MINISTRY OF EDUCATION AND RESEARCH
BUCHAREST POLYTECHNIC NATIONAL UNIVERSITY OF SCIENCE AND TECHNOLOGY

DOCTORAL THESIS

-SUMMARY-

Research on the optimization of logistics operations through the integration of Artificial Intelligence in Warehouse Management Systems

Scientific coordinator,

Univ. Prof. dr. eng. ec. Vasile BENDIC

PhD student,

Ramy OBEDIAT

- 2024 -

PART I.

Chapter 1. THE CURRENT STAGE IN THE EVOLUTION OF LOGISTICS GOODS ON THE DOMESTIC MARKET

1.1. Introduction

Logistics is an essential field for global economic development, having distant historical roots, but being defined as the science of production and distribution organization only relatively recently. The evolution of logistics is marked by continuous adaptation to modern technological and economic requirements, becoming a fundamental pillar of the world economy. In Romania, logistics has evolved significantly, from the rudimentary activities carried out by carvers and masons, to an organized trade and modern transport, deeply influencing the national economic development.

1.2. Current Status Assessment

The concept of logistics has its roots in ancient military and commercial activities, being associated with the efficient organization of transport and supply. Modern definitions of logistics include the combined organization of production and distribution factors, emphasizing the importance of resource optimization. In Romania, the first initiatives to modernize road networks began in the 1930s, with major projects connecting Bucharest with the main cities in the country. In the post-war period, reconstruction efforts included the restoration of infrastructure and the development of road, rail, naval and air transport, essential aspects for the economic development of the country.

The tasks or purpose of logistics management can be graphically illustrated by the concept of the 7 "Rights " or the 7 Matches if we translate from English, being also a widely spread and applied concept today.[1]

Fig. 1.1. Logistics tasks

1.3. Technologies and Modern Trends in Logistics

Automation and digitization of logistics processes have become essential in the current context. The introduction of IoT (Internet of Things) technologies allows real-time monitoring of transports, ensuring increased transparency and efficiency. Use of artificial intelligence (AI) and machine algorithms learning for route optimization and demand prediction, reduces costs and improves delivery times. Implementation of ERP systems (Enterprise Resource Integrated Planning) and WMS (Warehouse Management Systems) enables efficient management of stocks and warehouse operations, ensuring smooth supply chain management.

Blockchain is another emerging technology that is transforming logistics, providing an unprecedented level of transparency and security in supply chain management. By using blockchain , all transactions and cargo movements can be recorded in a distributed ledger that cannot be altered, thus ensuring data integrity and reducing the risk of fraud.

1.4. The Evolution of Industrial Spaces

In Romania, the industrial premises market has seen a significant development in the last decades, with major investments in logistics parks and distribution centers, and the most used classification of industrial premises is on classes A, B, C, D, etc., depending on infrastructure development, technical specifications and available services.

1.5. Goods handling techniques in logistics

When we talk about techniques for handling goods in industrial logistics, we need to understand a little about the processes that lead to the decision to technologize some operations, in order to optimize them. Although the logistics and distribution centers are in continuous development, forecasts must be made from the project phase on the future operations that will take place in them, so as to establish the level of their technology as correctly as possible.

Operations in a distribution/warehouse center have a fundamental set of activities in common that can be found in most business sectors:

1.5.1. Reception
1.5.2. Relocation to the waiting area
1.5.3. Storage
1.5.4. Order preparing (order picking)
1.5.5. Packaging and/or labeling
1.5.6. Sorting
1.5.7. Delivery

Globally, the highest level of order delivery accuracy is recorded in Japan, achieving a performance of 99.997%, compared to the average of the top companies which is 96%. [2]

By means of performance indicators, any manager can make an analysis of the need for points that require improvement, as well as whether the mechanization of operations is more productive or can facilitate productivity. A high level of automation can have the opposite of the desired effect, as automation involves very high costs, poor training of personnel, expensive periodic maintenance, process complexity, limitation of operations and difficult reconfiguration of them. Mainly, automation will not solve all the problems arising from the performance indicators, it is only recommended for complex, long-lasting processes involving repetitive actions, but the best approach to streamline activities in a warehouse is to operations are simplified as much as possible.

1.6. Storage Systems

From cabinets, cupboards, boxes, containers and up to countless types of shelves, the storage possibilities are in an extremely wide range.

The capacity of warehouses varies according to how goods can be stored, and today warehouse systems are tailored to general needs and the most popular such systems are in modular form, allowing the keeper flexibility to change them according to needs and size of the room/hall, respectively of the goods to be stored.

1.6.1. The most popular **racking systems** are **selective** pallet racking (**Fig. 1.2**) **(single- deep pallet rack)** . They are placed in pairs, back to back, and the paddles are supported on the crossbars.

Fig. 1.2. Selective shelving systems. *Photo source – Euroccoper S.A.*

The main advantage of these types of shelves is that they offer easy access to all stored goods, however, they also present a major disadvantage, which is the fact that they require a lot of space to move the handling equipment, thus resulting in an average loss of 50%-60% of usable floor space. There are cases when, due to the typology of goods that have the same product code on several pallets and are not subject to FIFO storage (first in- first out), the keeper chooses to use shelves with double storage.

In this summary I will stop here with the presentation of the shelf categories because this type of shelves will also be used in the warehouse that I will carry out simulations in the following chapters. Selective racks can be designed to cover a wide range of handling equipment and depending on their degree of complexity, up to 60% floor space can be exploited for VNA type equipment, which requires the narrowest aisle for movement.

1.7. Goods Handling Systems

In the following lines, I will make a classification of the main goods handling technologies and what factors should be taken into account when choosing them.

In the case of some handling equipment, such as the one with a retractable mast (reach - truck), one must choose between the advantage offered by the location (minimum width aisle) and the one offered by productivity (the greater width of the aisles allows easier access to the machines and faster).

Table 1.2. – Minimum aisle width for service

The type of machine	Aisle	Observations
Mini transporter/Forklift	600 - 800 mm	
Pallet conveyor	1200 - 1400 mm	
Two-way forklift and rail	1800 mm	
Forklift truck with three-way fork and rail	1700 - 1900 mm	
The cable guide for the above forklifts	+ 100 mm	Less accurate forklift
Articulated forklift with front fork	1800 - 2100 mm	Specialist forklift driver
Forklift with front forks	2000 - 3000 mm	
Forklift with retractable mast (reach truck)	2800 - 3000 mm	Min. 2700 mm
Order picker	1400 - 1600 mm	It depends on the height
Three wheel front fork lift truck	3500 - 4000 mm	
Four wheel front fork lift truck	4000 - 4500 mm	
Omnidirectional forklift		It depends on the load

The length of service aisles must be calculated for each project, but in general the following values are recommended:

- Between 30 – 60m, chute with outlet - for chute served by forklifts with directional forks. Obscured colors do not allow turning or returning to another aisle, they lead, except in special cases, to important losses of productivity. They do not provide good security conditions either.
- Between 60 and 120m, lanes served by forklifts. The length of the aisles served by the forklifts influences the cycle time only in a very relative way. In fact, the acceleration and deceleration periods are of constant duration; a surplus of length is traveled at a higher speed, so it does not consume more time.

Handling equipment or lifting machines, as referred to in the R1-2010 ISCIR technical prescription, in the industrial logistics segment, can be manual or automated.

1.8. Conclusions and Recommendations

In the context of new requirements in industrial logistics and technological advances, artificial intelligence (AI) plays an increasingly important role. AI enables real-time data analysis and demand prediction, thereby optimizing transport routes and inventory management. By implementing machine algorithms learning , companies can anticipate fluctuations in demand and adjust supply strategies to minimize costs and maximize efficiency. AI also helps automate repetitive processes, reducing human error and improving the accuracy of logistics operations.

Chapter 2. STORAGE SPACE OPTIMIZATION

2.1. Introduction

In order to understand more easily how to optimize the space of a warehouse, in this chapter, we will focus on a class A warehouse, with an area of 4,000m ^{2} , the ridge height 13m, of which 11m is useful, often being the reference size , for the compartmentalization of logistics centers newly built by real estate developers, with the exception of situations when the spaces are rented from the project phase, and are compartmentalized according to the client's requirements. The design of a warehouse has entered a much more sophisticated stage, due to the evolution of the operations that a distribution center can do, the technologies available today, the procedures of stock management and stock rotation, as well as according to the means of transport goods arriving for loading or unloading. A warehouse that is not designed to be easily adaptable to needs and new trends will not become profitable.

2.2. Determinants in storage space planning[1]

2.2.1. What categories of goods will arrive at the warehouse?

In any discussion that takes place to contract a customer, a logistics operator, before signing the contract and setting up his warehouse, must know the parameters of the goods that will arrive in the warehouse.

a) *The shape and dimensions of the goods* – define the technical means of handling and storage, to be used in the warehouse; Between the means of handling and those of storage, there is a connection that makes a warehouse work in optimal parameters and is a determining factor in its design;
   In the process of gathering information, we must also find out the form of storage of the goods, on which type of pallet /box they will arrive, being an indicator in the choice of equipment and storage systems.
b) *The volume/quantity of the stock* – define the degree of occupancy of the warehouse, as well as the need, as the case may be, of shelves. If the goods can overlap in high stacks, then most likely, the purchase of shelves will not be resorted to, being an expensive solution, as I presented in " *Chapter I, 1.3 - Goods handling techniques* " . The capacity of a warehouse is directly proportional to how the goods can be stored, in height.

The maximum height to which the goods can be overlapped is usually specified on the goods packaging and for safe storage, it should not exceed 5 times the short side of the pallet.

Block stacking on the floor is calculated for the footprint left by the pallet (1 EPAL occupies a floor footprint of 0.96m ^{2} , approximately 1m ^{2} , to which, as a rule, another 1m ^{2} must be sacrificed for the service aisles, which we'll see it in the sketch we'll use to exemplify all these values).

Block storage, on the floor, to meet the conditions of profitability, should respect the following values:

- The minimum area of a block of goods on the ground: 500m ^{2}
- Maximum storage height: 8 m
- Minimum distance between two blocks (alleys): 2 m
- Minimum distance from the top of the block to the ridge of the roof or to the heating system, lighting: 1 m

For the simulation we will perform, we will use pallets with the specifications in table 2.1 and figure 2.4 for stacking in blocks, on the floor

Table - 2.1

	L – *m* –	*w* – *m* –	*H* – *m* –	*S* – *m* ^{2} –	*V* – *m* ^{3} –	*M* *Kg.*	*Stack* – *pcs* –	*Stock* – *pcs* –
Industrial pallet	1.20	1.15	2.87	1.38	3.96	250	3	546

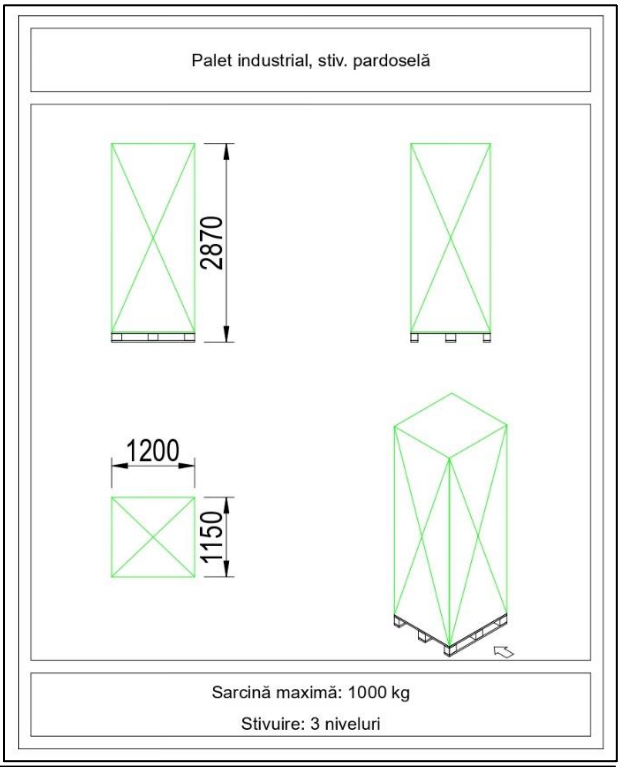


Fig. 2.4. – Graphic simulation for industrial pallet with the specifications we will work on

Bulk stacking is not always possible for all goods, being conditioned by **the fragility of the contents** , a condition often marked on the product packaging, by regulated graphic symbols that are mandatorily applied to the packaging, and by **the strength of the packaging edges** .

The height of the shelves is determined by that of the building and the machinery used to operate the stock.

c) *Stock accessibility* – defines the way in which the goods are delivered, how easily they must be accessible, depending on the lot, product code, storage principle (FIFO, FILO, LIFO, FEFO), picking or not , so that a small number of moves must be made to access them when orders need to be prepared.

Storage systems should be chosen according to the following stock characteristics [1]

1. "*The variety of products";*
2. *Size, shape and weight for each item;*
3. *Frequency of deliveries of an item;*
4. *Ratio of stocks to estimated volumes;*
5. *Changes in the volume of stored goods in order picking items;*
6. *Delivery requirements in smaller quantities than received.* "

, but also according to the requirements of the customer's orders:

1. *Number of orders to be processed/exchanged;*
2. *Number of items in an order;*
3. *The volume occupied by the orders to be prepared in one working hour or one shift;*
4. *The time taken from the moment an order is received until it is completed.*

Once we have the variables above, we can set the shelf storage mode, **fixed** or **variable**

To optimize the available space and create more shelf storage positions, we will opt for the shelf color required for a narrow aisle forklift (VNA), thus managing to use up to 65% of the shelf space.

2.2.2. How much space will be required to handle the received goods?

We can calculate the space required for handling the received goods knowing that we will operate 6 trucks loaded with 33 pallets daily and 2 full 40' containers weekly, from which we will estimate an average of 70 pallets /container.

The 6 trucks mean they will occupy a floor footprint of 190.08m ^{2} , if unloaded and not received, and then operated for racking or stacking. For this area, we did not take into account the spaces needed for circulation, when placed in the reception area, therefore the occupied area will be at least 20% larger than the estimated one, which could reach 228,096m ^{2} .

The simplified calculation formula will be as follows:

No. trucks X no. pallets / truck X pallet length X pallet width X 1.2.

$$6 \times 33 \times 1{,}2 \times 0{,}8 \times 1{,}2 \ = \ 228{,}096m^2$$

The containers will arrive in bulk, from which, after unloading according to the rule 1 pallet = 1 product code or EAN code [1], we will expect an average of 70 pallets /container.

[1] The EAN code represents the barcode, which is necessary for manufacturers, importers or exporters in order to distribute products in stores, supermarkets or hypermarkets equipped with barcode reading equipment.

Thus, for 2 containers, we will perform the following calculation:
No. containers X 70 pallets from a container X length of a pallet X width of a pallet X useful surfaces for traffic lanes.

$$2 \times 70 \times 1{,}2 \times 0{,}8 \times 1{,}2 \ = \ 161{,}28\text{m2}$$

In a week with 5 working days, we can expect to receive 1,130 pallets , with an average of 226 pallets / day.
Average no. pal. receive/week -$6 \times 33 \times 5 + 2 \times 70 \ = \ 1.130 \, pal.$
Average no. pal. receive/day $(6 \times 33 \times 5 + 2 \times 70)/5 \ = \ 226 \, pal.$

Goods arriving in trucks, as well as those at the container level, we will consider to be able to store on the shelf, subject to fast receipt and storage to clear the receiving areas. Otherwise, 226 pallets will occupy approximately 260.35m ^{2} daily. If they are not received from one day to the next and stored on the shelf, blockages begin to occur in the docks, service lanes for machinery are blocked, and this leads to damaged goods, delays in the operation of orders, and possibly accidents. work, due to the lack of room to move.

In the storage area on the floor, we will operate 4 receptions/day, of 20 pallets with dimensions of 1,200 x 1,150 x 2,850mm. About the pallets that can be stored on the floor, in our case, we also know that 3 can overlap, which offers the possibility to optimize the space allocated to them.

Space occupied by a truck =$\text{nr. pal.} \times \text{L} \times \text{l} \ \times \text{lost surface percentage}/\text{nr . stacked pal.}$

$$20 \times 1{,}2 \times 1{,}15 \ \times 1{,}2/3 = \ 11{,}04\text{m2}$$

The space occupied by the receptions of a day $= \text{nr. trucks} \times \text{nr. pal.} \times \text{L} \times \text{l} \ \times$ $\text{ost surface percentage}/\text{nr . stacked pal.}$

$$4 \times 20 \times 1{,}2 \times 1{,}15 \ \times 1{,}2/3 = \ 33{,}12\text{m2}$$

The space occupied by receptions in a working week =$5 \times \text{nr. trucks} \times \text{nr. pal.} \times \text{L} \times \text{l} \ \times$ $\text{lost surface percentage}/\text{nr . stacked pal.}$

$$5 \times 4 \times 20 \times 1{,}2 \times 1{,}15 \ \times 1{,}2/3 = \ 165{,}6\text{m2}$$

2.2.3. What and how many machines will be needed to operate the cargo handling?

The selection of machines must be determined according to the shelves chosen, the access method for storing the goods that will arrive in the warehouse, their dimensions and the degree of occupancy of the warehouse.

As we have established above, for our project, we will have a storage area with [2]narrow color selective standard shelving. In table 1.2, presented in Chapter 1 of the thesis, we will find some reference values that we must take into account when designing the warehouse.

Analyzing this table, we notice that the minimum value for a VNA is 1,700mm, and if the machine is one with an inductive wire, we have to add 100mm.

[2]Selective standard racks offer high selectivity and are suitable for a high mix of SKUs.

All warehouses that have a good floor should also be equipped with electric pallet trucks, being the most efficient in terms of cost/speed of work for unloading trucks. They have compact dimensions, can lift loads of up to 3 tons, run at up to 12 km/h, and have access to the narrow aisles for the VNA.

In the area dedicated to block storage on the floor, both front-loading forklifts and those with a retractable mast can be used. Knowing that the stacking height of the goods is 8.6m, as we have determined that the pallets can be stacked for our project, then it is advisable to use a forklift that has a retractable mast, having mast sections that can lift the loads to the level that we need

pallet trucks in a warehouse , so are front-loading forklifts, providing flexibility in many situations, when goods arrive loaded on top of each other and must be removed row by row or vice versa loading process.

Small vans will be able to be unloaded or loaded with the front forklift, but not infrequently a mechanical pallet truck will also be needed , which is often made available to drivers to reposition their goods in the vehicle.

Knowing the above, our warehouse should have at least the machines in table 2.5, in order to carry out its activity without encountering major problems.

Table 2.5. – Equipment needed for the project

No. crt.	**Equipment category**	**No. pc.**	**Power**	**Nominal load**	**H max -mm-**
1.	Forklift with retractable mast - Reach Truck	1	Electric	1600kg	9022
2.	Front loading forklift	1	Electric	1450kg	5770
3.	truck	3	Electric	2000kg	205
4.	truck	2	Mechanics	2000kg	207
5.	VNA_ManUP	2	Electric	1500kg	9780

2.3. Storage Plan

2.3.1. Space optimization layout

Centralizing the detailed summary information from the previous points, we can start sketching a warehouse space, according to our project, which aims to optimize the available space starting from a blank floor plan of a warehouse of approximately 4,000m ^{2} . See figure 2.8.

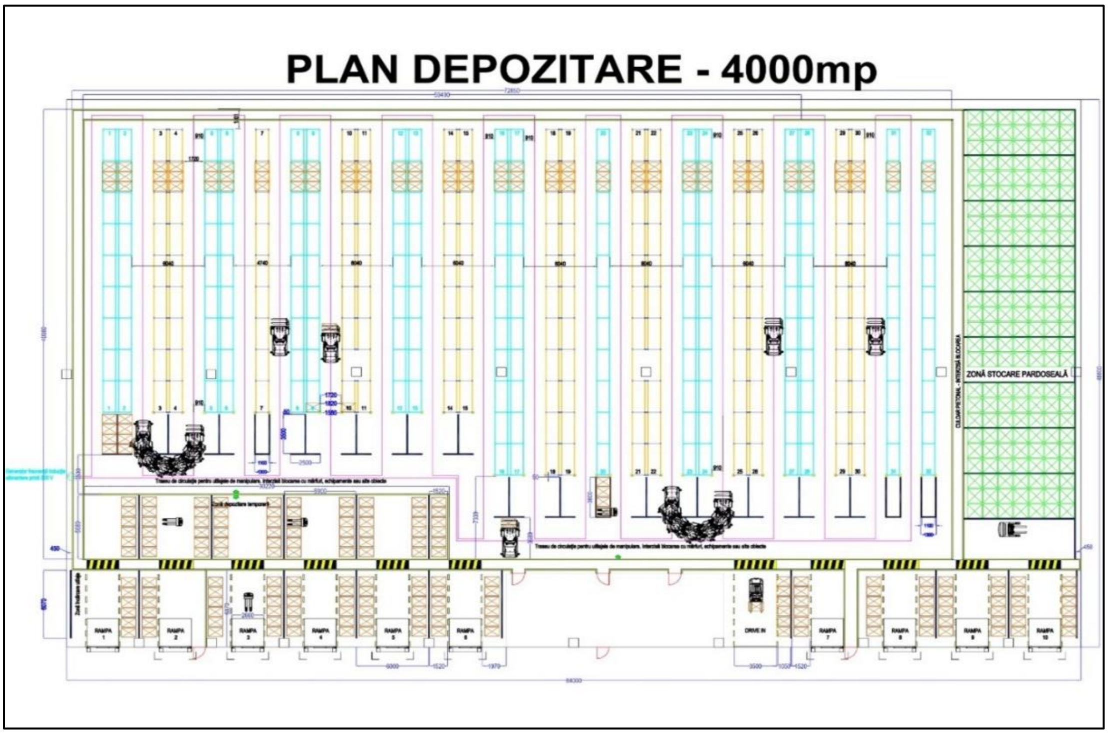


Fig. 2.8. – Storage plan with 32 shelves and floor storage area

The warehouse proposed in figure 2.8 will be able to provide a stock of goods with 3 different areas, as **follows:**

2.3.2. Shelf storage capacity with VNA, for shelves 1-15 – 2376 pallets with dimensions of 1200 x 800 x 1650mm, see figure 2.9 in the thesis. and figure 2.10.

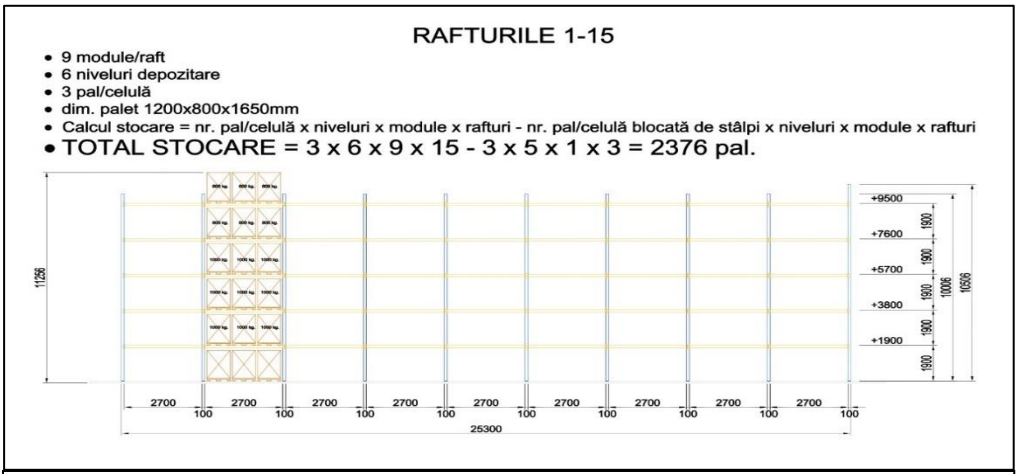
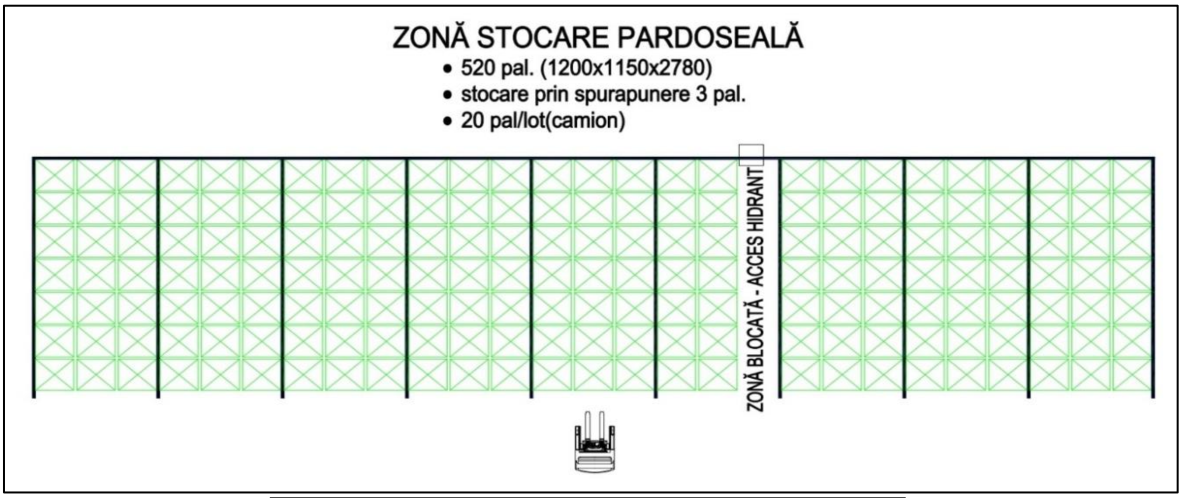


Fig. 2.10. – Storage plan for shelves 1-15 – 2376 pallets

2.3.3. Shelf storage capacity with VNA, for shelves 16 -32 – 3843 pallets with dimensions of 1200 x 800 x 1275mm., see figure 2.11 in and figure 2.12 in the thesis.

2.3.4. Floor storage capacity using a Reach -Truck or front-loading forklift (recommended to use a Reach -Truck due to the mast with the possibility of lifting to higher heights and narrower work aisle), for the area dedicated from the warehouse, it will be approximately 520 pallets , with dimensions 1200 x 1150 x 2780mm, equivalent to 26 shipments with 20 pallets /truck. See figure 2.12.



Figură 2.12. – Plan depozitare stocare pardoseală

2.4. Conclusions

Translating the above information into table 2.6. we end up with the following storage values.

Table 2.6. – Project storage capacities

Dim. pal. (mm)	1200x800x1650	1200x800x1275	1200x1150x2870	TOTAL	TOTAL-5%
R1-15 (pc.)	**2376**	**-**	**-**		
R16-32 (pc.)	**-**	**3848**	**-**		
Block Storage (pcs.)	**-**	**-**	**520**		
TOTAL				**6744**	**6422**

In a warehouse, it is advisable to keep a margin of at least 5% with empty spaces, to allow us to make relocations, when optimizing movements for order preparation, using the common Pareto's law and ABC classes. In logistics centers based on WMS, this optimization is done automatically by WMS, but no computer system is as efficient as a human, who makes predictions of stock rotations, only based on the turnover he had, not knowing what goods we will go into storage.

Chapter 3. OPTIMIZATION OF PROCESSES IN A LOGISTICS CENTER

3.1. Introduction

Using the technologies of the present and the future, a logistics operator has many solutions that he can integrate in order to carry out his activity in an optimal way, without wasting resources that he can allocate to development or any other project.

3.2. Process Performance

Operations in a logistics center begin with "inputs" and end with "outputs" or receipts from suppliers, customers, customers of customers, and are completed by the process of delivery to other customers.

A balanced performance measurement tool will have at least four sides: **financial; intern; external; organizational improvement.**

What should we measure?

performance measurement model in the warehousing activity that we can use with factors that must be taken into account when measuring operations by analyzing 4 essential success factors in the activity of a logistics center:

1. inventory accuracy;
2. productivity;
3. use of space/ degree of storage space occupancy;
4. customer service.

3.2.1.1. Drone and blockchain inventory – increased speed and more accurate inventory.

“ Blockchain allows warehouses, manufacturers, suppliers, distribution centers and retail partners to connect with each other through a permanent record of every transaction that takes place. All recordings are then stored and accessible to everyone on the network." [1]

Currently, inventory management is based on a reactive model, with replenishments being ordered once stock is depleted, or on a predictive model that estimates inventory completion, based on order statistics.

By using blockchain , inventory management will be able to be done with greater precision, thus ensuring the necessary type and quantities of goods to meet market demand in time.

Also, in large warehouses and especially distribution centers, inventory will be able to be taken using drones programmed to start at the end of the schedule, when the goods are no longer moving. Traveling the route between the shelves, it can simultaneously scan to the left and to the right, if it is equipped with 2 scanners, bidirectional. See fig. 3.1

By adopting the technologies of the future, it will certainly be possible to improve the activities of inventory and monitoring of stocks, the one presented above, being perhaps the fastest.

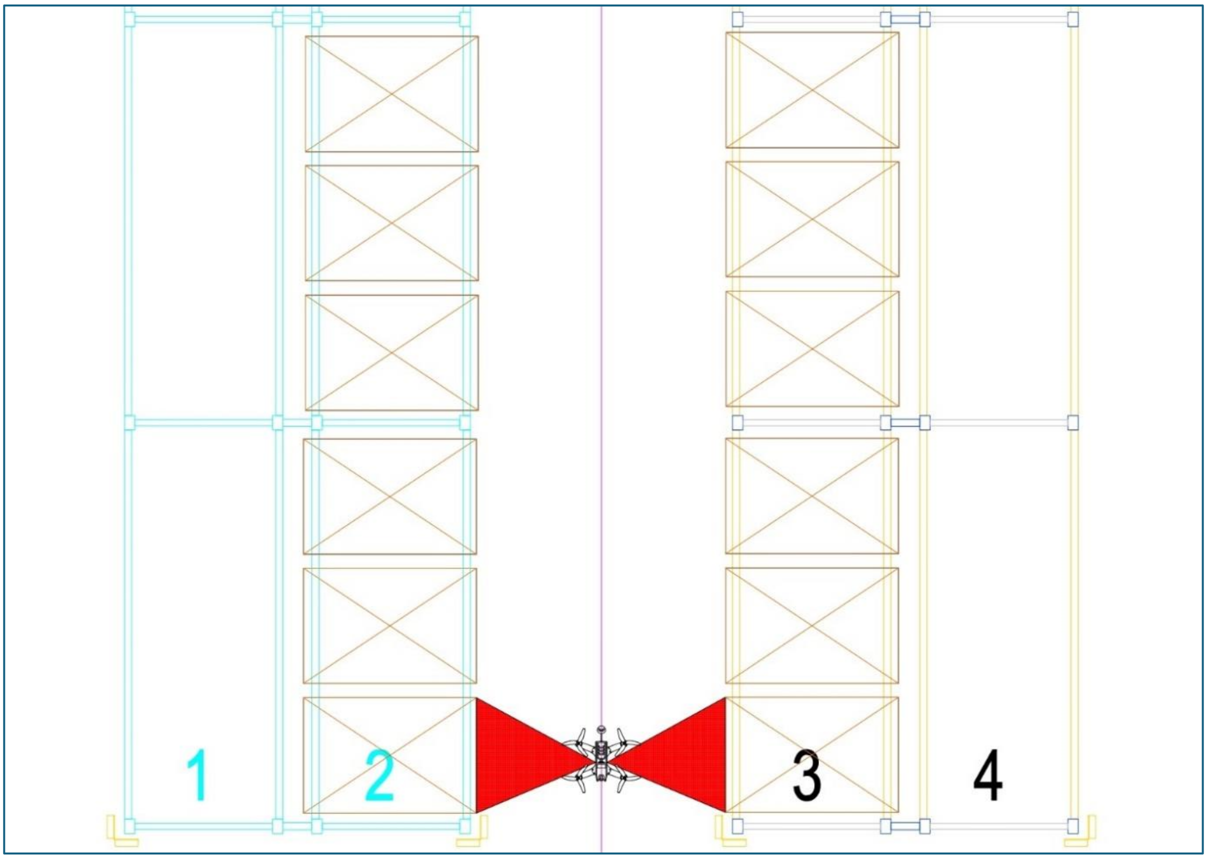


Fig 3.1. – Drone scanning

3.3. Performance Indicators

In the summary of this sub-chapter, only a part of the performance indicators used in the monitoring, evaluation and continuous improvement of logistics operations are highlighted.

3.3.1. Workmanship Indicators

Labor indicators are essential to assess the efficiency of the use of human resources in a warehouse. A classic example is **the degree of utilization of working time** , which reflects the percentage of hours actually worked out of the total hours paid:

$$\text{Degree of use of working time} = \frac{\text{worked hours}}{\text{paid hours}} \times 100\%$$

A **utilization rate** of 75% indicates that out of eight paid hours, only six were actually worked. This indicator is crucial for identifying and reducing unproductive activities.

Analysis and Improvement

real-time monitoring and AI solutions could be used to identify non-value-added activities (eg extended meetings) and automatically propose reorganization of the work schedule to maximize efficiency.

Labor Efficiency

Work efficiency, expressed by the ratio of hours earned to hours worked, indicates the skills of the operators and the efforts made:

$$\text{Efficiency} = \frac{\text{hours earned}}{\text{worked hours}} \text{ x } 100\%$$

For example, if a worker completes a task in six hours, but the standard time is five hours, his efficiency will be 83%.

Innovative Contributions

The use of AI-based **predictive technologies** can optimize the allocation of normative times by adjusting work dynamics based on past performance and operational context.

3.3.2. Productivity

Productivity reflects the ratio of hours earned to hours paid, providing an overview of overall production:

$$\text{Productivity} = \frac{\text{saved hours}}{\text{paid hours}} \text{ x } 100\%$$

machine algorithms could be applied **learning** to anticipate workload variations and optimize resource allocation, thus reducing unproductive hours.

3.3.3. Use of Space

The degree of space utilization is crucial in the efficient management of a warehouse, being frequently used to evaluate the allocation of storage space:

$$\text{Space usage} = \frac{\text{Actual ocupied space}}{\text{Total available space}} \text{ x } 100\%$$

Using a percentage of 80-90% is ideal to ensure a balance between maximum use of space and maintaining operational flexibility.

Analysis and Improvement

To improve this indicator, **IoT technologies** and **space monitoring sensors** can be used to optimize the layout of the warehouse, thus ensuring a more dynamic and efficient management of available spaces.

General Conclusion

The adoption of AI and other advanced technologies in logistics is not just a trend, but a necessity for companies that want to remain competitive in today's global economy. AI-based performance measurement systems offer a unique ability to dynamically optimize processes, reduce costs and improve customer satisfaction, thus ensuring the long-term success of logistics operations.

Part II.
Contributions to the development of METHODS FOR OPTIMIZING WAREHOUSE OPERATIONS THROUGH THE INTEGRATION OF ARTIFICIAL INTELLIGENCE AND OPERATIONAL DATA ANALYSIS

Chapter 4. DIRECTIONS, MAIN OBJECTIVE AND RESEARCH-DEVELOPMENT METHODOLOGY OF PROCESS OPTIMIZATION IN A LOGISTICS CENTER

4.1. Research and Development Departments

Based on the analysis of the current state of knowledge in the field of industrial logistics and the emerging trends in technology, the following research and development directions have been identified that are of particular relevance for the optimization of logistics operations. These directions are aimed at integrating artificial intelligence (AI) and advanced digital technologies into operational processes, to address current challenges and create innovative solutions that improve efficiency and performance in warehouses:

4.1.1. Dynamic Optimization of Logistics Operations [1]

Picking Routes : AI can continuously analyze operational data, such as backorders and inventory locations, to optimize picking routes .

Resource Allocation: AI can automatically adjust the distribution of resources based on changing demand, thus ensuring that resources are used optimally without overloading or underutilization.[3]

4.1.2. Demand Forecasting and Resource Allocation [12]

Advanced Predictive Models: AI can analyze large volumes of data in real-time and identify subtle patterns that might escape conventional analysis, ensuring warehouses are prepared to handle fluctuations in demand without experiencing losses or out-of-stocks. [4]

Inventory Optimization: Based on predictions, AI can optimize inventory management by dynamically allocating warehouse space, prioritizing fast-moving items, and adjusting stocked product quantities. [5]

4.1.3. Monitoring and Feedback in Real Time through AI

Continuous Monitoring: These systems can automatically detect anomalies or inefficiencies and send alerts or suggestions for adjustments to prevent problems before they become critical.

Adaptive Feedback: For example, in the event of a sudden increase in demand, AI can adjust priorities in real time, reorganizing tasks to maximize efficiency without compromising service quality.[6]

4.1.4. Integrating AI into Risk Management

Risk Identification and Monitoring: AI can be programmed to monitor risk factors such as equipment wear and tear, staff performance variations or unpredictable demand fluctuations.

Emergency Planning and Response: This ensures that the warehouse is prepared to respond effectively to unexpected events, such as major equipment failures or supply chain disruptions.

4.1.5. Simulations and Theoretical Models for Optimization in Logistics

Computational Simulations: Using the layout of a warehouse as a working base, we will create simulations that test the impact of different optimization strategies proposed by AI. These simulations allow the evaluation of system performance under varied conditions, without requiring expensive and risky implementations in the real environment.[10]

AI Model Validation: Simulations can be used to validate the proposed AI model by comparing the results obtained by traditional logistics management methods with those generated by the AI model.

4.2. The Main Objective of the Research-Development Activity

4.2.1. Context and Justification

Emerging technologies, especially artificial intelligence (AI), offer unprecedented opportunities for improving logistics processes. However, most existing solutions focus on static optimizations or management models that cannot effectively respond to rapid demand dynamics and operational fluctuations.

In this context, the main objective of the research-development activity proposed in this thesis is to test through simulation with real data the development and implementation of a system for dynamic optimization of logistics operations, based on the integration of artificial intelligence and real-time data analysis, to maximize operational efficiency and reduce costs in industrial warehouses.

This research direction responds to the industry's current needs to quickly adapt to changes and exploit the advantages offered by digitization and automation.

4.3. Conclusions

The R&D directions identified in this thesis focus on the dynamic optimization of logistics operations, demand prediction and resource allocation, continuous monitoring of operational performance and the integration of AI in risk management.

The main objective of the proposed research – the simulation of operations in a logistics center using an AI system for the dynamic optimization of logistics operations conducted today only through WMS. By integrating advanced AI algorithms and using a data infrastructure, this system promises to bring significant improvements in resource management and how warehouses respond to fluctuations in demand.

The research-development methodology proposed in this chapter provides a structured framework for achieving the main objective. Carrying out some simulations and validating them by evaluating them with the historical performance of the warehouse, will provide certainty that the proposed solutions are not only innovative, but also applicable in practice.

In conclusion, the integration of AI and real-time data analysis not only meets current industry needs, but also sets the stage for increased adaptability and efficiency in the long term.

Chapter 5. SIMULATION AND OWN CONTRIBUTIONS TO THE IMPLEMENTATION OF THE ARTIFICIAL INTELLIGENCE MODEL

5.1. Research and Development Directions

5.1.1. Introduction

This chapter of the thesis aims to present the simulation process and the steps required to implement an artificial intelligence (AI) model that could be developed to optimize operations in a 13,800 m² logistics warehouse. For this purpose, I used the layout of a warehouse designed by me to be released in the first trimester of the year 2025.

the Reach Truck racking area and the bloc storage area. The goal of the simulations is to test the AI model's ability to maximize operational efficiency and minimize operating times in a complex and variable logistics context.

5.1.2. Preliminary data of the storage project used for AI

In the simulations, we will use a warehouse layout that we designed, according to the figure. 5.1.

The warehouse will be divided into 3 large storage areas.

1. **Storage area on shelves having narrow aisles for VNA** . Detailed view of the shelves in figure 5.2, from where it will be seen that the storage capacity for this area will be **8416 pallets** on different height configurations, but as a pallet standard we will use EPAL, which has the size 1200x800mm, being the basic material for storage in most logistics operations in Europe.
2. **Storage area on shelves having aisles for Reach Truck.** Detailed view of the racks in figure 5.3, from where you will notice that the storage capacity for this area will also be **4447 pallets** on different height configurations, where as a pallet standard we will use all EPAL.
3. **Floor storage area or " block storage ”** as defined on the outline **.** This area will be divided into several islands to give easy access to the front loaders and pallet trucks that will most often service the area. In this area, cumulatively, it will be possible to store a minimum of **934 pallets** , if we take into account only 1 pallet /location, their number being directly influenced by their overlapping capacity, often many pallets can be overlapped and 4 each.
4. **The number of docks in the warehouse equipment**
    - on the front, where mainly receptions take place, but not only that there are **14 level docks and 3 Drive IN type;**
    - on the back, where only deliveries will be made, there are **5 level docks** and **2 Drive IN type.**
5. **The warehouse material handling equipment** will be those in table 5.1.

Table 5.1. – List of handling equipment

Equipment category	Power	No. pcs.	Nominal load	Travel speed km/h	H max -mm-
Reach Truck	Electric	2	1600kg	10	8200
Front loader	Electric	2	1600kg	15	3000
Front loader	Electric	2	3000kg	20	4750
pallet truck	Electric	2	2500kg	13	207
pallet truck	Electric	2	1500kg	5	205
pallet truck	Electric	8	2000kg	10	205
pallet truck	Mechanical	10	2300kg	5	200
VNA_ManDown	Electric	3	1500kg	14	9400

6. **The operational staff of the warehouse** will be those from the list below having a single work shift.
   - 3 forklift operators who will serve 3 forklifts for narrow aisles, type VNA;
   - 2 forklift operators who will serve 2 reach trucks;
   - 4 forklift operators who will serve the 4 front forklifts;
   - 22 handlers/ pickers who can use electric and mechanical pallet trucks ;
   - Managers and office staff will not be counted as they are not relevant in the calculations.
7. **Types of specific operations:**
   - Sorting, packing, storage, picking , repackaging, labeling, unloading/loading containers, transshipment, etc.
   - picking areas will be the floor level of all shelves in the reach truck area, from R31 to R46, the block area storage as well as from the VNA area and the floor areas of shelves R13-R17.
   - Fast-moving goods will be stored mainly in the upper end of the warehouse. In the VNA area from shelf modules 18.2 to the end of the shelf. In the Reach Truck area , they will be organized in the first 8 shelf modules to shorten the travel route.
   - Daily, a number of 40 trucks will arrive at the reception with an estimated time of 40-50 min./truck and similar deliveries, made both at the truck level and with smaller trucks, defined in Chapter 2 of this thesis .

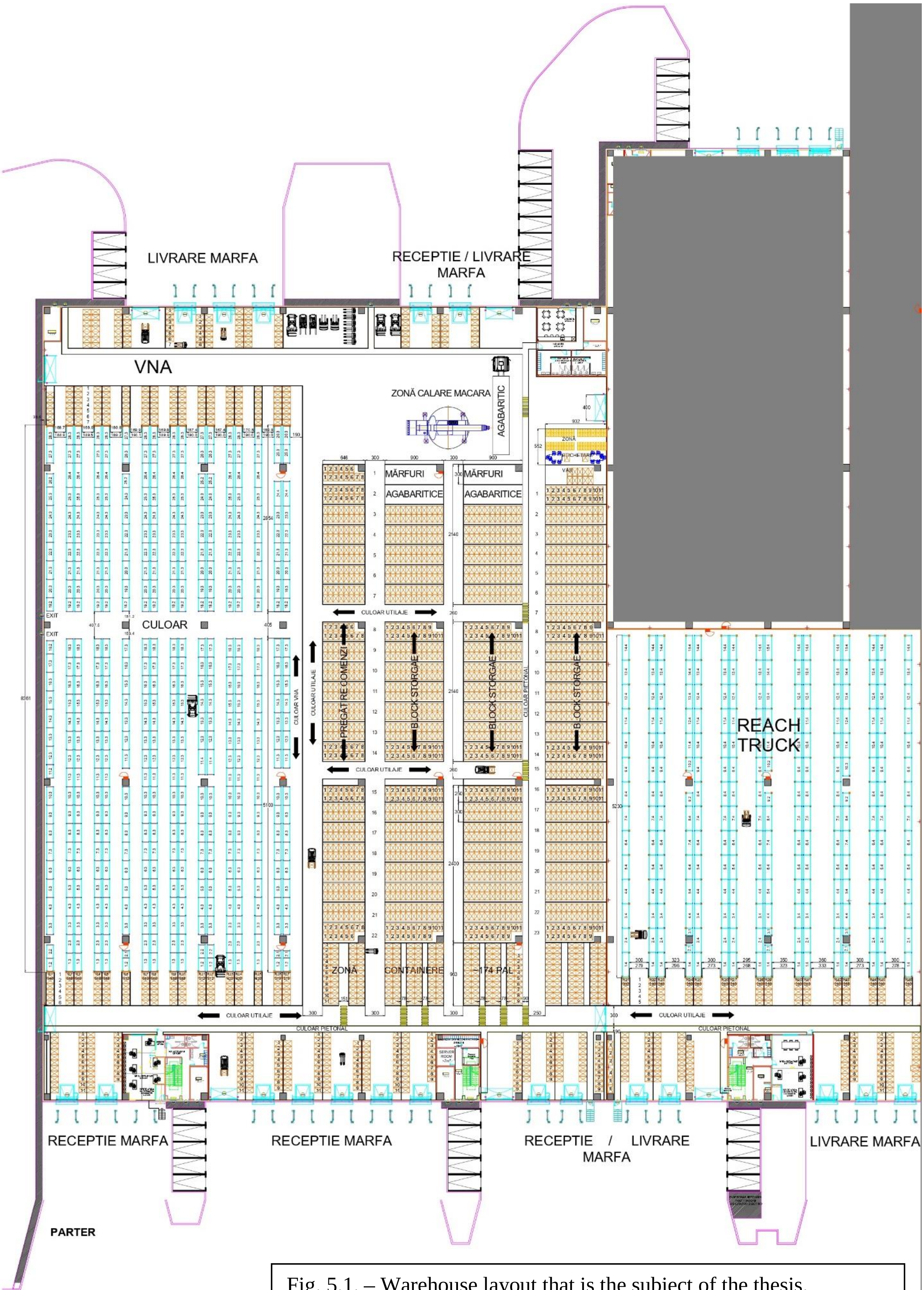


Fig. 5.1. – Warehouse layout that is the subject of the thesis.

5.1.3. Simulation scenarios for training the Artificial Intelligence model

To evaluate the performance of the AI model, we defined several simulation scenarios that reflect different operational conditions and challenges commonly found in logistics centers similar to the one in this project. The role of these scenarios is to test the flexibility, efficiency and adaptability of the model in variable situations, as often occur in such activities.[1][13]

Scenario 1: Fluctuating Demand Growth. This scenario simulates a sudden increase in demand during a peak period, such as Black Friday or major promotional campaigns.

Scenario 2: Maximum Use of Storage Capacities. In this scenario, we try to see how the AI model is tested to maximize the use of warehouse space without compromising operational efficiency and analyze the model's ability to dynamically reconfigure the warehouse to prevent bottlenecks and maintain an optimal operation flow.

Scenario 3: Random Equipment Failures. The scenario tests the AI model's ability to adapt to unexpected breakdowns of warehouse equipment, such as forklifts and pallet trucks, to assess how it can redistribute workloads and maintain operational efficiency.

5.1.3.1. Scenario 1: Fluctuating Demand Growth

Setting the simulation parameters:

- **Initial order volume:** 1,000 orders per day
- **Estimated increase in demand:** 50% (reaching 1,500 orders per day)
- **Number of machines:** The machines are detailed in table 5.1.
- **picking time without optimization:** 10 minutes/order

Relevant distances from the warehouse:

- **Average distance between picking areas and docks:** 400 meters (layout specific)
- **Average distance between racks in VNA areas:** 30 meters (layout specific)
- **Average distance between racks in Reach Truck areas:** 20 meters (layout specific)

Example without optimization:

- Total operating time $T_{total} \approx 115.28$ hours
- Productivity:

$$P_u = \frac{1.000 \text{ orders}}{115{,}28 \text{hours}} \approx 8{,}67 \text{orders/h}$$

Example with optimization:

- Total optimized time $T_{total-optimized} \approx 92.22$ hours
- Optimized productivity:

$$P_u = \frac{1.000 \text{ orders}}{92{,}22 \text{hours}} \approx 10{,}84 \text{orders/h}$$

Impact of Optimization in Scenario 1

Through the optimization that we can achieve with AI, the total operating time can be reduced and the productivity increased by about 25%. These results will be able to confirm that AI has the ability to significantly improve operational efficiency by reducing distances traveled and handling times.

5.1.3.2. Scenario 2: Maximum Utilization of Storage Capacities

Setting the simulation parameters

Maximum storage capacity:
- VNA area: 8,416 pallets
- Reach Area : 4,447 pallets
- Block Storage area : minimum 934 pallets

Types of goods stored:
- Reach Truck and Block Storage area : Fast moving goods
- VNA area: Medium and low turnover goods

Equipment used: Equipment detailed in table 5.1.

Dedicated Picking Areas :
- Reach Truck Area : Floor level of racks R31-R46.
- VNA area: Floor level of racks R13-R17.

Relevant distances from the warehouse:
- VNA shelf length: about 84 meters, with 10 colors for the whole area
- Rach Truck shelf length: about 52 meters, with 8 colors for the whole area
- Average distance traveled between racks in the VNA area: 50 meters (as in layout)
- Average distance traveled between shelves in the Reach Truck (RT) area: 20 meters (as in layout)
- Average access distance in the Block Storage (BS) area: 60 meters (as in layout)

Average distance to the picking areas :
- Reach Area : 40 meters
- VNA zone: 60 meters

1. **Calculation of Used Storage Capacity:**

To determine how efficiently the storage is being used, the AI must calculate the storage occupancy **(G)** :

$$G = \frac{N_{stocat}}{N_{max}}$$

Where:
- N_{stored} is the total number of pallets stored in an area
- N_{max} is the maximum storage capacity for that area

2. **Optimizing Inventory Allocation (Yes)**

The AI model must optimize inventory allocation according to the type of goods (fast, medium, slow turnover) so that fast turnover goods are positioned as close as possible to the picking areas .

$$O_s = \min\left(\sum_{i=1}^{n} (R_i \ x \ d_i)\right)$$

Where:

- R_i is the turnover of the commodity *i*
- *i* is the average distance to the picking area

3. **Recalculation of the Optimized Operating Time**

For Reach Truck (example):

- **Parameters:**
  - Travel speed of the Reach Truck: $v_{RT} = 10km/h \approx 2.78m/s$
  - Average distance between shelves: $d_{RT} = 20$ meters
  - Static time required for handling: $t_{static} = 5$ minutes = 300 seconds

The total operating time for fast moving goods will be calculated by adding the travel time to the static handling time:

$$T_{opt\text{-}RT} = \frac{d_{RT}}{v_{RT}} + t_{static}$$

- **calculation**

$$T_{opt\text{-}RT} = \frac{20m}{2{,}78m/s} + 300s \approx 307{,}19s/order$$

So the optimized operating time for fast moving goods in the Reach Truck area is about 307.19 seconds per order.

For the picking area in Reach Truck (R31-R46):

- **Parameters:**
  - Travel speed of the Reach Truck: $v_{RT} = 10km/h \approx 2.78m/s$
  - Average distance to the picking area : $d_{RT} = 40$ meters
  - The static time required for picking : $t_{static} = 2$ minutes = 120 seconds

- **Calculation:**
  - The total operating time for picking in the Reach Truck area is calculated as follows:

$$T_{opt\text{-}RT} = \frac{40m}{2{,}78m/s} + 120s \approx 134{,}38s/order$$

So, using the formula from the example above, the optimized time for picking in the Reach Truck area is approximately 134.38 seconds per order.

For goods with medium and low turnover in VNA (example):

- **Parameters:**
  - VNA travel speed: $v_{VNA} = 14km/h \approx 3.89m/s$
  - Average distance between racks: $d_{VNA} = 50$ meters

- Static time required for handling: t_{static} = 5 minutes = 300 seconds

- **Calculation:**
  - The total operating time for goods with average turnover is calculated as follows:

$$T_{opt\text{-}VNA} = \frac{50m}{3{,}89m/s} + 300s = 312{,}85s/order$$

Impact of Optimization in Scenario 2

By adjusting stock allocation so that fast-moving goods are located in the Reach Truck and Block Storage areas , and medium and low-moving goods are located in the VNA area, we will be able to optimize access and operating times. Optimized picking distances in these areas ensure improved operational efficiency and utilization of storage capacities.

5.1.3.3. Scenario 3. Random Equipment Breakdowns

1. **Simulated Faults:**
   - **Reach Trucks :** Failure of one of the two reach trucks.
   - **VNA forklifts:** Failure of one of the three VNA forklifts.
   - **Pallet trucks :** Failure of 3 pallet trucks out of the 22 available.

2. **Redistribution of Tasks:**
   - In this phase, the AI must **monitor the operations** and detect the failure of the machine.
   - **Task redistribution** involves reallocating handling and picking orders to the rest of the functional machinery that can complete the task, adjusting routes and priorities to reduce the negative impact on operating times.

Recalculation of Operating Time in Fault Conditions:

1. **Failure of a Reach Truck:**
   - **The expected impact** is to reduce the operational capacity of the Reach Truck area to 50%.
   - To **compensate,** the AI must redistribute loads to the second Reach Truck and, where possible (at the floor level of the racks), to electric pallet trucks for easier handling.
   - **Adjusted Operating Time:**
     - The average speed decreases at $v_{RT\text{-}defect}$ = 5km/h ≈ 1.39m/s
     - The total operating time is adjusted:

$$T_{opt\text{-}RT\text{-}defect} = \frac{20m}{1{,}39m/s} + 300s \approx 314{,}39s/order$$

     - The operation time increases to approximately 314.39 seconds per command.

Where,

- 20 m = average distance traveled for each command.
- 1.39 m/s = Expected reduced speed working with only a Reach Truck.
- 300 s: Additional time to handle and complete the order, taking into account the necessary adjustments.

2. **Failure of a VNA Forklift:**
   - **The expected impact** is to reduce the operational capacity of the VNA area which will decrease to approximately 66%.
   - To **compensate,** the AI must redistribute loads to the other two VNA forklifts, adjusting order priorities to maintain operational flow.
   - **Adjusted Operating Time:**
     - The average speed remains $v_{VNA} = 14km/h \approx 3.89m/s$, but the times increase due to the higher load on the other two machines.
     - The total operating time is adjusted:

$$T_{opt\text{-}VNA\text{-}defect} = \frac{50m}{3{,}89m/s} + 5{,}5\ min. \approx 12{,}85s + 330s = 342{,}85s/order$$

     - The operation time increases to about 342.85 seconds per command.

Where,

- 50 m = average distance traveled for each order.
- 3.89 m/s = speed of VNA forklifts that remain operational.
- 5.5 min (330 s) = the additional time to handle and complete the order due to the higher load on the other two VNA forklifts.

3. **Failure of 3 Pallet Trucks :**
   - **The expected impact** is to reduce the operational capacity of the Block Storage area and other areas where pallet trucks are used (loading/unloading trucks).
   - To **compensate,** the AI must redistribute commands to the remaining functional pallet trucks and, if possible, to the front-end forklifts.
   - **Adjusted Operating Time:**
     - The average speed for pallet trucks remains $v_{pallet\ truck} = 5km/h \approx 1.39m/s$
     - The total operating time is adjusted:

$$T_{opt\text{-}transpalet\text{-}defect} = \frac{60m}{1{,}39m/s} + 6min. \approx 43{,}17s + 360s = 403{,}17s/order$$

     - The operation time increases to approximately 403.17 seconds per command.

Where,

- 60 m = average distance traveled for each order.
- 1.39 m/s = speed of pallet trucks that remain operational.
- 6 min (360 s) = additional time to handle and complete the order due to the higher load on the remaining pallet trucks .

AI Impact Assessment and Adaptability

In scenario 3 I set out to demonstrate that although random machine failures can cause significant operational delays, the AI must be able to efficiently redistribute workloads to the remaining functional machines, thus reducing the overall impact on operations.

5.2. Simulations implementation

5.2.1. Description of the simulation model

5.2.1.1. Introduction and motivation

The integration of artificial intelligence (AI) into the management of warehouse operations will represent a critical step towards optimizing processes and increasing the efficiency of any logistics center. The AI model proposed in this thesis has the main purpose of validating the proposed solutions and testing their ability to adapt to the variability of operational conditions that may occur in a warehouse.

5.2.1.2. Structure of the simulation model

The simulation model is built on the basis of essential components, each with a well-defined role in the process of optimization and adaptation to changes in the environment:

Entry Data

Layout : The Warehouse Layout serves as the structure for the simulation model, providing a detailed representation of the distribution of storage spaces (VNA, Reach Truck, and Block Storage areas), their sizes, and the distances between them. This data is used to calculate optimal travel routes and time required to operate each type of equipment. The layout includes both details about the positioning of shelves and aisles, as well as about the dedicated picking areas (R31-R46 for Reach Truck and R13-R17 for VNA).

Equipment specifications: The technical specifications of the equipment used in the warehouse are essential for any AI model, as they include parameters such as travel speed, rated load and operation times specific to each machine.

Classification of goods: In the simulation model, the goods are divided according to turnover (fast, medium, low), this classification having the role of determining their allocation in the different areas of the warehouse. Fast turnover goods will be prioritized in the picking areas of Reach Truck and Block Storage , while medium and low turnover goods are stored in the VNA area.

Operational parameters: The model must consider a number of operational parameters, such as standard handling times, operating times for various logistics processes, and resource allocation based on current operating requirements.

5.2.1.3. Mathematical Algorithms for Processing and Optimization of Warehouse Operations

Machine -based optimization algorithms learning : These algorithms use optimization techniques, such as genetic algorithms, ant colony optimization, or neural networks, to calculate optimal routes and adjust operation times according to variables specific to each scenario.[17]

1. **Genetic Algorithms (GA):[10]**

In logistics, such algorithms can be used to optimize internal transport routes, ensuring that distances traveled are minimal and operating times are streamlined. For example, a genetic algorithm can find the optimal combination of routes that machines in the warehouse should follow to minimize total operating time.

Example: Optimization of internal transport routes in a warehouse [8]

Suppose we have 5 loading/unloading docks in the warehouse (A, B, C, D, E) and we want to find the shortest route to cover all these points. The problem can be formulated as a classic traveling problem salesman problem' (TSP), where we need to minimize the total distance traveled.

2. Optimization of Ant Colonies (Ant Colony Optimization - ACO):[18]

This optimization technique is one that mimics the collective behavior of ants in nature, which discover the shortest paths between food sources and their nest. ACO uses a virtual pheromone system to mark the most efficient routes, which other "ants" (candidate solutions) will follow and improve. As time passes, the pheromones from the less efficient routes fade, thereby reinforcing the optimal routes.

This is especially useful in dynamic environments where requirements and resources can change rapidly, which is what happens in warehouses that have more customers to manage, each with specific requirements.

Example: Optimizing the picking route in a warehouse

Suppose we have 4 picking points in a warehouse (P1, P2, P3, P4) and we want to find the shortest route to cover all the points.

3. Neural Networks :

machine models learning inspired by the structure and functioning of the human brain. They are able to learn complex relationships between variables and make predictions based on these learnings. A neural network can learn to predict the optimal time to perform a stock replenishment or adjust resource allocation based on demand forecasts.

Example: Predicting operating time for warehouse handling tasks.

Suppose we want to predict the time required to complete a handling task based on input variables such as distance traveled, weight of goods, and type of equipment.

Practical Example: Uptime Prediction

- **Inputs** : Distance traveled, weight of goods, type of equipment.
- **Processing** : The neural network processes these inputs through the hidden and output layers to make the prediction.
- **Output** : The predicted operating time for that task.
- **Continuous Training** : The neural network can continue to train and adjust its predictions based on new data collected during warehouse operation.

5.2.1.4. Route optimization: To determine the optimal route inside the warehouse, the AI model will also need to use route optimization algorithms such as Dijkstra or A*. It starts from the source node (eg the starting point of the forklift) and determines the shortest path to all other nodes in the graph.[3][7]

The general formula used for the least total cost route is:

$$\min \sum_{i=1}^{n} c_i \text{ x } d_i$$

where:

- c_i represents the cost associated with route segment *i* (eg energy consumption, equipment wear, travel time).
- d_i represents the distance associated with route segment *i* .
- The goal is to minimize the total sum of costs associated with all route segments.

5.2.1.5. Calculation of optimized operating times: The model can determine the optimized operating time for each machine based on the travel distance and speed of the machine. The formula used for this calculation is:

$$T_{opt} = \frac{d}{v} + t_{static}$$

where:

- T_{opt} represents the optimized operating time.
- *d* is the average distance traveled.
- *v* is the moving speed of the machine.
- t_{static} represents the static time required for handling the goods.

5.2.1.6. Optimized resource allocation: Resource allocation in the repository is done using optimization algorithms such as "simplex" or " branch and bound ", to maximize operational efficiency. The objective function used in this context is:

$$\max \sum_{j=1}^{n} r_j \text{ x } x_j$$

where:

- *Z* represents the objective function of maximizing operational efficiency.
- r_j represents the resource allocated to activity *j* .
- x_j represents the decision to allocate the resource to activity *j*.

5.3. Analysis of Results

5.3.1. Performance Evaluation [25]

When an Artificial Intelligence model is developed, it must be subjected to a performance evaluation, through simulations that have the role of highlighting its impact on the operational efficiency of the warehouse. In this section, we will present and discuss a series of results, with a particular focus on comparing the performance of the AI model with that of traditional logistics operations management methods, such as WMS.

5.3.1.1.Results Achieved

Simulations based on the AI model must generate significant results in terms of optimizing logistics operations in the warehouse for it to be worth implementing. These results are then analyzed in detail using the measurement/evaluation indicators presented in the thesis to compare the effectiveness of the AI model with that of traditional methods. Next, we'll discuss each set of results in detail and their implications for overall warehouse performance.

1.1. Reduction of Average Operating Time

Values obtained:

- The average operating time with AI ($T_{avg\text{-}AI}$) was 240 per order.
- The average traditional operating time ($T_{avg\text{-}Traditional}$) was 300 per order.

$$\text{Reduction} = \frac{T_{\text{avg-Traditional}} - T_{\text{avg-AI}}}{T_{\text{avg-Traditional}}} \times 100\% = \frac{300\text{-}240}{300} \times 100\% = 20\%$$

1.2. Improving Resource Utilization

Values obtained:

- The degree of utilization of resources with AI (U_{res-AI}) was 92%.
- The utilization rate of traditional resources ($U_{res-Traditional}$) was 80%.

$$\text{Improving} = \frac{U_{\text{res-AI}} - U_{\text{res-Traditional}}}{U_{\text{res-Traditional}}} \times 100\% = \frac{92\% - 80\%}{80\%} \times 100\% = 15\%$$

1.3. Reduction of Total Operating Cost

Values obtained:

- The total operational cost with AI ($C_{total-AI}$) was 873,147 RON per month.
- The total traditional operating cost ($C_{total-Traditional}$) was 970,164 RON per month.

$$\text{Reducerea} = \frac{C_{\text{total-Tradițional}} - C_{\text{total-AI}}}{C_{\text{total-Tradițional}}} \times 100\% = \frac{970.164 - 873.147}{970.164} \times 100\% = 10\%$$

1.4. Global Productivity Growth

Values obtained:

- Global AI productivity ($P_{global-AI}$) was 1,180 units /hour.
- Traditional global productivity ($P_{global-Traditional}$) was 1,000 units/hour.

$$\text{Creșterea} = \frac{P_{\text{global-AI}} - P_{\text{global-Tradițional}}}{P_{\text{global-Tradițional}}} \times 100\% = \frac{1.180 - 1.000}{1.000} \times 100\% = 18\%$$

1.5. Conclusion

The results obtained from the simulations of the AI model clearly highlight the advantages of its use in logistics operations, and the reduction of operating times, the increase of resource utilization, the reduction of operational costs and the increase of overall productivity underline the efficiency and flexibility of the AI model compared to traditional warehouses. These results suggest that the implementation of AI can bring significant improvements in warehouse management, ensuring greater efficiency, profitability and adaptability to current and future market conditions.

5.3.1.2.Comparison with Traditional Methods

Comparing the performance of the AI model with traditional methods of inventory management and logistics operations should be performed to understand the advantages and limitations of each approach, and further, we will detail how AI has the ability to outperform traditional methods with WMS in terms of flexibility, operational efficiency and costs, highlighting the significant impact of this technology on modern logistics.

1.1.Flexibility and Adaptability

Results and Observations: An AI model in optimizing processes in a logistics center is much more flexible and adaptable than traditional methods that only use a WMS, especially in scenarios involving rapid and unexpected changes, such as equipment failures or demand fluctuations.

- **Machine failures:** In situations where a machine has broken down, the AI can redistribute tasks to available machines, reducing downtime and preventing bottlenecks in the operational flow. WMS operations, based on manual interventions and pre-set planning, require additional adjustment times and not infrequently human operator intervention, leading to delays and a decrease in efficiency.
- **Demand Fluctuations:** AI is able to quickly adapt operations to sudden spikes in demand, optimizing warehouse routes and allocating additional resources to busy areas. Traditional methods have difficulty responding effectively to these changes, resulting in longer operating times and inefficient use of resources.

Analysis: AI's ability to react in real time to such changes gives it a significant advantage over traditional methods, which are more rigid and less able to adapt to unforeseen changes.

5.4. General Conclusions

This chapter of this thesis provides an in-depth analysis of how the artificial intelligence (AI) model can be integrated into logistics operations to optimize processes and improve the overall efficiency of a modern warehouse. By simulating various operational scenarios and evaluating the impact of AI on these processes, we demonstrated the considerable potential of this technology to radically transform the way resources and commodity flows are managed. The main purpose of the chapter was to confirm that AI can provide superior solutions to traditional logistics management methods using a WMS.

Chapter 6. VALIDATION OF THE ARTIFICIAL INTELLIGENCE MODEL SIMULATED IN RESEARCH

6.1. Description of Validation Methods

To validate the AI's effectiveness, historical operational data was used as well as simulations that replicated real-world conditions in a warehouse. This data allowed direct performance comparison between a warehouse managed by AI and one operated by a traditional WMS system.

6.1.1. Validation by historical data

This method involves applying the AI model to operational data previously collected from the warehouse, allowing the assessment of the model's ability to predict and optimize logistics processes based on real scenarios from the past.

Procedure:

1. **Collection of Historical Data:**

Data Set: We used a historical data set collected from warehouse operations over a period of 6 months.

Examples of Data:

- **Average Operating Time (historical):** $T_{\text{history}} = 300$s/operation
- **Average Routes Traveled by Vehicles (historical):** $D_{\text{Historical}} = 500$ m/day
- **Degree of Resource Utilization (historical):** $U_{\text{Historical}} = 80\%$

2. **Applying the Artificial Intelligence Model:**

Formulas and Algorithms:

- **Total Cost Function** : The total cost function for operating times and distances traveled is defined as:

$$C_{\text{total}} = \alpha \times \sum_{i=1}^{n} T_i + \beta \times \sum_{j=1}^{m} D_j$$

where:

– T_i is the operating time for operation i ,
– D_j is the distance traveled by machine j ,
– α and β are coefficients that reflect the relative importance of operating time and distance traveled.

- **Optimization Function:** The AI must minimize the total cost function C_{total}:

$$\min C_{\text{total}} = \min\left(\alpha \times \sum_{i=1}^{n} T_i^{AI} + \beta \times \sum_{j=1}^{m} D_j^{AI}\right)$$

where T_i^{AI} *și* D_j^{AI} are the times and distances optimized by the AI model.

- AI Model Predictions

Average Operating Time (AI prediction): $T_{AI} = 255$ s/operation thus achieving a 15% reduction compared to historical data.

Average Vehicle Routes (AI prediction): D_{AI} = 425 m/day with a 15% discount.

Resource Utilization Rate (AI prediction): U_{AI} = 92% showing a 12% increase over historical data.

3. **Comparison of Results**

Measurement and Evaluation Indicators:

- **Operating Time Efficiency:**

$$\Delta T = \frac{T_{istoric}\text{-}T_{AI}}{T_{istoric}} \times 100\% = \frac{300\text{-}255}{300} \times 100\% = 15\%$$

- **Route Efficiency:**

$$\Delta D = \frac{D_{istoric}\text{-}D_{AI}}{D_{istoric}} \times 100\% = \frac{500\text{-}425}{500} \times 100\% = 15\%$$

- **Improving Resource Utilization:**

$$\Delta U = \frac{U_{AI}\text{-}U_{istoric}}{U_{istoric}} \times 100\% = \frac{92\text{-}80}{80} \times 100\% = 15\%$$

Advantages:

By validating against historical data, the AI model not only optimizes logistics processes in simulated scenarios, but also provides real and measurable improvements in historical warehouse operations.

6.1.2. Validation in Real Time

This method involves integrating the AI model directly into the current operational flow and continuously monitoring its performance.

Procedure:

1. **Integrating the AI Model into the Warehouse Inventory Management System (WMS):**
   - **Description:** The AI model must be implemented in the warehouse inventory management system (WMS) to retrieve and analyze real-time operational data. This data includes operating times, location of machines in the warehouse, inventory status, and resource allocation.[3]
   - **Objective Function:** The AI model uses a complex objective function that aims to minimize costs and maximize operational efficiency. This function can be defined as:

$$\min C_{total} = \min\left(\alpha \times \sum_{i=1}^{n} T_i^{real} + \beta \times \sum_{j=1}^{m} D_j^{real} + \gamma \times \sum_{k=1}^{p} U_k^{real}\right)$$

where:

- T_i^{real} is the operating time for operation *i* in real time,
- D_j^{real} is the distance traveled by machine *j* in real time,
- U_k^{real} is the degree of utilization of resource *k* in real time,

– *α, β,* and *γ* are coefficients that reflect the relative importance of each component in the cost function.

2. **Route Optimization and Real-Time Resource Allocation**
   - **Dynamic Optimization Algorithms:** The AI model uses dynamic optimization algorithms, such as genetic algorithms or ant colony optimization, to calculate and recalculate optimal routes and resource allocation in real time. These algorithms take into account continuous changes in the state of the warehouse.
   - **Adaptability Function:** The AI model can use an adaptability function that is based on reinforcement learning, where the AI agent learns to make optimal decisions by evaluating rewards:

$$R(s,a)=\sum_{t=0}^{\infty}\gamma^t\, r(s_t ,a_t)$$

where:

– *s* represents the current state of the warehouse,
– *a* represents the action selected by the AI (eg route selected for a machine),
– $r(s_t, a_t)$is the reward obtained for state s_t and action a_t,
– *γ* is the discount factor, which determines the importance of future rewards over immediate ones.

3. **Real-Time Performance Monitoring and Evaluation:**
   - **Operation Time:** AI monitors in real time the time required to complete each operation and adjusts routes or resource allocation to minimize these times. This time can be calculated and optimized in real time by the formula:

$$T_{opt}=\min\left(\sum_{i=1}^{n}\frac{d_i}{v_i}\right)$$

where:

– d_i is the distance traveled by machine *i* ,
– v_i is the speed of movement of machine *i* .

,and **Productivity** can be assessed by monitoring the number of units handled per hour, where AI optimizes this aspect by efficiently allocating resources and reducing non-productive times. The productivity function can be defined as:

$$P_{real}=\frac{\sum_{i=1}^{n} U_i^{real}}{\sum_{j=1}^{m} T_j^{real}}$$

where $_{real}P$ represents real productivity.

4. **Comparison with Traditional Methods**

WMS limitations :

- **Static Planning** : Decisions are made based on historical data and assumptions about future demand, without being able to dynamically adjust operations.
- **Lack of Adaptability** : The WMS cannot react effectively to unforeseen events such as equipment breakdowns or sudden changes in demand.

- **Variable Productivity** : Productivity is strongly influenced by external factors and the ability of managers to react quickly to changes, which can lead to inefficiencies and increased operational costs.

AI approach :

- **Dynamic Planning** : Unlike WMS, AI can adjust operations in real time based on continuously updated data, providing quick and efficient solutions to unforeseen changes.
- **Machine Learning Algorithms** : AI uses machine learning to predict demand fluctuations, identify potential problems, and dynamically optimize resources and routes.
- **Adaptability** : AI can automatically redistribute tasks and resources based on current needs, reducing the impact of equipment failures and other disruptive factors.
- **Benchmark Function:** It is a math of improvement where AI performance is compared to traditional methods by evaluating performance metrics such as reduced operating time, cost, and increased productivity. The differences can be represented mathematically by the enhancement function:

$$\Delta P = \frac{P_{AI} - P_{traditional}}{P_{traditional}} \times 100\%$$

where P_{AI} and $P_{traditional}$ represent the productivity calculated by AI and traditional methods, respectively, and ΔP represents the percentage of productivity improvement by using AI compared to traditional methods.

6.1.3. Comparative Validation

Benchmarking is the method by which the performance of an AI model will be evaluated in relation to the reference method to be improved, in our case WMS.

Procedure:

1. **Definition of Test Scenarios:**
   - **Scenarios:** Several test scenarios are defined that simulate various operational conditions in the warehouse, such as demand fluctuations, equipment failures and variations in cargo volumes.
   - **Objective Functions:** For each scenario, an objective function is defined that the AI and the traditional method must optimize. This may include minimizing operating times, reducing costs or maximizing resource utilization:

$$\min C_{total} = \min\left(\alpha \times \sum_{i=1}^{n} T_i + \beta \times \sum_{j=1}^{m} D_j + \gamma \times \sum_{k=1}^{p} U_k\right)$$

where C_{total} is the total cost, T_i is the operating time, D_j is the distance traveled, and U_k is the degree of resource utilization.

2. **Application of AI Model and Traditional Method:**

Simulation: The AI model and reference method with WMS are simultaneously applied to each defined scenario.

Formulas and Algorithms:

- **Route Optimization in AI:** The optimization algorithm used by AI, such as genetic algorithm (GA) or ant colony optimization (ACO), calculates the optimal routes for machines. For example, the ACO could use a formula to determine the probability p_{ij} of choosing route *ij* :

$$p_{ij}= \frac{\tau_{ij}^{\alpha} \times \eta_{ij}^{\beta}}{\sum_{k\epsilon fezabil} \tau_{ik}^{\alpha} \times \tau_{ik}^{\beta}}$$

where τ_{ij} represents the intensity of pheromones on route *ij* , $\eta_{ij} = 1/ d_{ij}$ is the inverse of the distance, and α and β are tuning parameters.

- **Traditional Method:** ***The traditional method does not use dynamic optimizations, relying on fixed routes and predetermined resource allocations without real-time recalculations.***

3. **Performance Comparison:**

Performance Measurement Indicators: Each measurement indicator is calculated and compared to identify the advantages of AI over the reference method with WMS.

- **Operating Time:** The difference between the operating times obtained by AI and those obtained by traditional methods can be expressed by:

$$\Delta T= \frac{T_{traditional} - T_{AI}}{T_{tradițional}} \times 100\%$$

- **Operational Costs:** The reduction in operational costs due to the use of AI is calculated as follows

$$\Delta C= \frac{C_{tradițional} - C_{AI}}{C_{traditional}} \times 100\%$$

- **Resource Utilization:** Resource utilization is compared to see if the AI manages to improve this aspect:

$$\Delta U \frac{U_{AI} - U_{tradițional}}{U_{traditional}} \times 100\%$$

4. **Analysis of the Results:**

Evaluation of Improvements: The results obtained are analyzed to determine if the AI has made significant improvements over the traditional method. For example, if we notice that by using an AI model, the results obtained led to a 20% reduction in operating time and 15% lower costs, we analyze these values to identify the sources of these improvements.

Sensitivity Testing: It is possible to perform sensitivity analysis to assess how AI performance varies with changes in input data or changes in algorithm parameters.

6.2. Validation by Operational Data

In this stage of validation, known operational data should be used, which have the ability to provide a good framework for evaluating the performance of the model under conditions that faithfully reflect the operational reality.

6.2.1. Collection of Operational Data

This data includes detailed information on operating times, freight flows, machine routes through the warehouse, resource utilization and other relevant logistics variables. Integrating this data into the AI model provides a necessary foundation that allows algorithms to learn, predict and optimize warehouse processes in real time.

6.2.1.1.Techniques and Algorithms Used for Data Collection:

1. **Warehouse Management Systems (WMS):**

Data Collected: Operating times for each task (eg picking , storage), routes followed by machines, use of space and resources.

Extraction Algorithms: To "feed" the AI model with real information, data is extracted from the WMS using data mining and data integration techniques. Algorithms such as **ETL (Extract, Transform, Load)** can be used to collect, transform and load data into the AI model database.

2. **Internet of Things (IoT) technology:**

Data Collected with IoT sensors , are related to Routes traveled by machines, operating times of equipment, environmental conditions (temperature, humidity), movements and real-time locations of products.

Collection and Processing Algorithms: IoT data is collected using data streaming algorithms , which enable continuous and real-time processing of information. Algorithms such as **Complex Event Processing (CEP)** are used to detect significant patterns or events in the data stream.

3. **Machine techniques Learning for Preprocessing:**

Data collected from WMS and IoT is often "noisy" or incomplete, and machine learning techniques are integrated for this learning , which are used to preprocess this data before integrating it into the AI model. [6]

Algorithms Use:

- **Imputation of missing data: Imputation** algorithms such as k- Nearest Neighbors (kNN) or Linear Regression are used to fill in missing data.
- **Anomaly detection:** Algorithms such as **Isolation Forest** or **Autoencoders** are used to detect and remove anomalies from the collected data.
- **Dimensionality reduction :** Algorithms such as **Principal Component Analysis (PCA)** are used to reduce the complexity of data sets while preserving essential information.

4. **Data Aggregation Algorithms:**

After the data is collected and preprocessed, it must be aggregated to be effectively used by the AI model.

Aggregation Methods: In such situations, **aggregation algorithms based on time windows (Time- Window Aggregation)** to simplify the data collected in a defined period, such as calculating the average operating time per hour, day or week. **Location-based aggregation** algorithms are also used to analyze data based on locations in the warehouse, such as picking or storage areas.

5. **Collection and Processing of Geospatial Data:**

Geospatial data refers to the physical location of machinery and products in the warehouse, often collected via GPS, RFID or UWB (Ultra- Wideband) technology.

Processing Algorithms: Location and tracking algorithms are used to monitor equipment and product movements in real time. Algorithms such as **Kalman Filtering** or **Particle Filtering** is frequently used to improve positioning accuracy and remove errors from location data.

6.2.2. Comparative Analysis

Benchmarking is required to evaluate the performance of the AI model against traditional logistics operations management WMS. This analysis enables AI improvements to be identified and quantified using a set of key indicators such as reduced operating times, increased productivity, decreased costs and improved resource utilization. By comparing these indicators, it can be determined whether the implementation of the AI model offers significant advantages over the methods used to date and to what extent they contribute to the optimization of warehouse operations.

6.2.2.1. Indicators Used in Comparative Analysis

1. **Reduction of Operating Times:**

- **General Formula:**

$$\Delta T = \frac{T_{traditional} - T_{AI}}{T_{Traditional}} \times 100\%$$

where:

- $_{Traditional}\,t$ is the average operating time using traditional methods,
- T_{AI} is the average operating time after implementing the AI model.

- **Practical Example:**
  - If the average time to load/unload a truck using traditional methods is 50 minutes. After implementing AI, this time drops to 40 minutes.

$$\Delta T = \frac{50 - 40}{50} \times 100\% = 20\%$$

  - a 20% reduction indicates that AI has significantly improved the efficiency of the loading/unloading process.

2. **Productivity Increase:**

- **General Formula:**

$$\Delta P = \frac{P_{AI} - P_{tradițional}}{P_{tradițional}} \times 100\%$$

where:

- P_{AI} represents the productivity measured after the implementation of the AI model (e.g. the number of units processed per hour),
- $_{Traditional}\,p$ represents productivity measured using traditional methods.

- **Practical Example:**
  - If the productivity measured using traditional methods is 200 units per hour, and after implementing AI it increases to 240 units per hour:

$$\Delta P = \frac{240 - 200}{200} \times 100\% = 20\%$$

This shows that AI was able to increase productivity by 20%.

3. **Decrease in Operating Costs:**

- **General Formula:**

$$\Delta C = \frac{C_{traditional} - C_{AI}}{C_{traditional}} \times 100\%$$

where:

- $_{Traditional}\,C$ is the total operating cost using traditional methods,
- C_{AI} is the total operational cost after implementing the AI model.

- **Practical Example:**
  - If the total operational cost using traditional methods is 970,164 RON, and after implementing AI it drops to 873,147 RON:

$$\Delta C = \frac{970.164 - 873.147}{970.164} \times 100\% = 10\%$$

  - This result shows that AI reduced operational costs by 10%.

4. **Improving Resource Utilization:**

- **General Formula:**

$$\Delta U = \frac{U_{AI} - U_{traditional}}{U_{traditional}} \times 100\%$$

where:

- U_{AI} is the degree of resource utilization after implementing the AI model,
- $_{Traditional}\,u$ is the degree of resource utilization using traditional methods.

- **Practical Example:**
  - If the degree of utilization of resources with traditional methods is 80%, and after the implementation of AI it increases to 90%:

$$\Delta U = \frac{90 - 80}{80} \times 100\% = 12.5\%$$

– This suggests that AI improved resource utilization by 12.5%.

6.2.2.2.Applying Indicators in Simulations

Example 1: Reduction of Operating Times

In the simulation, the AI tested the optimization of the times consumed in the process of loading and unloading trucks. Operational data showed that using traditional methods, the average time for this operation was 50 minutes per truck. After implementing AI, the average time dropped to 40 minutes. Applying the above formula, the reduction in operating time is 20%, which indicates a significant improvement in efficiency.

Example 2: Increasing Productivity

In another scenario, AI was used to optimize warehouse picking processes. The data showed that productivity before AI implementation was 200 units per hour and after implementation it increased to 240 units per hour. Calculating the increase in productivity, using the above formula, shows a 20% improvement, which demonstrates the effectiveness of AI in increasing the volume of cargo processed in a given time frame.

Example 3: Lowering Operating Costs

In the simulations performed, AI was used to optimize the use of resources such as manpower and equipment. Historical operational data showed us total operational costs before AI implementation in the amount of 970,164 RON/month, and after optimization, these costs decreased to 873,147 RON/month. The cost reduction calculation shows a savings of 15%, which reflects the effectiveness of AI in reducing operational expenses.

Example 4: Improving Resource Utilization

In the simulation, AI was used to optimize resource allocation in the warehouse. Initially, resource utilization was 80%. After implementing AI, resource utilization increased to 90%. The resource utilization improvement calculation shows a 12.5% increase, showing how the AI has been able to optimize the distribution of tasks and the efficient use of available resources.

6.2.2.3.Conclusions of the Comparative Analysis

The comparative analysis based on the simulations showed that the AI model provides significant improvements over the currently used logistics center management mode in all analyzed indicators. Reduced operating times, increased productivity, decreased operational costs and improved resource utilization are indicators of superior AI efficiency. These results suggest that the implementation of AI in logistics operations can bring considerable benefits, justifying technology investments and promoting large-scale adoption of AI in the logistics warehousing industry.

Chapter 7. ASSESSING THE IMPACT OF THE ARTIFICIAL INTELLIGENCE MODEL USED IN RESEARCH

7.1. Impact Assessment on Operations

7.1.1. Impact on Efficiency

Evaluating the impact of AI model implementation on warehouse operations involves a detailed analysis of how AI has improved operational efficiency, reduced costs, and optimized resource utilization. For example, for the evaluation of energy efficiency, the energy consumption history of the warehouse for a whole year, measured in MWh, according to graph 7.1, was used in order to test the optimization algorithms.

1. **Impact on Operational Efficiency**

Key Indicators and Application:

- **Average Operating Time (TOM):**
  - **Formula:**

$$\Delta T_{average} = \frac{T_{average,\ traditional} - T_{average,\ AI}}{T_{average,\ traditional}} \times 100\%$$

  - **Real Data:** Historical average operating time for the picking process was 12 minutes per task. After AI optimization, this time has the potential to drop to 9 minutes, resulting in a 25% reduction.

$$\Delta T = \frac{12 - 9}{12} \times 100\% = 25\%$$

- **Handling Capacity (CM):**
  - **Formula:**

$$\Delta CM = \frac{CM_{AI} - CM_{traditional}}{CM_{traditional}} \times 100\%$$

  - **Actual Data:** Historical handling capacity was 220 pallets per hour. After implementation, AI increased this capacity to 270 pallets per hour, an increase of 22.7%.

$$\Delta CM = \frac{270 - 220}{220} \times 100\% = 22{,}7\%$$

2. **Reduction of Operating Costs**

Key Indicators and how to Apply:

- **Total Operating Cost (TOC):**
  - **Formula:**

$$\Delta COT = \frac{COT_{traditional} - COT_{AI}}{CM_{traditional}} \times 100\%$$

  - **Real Data:** Operational cost before AI implementation for the logistics center based on the historical data provided in Table 7.1. reached an average of 970,164 RON per month.

Jan. 23	Feb. 23	Mar. 23	Apr. 23	May 23	June 23	July 23	Aug. 23	Sept. 23	Oct. 23	Nov. 23	Dec. 23
960,410	894,590	901,413	863,846	1,077,927	1,002,484	993,112	1,057,520	1,017,331	933,003	970,164	970,164

- After optimizing the processes in the warehouse, using AI it was possible to observe a monthly average reduction of these costs by 10%, thus reaching savings made throughout the year in the amount of 1,164,196.4 RON

$$\Delta COT = \frac{970.164 - 873.147}{970.164} \times 100\% = 10\%$$

- **Energy Efficiency (EE):**
  - **Formula:**

$$\Delta EE = \frac{EE_{AI} - EE_{tradițional}}{EE_{tradițional}} \times 100\%$$

  - **Real Data:** Also, to evaluate the energy efficiency, historical data from table 7.1 was used. regarding monthly energy consumption in MWh. For example, in January, consumption was 39.45 MWh.
  - After AI implementation, consumption decreased by 15% to 33.53 MWh. The calculation of the improvement is:

$$\Delta EE = \frac{39,45 - 33,53}{39,45} \times 100\% \approx 15\%$$

  - This reduction may also be reflected in other months, such as June, where the initial consumption of 10.87 MWh was reduced to 9.23 MWh.

3. **Optimizing the Use of Resources**

Key Indicators and Application:

- **Equipment Utilization Degree (GUE):**
  - **Formula:**

$$\Delta GUE = \frac{GUE_{AI} - GUE_{traditional}}{GUE_{traditional}} \times 100\%$$

  - **Real Data:** Before AI, equipment utilization was 75%. After implementation, AI can increase utilization to 85%, which is a 13.3% improvement.

$$\Delta GUE = \frac{85 - 75}{75} \times 100\% = 13,3\%$$

- **Optimizing Storage Space (OSD):**
  - **Formula:**

$$\Delta OSD = \frac{OSD_{AI} - OSD_{tradițional}}{OSD_{tradițional}} \times 100\%$$

  - **Real Data:** Storage space was initially utilized at 78% of capacity, and after applying AI, space utilization increased to 90%, which is an improvement of 15.4%.

$$\Delta OSD = \frac{90 - 78}{78} \times 100\% = 15{,}4\%$$

7.1.2. Conclusions of the Impact Assessment on Operations

The algorithms used, such as route optimization, machine learning and clustering , contributed to these results through dynamic adjustment and continuous optimization of operations. AI's ability to dynamically adapt, predictively optimize, maximize resource utilization, scale out, and learn continuously gives it a considerable advantage over a WMS.

7.2. Impact on Customer Satisfaction

7.2.1. Improving Delivery Times

The role of AI:

A traditional WMS lacks the ability to learn and adapt based on past performance. Any adjustment requires human intervention, which can lead to delays and inefficiencies. In a WMS system, lead times are highly dependent on pre-set processes and the system's ability to handle requests efficiently. However,

On the other hand, the warehouse that adopts and implements **AI** is much more easily scalable, using route optimization algorithms and machine -based predictions learning that allow more precise scheduling of deliveries, reducing delays and increasing the reliability of deliveries. This, in turn, improves the customer experience and increases the level of satisfaction.

Example:

Initial Situation: The deposit has an *initial* contractual term *T = 24 hours* to prepare orders.

Situation after AI Implementation: By optimizing internal processes with the help of AI, the time required to prepare orders was reduced by 20%. This means that the average time to prepare orders decreased from 24 hours to 19.2 hours.

$$T_{AI} = T_{inițial} \times (1 - 0{,}20) = 24 \times 0{,}80 = 19{,}2 \text{ ore}$$

How do we translate this reduction into customer impact?

Reducing the average lead time to 19.2 hours means that the warehouse can have orders ready for shipment approximately 4.8 hours earlier than the agreed 24-hour deadline.

7.2.2. Reducing Delivery Errors and Improving Accuracy

The role of AI:

Warehouse with WMS: In a traditional warehouse with WMS, resources are allocated based on a set of predefined rules, which may not always take into account their optimal use. For example, a WMS can allocate equipment based on a fixed schedule without considering variations in workload in different areas of the warehouse.

Warehouse with AI: By using AI, these errors can be significantly reduced. AI using pattern recognition techniques and machine algorithms learning to check orders before shipping and ensure the correct products are properly prepared and shipped.

Example:

Implementing AI in simulations can reduce the delivery error rate from 2% to 0.5%. This reduction leads to a significant decrease in returns and complaints, thereby improving customer perception of the reliability and accuracy of the services provided.

The experimental data from table 7.2 were used for the simulations. and those in Chapter 5 where the warehouse processes 1000 orders per day and can reach a maximum of 1500 during peak periods, data that is based on a history of a warehouse of similar size and operations to the one we presented at beginning of chapter 5.

Table 7.2. - Command error scenarios

Scenario	Orders/day	Error Rate	Orders with Errors (without AI)	Orders with Errors (with AI)	Error Reduction
Normal (without AI)	1000	2%	20	-	**-**
Normal (with AI)	1000	0.5%	-	5	**15**
PEAK (without AI)	1500	2%	30	-	**-**
PEAK (with AI)	1500	0.5%	-	7.5	**22.5**

Conclusion: Implementing AI in the warehouse significantly reduces the delivery error rate. For the above scenario, in just one typical day, AI can reduce the number of erroneous orders from 20 to 5, which is a reduction of 15 erroneous orders per day. During peak periods, the reduction is even more significant, from 30 to 7.5 error orders, a reduction of 22.5 error orders per day. This improvement not only reduces the costs associated with returns and complaints, but also significantly improves customer perception of the reliability and accuracy of the services provided.

Chapter 8. Recommendations and Planning for the Practical Implementation of the AI Model

8.1. Impact Assessment on Operations

Following the research carried out in this thesis, the need to implement the artificial intelligence (AI) model in logistics operations is not only a technological innovation, but also a significant contribution to the optimization and modernization of warehouse management processes. This proposed integration between AI and warehouse management systems (WMS) underscores the importance of an intelligent logistics system capable of adapting in real time to the fluctuating demands of the operational environment. However, implementing AI in logistics operations requires a well-structured plan and a methodical approach to ensure the successful transition from a traditional WMS system to one based on artificial intelligence.

8.1.1. Own Contributions and Recommendations for Implementation

8.1.1.1. Integrating AI with WMS: Why is it necessary?

Own Contribution:

Innovation through Continuous Optimization: This thesis aimed to highlight the need to develop an AI model that seamlessly integrates with existing WMSs in most logistics centers everywhere, enabling continuous optimization of routes, resource allocation and uptime prediction . Through this integration, a hybrid system is created, capable of dynamically responding to changes in demand and variations in workflows.[2][4]

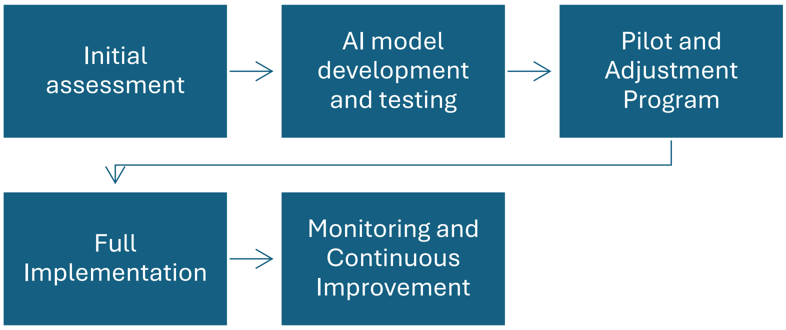
Optimization and Prediction Algorithms: Using machine algorithms learning and optimization techniques, such as genetic algorithms and ant colony optimization, make a significant contribution to improving operational performance. These techniques allow not only the optimization of routes, but also the dynamic adjustment of the use of resources according to the needs of the moment.[3][8]

8.1.2. Implementation Planning

8.1.2.1. Detailed Implementation Steps [10] [11]

Before implementing AI, it is essential to conduct a detailed assessment of operational needs and existing infrastructure. This assessment must include an analysis of IT capabilities, available human resources, and warehouse readiness for AI integration. Any implementation plan must be well structured to ensure the efficient transfer of the AI model from the simulated environment to the real environment.

The plan proposed in this thesis details the steps needed to ensure successful implementation and maximize the benefits of AI, as shown in Figure 8.1.



8.1.2.2. Post-Implementation Monitoring and Evaluation[7]

Post-implementation monitoring and evaluation is essential to ensure the long-term success of AI in the operations for which we want to deploy it. Detailed measures will be implemented to constantly assess AI performance and identify opportunities for improvement.

- **Periodic Evaluations** : At this stage, regular evaluations should be conducted to analyze AI performance and its impact on operational efficiency.
- **Feedback from Users:** This feedback will be integrated into the process of continuous adjustment of the AI model, thus ensuring that the system evolves according to the changing operational requirements and strategic objectives of the company.
- **Key Performance Indicators (KPIs):** Monitoring these KPIs will provide a clear picture of AI effectiveness and enable quick adjustments if performance is not up to expectations.
- **Periodic Audits:** The results of the audits will be used to make necessary adjustments and continuously improve the model.
- **Algorithms Update:** This update process will include recalibrating predictive models, adjusting optimization parameters, and integrating new emerging technologies such as the Internet of Things (IoT) and blockchain to increase AI accuracy and efficiency.
- **Integration of Feedback into the Decision-Making Process:** Continuous user feedback and collected data will be integrated into the strategic decision-making process. This will allow fine-tuning of AI's long-term goals and ensure that implementation remains aligned with the company's overall strategic direction.
- **Employee Impact Assessment:** Employee satisfaction surveys and performance reviews will be used to identify any AI adaptation issues and develop additional training programs if needed.
- **Contingency Scenarios:** In case the AI does not meet expectations or a major problem occurs, it is important to have contingency scenarios.
- **Reporting and Communication:** Effective communication of post-implementation results is critical to the long-term success of AI. Detailed reports on AI performance and impact will be distributed periodically to all stakeholders, including operational teams, senior management and external partners. These reports will provide an ongoing assessment of progress and include recommendations for future improvements.

Chapter 9. Final conclusions and main contributions to the optimization of warehouse operations by integrating AI in logistics centers

9.1. Introduction

The aim of this thesis was to demonstrate the efficiency and impact of the use of artificial intelligence (AI) in the optimization of logistics operations carried out in a warehouse or logistics center that benefits from the most common technologies in this field. The main objective of the research was to highlight how AI can complement and extend the capabilities of a warehouse's traditional inventory management systems (WMS) by applying advanced optimization algorithms and machine learning , aspects that I presented in chapters 5 and 6.

Route and Resource Optimization

In chapter § 5.1, we demonstrated how the use of AI in logistics operations can bring significant improvements in the optimization of routes and resource utilization.

Specifically, the simulations demonstrated that using AI to optimize routes, in a logistics center optimizations can even be achieved by:

- **Up to 20% of the distances traveled** by machines for picking and handling operations. AI also enabled dynamic adjustment of resources to ensure continuity of logistics flow in the event of unexpected machine breakdowns.
- A **reduction in operational costs** , thanks to the shorter route and more efficient use of resources such as forklifts and pallet trucks .
- **workflow** improvement , allowing to reduce bottlenecks and dead times during loading and unloading operations.

This optimization is not static as is typical of a WMS, but dynamic, with AI having the ability to adjust routes and resources based on current order volume, cargo locations and other operational factors.

Realistic Scenarios and Simulations

In §5.2, simulated scenarios were essential to test the ability of the AI model to adapt to different scenarios. We have defined and tested scenarios such as **machine breakdowns** , **demand fluctuations** , and **storage capacity optimization** , each reflecting situations that may occur frequently in a real warehouse environment.

For example:

- In case of a **random failure of a Reach Truck** , the AI manages to quickly redistribute the loads to other available machines, maintaining the workflow in a way that reduces delays. Simulations have shown that operating times in such cases have increased by only 15%, compared to an estimated 30% increase in traditional WMS warehouses that do not use AI.
- In the event of a VNA forklift failure, AI quickly adapted resource allocation to distribute the workload between the other two available forklifts, maintaining over 80% productivity in that area. Simulations demonstrated that this adaptive capacity prevented operational bottlenecks and allowed the warehouse to operate close to full capacity, even under fault conditions.

- In the event of a **sudden increase in demand (during peak periods)** , AI optimized resource allocation by focusing activity on fast-turnover picking areas. Thus, an efficient distribution of resources was achieved, minimizing the waiting time and optimizing the use of equipment.
- **The optimization of storage capacities** was also felt in that AI was able to maximize the use of space in areas of high demand, redistributing goods so that they are accessible in the shortest possible time.

Comparing AI to traditional warehouse inventory management methods, such as those based on **Warehouse Management Systems (WMS)** , has shown a significant improvement in operational performance.

In a **traditional WMS** , decisions are made based on fixed, pre-set rules that cannot adjust workflow or resource usage in real time. Static planning, in the absence of dynamic feedback, makes these systems unable to respond effectively to rapid changes in a warehouse, such as machine breakdowns or sudden fluctuations in demand.[1][2]

By contrast, **AI** :

- **Improves productivity by up to 18.75%** , according to calculations, thanks to the ability to dynamically adjust operations and redistribute resources efficiently.
- **Error Reduction:** AI has been able to significantly reduce operational errors, especially in the picking and shipping process, using pattern recognition techniques and automatic verification algorithms. In simulated scenarios, AI was able to reduce delivery errors from 2% to 0.5%, a significant decrease that had a positive impact on customer perception. This was made possible by accuracy control algorithms, which checked the correctness of orders before dispatch, thus avoiding the delivery of the wrong products or incorrect quantities.
  In contrast, WMS relies heavily on manual inputs, which are prone to errors **.**
- **It optimizes the use of resources and operating times by up to 15%** , adjusting tasks according to the state of equipment and the volume of orders, an aspect impossible in traditional WMS systems.

Thus, AI has been shown to offer a much more flexible and adaptable solution, leading to lower costs and better operating efficiency.

The Adaptive AI Model

The great advantage of an AI model is demonstrated by the fact that it is rapidly adaptable and able to adjust according to changing operational scenarios. Compared to a WMS system, which operates based on static and fixed rules, the AI model has the ability to:

- **Adapt routes and resources in real time : Using advanced** machine algorithms learning and optimization, AI adjusted operational dynamics based on real-time data from the warehouse, such as demand variations or equipment failures.
- **Learn from historical and current data** : Neural networks powered by an AI model enable continuous learning from historical data, making accurate predictions about demand volumes and adjusting resources to respond to fluctuations.
- **Dynamic redistribution of tasks** : At the same time, the AI Model, compared to a WMS, has the ability to redistribute operational tasks as unforeseen events (for example,

machine failures) occur. This flexibility has allowed downtime to be reduced and resource utilization to be maximized.

9.1.1. Potential Applications

The AI model proposed in this research has a significant potential to be applied not only in the logistics industry, but also in other sectors that require the optimization of operational flows, resource management and reduction of operational costs. Some of the areas where this AI model could make improvements are discussed below:

1. **Global supply chains:**

AI models can be applied globally, within supply chains that span multiple distribution centers. AI could optimize the flow of goods between different distribution points, dynamically adjusting routes and resource allocation to minimize transport costs and times.

Coordination between warehouses : By integrating AI into a global supply chain management system, AI could coordinate operations between different warehouses, redistributing stocks and adjusting priorities according to the needs of each center.

2. **Manufacturing industry:**

Production optimization and inventory management: AI could be used to optimize production flows in a factory, adjusting production tasks and resource allocation in real time, to respond more quickly to changes in demand and to minimize material or time wastage. In addition, AI can optimize inventory management of raw materials and finished products, thus ensuring smooth operation of production processes.

Maintenance prediction: Using machine algorithms learning can help predict machine and industrial equipment breakdowns, thus minimizing downtime and optimizing production processes.

3. **Urban transport and logistics industry:**

Route optimization for vehicle fleets: AI can be used to optimize the routes of transport vehicles, including freight trucks and local deliveries, to reduce fuel consumption and minimize carbon emissions. Such models could also be applied in urban logistics, where AI can optimize deliveries in densely populated areas by coordinating vehicles efficiently to avoid congestion and reduce delays.

Last -mile delivery systems : Another promising area for AI is the optimization of last -mile deliveries (the last stage of delivery to the final customer). AI could help identify the fastest and most efficient delivery routes in real time, taking into account traffic and other dynamic conditions.

9.2. Final conclusions

This PhD thesis focused on the integration of **Artificial Intelligence (AI)** in logistics processes, with the aim of improving the operational performance of industrial warehouses. In the research, we explored the potential of AI to overcome the limitations of traditional warehouse management systems such as **Warehouse Management Systems (WMS)** and demonstrated its superiority in route optimization, resource management and error reduction. The results obtained from the simulations and analyzes carried out have highlighted the fact that the integration of AI in the logistics processes allows a **significant increase in efficiency**.

Advanced algorithms have demonstrated the ability to reduce operating times by up to 18%, thus contributing to the optimization of workflows and a **more efficient use of resources.** AI has also demonstrated superior adaptability in handling unexpected equipment failures, maintaining operational continuity and minimizing their impact on logistics performance.

The main contribution of this thesis is to demonstrate the essential need to integrate artificial intelligence (AI) with traditional warehouse management systems (WMS). In a logistics era marked by exponential increases in complexity and dynamism, traditional WMSs face significant limitations in effectively managing resources and workflows. These systems operate on the basis of static and fixed rules, which do not allow real-time adjustment of logistics processes according to constantly changing demand, equipment failures or other unpredictable variables (see § 7). In contrast, AI brings more adaptability and flexibility through the use of optimization and machine learning algorithms.

Another key aspect highlighted in the research is the ability of AI to **reduce the rate of operational errors** . The implementation of machine learning algorithms led to a substantial reduction in picking and shipping errors, from 2% to 0.5%. This, I believe, can have a positive impact on customer satisfaction and on the perception of the quality of services provided. The integration of AI allows tighter control of orders and ensures **high precision in the execution of operations** compared to traditional methods.

The original contributions of this research consist in demonstrating innovative logistics optimization practices by introducing AI models with certain advanced optimization and machine learning algorithms, especially in terms of model adaptability to dynamic and unpredictable conditions. The proposed model can be successfully applied in different types of warehouses, contributing to the significant improvement of **productivity, accuracy and profitability** . Moreover, integrating AI with existing WMS systems brings a **substantial competitive advantage** , giving companies the ability to respond quickly and efficiently to global market challenges.

In conclusion, the research carried out in this PhD thesis underlines the need and benefits of implementing AI in the logistics industry, opening new horizons for the development of innovative technological solutions. With these conclusions, I believe I have provided a clear vision of how AI can revolutionize industrial logistics, improving not only operational performance but also long-term sustainability and competitiveness.