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Multi-criteria decision making in supply chain management based on inventory levels, environmental impact and costs

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A B S T R A C T

Supply chains in a global business environment operate within conflicting aspects. This research analyses correlation and interdependencies between inventory levels, costs and greenhouse gas emissions from replenishments within supply chain echelon. A simulation-based inventory optimisation conducted on 4000 experiments assumes the conditions of stochastic market demand, (*R*, *s*, *S*) inventory policy, target fill rates, predefined lead times and closing days constraint. It verifies the influence of operational and logistic decisions such as frequency of inventory replenishments or vehicle size selection on management objectives. Besides determining the best individual results for the objectives of minimum inventory levels, total costs and emissions, the overall best solutions in terms of three decision models – uniformly valued, cost-oriented and environmentally responsible model, were determined using multi-criteria decision-making methodology. These models are relevant for both scientific and practical managerial settings due to the evident lack of research simultaneously analysing inventory, cost and environmental performances of (*R*, *s*, *S*) policy. This study confirms that it is crucial in practice to perform an extensive simulation experiment analysis for each product to be able to determine its optimal settings. Inventory management software should have a direct influence on operational decisions in order to reduce costs or emissions within the same fill rate.

A R T I C L E I N F O

Keywords:
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1. Introduction

According to Cetinkaya *et al*. [1], there are three crucial factors which determine the business environment and the strategy of corporations nowadays: demand (customers and target groups), supply (competitors and suppliers) and general environment (regulations, natural resources, society, etc.). These factors are becoming increasingly complex and dynamic in today's business settings, determining the behaviour of market players. The unique objective of business until recent years was to acquire the maximum economic profit or to improve customer service [2-3]. During the quality revolution of the 1980s and the supply chain (SC) revolution of the 1990s, it has become clear that the best business practices require integration of environmental management with on-going business operations [4]. Severe deterioration of the environment, waste generation and resources depletion, together with legislation and customers' pressure, lead to the development of new concept - Green Supply Chain Management, which is often defined as an approach that implements ecological thinking into traditional supply chain management (SCM), products and services. However, this cannot be done to the detriment of quality, cost or service level, which leads to the growing need to treat inventory management inseparably from environmental and economic objectives [5-7].

The rest of this paper is organised as follows: a review of relevant literature is presented in Section 2. Section 3 provides a formulation of a simulation model and presents the methods used. In Section 4 the experimental results (inventory levels, costs and emissions) are analysed, together with the multi-criteria decision-making method, used to select the favourable solutions by several decision criteria. Finally, research conclusions are given in Section 5.

2. Literature review

In this research, we study the correlation between several aspects of modern SCM - economic performance, inventory management under (*R, s, S*) policy and environmental impact, to provide the useful insights for managerial decisions. The environmental impact of SC activities analysed in this work considers greenhouse gases (GHG) emissions resulting from inventory replenishments based on road freight transport, which is a significant contributor to CO_{2eq} emissions [8]. Venkat and Wakeland observed that carbon emissions, as an indicator of the environmental performance of SC, are highly sensitive to the frequency and mode of deliveries, as well as type and amount of stored inventory. This implies that, even though lean SCs typically have lower emissions due to reduced inventory, frequent replenishments generally increase the level of emissions, particularly with longer-distance trade and globalisation [9]. Increasing customer awareness about environmental issues, especially in Europe and the US, requires transport and storage providers to demonstrate their sustainability. At the same time, modern management forces companies to integrate transportation planning in their management decisions to achieve a reduction of costs and improved customer service [10-11]. To be able to move towards reduction of emissions caused by transportation, companies tend to either adopt electric and hybrid vehicles or to optimise their operational decisions, where operational adjustments might be more cost-effective than investing in more carbon-efficient technologies [12-13].

(*R, s, S*) or periodic review policy is widely present inventory model both in practice and academic literature. Due to its structure, it has been implemented in many business information systems, such as ERP and APS, without the simple algorithms or procedures to determine the optimal characteristic inventory levels in practice [14-15]. Reorder point *s* and order-up-to level *S*, together with review period *R*, are in practical business situations set by inventory managers. Decision-making process becomes even more complicated with opposed, real-life objectives and constraints, such as service or cost-based targets, limited resources and workforce, which is not acknowledged by most of the classic inventory formulas. Additionally, behavioural preference is a substantial factor which affects the decision-making strategies of companies, usually leading to deviations from profit maximisation [16].

Despite the presence of this inventory policy in practice, there is a study gap in the review of the current literature regarding inventory management using (*R, s, S*) policy and related environmental and economic aspects. In this context, papers analysing Economic Order Quantity (EOQ) or other production-inventory models are much more common. The review of relevant literature is shown in Table 1, with specified factors considered in the listed studies.

Kapalka *et al.* described the approach for determining optimal (*R*, *s, S*) policies for inventory management in a practical retail environment, in conditions of stochastic demand and lost sales [17]. Possible benefits are evident in inventory and cost reduction while fulfilling defined service level constraint. Kiesmüller *et al.* compared the economic performance of (*R, s, S*) and (*R, s, t,* Q_{min}) policies with new policy (*R, S,* Q_{min}), taking into an account minimum order quantity (MOQ) parameter [14]. Bijvank and Vis analysed lost sales inventory models with service level constraint, comparing the optimal replenishment policy to (*R, s, S*) policy [18]. Periodic review inventory systems with service level constraint are also studied in the work of Bijvank [19], showing cost performance similar to the optimal policy, justifying their use in practical settings. Gocken *et al.* used the simulation model to determine optimal inventory parameters and review model between continuous and periodic review (*s, S*) inventory policies [20]. Their work included cost analysis and selection of the best supplier.

Table 1 Sustainable inventory models; factors considered in the literature

Studies		Inventory management aspects					Operational aspects				Environmental aspects				Economic aspects				
		Inventory control policy		Demand model															
Authors	Year	Periodic review	Continuous review	Deterministic	Stochastic	EOQ /SEOQ model	Lead-time	MOQ constraint	Closing day constraint	Service-based constraint	Inventory impact on carbon emissions (CE)	CE from logistic activities (LA)	Fuel consumption by LA	Carbon policies	Holding costs	Order costs	Penalty/ lost sales costs	Backorder costs	Transport costs
Kapalka *et al.*	1999	•			•		•			•					•	•			
Wahab *et al.*	2011					•						•		•	•	•			•
Kiesmüller	2011	•			•		•	•							•			•	
Bijvank, Vis	2012	•			•					•					•	•	•		
Chen *et al.*	2013			•		•					•			•	•	•			
Digiesi *et al.*	2013				•	•	•			•		•		•	•		•		•
Benjaafar *et al.*	2013			•		•					•			•	•	•		•	
Konur and Schaefer	2014					•						•		•		•			•
Bijvank	2014	•			•		•			•					•	•			
Battini *et al.*	2014					•					•	•			•	•			•
Tang *et al.*	2015	•			•		•				•	•	•		•			•	•
Gocken *et al.*	2017	•	•		•		•								•	•	•		
Akhtari *et al.*	2019	•		•						•		•	•		•	•			•
This study	2020	•			•		•	•	•	•	•	•			•	•	•		•

Only a few papers that study periodic review policy considered the environmental aspects. The research of Tang *et al.* [21] examines the cost of cutting carbon emissions by reducing shipment frequency and adjusting the inventory control decisions. Akhtari *et al.* [22] used a simulation model to compare the main parameters of forest-based biomass SC for two inventory management systems. The results showed that the selection of inventory system slightly impacts demand fulfilment, but has a considerable influence on total costs and carbon emissions. As mentioned, consideration of factors that have environmental and cost impact is more prevalent within the studies using the EOQ model. An environmental approach to traditional EOQ is introduced in a few works as the new "Sustainable Order Quantity" model (SOQ). Digiesi *et al.* [23] analysed SOQ model with stochastic demand in regards to logistic and environmental costs performance, and Battini *et al.* [24] examined all sustainability factors connected to lot sizing, using the life-cycle assessment approach. Benjaafar *et al.* [13] presented how firms could effectively reduce their carbon emissions, without significantly increasing costs, by making only operational adjustments in regards to transportation, production, inventory management, or collaboration with other members of SC. Chen *et al.* [25] used the EOQ model to discuss a similar concept. In their work, emission reductions are achieved by modifications of order quantities without significant cost increase. Konur and Schaefer [26] studied the integrated inventory control using EOQ model and transportation decisions of a retailer under four different carbon emissions regulation policies. Wahab *et al.* [7] explored the problem of determining the optimal production-shipment policy in domestic and international SC with incorporated consideration of the environmental impact of operational decisions such as a number of shipments, shipment size, the return of defected items etc. Papers of Ferretti *et al.,* Darvish *et al.*, and Yu *et al.* [3, 27, 28] contributed to the problem formulation of this research in regards to environmental or economic aspects of SCM.

3. Formulation of the inventory system model

3.1 General inventory model settings

Inventory model considered in this research consists of a single echelon SC system with stochastic market demand. The model observes operating of a distribution centre (DC) in a period of 90 days, using (*R, s, S*) control policy for managing inventory levels and replenishments from the supplier to fulfil desired fill rates. Main model settings are specified in Fig. 1. Market demand is generated in software programmed in Python, and confirmed to be normally distributed by D'Agostino-Pearson omnibus K2 test in GraphPad Prism software, with P-value higher than the significance level (α = 0.05). Demand is modelled with a mean of 1000 products per day. Standard deviation of demand is defined as high (σ_H), with a value of 200, and low (σ_L) when it's value is 2. In total, our research is based on 400 simulated market demands, grouped per 200 for each standard deviation of demand. Tolerance of mean daily demand, in total observed period is 0, tolerance of standard deviation of demand is ±0.0001, and inventory fill rate tolerance is +0, –0.0001. Simulation model assumes that days without orders from customers may exist. The service-based constraint imposed on DC is defined with fill rates of 90 % and 100 %, calculated for the total observed period. Market demand, product deliveries and inventory levels are of non-negative, integer values. Inventory level is periodically reviewed at the end of each day.

In (*R, s, S*) inventory policy, lowest characteristic inventory levels can only be determined by applying exhaustive brute force search. Brute force search method results in a global minimum of characteristic inventory levels *s* and *S* at the expense of rapidly growing total number of simulation experiments (SE). In total, $1.13 \cdot 10^{13}$ SEs were tested to determine 4000 SEs with the lowest characteristic inventory levels satisfying boundary conditions for the observed period. For numerical analysis, HP ProLiant DL580 G7 server with four Xeon E7-4870 processors and 256 GB RAM was used. Each processor has 10 cores, and with hyperthreading we were able to conduct 80 separate searches parallelly. Generating 400 normally distributed market demands required approx. 8.5 h and brute force search for the lowest characteristic inventory levels of abovementioned 4000 SEs required approx. 23 h.

As our SC model tends to simulate realistic functioning of market-oriented SCs, Saturday and Sunday are defined as closing days for the supplier, while DC works seven days a week. The constraint of closing days makes the calculations more complex, reflecting on increased inventory levels, number of orders and their size, etc. Even though it is common in practice, one of the rare examples where such constraint can be found in the scientific literature is the study of Janssen *et al.* [29], related to perishable inventory model. Initial inventory level in SE is set to the *S* level. If current inventory position *x* at the time of review is equal to, or bellow *s*, an order of size (*S-x)* is placed. Average inventory level (AIL) is calculated for each SE as an average value of average daily inventory levels during the total observed period. MOQ is 1 unit of product. Supplier is reliable and supplying complete ordered quantity at predefined lead times of 0, 2, 5, 10 or 15 working days, meaning that products are delivered and available on the stock of DC in that time. Methods used in this paper are simulation modelling, statistical analysis and description and multi-criteria decision making.

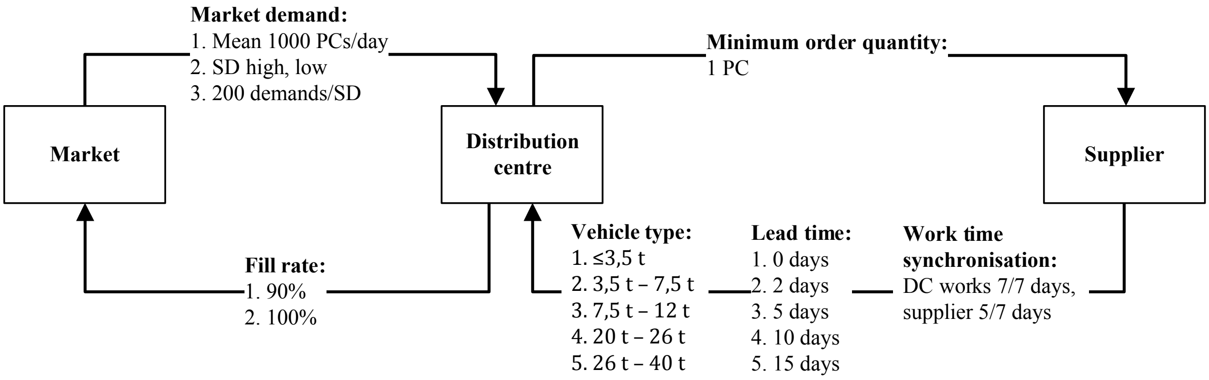

Fig. 1 The settings of the supply-chain echelon simulation model

3.2 Environmental impact of deliveries

Small and heavy-duty trucks together form more than 50 % of the GHG emissions in the transportation sector, which is one of the main contributors to GHG emissions in general [30]. In European Union, between 1990 and 2017, GHG emissions from transport increased by 10 %, although European Commission targets determine that emissions need to fall by around two thirds by 2050, in comparison to 1990 levels, to meet the long-term 60 % GHG emission from transport reduction [31, 32]. Operational decisions that tend to reduce emissions from transport activities can contribute to GHG emission reduction.

In our SC model, product deliveries from the supplier are organised via road freight transport, by five available vehicles of different types and payload capacities as presented in Table 2. The vehicle selection rule assumes using a single vehicle of the lowest category and sufficient payload capacity to transport the complete ordered quantity and weight in one trip. Transported product is of average goods freight type. Fuel used is diesel, emission standard EURO 6. SEs outputs provide information about the number and size of needed deliveries to keep defined fill rates at deterministic lead times. Notation and metrics used in this paper are visible in Table 3. GHG emissions are calculated in compliance with EN 16258, which specifies the methodology for calculation of transport services [33]. The energy consumption calculations are not considered in this study. The European norm EN 16258 prescribes calculation of emissions on tank-to-wheels (TTW) basis, concerning final emission production during vehicle operation, and on well-to-wheels basis (WTW), covering total emissions from the production of energy and vehicle operation. Emission calculations are verified with specialised software tool EcoTransIT by ETW in accordance with EN 16258 [34]. Total well-to-wheels (G_w) and tank-to-wheels GHG emissions (G_t) emitted during the period i = 90 days are calculated according to Eq. 1 and Eq. 2:

$$G_w = G_w(VOS) \cdot N_d \tag{1}$$

$$G_t = G_t(VOS) \cdot N_d \tag{2}$$

Well-to-wheels GHG emissions of the vehicle operating system (G_w (VOS)) for a round trip, are calculated according to [28], as in Eq. 3:

$$G_w(VOS) = F(VOS) \cdot g_w \tag{3}$$

Tank-to-wheels GHG emissions of the vehicle operating system (G_t (VOS)) are calculated according to Eq.4:

$$G_t(VOS) = F(VOS) \cdot g_t \tag{4}$$

3.3 The economic impact of inventory management

Costs taken into consideration in this research are the costs associated with holding and procurement of inventory, transportation costs and penalty costs, calculated for the total observed period. We use the following notation:

C_h are the holding costs, calculated by multiplying the average inventory level, as in the work of Urban [35], by the cost of carrying a single unit of inventory during the observed period, as in Eq. 5.

$$C_h = H \cdot i \cdot AIL \tag{5}$$

Table 2 Specification of fixed transport costs per vehicles

Vehicle type	Maximum total weight (MTW) of the vehicle	Maximum payload capacity, [t]	Maximum number of products per delivery,[PC]	Estimated vehicle price, [€]	Fixed transport cost, F_t, [€/vehicle/trip]
Van	≤3.5 t	1.5	1500	25000	24.7
Truck	3.5 t < MTW≤ 7.5t	3.5	3500	30000	29.64
Truck	7.5t< MTW≤ 12 t	6	6000	70000	69.17
Truck	20t< MTW≤ 26 t	17	17000	120000	118.58
Truck	26t< MTW≤ 40 t	26	26000	150000	148.22

Table 3 Notation and metrics used in this paper

Parameters	Values and units	Variables	Units
Observed period (i)	90 days	Holding costs in the observed period (C_h)	€
Demand mean value (μ)	1000 units/day	Ordering costs in the observed period (C_o)	€
Standard deviations of demand (σ_L, σ_H)	2, 200 units/day	Transportation costs in observed period (C_t)	€
Fill rate (β)	90, 100 %	Penalty costs in the observed period (C_p)	€
Minimum order quantity (MOQ)	1 unit	Total costs in the observed period (C_T)	€
Review period (R)	1 day	Number of deliveries in the observed period (N_d)	-
Fixed order cost (K)	20 €/order	Number of orders in the observed period (N_o)	-
Fixed holding cost (H)	0.005 €/unit/day	Average inventory level in observed period (AIL)	units
Fixed penalty cost (P)	0.1 €/unit/period	Total well-to-wheels GHG emissions in the observed period (G_w)	tonne CO_{2e}
Fixed transportation cost (F_t)	24.7, 29.64, 69.17, 118.58, 148.22 €/vehicle/trip	Total tank-to-wheels GHG emissions in the observed period (G_t)	tonne CO_{2e}
Delivery vehicle payload capacity	1.5, 3.5, 6, 17, 26 tonne	Lost sales factor in the observed period (LS)	units/ period
Well-to-wheels GHG emission factor for diesel (g_w)	3.24 kg CO_{2e}/l	Tank-to-wheels GHG emissions of the vehicle operating system (G_t (VOS))	kg CO_{2e}
Tank-to-wheels GHG emission factor for diesel (g_t)	2.67 kg CO_{2e}/l	Well-to-wheels GHG emissions of the vehicle operating system (Gw (VOS))	kg CO_{2e}
Lead time (L)	0, 2, 5, 10, 15 days	Fuel consumption used for the vehicle operating system (F(VOS))	l
Product weight	1 kg	Load factor (L_f)	-
Distance from the supplier to the DC	218 km		

C_o are the order costs, incurred with each replenishment order to the supplier, calculated according to Eq. 6.

$$C_o = K \cdot N_o \tag{6}$$

C_t are the total transportation costs related to inventory replenishments, as in Eq. 7. They consist of a fixed and variable component, as in the work of Bonney and Jaber [6]. In our model, fixed transportation costs are the costs per vehicle per trip (F_t), defined for each vehicle type, as specified in Table 2, calculated with the assumption that the purchasing price of the vehicle will be paid off in 4 years of utilisation. Vehicles are being used for transport activities of deliveries along the SC and in observed echelon are being used once per every working day, which means 1012 days in 4 year period. Variable transportation costs depend on the load factor (L_f).

$$C_t = F_t \cdot N_d\left(1 + L_f\right) \tag{7}$$

C_p are the penalty costs, charged for the lost sales due to the stock-outs, as in Eq. 8. Lost sales are expressed with LS factor, representing the number of unsold units in the total observed period due to unmet demand caused by a lack of inventory. In this paper, only penalty costs due to unmet demand will be calculated, not considering the loss of reputation, customers, or similar effects.

$$C_p = P \cdot LS \tag{8}$$

Total costs C_T are calculated according to Eq. 9:

$$C_T = C_h + C_o + C_t + C_p \tag{9}$$

4. Results and discussion

Inventory management parameters and related variables resulting from SEs, examined in this research are average inventory level (AIL), number and the size of inventory replenishments (deliveries), GHG emissions from deliveries and SC costs. All inventory, cost and emission variables are calculated on the level of single SE, and later on, grouped based on a standard deviation of demand, fill rate and lead time for transparency and understanding of the results.

4.1 Average inventory level (AIL)

Influence of lead time, fill rate and demand fluctuations on AIL is visible from Figs. 2 and 3. Expectedly, AIL has the highest value in the scenario of the most extended lead time scenario – L15 days, high fluctuations of demand and fill rate of 100 %. Results indicate that demand oscillations have a medium effect on average AILs. When comparing the values of average AILs, for the change of standard deviation from low to high between the groups of the same lead time and fill rate conditions, we find that they can decrease up to 8 % or increase up to 33.7 %. The peak value of 33.7 % occurs for lead time 0, fill rate of 100 % and change from low to high standard deviation of demand.

The influence of fill rate decreases with longer lead times. The maximum increase of average AILs for the shift in fill rate from 90 % to 100 % occurs for 0 days lead time and high standard deviation of demand. In general, average AILs increase with the increase of lead time, fill rate and standard deviation of demand. The highest percentage of average AIL increase, 105.5 %, dependent on the lead time lengthening from 0 to 2 days, occurs in the case of a 100 % fill rate and low standard deviation of demand. Very high increase of average AILs, from 76.9 % to 99.7 %, depending on the fill rate and demand oscillations, is registered for the change of lead time from 5 to 10 days.

The most significant difference between the minimum and maximum AILs occurs for a lead time of 15 days, 100 % fill rate and high standard deviations of demand, followed by those in the conditions of lead time 5 days, fill rate 90 % and high demand oscillations. It is interesting to mention that, depending on the fill rate and standard deviation of demand, a DC needs to have in average 8.4 times higher AILs in conditions of the lead time of 15 days, than of 0 lead times. Numerical simulations showed that the best solution from the aspect of the lowest average AIL levels would be the set of data with lead time 0, fill rate 90 % and high demand oscillations.

4.2 Costs

The structure of average total costs, and the shares of its components – holding, ordering, transportation and penalty costs, are shown in Figs. 4 and 5. It is evident that the minimum average total costs occur under conditions of lead time 0, fill rate 90 % and high demand oscillations. The highest total average costs occur in terms of lead time of 15 days, 100 % fill rate and high demand oscillations. From Figs. 4 and 5 it is visible that the average holding costs account for the significant share of average total costs, and that it increases with the increase of lead time. This share varies from 13.8 % in case of lead time 0, fill rate 90 % and high demand oscillations, up to 89.8 % when lead time is 15 days, fill rate 100 % and high demand oscillations. The highest average transportation costs, making 58.8 % of average total costs, are registered in the scenario with conditions of 0 lead time, low deviations of demand and fill rate of 100 % what corresponds with the maximum average number of deliveries in the total period.

Penalty costs occur only when market demand is not completely satisfied, meaning in scenarios of fill rate of 90 %. They can reach up to a maximum of 20.4 % of average total costs.

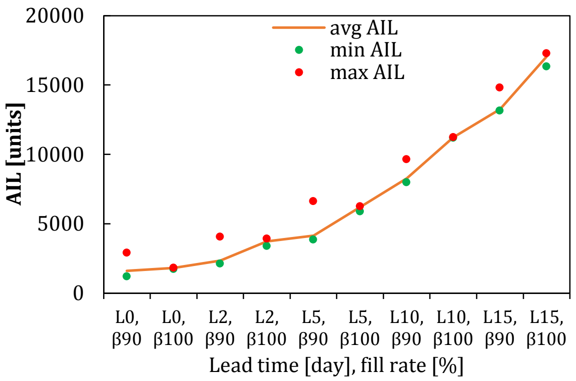

Fig. 2 Average, minimum and maximum AIL_i depending on fill rate and lead times for σ_L

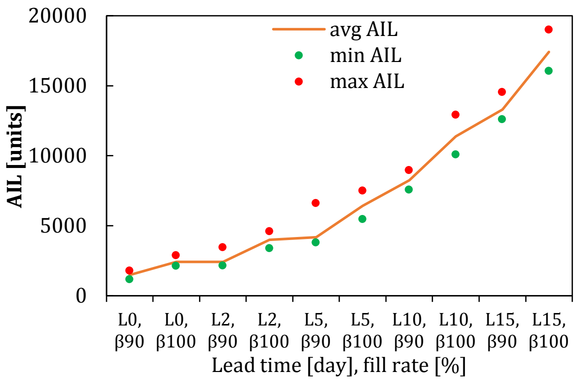

Fig. 3 Average, minimum and maximum AIL_i depending on fill rate and lead times for σ_H

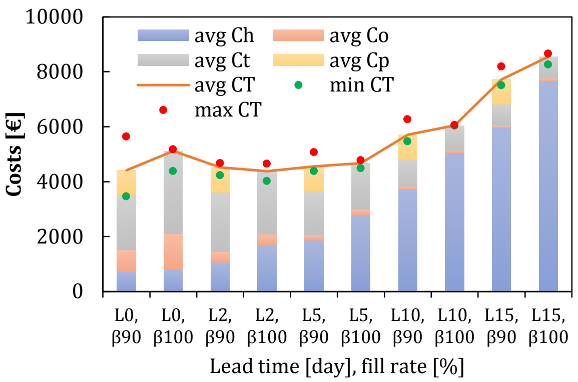

Fig. 4 Minimum, maximum and average total costs and its components for σ_L

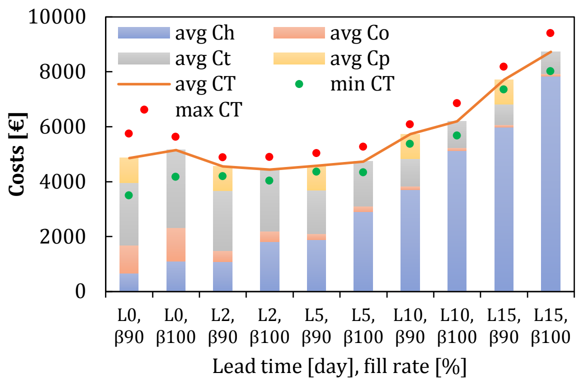

Fig. 5 Minimum, maximum and average total costs and its components for σ_H

Ordering costs have the smallest share, reaching up to maximum 25.2 % of total costs in case of everyday deliveries (lead time 0). Fluctuations of average total costs, depending on demand oscillations, are not significant. There is in average 2 % difference in total costs, when comparing high and low demand oscillations, for the same lead time and fill rate scenarios groups. Fluctuations of average total costs, depending on the fill rate change, are more evident. Per example, the maximum increase of average total costs of 15.8 % occurs for a fill rate increase from 90 % to 100 %, in conditions of lead time 0, and low demand oscillations. The increase in average total costs becomes strongly evident for 5 days lead time and longer. Lead time increase from 5 to 10 days implies the increase of average total costs from 25 % to 30.8 %, and from 10 to 15 days for up to 41.6 %, depending on fill rate and demand. Overall, the lowest average total costs are recorded in conditions of lead time of 2 days, 100 % fill rate and low demand oscillations.

4.3 GHG emissions

The number of deliveries directly influences the amount of GHG emissions. As presented in Figs. 6 and 7, the maximum average number of shipments in the observed period, 63.3, is registered in conditions of the shortest lead time (L0), low deviations of demand, and fill rate of 100 %. The same conditions result in the highest average WTW GHG emissions. Additionally, the lowest total WTW GHG emissions are registered in the situation of the longest lead time; for a lead time of 15 days, 100 % fill rate and low standard deviation of demand. Level of WTW GHG emissions decreases with longer lead times due to reduced frequency and number of deliveries. However, it is necessary to note that the reduction of the average number of deliveries does not cause a linear decrease in emissions. On the other hand, when comparing the average number of deliveries for the lead time of 5 and 10 days, they drop for 52.8 %, while the level of emissions decreases for only 16.3 %. In general, change from low to high demand oscillations within the same lead time and fill rate group, does not significantly influence the level of emissions.

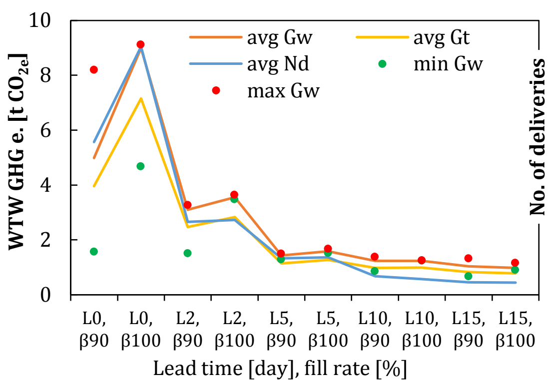

Fig. 6 Minimum, maximum and average total WTW GHG emissions and deliveries for σ_L

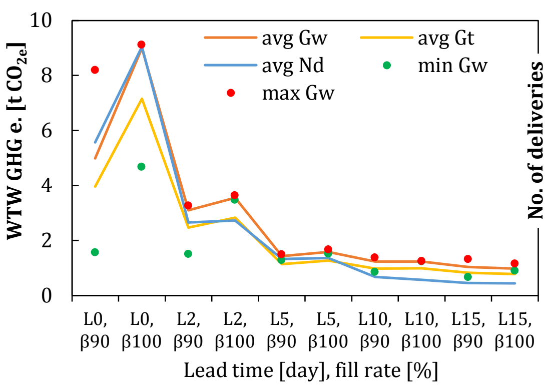

Fig. 7 Minimum, maximum and average total WTW GHG emissions and deliveries for σ_H

Fill rate increase from 90 % to 100 % results in WTW GHG emissions increase, within the same standard deviation of demand and lead time. The highest rise in emissions' level in an amount of 80.4% occurs in the case of the lead time of 0 days and low standard deviation of demand. With longer lead times, it drops to the levels from 14.6 % to 0.3 %. Only lead time group of 15 days differs from this behaviour, where emissions slightly decrease with the increase of fill rate. From this study results, gained from a single echelon model, it is justified to conclude that the frequency of deliveries strongly affects the emitted level of GHG emissions. Therefore, the decrease in deliveries frequency could contribute to deduction of overall emissions.

4.4 Multi-criteria decision making

Trends of the average inventory level, total costs and emissions resulting from SC activities, detailedly analysed in previous chapters, are presented in Figs. 8 and 9. To achieve the overall optimum results in a practical business environment, it is necessary to approach the decision-making process comprehensively, taking into consideration all aspects simultaneously. With this purpose, the weighted sum method (WSM) of multi-criteria decision making (MCDM) was used. Three decision criteria are selected as relevant for the evaluation of alternatives: (i) average inventory levels, (ii) total costs and (iii) WTW GHG emissions. These are all non-beneficial attributes, meaning that minimum value is desired.

In general, for m alternatives and n criteria, the best alternative is, in the minimisation case, the one that satisfies the Eq. 10:

$$PS^* = \min_i \sum_{j=1}^{n} a_{ij}\, w_j, for\ i = 1, 2, 3, \dots, m \tag{10}$$

where PS^* is the performance score of the best alternative, with n representing the number of decision criteria, a_{ij} the actual value of the i-th alternative in terms of the j-th criterion, and w_j the weightage of the j-th criterion. In this paper, values of 4000 alternatives resulting from the equivalent number of SEs, per each of the three decision criteria, are normalised according to Eq. 11 and rescaled in the range between 0 and 1 to be mutually comparable.

$$a_{i,norm} = \frac{a_i - a_{min}}{a_{max} - a_{min}} \tag{11}$$

Normalised values of the alternatives for each criterion are multiplied by the corresponding weightage, depending on the decision-making model. To get performance score of each alternative, all weighted normalised performance values for each alternative are summarised, where the best result is the one that yields the minimum total performance value, as per Eq. 10.

Three decision models which are relevant for both managerial practice and further scientific research are defined - uniformly valued, cost-oriented, and environmentally responsible decision model. Models differ based on the dominant aspect, as specified in Table 4.

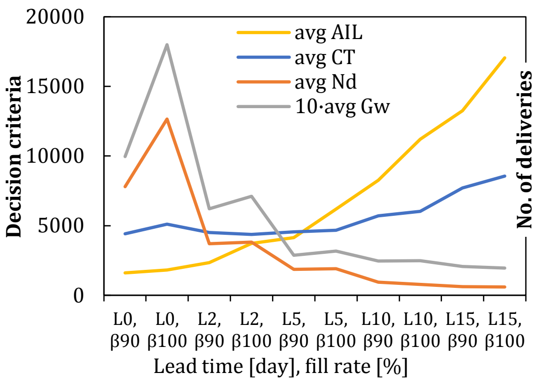

Fig. 8 Number of deliveries and decision criteria in conditions of σ_L

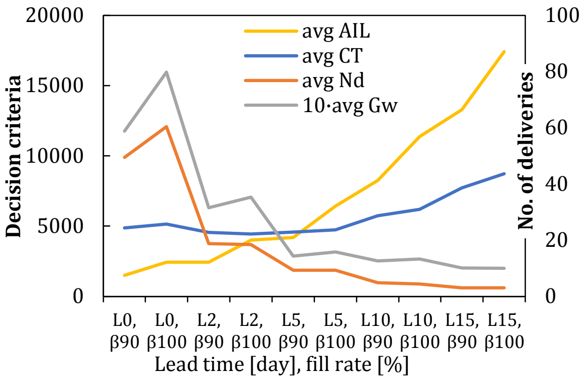

Fig. 9 Number of deliveries and decision criteria in conditions of σ_H

Models are defined based on the goal which wants to be achieved – better environmental or economic performance, or equal performance in regards to inventory levels, costs and emissions.

Weightage factors for uniformly valued decision model are determined according to the objective weighting method – Mean Weight, based on the assumption that all decision criteria are of equal importance. In cost-oriented and environmentally responsible decision model decision criteria are chosen by Point Allocation Method in a way that dominant decision criterion is of the three times higher value than the other two criteria (20-20-60). The number of points allocated to each criterion is assigned by the decision-maker, based on the experience and reasoning. Therefore, subjectivity in this step of the MCDM model, same as in the real world conditions, cannot be avoided entirely. However, there is no subjectivity in all the calculations that precede and follow this step.

Results gained are considerably different within the same lead time, fill rate and standard deviation of demand groups, which is visible from the range width between the maximum and minimum performance score (PS), as shown on Figs. 10 and 11. The difference is even more evident when comparing the overall best ranked (min PS) and worst ranked (max PS) solutions within each decision model. These results are presented in Table 5, together with corresponding decision criteria.

The overall best solution according to the settings of the uniformly valued decision model, occurs in case of shortest lead time and deliveries within the same day (L0), fill rate of 90 % and low standard deviations of market demand. If comparing the performance of the worst solution within the same group (L0, β = 90 %, σ_L), it shows 57.8 % lower AIL, 28 % higher total costs and 416.4 % higher GHG emissions. The overall worst solution would result in 552 % higher AIL, 113.4 % higher total costs and 36.8 % lower GHG emissions.

The overall best solution, according to the cost-oriented decision model, occurs in the same conditions as for uniformly valued decision model: L0, β = 90 %, σ_L. The same conditions, without optimally set parameters, could also result in 27.1 % lower AIL, 62.8 % higher total costs and 93.9 % higher GHG emissions. For the comparison, the overall least favourable solution (with worst performance score) results with 1027 % higher AIL, 171.5 % higher total costs and 76.3 % lower amount of GHG emissions.

The overall best solution according to the environmentally responsible decision model happens in the conditions of the lead time of 5 days, 90 % fill rate and high standard deviation of market demand. In these same conditions significantly worse scenario could occur – that one of 58.6 % higher AIL, 14 % higher total costs and 3.9 % higher GHG emissions. Additionally, when comparing the best solution to the worst-ranked one, the later results in 26.7 % lower AIL, 27.4 % higher total costs and 556.4 % higher GHG emissions. It is visible that the same lead time, fill rate and market demand oscillations level provide optimal solution according to uniformly valued and cost-oriented decision model; the conditions of the lead time of 0 days, fill rate of 90 % and low standard deviation of demand. In an environmentally responsible decision model, the best solution occurs for a lead time of 5 days, fill rate of 90 % and a high standard deviation of demand. In an environmentally responsible decision model, emissions are 302.87 % lower than in cost-oriented decision model, and 113.74 % lower than in uniformly valued decision model. However, this reduction results with 25.8 % higher total costs than in cost-oriented decision model and approximately the same level of the costs as in uniformly valued decision model.

Table 4 Decision-making models and criteria

Decision making model	Uniformly valued decision model (A)	Cost oriented decision model (B)	Environmentally responsible decision model (C)
Model characteristic	each decision criterion has the equal significance	total costs are the dominant decision criterion	environmental impact is dominant decision criterion
Weightage of the decision criteria	AIL : total costs : emissions is $^1/_3 : {}^1/_3 : {}^1/_3$	AIL : total costs : emissions is $^1/_5 : {}^3/_5 : {}^1/_5$	AIL : total costs : emissions is $^1/_5 : {}^1/_5 : {}^3/_5$

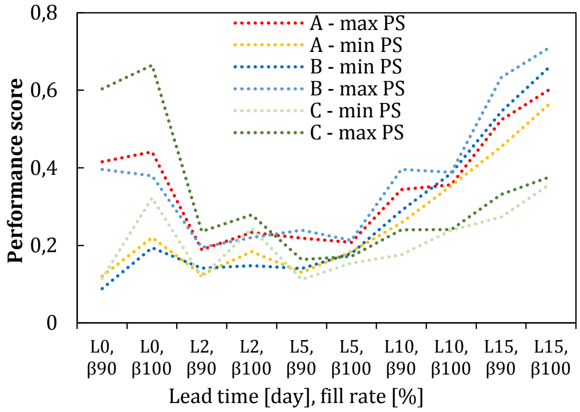

Fig. 10 Minimum and maximum performance scores for each decision model and σL

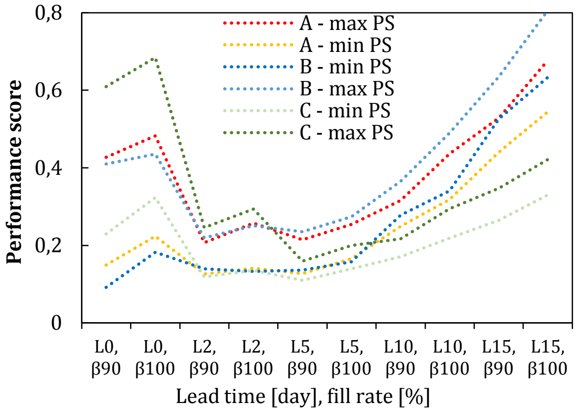

Fig. 11 Minimum and maximum performance scores for each decision model and σ_H

5. Conclusion

In this research, we studied a single echelon inventory system with (*R, s, S*) policy and normally distributed market demand, taking into an account market demand fluctuations, service-based constraints, predefined lead-times and closing days.

In total, 4000 simulation experiments were examined, providing relevant information about the behaviour of various SC performance factors, such as average inventory levels, costs, number and size of inventory replenishments and GHG emissions from delivery activities. To the practitioners in companies operating under (*R, s, S*) inventory policy this offers valuable insights on correlations and interdependencies of characteristic inventory, economic and environmental parameters in conditions of stochastic market demand; information which are not available without the extensive simulation analysis. Research conclusions can be transferred to real-life systems operating in similar situations as defined in our SC model to identify possible improvements for management, find optimal operational settings, enable cost or GHG emissions reduction without jeopardising any operational aspect of SC, etc.

Statistical analysis provides the conclusion about the conditions leading to the individual best solutions in regards to the inventory levels, costs or GHG emissions from transport activities. However, identification of the overall best configuration, considering these three crucial aspects simultaneously, requires a structured analysis of multiple criteria. Therefore, a multi-criteria decision-making method was used to select the optimal results, based on different decision models relevant for managerial business practice – uniformly valued, cost-oriented and environmentally responsible one.

Deviations between the best and the worst-ranked solution (performance score) indicate how much the results can oscillate even within the same lead time, fill rate and demand oscillations group. The results display that even more significant differences occur between the overall worst and best-ranked solution within the same decision model. These differences can reach up to maximum 1127 % for AIL (in cost-oriented decision model), 272 % for total costs (in cost-oriented decision model), and 656 % for GHG emissions (in environmentally responsible decision model), which gives a clear overview on the importance of correct decision-making.

Table 5 The overall best and worst solutions within decision models

Decision model	Rank	L	β	σ	SE	AIL	C_T	G_W	PS
A	the best-ranked score	L0	90	σ_L	5	2902.7	4399.19	1.57	0.120 (min)
A	the worst-ranked score	L15	100	σ_H	3858	18925.7	9389.03	0.99	0.677 (max)
B	the best-ranked score	L0	90	σ_L	61	1679.29	3458.16	4.18	0.089 (min)
B	the worst-ranked score	L15	100	σ_H	3858	18925.7	9389.03	0.99	0.806 (max)
C	the best-ranked score	L5	90	σ_H	1930	3816.38	4350.57	1.38	0.110 (min)
C	the worst-ranked score	L0	100	σ_H	761	2797.12	5544.71	9.05	0.684 (max)

Research results imply that it is crucial to perform complete SEs analysis for each product considered in SC echelon to be able to determine its particular optimal inventory management settings. Therefore, for optimal SCM that takes into an account a wide range of influential aspects, we find that continuous monitoring of inventory, demand, logistics, sales and marketing activities is necessary. Inventory management software should be implemented in the business software of the company at the bottom level, with direct influence on operational decisions. The proposed approach should raise the awareness that operational decisions such as the frequency and size of replenishment deliveries, vehicle category choice but also oscillations of market demand, target fill rates, etc., have a significant impact on inventory, economic and environmental performance in SC.

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