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Product Attributes Affected Manufacturing KPI to have Better Control of Quality: A Further Case Study of a 500-Workers Sheet Metal Manufacturer in China

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Key Performance Indicators (KPIs) is identified to monitor the organization's performance and strategic alignment. The choice of what should be the proper KPIs has quickly become a major field of study in recent years. All of these are either technically too complicated for most staff, while they carry out their usual daily duties, or are too administratively delayed in the sense that data (or the KPIs) have to be separately collected, slowly gathered, and collectively analyzed before they would turn into information that is meaningful to the top management. This paper is a study of manufacturing standard KPIs and product attributes to see if there is any correlation between them. Research data had been collected from a medium-size, traditional 500-worker sheet metal manufacturer located in China, in a period of over 9 months (including 98 shipments, each shipment had around 250,000 pieces of products)[1]. Using various analyses tools such as t-tests and k-means clustering,[2] factor analysis, linear regression and logistic regression were performed for data analysis to assess the effect of different combinations of product attributes (size, complexity - no. of production steps involved no. of manpower and no. of stamping

[1] Best Ideal Limited, a Hong Kong based private partnership limited, established in 1993; it is an ISO9001:2008, ISO14001:2004, and ISO 13485:2003 certified metal works factory, employed 500 workers with a factory floor area of over 400,000 square feet, located in Dongguan City in southern province of Guangdong, China. The company has received various international awards from customers. For details, see http://www.bestideal.com/

[2] k-means clustering analysis and further analysis already indicated in the paper "HOW PRODUCT ATTRIBUTES AFFECT KPI: A CASE STUDY OF A 500-WORKER METAL STAMPING FACTORY IN CHINA" (Cheng, Li, 2016)

machines, model types – New vs. Old models) to standard KPIs, like defect rate, yield loss, productivity, worker efficiency and etc. The analysis results showed only standard KPIs itself was just a performance measurement without helping the manufacturing business to make a profit. However, using product attributes together with KPIs, these could forecast the defect rate and yield loss. This helped Sales and Marketing to strategically target types of orders from customers, finally enhancing the organizational profit.

Key words: *Key Performance Indicator, Product Attributes.*

Introduction

Whenever it comes to managing manufacturing quality, many companies choose to implement their quality management systems through KPIs. In fact, KPIs can be identified from within both financial and non-financial factors to be used, procedurally or quantitatively (Jalote, et al., 2000), to help manage quality within the various areas of sales and marketing, procurement, production, and even in human resources (Service Now, 2016).

According to the Manufacturing Enterprise Solutions Association (MESA) (Davidson, 2013), the most common 28 manufacturing KPIs used to help manage quality of a manufacturing business fall within 8 core areas of factors, namely,
(a) improving customer responsiveness;
(b) improving quality;
(c) improving efficiency;
(d) reducing inventory;
(e) ensuring compliance;
(f) reducing maintenance;
(g) increasing innovation; and
(h) reducing costs.

Yet, in the case of the relatively low profit-margin, low-quantity e.g. order with few hundred pieces of products, urgent delivery schedule, and with labour shortage for sheet metal manufacturing businesses, using KPIs quantitatively for quality control can be inaccurate, because with small product batches, it would be mathematically impossible to arrive at anything statistically meaningful when sampling sizes are too small to justify statistical significance. This might explain why out of the latest 189 peer-reviewed SCI/ESCI/SCOPUS journal papers found related to the implementation of KPIs, only about 35 (or some 18.5%) of them dealt with manufacturing industries and the rest are about service industries (EBSCO Industries [EBSCO], Inc, 2016).

While less than 20% of the studies are about manufacturing, studies that are described are of businesses that are big enough to have their own customized KPI systems to help monitor or measure their manufacturing processes (as in statistical process control, i.e. SPC). No matter what kind of KPIs are collected in these studies, the characteristics of the product (i.e. the product attributes) are rarely considered as factors because of the need for generalization with generic models.

This research attempts to look at product attributes to see if they can help provide insights or constitute some kind of a “look-ahead mechanism” that might help foresee defect rates in the metal stamping production business. Besides looking at the product attributes, other traditional KPIs, including purchasing period, inventory level, yield loss, productivity and manpower allocation, will be studied to see if these could provide such insights. So, the research questions are as follows:

Research Question 1: *Could traditional KPI explain defect rate and yield loss?*
Research Question 2 : *Could the product attributes explain and forecast the defect rate and further yield loss?*

Literature Review

Typical metal manufacturing processes are shown in Figures 1 & 2 below.

Figure 1. Metal Manufacturing Processes

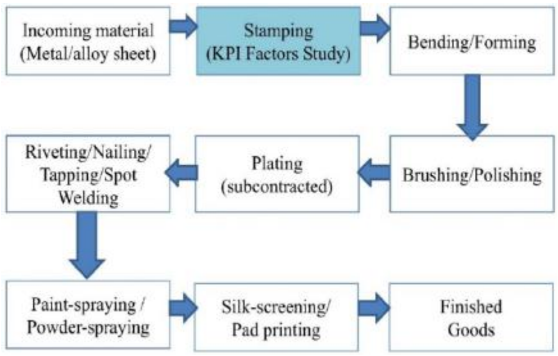
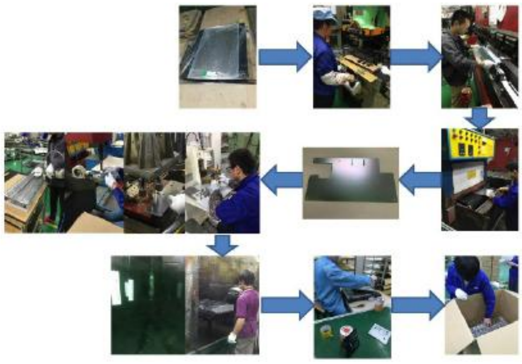


Figure 2. Metal Manufacturing Processes Photos



A Key Performance Indicator (KPI) is a performance measurement of an activity that is critical to the success of an organization (Construction Excellence Limited, 2015). Most organizations compete against each other to control operation costs, to increase profitability and to meet stakeholder expectations. The business success is commonly achieved by a measurement of both financial and non-financial gains of the organization. Many organizations use KPI as a performance measurement tool to evaluate the effectiveness and efficiency of the organization in certain key fields. Those areas of measurement vary from one organization to another. A product-based organization will have KPIs related to product quality, price and production cost while a service-based organization might emphasize on customer satisfaction KPIs.

Methodology

The research study involved 98 shipments of approximately 250,000 pieces of finished metal work products, mainly in the metal stamping process. The defect rate, productivity, overall equipment effectiveness (OEE), worker efficiency, and yield loss in these product batches were computed and recorded. These were then compared, using the t-test, factor analysis, k-means clustering and further anaysis linear regression and logistic regression were analyzed to see how different combination of product attributes could affect the resulting KPIs.

Findings and Discussions

It had the following linear regression analysis to compare the defect rate, productivity, OEE and yield loss with manufacturing KPIs (Jan, & Shieh, 2019; Su, & Yan, 2009). The results were shown as follows:

Table 1 : Linear Regression - Defect Rate

Model Summary (defect_rate)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.56	.32	.27	3.51

ANOVA (defect_rate)

	Sum of Squares	df	Mean Square	F	Sig.
Regression	521.84	6	86.97	7.04	.000
Residual	1124.13	91	12.35		
Total	1645.97	97			

Coefficients (defect_rate)

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	-1.48	6.67	.00	-.22	.825
order_qty	.00	.00	-.14	-1.59	.116
purchasing_period	.11	.02	.51	4.66	.000
worker_efficiency	.05	.08	.06	.70	.487
finished_goods_inventory	.00	.00	.14	.97	.336
incoming_material_inventory	.00	.00	-.30	-1.97	.052
no_of_workers_needed	-.50	.22	-.22	-2.29	.024

Table 2 : Linear Regression - Productivity

Model Summary (productivity)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.13	.02	-.05	5.87

ANOVA (productivity)

	Sum of Squares	df	Mean Square	F	Sig.
Regression	50.10	6	8.35	.24	.961
Residual	3135.11	91	34.45		
Total	3185.21	97			

Coefficients (productivity)

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	96.42	11.14	.00	8.65	.000
order_qty	.00	.00	.04	.37	.712
purchasing_period	.02	.04	.08	.62	.540
worker_efficiency	-.05	.13	-.05	-.42	.673
finished_goods_inventory	.00	.00	-.02	-.12	.901
incoming_material_inventory	.00	.00	-.04	-.23	.820
no_of_workers_needed	-.26	.37	-.08	-.70	.488

Table 3 : Linear Regression - OEE

Model Summary (oee)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.36	.13	.07	9.97

ANOVA (oee)

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1328.51	6	221.42	2.23	.047
Residual	9049.37	91	99.44		
Total	10377.88	97			

Coefficients (oee)

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	63.92	18.93	.00	3.38	.001
order_qty	.00	.00	.11	1.06	.290
purchasing_period	-.07	.07	-.12	-1.01	.315
worker_efficiency	.30	.22	.15	1.41	.161
finished_goods_inventory	.00	.00	.14	.90	.372
incoming_material_inventory	.00	.00	-.27	-1.54	.127
no_of_workers_needed	.82	.62	.14	1.32	.190

Table 4 : Linear Regression - Yield Loss

Model Summary (yield_loss)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.36	.13	.07	15.55

ANOVA (yield_loss)

	Sum of Squares	df	Mean Square	F	Sig.
Regression	3252.89	6	542.15	2.24	.046
Residual	22002.10	91	241.78		
Total	25254.99	97			

Coefficients (yield_loss)

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	24.32	29.52	.00	.82	.412
order_qty	.00	.00	-.01	-.09	.932
purchasing_period	.34	.10	.40	3.25	.002
worker_efficiency	-.13	.34	-.04	-.37	.709
finished_goods_inventory	.00	.00	-.10	-.64	.522
incoming_material_inventory	.00	.00	-.10	-.55	.585
no_of_workers_needed	-.53	.97	-.06	-.54	.589

The above results indicated that as the table 1 defect rate was the dependent variable with a regression coefficient of R=0.56 (p< 0.000), statistically significant, the factors purchasing period (p<0.000) and the number of workers needed (p<0.024) were significant.

Also, as the table 4 yield loss was the dependent variable with a regression coefficient of R=0.36 ($p < 0.046$), statistically significant, the factor, purchasing period ($p<0.002$), was significant. As the table 2 productivity and table 3 OEE were the dependent variables, there were not any factors statistically significant.

On Research Question 1: Could traditional KPI explain defect rate and yield loss?

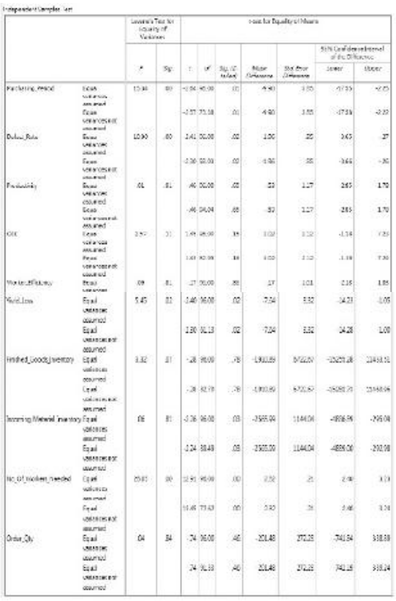
From above results, traditional, standard KPIs used by the manufacturing industries, like productivity, worker efficiency, or inventory, etc., could not explain and forecast, with statistical significance, or the defect rate and yield loss.

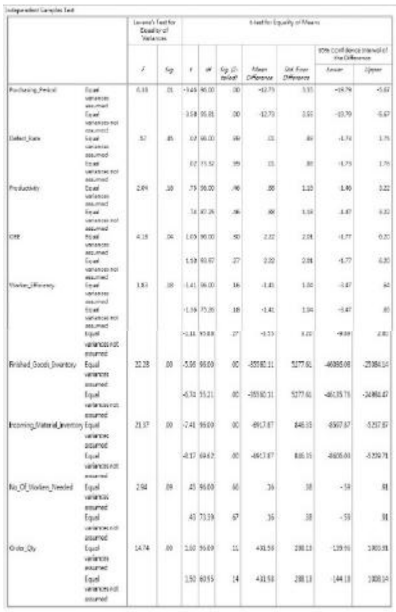
While regression did not yield any significant relationships between the various KPIs and defect rates or yield losses, a series of t-tests and other analyses reviewed something different.

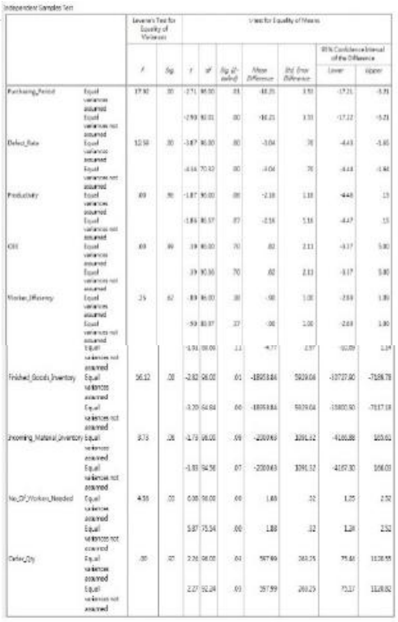
Further on Research Question 2: Could the product attributes explain and forecast the defect rate and further yield loss?

As KPI data was analyzed again through t-test, set alpha α level as 0.05 and the results for types of items[4] were as shown in the following tables 5-7 below:

Table 5: T-Test–Type I Items **Table 6:** T-Test–Type II Items **Table 7:** T-Test–Type III Items







Above t-test results of three types of items[4] have been summarised in table 8.

Table 8 : A Summary for Three Types Of Items and Their Significantly Different KPI Factors Relationship

KPI Factors / Type of Items	Purchasing Period	Defect Rate	Productivity	OEE	Worker Efficiency	Yield Loss	FG Inventory	Incom Mat'l Inventory	No Of Workers Needed	Order Qty
I - More Prd Step & Less Prd Step	S	S				S				
II - Large Size & Small Size	S						S	S		
III - New Model & Old Model	S	S				S	S			

Remarks: S = Significantly Different

It was found that each type of items had significant differences existing for KPI factors or order quantities, namely as follows:

- Type I[4] (complexity) Item, had significant difference in the KPI factors of raw material purchasing period, defect rate and yield loss.
- Type II[4] (size) Item, had significant difference in the KPI factor of purchasing period, finished goods inventory and incoming material inventory.
- Type III[4] (model) Item, had significant difference in the KPI factors of purchasing period, defect rate, yield loss and finished goods inventory.

[4] Type I (complexity) = More/Less-Production-Step, Type II (size) = Large/Small-Size, Type III (model) = New/Old-Model

To improve the interpretability of factors through axis rotation, the orthogonal rotation was carried out by varimax in PSPP (see tables 9-14).

Table 9 : Total Variance

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.35	25.76	25.76	3.35	25.76	25.76	2.14	16.43	16.43
2	2.24	17.27	43.03	2.24	17.27	43.03	2.63	20.24	36.66
3	1.27	9.80	52.83	1.27	9.80	52.83	.17	1.28	37.94
4	1.21	9.30	62.13	1.21	9.30	62.13	.16	1.21	39.15
5	1.03	7.93	70.05	1.03	7.93	70.05	.22	1.69	40.84
6	1.01	7.76	77.82	1.01	7.76	77.82	1.09	8.41	49.25
7	.88	6.73	84.55						
8	.74	5.68	90.23						
9	.46	3.55	93.77						
10	.33	2.57	96.34						
11	.19	1.49	97.83						
12	.15	1.15	98.98						
13	.13	1.02	100.00						

Table 9 indicates the Eigen-values in terms of the percentage of variance explained. Components 1-6 got through the extraction sums of squared loadings and rotation sums of squared loadings.

Before & After Rotation, tables 10 -11 below were shown

Table 10 : Component Matrix

Component Matrix

	Component					
	1	2	3	4	5	6
Item_Prd_Step	-.62	.46	-.19	-.17	.07	.02
Item_Size	.50	.51	-.10	-.02	-.21	-.14
Item_Model	.59	-.41	-.14	.05	-.14	.15
PUR_PRD_Period1	.76	.16	.02	-.02	-.09	.26
Defect_Rate1	.55	-.35	-.01	.04	-.01	-.40
Productivity	.07	-.18	.03	.01	.01	-.12
OEE	-.31	.11	.00	.00	.05	-.07
Worker_Efficiency	.24	.34	.01	-.04	.02	.01
Yield_Loss	.38	-.27	.00	-.04	.07	.18
Finished_Goods_Inventory	.60	.63	.19	-.16	.01	-.05
Incoming_Matl_Inventory	.71	.58	-.11	.17	.27	-.01
No_Of_Workers_Needed	-.58	.62	.08	.24	-.14	.06
Order_Qty1	-.06	.32	-.10	-.05	-.12	-.09

Table 11 : Rotated Component Matrix

Rotated Component Matrix

	Component					
	1	2	3	4	5	6
R_Item_Prd_Step	-.61	-.05	-.21	.04	.17	-.47
R_Item_Size	.07	.69	.07	.00	.31	.06
R_Item_Model	.71	.02	.03	.07	.08	.26
R_PUR_PRD_Period1	.59	.57	.06	-.03	.01	-.01
R_Defect_Rate1	.32	.13	.00	.05	.03	.67
R_Productivity	.06	-.07	.00	-.01	-.02	.21
R_OEE	-.30	-.10	-.02	.01	.00	-.10
R_Worker_Efficiency	.00	.41	-.01	.00	.03	-.07
R_Yield_Loss	.47	.03	-.07	.01	-.12	.11
R_Finished_Goods_Inven	.07	.88	-.01	-.18	-.01	-.01
R_Incoming_Matl_Inven	.17	.90	.00	.34	-.09	.02
R_No_Of_Workers_Needed	-.64	.07	.33	.02	.11	-.51
R_Order_Qty1	-.21	.20	.00	-.01	.22	-.11

Removing all components with loading magnitudes < 0.4, tables 12-13 below were shown

Table 12 : Component Matrix

Component Matrix

	Component					
	1	2	3	4	5	6
Item_Prd_Step	-.62	.46				
Item_Size	.50	.51				
Item_Model	.59	-.41				
PUR_PRD_Period1	.76					
Defect_Rate1	.55					-.40
Productivity						
OEE						
Worker_Efficiency						
Yield_Loss						
Finished_Goods_Inventory	.60	.63				
Incoming_Matl_Inventory	.71	.58				
No_Of_Workers_Needed	-.58	.62				
Order_Qty1						

Table 13 : Rotated Component Matrix

Rotated Component Matrix

	Component					
	1	2	3	4	5	6
R_Item_Prd_Step	-.61					-.47
R_Item_Size		.69				
R_Item_Model	.71					
R_PUR_PRD_Period1	.59	.57				
R_Defect_Rate1						.67
R_Productivity						
R_OEE						
R_Worker_Efficiency		.41				
R_Yield_Loss	.47					
R_Finished_Goods_Inven		.88				
R_Incoming_Matl_Inven		.90				
R_No_Of_Workers_Needed	-.64					-.51
R_Order_Qty1						

Through the factor analysis, the following table 14 was to summarise the correlation among the product attributes, KPIs and order quantities, with components 1-6 re-labelling.

Table 14 : A Correlation Among Three Types of Items, KPI Factors & Order Qty

Factor Analysis for 98 items, rotated

KPI Factors / Component	More Prd Step & Less Prd Step	Large Size & Small Size	New Model & Old Model	Purchasing Period	Defect Rate	Productivity	OEE	Worker Efficiency	Yield Loss	FG Inventory	Incom Mat'l Inventory	No Of Workers Needed	Order Qty	Type Of Item Related
1	V		V	V					V			V		I - More Prd Step & Less Prd Step III - New Model & Old Model
2		V		V				V		V	V			II - Large Size & Small Size
3														I - More Prd Step & Less Prd Step II - Large Size & Small Size III - New Model & Old Model
4														I - More Prd Step & Less Prd Step II - Large Size & Small Size III - New Model & Old Model
5														I - More Prd Step & Less Prd Step II - Large Size & Small Size III - New Model & Old Model
6	V				V							V		I - More Prd Step & Less Prd Step

Complex, New products requiring time to learn

Big-sized products affecting finance (inventory) and man hours

Complex products requiring time to learn

Remarks: V = Variance

As referred to in table 14 above, component 1 had major variable loading in More/ Less-Production-Steps (complexity), New/ Old-Models, Purchasing Period and No. of Workers Needed and had minor variable loading in Yield Loss. Therefore, component 1 belonged to Type I item (complexity) and Type III item (model), i.e. complex and new products needed workers to take time to learn the manufacturing process.

Component 2 had major variable loading in Size, Purchasing Period, Finished Goods Inventory and Incoming Material Inventory and had minor variable loading in Worker Efficiency. Therefore, component 2 belonged to Type II item (size), i.e. big size products affected inventory levels and workers' production efficiency.

Components 3-5 with no factors included, had no major or minor variable loading in any factors. Components 3-5 were considered as Type I item (complexity), or Type II item (size), or Type III item (model).

Component 6 had minor variable loading in More/ Less-Production-Steps (complexity) and was considered to be Type I item (complexity) and Type III item (model), i.e. complex products needed workers to take time to learn.

Through t-test, factor analysis, further analyses and k-means clustering, the results indicated that the product attributes had a relationship with traditional KPIs to affect the defect rate and yield loss.

Aligning Research Results with Real-life Situation

The current manufacturing industry in Guangdong of China is facing a few critical problems. These critical problems can be arranged in two types: Type one is the internal problems happened in China whereas the Type two is the external problems affected by the global economy.

For the internal problems, manufacturing industries are facing labour shortages. As the local Chinese government implemented the land & pro-rural state policies in the 21st century, to attract people to stay in the villages to help rural development and to improve the economy in the hinterland provinces[5] (Zhan, & Huang, 2013), many workers have become unwilling to work in the manufacturing industries in Guangdong provinces.

Further, the Chinese government implemented the One-Child Policy in 1979/1980 which has caused national social problems e.g. a demographic imbalance ratio of population between the old aged and young aged i.e. the number of young people is less than the number of old people, an imbalance ratio of gender between male and female i.e. the number of boys born are more than the number of girls because of preferred boys. Also, the current population is aging and the society has a higher percentage of old people than the percentage of young people (Zhan, 2009). As manufacturing industries prefer to employ the young female labours instead of the old male labours (Dai, & Jiang, 2018; Robert, 2004), the above reasons have caused serious a shortage of young female labour for the manufacturing industries. The Chinese government with the hukou system controlled the flow of rural migrants to cities. This also contributes to the labour shortage in Guangdong provinces (Zhan, & Huang, 2013).

For the external problems, the global world economy has experienced uncertainty and declines in recent years, especially with Brexit in 2016, and a Trade War happening between the US and China. As a result, the global economy as well as the customers' orders for manufacturing factories has been affected and economic activity has dropped.

With these internal problems (labour shortage) and external problems (economic downturn and low customer orders with low profit margin), some manufacturing industries have been shut down or moving to the other East South Asia countries such as Thailand, Malaysia, Vietnam, and others. The rest, like the metal manufacturing factory in this research study, strive to find opportunities to keep running their businesses. Therefore, some factories start to install robot arms or other automation machines to set up an automated production system so as to save on the cost of labour, reduce defects and yield loss, streamline their production processes and to increase productivity; mainly to make profit (Karabegovic, Karabegovic, & Hadzalic, 2012).

So, the metal manufacturing factory in this research has installed a set of industrial robots (articulated robots) alongside stamping machines to implement an automated stamping processes, involving limited labour (Karabegovič, Karabegovič, & Husak, 2012; World Robotics, 2018). Figure 3 shows the articulated robots installed alongside the stamping machines.

[5] "hinterland provinces" refers to the central and western regions in the mainland China.

Figure 3. Articulated Robots Installation Along with the Stamping Machines Line

Implications of the Study

After above a series of test and analyses, the product attributes and manufacturing KPIs have been proved for their correlation/ significance in the research framework. There is a next process to prove the research framework is applicable and workable for the real-life situations. Therefore, this study has carried out a logistic regression to show how the research framework works (Cox & Snell, 1989) (Table 15)

Table 15: Logistic Regression of "Acceptable Defects" (as a Flag) with Item Size / Model / Prod_Steps

Dependent Variable Encoding

Original Value	Internal Value
.00	0
1.00	1

Case Processing Summary

Unweighted Cases	N	Percent
Included in Analysis	98	100.00
Missing Cases	0	.00
Total	98	100.00

Model Summary

Step 1	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
	94.79	.28	.38

Classification Table

			Predicted defect_flag .00	Predicted defect_flag 1.00	Percentage Correct
Observed					
Step 1	defect_flag	.00	16	18	47.06
		1.00	9	55	85.94
	Overall Percentage				72.45

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	item_size	1.47	.55	7.20	1	.007	4.34
	item_model	3.27	.76	18.63	1	.000	26.35
	item_prd_step	1.60	.72	4.95	1	.026	4.96
	Constant	-2.60	.83	9.80	1	.002	.07

After a logistic regression analysis is used to test the tendency of how the product attributes affect the defect rate and the customers possibly accept the defect rate, the results in table 15 show that there is a significant effect between a tendency of the product attributes (complexity, size and model) causing the defect rate and the customers possibility of accepting the defect rate. This means that the customers do not tend to reject the shipments with defect items. As a result, this will then increase the sheet metal manufacturing companies, factories and businesses' profit.

As further testing the variables in the equation shown in table 15 by, the researcher has inserted a different combination of product attributes, there are testing result shown in table 16.

Table 16 : Different Combination of Product Attributes with Different Results by Using the Variables in the Equation.

Defect Flag = (Item _Size*1.47) + (Item_Model*3.27) + (Item_Prd_Step*1.60) – 2.60					
Items Combination					
Item_Size	Item_Model	Item_Prd_Step	=	Result	Significant?
0	0	0	=	-2.6	No
0	0	1	=	-1	No
0	1	0	=	0.67	Yes
0	1	1	=	2.27	No
1	0	0	=	-1.13	No
1	0	1	=	0.47	Yes
1	1	0	=	2.14	No
1	1	1	=	3.74	No

The above testing on the variables in the equation is done to prove and to further apply the research framework to a real situation (Menard, 2002).

The testing result by using the variables in the equation shows that there are significant differences : 0.67 in the combination of product attribute "model" and 0.47 in the combination of product attributes "size and complexity".

Therefore, this research has performed further statistical study in table 17 to find out how the probability that the different combinations of product attributes can cause the different levels of defect rate in order to find out which levels of defect rate the customers can tolerate to accept the shipment lots without any rejection.

Table 17 : The Different Level of Defect Rate Against the Different Combinations of the Product Attributes

Defining low defects?	Cox & Snell R^2	Nag R^2	What's significant? ($p<.05$)		
			Item Size?	Model?	Step?
0-0.5	.19	.28	☑	☑	☐
0-0.6	.21	.30	☑	☑	☐
0-0.625	.25	.35	☑	☑	☑
0-0.65	.25	.35	☑	☑	☑
0-0.675	.28	.38	☑	☑	☑
0-0.68	.28	.38	☑	☑	☑
0-0.7	.28	.38	☑	☑	☑
0-0.725	.26	.35	☑	☑	☑
0-0.75	.26	.35	☐	☑	☑
0-0.8	.19	.25	☐	☑	☑
0-0.9	.20	.27	☐	☑	☑
0-1	.21	.28	☐	☑	☑
0-1.1	.21	.28	☐	☑	☑
0-1.2	.21	.29	☐	☑	☑
0-1.3	.25	.33	☐	☑	☐
0-1.4	.26	.34	☐	☑	☐
0-1.5	.24	.31	☐	☑	☐

From table 17, it shows that there are different varieties of combination of product attributes, Cox & Snell R-Square & Nag R-Square values, and the defect rate level that customers can tolerate to accept the corresponding shipment lots. As the Cox & Snell R-Square 0.28 and the Nag R-Square 0.38 are the highest values of percentages among others, the corresponding combinations of product attributes are the best combination of complexity, size and model, and the corresponding range of defect rate level is from 0-0.675 to 0-0.7 which proves that customers can tolerate and accept the corresponding shipment lots within this range of defect rate. The research framework is workable and functional in a real situation.

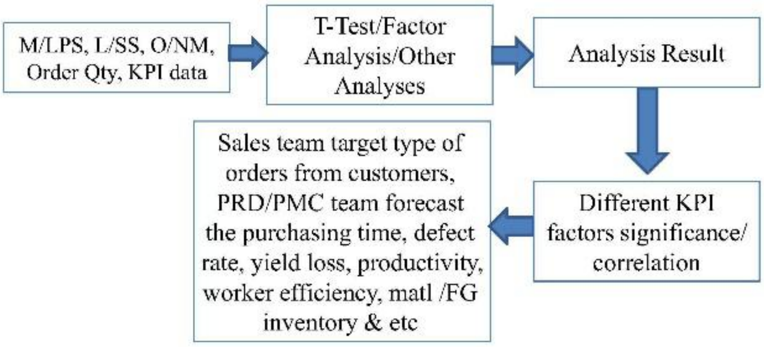
Based on the above research study results, similar sheet metal manufacturing factories with ISO certified systems can adopt this research framework with product attributes & KPIs concept in their production & operation to target the orders with controlling low defect rates and then yield losses, to improve productivity, to control low finished goods inventory or incoming material inventory, to reduce shipment delay and finally to get their business in a competitive situation.

Sales and marketing teams, based on above analyses, can forecast and target which orders from customers, are best for the factory to make; and take order which support more profit and easy production, easy material purchasing, less defect rate and yield loss.

The production Team can estimate and minimize the defect rate, yield loss for customer orders provided from the Sales team so as to complete the production on time with lower costs.

PMC can carefully manipulate those significant KPI factors such as lead time for the incoming material purchasing from suppliers, incoming material inventory supported for production and finished goods inventory controlled to meet on-time-delivery, without causing any dead stock. A summary of the implications are shown in Figure 4.

Figure 4. Analysis Result Processes



Conceptually, this means defects are no longer something controlled by the production line people but rather, the sales and marketing people are the ones who truly control defects and then yield loss.

Conclusions of the Study

As the manufacturing industries are mostly influenced by above internal and external problems, this research study has practical and factual results which can help the manufacturing industries in China to make profit and keep running their businesses.

Practically speaking, as the sales and marketing can forecast customer orders with certain amounts of profit margin i.e. the product attributes (complexity, size and models) with KPIs, the production team can consider the new KPIs to have better control of the quality of products/ items, to reduce the defect rate and yield loss of the overall production. While PMC can use these forecasting customer orders to predict the purchasing materials and have better control of both incoming material and finished goods inventory.

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