp}\right) \qquad \forall s \in 1,..,S,\ \forall p \tag{15}$$

$$m_{sp} \geq 0 \qquad \forall s \in 1,..,S,\ \forall p \tag{16}$$

Constraints (17-32) satisfy all other assumptions of Model Z. Readers may refer to Prakash and Mukherjee (2022) for details on Constraints (17-32).

$$\sum_{v=1}^{V} y_{svp} \leq 1 \qquad \forall s \in 1,..,S,\ \forall p \tag{17}$$

$$B_{rsvp} \leq L_v x_{rsvp} \qquad \forall r \in 1,..,S,\ \forall s \in 1,..,(S+1),\ \forall v,\ \forall p \tag{18}$$

$$Q_{csp} \leq W_{cs}\ \gamma_{cs}\left(\sum_{v=1}^{V} y_{svp}\right) \qquad \forall c,\ \forall s \in 1,..,S,\ \forall p \tag{19}$$

$$g\ \gamma_{cs}\left(\sum_{v=1}^{V} y_{svp}\right) \leq Q_{csp} \qquad \forall c,\ \forall s \in 1,..,S,\ \forall p \tag{20}$$

$$\sum_{c=1}^{C} wt_c Q_{csp} \leq \sum_{v=1}^{V} L_v y_{svp} \qquad \forall s \in 1,..,S,\ \forall p \tag{21}$$

$$\sum_{v=1}^{V}\sum_{r=0}^{S} B_{rsvp} + \sum_{c=1}^{C} wt_c Q_{csp} = \sum_{v=1}^{V}\sum_{r=1}^{S+1} B_{srvp} \qquad \forall s = 1,..,S;\ r \neq s,\ \forall p \tag{22}$$

$$\sum_{s=1}^{S} x_{0svp} = \sum_{s=1}^{S} x_{s(S+1)vp} \qquad \forall v,\ \forall p \tag{23}$$

$$\sum_{r=0,\ r\neq s}^{S} x_{rsvp} = \sum_{r=1,\ r\neq s}^{S+1} x_{srvp} = y_{svp} \qquad \forall s \in 1,..,S,\ \forall v,\ \forall p \tag{24}$$

$$B_{0svp},\ x_{0(S+1)vp},\ x_{s0vp},\ x_{(S+1)svp},\ y_{sv0} = 0 \qquad \forall s \in 1,..,S,\ \forall v,\ \forall p \tag{25}$$

$$x_{ssvp} = 0 \qquad \forall s \in 0,..,(S+1),\ \forall v,\ \forall p \tag{26}$$

$$EI_{c0} = IN_c \qquad \forall p \tag{27}$$

$$B_{rsvp} \geq 0 \qquad \forall r \in 1,..,(S+1),\ \forall s \in 0,..,(S+1),\ \forall v,\ \forall p \tag{28}$$

$$Q_{csp},\ EI_{cp},\ MA_{cp},\ A_p,\ SA_p \geq 0 \qquad \forall c,\ \forall s \in 1,..,S,\ \forall p \tag{29}$$

$$-\infty \leq I_{cp} \leq +\infty \qquad \forall c,\ \forall p \tag{30}$$

$$x_{rsvp} \in \{0,\ 1\} \qquad \forall r,s \in 0,..,(S+1),\ \forall v,\ \forall p \tag{31}$$

$$y_{svp} \in \{0,\ 1\} \qquad \forall s \in 1,..,S,\ \forall v,\ \forall p \tag{32}$$

In order to linearise Model Z, a temporary variable ω_{rsvp} is used to replace $B_{rsvp}x_{rsvp}$ in Expression (5), and Constraints (33-36) are added.

$$\omega_{rsvp} \geq L_v x_{rsvp} + B_{rsvp} - L_v \quad \forall r \in 0,..,S,\ \forall s \in 1,..,(S+1),\ \forall v\ ,\ \forall p \tag{33}$$

$$\omega_{rsvp} \leq L_v x_{rsvp} \quad \forall r \in 0,..,S,\ \forall s \in 1,..,(S+1),\ \forall v,\ \forall p \tag{34}$$

$$\omega_{rsvp} \leq B_{rsvp} \quad \forall r \in 0,..,S,\ \forall s \in 1,..,(S+1),\ \forall v,\ \forall p \tag{35}$$

$$\omega_{rsvp} \geq 0 \quad \forall r \in 0,..,S,\ \forall s \in 1,..,(S+1),\ \forall v,\ \forall p \tag{36}$$

In order to calculate the product shortage cost (ShC), A_p $(\forall p)$ is first obtained after solving Model Z. Then, SA_p is computed from

$$SA_p = \max\left(0,\ \left(RD_p - A_p\right)\right) \quad \forall p\,. \tag{37}$$

Thus, ShC is obtained as follows:

$$ShC = \theta \sum_{p=1}^{P} SA_p\,. \tag{38}$$

Notably, this study considers and reports an average of shortage costs obtained from a certain number of computational runs for a particular problem instance. Subsequently, the overall network cost (ONC) is calculated as

$$ONC = (TNC + ShC) = (MC + OC + PC + HC + FC + VTC + ShC)\,. \tag{39}$$

3.2 A HNSGA-II for the Bi-Objective Assembly IRP

The NSGA-II (Deb et al. 2002) is an efficient technique for solving the multi-objective IRP (Kaviyani-Charati et al. 2022; Tirkolaee et al. 2020). The steps of the HNSGA-II used in this study are as follows:

STEP 1: Genetare the initial population of N_c chromosomes. A chromosome is represented by a randomly generated binary matrix of S rows and P columns [Figure 3(a)]. Notably, the supply failure probability of a randomly selected (or visited) supplier in a specific period must be less than ψ^*. Figure 3(a) shows that supplier 1 is visited in period 1, whereas supplier 2 is not visited. Next, randomly generate a binary vehicle assignment matrix for each chromosome [Figure 3(b)]. Figure 3(b) shows that suppliers 1 and 3 are visited by a MDV and a LDV, respectively, in period 1.

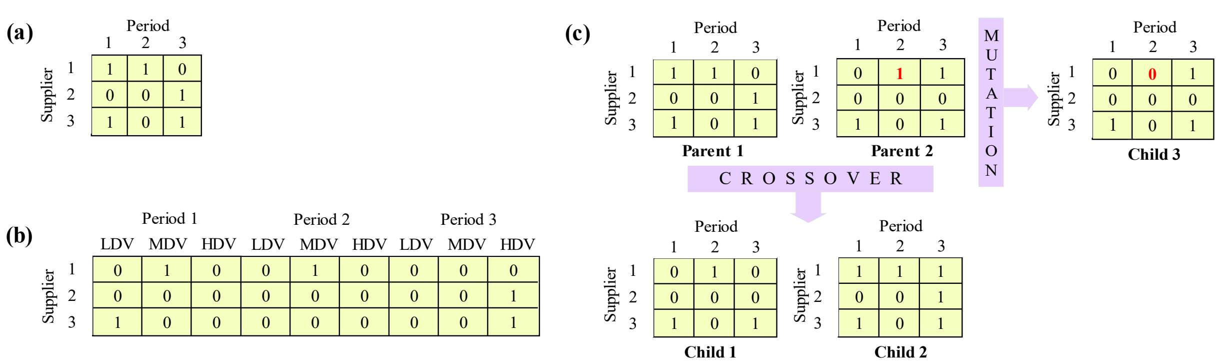

Figure 3. The crossover and mutation operators.

STEP 2: Construct a component collection matrix for each chromosome in the population. For each chromosome, generate a random sequence for all visited suppliers in each period. Starting from the first period, generate a random collection quantity between g and the supply capacity of each available component type from the first supplier of the random sequence. Continue the collection of components from successive suppliers in the sequence. Repeat this process from one period to the next such that the total collected quantity of a specific component type is within the maximum possible demand of that component type.

STEP 3: If the weight of collected (or picked up) components from a supplier in a chromosome is greater than the load-carrying capacity of the pickup vehicle, modify the component collection matrix for that chromosome.

STEP 4: Based on each vehicle assignment matrix, construct the vehicle routes using the cheapest insertion heuristic (Rosenkrantz et al. 1977). Subsequently, compute all other decision variables using y_{svp} $\left(\forall s \in 1,..,S,\ \forall v,\ \forall p\right)$ and Q_{csp} $\left(\forall c,\ \forall s \in 1,..,S,\ \forall p\right)$ obtained from vehicle assignment and component collection matrices. Accordingly, derive objective function values for each chromosome, and do non-dominated sorting (Deb et al. 2002) of N_c chromosomes. Notably, the minimum service level constraint is handled during non-dominated sorting.

STEP 5: Generate the children population using crossover (bitwise AND and bitwise OR) and mutation operators [Figure 3(c)]. In the mutation, the value of a randomly selected cell of a chromosome matrix is altered from 1 to 0 or 0 to 1, whichever is applicable.

STEP 6: Merge parent and children populations and generate a new parent population using the tournament selection method (Deb 2000). The newly generated population is the parent of the next generation.

STEP 7: Repeat Steps 2 to 6 till $MaxGen$ generations and obtain near-optimal Pareto fronts.

STEP 8: Use the 2-opt heuristic (Lin 1965) to improve the vehicle routes of each Pareto solution of the best near-optimal Pareto front.

STEP 9: The VlseKriterijumska Optimizacija I Kompromisno Resenje [VIKOR; Opricovic and Tzeng 2004] is an efficient method to select the best Pareto solution. However, it can provide more than one best Pareto solution. The Ranking method [R-method; Rao and Lakshmi 2021] can be used to select one among the multiple best Pareto solutions offered by the VIKOR. This study used an integrated VIKOR and R-method to select the Pareto solution.

4. Parameter Values and Levels Selection for the Optimization and Simulation Experiment

This study considered 6 problem instances with different S $(S \in \{10,\ 20,\ 40\})$, different P $(P \in \{4,\ 8\})$, one plant, and one depot. Parameter values and ranges were determined from the earlier relevant literature review (Cheng et al. 2016; 2017; Soysal et al. 2018; Torabi et al. 2015). These are listed in Tables 2-3.

Table 2. Parameter values and ranges.

Parameter	Value/Range	Parameter	Value/Range	Parameter	Value/Range	Parameter	Value/Range
BP_c	20 for $c \in \{1\}$	u_c	2 for $c \in \{1\}$	wt_c	5 for $c \in \{1\}$	β_c	4 for $c \in \{1\}$
	16 for $c \in \{2\}$		1 for $c \in \{2\}$		8 for $c \in \{2\}$		3.2 for $c \in \{2\}$
	12 for $c \in \{3\}$		2 for $c \in \{3\}$		6 for $c \in \{3\}$		2.4 for $c \in \{3\}$
IN_c	1400 for $c \in \{1,3\}$	X and Y coordinates of nodes	~ U[-50, 50]	λ_{sp}	~ U[0.01, 0.223] $\forall s \in 1,..,S,\ \forall p$	$E[D_p]$	~ U[300, 900] $\forall p$
	700 for $c \in \{2\}$						
CV	0.10	α	300	θ	90	$a,\ b$	70, 55
g	50	ψ^*	0.15	k	1	$SL,\ Z_{SL}$	95%, 1.645
Vehicle parameters							
L_v	2585 for $v \in \{1\}$	cr_v	0.083 for $v \in \{1\}$	cr_v^*	0.109 for $v \in \{1\}$		
	5080 for $v \in \{2\}$		0.125 for $v \in \{2\}$		0.165 for $v \in \{2\}$		
	17236 for $v \in \{3\}$		0.333 for $v \in \{3\}$		0.439 for $v \in \{3\}$		
ϕ_v	20 for $v \in \{1\}$	tc_v	0.110 for $v \in \{1\}$	ce	2.669		
	24 for $v \in \{2\}$		0.160 for $v \in \{2\}$				
	30 for $v \in \{3\}$		0.425 for $v \in \{3\}$				
Parameter levels for sensitivity analysis							
	Low level		Medium level		High level		
fp_{sp}	~ U[0.01, 0.15] $\forall s \in 1,..,40$, $\forall p$ and $\psi^* = 0.10$		~ U[0.01, 0.20] $\forall s \in 1,..,40$, $\forall p$ and $\psi^* = 0.15$		~ U[0.01, 0.25] $\forall s \in 1,..,40$, $\forall p$ and $\psi^* = 0.20$		
CV	0.05		0.10		0.15		

BP_c	15 for $c \in \{1\}$, 11 for $c \in \{1\}$,	20 for $c \in \{1\}$, 16 for $c \in \{1\}$,	25 for $c \in \{1\}$, 21 for $c \in \{1\}$,
	7 for $c \in \{3\}$	12 for $c \in \{3\}$	17 for $c \in \{3\}$
tc_v	0.010 for $v \in \{1\}$	0.110 for $v \in \{1\}$	0.210 for $v \in \{1\}$
	0.060 for $v \in \{2\}$	0.160 for $v \in \{2\}$	0.260 for $v \in \{2\}$
	0.325 for $v \in \{3\}$	0.425 for $v \in \{3\}$	0.525 for $v \in \{3\}$

Table 3. Supply capacities.

Component	Supplier																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	400	0	400	400	400	400	0	0	400	0	400	0	400	0	400	400	0	0	0	400
2	200	200	0	200	200	0	200	0	200	200	200	0	200	200	0	0	200	0	200	0
3	400	400	400	0	400	0	0	400	400	0	0	400	400	0	0	0	0	400	0	400
Component	Supplier																			
	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	400	400	400	0	0	400	0	0	0	0	0	0	400	400	400	400	0	0	0	0
2	200	200	0	200	0	0	0	200	0	200	0	200	0	200	0	0	200	0	200	200
3	0	400	0	0	400	400	400	0	400	0	400	400	400	0	400	0	0	400	0	400

5. Results and Discussion

The HNSGA-II was coded in MATLAB R2020a. The maximum number of generations $(MaxGen)$, population size (N_c), crossover rate (CR), and mutation rate (MR) were set to 600, 150, 0.85, and 0.30, respectively. The optimization results for six problem instances (based on Model Z) corresponding to their best near-optimal Pareto solutions are provided in Table 4. In Table 4, $SxPy$ denotes a problem instance with x number of suppliers and y number of periods.

An integrated VIKOR and R-method determined the best near-optimal solution for each problem instance. For each problem instance, the values in Table 4 are derived based on averages of 10 independent computational runs. For each computational run, λ_{sp} $(\forall s \in 1,..,x,\ \forall p \in 1,..,y)$ are randomly generated in $\sim$U[0.01, 0.223].

Table 4. Optimization results.

Instance	MC	OC	PC	HC	FC	VTC	ShC	Best near-optimal Pareto solution: ONC	TCE
$S10P4$	1438.00	6960.00	146497.63	17637.28	359.20	263.79	2736.00	175891.90	587.08
$S10P8$	3493.00	17580.00	341208.86	48104.64	885.20	721.14	1659.60	413652.44	1604.36
$S20P4$	1458.00	6840.00	144892.61	18314.08	328.00	238.10	1598.40	173669.20	530.60
$S20P8$	3580.00	16860.00	338113.19	50836.32	773.60	595.16	1515.60	412273.86	1334.04
$S40P4$	1646.00	7440.00	145123.47	18973.28	354.80	250.64	1818.00	175606.19	560.20
$S40P8$	3872.00	17700.00	337323.34	46663.20	869.20	645.42	2451.60	409524.76	1444.17

Figure 4 illustrates the best near-optimal solution for $S10P4$ using a specific set of λ_{sp} $(\forall s \in 1,..,10,\ \forall p \in 1,..,4)$. In Figure 4, the mean and standard deviation of the demand for the product were 800 and 8 in period 1. In period 1, a HDV visited supplier 8 to pick up 400 units of component 3. Components 1 and 2 were not available (NA) from supplier 8 (see Table 3). The HDV also picked up components from suppliers 9 and 4. Moreover, two MDVs and one LDV also picked up necessary components from other suppliers in period 1.

In period 1, the assembled product quantity was 1113. The service level achieved was 99.99%. 627, 514, and 719 units of components 1, 2, and 3, respectively, remained as expected inventories (at the end of period 1).

5.1 Impacts of Different Fleet Types on the Inbound IRP Network's Performance

Four bi-objective assembly IRP cases were investigated considering $S40P4$. In the first case (Case HET), Model Z was solved considering all three vehicle types. In the second case (Case LDV), third case (Case MDV), and fourth case (Case HDV), Model Z was solved considering only LDVs, only MDVs, and only HDVs, respectively. Table 5 shows the results for the four cases corresponding to their best near-optimal Pareto solutions.

Table 5. Impacts of homogeneous and heterogeneous fleets.

	Case HET	Case LDV	Case MDV	Case HDV	Relative deviation from Case HET (%)		
					Case LDV	Case MDV	Case HDV
ShC	1818.00	2656.80	3232.80	1555.20	46.1	77.8	-14.5
ONC	175606.19	179266.37	180825.64	182781.38	2.1	3.0	4.1
TCE	560.20	527.40	457.12	554.81	-5.9	-18.4	-1.0

Important insights (based on Table 5) can be outlined as follows:

(i) For the considered IRP network, using a heterogeneous fleet will help an assembly plant to reduce the overall network cost.
(ii) If an assembly plant's main target is to reduce emissions, a homogeneous fleet of MDVs should be used.
(iii) Using a heterogeneous fleet or a homogeneous fleet of HDVs will help reduce product shortages.

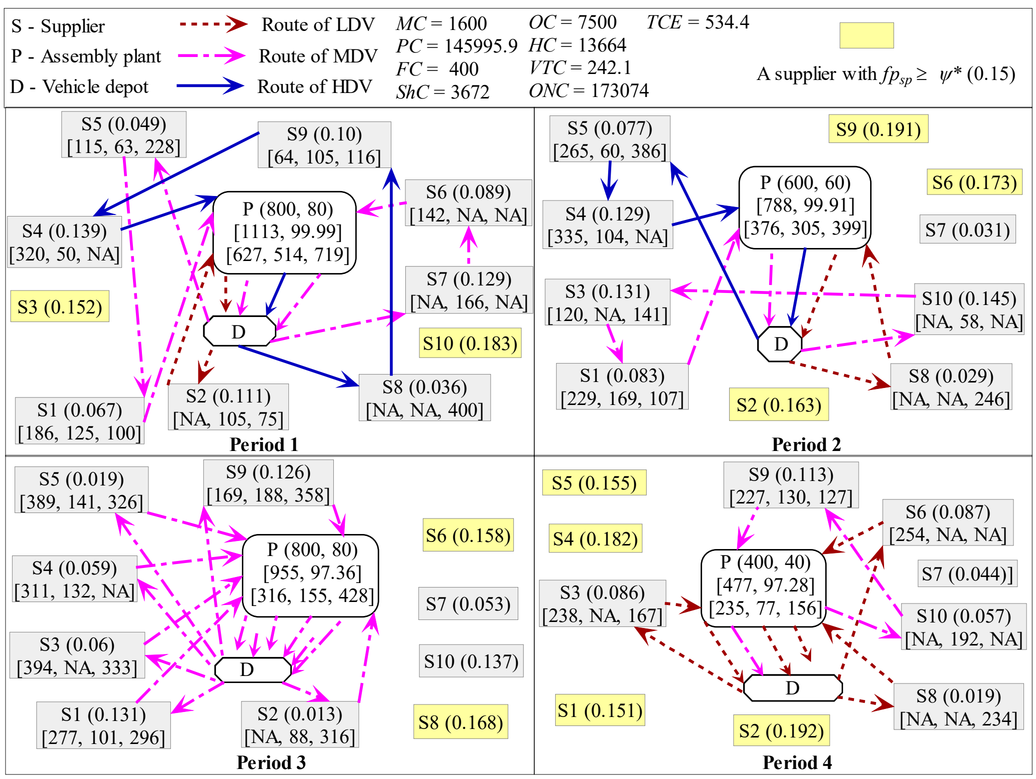

Figure 4. The best near-optimal solution for $S10P4$ (based on Model Z).

5.2 Sensitivity Analysis

The parameters fp_{sp}, CV, BP_c, and tc_v can vary over time. Table 2 lists three levels for each parameter. A full factorial-designed experiment was performed in MINITAB 19 to study the influence of these parameters on ONC, TCE, and ShC. The sensitivity study was based on $S40P4$. Based on the sensitivity analysis results (considering ANOVA and main and interaction effects plots), Table 6 provides important insights and recommendations.

Table 6. Sensitivity analysis-based insights and recommendations.

Indicator		Insights and recommendations
ONC	–	When demand variation is high or supply risks are low, an assembly plant should purchase product components from suppliers offering lower prices in order to reduce the overall network cost.
TCE	–	An assembly plant can effectively reduce carbon emissions and the overall network cost when demand variation is low or supply risks are high.
ShC	–	An assembly plant should keep a reserve inventory of components to deal with product shortages in a high demand variation scenario.

6. Conclusions

In this study, a bi-objective inbound IRP model was formulated considering stochastic supply failure risks, carbon emission control, product assembly, uncertainty in customer demand, and a minimum service level constraint. The model was solved using a HNSGA-II. Moreover, the impacts of different vehicle fleet types on the inbound IRP network's performance were studied. Finally, the influence of critical time-varying parameters on key performance indicators of the inbound IRP network was studied.

The key findings of this study can be highlighted as follows:

(i) A near-optimal solution scenario indicated that LDV and MDV are used more frequently for product component collection.
(ii) A heterogeneous vehicle fleet should be used if the priority is to reduce the total network cost.
(iii) If the priority is to reduce carbon emissions, a homogeneous fleet of MDVs is recommended.
(iv) Carbon emissions and network costs can be reduced in a scenario of low demand variation or high supply risks.
(v) The performance of the inbound IRP network is insensitive to variations in the travel cost per unit distance.

Moreover, the following are some important future research directions:

(i) Verify the applicability of the proposed model using real-life case studies.
(ii) Develop and verify a robust decision-making framework under the uncertainty of several parameters (e.g., demand, fuel price, vehicle travel cost per unit distance, base prices of product components).

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