MATERIAL DATA ANALYTICS THROUGH AUTOMATED RAW MATERIAL PARAMETER CORRELATION

Fredric Kristian Q. Besa
Karl Jason L. Agraviador
Ulysis J. Sebial

Engineering Department, MedTech and Specialty Audio
Knowles Electronics (Philippines) Corporation, Cebu Light Industrial Park, Basak, Lapu-Lapu City, Cebu
Fredric.Besa@knowles.com
Karl.Agraviador@knowles.com
Ulysis.Sebial@knowles.com

ABSTRACT

Automated data analytics is essential for managing manufacturing data in Balance Armature (BA) driver production, addressing challenges associated with manual data handling, such as errors and delays. Implementing automation improves process efficiency, accuracy, and time management.

Raw material variability in complex manufacturing workflows contributes to defects, yield loss, and performance inconsistencies. This paper examines the application of data analytics in raw material analysis for effective root cause diagnosis. By integrating advanced analytics as part of smart factory initiatives, manufacturers can trace process anomalies to specific material attributes, uncover hidden correlations, and identify patterns using a **material grading scorecard**—insights often overlooked in conventional inspection methods.

The integration of raw material data analytics enhances traceability, strengthens quality control, and facilitates continuous process optimization, leading to more reliable production outcomes

1.0 INTRODUCTION

1.1 Background of the Study

Balanced Armature (BA) drivers from Knowles Electronics Philippines function via electromagnetic induction, converting electrical signals into sound waves. An electric current generates a fluctuating magnetic field within a coil, causing a balanced armature (reed) to oscillate between two permanent magnets. This motion is transmitted through a drive rod to an aluminum diaphragm, producing sound waves. The internal structure of the BA driver is shown in Fig. 1.

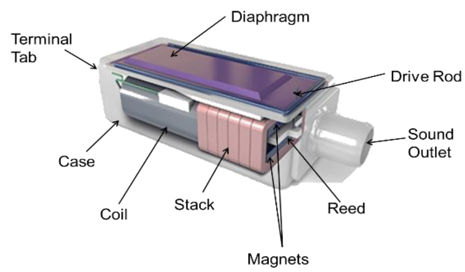

Fig. 1. Knowles Balance Armature (BA) Construction

Material is a key factor in the 5Ms of BA driver manufacturing, directly impacting product quality and consistency. Variations in raw materials such as coils and magnets can lead to defects and process instability. The volume of material data generated is substantial and often requires manual processing.

Each year, the Vigilance Analytics (VA) System evolves, enhancing automation in material data analysis and replacing manual processes (see Fig. 2).

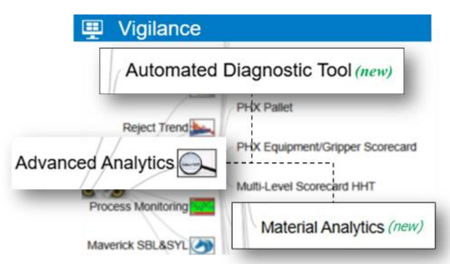

Fig. 2. Vigilance Analytics New Feature

The Automated Diagnostic Tool, a VA advancement, efficiently identifies root causes—man, machine, or material—in a single analysis (see Fig. 3)

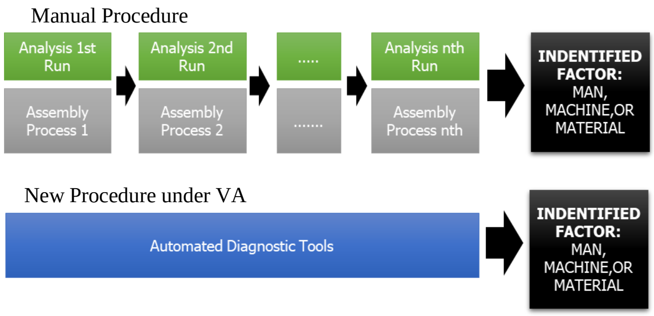

Fig. 3. Difference of Manual and Automated Diagnostic Tool

While the tool has already accelerated the identification of material-related issues, further refinement through enhancement tools can enhance its accuracy and diagnostic capabilities.

1.2 Statement of the Problem

The previous project framework primarily identifies the raw material type (e.g., yoke, reed, magnet), part number, and lot number associated with a concern. However, it does not specify the exact parameters within the identified material that contribute to the issue.

Without identifying the critical material parameter, actionable supplier feedback is impossible. Without raw material improvements, the only option is to isolate defective lots and assess subsequent batches through initial performance evaluations.

In addition to the risks of inconsistent quality and yield, the repetitive cycles of material lot validation introduce uncertainty in raw material availability, increasing the chances of supply disruptions and potential production line stoppages. (see Fig. 4)

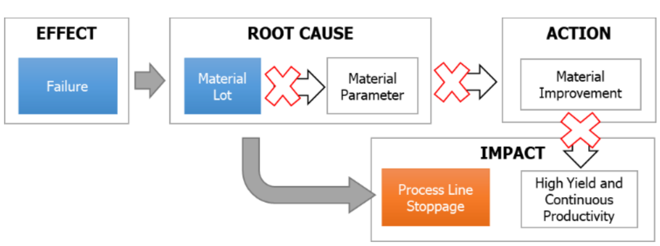

Fig. 4. Effect to Impact Flow

To identify the critical material parameter, engineers must analyze the correlation between test failures and material lot characteristics. This requires extracting test data, including raw material lot details, from the VA system and retrieving inspection data from the Incoming Quality Control (IQC) system, which provides measured material parameters (see Fig. 5).

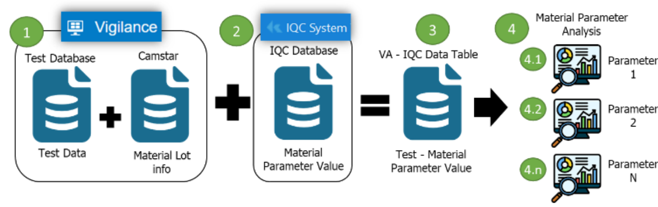

Fig. 5. Manual Material Parameter Analysis Flow

This process is labor-intensive and time-consuming due to the manual nature of data extraction and consolidation, thereby prolonging the investigation result and delaying potential actions execution

1.3 Objective of the Study

The objective of this study is to develop **automated** tools capable of retrieving, processing, and analyzing data from the existing VA database that contains test result and raw material job information, and Incoming Quality Control (IQC) database which contains the Raw Material Inspection Result. These tools will automatically identify the raw material parameter, among **multiple material parameters**, that significantly contributes to test issues (see Fig 6)

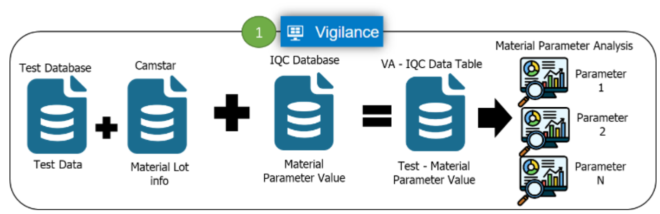

Fig. 6. Automated Material Parameter Analysis

The newly added features to the Vigilance Analytics System are part of the diagnostic phase of the comprehensive material analytics initiative. These features extend the analysis initiated by the existing Automated Z-Score Diagnostic tool. (see. Fig. 7)

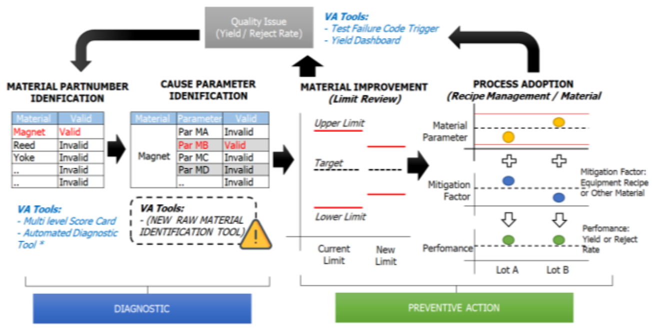

Fig. 7. Material Data Analytics Initiative with corresponding VA Tool

2.0 REVIEW OF RELATED WORK

Not applicable.

3.0 METHODOLOGY

This study employs the PDCA (Plan, Do, Check, Act) methodology, integrating it with the Software Development Life Cycle (SDLC) to systematically develop an automated tool in alignment with the research objectives

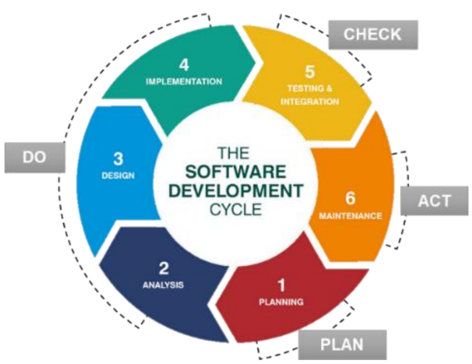

Fig.8 Software Development Life Cycle

3.1 Plan Phase

3.1.1 Planning

During the planning phase of the Software Development Life Cycle (SDLC), the team conducted a comprehensive analysis of project requirements, evaluating practical and technological feasibility to ensure viability.

Key milestones included problem analysis, solution identification, design assessment, development, and trial-based testing before deployment.

3.2 Do Phase

3.2.1 Do Analysis

The team conducted a framework analysis based on Fig. 6, integrating test results from the VA database with raw material parameters from the IQC database. This process involved retrieving, processing, and correlating data, followed by iterative relationship and time-series analysis of test failures associated with specific material parameters.

Manual data processing between the VA and IQC databases can be automated into a unified VA database. Additionally, parameter-specific relationship reports can be consolidated into a single-run VA relationship analysis tool, streamlining correlation assessments and enhancing analytical efficiency.

3.2.2 Design

Design is a critical stage where the system's architectural and technical specifications are defined, based on the functional and non-functional requirements gathered during the requirements analysis phase.

3.2.2.1 VA-IQC Database Design

The current Vigilance Analytics (VA) database stores test results, including failures, linked to specific raw materials. This data supports tools like the Multiple Level Scorecard and Automated Diagnostic Tool, as presented in previous ASEMEP Symposiums.

The Incoming Quality Control (IQC) system operates separately from the VA database. Fig. 9 illustrates the integration of IQC data into the VA system via a process that extracts, combines, and loads data into a unified VA-IQC database, establishing a central source for material-related analysis.

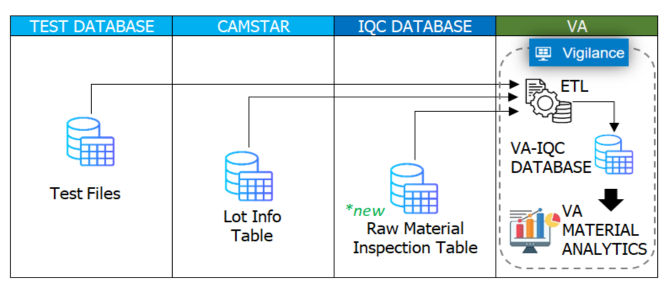

Fig.9. Vigilance Analytics Data Flow for Material Analytics

3.2.2.2 Test Failure - Material Parameter Correlation Design

3.2.2.2.1 Statistical Design

Correlation quantifies the strength and direction of a linear relationship between two variables, typically represented by the correlation coefficient (r), which ranges from -1 to +1. A value close to +1 indicates a strong positive correlation, while a value near -1 signifies a strong negative correlation. A value around 0 suggests no linear relationship between the variables. (see Fig. 10).

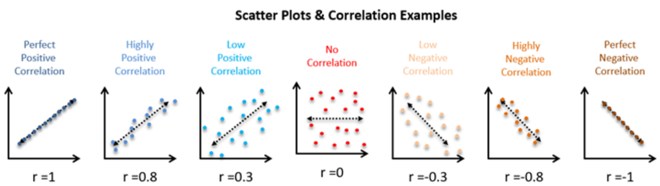

Fig.10. Vigilance Analytics Data Flow for Material Analytics

Statistical significance determines whether the observed relationship between an independent variable (predictor) and a dependent variable (outcome) is attributable to chance. It is typically assessed using a p-value, where a value $\leq$ 0.05 indicates a statistically significant effect, suggesting a minimal likelihood of random variation influencing the result.

In this context, the two variables under consideration are:

- **Independent Variable**: Raw Material Parameter Value
- **Dependent Variable**: Test Failure Rate

The analysis aims to determine whether variations in raw material parameters significantly influence the test failure rate. By calculating the correlation coefficient, we can assess the strength and direction of this relationship. Subsequently, statistical significance testing will ascertain whether the observed correlation is unlikely to have occurred by chance. The integration of both correlation and statistical significance analyses into the Vigilance Analytics (VA) system will culminate in the development of an **Automated Raw Material Parameter Correlation (ARMPC) System.**

In the ARMPC system, raw material parameters are averaged over defined periods, with corresponding test failure rates calculated per material lot.

A strong linear relationship is indicated when the correlation coefficient (r) exceeds 0.75 or falls below -0.75. However, statistical significance is determined using the associated p-value. If the p-value is above 0.05, the correlation is deemed insignificant, implying randomness. Even with a high correlation coefficient, a p-value exceeding 0.05 classifies the material parameter as not significantly linked to test failures. This ensures that only statistically validated relationships are incorporated into the VA's ARMPC System, enhancing analytical reliability.

3.2.2.2.2 Material Correlation and Significance Validation

The team used JMP's Multivariate to generate a Material Parameter Correlation Summary, aligning with system design. In Fig. 11, among four parameters linked to Material Part Number Y, only Parameter C exhibited a strong positive correlation with Failure Occurrence Rate or %FOR, with a coefficient exceeding 0.75 and a p-value below 0.05, confirming statistical significance.

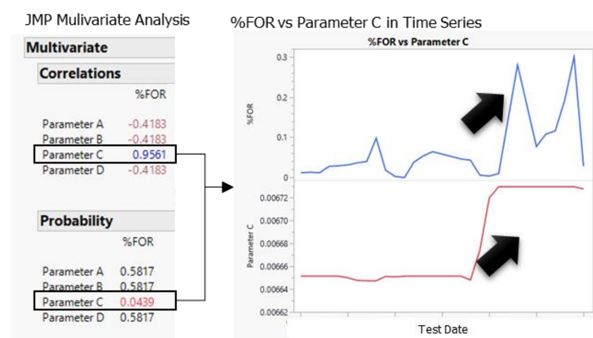

Fig.11. Correlation and Significance Validation using JMP with time series validation

For validation, a time series plot was created, tracking average parameter values for Material Y against %FOR over time, referenced by Material Job numbers. The plot revealed a clear trend: higher Parameter C values corresponded to increased %FOR.

3.2.2.2.2 Material Correlation Tool Design

Following a successful validation using JMP Statistical Software, the team proceeded with the design and development of the Automated Raw Material Parameter Correlation feature within the Vigilance Analytics (VA) System

Fig. 12 illustrates the proposed user interface for the ARMPC tool, presenting correlation analysis results in a structured summary table format for efficient data interpretation

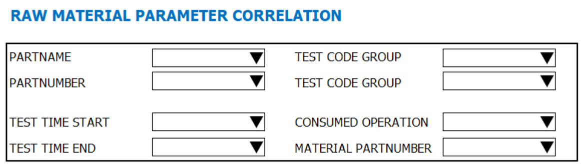

Fig. 12 Automated Raw Material Parameter Correlation User Interface

The system will generate a report summary table, as shown in Fig. 13, containing key data points such as Material Part Number, Material Parameter, and the correlation significance between Test Failure Rate and Parameter Value. Additionally, it includes descriptive statistics for both variables, including the mean (average).

CORRELATION SUMMARY TABLE

MATERIAL PARTNUMBER	MATERIAL PARAMETER	AVERAGE PARAMETER VALUE	AVERAGE TEST CODE RATE	CORRELATION COEFFICIENT	SIGNIFICANCE PROBABILITY
PARTNUMBER A	PARAMETER 1	0.01	2.123	0.79	0.015
	PARAMETER 2	2.12	2.123	0.46	0.136
	PARAMETER 3	0.51	2.123	0.45	0.163
	PARAMETER 4	3.32	2.123	0.61	0.074

Fig. 13. Material Correlation Summary Report

3.2.2.3 Implementation

After completing the development of the conceptual design, the team moved forward with the implementation of the Automated Raw Material Parameter Correlation Tool to the testing development environment

4.0 RESULT AND DISCUSSION

4.1 PDCA – Check Phase

4.1.1 Testing

The Material Correlation Tool was tested and evaluated for production user acceptance. Validation assessed data accuracy, integrity, and output reliability, along with performance testing for processing speed and functionality, ensuring seamless operation. See Table 1 for results.

Table 1. Test and Production User Acceptance Result

CHECK ITEM	CRITERIA	RESULT
Test the functionality of the feature	Needs to be consistent with the submitted requirements.	PASS
Test the accuracy of the result	Should be matched with the defined data set	PASS
Check the capability of the Data Download Option	Chart and tables including raw data can be downloaded	PASS
Check the report generation speed	It should 4 minutes	PASS

The manual process for generating reports takes about an hour—15 minutes for data extraction and another 45 minutes for analysis, considering an average of eight parameters per material part number. In contrast, the Material Correlation Tool streamlines this workflow, delivering results in just **four minutes**, reducing processing time **by 91%.** This significant efficiency gain not only saves time but also enhances analytical accuracy and decision-making. Following successful validation of all test criteria, the tool was approved for integration into the Vigilance Analytics production environment.

3.2.2.3 Implementation

The ARMPC System, now branded as "KEP Correlation Summary," has been successfully integrated into the Vigilance Analytics System, providing users with advanced correlation analysis capabilities. Released within the Material Analytics module, this feature enhances data-driven insights and operational efficiency, as illustrated in Fig.14.

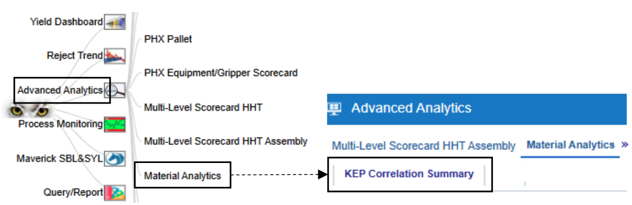

Fig.14. Integration of KEP Correlation Summary to Existing Vigilance Analytics

4.1.2 Sample Use Case of Material Correlation

Following the deployment of the Material Correlation feature in Vigilance Analytics, numerous use cases have demonstrated the tool's effectiveness in resolving quality issues related to material analysis.

One example involves Part Number PN AA, which experienced a failure identified as %FOR X. Using the Automated Diagnostic Tool, the issue was traced to the Material K. With the help of the new KEP Material Correlation tool, engineers analyzed 3 Parameters of Material K and found that only Parameter C showed a strong negative correlation of 0.7, with a significance level below 0.05. This indicated a clear link between Parameter C and the failure. As a result, the engineering team used lower value of Parameter C that reduced the %FOR X. (See Fig. 16)

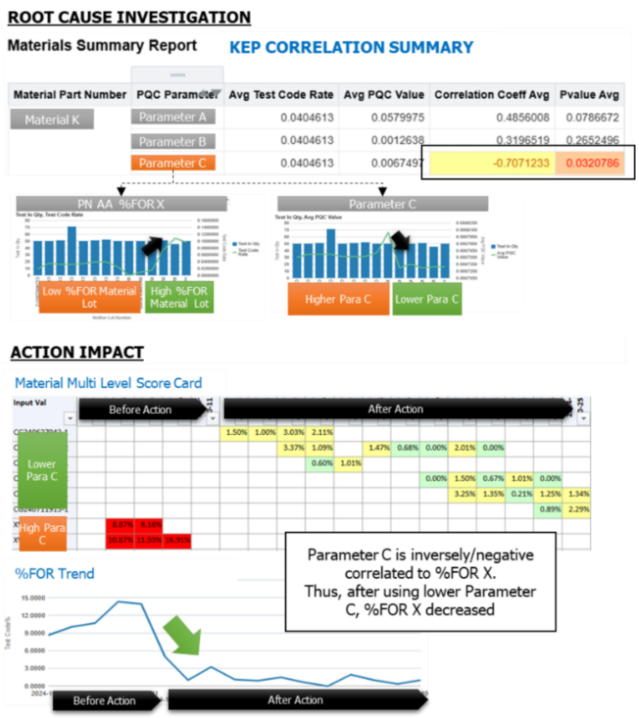

Fig. 16. KEP Correlation Summary identified the parameter causing failure and Action Impact based on the result

In this use case, the implementation resulted in savings of **$16,000 within three months**. Additionally, the total annual savings across all use cases amounted to **$69,000**.

Moreover, in several observed use cases, the raw material parameters identified by the KEP Correlation Summary tool have guided process adoption and material pairing strategies to optimize performance and reduce variability. These actions require Material Parameter Grading, which classifies material lots based on the significance level of their key parameter. This grading enhances material selection and process design decisions. See Fig.17 for illustration.

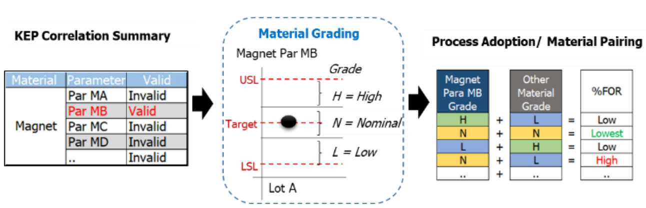

Fig. 17. Material Grading and its connection to KEP Correlation Summary and Adoption

4.2 PDCA – Act Phase

4.2.1 Maintenance

This Material Correlation tool user guide and tool details and other information were documented in the Vigilance Analytic System general user work instruction. (See Fig. 18)

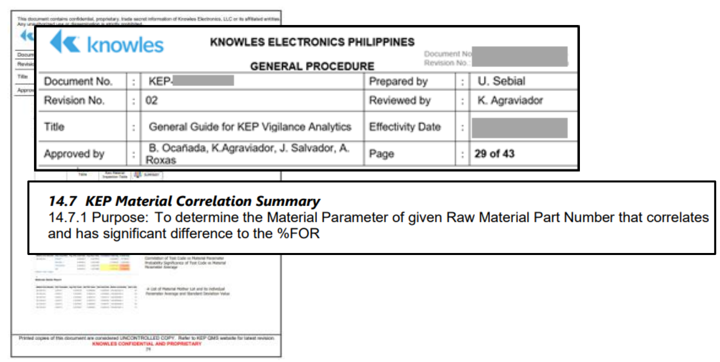

Figure 18. KEP Vigilance Analytics Document with the new KEP Correlation Summary

5.0 CONCLUSION

In conclusion, the deployment of the Automated Material Correlation tool within the Vigilance Analytics System addresses the analytical limitations of the previous Automated Diagnostic Tool, particularly in resolving raw material-related issues. This tool enhances the Material Analytics capability by not only identifying the implicated raw material lot but also pinpointing the specific parameter responsible for the failure.

In addition, its automation functionality streamlines the analysis process, making it significantly faster and easier for users to obtain actionable insights.

As a result, the tool supports quicker, more targeted, and effective corrective and improvement actions related to raw materials.

6.0 RECOMMENDATIONS

Expanding the use of the KEP Correlation Summary across all Knowles Electronics sites—not just in the Philippines—can enhance consistency and efficiency in addressing raw material-related quality issues company-wide. Additionally, the methodology behind this tool could benefit other organizations with similar data structures, enabling improvements in material analysis and quality processes.

While the KEP Correlation Summary tool effectively identifies key material parameters, further development of Material Parameter Grading is recommended. This enhancement will improve preventive and continuous improvement efforts by enabling precise classification of material lots, supporting informed decision-making in material selection and process control

7.0 ACKNOWLEDGEMENT

Sincere appreciation is extended to all who contributed to the successful completion of this technical paper. Special recognition goes to Knowles Management, IT, Engineering, MES, and the Global Vigilance Analytics support groups, as well as the Incoming Quality Control Team, for their invaluable support, collaboration, and technical expertise throughout the course of this work.

8.0 REFERENCES

1. Knowles Electronics. (2023). What is Balanced Armature? Knowles; LLC, Itasca, IL, USA. https://www.knowles.com/applications/ear solutions/premium-sound/what-is-balanced-armature

2. Practical Statistics for Data Scientists by Peter Bruce, Andrew Bruce, and Peter Gedeck

9.0 ABOUT THE AUTHOR

Fredric Kristian Q. Besa, a data analytics expert with 11 years of experience, specializes in quality assurance and decision-making. Holding a B.S. in Electrical Engineering, he optimizes material analytics at Vigilance Analytics. He co-authored research on automated Z-Score diagnostics, presented at the 2024 ASEMEP National Technical Symposium.

Karl Jason L. Agraviador, an engineering and analytics expert, has 20 years of experience in product, test, design evaluation, process, and yield engineering. A Magna Cum Laude graduate and 2004 King of Engineers, he holds degrees in Electronics Engineering and Business Management, driving efficiency at Knowles Electronics.

Ulysis J. Sebial, a Senior Vigilance Analytics Engineer at Knowles Electronics Philippines, has 14 years of experience. He holds a B.S. in Electronics and Communications Engineering and a Master's in Business Management. He applies data-driven insights for strategic decisions and presented at the 2024 ASEMEP National Technical Symposium.

10.0 APENDIX

Not Applicable