Assessing the environmental impact of integrated inventory and warehouse management

Johannes Fichtinger
Department of Information Systems and Operations, WU Vienna
(johannes.fichtinger@wu.ac.at)
Jörg M. Ries
Department of Law and Economics, Technische Universität Darmstadt
(ries@pscm.tu-darmstadt.de)
Eric H. Grosse
Department of Law and Economics, Technische Universität Darmstadt
(grosse@pscm.tu-darmstadt.de)
Peter Baker
Cranfield School of Management, Cranfield University
(peter.baker@cranfield.ac.uk)

Abstract: There has been considerable research on the environmental impact of supply chains but most of this has concentrated on the transport elements. The environmental impact of warehousing has received relatively little attention except within the context of distribution networks. A high proportion of total warehouse emissions emanate from heating, cooling, air conditioning and lighting and these aspects are largely related to warehouse size. This in turn is greatly influenced by inventory management, affecting stockholding levels, and warehouse design, affecting the footprint required for holding a given amount of stock. Other emissions, such as those caused by material handling equipment, are closely related to warehouse throughput and equipment choice. There is a substantial gap in the literature regarding this interaction between inventory and warehouse management and its environmental impact. The purpose of this paper is to contribute to filling this gap. Therefore, an integrated simulation model has been built to examine this interaction and the results highlight the key effects of inventory management on warehouse-related greenhouse gas emissions. In particular, it is found that decisions on supply lead times, reorder quantities, and storage equipment all have an impact on costs and emissions and therefore this integrated approach will inform practical decision making. Additionally, it is intended that the paper provides a framework for further research in this important area.

Introduction

In recent decades, there has been a continuing rise in global greenhouse gas (GHG) emissions which has led to a new peak of GHG in the atmosphere in 2013 (WMO, 2014). Among them, carbon dioxide (CO_2) emissions are considered as a major trigger of the greenhouse effect and are associated with substantial environmental damage. In the last decade alone, CO_2 emissions reached an average annual increase of about 3% which resulted in a new record of 34.5 billion tonnes of CO_2 being emitted in the year 2012 (Olivier et al., 2013). Taking into account all greenhouse gases, equivalent carbon dioxide (CO_2e) emissions reached a total amount of about 50 billion tonnes in the year 2012, and are forecasted to rise to 58 billion tonnes CO_2e in 2020 (UNEP, 2012; Olivier et al., 2013). While the consumption of energy and the consequent emissions have continually increased, transportation and storage are perceived as an essential driver of environmental pollution in global supply chains. It is estimated that about 2.8 billion tonnes of the overall GHG emissions, which is equivalent to

about 5.5% of the total GHG emissions, are caused by the logistics and transport sector (WEF, 2009).

Meanwhile, the environmentally sustainable management of logistic activities has become an essential element of business strategy and competitive advantage (Sarkis, 2003; Dey et al., 2011). Besides the appreciable social and political pressure to reduce GHG emissions caused by an increasing public awareness of induced global warming and climate changes, many companies have realized that the sustainable use of resources may also be associated with substantial financial savings (Plambeck, 2012). However, most research into the environmental impact of logistics has concentrated on the GHG emissions associated with transport activities (see, for example, Piecyk and McKinnon, 2010 or Ubeda et al., 2011). This is understandable as the World Economic Forum (2009) estimates that, globally, most supply chain emissions emanate from road transport (57%), followed by ocean freight (17%). However, logistics buildings, comprising warehouses and sortation facilities, are significant, accounting for 13% of supply chain emissions. This is more than each of the remaining categories of air freight (8%) and rail freight (5%). National figures, which normally exclude the international element of transport movements, however, emphasize the significance of warehouse-related emissions. In the United Kingdom, for example, the Department of Energy and Climate Change (2013) estimates that warehouses account for 2.1 million tonnes of oil equivalent energy usage (which equates to 4.0 million tonnes of primary energy, due to loss in electricity generation and transmission), compared to 7.7 million for heavy goods vehicles and 5.0 million for light goods vehicles. These figures clearly indicate that GHG emissions emanating from warehouses represent an important element in terms of overall supply chain emissions. The estimation of the overall environmental effect of logistic activities, and the potentially affordable reductions in emissions, requires a full life cycle analysis taking into account the carbon intensity of production, transportation, storage and handling operations (cf. Wu and Dunn, 1995; Dey et al., 2011). Otherwise, the underestimation of logistic-related emissions may lead to undesired effects. For example, the use of less carbon intensive offshore production could lead to higher overall emissions due to longer freight hauls, increased safety stocks and increasing warehouse capacities. Accordingly, the estimation of the overall environmental impact, requires a logistical trade-off analysis similar to those long applied in the economic optimization of logistics systems, but now recalibrated with respect to emissions. This calls for an integrated approach where environmental considerations are implemented in all related areas throughout the logistic chain, with inventory management and warehousing playing a significant role.

The intention of this paper is therefore to contribute to closing this gap in the measurement of logistics-related emissions by developing a structured framework for the assessment of the environmental effects of inventory and warehousing activities. As inventory and warehouse management are closely related, with both affecting the storage space and materials handling activities within warehouses and thus the resulting GHG emissions, they will be considered in an integrated manner. For example, effective inventory management may reduce total inventory levels while guaranteeing an adequate customer service level, leading to reduced inventory costs as well as improved efficiency of the order picking operations as the travel distances are reduced. Similarly, effective warehouse management may improve storage and throughput capacities that would otherwise restrict inventory policy. Thus, both areas are closely interrelated and an integrated view on this topic may lead to substantial savings (Strack and Pochet, 2010). A closer look at the literature, however, reveals that incorporating sustainability considerations into integrated inventory and warehouse management has largely been overlooked. Consequently, as inventory management decisions determine

warehouse operational requirements and vice versa (see van den Berg and Zijm, 1999; Strack and Pochet, 2010; Sainathuni et al., 2014) an integrated model for warehouse and inventory planning is presented in this paper. This enables the systematic estimation of GHG emission influencing factors within inventory and warehouse management by the use of simulation (cf. Figure 1).
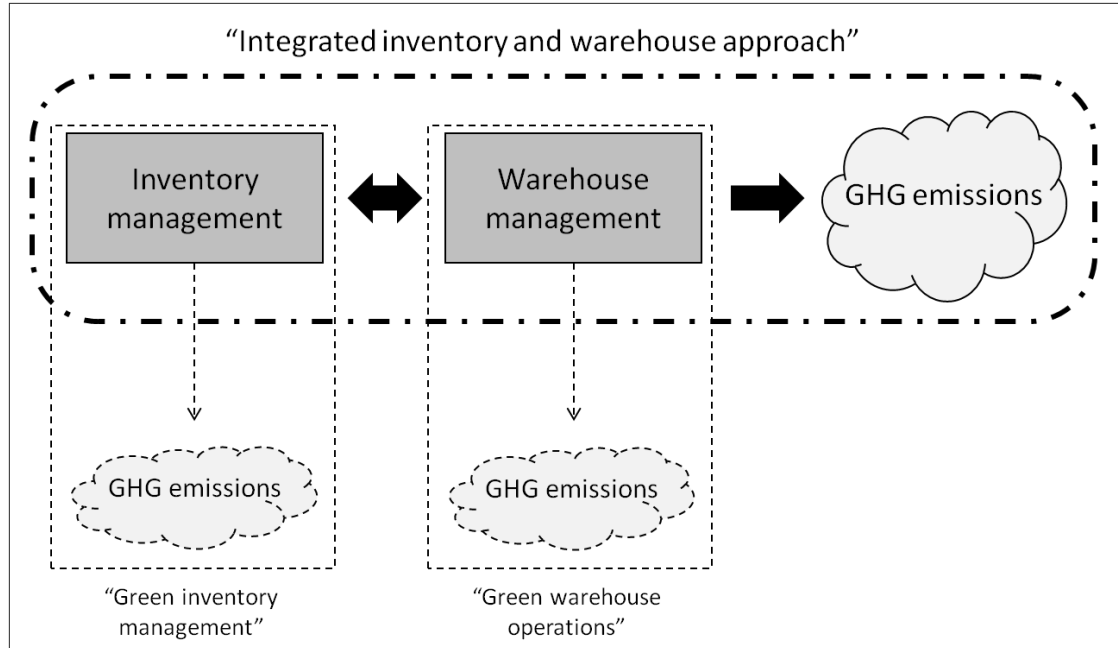

Figure 1: Integrated inventory-warehouse approach for the estimation of GHG emissions

The remainder of this paper is organized as follows: Section 2 provides a review of the relevant literature on energy consumption and GHG emissions related to inventory management and warehousing. Section 3 develops a structured framework for the assessment of the environmental impact of inventory management on warehouse emissions. It also outlines the assumptions and conditions used within the simulation model. The results of the model are presented in Section 4. Finally, the paper concludes with Section 5 presenting managerial implications and directions for future research.

Literature Review
In recent years, there has been a considerable number of papers dealing with sustainability issues in logistics (e.g., Seuring and Müller, 2008; Brandenburg et al., 2014), but there has been rather limited research into the environmental impact of warehousing and inventory management. This section explores the extent of the literature to date in these two areas.

Environmental impact of warehousing
The lack of extensive research to date manifests itself in the uncertainty as to exactly what the energy in warehouses is used for and, consequently, what contributes to warehouse emissions. In fact, even individual warehouse managers often only have knowledge of the total energy used by fuel type (e.g. electricity, gas or oil) from the invoices they receive. They therefore may not know how this is split by usage type (e.g. heat, light or equipment), as reported by Dhooma and Baker (2012). Contradictory figures result from this lack of information and research. For example, the United Kingdom Warehouse Association (2010) reported the results of a survey that indicated that most energy is used for lighting (65% of energy used), followed by heating (12%). This contrasts with estimates published by the

Department of Energy and Climate Change (DECC, 2013) indicating that lighting is only responsible for 29% of energy used whilst heating is more important at 37%. However, both sets of figures agree that equipment energy usage is of lesser importance than these two categories. A detailed study by Dhooma and Baker (2012) of four ambient distribution centres (operated by a distributor) shows figures that are broadly in line with those of DECC (2013), although interestingly fixed materials handling equipment did account for almost 30% of the energy used at one automated facility.

Building and energy literature
It is perhaps to be expected that given the significance of lighting and heating (and in warmer countries presumably ventilation and air conditioning) many of the research papers on these aspects have appeared in building and energy journals. Unfortunately, warehouses are often not specifically examined and in many statistics they are classified with other types of property under "non-domestic buildings". However, these papers are extremely useful for reporting investigations into specific aspects of building construction and energy use, for example, the energy performance of green roofs (Martens et al., 2008), life-cycle costing incorporating carbon taxes (Tsai et al., 2011) and the use of hemp-lime wall construction (Ip and Miller, 2012). One paper in an energy journal that has specifically examined the environmental impact of warehousing is Rai et al. (2011). This used a building computer simulation model to examine the heating and lighting energy impacts of different building attributes (e.g. insulation and rooflights), encompassing both the annual energy usage and the embodied energy within the materials used in construction. Another paper, in an architectural journal, that examined warehousing was that by Aynsley (2011) and this explored the energy savings achievable by de-stratification of air by the use of fans.

Operations management and logistics literature
Some operations management and logistics researchers have concentrated on equipment aspects. For example, Zajac (2011) examined the energy usage of fork lift truck movements, taking into account factors such as the pallet lift height and routing of the trucks, whilst Meneghetti and Monti (2013) examined low energy algorithms for automated storage and retrieval systems (AS/RS).
However, most have tended to examine warehousing as part of distribution network infrastructures. These papers merely use fairly simple measures of warehouse energy usage or emissions. Cholette and Venkat (2009) included warehouse emissions in their distribution network analysis of wine supply chains in the USA. The warehouse component was based on energy per square metre used. Harris et al. (2011) researched distribution network emissions for automotive aftermarket parts in Europe and used a similar basis of electricity usage per square metre whereas Rizet et al. (2010) examined food retail channel options in three European countries. Warehouse costs were estimated based on fuel used per volume of product handled. Zanoni and Zavanella (2012) compared chilled and frozen infrastructures for food products taking into account different temperature regimes and storage periods. The comparison was based on energy and other costs, rather than on energy usage or emissions. Mallidis et al. (2012) examined various distribution network options in South East Europe for white goods. Although warehouse and transport costs were included, only transport emissions were measured. More recent, Pan et al. (2013) examined alternative retail infrastructures in France, with particular reference to pooling supply chains. Again, transport emissions were modelled but not warehouse emissions.
As can been seen, the various sources of energy usage and emissions within warehousing have not been considered in detail within logistics decision models.

Environmental impact of inventory management

Meanwhile, there is a growing body of literature integrating environmental sustainability into inventory control policies. This literature generally focuses on (carbon) emissions which can be integrated in the inventory models in three different ways:

(i) Emissions are converted into a monetary cost which can be included in the objective function. Cost can refer to a carbon tax, carbon trading within a carbon cap-and-trade system, or internal (virtual) steering cost.

(ii) Emissions are considered as a second objective in a multi-criteria optimisation approach. This stream of papers typically analyses efficiency frontiers between cost and emissions.

(iii) Emissions are integrated as a constraint within the inventory optimisation model.

Following the first approach, Bonney and Jaber (2011) extended the economic order quantity (EOQ) model to include environmental cost. They showed that the optimal ordering policy including environmental cost leads to larger lot sizes than the classical EOQ model without environmental cost. Bouchery et al. (2012) is an example of the second approach and they studied the EOQ model in a multi-objective setting where emission criteria are included in the objective function. They identified the efficiency frontier between cost and carbon emissions and showed that carbon emissions could be decreased without increasing cost significantly. Similar conclusions were found by Chen et al. (2013) who analysed the EOQ with a constraint on total carbon emissions, as per the third approach. Other papers using one of these three approaches include Jaber et al. (2012) who modelled a two-stage supply chain where they considered carbon tax and an emission penalty. Hua et al. (2011) examined the impact of inventory management decisions within a carbon emissions trading scheme and assumed fixed, plus linear variable, carbon emissions per unit stored. Arikan et al. (2014) extended the scope of analysis into a wider supply chain setting by including carbon from inventory holding, warehousing and transportation in a dual sourcing setting. They explored the impact of inventory management decisions on transport and warehousing costs and emissions. This paper, however, used a fairly simple model for warehousing, based on emissions per storage unit per day. Similarly, Battini et al. (2014), who examined economic order quantities and transport modes, used emissions per cubic metre stored. However, even in inventory management, the consideration of environmental performance is still in its infancy. Hassini et al. (2012) stated that "one of the least investigated issues in sustainable practices is the choice of inventory management policy".

The literature review shows that:

(i) Integrated models for warehouse and inventory planning are rare, with some notable exceptions (e.g. Strack and Pochet, 2010; Sainathuni et al., 2014).

(ii) There is some research that considers environmental sustainability issues in either inventory management or warehouse management, but these works use rather simple or constant measures of warehouse energy usage or GHG emissions.

(iii) There is, to the best of the authors' knowledge, no work available that considers environmental sustainability in an integrated inventory and warehouse planning model.

This paper is intended to help fill this gap and, in particular, to provide a methodology for modelling the impact of inventory management on warehouse emissions. In addition this paper aims to detail the nature and extent of these emissions, for example in terms of heating, lighting and materials handling.

Model development

Framework and notations

In this section, we develop and present a structured framework which can be used to assess systematically the impact of inventory and warehouse management on GHG emissions resulting from material handling processes and warehouse operations (see Figure 2). This framework is built on an integrated approach of how inventory management affects warehouse requirements and processes (see Strack and Pochet, 2010, or Sainathuni et al., 2014, for other integrated approaches).

Based on customer demand characteristics, a company's inventory policy determines the timing of replenishments and the number of stock-movements in the warehouse, as well as the overall quantity of products stored, by setting appropriate cycle and safety inventories. These stock levels, combined with the number of inventory turns and the extent of cross-docking operations, specify the warehousing requirements of an operation. These requirements lead to decisions concerning warehouse building characteristics, such as sizing and dimensioning, together with the warehouse mechanization, space utilization, the required illumination and the heating, ventilation and air conditioning (HVAC).

Building characteristics impact on energy usage parameters. The lighting energy that is consumed for a necessary level of illumination within a warehouse can be deduced with the help of the lumen method, which is applicable for regular arrays of luminaries with uniform lighting. This also captures maintenance properties such as the deterioration of lamps as well as features that depend on the facility characteristics and operating methods. Aggregated HVAC energy considers the energy demands related to the creation of an appropriate warehouse climate that includes direct heating, cooling and ventilation energy consumption as well as energy wastage due to ventilation processes and heat loss. Heating energy usage in particular is based on building characteristics such as wall and roof insulation, state and quantity of rooflights and doors, and the outdoor temperature.

In addition, warehouses have a certain mechanization factor, i.e. which type of storage equipment is used within the warehouse. We differentiate between the energy consumption resulting from fixed material handling equipment (FMHE) and mobile material handling equipment (MMHE). FMHE energy and MMHE energy consider the energy consumption values of the warehouse equipment (operated by electricity or directly by fossil fuels) needed for the storage and retrieval processes. FMHE encompasses all steady conveyors such as belts or sorters whose energy consumption is merely related to length of the system rather than on the number of movements. In turn, MMHE contains all unsteady equipment such as forklifts, order picking trucks or AS/RS systems, whose energy consumption is dependent on the particular equipment specifications and movement processes. Distances traveled in warehouses are dependent on inventory-related requirements, such as warehouse size, as well as warehouse management decisions (for example routing methods and storage assignment strategies). The latter topics are addressed in Section 3.3.
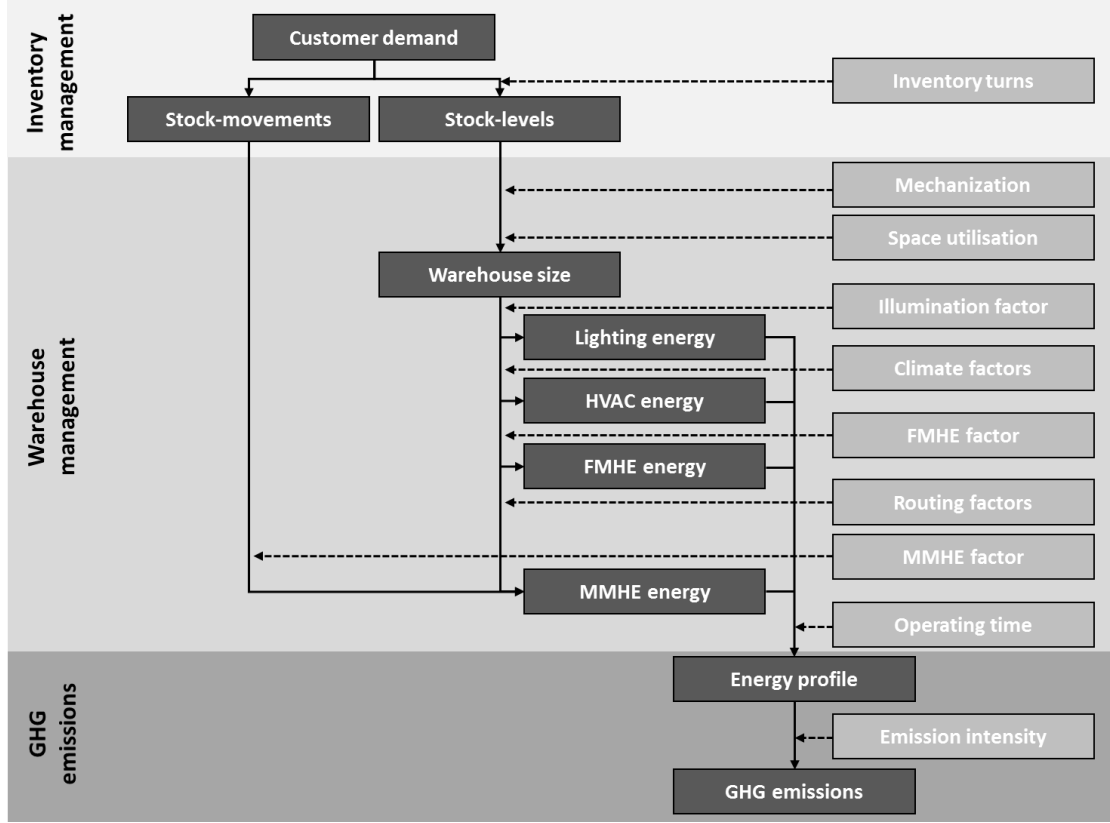
Figure 2: Systematic assessment of warehouse related emissions

Accordingly, the total GHG emissions of the warehouse can be estimated by the aggregated energy consumption values of the described areas within a certain timeframe. To assess GHG emissions of a certain energy profile, appropriate conversion factors that reflect the emission intensity of the specific energy source employed in the warehouse can be used (Carbon Trust, 2013). It is assumed in this paper that sizing and dimensioning decisions are undertaken in a green-field planning situation. Thus, improvements in terms of reduced inventories or movements will lead to changes in the warehouse requirements considered. Obviously, a brown-field or existing site may restrict some of the decision parameters (e.g. sizing and dimensioning) that can be adopted.

The following notations are used throughout the paper:

a	Warehouse shape parameter (lateral depth / longitudinal width)
A	Warehouse space area in [m²]
C_j	Unit cost per item j [€]
D_j	Daily mean demand of product j in [units]
δ_i	Fraction of movements made by equipment i [%]
E_S	Energy consumption related to warehouse space [KWh]
E_P	Energy consumption related to warehouse processes [KWh]
f_I	Illumination factor in [Wh/m²]
f_C	Climate factor in [Wh/m²]
f_A	Automation factor in [Wh/m²]
f_{M_i}	Energy consumption of mobile material handling equipment [Wh/m]
J	Total number of stock keeping units (SKUs) in the warehouse [units]
K_j	Fixed cost of ordering product j including fixed order and inbound transport cost [€]
M	Number of storage and delivery processes per day [units]
n	Number of order lines per order [units]

Q_j	Order quantity for item j [units]
r	Annual interest charges [%]
R_j	Reorder point for item j [units]
S	Aggregated inventory level [units]
SSL_j	Safety stock level of item j [units]
CSL	Target cycle service level [%]
u_D	Storage density as reserve pallet spaces per m^2 [%]
u_U	Space utilization of the warehouse [%]
W	Number of aisles in the warehouse [units]
$\bar{X}$	Average distance for storage and retrieval processes [m]

Inventory management parameters

This paper studies an integrated multi-item inventory-warehouse system of a UK retailer who has to decide on replenishments in the presence of uncertain customer demands. Daily demand in pallets for each stock keeping unit (SKU) is assumed to follow a Poisson distribution with mean daily demand as its parameter.

A UK study by Baker and Perotti (2008) showed that pallet storage is the most common form of storage, representing almost half of the good stored, and that most goods are shipped as full or split cartons. This is therefore the assumption of this model. Although the same study showed an overall average of 23,000 SKUs for large warehouses (i.e. those warehouses over 10,000 square metres in area), we have taken a lower figure of 8,150 SKUs so as to counteract the influence of small item warehouses using bins for reserve storage and to arrive at the dimensions of an average large warehouse in that study (see section 3.3.2).

Additionally, products are classified in three categories (A, B, C) based on their mean demand per SKU as shown in Table 1. The low demand rates resulting from the use of pallets as units are modelled using a Poisson distribution. This is common for slow moving items in the literature; see for example a case study by Boylan et al. (2008).

Table 1: Demand parameters for the three product classes

Product categories	A	B	C
Mean daily demand per product [pallets]	1.2	0.2	0.05
Probability of demand occurring per day	70%	18%	5%
# SKUs	150	1000	7000

It is assumed that the retailer uses a common continuous review inventory control system to determine the size and timing of orders and issues an order whenever the inventory position reaches the reorder point. Lead time is assumed to be deterministic and depends on the actual sourcing strategy. Three different sourcing scenarios are considered as follows: a classical offshore sourcing strategy from the Far East, a nearshore strategy with a supplier in Eastern Europe and an onshore supplier located in close proximity to the warehouse. The scheduled cycle service level (*CSL*) for all sourcing strategies is set at 98% and stockouts are assumed to be backordered. This setting is observable in many practical scenarios, for example in large distribution centres of electronic or apparel retailers.

Considering this scenario, the economic order quantity for item j in a multi-product inventory model is given as:

$$EOQ_j = \sqrt{2K_j D_j / r C_j}. \tag{1}$$

The optimal reorder level R_j for the given customer service level should satisfy:

$$G(R_j) = CSL, \tag{2}$$

where $G(x)$ denotes the cumulative distribution function (cdf) of the demand distribution during the lead time.

Let J denote the total number of items. The actual aggregated inventory level S of this (r,Q) inventory policy will fall between the maximum aggregated stock level $\sum_{j=1}^{J}(EOQ_j + R_j)$ and zero, with an average aggregated stock level of $\sum_{j=1}^{J} EOQ_j/2 + SSL_j$, where SSL_j denotes the safety stock level of item j. It is reasonable to assume that not all deliveries occur at the same time and thus backordered products from incoming deliveries will be cross-docked immediately. Accordingly, the average on-hand inventory determines the minimum storage space requirement in the warehouse.

Relevant warehouse management parameters are discussed in the next section.

Warehouse management parameters

In order to develop a consistent simulation study, we systematically deduce the warehouse parameters that are needed for the consistent evaluation of warehouse emissions (see Figure 2) in conformance with the literature (cf. Gu et al., 2007; de Koster et al., 2007).

In this paper, we study three different types of pallet storage warehouses, i.e. a) wide-aisle racking (WA), b) very narrow-aisle racking (VNA), and c) single-deep automated storage and retrieval systems (AS/RS). The assumptions made for each warehouse type are addressed in the subsequent sections. Firstly, warehouse layout parameters are discussed in Section 3.3.1. In Section 3.3.2 the assumptions for the size and dimensions of the three warehouses under study are summarized. Subsequently, the assumed operational strategies are mentioned in Section 3.3.3 while Section 3.3.4 discusses the transport equipment used. Finally, energy parameters that correspond to the assumed warehouse notations are introduced in Section 3.3.5.

Warehouse layout

The layout determines the configuration of each activity zone as well as the aisle orientation of the warehouse, which includes the numbers of aisles and cross aisles as well as their lateral depth and longitudinal width (Gu et al., 2007; Roodbergen et al., 2008). The standard warehouse layout is of rectangular shape, with aisles in a "north-south" or "east-west" direction. Only a few authors have proposed alternative warehouse layouts, such as U-shaped layouts (Glock and Grosse, 2012). The standard rectangular warehouse layout has frequently been analyzed in the literature (Petersen and Aase, 2004; Bozer and Kile, 2008). Typical layout configurations are presented in Oliver (2010) and these are adopted for the warehouse types under study in this paper. Example figures for the three assumed warehouse layouts are summarized in Figure 3.
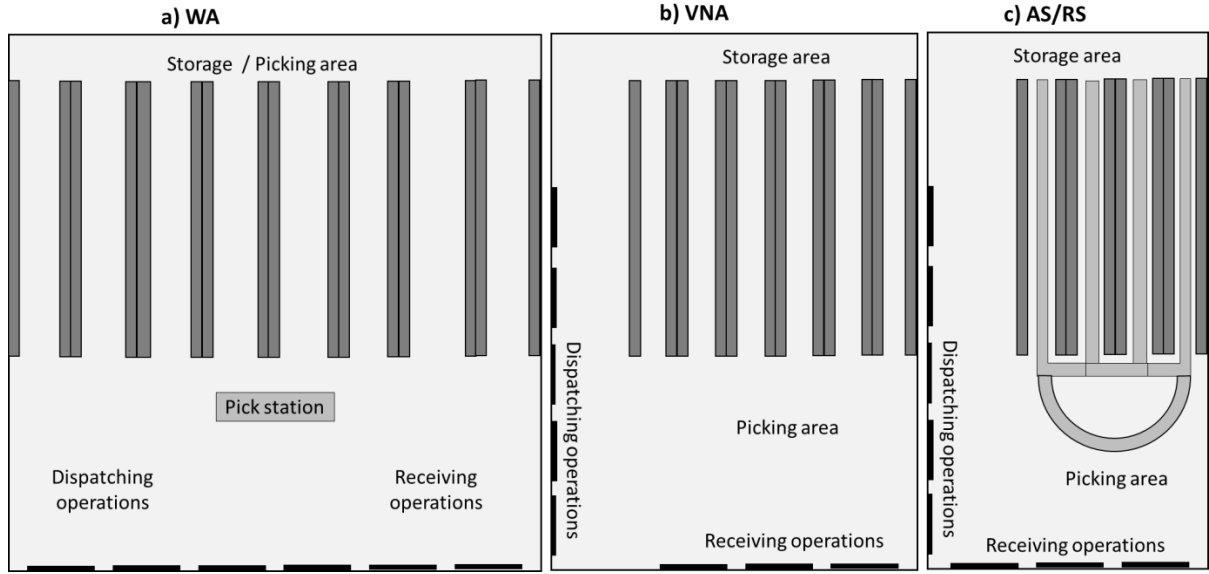
Figure 3: Considered warehouse layouts

A typical layout that is suitable for WA is shown in Figure 3(a). In turn, the layout assumed for VNA is shown in Figure 3(b). This latter type is very common in large warehouses in the UK (Baker and Perotti, 2008). The layout for the third warehouse type under study, i.e. AS/RS, is similar to the VNA configuration and is shown in Figure 3(c). The crane rails stop at the end of the aisles and the goods are taken away by a conveyor to the picking area. For example, AS/RS systems are used in 17% of large warehouses in the UK (Baker and Perotti, 2008).

Sizing and dimensioning

Subsequent to the general warehouse layout, the actual building size and dimensions have to be determined, together with the length and width of the racks, the width of the gap between two racks, and the width of the front and back aisle. Jones Lang LaSalle (2013) indicate that the average size of a large warehouse in the UK was 26,500m^2 during the period 2010 to 2012, and we have taken this figure for the VNA type (as Baker and Perotti, 2008, show this to be a common type). In addition, we have used the typical space percentages from Baker & Perotti (2008) to allocate floor area for pallet storage, picking, goods in/out and marshalling for the VNA solution and then recalculated these for the WA and AS/RS solutions. It is assumed that goods are stored on standard UK pallets with a base dimension of 1200 x 1000mm and a pallet height of 1300mm (including the wood). Taking into account the height limitations of the relevant MMHE and typical warehouse heights, it is assumed that for the three storage types of WA, VNA and AS/RS the pallets are stored at 5, 7 and 15 levels respectively, and with a service aisle width of 2.7m, 1.8m and 1.5m respectively. The storage density given as effective number of pallets per square metre is assumed to be 1.2, 2.6 and 6.0 for WA, VNA and AS/RS warehouse types. Considering further floor space for non-storing activities such as cross-docking or warehouse administration determining the location utilization, the total amount of warehouse space required can be derived as:

$$A = \frac{S}{u_D \cdot u_U}. \tag{3}$$

Further assumptions made for sizes and dimensions of the three warehouse types are deduced from basic warehouse management textbooks and are summarized in Table 2 (cf. Rushton et al., 2014; Gudehus and Kotzab, 2009).

Table 2: Comparative figures for the three warehouse types used as base case

	WA	VNA	AS/RS
Building eaves height (m)	10	13	Storage area: 25 Other areas: 8
Pallets high (no.)	5	7	15
Pallets high of reserve inventory (no.)	4	7	15
Reserve pallet spaces per m^2	1.2	2.6	6.0
Location utilisation (%)	95%	95%	95%
Storage floor area (m^2)	28,708	13,520	5,742
Picking area (m^2)	(included in above)	5,035	5,035
Goods in / out / marshalling (m^2)	4,240	4,240	4,240
Added value activities (m^2)	2,120	2,120	2,120
Other (m^2)	1,855	1,855	1,855
Total warehouse area (m^2)	36,923	26,500	18,992
Resulting storage area factor (%)	75%	50%	30%
Number of aisles (no.)	8	6	4

Operations strategy

The operations strategy determines the selection of receiving, storage, order picking and shipping methods (Gu et al., 2007). It is assumed that goods are received on pallets, stored as reserve inventory on pallets and despatched in full cartons (as per common methods found by Baker and Perotti, 2008). Typically, this step includes order picking decisions, such as assigning SKUs to storage locations and routing of order picking tours. The assumptions made for each kind of warehouse under study are as follows. For WA a picker-to-goods warehouse is assumed where the ground floor positions in the racking act as pick locations and all SKUs have a pallet pick face. Pallets are unloaded from the road vehicle and placed on the warehouse floor for receiving operations. Subsequently, pallets are picked up and placed in racking using a forklift truck. Storage assignment is assumed to be undertaken randomly, which is a reasonable assumption for large retailers as this reduces the required storage space compared to dedicated storage assignment (Frazelle, 2002a; Tompkins et al., 2010). The sequence in which items are retrieved from the storage locations in this type of warehouse is typically defined by order picking routing policies. Although an optimal algorithm for routing order pickers in a rectangular one-block warehouse exists (cf. Ratliff and Rosenthal, 1983), heuristic routing policies, are used in most practical applications (Petersen and Schmenner, 1999). Several routing policies have been evaluated in the literature (Hwang et al. 2004, Petersen and Aase, 2004). Among the most frequently studied policies is the so called S-shape routing policy. It states that the order picker traverses each aisle that contains at least one pick completely and then returns to the pick station, where each tour starts and ends. Assuming an S-shape routing strategy, the average distance for retrieval processes per day is given as (Hall, 1993):

$$\bar{X} = \sqrt{A}\left[\left(\frac{1}{\sqrt{a}}\right)\frac{2(n-1)}{(n+1)} + \sqrt{a}\left(W\left(1 - \left(\frac{W-1}{W}\right)^{n}\right) + 0.5\right)\right] \qquad (4)$$

where *a* is the warehouse shape parameter (lateral depth/longitudinal width) which we assume as 0.5, and *W* the number of aisles and *n* the number of picks per run. We assume on average n = 20.

For VNA, we assume that the operation is also picker-to-goods and is fairly traditional, as defined in the touch analysis of Frazelle (2002b). Pallets are picked up from a vehicle and placed on the warehouse floor for receiving operations. Pallets are then taken to a deposit station at the end of narrow-aisle racks and placed in racking. Upon order request, the pallet is retrieved from racking and placed in the picking area (assumed 20% of SKUs in ground floor pallet area and 80% of SKUs in bin shelving on mezzanine above, so as to reduce travel distance in the separate pick area which is recommended for VNA operations of this nature; see Rushton et al., 2014). It is assumed that the goods are lifted to the mezzanine through a pallet gate, then manually stacked onto shelves. All goods are picked onto pallets in the picking area. The full picked pallet is than retrieved from the ground floor pick area or mezzanine pallet gate and taken to the marshalling area (for dispatch operations). From there the pallet is loaded onto the vehicle. Here random storage is also assumed in the VNA pallet storage area. However, in comparison to WA, a single pallet is retrieved from the storage area and placed in the picking area. Thus, the average distance is given as

$$\bar{X} = (1 + a)\sqrt{a^{-1}A}. \tag{5}$$

For a comparative AS/RS operation, a similar pick face is assumed as for the VNA example. It is assumed that after checking at goods-in, the pallets are placed on a conveyor to the AS/RS and automatically picked up by the crane. For replenishment, the goods are transferred to a conveyor which takes the good to a spur next to the pick area (and onto the mezzanine in the case of medium/slow moving goods). Pallets are transported automatically on a conveyor to the pick area where the order picker retrieves the demanded cartons. From there, cartons are transported to the dispatching area. Although the automated cranes only move in a longitudinal direction, there will be a lateral powered movement of the pallets by conveyor to reach the appropriate aisle, and therefore Equation (5) is also used for the average distance in the AS/RS operation. It is further assumed that the AS/RS operates on a single command basis, i.e. only a single storage operation is performed by the machine, either a retrieval or a storage operation (Bozer and Cho, 2005).

In addition, vertical movements for retrieval processes dependent on the respective warehouse height (see Table 2) are considered for all three warehouse types.

Transport equipment
In the next step, the level of automation as well as the storage and material handling equipment, is selected (Gu et al. 2007). Fully automated order picking in warehouses involves a great deal of capital investment and leads to low flexibility, thus most warehouses employ humans with low to medium technical support (de Koster et al., 2007). All types of warehouses under study receive goods on pallets, store reserve inventory on pallets and despatch in full cartons, so in all types of warehouses forklift trucks are used for some or all of these operations. The differences for each type of warehouse in fixed and mobile equipment are assumed as follows.

For WA it is assumed that order picking is fairly traditional with only slight technical support. For example, in the UK most pallet warehouses use electrically powered low-level order picking trucks as mobile equipment (Baker and Perotti, 2008), so this is assumed for the WA warehouse. The order picker then starts walking through the aisles in the warehouse and retrieves items picking them directly onto a pallet placed on the low-level order picking

truck. After all items have been retrieved, he/she returns to the pick station and starts the next order. At the pick station, some rearrangement and stretch-wrapping activities are performed and the pallet is transported to the dispatching area.

For VNA it is assumed that storage and retrieval operations are performed using VNA trucks (so called turret trucks). After pallets have been transported to the picking area, order picking is performed manually there. On the mezzanine floor, hand-pushed trolleys are used.

For AS/RS it is assumed that there exists a conveyor as FMHE and the AS/RS as MMHE. Picking is as per the VNA warehouse model.

Energy parameters and GHG conversion factors

Energy consumption occurs within warehouses in several forms as discussed in Section 3.1. As per Figure 2, we differentiate between energy factors related to storage space or building characteristics (i.e. lighting, HVAC and FMHE) and energy factors related to storage and retrieval operations (MMHE).

Energy for which consumption is based on the effective storage area can be derived by considering the effective floor space and the relevant energy consumption factors (see also Table 3). Thus, the space-related energy consumption is given as:

$$E_S = A \cdot (f_I + f_C + f_A) \tag{6}$$

The energy consumption for storage and retrieval processes can be derived from the number of movements, the average movement distance and the energy consumption of the various types of equipment used to perform the processes (for a similar approach see Geerlings and van Duin, 2011) and is given as:

$$E_P = (M \cdot \bar{X}) \sum_{i=1}^{I} \delta_i f_{M_i} \tag{7}$$

Apart from the assumptions already stated, we assume the following hereafter in terms of energy parameters for the simulation study, as summarized in Table 3.

Table 3: Energy parameters for the three warehouse types

		WA	VNA	AS/RS	
				High bay (storage)	Low bay (picking, goods in/out/marshalling, added value activities, other)
Lighting energy [kWh/m²/year]		36			
HVAC energy [kWh/m²/year]		300		200	300
FMHE energy [MWh/year]		N/A	N/A	N/A	240
MMHE energy	Horizontal [Wh/m]	2		3.2	N/A
	Vertical [Wh/m]	20		32	N/A

Building characteristics are considered in conformance with the literature (Rai et al., 2011), assuming a medium envelope insulation level in all warehouses. Lighting parameters are set per Marchant and Baker (2010), UKWA (2010) and CIBSE (2002), assuming the use of T12 8ft fluorescent lamps in all types of warehouses. HVAC parameters are assumed according to Rai et al., (2011), CIBSE (2004) and Dhooma and Baker (2012). As regards FMHE a conveyor is assumed that transfers pallets from the AS/RS to the picking areas (for energy values, see Dhooma and Baker, 2012). Energy parameters are taken from product brochures

of storage equipment companies (for example SSI Schäfer). For MMHE (fork lift trucks, low-level order picking trucks) energy consumption to VDI Cycle, i.e. the German engineering standard as common in industry (VDI, 2012), is given per fork lift truck data sheets published by manufacturing companies (for example Still and Linde). Note that energy consumption for electrical driven forklift trucks may also be dependent on the type and age of battery and charging device.

In addition, following the framework in Figure 2, it is assumed for the parameter "operating days" that all types of warehouses work 5 days per week and 16 hours per day (as indicated as common timings in Baker and Perotti, 2008). Finally, to calculate GHG emissions of warehousing operations based on the integrated inventory and warehouse model, the emission intensity has to be determined. This is usually done by using appropriate conversion factors, which convert various types of fuels into kWh as a standard measure. Based on the kWh value, the resulting GHG emissions in $kgCO_2e$ can be calculated. Conversion factors for the fuel types, which are natural gas for heating and electricity for all other energy uses, are summarized in Table 4 (CIBSE, 2002; Carbon Trust, 2013). Note that GHG emissions for electricity are dependent on the energy mix used (e.g. the amount of solar-sourced, nuclear, hydro or wind power).

Table 4: Energy conversion factors

	Unit of supply	$kgCO_2e/kWh$
Natural gas	1 m^3 = 11.50 kWh	0.184
Electricity	-	0.445

Simulation model
This paper makes use of a simulation model to explore and compare the impact of inventory decisions on warehouse emissions for different warehouse design parameters as shown in Figure 2. Although the choice of fixed parameters and the ranges of variable parameters have been carefully selected from available warehouse statistics and case studies described in the literature, the simulation model presented in this paper models prototypical warehouses without direct representation in the real world. The aim of this simulation model is to generate insights on generic warehouses using representative data.

The calibration of input data was done using an iterative procedure. We first identified expected emission outputs from reports and statistics as discussed in our literature review on the environmental impact of warehouses, then run the simulation to compare the actual simulated emissions with the expected emissions. We tuned input parameters so that simulation output and expected values matched. Changes in model results were checked for plausibility and consistency with the expected direction of changes. Finally, the simulation model was validated by ensuring that the final input parameters as described in Tables 1-3 are plausible.

The purpose of the simulation model, which considers the integrated inventory management and warehouse operations system described above, is to derive realistic warehouse energy consumption figures that can be used as a proxy for CO_2e emissions. By using a structured approach, root causes of emission generation become clear and the effect of different actions for reducing inventory and warehouse related emissions emerge. Thus the following model facilitates the estimation of benefits from potential investments in environmental measures related to inventory and warehouse management, therefore enabling management to allocate financial resources effectively.

Additionally, we simulate inventory holding cost and compare changes in cost and emissions. Note that we do not aim for detailed modelling of fixed and variable cost of warehouse operations as there is no obvious way of comparing cost of different warehouse types.

However, we compare relative changes in emissions with changes in inventory holding cost as the focus of this paper lies on the impact of inventory management decisions on warehouse emissions.
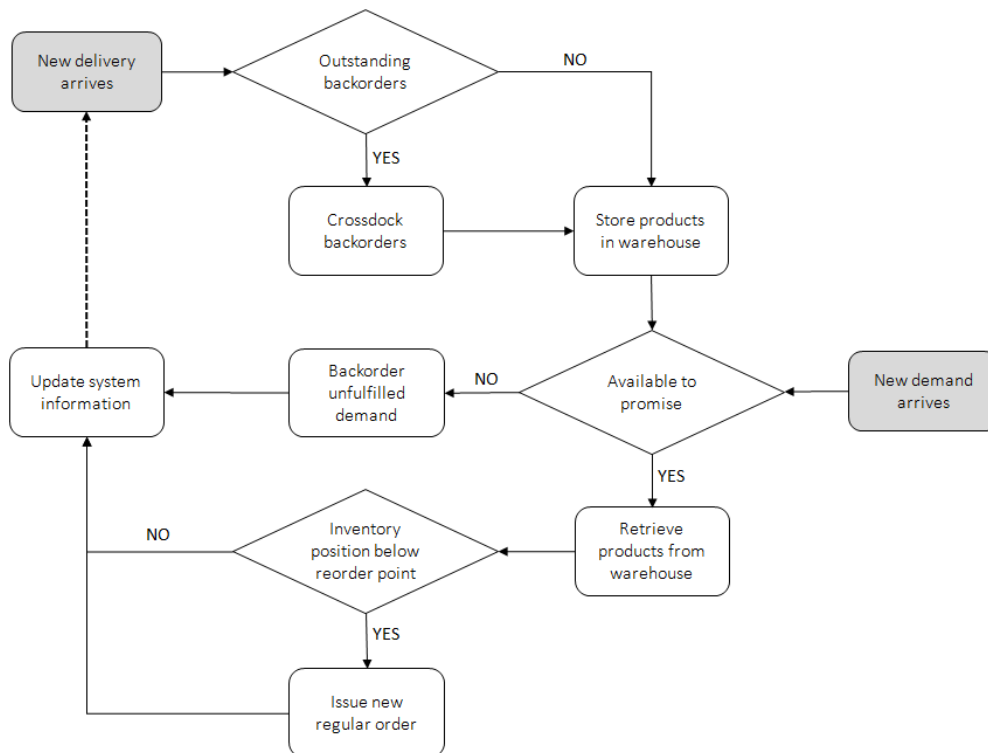

Figure 4: Simulation process chart

Figure 4 illustrates the decision process. As shown in the flow chart, the retailer faces a random daily demand which is satisfied from on-hand stock as long as possible. In doing so, the retailer executes retrievals from the applied storage system. Whenever the inventory position declines to or below the reorder level, an order is issued that is delivered by the particular supplier whose lead time is affected by the sourcing location (e.g. onshore, nearshore or offshore). Demands that cannot be fulfilled by on-hand stock will be backordered until the beginning of the subsequent order cycle. As soon as a delivery arrives, backordered demands are satisfied via cross dock and the remaining items are stored in the warehouse.

The simulation model itself has been implemented as a stochastic, discrete-event simulation model in Anylogic 7. The model was run for 100,000 decision periods (days) for each configuration. We used pseudo-random demand data for the simulation to be able to reproduce exactly the simulation results. In the following analysis we only report sample means as all standard errors are negligible because of sufficiently large sample sizes.

Numerical design

Three different sourcing scenarios (offshore, nearshore, onshore) are analysed for the three previously explained warehouse types (WA, VNA, AS/RS racking). The base case represents a classical offshore sourcing strategy from the Far East. Total lead time including supplier lead time and transit time is assumed to be 49 days into the UK warehouse. For a nearshore strategy we assume a supplier in Eastern Europe with a total lead time of 7 days including supplier lead time and transit time. As a third case we take an onshore supplier located in close proximity to the UK warehouse with a total lead time of 2 days. Order fixed costs K_j are

assumed to be 200, unit cost per item j is 100, and the holding cost per item is assumed to be 20% per annum (0.066% per day).

An ABC classification is adopted for all SKUs with equal demand characteristics within each class in order to simplify the simulation (see Table 1 for detailed demand parameters). Table 2 shows warehouse related parameters for the three warehouse types, and Table 3 provides energy and emission related parameters used in the simulation model. We simulate a full factorial design for all sourcing scenarios and warehouse types. The output of the simulation are the required warehouse space and activity figures of material handling equipment for a given inventory policy. We then report and analyse the consequent inventory cost and emission figures.

Simulation results

Based on the simulation approach, Table 5 shows the absolute emissions in $kgCO_2e/day$ for the three warehouse types and sourcing scenarios.

Table 5: Absolute emissions in $kgCO_2e/day$ for the three warehouse types and sourcing scenarios

	WA	**VNA**	**AS/RS**
Offshore	6,260	4,677	4,204
Nearshore	5,550	4,319	4,007
Onshore	5,322	4,203	3,942

It can be seen that in any considered scenario AS/RS warehouses have the lowest CO_2e emissions whereas WA warehouses have the largest emissions. This can be mainly explained by analysing the emissions of the different end-use categories HVAC, lighting, MMHE and FMHE as shown in Tables 6 and 7 and illustrated in Figure 5 which is based on the offshore scenario. Both HVAC and lighting roughly depend linearly on the total building size in m², which is smallest for AS/RS systems.
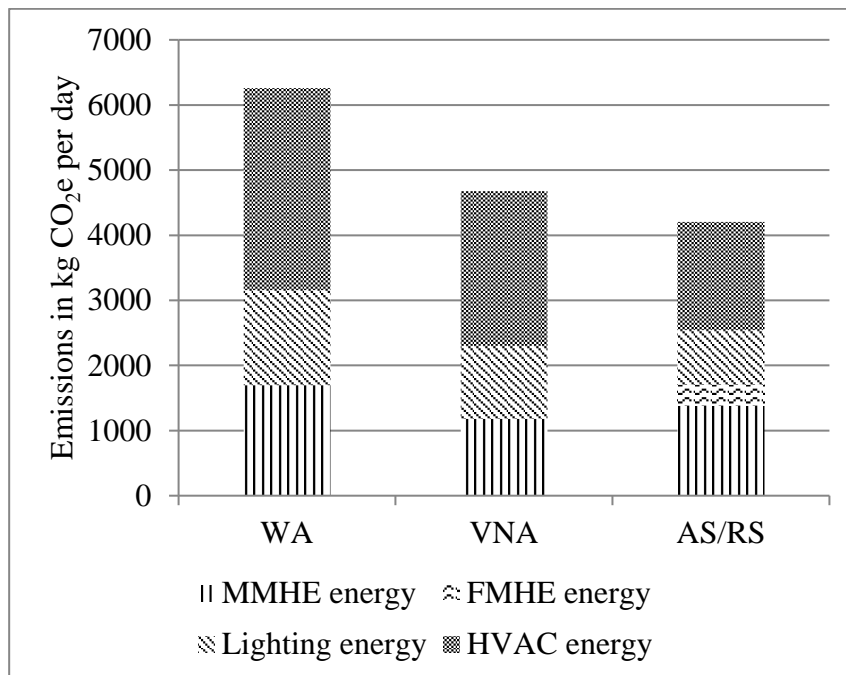

Figure 5: Emission split based on offshore scenario

As Tables 6 and 7 indicate, the emissions for the nearshore and onshore scenarios are proportionally smaller without significant changes in the distribution of emissions to the end-use categories.

Table 6: Emissions from each end-use category and total emissions for the different warehouse types and sourcing scenarios

	Offshore			Nearshore			Onshore		
	WA	VNA	AS/RS	WA	VNA	AS/RS	WA	VNA	AS/RS
MMHE	1,695	1,183	1,388	1,551	1,084	1,284	1,502	1,051	1,250
FMHE	0	0	314	0	0	314	0	0	314
Lighting	1,463	1,120	839	1,282	1,037	802	1,225	1,010	791
HVAC	3,101	2,375	1,664	2,718	2,198	1,606	2,596	2,142	1,588
Total	**6,260**	**4,677**	**4,204**	**5,550**	**4,319**	**4,007**	**5,322**	**4,203**	**3,942**

Table 7: Emissions in per cent of total emissions for each end-use category

	Offshore			Nearshore			Onshore		
	WA	VNA	AS/RS	WA	VNA	AS/RS	WA	VNA	AS/RS
MMHE	27.1%	25.3%	33.0%	27.9%	25.1%	32.1%	28.2%	25.0%	31.7%
FMHE	0.0%	0.0%	7.5%	0.0%	0.0%	7.8%	0.0%	0.0%	8.0%
Lighting	23.4%	23.9%	19.9%	23.1%	24.0%	20.0%	23.0%	24.0%	20.1%
HVAC	49.5%	50.8%	39.6%	49.0%	50.9%	40.1%	48.8%	51.0%	40.3%
Total	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %

An interesting observation is that the sourcing strategy does have a significant impact on the warehouse emissions. It is well-known that transportation emissions increase when sourcing from offshore suppliers rather than from onshore suppliers. The results in Table 8 show that warehouse emissions are also significantly affected by the sourcing strategy: For example in the WA scenario, offshore sourcing increases warehouse emissions by 15% compared to onshoring and 11.3% compared to nearshoring.

Table 8: Relative change in emissions if offshore strategy is changed to nearshore and onshore

	WA	**VNA**	**AS/RS**
Offshore	–	–	–
Nearshore	-11.3%	-7.7%	-4.7%
Onshore	-15.0%	-10.2%	-6.2%

There exists, however, a strong interaction effect with the warehouse type: As can be seen in Table 8, emissions of the WA warehouse are more sensitive to changes in the sourcing strategy than the VNA and AS/RS warehouse. The reason for this is that when extending the storage space of the warehouse to cope with larger safety stocks, areas for order picking and other operations, which only depend on throughput, remain the same. Since storage takes the largest proportion of overall warehouse space in the WA warehouse, an increase in safety stocks has a stronger impact for the WA warehouse. Comparing different warehouse types, the WA warehouse results in the highest emissions for all sourcing scenarios compared to VNA and AS/RS warehouse. The relative change in emissions if WA warehouse changes to VNA and AS/RS, respectively is shown in Table 9. In the offshore scenario for example,

changing from WA to VNA saves 25.3% emissions, or 32.8% emissions when changing to an AS/RS warehouse.

Table 9: Relative change in emissions if WA changes to VNA and AS/RS type

	WA	VNA	AS/RS
Offshore	–	-25.3%	-32.8%
Nearshore	–	-31.0%	-36.0%
Onshore	–	-32.9%	-37.0%

We did test the same for the nearshore and onshore scenarios as well. The effects are similar: In the nearshore scenario, emissions reduce by 31% (36%) when instead of the WA warehouse a VNA (AS/RS) warehouse is used. In the onshore scenario, emissions reduce by 32.9% (37%) when a VNA (AS/RS) warehouse is used.

In the analysis above cost optimal order quantities were assumed. However, changes in the inventory policy may also lead to changing emissions. In order to analyse the effect when other than cost optimal order quantities are used, we introduce a factor $\alpha \in [0,2]$ and define the order quantity for item j as $Q_j = \alpha * EOQ_j$. By plotting over α it is possible to aggregate energy consumption over SKUs. Note that $\alpha = 1$ refers to the cost optimal order quantity, any $\alpha < 1$ refers to a smaller order size than EOQ and vice versa.

For the analysis of the relative changes in cost and emission, let $TC(Q)$ denote the total inventory holding and ordering cost for a given order quantity and $TE(Q)$ the respective total emissions. The relative cost and emission change, $\Delta TC(\alpha)$ and $\Delta TE(\alpha)$, are defined as:

$$\Delta TC(\alpha) = \frac{TC(\alpha \times EOQ) - TC(EOQ)}{TC(EOQ)} \tag{8}$$

and

$$\Delta TE(\alpha) = \frac{TE(\alpha \times EOQ) - TE(EOQ)}{TE(EOQ)}. \tag{9}$$
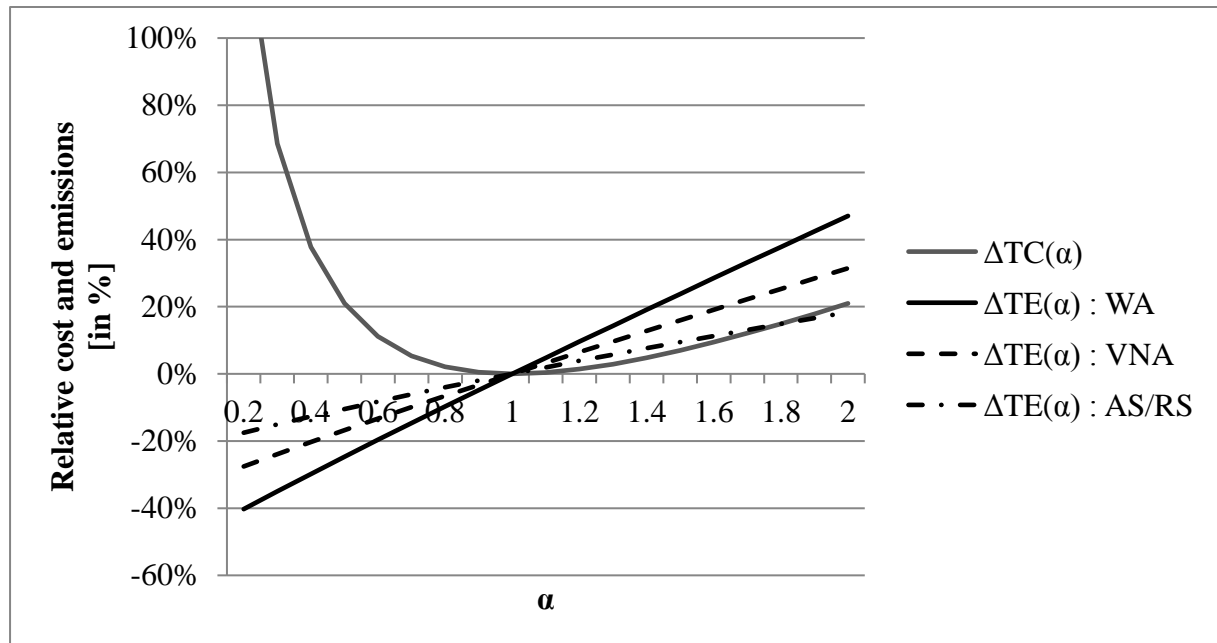

Figure 6: Relative cost and emissions changes when deviating order quantity from EOQ

We can see from Figure 6 that whilst relative costs have their minimum by definition at α, energy consumption is monotone and linear in relation to the order quantity (note that the

figure is based on the offshore scenario). The inventory cost function is relatively flat in the close neighbourhood of EOQ and increases exponentially with α, whilst total emissions are increasing linearly with α. This has the effect that a small deviation from optimal order quantity has a smaller impact on inventory cost than on energy consumption. This implies that significant energy savings can be made with very little cost implications. Our extensive numerical analysis shows that a typical energy reduction of between 10% and 12% can be achieved with a smaller than 2% increase in total inventory cost. Absolute values of this change are shown in Table 10.

Table 10: Absolute cost and total emission data when reducing the order quantity by 20% from EOQ, example for offshore scenario. All data are per day.

	Cost	Emissions [kg CO_2e per day]		
		WA	VNA	AS/RS
Q = EOQ	59,913	6,259	4,677	4,204
Q = 0.8 * EOQ	61,170	5,650	4,369	4,035

Table 11 shows the relative changes in cost and emissions for different α factors.

Table 11: Relative changes (in per cent) in cost and emissions for different α factors

	Offshore				Nearshore				Onshore			
	ΔTC	ΔTE			ΔTC	ΔTE			ΔTC	ΔTE		
α		WA	VNA	AS/RS		WA	VNA	AS/RS		WA	VNA	AS/RS
1.0	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.9	0%	-5%	-3%	-2%	1%	-5%	-4%	-2%	1%	-6%	-4%	-2%
0.8	2%	-10%	-7%	-4%	2%	-10%	-7%	-4%	2%	-12%	-8%	-5%
0.7	5%	-15%	-10%	-6%	6%	-15%	-11%	-7%	6%	-18%	-12%	-7%
0.6	11%	-20%	-13%	-8%	12%	-20%	-15%	-9%	13%	-24%	-16%	-10%
0.5	21%	-25%	-17%	-10%	23%	-25%	-19%	-12%	24%	-30%	-20%	-12%

As can be seen in Table 11 emission savings have a very steep increase for low cost values. A small increase in cost results in a relatively large emission saving. Comparing the three warehouse types, it can be seen that the WA warehouse has the largest potential for emission reduction by slight reduction of the order quantity from the cost optimal point. The AS/RS warehouse type has the smallest emission reduction potential by adjusting inventory parameters. The total possible energy saving for the AS/RS warehouse, even at high cost levels, does not exceed 10% significantly.

Figure 7 illustrates this situation by plotting the relative emission savings in percent as a function of relative cost increase, where the reference point is EOQ_j for all SKUs J.
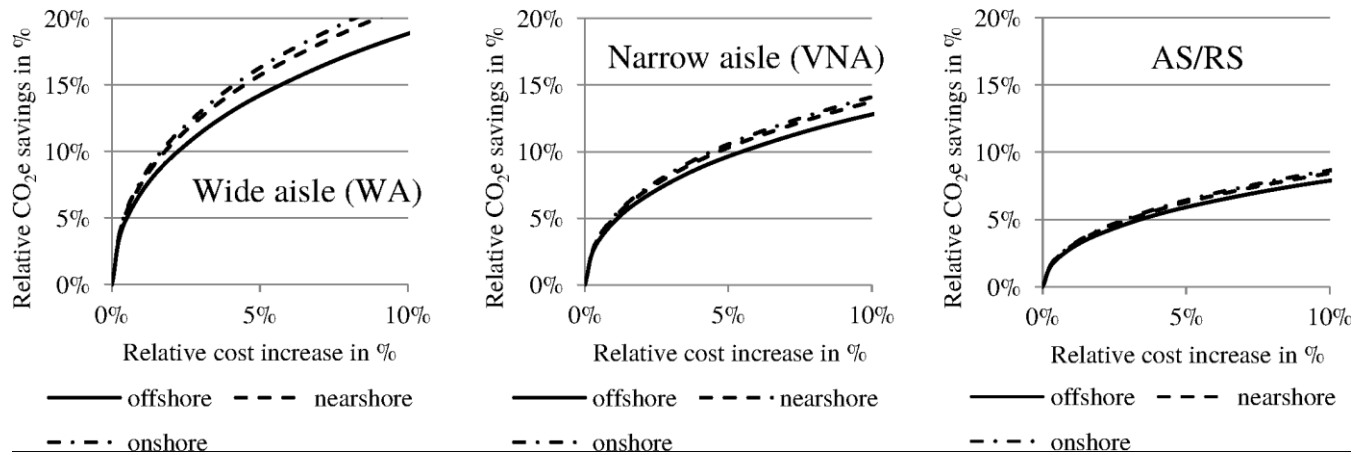
Figure 7: Relative emission savings in % as a function of relative cost increase in % for the three sourcing scenarios and warehouse types

Discussion

This paper has developed a structured framework for the assessment of the environmental impact of warehousing and material handling activities. Inventory management and warehouse management are closely related. Both affect the material handling processes and the storage requirements within a warehouse and, consequently, the resulting GHG emissions. Therefore, an integrated inventory warehouse approach is considered. The framework developed in this paper enables the systematic estimation of GHG emission influencing factors within warehouses by the use of simulation. Evaluating CO_2e emissions for three different sourcing scenarios and three different warehouse types shows that the choice of the inventory control policy and parameters does have a significant impact on warehouse energy consumption and hence emissions. In addition, the degree of warehouse mechanization influences the overall warehousing emission notably.

Managerial implications

Managers are increasingly finding that they are making decisions to try to optimise three objectives, namely: cost, service and the environment. This paper provides a framework to help managers trade-off the sometimes conflicting objectives of cost and the environment, for a given service level. In particular, the framework relates to inventory and warehouse cost and emissions, which are often rather neglected areas in such analyses.

An important managerial finding is that small changes of inventory parameters around EOQ have a significant impact on energy consumption with only very little impact on cost. This is due to the almost linear relationship of energy consumption to order quantity, and an exponential relationship of inventory cost to order quantity. Smaller order quantities are often linked to benefits of supply chain agility (for which it can be difficult to place a tangible value) and this research highlights a further potential benefit in terms of lower warehouse emissions.

Owing to the importance of HVAC and lighting related emissions, the AS/RS system leads to the lowest total CO_2e emissions, at any sourcing scenario, followed by the VNA and the WA warehouse. Also, the AS/RS warehouse has the lowest sensitivity in terms of emissions to changes in order quantity. Thus, companies with WA warehouses need to pay particular attention to order quantities if they wish to minimise emissions. In terms of network design, then this finding may tend towards an AS/RS solution in high stockholding operations, for example where demand and supplier lead times are volatile or where stockholding forms a significant part of a company's supply chain resilience strategy.

20

It is well documented that offshoring often leads to high transport emissions owing to the distances involved. This research indicates that offshoring may also lead to higher warehouse emissions, owing to the higher safety stock levels, the greater storage space required and hence the greater energy use required for HVAC and lighting.

In all these areas, this framework helps to fill the current gap in supply chain emission calculations by providing a systematic approach to estimating the precise nature of warehouse emissions. Management can therefore make much better informed decisions.

Implications for future research

Considering the importance of an integrated inventory and warehouse management approach to environmental impacts and the lack of research on this subject, we hope that the framework developed provides researchers with many potential topics for future research. This paper is theory building rather than theory testing. Admittedly, only a single prototypical warehouse has been selected for simulation of each warehouse type. Nevertheless, this research is based on carefully selected real world input parameters where results are interpreted in order of magnitude relative to the base case. The simulation model has shown to be robust when comparing the relative performance of warehouses. By robust we mean that although absolute values of simulation results are sensitive to the choice of input parameters, the order of magnitude of relative performance in per cent to the base case does not change significantly.

The model is based on a theoretical layout and operation, assuming a rectangular building, longitudinal and lateral routing of mobile equipment, random slotting of goods (e.g. not by Pareto allocation), no added value services, etc. These assumptions would need to be modified accordingly if used to model an existing, real-life warehouse. Validation of the simulation model in such a case, especially of energy consumption parameters, can follow a similar approach as used by Dhooma and Baker (2012).

This work outlined above can be extended in many ways. First of all, not only inventory cost but also variable and fixed cost of operating warehouses could be considered in a joint inventory and warehouse cost optimisation problem. An analytical model would provide further structural properties and optimality conditions of this problem. Another extension would be to consider zoning in the warehouse rather than random storage. The analysis of integrated warehouse and inventory management in a larger supply chain context taking into account the total landed cost including manufacturing and transport costs can be a valuable extension. Last but not least the implications of this paper may assist researchers in developing works on sustainable warehouse management (cf. Tan et al., 2010), which may integrate economic, social and environmental goals. Simultaneously increasing the efficiency of inventory management and warehousing processes for reducing their environmental impact (e.g. Arikan et al., 2014) as well as considering worker welfare, job satisfaction and occupational safety (e.g. Grosse et al., 2015), would contribute to achieving long-term sustainable inventory and warehouse operations.

References

Arikan, E., Fichtinger, J., Ries, J.M., 2014. Impact of transportation lead-time variability on the economic and environmental performance of inventory systems. International Journal of Production Economics 157, 279-288.

Aynsley, R., 2011. Estimates of winter de-stratification energy savings in large warehouses. Architectural Science Review 48 (3), 257-264.

Baker P., Perotti, S., 2008. UK Warehouse Benchmarking Report, Cranfield School of Management, Cranfield University, Cranfield, UK.

Battini D., Persona, A., Sgarbossa, F., 2014. A sustainable EOQ model: Theoretical formulation and applications. International Journal of Production Economics 149, 145-153.

Bonney, M., Jaber, M.Y., 2011. Environmentally responsible inventory models: Non-classical models for a non-classical era. International Journal of Production Economics 133 (1), 43-53.

Bouchery, Y., Ghaffari, A., Jemai, Z., Dallery, Y., 2012. Including sustainability criteria into inventory models. European Journal of Operational Research 222 (2), 229-240.

Boylan, J.E., Syntetos, A., Karakostas, G.C., 2008. Classification for forecasting and stock control: a case study. Journal of the Operational Research Society, 59 (4), pp.473–481.

Bozer, Y.A., Cho, M., 2005. Throughput performance of automated storage/retrieval systems under stochastic demand. IIE Transactions, 37 (4), 367–378.

Bozer, Y.A., Kile, J.W., 2008. Order batching in walk-and-pick order picking systems. International Journal of Production Research, 46 (7), 1887-1909.

Brandenburg, M., Govindan, K., Sarkis, J., Seuring, S., 2014. Quantitative models for sustainable supply chain management: Developments and directions. European Journal of Operational Research 233 (2), 299-312.

Carbon Trust, 2013, Conversion factors: Energy and carbon conversions, 2013 update. The Carbon Trust, London.

Chen, X., Benjaafar, S., Elomri, A., 2013. The carbon-constrained EOQ. Operations Research Letters 41 (2), 172-179.

Cholette, S., Venkat, K., 2009. The energy and carbon intensity of wine distribution: A study of logistical options for delivering wine to consumers. Journal of Cleaner Production 17 (16), 1401-1413.

CIBSE, 2002. Energy consumption guide 81. The Chartered Institution of Building Services Engineers, London.

CIBSE, 2004. Energy efficiency in buildings - CIBSE Guide F. The Chartered Institution of Building Services Engineers, London.

de Koster, R., Le-Duc, T., Roodbergen, K.J., 2007. Design and control of warehouse order picking: A literature review. European Journal of Operational Research, 182 (2), 481-501.

Department of Energy and Climate Change (DECC), 2013. Energy Consumption in the UK (2013), UK Government, London.

Dey, A., LaGuardia, P, Srinivasan, M., 2011. Building sustainability in logistics operations: a research agenda. Management Research Review 34 (11), 1237-1259.

Dhooma, J., Baker, P., 2012. An exploratory framework for energy conservation in existing warehouses. International Journal of Logistics Research and Applications, 15 (1), 37-51.

Frazelle, E.A., 2002a. World-class warehousing and material handling. McGraw-Hill, New York.

Frazelle, E.H., 2002b. Supply chain strategy. McGraw-Hill, New York.

Geerlings, H., van Duin, R., 2011. A new method for assessing CO_2-emissions from container terminals: a promising approach applied in Rotterdam. Journal of cleaner Production, 19 (6-7), 657-666.

Glock, C.H., Grosse, E.H., 2012. Storage policies and order picking strategies in U-shaped order-picking systems with a movable base. International Journal of Production Research, 50 (16), 4344-4357.

Grosse, E.H., Glock, C.H., Jaber, M.Y, Neumann, W.P., 2015. Incorporating human factors in order picking planning models: Framework and research opportunities. International Journal of Production Research 53(3), 695-717.

Gu, J., Goetschalckx, M., McGinnis, L.F., 2007. Research on warehouse operation: A comprehensive review. European Journal of Operational Research, 177 (1), 1-21.

Gudehus, T., Kotzab, H., 2012. Comprehensive Logistics, 2nd ed. Springer, Berlin Heidelberg.

Hall, R. W., 1993. Distance approximations for routing manual pickers in a warehouse. IIE Transactions, 25 (4), 76-87.

Harris, I., Naim, M., Palmer, A., Potter, A., Mumford, C., 2011. Assessing the impact of cost optimization based on infratstructure modelling on CO_2 emissions. International Journal of Production Economics 131 (1), 313-321.

Hassini, E., Surti, C., Searcy, C., 2012. A literature review and a case study of sustainable supply chains with a focus on metrics. International Journal of Production Economics 140 (1), 69-82.

Hua, G., Cheng, T.C.E., Wang, S., 2011. Managing carbon footprints in inventory management. International Journal of Production Economics 132 (2), 178-185.

Hwang, H., Oh, Y.H., Lee, Y.K., 2004. An evaluation of routing policies for order-picking operations in low-level picker-to-part system. International Journal of Production Research, 42 (18), 3873-3889.

Ip, K., Miller, A., 2012. Life cycle greenhouse gas emissions of hemp-lime wall constructions in the UK. Resources, Conservation and Recycling 69, 1-9.

Jaber, M. Y., Glock, C. H., El Saadany, A.M.A., 2012. Supply chain coordination with emission reduction incentives. International Journal of Production Research, 51 (1), 69-82.

Jones Lang LaSalle, 2013. Database of the take-up of large warehouses over 100,000 square feet (unpublished).

Mallidis, I., Dekker, R., Vlachos, D., 2012. The impact of greening on supply chain design and cost: a case for a developing region. Journal of Transport Geography 22, 118-128.

Marchant, C., Baker, P., 2010. Reducing the environmental impact of warehousing in: McKinnon, A. et al. (Eds.), Green logistics: improving the environmental sustainablity of logistics. Kogan Page, London, pp. 167-192.

Martens, R., Bass, B., Saiz Alcazar, S., 2008. Roof-envelope ratio impact on green roof energy performance. Urban Ecosystems 11 (4), 399-408.

Meneghetti, A., Monti, L., 2013. Sustainable storage assignment and dwell-point policies for automated storage and retrieval systems. Production Planning & Control, 24 (6), 511-520.

Oliver, M., 2010. Internal and external layouts, in Baker, P. (ed.): The Principles of Warehouse Design, The Chartered Institute of Logistics and Transport (UK), Corby, pp. 31-41.

Olivier, J., Janssens-Maenhout, G., Muntean, M., Peters, J., 2013. Trends in global CO_2 emissions: 2013 Report. The Hague: PBL Netherlands Environmental Assessment Agency, Ispra: Joint Research Centre.

Pan, S., Ballot, E., Fontane, F., 2013. The reduction of greenhouse gas emissions from freight transport by pooling supply chains. International Journal of Production Economics 143 (1), 86-94.

Petersen, C. G., Aase, G., 2004. A comparison of picking, storage, and routing policies in manual order picking. International Journal of Production Economics, 92 (1), 11-19.

Petersen, C.G., Schmenner, R.W., 1999. An Evaluation of Routing and Volume-based Storage Policies in an Order Picking Operation. Decision Sciences, 30 (2), 481-501.

Piecyk, M. I., McKinnon, A.C., 2010. Forecasting the carbon footprint of road freight transport in 2010. International Journal of Production Economics, 128 (1), 31-42.

Plambeck, E.L., 2012. Reducing greenhouse gas emissions through operations and supply chain management. Energy Economics, 34 (1), 64-74.

Roodbergen, K.J., Sharp, G.P.,Vis, I.F.A., 2008. Designing the layout structure of manual order-picking areas in warehouses. IIE Transactions 40 (11), 1032-1045.

Rai, D., Sodagar, B., Fieldson, R., Hu, X., 2011. Assessment of CO_2 emissions reduction in a distribution warehouse. Energy, 36 (4), 2271-2277.

Ratliff, H.D., Rosenthal, A.S., 1983. Order-picking in a rectangular warehouse: a solvable case of the traveling salesman problem. Operations Research, 31 (3), 507-521.

Rizet, C., Cornelis, E., Browne, M., Leonardi, J., 2010. GHG emissions of supply chains from different retail systems in Europe. Procedia Social and Behavioural Sciences 2 (3), 6154-6164.

Rushton, A., Croucher, P, Baker, P., 2014. The Handbook of Logistics & Distribution Management. 5th ed., Kogan Page, London, UK.

Sainathuni, B., Parikh, P.J., Zhang, X., Kong, N., 2014. The warehouse-inventory-transportation problem for supply chains. European Journal of Operational Research 237(2), 690-700.

Sarkis, J., 2003. A strategic decision framework for green supply chain management. Journal of Cleaner Production 11(4), 397-409.

Seuring, S., Müller, M., 2008. From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production 16 (15), 1699-1710.

Strack, G., Pochet, Y., 2010. An integrated model for warehouse and inventory planning. European Journal of Operational Research 204 (1), 35-50.

Tompkins, J.A., White, Y.A., Bozer, E.H., Tanchoco, J.M.A., 2010. Facilities planning, 4th ed. John Wiley & Sons, Hoboken, N.J.

Tan, K.-S., Ahmed, M.D., Sundaram, D., 2010. Sustainable enterprise modelling and simulation in a warehousing context. Business Process Management Journal 16 (5), 871-886.

Tsai, W-H., Lin, S-J., Liu, Liu, J-Y., Lin, W-R., Lee K-C., 2011. Incorporating life cycle assessments into building project decision-making: An energy consumption and CO_2 emission perspective. Energy 36 (5), 3022-3029.

Ubeda, S., Arcelus, F.J., Faulin, J., 2011. Green logistics at Eroski: A case study. International Journal of Production Economics 131 (1), 44-51.

United Nations Environment Programme (UNEP), 2012. The Emissions Gap Report 2012. United Nations Environment Programme, Nairobi.

United Kingdom Warehouse Association (UKWA), 2010. Save Energy, Cut Costs: Energy Efficient warehouse, London.

Van den Berg, J.P., Zijm, W.H.M., 1999. Models for warehouse management: Classification and examples. International Journal of Production Economics 59 (1-3), 519-528.

VDI, 2012. Type sheets for industrial trucks – VDI 2198. VDI-Handbuch technische Logistik, Band 2, Flurförderzeuge.

World Economic Forum (WEF), 2009. Supply Chain Decarbonization. World Economic Forum, Geneva.

World Meteorological Organization (WMO), 2014. WMO greenhouse gas bulletin. The state of greenhouse gases in the atmosphere based on global observations through 2013. ISSN 2078-0796.

Wu, H.J., Dunn, S.C., 1995. Environmentally responsible logistics systems. International Journal of Physical Distribution & Logistics Management, 25 (2), 20-38.

Zajac, P., 2011. The idea of the model of evaluation of logistics warehouse systems with taking their energy consumption under consideration. Archives of Civil and Mechanical Engineering X1 (2), 479-492.

Zanoni, S., Zavanella, L., 2012. Chilled or frozen? Decision strategies for sustainable food supply chains. International Journal of Production Economics 140 (2), 731-736.