DATA ANALYTICS THROUGH AUTOMATED Z-SCORE DIAGNOSTIC

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ABSTRACT

The utilization of automated data analytics in analyzing data in the manufacturing process of Balance Armature (BA) drivers is crucial for managing the data from the manufacturing processes efficiently. Manual handling of rapidly growing data may result in errors and delays, which makes data automation a practical solution that streamlines processes, improves accuracy and saves time.

The current complex setup and manufacturing flow of Knowles Electronics Philippines for balanced armatures pose challenges in conventional manual data analytics due to data inaccuracy and longer lead times for problem-solving.

This paper tackles how the Automated Diagnostic Tool Z-score feature in the data analytics framework of Knowles was developed and utilized to aid the engineers and line owners to hasten the analysis process of quality issues. Through this tool, the target users were able to quickly diagnose and analyze the reject issues by identifying the man, machine, and material contribution with the highest z-score value which led to the swift development of countermeasures to address the manufacturing concerns.

1.0 INTRODUCTION

1.1 Background of the Study

The Balanced Armature (BA) drivers[1] produced by Knowles Electronics Philippines operate on the principle of electromagnetic induction, converting electrical signals into sound waves.

These transducers function by using an electronic signal to create a varying magnetic field in a coil, causing a balanced armature (reed) to vibrate between two magnets. The motion of the balanced armature is then transmitted to a rigid aluminum diaphragm through a small drive rod, ultimately producing the sound waves that are heard by the user. Refer to the internal construction of a Balanced Armature (BA) driver in Figure 1.

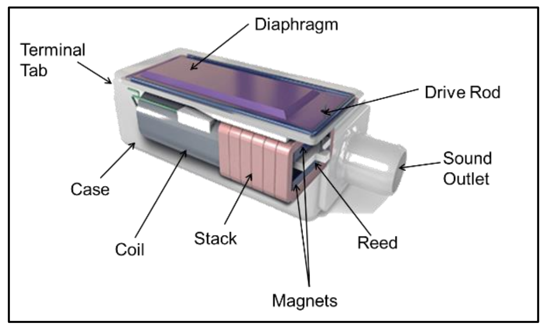

Fig 1. Knowles Balanced Armature (BA) Construction

The BA manufacturing of Knowles Electronics involves manual operator handling (MAN), also utilizing various equipment (MACHINE) and with key input of BA components and sub-assemblies (MATERIAL) (refer to Figure 2). These are considered to be key factors in the production of balanced armatures. Each of these factors contributes to a large amount of data that needs to be processed manually.

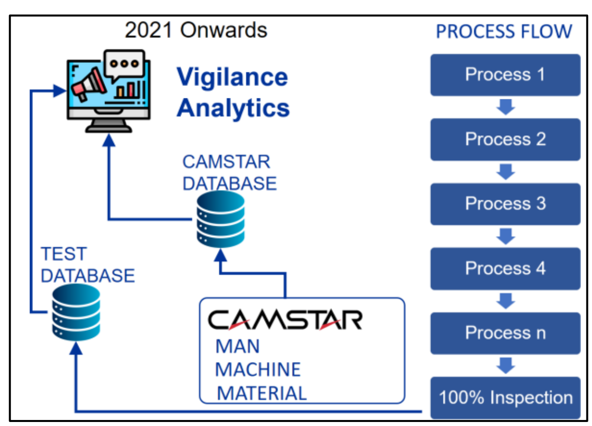

Fig 2. Knowles BA Manufacturing Process Flow.

In 2021, Knowles Electronics started the development of the Vigilance Analytics (VA) System which ventured toward automating the conventional manual data analytics. Features are continually being added to this VA System as shown in Figure 3.

Fig 3. Vigilance Analytics Feature Page

The previous project presented by the team during the 2023 ASEMEP National Technical Symposium entitled *"Failure Code Trigger and Multi-Level Scorecard for Yield Improvement using the Vigilance Analytics System*" tackled the use of the Failure Code Trigger and Multi-Level Scorecard features. The previous project aimed to improve the previous conventional method of manual data analytics.

The Failure Code Trigger provides an automated alert that an abnormal shift on a certain failure trend has occurred based on the Multiplication Rule Probability (MRP) concept (refer to Figure 4).

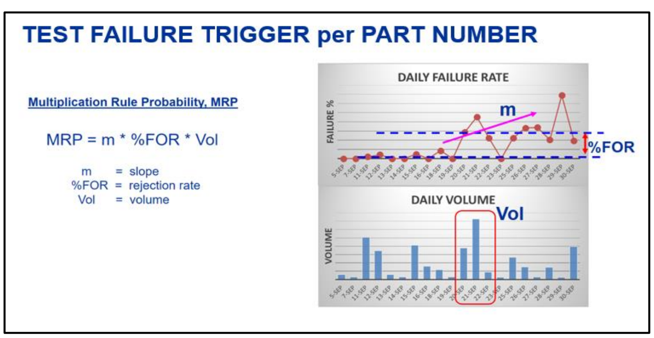

Fig 4. Test Failure Trigger Logic

On the other hand, the Multi-Level Scorecard as shown in Figure 5 identifies whether the contribution is coming from man, machine, or material.

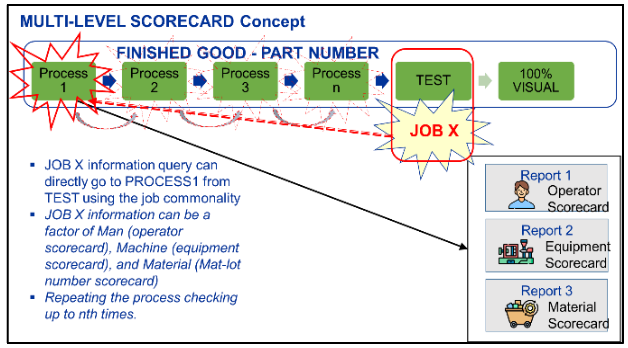

Fig 5. Multi-Level Scorecard Design

Although the enhancements have demonstrated results in hastening the analysis process, there were still some opportunities for improvement to continually improve the data analytics.

1.2 Statement of the Problem

The framework of the previous project involved multiple instances of running the Multi-Level scorecard per process. Manual scorecard trend interpretation per process at a time needs to be performed to obtain data from different factors (man, machine, material).

An engineer needs to check and validate the previous assembly processes from test processes **one by one** using the Multi-Level scorecard for man (operator scorecard), machine (equipment scorecard), and material (material mother lot scorecard and material part number scorecard). The detected failure code at test for JOB X is being brought back to previous process as illustrated in Figure 6.

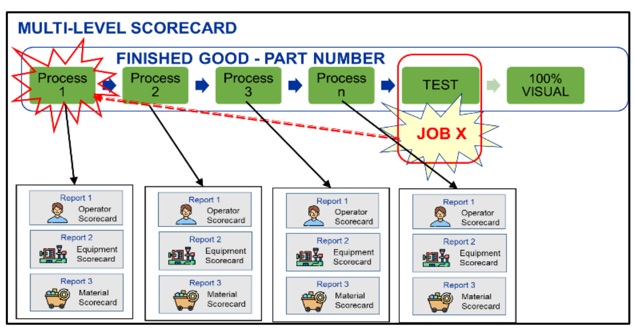

Fig 6. Existing Multi-Level Scorecard Concept

Running the Vigilance Analytics Multi-Level Scorecard Report per assembly process one at time then manually validating the daily trend from the change involves significant effort and time for an engineer to do the analysis. This process is very cumbersome wherein the procedure is repetitively performed on 10 to 15 assembly processes just to determine the right process mapping location suspected for man, machine, and material factors. The current state is reflected in Figure 7.

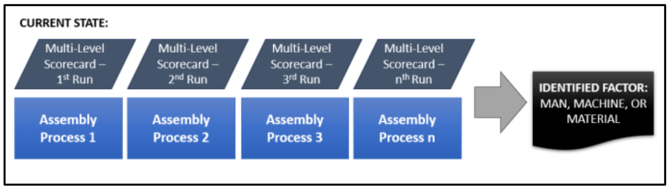

Fig 7. Current State – Multi-Level Scorecard Involving Multiple Runs

1.3 Objective of the Study

This study aims to present an automated solution to address the concerns in the existing data analytics using the Failure Code Trigger and Multi-Level Scorecard which led the team to develop another feature in the Vigilance Analytics System.

The feature would further expand the capability of the existing Failure Code Trigger and Multi-Level Scorecard feature.

The tool intends to provide the capability to automatically analyze multiple processes to answer - where (determine the specific process location) and who (identify the culprit of the issue whether man or machine) in a single run. The proposed conceptual framework can be seen in Figure 8.

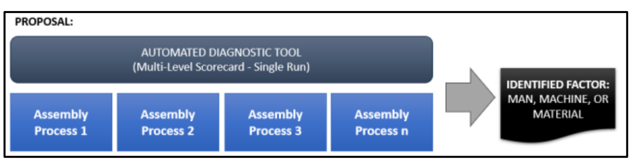

Fig 8. Conceptual Framework of the Automated Diagnostic Tool

2.0 REVIEW OF RELATED WORK

Not applicable.

3.0 METHODOLOGY

In this paper, the team adopted the PDCA (Plan, Do, Check, Act) Methodology which integrates the Software Development Life Cycle (Figure 9) to develop the automated tool in line with the objectives of the study.

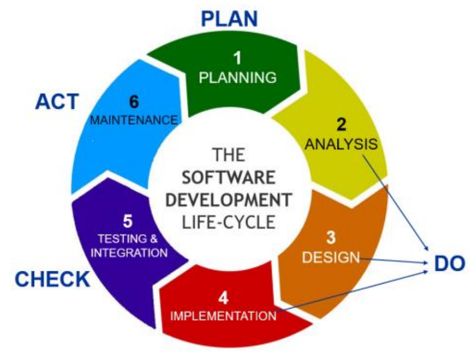

Fig 9. PDCA and Software Development Life Cycle

3.1 PDCA – Plan Phase

3.1.1 Planning

The planning phase of the Software Development Life Cycle sets the foundation for the entire development process. The team analyzed the requirements and determined if it was practically and technologically feasible to undertake the project.

Key milestones of the project involved the analysis of the problem, identification of solutions, review of the design, development execution, and testing of the solution at a small and large trial run before deployment to the line.

3.2 PDCA – Do Phase

3.2.1 Framework Analysis

The team made a comprehensive conceptual framework analysis as previously outlined in Figures 7 and 8. It can be seen that repetitively running the Multi-Level Scorecard analysis reports is needed to pinpoint the relevant factor (either man, machine, or material) that caused the shift in the data trend detected by the Failure Code Trigger. This can be streamlined by integrating the necessary reports into a single run through the development of an automated diagnostic tool.

3.2.2 Design

The design phase is a critical step and involves creating a detailed blueprint for the software solution. It considers the technical framework, components, and the system data flow.

3.2.2.1 Statistical Design: Adoption of Z-Score

The z-score measurement offers a quantitative representation of values relative to the mean, presenting a remedy to the deficiencies of preceding scorecard systems. This concept would need to be integrated to the Vigilance Analytics System which would then be referred to as the **Automated Z-score Diagnostic Tool.**

To interpret the data, if a z-score is 0, it is indicative that the point score is identical to the mean value. A z-score value of 1.0 indicates a value that is one standard deviation from the mean value. A z-score value may result in a positive or negative, where a positive value indicates it is above the mean, and a negative value indicates it is below the mean.

The statistical formula is; $Z = \frac{(x-\mu)}{\sigma}$

Where:
z = z-score
x = the value being evaluated
μ = the mean
σ = the standard deviation

Now in data analytics, the z-score is a statistical indicator that shows the variation of data sets from the rest of the datasets compared. It can best describe the normal distribution which shows the z-score value +1.0~+4.0 deviating on the positive score value while on the other side shows the -1.0~-4.0 deviating on the negative score value as shown in Figure 10.

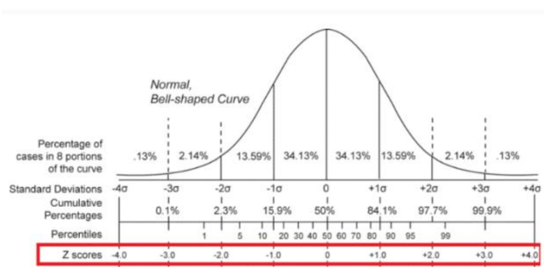

Fig 10. Normal Distribution Diagram for Z-score concept

The z-score was statistically designed to calculate the failure rate of reject failure code performance across the database with job level information that contained the processing date of the job, the operator information who transacted the lot at specified processes, the equipment used in lot processing, and the materials utilized. All this information will statistically be calculated using the designed z-score formula for a given date range. This will then likely identify the man, machine, and material factor contribution.

3.2.2.1.1 Z-Score Validation Through JMP Statistical Software

The team simulated the z-score calculation using the JMP statistical software tool) to establish confidence that the concept is effective in addressing the existing limitations of the existing data analytics. This explains (as shown in Figure 11) that the z-score value of OPERATOR A and EQUIPMENT A is the highest across all compared to other operators and equipment thus giving a hint as possible culprit of reject failure code B for Part Number Y. Using the Multi-Level Scorecard Report for Equipment and Operator, it is shown that the daily trend performance are comparably high reject rate trend compared to OPERATOR B and EQUIPMENT B.

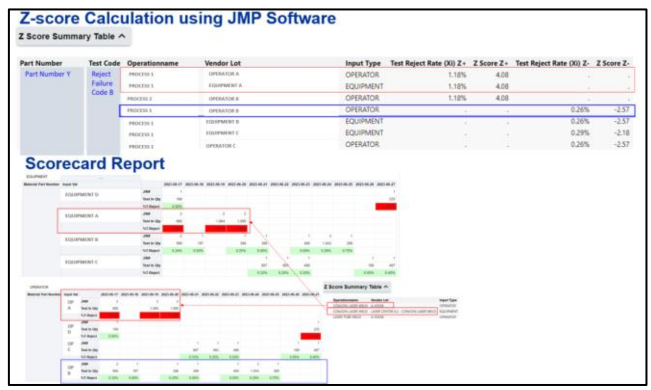

Fig 11. Z-score Calculation using JMP Software and Scorecard Report

3.2.2.2 Automated Z-Score Tool Design

With the validation of the results through the JMP Statistical Software, the team proceeded with the design and development of the z-score functionality in Vigilance Analytics System.

The user interface of the Automated Z-Score Diagnostic Tool is illustrated in Figure 12.

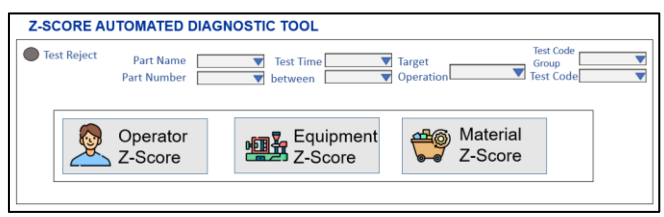

Fig 12. User Interface Design on Automated Z-Score Diagnostic Tool

As shown in Figure 13, the z-score table summary report defines the information on the material vendor lot, process operation name, test failure code, and part number.

Z-score Table Summary

Part Number	Test Code Failure	Operation Name (Process Name)	Vendor Lot	OPERATOR				MACHINE				MATERIAL			
				Test Reject Rate (HIGHEST)	Z Score Value (HIGHEST)	Test Reject Rate (LOWEST)	Z Score Value (LOWEST)	Test Reject Rate (HIGHEST)	Z Score Value (HIGHEST)	Test Reject Rate (LOWEST)	Z Score Value (LOWEST)	Test Reject Rate (HIGHEST)	Z Score Value (HIGHEST)	Test Reject Rate (LOWEST)	Z Score Value (LOWEST)
Part Number Y	Reject Failure Code B	PROCESS 1	A-0XXX	1.18%	4.08										
Part Number Y	Reject Failure Code B	PROCESS 2	MC-0XX					1.18%	4.08						
Part Number Y	Reject Failure Code B	PROCESS 3	MAT-0XXXXX									1.18%	4.08		
Part Number Y	Reject Failure Code B	PROCESS 1	A-0XXX			0.36%	-2.57								
Part Number Y	Reject Failure Code B	PROCESS 2	MC-0XX							0.36%	-2.57				
Part Number Y	Reject Failure Code B	PROCESS 3	MAT-0XXXXX											0.36%	-2.57

Fig 13. Z-Score Table Report Summary

Moreover, the percent cumulative contribution is summarized in another Z-score supplementary report (Figure 14). The lower the percent cumulative contribution would translate to a higher z-score rank. This report will aid the engineers which OPERATOR-EQUIPMENT-MATERIAL combination to be prioritized in the analysis.

Partition Location	Part Number	Input Type	Test Code	Operationname	Vendor Lot	Input Qty	Xbar	Test Reject Rate (HIGHEST)	Sigma	Z-Score Value (HIGHEST)	Cumm %	
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 9	OPERATOR B	148	0.000268817	0.006756757	0.001347533	4.814680765	17.57	RANK 1
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 1	OPERATOR C	842	0.000268817	0.002375297	0.000564955	3.728577650	23.65	RANK 2
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 2	OPERATOR D	447	0.000268817	0.002237136	0.000775383	2.538511568	27.79	RANK 3
KEP	PN ZZZ	EQUIPMENT	REJECT FAILURE CODE B	PROCESS 4	EQUIPMENT E	3600	0.000268817	0.000833333	0.000273224	2.066129051	31.16	
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 5	OPERATOR F	7911	0.000268817	0.000632031	0.000184312	1.970644677	34.37	
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 6	OPERATOR G	3798	0.000268817	0.000789889	0.000266007	1.958868269	37.56	
KEP	PN ZZZ	EQUIPMENT	REJECT FAILURE CODE B	PROCESS 7	EQUIPMENT H	3920	0.000268817	0.000765306	0.000261835	1.896192528	40.65	
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 8	OPERATOR I	3994	0.000268817	0.000751127	0.000259398	1.859343678	43.68	
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 10	OPERATOR J	2175	0.000268817	0.000919540	0.000351512	1.851209817	46.70	
KEP	PN ZZZ	OPERATOR	REJECT FAILURE CODE B	PROCESS 11	OPERATOR K	10738	0.000268817	0.000558763	0.000158201	1.832773521	49.69	

Fig 14. Z-Score Supplementary Table Report (% Cumulative)

In the interpretation of the results, **the highest z-score value is the most probable cause of the failure** code investigated for a given part number.

3.2.3 Implementation

Upon completion of the design and development of the conceptual design of the Automated Z-score Tool, the team proceeded to implement the tool in the testing development environment.

4.0 RESULTS AND DISCUSSION

4.1 PDCA – Check Phase

4.1.1 Testing

The Automated Z-Score Tool was subjected to the Test and Production User Acceptance Test. The check items and corresponding criteria are outlined in Table 1. Validating on these items would ensure the accuracy of the tool in terms of data matching and integrity; and guarantee speed and functionality by checking seamless data extraction.

Table 1. Test and Production User Acceptance Test Checklist and Results

#	CHECK ITEM	CRITERIA	RESULT
1	Test the functionality of the feature using a defined data set.	Should be aligned to the requirements submitted.	PASS
2	Test the accuracy of the result using a defined data set	Data results should be matched.	PASS
3	Check the capability of Download Data option	Charts and tables including raw data can be downloaded.	PASS
4	Check the speed in generating the report	Processing time should be less than 1 min.	PASS

The speed of data processing in terms of running the Automated Z-score Diagnostic Tool and generating the report was compared with the previous setup as shown in Table 2. Results revealed that the report can be generated in 0.5 minutes in contrast to 1 minute using the previous method. With an average of 15 processes being analyzed, it can be seen that there is **94% improvement** from 90 minutes to 5.5 minutes in terms of processing time which include both report generation and analysis.

Table 2. Automated Z-Score Lead Time Comparison

Comparison	Conditions	Average No. of Processes	Report Processing Time	Analysis Time	Total Time per Process	Total Time for all Processes	Improvement
BEFORE (Multi-level Scorecard + Analysis)	1. Single loading per process to MLSC 2. Repeat 15 times to have analysis for all processes.	15	1 min per process	5 min per process	6 mins per process	90 mins for all processes	94%
AFTER (Z-Score + Multi-level Scorecard + Analysis)	1. Load all process at one time to Z-Score 2. The top rank z-score value will be automatically drilled to MLSC for analysis	15	0.5 min per process	5 min for all processes	5.5 mins for all processes	5.5 mins for all processes	

After passing all the test requirements and the expected results were achieved, the tool was deployed to the Vigilance Analytics production environment.

4.1.2 Integration and Deployment

The integration and deployment ensure that all the logic in place will work seamlessly as intended during production use. It is then made available to all end-users of the automated z-score tool. The tool was released in the production environment and integrated as part of the advanced analytics tool features of the Vigilance Analytics System as shown in Figure 15.

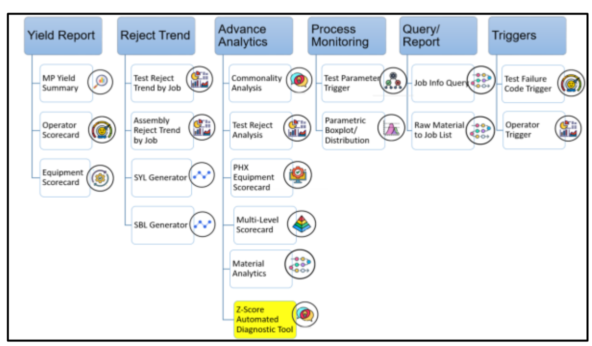

Fig 15. Vigilance Analytics Features Content

4.1.2 Sample Use Case of the Automated Z-score Tool

The practicality of the Z-score Automated Tool that was deployed in the production environment has been proven to have a realistic approach to resolving various quality excursion cases.

A case in point is for Part Number PN ZZZ on test code failure DIST as shown in Figure 16. As identified, the culprit of the failure DIST is traceable to EQUIPMENT D used in PROCESS 9 in contrast to the other factors considered in the analysis. As a result of this, the EQUIPMENT D was immediately repaired to address the failure DIST.

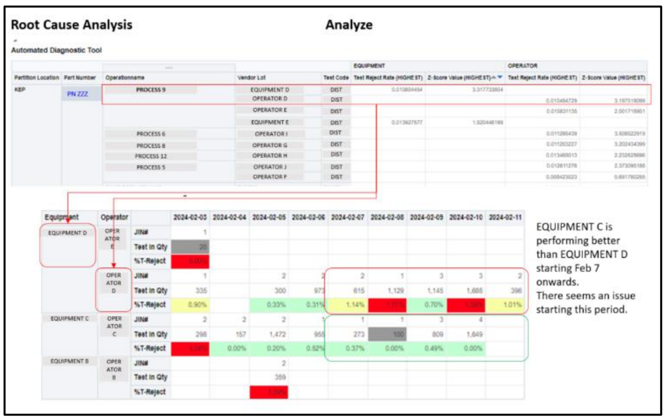

Fig 16. Sample Use Case on Part Number ZZZ Solving Failure Code DIST

4.2 PDCA – Act Phase

4.2.1 Maintenance

The maintenance of the tool after the software is deployed involves ongoing support, bug fixing, and enhancements as needed. It includes activities such as monitoring software issues, addressing end-user-reported problems, and improving user experience.

To standardize the use of the Automated Z-Score Diagnostic Tool, it was documented in a corresponding general user guide for Vigilance Analytics System (see Figure 17).

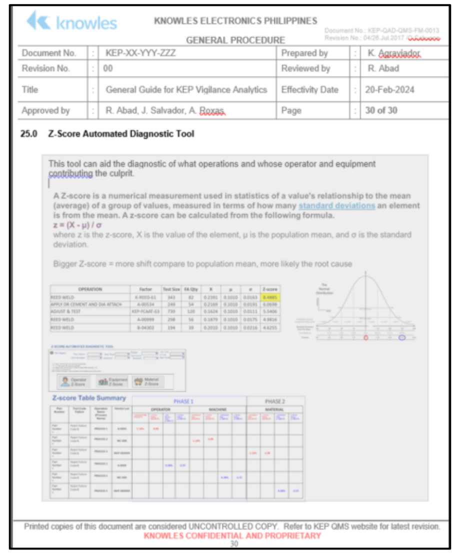

Fig 17. General User Guide for KEP Vigilance Analytics for Automated Z-score Diagnostic Tool

5.0 CONCLUSION

In conclusion, the objective to address the limitations of the previous data analytics was met through the development of the Automated Z-Score Diagnostic Tool in Vigilance Analytics. The tool was able to improve the efficiency to analyze multiple processes that answer - where (determine the specific process location) and who (identify the culprit of the issue whether man or machine).

By employing automated anomaly detection algorithms and diagnostic tool calculation and validation on scorecards, engineers and line owners can swiftly pinpoint the significant contributors to the quality excursions.

6.0 RECOMMENDATIONS

It is recommended for the full adoption of the Automated Z-Score Diagnostic Tool by the engineers to analyze quality issues encountered across various balanced armature families of Knowles Electronics. Furthermore, it is also recommended to be leveraged to other companies that process big data sets and have a similar structure in terms of data analytics.

7.0 ACKNOWLEDGMENT

The proponents would like to express their gratitude to those who have significantly contributed to the successful completion of this technical paper specifically to the Knowles Management, IT, Engineering, MES, and Global Vigilance Analytics support groups.

8.0 REFERENCES

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9.0 ABOUT THE AUTHORS

Ulysis J. Sebial received his B.S. in Electronics and Communications Engineering from the University of San Carlos Technological Center, Cebu in 2008 and Masters in Business Management from the University of San Jose Recoletos in 2021. With nearly 14 years of diverse experience spanning various domains in the industry, he has established himself as a seasoned engineering professional. Currently, he holds a position of Data Analytics Engineer at Knowles Electronics (Philippines) Corporation, where he has been instrumental in leveraging data-driven insights to drive strategic decision-making and operational excellence for the past three years and counting.

Raffy C. Cosep, a B.S. in Electronics and Communications Engineering graduate of Cebu Institute of Technology – University, brings extensive experience as a Quality Engineer, having worked in this role for eight years. Presently, he has been serving as a Sr. Analytics and Yield Engineer at Knowles Electronics (Philippines) Corporation for approximately three years. He participated in the 2023 ASEMEP National Technical Symposium and won Best Technical Paper for the Support Systems track for his paper on "*Data Analytics Through Failure Code Trigger and Multi-Level Scorecard*".

Fredric Kristian Q. Besa, a graduate of University of San Carlos with the degree of B.S. in Electrical Engineering. Worked as Quality Specialist and Data Analyst for 11 years and currently, working as Vigilance Analytics Engineer at Knowles Electronics (Philippines) Corporation for a year.

10.0 APPENDIX

Not applicable