# Digitalizing the Monitoring of Availability, Performance, and Quality Real Time Data Analytics and a Computer Science Driven Manufacturing Systems Approach

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**DOI: https://doi.org/10.47772/IJRISS.2026.101000056**

**Received: 09 October 2026; Accepted: 14 October 2026; Published: 29 October 2026**

## ABSTRACT

The research aims to improve Overall Equipment Effectiveness (OEE) monitoring in Malaysian SMEs through digitalization by tackling the problems associated with conventional ways that include, among others, the delay in data collection leading to outdated data, inaccuracies, and high costs. The study, based on the principles of Computer Science, data analytics and cloud solutions, is proposing a 3-D framework (Data Analysis, Structure, Collection) and ISO-based management systems for the integration of real-time analytics with Software/Cloud-as-a-Service (SaaS/CaaS) and low-code platforms like Microsoft Power Apps. With the adoption of Nakajima's OEE model (Availability, Performance, Quality) and compliance with IATF 16949 standards, the research is directed towards the creation of an interactive dashboard for real-time monitoring of OEE and predictive maintenance. Among other things, the main objectives are to analyze the traditional techniques of data collection and to fuse with the real-time analytics where the combination of statistical models and low-code platforms (LCP) will lead to increased accuracy and unlocking of the predictive optimization. Besides that, the research will look at low-code programming for the citizen developers, who will be able to perform the statistical analysis without much effort, as they will be supported during the process of data structuring and conducting advanced analytics. In this way, a data-driven culture would be produced. The use of low-code development derived from Computer Science methodology gives an offer to SMEs to adopt a scalable, cost-effective alternative to the traditional ERP systems that would help them close the gap in the adoption of Industry 4.0 technologies. The ultimate findings would comprise the organizations running more smoothly, with less downtime, and becoming more competitive, which are all in line with Malaysia's digitalization strategy and at the same time, the entire world would be able to benefit from the replication of such a framework for smart manufacturing practices.

**Keywords:** Digitalization, Computer Science, Overall Equipment Effectiveness (OEE), Real-Time; Data Analytics

## INTRODUCTION

Manufacturing has always been a pillar of economic expansion, especially in developed countries. On the flip side, the industry confronts challenges that never seem to end which include; lack of proper resources, poor performance and digital transformation as well. Production process optimization is one of the main areas determining the future of Malaysia, where small and medium businesses (SMEs) are major players in the economy that produces a lot of the country's GDP. OEE is one of the main, if not the most important, performance indicators in the manufacturing field. OEE or Overall Equipment Effectiveness can be explained as a method of measuring the productivity of the equipment by finding out how much the equipment was available, how efficient was its operation and how good the quality of the finished product was. Nevertheless, the traditional ways of monitoring OEE such as performing manual data entry and making calculations in

spreadsheets, are still the main ones used, and they do still allow for a certain level of errors, and delays which result in the not very effective use of OEE for decision-making in real time. OEE was introduced by Seiichi Nakajima in the 1980s as a means of measuring waste and has since become the gold standard for manufacturing efficiency. The OEE score will play a role not just in assessing but also in improving the production processes, with the benchmarks set from world-class (100%) to poor (under 40%).

The advent of Industry 4.0 technologies, including cloud computing, IoT (Internet of Things), and big data analytics (which range from few hundred thousand to millions of keep growing data from daily operation), presents an opportunity to revolutionize OEE monitoring. Real-time data collection and analysis can enhance accuracy, reduce downtime, and improve overall equipment performance. However, many Malaysian SMEs struggle with the high costs and technical complexities of adopting advanced Enterprise Resource Planning (ERP) systems (for e.g., SAP costs more than a million ringgit for multiple modules application or even easily few hundred thousand ringgits for SME, excluding cost of engaging IT Consultant to customize to internal needs) [1]. In this paper, a systematic overview of optimization technique in the use of low-code programming solutions, Microsoft Power Apps [2], which enables rapid, cost-effective application development without extensive coding expertise. By employing these technologies in conjunction with cloud-based data storage, the manufacturers are able to get the possibility of real-time OEE monitoring at a large-scale basis. One of the major difficulties in OEE execution is the correctness of data. The presence of either inconsistent or untrustworthy data might result in wrong conclusions being drawn, besides causing production to halt and increase the costs. The traditional techniques like paper-based checklists or Excel spreadsheets are not only slow but also prone to human error. This paper proposes a systematic model for gathering data that includes QR codes and mobile apps for automation and streamlining of the workflow, and as a final step, the use of desktop applications to present a dynamically auto-generated OEE dashboard based on the data from the pilot study. The system that has been suggested will not only maintain a higher level of data integrity but also speed up and make production management more responsive.

Moreover, the document delves into the capability of the non-technical personnel, known as citizen developers, who are empowered by low-code platforms to transform the manufacturing industry digitally. In contrast to traditional ERP systems that demand specialized IT teams, low-code solutions make it possible for factory workers to make and implement custom apps for OEE monitoring. Instant access to technology encourages creativity and cuts down the reliance on expensive software development simultaneously. In the end, this document will show how the creation of a scalable and economical OEE monitoring system that is in line with Malaysia's Industry 4.0 goals can be achieved. The merging of cloud computing, low-code development, and real-time analytics is expected to bring not only manufacturing efficiency but also the data-driven decision-making and the SMEs competitiveness that the proposed framework is aiming for. The results will not only support the academic literature on digital manufacturing but also give practical solutions from the industry point of view in respect of adoption.

The value of this paper is not limited to only the upgrade of the business processes. Just by improving the OEE, the manufacturers will be able to get rid of the waste, improve their energy usage, and get their product quality up to the standard of being the most important contributors to the sustainable development of the industrial sector. In the meantime, as Malaysia is trying to position itself as a high-tech manufacturing hub, the current research provides the mapping for the proper digital tools incorporation into the production processes, thus in the long run, granting economic stability and global competitiveness.

**Review Of Optimization Techniques in Data Collection for OEE**

Over the time of OEE introduction, various methodologies have come up one after the other and among them the most common are manual paper recording, spreadsheet calculation, and even IoT solutions. All these techniques are vital for determining the correct OEE value especially in the manufacturing sector. However, Small and Medium Enterprises (SME) hardly gained the momentum due to high investment cost of investing in ERP software as well as transforming from manually operated machine without any PLC (Programmable Logic Control) panel has not been encouraging at all. This section provides an overview and discusses prior research related to the OEE data collection, calculation, manipulation and results. The review acknowledges the

contributions of previous researchers and the techniques they employed to address the issue. Additionally, it highlights the achievement and identifies methods that were lacking in previous studies.

**Initial Approach**

OEE (Overall Equipment Effectiveness) is a widely used indicator in the evaluation of effectiveness of manufacturing systems. However, several authors published alternative approaches for its computation, complicating the implementation step for practitioners. This study analyses the literature regarding OEE, selects four main methodologies for its evaluation and examines the underlying differences between them. A real-world case study is examined to demonstrate the issues that occurred throughout the data gathering process and the variations in the results obtained, along with deducible conclusions for enhancing the performance of manufacturing systems, in both conventional and cutting-edge industrial plants, according to the principles of Industry 4.0.

**Japanese TPM Approach**

R. Singh Singh, R., Gohil, A. M., Shah, D. B., & Desai, S. (2013) A case study of the case study examines the application of Total Productive Maintenance (TPM) in an automotive parts machining shop with special emphasis on CNC turning centers. TPM was established to cure the manufacturing disorders like equipment failure, bad quality, and time waiting, and it was done by gradually asserting the eight pillars: 5-S, Jishu Hozen (Autonomous Maintenance), Planned Maintenance, Kaizen, Quality Maintenance, Training, Office TPM, and Safety, Health, and Environment. The main activities were operator training, preventive maintenance, Poka-Yoke equipment, and workplace tidiness. The research used Overall Equipment Effectiveness (OEE) as a measure of success, which went up from 63% to 79%, indicating better productivity and quality. Critical success factors were employee involvement and management support. However, defects from prior processes (e.g., casting) remained a challenge. The conclusion emphasizes sustained efforts across all organizational levels to achieve world-class OEE (≥85%). TPM proved effective in reducing waste and improving operational efficiency, highlighting its value in manufacturing settings. Nonetheless, manual recording in the study showed that it was not real-time practice, not fool-proof data accuracy and was not able to analyze OEE promptly for management to take immediate [3].

**OEE through PDCA Method**

The study expands on existing knowledge of menu Press automotive components manufacturer in Indonesia with the Overall Equipment Effectiveness (OEE) achievement was 60.7%, it was below than world company level as mentioned in Japanese Institute of Plant Maintenance (JIPM)- Total Productive Maintenance (TPM) standard, the biggest OEE components problem was availability value that achieved 63.3%, then the biggest availability problem was dies preparation time. Using TPM method and Plan-Do-Check-Act (PDCA) cycle with Pareto chart and Fishbone diagram, we succeeded to improve dies setting time within one month, it was quoted to increase the availability value from 63.3% became 67.8% and finally OEE value increased from 60.7% became 65.3%. [4]. This study mentioned Pareto Chart and Fishbone, and these data are typically collected manually, and plotted to study for quality improvement where it did not fully address data collection in real-time.

**Manufacturing approach through IoT and manual audits**

The study employed a hybrid data collection approach, combining IoT sensor logs from manufacturing equipment with manual audits recorded in spreadsheets to capture real-time machine performance metrics (availability, downtime) and production outputs. For analysis, the authors utilized AWS IoT Core for cloud-based data aggregation and Python libraries (Pandas, NumPy) to calculate OEE components—Availability (actual vs. planned production time), Performance (actual output vs. ideal cycle time), and Quality (defect-free units) while correlating results with maintenance records. Their OEE formula adhered to Nakajima's standard (OEE = A × P × Q), with findings visualized through dashboards to identify bottlenecks, demonstrating a 30% improvement in equipment uptime post-implementation, though the reliance on IoT sensors incurred higher upfront costs compared to low-code alternatives [5].

**Quantification of Machine Performance Through Overall Equipment Effectiveness**

Ramlan and colleagues (2015) studied the use of Overall Equipment Effectiveness (OEE) as a measure of a corrugator machine's performance to the point of the production plant. Various losses of productivity were to be measured through the examination of the OoO metrics for the three main OEE categories of Availability, Performance, and Quality over a period of twelve months and the results were to be compared with Nakajima's "Ideal OEE" benchmark that is 85%. The major outcomes indicated the OEE being 74.52%, with Availability (92.15%) surpassing the plans but Performance (85.77%) and Quality (94.29%) were lower owing to speed losses (e.g., machine wear) and defects (e.g., uncounted waste). The study emphasized the importance of OEE in pinpointing inefficiencies that can then be used as a guide for total productive maintenance (TPM) to know where to invest to increase operational awareness and cut down waste. The data was manually collected by the authors through production logs, interviews, and spreadsheets in Excel, and losses classified using Nakajima's "Six Big Losses" framework. Among the advantages were comprehensive and rich in context data (e.g., reasons for downtimes) and long-term tracking (12 months), which helped to eliminate biases of instant snapshots. On the other hand, there was the disadvantage of being dependent on manual data entry with all its risks of human error, and the lack of real-time monitoring which means corrective actions were not timely. While Excel made the analysis easy, it was not scalable to big datasets or dynamic decision-making, which gap was filled by modern low code/cloud solutions (e.g., Power Apps, AWS) in the case of contemporary studies like yours. The authors' work brings out the trade-off between the cost-effective manual methods and the advanced, automated systems in the OEE monitoring [6].

**Improving the OEE and UPH Data Quality by Automated Data Collection for the Semiconductor Assembly Industry**

Wang & Pan (2011) introduced an Automated Data Collection (ADC) system that was able to eliminate important data quality concerns in measuring Overall Equipment Effectiveness (OEE) and Units-Per-Hour (UPH) in semiconductor packaging. Start from the wire bonder equipment which is the bottleneck area; the authors' research has shown that manual techniques (like stopwatch sampling and making paper records) caused 6% of OEE losses to go unidentified and made UPH data unreliable, thus negatively affecting cost modeling and decision-making. Their Automated Data Collection (ADC) system, which was based on the combination of real-time machine sensing, Manufacturing Execution Systems (MES), and SEMI E10/E79 standards, managed to eliminate unidentified losses (bringing them down to almost 0%), increase accuracy, and allow dynamic OEE tracking all of which contributed directly to the improvement of operational efficiency and profit analysis in high-precision manufacturing. The study employed an automated approach using MES and machine communication protocols (HSMS) to collect real-time equipment data (downtime, speed losses, defects) and calculate UPH per production lot. Pros and Cons are highlighted , where in Pros side, Data Accuracy (Reduced manual errors, achieving near-perfect OEE loss tracking), Timeliness (Enabled real-time interventions (e.g., detecting motor precision issues)) and Scalability (Compliant with SEMI standards for industry-wide use), and the Cons side are Complexity (Required integration with legacy systems and adherence to SEMI protocols), Cost (High initial investment in ADC infrastructure and training. Compared to manual methods and, the ADC system offered superior precision but demanded greater technical and financial resources, underscoring the trade-off between automation benefits and implementation barriers in industrial settings. Cost-Ineffectiveness and Manual Equipment are the core considerations in Malaysia SMEs; hence it hinders such approach [7].

**OEE in manufacturing plants**

The article written by Dal et al. (2000) has the usage of Overall Equipment Effectiveness (OEE) as a metric for operational performance improvement at Airbags International Ltd (AIL) as an object of study. Among the main contributions are the showing of OEE's contribution to production loss detection such as downtime, speed losses, and defects, and its power as a tool for the ranking of doing Total Productive Maintenance (TPM) and Kaizen activities. The research exemplifies that different industries have different OEE figures in terms of acceptance and also points out that performing precise data-collection is the prior-condition to being able to measure performance with credibility. Among the techniques is that of action research, which includes longitudinal-case-study, participant-observation, and semi-structured-interviews, concentrating on AIL's weaving department for

the period of three months. One of the weaknesses in OEE data collection and analysis is that of having begun with inaccurate OEE figures because of not having defined properly what method to use for recording downtime and unrecorded minor stoppages that have thus weakened the reliability of data. OEE, however, going through the above-mentioned process has been able to open up the way of daily decision-making and pointing out the areas for improvement, though the extent of its power has been pretty much dependent on solid data-systems and human-labour involvement [8]. Overall Equipment Effectiveness (OEE) is one of the practices introduced in the manufacturing field through the work of Ljungberg (1998), who also considers OEE a prerequisite for Total Productive Maintenance (TPM) activities. The focus of the paper is on the improvement of capacity through the identification and classification of production losses, which OEE has facilitated. The author points out that while the losses from downtime (e.g., breakdowns) are often given top priority, the performance losses (e.g., minor stoppages, speed reductions) and planned downtime are also important contributors to low OEE but have been neglected in the analysis. Low OEE, which in the sample averaged 55%, is, therefore, mainly attributed to these losses being less recognized and less treated compared to others. The technique used was a combination of carrying out manual and automated data gathering on 23 different machinery systems, with the operators and researchers jointly designing the forms to boost accuracy and engagement. On the downside, the dependence on operators' reported data which may have introduced bias and the omission of systemic factors such as product complexity or design were among the drawbacks. The study even though having an operational focus, raised the necessity for the OEE to be integrated with other performance metrics of wider scope, citing that there are gaps in the strategic alignment. Some of the suggestions made were joint use of manual and automated data systems to achieve pixel-perfect reliability and still keep the operators involved [7].

According to Muchiri and Pintelon (2008), the Overall Equipment Effectiveness (OEE) has been the main topic of discussion in the industry in terms of its performance measure tool, and they traced its development right from Nakajima's TPM (Total Productive Maintenance) framework to even further reaching methods like TEEP (Total Equipment Effectiveness Performance) and OFE (Overall Factory Effectiveness). The authors review the OEE as a key element in revealing production losses (e.g., unplanned stoppage time, slower than expected pace, less than optimal quality products) and the universal adaptation of the measure. A major input is the suggested structure to break down production losses into external (e.g., market changes), internal (e.g., management problems), and operational (e.g., machines going down) classes. The structure that they come up with ultimately brings together different OEE variants, allowing for productivity improvement strategies tailored to specific situations. The authors have succeeded in their task of theoretical and physical OEE comparison through a research paper comprising a literature review and the study of two Western European companies (one a chemical industry and the other a packaging one) as well. They go on to say that the companies' loss measurements are based either on the actual output (tonnage) or time taken and they pinpoint the lack of uniformity as the problem. Their framework integrates the evidence to propose a single method for calculating Overall Asset Effectiveness (OAE) [9]. Shortcomings in the OEE Data Collection and Analysis Process:

1. Data Accuracy and Reliability: The manual collection of data that relies on operator's input is prone to inaccuracies resulting from minor stoppages which may be forgotten or reported wrongly. The automated systems, like MES/ERP, increase the precision but come at a high cost.
2. Scope Limitations: Giving attention to equipment-level metrics only, OEE neglects to consider systemic factors such as supply chain disruptions or product complexity, thus restricting its use in job-shop or batch areas.
3. Implementation Variability: Industrial practices are far from being uniform; for instance, some companies do not take into account critical losses (like commercial demand) or are not detailed enough in classifying internal failures, which in turn hampers their continuous improvement efforts [8].

## RESEARCH METHODOLOGY

Data collection could be very tedious due to no ending collection, movement and slow learning cycle due to frequent changes in requirements from the Operation Planning section, especially when customer orders change. These studies optimize the overall data collection concept, not only by leveraging Microsoft PowerApps low code programming, but also fully utilize cost-free QR Code (Quick Response Code), in combination advance camera feature of mobile phone (in any OS, be it, Android, iOS or HarmonyOS) to seamlessly get fast and

accurate data. Moreover, the design of data structure, from the perspective of Manufacturing, are key to success. Not only it enables quick analysis based on Microsoft PowerFx formula, but it also renders in seconds, with proper data grouping, to calculate and present results, including graphical results, overcoming data delegation in Microsoft PowerApps. Key elements have been prepared prior development of Applications including:

1. Data Structures
2. Microsoft Power Apps Premium subscription
3. Go Cloud Web Services subscription

**Data Structure (First-D)**

Following are the key structures are designed based on Screw and Nuts processing Semi-Auto manufacturing environment which has been collaborated for this OEE study since Oct 2024 for feasibility study prior pilot study for showing the pilot results.



**Figure 1.** Heading Machine, which is the Primary process for data collection during manufacturing

**Product BOM (Bill of Material)**

| product_bom |
|---|
| geenscrew_code |
| customer |
| product_code |
| product_name |
| material_code |
| material_usage_per_unit |
| material_unit |
| compliances |
| customer_part_no |
| updated_on |
| updated_by |
| assembly_code |
| note |
| packaging_inner_code |
| packaging_outer_code |
| assembly_code |

**Figure 2.** Product BOM, which provides product information to be used throughout the whole study.

**Machines Database**

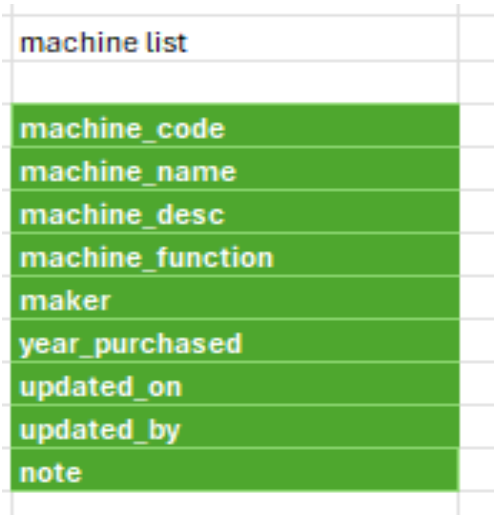



**Figure 3.** Machine List, which is bound to Work Order and Product Code to calculate OEE specifically by Machine

**Customer Order and Work Orders**

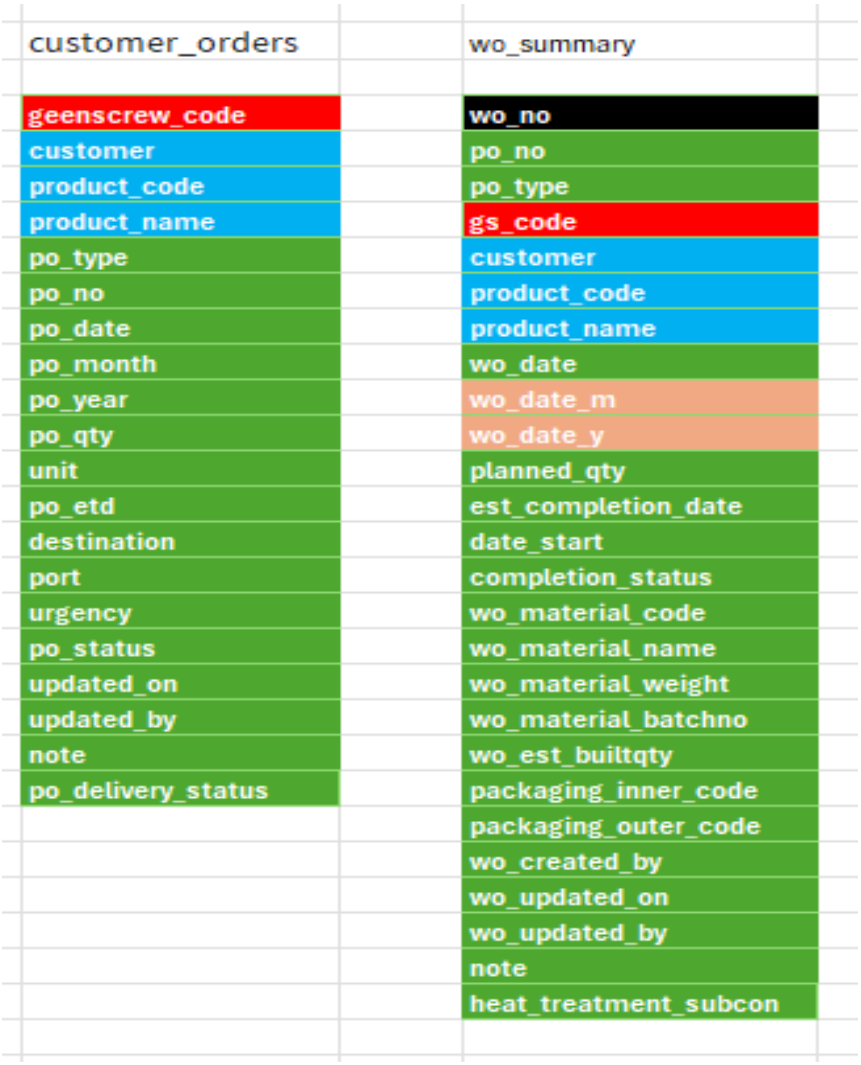



**Figure 4.** Customer orders trigger Planner to generate Work Order (WO) Summary, where QR Code is generated on all crucial fields / columns.

**Daily Production Output**




**Figure 5.** Production Output Data Structure – which is used to collect data specifically for (P – Daily Production Qty, DPR), (A – Availability based on Working Duration and Downtime Duration), and (Q – Reject Qty).

This QR Code is the core of the whole application where Data Accuracy of key product code and product name. Machine code and Operators are also generated with QR Code to enable exact match for OEE grouping based on WO and Machine analysis.

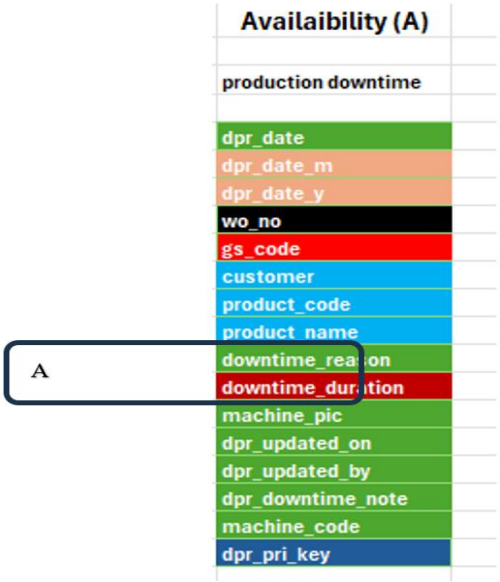



**Figure 6.** Detailing Downtime Duration as of Figure 3.5

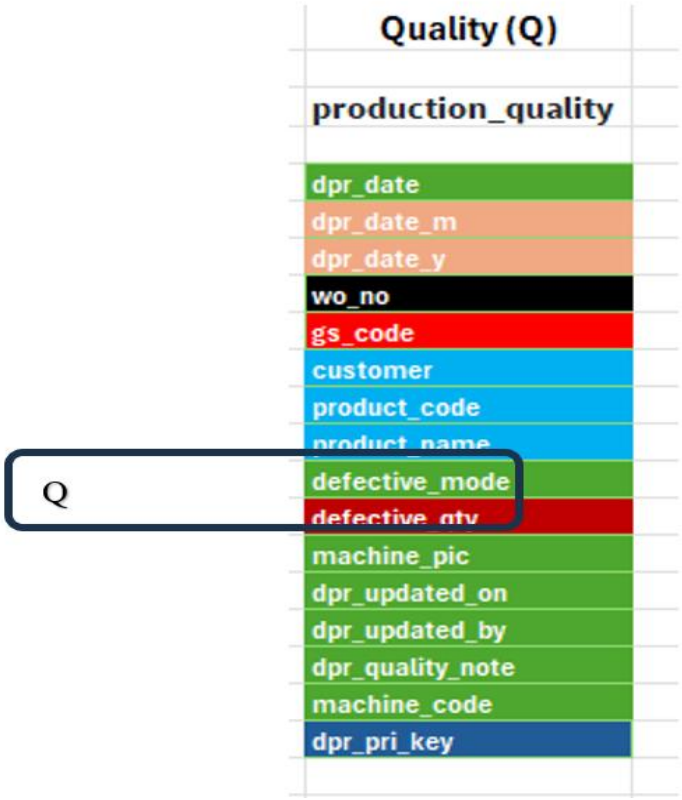



**Figure 7.** Detailing Reject Quantity as of Figure 3.5

**Data Collection (Second-D)**

(a) Tools Development

**1. Create Work Order with QR Code**

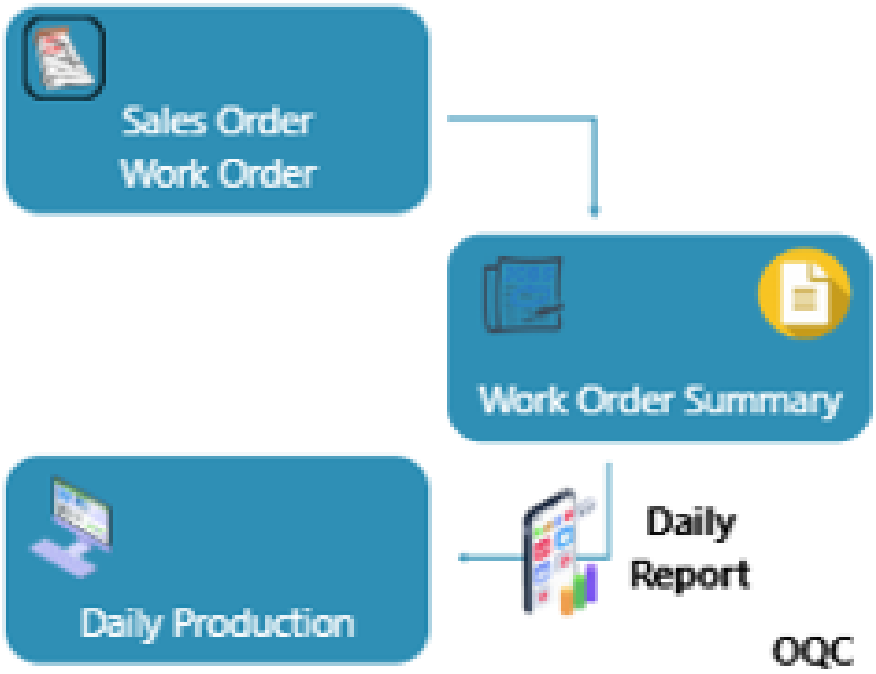



**Figure 8.** Flow chart for Ordering System from customer continues with internal Work Order

**Work Order with QR Code**

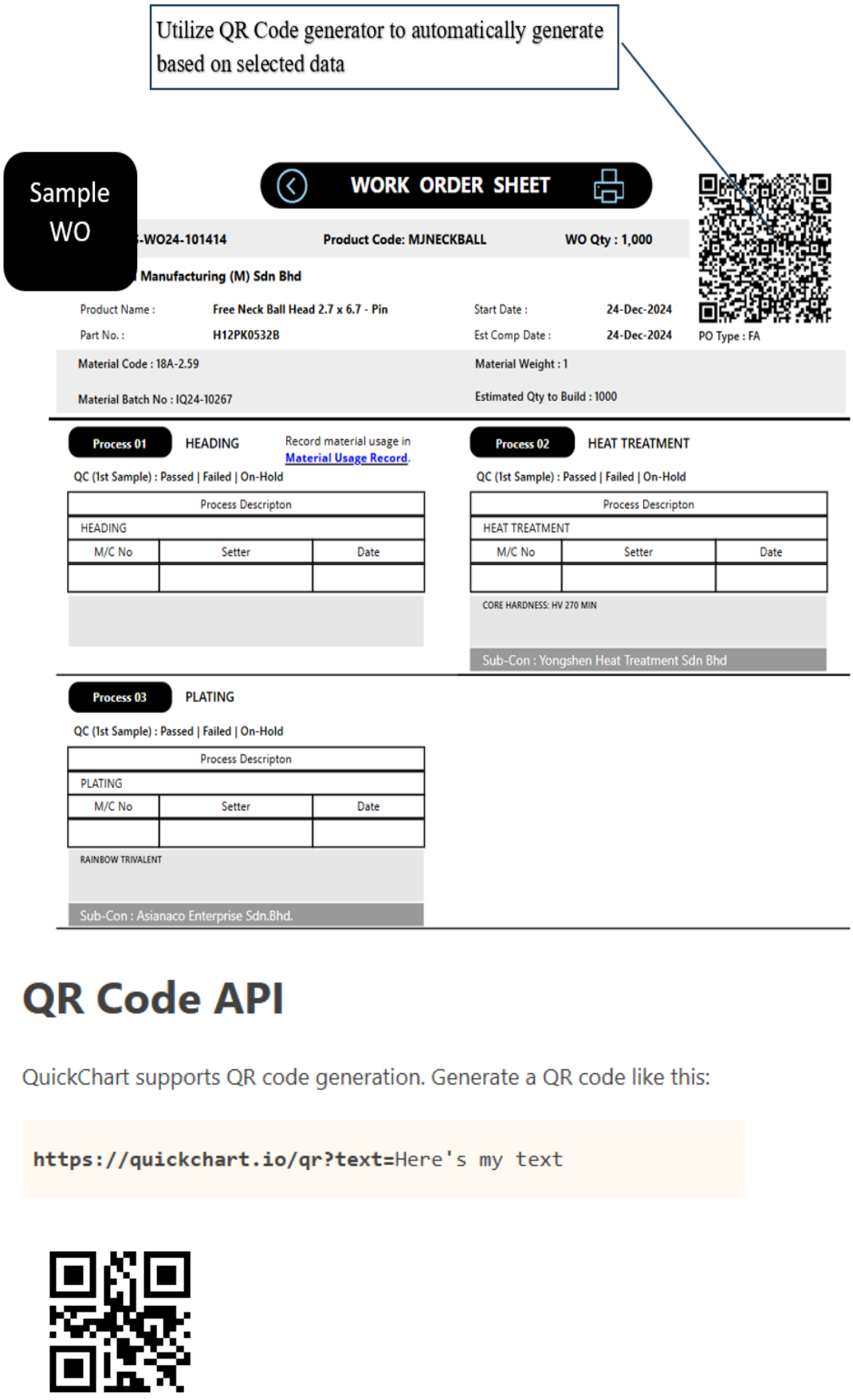



**Figure 9.** Generating Work Order (WO) with QR Code for Daily Production scanning using Mobile Apps

**Create Mobile Apps for Data Collection**

Key features of the apps:

(a) WO No: Work Order No extracts result from QR Code scanning
(b) Machine Code: Scan Machine QR Code to confirm accurate code
(c) Material Batch No: Extracted from WO QR Code Scanning
(d) Process Name: Extracted from WO QR Code Scanning
(e) Machine PIC: Scan QR Code of data collector
(f) WO Actual Start Date: Auto selection of Normal Hour or OT Hour based on current time (only Normal Hour is used for OEE calculation)
(g) Start Time – End Time : manual selection to auto calculate Duration
(h) Production Qty: Manual data entry based on weight-count from production by shift
(i) Reject Qty: Manual data entry with defective mode from production by shift
(j) Downtime: Manual data entry with downtime reason from production by shift




**Figure 10.** Mobile apps for data collection

**Pilot Data Collected from Manufacturing Co.**

**Data Collection Period: Jan ~ Mar-2025**

Total Machines under study : 40 Units

Type of Data:

1. **Work Order (WO)** where Production Planning is triggered with each WO with QR Code were generated for scanning using Mobile PowerApps to collect data. Total Data : 339 Records.
2. **Daily Production report** were the core data collected for OEE calculation (P, Performance, and Q, Quality). Total Data: 1,203 Records.
3. **Production Downtime** were also colllected during QR Code scanning, for the purpose of details downtime duration and reason. (A, Availability). Total Data: 6,341 Records.
4. **Engineering Process** were also extracted to match product code with cycle time for core Process 01 (Core Process - Heading). Total Data: 896 Records.

Key fields from all the 4 tables are necessary for OEE Calculation (based on Machine and Work Order, based on Year & Month):

- Work Order No
- Machine Code
- Year
- Month
- Customer
- Product Code
- Quantity (by Shift) (**Po: Total Produced**)
- Rejected Qty (by Shift) (**Qo: Rejected Quantity**)
- Working Duration (**To: Scheduled Production Time**)
- Downtime Duration (**Dti: Downtime**)
- Cycle Time (**from Eng Process, Ti**)

**General Equation for A, P, Ql**

**Availability (A)**

**Nomenclatures**

1. $T_0$ : Scheduled Production Time
2. $DT_i$ : Individual downtime (where i represents a specific downtime event)
3. $DT_1$ : Downtime event 1
4. $DT_2$ : Downtime event 2

**1. Downtime Calculation**

Total downtime is the sum of individual downtime events:

$$\text{Downtime} = \sum(DT_i) = DT_1 + DT_2 \quad (1)$$

**2. Actual Production Time**

Actual Production Time is calculated by subtracting total downtime from scheduled production time:

$$\text{Actual Production Time} = T_0 - \sum(DT_i) = T_0 - (DT_1 + DT_2) \quad (2)$$

### 3. Efficiency or Utilization

Efficiency (or Utilization) is the ratio of actual production time to scheduled production time, expressed as a percentage:

$$\text{Efficiency} = \frac{Actual\ Production\ Time}{Scheduled\ Production\ Time} \times 100\% \quad (3)$$

Substituting Equation (2) into Equation (3):

$$\text{Efficiency} = \left( \frac{T_0 - \sum (DT_i) = T_0 - (DT_1 + DT_2)}{T_0} \right) \times 100\% \quad (4)$$

This equation calculates the percentage of time that production running compared to the total scheduled production time, after accounting for downtime.

### Performance (P)

### Nomenclatures

1. $T_i$ : Cycle Time
2. $P_0$ : Total Produced
3. $T_0$ : Scheduled Production Time
4. $DT_i$ : Individual downtime (where i represents a specific downtime event)
5. $DT_1$ : Downtime event 1
6. $DT_\partial$ : Downtime event 2

### 1. Target Output Calculation

Target output is calculated by multiplying the cycle time by the available production time, which is the scheduled production time and minus the total downtime:

$$\text{Target Output} = T_i \times \left[ T_0 - \sum (DT_i) \right] = T_i \times \left[ T_0 - (DT_1 + DT_2) \right] \quad (5)$$

### 2. Percentage of Target Output Achieved

The percentage of target output achieved (P%) is the ratio of total products produced to the target output:

$$\text{P\%} = \frac{P_0}{Target\ Output} \times 100\% \quad (6)$$

Substituting Equation (5) into Equation (6):

$$\text{P\%} = \frac{P_0}{T_i \times \left[ T_0 - (DT_1 + DT_2) \right]} \times 100\% \quad (7)$$

This equation calculates the percentage of time that target output that was actually produces, taking into account the cycle time, scheduled production time and downtime.

**Quality (Q)**

**Nomenclatures**

1. $Q_0$ : Rejected Quantity
2. $P_0$ : Total Produced

**1. Total Good Parts**

The number of good parts is calculated by subtracting the rejected quantity from the total produced:

$$\text{Total Good Parts} = P_0 - Q_0 \tag{8}$$

**2. Quality Percentage**

Quality Percentage (Q%) is the ratio of total good parts to total produced, expressed as a percentage:

$$Q\% = \left( \frac{Total\ Good\ Parts}{P_0} \right) \times 100\% \ (/\ P_0) \times 100\% \tag{9}$$

Substituting Equation (8) into Equation (9):

$$Q\% = \left( \frac{P_0 - Q_0}{P_\partial} \right) \times 100\% \tag{10}$$

This equation calculates the percentage of good parts products out of the total produced, after accounting for rejected quantities.

**Develop the model**

S. Nakajima approach is the core reference for the study where it concentrates on:

$$OEE = A \times P \times Q \tag{11}$$

where,

A = Availability

P = Performance

Q = Quality

Automotive Industry Action Group (AIAG) has adopted in 2024 Mar 3rd Edition and clearly defined and integrated into IATF 16949: 2016 Clause: 8.5.1.5 (f),where:

**Total productive maintenance**

The organization shall develop, implement, and maintain a documented total productive maintenance system. At a minimum, the system shall include the following:

(a) identification of process equipment necessary to produce conforming product at the required volume,
(b) availability of replacement parts for the equipment identified in item a);
(c) provision of resource for machine, equipment, and facility maintenance;
(d) packaging and preservation of equipment, tooling, and gauging;

(e) applicable customer-specific requirements;
(f) documented maintenance objectives, for example: OEE (Overall Equipment Effectiveness), MTBF (Mean Time Between Failure), and MTTR (Mean Time To Repair), and Preventive Maintenance compliance metrics. Performance to the maintenance objectives shall form an input into management review (see ISO 9001, Section 9.3);
(g) regular review of maintenance plan and objectives and a documented action plan to address corrective actions where objectives are not achieved;
(h) use of preventive maintenance methods;
(i) use of predictive maintenance methods, as applicable;
(j) periodic overhaul

**Data analysis (Third-D)**

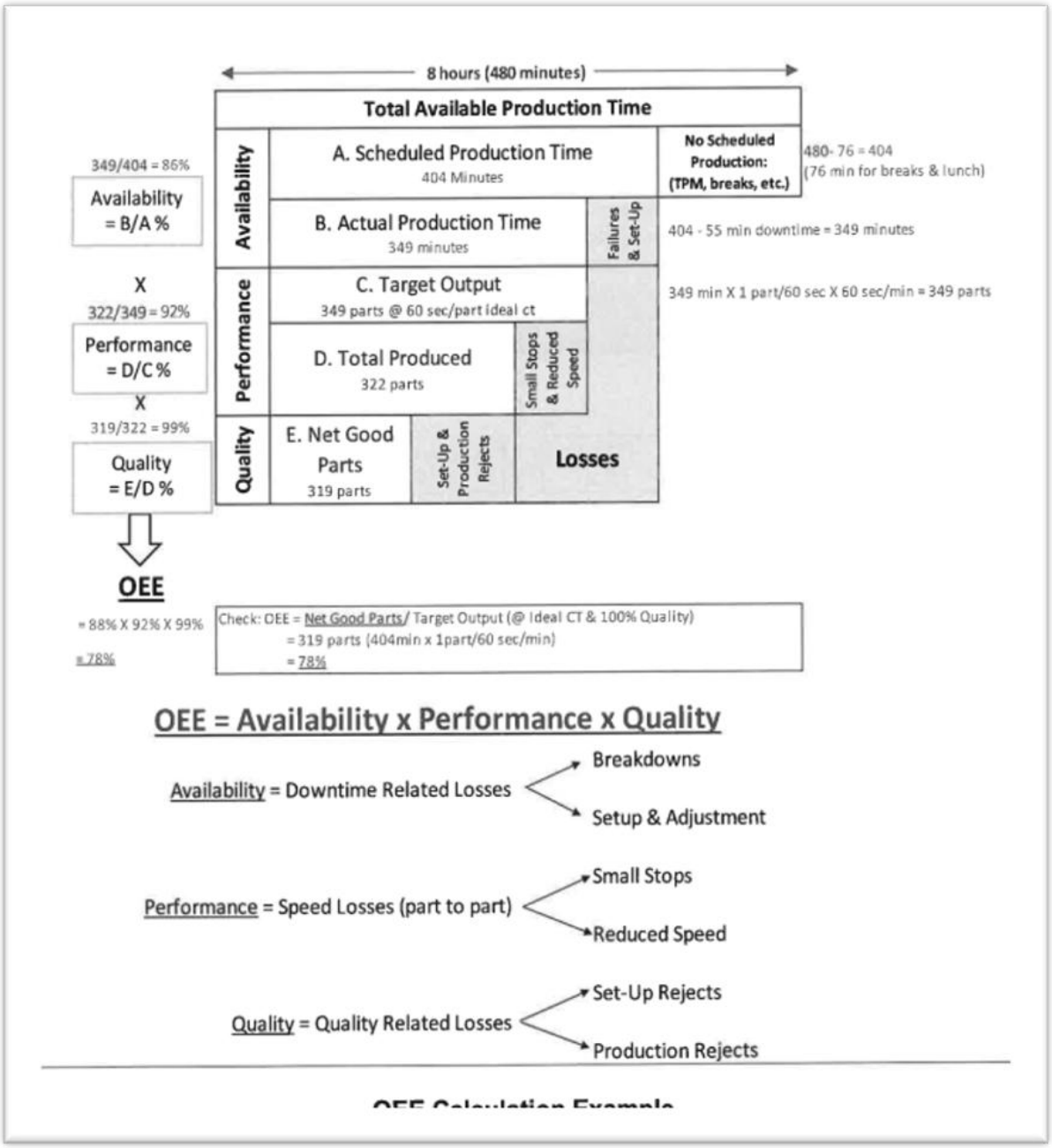



**Figure 11.** OEE Structure extracted International Automotive Task Force, IATF 16040: 2016 edition which depicts the overall concept of OEE, Overall Equipment Effectiveness.

OEE calculation formula as of following:

Overall Equipment Effectiveness (OEE)% = A% × P% × Q%

**Breakdown of Components**

**1. Availability (A%)**

$$\text{A\%} = \left( \frac{T_0 - (DT_1 + DT_2)}{T_0} \right) \times 100\% \tag{12}$$

$T_0$ : Scheduled Production Time

$DT_1 + DT_2$ : Total Downtime

**2. Performance (P%)**

$$\text{P\%} = \left( \frac{P_0}{T_1 \times [T_0 - (DT_1 + DT_2)]} \right) \times 100\% \tag{13}$$

$P_0$ : Scheduled Production Time

$T_1$ : Cycle Time

**3. Quality (Q%)**

$$\text{Q\%} = \left( \frac{P_0 - T_0}{P_0} \right) \times 100\% \tag{14}$$

$Q_0$ : Rejected Quantity

$P_0$ : Total Produced

**Final OEE % Formula**

Substituting Equation (12) – Equation (14) into the OEE% formula. This formula calculates the Overall Equipment Effectiveness (OEE %) by multiplying the Availability (A%), Performance (P%), and Quality (Q%) percentages.

**PowerFx Formula in getting OEE results within Power Apps**

```
// Update Context to store temporary data into variable

UpdateContext({selected_oee_year: myyear});

UpdateContext({vis_oee_save_gif: true});

// OEE = A x P x Q, for HEADING Process only

// Get Product BOM Cycle Time for Heading only

ClearCollect(
```

```
    process_heading,
    gs_engineering.SelectWhereProcess(
        "62fa4fd3c3847b46dfed1af1",
        "process_name",
        "HEADING"
    )
);
// dpr_note_2 = Normal Hour or OT Hour; so collect for Normal Hour Only
// Using ClearCollect to store table in cache memory
ClearCollect(
    month_year_prod_output_ori,
    AddColumns(
        gs_mrp.SelectWhereProductionoutput(
            "62dc0531c3847b46dfed0c29",
            "dpr_date_m=dpr_date_y~process_name=dpr_note_2",
            dd_oee_month.Selected.Value & "~" & dd_oee_year.Selected.Value & "~" & "HEADING"
        ),
        Cycle_Time_Heading,
        LookUp(process_heading, geenscrew_code = gs_code).cycle_time
    )
);
// by Machine, all data can be extracted from Production Output
// Running_day_per_machine = this will ensure even there are multiple WO running no
// A is based on Actual Normal Hours
ClearCollect(
    month_year_prod_output,
    AddColumns(
        GroupBy(
            month_year_prod_output_ori,
```

```
        machine_code,
        customer,
        product_code,
        product_name,
        Cycle_Time_Heading,
        Grp_All
    ),
    "Running_day_per_machine",
    CountIf(Distinct(Grp_All, dpr_date), true),
    "Running_hour_by_machine_month_year",
    Sum(Grp_All, working_duration),
    "Downtime_by_machine_month_year",
    Sum(Grp_All, downtime_duration),
    "A_by_machine_month_year",
    ((Sum(Grp_All, working_duration) - Sum(Grp_All, downtime_duration)) / Sum(Grp_All,
working_duration)),
    "P_by_machine_month_year",
    (Sum(Grp_All, dpr_qty) / (Sum(Grp_All, working_duration) * 60 / Cycle_Time_Heading)),
    "Q_by_machine_month_year",
    ((Sum(Grp_All, dpr_qty) - Sum(Grp_All, reject_qty)) / Sum(Grp_All, dpr_qty)),
    "OEE_by_machine_month_year",
    (((Sum(Grp_All, working_duration) - Sum(Grp_All, downtime_duration)) / Sum(Grp_All,
working_duration)) * ((Sum(Grp_All, dpr_qty) / (Sum(Grp_All, working_duration) * 60 /
Cycle_Time_Heading))) * (((Sum(Grp_All, dpr_qty) - Sum(Grp_All, reject_qty)) / Sum(Grp_All, dpr_qty))) *
100  )
```

## RESULTS AND DISCUSSION

This structured presentation ensures clarity in understanding the feasibility study demo data and the organization of the Monthly OEE. Overall OEE Results are:

**Availability : 80 ~ 87%**

Results rely on downtime recorded by Technician at defined period (to be differentiated from minor adjustments)

**Performance : 70 ~ 80%**

Results rely on Availability x Cycle Time (where it might be under estimated, resulting in > 100%)

**Quality : 100.0%**

Results rely on company policies on Quality judgement where manufacturing may skip quality inspection but depends on QC 100% inspection (hence 100%)

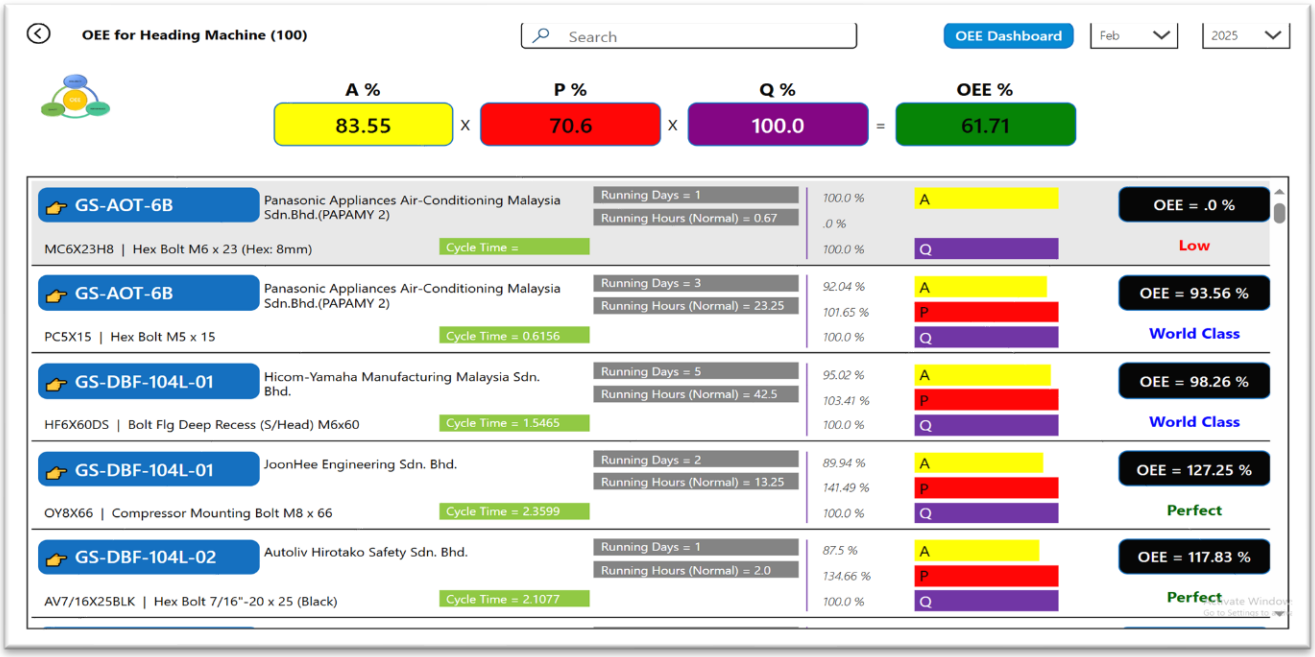
**OEE : 70.14% (average)**

When results are > 60% it is deemed to be a typical Manufacturing OEE where it meets management needs. There is still room to target 85% world class.

**Jan-2025: OEE = 64.61%**




**Feb-2025: OEE = 64.61%**



**Mar-2025: OEE = 66.72%**

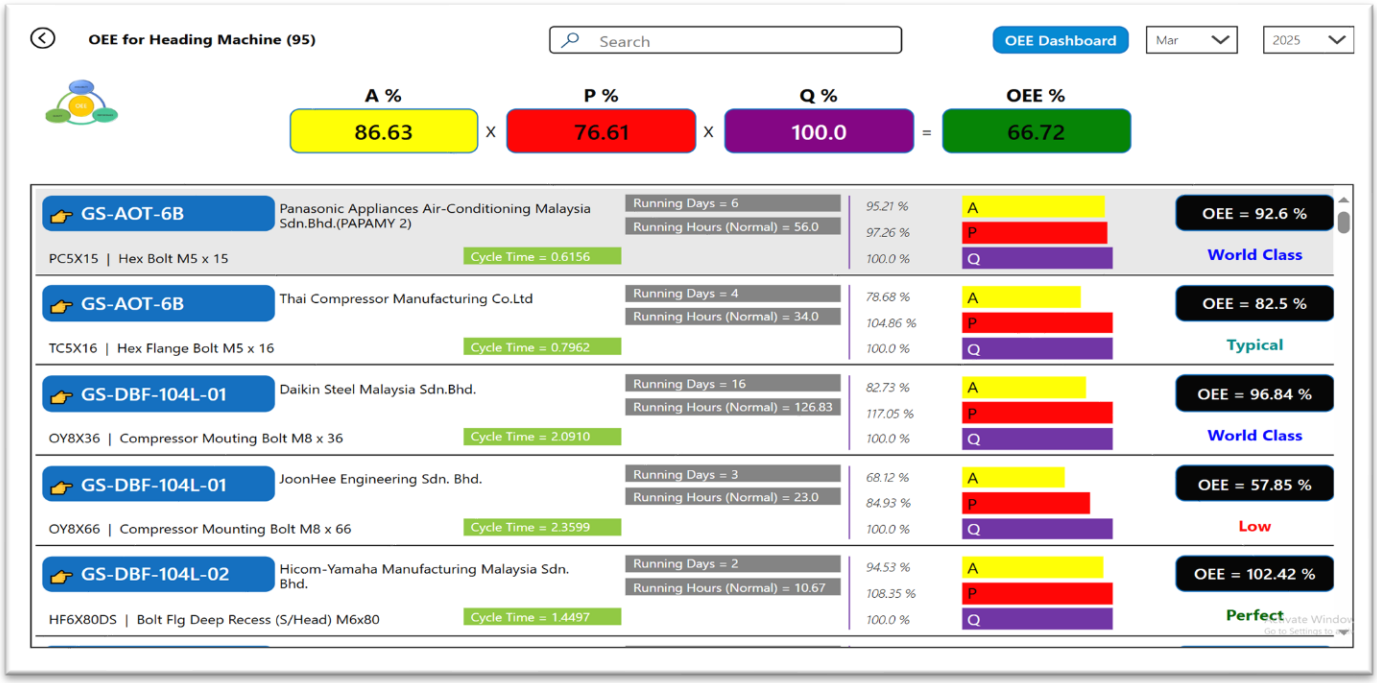



**Figure 12.** Presents the calculation of OEE by WO No and, Machine No, by Year and Month

### Key Features in Calculating OEE by Month-Year

Table 1 highlights the key features of the OEE by Month-Year dashboard, emphasizing real-time data analysis, efficiency, and interactive reporting.

**Table 1.** OEE by Month-Year dashboard

| Feature | Description |
|---|---|
| Real-Time Big Data Analysis | Enables real-time processing and analysis of large datasets for accurate OEE calculations. |
| Efficient and Interactive Reporting | Provides interactive and user-friendly reporting for enhanced decision-making. |
| Function Trigger | When navigating to the screen, PowerFx function triggers calculations for: |
| | Monthly OEE: Calculated as A x P x Q. |
| | Machine-Work Order Based OEE: Calculated for each machine and work order. |
| Visualization | Displays data in the following charts: |
| | i. A Chart: Availability in percentage. |
| | i. P Chart: Performance in percentage. |
| | i. Q Chart: Quality in percentage. |
| | OEE Chart: Overall Equipment Effectiveness in percentage for each Machine-Work Order. |

## CONCLUSIONS, CONTRIBUTION AND RECOMMENDATION

The execution of this study takes advantage of Low-code Programming (LCP) technology to deal with statistical problems in the manufacturing sector, the focus being on Overall Equipment Effectiveness (OEE) and Big Data Real-Time Analytics. The research intends to overcome the statistical hurdles thanks to the cutting-edge capabilities of LCP, and at the same time to make the whole process of real-time decision-making less

complicated, thus driving the operational efficiency in a way that the statistical faculty's area of expertise in data-driven solutions would match.

**Objectives Achievement**

Objective 1: To evaluate traditional data collection and integrate real-time analytics using SAAS and CAAS. The expected results are Statistical models integrated with LCP tools will enable real-time data processing, improving accuracy and enabling predictive analytics for operational optimization. Claim Supported by Pilot Study Results: The pilot study successfully replaced traditional data collection methods with a real-time system using Power Apps and QR codes, enabling real-time data processing. This improved data accuracy and provided the foundation for real-time analytics. Evidence from Results: Section 3.3 Data Collection" details the use of QR codes and mobile apps to streamline data collection, replacing manual methods. Section 3.7 Results and Discussion" shows the real-time OEE dashboard and calculations, demonstrating real-time analytics. Table 1 highlights the key features of the OEE by Month-Year dashboard, emphasizing real-time data analysis, efficiency, and interactive reporting.

Objective 2: To explore low-code programming for citizen developers. The expected results are LCP tools will simplify statistical analysis, allowing non-experts to design data structures and perform advanced analytics, fostering a data-driven culture. Claim Supported by Pilot Study Results: The study utilized Power Apps, a low-code platform, to develop the OEE monitoring system. This demonstrates the potential for citizen developers to create manufacturing applications. However, the pilot study did not explicitly measure citizen developer involvement. Evidence from Results: Section 3.1 Data Structure" and "Section 3.3 Data Collection" detail the development of the Power Apps application, showcasing the use of low-code programming. The document emphasizes the use of PowerApps, a low-code programming solutions, Microsoft Power Apps [2], which enable rapid, cost-effective application development without extensive coding expertise.

**Significant Contributions of Methodology and Novelty of the Application**

One of the main innovations of this study is the peculiar coalition of Microsoft Power Apps PowerFx formula for front-end data gathering and OpenAPI 2.0 [9] for the backend data management. As far as I know, this combination has not been used before in the OEE monitoring systems, especially for SMEs. The fantastic application of such a method is empowering OEE monitoring in SMEs by providing a low-cost, scalable, and user-friendly monitoring solution. It can allow manufacturers to data-driven decisions, enhance productivity, and be more competitive in the Industry 4.0 era. However, every system brings along its strengths as well as shortcomings / limitations.

**Strengths:**

- Comprehensive Data Collection: QR codes and mobile applications were used to set up a complete data collection system that would record all important data points (Work Order, Machine, Operator, Production Quantity, Downtime, etc.) automatically. This step is vital to get the right OEE measurement.
- Real-Time Calculation: With the help of Power Fx formulas in the app, A, P, Q, and OEE are calculated and thus, real-time monitoring is made possible which is a major benefit compared to old, manual techniques.
- Cloud-based Storage: The use of GoCloud as Web Services provide a high-speed data connection between PowerApps and Cloud Storage enabling data access from anywhere in the world. Hence improve connectivity.
- Visual Presentation: The dashboard with charts for A, P, Q, and OEE provides a clear and intuitive way to visualize the data, making it easier to understand trends and identify areas for improvement.
- Focus on SMEs: This system is tailored for SMEs by using low-code solutions to make it cost-effective and scalable, which is a key contribution.

**Limitations / Weakness:**

- Inconsistency of Data Collection: In the case of absences, this may result in lapse of data collection resulting in data in continuity, and hence inconsistency affecting OEE calculation.
- Poor Internet Connection: In the context of Malaysia indoor Wi-Fi connection strength as well as coverage, this plays crucial roles as unstable internet connection may hinder users from data collection as all apps are running under stable internet to perform smoothly.

## RECOMMENDATIONS

The gap analysis reveals that, despite the fact that the separate studies investigated or made use of low-code platforms for overall equipment effectiveness and cloud-based APIs for data management respectively, the integrated method put forth here is still to be more complete solution. It addresses the limitations of traditional methods by providing real-time insights and reducing the cost and complexity of implementation, which are critical barriers for SMEs. A thorough review of the existing literature, as presented in Section 2, did not reveal any studies that combine Power Apps with OpenAPI 2.0 in the manner proposed in this research. This highlights the innovative nature of the proposed system. Cost-effective devices as mobile devices for data collection is ideal to have an in-built SIM card for seamless data connection, especially with the introduction of 5G connection as part of the overall implementation to expedite this unique approach.The conclusion should address the research problem and objective. State the importance of the research and the implications. Do not recapitulate the results but make statements, and use compelling statements, avoiding the word “maybe”, “perhaps”, etc. Write the conclusion of your manuscript in a narrative/paragraph form if there is only one concluding statement, or give numbering if needed.

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