

Integrating Mathematical Programming and Stakeholder Consensus for Warehouse Inventory Compression: A Case Study

Nataliya Mutovkina

Department of Management and Social Communications, Tver State Technical University, Tver, 170012, Russia

Email: Letter-boxNM@yandex.ru

ORCID iD: <https://orcid.org/0000-0003-0137-4189>

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Abstract: The article discusses methods for preventing irrational product placement in warehouses. This problem is relevant for many manufacturing enterprises and trade organizations. The most common embodiments of the problem are unoccupied areas, or a lack of free storage space, difficulty in locating a specific product, and challenges in shipping it from the warehouse. All this leads to unnecessary costs for the business entity and hurts its financial and economic activities. The author suggests an integrated approach to warehousing. It integrates both classical optimization models and iterative approval procedures for accounting for the human factor. The key criteria in this case are minimizing costs, the cargo flow in the warehouse, and maximizing the utilization factor of the usable area. The optimal placement of goods is to achieve maximum compression of their residues in the warehouse while minimizing their movement. The presence of two contradictory criteria makes the task a task of consistent optimization. The article discusses the possibilities for solving the optimization problem when conflicting target criteria and differing preferences are present. We are using the example of a storage room with 16 racks for water heaters and similar equipment. As a result of matching optimization procedures, it was possible to reduce the average cost of moving goods by 7.1% and increase the free warehouse area by 15 times. We performed the experiments over the seven days of the warehouse's operation. The practical value of the research is that, through this approach, we find a compromise in conditions of conflicting opinions and interests.

Index Terms: Coordinated Optimization, Compression of Inventory, Optimization in the Warehouse, Turnover, Efficiency of Warehouse Area, Compromise.

1. Introduction

The tasks of optimizing storage facilities are reduced not only to the rational arrangement of shelves, but also to the design of logistics for the placement and shipment of goods. It is a system that combines the most efficient use of warehouse space and automation technologies for warehouse business processes. At the same time, the most important tasks are to reduce costs and accelerate acceptance and shipment operations. The researchers consider typical tasks of optimizing warehouse operations and algorithms for their solution in papers [1-4]. Now it's included in modern warehouse management software. However, the mathematically optimal solution is not always the solution for the participants in the business process. The expansion of constraints in mathematical models makes it difficult, and sometimes makes it impossible, to solve the problem.

The purpose of this study is to develop a method for optimizing the placement of goods in a warehouse at the end of the working day and at the beginning of the next day, taking into account the opinions of interested parties. As a result of optimization, we solve two problems. Firstly, we reduce the cost of placing goods on the shelves; secondly, we increase the coefficient of free warehouse area (CFA). That is important if providers are delivered a new batch of goods prematurely.

1.1. The Structure of the Study and Its Practical Significance

The description begins with an overview of approaches to solving optimization problems in the warehouse. These tasks are typical, but they have specific features due to the specifics of the company's products and activities. For example, in a manufacturing enterprise, the structure of warehouse business processes includes both processes related to the receipt, storage, and shipment of finished products and production materials. In trading companies, warehouse work

mainly concerns finished products. The author examines the trends in warehouse optimization processes and describes the task of optimizing inventory in a warehouse, in particular, inventory balances at the end of the working day and new receipts at the beginning of the next day. The author demonstrates the solution to the problem in MS Excel using the example of a warehouse store of water heaters and other equipment. The cost of placement and the number of empty shelves are considered elements of coordination (without optimization, using the optimal placement algorithm, and adjusting placement with the influence of the human factor). In conclusion, the author summarizes the results of warehouse management. The research results may be useful to those who implement WMS systems, work in warehouse logistics, and for educational purposes.

1.2. Methods for Solving Optimization Problems in a Warehouse

Modern warehouses have a wide range of management tasks. There are the organization of loading and unloading operations, allocation of goods, their movement around the warehouse, storage systems, options for equipment and personnel, and distribution of responsibilities. The key criteria in these tasks are minimizing warehouse costs, reducing labor intensity, improving the quality of inventory storage, and boosting warehouse business processes.

Depending on the formulation and economic essence of the optimization problem, different methods of its solution are distinguished. For example, to minimize warehouse cargo flow, one may use ABC/XYZ analysis [5,6], linear optimization [7-9], and a system of maximum and minimum stores [10].

ABC/XYZ analysis allows you to classify goods according to customer demand and their contribution to turnover. The results of the ABC/XYZ analysis help rationally organize the placement of goods. High-turnover goods are closer to the shipping area. Slow-moving goods are located on the upper tiers or in the depths of the warehouse.

One promising solution involves modern technologies in management processes. These are address storage, barcoding and labeling, and WMS systems. When choosing an algorithm, it is necessary to take into account the type of warehouse (store, production, capacity), product range (food, non-food products, production materials), and equipment (machinery, racks).

Inventory management is a typical structure in many ways. Four traditional inventory management strategies can be distinguished, each of which forms the basis of a specific company's management mechanism (Fig. 1).

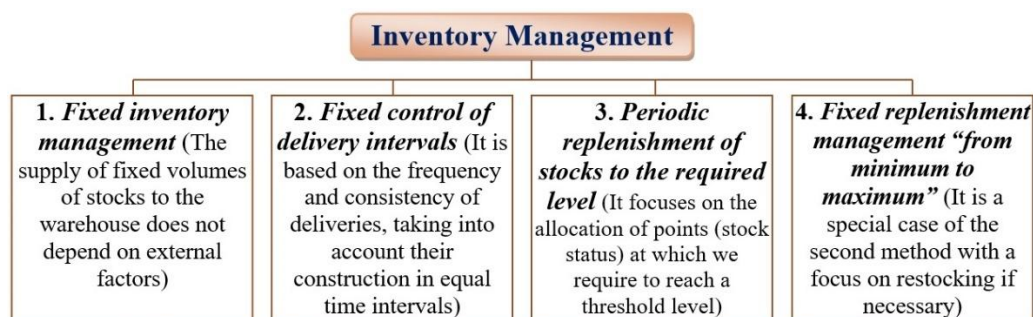


Fig. 1. Inventory Management Strategies.

The well-known Wilson model can be used to determine the optimal stock size. However, it has significant limitations. For example, it is applicable only for one type of product. The Wilson model does not account for possible fluctuations in demand, seasonality, marketing campaigns, or external events that may influence sales. There are other limitations [11].

Forecasting the demand for stocks and optimizing them is possible using machine learning methods. The algorithms of ARIMA and LSTM [12,13] enable more accurate determination of future market needs and inform order planning, reducing the risks of shortages or excess balances.

The introduction of an addressable storage system, the compilation of a heat map of the warehouse, and calculations of the optimal inventory volume collectively are effective measures to optimize warehouse operation [14]. Optimizing warehouse staff is also significant for maximizing productivity [15]. Thus, several areas of optimization for warehouse processes can be identified (Fig. 2).

The expert assessment method and the simplex method are suitable for organizational and personnel optimization. The expert assessment method identifies the most competent employees to solve specific tasks [16]. The simplex method solves the assignment problem when expert assessments of the professional compliance of employees with vacant positions are known [17].

Technical and technological optimization in a warehouse consists of solving the problem of selecting the necessary equipment, loaders, and robotics systems. The selection criterion may be the ratio between operating costs and the effect in the form of cost savings for the search, assembly, shipment of goods, the cost of correcting errors, and the cost of damage to goods.

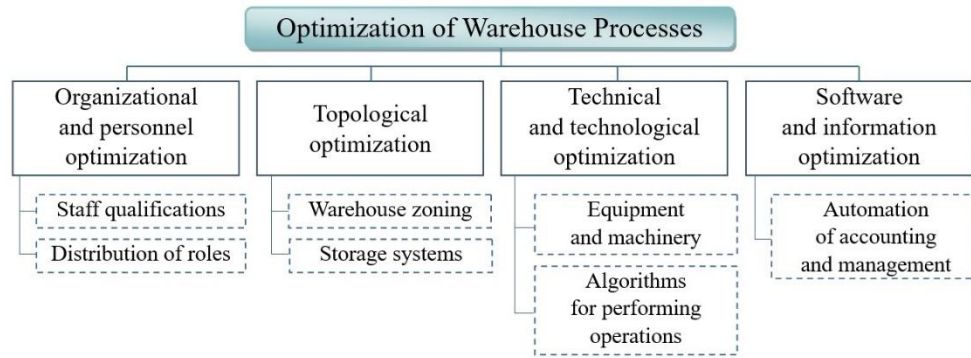


Fig. 2. Areas of Optimization of Warehouse Processes.

Software and information optimization also involves choosing a warehouse management software package. The warehouse management systems (WMS) track the movement of goods in real-time mode and automate the acceptance, placement, and assembly of orders [18]. Such systems can integrate with ERP platforms to manage the entire supply chain. The use of barcoding, RFID tags, and data collection terminals simplifies inventory, speeds up product processing, and reduces the likelihood of errors.

Topological optimization can divide the warehouse into zones and cells. Each cell has its own unique address. That speeds up the search, minimizes errors, and reduces employee training costs. The rational layout of the warehouse, combined with various storage types (floor, shelf, wide-aisle, and narrow-aisle racks) and vertical storage (multi-tiered racks and high-rise systems with cranes), can increase storage capacity [19]. Processing routes in the warehouse, taking into account the frequency of calls to certain goods, reduces the time for their assembly and transportation. In this study, we select the task of optimizing the placement of goods (compressing inventory) with route optimization (minimizing the distances traveled by the loader) from the set of designated tasks.

Many works consider algorithms for solving such problems [20–23]. For example, Yifan Shen, Yansong Wu, Ning Zhao, and Weijian Mi consider an approach based on deep reinforcement learning (DRL) to solve the Storage Space Allocation Problem (SSAP) [20]. The authors created a comprehensive SSAP model. Its goals and limitations still reward functions and environmental rules within the DRL framework. DQN learns optimal resource allocation strategies by interacting with a simulated terminal environment. That approach is fully justified precisely in the operations of container terminals, which are known for their scale. The work uses a reinforcement learning neural network, but large datasets are needed to train and verify its adequacy. Such datasets do not exist in a small warehouse that has not operated for a long time.

Zhang, Dingnan, Boyang Liu, Enqi Yue, and Dongsheng Wu proposed a comprehensive system in which algorithms for distribution, scheduling, and a model of energy-intensive loader trajectories operate in feedback mode, which significantly increases the overall productivity and environmental friendliness of modern automatic control and control systems [21]. This work is related to this study, but it is much more extensive and does not include the human factor.

Wang, Xiaohan, Zhihong Jin, and Jia Luo propose an innovative resource allocation strategy between the seaport and the railway container terminal, focusing on the sharing of warehouse space and domestic trucks [22]. The authors developed an integer programming model for indirect transshipment operations between ships, ports, railway container terminals, and trains. The model aims to minimize the cost of container transshipment and the weighted turnaround time of ships and trains. This model simultaneously determines the distribution of warehouses, container transshipment, and truck allocation.

The multitude of parameters and the need to use large amounts of data to verify this model also make it inapplicable in a small retail warehouse. A review of these and other publications on the research topic allows us to conclude that it is advisable to take into account not only the warehouse objective working conditions for optimization, but also human resources.

2. The Task of Optimizing the Placement of Inventory in the Warehouse

2.1. Problem Description

Due to high turnover caused by daily deliveries and shipments of goods from the warehouse, the problem of suboptimal inventory storage arises. The products are on storage racks, each consisting of three tiers. There are three units of products (boxed packaging) on each tier. The products arrive at the warehouse daily, and each arrival is a separate batch. The products are non-food, have a long shelf life, differ in design and several functional properties, and there are no special requirements for their placement in product spaces. However, it is advisable to sell products to customers using the FIFO method [24]. Products can be placed in any available commodity area or added to a

commodity space that already contains individual product units. The products in question are individual, and we can transfer them to a complete set from different locations in one working day. At the end of the working day, a different number of goods remains on the shelves (Fig. 3). To place a new product, you need free storage racks or at least separate shelves for it. That creates the problem of compressing inventory balances. The solution involves relocating unsold items from one storage rack to another. It is advisable to reposition from the racks with the smallest leftovers.



Fig. 3. Stock Balances at the End of the Working Day.

We are in the situation at the beginning of the next working day, when a certain amount of inventory is in each rack, and we need to deliver new products into free cells. At the same time, we can't ship those remaining inventory that is further from the entrance, near the walls of the product space, due to new arrivals. The FIFO principle does not apply, the distribution of new goods takes a long time, and the costs of intra-warehouse logistics are increasing. The problem is the suboptimal use of storage capacity. The more such partially occupied product spaces there are, the fewer vacant product spaces that are available to accept new shipments.

The idea is to place the remnants of goods from different shipments at the end of the working day in one or several product spaces, depending on the number of remnants and the complexity of such placement. We characterize the complexity of combining commodity residues by the distance between the racks and the cost of moving.

2.2. The Algorithm for Compressing Inventory Balances

The initial data for the optimization algorithm are:

The number of racks in the warehouse (n), and any rack can act as a "donor" (inventory residues are from it) and as a "recipient". Therefore, in the future, we will use two values: m is the number of "donors", and n is the number of "recipients". MS Excel tables of dimension $m \times n$ are used for simulation, where i is the row number (of the "donor" rack); j is the column number (of the "recipient" rack). Each rack contains w_j storage spaces. This value depends on the type and configuration of the racks. The number of occupied goods on each "donor" rack is u_i , and the number of occupied goods on the "recipient": racks is v_j . The distance between each pair of racks is also known, but we use the average distance that a loader travels from one rack to another per shift. The loader moves along marked paths and cannot violate the boundaries. The average cost of moving one commodity unit per unit of distance between the racks is also known. After entering these values, formula (1) calculates the differences in the quantities of goods on the racks. Thus, we determine the "donor" racks. Fulfillment of conditions (2)-(5) makes it possible to construct a matrix of optimal movements of commodity balances. The replacement is if $x_{ij} = 1$.

$$\delta_{ij} = u_i - v_j \quad (1)$$

$$d_{ij} = \min_j d_{ij}, i \neq j \quad (2)$$

$$u_i \neq 0 \quad (3)$$

$$\delta_{ij} < 0 \quad (4)$$

$$v_j + u_i \leq w_j \quad (5)$$

We form a matrix of optimal movements, in which $\sum_{j=1}^n u_i \cdot x_{ij}$ is the quantity of moving goods. We calculate the new values of v_j and u_i according to conditions (6), (7).

$$\text{If } x_{ij} \text{ in column } j \text{ is equal to one, Then } v_j^t = v_j^{t-1} + u_i^{t-1}, \text{ Else } v_j^t = v_j^{t-1} \quad (6)$$

$$\text{If } x_{ij} \text{ in row } i \text{ is equal to one, Then } u_i^t = 0, \text{ Else } u_i^t = v_j^t \quad (7)$$

The quantity of goods in the warehouse after moving (U) must match the quantity before moving (new goods will be at the beginning of the next business day).

$$U = \sum_{i=1}^m u_i^t, U \leq \sum_{j=1}^n w_j \quad (8)$$

Figure 4 shows this algorithm.

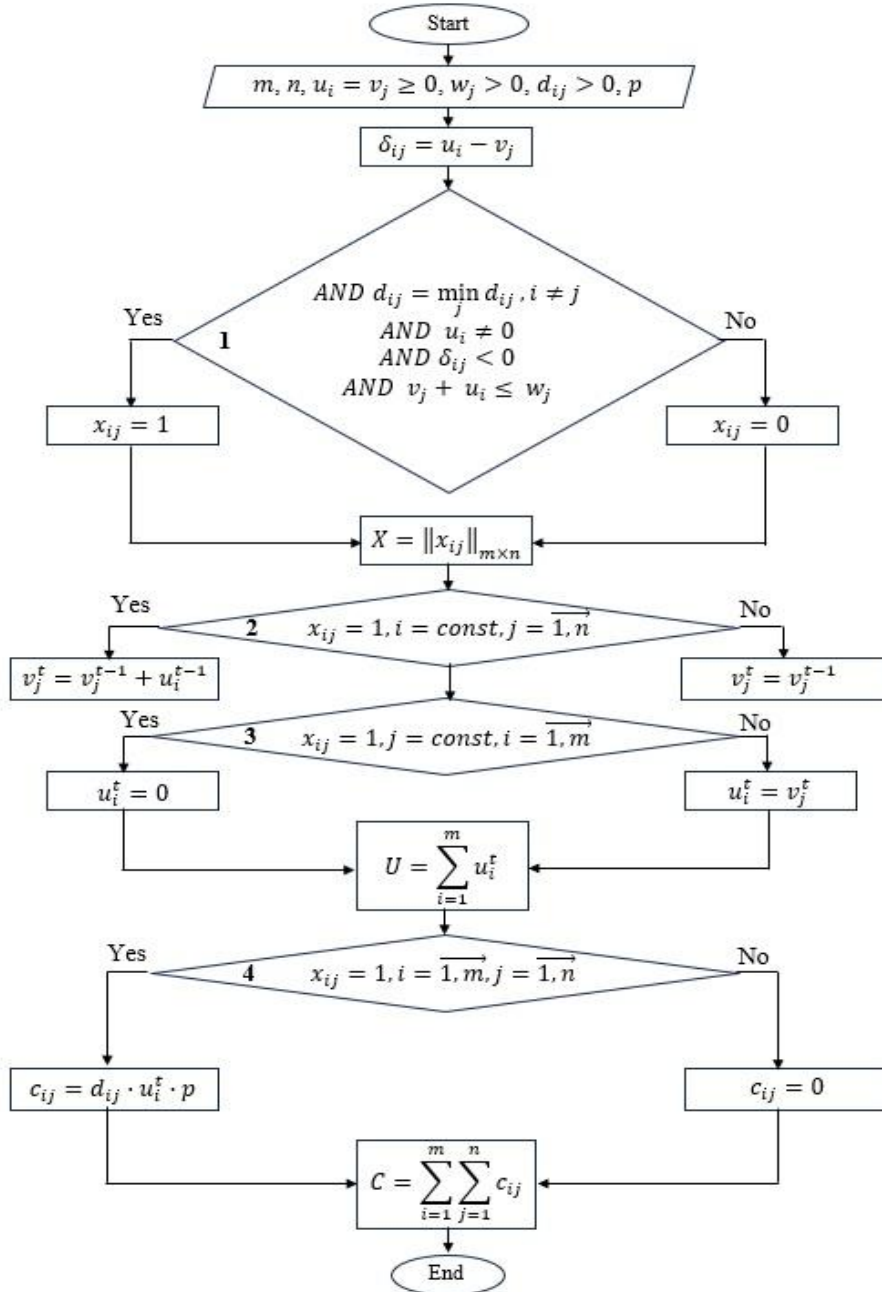


Fig. 4. A Block Diagram of the Inventory Balances Optimization Algorithm.

To calculate the cost of moving the leftovers, we check the condition of equality to 1 in the optimal movement matrix $X = ||x_{ij}||_{m \times n}$ (condition 4 in Fig. 4). If this condition is met, the costs are calculated using the formula (Fig. 4); if not, the costs are zero. The last action determines the total cost (C).

2.3. The Algorithm for Coordinating the Movement of Inventory Balances

After optimal placement of inventory, the process can end, but there are other opinions regarding the criterion of optimality. For example, warehouse workers face an irrational workload; the target criterion is to free as many racks as possible from inventory. Therefore, they can offer a solution to “compress” inventory based on their own experience. As an indicator of movement, we can use the arrival dates of goods that are still in stock. Warehouse workers perform additional movements for items whose arrival dates coincide with or are close to the warehouse. The initial data for new movements are the number of racks in the warehouse (m), the results of the optimization algorithm (Fig. 4), and the coefficients of free area in the warehouse in the employee’s representation k (CFA_k). The number of available racks in the warehouse after optimization and the free area coefficient are calculated using formulas (9) and (10).

$$s = \text{COUNT IF } (u_i^t, u_i^t = 0) \quad (9)$$

$$CFA^t = s/m \quad (10)$$

If the CFA coincides with the CFA estimated by warehouse staff, then the approval process ends. If not, then a consistent optimization procedure is implemented. The matrix is based on employee representation. The new costs for the proposed relocation are calculated by formula (11).

$$c_{ij}^{t+1} = d_{ij} \cdot u_i^{t+1} \cdot p \quad (11)$$

The matching of the free area coefficients is repeated (Fig. 5).

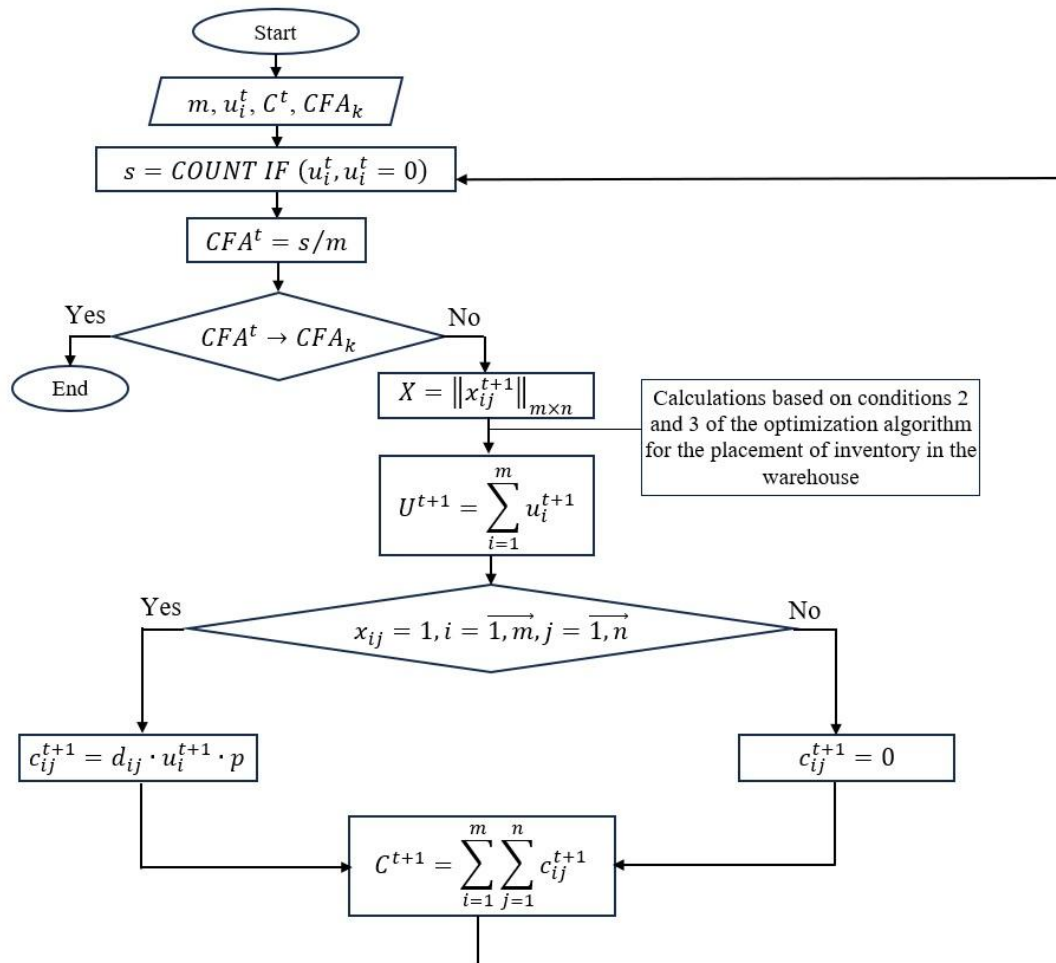


Fig. 5. A Block Diagram of the Displacement Coordination Algorithm.

The new cost value (C^{t+1}) is compared with the previous one. If exceeding this amount is acceptable, then a decision is made on additional moving.

2.4. The Algorithm for the Distribution of New Goods

The previous algorithms reduce the complexity of distributing new product receipts to the warehouse. The more free racks there are, the faster, easier, and cheaper it is to place new products. However, there is a question of optimizing new placements. Fig. 6 shows this algorithm.

The initial data are: the number of racks (m), the number of occupied shelves on each rack before new arrivals (u_i^t), the rack's capacity (w_j), the distance from the warehouse entrance to each rack (d_{ej}), and the volume of new merchandise receipts (Y^t). The new product is placed, first of all, on racks closest to the entrance, which are the least filled (or vacant). We calculate the value of r_i^t at all conditions in block 1 (Fig. 6). The value of r_i^t serves as a restriction on the placement of new products. If at least one condition from block 1 is not satisfied, then the r_i^t restriction is zero. We exclude this rack from consideration at this stage. The value y_i is the distributable quantity of goods per rack i . For the first rack, this value corresponds to Y^t . We use condition block 2 (Fig. 6) to calculate the quantity of goods for the next rack. These conditions are "responsible" for the distributable value "behavior" of the new product. To calculate the quantity of goods placed on rack i , we apply condition blocks 3 and 4. The value of b_i can take one of three values, depending on these conditions. When the distributed quantity y_i falls below b_i , the distribution ends, and the number of filled shelves on rack i remains unchanged. These actions are performed sequentially for all m racks. We calculate the number of distributed goods (B^{t+1}). If we distribute all new items, the process ends. If not, the next iteration begins, in which the initial distributable value will be Y^t , reduced by the distributed value B^{t+1} .

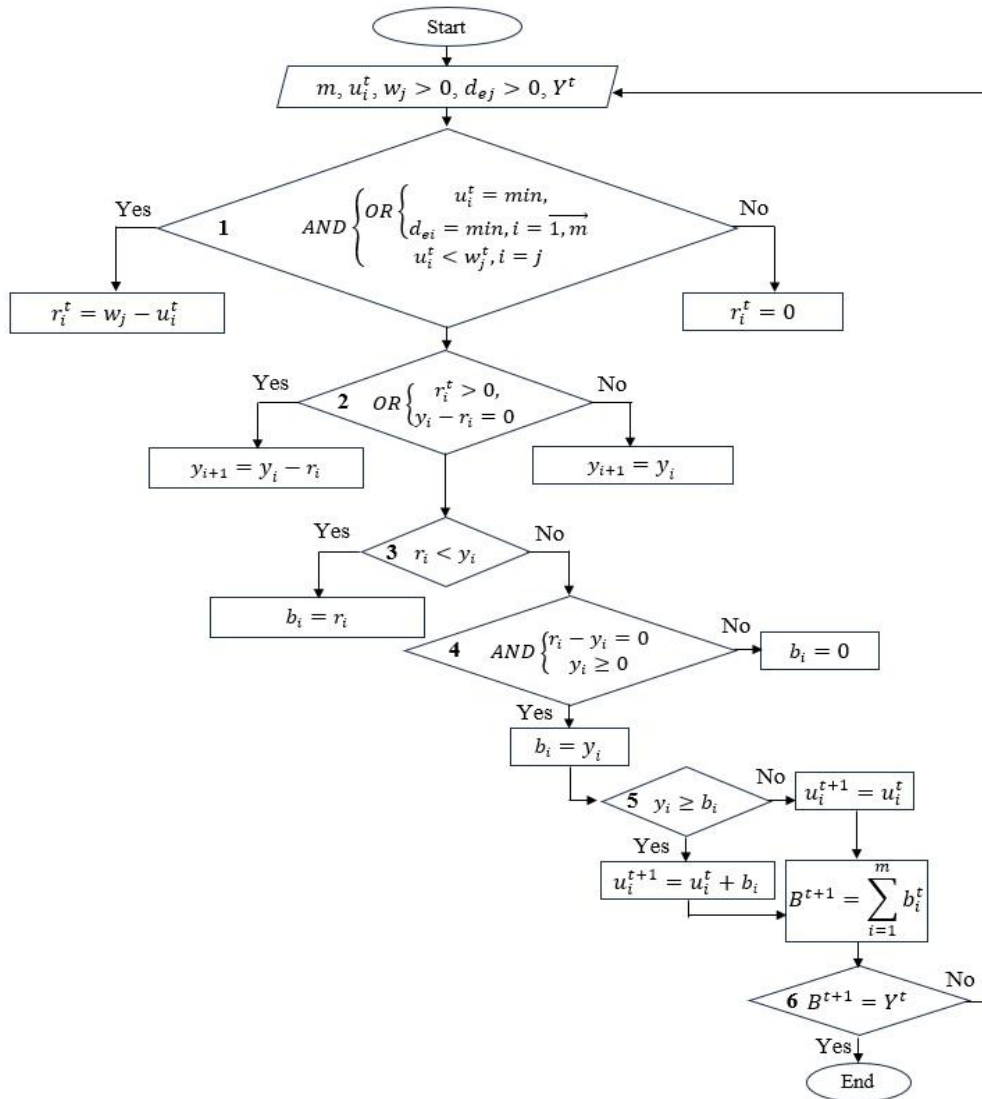


Fig. 6. A Block Diagram of the Algorithm for the Distribution of New Goods.

The third section of the article discusses the application of optimization and matching algorithms using the example of a warehouse of water heaters.

3. Results and Discussions

This section contains a demo example of a coordinated optimization model for the distribution of water heaters in a warehouse of a household appliance store. We consider the receipt of goods at the warehouse within one week. The analysis includes the results and comments on them. The section concludes with a discussion of the effects and method limitations.

3.1. Initial Data

The initial data:

The quantity of racks ($m = n = 16$).

The quantity of cells in each rack ($w_i = w_j = 9$).

$W = \sum_{j=1}^n w_j = 144$ is the capacity of the warehouse.

Fig. 7a) shows the warehouse from above, and Fig. 7b) shows its side view.



Fig. 7. The Warehouse Model.

The matrix of distances between racks is Table 1.

Table 1. Matrix of distances between racks, in meters.

Numbers of Racks	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0	4	8.3	14.5	2	4.5	9	14.5	5.5	6.5	11	15.7	7.5	9.5	13.3	19.2
2	4	0	4	8.3	4.5	2	4.5	9	6.5	5.5	6.5	11	9.5	7.5	9.5	13.3
3	8.3	4	0	4	9	4.5	2	4.5	11	6.5	5.5	6.5	13.3	9.5	7.5	9.5
4	14.5	8.3	4	0	14.5	9	4.5	2	15.7	11	6.5	5.5	19.2	13.3	9.5	7.5
5	2	4.5	9	14.5	0	4	8.3	14.5	3	6.3	10.3	15.3	5.5	6.5	11	15.7
6	4.5	2	4.5	9	4	0	4	8.3	6.3	3	6.3	10.3	6.5	5.5	6.5	11
7	9	4.5	2	4.5	8.3	4	0	4	10.3	6.3	3	6.3	11	6.5	5.5	6.5
8	14.5	9	4.5	2	14.5	8.3	4	0	15.3	10.3	6.3	3	15.7	11	6.5	5.5
9	5.5	6.5	11	15.7	3	6.3	10.3	15.3	0	4	8.3	14.5	2	4.5	9	14

10	6.5	5.5	6.5	11	6.3	3	6.3	10.3	4	0	4	8.3	4.5	2	4.5	9
11	11	6.5	5.5	6.5	10.3	6.3	3	6.3	8.3	4	0	4	9	4.5	2	4.5
12	15.7	11	6.5	5.5	15.3	10.3	6.3	3	14.5	8.3	4	0	14	9	4.5	2
13	7.5	9.5	13.3	19.2	5.5	6.5	11	15.7	2	4.5	9	14	0	4	8.3	14.5
14	9.5	7.5	9.5	13.3	6.5	5.5	6.5	11	4.5	2	4.5	9	4	0	4	8.3
15	13.3	9.5	7.5	9.5	11	6.5	5.5	6.5	9	4.5	2	4.5	8.3	4	0	4
16	19.2	13.3	9.5	7.5	15.7	11	6.5	5.5	14	9	4.5	2	14.5	8.3	4	0

Important additions are: We replace diagonal elements in the model with values significantly more than the maximum distance. For example, we took 100 meters. That is necessary for the algorithm to work correctly. In one iteration, goods move only once. Table 2 shows the initial data for the simulation.

Table 2. Modeling Data.

Numbers of Racks Quantity of Goods		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
		3	1	4	2	5	4	6	5	3	6	2	5	4	6	5	3
1	3	100	4	8.3	14.5	2	4.5	9	14.5	5.5	6.5	11	15.7	7.5	9.5	13.3	19.2
2	1	4	100	4	8.3	4.5	2	4.5	9	6.5	5.5	6.5	11	9.5	7.5	9.5	13.3
3	4	8.3	4	100	4	9	4.5	2	4.5	11	6.5	5.5	6.5	13.3	9.5	7.5	9.5
4	2	14.5	8.3	4	100	14.5	9	4.5	2	15.7	11	6.5	5.5	19.2	13.3	9.5	7.5
5	5	2	4.5	9	14.5	100	4	8.3	14.5	3	6.3	10.3	15.3	5.5	6.5	11	15.7
6	4	4.5	2	4.5	9	4	100	4	8.3	6.3	3	6.3	10.3	6.5	5.5	6.5	11
7	6	9	4.5	2	4.5	8.3	4	100	4	10.3	6.3	3	6.3	11	6.5	5.5	6.5
8	5	14.5	9	4.5	2	14.5	8.3	4	100	15.3	10.3	6.3	3	15.7	11	6.5	5.5
9	3	5.5	6.5	11	15.7	3	6.3	10.3	15.3	100	4	8.3	14.5	2	4.5	9	14
10	6	6.5	5.5	6.5	11	6.3	3	6.3	10.3	4	100	4	8.3	4.5	2	4.5	9
11	2	11	6.5	5.5	6.5	10.3	6.3	3	6.3	8.3	4	100	4	9	4.5	2	4.5
12	5	15.7	11	6.5	5.5	15.3	10.3	6.3	3	14.5	8.3	4	100	14	9	4.5	2
13	4	7.5	9.5	13.3	19.2	5.5	6.5	11	15.7	2	4.5	9	14	100	4	8.3	14.5
14	6	9.5	7.5	9.5	13.3	6.5	5.5	6.5	11	4.5	2	4.5	9	4	100	4	8.3
15	5	13.3	9.5	7.5	9.5	11	6.5	5.5	6.5	9	4.5	2	4.5	8.3	4	100	4
16	3	19.2	13.3	9.5	7.5	15.7	11	6.5	5.5	14	9	4.5	2	14.5	8.3	4	100

Thus, in this example, 64 items are stored in the warehouse. That is the filling at the end of the first day of the working week.

3.2. Application of the Algorithm of “Compression” of Inventory Balances

Next, an optimization algorithm is applied (Fig. 4). Table 3. has a matrix of differences $\Delta = \|\delta_{ij}\|_{m \times n}$ calculated using formula (1).

Table 3. The Matrix of Differences in the Volume of Goods on the Racks.

Numbers of Racks Quantity of Goods		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
		3	1	4	2	5	4	6	5	3	6	2	5	4	6	5	3
1	3	0	2	-1	1	-2	-1	-3	-2	0	-3	1	-2	-1	-3	-2	0
2	1	-2	0	-3	-1	-4	-3	-5	-4	-2	-5	-1	-4	-3	-5	-4	-2
3	4	1	3	0	2	-1	0	-2	-1	1	-2	2	-1	0	-2	-1	1
4	2	-1	1	-2	0	-3	-2	-4	-3	-1	-4	0	-3	-2	-4	-3	-1
5	5	2	4	1	3	0	1	-1	0	2	-1	3	0	1	-1	0	2
6	4	1	3	0	2	-1	0	-2	-1	1	-2	2	-1	0	-2	-1	1
7	6	3	5	2	4	1	2	0	1	3	0	4	1	2	0	1	3
8	5	2	4	1	3	0	1	-1	0	2	-1	3	0	1	-1	0	2
9	3	0	2	-1	1	-2	-1	-3	-2	0	-3	1	-2	-1	-3	-2	0
10	6	3	5	2	4	1	2	0	1	3	0	4	1	2	0	1	3
11	2	-1	1	-2	0	-3	-2	-4	-3	-1	-4	0	-3	-2	-4	-3	-1
12	5	2	4	1	3	0	1	-1	0	2	-1	3	0	1	-1	0	2
13	4	1	3	0	2	-1	0	-2	-1	1	-2	2	-1	0	-2	-1	1
14	6	3	5	2	4	1	2	0	1	3	0	4	1	2	0	1	3
15	5	2	4	1	3	0	1	-1	0	2	-1	3	0	1	-1	0	2
16	3	0	2	-1	1	-2	-1	-3	-2	0	-3	1	-2	-1	-3	-2	0

Table 4 provides a matrix of optimal product movements. It is by checking the conditions of block 1 (Fig. 4).

Table 4. The Matrix of Optimal Displacements.

Numbers of Racks	Quantity of Goods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
		3	1	4	2	5	4	6	5	3	6	2	5	4	6	5	3
1	3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
5	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
12	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	3	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0

Table 5 shows the result of the optimization model in Excel. The quantity of goods on the racks is in the second column of Table 5, on condition (7). These values are in blue. The values in the second row of Table 5, which are in black italics, are auxiliary calculations according to formula (6).

Table 5. The Optimization Results.

Numbers of Racks	Quantity of Goods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
		3	1	4	2	8	5	6	7	3	6	2	8	7	6	7	3
1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
5	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
12	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0

As a result, we free up six racks. We can fully place the 54 new items on the first, second, fourth, ninth, eleventh, and sixteenth racks. The criteria for movement efficiency are the costs (formula (11)) and the coefficient of free area (formula (10)). At $p=0.5$, we get: $c=14$ monetary units, $CFA=0.38$.

3.3. Application of the Algorithm of the Displacement Coordination

Based on considerations of saving time and costs for unloading and placing a new batch of goods, the storekeepers proposed to vacate the sixth rack by moving four units from it to the twelfth rack; move three units from the sixteenth rack to the eighth rack, send two units from the fourth rack to the third rack, and remove one unit from the second rack to the seventh rack (these are products of the same brand). Table 6 shows the new distribution of goods at the end of the first working day.

Thus, it was possible to increase the coefficient of free area to 0.44, but the costs also increased to 43.1 monetary units. When making a decision, management should determine which is more important: minimizing the cost of “compressing” inventory or maximizing the free area factor. For example, if a batch of 63 items is to arrive, it is

advisable to adopt the second “compression”. The warehouse management should coordinate the staff actions with the plan for the next working day.

Table 6. Results of Coordinated Optimization

Numbers of Racks Quantity of Goods		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
		3	1	6	2	8	4	7	8	3	6	2	9	7	6	7	3
1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
7	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
12	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

3.4. Application of the Algorithm for the Distribution of New Goods

We applied the algorithm for optimizing the distribution of new goods to the three scenarios of inventory distribution already obtained at the previous stages. Figure 8 shows a fragment of the distribution Y^t according to the first variant (without optimization). We assumed 25 items would arrive at the beginning of the next day.

[illegible]

Fig. 8. A Fragment of the Distribution Model for New Arrivals of Goods to the Warehouse.

As Figure 8 shows, it took only two iterations to distribute 25 units. Column “M” shows the placement of goods on the racks. The target function (TF) was 89 commodity units with the placement costs of 76.9 monetary units. The cost calculation deserves special attention. The goods are transported to the warehouse by a forklift. Its capacity equals 9 units. The more goods the loader delivers at one time, the lower the cost. Based on these considerations and cost accounting statistics, we introduce the cost indicator ($k_{c_i}^t$). The more goods a loader transports at a time (one move), the lower the value of this coefficient. So, for nine units, $k_{c_i}^t = 0.11$; for eight units, $k_{c_i}^t = 0.22$; for seven units, $k_{c_i}^t = 0.33$; for six units, $k_{c_i}^t = 0.44$; for five units, $k_{c_i}^t = 0.55$; for four units, $k_{c_i}^t = 0.66$; for three units, $k_{c_i}^t = 0.77$; for two units, $k_{c_i}^t = 0.88$; for one unit, $k_{c_i}^t = 0.99$.

The costs in this case are calculated using the formula:

$$C^t = b_l^t \cdot d_{ej} \cdot k_{ci}^t \quad (12)$$

The total cost of distributing new products is the sum of the costs of all iterations.

Fig. 9 shows the distribution of 25 units of the new batch. As initial values u_i^1 , we took the results of movements of inventory balances from Table 5.

In this case, the cost of placement was only 53 monetary units, which is 31% lower than the previous result. The distribution took place in one iteration. The distribution, with the initial data taken from Table 6, presents the same picture (TF=89 units, $C^1 = 53$ monetary units). However, now there are four free racks.

A series of experiments allowed us to draw the following conclusions:

1) Coordinated optimization is an effective tool when there are several criteria in an optimization problem. It is advisable to use the algorithm in Figure 5 if we plan a large batch of goods to arrive. In this case, it is critically important to have absolutely free racks. The matching algorithm allows you to determine and coordinate the costs of moving inventory before the planned shipment arrives. We achieve cost control.

2) If we plan a small batch of goods to arrive, then it is advisable to use the classical optimization algorithm (Fig. 4), but only if the results of the algorithm are sufficient to accommodate the planned receipts. If the exact quantity of the product is unknown, a coordinated optimization procedure should be applied.

3) Coordinated optimization allows us to find a balance between several criteria or target functions. In this case, it is a balance between the cost of moving goods and the CFA.

[illegible]

Fig. 9. Distribution of New Product Receipts with Optimal Initial Data.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y		
1	Rack (i)	Exp 1						Exp 2						Exp 3						Exp 4							
2		Before	After	CO	RG	B	RG	A	RG	CO	Before	After	CO	RG	B	RG	A	RG	CO	Before	After	CO	RG	B	RG	A	RG
3	1	3	0	0	3	9	9	9	1	1	0	9	6	9	1	1	0	9	9	9	2	0	0	2	9	9	9
4	2	1	0	0	9	9	9	6	6	8	6	6	8	6	6	8	6	6	8	1	0	0	9	8	8	8	
5	3	4	4	6	4	4	6	2	0	0	9	9	9	2	0	0	9	9	9	8	8	8	8	8	8	8	
6	4	2	0	0	9	7	7	9	9	9	9	9	9	9	9	9	9	9	9	7	7	7	7	7	7	7	
7	5	5	8	8	9	8	8	9	9	9	9	9	9	9	9	9	9	9	9	5	7	7	9	7	7	7	
8	6	4	5	0	4	5	0	4	4	4	4	4	4	4	4	4	4	4	4	3	4	4	3	4	4	4	
9	7	6	6	7	6	6	7	5	7	8	5	7	8	5	7	8	5	7	8	3	3	0	3	3	0	0	
10	8	5	7	8	5	7	8	3	3	0	3	3	7	3	3	0	4	3	9	7	7	7	7	7	7	7	
11	9	3	0	0	9	0	0	7	7	8	9	9	8	7	7	8	9	9	9	6	7	7	9	7	7	7	
12	10	6	6	6	6	6	6	6	6	8	6	6	8	6	6	8	6	6	8	6	9	9	6	9	9	9	
13	11	2	0	0	2	0	0	2	2	0	2	2	0	2	2	0	9	9	9	4	4	7	4	4	4	7	
14	12	5	8	9	5	8	9	5	6	6	5	6	6	5	6	6	5	6	6	1	0	0	3	0	0	0	
15	13	4	7	7	4	7	7	3	3	3	3	3	3	3	3	3	3	3	3	1	0	0	1	0	0	0	
16	14	6	6	6	6	6	6	6	6	8	6	6	8	6	6	8	6	6	8	3	0	0	3	0	0	0	
17	15	5	7	7	5	7	7	2	2	0	2	2	0	2	2	0	9	7	3	8	8	8	8	8	8	8	
18	16	3	0	0	3	0	0	1	0	0	9	9	0	1	0	0	9	9	0	8	9	9	8	9	9	9	
19	Sum	64	64	64	89	89	89	71	71	71	96	96	96	71	71	71	111	111	111	73	73	73	90	90	90	90	
20	Y ^t	25	25	25				25	25	25				40	40	40				17	17	17					
21	Costs	0	14	43.1	76.9	53.0	53.0	0	3	22	76.07	49.08	56.8	0	3	21.8	137.3	112.1	82.4	0	8	13	65.56	20.0	20.0		
22	Quantity of Available Racks	0	6	7	0	3	4	0	2	6	0	0	3	0	2	6	0	0	1	0	5	6	0	3	4		
23	CFA	0	0.38	0.44	0	0.188	0.25	0	0.13	0.38	0	0	0.19	0	0.13	0.38	0	0	0.06	0	0.31	0.4	0	0.188	0.25		

Fig. 10. A Fragment of Experiments.

Fig. 10 illustrates the experimental results supporting these conclusions. In the first experiment, 64 items remained at the end of the working day. They are on all the racks in different quantities. If the current configuration is maintained, there will be no relocation costs. However, when a batch of 25 units arrives the next day, the cost of their distribution will amount to 76.9 monetary units. There will be no empty racks, and in case of emergency, this would create additional difficulties for placing new goods. If we apply an optimization algorithm (Fig. 4), the cost of “compression” will amount to 14 monetary units. Six racks are freed up. Upon receipt of 25 units, the cost of their placement will amount to 53 monetary units. Three racks will remain empty. Using a matching algorithm increases the cost of “compression” but frees up another rack. However, it seems superfluous for 25 units. Nevertheless, if an unexpected arrival of goods is possible, the matching algorithm becomes advantageous.

3.5. Discussion of the Possibilities of Integrating Mathematical Programming and Stakeholder Consensus

Coordination procedures are constructive for resolving various contradictions and reconciling interests between the parties involved in decision-making. They are achieving a mutually acceptable result through consistent actions that reconcile divergent positions [25]. The main characteristics of the matching procedures are:

- Versatility. They can be applied at any stage of a conflict situation and in different areas of decision-making.
- They are systemic in nature.
- They include certain sequential actions, for example:
 - Identifying the core conflict between the parties;
 - Formulating dispute resolution options;
 - Conducting a discussion to reach agreement using compromise, consensus, or unanimity;
 - Formalizing the agreement reached in the form of a decision.
- The possibility of embedding matching procedures into optimization algorithms, with a certain loss of optimality from a mathematical point of view, but gaining consistency and greater coherence of actions of participants in decision-making.

Table 7 contains the final experimental results. The initial data for these experiments are the daily arrivals and shipments of goods from the warehouse. Table 7 shows three indicators: the total cost of moving goods, CFA before new goods arrive at the warehouse, and CFA after the goods arrives. In terms of cost, the coordinated optimization option ranks second in terms of optimality. The average cost was 78.2 monetary units. This value is lower than the “Before” option (when we did not perform movements) but more than the “After” option (which uses an optimization algorithm). This is expected, as the coordination procedures and the subsequent decision also require certain costs.

Table 6. Results of Coordinated Optimization

Experiment	The Total Cost of Moving Goods, monetary units			CFA before the Arrival of New Goods			CFA after the Arrival of New Goods		
	<i>Before</i>	<i>After</i>	<i>CO</i>	<i>Before</i>	<i>After</i>	<i>CO</i>	<i>Before</i>	<i>After</i>	<i>CO</i>
1	76.9	67.0	96.1	0.00	0.38	0.44	0.00	0.19	0.25
2	76.1	52.1	78.5	0.00	0.13	0.38	0.00	0.00	0.19
3	137.3	115.1	104.2	0.00	0.13	0.38	0.00	0.00	0.06
4	65.6	28.0	32.5	0.00	0.31	0.38	0.00	0.19	0.25
5	77.7	76.1	81.3	0.00	0.38	0.44	0.00	0.13	0.19
6	34.6	71.1	72.1	0.13	0.50	0.56	0.00	0.31	0.31
7	121.1	74.7	82.7	0.13	0.50	0.56	0.00	0.19	0.19
Average Values	84.2	69.2	78.2	0.04	0.3	0.4	0.00	0.1	0.2
Average Square Deviations	34.5	26.4	22.9	0.06	0.16	0.08	0.00	0.11	0.08
Coefficients of Variation, %	41.0	38.2	29.3	170.8	47.3	18.8	–	78.7	38.2

The coefficient of variation in the “CO” variant shows uniformity of the results ($V=29.3\%<33.0\%$), and they are predictable. The average values of the other two indicators in the “CO” variant are also the highest, which is a good result. Coordinated optimization allows for increasing the free warehouse area both before and after the arrival of new goods. That is important in case of an unexpected arrival of goods.

4. Conclusion

Warehouses play a critical role in various logistics systems. In some companies, the warehouse is a key element of the main business processes. These are usually logistics companies and online stores. For industrial enterprises and wholesale companies, a warehouse is an important part of the production process, a facility for storing finished products. Other companies use the warehouse only to store safety stock. Therefore, to operate effectively, companies must:

- Understand customer needs well.
- Establish communication with contractors and between departments of the company itself.
- Use information and communication technologies and warehouse automation programs.

An effective tool for achieving these goals is a combination of classical optimization methods, mathematical programming, and negotiation procedures. First, we recommend obtaining the optimal solution using classical optimization methods.

After we advise on adapting the solution to the specific circumstances.

This study identified several issues in the warehouse of a retail store selling household appliances. The most serious problem was the lack of an inventory accounting system. Goods were shipped randomly from the warehouse, and new arrivals were placed on any available shelves. It took a lot of time to find the right item, and the costs associated with the irrational movement of loaders. The system of proposed algorithms allowed us to solve these problems, reducing the risk of stranded inventory, the search time for the right product, and the costs associated with placing new arrivals. This resulted in significant economic benefits. These algorithms are applicable in dynamic demand conditions, but they have limitations regarding warehouse volumes and product variability. For example, they are effective in large-scale operations, but when dividing a large warehouse into several sections. Ideally, each section should store homogeneous goods or materials. We consider the possibilities of using optimization and matching algorithms in combination with addressable storage of goods. The arrival date of goods or the results of ABC/XYZ analysis can serve as criteria for decision-making.

Further research on this and related topics seems promising, especially with increasing competition and economic instability.

All the Declarations and Statements

Author Contributions Statement

Nataliya Mutovkina – All sections of the study.

Conflict of Interest Statement

The author declares no conflicts of interest.

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Data Availability Statement

The dataset about the warehouse used in this study can be obtained from the corresponding author upon reasonable request.

Ethical Declarations

This study does not involve any experiments on human participants or animals. The data used in this research were obtained from publicly available sources and do not contain any personally identifiable information. Therefore, ethical approval was not required for this study.

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Declaration of Generative AI in Scholarly Writing

During the preparation of this manuscript, the authors used generative AI tools to improve the language. The use of these tools was limited solely to the writing process. Generative AI tools were not used for data analysis, interpretation of results, or drawing conclusions.

Abbreviations

The following abbreviations are used in this manuscript:

ARIMA - Autoregressive Integrated Moving Average
 CFA - Coefficient of Free Area
 CO - Coordinated Optimization
 DQN - Deep Q-Network
 DRL - Deep Reinforcement Learning
 ERP - Enterprise Resource Planning
 FIFO - First-In, First-Out
 LSTM - Long Short-Term Memory
 RFID - Radio Frequency Identification
 SSAP - Storage Space Allocation Problem
 TF - Target Function
 WMS - Warehouse Management Systems

Appendix A\B\C..., with appendix tile

None.

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Authors' Profiles



Nataliya Mutovkina, Ph.D, received a professional degree in Applied Computer Science (in Economics) and additional education with the qualification of a Teacher of Higher Education at Tver State Technical University, Tver. In 2009, she completed postgraduate studies at Tver State Technical University and received a Ph.D. in Technical Sciences. Her research interests include computer modeling, fuzzy logic, systems analysis and theory, and finance. She is a Lecturer at Tver State Technical University (Department of Accounting and Finance), Tver, Russia.

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