An Integrated Decision Support System for Intra-Logistics Management with Peripheral Storage and Centralized Distribution

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Keywords: Decision Support System, Intra-Logistics, Digitalization, Optimization.

Abstract: Intra-logistics optimization plays a crucial role in ensuring efficiency and reducing non-value added activities, especially in scenarios with a central shipping point and multiple peripheral warehouses. The goal of this study is to create an automated and optimized Decision Support System (DSS) using an integer linear programming (ILP) model. The DSS optimizes the order management process by determining optimal load configurations from peripheral warehouses onto transport vehicles. The resulting transportation plan, generated through this approach, aims to meet customer demands while minimizing overall costs. Computational tests, conducted on a real-world case study, validated the efficiency of the proposed system.

1 INTRODUCTION

One of the critical challenges faced by industries is intra-logistics, the logistics component that take place within the company. Intra-logistics involves two main functions: internal transport of materials, and information flow management. The former includes the movement of products between different production plants and warehouses, while the latter refers to software systems that tracks the movements of the physical goods. Both functions are essential to ensure logistics efficiency and must be effectively integrated. In addition, in a large number of companies products are handled between different warehouses, consuming valuable space and operational time. Therefore, warehouse management plays a crucial role in ensuring efficiency and reducing logistics expenses.

This study focuses on order management in a business context characterized by a central shipping site for orders consolidation and various peripheral storage sites for production and stocking. Similar examples can be found in the literature related to the transshipment problem (Chiou, 2008), where models are used to decide how to move stocks between warehouses of the same company to satisfy the demand (Patil et al., 2021). Particular attention to this topic is given in the online retailing context, in which individual stock units are shipped to central warehouses to consolidate orders (Zhang et al., 2021). Some authors also incorporate the selection of transportation modes in the model (Mishra et al., 2023). Moreover, studies have explored the profitability of integrating package selection into the shipping decisions by integrating different unit configurations (Li et al., 2020).

Despite the primary focus on product transshipment in this study, the presence of a central shipping point and distributed warehouses makes our problem similar to the supplier selection problem (Chai et al., 2013). In this scenario, the central depot and the distributed warehouses can be viewed as the plant and the individual suppliers, respectively. Many studies address the issue of supplier selection and order quantity allocation in multi-stage supply chain (Pazhani et al., 2016), more precisely, for those companies with many potential suppliers (Mendoza and Ventura, 2008). Some authors also consider how to assign shipment to different modes of transportation (Glickman and White, 2008). However, to the best of our knowledge no study integrates simultaneous decisions about warehouses, optional feature, stock unit configuration, and transportation modes.

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Dotti, G., Iori, M., Subramanian, A. and Taccini, M.
An Integrated Decision Support System for Intra-Logistics Management with Peripheral Storage and Centralized Distribution.
DOI: 10.5220/0012581600003690

In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024) - Volume 1*, pages 612-619
ISBN: 978-989-758-692-7; ISSN: 2184-4992

Also, in many companies, order management is manual, involving stages that slow down the process and consume resources in non-value added activities. Human decisions in the process may lead to errors or sub-optimal outcomes. Hence, a Decision Support System (DSS) for supplier selection was proposed in the literature (Scott et al., 2015), as well as for order allocation problems (Erdem and Göçen, 2012).

This study proposes an automated and optimized DSS to enhance order management in production companies. Automation is achieved by fully integrating the proposed software architecture into the company's existing procedures, thereby eliminating inefficiencies associated with non-value-added activities. Optimized decisions are achieved by means of an integer linear programming (ILP) model, which selects goods from peripheral warehouses and arranges loads on transport vehicles, reducing inefficiencies related to human decisions and minimizing total order management costs. The research is inspired by a real-world case study arising in the ceramic tile production (discussed in detail in Section 5 below), but it is very general and can encompass a variety of applications.

The remainder of this paper is structured as follows. Section 2 presents a complete problem description. Section 3 focuses on detailing the decision support system. Section 4 outlines the mathematical model used for optimization. Section 5 presents the real-world case study and Section 6 discusses the results obtained. Lastly, Section 7 summarizes the study and presents future research directions.

2 PROBLEM DESCRIPTION

This section provides a comprehensive overview of the problem by exploring both functions of intra-logistics. It delves into materials flow in Section 2.1 and information flow in Section 2.2.

2.1 Material Flow

The primary challenge is efficiently fulfilling incoming orders, requiring goods transportation from peripheral warehouses to a central facility for order consolidation and customer shipment.

Each order requests a single item along with a specified number of boxes. Multi-line orders can be simplified by preprocessing and segmenting them into separate orders, each with a single order line. Orders may also specify additional product features. In this context, a feature refers to a distinguishable attribute or characteristic of the products, such as their color or shade, that the client can specify when placing an order. If the feature is specified by the client, the preference must be respected throughout the order fulfillment. On the other hand, when a client does not explicitly request a specific feature for the order, the company has the flexibility to select it. Nevertheless, in both scenarios, it is essential to ensure that all boxes shipped for the same order have not only the same item, but also the same chosen feature to ensure order homogeneity.

Furthermore, each item and feature may have various pallet configurations, each containing a specific number of boxes. It should be noted that pallets cannot be divided into smaller units.

Items are stored in various warehouses, each with different travel times from the central depot and stocked with specific pallet configurations for items with certain features. Picking each box incurs a cost depending on the warehouse. In addition, peripheral warehouses can be accessed via different transportation options, each with an hourly cost and weight capacity. Each box contains copies of a single item, with its weight depending on the item's weight. The set of boxes loaded onto a mode of transport must adhere to its capacity, and each mode can only serve one warehouse per transfer order release.

The optimization process involves several decisions: (i) assigning a feature to orders without specifications; (ii) determining the number of pallets of each configuration to pick from each warehouse; (iii) allocating each mode of transportation to a single warehouse; and (iv) designing how to load the picked pallets onto modes of transportation to respect the capacity. In some companies, the decision-making process is entirely manual, with an operator deciding based on their judgment. This study aims to meet demand while minimizing total transport and retrieval costs and enhancing system performance.

2.2 Information Flow

The material flow outlined in Subsection 2.1 requires a cohesive information flow to track operations and order status. Typically, the information flow involves manual steps carried out by various stakeholders:

- sales representatives initiate the process by emailing logistics operators for goods transportation;
- logistics operators aggregate requests, waiting until they have enough to fill at least one transfer capacity. Once the threshold is reached, they manually organize transportation logistics, making decisions based on their expertise;
- decisions are communicated via email to the commercial department;

- upon items reaching the centralized distribution center, the logistics department manually notify sales representatives;
- sales representatives input the newly arrived item into the order management software to progress order fulfillment.

The described process is costly, resulting in slow and repetitive operations that consume valuable time and resources and ultimately provide little added value to the end customer. Some of the most prevalent issues include:

- the fulfillment of each order requires numerous manual steps, resulting in time inefficiencies;
- since each sales representative initiates an independent information flow, visibility on available items is compromised. This lack of awareness among sales representatives may lead to the same pallet in stock being requested for two distinct orders, as representatives are unaware of each other's requests;
- as previously indicated, the picking process exclusively accommodates orders for complete pallets. Consequently, order quantities must be rounded up. In a situation where two operators require the same product in quantities less than a full pallet, they may have the option to combine their orders, approximating to one pallet instead of two. However, the lack of mutual awareness among operators about each other's orders precludes the effective aggregation of quantities, resulting in the costly picking of unnecessary products;
- the process is highly dependent on both total loads and operators availability, making it inherently non-scalable;
- as a significant amount of time elapses from the initial request, the sales department may repetitively solicit the logistics team via email, placing an additional workload on the operators.

In response to the identified challenges, this study aims to automate and digitalize the process, with the goal of reducing logistic operator overhead, improving response time, and improving process scalability.

3 DIGITALIZATION

3.1 Process Overview

As outlined in Section 2.2, the digitalization of the information flow is designed to reduce the workload overhead for both sales representatives and logistics operators. To address this issue, we developed a DSS, which is extensively described in this section.

The new digitalized flow follows four main steps. The first step, schematized in Figure 1, is executed periodically and involves reading orders from the Enterprise Resource Planning (ERP) system to populate the database. Such orders contain the required information and are manually added to the ERP system by sales representatives.

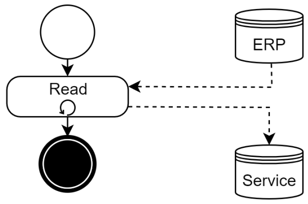

Figure 1: Reading component of DSS architecture.

The second, third, and fourth steps, schematized in Figure 2, are executed consecutively when the optimization time is reached. The second step performs a check to ensure that there is enough stock in the peripheral warehouses to fulfill all orders. If inadequacies are identified, unsatisfiable orders are flagged in the service database and excluded from subsequent steps. Moreover, notifications are dispatched to the respective sales representatives who added these unsatisfiable orders. On the contrary, if the orders are satisfiable, the software generates an instance for the optimization step.

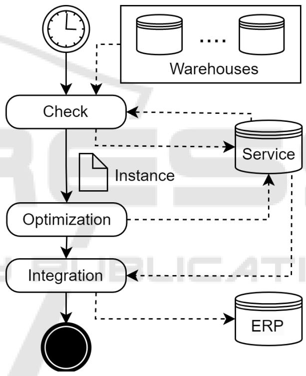

Figure 2: Control, optimization, and integration components of DSS architecture.

Subsequently, the third step involves the execution of the optimization model, described in Section 4. Upon completion of the optimization step, the database is updated with new decisions, such as selected features, chosen warehouses, pallet types, and transportation configurations.

Finally, the fourth step is integrated into the ERP system. Specifically, this step considers all decisions made by the optimization step from the service database and, through APIs, transmits them to the ERP system. Once this integration is completed, the operators of the peripheral warehouses gain visibility into the items they need to prepare for transportation.

3.2 Technologies

We have designed a user-friendly DSS to help companies manage customer orders efficiently and make optimization algorithms accessible to non-experts. Our DSS runs on Docker, a software platform for developing and deploying applications in isolated containers. Docker ensures future scalability, portability and accelerates deployment, keeping the hosting machine unmodified.

In particular, three distinct containers have been developed:

- *Service container*, that hosts the MySql service database for storing transfer requests and monitoring their progression through different stages.
- *Job orchestrator container*, equipped with database connection drivers, Python and Node-RED. It includes different Python-based jobs used to build the new digitalized flow that is scheduled directly by Node-RED. If necessary, this flow can also be run manually to ensure flexibility. This flexibility proves beneficial, especially when the daily volume of requests is low, allowing the logistics department to defer optimization until subsequent days to accumulate more orders and efficiently plan material transportation.
- *User interface container*, to assist sales representatives in monitoring their orders we developed an intuitive and user-friendly web interface. The interface is built on Flask micro-web framework, written in Python, which encompasses both a back-end and a front-end.

4 OPTIMIZATION

This section provides a formal definition of the optimization problem addressed in this work, as well as an ILP-based mathematical model.

4.1 Problem Definition

The problem we face can be formalized as follows. A set I includes different items, each characterized by its weight w_i. The set J represents orders, each requiring one item i in quantity d_{ij}. Additionally, orders may specify a desired feature from the features set K: if feature k is chosen for order j, the corresponding parameter f_{jk} is set to 1; otherwise, it is set to 0.

Set H represents peripheral warehouses, each defined by the travel time r_h from the central depot and the processing cost u_h per box. Items can be arranged in different pallet configurations, contained in set P, each counting q_{ip} boxes. Pallet configurations cannot be split into smaller units. Each warehouse h maintains a stock s_{hpik} of item i with feature k in pallet configuration p.

Finally, set T denotes the modes of transport, each characterized by a capacity c_t and an hourly cost m_t.

A feasible solution for the problem must satisfy the following constraints: (i) each feasible order request is fulfilled, providing items with uniform features; (ii) if specified, the feature must respect customers' choice; (iii) pallets of items must be picked from the warehouses according to their stock; (iv) picked pallets must be loaded into modes of transportation according to their capacity; (v) each mode of transportation can perform only one route in a single day, visiting a single warehouse. The objective of the problem is to obtain a feasible solution that minimizes the total cost of order management, including transportation and internal movement costs.

Note that the problem described above generalizes the well-know bin packing problem, which is NP-hard, when we consider a single warehouse ($|H| = 1$), no optional features ($|K| = 0$), no pallet configurations ($|P| = 0$), transports with identical capacities (c_t is constant, $\forall t \in T$), unitary transportation costs ($m_t = \frac{1}{r_h}$, $\forall t \in T$, $\forall h \in H$), and no retrieval costs ($u_h = 0$, $\forall h \in H$). Therefore, our problem is also NP-hard.

4.2 Mathematical Formulation

Let x_{jk} be a binary variable that takes the value 1 if feature k is assigned to order j and 0 otherwise. An integer variable y_{hpik} identifies the number of pallets of item i in feature k with pallet configuration p picked from warehouse h. An integer variable z_{hpit} specifies the number of pallets of item i in pallet configuration p loaded onto modes of transport t departing from warehouse h. Lastly, let v_{ht} be a binary variable that is equal to 1 if mode of transportation t is assigned to warehouse h and 0 otherwise. An ILP formulation for the problem can be expressed as:

$$\min \quad \sum_{h \in H} \sum_{t \in T} m_t r_h v_{ht} + \sum_{h \in H} \sum_{p \in P} \sum_{i \in I} \sum_{k \in K} u_h q_{ip} y_{hpik} \quad (1)$$

$$\sum_{k \in K} x_{jk} = 1, \qquad j \in J \quad (2)$$

$$x_{jk} \geq 1, \qquad j \in J, \; k \in K : f_{jk} = 1 \tag{3}$$

$$\sum_{h \in H} \sum_{p \in P} q_{ip} y_{hpik} \geq \sum_{j \in J} d_{ij} x_{jk}, \qquad i \in I, k \in K \tag{4}$$

$$y_{hpik} \leq s_{hpik}, \qquad i \in I, k \in K, \; h \in H, p \in P \tag{5}$$

$$\sum_{k \in K} y_{hpik} = \sum_{t \in T} z_{hpit}, \qquad i \in I, \; h \in H, p \in P \tag{6}$$

$$\sum_{h \in H} v_{ht} \leq 1, \qquad t \in T \tag{7}$$

$$\sum_{i \in I} \sum_{p \in P} q_{ip} w_i z_{hpit} \leq c_t v_{ht}, \qquad t \in T, h \in H \tag{8}$$

$$x_{jk} \in \{0,1\}, \qquad j \in J, k \in K \tag{9}$$

$$v_{ht} \in \{0,1\}, \qquad h \in H, t \in T. \tag{10}$$

$$y_{hpik} \geq 0, \text{integer}, \qquad h \in H, p \in P, \; i \in I, k \in K \tag{11}$$

$$z_{hpit} \geq 0, \text{integer}, \qquad h \in H, p \in P, \; i \in I, t \in T. \tag{12}$$

The objective function (1) minimizes the transport and picking costs. Constrains (2) impose that only one feature is chosen for each order. Constraints (3) ensure that the requested feature of a line is respected, keeping consistency with customer requests when indicated. Constrains (4) state that the demand of each order is satisfied. Constraints (5) prevent the picking of items from warehouses in amounts that exceed their actual stock levels, maintaining the integrity of the inventory. Constraints (6) ensure that every picked pallet is shipped. Constraints (7) impose that each mode of transport is associated with at most one warehouse, and constraints (8) guarantee that the capacity of the modes of transport is not exceeded. Constraints (9)–(12) describe the domain of the variables.

5 CASE STUDY: THE CERAMIC TILE INDUSTRY

The research was conducted in collaboration with an international ceramic tile company headquartered in Italy. Over the last decade, the global tile market has experienced significant growth and increasing importance, with global tile production reaching 16.8 billion square meters worldwide (ACIMAC Research Department, 2023). Focusing on Italy, the country stands out as the leading global exporter by revenue and ranks seventh in production volume. Italy produced 431 million square meters of tiles, generating €7.2 billion in revenue, highlighting the sector's significance for the country. Consequently, intralogistics optimization in the sector is crucial for effectively controlling non-value-added costs.

A notable issue within the ceramic sector is the Lack of Homogeneity in the Product (LHP), a phenomenon arising from uncertain production processes (Alemany et al., 2013). Consequently, despite the utilization of homogeneous inputs, these processes generate heterogeneity in the outputs. This characteristic is particularly relevant in the ceramic industry, due to the use of clays and stochastic elements such as humidity and temperature. Specifically, one of the main tile characteristics affected by LPH is shade, which in this context refers to the variation in color within a particular batch or set of tiles. In industrial manufacturing processes, due to LHP, achieving tiles with the same color shade can be challenging. To address this, manufacturers group tiles based on shade uniformity before packaging to ensure a consistent appearance upon installation. As a result, shade can be addressed as the optional feature outlined in the model: customers have the option to request a specific shade if needed (i.e., to match a previous order). However, even when the shade is not specified, every tile within of the order must be shipped in the same shade to guarantee aesthetic homogeneity.

The ceramic tile company studied has a structure consisting of a central shipping center and two peripheral warehouses. The DSS, outlined in Section 3, was implemented and tested using real-world instances collected from the company over a month. It retrieves data from various databases that include information about warehouses, orders, and transportation resources. The aim is to generate an optimized transportation plan that specifies the most efficient load configuration from each warehouse to meet customer demands while minimizing overall costs. This plan is intended to be provided daily or weekly, depending on the number of orders that can be aggregated for efficiency.

6 COMPUTATIONAL RESULTS

The optimization model was solved using three distinct solvers: Gurobi, CBC, and HiGHS. This approach was chosen to facilitate a comprehensive performance comparison, considering Gurobi's superior performance, as well as the advantageous open-source licenses of HiGHS and CBC. In fact, the company is inclined to purchase the solver license only if the results exhibit significant improvement compared to those provided by the open-source solvers.

Computational experiments were conducted on an Intel(R) Xeon(R) CPU E5-2640 v3 at 2.60 GHz with 64 GB of RAM, running Microsoft Windows 10 and using up to 32 threads. A time limit of 600 s was set, and a relative MIP tolerance of 10^{-4} was imposed.

Table 1 presents the computational results for 23 real-world instances, solved with the three different proposed solvers. Since the optimization interval is determined by the company, the number of orders in the instances can be controlled. Therefore, the instances in the table are ordered based on the number of orders, denoted as $|J|$.

For Gurobi we report the objective value expressed as the total cost in euros, the total computing time in seconds, and the time elapsed to find the incumbent solution. Regarding HiGHS and CBC, we provide the gap between the incumbent solution and the lower bound found by the respective solver (Gap_a), as well as the gap between the incumbent solution found by the open-source solvers and the best primal solution found by Gurobi (Gap_b). Specifically, Gap_a and Gap_b are computed as in (13) and (14), respectively, where i is the incumbent solution value, lb is the lower bound, gs is Gurobi's solution value and glb is Gurobi's lower bound. We also report the computing time and time to achieve the incumbent solution.

$$\text{Gap}_\text{a} = \frac{i - lb}{i} \tag{13}$$

$$\text{Gap}_\text{b} = \frac{i - gs}{glb} \tag{14}$$

As depicted in the table, Gurobi consistently exhibited rapid convergence to optimality across all instances, except for instances 16 and 23, where it reached the predefined time limit, with a gap of 0.02% for instance 16 and 1.3% for instance 23.

Although open-source solvers HiGHS and CBC may not guarantee optimality within the time limit, a comparison with Gurobi reveals that they often find the optimal solution value. For instance 16, HiGHS and CBC provide identical solutions, whereas HiGHS outperforms CBC on instance 19, 20, 21, and 23. However, in instance 18, CBC achieves the optimal solution value while HiGHS reaches a Gap_b of 0.08%. Comparing HiGHS with CBC, HiGHS reaches the incumbent solution faster for more than half of the instances. Moreover, HiGHS finds the optimal solution in 20 instances, while CBC achieves this in 17 instances, consistently with a better internal gap. Overall, considering the minimal difference between commercial and open-source solvers on the reported instances, exploring the utilization of open-source solvers could lead to potential cost savings for the company.

Given that the process in the case study is carried out manually by operators, the solutions generated by the solver were subsequently compared to the manual calculations performed by operators. Table 2 illus-

Table 1: Computational results of the real-world instances solved with Gurobi, HiGHS and CBC.

Instance		Gurobi			HiGHS				CBC			
#	$\|J\|$	Obj. Value (€)	Total Time (s)	Time Incumbent (s)	Gap_a (%)	Gap_b (%)	Total Time (s)	Time Incumbent (s)	Gap_a (%)	Gap_b (%)	Total Time (s)	Time Incumbent (s)
1	7	295.07	0.08	0.02	0	0	0.18	0.02	0	0	26.14	2.56
2	10	301.14	0.05	0.01	0	0	0.12	0.10	0	0	1.89	0.44
3	30	332.63	0.06	0.03	0	0	0.99	0.60	0	0	85.39	1.39
4	50	352.24	0.08	0.02	0	0	0.54	0.50	0	0	59.45	1.00
5	53	666.75	1.46	1.44	0	0	8.06	3.40	45.35	0	tlim	2.67
6	70	471.40	0.69	0.04	0	0	2.14	1.80	14.53	0	tlim	1.52
7	81	763.16	1.74	0.32	0	0	7.71	3.10	8.16	0	tlim	3.42
8	95	941.47	3.03	2.80	0	0	304.36	12.00	21.78	0	tlim	14.96
9	100	770.34	1.81	0.30	0	0	5.44	0.90	5.50	0	tlim	3.94
10	103	900.52	1.94	0.33	0	0	6.52	2.80	5.22	0	tlim	121.86
11	106	3983.02	18.90	2.10	2.10	0	tlim	194.30	2.21	0.01	tlim	507.87
12	107	1234.02	2.64	0.80	0	0	465.27	5.80	11.04	0	tlim	110.00
13	108	1102.63	2.56	2.44	10.80	0	tlim	39.10	13.06	0	tlim	76.75
14	115	1204.98	2.33	0.94	2.10	0	tlim	10.40	16.23	0	tlim	14.67
15	121	905.31	1.87	0.61	0	0	149.54	8.90	11.00	0	tlim	4.26
16	164	1896.26	tlim	600.85	5.20	4.56	tlim	62.40	5.47	4.56	tlim	122.95
17	167	1557.90	14.22	11.62	6.10	0	tlim	76.10	7.90	0	tlim	108.23
18	179	2001.93	13.90	12.06	6.00	0.08	tlim	65.40	6.28	0	tlim	266.78
19	190	1985.83	40.62	40.59	4.20	0	tlim	62.7	4.56	0.02	tlim	10.08
20	201	2083.28	33.17	32.95	9.00	0	tlim	227.90	10.40	0.03	tlim	469.05
21	201	2781.75	149.83	149.66	2.70	0	tlim	455.10	2.81	0.03	tlim	188.24
22	213	1720.52	15.66	15.65	5.30	0	tlim	210.20	5.92	0	tlim	108.51
23	356	4001.71	tlim	601.92	3.80	1.58	tlim	448.00	6.25	3.81	tlim	547.32

trates the comparison between the objective function values computed by the three different solvers and those manually calculated. The table indicates a direct correlation between the total cost of the solution and the instance size, due to the increasing number of required transportations. Consequently, for instances with a small number of orders (e.g., instances 1, 2, and 3), savings are limited as all materials can fit in a single truck, minimizing potential gains. However, as the instance size grows, the manual decision-making complexity also increases proportionally, expanding the possibility of improvement. Therefore, employing an optimization model can lead to cost reductions of up to 40% in material flow. Furthermore, on average, all solvers demonstrate savings of at least 24% compared to the operators' manual solutions. Notably, even for instance 23, which was not optimally solved by any of the solvers, a substantial 28% reduction in costs was achieved.

Moreover, the savings are significantly enhanced by the digitalization of the information flow, leading to a reduction in time allocated to non-value-added activities. To quantify this enhancement, an estimation of the time required by operators for the manual steps described in Section 2.2 was conducted within the company. The time required for the operator is heavily dependent on the number of orders received. On average, the company estimated that 40-50 requests are received per day, requiring a logistic operator's commitment of 4 hours. However, it is crucial to note that for increasing workloads, the required time grows more than linearly, due to the additional human interactions involved. Additionally, digitalization also reduces the time needed for sales representatives for email management. The estimated savings, considering the average email response time, amount to 30 hours per month. Overall, the digitalization of the process allows for a minimum saving of 120 hours monthly, which can be redirected to higher-value activities.

7 CONCLUSIONS

DSS are gaining increasing popularity within companies. This paper outlines the creation of a model-driven DSS designed to address the challenges posed by intra-logistics. In particular, the proposed DSS addresses a context with peripheral storage and centralized distribution, optional feature selection, and different stock unit configurations.

The DSS has been implemented to optimize both information and material flows. Regarding information, the process has been digitalized, eliminating repetitive and non-value-added information streams. This was made possible through a custom software

Table 2: Saving comparison between manual and optimization solutions.

		Operator	Gurobi		HiGHS		CBC	
#	$\|J\|$	Obj. Value (€)	Obj. Value (€)	Saving (%)	Obj. Value (€)	Saving (%)	Obj. Value (€)	Saving (%)
1	7	296.91	295.07	0.62	295.07	0.62	295.07	0.62
2	10	305.98	301.14	1.58	301.14	1.58	301.14	1.58
3	30	361.05	332.63	7.87	332.63	7.87	332.63	7.87
4	50	582.67	352.24	39.55	352.24	39.55	352.24	39.55
5	53	707.73	666.75	5.79	666.75	5.79	666.75	5.79
6	70	716.64	471.40	34.22	471.40	34.22	471.40	34.22
7	81	1023.82	763.16	25.46	763.16	25.46	763.16	25.46
8	95	1216.47	941.47	22.61	941.47	22.61	941.47	22.61
9	100	1130.22	770.34	31.84	770.34	31.84	770.34	31.84
10	103	1289.91	900.52	30.19	900.52	30.19	900.52	30.19
11	106	4289.64	3983.02	7.15	3983.02	7.15	3983.43	7.14
12	107	1720.06	1234.02	28.26	1234.02	28.26	1234.02	28.26
13	108	1606.58	1102.63	31.37	1102.63	31.37	1102.63	31.37
14	115	1584.86	1204.98	23.97	1204.98	23.97	1204.98	23.97
15	121	1516.47	905.31	40.30	905.31	40.30	905.31	40.30
16	164	2713.36	1896.26	30.11	1982.65	26.93	1982.80	26.92
17	167	2436.15	1557.90	36.05	1557.90	36.05	1557.90	36.05
18	179	2783.97	2001.93	28.10	2003.51	28.03	2001.93	28.10
19	190	2719.10	1985.83	26.97	1985.83	26.97	1986.23	26.95
20	201	2870.88	2083.28	27.43	2083.28	27.43	2083.69	27.42
21	201	3712.04	2781.75	25.06	2782.32	25.04	2782.72	25.03
22	213	2573.06	1720.52	33.13	1720.52	33.13	1720.52	33.13
23	356	5607.28	4001.71	28.63	4012.19	28.45	4100.33	26.87

architecture based on containers. Decisions regarding material flow have been optimized through an ILP model that determines the optimal choices for transferring goods from each warehouse and composing loads on transportation vehicles.

The proposed approach has been tested on real-world instances with different numbers of orders. Three different solvers were employed to evaluate the trade-off between Gurobi's superior performance and HiGHS and CBC's open-source licenses. Computational results were compared in terms of solutions and required time. Gurobi successfully solves nearly all instances relatively fast, while CBC and HiGHS usually achieve optimal values for the objective function, although without demonstrating optimality within the specified time limit. Overall, the results show a significant reduction in total costs compared to the company's manually calculated solution by operators. Furthermore, the digitalization of the process minimizes non-value-added time for both logistics and sales operators. Therefore, the implementation of the DSS offers economic benefits to the company by lowering expenses associated with stock transfers and gaining valuable working hours.

Nevertheless, further enhancements are possible. Currently, optimization occurs daily. Exploring optimization frequency via sensitivity analysis could balance economic gain and service level trade-offs. Less frequent optimization accumulates more orders, potentially improving margins. Yet, order accumulation delays shipments, reducing service levels.

Moreover, running the model for large instances can conflict with the company's needs due to significant time requirements. Since material quantities are updated only upon order consolidation and solution validation, sales operators using the system in real-time may concurrently request the same material, leading to resource contention. To address this issue, heuristic algorithms could be implemented to obtain good solutions in a limited amount of time.

ACKNOWLEDGEMENTS

Manuel Iori gratefully acknowledges financial support under the National Recovery and Resilience Plan (NRRP), Mission 04 Component 2 Investment 1.5–NextGenerationEU, Call 3277, Award 0001052.

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