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Modeling of sustainable integrated supply chains under the consideration of European Union regulations

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Abstract
This work introduces a multi-period, multi-commodity, inventory-routing problem with strategic fleet scheduling decisions, under the consideration of speed limits, as well as strict European Union regulations on truck drivers' working and driving time. To address the new problem, a mixed integer linear programming model was developed. Several artificial but realistic problem instances were randomly generated following relative guidelines from the open literature, to validate and assess the performance of the novel mathematical model. Furthermore, in an effort to produce useful managerial insights, several sensitivity analyses were performed considering different fluctuation rates on key model parameters.

Keywords Supply chain management · Inventory-routing · Fleet scheduling · Sustainability · Optimization

1 Introduction

Inventory routing problem (IRP) is a classic combinatorial optimization problem that integrates critical supply chain activities, through intertemporal coordination of tactical and operational decisions (Manousakis et al. 2021). Several research contributions have addressed operational research approaches for the efficient solution of the IRP and its variants (Hu et al. 2018). Most of these scientific works have focused exclusively on the optimization of economic criteria.

The increased environmental concerns as well as the fact that supply chain activities emit pollutants lead to simultaneous consideration of economic and environmental decisions (Tirkolaee et al. 2023). To this end, several research contributions

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have proposed green IRP variants (Cheng et al. 2016, 2017). Typically, environmental decisions are related to fuel or energy consumption, emissions taxation policies, adoption of alternative fuels, and environmentally friendly vehicles (Cheng et al. 2017).

However, modern supply chain practices focus on the adoption of holistic sustainable approaches (Weber et al. 2023). A sustainable supply chain (SSC) relies on the integrated management of economic, environmental, and societal criteria (Martins and Pato 2019; Karakostas et al. 2020; Lotfi et al. 2023; Hashim et al. 2023; Shahsavani and Goli 2023). Working hours constitute a critical criterion for social sustainability (Resat and Unsal 2019). In the case of truck drivers, the European Union (EU) has published specific regulations that provide rules on driving and working times, breaks, and rest periods (Sartori et al. 2022). Respecting these rules can ensure the safety of drivers and their overall satisfaction with their job (Guo et al. 2022).

More specifically, the EU Directive 2002/15/EC (European Commission 2002) and the EU Regulation no. 561/2006 (European Commission 2006) stipulates that:

- The accumulated driving time between two break periods must not exceed the limit of four and a half hours.
- The duration of a route must not exceed the limit of nine hours.
- The accumulated working time of the truck drivers must not exceed the limit of six hours.
- Breaks should last 45 min.

This work introduces a novel sustainable supply chain network optimization problem that integrates strategic, tactical, and operational decisions. More specifically, a fleet size and mix pollution multi-period, multi-commodity IRP is proposed with further consideration of EU drivers' working hours regulations as well as speed limits. Strategic decisions are related to the composition of a heterogeneous fleet of vehicles. Tactical decisions are related to inventory control and replenishment rates, and operational decisions consider the delivery schedules in each time period. According to sustainability criteria, the proposed optimization problem considers economic criteria, such as the costs of the supply chain system, environmental criteria, such as fuel consumption and CO_2 emissions, and social criteria, such as work hours and breaks for drivers.

The key novelty of this work is the introduction of a novel integrated mixed integer linear programming (MILP) model that can assist logistic managers in small and medium enterprises in their effort to make optimized planning decisions (Caceres-Cruz et al. 2014). Such enterprises typically have to serve a limited number of customers regularly over a period of time. Therefore, an integrated optimization tool is required to address classic hard logistics optimization decisions under the effect of strict EU regulations. Computational analyses were performed to justify the significant impact of such regulations in the configuration of an optimal distribution system.

2 Literature review

This section is divided into three parts. The first provides a brief overview of research contributions on IRPs, while the second focuses on research contributions on the truck driver scheduling problem, and the third one focuses on the exploration of recent research works conducted on the optimization of sustainable supply chain networks.

2.1 Recent contributions on IRP

Cheng et al. (2017) studied a green IRP with multiple time periods, a single type of product, and fleet scheduling decisions. The authors developed a MILP model to formulate the problem under consideration. To address environmental-oriented decisions, they adopted a comprehensive fuel consumption model that was integrated into the MILP formulation developed. According to their computational analysis, the benefits of adopting a comprehensive objective function, as well as a mixed fleet of vehicles, were illustrated in terms of the total cost of the system and the environmental impacts. Soysal et al. (2018) delved into the potential benefits of employing a horizontal collaboration approach within the context of a green IRP featuring multiple periods and various types of food products subject to demand uncertainty. The authors constructed a chance-constrained programming model to mathematically formulate the considered problem. From an environmental standpoint, they took into account factors such as fuel consumption, pollutant emissions, and food waste. Their numerical analyses revealed that horizontal collaboration could result in significant savings of 17% in costs and a substantial reduction of 29% in emissions.

Micheli and Mantella (2018) developed a base case model to study economic and environmental criteria through an IRP with multiple time periods, multiple products, and a heterogeneous fleet of vehicles under uncertainty of demand. The authors investigated the impact of different carbon emissions control policies on several key performance indicators. Their numerical analyses showed that the use of heterogeneous vehicles can also lead to less driving time than adopting a homogeneous fleet. Alinaghian et al. (2021) investigated a green IRP with hard time windows. The authors examined a multi-period single-commodity supply chain system featuring a heterogeneous fleet of vehicles under the maximum stock inventory policy. They formulated the problem as a MILP model and introduced an augmented tabu search and differential evolution heuristic algorithm for solving multiple instances of the problem. Additionally, to address routing decisions effectively, they implemented supplementary heuristic approaches, including an improved Clarke–Wright algorithm, an enhanced push-forward insertion heuristic method, and a speed optimization heuristic algorithm.

A multi-period IRP system within the cold supply chain for food distribution was investigated by Wei et al. (2019). The authors categorized customers into two groups based on their proximity to the depot. Customers close to the depot were served by self-owned vehicles, while the other group was served by outsourced vehicles. Additionally, the authors assumed shorter route time limits for self-owned vehicles compared to outsourced vehicles. The problem was formulated as an MILP model. Small-sized problem instances were addressed using the CPLEX commercial solver, and larger cases were tackled using a genetic algorithm (GA) developed by the authors. Schenekemberg et al. (2020) examined a multi-period IRP involving homogeneous fleet management decisions, such as fleet rentals and vehicle cleaning. A branch-and-cut algorithm was employed for small-sized problems, while larger instances were addressed by a matheuristic based on adaptive large neighborhood search. Coelho et al. (2020) explored an extension of the multi-depot IRP, considering a multi-commodity supply chain system with heterogeneous vehicles and a limit on route duration.

Manousakis et al. (2021) proposed an improved branch and cut algorithm for the solution of a multi-period two-commodity flow IRP, under the consideration of a limited homogeneous fleet of vehicles. Mahjoob et al. (2021) developed a modified adaptive GA for the solution of a multi-period, multi-product IRP, with a heterogeneous fleet of vehicles. Soysal et al. (2021) studied a closed-loop, multi-period IRP, under the consideration of a mixed fleet of electric and conventional vehicles. The authors developed an MILP and solved small-sized problem instances using a commercial solver, while a fix and optimize algorithm was developed for the solution of larger problem cases. The authors conducted several numerical analyses to extract useful managerial insights. Neves-Moreira et al. (2022) studied a multi-commodity IRP with pickups and deliveries under the effect of both deterministic and uncertain demand.

2.2 Contributions on the truck drivers scheduling problem

Kok et al. (2011) studied the vehicle departure time optimization problem (VDO), as a post-processing approach to the well-known vehicle routing problem with time windows, considering real-life conditions, such as driving hours regulations. The authors formulated the problem as an MILP model and developed an insertion construction heuristic for its efficient solution. Goel (2012) developed an MILP for a variant of the TDSP, considering rest periods at customer locations or at suitable rest areas. The objective of the problem was the minimization of the duration of the route with respect to the relative regulations. The solution of the problem was carried out using a dynamic programming approach.

Goel and Vidal (2014) studied a problem with scheduling for truck drivers with time windows taking into account the hours of service regulations of drivers. More specifically, the authors investigated the impact of such regulations from the United States, EU, Canada, and Australia on transportation costs. They developed a hybrid metaheuristic optimization method to solve the problem under consideration. According to their findings, EU regulations were found to be associated with the highest safety rates, while Canadian truck driver rules led to more economically efficient solutions. Rincon-Garcia et al. (2020) developed a metaheuristic algorithm based on a large neighborhood search for the solution of time-dependent VRP with time windows taking into account both the regulations of EU truck drivers' working hours and the regulations of the UK road transport working time. The proposed solution method produced solutions with 19% fewer vehicles, 17.7% less traveled distance, and 4.4% less duration of the route. Sartori et al. (2022) introduced the truck driver scheduling problem with interdependent routes, considering EU regulations. The authors introduced a set of constraints into an MILP to produce feasible schedules, as well as a label propagation algorithm. According to their findings, the proposed solution method can produce valid schedules for problem cases with several drivers, and a large number of interdependent routes.

2.3 Recent contributions on the optimization of sustainable supply chains

A multi-objective optimization problem for designing a sustainable closed-loop supply chain network in the aluminum industry was investigated by Pahlevan et al. (2021). The authors took into account the life cycle of products to calculate the environmental impacts of the proposed network. The problem was formulated mathematically as a multi-objective MILP, and three novel multi-objective metaheuristic methods were developed for its efficient solution. Pervin et al. (2023) devised a sustainable inventory model considering the composite demand of products with a fixed lifespan, time-dependent holding costs, and warehouse carbon emissions. Meanwhile, Ghosh et al. (2023) investigated a multi-objective sustainable waste management problem framed as a solid transportation problem with three objectives. The first objective pertains to the total system profit, representing the economic aspect of sustainability. The second objective, total elapsed time, encompasses transportation, loading, and unloading times, reflecting the social aspect of sustainability. The third objective addresses the environmental aspect by focusing on total carbon emissions. To address the presented problem, the authors proposed two solution methods-one relying on neutrosophic linear programming and the other employing the ϵ-constraint method.

In a recent study, Tirkolaee et al. (2023) delved into the domain of municipal solid waste management by investigating a sustainable periodic capacitated arc routing problem. This problem encompasses the simultaneous optimization of multiple conflicting objectives, namely total cost minimization, total pollution reduction, and maximum job opportunity utilization. To address this complex optimization challenge, the authors devised a novel multi-objective MILP model that effectively captures the intricate interrelationships between these objectives. Additionally, they proposed two robust multi-objective Pareto-based metaheuristic algorithms tailored to efficiently navigate the intricate solution space and generate a diverse range of non-dominated solutions, catering to various stakeholder preferences and decision-making scenarios. A recent study proposed a comprehensive framework for designing a sustainable supply chain that incorporates the Internet of Things (IoT) to achieve cost reduction, carbon emission minimization, and social impact maximization through job creation (Goli et al. 2023). The proposed supply chain model encompasses both strategic and operational aspects, including supplier selection, facility location, transportation mode optimization, and product distribution level determination. To attain these objectives, the authors developed a multi-objective MILP model, which was subsequently transformed into a single-objective model using goal programming (GP). In their study, Goli et al. (2023) delved into the design of a sustainable five echelons canola oil-based biodiesel supply chain network, while considering the inherent uncertainties in supply and demand. They employed a mixed integer non-linear programming (MINLP) model to address the strategic and tactical-level decisions, aiming to minimize total system costs and carbon emissions while simultaneously maximizing the social impact through job creation. Barman et al. (2023) explored a supply chain inventory management problem that encompasses both synchronous and asynchronous rework of defective products, alongside the consideration of three established carbon emission policies.

Giri et al. (2023) examined the optimization of an electric sustainable supply chain network, incorporating economic, environmental, and social considerations. They devised a multi-objective MILP model to address these multifaceted objectives. Additionally, they introduced a multi-choice conic goal programming solution method integrated with a utility function to effectively tackle the complex problem at hand. Ala et al. (2024) devised a novel fuzzy multi-objective optimization model to investigate a sustainable healthcare supply chain network problem, encompassing multiple echelons, multiple products, and a fuzzy approach to address the uncertainty associated with a subset of critical model parameters. They introduced three multi-objective metaheuristic algorithms, along with the well-established ϵ-Constraint exact method, to effectively tackle the complex problem at hand. Das et al. (2024) meticulously delved into the optimization of a sustainable two-stage solid logistics network by formulating a multi-objective multi-facility location-allocation problem. The authors effectively addressed uncertainties by employing triangular type-2 neutrosophic numbers and employing a novel ranking approach. To optimize three conflicting objectives, they employed the ϵ-Constraint approach and demonstrated its effectiveness through numerical examples. They also conducted a comparative study against other Pareto-based multi-objective approaches.

3 Problem statement and mathematical formulation

This work introduces the fleet size and mix pollution inventory routing problem (FSMP-IRP), a multi-period, multi-commodity optimization challenge that incorporates EU truck drivers' working hours regulations and speed limits. The problem is formulated on a complete graph $G = \{V, E\}$, where V denotes the set of nodes comprising geographically dispersed customers $I = \{1, \dots, |I|\}$, and an additional node $|I| + 1$ represents the depot. The set of edges is defined as $E = \{(i,j) : i,j \in V, i \neq j\}$. The supply chain system encompasses the distribution of multiple product types $P = \{1, \dots, |P|\}$ across a finite time horizon $T = \{1, \dots, |T|\}$. The distribution task involves a fleet of heterogeneous vehicles $K = \{1, \dots, |K|\}$, which includes light-duty trucks $K_L = \{1, \dots, |K_L|\}$, medium-duty trucks $K_M = \{|K_L| + 1, \dots, |K_M|\}$, and heavy-duty trucks $K_H = \{|K_M| + 1, \dots, |K|\}$. Each selected vehicle can traverse between two nodes at a specified speed level chosen from a set of available speed levels $L = \{1, \dots, |L|\}$.

Table 1 Common vehicle parameters

Parameter	Explanation	Value (Cheng et al. 2017)
ϵ	Fuel-to-air mass ratio	1
g	Gravitational constant (m/s^2)	9.81
ρ	Air density (kg/m^3)	1.2041
CR	Coefficient of rolling resistance	0.01
η	Efficiency parameter for diesel engines	0.45
f_c	Unit fuel cost (Euros/L)	0.87
f_e	Unit CO_2 emission cost (Euros/kg)	0.29
f_d	Driver wage (Euros/s)	0.0025
σ	CO_2 emitted by unit fuel consumption (kg/L)	2.669
$HVDF$	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/s to L/s)	737
θ	Road angle	0
τ	Acceleration (m/s^2)	0

Table 2 Vehicle-specific parameters (Cheng et al. 2017)

Parameter	Explanation	Light-duty	Medium-duty	Heavy-duty
CW_k	Curb weight (kg)	4672	6328	13,154
EFF_k	Engine friction factor (kJ/rev/L)	0.25	0.2	0.15
ES_k	Engine speed (rev/s)	39	33	30.2
ED_k	Engine displacement (L)	2.77	5	6.66
CAD_k	Coefficient of aerodynamics drag	0.6	0.6	0.7
FSA_k	Frontal surface area (m^2)	9	9	9.8
$VDTE_k$	Vehicle drive train efficiency	0.4	0.45	0.5
VUK_k	Usage cost of vehicle k	1463.1	2127	3297.3

Each customer exhibits a period-dependent demand for each type of product in every time period, denoted as d_{ipt}. Additionally, it is assumed that distinct product types share identical storage conditions. Consequently, a generalized holding cost, h_i, is assigned to each customer. Every vehicle is characterized by a space capacity, SC_k, and a payload capacity, PC_k. Specific units of space within each type of vehicle are required for each unit of product type, indicated by sr_{pk}. Moreover, each unit of product type p is associated with a specific weight, PW_p. Similarly, ST_{pk} represents the time necessary to unload each unit of product type p from vehicle k.

Tables 1 and 2 provide the common and specific parameters of the vehicle types and their corresponding values, respectively.

The parameters, which represent the working and driving hours limits of truck drivers, according to EU regulations, are summarized in Table 3.

Table 3 Limits of working and driving hours

Parameter	Explanation	Value (in s)
DMD	Driving maximum duration	16,200
WMD	Working maximum duration	21,600
MBD	Minimum break duration	2,700
MRD	Maximum route duration	32,400

The decision variables required to mathematically formulate the problem under investigation are provided in Table 4.

The objective of the problem under consideration is to minimize the total cost of the supply chain system, consisting of general routing costs, inventory costs, fuel consumption costs, CO_2 emissions taxation costs, vehicles' usage costs, and drivers' wages costs. Based on fuel consumption, the Comprehensive Modal Emission Model (CMEM) of Barth et al. (2005) and Barth and Boriboonsomsin (2009) has been adopted. CMEM has been successfully applied in several supply chain network optimization studies (Koç et al. 2016; Dukkanci et al. 2019; Karakostas et al. 2020). The following formulas are provided to simplify the mathematical expression of fuel consumption:

- $\lambda = \frac{\epsilon}{HVDF \cdot \psi}$,
- $\gamma_k = \frac{1}{1000 \cdot VDTE \cdot \eta}$,
- $\alpha = \tau + g \cdot CR \cdot \sin\theta + g \cdot CR \cdot \cos\theta$,
- $\beta_k = 0.5 \cdot CAD \cdot \rho \cdot FSA_k$.

To this end, a mixed integer linear programming model is proposed as follows:

Table 4 Decision variables of the model

Parameter	Explanation
x_{ijkt}	1 if and only if vehicle k moves from node i to j in time period t
z_{ijklt}	1 if and only if vehicle k moves from node i to j in time period t with speed level l
vs_{kt}	1 if and only if vehicle k is selected in time period t
a_{ijkt}	Load weight of vehicle k while traveling from node i to j in time period t
q_{ipkt}	Quantity of product p delivered to customer i with vehicle k in time period t
w_{ipth}	Quantity of product p delivered to customer i in period h for satisfying its demand in period t
AT_{ktv}	Arrival time of vehicle k in node v in period t
AWT_{ktv}	Accumulated working time of the driver of vehicle k after the service of customer i in period t
ADT_{ktv}	Accumulated driving time of the driver of vehicle k while arriving at node v in period t
BW_{ktv}	1 if and only if the driver of vehicle k is performed a break in period t after the service of node v

$$\begin{aligned}
\min & \sum_{i \in I} h_i \cdot \sum_{p \in P} \sum_{t \in H} \left(\tfrac{1}{2} \cdot d_{ipt} + \sum_{h \in T, h<t} w_{ipth} \cdot (t-h) + \sum_{h \in T, h>t} w_{ipth} \cdot (t-h+|T|) \right) \\
& + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \sum_{t \in T} c_{ij} \cdot x_{ijkt} \\
& + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \sum_{l \in L} \sum_{t \in T} fd \cdot \frac{\left(z_{ijklt} \cdot c_{ij}\right)}{s_l} \\
& + \sum_{k \in K} \sum_{t \in T} vs_{kt} \cdot VUC_k \\
& + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \sum_{t \in T} \left\{ \lambda\left(f_c + \left(f_e \sigma\right)\right) \left(\sum_{l \in L} \frac{\left(z_{ijktl} \cdot EFF_k \cdot ES_k \cdot ED_k \cdot c_{ij}\right)}{s_l} + \left(\alpha \cdot \gamma_k \cdot \left(CW_k \cdot x_{ijkt} + a_{ijkt} \right) \cdot c_{ij} \right) \right. \right. \\
& \left. \left. + \left(\beta_k \cdot \gamma_k \cdot \sum_{l \in L} \left(s_l^2 \cdot z_{ijktl} \right) \right) \right) \right\}
\end{aligned} \tag{1}$$

subject to

$$\sum_{l \in L} z_{ijktl} = x_{ijkt}, \quad \forall i,j \in V,\ \forall k \in K, \quad \forall t \in T \tag{2}$$

$$\sum_{l \in L} x_{iikt} = 0, \quad \forall i \in V,\ \forall k \in K, \quad \forall t \in T \tag{3}$$

$$\sum_{j \in V} \sum_{k \in K} x_{ijkt} \le 1, \quad \forall t \in T, \quad \forall i \in I \tag{4}$$

$$\sum_{j \in V} \sum_{k \in K} x_{jikt} \le 1, \quad \forall t \in T, \ \forall i \in I \tag{5}$$

$$\sum_{j \in V} x_{ijkt} - \sum_{j \in V} x_{jikt} = 0, \quad \forall i \in V,\ \forall k \in K, \quad \forall t \in T \tag{6}$$

$$\sum_{i \in I} x_{i(n+1)kt} \le 1, \quad \forall\, k \in K, \quad \forall\, t \in T \tag{7}$$

$$U_{ikt} - U_{jkt} + \left(|I| \cdot \sum_{l \in L} x_{ijkt} \right) \le |I| - 1, \qquad \forall\, i,j \in I, \forall\, k \in K, \forall\, t \in T \tag{8}$$

$$\sum_{i \in V} a_{ijkt} - \sum_{i \in V} a_{jikt} = \sum_{p \in P} q_{jpkt} \cdot PW_p, \quad \forall j \in I,\ \forall k \in K, \quad \forall t \in T \tag{9}$$

$$a_{ijkt} \le x_{ijkt} \cdot PC_k, \quad \forall i,j \in V,\ \forall k \in K,\ \forall t \in T \tag{10}$$

$$\sum_{i \in I} \sum_{p \in P} q_{ipkt} \cdot sr_{pk} \le SC_k, \quad \forall\, k \in K, \quad \forall\, p \in P \tag{11}$$

$$\sum_{i\in I}\sum_{p\in P} q_{ipkt}\cdot PW_p \le PC_k,\quad \forall\, k\in K,\quad \forall\, p\in P \tag{12}$$

$$\sum_{h\in T} w_{ipth} = d_{ipt},\quad \forall i\in I,\ \forall p\in P,\ \forall t\in T \tag{13}$$

$$\sum_{t\in T} w_{ipth} = \sum_{k\in K} q_{ipkh},\quad \forall i\in I,\ \forall p\in P,\ \forall h\in T \tag{14}$$

$$w_{ipth} \le d_{ipt},\quad \forall i\in I,\ \forall p\in P,\ \forall t,h\in T \tag{15}$$

$$q_{ipkt} \le M_1\cdot\sum_{j\in V} x_{ijkt},\quad \forall i\in I,\ \forall p\in P,\ \forall k\in K,\ \forall t\in T \tag{16}$$

$$\sum_{j\in V} x_{ijkt} \le M_1\cdot q_{ipkt},\quad \forall i\in I,\ \forall p\in P,\ \forall k\in K,\ \forall t\in T \tag{17}$$

$$vs_{kt} \le \sum_{i\in V}\sum_{j\in V} x_{ijkt},\quad \forall k\in K,\ \forall t\in T \tag{18}$$

$$x_{ijkt} \le vs_{kt},\quad \forall i,j\in V, i\neq j,\ \forall k\in K,\ \forall t\in T \tag{19}$$

$$\sum_{l\in L, l>3} z_{ijklt} = 0,\quad \forall\, i,j\in I, \forall\, k\in K, \forall\, t\in T,\ c_{ij}\in\left[0,\frac{\overline{c}}{3}\right) \tag{20}$$

$$\sum_{l\in L, l>8} z_{ijklt} = 0,\quad \forall\, i,j\in I, \forall\, k\in K, \forall\, t\in T,\ c_{ij}\in\left[\frac{\overline{c}}{3},\frac{\overline{c}}{2}\right] \tag{21}$$

$$\begin{aligned} ADT_{ktj} \ge\ & ADT_{kti} + \left(\sum_{l\in L} z_{ijklt}\cdot\frac{c_{ij}}{s_l}\right) - (BW_{kti}\cdot DMD) - \left[\left(1-\sum_{l\in L} z_{ijklt}\right)\cdot MRD\right],\\ & \forall i,j\in V,\ i\neq j,\ i\neq |I|+1,\ \forall k\in K,\ \forall t\in T \end{aligned} \tag{22}$$

$$\begin{aligned} ADT_{ktj} \ge & \left(\sum_{l\in L} z_{ijklt}\cdot\frac{c_{ij}}{s_l}\right) - (BW_{kti}\cdot DMD) - \left[\left(1-\sum_{l\in L} z_{ijklt}\right)\cdot MRD\right],\\ & \forall i = |I|+1,\ j\in I,\ \forall k\in K,\ \forall t\in T \end{aligned} \tag{23}$$

$$ADT_{ktj} \ge \sum_{l\in L} z_{ijklt}\cdot\frac{c_{ij}}{s_l},\quad \forall i,j\in V, i\neq j,\ \forall k\in K,\ \forall t\in T \tag{24}$$

$$AWT_{ktj} \geq AWT_{kti} + \left(\sum_{l \in L} z_{ijklt} \cdot \frac{c_{ij}}{s_l} \right) + \left(\sum_{p \in P} q_{jpkt} \cdot ST_{pk} \right) - (BW_{kti} \cdot WMD) - \left[\left(1 - \sum_{l \in L} z_{ijklt} \right) \cdot MRD \right], \quad \forall i,j \in V, i \neq j,\ i \neq |I|+1,\ \forall k \in K,\ \forall t \in T \tag{25}$$

$$AWT_{ktj} \geq \left(\sum_{l \in L} z_{ijklt} \cdot \frac{c_{ij}}{s_l} \right) + \left(\sum_{p \in P} q_{jpkt} \cdot ST_{pk} \right) - (BW_{kti} \cdot WMD) - \left[\left(1 - \sum_{l \in L} z_{ijklt} \right) \cdot MRD \right], \quad \forall i = |I|+1,\ \forall j \in I,\ \forall k \in K,\ \forall t \in T \tag{26}$$

$$AWT_{ktj} \geq \left(\sum_{i \in V} \sum_{l \in L} z_{ijklt} \cdot \frac{c_{ij}}{s_l} \right) + \left(\sum_{p \in P} q_{jpkt} \cdot ST_{pk} \right) - \left[\left(1 - \sum_{l \in L} z_{ijklt} \right) \cdot MRD \right], \quad \forall j \in V,\ \forall k \in K,\ \forall t \in T \tag{27}$$

$$AT_{ktj} \geq AT_{kti} + \left(\sum_{l \in L} z_{ijklt} \cdot \frac{c_{ij}}{s_l} \right) + \left(\sum_{p \in P} q_{ipkt} \cdot ST_{pk} \right) + (BW_{kti} \cdot MBD) - \left[\left(1 - \sum_{l \in L} z_{ijklt} \right) \cdot (2 \cdot MRD) \right], \quad \forall i,j \in V, i \neq j, i \neq |I|+1,\ \forall k \in K,\ \forall t \in T \tag{28}$$

$$AT_{ktj} \geq \left(\sum_{l \in L} z_{ijklt} \cdot \frac{c_{ij}}{s_l} \right) + (BW_{kti} \cdot MBD) - \left[\left(1 - \sum_{l \in L} z_{ijklt} \right) \cdot (2 \cdot MRD) \right], \quad i = |I|+1,\ \forall j \in I,\ \forall k \in K,\ \forall t \in T \tag{29}$$

$$AT_{kti} \leq \sum_{j \in V} \sum_{l \in L} z_{jiklt} \cdot MRD, \quad \forall i \in V,\ \forall k \in K,\ \forall t \in T \tag{30}$$

$$\sum_{i \in V} BW_{kti} \leq M_2 \cdot vs_{kt}, \quad \forall k \in K,\ \forall t \in T \tag{31}$$

$$BW_{kti} \leq \sum_{j \in V, j \neq i} \sum_{l \in L} z_{jiklt}, \quad \forall i \in V, \forall k \in K, \forall t \in T \tag{32}$$

To clarify, the parameter M_1 is set equal to the total demand of the customers for each type of product in all time periods, while the parameter M_2 is set equal to the number of customers.

The objective function (1) refers to the minimization of the total cost of the supply chain system, which consists of inventory costs (average holding costs and penalty costs of deferred deliveries), general routing costs, driver wages costs, vehicles' usage costs, fuel consumption costs, and carbon emission taxation costs. Constraints (2) indicate that the movement from a node to another with a selected vehicle in a specific time period will be performed with at most one specific speed level. Constraints (3) eliminate the one-node cycles in the supply chain network. Constraints (4) and (5) guarantee that a customer is serviced by at most one vehicle in each time period. Constraints (6) establish the balance between the interior and exterior flows of vehicles in each node in each time period. Each vehicle can perform at most one route in each time period, as imposed by constraints (7). The Miller-Tucker-Zemlin subtour elimination constraints are formulated as presented in Equations (8). Constraints (9) impose the balance between the interior and exterior flows of product load in each customer over each period of time. Constraints (10) guarantee that the product load in the vehicle moving between two nodes of the network cannot exceed the payload capacity of this vehicle. Constraints (11) impose that the space requirements of the products delivered to a customer in a specific time period by a selected vehicle cannot exceed its space capacity. Similarly, Constraints (12) guarantee that the weight of products transported by a selected vehicle in a specific time period cannot exceed its payload capacity. Constraints (13) denote that the deferred scheduled deliveries to a specific customer for a specific period of time must be equal to the demand of this customer. Moreover, constraints (14) impose that the deferred scheduled deliveries to a specific customer for a specific time period must be equal to the actual deliveries in this time period. Constraints (15) impose that a deferred scheduled delivery to a customer cannot exceed the corresponding demand of this customer. Constraints (16) and (17) guarantee that a vehicle will deliver to a customer if and only if this vehicle is scheduled to visit this customer. Constraints (18) and (19) ensure that a vehicle can perform a route in a specific time period if and only if it is selected in this time period. Constraints (20) and (21) guarantee the abidance to the speed limit regulations.

The following constraints refer to EU regulations on the working and driving times of truck drivers. Constraints (22), (23), and (24) focus on the accumulative driving time. In general, the accumulative driving time for a specific vehicle in a specific time period for each customer must be greater than the accumulative driving time of the previous customer plus the driving time to reach the current customer minus the duration of a possible break. Constraints (25), (26), and (27) refer to accumulative working time. The accumulative working time consists of both driving and servicing (products unloading) times. In general, the accumulative working time after the service of a specific customer in a specific time period must be greater than the accumulative working time after the service of the previous customer plus the driving time to reach the current one, plus the necessary time to service the current customer minus the duration of any possible break. Constraints (28), (29), and (30) address the feasibility of the arrival time to each node in each time period. It should be clarified that the constraints (30) guarantee that the overall duration of a route will not exceed the corresponding limit. Finally, constraints (31) and (32) impose that only a driver of a selected vehicle can perform a break in a specific time period.

4 Computational analyses

4.1 Computing environment and problem instances

The proposed MILP model was developed using the Gurobi Python interface. The commercial solver ran on a laptop PC (Windows 10 Home 64-bit), with an Intel Core i7-9750 H CPU at 2.6 GHz and 16 GB RAM. The execution time limit was set to two hours. To avoid potential "Out-Of-Memory" errors, the parameter "NodeFileStart" was set equal to 0.5 to utilize disk space for the storage of nodes. To validate the proposed model and perform the necessary computational analyses, 15 problem instances were randomly generated. The new benchmark set is publicly available at https://sites.uom.gr/sifalera/benchmarks.html.

The name of each problem case has the form "X-Y-Z", where "X" denotes the number of customers, "Y" is the number of product types, and "Z" denotes the number of time periods. The first line in each file provides these three numbers (Customers, Types of Products, and Time Periods). The second line provides the coordinates of the location of the depot. The next "X" lines contain the coordinates of the location of the customers and their corresponding holding costs. Customer and depot locations' coordinates were randomly generated following a uniform distribution in the range [0,80].

The following "Customers $\cdot$ Periods" lines present the period-dependent demand for each customer for each type of product. The period-dependent demand of each customer for each type of product was generated following the normal distribution. For each demand value, the mean and standard deviation of the normal distribution were also randomly produced following the uniform distribution in the ranges of [5,15] and [0,5], respectively. The next line in each instance file provides the space required per type of product to load it into a truck. These values were randomly generated following the uniform distribution in the range of [1,3].

The space capacity of each type of truck is presented in the next line. Space capacity data of light-duty trucks were generated following the uniform distribution in the range of $[\text{MaxDemand} \cdot \text{MaxSpace}, \frac{\text{TotalDemand} \cdot \text{MaxSpace}}{2 \cdot \text{Periods}}]$, where "MaxDemand" denotes the maximum value of demand produced, "MaxSpace" represents the maximum value of space required for the loading of one unit of product under the consideration of all product types, and "TotalDemand" = $\sum_{i \in I} \sum_{p \in P} \sum_{t \in T} d_{ipt}$.

The space capacity of medium-duty trucks is equal to 1.2 times the space capacity of light-duty trucks, while the space capacity of heavy-duty trucks is 1.44 times greater than the space capacity of light-duty trucks.

The following $|P|$ lines provide the time required to unload each unit of each type of product from each type of vehicle. Initially, for each type of product, a random number was produced from the uniform distribution on the interval [1,3]. The generated number was transformed into seconds by multiplying by 60. This product was set as the unloading time of the selected type of product in the case of light-duty trucks. In the case of medium-duty trucks, the previously produced time is increased by 1.05 times, while in case of heavy-duty trucks, it is increased by 1.08 times.

Based on the weight of each type of product, the corresponding data are provided in the next line of each instance file. The product weight for a specific product type was generated from the uniform distribution in the interval [1.5,5]. The last line in an instance file presents the payload capacity of each vehicle type. The payload capacity of light-duty trucks was randomly generated from the uniform distribution on the interval $[\text{MaxDemand} \cdot \text{AvgProductWeight}, (\frac{\text{TotalDemand}}{2 \cdot \text{Periods}}) \cdot \text{AvgProductWeight}]$, where "AvgProductWeight" is equal to the average unit weight of all product types. Similarly to the space capacity, the payload capacities of medium and heavy trucks are increased by 1.2 and 1.44 times the payload capacity of light-duty trucks, respectively.

4.2 Computational results

Table 5 provides the total and individual costs according to the best-found solution for each instance.

Table 6 provides the fleet composition as it has been scheduled in the best-found solutions for each problem case.

An important decision in designing the considered supply chain system involves scheduling drivers' breaks. In this context, we present an illustrative example of such schedules for the specific problem instance "8-3-3". Three breaks are scheduled, one for each time period. To elaborate, the driver of the heavy-duty truck is planned to take a break after visiting "Customer_4" in the first time period, another break is scheduled in the second time period after visiting "Customer_2", and in the third time period, the driver of a heavy-duty truck will take a break after visiting "Customer_8". The break schedule is summarized as follows:

- **8-3-3:**
  - *First break:* (Heavy-duty, Period_1, Customer_4)
  - *Second break:* (Heavy-duty, Period_2, Customer_2)
  - *Third break:* (Heavy-duty, Period_3, Customer_8)

Table 5 Summary of total and individual costs

Instance	Total cost	Routing cost	Inventory cost	Vehicles cost	Drivers cost	Fuel cost	CO_2 Taxation cost
5-2-3	476,131.65	460,388.25	92.12	15,316.20	82.86	133.49	118.76
5-3-3	905,266.64	884,750.08	57.69	19,783.80	159.24	272.98	242.86
5-3-5	784,603.48	760,754.95	186.07	23,081.10	136.92	235.20	209.25
5-4-5	583,791.29	556,474.15	232.86	26,671.20	100.16	165.59	147.32
5-5-5	685,474.25	657,348.66	297.31	27,335.10	104.40	215.27	191.52
6-3-3	873,971.55	846,819.79	127.63	26,378.40	152.42	261.06	232.26
6-4-5	610,646.21	584,452.11	534.31	25,208.10	95.93	188.26	167.49
7-2-3	787,022.68	759,962.64	102.79	26,378.40	136.78	233.94	208.13
7-4-5	1,132,508.39	1,071,114.80	277.88	60,308.10	192.79	325.36	289.47
7-4-6	1,230,446.98	1,183,904.46	644.97	44,991.90	213.09	366.50	326.06
8-3-3	1,306,918.16	1,265,029.48	130.88	40,817.10	227.69	377.32	335.69
8-4-5	1,644,797.14	1,573,678.59	414.91	69,536.10	283.24	467.96	416.33
10-3-3	1,025,817.05	992,661.61	321.15	32,095.50	178.66	296.42	263.71
10-4-5	2,069,124.31	1,988,216.71	474.30	78,921.60	357.85	610.61	543.24
15-4-5	1,516,162.85	1,456,154.37	1192.11	57,731.70	260.47	436.16	388.04
Average	1,042,178.84	1,002,780.71	333.16	38,303.62	178.83	305.74	272.01

Table 6 Fleet schedule based on the solutions of basic model

Instance	Light-duty	Medium-duty	Heavy-duty	Instance	Light-duty	Medium-duty	Heavy-duty
5-2-3	0	1	2	7-4-5	0	1	5
5-3-3	0	0	3	7-4-6	0	1	3
5-3-5	0	0	2	8-3-3	1	1	5
5-4-5	1	1	2	8-4-5	1	1	5
5-5-5	0	1	3	10-3-3	1	1	4
6-3-3	0	0	4	10-4-5	0	1	5
6-4-5	0	1	2	15-4-5	2	1	5
7-2-3	0	0	4				

4.3 Managerial insights

This section is dedicated to the computational sensitivity analysis of the potential impact on the total cost and structure of the supply chain system, due to possible fluctuations in key model parameters. The flow of these sensitivity analyses is summarized in Figure 1.

4.3.1 Impact of CO_2 taxation cost fluctuations

Carbon emissions taxation constitutes a key policy for the reduction of carbon emissions (Zhou et al. 2021; Xu et al. 2022). Thus, it is crucial to investigate the potential

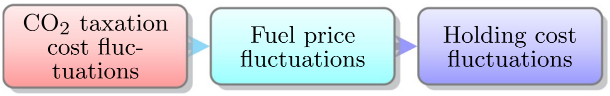

Fig. 1 The sequence of different sensitivity analyses

impact of CO_2 taxation cost fluctuations on the emissions produced by the supply chain system, as well as on its overall structure. To this end, four CO_2 taxation policies were examined. The first policy considers the absence of any taxation on CO_2 emissions. The second policy considers an increase of 10% on the initial tax, while the third and fourth refer to the application of increased taxation rates by 15% and 20%, respectively. Figure 2 illustrates the trade-offs between different CO_2 taxation policies and the produced emissions.

The examination of various CO_2 taxation levels and their impact on average CO_2 emissions provides insightful findings. Firstly, it is evident that the introduction of a CO_2 taxation policy plays a pivotal role in reducing emissions. The average CO_2 emissions are observed to be at 947.97 kg, when no taxation is applied. Introducing an initial taxation level results in a slight reduction in average CO_2 emissions to 937.96 kg, indicating a potential influence of taxation on emission levels. Further adjustments, such as a 10% increase in taxation, lead to a decrease in average CO_2 emissions to 934.72 kg. However, the efficacy of carbon emission management measures diminishes when transitioning to more stringent taxation policies. This deterioration may be attributed to disparities in fleet composition as well as routing patterns, during specific time periods, possibly influenced by strict EU driving and working regulations. Figure 3 illustrates the slight differences in the average cost of the fleet composition under the effect of each CO_2 taxation policy, while Fig. 4 presents the impact of different CO_2 taxation policies on routing costs.

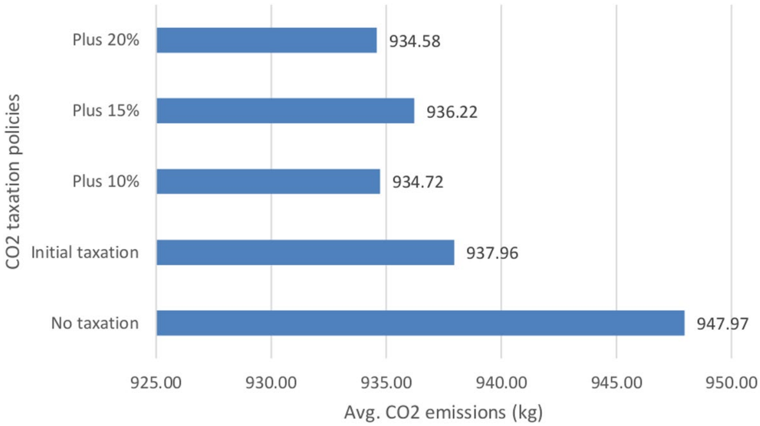

Fig. 2 Impact of CO_2 taxation policies on carbon emissions

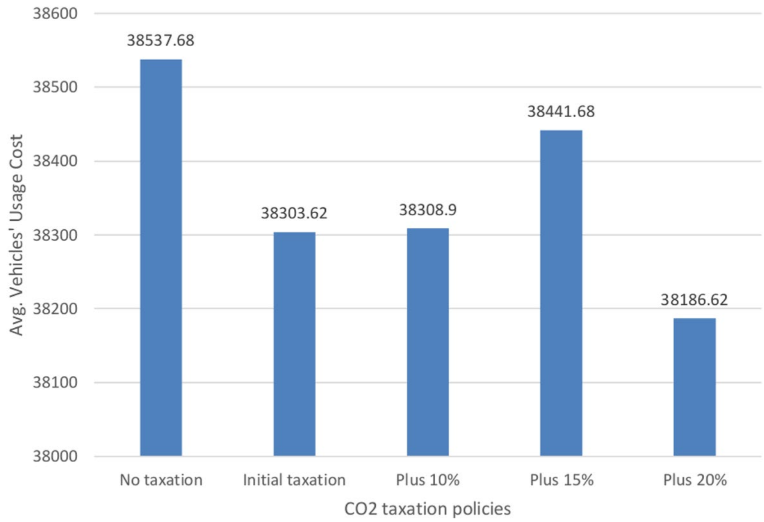

Fig. 3 The relationship between different CO_2 taxation policies and average vehicles usage costs

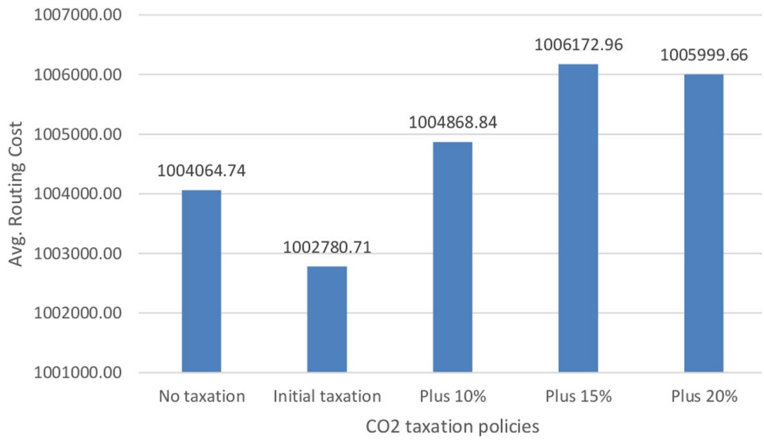

Fig. 4 The relationship between different CO_2 taxation policies and average routing costs

From a total cost perspective, no significant effects of different taxation policies have also been observed. Table 7 summarizes the average total and individual costs of the supply chain system under the effect of different CO_2 taxation policies.

Table 8 focuses on two problem instances and provides fleet requirements per time period, aiming to better understand the impact of different carbon taxation policies on fleet composition.

Table 7 Cost comparisons between different CO_2 taxation policies

Avg. Costs	Initial taxation	No taxation	Plus 10%	Plus 15%	Plus 20%
Total Cost	1,042,178.84	1,043,429.31	1,044,295.53	1,045,750.34	1,045,341.91
Routing cost	1,002,780.71	1,004,064.74	1,004,868.84	1,006,172.96	1,005,999.66
Inventory Cost	337.93	341.05	335.71	338.68	346.29
Vehicles' Usage Cost	38,303.62	38,537.68	38,308.90	38,441.68	38,186.62
Drivers' Cost	178.83	176.84	179.21	179.62	179.46
Fuel Cost	305.74	309.00	311.35	305.17	304.64
CO_2 taxation Cost	272.01	0	298.18	312.23	325.24

Table 8 Differences in fleet composition and routing schedules based on CO_2 taxation policies

Instance	Period	No taxation	Initial taxation	Plus 10%	Plus 15%	Plus 20%
8-4-5	1	4 H	1 M, 4 H	6 H	4 H	1 M, 2 H
	2	1 M, 4 H	4 H	1 M, 3 H	1 M, 4 H	2 M, 3 H
	3	1 M, 3 H	4 H	1 M, 4 H	4 H	2 M, 2 H
	4	4 H	3 H	3 H	1 M, 4 H	2 M, 2 H
	5	1 M, 4 H	1 L, 5 H	1 M, 3 H	1 M, 3 H	1 L, 2 M, 3 H
10-4-5	1	1 L, 1 M, 5 H	4 H	1 L, 3 H	1 M, 5 H	2 L, 1 M, 2 H
	2	2 L, 3 H	4 H	1 L, 6 H	2 M, 1 H	1 L, 1 M, 4 H
	3	5 H	1 M, 5 H	1 L, 2 M, 2 H	2 M, 4 H	1 L, 1 M, 3 H
	4	1 M, 3 H	1 M, 3 H	1 M, 5 H	5 H	1 M, 2 H
	5	5 H	1 M, 6 H	1 L, 2 M, 2 H	1 L, 1 M, 4 H	1 L, 1 M, 6 H

4.3.2 Impact of fuel price fluctuations

Fuel price fluctuations can significantly affect traffic flows (Zhang and Burke 2020). Therefore, investigating the potential impact of fuel price fluctuations on the supply chain system under consideration constitutes an interesting research objective. Figures 5, 6, and 7 illustrate how changes in fuel price affect average fuel consumption, fleet composition, and average transportation cost.

According to the numerical analysis, there is a slight relationship between fluctuation in fuel prices and average fuel consumption. It has been observed that as the price of the fuel increases, the average fuel consumption gradually decreases. To handle such fluctuations, the solver attempted to provide a different fleet composition and delivery schedules. More specifically, an increase of 10% in fuel prices leads to fewer vehicles being used compared to the basic case, while a more severe increase of 20% leads to the utilization of more vehicles, but to more efficient routing patterns. However, a slight increase in fuel consumption was observed when the fuel price increased by 15%. This unanticipated outcome can

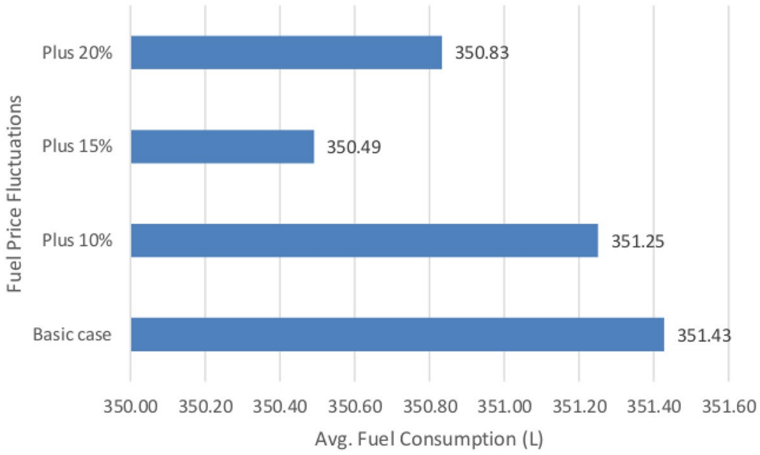

Fig. 5 The impact of fuel price fluctuations on the average fuel consumption

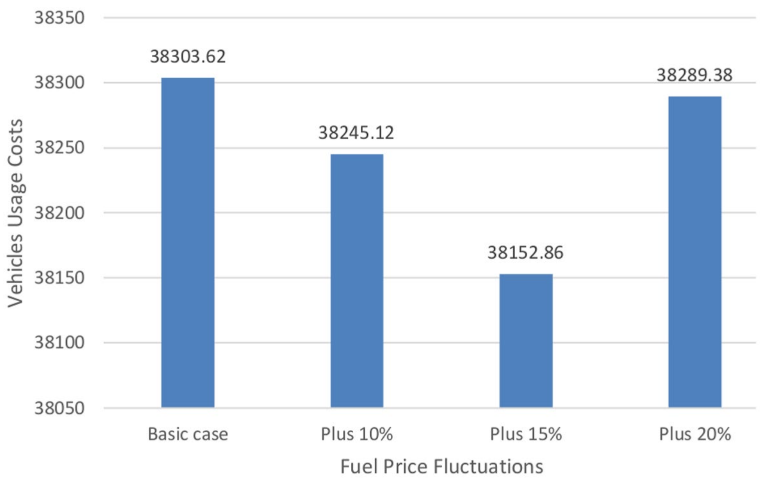

Fig. 6 The impact of fuel price fluctuations on the average vehicles usage cost

possibly be caused by the effect of both strict EU regulations and the consideration of speed limits. To this end, the solver produces an inefficient routing scheme to produce a time-feasible solution that fully satisfies customers' demands.

Table 9 provides the average total and individual costs of the supply chain system under the effect of different fuel price fluctuations.

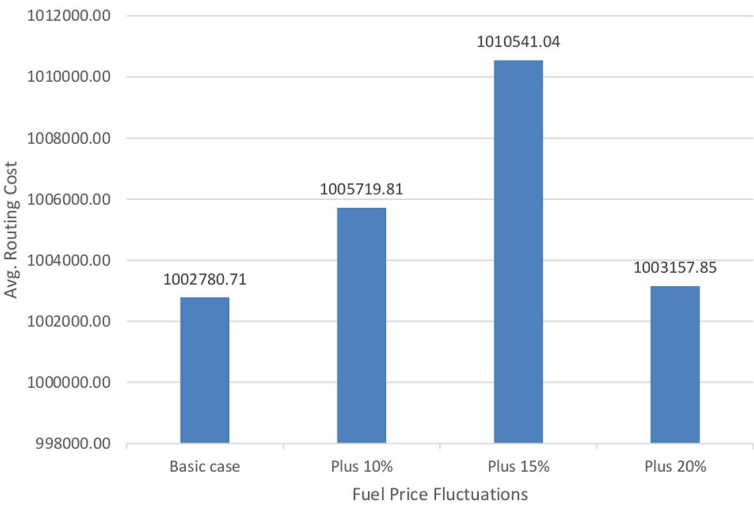

Fig. 7 The impact of fuel price fluctuations on the average routing cost

Table 9 Cost comparisons under the effect of different fuel price fluctuations

Avg. costs	Basic case	Plus 10%	Plus 15%	Plus 20%
Total cost	1,042,178.84	1,045,091.99	104,984.76	1042,609.24
Routing cost	1,002,780.71	1,005,719.81	1,010,541.04	1,003,157.85
Inventory cost	337.93	339.12	338.52	344.99
Vehicles' usage cost	38,303.62	38,245.12	38,152.86	38,289.38
Drivers' cost	178.83	179.35	180.39	179.18
Fuel cost	305.74	336.47	350.67	366.27
CO_2 taxation cost	272.01	272.13	271.28	271.55

4.3.3 Impact of holding cost fluctuations

Recent studies have underlined the important role of holding cost changes in a supply chain system (Hu et al. 2018). To this end, the potential impact of holding cost fluctuations on the supply chain system under consideration has been set under investigation. More specifically, two cases have been considered. According to the first, an increase in holding costs of 10% was applied. Similarly, an increase of 15% was considered in the second case. Table 10 provides the average total and individual costs under the effect of fluctuation of the holding cost.

The numerical analysis revealed the significant impact of holding cost fluctuations on the average overall cost of the supply chain system. There is an obvious strong impact on average inventory cost (increased by 15% and 22% respectively) as well as on routing cost (increased by 5% and 1.5% respectively).

Table 10 Cost comparisons under the effect of holding cost fluctuations

Avg. costs	Basic case	Plus 10%	Plus 15%
Total cost	1,042,178.84	1,095,257.13	1,057,992.69
Routing cost	1,002,780.71	1,056,316.91	1,018,633.55
Inventory cost	337.93	389.30	411.20
Vehicles' usage cost	38,303.62	37,777.12	38,191.90
Drivers' cost	178.83	188.77	182.98
Fuel cost	305.74	309.60	303.26
CO_2 taxation cost	272.01	275.44	269.81

Figures 8, 9, and 10 illustrate the replenishment plan for all types of product in all time periods for the third customer of the problem instance "6-4-5", under the effect of holding cost fluctuations.

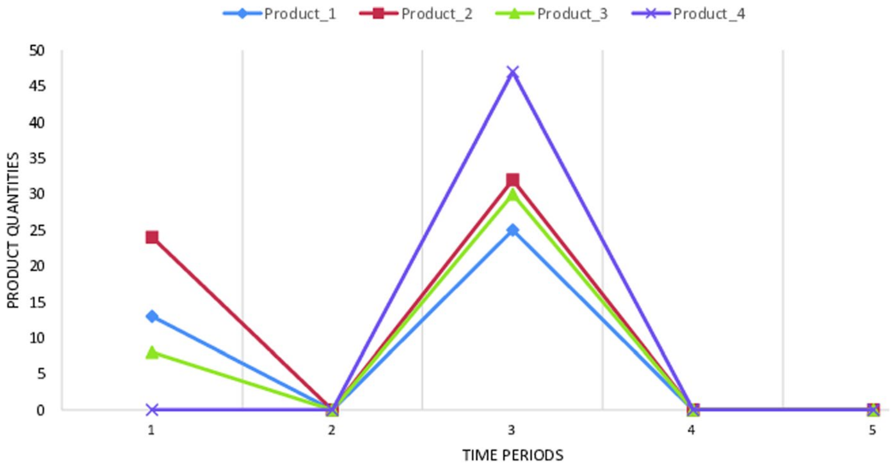

Fig. 8 Replenishment plan for the third customer in the basic case of instance "6-4-5"

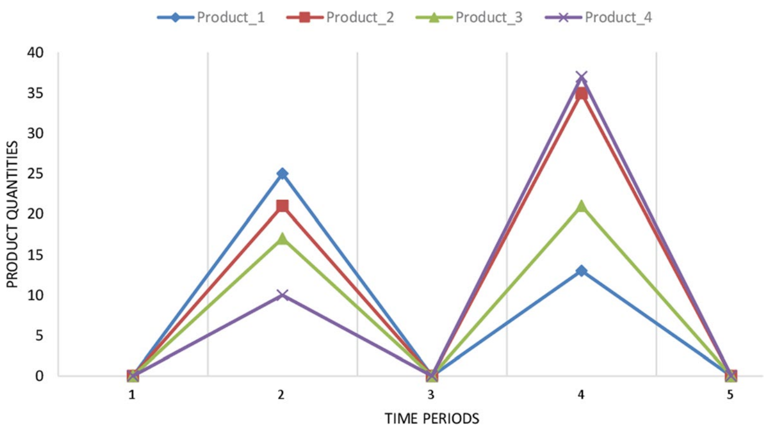

Fig. 9 Replenishment plan for the third customer under the effect of the first holding cost fluctuation of instance "6-4-5"

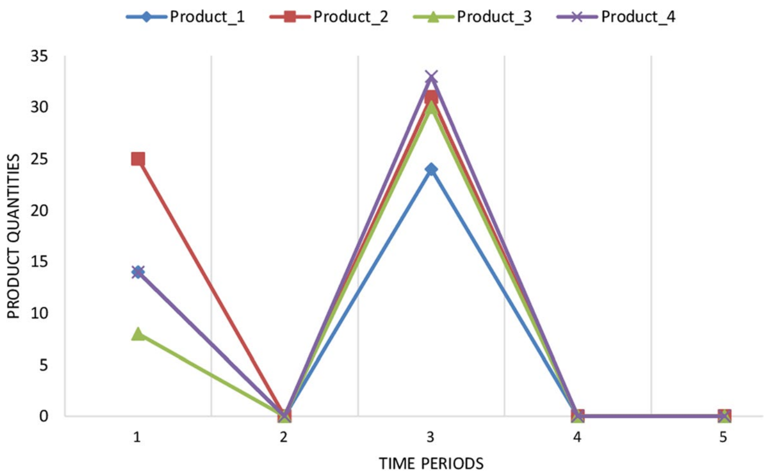

Fig. 10 Replenishment plan for the third customer under the effect of the second holding cost fluctuation of instance "6-4-5"

5 Conclusions

Sustainability has emerged as a cornerstone of competitive advantage in today's dynamic and multifaceted business landscape. To address this prevailing challenge, this study has proposed a novel sustainable supply chain network optimization problem that simultaneously considers strategic, tactical, and operational decisions, encompassing economic, environmental, and social aspects, while adhering to stringent EU regulations on truck drivers' working hours and driving schedules. To effectively address this intricate problem, an MILP model has been developed and implemented using the Gurobi-Python interface. Moreover, artificial problem instances were generated based on established guidelines from the open literature and solved using the Gurobi solver, yielding valuable insights into the problem's behavior.

This study has investigated the impact of various external factors, including carbon emission taxation policies, fuel price fluctuations, and holding cost variations, on a sustainable supply chain network optimization problem. The findings provide valuable insights into the trade-offs between economic, environmental, and social objectives. The results indicate that carbon emission taxation policies play a pivotal role in reducing CO_2 emissions. However, the efficacy of these policies diminishes when transitioning to more stringent taxation policies due to the associated increase in fuel costs. This highlights the need for careful consideration of the balance between emission reduction and economic viability when implementing carbon emission taxation policies. Fuel price fluctuations have a significant impact on average fuel consumption and fleet composition. Our study shows that as fuel prices increase, the solver attempts to provide a different fleet composition and delivery schedules to minimize fuel costs. This adaptation is crucial for maintaining operational efficiency and reducing fuel-related emissions. However, a slight increase in fuel consumption was observed when the fuel price increased by 15% due to the combined effect of strict EU regulations and speed limits. This underscores the importance of considering these regulatory and infrastructural factors when analyzing the impact of fuel price fluctuations. Holding cost variations have a significant impact on the overall cost of the supply chain system. The sensitivity analysis of holding cost fluctuations reveals a significant impact on both the total cost and inventory management of the supply chain system. The increase in holding costs leads to higher inventory levels, which translates to increased inventory costs and higher total transportation costs. To mitigate these cost increases, the solver adjusts the replenishment plan by delivering more frequently to customers, leading to shorter replenishment cycles and lower inventory levels. In summary, the sensitivity analysis highlights the importance of considering holding costs when optimizing supply chain operations. Holding costs can significantly impact the overall cost structure and inventory management practices. The proposed MILP model provides valuable insights into the trade-offs between inventory management, transportation costs, and total cost of the supply chain system under varying holding cost scenarios.

While the FSMP-IRP model presented in the research paper represents a significant advancement in supply chain optimization, it is important to acknowledge certain limitations that can be addressed in future research:

Model Complexity: The model's comprehensiveness in addressing multiple objective function components and incorporating various constraints leads to its increased computational complexity. Further optimization techniques may be needed to enhance the computational efficiency of the model, especially for large-scale problem instances. Developing an efficient heuristic solution method will be an interesting research direction, as it can obtain solutions for larger problem cases in a short computational time.

Uncertainty and Adaptive Problem Features: The model assumes deterministic demand patterns and does not explicitly consider stochastic factors or disruptions that may arise during operations. Incorporating probabilistic modeling and robust optimization techniques can improve the model's resilience to uncertainties and disruptions. Moreover, from a problem perspective, the consideration of product-dependent holding costs and emission-based tax rates will be an interesting research direction.

Social Responsibility Considerations: While the model incorporates social responsibility aspects, such as driver working hours, further research can delve into more nuanced social factors, such as fair labor practices and ethical sourcing. It would be of great research interest to explore human resource management decisions related to the staffing of truck drivers and warehouse personnel within the current iteration of the problem (Graczyk-Kucharska et al. 2020).

Sustainability Impact Evaluation: The model estimates CO_2 emissions and assesses the environmental impact of supply chain operations. However, a more comprehensive evaluation of the overall sustainability impact of the model would enhance its applicability in sustainable supply chain management.

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Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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