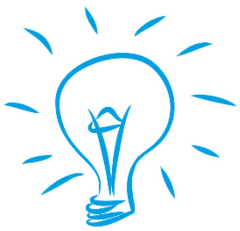
3. OPTIMIZATION IN SUPPLY CHAIN MANAGEMENT



In the chapter, the most important issues related to inventory management have been presented. Particular emphasis has been placed on the analysis of logistic data, for which a spreadsheet can be utilized. Here you will find:

- concept of optimization in logistics,
- the role of the warehouse in the supply chain,
- determining warehouse space,
- selected methods of inventory management in the supply chain,
- the Solver tool.

3.1. Introduction

Optimization in logistics is the process of finding the most effective way of organizing the flow of goods, information, and resources throughout the entire supply chain, from the initial point to the final one, with the minimization of operational costs while simultaneously ensuring high quality and meeting customer requirements (Reszka, 2012). The goal of optimization in logistics is to improve various aspects of activity, such as (Antoniuk et al., 2021; Gupta et al., 2022):

- reduction of goods flow time,
- optimization of transportation, warehousing, and handling costs,
- improvement of logistics service quality,
- increased flexibility and responsiveness to changes in demand,
- reduction of inventory levels while ensuring continuity of supply,
- improved management of warehouse space and transportation resources,
- integration and automation of logistics processes.

Logistical optimization models are applied in reference to (Smyk, 2023): (1) distribution network design (determining the locations of distribution centers) – described in the chapter on Logistic Network Optimization, (2) designing transportation systems (optimization of transport tasks, minimization of empty runs, determining delivery routes) – described in the chapter on Transport Optimization, (3) inventory management (allocation of stocks, estimating their size, determining order placement timings) – described in the chapter on Analytics in Supply and Procurement and below in the subsection Selected Methods of Inventory Management in the Supply Chain, (4) designing and managing warehouse activities (maximizing warehouse space efficiency) – described in the subsection Determining Warehouse Space.

In the context of optimization models, there are many optimization methods where the main classification of these methods is based on the type of optimization task to be solved. The following **optimization methods** can be distinguished according to (Jayarathna et al., 2021; Kusiak et al., 2021):

- type of problem being solved: linear programming methods, nonlinear optimization methods,
- constraints: unconstrained optimization methods, constrained optimization methods,
- dimension of the problem (number of optimization variables): univariate methods, multivariate methods (multiple optimization variables),
- optimization criteria: single-criterion methods; multicriteria methods (multiple optimization criteria).

In logistics, the number of criteria is often considered, and optimization tasks are formulated as either single-criterion or multicriterion. In practice, single-criterion optimization tasks are usually solved, mainly due to the simplicity of the models and their ease of application. Multicriterion optimization tasks require complex models, which often leads to situations where an optimal solution according to one criterion may negatively affect the outcome aligned with another criterion's goal. As a result, multicriteria solutions necessitate forging a compromise between different objective functions, complicating the determination of the unequivocally best, optimal solution (Smyk, 2023). Therefore, in seeking partial criteria and objectives for the optimization of logistical tasks, it is important to ensure that they are (Silva et al., 2005):

- complete (affecting a specific decision problem),
- non-redundant,
- minimized (aiming to reduce the decision problem size),
- operational (measurable),
- differentiating solutions (allowing the identification of the best – optimal solution).

In business activities, it is crucial that the optimization criterion is clearly defined, and the optimization model should correspond to the fundamental nature of the analyzed problem (Smyk, 2023). This criterion is referred to as the objective function and is selected in the context of the decision being made or at the initial stage of logistical planning. This function serves as a measure for evaluating the quality of the solution, where the optimal solution is achieved when the function takes an extremum (minimum or maximum) (Gupta et al., 2022).

3.2. The role of the warehouse in the supply chain

In a modern logistics system, every material manipulation is subject to thorough verification already at the design stage. Even minor shifts of goods over short distances, which usually occur within a building or between the facility and a transport intermediary, are starting to play a very important role. The **warehouse** is intended for storing material goods in a designated space of the warehouse building, according to established technology, equipped with appropriate devices and technical means, managed and serviced by a team of people equipped with the necessary skills (Miszewski, 2019). The best possible placement of goods in a given space allows for fuller utilization of the facility's limited capacity and reduces the number of manipulations with a given inventory (Ghiani, 2004; Muller, 2002).

In the context of the supply chain, the warehouse have an extremely important role, serving as a key center for coordination and storage of goods, which is essential to ensure the smooth flow of products from producers to consumers. Its operation is fundamental for effective inventory management, allowing for the minimization of the risk of shortages and excesses, thereby maintaining a balance between demand and supply. Moreover, the warehouse plays an important role in the quality control process, offering the possibility to check and prepare products for further distribution, ensuring their compliance with standards and customer expectations. The introduction of modern **Warehouse Management Systems** (WMS) contributes to significant optimization of logistic processes, which in turn increases operational efficiency and allows for the reduction of operational costs. Finally, warehouses are extremely important in adapting the supply chain to dynamically changing market conditions, enabling organizations to quickly respond to the evolution of demand and changing consumer preferences, which is key in maintaining market competitiveness (Gu et al., 2007; Ramaa et al., 2012).

3.3. Determining warehouse space

Basic requirements in warehouse operations include receiving **stock keeping units** (SKUs) from suppliers, storing SKUs, taking orders from customers, picking SKUs and assembling them for shipment, and sending completed orders to customers. Designing and operating a warehouse that meets these requirements involves many issues. Resources such as space, labor, and equipment must be allocated among various warehouse functions, and each function must be carefully implemented, operated, and coordinated to meet system requirements in terms of capacity, throughput, and service at the minimum resource cost. Warehousing deals with the organization of goods in the warehouse to achieve high space utilization and enable efficient material transport (Gu et al., 2007).

The storage function is shaped by three basic decisions: how much inventory of a given SKU should be stored in the warehouse; how often and at what time the inventory for an SKUshould be replenished; and where within the warehouse the SKU should be stored, distributed, and moved between different storage areas. The first two questions lead to issues related to batch size and problems that fall into the traditional area of inventory control (Hariga & Jackson, 1996). The two main criteria for making decisions about allocation to storage zones are storage efficiency, which corresponds to storage capacity, and access efficiency, which corresponds to the resources consumed by sales and order fulfillment (Gu et al., 2007).

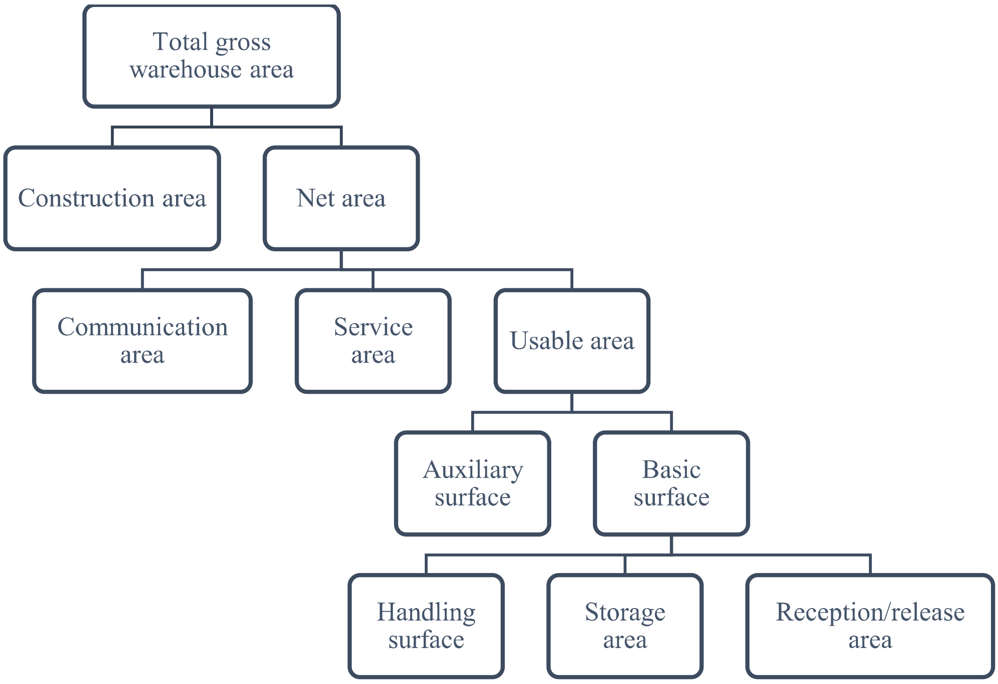


Figure 3.1. Division of warehouse space

Source: (Dudziński & Kizyn, 2002)

Calculating warehouse space requires consideration of its various types (Fig. 3.1). In an enterprise, the usable area is divided into zones corresponding to the phases of the warehousing process: receiving, storage (short and long-term), order picking, dispatch, as well as handling and auxiliary space. The size and shape of the warehouse depend on the following variables:

- the types, number, and dimensions of positions where warehouse activities are performed in the receiving and dispatching zones,
- the dimensions and quantities of storage fields in the storage area,
- the dimensions and quantities of laydown areas,
- parameters of shelving rows and the number of columns in rows,
- the width of the working aisle for the selected forklift,
- the width of communication paths for equipment and personnel.

The total warehouse area S can be expressed by the formula:

$$S = f_s + f_p = f_s + f_w + f_d + f_a$$

where:

f_s – storage area,

f_p – auxiliary area,

f_w – area designated for receiving, sorting, and dispatching materials,

f_d – area occupied by passages and driveways,

f_a – administrative and social area.

Formula used in Excel:

S = [the storage area] + [the auxiliary area] = [the storage area] + [the area designated for receiving, sorting, and dispatching materials] + [the area occupied by passages and driveways] + [the administrative and social area]

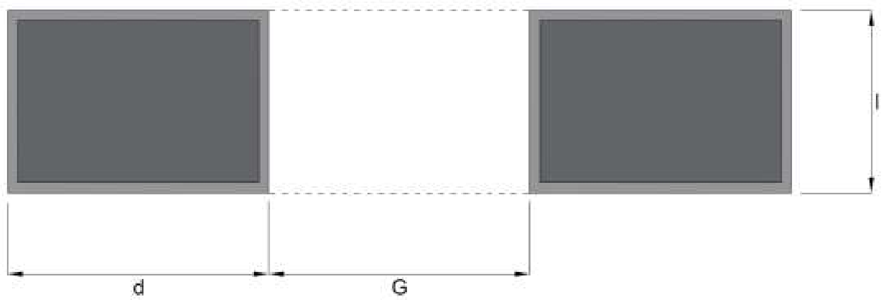


Figure 3.2. A warehouse module for row storage without equipment with perpendicular arrangement of palletized LU

Source: own study

The part of the warehouse area that includes the horizontal projection of the smallest repeatable part of two rows or blocks of load units (LU) along with handling clearances for storage and the handling path between them is the warehouse module. Adopting this size allows for estimating the size of the warehouse area. Warehouse modules for row storage without equipment can be arranged in two ways (Fig. 3.2 and Fig. 3.3).

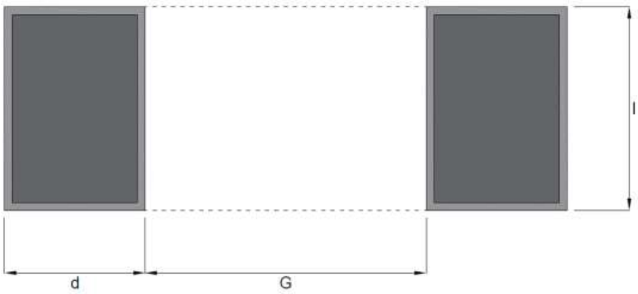


Figure 3.3. A warehouse module for row storage without equipment with parallel arrangement of palletized LU

Source: own study

The area of a warehouse module for row storage without equipment is calculated using the formula:

$$M = (2 \times d + G) \times l$$

where:

d – width of the laydown area [m],

G – width of the handling path [m],

l – length of the storage field [m].

The capacity of the module is equal to 2 palletized load units for single-level storage and $2 \times n$ palletized load units for stacked storage when stacking in n levels.

Formula used in Excel:

M = (2 * [width of the laydown area] + [width of the handling path]) * [length of the storage field]

Warehouse modules for block storage without equipment can be arranged as shown in Fig. 3.4.

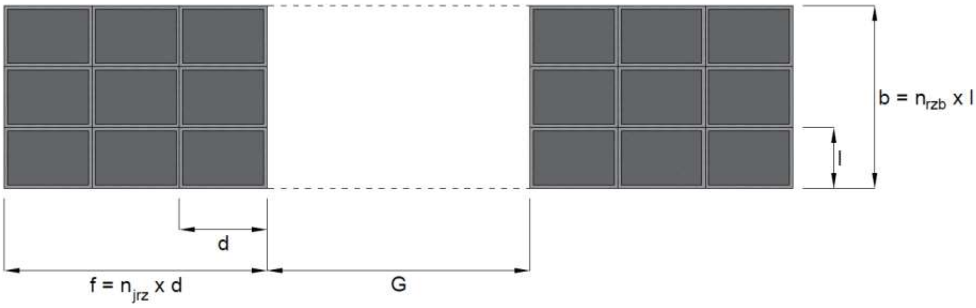


Figure 3.4. Warehouse module for block storage without equipment

Source: own study

The area of a warehouse module for block storage without equipment is calculated using the formula:

$$Mb = (2 \times f + G) \times b = (2 \times n_{LUz} \times d + G) \times n_{LUb} \times l$$

where:

f – block width [m],

G – width of the handling path [m],

b – block length [m],

n_{LUz} – number of loading units in a block row,

d – width of the storage area [m],

n_{LUb} – number of rows in the block,

l – length of the storage field [m].

The capacity of the module is equal to $2 \times n_{LUz} \times n_{LUb}$ palletized load units for single-level storage and $2 \times n_{LUz} \times n_{LUb} \times n$ palletized load units for stacked storage when stacking in n levels.

Formula used in Excel:

Mb = (2 * [block width] + [width of the handling path]) * [block length]

Additionally, the volume can be calculated for storage modules – taking into account the height of the loading unit or when loading units are stacked. The **volume of a storage module** (module capacity) depends on its surface area (*Mb*) and the height at which the loading unit was formed (*h*). The volume of the module is calculated from the formula:

$$V_M = [(2 \times f + G) \times b] \times h$$

$$h = n_{rh} \times h_0 + h_p$$

where:

f – block width [m],

G – width of the handling path [m],

b – block length [m],

h – high palletized load units [m],

n_{rh} – number of layers per palletized load units,

h_0 – height of the collective packaging [m],

h_p – media height [m].

The first part of the formula is the formula for the module surface area, and the second part is the height of the formed loading unit.

Formula used in Excel:

V_M = {(2 * [block width] + [width of the handling path]) * [block length]} * [high palletized load units]

The **volume of the warehouse module** (module capacity) depends on its surface area (Mb) and the height to which the load unit (H) has been formed. The volume of the module is calculated using the formula:

$$V_M = [(2 \times f + G) \times b] \times H$$

$$H = n \times h = n \times (n_{rh} \times h_0 + h_p)$$

where:

f – block width [m],

G – width of the handling path [m],

b – block length [m],

H – block height [m],

n – number of units piled up,

h – high of palletized load units [m],

n_{rh} – number of layers per palletized load units,

h_0 – height of the collective packaging [m],

h_p – media height [m].

Formula used in Excel:

V_M = {(2 * [block width] + [width of the handling path]) * [block length]} * [block height]

The utilization of warehouse space is assessed by the ratio of the used area to the total available area. In warehouses where pallet racks are not used, achieving the highest value of this indicator is ensured by storing materials in a block layout, with space utilization values ranging from 0.6 to 0.8. For comparison, this indicator for a row storage layout ranges from 0.25 to 0.6. Striving to optimize space utilization with this type of storage leads to limitations in the conditions for stacking materials and lack of access to the assortment located in the middle of the blocks, and is only applicable for homogeneous assortments, without requiring additional financial outlays for warehouse equipment. In cases where the only criterion for evaluation is to increase the quantity of stored assortment, a good solution turns out to be the use of flow-through pallet racks. They provide a high utilization rate due to the limitation of the number of transport paths, but at the same time, they require the use of the FIFO (First In, First Out) principle. Maximum utilization of available warehouse space is possible thanks to the use of the free space storage method, which assumes that the assortment can be placed in any free rack slot (Kisielewski & Talarek, 2020).

3.4. Selected methods of inventory management in the supply chain

Inventory management in the supply chain is a key element that ensures operational fluidity, cost minimization, and customer satisfaction. There are many methods of inventory management, each of which may be appropriate depending on the specifics of the industry, product characteristics, demand dynamics, and other operational factors (Cyplik & Hadaś, 2012).

The classic concept of inventory management allows for managing inventories in a distribution network, where they are usually located in various places. Solving the problems of inventories located in multiple locations focuses primarily on analyzing the size of safety stocks (Mascle & Gosse, 2014). Safety stock depends on the variability of demand in the inventory replenishment cycle, expressed as the standard deviation of demand in that period and a safety factor dependent on the adopted service level. If the same service level is assumed for different inventory storage locations, then the level of safety stock depends on the demand variability served from a given location. In the formulas, it is assumed that the same service level has been adopted at all market service points ($\omega_{MR1} = \omega_{MR2} = \omega_{MR3} = \ldots = \omega_{MC}$) and the same inventory replenishment system are adopted in all market service points (Cyplik & Hadaś, 2012).

The safety stock depends on the variability of demand in the inventory replenishment cycle, expressed by the standard deviation of demand in this period, and a safety factor dependent on the adopted service level. If the same service level is assumed for different inventory storage locations, the level of safety stock depends on the demand variability served from a given location. The problem is not calculating the total demand in the case of multiple demand location points (the total demand is the sum of the average demands in each location). To calculate the standard deviation of the sum of demands, one should use the square root law, which assumes that the standard deviation of the sum of demands is equal to the square root of the sum of their standard deviations. Below are formulas that allow for these calculations. The obtained results will be correct under the assumption that the same service level ($\omega_{L1} = \omega_{L2} = \omega_{L3} = \ldots = \omega$) and the same inventory replenishment system are adopted in all market service points (Cyplik & Hadaś, 2012).

Formula to calculate safety stock:

$$S_S = \omega \times \sigma_{DT}$$

Formula to calculate the standard deviation of the sum of demands:

$$\sigma_{(D1+D2+D3+\ldots Dn)} = \sqrt{\sigma_{D1}^2 + \sigma_{D2}^2 + \sigma_{D3}^2 + \ldots + \sigma_{Dn}^2}$$

where:

n – number of localization,

D_n – individual demand value in the n localization.

The total safety stock for demand handled e.g. from a central warehouse can be calculated as:

$$S_{ST} = S_{S(D1+D2+D3+\ldots+Dn)} = \omega \times \sigma_{(D1+D2+D3+\ldots Dn)} =$$

$$= \omega \times \sqrt{\sigma_{P1}^2 + \sigma_{P2}^2 + \sigma_{P3}^2 + \ldots + \sigma_{Pn}^2} =$$

$$= \sqrt{\omega^2 \times \sigma_{P1}^2 + \omega^2 \times \sigma_{P2}^2 + \omega^2 \times \sigma_{P3}^2 + \ldots + \omega^2 \times \sigma_{Pn}^2} =$$

$$= \sqrt{S_{SL1}^2 + S_{SL2}^2 + S_{SL3}^2 + \ldots + S_{SLn}^2}$$

where:

S_{ST} – total safety stock,

S_{SLn} – safety stock in n location.

In the special case, if the safety stock at all points in the location is the same (generally as a result of the same demand served by each of these points) and is equal to S_{STn}, then the centralized stock S_{STD} is equal to:

$$S_{STD} = S_{STn} \times \sqrt{n}$$

where n is the number of stock location points.

Formula used in Excel:

SST = [safety factor] * [standard deviation of the sum of demands at points D1-Dn in the replenishment cycle] = [safety factor] * SQRT[(STDEV.P([cell range for D1])^2) + (STDEV.P([cell range for D2])^2) + ... + (STDEV.P([cell range for Dn])^2)]

One of the issues requiring analysis in the context of supply chain optimization is the location of warehouses, taking into account the relationship between significant parameters. The way of stock location can be considered in two ways – as dispersed stock or centralized stock.

In the case of dispersed stock (Fig. 3.5), customers are served directly from stock located in regional warehouses (RW), where the safety stock is maintained. For calculation purposes, the following assumptions are made (Krzyżaniak, 2006):

- demand is evenly distributed across n regional warehouses,
- weekly demand in each of these warehouses can be described by a distribution with an average demand of D_{RW} and a standard deviation of σ_{DRW},,
- the purchase price from the supplier is equal to P,
- the coefficient of weekly inventory carrying cost is u_t and is the same in all warehouses,
- the replenishment cycle time in regional warehouses is equal for each warehouse and amounts to T_1 (without significant deviations).

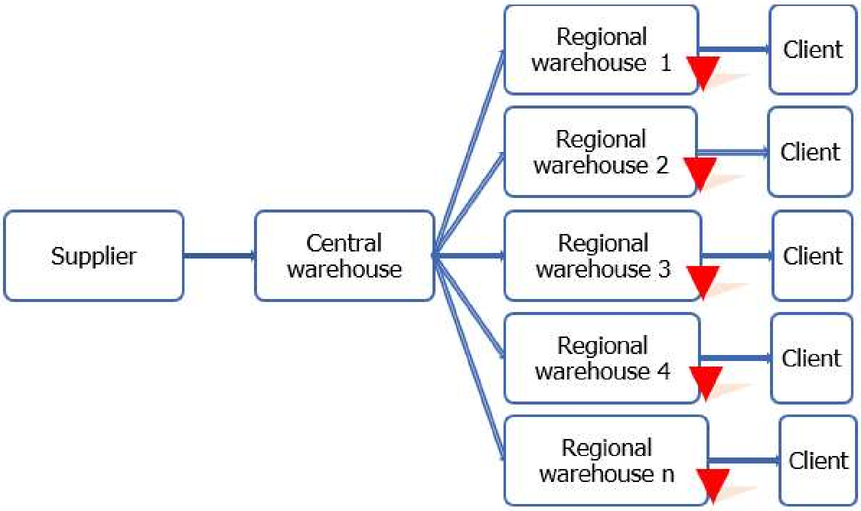


Figure 3.5. Distributed inventory case illustration

Source: (Krzyżaniak, 2006)

Given the assumptions, the total weekly cost of maintaining safety stock in the network is equal to:

$$C_1 = \sum_{1}^{n} HCSS_{RW}$$

With an even distribution of demand among all warehouses, we obtain:

$$C_1 = n \times SS_{RW} \times P \times u_t = n \times \omega \times \sigma_{DRW} \times \sqrt{T_1} \times P \times u_t$$

where:

ω – safety factor, dependent on the chosen service level and the type of distribution describing the given frequency distribution of demand,

SS_{RW} – safety stock in each of the regional warehouses.

Since $\sigma_{DRW} = V \times D_{RW}$, where V is the coefficient of variation $V = \frac{\sigma_D}{D}$, the formula takes the form:

$$C_1 = n \times \omega \times V \times D_{RW} \times \sqrt{T_1} \times P \times u_t$$

In the general model for centralized stock (Fig. 3.6), customers are served from the central warehouse (CW) with direct deliveries, such as courier shipments. For calculation purposes, the following assumptions are made (Krzyżaniak, 2006):

- the weekly demand in the central warehouse is the sum of the demands observed in the markets associated with the individual regional warehouses and can be described by a distribution with an average $D_{CW}=n \cdot D_{RW}$ and a standard deviation $\sigma_{DCW} = \sigma_{DRW} \times \sqrt{n}$ (according to the square root law),
- the weekly inventory carrying cost coefficient u_t is the same as for the regional warehouses,
- the replenishment cycle time in the central warehouse is T_2,
- in case of demand from customers, the product is shipped directly to the customer in the form of a courier shipment with a unit cost c_{CS}, which allows maintaining a similar customer order fulfillment time as in the case of service from regional warehouses.

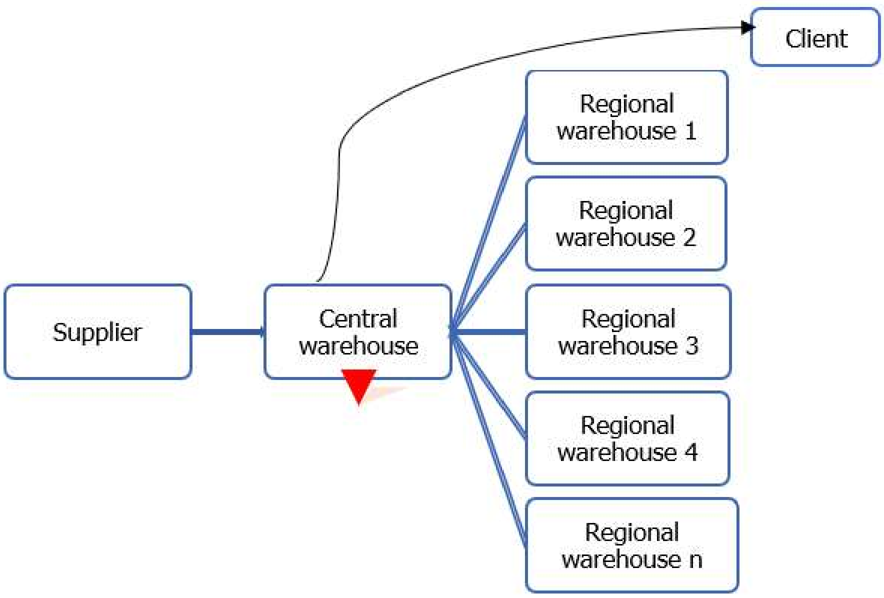


Figure 3.6. Centralized inventory case illustration

Source: (Krzyżaniak, 2006)

The weekly cost of maintaining safety stock in the central warehouse is equal to:

$$C_{2(SS)} = SS_{CW} \times P \times u_t = \omega \times \sigma_{DCW} \times \sqrt{T_2} \times P \times u_t.$$

Because, as intended $T_2 = \alpha \times T_1$:

$$C_{2(SS)} = \omega \times \sigma_{DCW} \times \sqrt{\alpha \times T_1} \times P \times u_t = \omega \times \sigma_{DRW} \times \sqrt{n \times \alpha \times T_1} \times P \times u_t$$

Because it happens $\sigma_{DRW} = V \times D_{RW}$, where V is the so-called coefficient of variation $V = \frac{\sigma_P}{D}$, then the pattern takes the form:

$$C_{2(SS)} = \omega \times V \times D_{RW} \times \sqrt{n \times \alpha \times T_1} \times P \times u_t$$

It is worth noting that the assumption $T_2 = \alpha \times T_1$ takes into account different solutions for organizing deliveries for both cases. For example, in the case of distributed stocks, deliveries to regional warehouses may be carried out according to the periodic review system, and in a centralized system based on the so-called reorder point (information level). It can be assumed that this will usually occur $T_2 < T_1$.

Total weekly direct courier costs to the customer are equal:

$$C_{2(supplies)} = n \times D_{RW} \times c_{cs}$$

Asking the question: when is it profitable to disperse inventory, that is, when will it be cheaper to maintain safety stock in n regional warehouses and serve local customers from them than to concentrate inventory in a central warehouse and fulfill customer orders with direct deliveries, the answer comes down to solving the inequality:

$$C_1 < C_{2(SS)} + C_{2(supplies)}$$

that is:

$$n \times \omega \times V \times D_{RW} \times \sqrt{T_1} \times P \times u_t < \omega \times V \times D_{RW} \times \sqrt{n \times \alpha \times T_1} \times P \times u_t + n \times D_{RW} \times C_{cs}$$

After transformations we get::

$$V < \frac{n \times c_{cs}}{\omega \times \sqrt{T_1} \times P \times u_t \times (n - \sqrt{n \times \alpha}}$$

From this form we obtain dependencies, the fulfillment of which guarantees the fulfillment of the inequality $C_1 < C_{2(SS)} + C_{2(supplies)}$ and the condition imposed:

$$V < \frac{\left[\frac{c_{cs}}{P \times u_t}\right]}{\omega \times \sqrt{T_1} \times \left[1 - \sqrt{\frac{\alpha}{n}}\right]}$$

or

$$\omega < \frac{\left[\frac{c_{cs}}{P \times u_t}\right]}{V \times \sqrt{T_1} \times \left[1 - \sqrt{\frac{\alpha}{n}}\right]}$$

However, the following relationship is the most informative because it combines all cost elements in the expression on the left side of the inequality, and on the right side, parameters related to implementation and the required level of service:

$$\left[\frac{c_{cs}}{P \times u_t}\right] > V \times \omega \times \sqrt{T_1} \times \left[1 - \sqrt{\frac{\alpha}{n}}\right]$$

The strengths of the classic inventory management concept are as follows:

- simplicity and clarity – they are easy to understand and implement,
- help in minimizing the total costs of inventory management by balancing the costs of ordering and holding inventory, aiming for economic order quantity,
- clear and defined decision-making processes that help manage orders and inventory based on calculations and predefined rules.

The weaknesses of the classic inventory management concept include:

- the need for an assumption of constant and predictable demand, which does not always correspond to the dynamic and variable market realities.
- not accounting for demand variability and risk in the supply chain (e.g., delivery delays, market changes),
- lack of flexibility in responding to rapid changes in the market or supply chain, as they are based on fixed parameters and do not anticipate dynamic adaptation to new conditions.

The classic concept of inventory management has its place in the theory and practice of operational management, but in the modern, rapidly changing business world, it is often supplemented with more advanced and flexible methods and analytical tools.

DRP (Distribution Requirements Planning) – coordinates demand with inventory levels in various locations. It is one of the methods optimizing the management of final product deliveries to the distribution network and is used to plan the level and location of inventory storage throughout the supply chain. The purpose of using the distribution demand planning method is to reduce inventories in the distribution network (Nugroho, 2019). At the level of sales points, due to the risk of demand fluctuations, a safety stock is created for each product in each of them, calculated using formulas from the classic theory of inventory management (Magdalena & Suli, 2019).

Demand planning begins at the lowest level (e.g., at a retail sales point) and ends at the highest level (e.g., in a factory warehouse). The needs at the lower level are input data for the next level. The demand from the highest level can be used as input data for working on the production schedule (Fertsch, 2006). Demand from distribution centers is used to create an inventory demand schedule and is passed on to production. After comparing with previous forecasts, a production plan, material requirements, and distribution with a delivery schedule to individual distribution centers are developed (Ngatilah et al., 2020). Thanks to DRP, the service level for supply chain links that have direct contact with the customer is determined (batch size, inventory availability, delivery deadlines) (Fechner, 2007).

The DRP system allows for estimating delivery schedules for each stock keeping unit (SKU) to sales points. It requires having the following information (Mukhsin & Sobirin, 2022):

- the structure of the distribution channel through which the SKU flows,
- forecast of demand for individual SKUs at the point of sale level,
- the current stock level (on-hand stock) of a given SKU,
- target level of safety stock,
- recommended replenishment amount,
- replenishment delivery time.

DRP Algorithm (Ngatilah et al., 2020):

1. Netting – projected on-hand is an on-hand inventory. It can be calculated using formulation below:

$$\textbf{Projected on Hand}_{(t)} = (\textbf{On Hand}_{(t-1)} + \textbf{Scheduled Receipt}_{(t)} + \textbf{Planned Order Receipt}_{(t)} - \textbf{Gross Requirement}_{(t)})$$

Net Requirement can be calculated using formulation below:

$$\textbf{Net Requirement}_{(t)} = (\textbf{Gross Requirement}_{(t)} + \textbf{Safety Stock}) - (\textbf{Scheduled Receipt}_{(t)} + \textbf{Projected on Hand}_{(t-1)})$$

2. Lotting is the process to find the order or production lot size in every network distribution. There are several lottting method. Lotting in DRP represented by plan order receipt (Porec). Planned order receipt (Porec) is a Net Requirement that has been adjusted according to the Lot size order or production.

3. Offsetting is an order quantity that is planned to be ordered in the planned time period. Offsetting in DRP represented by plan order release (Porel). Porel is a Porec that has been adjusted according to the Lead time order or production.

4. Explosion – total inventory and distribution cost can be obtained using formulation below:

Total Inventory and Distribution Cost = Ordering Cost +
+ Holding Cost + Delivery Cost

The DRP model is particularly useful in large, complex organizations where managing the flow of products through the distribution network is crucial for operational efficiency and customer satisfaction. The strengths of the DRP model include:

- improved coordination in the supply chain through better information and goods flow from the producer to the consumer, leading to more efficient distribution,

- increased forecasting accuracy, as it considers actual order data and inventory levels throughout the chain, which helps optimize inventory levels and reduce costs,
- improved product availability by ensuring that stocks are placed where they are most needed, thereby minimizing the risk of shortages and production downtime.

The weaknesses of the DRP model are associated with the following elements:

- complexity of implementation, especially in large organizations with extensive supply chains, which requires precise planning and coordination,
- high initial costs related to purchasing software, hardware, and employee training,
- dependency on the accuracy and timeliness of input data, inaccuracies in the data can lead to forecasting and planning errors, which ultimately may cause excessive or insufficient inventories.

Despite its advantages, the DRP model requires precise execution and ongoing management to effectively support operational decisions within the supply chain.

EOQ (Economic Order Quantity) is a mathematical model used to determine the optimal order quantity that minimizes the total costs associated with ordering and holding inventory. This method is ideal for products with stable and predictable demand. The method makes the following assumptions (Battani et al., 2015):

- monthly or annual demand for the ordered product is known and predictable,
- the product is delivered very quickly after ordering,
- the cost of a unit order is fixed.

The Wilson formula is used to calculate the Economic Order Quantity (Krzyżaniak, 2005; Muckstadt, 2010).

Formula to calculate EOQ:

$$\boldsymbol{EOQ} = \sqrt{\frac{\mathbf{2} \times \boldsymbol{D} \times \boldsymbol{C_S}}{\boldsymbol{C_K}}}$$

where:

D – expected demand over a longer period of time,

C_S – cost of stockpiling – purchasing one batch, independent from its size,

C_K – the cost of keeping one unit of a given product in stock over a given period of time, most often defined as a certain fraction of the purchase price, and therefore:

$$C_K = \mu_o \times P$$

P – purchase price,

μ_o – percentage of the maintenance cost in the purchase price.

Formula used in Excel:

EOQ = SQRT((2 * [expected demand] * [cost of stockpiling]) / [the cost of keeping one unit])

The EOQ model is particularly useful in inventory management for standard products with stable demand. It is an analytical tool that assists in making decisions about order quantities but requires accurate data on costs and demand. The strengths of the EOQ model are:

- minimization of total costs – EOQ identifies the order quantity that optimizes the balance between ordering costs and storage costs, aiming to minimize the total inventory-related costs,
- increased operational efficiency – by establishing an optimal order schedule, the EOQ model enables better planning and resource management, which translates to smoother operations and a lower likelihood of production interruptions caused by shortages or excess stock,
- simplification of the decision-making process in inventory management – EOQ provides clear guidelines on when and how much to order, which helps in standardizing purchasing processes and may reduce the need for continuous monitoring and decision-making regarding stock levels.

However, the EOQ model requires the adoption of certain assumptions, which are associated with the following weaknesses:

- the need for a constant demand assumption – EOQ assumes that the demand for the product is constant and predictable at all times; in reality, demand is often variable and influenced by seasonality, market trends, competitive actions, and other external factors, which can make the accurate application of the EOQ model challenging in dynamic market conditions,
- the need for an assumption of fixed ordering and holding costs – in practice, these costs can vary based on many factors, such as changes in material prices, transportation costs, warehouse rental rates, labor rate changes, or inflation,
- lack of flexibility in responding to changes – the EOQ model generates a fixed number of orders for a specific period and does not anticipate automatic adjustments to rapidly changing market or operational conditions; this means that it is necessary to manually review and adjust EOQ orders to avoid excessive stock accumulation or the risk of stockouts, which can be time-consuming and complicated.

Given these limitations, many companies use the EOQ model as a starting point or preliminary guideline, while adapting their inventory management strategies to accommodate market dynamics and operational specifics.

3.5. Using the Solver tool in solving optimization problems

Solver is an add-in for Microsoft Excel used for advanced analysis and solving optimization problems. It allows users to define multiple decision variables, constraints, and objectives, and then employs various mathematical methods to find optimal solutions (see chapter Introduction to spreadsheet analysis). It is particularly useful in situations requiring complex computations, such as logistics path planning, resource allocation, or budget optimization (Bomba & Kwiecień, 2012; Mason, 2013).

Solver is used to solve single-criterion optimization tasks where the number of decision variables does not exceed 200. Its application requires creating a mathematical model within the spreadsheet workspace. The optimization model consists of three elements (Baj-Rogowska, 2013; Mason, 2012):

- objective cells (objective function) – these are cells in the spreadsheet model that, when Solver is applied, are to minimize, maximize, or set to a specified real number value,
- variable cells (decision variables) – they are cells containing the sought-after values, which are iteratively changed and substituted by the Solver add-in into the objective function until an optimal solution is found,
- constraint cells (can be applied concerning the value of the objective cell and variable cells) – introduced constraint conditions in the form of formulas within spreadsheet cells, where the value must be within specified limits or reach target values.

Solver in Excel utilizes various optimization methods to find the best solutions for defined problems. Each method has its specific applications and is chosen based on the nature of the optimization problem. Solver allows the user to select the appropriate method depending on the characteristics of the problem to be solved. The main methods include (Baj-Rogowska, 2013; Delgado-Aguilar et al., 2018):

- Simplex Method (Simplex LP) – this is the most commonly used method for solving linear programming (LP) problems; it is effective in situations where the objective function and all constraints are linear,
- GRG Method (Generalized Reduced Gradient) – it is an advanced method used to solve nonlinear problems; it is particularly useful when the objective function or constraints are nonlinear but still continuous and differentiable,
- Evolutionary Method – it is used to solve global optimization problems, especially when the objective function is complex, nonlinear, and discontinuous; the evolutionary method employs techniques similar to genetic algorithms, exploring various possible solutions to find the best one,
- Integer Constraints – Solver can be used to solve problems where some or all decision variables must take integer values; this is useful in situations where

solutions require discrete values, such as the number of units to produce or the number of employees to hire.

Solver in supply chain optimization is valuable when there is a need to optimize complex problems, such as minimizing transportation costs, optimizing delivery route planning, or managing inventory. It is particularly useful in situations that require the analysis of multiple variables and constraints, where traditional methods may be insufficient or too time-consuming.

3.6. Optimizing the use of warehouse space – an example of using the Solver tool

The content of the task

The Alfa company has a warehouse with a total area of 10,000 m², which must accommodate three types of products: A, B and C. Each of these products has different requirements for warehouse space, has its own specific safety stock and generates different profits per product unit:

- product A: requires 14 m² per unit, safety stock is 40 pcs., generates a profit of 30 euro,
- product B: requires 12 m² per unit, safety stock is 60 pcs., generates a profit of 32 euro,
- product C: requires 18 m² per unit, safety stock is 90 pcs., generates a profit of 23 euro.

Products A, B and C go to markets X, Y and Z. The total demand for all products in the markets is:

- market X: 220 pcs.,
- market Y: 230 pcs.,
- market X: 332 pcs.

How many units of each product should be held in the warehouse to maximize the total profit from the warehouse space used without exceeding the total warehouse space available, assuming that Alfa meets all demand?

Solution:

Objective function: maximizing the total profit from products.

Constraint: size of warehouse space, storage space for a unit of product, volume of market demand.

[1] preparing a data sheet,

[2] defining decision variables,

[3] calculation of auxiliary variables,

[4] determining the objective function,

[5] configuring Solver,

[6] indication of the optimization method,

[7] run Solver,

[8] evaluation of the obtained solution.

Example in Excel:

[1] Prepare and complete the table with input data from the task: safety stock for each product, unit warehouse space, unit profit, demand in each market, total warehouse space

		Market			Safety stock	Unit warehouse space	Profit individual
		X	Y	Z			
Product	A				40	14	30
	B				60	12	32
	C				90	18	23
		220	230	332			

Total warehouse area
10000

[2] Define decision variables – the number of products of each type in stock

		Market			Safety stock	Unit warehouse space	Profit individual
		X	Y	Z			
Product	A				40	14	30
	B				60	12	32
	C				90	18	23
		220	230	332			
						Total warehouse area	
						10000	

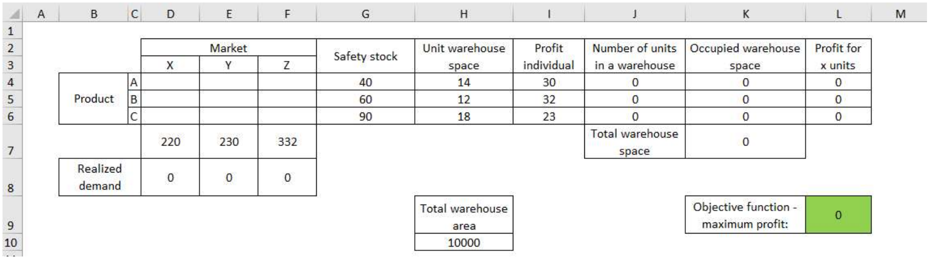
[3] Calculate auxiliary variables

- **Number of units in stock: = SUM([cell range for each market and single product])**
- **Occupied warehouse space: = [Unit area Warehouse] * [Number of units in stock]**
- **Profit for x units: = [Number of units in stock] * [Profit unitary]**
- **Realized demand: = SUM([range of cells for each market])**
- **Sum of warehouse space: = SUM([Occupied warehouse space])**

		Market			Safety stock	Unit warehouse space	Profit individual	Number of units in a warehouse	Occupied warehouse space	Profit for x units
		X	Y	Z						
Product	A				40	14	30	0	0	0
	B				60	12	32	0	0	0
	C				90	18	23	0	0	0
		220	230	332				Total warehouse space	0	
Realized demand		0	0	0		Total warehouse area				
						10000				

[4] Determine the objective function - maximizing profit from product sales

Objective function: **=SUM([Profit for x units])**



[5] Configure Solver

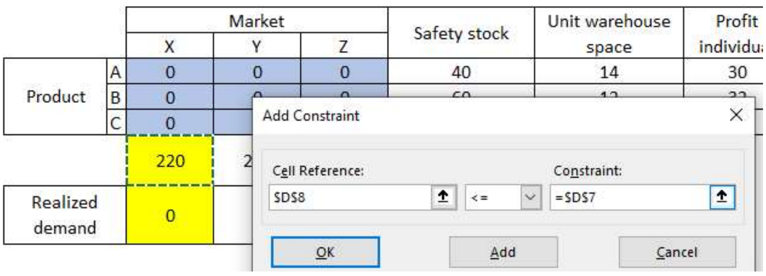
Set the goal – cell with the goal function and maximization of the goal function

Indicate the cells whose values are to be set – the number of products of each type in stock

Add restrictions:

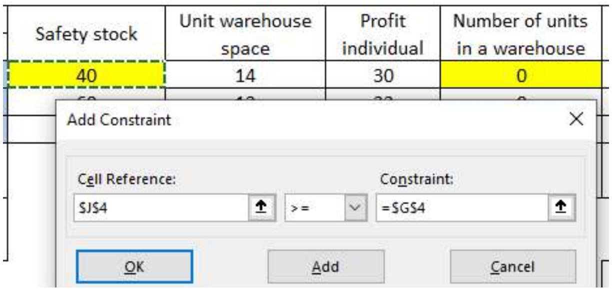
- occupied warehouse space = maximum warehouse space

- realized demand in market X <= demand in market X



- realized demand in market Y <= demand in market Y

- realized demand in market Z <= demand in market Z
- number of units of product A in stock >= safety stock for product A



- number of units of product B in stock >= safety stock for product B
- number of units of product C in stock >= safety stock for product C

[6] Indicate the optimization method – e.g. LP Simplex

[7] Run Solver – press the Solve button

[8] Evaluate the solution you received

		Market			Safety stock	Unit warehouse space	Profit individual	Number of units in a warehouse	Occupied warehouse space	Profit for x units
		X	Y	Z						
Product	A	0	0	40	40	14	30	40	560	1200
	B	220	140	292	60	12	32	652	7820	20853
	C	0	90	0	90	18	23	90	1620	2070
		220	230	332				Total warehouse space	10000	
Realized demand		220	230	332						
						Total warehouse area			Objective function - maximum profit:	24123
						10000				

Chapter Questions

1. How can the Solver add-in in Microsoft Excel support decision-making processes in an enterprise?
2. How does the selection of the appropriate optimization method affect the results of the analysis?

REFERENCES

Antoniuk, I., Svitek, R., Krajčovič, M., & Furmannová, B. (2021). Methodology of design and optimization of internal logistics in the concept of Industry 4.0. Transportation Research Procedia, 55, 503-509.

Baj-Rogowska, A. (2013). Planowanie tras z wykorzystaniem narzędzia Solver, jako zadanie logistyczne w małej firmie. Optymalizacja systemów i procesów logistycznych, 169-178.

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

Bomba, I., & Kwiecień, K. (2012). Zastosowanie dodatku SOLVER aplikacji MS Excel w projektowaniu jednostki paletowej. TTS Technika Transportu Szynowego, 19.

Cyplik, P., & Hadaś, Ł. (2012). Zarządzanie zapasami w łańcuchu dostaw. Wydawnictwo Politechniki Poznańskiej.

Delgado-Aguilar, M., Valverde-Som, L., & Cuadros-Rodríguez, L. (2018). Solver, an Excel application to solve the difficulty in applying different univariate linear regression methods. Chemometrics and Intelligent Laboratory Systems, 178, 39-46.

Dudziński, Z., & Kizyn, M. (2002). Vademecum gospodarki magazynowej. Ośrodek Doradztwa i Doskonalenia Kadr.

Fechner, I. (2007). Zarządzanie łańcuchem dostaw. Poznań: Wyższa Szkoła Logistyki.

Fertsch, M. (ed.). (2006). Słownik terminologii logistycznej. Poznań: Instytut Logistyki i Magazynowania.

Ghiani, G. (2004). Introduction to Logistics Systems Planning and Control. Chichester: John Wiley & Sons Ltd.

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

Gupta, P., Mehlawat, M. K., Aggarwal, U., & Khan, A. Z. (2022). An optimization model for a sustainable and socially beneficial four-stage supply chain. Information Sciences, 594, 371-399.

Hariga, M.A., & Jackson, P.L. (1996). The warehouse scheduling problem: Formulation and algorithms. IIE Transactions 28, 115-127.

Jayarathna, C. P., Agdas, D., Dawes, L., & Yigitcanlar, T. (2021). Multi-objective optimization for sustainable supply chain and logistics: A review. Sustainability, 13(24), 13617.

Kisielewski, P., & Talarek, P. (2020). Optymalizacja procesu magazynowania wysokoskładowego. (ed.) Sosnowski Z. Symulacje komputerowe w badaniach i rozwoju. Oficyna Wydawnicza Politechniki Białostockiej. Białystok. DOI: 10.24427/978-83-66391-28-4_11

Krzyżaniak, S. (2005). Podstawy zarządzania zapasami w przykładach (Wydanie III). Poznań: Instytut Logistyki i Magazynowania.

Krzyżaniak, S. (2006). Lokalizacja zapasów w sieci dystrybucji. LogForum, 2(1), 2.

Kusiak, J., Danielewska-Tułecka, A., & Oprocha, P. (2021). Optymalizacja. Wybrane metody z przykładami zastosowań. Wydawnictwo Naukowe PWN.

Magdalena, R., & Suli, T. (2019). Forecasting Methods and Implementation of DRP (Distribution Requirement Planning) Methods in Determining the Master Production Schedule. In IOP Conference Series: Materials Science and Engineering, 528(1).

Mascle, C., & Gosse, J. (2014). Inventory management maximization based on sales forecast: case study. Production Planning & Control, 25(12), 1039-1057.

Mason, A. J. (2012). OpenSolver-an open source add-in to solve linear and integer progammes in Excel. In Operations Research Proceedings 2011: Selected Papers of the International Conference on Operations Research (OR 2011), August 30-September 2, 2011, Zurich, Switzerland (401-406). Berlin, Heidelberg: Springer Berlin Heidelberg.

Mason, A.J. (2013). SolverStudio: A new tool for better optimisation and simulation modelling in Excel. INFORMS Transactions on Education, 14(1), 45-52.

Miszewski, P. (2019). Rola nowoczesnych rozwiązań technologicznych w optymalizacji pracy współczesnego magazynu. Journal of TransLogistics, 5(1), 175-182.

Muckstadt, J.A., Sapra, A., Muckstadt, J.A., & Sapra, A. (2010). EOQ model. Principles of Inventory Management: When You Are down to Four, Order More, 17-45.

Mukhsin, M., & Sobirin, M.T. (2022). Scheduling Process Analysis Distribution of Product Using the Distribution Requirement Planning (DRP) Method. AFEBI Management and Business Review, 7(2), 78-89.

Muller, M. (2019). Essentials of inventory management. HarperCollins Leadership.

Ngatilah, Y., Rahmawati, N., Pujiastuti, C., Porwati, I., & Hutagalung, A.Y. (2020). Inventory control system using distribution requirement planning (drp)(case study: Food company). In Journal of Physics: Conference Series (Vol. 1569, No. 3, p. 032005). IOP Publishing.

Nugroho, M., Ellianto, M.S.D., & Nurcahyo, Y.E. (2019). Planning and Implementation Enterprise Resource Planning Module Distribution Management Using the Methods of Distribution Requirement Planning in MSMES UD Adhi Teknik. International Review of Management and Marketing, 9(6), 179.

Ramaa, A., Subramanya, K.N., & Rangaswamy, T.M. (2012). Impact of warehouse management system in a supply chain. International Journal of Computer Applications, 54(1).

Reszka, L. (2012). Koniunkcja logistyki i optymalizacji. Acta Universitatis Nicolai Copernici. Zarządzanie, 39, 109-118.

Silva, C.A., Sousa, J. M. C., Runkler, T., & Palm, R. (2005). Soft computing optimization methods applied to logistic processes. International Journal of Approximate Reasoning, 40(3), 280-301.

Smyk, S. (2023). Optymalizacja jako wyzwanie dla menedżerów ds. logistyki. Gospodarka Materiałowa i Logistyka.