AYDEP

Team 18

A101 Depo

A101

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Abstract

This project aims to optimize warehouse operations for A101. The current product arrangements in the warehouses are experience-based. This causes inefficiencies in selector travel distance, pallet stability, and overall order preparation time. The project proposes a data-driven optimization framework that integrates product slotting, routing, and palletizing decisions. A multi-objective mathematical model supported by metaheuristic algorithms is planned to minimize total travel distance. The final output will be a Decision Support System which is capable of generating optimal product arrangements and selector routes. This systematic transformation is expected to reduce operational costs and increase selector efficiency. Standardized, sustainable warehouse management structure also targeted.

Keywords: Warehouse optimization, Order picking, Palletizing, Metaheuristics, Decision Support System

Contents

1 Description of the System

A101 is one of Turkey's largest and fastest growing retail store chains. The company operates in all 81 provinces with more than 13,000 stores and works with 70,000 employees. A101 has a network of more than 1,200 suppliers. A101 is the 5th fastest growing retail company in the world, according to Deloitte's Global Powers of Retailing 2022 Report. A101 offers its store service with different platforms such as A101 Kapıda and HADİ apps. These services contribute to the daily order circulation. A101 operates one of the most extensive and integrated supply chain systems in Turkey's retail industry. The logistics and distribution operations of A101 are designed to ensure high product availability, cost efficiency, and on-time delivery to all regions with over 13,000 stores nationwide. The company's supply chain structure is built on a centralized distribution model which is supported by an expanding network of regional distribution centers strategically located across the country. A101 works with more than 1,200 suppliers, the majority of whom are domestic producers. On the other hand, there are several abroad contacts. This huge operational volume requires reevaluating and updating operational methods. Since A101 holds the fame of reaching every district and offering cheap products, they care about protecting their current status. For this reason, A101 focuses on protecting its product and service performance standards. Products that meet A101's strict audit, quality, and supply standards are included in its assortment, and these reflect its commitment to customer satisfaction and reliability. Products from suppliers are first transported to regional distribution centers, where they are received, stored, and sorted according to store demand. A101's logistics system uses a hub covering model. In this model, regional warehouses act as hubs supplying hundreds of stores in their assigned regions. Each warehouse is equipped with advanced inventory management systems that are able to track product quantities, expiration dates, and delivery schedules according to orders coming from SAP. Daily shipments are then dispatched to stores according to the order input of the store data collected from the company's integrated digital system. This method allows for frequent deliveries, which minimizes the profit loss due to understock cases in the store, while relaxing the available space in inventory and reducing inventory holding costs. A101 enables data driven decision making by integrating sales data, supplier information, and logistics performance metrics into a centralized system. The company's online platforms, such as A101 Kapıda, also provide valuable data on customer preferences and regional consumption patterns, which also help to make better supply chain decisions. The socioeconomic structure of the districts causes various demands with respect to both product type and product brand. In line with these changing retail trends, A101 increasingly focuses on sustainability within its supply chain. Additionally, in the current operational system, high volume customer orders from stores and online platforms fluctuate according to spot product delivery and discount days. For this reason, on time delivery and the product assortment of warehouses need to be carefully considered. Since there are 59 regional warehouses A101 manages a huge supply chain network. This complex intertwined network initiates from the order of each store via SAP and sales department as daily and weekly order lists. The digital system analyzes and makes suggestions before informing the warehouse and finalizing the order lists. The assigned regional warehouses receive information and guide selectors (blue collar workers) for the accumulation of product orders while trucks wait to fill completely before delivery. Warehouses have different shapes such as L, U, and I. These warehouses are mainly separated into 5 as Dry storage, Cold (+4°C), Fruit/Vegetable (+12°C), Frozen (-18°C) and Meat/Poultry (0-2°C), respectively. From them, the dry storage area occupies more than half of the available space due to various products. The dry storage section is classified as letters for each row and numbers for each column. This helps to insert every categorized product and locate similar sequences for order accumulations. Products are picked manually by selectors from the specific cells according to the order list. These visits take various times due to the different locations of products in the warehouse, which usually leads to wasted time during the traveling time to the cells for selectors. Product sequencing varies according to different focuses at each warehouse considering the needs such as weight, dimension or sales frequency of products. These objective sequence focuses are decided by prioritizing warehouse needs and drawing on past experiences of experienced selectors A101 (nd).

2 Current System Analysis and Problem Definition

The warehouses used by A101 contain areas dedicated to various purposes. These areas are categorized as: incoming product holding area before storage, shelves where products are placed, empty areas where overstocked products are stored, empty pallet holding areas, space reserved for pallet stretch wrapping machines, and areas where pallets are held ready for shipment, which can be seen in Appendix A. The upper parts of the shelves where products are placed are used for general storage, while the floor shelves are used for picking. Products on the floor shelves are arranged from the heaviest and most durable to the lightest and most fragile. The floor shelf is named as a picking cell, and it can contain three different products. Shelves are arranged alphabetically, while cells within the same row are named numerically. We analyzed two months of order data from the Esenboğa Warehouse, which we requested from the company. The data includes 1,389 different products, 17 different product groups, and 309 different groups of goods, across 415 orders placed by 10 different stores. This means each order contains an average of approximately 72 different products (Table 1).

Table 1: Summary of distinct counts for each variable based on data from Esenboğa Warehouse, dates between August 20 and October 20

Days	Store	Products Code	Product Group	Group of Goods
51	10	1396	17	309

2.1 Warehouse Organization and Order Processing

The warehouse organization and order processing process consists of four main stages (Figure 1).

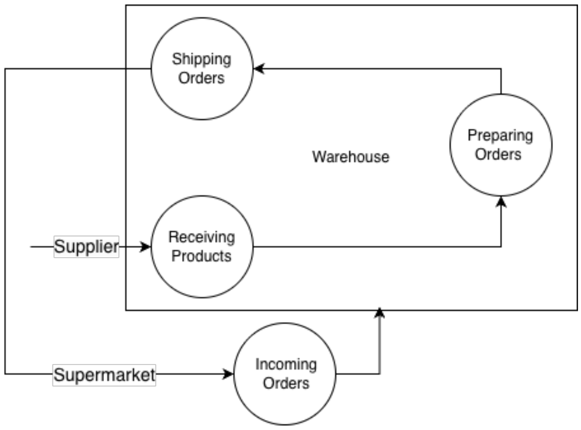

Figure 1: Flow of Warehouse

First, the incoming products from suppliers are received and placed on the upper shelves, which are empty for storage, by forklifts. When inventory on the floor shelves begins to run out, they are placed in picking cells, again by forklifts. Then, incoming orders are placed by stores according to their inventory shortages. Store enters its orders into the SAP system by a definite cut-off time at the end of the day, which can vary for each warehouse. Orders are assigned to operator handheld terminals by the warehouse's order and shipment planning team. Operators use handheld terminals that display the entire order to fulfill their assigned tasks using selectors and Euro pallets (80x120 cm) UIC Communications (2011). The suggested picking route for the products on the handheld terminal follows a sequential alphabetical and numerical order of the product locations in the warehouse, which can be seen in Appendix B. However, as a result of reviewing the data we requested from the company, we realized that an order usually has to be shipped by more than one pallet. The operator's initiative and experience determine the process of dividing the order into pallets. A pallet is generally expected to have a height of between 160 and 190 cm. A pallet height greater than 190 cm results in loading and unloading issues on shipping trucks, while a pallet height less than 160 cm results in inefficient use, increasing the logistics cost per pallet. As the warehouse manager remarked, novice operators can pick significantly less efficiently than experienced operators. Besides, the data we received from warehouse personnel demonstrates the change in pallet picking performance (Figure 2).

Package Quantity	Product Quantity	Selector	Start Date	Completion Date	Pallet Quantity	Total Duration	Average Duration	Package Frequency	Packages per Pallet
239	164	Mahsun	13:14	13:59	2	0:45	0:22	1.46	119.5
174	168	Tolga	13:46	14:53	3	1:07	0:22	1.04	58
141	132	Mete	14:15	15:21	2	1:06	0:33	1.07	70.5
120	86	Huseyin	13:15	13:45	2	0:30	0:15	1.4	60
221	171	Sahin FRH	14:43	16:32	3	1:49	0:36	1.29	73.67
231	220	Mahsun	10:31	11:31	2	1:00	0:30	1.05	115.5
157	126	Elif	15:24	16:39	2	1:15	0:37	1.25	78.5
179	140	Hüseyin Aslan	16:28	17:02	2	0:34	0:17	1.28	89.5
339	255	Emre	14:46	16:34	5	1:48	0:21	1.33	67.8
216	182	Cesur	1:09	2:04	3	0:55	0:18	1.19	72
403	222	Hüseyin	9:45	11:17	4	1:32	0:23	1.82	100.75
378	216	Mert	15:22	16:41	4	1:19	0:19	1.75	94.5
206	158	Elif	9:45	11:23	4	1:38	0:24	1.3	51.5
238	182	Sahin	8:23	10:19	4	1:56	0:29	1.31	59.5
392	226	Tırpan	1:09	2:30	5	1:21	0:16	1.73	78.4
125	120	Elif	16:43	17:06	2	0:23	0:11	1.04	62.5
148	110	Mahsun	16:09	16:50	2	0:41	0:20	1.35	74
3907	2878				51		0:23		78.01

Figure 2: Pallet Datas from Warehouse

The data change graph can be found in Appendices C and D. Finally, pallets stacked by selectors are stretch-wrapped with a stretch wrapper machine and placed on hold, ready for shipment. This can be seen in Appendix E.

The warehouse's product layout strategy is based on the assumption that each selector will travel the entire warehouse and aims to distribute all products homogeneously throughout the warehouse. Nonetheless, the lack of a standardized system results in warehouse layout planning by managers with varying experience across warehouses. Using a data-independent process when placing products on picking shelves necessarily maximizes operator route length. Palletizing all assigned store orders based on operator experience and discretion leads to inefficient pallet utilization and time loss due to unforeseen errors. We will optimize the system to address these issues using a year's worth of order and shipment palletization data from various regions, which we obtain from the company

3 Review of Resources

3.1 Literature Review

Effective warehouse slotting which means the assignment of each product type to storage locations is the fundamental operation to reduce the selector travel time. Slotting studies show that placing correlated SKUs shortens order tours and cuts labor costs Aase and Petersen (2022). This is called the Apriori algorithm. The Apriori algorithm is generally used for "market-basket analysis". The algorithm takes the warehouse data as input and determines the product groups that are frequently ordered together. The results obtained are used to determine product placement in the warehouse. It ensures that products frequently ordered together are positioned side by side or in nearby areas. For instance, Lesch et al. (2023) used Apriori association rules in storage allocation to demonstrate that grouping correlated products can improve picking performance. Similarly, Xu and Ren (2020) used the Apriori algorithm to calculate the demand correlation between products in a dynamic storage location allocation (DSLA) problem and suggested placing SKUs with high correlations in the same or adjacent areas.

Pareto principle and ABC classification are also used in slotting optimization. It is generally assumed that 80%of demand comes from a product group representing approximately 20%. Viveros et al. (2021) Products with this high order average are defined as "Class A." These Class A products are assigned to premium shelves in the warehouse (near the entrance, exit or peak locations) to ensure quick access. This method is referred to in the literature as the ABC classification. For example Viveros et al. (2021) conducted a study where SKUs are divided into classes A, B and C according to the Pareto principle according to the demand amount and separate storage priorities are defined for each class. Such empirical results align with the needs of the A101 warehouse. By using actual order data, a slotting and picking optimizer can reduce the hundreds of meters each selector walks per day.

Order picking is one of the most labor intensive and costly operations in manual warehouses. It is estimated to account for approximately 50-60% of operating costs Kordos et al. (2020). As a result, many strategies focus on reducing selector walking distance. Research confirms that optimizing product arrangement in warehouses and using efficient routing strategies can shorten travel times Kordos et al. (2020). For instance, class based storage combined with specific routing policies helped reduce travel distance. While implementing this system, fast moving SKUs are placed in the front or peripheral aisles and routes like "Largest Gap" are used to minimize backtracking. The same research shows that treating slotting and routing as integrated models yields better overall efficiency Van Gils et al. (2018). In another research, it is mentioned that a combined slotting and picking optimization model is used. This model highlights that integrated strategies can significantly improve warehouse operations. Duque-Jaramillo et al. (2024)

Besides picking, the stacking of selected products on the pallet is also an important part of the process. This problem can be modeled as a three dimensional bin packing problem (3D-BPP). This 3D-BPP is an NP hard optimization problem because it involves placing products of different sizes and shapes on a limited volume pallet under certain constraints. Therefore, heuristic and metaheuristic algorithms are primarily used in the literature instead of methods that seek optimal solutions Sawicki and Sawicka (2023). For example, in layer based placement approaches, products are first grouped according to their height and stacked in layers. Then each layer is arranged separately, the algorithm treating it as a one dimensional (1D) placement problem. This helps to design a load balanced and stable pallet while simplifying the solution by breaking the multi dimensional placement problem into smaller subproblems Švaco et al. (2023). A similar study conducted by Dell'Amico and Magnani (2021) also provided similar results.

Additionally, palletizing strategies such as picking heavy items first and covering the bottom of the pallet during picking ensure a stable pallet lift. This method also reduces the extra workload that can result from overall imbalance. In general, the literature presents numerous methods (from heuristic routing algorithms to layout zones and batch optimization) that consistently reduce selector travel distance and increase order picking efficiency Kordos et al. (2020) Van Gils et al. (2018).

Genetic Algorithm is used for the complex slotting and layout problems. GAs find large combinations of SKU placements and multi product aggregations and can comfortably handle nonlinear objectives such as walking distance. Kordos et al. (2020) implemented a fully automated GA that simultaneously optimizes product placement and selector routes. In their study, GA driven slotting and route planning reduced total picking time by 79%. Other studies have also shown that multi-purpose GA variants (e.g. NSGA-II, SPEA2) have been applied to warehouse design. For example, one study considered warehouse optimization as a three objective GA problem. The objectives are: minimizing travel distance, maximizing rack stability and respecting item similarities. Research finds that GA quickly produced near optimal layouts even on large SKU sets Wang et al. (2017). This study demonstrates that GA based approaches can flexibly address multiple objectives (distance, stability, stacking rules, etc.) for A101's 1500+ SKUs when adjusted based on the data that we take from the company.

Machine Learning algorithms are starting to play an increasingly important role in warehouse optimization. ML methods are used in warehouse planning by processing large volumes of data, such as historical order data. ML techniques are particularly recommended for complex decision making situations such as Storage Location Allocation (SLAP) and Order Picking (OPP) problems. ML based techniques can optimize selector routes by predicting the distances of order picking routes. In summary, ML applications in the literature displayed significant benefits in functions such as warehouse slotting and picking distance prediction by learning from historical data de Assis et al. (2024).

Warehouse optimization contains multiple objectives like maximizing space utilization while minimizing walking distance. It also contains stacking constraints like stability and no damage to goods. For example, heavy items should not be placed on lighter or fragile items and pallet height/weight limits must be taken into consideration Sawicki and Sawicka (2023). Researchers developed multiobjective models that incorporate these stacking rules. Sawicki and Sawicka (2023) present a pallet loading optimization that minimizes the number of pallets used while respecting stacking constraints. Similarly, integrated order picking and palletization algorithms were used to jointly determine the picking route and the stacking of products on pallets Ding et al. (2025). These studies demonstrate how multiobjective approaches can balance efficiency with safety and feasibility.

A decision support system (DSS) can link these methods to A101's data. DSS platforms combine databases, models, and interfaces to assist with problems in planning processes Younis and El Masry (2017). In warehousing, DSS is built to take actual picking and demand data and then output palletizing or routing recommendations. For example, Aase and Petersen implemented a Microsoft Access based DSS for reslotting. It reads historical pick counts and suggests SKU swaps under an ABC class rule. Then, it uses simulation to quantify distance savings Aase and Petersen (2022). More generally, DSS methodology literature emphasizes that such systems help managers select among many options by quickly analyzing large data sets and optimization models Younis and El Masry (2017). We can use the warehouse's actual SKU and order data as input to the optimization tool in our project. This will allow for data-driven product placement within the warehouse. In short, studies on warehouse DSS show that running optimization models with real warehouse data can significantly improve pallet picking efficiency Younis and El Masry (2017).

3.2 Engineering Standards and Regulations

As part of this project, product layout and route optimization efforts at A101 distribution centers must be conducted in full compliance with international engineering standards and occupational safety regulations. Each optimization strategy implemented in the warehouse will be designed to comply with standards such as employee safety, equipment capacity and ergonomic limits.

3.2.1 Weight and Carrying Standards

Various standards must be considered to ensure ergonomics and the structural safety of racking systems in warehouse operations. The ISO 11228-1 Ergonomics Standard defines internationally accepted limits of manual lifting and carrying tasks. According to this standard, the maximum load an adult worker can lift at one time under ideal conditions is approximately 25 kg. This value is the upper limit for a healthy adult male. Lower levels are recommended for women and other age groups. Furthermore, ISO 11228-1 recommends that the maximum load must be below this value if the work has repetitions or if the working posture becomes inconvenient. (International Organization for Standardization [ISO], 2021). Also there are European standards for the carrying capacity of warehouse racking systems. EN 15512 and EN 15635 define the requirements for the design, installation, use and maintenance of steel industrial racking. In particular TS EN 15635 establishes specific safety criteria regarding racking capacity and material strength.TMMOB Makina Mühendisleri Odası (2018)

3.2.2 Warehouse Traffic and Aisle Widths

Safe management of vehicles and safe pedestrian traffic in the warehouse are of great importance for operational efficiency and occupational safety. OSHA 29 CFR 1910.176(a) legislation requires aisles where mechanical handling equipment such as forklifts or pallets is using, should have sufficient width and appropriate markings. In practice, main aisle widths must be at least 3.7 meters for easy maneuvering of forklifts. Emergency exit routes must also be placed at a certain width for quick and safe evacuation in emergencies. According to OSHA's regulations on exit routes, an emergency exit route must have a minimum width of 71 cm at its narrowest point Occupational Safety and Health Administration (nd). Another important aspect of warehouse traffic management is the separation of pedestrian and forklift paths and the installation of floor markings. In accordance with occupational safety standards, pedestrian walkways or lanes should be painted on the warehouse floor to identify walkways for employees and potential interaction points between forklift operators and pedestrians should be minimized.

3.2.3 Fire Safety Standards

The NFPA 13 (National Fire Protection Association) standard is the fire safety standard for warehouses. According to NFPA 13, a minimum vertical clearance of 45 cm must be maintained between sprinkler heads and the materials stored under them Occupational Safety and Health Administration (nd).

3.2.4 Occupational Health and Safety Legislation in Türkiye

Within the scope of occupational health and safety legislation in Türkiye, there are detailed obligations to ensure the safety of employees in warehouse activities. Occupational Health and Safety Law No. 6331 and the regulations issued under this law (Manual Handling Work Regulation and the Health and Safety Conditions in the Use of Work Equipment Regulation etc.) contain provisions that are parallel with the international standards. According to this legislation, employers are obligated to provide a safe working environment for their employees Türkiye Cumhuriyeti (2012).

In our discussions with IA, it was indicated that all warehouse operations are carried out in compliance with recognized engineering standards and national occupational health and safety laws. The company says that the principles they are following, created in accordance with Occupational Health and Safety Law No. 6331. These are taken from standards such as NFPA, EN, and ISO series. Therefore, this project will be planned and carried out in accordance with these standards to ensure both operational efficiency and compliance with A101's internal standards.

4 Proposed Solution Strategy

This part presents a detailed, data-driven, multi-stage approach to solve the A101 warehouse product placement problem. The suggested plan is to switch from the current experience-based system to a mathematical system that can be the basis of a scalable and sustainable Decision Support System (DSS).

4.1 Critical Assumptions

The accuracy and usefulness of our model depend on the following assumptions:

- Data Accuracy: The one-year historical order data by A101 is expected to be a statistical representative of future demand and product popularity.

- Physical Stability: The physical layout of the warehouses is supposed to be the same throughout the duration of the project.

- Quantification of Durability: A numerical "Durability Coefficient" based on products' physical properties (weight, packaging, etc.) is assumed to be developed and calibrated with the expert opinions of A101's experienced warehouse staff.

4.2 Major Constraints

Our solution approach will be influenced by the operational and regulatory constraints that are based on the company's regulations or restrictions.

- Applicability: The optimization model will be applicable for different A101 warehouses, where it will be scalable and adaptable regardless of their physical structure variations (L, U, I types).

- System Integration: The means of the A101 SAP based infrastructure and the handheld terminals used by selectors will be the designed outputs of the proposed solution to fit in with.

4.3 Objectives

The main goal of this project is to create a standardized warehouse slotting model that will lead to less total travel distance for selectors, thus lowering the order preparation time and the related labor costs. An additional aim is to coordinate the product sequence on the pallet with the shelf layout of the store in order to speed up the in-store product placing process. The main goal is to offer a formalized structure that can serve as a dynamic Decision Support System (DSS) for the whole warehouse network of A101.

4.4 Solution Approach

The solution approach is depicted as a multiple phase framework that sequentially progresses from data analysis to a robust optimization model. The framework is designed to be flexible in terms of the selection and implementation of specific tools.

4.4.1 Data-Driven Parameterization

The first phase will focus on the transformation of operational data and expert knowledge into numerical parameters for the mathematical model. This means that two main metrics will be developed for two objectives:

- "Durability Coefficient" is a calculation for each product that numerically shows how suitable it is to be placed at the bottom of a pallet. This will be dependent on the product's physical characteristics such as weight, packaging type, and fragility.

- "Frequency Coefficient" is a measure of each product frequency which will be computed from one year of historical sales data. This coefficient will be obtained by normalizing the total order quantity of each item, thus giving a clear indication of the product's demand.

Furthermore, to solve the problem of store shelf space optimization, data mining methods will be used. One such method is Association Rule Mining (e.g., the Apriori algorithm) which will be evaluated for its ability to identify products that are ordered together most frequently and thus suggest the formation of product locations.

4.4.2 Development of a Multi-Objective Optimization Framework

The main component of our plan is the development of a mathematical representation that aims to achieve the goals of warehouse efficiency. The model will be designed to look at a layout that merges the following objectives:

- Travel Efficiency: Locating the most demanded products at the points where it is shortest and fastest to the warehouse start/end, for example, from heavy-loaded products such as the ones with a high "Frequency Coefficient".
- Palletizing Efficiency: Putting materials with a high "Durability Coefficient" right at the beginning of the picking route so that a temporary stable base of the pallet can be formed from the very first layer.

Because of the number of possible product-location combinations, this model is in the category of NP-hard problems, which means that it is infeasible to solve for an optimal solution with exact methods. Hence, our approach will be investigated towards metaheuristic algorithms which are appropriate tools for dealing with a huge and complicated solution space. The Genetic Algorithm (GA) is the leading candidate in this respect because of the success it has already had in solving multi-objective optimization problems.

4.4.3 Post-Optimization and Refinement

There will be a stage of final refinement after the layout that is nearly optimal has been achieved by the main optimization model. This stage will be about the secondary objective, that is, improving in-store stocking efficiency. By utilizing the product harmonies determined in 4.4.1, we intend to employ heuristic techniques, such as a Local Search, to effect minor changes in the layout. The aim here is to group the related products more closely and thus make in-store placement easier while the travel distance efficiencies realized in the primary optimization phase will not be significantly endangered.

5 Outcome and Deliverables

5.1 Outcome

The primary output of this project is an optimized warehouse product layout plan developed to maximize warehouse operational efficiency. This plan aims to bring a systematic and mathematical approach to the existing, experience-based product layout. Among the targeted outputs is the development of a plan that can be implemented in A101's other warehouses with different physical conditions. This plan aims to minimize total order picking distance and preparation time by rearranging product locations in the warehouse based on picking frequency, likelihood of being ordered together (frequency), physical volume and weight constraints (durability). The goal is to reduce post-shipment in-store product placement time, while prioritizing the primary outcome and not reducing warehouse operational efficiency.

5.2 Deliverables

The integrated Product Layout and Optimization System to be delivered to A101 under this project is designed to optimize the product layout and picking processes. This system primarily provides a central database infrastructure that houses the physical definitions for all products, such as weight and dimensions, and allows for items to be added or removed as needed. A critical component of the system is a "durability coefficient" module, calculated for each product based on its case weight and dimensions. The developed layout algorithm will simultaneously consider this coefficient and the distance between products when determining the optimal product layout (rack setup). As an extension of this optimization system, a selector Routing Module will also be delivered. This module will calculate the most suitable route for the picker for a given order list, based on the established product layout and "durability coefficients". An interface allowing this generated route to be displayed on the pickers' hand terminals is included in this deliverable. This integrated system is designed to be scalable, allowing it to be integrated into other warehouses, based on the fact that similar products are sold nationwide.

5.3 Benefits to the Company

The current approach, where warehouse product locations are determined based on experience which leads to inefficiency, will be replaced by a sustainable applicable decision support system. Because similar products are sold nationwide, this system's ability to be adapted to different physical structures, such as A101's 59 warehouses, will allow for the creation of a standard operational efficiency model across all depots. This systematic transformation will enable the "reduction of warehouse picking distance and time" through optimized layout plans. This increase in operational efficiency will allow for an increase in the number of cases collected daily by the selector and, as a natural consequence, savings in labor costs. Additionally, the objective of palletizing suitable for product layout in stores, based on the durability coefficients (mentioned in 5.2), will reduce operational losses and product damage caused by improper stacking (e.g., heavy items on light items). Finally, this optimized pallet structure will also directly contribute to the acceleration of the in-store product stocking process once the pallets arrive at the stores.

6 Project Plan and Work Package Assignments

Our project team, which aims to optimize A101 warehouse planning, consists of seven people. While we visited the Esenboğa A101 warehouse as a group to inspect and analyze the warehouse, we also examined the warehouse's structure. Our detailed schedule for this project can be seen in the table below (Figure 3.)

Date	Task	Assigned Member
8.10.2025	Kick - off Meeting	All
9.10.2025	Visiting the A101 Esenboğa Warehouse	All
9/10/2025 - 14/10/2025	Performance Analysis and Problem Definiton of Current System	Oğuz Oral, Oğulcan Yavuz, Kaan Öztürk
14/10/2025 - 16/10/2025	Data Analysis of Order and Picking Time in Warehouse	Erberk Saydan, Hasan Utku Şenkaya
14/10/2025 - 20/10/2025	Literature Review for Algorithm Methods and Similar Solutions	Kerem Arda Tantekin, Selin Uysal
8/10/2025 - 22/10/2025	Proposal Draft	All
30/10/2025 - 19/11/2025	Proposal Presentation	All
19/11/2025 - 23/11/2025	Data Analysis and Structuring	Erberk Saydan, Hasan Utku Şenkaya, Selin Uysal
19/11/2025 - 21/11/2025	Warehouse Flow Mapping And Layout Modelling	Oğulcan Yavuz, Kaan Öztürk, Oğuz Oral
21/11/2025 - 23/11/2025	Engineering Standards and Ergonomic Analysis of the System	Selin Uysal, Kaan Öztürk
23/11/2025 - 26/11/2025	Parameter Development and Mathematical Model Study	Hasan Utku Şenkaya, Erberk Saydan, Kerem Arda Tantekin
26/11/2025 - 01/12/2025	First Meeting with CC	All
01/12/2025 - 12/12/2025	Mathematical Model Formulation	Kerem Arda Tantekin, Oğuz Oral, Oğulcan Yavuz
12/12/2025 - 20/12/2025	Algorithm Integration	Hasan Utku Şenkaya, Erberk Saydan
20/12/2025 - 29/12/2025	Decision Support System Architecture and Interface Planning	Kerem Arda Tantekin, Selin Uysal, Kaan Öztürk
07/01/2026 - 08/01/2026	Second Meeting with CC	All

Figure 3: Detailed Schedule

Also, we organized a plan of distribution of tasks among the group members. Mapping the flow of products within the warehouse and developing a map for the optimal packaging process is assigned to Oğuz Oral. Oğulcan Yavuz will assist Oğuz Oral with this analysis, incorporating physical maps of L, U, and I types of warehouses. Erberk Saydan, as a team leader, will also work with the group's contact person (Hasan Utku Şenkaya) to request the necessary data and arrange meetings with the company and the team. Hasan Utku Şenkaya, working with Erberk Saydan during the field analysis phase, will also review data received from the company and gather the necessary information. Order information from 10 different stores belonging to the company covers one year, and Erberk Saydan will be responsible for organizing and cleaning this data.

Furthermore, the durability coefficient and order frequency, which are among the coefficients used in the model for product alignment, will be determined as parameters. Kerem Arda Tantekin and Selin Uysal will conduct a literature review to address our main project objectives: faster palletization of products in the warehouse and reduced distance traveled by employees. Our literature review for the project, which aims to improve warehouse optimization, covers various algorithms, such as apriori algorithms, genetic algorithms, and meta-heuristic methods. Additionally, Selin Uysal will integrate ergonomic principles into the project, considering engineering and occupational health and safety. Kaan Öztürk will conduct a study on this system using engineering standards (ISO 11228-1, EN 15635, OSHA 1910.176) and Turkey's Occupational Health and Safety Law No. 6331.

The information gathered during these preparation steps will be used in the mathematical modeling process. Kerem Arda Tantekin will work on creating this mathematical model. In this phase, Oğuz Oral is responsible for establishing a model that optimizes the process of placing products on pallets with assistance from our academic advisor, Gizem Özbaygın, and course coordinator, Emre Nadar. Reducing employees' total picking order distance and product picking time will be the main objectives of the model's objective function. During this process, a decision support system will be implemented to optimize the warehouse plan, improving the product collection map for employees. We will also work on this project and ensure the integration of data into the model and decision support system as a group. Oğulcan Yavuz will contribute to the creation of the model and will also try to integrate the Apriori algorithm into the system. This integration aims to facilitate the product placement of the employee in the store, which is one of the main objectives of the problem. Erberk Saydan will collaborate with Hasan Utku Şenkaya to correctly integrate the store structure into the system for implementing the Apriori algorithm. They will also work with Kaan Öztürk on the system designed to reduce time spent in the store. The final project report will also be finalized, including the formatting of visuals and presentations. Consequently, the group will work in an integrated manner throughout the project, striving to solve the problem as accurately and efficiently as possible, in conjunction with the course coordinator and industrial advisor. In the first semester, the integration of data collected from the company, the necessary literature research, and the creation of an appropriate model for the problem will be undertaken. In the second semester, the focus will be on testing the algorithms used in the model, their integration into the system, and reporting. The project flow diagram can be seen in Appendix F. Also, Gantt Chart of the project can be seen in Appendix G.

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Appendices

A Warehouse Layout

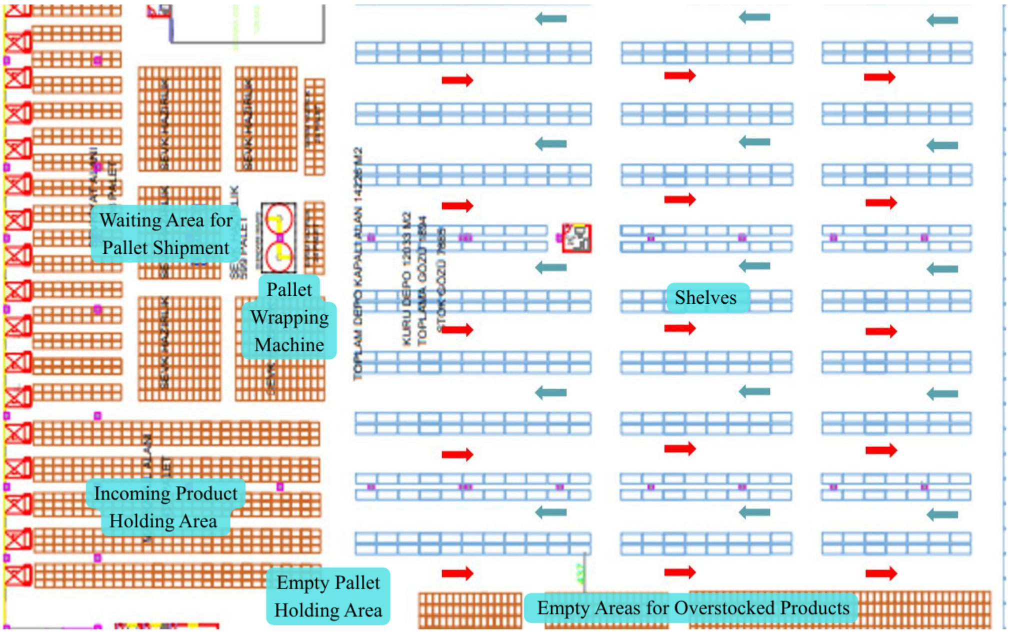

Figure 4: Warehouse Layout

B Handheld Terminal

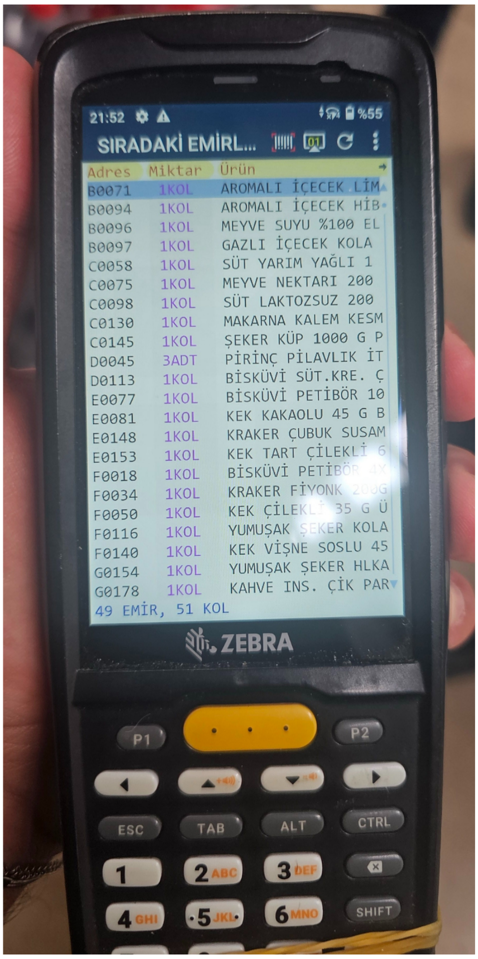

Figure 5: Selectors' handheld terminal for picking

C Average Time per Pallet

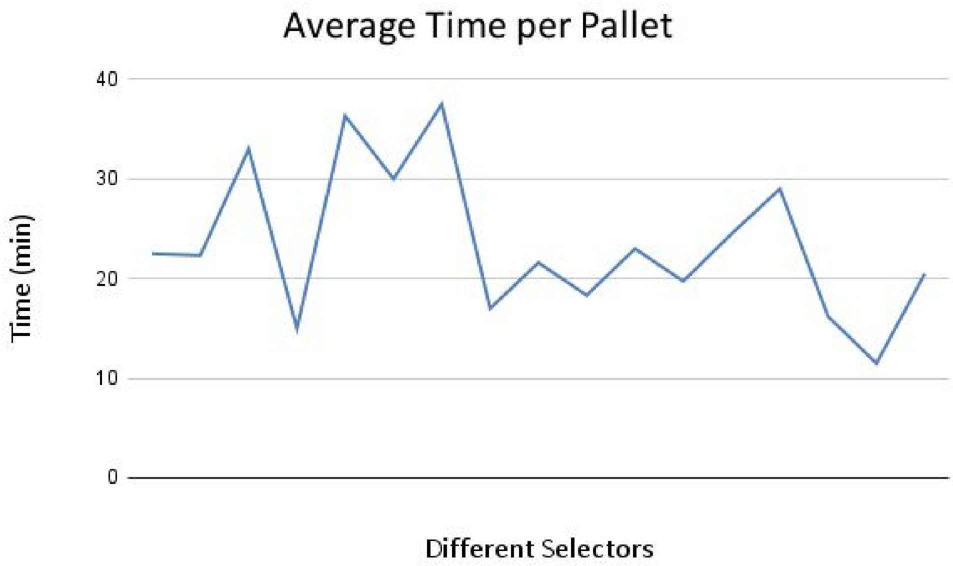

Figure 6: Different selector average collecting times for a pallet

D Package per Pallet

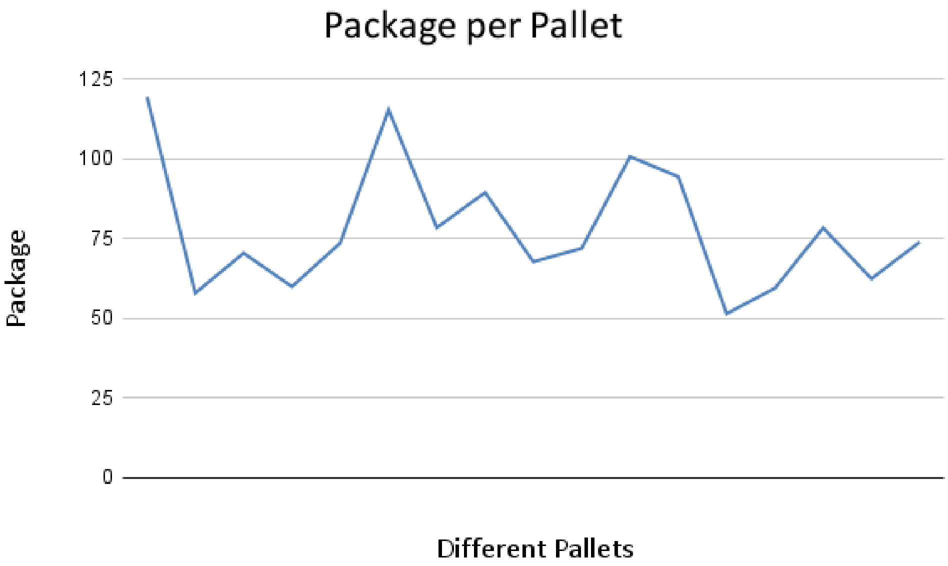

Figure 7: Quantity of packages per pallets

E Pallet Wrapping Machine

Figure 8: Machine wraps pallets for delivery

F Flow Diagram

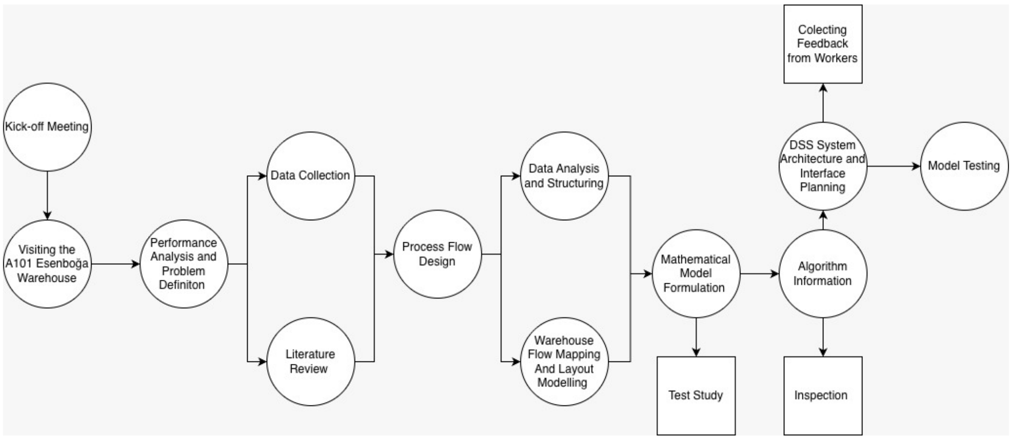

Figure 9: Flow diagram of project for fall semester

G Gantt Chart

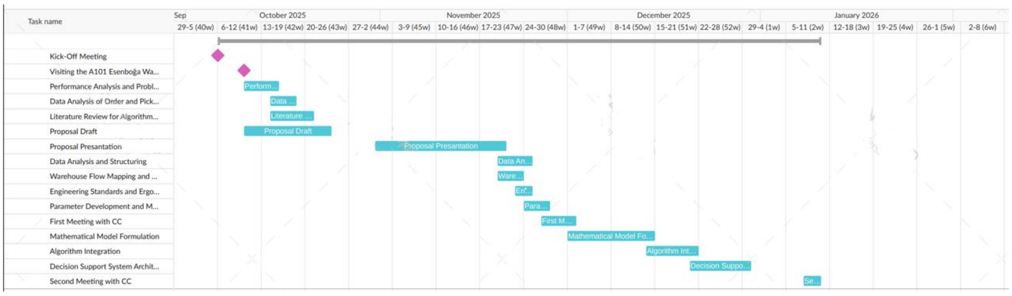

Figure 10: Gantt chart of project for fall semester