



Enhancing Finished Paper Products Logistics with Artificial Intelligence: Data-Driven Approach



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Abstract:

This paper presents a comprehensive review of the existing Automated Storage and Retrieval System (ASRS) for finished paper products at Tamil Nadu Newsprint and Papers Limited (TNPL). The current operational efficiencies are analyzed, bottlenecks are identified, and opportunities for improvement are explored. A data-driven approach is employed to analyze operational data, uncover hidden patterns, and derive actionable insights.

The analysis reveals areas where a data-driven strategy can be leveraged to optimize storage and retrieval processes, improve inventory management, and increase overall operational efficiency. Predictive analytics techniques, including the application of the Auto Regressive Integrated Moving Average (ARIMA) model, were explored to forecast demand patterns and optimize inventory management using 14 years of historical Warehouse Management System (WMS) and ERP data. By adopting a data-driven approach, significant improvements in logistics operations are expected, including increased productivity, reduced cycle times, and enhanced customer satisfaction.

Keywords: Automated Storage and Retrieval System (ASRS), Warehouse Management System (WMS), Data Analytics, Auto Regressive Integrated Moving Average (ARIMA).

Introduction

The evolution of warehousing and logistics has been driven by the need for faster, more efficient, and highly accurate storage and retrieval processes. As global supply chains grow increasingly complex, businesses must find ways to optimize their warehouse operations to meet rising customer demands and maintain competitiveness. Automated Storage and Retrieval Systems (ASRS) have emerged as a key technology in modern warehouse management, offering significant improvements in storage density, order accuracy, and operational efficiency. However, despite their advantages, traditional ASRS systems still face challenges related to throughput limitations and data validation inefficiencies, particularly in high-volume industries such as paper manufacturing.

The paper industry presents unique challenges in logistics, where bulk production and large-scale distribution demand precise and efficient handling of finished products. Tamil Nadu Newsprint and Papers Limited (TNPL), a leading paper manufacturer, relies on ASRS to manage its inventory of finished paper products. The ASRS system at TNPL has been successfully integrated with the Enterprise Resource Planning (ERP) system for operations, ensuring smooth and automated material entry. However, inefficiencies in cycle times and the integration of shrink machine bundles with palletizing units posed significant challenges in maintaining optimal throughput rates.

To address these challenges, TNPL has adopted a data-driven strategy to enhance ASRS operations, focusing on cycle time reduction and seamless integration of shrink machine output with palletizing units. Predictive analytics techniques utilizing 14 years of historical data have been proposed to forecast demand trends and optimize resource allocation.

By implementing these data-driven strategies, TNPL aims to achieve higher operational efficiency, reduced cycle times, and enhanced customer satisfaction, positioning itself as an industry leader in logistics optimization.

I. Machine Learning and Data Driven Optimization of ASRS Operations at TNPL

The Automated Storage and Retrieval System (ASRS) at Tamil Nadu Newsprint and Papers Limited (TNPL) is a critical component in managing the storage and dispatch of finished

paper products. Despite the benefits of automation, the system encountered several operational challenges that hindered efficiency and throughput performance.

★ Problem Identification

One of the primary challenges was inconsistent infeed cycle times, with bundle processing taking as long as 32 seconds in certain instances. This variability caused disruptions in production flow and led to delays in palletizing and dispatch operations. Additionally, the manual intervention required for feeding shrink-wrapped bundles to the palletizer introduced inefficiencies, increasing labor costs and the risk of bundle damage due to mishandling. Another critical issue was the integration of shrink machine bundles with the palletizing unit, where improper synchronization between the two systems resulted in bundle backlog and conveyor jams. Given these challenges, a comprehensive data-driven approach was necessary to enhance operational efficiency by reducing cycle times, improving bundle handling, and ensuring seamless integration between the shrink machine and the palletizer.

★ Approach for Process Optimization

To address the identified inefficiencies, TNPL implemented a data-driven optimization strategy aimed at streamlining ASRS operations. This approach involved a systematic evaluation of operational data, process modifications, and the introduction of automated solutions.

A. Data Collection and Cleaning

A detailed data collection process was carried out to capture key performance metrics related to ASRS operations.

C. Process Modifications Implemented

Based on insights derived from data analysis, several process modifications were introduced to enhance throughput and reduce cycle time variations. Key improvements included:

- **Cycle Time reduction:** At the infeed area, a barcode reader installed to scans the bundle barcode. The read barcode is validated against our ERP product database. Once a valid bundle is detected, it is allowed inside the palletizing unit, while invalid bundles are stopped by the reject gate stopper plate. Valid bundles are then arranged by the robotized palletizer unit in a programmed pattern selected by the operator. After palletizing, the bundles' data on the pallet are validated with ERP, which was found to delay the process flow. Analysis with the WMS task running cycle (Fig.2) revealed that the entire cycle consumed about 32 seconds for validation of each bundle at the reject gate stopper.

Sources of data included: Cycle time logs from WMS Server, Data related to Conveyor speed and palletizer processing rates, Error logs related to barcode mismatches and manual interventions.

B. Root Cause Analysis

The cleaned data was analyzed using statistical methods to identify key factors contributing to delays and inefficiencies (Fig.1). The primary observations included:

- Irregular bundle feeding patterns caused by varying operator efficiency
- Misalignment between shrink machine output and palletizer intake capacity
- Frequent gate stuck-ups due to improper material flow settings

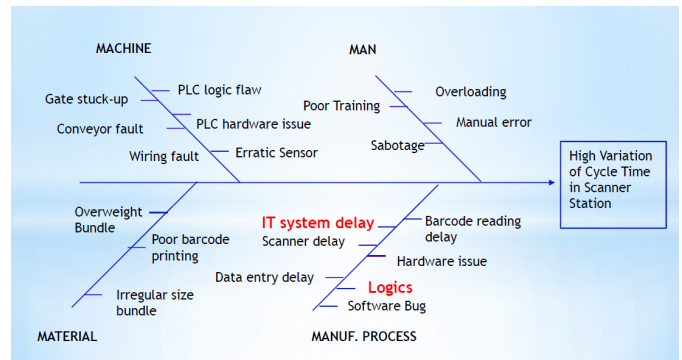


Fig.1: Factors attribute to Bundle Scanning Cycle Delay

```

Global Script - Diagnostics
09:49:26 MakeSQLQuery2() ->ERROR-78:Operation is not allowed when the object is closed.
09:49:26 MakeSQLQuery2() ->ERROR-8:Item cannot be found in the collection corresponding to the requested name or ordinal.
09:49:26 MakeSQLQuery2() ->SQL-ERR:EXEC SEND_TRANSACTION_HISTORY '3494', 'T', 6924
09:49:26 MakeSQLQuery2() ->ERROR-9:Item cannot be found in the collection corresponding to the requested name or ordinal.
### CurrOper=3, CurrOper_LEAVE=3, scTaskInb=1471, TakeTaskInb=1=1471, TI=
### UpdateTask2() BEGINS
09:49:26 UpdateTask2() ### -> SQL = SELECT * FROM CTransfers WHERE DEV_ID = 610 AND TakeTaskInr = 1470
09:49:26 UpdateTask2() ### -> SQL = UPDATE CTransfers SET State = 13 WHERE DEV_ID = 610 AND TakeTaskInr = 1470
### CurrOper=3, cCurrOper_LEAVE=3, scTaskInb=7514, TakeTaskInb=1=7514, TI=
### UpdateTask2() BEGINS
09:49:26 UpdateTask2() ### -> SQL = SELECT * FROM CTransfers WHERE DEV_ID = 620 AND TakeTaskInr = 7513
09:49:26 UpdateTask2() ### -> SQL = UPDATE CTransfers SET State = 13 WHERE DEV_ID = 620 AND TakeTaskInr = 7513
### CurrOper=2, cCurrOper_LEAVE=3, scTaskInb=1715, TakeTaskInb=1=1715, TI=
### UpdateTask2() BEGINS
09:49:27 UpdateTask2() ### -> SQL = SELECT * FROM CTransfers WHERE DEV_ID = 630 AND TakeTaskInr = 1715
09:49:27 UpdateTask2() ### -> SQL = UPDATE CTransfers SET State = 2 WHERE DEV_ID = 630 AND TakeTaskInr = 1715
09:49:27 TC_TaskCreation() ->SQL: SELECT * FROM (SELECT COUNT(*) FROM TransferCar TC WHERE TC.State=16 AND TC.Load_ID = 10,Load_ID AND TC.TaskType = 'AUT') AS TASK_COUNT FROM Clouds LO WHERE Location_A=11 AND Targ
*** LOOP:1
09:49:27 TC_TaskCreation() ->Load: 3785, TASK_COUNT: 0
09:49:27 TC_TaskCreation() ->Location_A: 11, location_ID: 550, Target_A: 11, Target_Loc: 340
09:49:27 ChooseTC() ->### BEGINS ###
09:49:27 ChooseTC() ->ITAKEStation: 550, REAVEStation: 340
09:49:27 ChooseTC() ->TC410_running: 1, TC420_running: 1
09:49:27 ChooseTC() ->Priority(Station): TC410=8, TC420=3
09:49:27 ChooseTC() ->Priority(TaskCount): TC410=7, TC420=2
### 410 ### 0
### 420 ### 0
09:49:27 ChooseTC() ->Priority(Task2): TC410=7, TC420=2
09:49:27 ChooseTC() ->Priority(final): TC410=7, TC420=2
09:49:27 ChooseTC() ->USE THIS TC: 410 (priority)
09:49:27 ChooseTC() ->### ENDS ###
09:49:27 TC_TaskCreation() ->DEV_ID: 410, ITAKEStation: 550, REAVEStation: 340
09:49:27 TC_TaskCreation() ->boolFAKPerm: 1, boolLEAVEPerm:
09:49:27 CreateNewTask() ->SQL: INSERT INTO TransferCar (DEV_ID, TakeTaskInr, Priority, TaskType, OperationType, Load_ID, TakePos, LeavePos, CreationTime, State, UpdateSldo) OUTPUT INSERTED.TakeTaskInr SELECT 410,6926,6,'AUT',2,3785,5
09:49:27 CreateNewTask() -> New Task 6926 created
09:49:27 TC_TaskCreation() ->NEW TASK=6926, IPriority: 6, sload_ID: 3785
09:49:28 GetLoadTC() ->PARAMETER FAILURE
09:49:29 SendTCMsg() ->BEGINS
DEV_ID=410
TaskInr=6926
09:49:29 SendTCMsg() ->TC msg sent: DEV_ID=410, Task=6926, Pallet=3785, TargetPos=550, OperationType=2, Weight=1134, WeightTolerance=15, MessType=1
09:49:29 TC_Commands() ->No action: NewMsg from TC=1, must be 0.
BundleCheckMCS function BEGINS 2025-01-28 09:49:31
BundleCheckMCS function end 2025-01-28 09:49:31
ProductID-PLC=U1HRBDS07805850910003
09:49:31 BundleCheckMCS() ->sql: SELECT BNDL_NO, SEGMENT1, MACH_NO FROM TNPL_ASRS_ITEM_MST_V WHERE BNDL_NO='S1V120250128A046672'
Bundle accepted: S1V120250128A046672 - S1V120250128A046672, U1HRBDS07805850910003 - U1HRBDS07805850910003, 1=1
09:49:32 InUpMCSPutAwayTable() ->BEGINS...
09:49:33 InUpMCSPutAwayTable() ->ENDS...
BundleCheckMCS function end 2025-01-28 09:49:33
BundleCheckMCS check ACTION ->ERROR-999: 424 Object required
    
```

Fig. 2: WMS Task Debugger

The data-driven approach helped identify this issue, and necessary rules were modified (Fig.3). The scanning time for the bundle got reduced to 10 seconds.

```

300 *      MC_NO = HMIRuntime.Tags(ConvTPrefix & "MachineNumber").Read
301 *      Else
302 *          MC_NO = 0
303 *      End If
304 *
305 *      End If
306 *
307 *      End If
308 *      'get mac
309 *
310 *      '10.8.2019 Add Product_ID & Machine number for bundle
311 *
312 *      If HMIRuntime.Tags("AcceptAllBundles").Read = 1 Then 'USE WMS product_ID
313 *          ProdID = Trim(HMIRuntime.Tags(ConvTPrefix & "SelectedProduct").Read)
314 *          MC_NO = HMIRuntime.Tags(ConvTPrefix & "MachineNumber").Read
315 *      ElseIf HMIRuntime.Tags("MCS_comm_ok").Read = 1 Then 'USE WMS product_ID
316 *          ProdID = Trim(HMIRuntime.Tags(ConvTPrefix & "SelectedProduct").Read)
317 *          MC_NO = HMIRuntime.Tags(ConvTPrefix & "MachineNumber").Read
318 *      End If
319 *
320 *      'ADD REAM_WT & PER_BUNDLE HERE IF NEEDED
321 *
322 *      If resultSet("BundleExist") > 0 Then 'Bundle exist (UPDATE)
323 *          sql = "UPDATE CloadItems SET "
324 *          '16.03.2012 sql= sql & " Load_ID=" & Trim(HMIRuntime.Tags(TPrefix & "Pallet_ID").Read(1)) & ""
325 *          sql= sql & " Load_ID=" & Trim(Pallet_ID) & ""
326 *          sql= sql & " Load_Pos=" & HMIRuntime.Tags(TPrefix & "Layer").Read
327 *          sql= sql & " Item_State=" & ""
328 *          sql= sql & " Qty=" & ""
329 *          '25.08.2010 JLI Infeed and Outfeed times added
330 *          sql= sql & " InfeedTime=GETDATE()"
331 *          sql= sql & " OutfeedTime=NULL"
332 *          sql= sql & " Weight=(SELECT ISNULL(Weight,0) FROM CProducts WHERE Product_ID=" & ProdID & """) '6.4.2011
333 *          sql= sql & " Product_ID=" & ProdID & ""
334 *          sql= sql & " MC_NO=" & MC_NO
335 *          sql= sql & " WHERE Item_ID=" & BundleID & ""
336 *
337 *          HMIRuntime.Trace Time & " " & cFuncName & "->sql: " & sql & vbCrLf
338 *          Set resultSet = connect.Execute(sql)
339 *
340 *      If Err <> 0 Then
341 *          HMIRuntime.Trace "ERROR OCCURED: " & Err.Number & " " & Err.Description & vbNewLine
342 *          '16.03.2012 AddLog 0,0,"PalletReady()",ERROR: " & Err.Number & " " & Err.Description,Trim(HMIRuntime.Tags(TPrefix & "Pallet_ID").Read(1)),Bundle
343 *          AddLog POS_ID,0,"PalletReady()",ERROR: " & Err.Number & " " & Err.Description,Trim(Pallet_ID),BundleID,0,"",0,0,0 "AddLog "iDevice","Level",
344 *          Exit Sub
345 *      End If
346 *
347 *      '16.4.2012
348 *      WeightForOra = MakeSQLQuery2("SELECT ISNULL(Weight,0) FROM CProducts WHERE Product_ID=" & ProdID & """)
349 *      'TMCSTransactionHistory ProdID,BundleID,Pallet_ID,WeightForOra,MC_NO,"ADDED TO PALLET", "", "", "", 0 "Insert
350 *

```

Fig. 3: Modified Program to Reduce the Scanning Cycle of the Bundles Validation

- Mechanized Bundle Feeding:** The cycle time was significantly reduced, paving the way for further process improvements. Subsequently, the shrink bundle machine was integrated with the ASRS, allowing for automated wrapping of bundles. With the output from the shrink machines being directly fed into the infeed conveyors, the overall process became more streamlined and efficient, ultimately leading to a substantial increase in throughput (Fig.4).

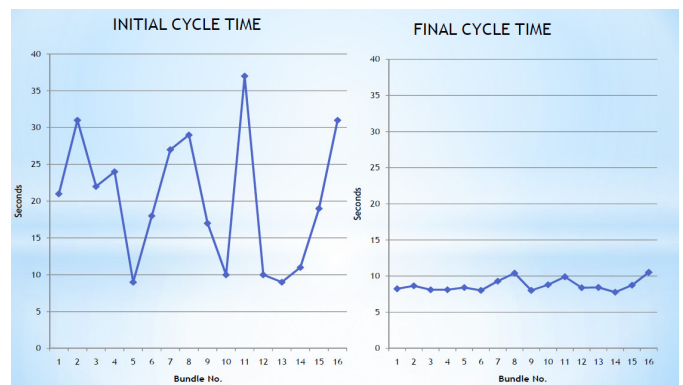


Fig.5: Bundles Scan time comparison



Fig. 4: Integrated Shrink Machine with ASRS infeed

D. Results and Key Improvements

The implementation of the data-driven process improvements led to significant operational enhancements across TNPL's ASRS facility. The key results achieved include:

- Reduced Cycle Time:** The infeed bundle scan time was successfully reduced from 32 seconds to an average of 6-10

seconds, enhancing throughput rates and minimizing idle time (Fig.5).

- Increased Throughput:** The optimized system achieved a 50% increase in machine utilization, enabling more efficient order fulfillment and better production flow.
- Reduction in Manual Intervention:** Automation of the bundle feeding process eliminated human errors, ensuring consistent material handling and improving worker productivity. One shift operation got reduced completely.
- Enhanced Bundle Handling:** Seamless integration of shrink-wrapped bundles with the palletizing units eliminated jamming issues, resulting in smooth operations.

E. Financial Impact

The optimization project delivered significant financial benefits, highlighting the cost-effectiveness of adopting a data-driven approach to warehouse automation. The key financial outcomes include:

- Monthly Savings: INR 2,00,000 attributed to improved operational efficiency and reduced manual labor.
- Annual Savings: INR 30,00,000 realized through better machine utilization and minimized production downtime.

By investing in Machine Learning and data-driven process improvements, TNPL successfully enhanced ASRS operations while achieving substantial cost reductions, reinforcing the financial viability of warehouse optimization initiatives.

II. AI-Driven Predictive Analytics to Optimize Warehouse Operations

Effective warehouse management is crucial for ensuring the seamless movement of finished paper products from storage to dispatch. Tamil

Nadu Newsprint and Papers Limited (TNPL) have accumulated 14 years of historical warehouse data, comprising infeed and outfeed operations, cycle times, and ERP order records. This extensive dataset presents a valuable opportunity to apply advanced predictive analytics techniques to enhance operational efficiency and optimize inventory management.

Among the various AI-driven predictive analytics techniques, the AutoRegressive Integrated Moving Average (ARIMA) model has emerged as a powerful tool for forecasting demand trends, optimizing resource utilization, and improving throughput. By leveraging ARIMA, TNPL can gain valuable insights into warehouse operations, enabling data-driven decision-making and proactive planning.

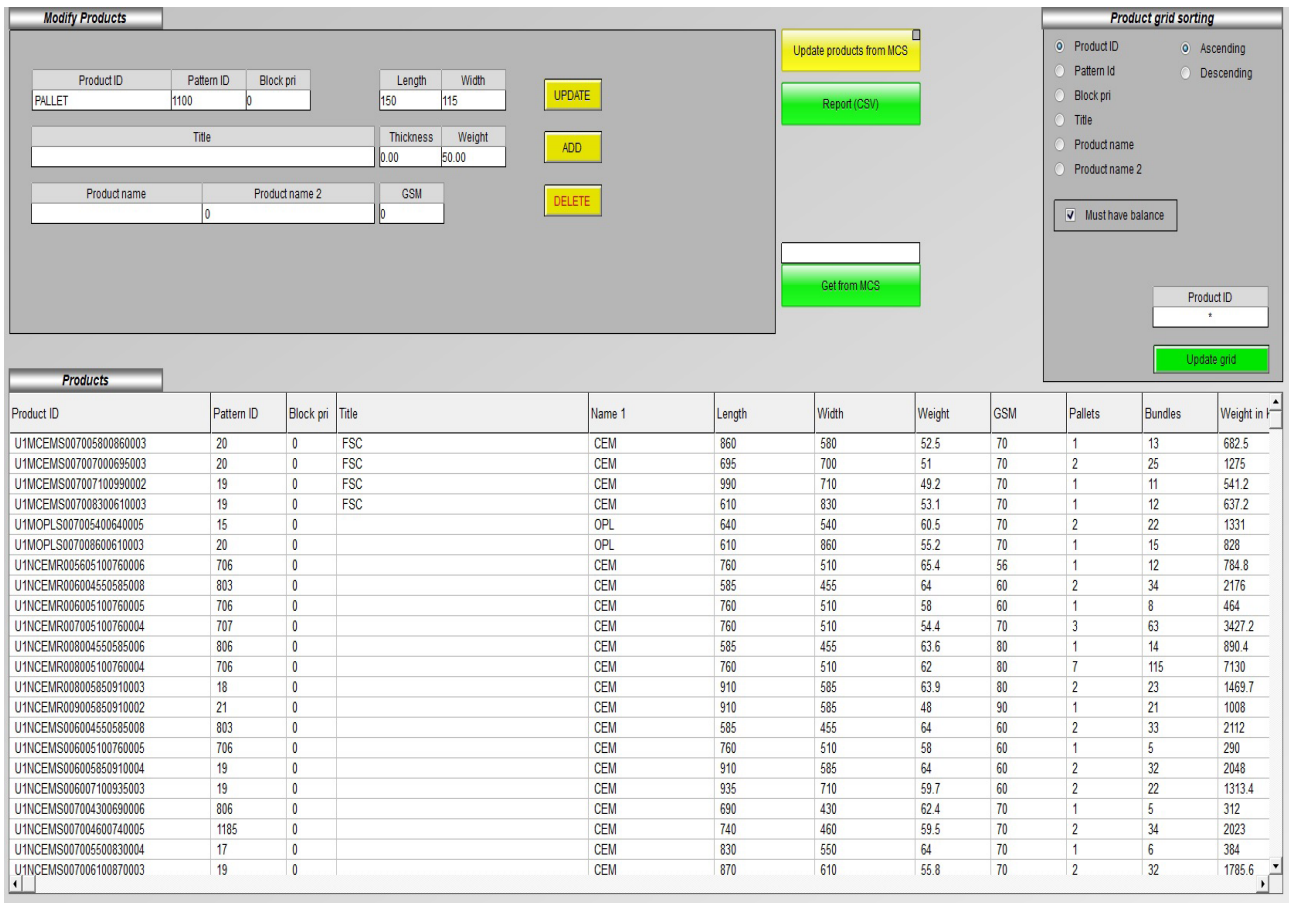


Fig. 6: Product Database at ASRS WMS

Understanding ARIMA and Its Relevance to TNPL's Warehouse Operations

The ARIMA model is a widely used time series forecasting method that combines three key components—AutoRegression (AR), Differencing (I), and Moving Average (MA). ARIMA is particularly well-suited for TNPL's warehouse operations due to its ability to identify and analyze patterns in historical data, account for seasonality, and make accurate short- and long-term forecasts. In TNPL's context, ARIMA can be instrumental in forecasting infeed and outfeed demand, optimizing stock levels, and identifying potential operational bottlenecks. By analyzing historical trends, ARIMA can uncover recurring patterns in inventory fluctuations, peak demand periods, and supply chain inefficiencies, allowing TNPL to take proactive measures to streamline operations.

Application of ARIMA in Warehouse Operations

A. Demand Forecasting for Inventory Optimization

A primary challenge in warehouse management is ensuring that stock levels are optimally maintained to meet customer demands without leading to overstocking or shortages. ARIMA enables TNPL to analyze historical order fulfillment data and generate accurate demand forecasts by identifying seasonal patterns, sudden demand spikes, and declining trends.

By leveraging ARIMA-driven forecasts, TNPL can determine the optimal inventory levels required for different periods, adjust procurement schedules accordingly, and minimize holding costs. This predictive capability helps prevent stock outs and ensures that customer orders are fulfilled without delays.

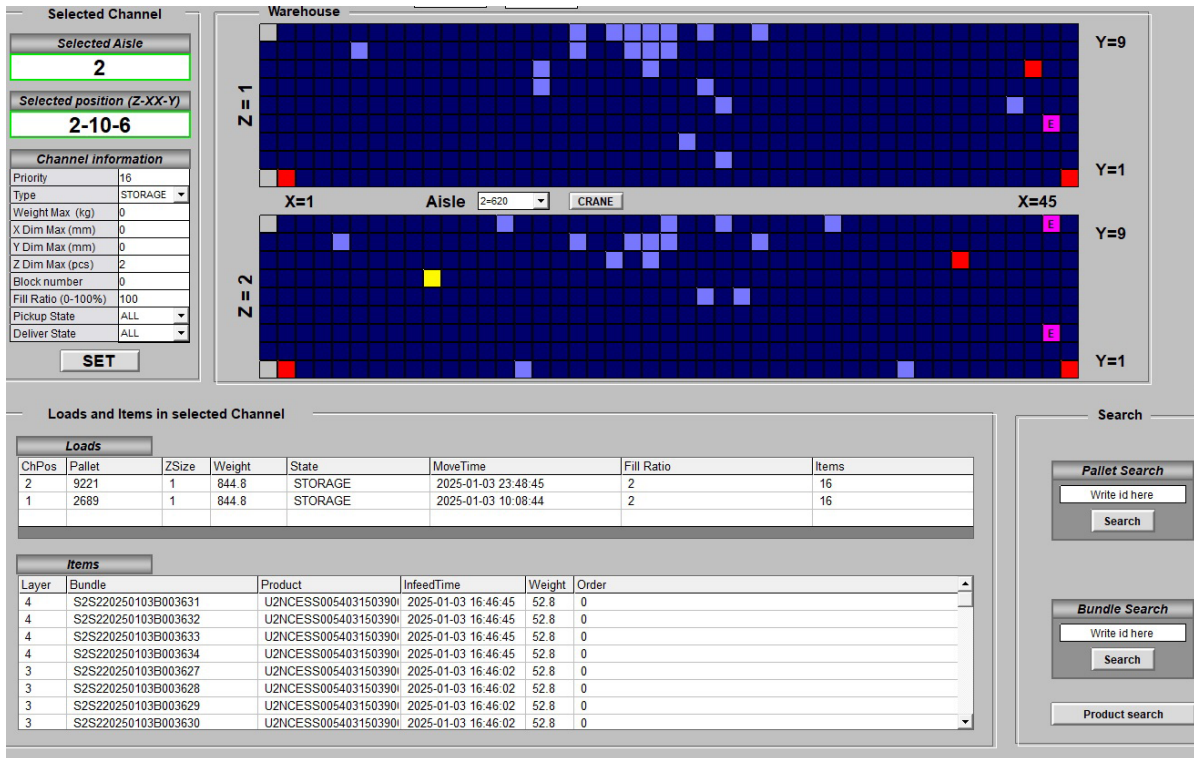


Fig. 7: Warehouse Layout

B. Supply Chain Planning and Resource Allocation

Efficient warehouse operations require effective coordination between production, storage, and distribution teams. ARIMA can facilitate better supply chain planning by providing accurate predictions of inbound and outbound finished products. With ARIMA-driven insights, TNPL can optimize truck scheduling, warehouse space allocation, and labor deployment. This predictive approach ensures that resources are utilized efficiently, reducing idle times and improving overall operational efficiency.

Implementation Framework for ARIMA in TNPL's Warehouse Operations

To successfully implement ARIMA for warehouse optimization, a structured approach must be followed, starting from data collection to full-scale deployment.

A. Data Collection and Pre-processing

Effective forecasting requires clean, high-quality data. TNPL's

historical data from WMS and ERP systems will be consolidated and preprocessing steps such as missing value imputation, outlier removal, and normalization will be performed. To effectively implement AI-driven predictive analytics, TNPL can begin by leveraging its existing warehouse data, including:

- Infeed Data:
 - Volume of incoming bundles over time.
 - Processing speeds and cycle times.
 - Seasonal and operational trends.
- Outfeed Data:
 - Order fulfillment patterns and dispatch schedules.
 - Storage duration and retrieval frequency.
 - Peak dispatch periods and corresponding bottlenecks.
- Inventory Management Data:
 - Stock movement trends.
 - Order accuracy rates and shrinkage data.
 - Storage utilization efficiency.

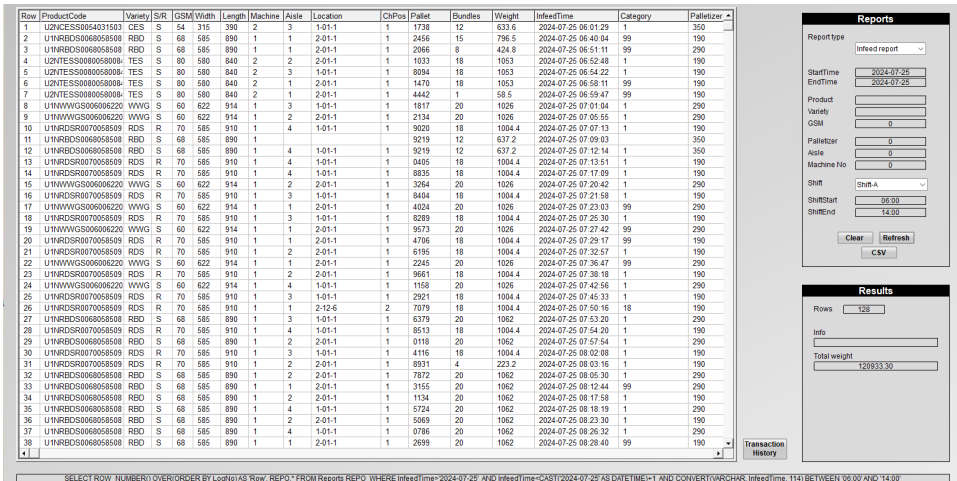


Fig. 8: Warehouse Infeed Report

B. Model Training and Validation

Once the data is prepared, the ARIMA model will be trained using a portion of the historical data while keeping a separate dataset for validation. The parameters of the ARIMA model, such as the autoregressive (p), differencing (d), and moving average (q) components, will be fine-tuned based on statistical tests.

The trained model will then be validated using key performance indicators such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to ensure forecasting accuracy.

C. Integration with ERP and WMS

Upon achieving satisfactory forecasting accuracy, the ARIMA model will be integrated with TNPL's ERP and WMS systems to provide real-time demand forecasts, stock level projections, and cycle time predictions. This integration will allow warehouse managers to make informed decisions based on AI-driven insights.

D. Continuous Monitoring and Improvement

The ARIMA model will be continuously monitored for accuracy and updated with new data to reflect changing market trends and operational dynamics. Regular evaluations will help fine-tune the model parameters, ensuring sustained performance improvement.

★ Expected Benefits of ARIMA Implementation at TNPL

By implementing ARIMA-based predictive analytics, TNPL can achieve several tangible benefits, including:

▸ **Improved Inventory Planning:** Reduction in under stock and over stock, leading to optimized storage utilization.

▸ **Enhanced Throughput Efficiency:** Accurate cycle time predictions enabling better resource allocation.

▸ **Cost Savings:** Reduced holding costs and operational inefficiencies through proactive planning.

▸ **Risk Mitigation:** Early detection of potential break down and quick corrective action.

By leveraging historical data and advanced forecasting techniques like ARIMA, TNPL can enhance inventory management, reduce cycle times, and optimize resource utilization. Moving forward, AI-driven insights will play a pivotal role in streamlining operations, improving customer satisfaction, and strengthening TNPL's position in the competitive paper manufacturing industry.

Conclusion & Future Scope

The optimization of TNPL's Automated Storage and Retrieval System (ASRS) through a data-driven approach has led to significant improvements in operational efficiency, including reduced cycle times, increased throughput, and minimized manual intervention. These enhancements have streamlined warehouse operations, resulting in better resource utilization and substantial cost savings. The proposed implementation of predictive analytics, using methods such as the Auto Regressive Integrated Moving Average (ARIMA) model, highlights TNPL's focus on proactive inventory management and demand forecasting. TNPL's commitment to continuous improvement through data-driven strategies will enable the company to achieve greater operational efficiency, improved customer satisfaction, and long-term competitiveness in the evolving paper manufacturing industry.