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Modelling the Vehicle Routing Problem with Delivery and Pickup in E-Commerce Forward-Reverse Logistics Networks Based on the Triple Bottom Line Framework

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With the recent surge of industrialisation and advancement of technologies, supply chain management has been widely permeated by the practice of reverse logistics and zero-waste circular economy. Literature on these topics has covered several reverse logistics optimisation problems; however, the area of the vehicle routing problem has only been explored to a limited extent, notwithstanding the costs associated with route planning under bi-directional pathways. E-commerce logistics is not well-represented in previous works; and of such existing studies, no model has quantified the performance of the routing plan on the basis of all three sustainability measures. In this light, the objective of the present paper is to model the forward-reverse logistics network of e-commerce organisations and determine optimal routing plans based on economic, environmental, and social performance measures. To fulfil this, a mixed-integer linear programming problem (MILP) integrating the minimisation of three types of costs, namely (1) operational costs, (2) carbon emissions, and (3) highest energy use of vehicle drivers, was formulated and then evaluated using a hypothetical case study. The findings indicated that the proposed model was successful in optimising all three aspects of sustainability, with a weighted average deviation of a minimal 9.02 % from the potential of each objective. Under the optimal routing scheme, all vehicles are deployed and assigned paths such that they leverage the unique benefits of the vehicles in sustainable terms.

1. Introduction

In every supply chain, logistics plays a crucial role as it facilitates the train of activities that constitute the network. By ensuring the efficient flow of goods from suppliers to customers, this domain of supply chain management integrates various business transactions into a cohesive whole. Its significance is further highlighted as transportation and warehousing contribute to as much as 25 % and 8-10 % of product costs. With these, logistics has been a promising avenue for companies to improve operations and gain a competitive edge. As much as logistics processes spur economic growth, however, their environmental impacts cannot be overstated. With rapid industrialisation, transportation has introduced a wide range of negative externalities to the environment. According to the International Energy Agency (2019), one-fourth of the global emissions in 2016 can be attributed to transportation. Of this, freight transport contributed 42 %, which is predicted to jump to 60 % by 2050. Along with greenhouse gas emissions, freight transport has been driving factors of air pollution, environmental noise, ozone degradation, and fossil fuel depletion—from which more serious issues arise, notably global warming and climate change. Naturally, these concerns created the concept of green logistics.

Green logistics is the process of “greening” the different elements of logistics, such as transport, material handling, warehousing, distribution, packaging, and waste management. One of the strategies that have received considerable attention in this area is reverse logistics, which studies the movement of goods from customers to depots for purposes such as recycling, returns, and disposal. The environmental benefits of this practice are primarily realised by means of waste minimisation. It is an essential component of closed-loop supply chains, which propose a shift from a 'take-make-waste' linear to a zero-waste circular economy where materials and energy that would otherwise escape as waste after usage efficiently circulate within the system. Unlike typical networks, closed-loop supply chains entail the management of both forward and reverse product flows and present new challenges, such as uncertain forecasting, non-uniform products, and variable inventory.

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Due to such complexities, operations research is a tool that has been extensively used in the field, with proven usefulness in optimising decisions. For instance, in the paper of Yu and Solvang (2018), a two-stage stochastic bi-objective MILP was presented to solve a network design problem for a sustainable reverse logistics system. Li et al. (2017), on the other hand, formulated Mixed-Integer Non-Linear Programming (MINLP) to optimise the solution for a location-inventory problem.

Within the research interest of reverse logistics, a substantial number of studies have been dedicated to optimising routing schemes, with the topic formally termed the vehicle routing problem in reverse logistics (VRPRL). Of existing studies on VRPRLs, however, there is a small percentage focusing on the e-commerce industry despite the massive growth of online purchasing and the number of product returns associated with e-commerce environments. Notable differences exist between e-commerce and other business models with regard to the VRPRL. For one, product distribution in traditional business models typically involves delivering products from a central warehouse to physical retail stores. In contrast, e-commerce companies deliver products directly to customers' homes or designated pickup locations, implying the need to deal with last-mile delivery, which is often more complex and expensive than traditional distribution methods. Additionally, e-commerce businesses often have a wider range of products and a larger customer base, further adding to the difficulty associated with solving the VRPRL. Most notably, e-commerce companies face unique challenges related to product returns and exchanges, which require additional planning and resources for reverse logistics.

Zhang et al. (2020), one of the few studies that tackled the VRPRL in e-commerce, developed an MINLP model minimising the total cost of transportation and penalties due to late deliveries. Li et al. (2021) extend the work by incorporating customer satisfaction levels and logistics and distribution costs in a single objective function. Similarly, Deng et al. (2014) were able to minimise forward and backward logistics costs while maximising customer satisfaction. As of writing, however, no study has been able to subsequently incorporate the environmental impacts of transportation in similar networks. Related VRP works that consider minimizing transport emissions, such as that by Di Pretoro et al. (2022), exist but the models formulated operate on a single direction only. In hopes of moving toward a sustainable future, the objective of this study is to model the multi-objective vehicle routing problem with delivery and pickup for the forward-reverse logistics network of e-commerce firms. The VRPRL is to be formulated as a MILP with a view of simultaneously minimising operational costs, carbon emissions, and maximum driver energy use. The contribution of this research is three-fold; to the best of the author's knowledge, it is the only study that simultaneously addresses: (1) routing in reverse logistics, (2) product returns in e-commerce, and (3) optimisation based on all sustainability pillars.

2. Problem definition

The multi-objective VRPRL undertaken in the study is defined as an e-commerce logistics network with a set of customers and one supplier depot. Each customer must be visited exactly once by a vehicle to both deliver and pick up a certain amount of goods to and from the location. A heterogeneous fleet of vehicles is available to perform these operations, each having different load capacities, carbon emission factors, fuel consumption, etc. Every vehicle is manned by one driver, which also varies in several characteristics. All routes begin with the vehicle departing from the depot carrying the total amount it intends to deliver to customers and ends with returning to the depot having a load equal to the total amount picked up. For each customer, there is a specific time window that the service can be performed and a length of time spent on the service, which includes the time to load and unload the goods. The total route time associated with a vehicle is the sum of travel time, service time, and waiting or idle time. The average speed of the vehicles is assumed constant, so travel time is proportional to the distance travelled. The total distance travelled by a vehicle must not exceed the set maximum. At each point of the trip, the load they carry must be within their respective capacities. The goal of the problem is to determine the optimal routing scheme simultaneously considering economic costs, carbon emissions, and driver workload balance, following their assigned levels of importance.

3. Model formulation

The MILP formulation of the problem is given as follows. Tables 1 to 3 summarise the nomenclature for the sets, indices, variables, and parameters used in expressing the model's objective function and constraints.

Table 1: Sets and their indices

Notation	Definition
N	Set of nodes (customers and depot), where $i, j \in N$
V	Set of vehicles, where $k \in V$

Table 2: Decision and system variables

Notation	Definition
x_{ijk}	1 if arc (i,j) belongs to the route travelled by vehicle k; 0 otherwise
u_{ij}	Demand picked up from customers up to node i and transported in arc (i,j)
v_{ij}	Demand to be delivered to customers routed after node i and transported in arc (i,j)
s_{ik}	Time that vehicle k starts serving customer i
l_k	Time that vehicle k finishes all services
e_{ik}^{l}	Amount of energy the driver operating vehicle k spends for lifting products at node i
e_k^d	Amount of energy the driver operating vehicle k spends on driving
E_k	Total energy consumption of the driver operating vehicle k

Table 3: Parameters

Notation	Definition	Notation	Definition
d_{ij}	Distance between nodes i and j	h_1	Starting height when lifting cargo
t_i	Service time at customer i	h_2	Ending height when lifting cargo
t_{ij}	Travel time between nodes i and j	β	Unit of energy spent
DD_i	Delivery demand of customer i	BW_k	Body weight of driver at vehicle k
PD_i	Pick-up demand of customer i	c_k^v	Hourly cost of vehicle k use
ρ	Density of the product being delivered	c^d	Hourly wage of a driver
E_i	Earliest time a vehicle can visit customer i	c^f	Cost of fuel per Litre
L_i	Latest time a vehicle can visit customer i	R_k	Fuel consumption rate of vehicle k
CCF_k	Carbon emission factor for vehicle k	Q_k	Weight capacity of vehicle k
EC_k	Daily energy capacity of driver at vehicle k	V_k	Volume capacity of vehicle k
MD	Total maximum distance that a vehicle can travel	w_1	Weight of economic objective
a_k	Parameters related to the gender of the driver at vehicle k	w_2	Weight of environmental objective
b_k	Parameters related to the gender of the driver at vehicle k	w_3	Weight of social objective

3.1 Objective function

The model's objective function, as written in Eq(1), is equivalent to the weighted gap of the solution's economic, environmental, and social costs with the optimal cost if each objective were to be minimised in a single-objective model. It represents the potential for improvement of the multi-objective model's performance relative to the case where the objectives operate independently. In effect, the function seeks to maximise the fulfillment of the three sustainability goals without compromising one for the other. The weights convey the relative importance of each component to the system's overall performance, and they are subjectively determined by the model's decision-maker.

Minimize

$$Z = w_1 \frac{F^{eco} - F^{eco_{best}}}{F^{eco_{best}}} + w_2 \frac{F^{env} - F^{env_{best}}}{F^{env_{best}}} + w_3 \frac{F^{soc} - F^{soc_{best}}}{F^{soc_{best}}} \tag{1}$$

Shown in Eq(2), the cost associated with the economic objective consists of three elements: (1) driver wage (2) vehicle use, and (3) fuel consumption. In this calculation, it is assumed that drivers are paid from the beginning of the period, regardless of the time they begin actual travel or service, up to the time they arrive back at the depot; as a result, daily wage also accounts for inter-service idle times. Costs for vehicle use and fuel consumption, on the other hand, only consider the total travel time. Environmental sustainability is captured in Eq(3) using the total amount of carbon emissions, which is calculated using the respective carbon emission factor of each vehicle. Meanwhile, social cost is measured by taking the worst percentage energy expenditure among all drivers adopting the established ergonomics-based approach of Pilati and Tronconi (2022) in order to obtain a single fairness indicator that can be easily incorporated into the objective function. Note that Eq(4) can be linearized by equating F^{soc} to an auxiliary variable constrained to be greater than each E_k.

$$F^{eco} = \sum_k c^d l_k + \sum_i \sum_j \sum_k \left(c_k^v t_{ij} + R_k c^f d_{ij}\right) x_{jik} \tag{2}$$

$$F^{env} = \sum_i \sum_j \sum_k CCF_k d_{ij} x_{ijk} \tag{3}$$

$$F^{soc} = \max\{E_1, E_2, \ldots E_{|K|}\} \tag{4}$$

3.2 Constraints

The standard VRP-SPDTW constraints are detailed in the set of equations below. Eq(5) limits the number of vehicles visiting each customer to exactly one. The flow balance constraint, which ensures that a vehicle entering a node also departs from it, is expressed in Eq(6). Eq(7) restricts the number of trips taken by each vehicle to one. Eq(8) and Eq(9) define the demand flow equations for pick-up and delivery operations. The load capacity constraints, stating that each vehicle cannot carry goods weighing over its capacity in terms of weight and volume, are enforced in Eq(10) and Eq(11). Eq(12) and Eq(13) establish the time window requirements of each customer. Eq(14) guarantees no route involves travelling over the maximum allowable distance. Lastly, Eq(15) and Eq(16) describe the nature of the decision variables as taking binary or non-negative values.

$$\sum_i \sum_k x_{ijk} = 1 \quad \forall \quad j \neq 0 \tag{5}$$

$$\sum_i x_{ijk} - \sum_i x_{jik} = 0 \quad \forall \quad j,k \tag{6}$$

$$\sum_j x_{0jk} \leq 1 \quad \forall \quad k \tag{7}$$

$$\sum_i u_{ji} - \sum_i u_{ij} = PD_j \quad \forall \quad j \neq 0 \tag{8}$$

$$\sum_i v_{ij} - \sum_i v_{ji} = DD_j \quad \forall \quad j \neq 0 \tag{9}$$

$$u_{ij} + v_{ij} \leq \sum_k Q_k x_{ijk} \quad \forall \quad i,j \tag{10}$$

$$\frac{u_{ij}+v_{ij}}{\rho} \leq \sum_k V_k x_{ijk} \quad \forall \quad i,j \tag{11}$$

$$s_{ik} + t_i + t_{ij} - M(1 - x_{ijk}) \leq s_{jk} \quad \forall \quad i, \forall \ j \neq 0 \tag{12}$$

$$E_i \leq s_{ik} \leq L_i \quad \forall \quad i,k \tag{13}$$

$$\sum_i \sum_j d_{ij} x_{ijk} \leq MD \quad \forall \quad k \tag{14}$$

$$x_{ijk} \in \{0,1\} \quad \forall \quad i,j,k \tag{15}$$

$$u_{ij} \geq 0, v_{ij} \geq 0, s_{ij} \geq 0 \quad \forall \quad i,j,k \tag{16}$$

The following set of equations presents additional constraints that support the definition of the objective function components. Eq(17) determines the time each vehicle returns to the depot after serving all assigned customers, which is necessary in calculating the driver's wage under the economic objective. Similarly, the maximum function can be linearized by using an auxiliary variable assigned to be greater than each s_{ik} value. Eq(18) to Eq(20) pertain to computations related to the social cost. In these constraints, it is supposed that all drivers have a daily energy capacity, which varies according to their gender. Eq(18) calculates the amount of energy drivers spend on lifting activities per customer served, which is a function of several parameters, including their body weight, amount of load, and lifting heights, based on the method proposed by Iqbal et al. (2014). On the other hand, Eq(19) denotes the energy expenditure for driving activities, which depends on body weight and the unit of energy spent β per time-mass. To sum up the two sources of workload and compare the total energy consumption to each driver's energy capacity, Eq(20) is established. The lifting component was multiplied by a factor of 4 as drivers lift each order four times for each arc, twice at the initial point and twice at the destination.

$$l_k = max_{\{s_{1k,}s_{2k}, \dots s_{|N|k}\}} + \sum_i x_{i0k} t_{i0} \tag{17}$$

$$e_{jk}^l = 0.01 \sum_i \left(x_{ijk} \left(a_k + 0.4 BW_k (0.76 - h_1) + b_k (DD_i + PD_i)(h_2 - h_1) \right) \right) \quad \forall \quad j,k \tag{18}$$

$$e_k^d = \beta \cdot BW_k \sum_i \sum_j t_{ij} x_{ijk} \quad \forall \quad k \tag{19}$$

$$E_k = \frac{e_k^d + 4 \sum_i e_{ik}^l}{EC_k} \quad \forall \quad k \tag{20}$$

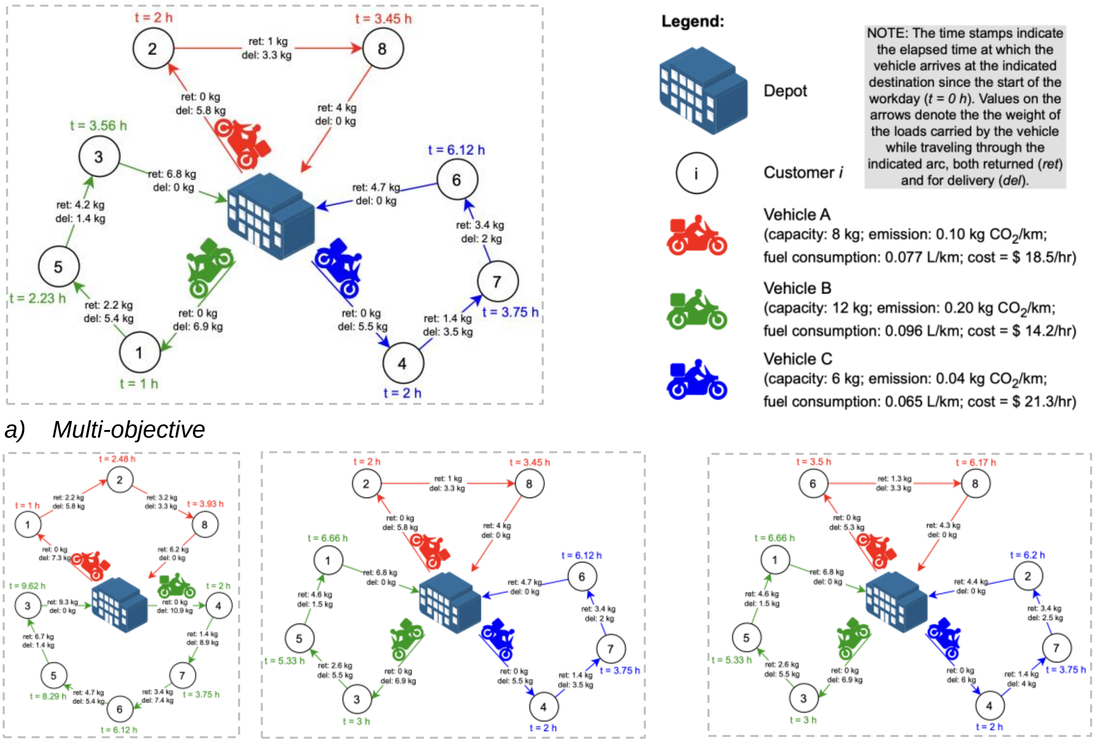
4. Illustrative case study

To validate the formulated model, a hypothetical case approximating real-world conditions was studied. The transportation network of this case includes eight customers, one depot, and three motorcycle vehicles. The estimation of realistic parameters was performed by patterning the values after those in previous similar VRP studies. To clearly observe how the model handles real-life complexities and conflicts in priorities, the parameters were structured such that the decision-making process does not yield straightforward results.

The MILP was coded using the General Algebraic Modeling System (GAMS) and solved through the CPLEX solver on a Macbook Pro 2020 with an Apple M1 chip and 8 GB RAM. The base program resulted in an optimal solution with an execution time of 12.756 s. The results were analyzed under four scenarios, the first three being the minimization of the economic, environmental, and social costs individually, and the last being the multi-objective model considering all three. Note that it was necessary to run the single-objective variants of the model prior to the complete version to determine the lowest possible cost for each of the three sub-objectives. In the multi-objective model, the economic, environmental, and social goals were assigned importance weights of 0.50, 0.25, and 0.25. A summary of the resulting optimal delivery and pick-up routes is given in Figure 1 with a comparison of their associated costs and efficiency levels in Table 4. For the multi-objective model, the optimal solution deviates from the potential values by a weighted average of 9.02 %. Overall, the results clearly illustrate how the recommended routing scheme varies depending on the priority of the decision-maker and how the model effectively manages conflicting sustainability goals.

Table 4: Objective function values

	Potential	Minimizing Cost		Minimizing Emissions		Minimizing Highest Energy Use		Multi-Objective	
			Eff.		Eff.		Eff.		Eff.
Cost, $	647.38	647.38	1.00	783.39	0.79	843.77	0.70	726.19	0.88
Emissions, kg CO_2	77.90	112.00	0.56	77.90	1.00	83.00	0.93	77.90	1.00
Highest Energy Use, %	12.04	19.75	0.36	13.45	0.88	12.04	1.00	13.45	0.88



a) *Multi-objective*

b) *Minimizing cost* c) *Minimizing carbon emissions* d) *Minimizing highest energy use*

Figure 1: Optimal delivery and pick-up routing schemes (not drawn-to-scale)

Under the cost minimization model, the utilization of vehicle B was maximized with it serving more than half of the customers. This is an expected result given that the vehicle is associated with the lowest hourly cost among all vehicles and the highest load capacity. In real-life situations, vehicle B represents large vehicles that allow a lower number of trips needed to serve customers and lower transportation costs, but at the same time, are fuel-inefficient and emit more pollutants, leading to an increased environmental impact. However, since the objective function for this scheme had no regard for the effects of transportation on the environment, then the vehicle was used to its maximum capacity without significant constraint. This is evident in Table 4, which shows that the cost minimization model results in only a 56 % efficiency in terms of carbon emissions. Because there was also no consideration for social sustainability, the model did not penalize energy use imbalances at the expense of the driver at vehicle B, pulling down the social cost efficiency to 36 %.

A different vehicle routing plan is obtained when the environmental objective is prioritized, as shown in Figure 1c. Under this arrangement, all vehicles are deployed, including vehicle C, which has the lowest load capacity and highest hourly rate, but is associated with the lowest carbon emission factor. In contrast to vehicle B, vehicle C corresponds to small vehicles that are fuel-efficient and significantly emit less carbon. As such, the usage of which was beneficial to the environment-oriented model. As a consequence, however, cost increased from $ 647.38 to $ 783.39, which can be attributed to the high variable cost of using vehicle C and the fact that vehicle C's capacity necessitates longer travels to serve customers. Nevertheless, social cost improved considerably relative to the first model given that the driver operating vehicle B is freed up some load by the new vehicle.

The model minimizing the highest energy use among drivers yields similar results to the model concerned with environmental sustainability, indicating that the environmental and social goals are not markedly incompatible.

Most of the differences can be attributed to changes in the customers served by the vehicles such that some workload of the driver at vehicle C, in the form of energy consumed for driving activities, is transferred to that for vehicle A, resulting in a more level work distribution. Specifically, this entailed switching from customer 2 to customer 6, which given the differences in distances, led to a reduction in driving time by approximately 1 h.
When the three objectives are considered in the routing decision, the model suggests a scheme that involves the use of all vehicles. In terms of carbon emissions, the solution performs at maximum efficiency, and at 88 % for the economic and social aspects. The way in which the model manages to balance competing goals becomes apparent when examining how the plan shifts from the models that focus on a single objective. For one, it is shown from a comparison between Figures 1a and 1c that the order by which vehicle B was made to serve the customers was reversed, the purpose of which being to reduce idle times, allowing the driver to finish their service 3 h earlier and reducing wages that have to be paid. As a result, the model focusing on environmental costs marginally improved, in fact, without changes in the total amount of carbon emissions since the only change involved was the sequence of nodes to visit. On the other hand, the shift was significant from the cost minimization to the multi-objective model, indicating that there is a high tendency for economic goals to have adverse environmental and ethical impacts.

5. Conclusions

Given the accelerating amount of product returns in online businesses and the recognition of corporate sustainability, there is a need to devise effective strategies for managing logistics operations in a sustainable manner. To this end, the present study proposes a multi-objective optimization model addressing the VRPRL based on the tripartite description of sustainable development. The problem was formulated as an MILP model incorporating several real-life conditions, including simultaneous delivery and pick-up operations, capacitated vehicles, and time windows. The proposed model optimizes three goals: economic efficiency, environmental impact, and social equity. To evaluate its performance, a numerical analysis was carried out on one set of benchmark instance. The results demonstrated that the proposed model can effectively optimize the three sustainability dimensions, deviating from the potential of each objective by only an average of 9.02 %. It was found that using fewer vehicles, with priority on low-cost and fuel-inefficient transportation was the tendency of decisions if economic goals were prioritized; the opposite applies when the other goals are the primary concern, highlighting the importance of dealing with competing sustainability objectives. Overall, this study represents a significant step forward in addressing the e-commerce VRPRL in a sustainable and cost-effective manner. For future studies, additional factors, such as traffic congestion, weather conditions, and customer preferences, which can significantly impact the sustainability and efficiency of logistics operations may be considered.

References

Deng S., Li Y., Zhou, T., Cao Y., 2014, Study on recyclable reserve logistics network optimization based on e-commerce, 2014 International Conference on Management of e-Commerce and e-Government, 337–340, DOI: 10.1109/ICMeCG.2014.75.

Di Pretoro, A., Negny, S., Montastruc, L., 2022, Minimizing transport emissions for products delivery: accounting for uncertainty on industrial supply chains, Chemical Engineering Transactions, 96, 511-516.

International Energy Agency, 2019, CO_2 Emissions from Fuel Combustion Highlights (2019th ed), International Energy Agency, <iea.blob.core.windows.net/assets/eb3b2e8d-28e0-47fd-a8ba-160f7ed42bc3/CO2_Emissions_from_Fuel_Combustion_2019_Highlights.pdf>, accessed 16.03.2023.

Iqbal M., Tadjuddin M., Hasanuddin I., 2014, Mathematical models to determine the metabolic energy consumption of stoop and squat lifting, Proceedings of the 2nd International Conference on Natural and Environmental Sciences (ICONES), September 9-11, 2014, Banda Aceh, Indonesia, ISSN 2407-2389.

Li J., Zhao Z., Cheng T., 2021, Research on LRP integration of e-commerce logistics under the background of integration of collection and distribution, Discrete Dynamics in Nature and Society, 2021, 1–11.

Li Y., Guo H., Zhang Y, 2017, An integrated location-inventory problem in a closed-loop supply chain with third-party logistics, International Journal of Production Research, 56(10), 3462–3481.

Pilati F., Tronconi R., 2022, Social-economic sustainable vehicle routing problem for local e-commerce platforms, IFAC PapersOnLine, 55(10), 470-475.

Yu H., Solvang W. D., 2018, Incorporating flexible capacity in the planning of a multi-product multi-echelon sustainable reverse logistics network under uncertainty. Journal of Cleaner Production, 198, 285–303.

Zhang M., Pratap S., Zhao Z., Prajapati D., Huang G. Q., 2020, Forward and reverse logistics vehicle routing problems with time horizons in B2C e-commerce logistics. International Journal of Production Research, 59(20), 6291–6310.