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Criticality Analysis Based on Reliability and Failure Propagation Effect for a Complex Wastewater Treatment Plant

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Abstract: Wastewater treatment is a critical and necessary task every human settlement is obligated to address. If not, the consequences might be catastrophic, not just for humans but for the ecosystems as well, pushing research into finding new ways to improve wastewater treatment processes to make them safer and more efficient. Hence, there is a need to address matters, such as reliability and maintainability of Wastewater Treatment Plants (WWTP), when analyzing the availability and operational conditions. These should be addressed by analyzing the plant operational effectiveness impact (P-OEI), and in this article specifically, a WWTP study case to identify design flaws or improvement opportunities. A vital aspect of a complex system is to determine the contribution to resilience, reliability, and availability of every element embedded in the system. This is performed by adapting and applying the P-OEI methodology and real data of a WWTP located in Chile. This methodology breaks down the system into several levels of disaggregation similar to RBD methodology, analyzing the upstream for availability and the downstream for the P-OEI analysis from the system itself to the individual elements within subsystems. The potential impact on the overall system's lack of efficiency is also quantified by an Expected Operational Impact (EOI) index, which is also calculated by the methodology. The P-OEI and EOI analyses performed in this study are powerful tools to assess the design and performance of complex systems and WWTP in particular.

Keywords: system resilience; maintenance optimization; operational effectiveness; reliability

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1. Introduction

Water relevance for all aspects of life resides in the several roles it plays on planet Earth from temperature regulation carried by glaciers and the ocean to nutrient transportation within all life forms, no matter how big or small. As human-kind thrives in this and the nearby worlds, they pollute at a dramatical rate, affecting Earth's ecosystems and even human life; in fact, *"two million tons of sewage, industrial and agricultural waste is discharged into the world's waterways and at least 1.8 million children under five years-old die every year from water related disease, or one every 20 s"* [1]. This pushes research into finding new and better ways to improve water quality for human consumption whilst minimizing the impact of wastewater produced by human activity. Furthermore, in 2010 a press release by the UN claimed that "improved sanitation and wastewater management are central to poverty reduction and improved human health" [1]. Hence, wastewater treatment processes must aim to transform hazardous wastes into a clean and safe resource for humanity and the environment.

Processing wastewater is one of the main tasks every human settlement is forced to address because of the potential hazard risk present in all large-scale biological decomposition processes (or large-scale waste management processes). In fact, on the same press release mentioned before by the UN [1], they coined the term "sick water" to establish a more accurate and real definition for wastewater. Therefore, failure consequences in this context may not only impact the production or monetary costs rising but also they may have a direct impact on the environment and human health. Because of this, wastewater treatment processes must be as reliable, effective, and safe as possible.

This paper addresses the potential consequences of equipment ineffectiveness and design flaws on the performance of a wastewater treatment process by further analyzing the effect of failure propagation on RAM indicators of a complex system.

An important tool to assess the resilience and performance of the system is to focus on production effectiveness [2]. Nevertheless, system effectiveness is mostly measured using indicators of reliability and availability under the perspective of a life cycle economic analysis [3,4].

When addressing the main sources of reduction for economic benefit, research shows that most of these sources relate directly to reliability, availability, and maintainability (RAM) indicators [5–7].

Performance is the process in which an action under a certain context is quantified to assess such action [8] in order to make decisions and define strategies by using performance indicators [9,10]. In the current literature, there are no methodologies or tools to evaluate the performance of the system related to the performance of a single piece of equipment. This gap increases when, for the sake of analysis, the process within the system is disaggregated in many sub-processes, which at the same time are disaggregated into several pieces of equipment. Therefore, to effectively assess the system and the above-mentioned hidden relationships within the system, it is necessary to perform a quantitative reliability impact analysis using classical RAM analysis complemented with indicators, such as the Birnaum importance measure (IM) [11], identifying and characterizing the system's behavior, and improvement opportunities.

Furthermore, efficiency and effectiveness are addressed in this study, considering that efficiency is the measure in which the economic resources are being used to achieve targets, and effectiveness is the measure in which the objectives or operational requirements are achieved [12].

This article comprehensibly analyses a Wastewater Treatment Plant production effectiveness by further developing a methodology proposed by Kristjanpoller et al. (2016) [13,14] called operational effectiveness impact (OEI) analysis, in which they analyze the operational effectiveness of a biomethanation plant by disaggregating the system into several levels of detail-identifying subprocesses and the individual pieces of equipment embedded on said subprocesses, similar to an RBD [15].

Problem Statement

For most industrial operations, there is no standard framework to accurately establish and assess the consequences of odd behavior, failure, or unscheduled stoppages, and therefore, decisions related to asset replacements or maintenance are made based on experience and inaccurate frameworks that usually focus on the overall process as a whole and not as part of the business process, although failure propagation has been studied in order to assess reliability [16,17], the criticality of the elements embedded in the system has not been studied. These issues push the necessity to define key performance indicators (KPI) for production systems [18] accountable for dependency and hierarchy, measuring the effectiveness of the KPI impact on every singular element of an industrial process. For this reason, one of the most important tools, in order to achieve the objectives of the KPI and address high impact consequences, is to acknowledge the real and effective impact of failure and stoppages underlaying in the equipment.

In this regard, the OEI analysis helps identify opportunities for improvement in asset management. One of the most important aspects when measuring industrial performance is the operational effect linked to each element of the system, which is measured as a loss of production capacity or quality. When focusing on the impact of a single element, it must not be observed as a static parameter but as a dynamic and ever-changing parameter because of its dependency with other elements on the system, as well as its dependency on its own individual reliable and sustainable performance.

Hence, for OEI analysis to accurately identify the above-mentioned improvement opportunities and resiliency factors, the following questions must be addressed. Which and where are the bottlenecks of the system? What causes and situations explain production loss? What is the availability of the system? Where are the most impactful opportunities for improvement?

The objectives of this article can be summarized as follows. First and foremost, to propose a novel methodology to develop a framework that accurately analyzes the reliability and sustainability of a plant regarding its operational effectiveness and accurately identify and quantify the importance of the main assets relative to the whole system while improving the decision-making related to asset management. Secondly, to apply the proposed methodology in a wastewater treatment plant located in Chile using real data.

2. Methodology

The methodology [13,14] proposal performs an analysis based on an RBD [19,20] configuration and desegregates the overall process into levels in which the highest level represents the system itself, and the lower levels represent singular indivisible units. More specifically, the availability analysis is performed from the lower levels to the highest, running from the singular elements to the system itself. On the contrary, impact analysis is carried out from the highest level (system) to the lower levels (indivisible units). Moreover, during implementation and analysis, the methodology should also account for the joint processes necessary for the identification of improvement opportunities regarding maintenance activities and suggest recommendations for maintenance and sustainability. Summarizing, these activities and considerations can be abridged into four milestones of the analysis:

1. Data Management: correct or remove inaccurate and missing data. Collect, store, and organize useful data.
2. RAM Analysis: upstream analysis of availability and reliability.
3. P-OEI Analysis: downstream analysis of operational effectiveness accountable for propagation effects.
4. Decision Making: result and analysis evaluation to make decisions regarding maintenance and operations.

Adapting the proposed methodology to the specific case of a WWTP, an upstream analysis is performed to calculate RAM indicators starting from the lowest level units building up to the entire system using logical dependencies of the RBD [19,20]. A second stage analysis is carried out from the highest level (system) and goes downstream to the lowest level units quantifying the impact on operational effectiveness through production capacity loss or level of contaminant removal in the case of a wastewater treatment plant [21]. In this manner, by assessing all possible scenarios and the likelihood of each scenario for complex configurations, it is possible to calculate the P-OEI and the contribution produced by each element to the lack of effectiveness of the system based on production loss due to unavailability and the expected operational impact (EOI). The latter explains how failure or unscheduled stoppages may impact the effectiveness of the system.

Stage 1: Upstream RAM analysis starting from indivisible elements or singular machines (lowest level) escalating to the overall system by using RBD methodology to carefully account for the functional dependencies and adequate mathematical relations to compute reliability and availability. The latter of which is an expression of the probability that in a given window of time, the equipment will be available as required [22]. Considering the latter and under the assumption that required equipment must always be operational and that the work orders are immediately executed after failure, the expected availability of any equipment is [13,14]:

$$A_i = \frac{MTTF}{MTTF + MTTR} \quad (1)$$

where

A_i: expected availability of the equipment.

$MTTF$: mean time to failure of the equipment.
$MTTR$: mean time to repair of the equipment.

When calculating availability for any series configuration subsystem, the functional dependency of the elements of must be accounted for. Therefore the availability of the subsystem is as follows:

$$A_{series} = \prod_{i=1}^{n} A_i \tag{2}$$

Regarding subsystems in full redundancy configuration (parallel), which is characterized by the simultaneous operation of each element and the capability of each element to withstand 100% of the workload, the following expression is considered for a redundant non-reparable system:

$$MTTF_{parallel} = \frac{1}{\lambda_1} + \frac{1}{\lambda_2} - \frac{1}{\lambda_1 + \lambda_2} \tag{3}$$

where

λ_i: average failure rate of each piece of equipment that participates in the system.

Using the Weibull distribution, the latter is represented by:

$$\lambda_i = \frac{1}{\alpha \times \Gamma \times \left(1 + \frac{1}{\beta}\right)} \tag{4}$$

$$MTTR_{parallel} = \frac{\sum_{i=1}^{n} MTTR_i}{n} \tag{5}$$

and finally,

$$A_{parallel} = \frac{MTTF_{parallel}}{MTTF_{parallel} + MTTR_{parallel}} \tag{6}$$

Cold standby is considered regarding the subsystems in the standby configuration, which means that at any time, only one piece of equipment operates until failure, at which point the following standby piece of equipment starts operation. It is also considered that maintenance is performed at the same time for every piece of equipment under this configuration. In this sense, the following analysis is used:

$$MTTF_{sandby} = \frac{1}{\lambda_1} + \frac{1}{\lambda_2} \tag{7}$$

$$MTTR_{standby} = \min\{MTTR_i\} \tag{8}$$

and finally,

$$A_{standby} = \frac{MTTF_{standby}}{MTBF_{standby} + MTTR_{standby}} \tag{9}$$

For partial redundancy, which is characterized by the ability of the subsystem to meet 100% of the workload using only a fraction of the items embedded in the subsystem, the expression used is an extension of the reliability model:

$$A_{partial} = \sum_{j=r}^{n} \binom{n}{j} A^j (1 - A)^{n-j} \tag{10}$$

where

n: total number of elements.
r: minimum number of elements to meet the required load.

Regarding the load-sharing configuration [23], which is characterized by the ability of the subsystem to meet more than 100% of the workload because of the capability of the joint items of the subsystem that sums up more than the required capacity. To evaluate the loss, a ratio of capacities is used to determine the equivalent subsystem availability:

$$A_{load\ sharing} = \sum_{i=1}^{n} \left(A_i \times \frac{Q_i}{Q_T} \right) \tag{11}$$

where

Q_i: capacity of element i.
Q_T: total capacity of the subsystem.

Stage 2: Downstream impact determination starts the analysis from the highest level (system) to the lower levels, where single units can be found.

During this phase, the P-OEI of each identified element and level of the system is determined by breaking down the global index (i.e., $POEI_{system}$), assigning relative weight to each element according to its availability calculated in phase 1 as follows:

$$POEI_{system} = 1 \tag{12}$$

where

$POEI_{system}$: global plant operational effectiveness impact index.

Weight assigning for each level is performed by applying the following mathematical expression:

$$\sum_{j=1}^{n} POEI_{i,j} = POEI_{i-1},\ \ \forall\, i \in \{1, \ldots, r\}\ \wedge\ \forall\, j \in \{1, \ldots, n\} \tag{13}$$

$$\frac{POEI_{i,j}}{POEI_{i,j+1}} = \frac{1 - A_{i,j}}{1 - A_{i,j+1}},\ \ \forall\, i \in \{1, \ldots, r\}\ \wedge\ \forall\, j \in \{1, \ldots, n\} \tag{14}$$

where

$POEI_{i,j}$: P-OEI of element j (from 1 to n) within level i (from 1 to r) of the decomposition.

In this regard, it is possible to observe that P-OEI simply assigns a relative weight to the contribution coming from each level and unit to the ineffectiveness of the system by quantifying the potential production loss. Accordingly, the sum of all the relative weights starting from level 1 (which is different from the system level) to the lowest level (r) is equal to 100% (i.e., the P-OEI of the system).

$$\sum_{i=1}^{r} \sum_{j=1}^{n} POEI_{i,j} = 1 = POEI_{system} \tag{15}$$

Finally, once the $POEI_{i,j}$ is known for each and every element of the system, the potential contribution to the production loss can be broken down into two main aspects, these are frequency (i.e., unavailability index of the element) and consequence (through the impact of said unavailability). This article refers to the latter as the expected operational impact ($EOI_{i,j}$), which is the quantification of the effect of an unscheduled stoppage of element j from level i on the system. Furthermore, because of the dependence between elements, $EOI_{i,j}$ may show different results for each element on the same level depending on the state of the elements that form a level.

$$EOI_{i,j} = \frac{POEI_{i,j} \times \left(1 - A_{system}\right)}{1 - A_{i,j}} \tag{16}$$

where

$EOI_{i,j}$: the EOI of element j (from 1 to n) within decomposition level i (from 1 to r).
$POEI_{i,j}$: the P-OEI of element j (from 1 to n) within decomposition level i (from 1 to r).

$A_{i,j}$: the expected availability of element j (from 1 to n) within decomposition level i (from 1 to r).

3. Case Study Application

3.1. Industrial Context

Because of the potentially catastrophic consequences for the environment and life itself involved in the wastewater treatment process, every human settlement is forced to address the problem of returning sick water into the environment in a manner that is both responsible and as efficient as possible. In this regard, several studies have been conducted aiming to optimize wastewater treatment processes or even critical subprocesses, such as the anaerobic digestion [24], addressing the mentioned criticality.

It is known that failure is a dormant threat constantly waiting to arise randomly; this is also true for wastewater treatment and is even more critical because of the mentioned catastrophic consequences. Furthermore, raw materials for this process differ from any other industrial process in the fact this raw material is human residue, and because of this, it is extremely hard to predict what kind of material will arrive at the plant. In this regard, every system and subsystem embedded in the wastewater treatment process is exposed to different and unpredictable types of materials, which can damage and produce failures along the process, producing a negative effect on reliability and availability levels.

A generic layout for a Wastewater Treatment Facility (WWTF) is usually divided into two stages: a primary stage, which is mainly focused on disposing of large and medium-size elements extracted by physical means, and a secondary stage, where wastewater and biosolids undergo chemical and physical processes in order to return "safe" water and solids to the environment [25].

3.2. WWTP Application and Modelling

There are many different possible settings within the above-mentioned stages. Hence, for the purpose of analysis, this article will consider the following settings for these stages:

1. Primary stage: It starts with collecting wastewater from the city through the sewage system, which flows into the facility after being screened by two self-cleaning screens in load-sharing configuration with a 65% overcapacity each (meaning that each screen can withstand up to 65% of the workload), then grit removal is performed by a single cyclone separator to dispose of medium-size elements to finally arrive at the primary clarification process, which is performed by four primary clarifiers in a load-sharing configuration with 30% overcapacity where suspended solids are collected through settling, this last collected material is known as "primary sludge" or waste activated sludge (WAS).
2. Secondary stage: After primary clarification, the process is divided into two: on the one hand, wastewater collected from the primary clarifier flows into a secondary biological treatment, which takes place in a set of two anaerobic and four aerated basins where the anaerobic basins are configured with baffles in an "N" pattern for phosphorus removal and set in a load-sharing configuration with 60% overcapacity, the aerated basins are also set in a load-sharing configuration, but with a 35% overcapacity each. Effluent from the basins goes into a secondary clarification process performed by four clarifiers in a load-sharing configuration with 30% overcapacity each. From here, most of the return activated sludge (RAS) is sent back into the anaerobic zone, and a portion is sent back to the primary clarifier. Effluent from the secondary clarification process is then disinfected by a single disinfection unit with chlorine (and then dechlorinated in the same unit) before being discharged into the environment. On the other hand, waste activated sludge from the primary clarifier combined with the RAS sent back from the secondary clarifier flows to three primary anaerobic digesters in a 3/2 partial redundancy (meaning that only two clarifiers are needed to withstand the complete workload) before going into three secondary anaerobic digesters also in a 3/2 partial redundancy to finally arrive at two belt

thickeners (one at 2 m and the other at 3 m) in a series configuration to reduce the water content, which is sent to the primary clarifier. Thickened and digested sludge is stored in one storage tank before going into landfills.

The graphical layout of the above description is provided in Figure 1, and details of the equipment functions can be found in Table 1.

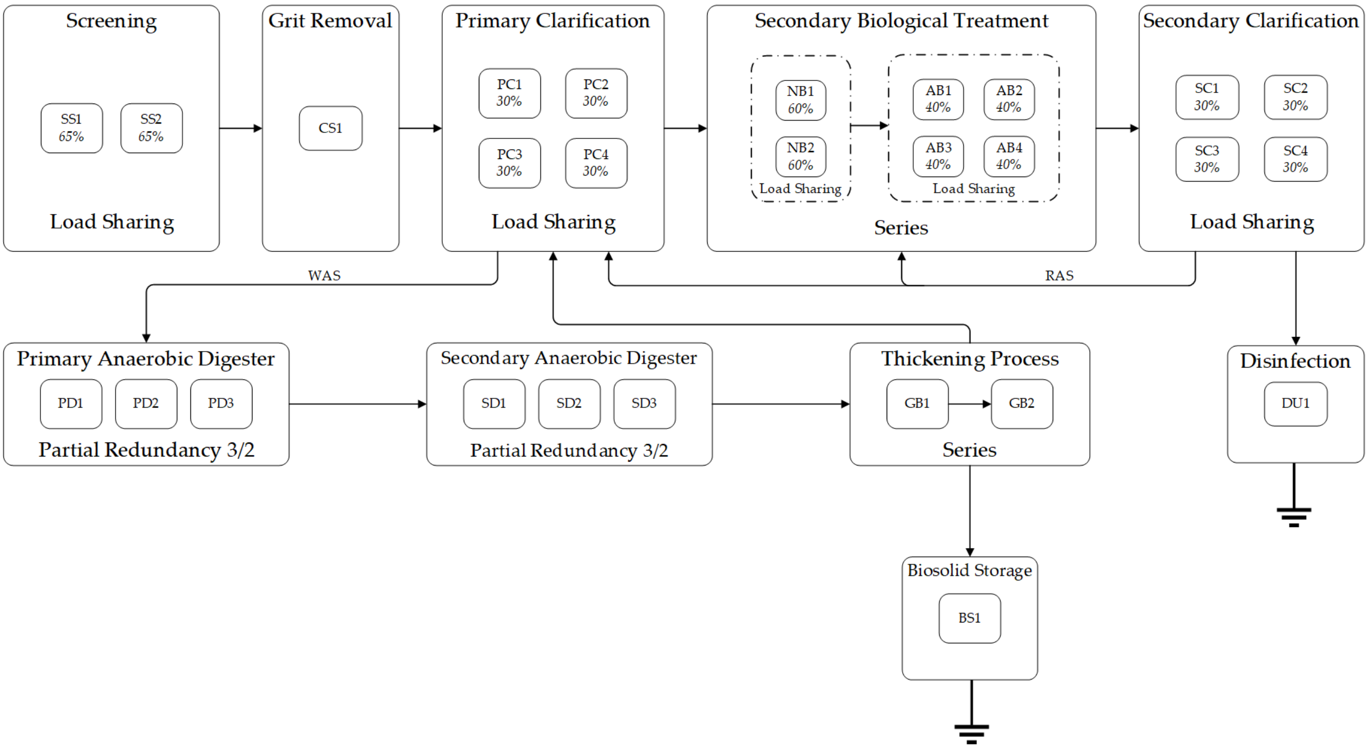

Figure 1. Operational Layout and Configuration of the WWTP.

Table 1. Equipment Description.

Equipment	Code Name	Description
Self-cleaning Screen	SS1 and SS2	Large solids removal.
Cyclone Separator	CS1	Medium inorganic solids. Removal such as grit, sand, and gravel, among others.
Primary Clarifier	PC1, PC2, PC3, and PC4	Removal of settable organic solids.
Anaerobic Basin	NB1 and NB2	Phosphorus removal.
Aerobic Basin	AB1, AB2, AB3, and AB4	Aerobic biodegradation of organic contaminants. Oxygen allows bacteria to perform biodegradation processes.
Secondary Clarifier	SC1, SC2, SC3, and SC4	Removal of settable organic solids. RAS is conveyed to the secondary biological treatment.
Disinfection Mixing Unit	DU1	Disinfects effluent from the secondary clarifiers using chlorine before dechlorinating and releasing to the environment.
Primary Digester	PD1, PD2, and PD3	Bacteria degrade organic waste into water and gases.
Secondary Digester	SD1, SD2, and SD3	Undigested organic waste from the primary digester is degraded.
Gravity Belt	GB1 and GB2	Partial water removal from digested waste.

Following the proposed methodology and the exposed logical configuration of the system, an availability analysis is performed for each level using the MTBF and MTTR individual data for each level and element of the system. Level disaggregation of the plant identifies four levels, from the singular elements in the lower levels to the level of the system as follows:

- Level 4: This includes all the equipment of the system, this is, the Self-cleaning Screens (SS1 and SS2), Cyclone Separator (CS1), Primary Clarifiers (PC1, PC2, PC3, and PC4), Anaerobic Basins (NB1 and NB2), Aerated Basins (AB1, AB2, AB3, and AB4), Secondary Clarifiers (SC1, SC2, SC3, and SC4), Disinfection Mixing Unit (DU1), Primary Digesters (PD1, PD2, and PD3), Secondary Digesters (SD1, SD2, and SD3), and Gravity Belts (GB1 and GB2).
- Level 3: This level includes the subsystems clustered into the secondary biological treatment, this is, Biological Nutrient Removal (BR) and Aeration (AX).
- Level 2: This level includes all subprocesses from the main process, this is, the Screening Process (SP), Grit Removal (GR), Primary Clarification (PC), Secondary Biological Treatment (ST), Secondary Clarification (SC), Disinfection (DX), Primary Anaerobic Digestion (PD), Secondary Anaerobic Digestion (SD), and Thickening Process (TP).
- Level 1: This level considers the system as a whole.

Figure 2 explains the hierarchical levels of the plant. Note that level 3 only exists because of the existence of two subprocesses, Biological Nutrient Removal (BR) and Aeration (AX), within the Secondary Biological Treatment (ST). In contrast, the rest of the processes only consist of the process itself.

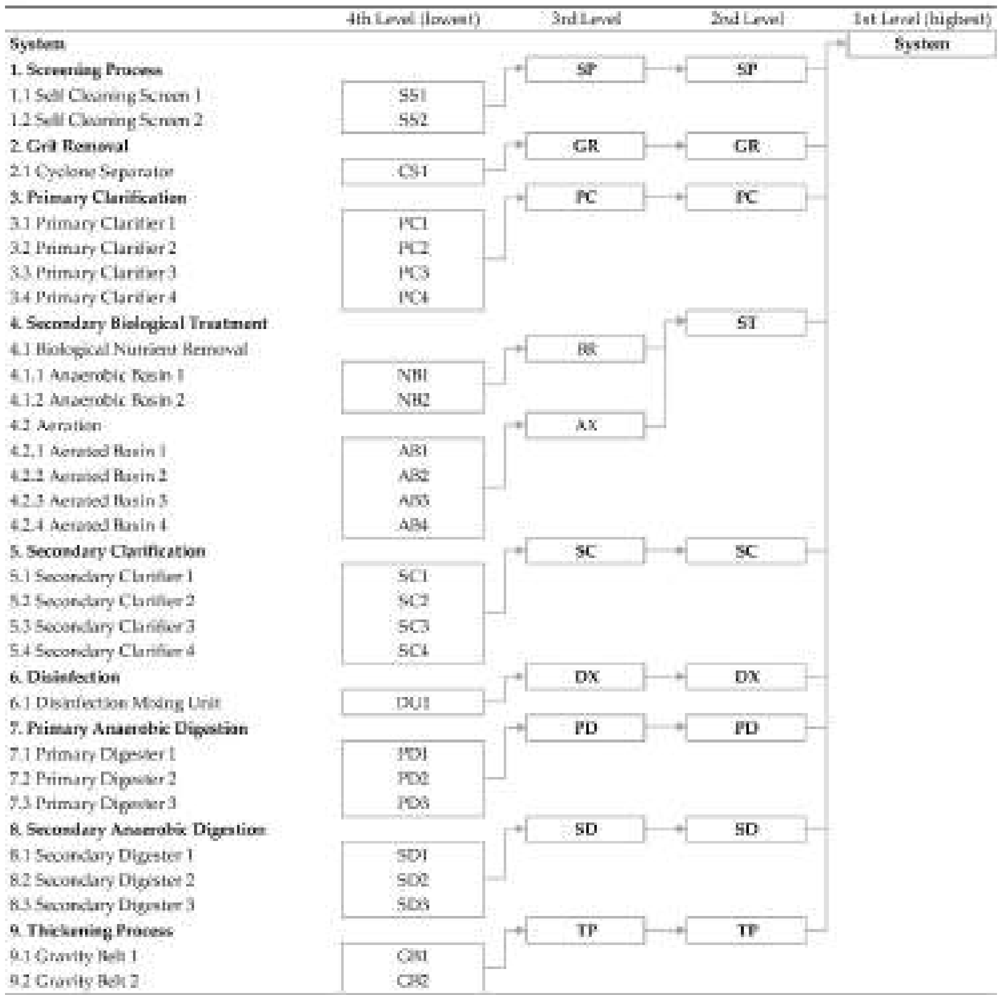

Figure 2. Hierarchical breakdown of the WWTP.

Figure 3 shows the expected availability of the system, subsystems, and individual elements.

	Code Name	4th Level Avail.	3rd Level Avail.	2nd Level Avail.	1st Level Avail.
System					87.68%
1. Screening Process	**SP**		98.75%	98.75%	
1.1 Self Cleaning Screen 1	SS1	98.02%			
1.2 Self Cleaning Screen 2	SS2	98.43%			
2. Grit Removal	**GR**		97.04%	97.04%	
2.1 Cyclone Separator	CS1	97.04%			
3. Primary Clarification	**PC**		99.10%	99.10%	
3.1 Primary Clarifier 1	PC1	96.58%			
3.2 Primary Clarifier 2	PC2	98.64%			
3.3 Primary Clarifier 3	PC3	97.56%			
3.4 Primary Clarifier 4	PC4	98.72%			
4. Secondary Biological Treatment	**ST**			99.11%	
4.1 Biological Nutrient Removal	BR		99.30%		
4.1.1 Anaerobic Basin 1	NB1	98.85%			
4.1.2 Anaerobic Basin 2	NB2	97.62%			
4.2 Aeration	AX		99.81%		
4.2.1 Aerated Basin 1	AB1	96.55%			
4.2.2 Aerated Basin 2	AB2	96.34%			
4.2.3 Aerated Basin 3	AB3	96.82%			
4.2.4 Aerated Basin 4	AB4	97.03%			
5. Secondary Clarification	**SC**		99.03%	99.03%	
5.1 Secondary Clarifier 1	SC1	97.52%			
5.2 Secondary Clarifier 2	SC2	97.83%			
5.3 Secondary Clarifier 3	SC3	97.41%			
5.4 Secondary Clarifier 4	SC4	98.15%			
6. Disinfection	**DX**		97.28%	97.28%	
6.1 Disinfection Mixing Unit	DU1	97.28%			
7. Primary Anaerobic Digestion	**PD**		99.63%	99.63%	
7.1 Primary Digester 1	PD1	96.82%			
7.2 Primary Digester 2	PD2	97.14%			
7.3 Primary Digester 3	PD3	95.26%			
8. Secondary Anaerobic Digestion	**SD**		99.62%	99.62%	
8.1 Secondary Digester 1	SD1	97.18%			
8.2 Secondary Digester 2	SD2	95.31%			
8.3 Secondary Digester 3	SD3	96.64%			
9. Thickening Process	**TP**		97.43%	97.43%	
9.1 Gravity Belt 1	GB1	98.79%			
9.2 Gravity Belt 2	GB2	98.62%			

Figure 3. Upstream Analysis: Availability.

Finally, using the availability indexes, the operational effectiveness impact (OEI) for each element is calculated, which is the loss percentage of either availability, production, or operational capability in the top-level. As it was described in the Section 2, the P-OEI and EOI of the system (top-level) will always be 100%. In other words, P-OEI is the quantified involvement of each element to the ineffectiveness of the system quantified as the potential capacity loss due to unavailability. On the other hand, the expected operational impact (EOI) is the expected responsibility or consequence if the said element should fail. The results are presented in Figure 4.

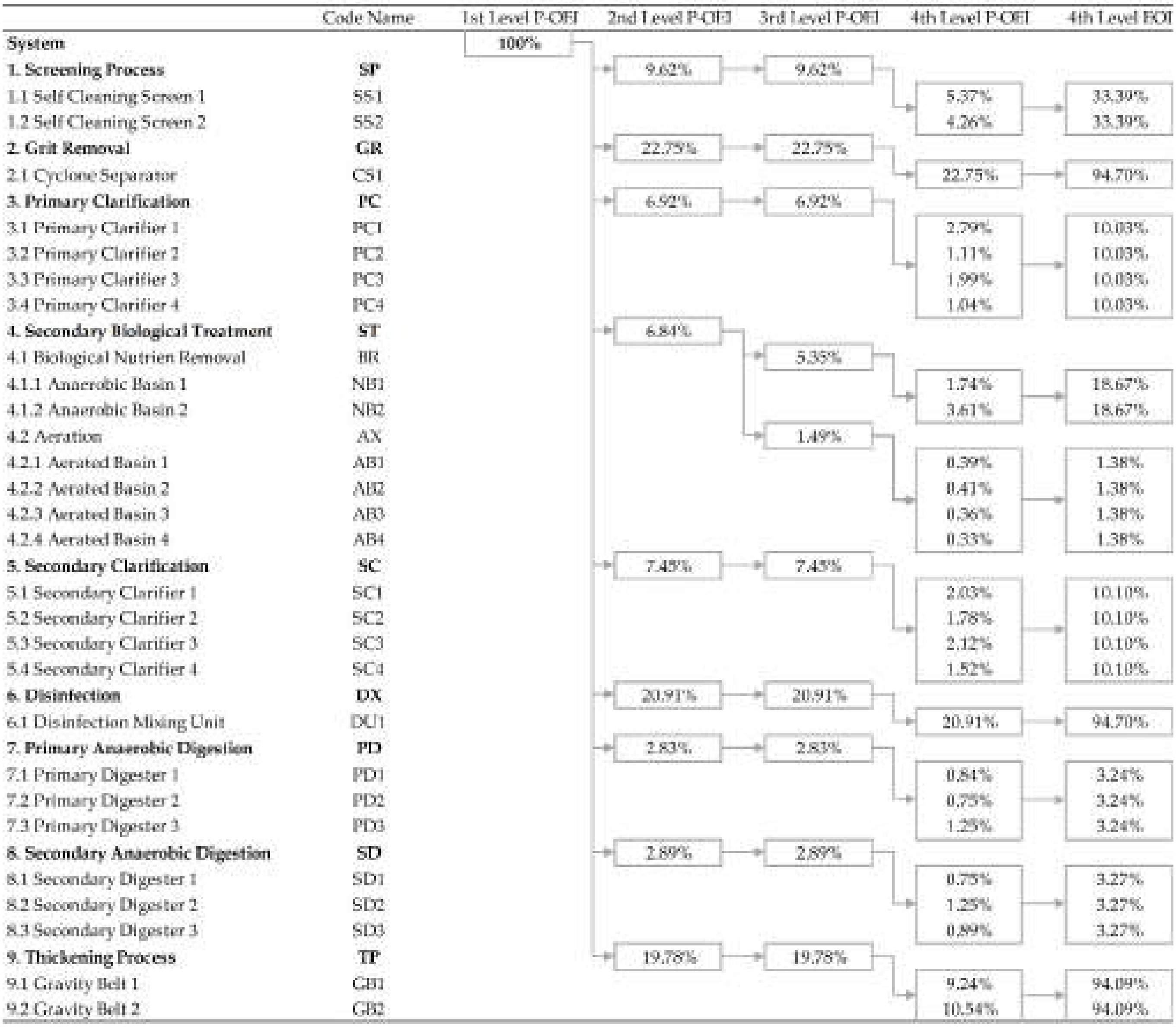

Figure 4. Downstream Analysis: P-OEI and EOI.

The results show that elements with higher P-OEI indexes (fourth level P-OEI) are the Cyclone Separator (22.75%), Disinfection Mixing Unit (20.91%), and Gravity Belts (9.24% and 10.54%, respectively), this means that these four elements are responsible for more than the 60% of the system's ineffectiveness, for example, the Cyclone Separator alone is responsible for the 22.75% of loss of production due to unavailability and EOI. To seize the impact of each element in loss of production, let us observe that, for example, Aerated Basin 4 and Cyclone Separator exhibit very similar expected availability indexes (97.03% and 97.04%, respectively), but very different P-OEI indexes (0.33% and 22.75%, respectively). This dramatic difference is mainly because of the EOI index they present, which relates to the fact that the Cyclone Separator is a single element connected in series to the system while the Aerated Basin 4 is set in a 40% overcapacity load-sharing configuration, which is part of one out of two subsystems within the Secondary Biological Treatment (ST). In fact, the EOI of the Cyclone Separator is 94.70%, while for Aerated Basin 4 the EOI is 1.38%. The latter suggests that the Aerated Basin 4 will barely impact production since it is highly probable that if the Aerated Basin 4 should fail, the others will be available and withstand the workload.

Figure 5 displays a scatter plot to better comprehend the concept of the P-OEI index, which, in simple words, can be described as the consequence (represented by the EOI index in the *Y*-Axis) times the frequency (represented by the unavailability in the *X*-Axis). Indeed, the Cyclone Separator (CS1) and the Disinfection Mixing Unit (DU1) present the highest indexes of P-OEI since their unavailability indexes are the highest among all the elements of the process even though they share similar expected operational impact (EOI) indexes with the Gravity Belts (GB1 and GB2).

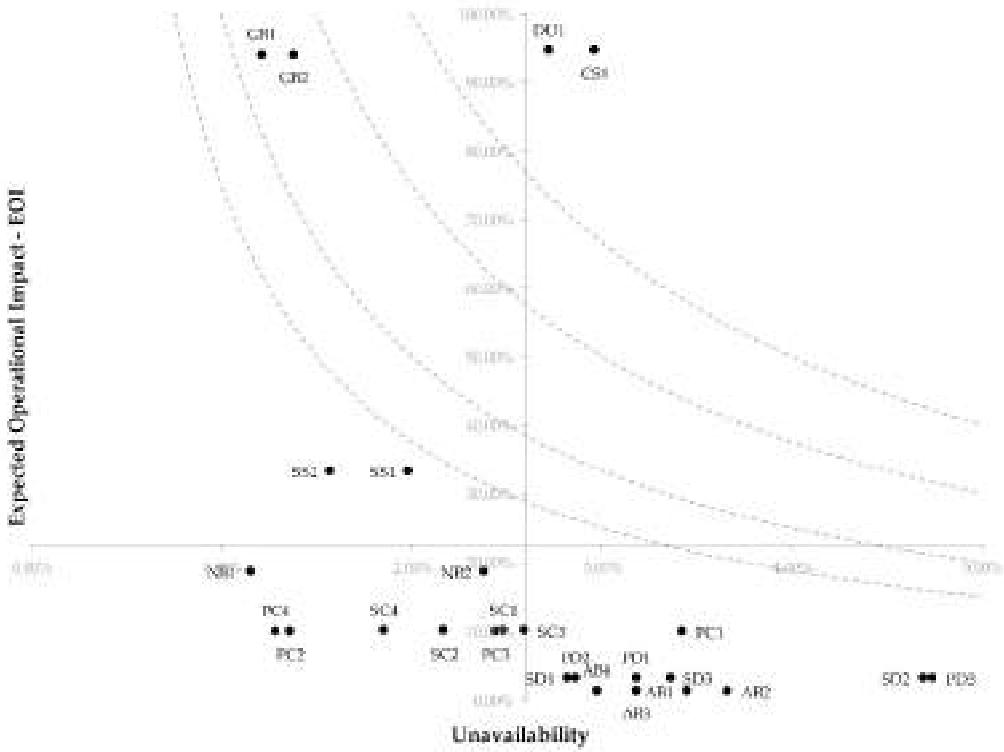

Figure 5. Criticality scatter plot.

It is also important to note the difference between the equipment with very high EOI (CS1, DU1, GB2, and GB1) and most of the other pieces of equipment which present lower EOI indexes. This difference resides in the fact that the lower EOI indexes belong to subsystems under redundancy or load-sharing configurations, which dramatically reduces the criticality in the system [26] in contrast with the highest EOI indexes, which belong to subsystems without any kind of redundancy or overcapacity.

4. Results

Once the methodology has been applied to the wastewater treatment plant, data are available to clearly observe all the lack of effective sources in the plant. More precisely, it presents important results regarding the performance and design of the plant, where more than 60% of the production loss is explained by only four elements, which share high EOI. Furthermore, it is possible to establish that bottlenecks are caused by elements with an EOI of over 90%. Therefore, it might be favorable to consider redundancies or overcapacity configurations on these elements (such as the cyclone separator) to reduce the expected loss of production. Moreover, since the expected availability of the system is 87.78%, decision-makers can develop production plans according to more accurate capacity forecasts.

It is also very advised to make use of data from reliable information systems in order to make decisions or data analysis [27,28], between the most recommended information systems and methods is possible to identify online data capture in real-time, recording data from production, as well as from maintenance activities or related events, such as stoppages and equipment parameters, as it is the case for a constructed wetland for the treatment of winery wastewater in Italy [29]. In fact, by combining the use of networked equipment with advanced data analytics, wastewater treatment plants can improve their operations by performing in a more synergistically, efficient, and resilient manner. The latter is a concept widely known as Industry 4.0, which is defined by Cyber-physical Systems (CPS) as transformative technologies mainly focused on the management of linked and dependent systems of physical assets with the plant's computational capabilities [30]. The scope of this concept comprehends more than just maintenance, but production, logistics and other services managed by an organization. It aims to strongly improve the economic potential of today's factories [31].

The most powerful opportunities of the proposed methodology aim to improve the availability of components with high P-OEI, reducing the impact brought by the unavailability of certain equipment, pushing reliable and sustainable actions at the same time as intelligent investments are placed on the plant by including redundancies that will strategically reduce risks and costs.

5. Conclusions

Regarding the established objectives, it is possible to ascertain when applying the proposed P-OEI/EOI methodology for a wastewater treatment plant helps to identify several improvement opportunities, as well as several design flaws, in order to make more effective decisions related to asset management. Therefore, this methodology may act as the main support activity for implementation leaders and decision-makers regarding maintenance plans by helping to define priorities and identify flaws and opportunities.

The importance or operational effect coming from each piece of equipment embedded in the system has been identified. More importantly, the propagation of the operational effect has been analyzed and quantified using the proposed methodology, and it is reflected on each of the calculated P-OEI and EOI indices. Furthermore, by using the proposed methodology, the expected availability for each element on the system has been calculated carefully, accounting for the mentioned propagation effect. Indeed, P-OEI analysis provides vital information regarding the design of the plant and its performance in order for the decision-makers to choose better strategies and maintenance plans.

As mentioned, since vital information is now available regarding design and performance, managers can now focus on improving asset performance by decreasing the P-OEI in critical assets. Efforts should be directed to the highest portion of the scatter plot in Figure 5 and covering from right to left, i.e., begin with the elements with the highest EOI but prioritize the most unavailable elements first. In this regard, the measures that should be taken include developing more efficient maintenance strategies and procedures accountable for the newly identified priorities, redesigning processes by including redundancies or overcapacity configurations when possible, and performing spare part analysis, among others. Moreover, by focusing on the most unavailable elements (right portion of the scatter plot), it is possible to reduce the P-OEI by including the mentioned measures.

Finally, it is important to note that the P-OEI methodology developed in this article can be embedded into any Computerized Maintenance Management System (CMMS), which also helps improve the analysis by adding impact assessment in real-time.

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Nomenclature

α	Scale parameter of Weibull Distribution
β	Shape parameter of Weibull Distribution
Γ	Gamma function
λ	Failute rate
A	Availability
WWTP	Wastewater Treatment Plant
CMMS	Compurtarised Maintenance Management System
P-OEI	Plant Operational Effectiveness Impact
EOI	Expected Operational Impact
KPI	Key Performance Indicators
LCSA	Life Cycle Sustainability Assessment
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
RAM	Reliability, Availability and Maintainability
RBD	Reliability Block Diagram

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