A methodology for assessing and monitoring risk in the industrial wastewater sector

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\textbf{ABSTRACT}

The concept of sustainable risk assessment in industrial wastewater treatment is vital to determine the causes and consequences of plant failure. The potential wastewater-related risks that could hamper the operation of the entire manufacturing facility are currently inadequately defined and under researched. This work proposes a framework that includes the comparison of literature and experimental data to quantify the impact of the significant process parameters on the critical process outputs. From the business perspective, managing and minimising risks will be possible when the number of impact parameters is low and the relationships between different parameters are clearly understood. The results show that even only the evaluation of technical risks can provide an assessment platform template for other risk types. Also, the structured and statistically analyzed data sets applied might be further used in the design and development of machine learning platforms algorithms to inform sustainable process outcomes adjusted for various geographical locations and human factors which significantly affect the industrial water sector globally.

\section{Introduction}

The definition of the term “risk” is essential for the successful management of many activities and technologies \cite{1}. The risk definition can affect the outcome of policy debate, the allocation of resources among safety measures, and the distribution of political power in society \cite{2}. A general framework development depends on the risk definition that can be considered as a political act expressing the definer's values leading to adverse consequences for a particular decision \cite{1}. No definition of the term “risk” can be advanced as the correct approach because there is no one definition that is suitable for all definers’ values \cite{3}. Water risks can only be coordinated as a collective action from industry, policy makers, customers, and citizens aiming to protect water resources and mitigate long-term water-related risks \cite{4}. The effectiveness of the possible risk mitigation depends on the selection of methods and tools used for the residual risk measurement \cite{5,6}. The establishment of a risk assessment framework will guide enterprises on how to reduce their impact on global water resources through development of an innovative risk management culture \cite{7}. Development of new approaches to assess and evaluate various risks could open new possibilities to manage water resources worldwide \cite{68}.

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The risk of an emerging “global water crisis” is regarded as the third highest ranked risk, in terms of overall impact on the industry [2]. There is a clear need for the implementation of better practices and more holistic measures that can rectify risks related to water use on industrial sites. In common with many other industries, the water sector is formalizing explicit approaches to risk management and decision-making, that have formerly been implicit [8]. Many industries follow the accepted standards of performance and codes of practice [9]. However, the overall complexity of the industrial water sector may require the integrated risk analysis to better understand what drives the risk from or to the plant, process, or operation. Risk management frameworks establish a platform based on the risk identification, evaluation, and management to drive decision making by industrial stakeholders [10]. The framework of an iterative approach recognizes that continuous improvement of the risk analysis to develop a mature capacity in risk management [11]. The implementation of a portfolio of risk techniques within a water sector depends on enterprise size, existing management culture, and the governmental regulations [12]. The implementation of a risk assessment framework should not be considered as the end-point of risk management, but as an inspiration for the continuous process re-assessment to mitigate any potential risk [13]. Overall, risk analysis can be considered as a tool that informs the decision-making process [14]. The risk management activity should reflect sensible and meaningful conclusions rather than theoretical perspectives, as previously suggested [15,16]. The efficient risk management of a water utility requires both methods for proper risk assessment and multiple criteria decision analysis [17]. Risks are not limited to the boundaries of a single enterprise and are often driven by customer pressures and increased stakeholder interest [18]. Thus, the dependencies between suppliers, customers, competitors, and organization must be identified, assessed, mitigated, and monitored. To the author knowledge, no previous work has been carried out on the development of qualitative methods for integrated risk assessment in the wastewater sector.

Moreover, the previous business risk models were mostly used for the evaluation of risks arising from domestic water use [19,20]. The emergence of industrial 4.0 technologies have enabled the detailed evaluation of various risks across business operations and supply chains [21]. The identification of risks arising within the framework of Industry 4.0 includes the data analysis and development of additional statistical tools [22]. The structural complexity of supply chain networks significantly influences overall system complexity and can be comprehensively assessed by statistical tools, i.e., JMP, MINITAB tools to reduce the amount of information needed to specify the system and its components [23]. Heat maps are often used with the simultaneous combination of univariate and multivariate data and statistical assessments for the statistical modeling of parameters [24]. Previous studies have recommended a risk modeling approach-framed by Industry 4.0 concepts that includes a clustered heat map to reduce the model complexity and includes options for the risk ranking [25].

Understanding risks originating from human errors, management weaknesses, technological failures, irrational exploitation of natural resources and generation of non-disposable waste can prevent industry from accidents, disruptions, and financial bankruptcy [26]. Risk management is often linked to significant uncertainties and associated complexity, which emphasize the need for the development of rigorous and sophisticated modeling approaches [27]. Supply chain consideration have attracted an increasing focus on wastewater-related risks [28,29].

The aim of this paper is to provide a tool for qualitative and quantitative risk assessment, and decision support for industrial sites. One single approach cannot be used to access all risk-related problems [30]. Hence, quantitative methods such as risk ranking are also required. This work presents a new approach in assessing risks in a common structured way, using process performance metrics to develop a real time risk ranking methodology to guide risk-reduction measures and decision making. A decision model is developed that combines risk ranking with multi-criteria decision analysis and take uncertainties into consideration using statistical evaluation platform.

Fig. 1. Flowchart of the risk assessment methodology.
2. Materials and methods

2.1. Risk assessment

Risk assessment can be performed in a closed loop. Implicit to Fig. 1 are an initial identification of the roots causing risks; an analysis of roots and consequences of the risk being realized in the industrial and public water sectors; a consideration of their combined outcome by evaluating the magnitude of the risk; some judgement of the significance of the acceptability of the risk; and then a decision to act - either in risk mitigation or in demonstrating that the risk is low, and the residual risk is being acceptably managed. The risk assessment process is represented by the continuous control loop that is an iteration of data collection, analysis and decision making. Fig. 1 is a framework suggesting actions which can effectively manage the risk followed by any additional analysis or action to mitigate the risks. The risk assessment is shown as an iterative process that can be repeated an unlimited number of times to mitigate the risks. Risk assessment is considered as a process that does not reduce risk alone [31, 32]. Its purpose is to inform decision making and associated actions to manage risk in the enterprise. Management action related to risk mitigation assumes the responsibility has been passed to the risk owner who is accountable for action and takes responsibility for seeing the actions and its completion, so that the risk is mitigated accordingly [33].

The enterprise water use may exacerbate the water risk by depleting the water catchment area it relies on for sustained operations. Therefore, companies must take measures to respond to water risk. Responses to water-related risk range from purely financial strategies to actions that reduce demand or increase supply, and usually include a mix of these actions [31]. Fig. 1 illustrates a decision framework for analysing the consequences of industrial revenue maximization, minimization of environmental impact, integration of novel and cost-efficient technological solutions, etc. and developing a response strategy. When examining water use, it is critical to understand when and where the water is withdrawn. Unlike greenhouse gas emissions, which have the same impacts regardless of where the emissions are generated geographically, the absolute volume of water used is often less important than the timing and location of use. Previous studies showed that one cubic meter used in an arid urban region poses a greater physical risk than one cubic meter used in a wet rural region because the uncertainty of water supply in the future is significantly greater [30]. Consequently, organisations need to examine their water carbon footprint and identify whether there are any physical water-risk hot spots in their value chain.

2.2. Risk-response decision framework

Fig. 1 illustrates the necessity to identify which risks may materialize when managing the water supply. The risks must be categorized according to the literature or professional experience of the management committee through the careful audit of the available data. In this work, JMP SAS software will be used for the statistical data evaluation and identification of appropriate control parameters. The upper specification (USL) and lower specification (LSL) limits of each individual risk can be determined using literature and measured data sets using statistical evaluation tools and defined organizational limits. The results of the preliminary analysis will identify gaps which require additional data collection and analysis. The collected data will be classified using the JMP software with the further establishment of the statistical model and later a modified Failure Mode and Effect Analysis (FMEA) for risk assessment. In the next step, the data will be validated at several industrial sites or using support of various local communities with respect to regulations and future changes in policymaking. The results will be shown as a map using five risk indicators for each risk level. Each indicator will be color coded from green, indicating low risk to red indicating high risk. The output will be limited by the accuracy of the reference data from the literature and industrial sites which may contribute to some error in the model outputs. However, this approach is considered perturbative in nature and is the first step in identifying the major risks to the organization with the potential to be extended in the future with the more comprehensive data output.

2.3. Data collection

The operational data is collected using literature sources [34, 35] and using online monitoring tools at industrial sites. A large number of different types of sensors distributed across the system is involved in the data collection. This network is often associated with a distributed data storage and pre-processing/control units. The collected data passes through many connections and middleware and therefore it is crucial to guarantee that the data is being reliably transmitted and received at the destination in a timely manner. Also, the collected data should be properly stored for future analysis to obtain higher accuracy levels [34]. However, qualitative aspects of the data collection have a strong impact on the way the data can be statistically processed and evaluated using various risk assessment tools [35].

The efficiency of wastewater treatment is basic indicator of wastewater treatment plant function [36]. Municipal wastewater is mainly comprised of water together with relatively small concentrations (<0.01%) of suspended and dissolved organic and inorganic solids [37]. Among the organic compounds present in sewage fraction are carbohydrates, lignin, fats, soaps, synthetic detergents, proteins, and their decomposition products, etc. [38]. Overall, the wastewater plant efficiency depends on the amount and composition of wastewater, on condition and type of sewer network, plant operating conditions, equipment design, geographic location, and climatic conditions [39, 40]. The efficiency of the wastewater plant is often associated with COD that is indirectly used to determine the concentration of organic compounds in water by measuring the mass of oxygen needed for the total oxidation to carbon dioxide [41]. The wastewater processes depend largely on the level of treatment required as prescribed by the discharge permit issued by the governmental agency. Levels of treatment required are defined customarily as “preliminary” with the removal of coarse solids,
“secondary” with the substantial removal of organic material and suspended and dissolved solids, and “tertiary” with the complete removal of organic matter and suspended solids, which are typically accompanied by the reduction in nutrients such as nitrogen and phosphorus [42]. Previous studies have shown that suspended solids, chemical oxygen demand, total nitrogen and ammonia content are main indicators of effluent quality of wastewater treatment [43]. The list with output parameters can be also extended to active autotrophic biomass, active heterotrophic biomass, slowly biodegradable substrate, biological oxygen demand (BOD), Kjeldahl nitrogen, etc. [44]. However, the inclusion of more output parameters can make the model more complicated and less accurate due to the absence of available validation data and missing equipment to characterize these parameters within the required sensitivity range [45].

In the present work, the risk assessment tool was developed using a case study on wastewater treatment plant (WWTP) used for the water cleaning from pharmaceutical production in Ireland. The data was collected in 2017–2018. The measurements were recorded on the daily basis in the morning. The values of Chemical Oxygen Demand (COD), nitrates, total nitrogen, phosphorus, ammonia, and suspended solids were determined using monitoring tools at the wastewater plant. For the risk assessment model, the collected data for the wastewater treatment plants were also combined with the upper and lower specification limit results which were found in the literature [46–50] and compared with the data provided by the industrial sites. Statistical analysis using control charts was performed on the industrial experimental data to determine the upper and lower specification limits.

2.4. Statistical model

The risk model is based on the statistical analysis using the control charts which were generated with the JMP software. Control charts are defined as a graphical and analytic tool for monitoring process variation. The natural variation in a process can be quantified using a set of control limits. Control limits help distinguish common-cause variation from special-cause variation. Typically, action is taken to identify and eliminate special-cause variation and to quantify the common-cause variation in a process because it can determine the process capability. In the present work, the data was visualized using a Levey Jennings plot.

The upper and lower critical regions were introduced from the literature and collected data at the industrial site. Previous studies showed the critical ranges for various operating parameters [31,32]. The literature data with respect to minimal and maximal values significantly varied from one study to another which was related to the variability of geographical location of cooling towers. The experimental data were also provided by the industrial users to determine the outlier data which are below or above the minimal and maximal values. JMP software was used to detect the outliers by visualization from three-dimensional control charts. The calculations using an excel model were conducted with data series from the literature that required rescaling to display minimal and maximal values of the related risk.

2.5. FMEA characterization and heat mapping

Failure Mode and Effect Analysis (FMEA) is the most important tool used to address the drawbacks of the conventional risk priority number calculation with the neglected group effects and interrelationships on measurements [33]. A risk framework was proposed by weighing the impact of each parameter on the potential risk in water technologies. The parameter weight was calculated in a systematic way and ranked according to the probability to occur from low to high risk. The combined statistically processed data and normalized excel data model provides the information on low and high-risk causing parameters which are inputs for the grouping and ranking of potential risks in the water sector using FMEA modeling.

A heat map is a method of visualizing two-dimensional data where the hue or intensity of color varies according to a given value criterion referred to as “color-shaded matrix display” [51]. In a clustered heat map, similar color patterns are grouped together to reveal larger structural properties of the data. In order to interpret the heatmap, a number of rules and visualization techniques have been developed. Color coding, which for simplicity will be limited to 3 unique colours, will signal to the user the dimension status. The red, yellow, and green colours are chosen as they are internationally recognizable.

1. Green color means an acceptable risk that is an event irrelevant to the general operation of the facility as a “daily risk”; it does not require special security measures.
2. Yellow color illustrates a tolerable risk that is called as a moderate risk requiring intervention and providing the cost of reducing the risk that is reasonable for the damage caused.
3. Red color shows an unacceptable risk meaning an immediate threat to the environment and people, requiring immediate steps to limit it.

In the model, the risks were assessed using the combined results from statistical analysis and heat mapping of data. The estimate of effect coefficient (β) can be obtained in eq. (1)[52]:

$$\beta = (X'X)^{-1} X' y$$  \hspace{1cm} (1)

In eq. (1), (X’X) is the matrix for m replicates of the design, X’ is a factor and y is a vector. The equation has a unique solution, which is the vector of ordinary least-squares estimates. In design of experiment, each factor that can influence the response variable needs to be estimated individually [52]. The effect can be estimated by getting the average of the responses at each level of the factor.

Since the literature defined the Risk Priority Number (RPN) as the product of three risk factors which were equally treated [33], this
study considers the relative importance weights of the risk factors using a sum of products of factor effect coefficients multiplied by the measured value, as shown in eq. (2):

\[
RPN = \left( \sum_{i} (\beta_i \times x_i) \right) + \varepsilon
\]  

[2]

In eq. (2) \( \beta_i \) is a factor effect coefficient, \( \varepsilon \) is a random error, and \( x_i \) is the measured concentration value on the industrial site which was continuously collected for each single risk factor (nitrates, phosphorus, total nitrogen, ammonia, chemical oxygen demand, total suspended solids) over the time period.

Fig. 2. Levey Jennings plots of (a) nitrate, (b) phosphorus; (c) total nitrogen; (d) ammonia; (e) suspended solids; (f) COD in mg/l. Magenta marked lines indicate the concentration limits according to the literature [51,52].
2.6. Limitation of the present work

Previous studies have identified that where there is a lack of overarching company or government policy and structure around water conservation, cultural attitudes to minimising water use and effluent discharge [53,54]. In the present methodology, only the risks related to the environmental impact, health and technology will be assessed. Overall, this work focuses on how risk assessment results can be used in decision analysis to evaluate and compare measures for the risk reduction. Since an integrated approach is used, the work aims to include a wide range of possible scenarios and water technologies instead of analysing only a specific type of event or specific water system that may cause harm. This manuscript does not deal with designing specific measures for reducing certain risks or the process of implementing and monitoring selected measures. Although risk assessment and decision analyses play an important role in the development of risk reduction strategies, this work focuses on outlining a general strategy for the development of a comprehensive tool for recording information regarding water system processes. Although risk assessments and decision analyses play an important role in the development of risk reduction strategies, this work focuses on outlining a general strategy for the development of a comprehensive tool for recording information regarding water system processes.
Table 1
Process Failure Modes and Effects Analysis Form using SMRA method showing 3 potential risk outcomes (a) low-risk; (b) medium-risk; (c) high-risk.

(a) Model for the low-risk outcome.

| Process Effects of Failure | Potential Failure Model | Risk Priority Number (RPN) | Chemical Oxygen Demand |
|----------------------------|-------------------------|---------------------------|------------------------|
| Eutrophication             | Nitrate, Phosphorus, Ammonia, Total Nitrogen, Suspended Solids | 229                       | 0.49, 0.045, 0.68, 0.89, 0.74, 0.77 |
| USL                        | 15, 15, 50, 25, 250, 2000 |                           |                        |
| Evaluation Low Risk        | 10, 10, 20, 20, 50, 200  |                           |                        |

(b) Model for the medium-risk outcome.

| Process Effects of Failure | Potential Failure Model | Risk Priority Number (RPN) | Chemical Oxygen Demand |
|----------------------------|-------------------------|---------------------------|------------------------|
| Eutrophication             | Nitrate, Phosphorus, Ammonia, Total Nitrogen, Suspended Solids | 315                       | 0.49, 0.045, 0.68, 0.89, 0.74, 0.77 |
| USL                        | 15, 15, 50, 25, 250, 2000 |                           |                        |
| Evaluation Medium Risk     | 20, 30, 30, 40, 230, 100 |                           |                        |

(c) Model for the high-risk outcome.

| Process Effects of Failure | Potential Failure Model | Risk Priority Number (RPN) | Chemical Oxygen Demand |
|----------------------------|-------------------------|---------------------------|------------------------|
| Eutrophication             | Nitrate, Phosphorus, Ammonia, Total Nitrogen, Suspended Solids | 1435                      | 0.49, 0.045, 0.68, 0.89, 0.74, 0.77 |
| USL                        | 15, 15, 50, 25, 250, 2000 |                           |                        |
| Evaluation High Risk       | 15, 50, 60, 40, 260, 1500 |                           |                        |
role in crisis management, this work is not focused on crisis management. The financial and reputational risks (i.e. water price, market regulations, basic human rights, etc.) will be outside the scope of the current research.

3. Results

3.1. Statistical data analysis

Different statistical analysis could help identify the interconnectedness of the variables to facilitate assessment of overarching trends and quantify operational performance [55]. In the present study, a simple and reliable predictive statistical model will be able to correlate output variables with input parameters such as nitrates and phosphorus into the wastewater [56]. The recovery of nitrates and phosphorus containing nutrients from wastewater sludge reduces the burden on the reactive nitrates and phosphorus demand in the synthetic fertilizer manufacturing industry [57]. The development of a platform for the control of nitrate and phosphorus input can ensure the efficient and sustainable use of sewage sludge nutrients leading to less adverse effect on the environment. The water quality data for 24 months collected in 2017–2018 is summarized in Fig. 2. The collected data were shown as Levey Jennings plot to indicate fluctuations and outliers in the output parameters. The control limits indicate that mostly all industrially provided parameters do not exceed the standard parameters measured in previous work [52,53].

When the outliers for the nitrate and phosphorus concentrations were compared, it seems that the maximal outlier in phosphorus amount increased just once in June 2018. The operator’s notes indicated that this is due to the breakage of sensors which were involved in the measurement of phosphorus concentration. The fluctuations in the nitrate concentration were high due to the higher concentrations of biological sludge entering the wastewater facility and significantly affecting the denitrification process.

The outliers in total nitrogen and ammonia concentrations were related more to the operational challenges at the wastewater facility than to seasonal changes, confirming previous results [58,59]. This is due to the mild weather in Ireland over the entire year with an average temperature of 10.9 °C. The strong and significant correlation of datasets confirmed that the population abundance of ammonia-oxidizing bacteria is relatively stable throughout the year in Ireland and does not change significantly when wastewater temperature dropped in the winter months. It was also observed that the COD and TSS concentrations were significantly below the literature determined limits which describes the wastewater treatment plant as an efficient and sustainable facility. These interactions indicate the overall excellent quality of the wastewater plant with the occasional changes in the pH and alkalinity monitored satisfactorily during the measurement recordings to avoid any risks related to environmental toxicity. Moreover, the present data analysis has also shown that the differences in wastewater treatment in 2017 and 2018 were small.

3.2. FMEA characterization and heat mapping

Failure Mode and Effects Analysis (FMEA) is a method that examines potential failures in products or processes and has been used in many quality management systems [31]. One important issue of FMEA is the determination of the risk priorities of failure modes. The FMEA tool combines the human knowledge and experience to: (1) identify known or potential failure modes of a product or process, (2) evaluate the failures of a product or process and their effects, (3) assist operators with strategies on how to minimize the risks, and (4) eliminate or reduce the chance of the failures occurring in the future [67].

In this work, we propose a modified FMEA approach, System Modeled Risk Analysis (SMRA) to determine the risk priorities of failure modes using both statistical model and risk assessment model for the wastewater treatment plant. The proposed method will categorize the risks and provide recommendations on how to minimize the risks in each category using a point grading system. The risk priorities are determined in terms of overall risks rather than maximum or minimum risks only. Incomplete and imprecise information on the evaluation of risk factors can also be considered in the SMRA assessment. The SMRA assessment process includes several steps:

Step 1. Estimate the Potential Failure Mode
Step 2. Describe the Potential Effects of Failure
Step 3. Calculate the β effect coefficient
Step 4. Determine the Current Process Controls (USL) using literature
Step 5. Measure the concentration of a parameter causing any associated risk
Step 6. Calculate the risk priority number using eq. (2)
Step 7. Fill out the FMEA form, as shown in Table 1

The SMRA form is filled out using colours in a scale green for the low-risk situations to the red marked highest risk. Overall, TSS and COD have the greatest influence on the risk classification of the wastewater treatment process. In the present study, the RPN was classified according to the concentration of nutrients which remain in a sludge (nitrate and phosphorus), total nitrogen in the wastewater, amount of formed ammonia and TSS during treatment and COD required for the highly efficient wastewater treatment process. RPN numbers below 250 belong to low-risk situations and this can be expected when the concentration of TSS and COD are significantly below USL, whereas the other parameters can near the maximum USL value. Quantitatively moderate-risks showed RPN values ranging from 300 to 350 when the concentration of TSS is near the maximal USL value. The other parameters can be equal or slightly greater than the USL, whereas the COD concentration remains significantly lower than the USL value suggested by the
literature or experimental site measurement. High-risks obtained RPN values which are greater than 350 and can be expected when high amounts of TSS are formed with the concurrent high consumption of chemical oxygen in the wastewater treatment process. The high-risk indicates the unbalanced ecosystem with the modified chemical composition that makes the water body unsuitable for recreational purposes and human consumption. When eutrophication occurs, the oxygen in the water is used up; surrounding living microorganisms die, and high concentrations of suspended solids are formed in the pond.

In the present work, the collected data at the industrial site was used for the validation of the FMEA model. Table 1 shows that the selected values must be within the USL range that was statistically calculated using the industrial maximal outliers. It is highly recommended to conduct the model validation using more data sets collected by various industrial sites to justify the USL range according to the increasing efficiency of the wastewater treatment technology in the next decades. The proposed risk assessment method is only adequate for sites that have complete and good-quality historical data (detailed, consistently described, regularly collected), because it is based on risk identification. The present SRMA model includes six parameters which have an impact on wastewater treatment. However, various literature sources contain different information on the significance of input and output parameters.

Previous studies suggested the consideration of pH value, biochemical oxygen demand (BOC), heavy metals (copper, lead, chromium, zinc), phenols, etc. However, other sources indicated that pH value and BOC concentrations enter the model through the input of COD parameter. The concentration of heavy metals and phenols are often associated with the TSS material that is one of the output parameters in the present model. Selection of the USL value and multilinear regression coefficient are two major parameters affecting the risk priority number. The list of process effects of failure can be extended using the literature and observations of plant operators. Increased eutrophication is one of the major failures in wastewater treatment that is caused by the high anthropogenic loads of biogenic substances discharged into water bodies. Municipal wastewaters, containing large amounts of nitrogen and phosphorus play of key roles in the acceleration of eutrophication intensity. The main direction in the prevention of eutrophication caused by wastewater discharge is to decrease nutrient loads introduced to wastewater receivers.

The previous identification of weights for individual frequency of occurrence and the start size can also significantly impact the wastewater treatment process. Therefore, more data collected over several years will be required from different industrial facilities to identify the most accurate descriptors for the wastewater treatments. Based on the results obtained, the next stage of research is to develop appropriate weights for individual technological line devices. This will permit a more accurate risk assessment due to the rely

Fig. 3. Risk assessment using classification of articles.
on the individual frequency of the parameters and the start size and less rely on the maximal significance of all risk parameters.

4. Discussion

This work presents a research framework detailing how to identify and prevent risks in the water sector. A case of risks related to eutrophication at the wastewater treatment facility has been used to develop a methodology and validate the results to minimize risk and to prepare risk management procedures. However, the established relationship is hypothetical and further laboratory scale work is required to validate the proposed model. Overall, literature research has shown that there is a lack of unified procedures for managing risk at wastewater treatment plants. The introduction of procedures and collection of experimental data sets at different global locations could facilitate the management of wastewater treatment plants.

The data analysis indicated that the outliers from the experimental data significantly deviate from the results which were found in the literature. This indicates that more experimental data should be collected to understand these variations. However, control charts suggested that there is a clear correlation between the concentration of ammonia, total nitrogen, suspended solid and chemical oxygen demand. Overall, fluctuations in the collected wastewater data were small indicating the effluent wastewater nutrient loading did not significant vary over the two years. This can be attributed to the uniformed removal performance of the treatment plant. The outliers were mostly related to technical problems during the plant operation and accidental overdosing with high concentrations of organic matter. The results presented are mostly used for the assessment of technical risk which are related to the wastewater treatment plant operation. The developed model is unique because it has the potential to be further developed to additionally assess risks related to economics, ecology, and presented in a format to best meet stakeholders needs, such as furthering the Industry 4.0 agenda.

Previous risk assessment models in the water sector were complex and did not provide an easy to communicate tool which links the heat mapping to sustainable output [65,66]. The present study led to the development of the comprehensive and simple research framework for risk assessment in the water sector, as shown in Fig. 3. The main input variables enter a risk assessment framework with the integrated impact factors influencing the present system. Initially, all potential risk sources can be analyzed using statistical tools, then evaluated and later minimized or prevented.

Most of the current research focuses on the risk data processing either historical or real-time numerical data [65]. However, research on the use of combined literature and industrially collected data to prevent risk assessment is comparatively uncommon. The reason for this may be linked to the nature in which the data is collected, usually by human narratives. Previous studies [52,53] were limited to the description of excellent data sets without giving equal attention to the outliers and missed data which could require additional post-treatment.

The development of a methodology that includes a comparison of the USL and LSL limits from the literature and industrial experimental facility will facilitate the improvement of machine learning algorithms, which can be used as building stones for a model in the Industry 4.0 domain. The model could be used to develop digital twins of physical operations, which can then be used by artificial intelligence algorithms in the simulation and prediction of sustainability outcomes. The proposed assessment concept is assumed to run in the cyber safe environment to exclude risks which are related to the external attempts to prevent the model operation.

The developed framework is the first attempt in the academic literature to assess the potential risks in the industrial wastewater treatment sector. The present model has limitations which are related to the SMRA design that is based on the maximal significance of all risk parameters. The next stage of research could be the development of appropriate weights for individual risk parameters which may include ecology, economics, health, and social sciences. They will be assigned to individual parameters based on their impact on the quality of treatment plant operations and possibly geographical location. These weights are necessary to define strategies to minimize risks and to prepare the risk management procedures in the industrial water sector. Moreover, confirmatory runs will be required to assess the industrial plants according to the existing legislations and health standards at various geographical locations.

5. Conclusions

The novelty of the present work relies on the fact that the developed framework can predict and minimize the risks at the wastewater treatment plants using a simple SMRA method. The results have shown that the risk assessment must integrate analysis, evaluation, and control steps of data using statistical tools, literature research, and heat mapping within the process failure model. The extension of the framework to identify further aspects, such as for instance the significance of the parameters from technical, ecological, social, health, and economic spheres would provide a platform for future research. Also, interdependence among parameters, such as the frequent coexistence of risks, or risks amplifying each other, are recommended avenues of research to be further investigated and experimentally validated. Overall, the developed framework is simple, comprehensive, safe and it can provide a sustainable outcome in combination with Industry 4.0 technologies and process integration tools to minimize the risks in the industrial water sector.

Author contributions

Conceptualization, A.T., S.M., P.C. and K.S.; methodology, A.T. and S.M.; software, A.T.; validation, Sha. M, W.H. and A.T.; formal analysis, A.T. and W.H.; investigation, A.T. and S.M.; resources, Sha. M, K.S. and P.C.; data curation, P.C. and W.H.; writing—original draft. preparation, A.T.; writing—review and editing, S.M. and A.T.; visualization, Sha. M, A.T. and P.C.; supervision, S.M.; project
administration, Sha. M. P.C. and K.S.; funding acquisition, Sha. M. P.C. and K.S. All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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