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Resource Overall Equipment Cost Loss indicator to assess equipment performance and product cost

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Abstract

Purpose – This paper aims to overcome the inability of both comparing loss costs and accounting for production resource losses of Overall Equipment Effectiveness (OEE)-related approaches.

Design/methodology/approach – The authors conducted a literature review about the studies focusing on approaches combining OEE with monetary units and/or resource issues. The authors developed an approach based on Overall Equipment Cost Loss (OECL), introducing a component for the production resource consumption of a machine. A real case study about a smart multicenter three-spindle machine is used to test the applicability of the approach.

Findings – The paper proposes Resource Overall Equipment Cost Loss (ROECL), i.e. a new KPI expressed in monetary units that represents the total cost of losses (including production resource ones) caused by inefficiencies and deviations of the machine or equipment from its optimal operating status occurring over a specific time period. ROECL enables to quantify the variation of the product cost occurring when a machine or equipment changes its health status and to determine the actual product cost for a given production order. In the analysed case study, the most critical production orders showed an actual production cost about 60% higher than the minimal cost possible under the most efficient operating conditions.

Originality/value – The proposed approach may support both production and cost accounting managers during the identification of areas requiring attention and representing opportunities for improvement in terms of availability, performance, quality, and resource losses.

Keywords Data collection, Cyber-physical system, Key Performance Indicator, Productivity, Industry 4.0, Resource efficiency

Paper type Research paper

1. Introduction

A Key Performance Indicator (KPI) is a “quantifiable level of achieving a critical objective” (ISO, 2014a), which is very important for understanding and improving manufacturing performance (ISO, 2014b). The use of KPIs allows managers to control and guide the company

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towards improvement, make effective decisions, and lead and reward employees (Schiraldi and Varisco, 2020).

Among the existing KPIs, Overall Equipment Effectiveness (OEE) has been widely used in the industry (Bougain *et al.*, 2015; Kumar and Kumar, 2019), and the interest towards it has recently increased (Ng Corrales *et al.*, 2020). Nowadays, it is considered as one of the most important performance metrics (Mahmoud *et al.*, 2019). It provides a simple and comprehensive metric for equipment performance (De Ron and Rooda, 2006; Wudhikarn, 2012), measuring the effectiveness of a machine or equipment (Nota *et al.*, 2020; Singh *et al.*, 2013; Wudhikarn, 2016; Zhou *et al.*, 2020). OEE is a powerful tool to identify and eliminate manufacturing losses, namely availability, performance, and quality rate (Mathur *et al.*, 2011; Muchiri and Pintelon, 2008; Singh *et al.*, 2021; Tsarouhas, 2020). Losses are activities consuming and absorbing resources without value creation (Muchiri and Pintelon, 2008).

Nevertheless, there is a debate in the literature related to the main weaknesses of OEE. Several authors point out that the elements involved in its calculation are not sufficient to fully describe the effectiveness of a production system, and other aspects (e.g. costs) are not reflected by this metric (Garza-Reyes *et al.*, 2008; Kuan Eng and Kam Choi, 2016; Muchiri and Pintelon, 2008). Cost represents one example of production environment factor that may impact the performance of a machine and that is not considered by OEE (Garza-Reyes, 2015). OEE is usually used to rank problematic equipment in terms of effectiveness, but the lowest OEE machine may not be responsible for the largest economic losses, and machines that are equal in terms of availability rate, performance efficiency, and quality rate do not necessarily have similar economic losses (Wudhikarn, 2016). Therefore, it is necessary to consider both losses and costs to properly prioritise problematic equipment (Wudhikarn, 2016). Although OEE identifies and measures losses of important manufacturing aspects to support the equipment effectiveness and productivity (Muchiri and Pintelon, 2008), it does not account for inefficiencies in material utilisation and process cost variations that do not cause an extension of production times (Garza-Reyes *et al.*, 2008), and it does not measure how effectively a machine or equipment uses energy and other production resources (Braglia *et al.*, 2020). The losses impeding the effective use of production resources represent major losses that affect the manufacturing performance and efficiency, which should need to be accounted for appropriately to achieve world-class performance (Ahuja and Khamba, 2008). Differently from other major losses related to planned shutdown losses at the production planning level or worker efficiency (Ahuja and Khamba, 2008), losses about production resources may occur unexpectedly and directly be linked to the machine or equipment health status. Such losses regard material, consumables, and energy (Ahuja and Khamba, 2008).

By extending the definition about energy losses proposed by Wen *et al.* (2021), production resource losses can be defined as the overconsumption of resources occurring during the transformation of raw materials or semi-finished products into valuable products. Their identification in manufacturing systems represents one fundamental step to find out significant resource use and this offers considerable potential for resource efficiency improvement. The interest towards the production resource topic has attracted increasing attention over the years due to the climate change mitigation, reduction of carbon dioxide emissions, adoption of more stringent regulations, scarcity of resources, and increment in energy costs (May *et al.*, 2017; Renna and Materi, 2021). Resource and, particularly, energy efficiency are key concerns in several industries (Cesarotti *et al.*, 2013, 2016), and their integration in manufacturing has been recognised as a means to foster economic and environmental performance, increase competitiveness, and achieve sustainable production (Braglia *et al.*, 2020; May *et al.*, 2017). This is gaining even more importance in the current post-pandemic economic and global geopolitical context. Although integrating resource efficiency as a key criterion in production management is critical to increasing efficiency while maintaining productivity in manufacturing systems, integration of energy and, in general, resource efficiency into production management at the level of productivity variables seems to be a quite unexplored field (Wen *et al.*, 2021). Moreover, to assess the resource-related efficiency or effectiveness of an equipment, the time-based view alone is not sufficient (May *et al.*, 2015); indeed, for example the energy consumption of a machine could be different from the typical one under optimal conditions without causing a change in production times. To the best of our knowledge, only a limited number of studies based on OEE consider production resources in manufacturing systems and measure losses in an economic way. The metric defined by Garza-Reyes *et al.* (2008) and Garza-Reyes (2015) is focused on material efficiency as a cost-based measure, while the KPI developed by Morella *et al.* (2020a) considers the cost of energy in the calculation of the total cost. However, in these approaches, material and energy issues are not recognised and modelled as losses of the production system.

Consequently, this paper aims to overcome the inability of both comparing loss costs and accounting for resource losses of OEE-related approaches. The paper objectives are: (1) to develop a new KPI, called Resource Overall Equipment Cost Loss (ROECL), expressed in monetary units and including production resource losses, and (2) to use ROECL to quantify and analyse the impacts on the product cost due to inefficiencies and deviations of the machine or equipment from its optimal operating status occurring during the manufacturing of a production order. The ultimate objective is to propose a general approach able to support production and cost accounting managers in the identification of areas requiring attention and representing opportunities for improvement.

The possibility to quickly calculate ROECL is provided by Industry 4.0 technologies. Such technologies permit acquiring data and analysing the most appropriate variables to estimate a KPI in real-time (Morella *et al.*, 2020a). A Cyber-Physical System (CPS) is the core foundation of Industry 4.0 (Xu *et al.*, 2018): it is a physical and engineered system whose operation is monitored, co-ordinated, controlled, and integrated by a computing and communication core (Kocsi *et al.*, 2020). CPS enables acquiring real-time data for making decisions that enhances the idea to create an accurate costing system (Morella *et al.*, 2020a). It is also useful to obtain real-time data on factors such as energy or material consumption (Morella *et al.*, 2020b). Therefore, the opportunities offered by Industry 4.0 technologies make it possible to address one of the main problems related to the OEE determination: the ability to acquire and collect accurate and reliable measures and data (Dal *et al.*, 2000; De Ron and Rooda, 2006; Elevli and Elevli, 2010; Jeong and Phillips, 2001; Muchiri and Pintelon, 2008; Singh *et al.*, 2021; Zhou *et al.*, 2020).

The remainder of this paper is organised as follows. Section 2 summarises the theoretical background of the study. Section 3 details the methods employed for the research. The ROECL indicator and the approach for quantifying and analysing product costs are presented in Section 4, and their application in a real case study is described in Section 5. The case study results, and the strengths and limitations of the proposed approach are discussed in Section 6. Concluding remarks are provided in the final section.

2. Theoretical background

OEE was proposed by Nakajima (1988) as part of the Total Productive Maintenance (TPM) approach. It represents a quantitative metric to identify and measure the productivity of individual equipment (En-Nhaili *et al.*, 2016; Muchiri and Pintelon, 2008; Nachiappan and Anantharaman, 2006; Ng Corrales *et al.*, 2020; Zhou *et al.*, 2020).

OEE identifies and is measured in terms of six big losses comprising aspects of availability, performance, and quality reducing equipment effectiveness (Dal *et al.*, 2000; Juric and Goti, 2006; Muchiri and Pintelon, 2008; Ng Corrales *et al.*, 2020; Wudhikarn, 2010). In particular, Nakajima (1988) identifies the following six big losses:

(1) breakdowns and equipment failures: time losses when productivity is reduced and quantity losses caused by defective products due to sporadic and/or chronic failure;

(2) set-ups and adjustments: losses caused by a series of operations related to setting up or occurring when production of one item ends and the equipment is adjusted to meet the requirements of another item;

(3) idling and minor stoppages: losses happening when the production is interrupted by a temporary malfunction or when a machine is idling;

(4) reduced speed: losses referring to the difference between equipment design speed and actual operating speed;

(5) defects and reworks: losses related to defects and reworks (disposal defects), product downgrading, repairing of defective products to turn them into excellent products;

(6) reduced yield, start-up, rejects: losses about start-up after periodic repair, suspension, holidays, and/or breaks, happening from machine start-up to stabilisation.

The first two losses are “downtime losses” and are used to calculate the availability rate, the third and fourth losses are “speed losses” for measuring the performance efficiency, and the last two losses are “quality or defect losses” affecting the quality rate of the machine or equipment. The availability rate, performance efficiency, and quality rate (in %) are calculated through Eqs. (1)–(3), respectively, as proposed by Nakajima (1988).

$$A = \frac{\text{Operating time}}{\text{Loading time}} = \frac{\text{Loading time} - \text{Downtime}}{\text{Loading time}} \tag{1}$$

$$P = \frac{\text{Net operating time}}{\text{Operating time}} = \frac{\text{Ideal cycle time} \times \text{Processed amount}}{\text{Operating time}} \tag{2}$$

$$Q = \frac{\text{Valuable operating time}}{\text{Net operating time}} = \frac{\text{Processed amount} - \text{Defect amount}}{\text{Processed amount}} \tag{3}$$

where:

(1) operating time is the amount of time a facility is open and available for equipment operation;

(2) loading time is the planned time available per time period for production operations, after removing all planned stops;

(3) downtime is the stoppage time loss due to breakdowns, equipment failures, set-ups, and adjustments;

(4) net operating time is the time during which the machine or equipment is producing at the standard production rate;

(5) ideal cycle time (or theoretical cycle time) is the minimum time to complete the processing on one unit of production, assuming no efficiency losses;

(6) processed amount is the number of items processed per time period;

(7) valuable operating time is the fraction of time an equipment works under optimal operating conditions;

(8) defect amount is the number of items rejected due to quality defects, and require rework or become scrapped.

OEE (%) is determined by means of Eq. (4), while its pivotal elements are depicted in Figure 1, based on Nakajima (1988). In the literature, other loss classifications (e.g. Jeong and

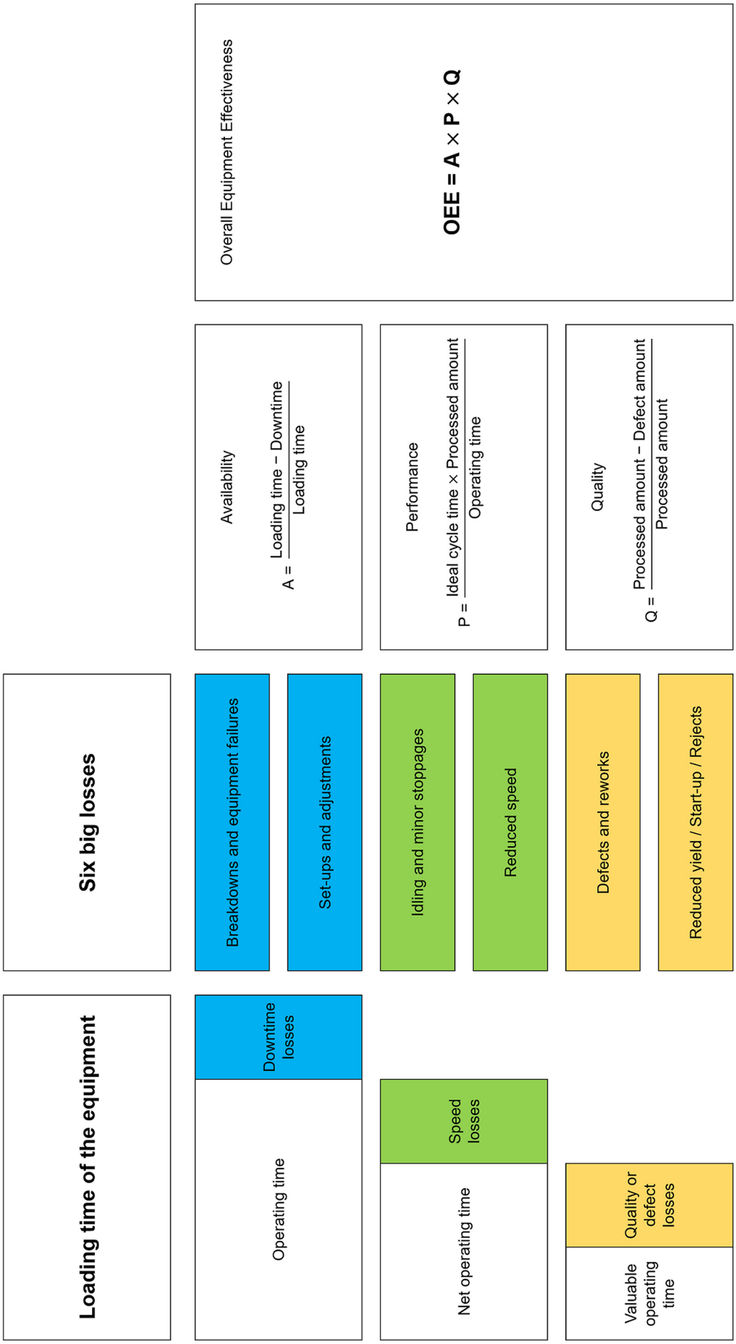


Figure 1.
OEE overview in terms of timing of the equipment, six big losses, and components

Phillips, 2001) and different equations to calculate the OEE components (e.g. Stadnicka and Antosz, 2018) are also proposed.

$$\mathrm{OEE} = \mathrm{A} \times \mathrm{P} \times \mathrm{Q} \tag{4}$$

OEE can be applied to any manufacturing organisation (Badiger and Gandhinathan, 2008) and is an effective method to analyse the efficiency of a single machine as well as an integrated machinery system (Wudhikarn, 2011). It represents a best practice lean metric (Braglia *et al.*, 2018, 2019), and the gold standard for measuring manufacturing productivity (Nota *et al.*, 2020). It is not only an operational measure, but also a driver of process and performance improvement activities within a manufacturing environment (Dal *et al.*, 2000; Singh *et al.*, 2018; Wudhikarn, 2010, 2012; Yuan *et al.*, 2021). Indeed, it permits strengthening and successfully controlling the utilisation of a machine or equipment (Elevli and Elevli, 2010), and providing the basis to set improvement priorities and perform root cause analyses (Muchiri and Pintelon, 2008). OEE considers process improvement initiatives, prevents the sub-optimisation of individual equipment or product lines, provides a systematic method to establish production targets, and incorporates practical management tools and techniques to achieve a balanced view of process availability, performance rate and quality (Badiger and Gandhinathan, 2008; Dal *et al.*, 2000). The relevance of these aspects is also emphasised by Braglia *et al.* (2018): "one distinctive, and contemporarily appealing, feature of OEE with respect to other analogous KPIs is that it provides a breakdown structure for process losses that simplifies the task of evaluating the current performance and, at the same time, individuates both the source of losses and the corresponding remedy". In this sense, it is a crucial indicator used for short-term and long-term decision making (Wudhikarn, 2011): the use of this KPI can help management to unleash hidden capacity, eliminate waste, reduce overtime expenditures, decrease process variability, allow deferral of major capital investment (Muchiri and Pintelon, 2008; Yuan *et al.*, 2021), and reduce the cost of ownership (Wudhikarn, 2011). Therefore, OEE continuously focuses the plant on the concept of zero-waste (Badiger and Gandhinathan, 2008) and is a partnership between maintenance and production functions in the organisations (Singh *et al.*, 2021).

Although the benefits related to the OEE use, different limitations have also been highlighted. For instance, the calculation of OEE alone is not sufficient because no machine is isolated in the production unit, but pieces of equipment operate jointly in a production line (Braglia *et al.*, 2009; Kumar and Kumar, 2019; Mathur *et al.*, 2011; Scott and Pisa, 1998). Its focus is on individual equipment, not representing a measure of overall manufacturing system effectiveness (Mathur *et al.*, 2011), and it does not provide a global vision at the production system level (Durán *et al.*, 2018).

OEE is best suited for high-volume process-based manufacturing, while it is not appropriate or suitable for manual manufacturing processes (Dal *et al.*, 2000; De Ron and Rooda, 2005; Garza-Reyes *et al.*, 2008; Mathur *et al.*, 2011). Its use is not beneficial in low-volume job shops, some batch processes and for production processes with buffers in between (Muchiri and Pintelon, 2008).

OEE is characterised by equivalent weights in its components, and this might lead to not appropriately prioritise problematic equipment or machine (Raouf, 1994; Wudhikarn, 2010, 2012, 2016; Wudhikarn *et al.*, 2010). Therefore, it is not suitable to compare differences in machine type, capacity, and production cost (Mahmoud *et al.*, 2019; Wudhikarn, 2012, 2016; Wudhikarn *et al.*, 2010). To solve this weakness, Wudhikarn *et al.* (2010) and Wudhikarn (2016) propose Overall Equipment Cost Loss (OECL) based on the traditional three elements of OEE, but in which the loss in each element is dissimilar and depends on resource usage. OECL evaluates the performance of different pieces of equipment, converting the six big losses into monetary units. It can support the ranking of problematic equipment by accounting for production elements together with finance elements, and can be used with a machine that manufactures various products, if the costs of the products can be completely separated. OECL is proposed in Eq. (5).

$$\mathrm{OECL} = \mathrm{AL} + \mathrm{PL} + \mathrm{QL} \tag{5}$$

where AL, PL, and QL are availability, performance, and quality losses, respectively, which are expressed in monetary units.

Further OEE refinements and new metrics have been proposed to address the lack of financial components in OEE calculation (Kuan Eng and Kam Choi, 2016) and the impossibility to express it as a financial indicator (Rødseth *et al.*, 2015). For instance, Juric and Goti (2006) define a money-based OEE, considering the main cost types for each type of inefficiency to make comparisons between the economic importance of different inefficiency types and focus improvement efforts on the most expensive ones. En-Nhaili *et al.* (2016) propose Technical-Economic OEE (OEE-TE) by using technical and economic factors, which depends on availability, performance, quality, and average cost performance. Kuan Eng and Kam Choi (2016) present an approach to relate the OEE index and equipment throughput in monetary term in the form of the production part cost. Their approach is based on the establishment of OEE and throughput, and the consequent determination of the production part cost by means of the ratio between the total production cost incurred and the production throughput. A quite different study for addressing the financial OEE limitation was provided by Rødseth *et al.* (2015), who develop Profit Loss Indicator (PLI). PLI depends on loss in turnover and loss in extra costs, and its calculation can be supported by a cube composed of the dimensions of physical asset, accounting, and categories for time losses and waste.

The introduction of other cost elements in the original OEE formulation was also proposed by Garza-Reyes *et al.* (2008) and Garza-Reyes (2015), who introduce Overall Resource Effectiveness (ORE). ORE evaluates how efficiently a process utilises material and resource inputs taking as a reference its material and resources outputs. It considers the three traditional OEE elements and other performance factors having a significant contribution to process performance, including material efficiency, process cost, and material cost variations. These studies also contribute to capture some material losses in a manufacturing process such as overfilling or overweight: in this sense, they permit evaluating other loss categories in comparison to those calculated by OEE.

Indeed, OEE does not consider all factors reducing the capacity utilisation (Ljungberg, 1998), does not explicitly include material losses and material usage effectiveness (Braglia *et al.*, 2018), and neglects investigations with respect to energy, material, and labour (Braglia *et al.*, 2021). OEE accounts only for six of the sixteen major losses, as defined by Shirose (1996), impeding manufacturing performance (Ahuja and Khamba, 2008). The sixteen major losses are grouped into four categories: (1) losses that impede overall equipment efficiency, (2) losses that impede equipment loading time, (3) losses that impede worker efficiency, and (4) losses that impede efficient use of production resources. OEE measures only the effectiveness of planned production schedules, not considering planned shutdown losses (e.g. downtime for scheduled maintenance activities), that could be particularly relevant in capital-intensive and continuous line manufacturing industries (Jeong and Phillips, 2001; Mathur *et al.*, 2011; Nachiappan and Anantharaman, 2006). To overcome this limitation and account also for losses that impede equipment loading time, another KPI was proposed, called Overall Plant Efficiency (OPE), which measures the OEE relative to every minute of the clock, including planned downtime (Hansen, 2002).

Further OEE-related studies considering resource issues can be classified in two groups: (1) studies regarding the development of approaches and models, and (2) contributions proposing new indicators. In the first group, different contributions focus on energy as a key resource of manufacturing systems. For instance, Benedetti *et al.* (2014) provide a simulation model to study the connection between energy efficiency and productivity using OEE index, while Cesarotti *et al.* (2013, 2016) use regression analyses for investigating the relation between the OEE losses and the energy consumption and efficiency of the system. These studies demonstrate that OEE-related losses affect both plant efficiency and energy consumption. Recently, Nota *et al.* (2020) propose an approach combining the analysis of OEE with energy consumption and other variables managed by the Cyber-Physical Production System (CPPS). Their focus is on the obtainment of quantitative data about energy losses in batch production processes to reduce the energy consumption.

The investigation of some kind of resource losses in the traditional OEE concept has been mainly dealt with the definition of new metrics. For instance, Braglia *et al.* (2018) provide an indicator called Overall Material usage Effectiveness (OME) to measure the effective use of materials and to locate material losses within a production process. Eswaramurthi and Mohanram (2013) address the losses associated with resources and take into account readiness, availability of facility, changeover efficiency, material availability, man power availability, performance efficiency, and quality losses in order to propose ORE. Regarding energy, Bougain *et al.* (2015) propose Energy OEE (EOEE) for estimating the energy savings from the whole facility, considering both OEE and energy efficiency of a machine or equipment with a working process, as summarised in Eq. (6).

$$\mathrm{EOEE} = \mathrm{OEE} \times \mathrm{EE} = \mathrm{A} \times \mathrm{P} \times \mathrm{Q} \times \mathrm{EE} \tag{6}$$

where A, P, and Q represent the traditional OEE elements, while EE is the energy efficiency of the machine or equipment. When the assessment focuses on the whole facility, EE is the average of energy efficiency values of all the equipment within the facility. A similar indicator was proposed by Barletta *et al.* (2015) through discrete event simulation: their Energy OEE indicator measures energy performance, and serves as a decision support tool for managing operations in a manufacturing plant. Energy OEE permits assessing impacts of energy consumption losses rather than time losses.

In recent times, two other KPIs have been proposed to include energy issues and quantify costs in the six big losses approach. Energy Consumption Losses (ECL) by Morella *et al.* (2020b) measures the impact of energy consumption on the six big losses and represents the losses associated with the six big losses during a specific period. It is defined in energy units and as a carbon footprint, and is expressed as the sum of the energy consumption associated with availability, performance, and quality. On the contrary, Cost Loss Indicator (CLI) by Morella *et al.* (2020a) quantifies the costs associated with the six big losses during a specific period. It is defined in economic terms, and is expressed as the sum among the availability, performance, and quality cost losses. These authors consider different types of costs, among which energy. Energy is assumed as a consumable cost, as well as tools, tooling, and fluids, and is not identified as one of the losses of the production system.

Therefore, several attempts have been made in the literature to propose OEE-based KPIs enabling comparison of loss costs or accounting for resource losses, but none approach appears able to tackle both issues in a comprehensive way.

3. Methods

To achieve our objectives, we implemented a strategy composed of a literature review, the approach development, its evaluation and improvements, and a test on a real case study.

The literature review had the purpose to identify those studies combining OEE with monetary units and/or resource issues. We searched for scientific publications through various combinations of keywords (e.g. OEE, "Overall Equipment Effectiveness", money, monetary, financial, cost, resource, material, energy, loss) in relevant electronic (bibliographic) databases (i.e. Emerald, ScienceDirect, Scopus, Taylor & Francis, Web of Science). Such groups of keywords are merged in different search strings through Boolean operators, which we implemented in title, abstract, and keywords fields of the databases. We focused on English documents, including journal articles, conference papers, reviews, and book chapters. The list of references in each study was examined manually to capture any other interesting documents. We rated the document relevance by reading the full text. We excluded studies proposing frameworks based on OEE and factors different from resource losses, describing methodologies for measuring energy use without estimating manufacturing losses, or developing indicators not related to costs.

The literature review results were critically analysed, and allowed identifying the main contributions, assumptions, and features about the approaches enhancing the OEE formulation by means of the introduction of resource issues and/or providing any relationship between such KPI and costs. A critical analysis of the studies and several brainstorming sessions among the authors enabled the development of ROECL as a new OEE-based KPI. In particular, we started from OECL by Wudhikarn *et al.* (2010) and Wudhikarn (2016) because of its peculiarity of considering losses in monetary units. We introduced a component devoted to energy consumption taking inspiration from the contributions by Bougain *et al.* (2015) and Barletta *et al.* (2015). Finally, we refined such component and the indicator formulation in order to consider losses of other production resources, including material and consumables.

The preliminary version of ROECL was then evaluated during two review sessions by a panel of entrepreneurs, managers, researchers, and consultants, which were experts of production systems in the context of Industry 4.0. The improvement suggestions from the experts were collected and incorporated in the preliminary version to obtain an improved one, which was presented to the experts in the second session and further refined. The main suggestions regarded the identification of data that can be collected by means of a CPPS, the definition of an approach that can be easily adopted in companies for decision-making processes, and the selection of product cost metrics most relevant from the cost accounting perspective.

ROECL applicability was tested in a real case study, during which the authors of this paper supported the company in its implementation. The company was interested in assessing the inefficiencies in the production system and their impacts on costs, and was equipped with a smart machine able to collect different types and massive volume of data about production (e.g. timing, energy consumption, quality parameters) in real-time. The authors organised a couple of preliminary sessions to share the approach with the company's personnel (belonging to both production and cost accounting departments), and create a simplified spreadsheet to collect data and calculate ROECL. Monthly meetings permitted checking the quality of collected data, increasing the usability of the spreadsheet file, and analysing the obtained results.

4. Resource Overall Equipment Cost Loss indicator

ROECL is expressed in monetary units and able to account for production resource losses in addition to the six big losses proposed by Nakajima (1988). It represents the total cost of availability, performance, quality, and resource losses caused by inefficiencies and deviations of the machine or equipment from its optimal operating status occurring over a specific time period. Similarly to OEE, ROECL focuses on the effectiveness of planned production schedules, not considering the planned shutdown loss category. It also disregards the five major losses related to worker efficiency, since they are not caused by deviations of the machine or equipment from its optimal health status.

The steps to calculate ROECL and use it to assess equipment performance and product cost are reported in Figure 2 and described in the following sections.

4.1 Data collection

In this first step, the machine or equipment subject to investigation should be defined. Afterwards, all the data to calculate ROECL need to be collected, such as:

(1) production cycle of each product and ideal cycle times;

(2) work schedule, production orders, processed amount, and production times;

(3) production stoppages (including planned shutdowns and maintenance activities) and their causes;

(4) amount of defects, reworks, and rejects for each production order;

(5) historical trends of actual measured production resources (material, consumables, and energy) used by a machine or equipment for obtaining a product;

(6) variable and fixed costs, and procedure for estimating the product cost.

Data related to production cycles and times, stoppages and abnormal activities, and resource consumptions can be collected by employing a CPPS. This allows acquiring real-time data that can be used to quickly estimate ROECL.

4.2 Calculation of availability, performance, and quality losses

After data collection, the losses in the production process can be identified and quantified according to the classification by Nakajima (1988). To study inefficiencies in monetary terms, we refer to AL, PL, and QL defined by Wudhikarn *et al.* (2010) and Wudhikarn (2016) for the OECL development (Eq. (5)). AL, PL, QL, and OECL are expressed in €.

The total losses of the availability rate element are the sum of the opportunity loss and the production cost loss for availability rate; the total losses of the performance efficiency component are the sum between the opportunity loss and the production cost loss for

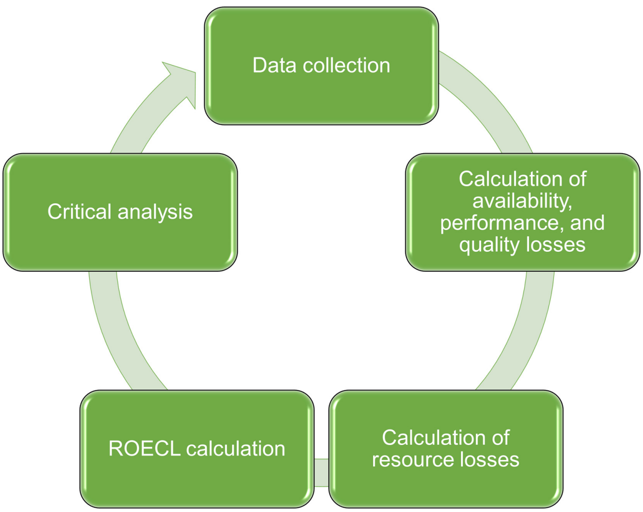


Figure 2.
ROECL calculation and use procedure

performance efficiency; the total losses of the quality rate element are the sum of the reject losses and the rework ones. The former depends on the opportunity loss, the direct material cost loss, and the production cost loss for quality rate reject sub element, whereas the latter on the production cost loss for quality rate rework sub-element and the rework loss. Further details about the loss calculation are provided by Wudhikarn *et al.* (2010) and Wudhikarn (2016).

4.3 Calculation of resource losses

In the OECL formula we introduce resource losses (RL) to consider the cost variations related to changes in resource consumption due to inefficiencies and deviations occurring to the machine or equipment during manufacturing. Three types of resource losses are considered: (1) *material losses* due to differences in the weight of the input materials and the weight of the quality products; (2) *consumable losses* due to overconsumption of consumable materials in processing (e.g. lubricants, tools); (3) *energy losses* due to overconsumption of input energy (e.g. electricity, gas, fuel oil, etc.) in processing.

For this purpose, we adapted Eq. (7) from Bougain *et al.* (2015) for estimating the resource efficiency of the machine or equipment with respect to the *i-th* production resource (RE_i, in %), and then we propose Eq. (8) to calculate the loss related to the *i-th* production resource (RL_i, in €).

$$RE_i = \frac{\min(\text{Resource\_consumed}_i)}{\text{Resource\_consumed}_i} \tag{7}$$

$$RL_i = U_{RC,i}\,(\text{Resource\_consumed}_i - \min(\text{Resource\_consumed}_i)) \tag{8}$$

where:

(1) $\text{Resource\_consumed}_i$ is the actual measured amount of the *i-th* resource consumed by a machine or equipment for production over a specific time period;

(2) $\min(\text{Resource\_consumed}_i)$ is the minimal amount of *i-th* resource consumable by a machine or equipment for production over a specific time period on the basis of the actual measured historical minimal resource consumption values;

(3) $U_{RC,i}$ is the unitary resource cost of the *i-th* resource considered (e.g. € $(kWh)^{-1}$ for electricity).

When a minimal resource consumption value is beaten, it is automatically replaced with the smaller one: if an actual measured resource consumption value lower than the minimal resource consumable by the machine or equipment is recorded, the minimal resource value is replaced by this new minimal value. If in the time period under investigation, different products have been manufactured by the machine or equipment, the resources consumed should be calculated by summing the resource consumption values related to all these products.

Finally, RL are calculated as the sum of all the RL_i by applying Eq. (9).

$$RL = \sum_{i=1}^{n} RL_i \tag{9}$$

where *n* is the total number of resources involved in the manufacturing system.

4.4 ROECL calculation

ROECL for the machine or equipment (€) is determined through Eq. (10):

$$ROECL = OECL + RL = AL + PL + QL + RL \tag{10}$$

where the sum of AL, PL, and QL is OECL developed by Wudhikarn *et al.* (2010) and Wudhikarn (2016), whereas RL represent the resource losses (Eq. (9)).

4.5 Critical analysis

ROECL allows ranking the most critical production machines and identifying which ones require immediate attention. In addition, by breaking down ROECL into its components it is possible to analyse which type of losses are most critical in terms of economic impact for each machine or equipment. This allows prioritising improvements to reduce such losses.

In addition to ranking problematic machines or equipment, ROECL could support a precise estimation of the actual product cost. To this regard, we define Product Cost Increase (PCI) as the variation of the product cost that occurs when a machine or equipment involved in the process changes its health status from optimal operating conditions. Indeed, when a machine or equipment does not operate in optimal operating conditions, some inefficiencies occur (in terms of availability, performance, quality, and/or resource consumption) and, as a result, costs increase. The related cost increase should be assigned to the products that were being processed at the time. To this aim, the single production order has to be assumed as the time period. PCI (€ $unit^{-1}$) is calculated in Eq. (11).

$$PCI = \frac{ROECL}{\text{Processed amount} - \text{Defect amount}} \tag{11}$$

The sum between PCI and the minimal cost of the product that is possible under the most efficient operating conditions (C_{min}, in € $unit^{-1}$) is the actual product cost (Eq. (12), in € $unit^{-1}$).

$$C_{actual} = PCI + C_{min} \tag{12}$$

The C_{actual} calculation permits carrying out analyses for identifying criticalities from the cost accounting perspective, which can represent a stimulus for pinpointing improvements. For instance, it is possible to measure to what extent producing a unit of product costs more than the minimum possible. To this purpose, Eq. (13) proposes the indicator % C_{min}, expressed as a percentage of C_{min}, for estimating the variation of the C_{actual} with respect to C_{min}. % C_{min} can assume only positive (or null) values.

$$\% \, C_{min} = \frac{C_{actual} - C_{min}}{C_{min}} = \frac{PCI}{C_{min}} \tag{13}$$

The comparison between C_{actual} and the standard product cost ($C_{standard}$, in € $unit^{-1}$) could highlight if the latter provides a reasonable approximation of the former, and give insights about the precision of the company's quotes used for budgeting. A standard cost is a predetermined and target cost that should be incurred under efficient operating conditions (Drury, 1992). To compare C_{actual} and $C_{standard}$, Eq. (14) proposes the % $C_{standard}$ indicator.

$$\% \, C_{standard} = \frac{C_{actual} - C_{standard}}{C_{standard}} \tag{14}$$

% $C_{standard}$ represents the variation of C_{actual} with respect to $C_{standard}$, expressed as a percentage of $C_{standard}$. It could assume negative, null, or positive values. % $C_{standard}$ does not measure the inefficiency of the production system, but the accuracy of the standard cost used for budgeting reasons and for defining the sell price. If % $C_{standard}$ is negative, the company is using standard costs higher than actual product costs, thus selling the product at price higher than necessary. If it is positive, the standard cost is not high enough to cover the actual product cost, and this means that the company is probably selling at a loss.

All the above comparisons among costs make sense only if the elements included in the calculation of each cost (e.g. types of variable costs) are the same.

5. Case study

To test our approach, we applied it in a real case study. We considered a smart multicenter three-spindle machine used to produce valves in a company in the north of Italy. Such a machine is a transfer line with a rotary table and three flexible numerically controlled modules, where different processing units (composed by a spindle and axes) work independently (Wójcicki and Bianchi, 2018).

The company calculated the product cost by means of Activity-Based Costing (ABC), according to which costs are assigned to products based on consumption of individual products or demand for each activity (Cooper and Kaplan, 1988). The company was composed of different cost centres, which were characterised by hourly rates (comprising of the depreciation, labour in terms of direct operators, equipment, operator devoted to set-ups, and utilities) that were budgeted at the beginning of the year and kept fixed throughout the year. Consequently, the standard product cost depended on: (1) hourly rates, (2) production times, (3) other costs about materials, activities carried out by subcontractors, indirect personnel, logistic movements, quality controls, and (4) an efficiency rate for considering potential production inefficiencies in the estimation of minimum cycle times.

In this case study, we analyse a set of 11 production orders to estimate and analyse ROECL, C_{actual}, % C_{min}, and % $C_{standard}$. Note that in this case ROECL is calculated per single production order manufactured by the smart multicenter. Therefore, we will be able to rank the most critical orders manufactured by the same machine, rather than rank different machines. However, as done by Wudhikarn (2016), our approach could also be applied to rank the most critical machine or equipment. To do that, it would be enough to consider more than one machine or equipment, and aggregate the data related to each machine or equipment over a defined period of time.

5.1 Data collection

The data required for the case study were gathered by the installed CPPS or provided by the information systems of the company. They were integrated by historical data about stoppages and their causes, and information from surveys and interviews with production and accounting managers. Specifically, for each production order we collected the following data:

(1) work schedule, processed amount, start and end date of production order, minimum cycle time, and actual cycle time to produce a batch;

(2) total time for breakdowns, equipment failures, set-ups, and adjustments;

(3) total time for idling, minor stoppages, and reduced speed;

(4) defect and rework amounts, reduced yield, and rejects;

(5) profit per unit, expense of production cost for availability rate, expense of production cost for performance efficiency, expense of direct material cost, expense of production cost for quality rate reject, expense of production cost for quality rate rework, and expense of rework;

(6) actual measured machine power and historical minimal energy consumed by the machine;

(7) hourly energy cost (we assumed the Italian average energy cost, equal to 0.1661 € $(kWh)^{-1}$);

(8) variable costs and hourly rates related to the depreciation, labour in terms of direct operators, equipment, operator devoted to set-ups, and utilities.

5.2 Calculation of availability, performance, and quality losses

To calculate AL, PL, and QL, we analysed the causes of machine stoppages and classified them according to the six big losses introduced by Nakajima (1988). For instance, the tool replacement represents a breakdown loss, the modification of terminals a set-up and adjustment loss, the absence of the toolmaker an idling and minor stoppage loss, switching the machine on and off a reduced speed loss, the time for recovering scraps a defect and rework loss. No stoppages were identified as a reduced yield loss. Scheduled stops (e.g. planned maintenance) were excluded from the loading time calculation because they are not inefficiencies and do not affect the product cost increase.

Afterwards, we considered the several hourly rates of the company to recognise which of them to include in the expenses of AL, PL, and QL. For instance, depreciation and utilities rates were included in expenses of production cost for performance efficiency, for quality rate rejects, and for quality rate rework elements, whereas machine rates were included in the expenses of production cost for all the three types of losses.

Figure 3 displays the values of AL, PL, and QL for each production order.

The highest AL and PL are obtained for production order 3. Also orders 1 and 4 present significant AL, whereas production order 5 has the lowest AL. Regarding PL, the lowest value is recorded for order 8. However, all the production orders, except for order 3, have results lower than 400 €. In 9 orders out of 11, AL exceed PL. QL do not represent a critical aspect for the considered production orders.

5.3 Calculation of resource losses

Since the CPPS was able to record only actual electricity consumption, this was the only resource loss that we could consider in this case study. We estimated RE for each production

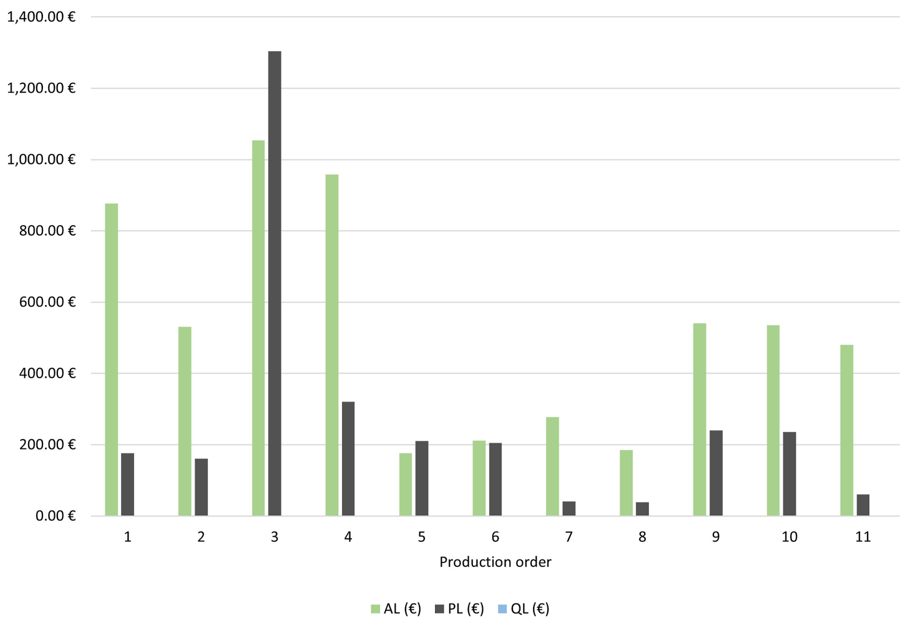


Figure 3.
AL, PL, and QL for each production order

order using Eq. (7) and by employing data about power and historical minimal energy consumed by the machine. Through Eq. (8) we combined RE results with the energy cost and the historical minimal energy cost to calculate RL.

The calculated RE and RL values are presented in Table 1, where the red cells identify the most critical results.

In terms of RE and RL, the most critical production order is 5. Such order is the only one having an RE value lower than 90%, while the others are characterised by values equal to 98–99%. Therefore, for all the analysed orders, except for order 5, RL values are extremely low and, thus, almost negligible.

5.4 ROECL calculation

We then used AL, PL, QL, and RL to calculate ROECL (Eq. (10)). Figure 4 compares ROECL and OECL for each order, while Figure 5 displays the contribution of each loss component to ROECL.

5.5 Critical analysis

The highest and most critical ROECL value is obtained for production order 3, while the lowest one for production order 8. The ROECL result for order 3 is linked to both AL and PL, which remain the highest losses among the 11 orders. In addition to production order 3, also orders 1 and 4 present the most critical ROECL values, mainly due to AL.

In average terms, AL represent the most critical aspect for the considered orders and are the main ROECL component. On the contrary, QL do not represent a critical aspect from the ROECL perspective. RL have a limited impact on the total amount of analysed losses.

After the ROECL determination, it is possible to estimate PCI by means of Eq. (11): the case study results are reported in Table 2, where the three most critical values are highlighted in red.

Figure 6 is composed of several bars representing % C_{min} (green bars) and % $C_{standard}$ (blue bars) for each production order (identified in *y*-axis). The numerical results of these variations are reported as labels to the right or left of the bars. These results are based on variable costs, excluding other costs not depending on the inefficiencies (e.g. overheads).

The lowest PCI value is obtained for order 11 that is also characterised by the lowest % C_{min}. The highest PCI values are obtained for production orders 1, 4, and 7, which present a PCI higher than 1 € per unit produced. For these orders, the inefficiencies and deviations

Table 1.
RE and RL for each production order

Production order	Material code	Machine power (kW)	RE (%)	Energy cost (€)	Historical minimal energy cost (€ unit^{-1})	RL (€)
1	A	3,300,543.50	98.00%	152.28	0.15	3.05
2	B	4,987,758.94	98.00%	230.13	0.15	4.60
3	C	20,981,962.20	99.00%	968.08	0.19	9.68
4	D	4,082,953.66	99.00%	188.38	0.16	1.88
5	E	8,935,610.16	89.82%	412.28	0.12	41.95
6	F	3,811,920.33	99.00%	175.88	0.14	1.76
7	G	836,706.10	98.00%	38.60	0.13	0.77
8	H	892,256.10	99.00%	41.17	0.14	0.41
9	I	14,833,513.82	98.00%	684.40	0.14	13.69
10	E	15,250,165.45	99.00%	703.63	0.12	0.00
11	L	5,051,652.03	98.00%	233.08	0.05	4.66

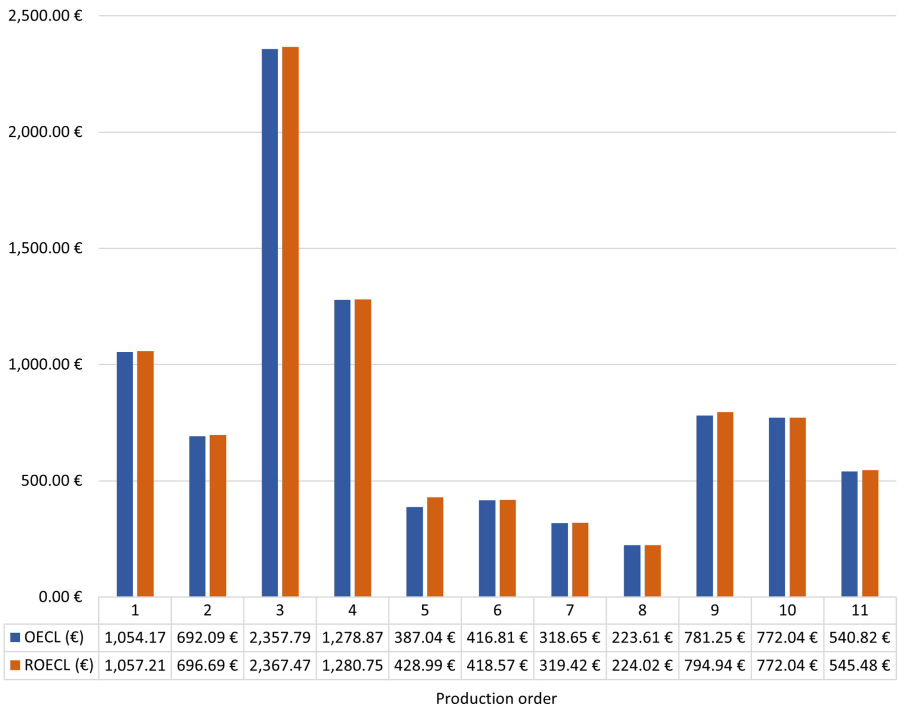


Figure 4.
OECL and ROECL for each production order

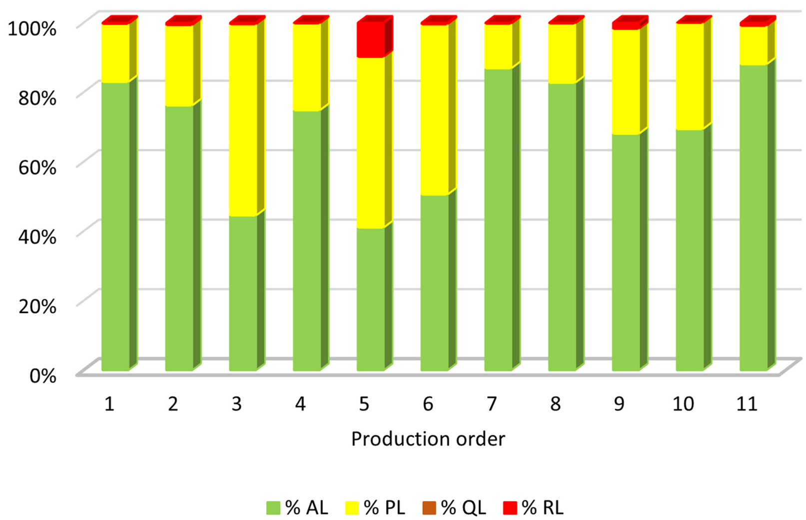


Figure 5.
Contributions of AL, PL, QL, and RL to ROECL

cause respectively a 64.81%, 59.25%, and 66.99% increase of the actual cost with respect to C_{min}, which represent the most severe percentage variations in terms of % C_{min}. Production orders 1 and 4 are also characterised by the highest % $C_{standard}$ (higher than 30%), while the

Table 2.
PCI and cost estimations

Production order	Material code	PCI (€ unit^{-1})	C_{min} (€ unit^{-1})	C_{actual} (€ unit^{-1})	$C_{standard}$ (€ unit^{-1})
1	A	**1.01**	1.55	2.56	1.93
2	B	**0.46**	1.46	1.92	1.76
3	C	**0.47**	1.57	2.04	2.22
4	D	**1.07**	1.80	2.87	2.05
5	E	**0.14**	1.17	1.31	1.60
6	F	**0.32**	1.28	1.60	1.97
7	G	**1.10**	1.64	2.75	3.33
8	H	**0.75**	1.60	2.35	1.82
9	I	**0.16**	1.18	1.34	1.56
10	E	**0.14**	1.19	1.32	1.60
11	L	**0.11**	1.13	1.24	1.46

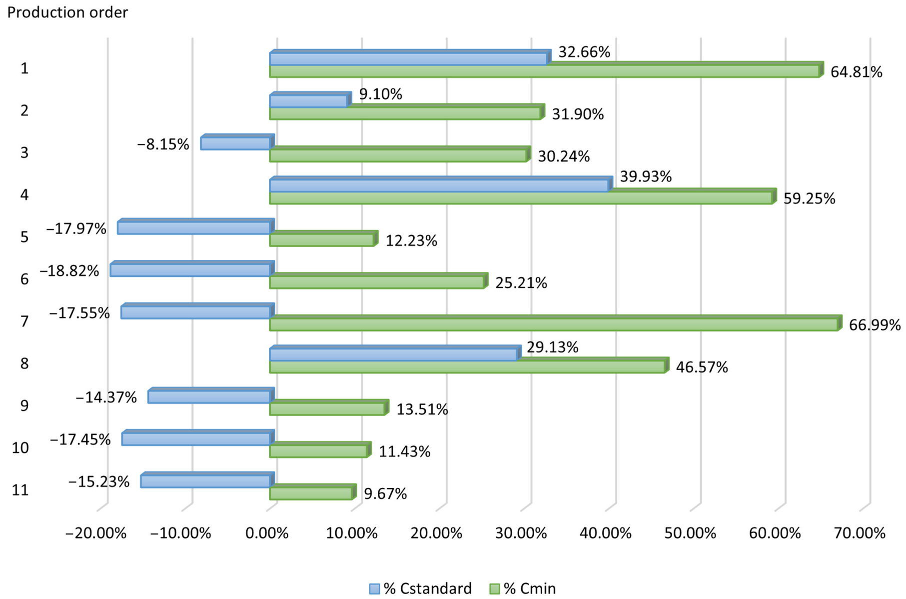


Figure 6.
% C_{min} and % $C_{standard}$ for each production order

majority of the orders by negative values for % $C_{standard}$ (their actual costs are lower than standard costs).

6. Discussion

6.1 Evidence from the case study

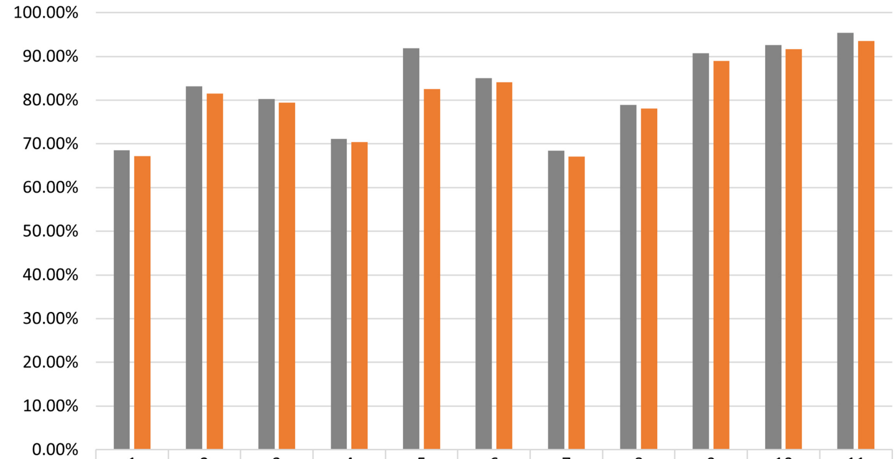
The proposed case study is a first application of ROECL and its use for analysing the impact on product cost of inefficiencies and deviations occurring during the manufacturing of a given production order. The approach is composed of several steps that allow calculating AL, PL, QL, and RL, and estimating C_{actual}, % C_{min}, and % $C_{standard}$ for the production orders under investigation. As a result, the production orders can be ranked to highlight critical aspects and prioritise improvements. The rankings for the orders processed by the multicenter three-spindle machine in the case study are reported in Table 3. In this table, we

Rank	Ranking for OEE	Ranking for OECL	Ranking for EOEE	Ranking for ROECL	Ranking for % C_{min}	Ranking for % $C_{standard}$
1	7	3	7	3	7	4
2	1	4	1	4	1	1
3	4	1	4	1	4	8
4	8	9	8	9	8	2
5	3	10	3	10	2	6
6	2	2	2	2	3	5
7	6	11	5	11	6	7
8	9	6	6	5	9	10
9	5	5	9	6	5	11
10	10	7	10	7	10	9
11	11	8	11	8	11	3

Table 3. Ranking of the production orders according to the different metrics

also include the ranking of orders according to OEE, OECL, and EOEE (whose numerical results are reported in Figure 4 for OECL and Figure 7 for OEE and EOEE) to compare the different metrics. In Table 3, the first column reports the position in the ranking (where rank 1 means the most critical value and high priority), whereas the other columns propose the rankings for the different calculated metrics. Each cell of these columns contains a specific production order.

Table 3 highlights that the production order rankings produced by the metrics are different. This is because the metrics consider different aspects in their calculation, and they represent the output in different forms (percentage or monetary unit). However, similar order rankings are obtained by OEE and EOEE on one side, and by OECL and ROECL on the other one. This is reasonable due to the similarities between the approaches, and it is also accentuated by the limited number of orders in the analysed dataset and the limited RL



	1	2	3	4	5	6	7	8	9	10	11
OEE (%)	68.58%	83.15%	80.24%	71.10%	91.92%	84.99%	68.44%	78.87%	90.74%	92.58%	95.43%
EOEE (%)	67.21%	81.49%	79.44%	70.39%	82.57%	84.14%	67.07%	78.08%	88.93%	91.66%	93.52%

Source(s): Based on Nakajima (1988)

Figure 7. OEE and EOEE values for each production order

impact. OEE and EOEE are expressed in percentages and equally influenced by the different losses, even though they should not be considered equal. Indeed, in OEE and EOEE methodologies the percentage weights of all elements (i.e. A, P, Q, and EE) are identical, and it is not possible to determine the differences in magnitudes between these elements (Wudhikarn, 2012, 2016). For example, a given AL percentage is assumed to be equal to the same QL percentage, but, in reality, an equipment breakdown could result in smaller losses than rejected products (Wudhikarn, 2012, 2016). Nevertheless, percentages are relative values and therefore facilitate comparisons.

On the contrary, OECL and ROECL are based on losses expressed in monetary units and, thus, are expressed in absolute values. This implies that OECL and ROECL consider dissimilarities of magnitude among loss elements. However, if the aggregation basis is not homogeneous, e.g. data aggregated based on production orders, but with orders very different in size, the comparison of absolute values might be difficult. In these cases, % C_{min} and % $C_{standard}$ (that are estimated by means of the costs of individual units) could allow an easier comparison of the various production orders.

Regarding the results of the case study, Table 3 highlights that production order 7 has the lowest values for OEE and EOEE, and thus is assigned rank 1. This means that this order has the highest losses. The main criticality of this order is related to the availability rate: in the company under investigation, several events are classified as availability losses (e.g. maintenance, technical failure, change of robot positions, setting of robot parameters) that are responsible for the loading time reductions. Such order is not ranked as problematic from OECL and ROECL perspectives. However, the number of units produced in this order is significantly lower than the others, and this suggests referring to % C_{min} as a more relevant KPI. Indeed, order 7 is particularly critical also according to such indicator. Consequently, the company should focus on AL type and duration to decrease them and thus the deviations of the product cost. The inefficiencies and deviations of the machine from its optimal operating status occurring during the manufacturing of this production order cause the greatest increase of the product cost.

According to OEE and EOEE approaches, production order 3 is ranked fifth, while it is ranked first from OECL and ROECL perspectives. Such order has the highest AL and PL. In the company, the performance losses can occur for lack of power, lack of tooling, switching the machine on or off, cleaning the washing machine. Therefore, potential improvements in terms of the ideal cycle time and/or the assignment of an appropriate number of operators could be introduced. However, the criticality of this order is not confirmed by % C_{min} and % $C_{standard}$: the cost losses do not lead to the most critical percentage variations of the minimal and standard product costs.

% C_{min} values requiring crucial attention are related to production orders 1 and 4 (that are also characterised by low OEE and high OECL values). The inefficiencies and deviations of the machine from its optimal operating status occurring during the manufacturing of these orders are mainly characterised by AL that cause increases of about 60% of the actual cost with respect to C_{min}. Improvements could be obtained by reducing ROECL in terms of AL, and thus focusing on decreasing the opportunity loss and/or the production cost loss for the availability rate. For instance, a reduction of 25% of AL for production order 1 could allow obtaining % C_{min} equal to 51.37%, which means a reduction compared to the previous value equals to 13.44%. Further in-depth sensitivity analyses should be conducted on larger samples for identifying the determinants that contribute mostly to percentage variations of the product costs.

Production orders 1 and 4 are also ranked in the first positions from the % $C_{standard}$ perspective. This should capture the attention of the company: since these values are positive, $C_{standard}$ is not high enough to cover C_{actual}, and the company is probably selling at a loss (depending on the profit margin). On the contrary, 7 orders out of 11 present negative values for % $C_{standard}$: the standard product cost for budgeting is calculated in a conservative way that could lead to setting sales prices higher than necessary. In this regard, the adoption of the procedure described in this paper could allow the company to monitor in real-time the changes of the actual costs to promptly estimate the product cost and thus better define the price offer to customers. A more precise estimation of the prices could then drive increased demand and new customer acquisition.

6.2 Strengths and implications of the approach

The research presented in this paper is the first attempt to tackle both loss costs and production resource losses in a comprehensive KPI based on the well-known OEE. This has both theoretical and practical implications.

On the theoretical side, a new OEE-based-resource-related KPI called ROECL is proposed. Similarly to OEE, it permits analysing and controlling equipment effectiveness as a function of availability, performance, and quality aspects in order to set improvement priorities, but in addition it introduces resource losses due to inefficiencies and deviations of the machine or equipment in the original OEE formulation. Therefore, our KPI takes into consideration resource efficiency and management, which is an important facet of sustainability (Nota *et al.*, 2020). The introduction of the resource topic in OEE has been already proposed by Garza-Reyes *et al.* (2008), Garza-Reyes (2015), and Morella *et al.* (2020a). However, Garza-Reyes *et al.* (2008) and Garza-Reyes (2015) focus on only material efficiency, while Morella *et al.* (2020a) only on energy. Additionally, differently from these three studies, we recognise and model resources as one of the losses in the production system (and not a mere cost or investment) that should be taken into account to manage and optimise the production processes.

The definition of resource losses in OEE-based KPIs represents a novelty also in comparison to OECL by Wudhikarn *et al.* (2010) and Wudhikarn (2016), from which ROECL has been inspired. Both OECL and ROECL contribute to overcoming some OEE weaknesses regarding the ranking of problematic equipment thanks to the consideration of losses in monetary units. In this regard, our structured approach is able to integrate production and financial elements. The focus on economic elements, rather than time inefficiencies, highlights that the latter is not sufficient to achieve an overall optimisation, and the impact of the different costs should be investigated in depth.

In addition to OECL, we endeavoured to suggest the cost translation of OEE for management, whose significance is clearly underlined in the literature (Muchiri and Pintelon, 2008). For this purpose, we defined PCI, % C_{min}, and % $C_{standard}$ in order to overcome possible issues related to not homogeneous aggregation basis, relate machine or equipment performance with the product cost, and thus create a link between production management and cost accounting. Therefore, our approach could help assigning possible variation of costs produced by inefficiencies in terms of availability, performance, quality, and/or resource consumption to the products, and could support a precise estimation of the actual product cost. This could be used also for budget development and sell price definition.

On the practical side, ROECL could support decision-making processes in companies. Indeed, it permits analysing the causes responsible for the inefficiencies and deviations of the machine or equipment from its optimal operating status occurring over a specific time period, evaluating the most critical losses in terms of economic impact, and ranking the most critical production machines. This helps managers to recognise the losses absorbing resources without value creation and investigate their impacts on actual product costs during the manufacturing of a production order. Such analysis could stimulate the definition of common strategies for those products characterised by the same types and magnitude of losses. Our approach may also assist maintenance departments when inefficiencies and deviations in terms of availability, performance, quality, and resource consumption aspects of the machine or equipment occur: it allows identifying and prioritising effective corrective actions, and distinguishing those actions that should be implemented immediately from the ones that can be deferred to a more convenient timing.

In addition, based on ROECL, companies could monitor in real-time the actual product costs and promptly identify unexpected increases of the product cost that lead to a profit margin reduction. Therefore, the proposed approach represents a valuable exploitation of Industry 4.0 technologies for collecting accurate data and enabling real-time decision making, thus increasing the overall resilience of the production system.

6.3 Limitations and future research

From the research point of view, the main limitation of our approach regards the testing phase. Indeed, it was tested in a simplified case study by considering only electricity consumption as RL and a limited number of orders in the dataset. Other case studies should be conducted to investigate the potentialities of our approach when different kinds of resources and energy utilities are involved in the production process, and thus different kinds of resource losses have to be considered. The employment of datasets covering longer time periods would also allow better investigation of RL impacts on the product cost and analysis of differences in the order rankings attained by the various metrics and cost variations.

Future research activity may also focus on the combination of our approach with machine learning techniques. Such techniques could support the identification of relationships between the deviations of technical parameters (e.g. speed, pressure) of a machine or equipment and the respective cost deviations (in terms of availability, performance, quality, and resource efficiency). This could highlight when an increase in product cost, and therefore an inefficiency in the machining process, is related to an anomaly in the machine or equipment (e.g. excessive tool wear or lack of lubrication), and thus be used for preventive optimisation purposes.

From the practical point of view, one main limitation of the proposed approach relates to the data collection effort. Data collection is challenging for every OEE-based KPI, but this is further increased in our approach due to the need of additional data of different kinds (e.g. production, energy, resource, and cost ones). Although Industry 4.0 technologies could help in overcoming this issue, at the moment their uptake, especially in Small and Medium-sized Enterprises (SMEs), is limited, and this might represent a barrier to the adoption of our approach. The lack of adequate technologies may hinder the gathering of accurate input data, and this may have an impact on the attainment of reliable results. Moreover, data collection could be too resource intensive due to the necessary involvement of various human resources with different competences inside the company, who should extract the required input values with a reasonable frequency for performing a proper monitoring and capturing any deviations of a machine or equipment.

The approach may also be perceived as difficult to implement by managers and practitioners. For this reason, one of the next steps will be the design of a proper tool (e.g. spreadsheet workbook) for guiding them during the collection of needed data, calculation of losses and ROECL, and critical analysis. The creation of a user-friendly interface and dashboards may further facilitate the implementation and immediately display outputs and variations requiring attention from the production and cost accounting management.

7. Conclusions

This paper proposes a new KPI called ROECL and some related cost analyses to quantify and examine the impacts of inefficiencies and deviations of a machine or equipment on product cost. ROECL does not only estimate availability, performance, and quality losses, but also quantifies production resource losses as a function of the unitary resource cost and resource consumption by the investigated machine. PCI provides insights into the product cost variations occurring when the machine or equipment deviates from its optimal operating conditions.

This approach was tested in a real case study about a multicenter three-spindle machine. In such case study, 11 production orders were analysed from ROECL and cost perspectives. The approach supported the investigation of the greatest inefficiencies causing the highest product cost increases. Indeed, it enabled the identification of the three most critical orders characterised by the highest PCI values (higher than 1 € per unit produced). For these orders, the inefficiencies and deviations of the machine from its optimal operating status caused an increase of the actual production cost of about 60% with respect to the minimal cost of the product that is possible under the most efficient operating conditions. In addition, for two of these orders the actual cost is 30–40% higher than the standard cost used for budgeting reasons and for defining the sell price. This highlights that the company is probably selling those products at a loss (depending on the profit margin). In addition, the approach supported the identification of the areas requiring attention and representing opportunities for improvement. Since it distinguishes the contribution of each loss component, for the three most critical orders it was possible to realise that the highest contribution is from AL (higher than 75%). Finally, it enables the quantification of the cost impact of different strategies able to mitigate those losses. For instance, a reduction of 25% of AL for production order 1 could allow obtaining PCI equal to 0.80 € per unit produced, which means a reduction compared to the previous value equals to 20.74%.

In conclusion, the case study has proven the applicability of the ROECL indicator, and its use to assess equipment performance, product cost, and potential improvements.

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