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Streamlining and digitalising OEE and loss calculation methodologies to enhance industrial usability

Annemieke Moerkerken[a], Ivo Adan[a], Sebastian Thiede[b]

[a]*Eindhoven University of Technology, Groene Loper 3, Eindhoven, 5612 AE, the Netherlands*
[b]*University Twente, Drienerlolaan 5, Enschede, 7522 NB, the Netherlands*

* Annemieke Moerkerken. Tel.: +31-634196751. *E-mail address:* a.moerkerken@sxils.com

Abstract

This paper explores the evolution and current challenges of Overall Equipment Effectiveness (OEE) as a key performance indicator in manufacturing environments, emphasizing its practical but inconsistent application across industries. It highlights methodological shortcomings, particularly in the interpretation of loss categories and parameter definitions, which hinder operational alignment and benchmarking. Through interviews with several companies, the study reveals variations in OEE definitions, data practices, and governance structures. The authors advocate for digitalization as a means to enhance OEE usability, proposing frameworks like for example Asset Administration Shells (AAS) and Unified Name Space (UNS) to standardize data integration. A decision-support function and user friendly interface are introduced to improve accessibility and facilitate shopfloor engagement. Ultimately, the paper calls for a globally open accessible library and standardized calculation methodology to unlock OEE's full potential as a driver of continuous excellence.

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Keywords: OEE; TPM; Six Big Losses; Digitalization; Operational Excellence; Benchmarking; Data Integration

1. Introduction

OEE is a widely recognized key performance indicator (KPI), yet it poses certain limitations from both application and methodological points of view [8]. Originally developed in the late twentieth century and rooted in manual data collection practices [4], its foundational principles can be debated. Moreover, the notion of what constitutes "good performance" has evolved significantly over the past decade. The advent of digitalization offers promising opportunities to improve the application of OEE—particularly through improved data acquisition, standardized calculation methodology, and customizable, role-specific reporting.

What makes OEE intriguing is not only its simplicity—availability, performance, and quality combined into one figure—but also the complexity hidden beneath. Each of these dimensions translates into different types of losses, from breakdowns and changeovers to minor stops, reduced speed, startup inefficiencies, and quality defects. In theory, these six losses provide a clear lens for identifying opportunities for improvement. However, in practice, companies interpret and classify them differently, leading to striking variations in reported OEE values. This tension between clarity and ambiguity raises a central question: can OEE truly serve as a universal benchmark, or does its strength lie in guiding local improvement?

By exploring these inconsistencies and the role of digitalization in resolving them, this paper invites the reader to reconsider OEE not as a static KPI, but as a dynamic tool whose usability depends on how transparently losses are defined and how effectively data are integrated.

2. OEE as manufacturing KPI

This chapter introduces the origins, definition, and loss categories of OEE, establishing its role as a key performance indicator in manufacturing.

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2.1. History of OEE

OEE was originally developed by Seiichi Nakajima in the late 1980s at Nippondenso, a Toyota supplier, as part of the Total Productive Maintenance (TPM) concept, which focuses on optimizing and maintaining equipment efficiency [1].

Although initially focused mainly on maintenance, it has been extended to areas such as performance measurement and productivity improvement [2]. OEE was officially standardized in ISO 22400 part 2 [3]. The global timeline is shown in Figure 1. OEE is intended to assess how efficiently companies operate across industry, whilst the underlying losses are intended to steer production improvement on the shop floor.

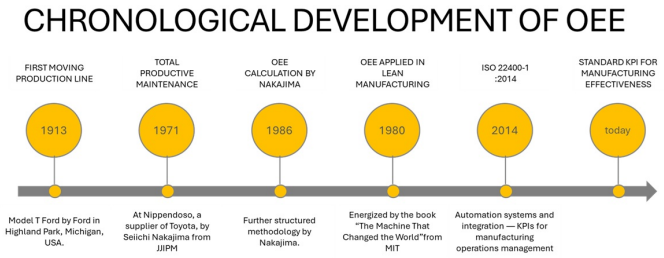

Fig. 1. Timeline of OEE evolution.

2.2. Definition of OEE

OEE measures efficiency based on three core aspects [2]: availability, performance, and quality. Each component has a specific formula as can be seen in equation 1. It can be expressed in percentages or hours. The three categories are then further divided into specific loss categories, of which examples are given in Section 3. These underlying losses can also be expressed in quantities.

$$OEE = Availability \times Performance \times Quality \tag{1}$$

$$Availability = \frac{\text{Planned Production Time} - \text{Availability Losses}}{\text{Planned Production Time}} \tag{2}$$

$$Performance = \frac{\text{Ideal Cycle Time} \times \text{Actual Output}}{\text{Run Time}} \tag{3}$$

$$Quality = \frac{\text{Actual Output} - \text{Defective Output}}{\text{Actual Output}} \tag{4}$$

The formulas, initially introduced by Nakajima [4], have evolved over time to better meet real-world manufacturing needs. However, their core principles remain unchanged for measuring and optimizing production efficiency. The outcome is often plotted as a waterfall plot.

2.3. Loss categories

The three key components (availability, performance and quality) correspond to different types of production losses, classified into six major equipment losses [4], as shown in Figure 2.

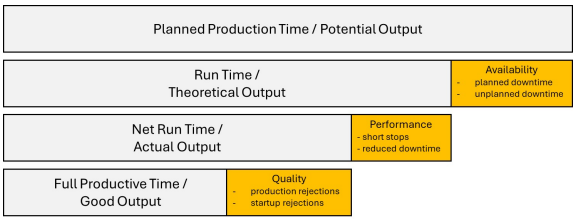

Fig. 2. OEE and the 6 losses

The loss categories are defined according to the TPM methodology [2].

- Planned Downtime: losses such as planned maintenance, change over, setup.
- Unplanned Downtime: equipment failure or breakdowns (time).
- Short Stops: Minor or short stops when the equipment temporarily stops or is interrupted.
- Reduced Downtime: speed difference between the actual operating speed and the theoretical speed per equipment design.
- Production Rejections: quality defects or rework due to incorrect production processes or malfunctioning.
- Start up Rejections: start up losses from lower yield during ramp up.

2.4. Application of OEE in industry.

In the last 20 years, output and cost have been the key drivers in manufacturing in industry, where OEE was the primary KPI for determining the output. Although 50 to 90% of companies use OEE, there is no reliable global database or library to benchmark (Figure 3). A contributing factor is the absence of standardized methodologies for calculating OEE, which undermines the reliability of comparisons between companies. Although data-collection initiatives by commercial consultancy firms are generally regarded as trustworthy within industry, their usefulness remains limited due to the persistent variation in calculation approaches.

	Adoption	Low	World-Class
Automotive & Aerospace	80-90%	<65%	>85%
Pharmaceuticals & Medical Devices	70–85%	<60%	>80%
Electronics & Semiconductors	75–90%	<70%	>88%
Food & Beverage	50–70%	<55%	>75%
Plastics, Packaging, and Metalworking	40–60%	<60%	>80%
Metalworking		<50%	>70%

Fig. 3. Usage of OEE [5], [6], [7]

3. Methodological shortcomings

The calculation of OEE and its underlying loss categories is extensively described in the (management) literature, for example in [1]. A practical example provides the clearest illustration of how seemingly minor interpretative differences can substan-

tially influence both the resulting OEE values and their implications.

3.1. A practical example

Imagine taking a bottling line that could produce an output of 140,000 bottles per hour. An order of 1.5 M bottles has been placed. Therefore, planning prepared a slot for this batch of 19.5 hours. In this time frame, maintenance requested a 3 h slot for the overhaul of a gearbox.

After the batch was completed, operations extracted all production data to calculate the OEE. During the batch, there was an (unplanned) breakdown of 1 h due to a broken filler head. In addition, operations needed 0.5 h for the equipment changeover from the previous batch. The Manufacturing Execution System (MES) recorded that the equipment was in 'running' status for 15 h in total. MES also recorded that there were 30 stops of 1 minute, so 0.5 hours in total. The line actually produced a bit more since 100,000 were thrown away because of poor crown placement.

So, the line finally produced 1.5 M good bottles in 10.7 hours. In fact, it produced 1.6 M bottles in 11.4 hours, but part of it had to be thrown away. In total, 19.5 hours were needed to produce these 1.6 M bottles due to (planned and unplanned) downtime. This would have taken 15 h if the machine was running at ideal speed constantly. Under ideal circumstances, it could have produced 2.73 M bottles in these 19.5h. Note that non-scheduled production hours, due to no demand, are out of scope. Leaving an availability rate of 76.92%, a performance rate of 76,19%, a quality rate of 93,75%, resulting in an OEE of only 54.95% .

The example is shown in the waterfall plot in figure 4. Please, bear in mind that, as stated in the first part of the paper, there are different ways of interpreting the losses and including them into the OEE calculation.

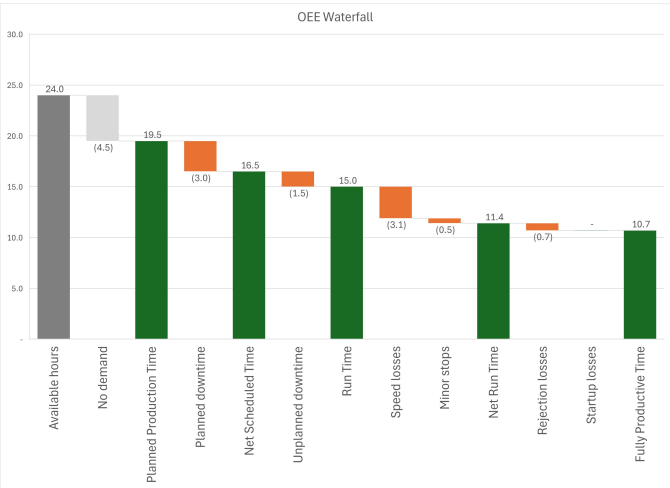

Fig. 4. Visual example of OEE

3.2. Methodological differences

Although OEE is clearly defined in the literature, previous studies highlight that differences in the way underlying loss factors are interpreted often lead to variations between companies [8], [9]. The precision of OEE measurements largely depends on an organization's data collection capabilities, defined calculation definitions, and the required level of precision.

Furthermore, since equipment efficiency is influenced by its operational environment, the OEE results are also shaped by the operator's behavior and the company's production planning and control strategies. In addition, many organizations struggle to extract data directly from machines and to aggregate it consistently at the plant level, which further complicates accurate OEE measurement [2].

The issue with OEE is not a matter of incorrect calculation, but rather the variability in how data is extracted from machines and subsequently aggregated at the plant level and how it is ultimately computed. There are multiple approaches, each of which significantly impacts the final OEE value. Because many companies incorporate OEE into individual performance evaluations, plant managers in particular often experience considerable pressure to keep this KPI at a high level. Some typical examples are given below.

3.3. Loss allocation

The challenge often lies in deciding how to classify certain losses. For example, if an unplanned stoppage lasts so long that planned maintenance is scheduled during it, should this be recorded as planned maintenance or as an (extended) unplanned stop? Planned would be the responsibility of the technical department, while unplanned often is addressed by the production team.

3.4. Equipment speed

A critical parameter is the speed of the equipment (ideal cycle time), which, by definition, should be based on the original speed quoted in the original equipment manufacturer's (OEM) specifications. But in reality, many equipments run for 50 years in a plant, so the performance changes over time. In addition, equipments are often modified or updated, which can affect the output. Therefore, some companies are using the highest speed achieved in recent months or batches instead. In previous example, increasing the speed from 140,000 to 150,000, would negatively impact the OEE from 54.95 to 51.28%.

3.5. Short versus long stops

A long unplanned stop is perceived as a technical breakdown, often adding the requirement that a part be replaced and the maintenance team be involved. A short stop is seen as an operating issue, often related to the raw materials or process parameters, and therefore should be tackled by production. However, companies split stops into long vs. short stops differently, with thresholds ranging from 1 to 30 minutes for more mature

plants. As a result, the loss is assigned to a different team, who will be held responsible for resolving it.

3.6. Maintenance in the weekend

Plants often schedule maintenance during weekends, when the facility is already shut down and no shifts are operating. In such cases, the OEE remains unaffected, whereas maintenance performed during the week does impact the OEE. Consequently, this strategy is often preferred when there is significant pressure to maintain high OEE levels. In contrast, failing to adopt this approach can lead to increased maintenance costs. In above example, planning the gearbox overhaul in the weekend could increase the OEE from 54.95 to 64.10%.

3.7. High-mix portfolio

Plants that experience frequent changeovers due to a wide range of SKUs will naturally report a lower OEE compared to facilities running long production batches with minimal changeovers. This is because changeover times are recorded as planned downtime losses for each batch switch. As a result, even highly efficient batch execution can still yield a relatively low OEE. For plant managers, this means that agility and flexibility in production can appear unfavorable in OEE metrics compared to operations focused on a limited product mix. In above example, increasing the change over time to 1.5h would negatively impact the OEE from 54.95 to 52.26%.

3.8. Capex prevention

Another example is that plants often choose to continue operating with existing equipment rather than completely replacing it through capital expenditures (Capex). Although this approach can reduce long-term investment costs, it typically requires additional downtime for planned maintenance activities. As a result, the trade-off becomes clear: higher OEE in the short term versus lower overall costs in the long run. This raises an important discussion point for plant managers—whether to prioritize immediate performance metrics or accept temporary OEE losses in favor of sustainable cost savings and asset longevity.

4. Industrial perspectives based on interviews

Building on the methodological challenges outlined in Chapters 1–3, a series of structured interviews was conducted with six companies in the food and beverage sector. Although the number of interviews is limited, the participating organizations represent major multinational brands with substantial operations in food and beverage manufacturing. The purpose of these interviews is to explore whether the challenges surrounding OEE identified in the literature are shared in practice, with the aim of informing the development of improved calculation methodologies, rather than to produce statistically significant or generalizable performance gaps.

4.1. Interview set-up

The interviews were designed to probe the practical application of OEE by focusing on the same themes discussed earlier in the paper: the definition of input parameters, the classification of losses, and the calculation standards used in daily operations. Each interview followed a consistent format, covering topics such as stop-time thresholds, speed determination methods, benchmarking practices, the integration into shopfloor decision-making, and how companies currently extract and process data from their manufacturing systems. This provided valuable context on the role of MES, ERP, and local tools in shaping OEE calculations. Furthermore, each interview concluded with an open brainstorm, inviting participants to share their ideas for improving OEE usability and comparability, both within their own organizations and across the industry.

This combined approach allowed us to directly link the theoretical shortcomings described in the literature to the realities observed in practice. By asking comparable questions and encouraging open dialog, the interviews provided a structured lens on how methodological differences manifest themselves in industry and how companies envision overcoming them.

Table 1 presents the outcomes of these interviews in tabular form, offering a comparative overview of the parameters, practices, and governance structures reported by the participating companies. The general results of the interviews can be structured into four key insights.

4.2. Procedures and Organization

All companies used their own terminology for OEE losses, highlighting the lack of standardization around this KPI. Although OEE offers valuable information on plant performance and losses, the absence of uniform definitions leads to inconsistencies between sites within the same organization and externally. To be able to benchmark (internally), companies need to develop complex internal procedures and governance, as also described in the literature [10]. Typically, teams of at least two to five people are required to establish these frameworks and align the outcomes between plants.

4.3. Driving Shop Floor Performance

Although OEE serves as a valuable metric for comparing output at the corporate level, it is less suited to guide day-to-day operations on the plant floor. Operators would need detailed loss information—typically expressed in volumes or units rather than hours or percentages—to manage and improve performance more effectively. Many companies indicate that they seek a sharper distinction between avoidable losses (e.g., unplanned short stops) and strategically chosen losses (e.g., high volume mix).

4.4. Benchmarking

The performance of the reported OEE varies considerably, generally ranging from 50% to 90%, although most companies

Product, Role	OEE Range	Benchmarking Practice	Stop Time Definition	Speed Calculation Method	Suggestions for OEE Calc.
Household and Personal care, Digital Manger global	70%, slightly above if breaks excluded	McKinsey reports; P&G benchmark; 85% best-in-class for filling lines	Breakdown = part replacement; split at 10–30 min	Based on machine acceptance test	Advises not to omit losses
Beverages, Plant Manager top 5	55–70%; Technical OEE 95%	Internal benchmarking across 180 plants	5-minute threshold	Supplier specification; speed rarely increased	Emphasizes clear breakdown definitions
Food. Plant Manager top 5	Technical OEE 95%; overall unknown	Asset Utilization benchmarked; no OEE	Previous PE used 20 min; current unclear	OEM nameplate speed; adjusted only if underperforming	Advocates global consistency
Beverages, Plant Manager top 5	75–85% in packaging; site level unknown	Internal benchmarking only	10-minute threshold; part change optional	OEM speed; some teams allowed to adjust	Stresses accurate data capture
Food + Beverages, Gobal Maintenance lead	55–85% depending on site and line	Internal benchmarking	10-minute threshold; part change included but not always followed	One max speed used; no deviation for slower products	Suggests clear separation of breakdowns and short stops
Beverages, Digital Manger global	62–70%; lines 50–65%	P&G used as external benchmark	Breakdown vs frequent short stops; part change required	Bottleneck validated speed; changes require approval	Recommends global calculation and clear ownership

Table 1. Interview outcomes

cluster between 60% and 75%. OEE is used primarily for internal benchmarking, particularly at the corporate level rather than the plant level. For external reference, P&G's IWS benchmark of 85% is often cited as a "best-in-class" standard. However, external benchmarking remains limited due to inconsistencies in how OEE is calculated between organizations. Also, there is limited to no benchmarking for Small to Medium sized Enterprises (SMEs). A common concern shared among companies is the risk of focusing too heavily on the metric itself, rather than leveraging it as a tool to drive meaningful operational improvements.

4.5. Data extraction and IT tools

Most organizations still operate in a fragmented landscape, relying on a combination of Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP), Supervisory Control and Data Acquisition (SCADA), and vendor-specific formats. Extracting data from key machines is often complex, inconsistently structured across equipment, and only minimally supported by OEMs. Aggregated data are frequently accessed through Excel, Power BI, or other local tools, and while there are digital twins and historians, they remain siloed and rarely deployed on an enterprise-wide scale. This reliance on disparate systems complicates standardization and limits the ability to generate consistent insights.

In recent years, however, some organizations have begun to experiment with advanced technologies such as artificial intelligence and sensor integration to support root cause analysis, predictive insights, and real-time optimization. Investments are also directed toward edge devices, SQL standardization, and unified namespaces. Despite these advances, limited vendor cooperation, legacy infrastructure, and internal skill gaps continue to hinder the broader adoption of AAS.

5. Improvements through digitalization

Addressing the challenges identified by industry from a scientific standpoint, the following sequence of improvements is proposed and elaborated in the subsequent paragraphs and includes establishing standardized data-structuring and extraction, enabling flowchart-based decision supportand developing a turnkey, low-cost tool.

5.1. Data structuring

A major challenge in manufacturing environments, particularly in larger and older facilities, is the heterogeneity of equipment and systems. Production lines are often made up of equipments from different vendors, each having different PLC's and (HMI) interfaces, protocols, and data models. This heterogeneity is not limited to physical assets: digital systems such as MES, RMS (Recipe Management Systems), and WMS (Warehouse Management Systems) also vary widely between vendors. As a result, integrating these components into a cohesive, interoperable system remains a costly and time-consuming task, often involving custom engineering for each interface [11]. Increasingly, equipment data retrieval has also become a paid service, limiting the information available to the asset owner.

Two challenges mainly arise. One is the possibility to externally access the machine database and second the different setup and structure of these databases once aggregated. Additionally, some machines or parameters required to calculate OEE

are not measured at all. Frameworks such as AAS and UNS uniformize data exports between equipment. Today, IT/OT solutions and data lakes support sustainable manufacturing by offering real-time performance insights with minimal sensor infrastructure, making it especially useful for retrofitting older equipment. A compact autonomous "smart box" could help industrial companies —especially SMEs— to collect, process, and integrate IIoT data locally [12].

5.2. Decision support function

To support consistent and transparent benchmarking of OEE in diverse industrial contexts, a flowchart-based methodology is proposed. This approach systematically maps the key decision points and contextual parameters that influence the calculation of the OEE, including industry type, production setup, SKU diversity, and asset age. It also captures operational choices such as the categorization of fixed maintenance intervals, the determination of the nominal speed of the equipment, and the threshold definitions for distinguishing between short and long stops. By explicitly documenting these variables, the methodology facilitates external benchmarking and promotes cross-site comparability. AAS and UNS frameworks further enhance this process by standardizing machine data structures, enabling seamless integration and retrieval across heterogeneous systems. These technologies provide scalable, real-time access to performance data, supporting both legacy equipment and modern digital infrastructures. In figure 5 an example is given of how, only part, of this decision tool could look like.

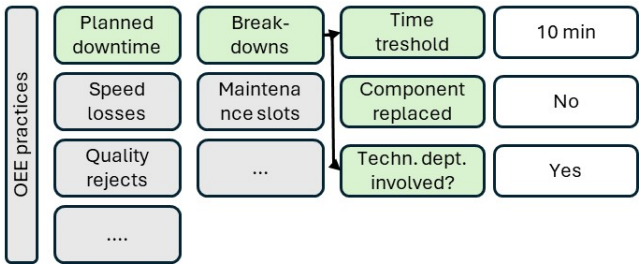

Fig. 5. Decision Flowchart example

5.3. Turn-key retrofitting solution

Introducing OEE and aligning it's calculation can be time consuming and costly, especially for SMEs. A simplified and freely accessible tool is proposed that features a user-friendly interface with guided input fields, the decision flowchart, and a streamlined calculation engine. Its design aims to reduce both technical complexity and financial barriers to adoption.

The tool emphasizes intuitive visualization, with outputs rendered in accessible formats such as Power BI dashboards, making performance insights directly actionable on the shop floor. By focusing on ease of use and minimal setup, the solution allows (SME) companies to identify and address production losses effectively, even in low-automation environments. In addition, the tool could house global benchmarking data across various industries. This could especially help companies benchmark themselves (externally) and identify areas for improvement. This approach democratizes access to performance monitoring and supports continuous improvement in a broader industrial base, especially for smaller companies. Once the (machine) data extraction is simplified and structured simultaneously, and the calculation of OEE and its losses standardized and comparable, the development of such a tool should be straightforward and relatively simple.

6. Next steps

The next step is to develop and validate the flowchart with a broader set of plants and industries to confirm its applicability. In parallel, a standardized, open data model should be developed and tested on heterogeneous equipment to ensure interoperability. A pilot tool can then be built and evaluated in both large-scale and SME environments. Together, these steps would require an estimated €150k–€300k, depending on pilot scale, number of participating sites, and the depth of IT/OT integration needed.

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