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DATA-DRIVEN PLANNING OF A WAREHOUSE USING TX PLANT SIMULATION

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Abstract: Effective warehouse management plays a key role in optimising supply chain operations and ensuring on-time delivery of goods. As logistics systems become increasingly complex, the need for data-driven approaches and advanced planning tools becomes essential. This work focuses on integrating input data processing and simulation-based modelling for warehouse logistics planning using TX Plant Simulation, a powerful tool for modelling, simulating, and optimising discrete-event logistics systems. The presented article aims to show how accurate input data processing combined with simulation support can contribute to more efficient warehouse layout, improved material flow, and resource optimisation. In our case, this involves the creation and testing of a simulation model of a new warehouse. The first phase involves the collection and analysis of real or realistically generated input data related to warehouse operations, such as inbound and outbound flows, order picking strategies, storage methods, transport routes, and resource utilisation. The data required for the analysis were processed based on data available from previous periods from warehouse management within the original warehouse. This data thus formed a relevant input base for creating a simulation model that replicates real warehouse movements. This data is then cleaned, structured, and prepared for use in a simulation environment. Using TX Plant Simulation, a digital twin of the warehouse system is created to test different planning scenarios. Simulation experiments provide valuable insights into the impact of layout configurations, planning strategies, and process improvements. In addition, simulation allows for the safe testing of optimisation strategies without disrupting real operations. The results highlight the importance of high-quality input data and proper model calibration for reliable simulation results. The simulation findings support decision-making processes in warehouse planning and help identify areas for cost reduction, capacity improvement, and increased operational flexibility. The integration of data analysis and simulation tools proves to be an effective approach to solving real-world challenges in warehouse management. This study confirms the potential of TX Plant Simulation as a decision-support tool in logistics engineering and highlights the value of data-driven planning in the context of modern warehouse systems. The proposed methodology can be applied for academic research and industrial practice for strategic and operational planning of warehouse processes.
Key words: warehouse, optimisation, simulation, modelling, data.

1. INTRODUCTION

Decision-making regarding the appropriate inventory management model within warehouse operations should be based on a clearly defined problem and key assumptions that significantly impact the performance of the entire supply system. Effective warehouse management requires bridging the gap between theory and practice and building a database of relevant input data. These inputs are the foundation for objective analysis, monitoring stock development, and optimising warehouse processes [1-3].

Many theoretical models remain unused in practice due to the lack of high-quality data and limited applicability to real business conditions. Therefore, it is important to promote an approach that connects academic research with business practice and generates effective, practical recommendations for daily inventory management.

In real-world conditions, particularly in larger organisations, stock levels often reflect uncoordinated decisions made by individual departments, leading to partial optimisation and decreased overall efficiency of warehouse operations. These negative impacts can be reduced through improved data collection, evaluation, and information sharing across the company [4,5].

A potential solution is the implementation of software tools that ensure transparency, integrate data, and enable effective inventory management in warehouses based on real needs and accurate data. Such systems can significantly enhance the reliability, responsiveness, and overall performance of enterprise logistics processes [6-8].

In the context of warehouse inventory management, the traditional Material Requirements Planning (MRP) system has long been a widely used approach. This system relies on fixed parameters such as scheduled delivery times, production cycles, and minimum stock levels. While MRP is effective in stable environments with predictable demand, it faces significant limitations in today's dynamic and volatile market conditions [9,10].
One of its main drawbacks is low flexibility and the inability to respond quickly to demand fluctuations. Because MRP is based on static assumptions, it often leads to excess inventory or stockouts, resulting in inefficient use of warehouse capacity and increased operational costs. Therefore, there is a growing need to implement inventory control systems that can adapt to changing market conditions and customer demands. Adaptive warehouse management involves real-time responsiveness, working with up-to-date input data, and making decisions based on actual consumption and accurate forecasting. Increasing adaptability requires not only modern software solutions but also a shift in management philosophy—from reactive planning to continuous data evaluation and dynamic decision-making. An example of such an approach is the DDMRP (Demand-Driven MRP) methodology, which focuses on demand-based inventory management and enables greater flexibility in supply and warehouse processes [11-13]. Ultimately, the goal is to build warehouse systems that not only monitor current inventory levels but also optimize them in line with market movements and changes in customer behavior. Adaptive systems thus represent a key prerequisite for increasing a company's competitiveness in a digital and unpredictable business environment. TX Plant Simulation is a software focused on creating discrete event simulations (DES). It provides a range of easy-to-use tools for analysing models with deterministic and stochastic processes, calculating the distribution of sample values, managing simulation experiments, and determining optimised parameters of the tested system. By simulating a model of an existing production system, it is possible to modify various variables. The simulation model can be used for the evaluation process and for testing extreme case scenarios in a simulation-set time interval (e.g. a year) that would not be possible to test in reality due to safety issues, regulations, etc. The simulation can also be extended to test the potential for implementing lean manufacturing principles, which are supported by TX Plant Simulation software, and thus arrive at outputs that can be compared with the real production system. The optimisation capabilities of TX Plant Simulation support users in optimising multiple system parameters at once, such as the number of conveyors (carts), buffer/storage capacity, etc., while taking into account multiple evaluation criteria, such as reduced inventory, increased utilisation, increased throughput, etc. [14-16].

2. MATERIALS AND METHODS

The methodological framework integrates data-driven analysis, discrete-event simulation, and demand-driven inventory planning to support the design and performance evaluation of a new warehouse system. The approach consists of five phases: (1) data acquisition and preprocessing, (2) process analysis and warehouse-flow modelling, (3) development of a digital simulation model in TX Plant Simulation, (4) model verification and validation, and (5) optimisation experiments including DDMRP integration.
Data Acquisition and Preprocessing: Operational data from the collaborating manufacturing–distribution company were collected, cleaned, and transformed into a structured simulation dataset. The annual dataset included inbound/outbound pallet flows, order structures, turnover dynamics across chilled, frozen, and dry-goods segments, seasonal peaks, replenishment behaviour, and product-group projections to 2030. Given the presence of perishable goods, batch tracking and shelf-life characteristics were incorporated. Statistical analysis was used to derive process-time distributions, interarrival patterns, and variability parameters required for stochastic modelling.
Process Analysis and System Modelling: A detailed analysis of existing and planned warehouse processes was conducted, covering receiving, internal transport, picking and replenishment, dispatching, and inter-zone movements. The modelled layout reflects the real facility, comprising three storage areas (400 chilled, 300 frozen, 120 dry pallets). Material-flow diagrams and activity sequences defined resource interactions, routing logic, and operational constraints, forming the basis for the digital twin.
Simulation Model Development in TX Plant Simulation: A discrete-event model combining 2D logic and 3D visualisation was implemented. Model components comprise storage racks and buffers, forklifts and transport resources, operator workflows, routing mechanisms, and SIM Talk scripts for prioritisation and material-handling logic. The model represents deterministic and stochastic processes and supports scenario testing for regular operations, peak loads, and forecasted future demand. DDMRP buffer logic (decoupling points, buffer zones, colour-coded levels) was embedded to simulate demand-driven behaviours.

Model Verification and Validation: Verification was performed through iterative checks of element behaviour, logical sequencing, resource synchronisation, routing consistency, and FEFO/FIFO rules. Validation relied on comparison with historical data, focusing on pallet throughput, storage duration, picking times, forklift utilisation, and daily flow profiles. Deviations remained within acceptable statistical thresholds, confirming model fidelity.
Simulation-Based Forecasting and Scenario Analysis: Demand projections until 2030 were derived from company growth coefficients and translated into category-specific storage forecasts. The model was executed under baseline, annual forecast, peak-day, alternative-layout, and DDMRP/non-DDMRP scenarios. Performance was assessed using lead time, resource utilisation, handling intensity, storage occupancy, and service-level metrics.
Integration of DDMRP Logic: DDMRP elements were operationalised within the simulation through explicit modelling of decoupling points, buffer protection levels, dynamic replenishment signals (Net Flow Position), and real-time adjustment of replenishment quantities. Resulting stock-behaviour patterns under varying demand conditions were analysed.

3. RESULTS AND DISCUSSION

The presented study focuses on testing a warehouse with a wide range of products with a limited shelf life while simultaneously providing permanent availability of high-turnover items. It will take into account seasonal fluctuations in sales. The goal will be to achieve effective picking solutions while increasing the productivity of warehouse and picking activities. The problem with perishable products is that on the same pallet or shelf there are often several production batches with several expiration dates. This limits the ability to identify product data, it takes an extremely long time to manually determine expiration dates. The inability to access product data regarding their shelf life promptly can hinder inventory management and monitor products just before expiration, which contributes to higher product expiration in warehouses. Input information for the simulation of product movement in individual warehouses was processed in cooperation with the manufacturing-distributive company. The days in the months that represent the largest volume for the company from a seasonal perspective, when there is an increased need to stock input raw materials and processed products, Table 1 was selected.

Table 1. Frozen items for June 2021 - measured values, selection

Month	Number of pallets from production	Number of pallets from BA	Other suppliers	Arrived IN (sum)	Number of pallets in the warehouse	Difference
1.6.2021	7	17	3	27	1100	22
2.6.2021	6	0	8	14	1105	11
3.6.2021	4	0	16	20	1108	18
4.6.2021	4	13	4	21	1110	19
5.6.2021					1112	
6.6.2021					1112	
7.6.2021	5	5	16	26	1112	23
8.6.2021	7	10	1	18	1115	22
9.6.2021	6	1	10	17	1111	11
10.6.2021	4	4	40	48	1117	33
11.6.2021	0	15	38	53	1132	27
12.6.2021					1158	
13.6.2021					1158	
14.6.2021	0	0	9	9	1158	59
15.6.2021	7	1	35	43	1108	28
16.6.2021	6	9	50	65	1123	58
17.6.2021	4	13	0	17	1130	38
18.6.2021	4	13	5	22	1109	19
19.6.2021					1112	

20.6.2021					1112	
21.6.2021	9	0	46	55	1112	48
22.6.2021	10	1	3	14	1119	25
23.6.2021	11	23	49	83	1108	47
24.6.2021	2	16	3	21	1144	61
25.6.2021	7	26	33	66	1104	45
26.6.2021					1125	
27.6.2021					1125	
28.6.2021	0	1	45	46	1125	71
29.6.2021	3	23	2	28	1100	67
30.6.2021	7	0	48	55	1061	49

The simulation model was based on the floor plan of the warehouse hall, which consists of a cooling, freezing, and dry goods section. The capacity of the simulation model of the warehouse for cooling and frozen goods was determined according to input information from the focused company:
-Cooled goods warehouse with 400 pallet spaces;
-Frozen goods warehouse with 300 pallet spaces;
-Dry goods warehouse, 120 pallet spaces.
The output of the simulation was the graphic course of movements in the warehouse for a specific month, selected by the company as reference, since the seasonality of consumption in selected types of goods is significantly manifested during the year, Fig. 1.

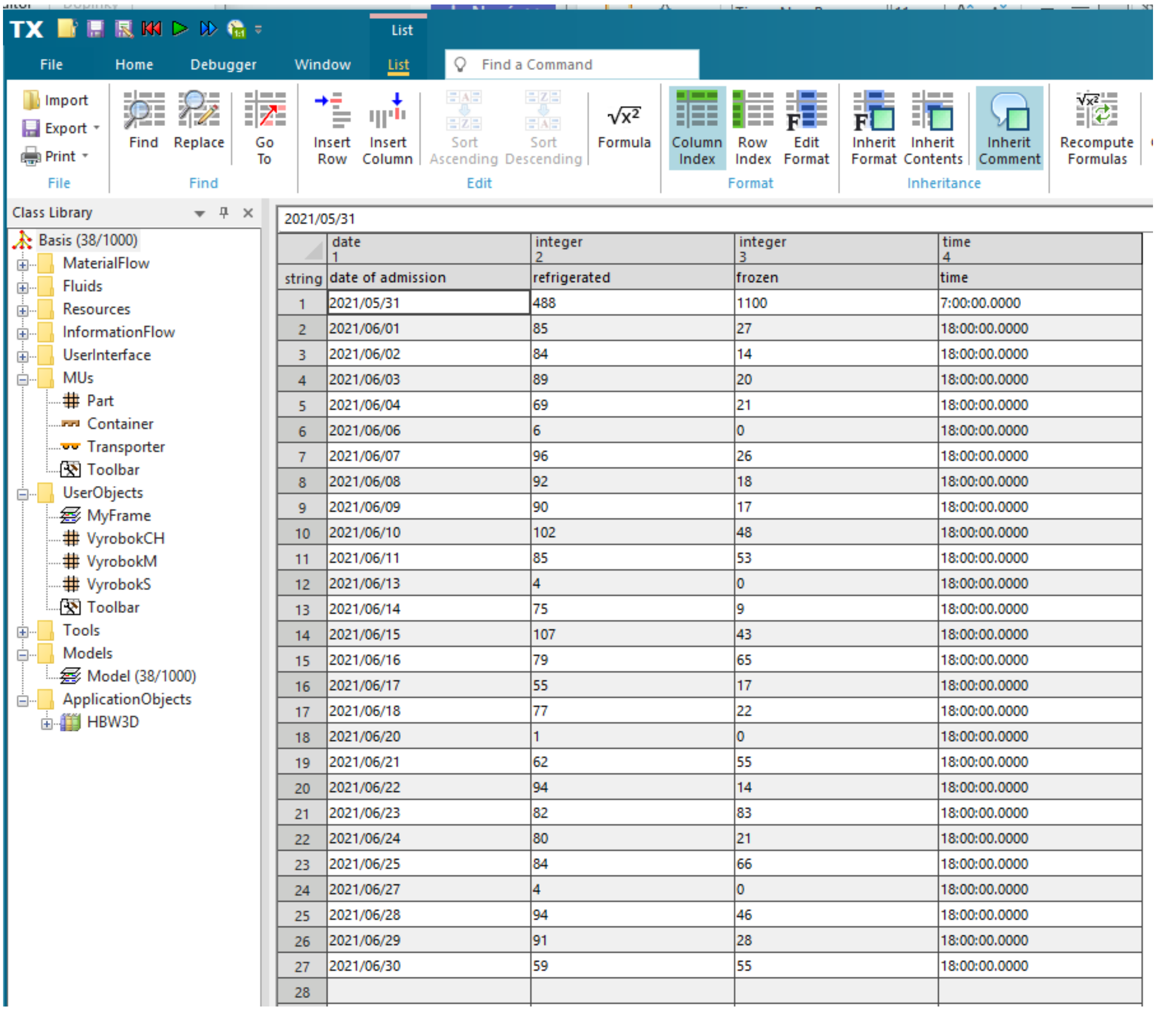

Fig. 1. Receiving into the TX Plant Simulation warehouse according to measured values – printscreen from software

Fig. 2 illustrates the integrated 2D/3D simulation model in TX Plant Simulation, which is used to design and evaluate future warehouse operations. The 2D view enables precise modelling of material flows and control logic, while the 3D environment verifies spatial layout, resource interactions, and overall operability. Workflow logic is algorithmized using SIM Talk, allowing for the implementation of dynamic routing, prioritization rules, and adaptive buffer management. The proposed future warehouse workflow was verified on the simulation model, confirming the feasibility and stability of planned processes before implementation. The model thus serves as a robust tool for assessing scenarios and supporting the optimisation of warehouse performance and flexibility.

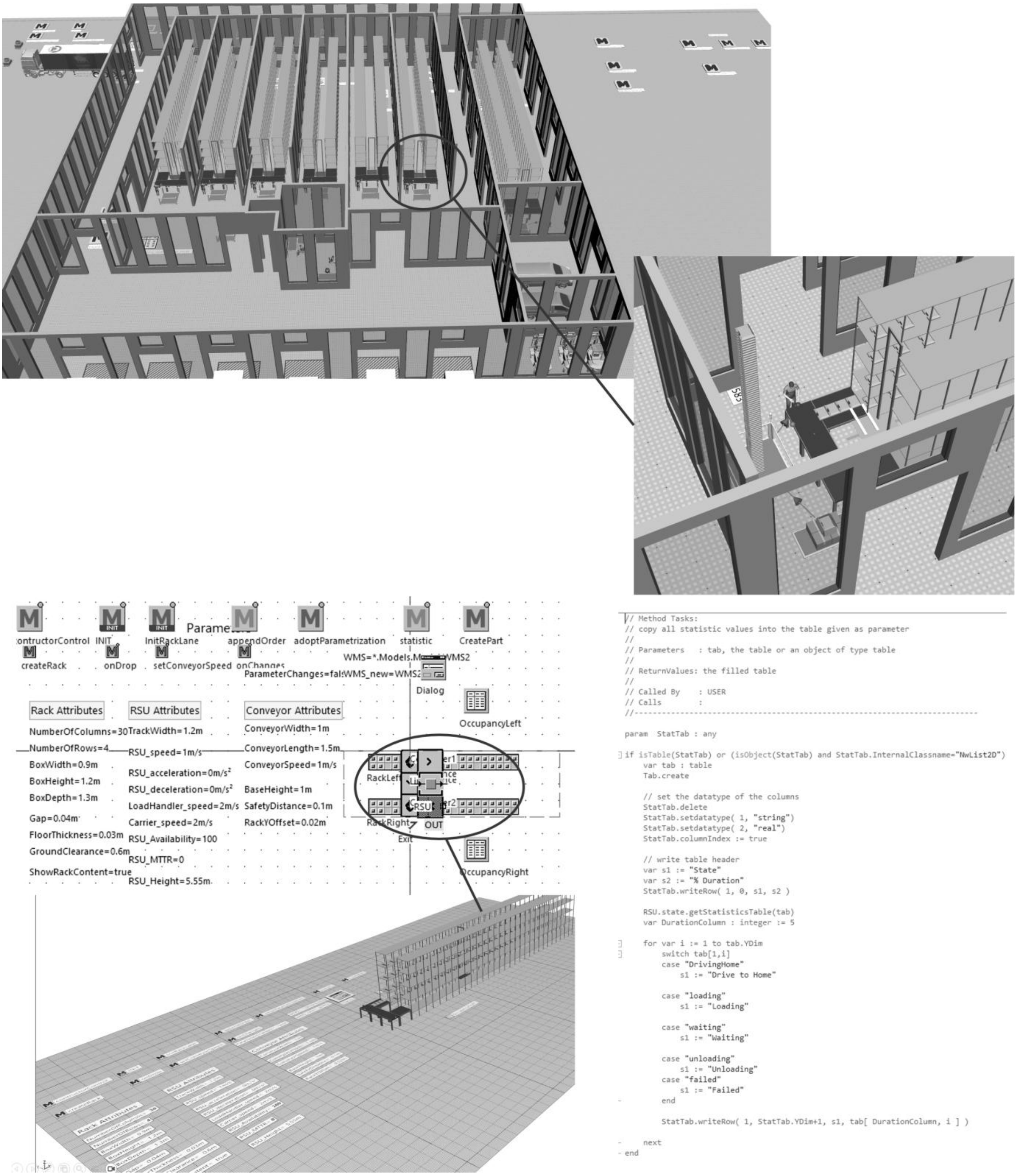

Fig. 2. 2/3D simulation model and algorithmization of warehouse workflow in Tx Plant Simulation using the SIM Talk

Based on the course of the simulation, Fig. 2, a peak point was determined, which was the reference for processing the prediction until 2030, Tab.2 The growth coefficient determined by the company was % of the turnover from the given peak day, Fig. 3

Table 2. Forecast of product range growth by selected company

%	2023	2024	2025	2026	2027	2028	2029	2030
Mayonnaise and condiments	5.0%	5.0%	5.0%	23.3%	23.3%	23.3%	23.3%	23.3%
Marinated	5.0%	5.0%	5.0%	5.1%	5.1%	5.1%	5.1%	5.1%
Spreads	5.0%	5.0%	5.0%	12.3%	12.3%	12.3%	12.3%	12.3%
Fish salads	5.0%	5.0%	5.0%	21.9%	21.9%	21.9%	21.9%	21.9%
Salted	5.0%	5.0%	5.0%	2.0%	2.0%	2.0%	2.0%	2.0%
Other salads	5.0%	5.0%	5.0%	14.3%	14.3%	14.3%	14.3%	14.3%
Mayonnaise salad	5,.0%	5,.0%	5,.0%	14.3%	14.3%	14.3%	14.3%	14.3%
Cod	5.0%	5.0%	5.0%	7.4%	7.4%	7.4%	7.4%	7.4%
Smoked	5.0%	5.0%	5.0%	21.2%	21.2%	21.2%	21.2%	21.2%
Products - frozen	5.0%	5.0%	5.0%	1.3%	1.3%	1.3%	1.3%	1.3%

The growth prediction is processed in Tab. 3. Products or raw materials were divided by the company into groups, see Fig. 4. Depending on the defined objectives of the simulation study, experiments are then carried out. The test plan sets out the input data, objectives, and expected results from the simulation run. It is also important to define the time frame for the simulation experiments so that the results are relevant and realistic. Simulation runs can last several hours, depending on the conditions. The input and output data and basic parameters of the simulation model must also be documented for each experiment carried out.

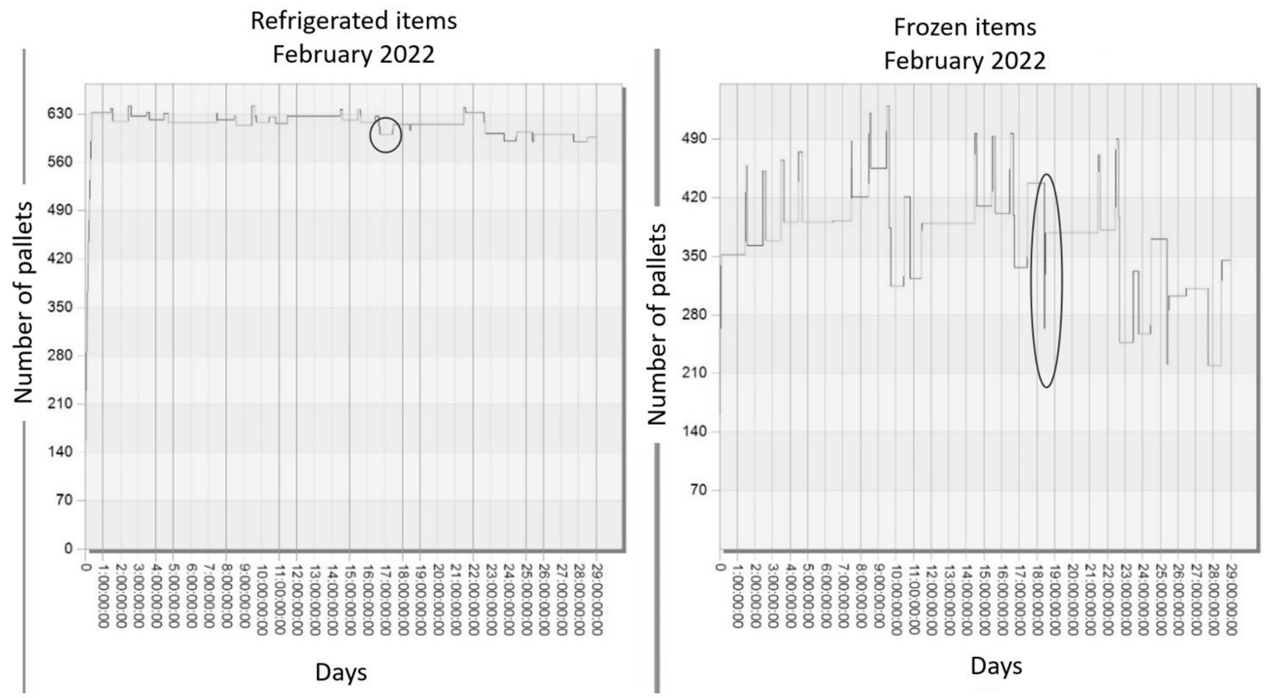

Fig. 3. Warehouse refrigerated and frozen items – peak for February

The priority objectives that can be defined when using simulation tools, and which were also taken into account when solving the study, include:

- minimise the lead times of production and logistics processes;
- maximise the use of machines, equipment, and warehouse space;
- minimise the level of inventory;
- maximise the flexibility of deliveries (input and output).

All defined objectives must be collected and statistically analysed at the end of the simulation cycles, thus achieving a certain required level of concretisation for the simulation model.

Table 3. The growth prediction of products

	2022	2023	2024	2025	2026	2027	2028	2029	2030
Chilled other	170	170	170	170	170	170	170	170	170
Frozen	359	371	383	399	403	408	411	413	415
Spreads	6	6	6	7	7	7	7	7	7
Mayonnaise	5	5	5	5	6	6	7	7	8
Marinated	63	64	65	66	68	70	73	74	75
Salads other	42	43	44	47	51	59	65	74	83
Mayonnaise salads	34	34	35	36	41	43	47	52	56
Cod	147	154	161	168	178	190	204	218	233
Fish salads	19	20	20	20	22	26	31	34	39
Salted	7	7	7	7	7	8	8	8	8
Smoked	6	6	6	6	7	8	11	12	15
Froneri	112	112	112	112	112	112	112	112	112
Raw material	259	259	259	259	259	259	259	259	259
Frozen fish	112	112	112	112	112	112	112	112	112
Total frozen	842	854	866	882	886	891	894	896	898
Total chilled	499	509	519	532	557	587	623	656	694
Total total	1341	1363	1385	1414	1443	1478	1517	1552	1592

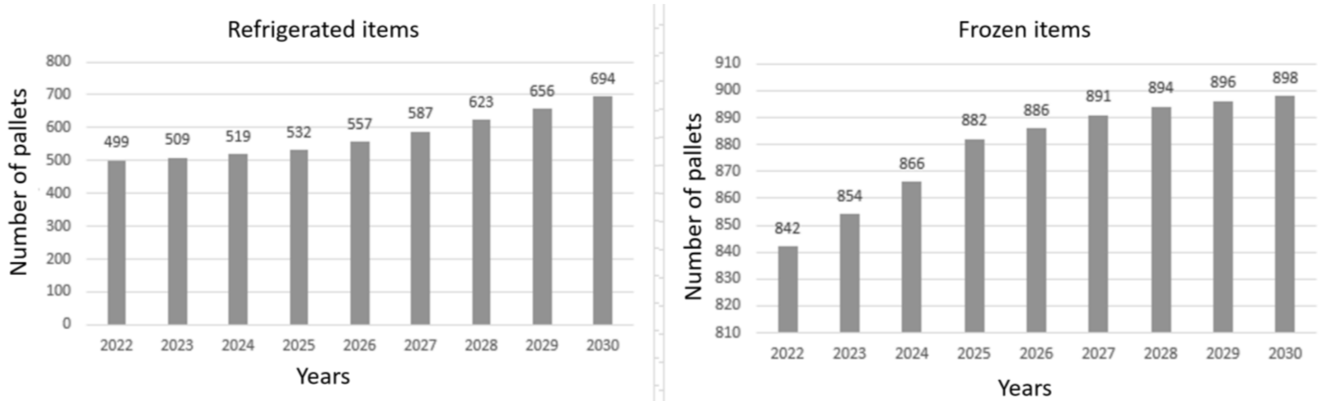

Fig. 4. Graphical display of stock movement prediction until 2030 according to peak 9.2.2022

Fig. 3 and Fig. 4 present analytical outputs supporting long-term capacity planning for the storage of refrigerated and frozen items. Fig. 3 presents the daily number of pallets of refrigerated (left chart) and frozen items (right chart) throughout February 2022, identified as the most demanding month in terms of storage capacity requirements. In the left chart, the number of refrigerated pallets remains consistently high and relatively stable, mostly ranging between 560–630 pallets. Minor fluctuations, highlighted by the marked point, represent short-term variations caused by irregular deliveries or accelerated dispatching. This peak-load profile is essential for evaluating whether the existing chilled-storage capacity can sustainably absorb seasonal demand. The right chart shows more pronounced fluctuations in the number of frozen pallets, varying approximately between 280–490 pallets. The highlighted area indicates days with a significant drop followed by a rapid increase in storage occupancy. Such variability reflects higher demand dynamics and more complex planning requirements in the frozen-goods warehouse. Identifying these extreme values enables accurate sizing of freezing capacity, optimisation of material handling, and planning of the necessary operational buffer. The outputs presented in Fig. 3 form a key basis for long-term capacity planning, as they reveal seasonal peaks, logistical constraints, and areas where infrastructure reinforcement, process optimisation, or inventory policy adjustments may be needed. Fig. 4 illustrates the predicted development of pallet quantities for refrigerated and frozen items up to the year 2030. The forecast shows a continuous increase in required pallet capacity for both categories. Refrigerated items grew from approximately 499 pallets in 2022 to about 694 pallets in 2030, indicating a steady upward trend and a gradual acceleration in later years. Frozen items follow a similar pattern, rising from around 842 pallets in 2022 to roughly 898 pallets in 2030, though with a more moderate increase and signs of stabilisation after 2026. These projections reflect long-term growth in storage demand, with frozen items consistently requiring higher capacity than refrigerated ones. This model applies extrapolation of historical trends and accounts for long-term changes in demand, enabling simulation of future capacity needs. The prediction supports strategic decision-making regarding infrastructure investments, warehouse process optimisation, and inventory policy adjustments. The outputs of both figures provide an essential basis for designing a flexible, scalable, and long-term sustainable warehouse management system.

Possibilities of using DDMRP data in simulation using TX Plant Simulation

The DDMRP (Demand Driven Material Requirements Planning) methodology brings a modern approach to planning and managing inventories, which is based on real demand and takes into account dynamic changes in the supply chain. Outputs from DDMRP – such as buffer sizes, protection zones, dynamic replenishment signals or demand profiles – represent valuable data that can be effectively used in the simulation of logistics and production processes in the Tecnomatix Plant Simulation software.

TX Plant Simulation is a tool that enables detailed modelling, analysis and optimisation of business processes. Connecting DDMRP data to this simulation environment allows you to verify the impact of planning decisions in a safe, virtual environment before their real implementation into practice.

Specific possibilities of using DDMRP data in TX Plant Simulation:

1.Simulation of buffer location and behaviour:

- DDMRP defines the optimal locations where storage points (stock buffers) should be located.
- In the simulation, these points can be modelled and their impact on system throughput, warehouse utilisation, and waiting times can be verified.

2.Dynamic inventory management based on replenishment signals:

- DDMRP generates the so-called "net flow position" - an indicator of when inventory should be replenished.
- In TX, these signals can be modelled as order or production triggers, thus simulating the system's behaviour in real time.

3.Verification of system capacity and responsiveness:

- Based on DDMRP data, the company's response to changes in demand (e.g. sudden increase/decrease in orders) can be tested.
- Simulation allows for comparison of multiple scenarios - without using DDMRP, with DDMRP and with different buffer settings.

4.Analysis of performance indicators:

- Thanks to the simulation, it is possible to measure delivery reliability, inventory levels, lead time and other KPIs.
- The results show to what extent the implementation of DDMRP helps to achieve more agile and resilient logistics processes.

Demand Driven MRP (DDMRP) offers benefits in demand-based planning but shows significant limitations when managing inventory with expiration dates. It does not natively account for expiry, batch tracking, or FIFO/FEFO principles, increasing the risk of obsolete or wasted stock. [11,12].

Key drawbacks of DDMRP for expiring goods:

- Does not consider shelf life or stock ageing – can lead to accumulation of near-expiry items.
- Lacks FIFO/FEFO issuing logic – older inventory may not be consumed first.
- Limited analytics and simulation tools – harder to prevent spoilage or write-offs.
- Requires integration with WMS or specialised ERP to enable batch and expiry tracking.

Improvement recommendations:

- Integrate DDMRP with WMS – ensure FEFO-based issuing and batch-level tracking.
- Include ageing logic in buffer calculations – consider inventory health, not just quantity.
- Use BI tools to visualise stock age and quickly act on critical items.
- Adopt hybrid planning – use DDMRP for volume, FEFO logic for issuing.
- Test through simulation – to optimise buffer sizes and replenishment frequency.

DDMRP alone is insufficient for managing perishable or regulated inventory. However, when combined with supporting tools, it can be a reliable part of an effective and robust supply chain strategy. The combination of the DDMRP methodology with TX Plant Simulation creates a powerful tool for decision support in the field of production planning and inventory management. Such a combination allows companies to reduce risk when implementing new planning strategies, optimise inventory, improve system throughput, and prepare for changing market conditions before real changes occur in operations.

4. CONCLUSIONS

Based on the case study, it can generally be concluded that demand-driven inventory management methods represent a modern approach to planning inventories and material flows that respond to actual demand, not just predictions. In the special method, DDMRP uses strategic placement of inventories (so-called buffers) in the chain and flexible replenishment rules, which help to reduce excess inventory and, at the same time, increase the availability of materials. In the context of warehouse management, DDMRP plays an important role in deciding what, where, and how much inventory should be stored to ensure smooth processes. A simulation model, which was used in the case study created in the TX Plant Simulation environment, allows you to verify the impacts of implementing DDMRP principles in warehouse management before they are put into practice. Using simulation, we can test various scenarios - how the warehouse will behave at different inventory levels, how a change in demand will affect the flow of materials, or where bottlenecks arise. Simulation thus serves as a decision-making support tool that allows you to reduce the risk of inefficient changes.

The link between demand-driven inventory management and simulation is extremely useful in optimising warehouse processes. Thanks to simulation, it is possible to verify the suitability of the designed buffers, evaluate their response to fluctuations in demand, and adjust logistics parameters (e.g., replenishment cycles, capacity, number of operators). At the same time, it is possible to simulate the impacts of new rules on warehouse performance, for example, on order fulfilment time, inventory turnover, or warehouse equipment utilisation.

This combination of demand-driven inventory management, simulation modelling, and active warehouse management allows the creation of resilient, flexible, and efficient warehouse systems that can quickly respond to changes in demand and market conditions. In industrial practice, this means higher performance, lower costs, and more satisfied customers.

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