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Overall Water Effectiveness: a new Lean indicator for digital evaluation of water efficiency in industrial processes

Abstract

Water management is becoming an increasingly critical challenge for manufacturing industries due to growing environmental concerns, stricter regulatory requirements, and rising pressure from clients demanding more sustainable practices. Efficient and transparent use of water resources is no longer optional but a strategic necessity across industrial sectors. In this paper a new Lean performance indicator for evaluating water usage in industrial processes is presented. The proposed indicator, named Overall Water Effectiveness (OWE), aims to systematically assess industrial water performance by quantifying the gap between actual and ideal performance. It builds on the logic of Overall Equipment Effectiveness (OEE) to identify water-related losses and support informed decision-making for continuous improvement while introducing a comprehensive industrial loss structure specifically designed for water use and consumption. Jointly, two key additional indicators are introduced: one measures how effectively the production process consumes input water, while the other evaluates the dependency on external water sources, taking into account the contributions of recycled and returned water. By translating high-level sustainability goals into actionable operational metrics, this new set of indicators enables the integration of water management into daily industrial operations through a practical, easy-to-use tool. The approach is applied in a major textile manufacturing company, demonstrating its practical utility in evaluating water use and consumption, identifying loss patterns, and leading the identification of improvement actions.

Keywords: Lean Manufacturing, Water management, Sustainable management, Overall Equipment Effectiveness, Textile industry, Digital transformation

1. Introduction

At the UN 2023 Water Conference, water was declared a "*As humanity's most precious global common good, water unites us all. That's why water needs to be at the centre of the global political agenda*" [1]. Yet, global progress on water-related targets remains critically off course, threatening the broader sustainability agenda [1]. Water management has hence emerged as a critical issue for industrial sectors [2]. For instance, the fashion industry alone consumes around 79 billion cubic meters of water annually, illustrating the scale of water dependency across industrial sectors [3]. Industries face rising pressure from regulatory bodies and sustainability initiatives to reduce water consumption and improve their environmental performance [4]. The environmental impacts of

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industrial water use, such as resource depletion and pollution, underscore the need for more efficient and sustainable practices [5].

International standards like ISO 14046:2014 “Environmental management – Water footprint – Principles, requirements and guidelines” [6] and ISO 46001:2019 “Water efficiency management systems – Requirements with guidance for use” [7] provide valuable frameworks for assessing Water Footprint (WF) and implementing Water Efficiency Management Systems (WEMS), but translating these high-level guidelines into actionable improvements on the shop floor remains a challenge. Similarly, the Water Pinch Analysis [8] offers comprehensive insights and optimization strategies, yet its application in daily operations is often limited by complexity and lack of integration with Lean practices.

Notably, such tools and frameworks have recently gained momentum due to increased data availability. Indeed, the widespread adoption of advanced sensor systems is transforming how water management, and sustainability more broadly, is addressed. The growing volume of data now enables real-time sustainability monitoring systems capable of detecting anomalies and mitigating environmental impacts [9,10]. Furthermore, collecting this data facilitates the application of big data analytics to identify trends and improvement pathways. Properly managing and leveraging such data is therefore a critical factor in driving sustainability progress [11].

The increasing availability of real-time data on resource flows provides new opportunities to monitor sustainability performance; however, these insights must be embedded into operational practices to deliver tangible improvements. Lean frameworks, and particularly Overall Equipment Effectiveness (OEE), have proven effective because they translate complex performance dimensions into clear, actionable metrics that guide daily decisions on the shop floor. Originally developed within the Total Productive Maintenance (TPM), OEE has become one of the most extensively applied tools in Lean Manufacturing [12], particularly when integrated with Industry 4.0 (I4.0) technologies [13]. OEE has since evolved to include other dimensions, such as labour [14], space efficiency [15] and operations flow [16], as well as environmental factors like energy [17], greenhouse gas emissions [18], material consumption [19].

In this evolving landscape, water remains a largely underexplored dimension in Lean efficiency frameworks. Given the urgency of Sustainable Development Goal 6 (SDG 6: *Ensure availability and sustainable management of water and sanitation for all*) [20] and the growing need for water-efficient manufacturing, the development of dedicated tools can help industries monitor and reduce water-related losses, enabling a structured, measurable, and operationally integrated approach to water sustainability. Building on this logic, extending the OEE approach to water enables industries to

operationalize sustainability targets within a familiar structure, bridging the gap between high-level data availability and practical efficiency improvement.

This provides a rationale for introducing a new Lean performance indicator for evaluating and optimizing water usage and consumption in industrial processes. The proposed indicator, called Overall Water Effectiveness (OWE), systematically assesses water performance by quantifying the gap between actual and ideal usage. OWE measures how efficiently the total available water is converted into valuable output. Jointly, two additional indicators are introduced: Internal Water Efficiency (IWE) evaluates the efficiency of water consumption within the production process, while Global Water Efficiency (GWE) assesses the reliance of the process on external water sources, considering key factors such as recycled and returned water. Together, these indicators:

1. enable a quantitative evaluation of current water use, helping organizations assess their alignment with sustainability goals and quantify any deviation from target performance, using a comprehensive and tailored structure of industrial water-related losses.
2. provide a structured diagnostic approach to identify water-related inefficiencies, allowing companies to pinpoint critical stages in their operations where water losses occur and supporting targeted actions for improvement.

By translating strategic sustainability targets into actionable operational metrics, this set of indicators allow the integration of water management into day-to-day industrial operations through a practical and easy-to-implement tool, and the alignment with international standards and sustainability goals, such as ISO 14046, ISO 46001, and UN SDG 6. This dual focus allows companies to reduce both environmental impact and operating costs, contributing to a more sustainable and resilient industrial system without sacrificing productivity.

The remaining part of this manuscript is organized as follows. Section 2 frames this work into the relevant literature and highlights research gaps. Section 3 presents OWE and the two complementary indicators. To show the operating principles and potential results of this novel tool, a real industrial implementation concerning a major textile manufacturing company is presented in Section 4. Finally, Section 5 is devoted to conclusions and future remarks.

2. Theoretical background and relevant literature

This section explores the foundational concepts and tools that underpin the development of the OWE, with a particular focus on international standards (ISO 14046 and ISO 46001). It also examines the relevance of Water Pinch Analysis for industrial water optimization and the potential of adapting OEE to address both operational and environmental sustainability challenges by analysing different

production factors and input resources. Collectively, these tools and methodologies provide the theoretical grounding for integrating water sustainability into industrial efficiency metrics.

2.1. Water footprint, Water Efficiency Management Systems and Water Pinch Analysis

The ISO 14046 standard provides guidelines for conducting a WF assessment within the framework of a Life Cycle Assessment (LCA). It evaluates the environmental impacts associated with water use and consumption, considering factors such as water scarcity, pollution, and degradation of water quality. The blue WF measures the consumption of surface and groundwater resources, while the green WF accounts for the use of rainwater, and the grey WF assesses water pollution and its impact on water quality.

The standard takes a holistic approach by incorporating both direct and indirect water usage throughout the product lifecycle, making it a key tool for industries aiming to improve their water sustainability performance. ISO 14046 has been widely adopted in industries such as agriculture, manufacturing, and energy, where water is a critical resource. Recent research has focused on applying WF assessments in industrial settings to identify opportunities for improving water efficiency. For example, several have demonstrated how WF can be integrated into production systems to reduce water consumption and improve environmental performance [21,22]. These studies underscore the importance of adopting a process-specific approach to water management, which complements the high-level assessments provided by standards like ISO 14046.

In parallel, the ISO 46001 standard provides a framework for establishing a WEMS in industrial settings. The standard emphasizes the importance of continuous monitoring and improvement of water efficiency, encouraging industries to adopt a systematic approach to water management. ISO 46001 is particularly relevant for industries that face regulatory pressures to reduce water consumption. By aligning with the Plan-Do-Check-Act (PDCA) cycle, ISO 46001 enables organizations to establish measurable water efficiency goals, monitor progress, and make data-driven decisions to improve water use.

Water Pinch Analysis is a systematic approach aimed at reducing water consumption, minimizing wastewater generation, and lowering the overall WF in industrial processes [8]. Derived from the broader concept of “pinch analysis” was initially developed for energy efficiency and was applied for scarce resources in general [23], this method provides a structured framework for optimizing water use by integrating process streams more effectively. The technique identifies opportunities for water savings by matching water sources within a facility with water sinks, or process units requiring water, while considering specific water quality requirements, such as contaminant concentrations. The goal is to maximize water reuse, thereby minimizing the need for fresh water and reducing wastewater generation to the smallest feasible volume.

2.2. Lean manufacturing and water efficiency

Lean manufacturing principles have increasingly been applied to reduce the environmental footprint of industrial processes and products [24]. The integrative adoption of Lean–Green tools has been shown to positively influence sustainability performance [25]. For instance, Vais et al. [26] implemented a combination of Lean practices, including 5S and Kaizen, in a paper and board mill, achieving an approximately 87% reduction in wastewater discharge. Value Stream Mapping (VSM) has also been adapted for sustainability assessments. Torres and Gati [27] proposed the Environmental VSM (EVSM) tool to align economic and environmental aspects of production processes. In their case study on sugar refinement, EVSM successfully identified critical phases, such as the evaporation–spray drying process, where elevated operating temperatures led to a 24% increase in water waste. Another relevant tool is Single Minute Exchange of Die (SMED) [28], which standardizes changeover procedures and incorporates improvements to minimize machine setup times. Braglia et al. [29] integrated environmental and temporal aspects in SMED analysis in an industrial application, demonstrating a 20% reduction in water use-equivalent to 115 litres saved for each setup.

2.3. OEE and performance indicators related approaches

Apart from WF-based approaches, the literature proposes several metrics for monitoring and improving water efficiency. Most indicators are defined as ratios and primarily serve a monitoring function. For example, the International Water Association (IWA) has developed a comprehensive manual on "performance indicators", which defines a broad set of metrics covering different aspects of water utility management, including their calculation formulas, time scales, and recommended frequencies of evaluation [30].

One of the most widely adopted measures is the Water Intensity Indicator (WII), which expresses the volume of water used or consumed per unit of product (e.g., litres per kilogram, litres per piece) or per unit of resource (e.g., litres per square meter, litres per worker). Ferreira et al. [31], for instance, applied several WIIs (per store area, per store, per worker, per revenue) to assess water consumption in the retail sector. The reciprocal of WII, Water Productivity (WP), is also frequently used. Exposito et al. [32] applied WP in the irrigation context, analysing the Guadalquivir river basin to identify the drivers influencing the evolution of irrigation WP, defined as the monetary value generated per unit of water used (EUR/m^3).

While such indicators provide effective means of monitoring water use and benchmarking performance, they are limited in their ability to guide strategic decision-making. Tracking the trend of a single indicator is rarely sufficient to identify where inefficiencies arise or which issues should be prioritized. For an improvement program to be effective, especially under resource constraints, it

is essential to pinpoint the causes of inefficiency so that efforts can be directed where they are most needed. To address this limitation, researchers have proposed more structured approaches based on Key Performance Indicators (KPIs). One important line of development in this direction is the design of tools inspired by OEE methodologies.

The OEE has long been recognized as a key tool for monitoring and improving operational efficiency in manufacturing context [33]. OEE measures equipment performance by evaluating three components: availability, performance, and quality, each of which represents a different aspect of production efficiency. OEE has been widely adopted across industries to identify and eliminate production bottlenecks, reduce downtime, and improve overall productivity. Despite its success in optimizing machine performance, OEE has traditionally focused on equipment availability and throughput, without attention to resource-specific inefficiencies such as water usage.

To fill this gap, researchers have explored the potential of adapting OEE to address operational and environmental sustainability challenges. Moreover, other structured approaches not based on OEE are to be found in the literature (Table 1). The identified papers have been categorized according to the production factor or resource considered for the analysis (Energy, Materials, Water and Others such as time, labour, operations flow, etc…).

Authors	**Production factor/resource considered**			
	Energy	**Materials**	**Water**	**Others**
Muchiri and Pintelon, 2008 [34]				x
Hiregoudar and Soragaon, 2011 [35]				x
Soragaon et al. [36]		x		x
Chien et al., 2014 [37]				x
Chien et al., 2015 [38]		x		
Domingo and Aguado, 2015 [39]	x	x	x	
May et al, 2015 [17]	x			
Nafi et al. [40]			x	x
Chien et al., 2016 [15]				x
Sachidananda et al., 2016 [41]			x	
Afy-Shararah and Rich, 2018 [16]				x
Braglia et al., 2018 [19]		x		x
Munoz-Villamizar et al., 2018 [42]	x	x	x	
Sachidananda et al. 2020 [43]			x	
Braglia et al., 2021 [14]				x
Braglia et al., 2024 [18]				x
Braglia et al., 2024b [44]				x

Table 1. Relevant papers in literature.

Among the 17 identified relevant papers, only five dealt with water. Domingo and Aguado [39] introduced the Overall Environmental Equipment Effectiveness (OEEE), an innovative metric that incorporates a sustainability factor into the conventional OEE framework. This development marks the first notable effort to integrate environmental considerations into traditional Lean efficiency assessments based on OEE. The OEEE metric evaluates sustainability by considering the complementary value of the ratio between a specific environmental impact of the workstation and the total specific environmental impact of the production process. Among the possible impacts, water consumption can be considered. This impact is measured using established indicators such as Ecoindicator-99 [45], which are not specifically designed around an industrial loss structure tailored for efficiency analysis. Munoz-Villamizar et al. [42] developed the Overall Greenness Performance (OGP) metric to evaluate the environmental sustainability of manufacturing processes. OGP assesses key aspects such as energy efficiency, resource utilization, environmental impact (including water consumption), recyclability, and compliance with sustainable practices. Similar to OEE, it incorporates a hierarchical structure. However, unlike OEE, OGP does not rely on a tailored set of industrial losses. Instead, it focuses on broader environmental factors, evaluated through established environmental indicators rather than loss structures specifically designed for industrial efficiency analysis.

Nafi et al. [40] developed a methodology to evaluate the Overall Performance (OP) of water utilities by aggregating 18 indicators across four pillars: Finance and Economy, Human Resources, Patrimony and Assets, and Environment. To synthesize the information from these indicators, they constructed an overall performance metric. Unlike OEE-based approaches, this framework does not focus on equipment effectiveness but instead provides an assessment of utility water management. By monitoring variations in OP over time, it becomes possible to identify trends resulting from management improvements.

Sachidananda et al. [41] proposed a structured approach to evaluate and enhance water conservation in manufacturing, distinct from other OEE-based approaches. They introduced the concept of Water Efficiency Ratios (WERs) based on three key metrics that facilitate a detailed analysis of water usage, distinguishing between production and non-production water, as well as categorizing water as consumed or discharged. For consumption, the framework identifies embedded and lost water, while for discharge it differentiates between renewable water (reusable or recyclable) and non-renewable water (effluent). This classification supports a clearer understanding of process performance in terms of water intensity and efficiency, representing a significant advancement in practical tools for water management. However, the framework stops at flow categorization and does not extend to analysing each flow in depth to identify the inefficiencies. More recently, the same

authors developed a decision-support tool for improving water efficiency in manufacturing processes, building on the previously introduced concept of WERs [43]. The tool guides improvement by identifying hotspots through WER analysis, formulating water reduction proposals, and prioritizing them using the Analytic Hierarchy Process. While this approach provides valuable support for reducing water use, its classification of water flows remains limited to WERs. As a result, it does not categorize flows in relation to specific water losses. For example, water associated with scraps and product reworks is not explicitly recognized as a form of water loss.

2.4. Research gaps

Based on the studies reported in the previous sections, the following research gaps are identified:

1. Lack of a water-specific industrial loss structure. While extensions of the OEE framework have been proposed to incorporate environmental dimensions such as energy and material efficiency, none have introduced a dedicated loss structure tailored to the dynamics of water use and consumption within industrial processes. Existing metrics (e.g., OEEE, OGP) tend to rely on generic environmental indicators, which do not capture the process-specific inefficiencies related to water.
2. Limited integration of water management standards into operational metrics. International standards such as ISO 14046 and ISO 46001 offer strategic-level guidance for water sustainability and efficiency. However, there is a noticeable lack of integration between these high-level frameworks and day-to-day operational metrics, leaving a gap in their applicability for continuous improvement within production systems.
3. Absence of a hierarchical, water-oriented structure. Despite efforts to develop comprehensive sustainability metrics, none offer a hierarchical structure explicitly adapted to water that mirrors the well-established OEE dimensions of availability, performance, and quality. The framework proposed by [41] provides useful distinctions (such as consumed vs. discharged water) but lacks integration into a unified, Lean-based performance structure capable of supporting targeted improvements at the operational level.
4. Existing indicators are not designed to support the automated and complex monitoring required by modern production systems, which are increasingly equipped with sensors and interconnected in accordance with I4.0 principles. This gap may hinder the effective exploitation of data generated by these systems, limiting their potential to provide actionable insights into efficiency performance, loss detection and quantification.

To bridge these gaps, this paper introduces OWE and two complementary key indicators grounded in a structured classification of water-related losses. This set of indicators is designed to evaluate

water performance in industrial contexts and to support continuous improvement initiatives aimed at optimizing water use and consumption. By translating international standards into a Lean-compatible and digitally operable framework, these joint indicators allow the integration with data streams generated by modern, sensor-equipped production systems. This enables more effective use of information from intelligent machines for real-time monitoring and efficiency analysis. As a result, the set of indicators supports the transformation of raw data into actionable insights, advancing both operational performance and sustainability at the production-floor level.

3. Methodology

This section describes the structure and functionality of the proposed set of indicators. The new set of indicators has been developed following the structure outlined in [14,18,19]. The approach begins with the definition of clear temporal and spatial boundaries for the analysis [18]. It then leverages the newly introduced classification of industrial water losses, specifically tailored to the resource under consideration [14]. Building on this foundation, the structured metrics are constructed to support both performance evaluation and strategic decision-making [19]. The first subsection outlines the spatial and temporal boundaries used for the analysis and introduces a proposed decomposition of water losses. The second subsection presents and discusses the indicators.

3.1. System boundaries

As a first step, it is essential to establish precise spatial and temporal boundaries for evaluating water-related efficiency losses:

- Spatial Domain: the spatial boundary refers to the physical limits within which water use and consumption are evaluated. Typically, this boundary coincides with the physical perimeter of the plant or facility, depending on the specific site and context of the study. The selected spatial domain should encompass all relevant processes involving water usage and potential water losses, thereby ensuring a comprehensive assessment of water efficiency. When defining the spatial domain, it is crucial to consider the available water monitoring systems, as these directly influence the detection and quantification of water flows. Indeed, many companies (especially Small and Medium-sized Enterprises) are in the early stages of implementing water management and monitoring practices, often lacking comprehensive systems for plant-wide analysis. In such contexts, the authors recommend adopting an incremental or “oil-spot” approach, beginning with a focused assessment at a single machine or process unit and progressively extending the analysis to additional equipment, departments, and ultimately, the entire facility.

- Temporal Domain: the temporal boundary refers to the time horizon over which water usage and losses are analysed. While this period can vary, it should align with the timeframe required for effective decision-making, typically covering a full-year or half-year interval. Such a duration ensures that the analysis adequately captures seasonal variations and long-term trends in water consumption. Regarding the frequency of evaluation, two scenarios are identified by the authors. For plants equipped with continuous water monitoring systems, batch-level real-time monitoring is ideal, as it enables live tracking of water performance over a movable time window suitable for the type of production under analysis (such as a week). Conversely, when only periodic monitoring systems are available, indicators should be reassessed at intervals matching the monitoring frequency. The choice between these scenarios depends primarily on resource availability, including financial investments for system implementation and personnel capacity for conducting evaluations.

3.2. The new classification of water losses

After establishing the spatial and temporal boundaries, the next step is to identify and categorize water losses to enable a more precise analysis. The description of water flow quantity reported in Figure 1 is the following:

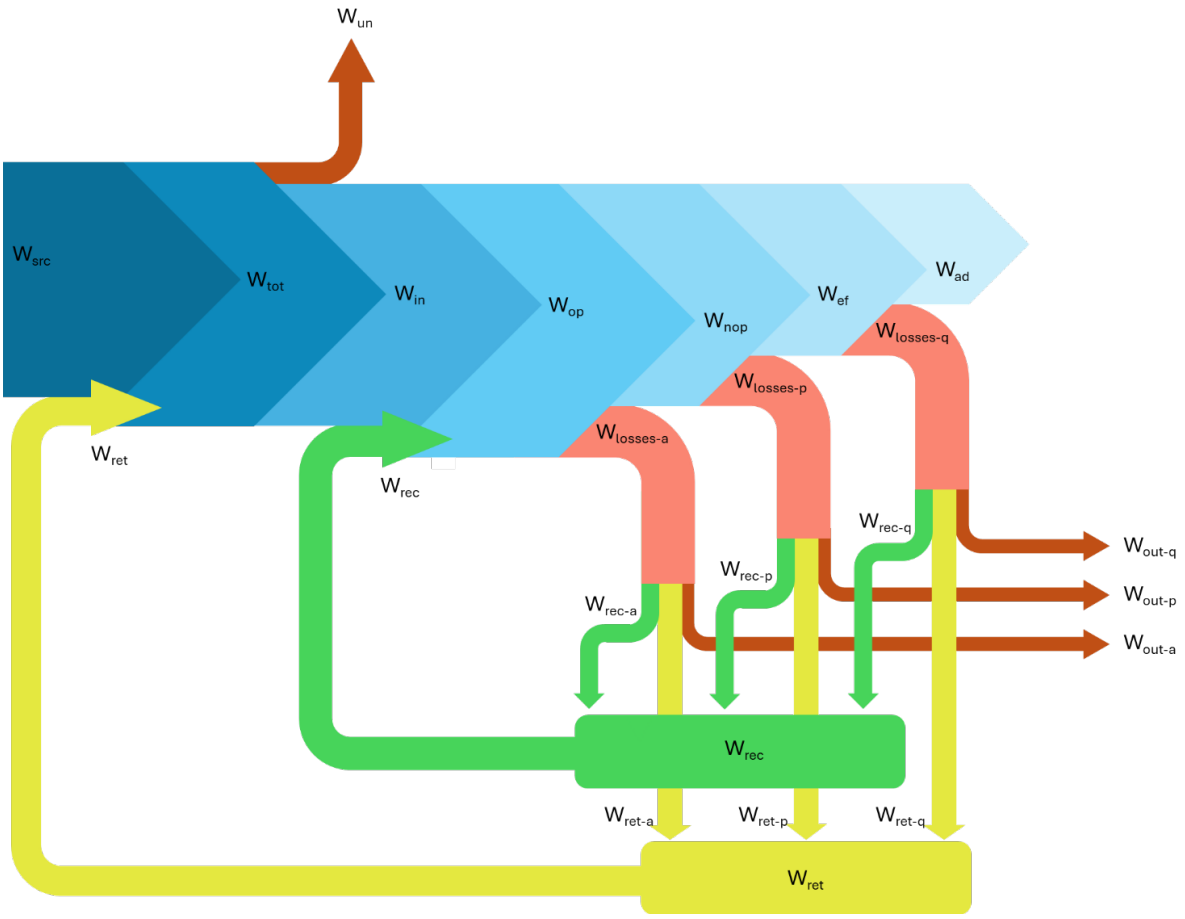


Figure 1. New classification of industrial water losses.

- Water Source (W_{src}): This represents the volume of water required to replenish the virtual water source, which is considered "virtual" because it refers to the external supply volume relative to the defined spatial domain. The virtual source can draw water from multiple origins, including natural catchments (such as lakes, basins, and rivers), upstream machines within the same production line, other departments in the same facility, separate plants, or even systems for rainwater harvesting (Figure 2). The concept of a virtual water source allows OWE to be flexibly applied at different scales, ranging from a single machine to a production line, department, or entire facility. The classification of water as either internal or part of the external source depends entirely on the chosen spatial domain for the analysis. For example, when the analysis focuses on a single machine within a production line, the upstream machines are treated as part of the virtual water source. Conversely, if the spatial domain includes the entire production line, such internal flows are no longer counted as inputs from the virtual source, and the upstream machine is considered part of the internal system rather than the virtual water source.
- Total Water Input (W_{tot}): Represents the gross volume withdrawn from the water source. It is the sum of two contributions: W_{src} and W_{ret} (sum of all water streams returned to the virtual water source). A portion of this input may be lost due to uncontrollable factors, such as external pipe leakages, supply chain quality issues (e.g., contamination) or regulatory constraints. These losses, referred to as Unmanageable Water Losses (W_{un}), lie outside the direct control of the system under analysis.
- Input Water (W_{in}): Defined as the difference between W_{tot} and W_{un}, this represents the actual volume of water entering the spatial domain from the external virtual water source.
- Operative Water (W_{op}): Defined as the sum of W_{in} and W_{rec} (sum of all water streams recycled within the system), this represents the volume of water available for production purpose. A portion of this is lost due to activities whose water consumption can be directly measured through the measurement sensor systems such as cleaning, washing, drying and so on. These Availability Water Losses, denoted as $W_{losses\text{-}a}$, reduce the water volume effectively available for production operations and can be further categorized into three distinct components:
    - Availability Recycled Water Losses ($W_{rec\text{-}a}$): The volume of water associated with losses that is, if conditions allow, treated and then reused within the spatial domain. Typical examples include water used for heating, cooling, cleaning, and washing.

- Availability Returned Water Losses (W_{ret-a}): The volume of water that, after appropriate treatment, is returned to the original virtual water source.
- Availability Out Water Losses (W_{out-a}): The volume of water that cannot be recovered due to evaporation or degradation in quality beyond acceptable thresholds, even after treatment.

This categorization is consistently applied to subsequent stages of water loss analysis. To facilitate tracking and visualization, the total volume of recycled water streams (W_{rec}) is aggregated into a virtual basin (green), representing the contribution of recycled water to W_{op}. Similarly, all returned water streams (W_{ret}) are collected into a virtual basin (yellow), representing the volume of treated water reintegrated into the virtual water source.

- Net Operative Water (W_{nop}): Defined as the difference between W_{op} and $W_{losses-a}$, this represents the net volume of water actually used for production operations. A portion of this water volume is consumed by activities whose water losses cannot be directly measured by sensor systems. These Performance Water Losses, noted as $W_{losses-p}$, may arise from events such as changeover processes, minor equipment stoppages, or gradual performance degradation. As before, $W_{losses-p}$ is categorized into three components: Performance Recycled Water Losses (W_{rec-p}), Performance Returned Water Losses (W_{ret-p}), and Performance Out Water Losses (W_{out-p}). This classification reflects the fact that losses affecting performance can be managed differently depending on the specific operational context. For example, additional water used during extended washing cycles, which reduces water performance, may be treated and either recycled for internal reuse or returned to the virtual water source. In less favourable scenarios, however, such water may be too contaminated to allow for any form of recovery, in which case it must be discharged.
- Effective Water (W_{ef}): Defined as the difference between W_{nop} and $W_{losses-p}$, this represents the volume of water effectively used to produce final goods. However, not all output meets the required quality standards. A portion of this water is therefore lost due to defects, scraps, and rework. These losses are categorized as Quality Water Losses ($W_{losses-q}$) and are broken down into three groups: Quality Recycled Water Losses (W_{rec-p}), Quality Returned Water Losses (W_{ret-p}) and Quality Out Water Losses (W_{out-p}). The classification of a given loss into one of these categories depends strictly on the nature of the product involved. For recyclable products, such as paper, production scraps typically re-enter the process at early production stages and can therefore be considered either recycled or returned losses, depending on the defined spatial domain of the system. In contrast, for non-recyclable products or those requiring complex end-of-life treatments, such as

coloured fabrics, scraps generally exit the system without re-entering the production cycle directly and are thus classified as out losses.

- Value Added Water (W_{ad}): Defined as the difference between W_{ef} and $W_{losses\text{-}q}$, this is the exact amount of water required to produce quality-compliant products. It is generally composed of two main contributors: embedded water and necessary lost water. Embedded water refers to the portion of water physically incorporated into the final product, such as the water contained in a bottled beverage. Necessary lost water, by contrast, is the volume necessary required by the production process but not present in the final product. This includes, for example, water lost through evaporation during cooking, or the evaporated water in paper production, which is currently unavoidable given existing process technologies. Importantly, the classification of water as "necessary lost" depends on the technological state of the art within the specific industrial sector. If a system capable of recovering evaporated water, such as steam, exists and is economically viable, that volume should not be considered part of W_{ad}. Conversely, if such recovery technologies are unavailable or not economically sustainable, the associated evaporated water must be included in W_{ad} as an intrinsic requirement for producing a conforming product, rather than being categorized as a process loss.

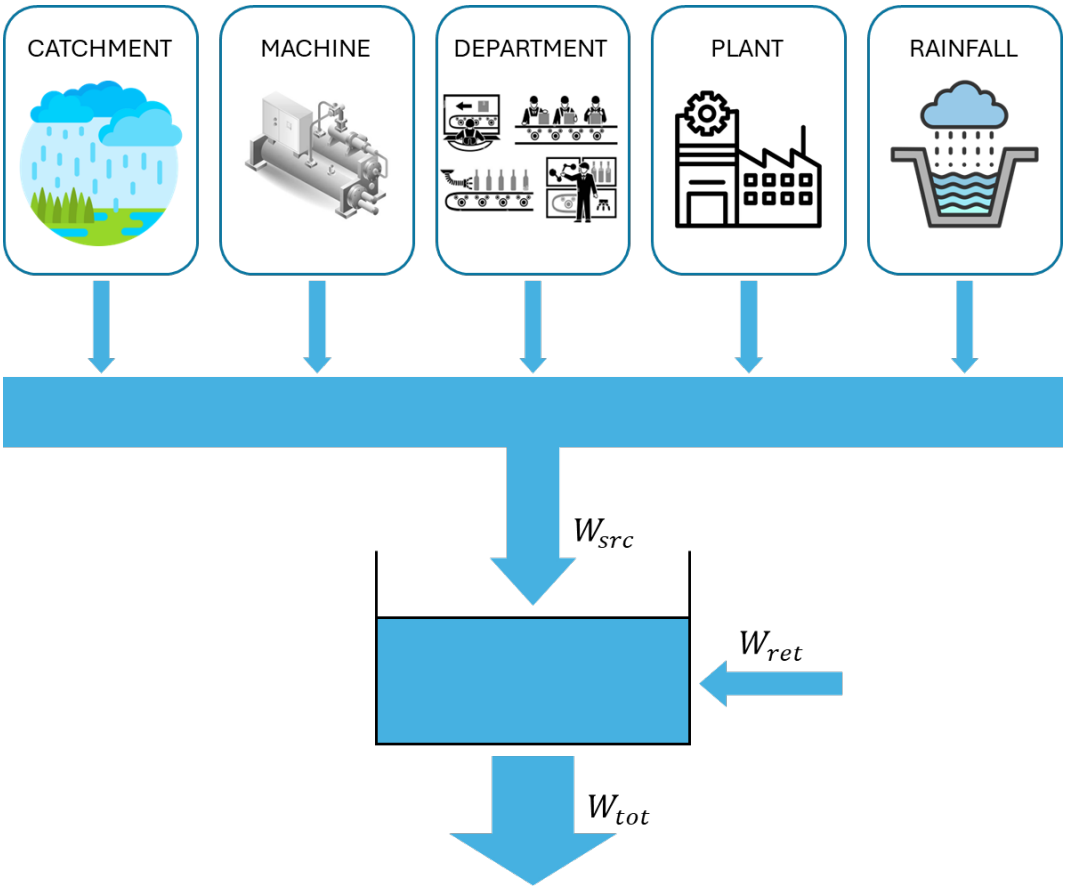


Figure 2. Possible streams within the virtual water source.

It is important to stress that measuring all water losses in an industrial setting poses significant challenges due to both technical and economic constraints. Although theoretically possible, quantifying every instance of water loss would require the installation of measurement devices at each water input and output point across every process and piece of equipment that uses water. This would involve monitoring complex pathways, such as individual production units, cooling systems, and various ancillary processes, to capture the precise water consumed or lost at each stage. However, this level of monitoring is often economically unsustainable for most companies. Installing extensive instrumentation and monitoring systems comes with high upfront costs for the equipment itself, as well as ongoing maintenance expenses. Additionally, many production environments require frequent reconfigurations or adjustments to equipment and processes, making it impractical to continually update monitoring systems to capture accurate data. The operational complexity and cost of managing such a granular measurement system outweigh the benefits, especially since certain losses, such as minimal leaks or temporary inefficiencies, may have only a marginal impact on total water use.

As a result, only the losses that are economically feasible to measure or calculate, are quantified directly ($W_{losses\text{-}a}$). In contrast, $W_{losses\text{-}p}$ are acknowledged but remain hidden due to the prohibitive costs associated with capturing this data.

A breakdown of potential water losses is provided in Table 2. Specifically, the examples of losses have been conceived by enriching those presented in the literature [18,19,46] with typical criticalities related to water management, collected during dedicated meetings with key personnel from three industrial companies (labeled A, B, and C). Company A, which will be better described in the Section 4, is a major textile manufacturing company specializing in fabric dyeing and finishing, characterized by high water consumption in washing and boiling processes. Company B is a major company in the plywood production sector, involving wood processing (debarking, peeling, and hot pressing), with significant water use in adhesive production mix. Company C is a large railway company specializing in the engineer-to-order assembly of train wagons, with water use primarily related to complex cleaning and quality control processes. The input was gathered in a meeting with the work team, which included project managers, production managers, site supervisors, and employees from technical and design offices from the participating companies.

It is essential to emphasize that, when implementing the methodology, analysts should develop a specific decomposition of water losses tailored to the industrial context under consideration. For example, water losses related to paper drying in a paper production plant would differ significantly from those encountered in a textile dyeing facility, and vice versa. Furthermore, within a specific plant, the categorization of water losses may vary depending on the extent and sophistication of the monitoring system in place. For instance, with a comprehensive monitoring system, water usage associated with a changeover process can be directly quantified and classified under measurable losses. Conversely, if monitoring capabilities are limited, such water losses cannot be measured directly and may instead be detected indirectly through reduced production output. It is crucial to recognize the significant implications of this distinction: direct measurement enables analysts to clearly identify the causes of water losses and take targeted corrective actions, whereas indirect measurement aggregates water losses, obscuring individual contributions and hindering precise interventions. This situation parallels the performance losses considered in OEE. Specifically, the duration of speed losses or minor stoppages typically cannot be measured directly in most manufacturing systems. Consequently, these losses are evaluated indirectly by comparing theoretical output with actual output over a defined time frame.

Category	Subcategory	Examples	Braglia et al., 2018 [19]	Braglia et al., 2024 [18]	Shublaq et al. 2020 [46]	Interviews with industrial companies		
						A	B	C
Unmanageable Water Losses		Supply quality issues		✓		✓		
		Production fragmentation					✓	
		Supply regulatory issues				✓		
		Pipe leakages		✓				
Manageable Water Losses	Availability Water Losses	Cleaning	✓			✓		✓
		Washing	✓		✓			
		Drying			✓		✓	
		Cooling			✓			
		Heating			✓			
		Lubrication			✓			
	Performance Water Losses	Pipe leakages		✓				
		Performance degradation of equipment		✓				
		Inefficient use of equipment		✓				
		Failure		✓				
		Changeover				✓		✓
		Missing procedure/documentation		✓		✓		
	Quality Water Losses	Scrap	✓	✓			✓	
		Rework	✓	✓		✓	✓	✓
		Obsolescence	✓			✓		

Table 2. Examples of industrial water losses.

3.3. The new set of indicators

Starting from the classification of water losses previously reported, a new set of Lean indicators aimed at assessing water efficiency is proposed. These indicators offer a structured approach to evaluating water performance across various stages of usage, from input to value-added water, aligning closely with the hierarchy illustrated in Figure 3. Each indicator is calculated based on the elements in Figure 3, providing an assessment of water utilization that highlights areas for potential waste reduction and efficiency gains.

Unlike the traditional loss decomposition used in OEE, the proposed structure introduces an innovative approach that enables the analyst to account for factors extending beyond simple "efficiency erosion". In OEE, each sub-indicator is calculated as the ratio between two time-based values, where the numerator of one becomes the denominator of the next. This reflects the fact that time is a resource that can only be consumed and cannot be recovered or reused. Such approach has been applied in several OEE-related works, such as [14,15,18]. However, when dealing with environmental resources such as water, it is a different condition. Water, unlike time, can be recycled or returned after appropriate treatment, which is an essential distinction that must be acknowledged. This consideration applies to other environmental resources as well, such as materials.

In the proposed loss decomposition, water losses are categorized into recycled, returned, and out losses. This classification allows for the evaluation of different operational scenarios. Accounting for recycled water enables the assessment of water consumption in terms of the volume drawn from the virtual water source, while returned water provides a means to evaluate the dependency on external water supply beyond the spatial domain. This approach enhances the accuracy and relevance of water performance indicators in modern industrial contexts.

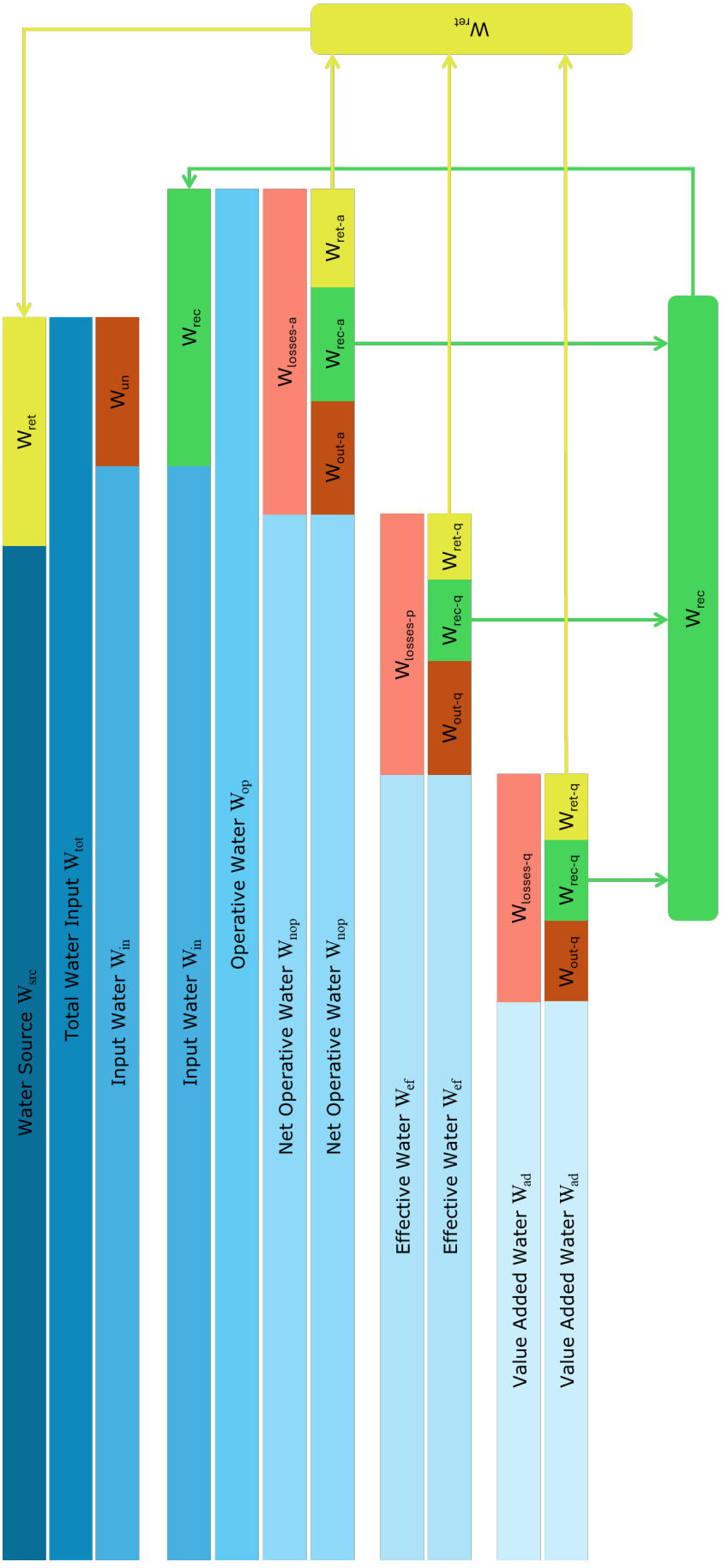


Figure 3. Structure of the new set of indicators.

The framework includes a primary structured indicator, OWE, complemented by two additional indicators: Internal Water Efficiency (IWE) and Global Water Efficiency (GWE). These joint indicators account for how water losses are managed, providing a more comprehensive view of water use performance. The indicators are defined as follows:

$$OWE = \frac{W_{ad}}{W_{op}} = \frac{W_{ad}}{W_{in} + W_{rec}} \quad (1)$$

$$IWE = \frac{W_{ad}}{W_{in}} \quad (2)$$

$$GWE = \frac{W_{ad}}{W_{src}} \quad (3)$$

Where, *OWE* shows how efficiently all available water is turned into valuable output, *IWE* indicates how efficiently input water is consumed by the production process, and *GWE* measures how much the process depends on external water sources.

The three indicators (OWE, IWE, and GWE) enable the investigation of water performance across distinct but complementary levels. As highlighted in WF methodology, focusing solely on water use at the process level is insufficient. Both use and consumption should be assessed in parallel to evaluate not only the gross volume of water required, but also the net volume actually withdrawn from water resources and the impact of the production process in terms of water sustainability. This distinction is crucial for understanding the degree of resource dependency and fragility that must be considered when planning and implementing water management projects. *OWE* assesses the efficiency of total water usage by comparing the water resulting in value-adding products (W_{ad}) to the operative water available within the system (W_{op}). This indicator captures the intrinsic productivity of water within the production process, quantifying how effectively the available water is converted into high-quality output. By focusing on value-adding transformation, it moves beyond simple input–output ratios and provides a more meaningful measure of how well water resources are utilized at the core of industrial operations. *IWE* measures water consumption efficiency by comparing W_{ad} to the volume of water introduced from the source (W_{in}). A significantly higher value of *IWE* compared to *OWE* suggests that a substantial portion of water is recycled internally before exiting the system, thereby reducing the demand for freshwater inputs. Finally, *GWE* compares W_{ad} to the volume of water required to replenish the original source (W_{src}). This indicator evaluates the effectiveness of the systems from an external environmental perspective, highlighting the extent to which the process relies on water extracted from outside the defined spatial domain.

A parallel can be drawn between the proposed set of indicators and OEE-framework and the concept of productivity. Just as OEE represents the intrinsic productivity of a machine relative to its available production time, OWE reflects the intrinsic water productivity of a system relative to the total amount of water available for production. In this analogy, productivity measures output over total calendar time, while GWE expresses water productivity relative to the total volume of water required to sustain the virtual water source. Lastly, IWE can be viewed as an internal water productivity metric, analogous to productivity measured during the actual operating time of the system, since it evaluates performance based on the volume of water physically withdrawn from the source.

Furthermore *OWE*, similarly to OEE, can be computed as follows (Formula 4):

$$OWE = Availability \times Performance \times Quality \quad (4)$$

This decomposition allows for a more detailed diagnostic of water-related inefficiencies within the production system. The first sub-indicator is Availability (*A*) (Formula 5):

$$Availability\ (A) = \frac{W_{nop}}{W_{op}} = \frac{W_{op} - W_{losses-a}}{W_{op}} = \frac{W_{op} - W_{rec-a} - W_{ret-a} - W_{out-a}}{W_{op}} \quad (5)$$

It is designed to evaluate the proportion of available water that is not lost through measurable events, thereby quantifying the impact of directly measurable water losses relative to the total water available for production. The A indicator is particularly valuable, as it highlights the specific causes of inefficiency that reduce the amount of water usable for actual production operations. Notably, the numerator captures this by excluding W_{losses_a}, which is further decomposed into its three components: recycled, returned, and lost water. This detailed breakdown provides insight into how water losses are managed and lays the groundwork for subsequent analysis of internal versus external water consumption.

As far as the Performance (*P*) sub-indicator is concerned, it is evaluated through Formula 6:

$$Performance\ (P) = \frac{W_{ef}}{W_{nop}} = \frac{W_{nop} - W_{losses-p}}{W_{nop}} = \frac{\sum_{i=1}^{N} V_{s_i} \times M_i}{\sum_{i=1}^{N} (\sum_{j=1}^{B} Vb_{i,j} \times m_{i,j})} \quad (6)$$

This metric aims to assess the amount of water lost in ways that are not directly measurable. Specifically, it reflects the ratio of water effectively used in production to the water theoretically required for equivalent production. Because these losses cannot be measured directly, they are often estimated indirectly. Following a logic similar to that used in the calculation of OEE, P can be computed as the ratio between the ideal water volume associated with effectively realised products

and actual water volume associated with them. The numerator corresponds to the sum, over all N products, of the ideal specific water volume for product i (V_{s_i}) multiplied by the total quantity of product i produced M_i, where M_i can refer either to mass or unit count, depending on the context. The denominator is calculated by summing, for each of the B production batches and for all N products, the actual specific water volume for product i in batch j (denoted as $Vb_{i,j}$) multiplied by the quantity of product i in batch j ($m_{i,j}$).

This formulation highlights the gap between actual and potential production in terms of water usage, offering a practical way to assess performance-related inefficiencies in water consumption. This challenge is analogous to the calculation of Performance in OEE, where knowledge of the Ideal Cycle Time is crucial. Just as short stops and speed reductions are often difficult to quantify in OEE, unmeasurable water losses in production present similar estimation difficulties.

Finally, the Quality (Q) sub-indicator is calculated according to Formula 7.

$$Quality\ (Q) = \frac{W_{ad}}{W_{ef}} = \frac{W_{ef} - W_{losses-q}}{W_{ef}} = \frac{\sum_{j=1}^{M} V_{s_j} \times M_j + \sum_{k=1}^{P} V_{r_k} \times M_k}{\sum_{i=1}^{N} V_{s_i} \times M_i} \quad (7)$$

This metric reflects the proportion of water associated with compliant products versus total products. The difference between these two quantities primarily represents water lost due to scrap and rework ($W_{losses\text{-}q}$).

The denominator corresponds to the same value used as the numerator in the calculation of the sub-indicator P. The numerator is composed of two parts. The first is the sum, over all M compliant products, of the ideal specific water volume for product j V_{s_j} multiplied by the quantity of product j produced M_j (mass, number of products or volume depending on the case). The second part accounts for reworked products. It consists of the sum, over all P reworked products, of the specific water volume for rework V_{r_k}, multiplied by the quantity of reworked product k M_k. V_{r_k} represents the value-added water volume associated with non-compliant products that require only rework, rather than being completely discarded. Since reworked products retain part of the original water value, V_{r_k} is lower than V_{s_k}, reflecting the partial recovery of water investment.

This hierarchical model, together with the defined ratios, offers a comprehensive view of water performance across different stages, from total input to value-added output. Each ratio highlights specific opportunities for improvements, from reducing waste to enhancing quality-related water efficiency. By multiplying the sub-indicators, it is possible to derive overall indicators that provide a broad perspective on water efficiency. These indicators are intended as tools for assessing and

continuously improving water performance within a Lean Manufacturing context, analogous to how OEE is used to monitor equipment efficiency.

At this point, it is important to highlight the strong formal similarity between OWE and OEE, as clearly illustrated in Table 3. The latter metric is widely recognized as the archetype of all effectiveness indicators, and its structure has become a reference model for both researchers and practitioners.

a) Overall Equipment Effectiveness (OEE)	b) Overall Water Effectiveness (OWE)
Breakdown of losses	

• Availability
  ○ Breakdowns
  ○ Setups and adjustments
  ○ Changeovers
  ○ Equipment failures
• Performance
  ○ Reduced speed
  ○ Minor stops
  ○ Idling and stoppages
• Quality
  ○ Defects
  ○ Rework
  ○ Scrap
	• Availability
	  ○ Cleaning
	  ○ Washing
	  ○ Drying
	  ○ Cooling/Heating
	  ○ Lubrication
	• Performance
	  ○ Inefficient use of equipment
	  ○ Performance degradation
	  ○ Failures
	  ○ Changeovers
	  ○ Missing procedure
	  ○ Missing documentation
	• Quality
	  ○ Defects
	  ○ Rework
	  ○ Scrap

Overall concept	
Efficiency of equipment in turning available time into quality output	Efficiency of available water in being converted into value-added water
Main objective	
Improve equipment productivity and reduce production downtime	Improve water productivity and reduce environmental impact
Resource type	
Time (non-recoverable resource)	Water (recyclable, returnable, or irreversibly lost)
Formula	
OEE = Availability × Performance × Quality	OWE = Availability × Performance × Quality
Application domain	
Manufacturing equipment and production lines	Water efficiency management in production and resource-intensive activities

Table 3. OEE (a) and OWE (b) comparison.

Both indicators rely on the three pillars of Availability, Performance, and Quality and aim to quantify the gap between actual and ideal effectiveness, thereby supporting continuous improvement.

The key distinction lies in the resource considered: while OEE focuses on time as a non-recoverable input, OWE addresses water, a resource that can be recycled, returned, or irreversibly lost. This requires a richer classification of losses, distinguishing between recycled, returned, and out flows. Moreover, OEE measures equipment productivity, whereas OWE extends the framework to an environmental dimension by evaluating water productivity in manufacturing systems. Finally, OWE introduces two complementary indicators - IWE and GWE - which assess internal consumption efficiency and external resource dependence. Overall, OWE maintains the Lean logic and operational clarity of OEE, while broadening its scope into sustainability-oriented performance measurement tailored to water management.

3.4. Numerical examples

To support a clearer understanding of the calculation and interpretation of the set of indicators, four key illustrative numerical examples are presented (Figure 4). In all scenarios, water is drawn from a virtual water source, and the spatial domain of the system is represented by the dashed green rectangle. The output streams from the spatial domain consist of a value-added stream (W_{ad}) and a water losses stream (W_{losses}) which includes the cumulative losses associated with A, P, and Q. These output streams remain constant across all scenarios to allow for a consistent basis of comparison. What varies across the panels is the input configuration and the handling of water losses, allowing for the exploration of different operational and environmental conditions. Each panel illustrates a potential scenario, demonstrating how variations in water input, recycling, or return strategies influence the resulting values of the indicators.

In panel a, all water losses are discharged without any form of recycling or return to the virtual water source. As a result, *OWE* and *IWE* yield identical values, indicating that water usage and internal efficiency are equivalent. Conversely, *GWE* is slightly lower due to the presence of unmanageable water losses, which increase the demand on the external water supply.

In panel b, a portion of the water losses is treated and returned to the virtual water source. In this scenario, *OWE* and *IWE* remain unchanged, as the amount of water available for production and internally consumed water does not vary. However, *GWE* increases because less water is needed to replenish the virtual source, thanks to the returned volume.

In panel c, a portion of the water losses is treated and directly recycled within the system, reducing the demand for water from the virtual source. Since the amount of water drawn from the source decreases, the volume of unmanageable losses (proportional to the intake from the source) also declines. In this case, *OWE* remains constant because both the numerator (value-added water) and

denominator (operative water) do not change. *IWE* increases due to the reduction in water consumption, and *GWE* also increases as less water is required to restore the virtual water source.

In panel d, water losses are partially recycled and partially returned to the virtual water source, resulting in a lower discharge volume. As in the previous case, *OWE* remains unchanged. *IWE* maintains the same value as in panel (c), as it is influenced only by the recycled fraction. *GWE* reaches its highest value, reflecting the combined benefit of recycling and returning, which together produce the greatest reduction in the need for external water replenishment.

These numerical examples clearly illustrate the critical role of recycling and returning in improving water consumption performance. While *OWE* is unaffected by the origin of the supply and focuses solely on the use of water within the production system, *IWE* can be significantly enhanced through recycling. *GWE*, on the other hand, benefits from both recycling and returning water to the virtual source, thereby reducing dependency on external water supplies. As demonstrated, this set of indicators effectively captures these dynamics, offering a comprehensive framework for assessing water efficiency performance across different operational scenarios.

Another important aspect to emphasize is that the way a loss is treated, whether it is recycled, returned, or discharged as an out loss, depends on the technical capacity and economic feasibility available to the company implementing the indicators. In general, when the loss occurs as a wastewater stream, it is more feasible to implement recycling or returning systems, such as conventional wastewater treatment solutions. In contrast, when the loss takes the form of steam, recovery tends to be more technically challenging and economically demanding.

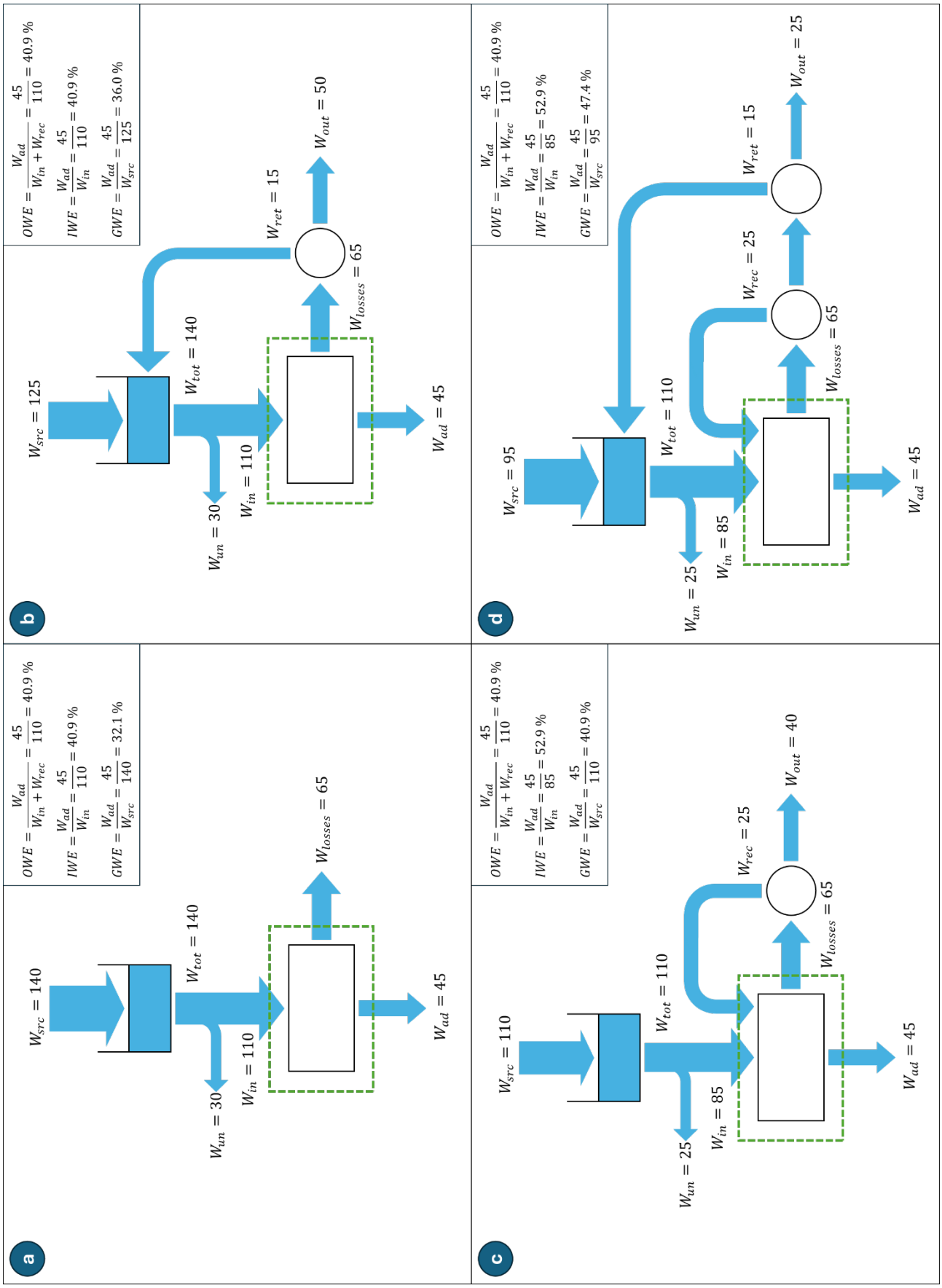


Figure 4. Numerical examples: (a) no recycling or returning, (b) only returning, (c) only recycling, (d) combination of recycling and returning.

4. Case study

To validate the functionality, practicability, and effectiveness of the proposed approach, the set of indicators is tested in a textile company specializing in fabric dyeing. Over recent years, the company has initiated a sustainability-focused transition aimed at improving competitiveness and meeting increasingly stringent environmental requirements from international fashion clients. Specifically, the company identified three main sustainability areas to target. First, enhancing energy efficiency to reduce greenhouse gas emissions and fossil fuel consumption (primarily natural gas) whose prices have experienced recent significant volatility. Second, improving traceability of products and processes to offer greater transparency to customers. Lastly, reducing water consumption, recognizing that textile manufacturing has a substantial environmental impact, and aligning with increased consumer sensitivity toward product sustainability. Consequently, the company implemented an extensive water monitoring system designed to accurately track multiple water flows within its textile facility.

4.1. Water flows monitoring system

The schematic representation of the hydraulic circuit and water monitoring system is provided in Figure 5, with distinct water flows identified by specific colours. The hydraulic system of the plant comprises three distinct water flows: hard water (HW) in blue colour, hot softened water (HSW) in red colour, and cold softened water (CSW) in green colour. Water is drawn from eight separate wells located within the industrial perimeter, pre-treated through filtration, and subsequently stored in a 1000 m^3 storage tank. This tank serves as the HW reservoir, supplying water throughout the facility. The HW undergoes softening through a dual softening system comprising two softeners operating alternately, while one softener is active, the other regenerates and vice versa. The softened water output constitutes the CSW flow. Subsequently, CSW is heated resulting in the production of HSW, which is stored in an 80 m^3 tank.

The implemented water-flow monitoring system comprises multiple measurement points with varying monitoring granularity. At the highest level, total water extraction from the wells is measured immediately upon withdrawal. Subsequently, HW, CSW, and HSW flows are individually monitored at the point of entry into the dyeing department. At a more detailed level, each dyeing machine is equipped with a water meter and four monitoring automatic valve openings: one dedicated to each water flow (HW, CSW, HSW), plus an additional meter for mixed water obtained by blending hot and cold streams. The monitoring system integrates with the machine control system, enabling differentiation between HW used directly in the dyeing processes and HW allocated for machine washing and cleaning operations.

Effluent water resulting from dyeing operations is gravity-collected and routed into the wastewater management circuit, where it undergoes partial purification by a mechanical separation system that removes fabric impurities before discharge into the sewage system.

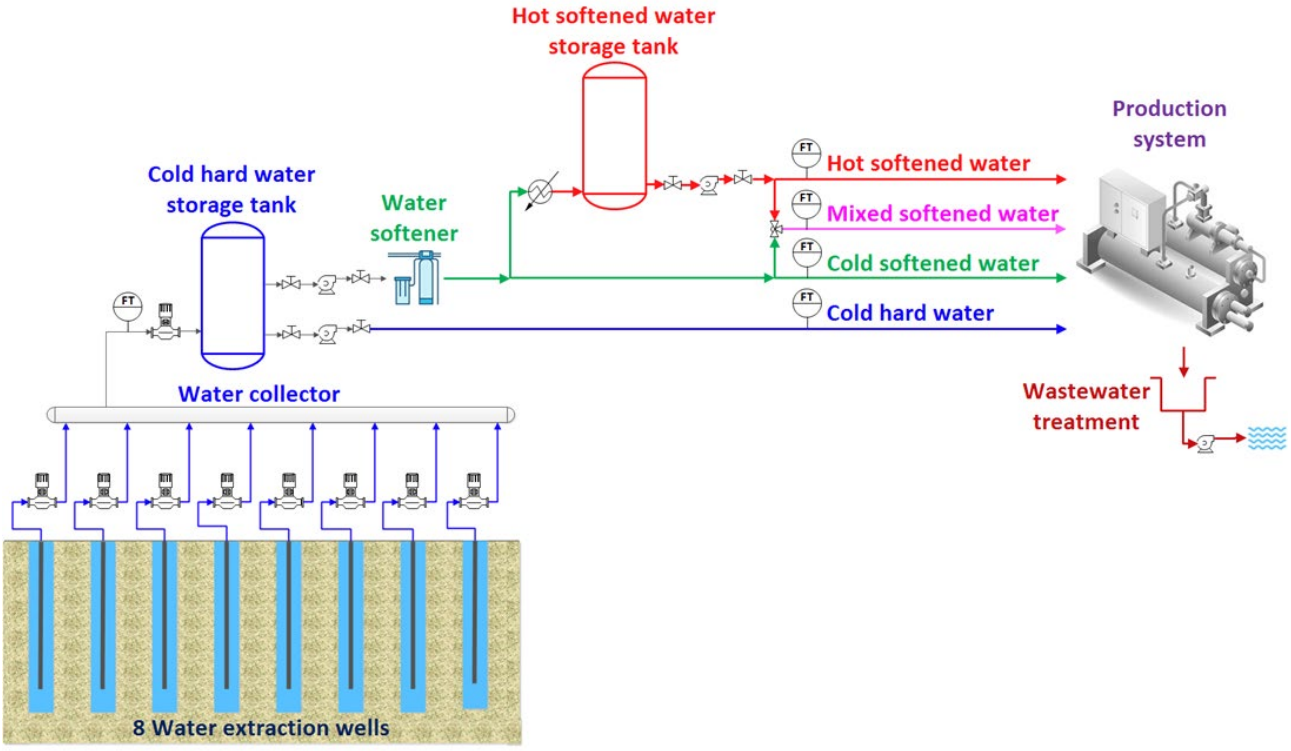


Figure 5. A schematic representation of the hydraulic circuit and water-monitoring system.

4.2. Dying process

The dyeing department comprises 26 machines. The production processes vary significantly based on the material being processed; wool, cotton, and synthetic fibres each undergo distinct treatment methods. Regardless of product composition, the dyeing process occurs in water mixed with coloured pigments following specific dyeing recipes. The product is continuously moved within the dyeing machine to ensure optimal colour absorption. After the initial dyeing step, the coloured water is drained and replaced with fresh water for washing to ensure color-fastness during the initial customer wash.

The specific dyeing temperature and associated chemical substances, employed to stabilize the process and enhance colour absorption, depend significantly on the material. Wool products, for example, typically require higher temperatures and pressures compared to cotton products. Products composed of multiple materials often require multiple dyeing stages at varying temperatures. When feasible, water from the final rinse cycle is conserved and reused for subsequent dyeing operations, achieving an approximate water saving equivalent to one machine volume, though adjustments are typically necessary. This reuse depends on colour compatibility between successive dyeing batches

and is therefore influenced by how daily production is scheduled to encourage water savings. However, this strategy is constrained by the nature of client demand, which is highly fragmented and variable. As a result, opportunities for reuse are often limited, since incompatible colour sequences can compromise dyeing quality and lead to defective products or scrap. For different product colours or materials, machines undergo a cleaning process. In most of the cases such cleaning consists of a manual washing while for very different colours a “boiling” operation is necessary, involving a no-load operation where process water is circulated within the machine and then discharged before initiating a new dyeing cycle.

Upon completion of the dyeing process, products undergo rigorous quality inspection by specialized operators. Non-compliant conditions, such as uneven coloration, residual traces of previous dye batches, or fabric folds, may be identified. In most cases, non-compliant products require reworking. However, severely compromised products must be discarded.

The water-flow monitoring system records the types and volumes of water consumed in each dyeing operation as well as the results of the operation (compliant and non-compliant cases). Every three months, the dyeing department receives a detailed spreadsheet documenting each dyeing operation across all machines.

4.3. Indicators calculation

The first step in calculating the set of indicators involves assembling a multidisciplinary analysis team. The working group comprises participants with diverse professional backgrounds, including the heads of the technical and dyeing departments and experienced dyeing operators. From academia, specialists in Lean methodologies participate alongside a data mining expert, given the large volume of water consumption data to analyse. This heterogeneous team ensures comprehensive understanding and provides the breadth of expertise necessary to tackle the challenges associated with implementing such innovative tool.

As outlined in Section 3.1, It is necessary to define both temporal and spatial boundaries. Temporally, the analysis considerers one full year of dyeing operations (2024). Spatially, the entire dyeing department is included in the analysis for two primary reasons: first, this scope allows for a comprehensive evaluation across all 26 dyeing machines; second, detailed monitoring of water flows both at the departmental and individual machine levels facilitates precise analysis. Consequently, the virtual water source is defined as the set of wells supplying water to the plant, consistent with the spatial domain that encompasses the entire dyeing department.

4.3.1. Data curation

Before quantifying the indicators, preprocessing of the spreadsheet data obtained from the water monitoring system is required. Although the entire dataset encompasses approximately five years of records, only data from the last year is fully usable. Several factors contribute to this limitation: firstly, the measurement system on the machines was implemented gradually, achieving complete departmental coverage only in 2023. Additionally, accurate tracking of non-compliant cases is consistently established only in the final year of data collection. Consequently, reliable monitoring of water consumption becomes feasible starting from 2024. Therefore, the initial analytical step involves isolating data entries corresponding exclusively to the year 2024.

Despite this selection, some records still exhibit significant missing information due to monitoring system errors; such entries are subsequently removed. Moreover, the dataset initially includes data from an impregnating machine used for pre-treating certain products with specialized chemicals. As this equipment does not strictly belong to the dyeing department, the corresponding records are also excluded. After applying these filtering criteria, a total of 6,250 valid samples remains, corresponding to a cumulative water consumption of approximately $5.87 \cdot 10^4\ m^3$ (W_{tot}) drawn from the virtual water source.

4.3.2. Water losses identification

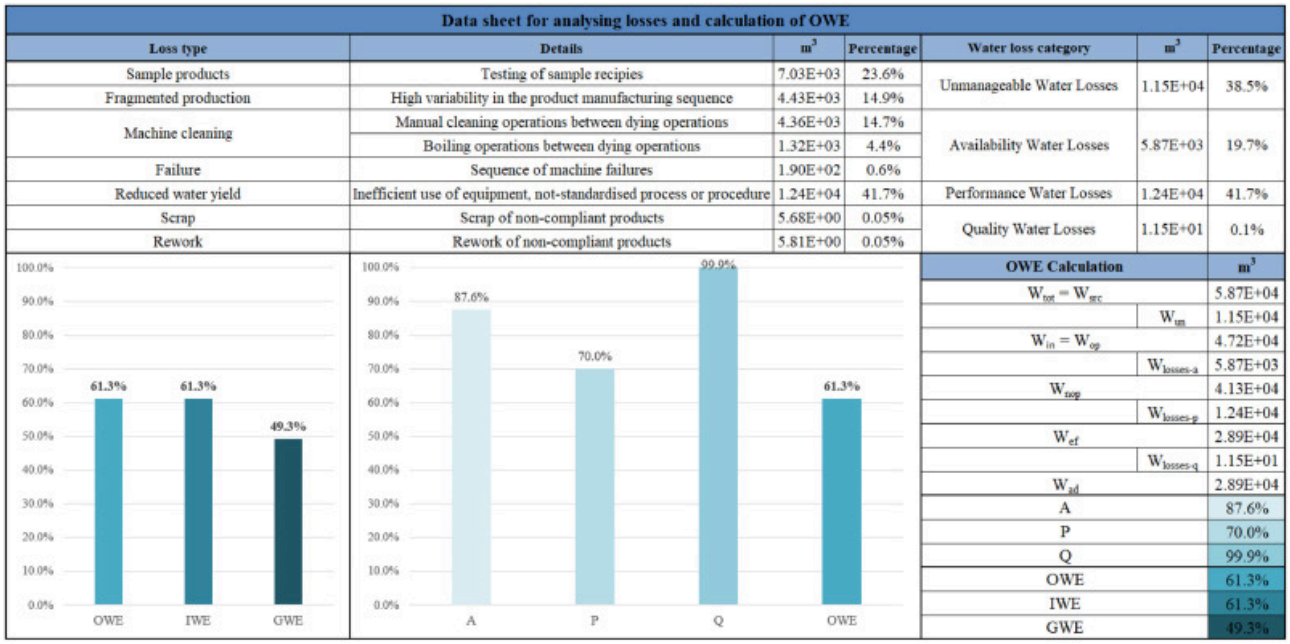
As detailed in Table 2 of Section 3.2, water losses must be categorized into manageable and unmanageable to enable effective analysis and targeted improvements. In the context of the dyeing process, unmanageable losses primarily arise from two main sources. Firstly, due to the necessity of testing newly developed dye recipes, water usage for samples is unavoidable and beyond the control of the dyeing department. Secondly, due to the high variability of products requested by the clients, it is not always possible to plan the production to maximise the water saving coming from reusing washing water for dying operations. Such missing water saving is the difference between water saving that could be achieved with an optimised sequence of products realisation, and the actual sequence which does not always allow to reuse washing water from previous product for the subsequent dying operation. As these types of loss falls outside the control of the dyeing department, the team classifies it as unmanageable (W_{um}). After excluding these unmanageable losses, the dataset is reduced to 4,984 valid records. At this stage, it becomes possible to determine the parameter W_{in}, representing the total volume of water entering the spatial domain from the water source.

The first sub-indicator to be evaluated is the A. The denominator is given by W_{op} which is the sum of W_{in} and W_{rec}. For the case at hand not water is recycled nor returned and hence W_{op} is equal to W_{in}. Regarding the numerator, $W_{losses\text{-}a}$ is determined by accounting for three specific contributors: the manual washing of the machines, the “boiling” process described in Section 4.3, analogous to a changeover in OEE calculation; and a sequence of failure events.

The second sub-indicator evaluated is P. Similar to the OEE, this metric cannot be computed directly but requires an indirect evaluation, calculated as the ratio between the water volume associated with effective products (W_{ef}) and the water volume that would have been associated with production if the entire W_{nop} had been fully converted into products. Determining W_{ef} involves identifying the theoretical water consumption for each specific product-dyeing combination. Any deviation between the theoretical and actual consumption represents inefficiencies analogous to reduced operational speed in OEE calculations. Practically, this theoretical benchmark is established by analysing water consumption distributions for each product-dyeing combination and selecting the lowest consumption value still resulting in compliant products. Subsequently, the difference between the actual and theoretical water consumption, multiplied by the mass of processed products, quantifies the water volume lost due to equipment inefficiencies ($W_{losses\text{-}p}$). According to insights from experienced operators and the head of the dyeing department, the observed discrepancy in water consumption efficiency arises primarily from two factors. First, a lack of standardized procedures during the pre-treatment phase often results in deviations from optimal dyeing conditions. This issue is further intensified by the inconsistent composition of the fabric, which is not always uniform due to the presence of regenerated components. Second, inefficiencies come from varying operator expertise, as newly hired personnel lack the deep understanding of product composition and dyeing effectiveness possessed by seasoned operators. Indeed, many operators within the dyeing department have over 20 years of experience, contributing to a level of skill and sensitivity challenging to replicate in less experienced staff.

The final sub-indicator calculated is Q, defined as the ratio between the water volume associated with compliant products (W_{ad}) and the total water volume used for all products (W_{ef}). Differences between these volumes result from products failing to meet the stringent quality standards required by high-fashion clients, which must consequently be discarded as scrap or reworked. All the calculations described above are summarized in Figure 6.

The calculated *OWE* is 61.3%. This result suggests that current dyeing operations present relevant room for improvements. In detail, A is approximately 87.6%, P reaches 70.0% while Q scores 99.9%. *IWE* is 61.3% and, to assess the exploitation of the virtual water source, *GWE* is calculated at 49.3%.



Data sheet for analysing losses and calculation of OWE						
Loss type	Details	m^3	Percentage	Water loss category	m^3	Percentage
Sample products	Testing of sample recipies	7.03E+03	23.6%	Unmanageable Water Losses	1.15E+04	38.5%
Fragmented production	High variability in the product manufacturing sequence	4.43E+03	14.9%			
Machine cleaning	Manual cleaning operations between dying operations	4.36E+03	14.7%	Availability Water Losses	5.87E+03	19.7%
	Boiling operations between dying operations	1.32E+03	4.4%			
Failure	Sequence of machine failures	1.90E+02	0.6%			
Reduced water yield	Inefficient use of equipment, not-standardised process or procedure	1.24E+04	41.7%	Performance Water Losses	1.24E+04	41.7%
Scrap	Scrap of non-compliant products	5.68E+00	0.05%	Quality Water Losses	1.15E+01	0.1%
Rework	Rework of non-compliant products	5.81E+00	0.05%			

OWE Calculation		m^3
$W_{tot} = W_{src}$		5.87E+04
	W_{un}	1.15E+04
$W_{in} = W_{op}$		4.72E+04
	$W_{losses-a}$	5.87E+03
W_{nop}		4.13E+04
	$W_{losses-p}$	1.24E+04
W_{ef}		2.89E+04
	$W_{losses-q}$	1.15E+01
W_{ad}		2.89E+04
A		87.6%
P		70.0%
Q		99.9%
OWE		61.3%
IWE		61.3%
GWE		49.3%

Figure 6. Datasheet for OWE calculation.

4.4. Sensitivity analysis

To evaluate the robustness of the proposed indicators, a sensitivity analysis was carried out using a Monte Carlo sampling method with 10,000 iterations. This number of iterations was selected because it represents the threshold at which the simulation results stabilize, ensuring the reliability and consistency of the analysis. This technique is widely adopted in the literature for assessing the robustness of results in industrial applications [29,47]. In each iteration, random perturbations were introduced to all values of water losses. The perturbation was defined as a variation of ±5% around the reported measurements, in line with the accuracy of industrial water meters. For every iteration, all indicators were recalculated, and the corresponding distributions were obtained. Table 4 reports the basic statistical information derived from the analysis results.

	Mean	Min	Max	Std	Median
A	0.874	0.859	0.886	0.005	0.874
P	0.699	0.661	0.734	0.014	0.700
Q	0.999	0.999	0.999	0.000	0.999
OWE	0.612	0.570	0.649	0.015	0.611
IWE	0.612	0.570	0.649	0.015	0.611
GWE	0.491	0.450	0.530	0.015	0.049

Table 4. Results of sensitivity analysis.

The simulation confirms the robustness of the proposed indicators. A remains high (around 0.87) with very low variability, showing that measurable water losses such as cleaning or washing are not significantly influenced by input fluctuations. Q is almost constant at 0.999, indicating that scrap- or rework-related water losses are negligible. P, by contrast, shows both a lower average value (around 0.70) and higher sensitivity to fluctuations, confirming it as the weak point of the system since unmeasurable losses amplify small variations in input data. Consequently, OWE and IWE, which both score around 0.61 with a standard deviation (Std) of ±0.015, are robust but largely driven by the behaviour of P. GWE, with an average of 0.49 and similar standard deviation, highlights the stronger dependence on external water sources. Overall, the analysis demonstrates that measurement uncertainty does not alter the main conclusions of the study, but it underlines that P is both the most critical and the most sensitive dimension, and therefore the most important target for improvement actions.

5. Results and Discussion

From the evaluation of the indicators, the company gains valuable insights into the current management of its dyeing operations. The indicators reveal that approximately more than one third of the total water volume is not efficiently utilized; specifically, *OWE* and *IWE* score 61.3%, and *GWE* reaches 49.3%. Thanks to the structured nature of these indicators, the analysis provides deeper insight into the underlying causes of performance inefficiencies. In the current scenario, where no water is recycled, *OWE* and *IWE* achieve identical results. This outcome highlights that, irrespective of the magnitude of water losses, the absence of steam-related losses presents an opportunity for improvement through the implementation of a recycling system. Such a system could substantially enhance both internal and external consumption performance, while also reducing reliance on external water supply. A similar argument applies to the introduction of a water return system, which would further contribute to improved sustainability by reintegrating treated water into the virtual source.

The A indicator registers 87.6%, indicating good value of water availability. Machine cleaning (both manual and boiling) accounts for over 19% of total water losses, highlighting the need for improved operational management. An effective strategy is to develop standardized procedures aimed at reducing the water consumption associated with cleaning operations, following a logic similar to set-up time reduction in the OEE framework. In this context, adopting a structured approach inspired by the SMED methodology could be particularly useful for identifying phases within the cleaning process where water use can be minimized without compromising operational effectiveness. Additionally, failures in dyeing machines represent a minor source of inefficiency, accounting for

0.6% of water losses. Nevertheless, the company should adopt a proactive maintenance strategy, leveraging predictive signals from equipment to anticipate and prevent breakdowns.

The *P* sub-indicator scores 70.0%, indicating major room for improvement in water consumption yield. The primary cause for this inefficiency is attributed to inadequate expertise among newer operators and lacking clear standardisation of processes and procedures. In detail, the washing phase following the dyeing operation is often carried out without a standardized procedure, leading to a significant increase in water consumption. To address this, the company should conduct extensive training programs facilitated by experienced operators, many of whom are nearing retirement, to ensure knowledge transfer. Given the ongoing staff transition within the company due to retirements, this initiative is particularly critical. Additionally, improved organizational management of the dyeing process is necessary. Processes for all product types should be thoroughly documented and standardized, providing clear procedural guidelines to assist newly hired operators and standardize operational practices. Lastly, the *Q* sub-indicator achieves the highest score at 99.9%, indicating that the majority of products meet high-quality standards.

Overall, the application of the set of indicators provides critical insights into the dyeing process, demonstrating its effectiveness in assessing water performance from an efficiency perspective. Unlike traditional methods that focus solely on absolute water consumption, the set introduces a comparison against an ideal performance benchmark, allowing the company to evaluate its current state and set future improvement targets. Based on the initial results, the company has established a short-term goal of improving water efficiency by 5% over the next three months, with targets to be revised according to progress.

A key strength lies in its structural alignment with the OEE. This enables a multi-dimensional analysis across three performance dimensions: availability of water for dyeing operations, performance relative to an ideal yet practical standard, and quality rate of finished products. The company underscores the importance of identifying losses behind suboptimal water efficiency performance. In particular, it has quantified the volume of water lost due to fragmented production and during set-up operations between production batches with differing dyeing requirements. This issue is especially critical as high-profile clients are increasingly imposing stringent water efficiency targets, often without accounting for the specific production profiles of their suppliers. Through the application of OWE, the company can demonstrate that client expectations should be contextualized considering the production mix of the supplier. Manufacturers with limited product variety undergo fewer set-up operations and therefore tend to achieve better absolute water efficiency (as in case of OEE). Conversely, suppliers managing a high-rotation production mix experience more frequent set-ups, which can distort water performance metrics. OWE offers a robust tool that both fashion clients

and suppliers can leverage: clients can evaluate water consumption performance more fairly by isolating structural inefficiencies due to production variability, while suppliers, for the first time, gain a quantitative tool to highlight how their production complexity impacts water efficiency in ways that are often overlooked. Moreover, the breakdown highlights several areas for targeted improvement, including: (i) improved machine cleaning processes to save more water and reduce consumption of manual cleaning and boiling operations, (ii) implementation of an effective maintenance strategy to address equipment failures, (iii) training programs for new operators that leverage the experience of seasoned staff, (iv) standardization of dyeing processes across similar product types.

Compared to existing tools and methodologies in the literature, OWE offers several innovative advantages. First, it transcends traditional consumption metrics by introducing a performance-based benchmark, allowing for more strategic and goal-oriented resource management. Once a baseline is established, companies can define progressive targets aimed at reducing water consumption and enhancing environmental sustainability. Second, the sub-indicator structure facilitates root-cause analysis, making the source of inefficiencies more transparent. Finally, OWE provides companies with a robust, quantitative tool to support decision-making and demonstrate the effectiveness of environmental improvement initiatives. This is especially valuable for organizations with limited resources seeking to prioritize and justify sustainability efforts. Notably, the structure of OWE is sufficiently versatile to be applied in other sectors where water is a critical resource. Agriculture, for example, is among the most water-sensitive industries and has long developed water-saving practices such as irrigation recycling, precision irrigation, and sensor-based monitoring. In this context, OWE could serve as a complementary performance benchmark, building on the wealth of experience already available in the sector. While sector-specific definitions of losses would be required, the underlying identification strategy remains consistent. The sub-indicators A, P, and Q would retain their diagnostic function, enabling the assessment of how effectively available water is used for production, the extent to which hidden losses undermine performance, and the share of water ultimately converted into valuable products.

Despite its strengths, the OWE approach presents limitations that must be acknowledged. First and foremost, as for other structured indicators, successful implementation requires a substantial investment in machine sensorization. Without a robust and granular data collection infrastructure, the reliability of the indicator is significantly compromised, as it is essential not only to quantify total water consumption but also to determine its specific points of use. This capability is critical for identifying improvement opportunities and designing effective interventions. Second, the implementation process relies heavily on the formation of a multidisciplinary analysis team. This team must possess both a deep understanding of the production process and the analytical skills

needed to manage large datasets which is a combination of expertise that can be difficult to find in practice.

Another important consideration is the need for multidimensional assessment when comparing processes that differ from a broader environmental perspective. For example, in surface finishing, traditional galvanic processes consume and waste significant amounts of water, whereas Physical Vapor Deposition is far less water-intensive but considerably more energy-demanding, in addition to relying on different base materials [48]. OWE should be regarded as an effective KPI for assessing water efficiency, particularly in contexts where water consumption and use represent the primary concern. For broader assessments, it should be used alongside other KPIs that capture additional environmental impacts.

To further support the robustness of the OWE framework, a sensitivity analysis was conducted on the indicator values to evaluate the impact of input data fluctuations on the results. The analysis confirmed the relative robustness of OWE, thereby reinforcing the consistency and reliability of the tool as a support for decision-making in water management projects.

6. Conclusions

In this paper, a novel set of Lean indicators to digitally assess operational water efficiency is presented. These indicators are designed to quantitatively evaluate the performance of a machine, production line, department, or whole plant by comparing the ideal amount of water required to produce value-added output with the actual water input. To consider different level of investigation three global indicators are presented to assess usage, internal and external efficiency. In line with the objectives of digitalisation era, the indicators are fully compatible with sensor-equipped systems and real-time data acquisition, enabling their integration into digital platforms for sustainability monitoring and decision support.

Structured following the OEE logic, OWE is decomposed into three sub-indicators that assess: (i) the actual availability of water for manufacturing operations; (ii) the yield of water consumption compared to an optimal benchmark; and (iii) the quality rate of the final products.

To test the effectiveness of the set, the indicators are implemented in a real industrial setting within the dyeing department of a textile production company. The results confirm the capability of the tool to quantitatively assess operational water performance, yielding an *OWE* of 61.3%, an *IWE* of 61.3%, and a *GWE* of 49.3%. Among the sub-indicators, *P* emerges as the weakest (70.0%), highlighting inefficiencies in current operational practices. Conversely, *Q* scores above 99.9%, reflecting the strong ability of the dying department to meet stringent quality standards. Component *A* achieves a good value of 87.6%.

Thanks to its layered structure, this set of indicator provides not only a baseline for future performance comparisons but also a clear approach for defining strategic improvement actions. These include: (i) improved machine cleaning processes to increase water saving and reduce the water consumption in machine cleaning operations; (ii) a preventive maintenance strategy to reduce equipment failures; (iii) structured training programs for newly hired staff that leverage the knowledge of experienced operators; (iv) standardization of dyeing procedures across product types.

From a theoretical perspective, OWE advances beyond traditional consumption metrics by introducing a performance-based benchmark that enables both monitoring and strategic target-setting. Its sub-indicator structure supports root-cause analysis, offering greater transparency in identifying inefficiencies. From an industrial perspective, OWE provides a practical, quantitative and novel tool that strengthens decision-making and helps organizations, especially those with limited resources, prioritize and justify water sustainability initiatives. Moreover, it enables the quantification of aspects that traditionally fall outside the scope of water analysis, such as changeover operations, thereby broadening the range of factors and production activities considered in water management.

As for future research, the set of indicators would benefit from the integration of a structured decision-making approach to prioritize improvement actions, especially in contexts where not all potential interventions are economically feasible. Additionally, the set could be expanded to incorporate other critical aspects of water management, such as wastewater quality, in order to more accurately evaluate the treatment and classification of W_{rec} and W_{ret}. Finally, the innovative loss decomposition proposed here holds promise for broader applications, including the assessment of raw material usage, reuse, and recycling across machines, lines, or entire plants, further supporting sustainability goals in the context of Industry 4.0.

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Overall water effectiveness: a new lean indicator for digital evaluation of water efficiency in industrial processes

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