To: Sylvan Porter (President, WDC)

From: Ossington Analytica

Date: June 30th, 2018

Subject: Analysis of Manufacturing, Marketing, and Logistics at Wooden Door Company (WDC)

As per your request, Ossington Analytica has spent considerable time understanding the manufacturing, sales and logistics operations at WDC to highlight underlying issues that are negatively impacting your profitability.

Problem

The Aurora production facility has been struggling with increasing its daily output while minimizing quality problems. The Aurora Plant Manager needs a short-term production target and a plan for the long run. The Sales and Marketing team ran a promotion on D04-32 in Toronto. WDC would like to know if it was successful and if they should run one in Montreal. On the logistics and distribution side, backordering of unplanned sales are costing the WDC excessive shipping charges. There is a need for a new inventory management strategy that outperforms the current strategy.

Conclusion and Recommendation

Aurora Production Facility

A short-term production target for the Aurora Production Facility is at least 200 doors per day (Appendix A figure 4). Rework costs are the main driver for production issues at Aurora. One of two actionable trends identified by the team are that defect rate (defects per door) are considerably lower on Fridays compared to any other day of the week (Appendix A figure 6). The second visible trend is that defect rate increases with production quantity - which indicates that the rework shop becomes overburdened as production increases (Appendix A figure 3). A quick improvement at Aurora would be a material rework database that would include defect type, production line, potential defect source, location on door etc. This would enable Aurora to track where the rework is concentrated. If Aurora is able to half its rework costs (from 6 to 3%) this would save the company $5 per door (Appendix A figure 5). To sustain long term quality and introduce a data-driven culture, Ossington Analytica suggests an Integrated Production Monitoring system (Appendix B), these systems are a necessity to obtain a competitive edge.

Sales and Marketing

The promotion reduced profit margin by $20. A 29% increase in Sales is required to offset this reduction in margin. If the focus of the sale is to improve profit, then our recommendation is to not run a promotion in Montreal because there is no conclusive evidence that the promotion increased sales by 29% (Appendix C Figure 11-13). Our recommendation is to have the Sales & Marketing department use SKU-level sales data to better forecast demand for use by the Logistics & Distribution department in a new inventory management system to reduce inventory waste.

Logistics and Distribution

Ossington Analytica team was able to determine backordering costs will be reduced by $5M (Appendix D figure 16) and forecasting discrepancy reduced from 25% to 5% (Appendix D). In addition, a new Inventory Management System linked to a better production plan can also be implemented. This forecasting analysis has shown that there is potential for driving further efficiencies and cost savings by utilizing supply chain analytics and statistical analysis.

Implementation Plan

Aurora Production Facility

In the long run the production facility would benefit from a database for all rework activities that includes nature of defects, their location, cost of repair, etc. The company should also consider implementing an integrated production monitoring system. This is a major investment but could help to identify equipment that results in defective parts, it could reduce inefficient processes (bottlenecks), it could monitor equipment efficiency, help with IoT integration, etc. (Appendix B)

Sales and Marketing

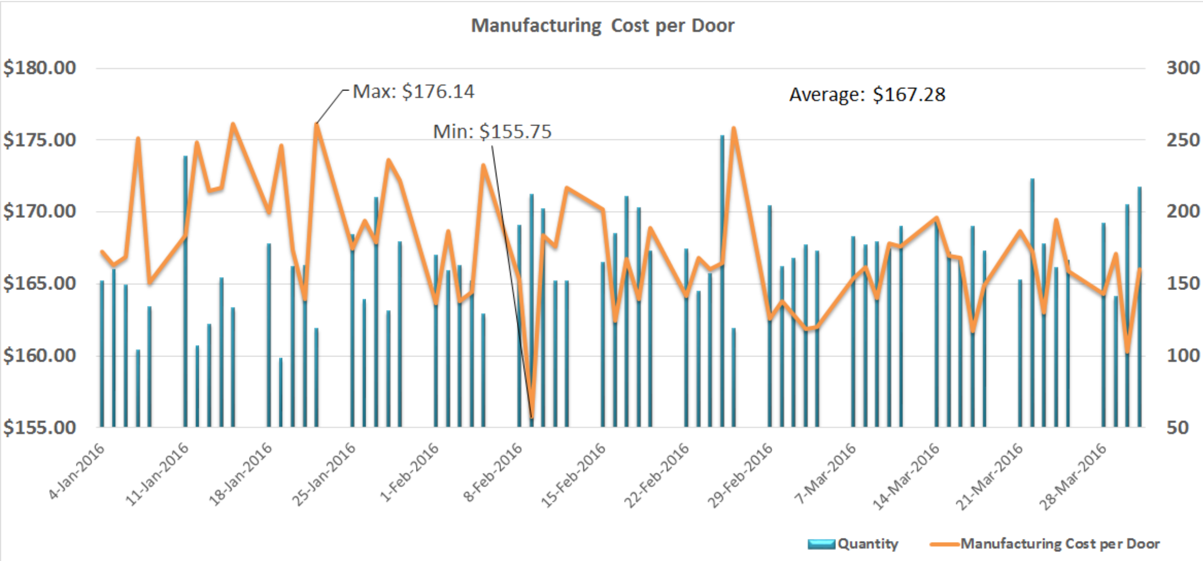
At this point in time, there is not enough data to determine this. The action plan is to work towards a data-sharing relationship with our distributors and their retailers. Sales data (price, unit cost, location, time) should flow from retailer-to-distributor-to-WDC at SKU-level and promotional/product information in the reverse direction to the retailer. This will allow the WDC to determine the change in demand relative to location/partners. It will optimize promotion to maximize profit and give a greater understanding of sales performance with different partners. Creating promotions that strategically bundle doors and accessories could help close the promotional margin. Knowing the change in demand relative to the price reduction is critical to run a successful promotional campaign.

Logistics and Distribution

Tracking retail data and figuring out why the current forecasting is on average incorrect by 27% is an immediate priority. Proper collection and analysis of sales data can help project and control demand in such a way that it could reduce the inefficiencies of holding extra inventory for unplanned sales. In the long run, machine learning can improve production planning and factory scheduling accuracy by taking into account multiple constraints and optimizing for each.

Appendix A: Analysis of Aurora Manufacturing Facility

Figure 1: Manufacturing cost per door for Jan-Mar 2016 @ Aurora Facility



The manufacturing cost per door is based on raw material (fixed at $135 per door), facility ($3600 per day), and rework (variable data from WDC). Variability in the data is a result of the rework cost that tends to fluctuate during the week.

Figure 2: Breakdown of manufacturing cost per door for Jan-Mar 2016 @ Aurora Facility

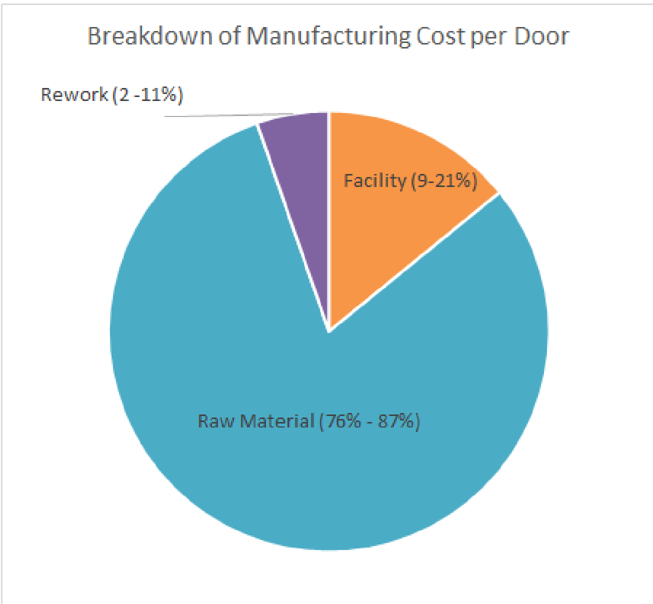
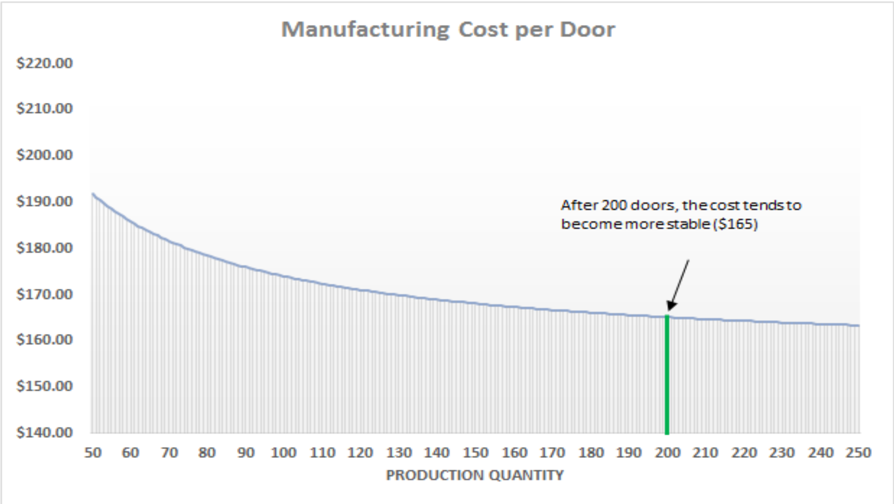


Figure 3: Defect rate vs quantity regression

Defect Rate was found through normalizing the defects with production quantity, this data was plotted against the daily production quantity to determine the positive trend shown above.

Figure 4: Manufacturing cost model

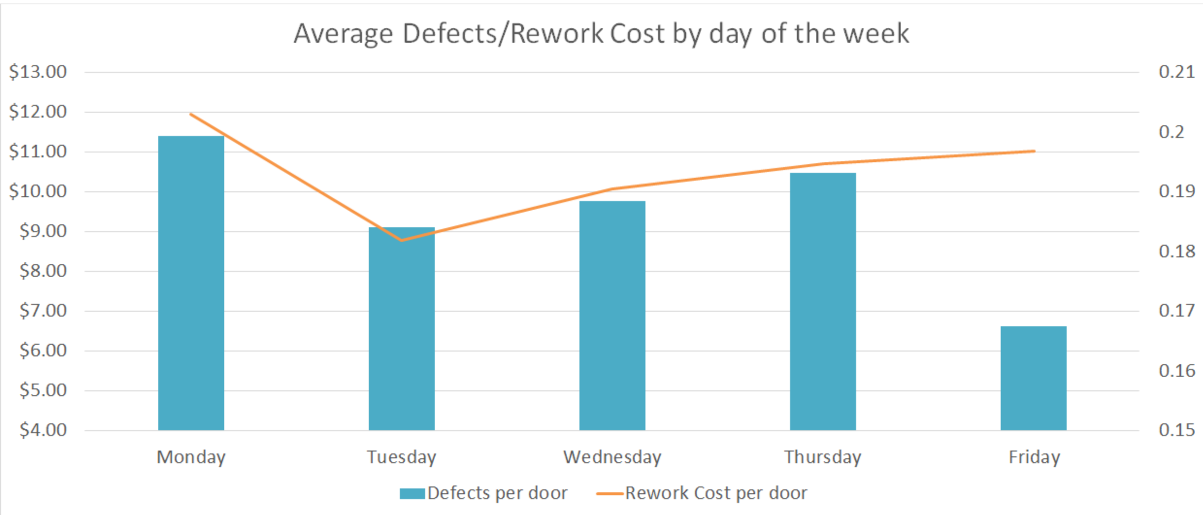


The above model is based on a fixed daily facility cost of $3600, raw material cost of $135 per door, and rework cost is modelled through a simple linear regression of rework cost versus production quantity from the 3-month data that was provided for Aurora Facility. It shows that after 200 doors, the cost per door stabilizes, for this reason Ossington Analytica suggests a minimum of 200 doors per day as a daily production target. The table below shows the effect of reducing rework cost for production quantities of 100,150, and 200 doors.

Figure 5: Manufacturing cost variability through different quantities/rework costs

No. of doors	Percentage of Rework Cost	Per Door Cost	Difference from Current Average ($167.28)
100	10%	$188.10	20.82
100	6%	$181.26	13.98
100	3%	$176.13	8.85
150	10%	$174.90	7.62
150	6%	$168.54	1.26
150	3%	$163.77	-3.51
200	10%	$168.30	1.02
200	6%	$162.18	-5.10
200	3%	$157.59	-9.69

Figure 6: Analysis of rework cost by day of the week



The data shown above has been normalized by the production quantity. Even though the rework cost tends to be fairly consistent each day of the week, the number of defects produced on Monday-Thursday are significantly higher than Friday, which can be confirmed in the hypothesis test shown on the next page.

Figure 7: Analytical test comparing defects on different days of the week

<u>Generalized Hypotheses:</u>

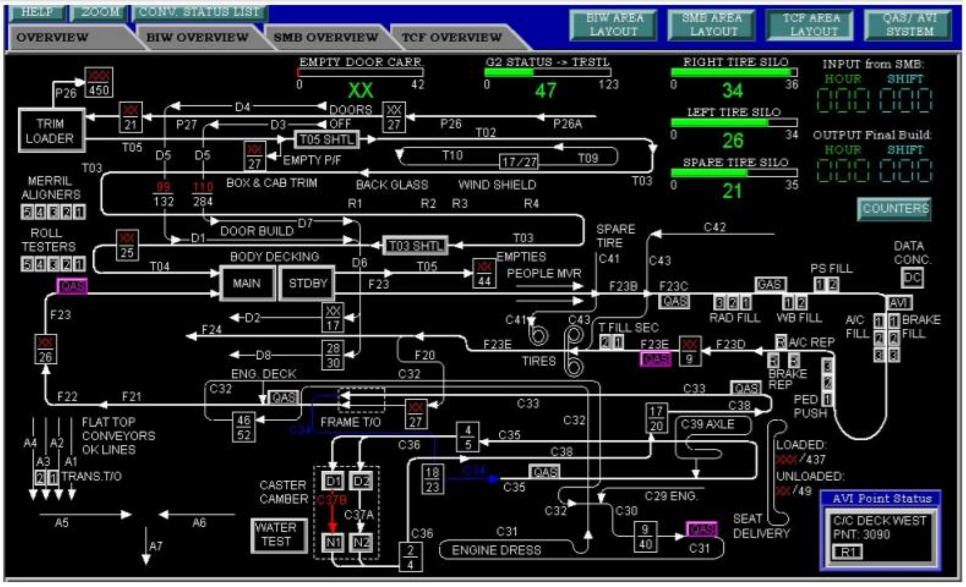
Null Hypothesis: The number of defects per door are not higher on any particular day than others
Alternate Hypothesis: The number of defects per door are higher on certain days compared to others

t-Test: Two-Sample Assuming Equal Variances											
	Monday	*Tuesday*		*Monday*	*Wednesday*		*Monday*	*Thursday*		*Monday*	*Friday*
Mean	0.196945626	0.176861677	Mean	0.196945626	0.184642661	Mean	0.196945626	0.185981915	Mean	0.196945626	0.163359485
Variance	0.000521441	0.001347443	Variance	0.000521441	0.00071508	Variance	0.000521441	0.001384387	Variance	0.000521441	0.00071067
Observations	13	12	Observations	13	13	Observations	13	13	Observations	13	12
Pooled Variance	0.000916486		Pooled Variance	0.000618261		Pooled Variance	0.000952914		Pooled Variance	0.000611942	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	23		df	24		df	24		df	23	
t Stat	1.657213848		t Stat	1.261480708		t Stat	0.905497852		t Stat	3.391543377	
P(T<=t) one-tail	0.055527914		P(T<=t) one-tail	0.109629752		P(T<=t) one-tail	0.18710139		P(T<=t) one-tail	0.001254705	
t Critical one-tail	1.713871528		t Critical one-tail	1.71088208		t Critical one-tail	1.71088208		t Critical one-tail	1.713871528	
P(T<=t) two-tail	0.111055829		P(T<=t) two-tail	0.219259504		P(T<=t) two-tail	0.374202781		P(T<=t) two-tail	0.00250941	
t Critical two-tail	2.06865761		t Critical two-tail	2.063898562		t Critical two-tail	2.063898562		t Critical two-tail	2.06865761	
	Tuesday	*Wednesday*		*Tuesday*	*Thursday*		*Tuesday*	*Friday*			
Mean	0.176861677	0.184642661	Mean	0.176861677	0.185981915	Mean	0.176861677	0.163359485			
Variance	0.001347443	0.00071508	Variance	0.001347443	0.001384387	Variance	0.001347443	0.00071067			
Observations	12	13	Observations	12	13	Observations	12	12			
Pooled Variance	0.001017515		Pooled Variance	0.001366718		Pooled Variance	0.001029056				
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0				
df	23		df	23		df	22				
t Stat	-0.609335402		t Stat	-0.616252942		t Stat	1.031003896				
P(T<=t) one-tail	0.274137335		P(T<=t) one-tail	0.271889619		P(T<=t) one-tail	0.156870493				
t Critical one-tail	1.713871528		t Critical one-tail	1.713871528		t Critical one-tail	1.717144374				
P(T<=t) two-tail	0.54827467		P(T<=t) two-tail	0.543779238		P(T<=t) two-tail	0.313740985				
t Critical two-tail	2.06865761		t Critical two-tail	2.06865761		t Critical two-tail	2.073873068				
	Wednesday	*Thursday*		*Wednesday*	*Friday*						
Mean	0.184642661	0.185981915	Mean	0.184642661	0.163359485						
Variance	0.00071508	0.001384387	Variance	0.00071508	0.00071067						
Observations	13	13	Observations	13	12						
Pooled Variance	0.001049733		Pooled Variance	0.000712971							
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0							
df	24		df	23							
t Stat	-0.105385351		t Stat	1.991098864							
P(T<=t) one-tail	0.458472948		P(T<=t) one-tail	0.029239217							
t Critical one-tail	1.71088208		t Critical one-tail	1.713871528							
P(T<=t) two-tail	0.916945896		P(T<=t) two-tail	0.058478434							
t Critical two-tail	2.063898562		t Critical two-tail	2.06865761							
	Thursday	*Friday*									
Mean	0.185981915	0.163359485									
Variance	0.001384387	0.00071067									
Observations	13	12									
Pooled Variance	0.001062174										
Hypothesized Mean Difference	0										
df	23										
t Stat	1.733938571										
P(T<=t) one-tail	0.048157586										
t Critical one-tail	1.713871528										
P(T<=t) two-tail	0.096315171										
t Critical two-tail	2.06865761										

Comparing Fridays to Mondays, Tuesdays, Wednesdays, and Thursdays - we have P-values of 0.1%, 15%, 3%, and 5%. This shows a strong indication that Fridays have a lower defect rate compared to all other days of the week (with the exception of Tuesdays).

Appendix B: Example of Manufacturing Analytics

Figure 8: Example of an integrated factory monitoring system (https://ps.extra.chrysler.com/sites/apics/Documents/FIS_Implementation_Rev2.10.pdf)



The above picture shows an example of an integrated factory/production monitoring system. Although this is a major infrastructure investment, availability of data is mandatory for quality improvement, waste minimization, and smooth manufacturing. Examples of data that can be obtained in real-time include:

1. Equipment power consumption and health - Allows predictive maintenance instead of dealing with costly equipment breakdowns
2. Various technical parameters - Allowing technicians/engineers to diagnose quality/production issues
3. Machine cycle times - Optimization of cycle times can increase production capacity by eliminating bottlenecks
4. Local inventory management
5. Error Mistake Proofing - Engineering Controls to avoid common mistakes
6. Internet of Things (IoT) integration - Future Big Data integration if WDC manufacturing wants to move in that direction

An example of a factory monitoring product: https://www.redviking.com/products/manufacturing-execution-systems-products/oee-factory-information-systems/

An article that can be referenced manufacturing analytics: https://www.mckinsey.com/business-functions/operations/our-insights/manufacturing-analytics-unleashes-productivity-and-profitability

Appendix C: Sales and Marketing

Figure 9: Sales per month (left) and sales per quarter (right)

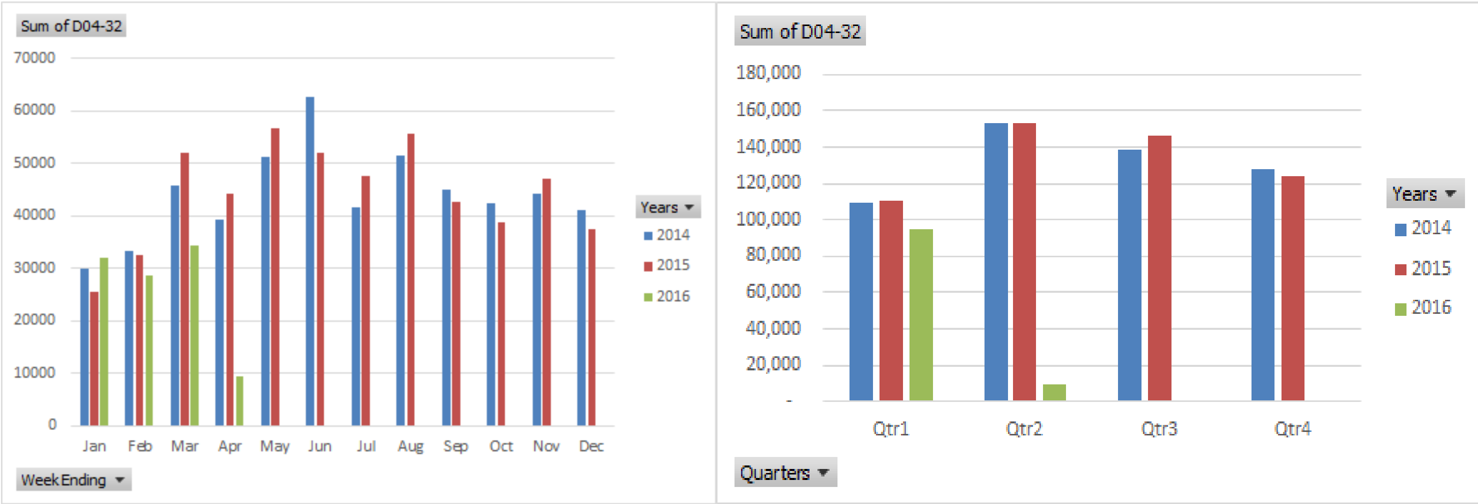


Figure 10: Increase in sale from promotion vs number of doors sold

Number of Doors Sold	Increase in Sale from Promotion										
	20%	**21%**	**22%**	**23%**	**24%**	**25%**	**26%**	**27%**	**28%**	**29%**	**30%**
10	-60	-53	-46	-39	-32	-25	-18	-11	-4	3	10
20	-120	-106	-92	-78	-64	-50	-36	-22	-8	6	20
30	-180	-159	-138	-117	-96	-75	-54	-33	-12	9	30
40	-240	-212	-184	-156	-128	-100	-72	-44	-16	12	40
50	-300	-265	-230	-195	-160	-125	-90	-55	-20	15	50
60	-360	-318	-276	-234	-192	-150	-108	-66	-24	18	60
70	-420	-371	-322	-273	-224	-175	-126	-77	-28	21	70
80	-480	-424	-368	-312	-256	-200	-144	-88	-32	24	80
90	-540	-477	-414	-351	-288	-225	-162	-99	-36	27	90
100	-600	-530	-460	-390	-320	-250	-180	-110	-40	30	100
110	-660	-583	-506	-429	-352	-275	-198	-121	-44	33	110
120	-720	-636	-552	-468	-384	-300	-216	-132	-48	36	120
130	-780	-689	-598	-507	-416	-325	-234	-143	-52	39	130
140	-840	-742	-644	-546	-448	-350	-252	-154	-56	42	140
150	-900	-795	-690	-585	-480	-375	-270	-165	-60	45	150

Figure 11: Analytical test of the D04-32 sales (with seasonality)

Promotion took place between 2015-03-01 and 2015-04-30. Sales data are track on a weekly basis, as a result of this there are data points with promotinal and non promotional sales. Those data points will be excluded from the promotion period

H1: If promotion weekly sale is greater > non promotion weekly sale then sale is working
H1: Promotion Sale > Weekly Sale
H0: Promotion Sale <= Weekly Sale

Since promotion is costly we will need an high degree of confidence to reject. Alpha = 1%
P Value > Alpha, fail to reject Null Hypotheis

t-Test: Two-Sample Assuming Equal Variances

	Promotion Period	*Non Promotion Period*
Mean	10,869	9,811
Variance	432866.8571	4369558.273
Observations	8	110
Pooled Variance	4131999.308	
Hypothesized Mean Difference	0	
df	116	
t Stat	1.4218666	
P(T<=t) one-tail	7.9%	
t Critical one-tail	1.658095744	
P(T<=t) two-tail	0.157748144	
t Critical two-tail	1.980626002	

Figure 12: Analytical test of the D04-32 sales (with seasonality removed)

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	10869	10578.81928
Variance	432866.8571	2763224.979
Observations	8	83
Pooled Variance	2579938.385	
Hypothesized Mean Difference	0	
df	89	
t Stat	0.488008329	
P(T<=t) one-tail	0.313372028	
t Critical one-tail	1.662155326	
P(T<=t) two-tail	0.626744056	
t Critical two-tail	1.9869787	

Using the graphs from Figure 1, we see that January and February are outliers in the sample. Another T-test was done by excluding the outlier, and the results of the thet test was the same.

Figure 13: Analytical test of the A05-003 sales

t-Test: Two-Sample Assuming Equal Variances		
	Promotion Period	*Non Promotion Period*
Mean	6180.625	5883.681818
Variance	163601.6964	1149895.136
Observations	8	110
Pooled Variance	1090377.429	
Hypothesized Mean Difference	0	
df	116	
t Stat	0.776578323	
P(T<=t) one-tail	21.9%	
t Critical one-tail	1.658095744	
P(T<=t) two-tail	0.438988233	
t Critical two-tail	1.980626002	

Appendix D: Logistics and Distribution

Figure 14: Demand equation model

	Y	X_1	X_2	X_3	X_4	X_5
Demand	**8,148.22**	**-5.51**	**-781.59**	**1,441.36**	**2,781.54**	**4,427.84**

Y= Based demand
X_1= Weekly adjustment factor
X_2= Low Seasonality adjustment factor
X_3= Medium-Low Seasonality adjustment factor
X_4= Medium-High Seasonality adjustment factor
X_5= High Seasonality adjustment factor

Figure 15: Demand regression analysis

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.9007
R Square	**0.8113**
Adjusted R Square	**0.8029**
Standard Error	789.82
Observations	118.00

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5.00	300,452,906.82	60,090,581.36	96.33	0.00
Residual	112.00	69,866,539.52	623,808.39		
Total	117.00	370,319,446.34			

		Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Y_1	Intercept	8,148.22	425.73	19.14	0.0000	7,304.70	8,991.75	7,304.70	8,991.75
X_1	Week of the Year	-5.51	2.16	-2.56	0.0119	-9.79	-1.24	-9.79	-1.24
X_2	Low	-781.59	438.38	-1.78	0.0773	-1,650.18	87.00	-1,650.18	87.00
X_3	Medium Low	1,441.36	416.74	3.46	0.0008	615.65	2,267.08	615.65	2,267.08
X_4	Medium High	2,781.54	414.26	6.71	0.0000	1,960.74	3,602.33	1,960.74	3,602.33
X_5	High	4,427.84	441.09	10.04	0.0000	3,553.88	5,301.80	3,553.88	5,301.80

By analyzing the regression model output, (which has resulted in the new demand equation model) we are able to conclude that 80% (Adjusted R Square) of the total demand variability is derive by the 4 seasonality variables. In addition, the model has proved its fit given the that the Significance F is equal to “0” and fit is 96%.

Figure 16: Predicted savings with new forecasting model

Total Cost	Multiple Regression Forecats	Variance	Holding Cost vs. Back order $15 vs. $45
39,000	6,788	-478	7,163
14,220	7,564	-2,080	31,195
76,290	6,777	799	35,976
105,600	8,994	-419	6,285
62,340	6,766	390	17,572
33,060	7,542	-1,340	20,094
26,910	6,754	-192	2,887
14,850	6,749	-24	359
61,680	8,966	-115	1,731
34,290	8,961	-458	6,868
52,410	8,955	282	12,673
54,030	8,950	384	17,286
40,920	8,944	40	1,785
34,110	8,939	78	3,518
$7,032,150	1,155,470	- 0	$1,656,764
Savings of			-$5,375,386

An article that can be consulted for future AI and Machine Learning implementation for Logistics and Distribution: https://www.logistics.dhl/content/dam/dhl/global/core/documents/pdf/glo-artificial-intelligence-in-logistics-trend-report.pdf