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Towards Sustainable Water Management in Manufacturing - A Review of Various Facets of Water Efficiency and Effectiveness

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Abstract

Sustainable water management is critical for the manufacturing sector due to the substantial volumes of water required for various manufacturing processes such as cooling, cleaning and production. This high demand places a strain on water resources, especially in water scarce regions. In addition, effective water treatment is crucial due to the significant opportunities for water recovery, which can help address the high demand for water in manufacturing. Thus, as water scarcity intensifies and regulatory pressures increase, optimizing water usage and treatment are the two focal areas for both operational efficiency and environmental sustainability in manufacturing. This paper reviews the state-of-the-art technologies for managing water usage and treatment, focusing on real-time monitoring and analytics to optimize consumption and enhance recycling rates. The study examines the limitations and gaps identified in the existing literature, thereby equipping industrial decision-makers with a holistic understanding of diverse water management strategies.

Keywords: Manufacturing, water efficiency, effectiveness, optimization, water network

1. Introduction

Water scarcity is a growing global issue due to rising population, urbanization, and increasing demand from various sectors such as manufacturing [1]. As water scarcity intensifies in many parts of the world, the costs associated with water consumption for manufacturing sectors are rising substantially. In addition, most countries have stringent regulations regarding allowable water consumption and wastewater discharge limits to promote water sustainability and environmental protection [2]. There is a clear need for industries to increase their awareness of resource efficiency improvement strategies and to implement such strategies to improve water reuse and recovery in their operations. Adopting sustainable water management practices can help manufacturing facilities address critical issues like their carbon footprint from water usage and wastewater discharge while also gaining control over escalating water costs. For manufacturers to achieve water sustainability, practical systematic solutions that can be implemented at the shopfloor/production level are necessary. Such solutions require monitoring techniques and analytical methodologies for water use in manufacturing processes as well as for wastewater treatment.

This paper explores some of the state-of-the-art methods and technologies that manufacturing facilities can employ to improve in-house water management practices and wastewater treatment processes. The critique of the relevant literature on water management techniques is organized into the various sections below.

Firstly, Section 2 reviews various Internet of Things (IoT) enabled monitoring technologies that can be deployed to obtain real-time insights into industrial water usage. This includes an examination of different performance metrics and optimization algorithms that facilitate targeted reduction of water consumption. Next, Section 3 presents an overview of commonly used sensor technologies for wastewater treatment.

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It also outlines available in-house treatment setups and methodologies to maximize the rate of recycled water recovery. Lastly, the paper concludes by identifying existing gaps and limitations in the current research that may prevent the widespread practical application of optimal water management solutions in real industrial environments. The research questions summarized can help steer future studies in this domain

2. Water consumption management

Water is a critical resource for many industrial processes, but its efficient use and conservation remain a challenge for manufacturers seeking to control costs and meet sustainability targets. One important step is implementing advanced monitoring systems to collect high-quality water usage data at the shop floor level, where processes are carried out. Such monitoring systems allow manufacturers to benchmark performance across facilities, identify inefficiencies, track the impacts of process changes over time, and accurately measure the results of water stewardship initiatives. Beyond collecting water usage data, data analysis to derive actionable insights provides manufacturers with the true value. Statistical analysis and machine learning algorithms can be leveraged to detect patterns in water consumption data and recognize opportunities for efficiency improvement and reduction in consumption.

2.1. Water monitoring using IoT technology

With the help of IoT development and sensor technology, water consumption and water quality can be monitored in real time. The monitoring platform commonly consists of four components [3-5]:

- Sensors: Water flow meters, temperature sensors, pH sensors, and turbidity sensors can provide real-time data on water usage, temperature, acidity levels, and clarity.
- Communication: Sensors communicate wirelessly via protocols like LoRaWAN, Bluetooth, or WiFi to a central controller/gateway. It enables monitoring from a remote location.
- Controller: The controller gathers data from all connected sensors via the communication network. It stores, analyzes, and transmits data. Controllers often use edge computing capabilities.
- Dashboard: Via a web or mobile app interface, users can view live and historical data charts, maps, and alerts on things like daily/monthly water use, temperature fluctuations, or water quality parameter changes over time.

The simple structure of components is illustrated above in Figure 1. To gather real-time information, the in-line sensors are key components.

Flow measurement devices can be broadly classified into two categories based on their method of operation - intrusive and non-intrusive types. Intrusive meters require sensors to have direct contact with the medium being measured. Typical intrusive meters include vortex meters, mass flow meters and Coriolis meters [6]. [7] summarizes three types of non-intrusive meters: optical, electrical and electromagnetic. Optical water flow meters detect fluctuations in the velocity of suspended

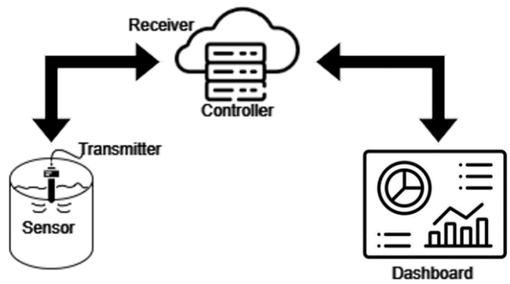

Figure 1 Cyber-physical water monitoring system

particles or bubbles in water. Electromagnetic flow meters generate a magnetic field and measure the voltage induced in a conductive liquid by its flow. Ultrasonic flow meters use transducers to transmit and receive ultrasonic pulses affected by the speed of flowing liquid. By calculating the time-of-flight differences, flowrate can be determined without contacting the fluid. Those are installed externally on the outside of pipes without cutting and welding the water pipes.

2.2. Water consumption performance matrix

2.2.1 Shopfloor level water measurements

The volume of water consumption is a direct key performance indicator (KPI) to measure water efficiency in a factory. This can then be broken down into direct water consumption in production as well as indirect water consumption in facilities and auxiliary systems at shop floor. An example from automotive vehicle manufacturing evaluates water usage for entire factory is using below KPI [8]:

$$\text{Water use } (m^3/\text{vehicle}) = \frac{\text{Water input } (m^3)}{\text{number of vehicles}} \quad (1)$$

Water consumption refers to the withdrawal of freshwater that is either evaporated or integrated into products and waste, and does not revert or return to its original source. Calculating the volume of water utilized per unit of production serves to standardize consumption measurement independent of production rate fluctuations. Tracking this ratio over time allows identification of trends and benchmarks process line efficiencies.

However, this ratio does not account for the entire water assessment. For example, assessing indirect water use and renewable water sources is also important to evaluate a factory's holistic water footprint. [6] proposed an integrated framework that categorizes production and non-production water into four types - consumed embedded, consumed lost, discharged renewable, and discharged non-renewable - forming ratios around water usage effectiveness, water efficiency, and wastewater treatment efficiency. Analyzing trends across these metrics enables manufacturers to identify potential consumption reduction opportunities throughout diverse operational areas. With a systematic view of water flows, this approach supplies comprehensive visibility into performance to support strategic planning and management.

From a costing perspective, the total water and wastewater treatment costs are significant KPIs to be tracked, especially for high water consumption industries like steelmaking [9]. The paper proposes a list of well-structured KPIs, which assesses the economic value of water consumption in water loops. It extensively considers various factors related to water, such as energy, labor, and maintenance costs involved in water management. The holistic cost assessment framework enables industries to better understand their total water-related expenditures and make more informed data-driven decisions regarding water efficiency improvements.

2.2.2 Factory level water measurements

Water footprint is a performance metric that quantifies freshwater consumption and pollution loads associated with an individual, process, product, industry or nation, accounting for both direct and indirect water uses [7]. It considers three water volumes - blue for surface and groundwater withdrawal, green for rainwater and grey for the amount of freshwater required to dilute pollutants to ambient levels. By tracing water needs throughout supply chains, the water footprint method provides a holistic view of water impacts from production through distribution and identifies opportunities to reduce pressures on local and global water resources. While a large footprint does not inherently signify unsustainability, it helps prioritize investments in efficiency improvements and pollution prevention.

A study that focuses on the greywater footprint at the industrial park level is presented in [8], specifically in the Changzhou Economic & Technology Development Zone in China. It aims to develop an assessment framework and test it in the industrial park to provide valuable insights for industrial park managers to prepare more appropriate wastewater reduction policies. [10] discusses the water usage in the brick-making industry and the need for efficient water management. It introduces the concept of water footprint, which quantifies, and maps water use and explains the different components of the water footprint. The paper also explores water pinch analysis techniques for reducing freshwater usage and wastewater generation in industry. It provides a case study of a brick manufacturing site and evaluates the potential for water footprint reduction through systematic water management strategies. As a comprehensive indicator, water footprint can help the manufacturing sector to understand the holistic impact of water consumption, identify high water use/risk areas and consequently set more representative and realistic reduction targets.

2.3. Optimization methodologies for enhancing water efficiency

In the manufacturing sector, Data envelopment analysis (DEA) is commonly implemented for industrial facilities water efficiency comparison and benchmarking [11,12]. DEA establishes an efficient frontier based on input-output data from multiple plants. It assigns each plant an efficiency score between 0-1 relative to the frontier. Water volume, production values, factory asset value and operational costs are common inputs/outputs. DEA allows comparison of inherently different operations and scales. It provides a standardized means to evaluate relative water efficiency on a large comparative scale and identify the ideal consumption through historical data collection.

Precise closed-loop water flow management, achieved through strategically placed sensors throughout the water network, enables effective water conservation. [13] showcases a practical implementation of a soft sensor model and innovative sensor network configuration. Through its optimized design function, this system achieves up to 95% savings in high-quality make-up water consumption.

Detecting and minimizing leakage is another critical component of effective water efficiency monitoring programs. Significant volumes of unaccounted for water can be lost through leaks in distribution pipelines, representing a substantial portion of overall usage. Active techniques like noise loggers and pressure sensors help pinpoint exact leak locations [14, 15], while passive monitoring of volume changes assesses background leakage levels over time [15]. Advanced data analytics combining usage patterns, infrastructure attributes and other factors can further help utilities target inspection and prevention efforts in areas more prone to leakage issues [16, 17]. Comprehensive monitoring thus enables prompt detection and repair of leaks through integrated leakage management. This helps reduce water and financial losses from distribution systems over the long term, improving supply sustainability. Reducing leakage has become an important priority area for water utilities facing increasing expectations around enhanced efficiency and water loss reporting.

While many optimization algorithms have been developed for water conservation, most focus on ensuring optimal water supply and resource allocation such as water distribution optimization considering economic, social, and environmental impacts [18, 19]. Multi-objective non-linear optimization methods are proposed to maximize the effectiveness of water usage and minimize wastage. Comparable approaches are particle swarm optimization and genetic algorithms, they are typically applied at a regional scale, utilizing optimization techniques to apportion limited water reserves between municipal, industrial and agricultural needs [20, 21]. Models [22] also project future demands and supplies under varying conditions and predictions to provide direction for long-term infrastructure planning and policymaking. However, the proposed optimization models are mostly implemented within the agriculture domain. At present there is a lack of study to address input water demand and water source optimization for industrial manufacturing and production context.

3. Wastewater and treatment management

Many manufacturers implement on-site wastewater treatment facilities due to the specific nature of the wastewater generated from the processes within the facility. Manufacturing wastewater frequently contains hazardous chemicals, heavy metals, excess heat, and high concentrations of dissolved solids that municipal treatment plants are not designed to process within regulated discharge limits. By implementing in-house treatment, manufacturers can adequately treat contaminants to meet local regulatory standards before disposal or for reuse within operations. Designing a tailored on-site treatment allows them to lower treatment costs by minimizing the need for off-site third-party waste management and in some cases, enabling the recovery of resources from the wastewater. Despite all the potential benefits, wastewater treatment systems are still regarded as expensive and complex to run efficiently resulting in many opportunities for improvement and optimization.

3.1. Water quality monitoring and sensor technology

Wastewater treatment plants present many challenges for process monitoring and control due to the large number of variables across treatment stages, variability in incoming wastewater composition and flow, and use of toxic chemicals. Close monitoring and control are needed to manage interactions between biological, chemical and physical processes, to ensure safe chemical usage, achieve target effluent standards while minimizing environmental risks posed by ineffective treatment or operational mishaps.

In a general manufacturing environment, common water quality parameters to be measured are listed in Table 1 [23, 24]:

Table 1. Common water quality parameters

Parameters	Description
pH	Measures acidity or alkalinity. Most wastewater treatment systems work best within a pH range of 6-9.
Conductivity	Measures how well water conducts electricity, determined by dissolved ions. Higher conductivity means more dissolved minerals and contaminants.
Biological Oxygen Demand (BOD)	Measures the amount of dissolved oxygen needed by aerobic microorganisms to break down organic material present in wastewater. Higher BOD means more organic pollution.
Total Suspended Solids (TSS)	Measures the amount of solids suspended in wastewater that can be removed by filtration. High TSS can harm aquatic life and clog filtration systems.
Oil and Grease	Important to measure if present from manufacturing processes using oils, lubricants, hydraulic fluids, etc.
Chemical Oxygen Demand (COD)	Measures the total amount of organic compounds in wastewater that can be broken down by chemical oxidants. Indicates pollution load and is often used alongside BOD.

There are many in-line sensors utilizing sensor probes installed directly into water pipes or tanks to continuously measure and transmit data signals instantly. This allows for real-time process monitoring and control. Common parameters that can be monitored using inline sensors include pH, temperature, turbidity, dissolved oxygen, conductivity and oxidation reduction potential. Data from inline sensors provides operators with information on parameter fluctuations much more frequently when compared to periodic manual sampling.

While direct water quality monitoring using physical sensors provides definitive measurements, the cost of deploying a comprehensive sensor array can be prohibitive. Sensors for certain parameters like COD and TSS require substantial capital expenditure that may exceed budgetary constraints for many facilities. In addition, the in-line sensors which are much more costly than off-line sensors also require manual operations such as top up of reagents, replacement of consumables and regular maintenance. However, the need to closely monitor these influent and effluent characteristics to ensure process performance and regulatory compliance remains a vital part of operations.

To address these challenges, researchers have proposed soft-sensing techniques as a cost-effective alternative. Soft-sensing algorithms leverage historical data correlations to develop mathematical models linking unmeasured variables to other parameters that can be easily and inexpensively monitored online [25, 26]. For example, turbidity, pH, and temperature sensors are relatively affordable compared to COD or TSS probes. By training algorithms on past data patterns, these indirectly measured variables can act as proxies to accurately estimate concentrations like COD through inferred relationships [27, 28].

Developing effective machine learning and soft sensing for wastewater treatment faces challenges. Machine learning models require large, varied data sets to capture full operational variability. However, each treatment system is highly site-specific, meaning models apply only to a single or few implementations. A generalizable methodology and algorithms are needed to analyze data from multiple plants and produce insights applicable industry-wide, expanding the benefits of these advanced approaches for optimizing monitoring.

3.2. In-house wastewater treatment procedure

In-house wastewater treatment systems are commonly employed by manufacturing facilities to process waste streams before discharge or reuse. A multi-stage treatment approach is typically utilized to achieve regulatory compliance for various contaminants. Preliminary treatment processes aim to separate solids and adjust the wastewater for optimal downstream biological and chemical removal mechanisms. Primary sedimentation allows fats, oils, greases and settleable solids like grit to separate from the water through precipitation.

[28] introduced chemical precipitation or coagulation to remove non-degradable metals and toxins, air stripping towers are used to volatize volatile organic compounds, as well as advanced oxidation using ozone or UV to fully degrade resistant organics. The need for these added technologies is assessed on a case-by-case basis depending on industry type, specific wastewater constituents, their treatability, and local regulatory discharge quality standards that mandate the removal of components not readily eliminated through conventional treatment alone.

Advanced treatment such as filtration, disinfection and proper sludge handling further polish the effluent before controlled discharge or reuse [29]. With a well-designed sequential treatment process, in-house facilities can effectively clean industrial wastewater streams to the required standards before releasing or recycling the water back into the environment or process. As previously described, this paves the way for many opportunities for optimization and improvements in terms of resource efficiency due to the large variation of processes, process parameters and incoming quality of wastewater.

3.3. Wastewater treatment optimization

Machine learning and artificial intelligence show promising applications for improving the efficiency and performance of wastewater treatment operations [30, 31]. By analyzing the immense volumes of historical plant data on influent characteristics, sensor readings, equipment parameters and operational records, machine learning models can predict future conditions and process needs and detect anomalies in real-time that may indicate issues. It can also provide automated decision support and control of treatment processes through optimal setpoint adjustment, estimate unmeasured parameters through virtual sensing correlations, benchmark current performance against peer facilities to identify underperforming assets, anticipate long-term capacity and infrastructure requirements based on demand forecasts, and enhance cybersecurity monitoring. All these features will help operators optimize resource usage, maintain compliance standards, minimize costs, and maximize treatment effectiveness through data-driven insights gained from AI-powered applications.

[30] presented a data-driven approach for analyzing and forecasting wastewater treatment optimization. Firstly, the study applied statistical methods to evaluate the treatment plant's performance. Secondly, it developed a data-driven predictive model using Support Vector Machines (SVM) to forecast the plant's production levels one month ahead. Multiple machine learning models were tested. Principal component analysis effectively simplified the operational data, revealing correlations between conditions and power output. The SVM model produced the most accurate forecasts. Overall, the research aimed to generate useful insights for improving the plant's operability and sustainability by leveraging data-driven analysis and predictive modeling techniques.

Apart from algorithms and models, advanced filtration technologies can also enhance the recovery rate of treated water [32, 33]. [33] provides insights into the optimization and operational analysis of domestic greywater treatment using electrocoagulation filtration. The paper provides comprehensive review of electro-coagulation for water treatment, emphasizing the potentials and challenges associated with this method. It suggests the ECF significantly reduces the pollutant load in greywater, showing the aluminum-iron-based electrodes as a viable option to treat greywater with optimal operational costs.

To promote the adoption of innovative filtration and other wastewater treatment, a model-based simulation is proposed to evaluate the feasibility and quality of the new treatment technology. [34] proposed a simulation tool which models various operational units within water treatment in steelworks, enabling the assessment of new filtering technologies aimed at reducing suspended solids in water networks meanwhile achieving 64% water saving. As an example, the implementation of a new filtration system can be modelled, and the results of the simulation can provide a comprehensive analysis of water consumption, the operational cost of updating the water pipeline and layout, and return of investment can be developed to support the decision making on upgrading or modifying wastewater treatment procedures.

4. Discussion and Conclusion

This paper reviewed various methodological approaches utilized in manufacturing settings for water and wastewater management. Specifically, the practices for water monitoring to gain operational insights to form strategies to optimize water conservation across industrial processes, wastewater treatment techniques employed to clean effluent, and means of enhancing treatment systems for more sustainable water recycling are explored. Through the review, several research gaps have been identified that still need to be addressed in future work.

Gap 1: Increasing the granularity of monitoring requires installation of more meters which may be costly

While IoT systems offer extensive monitoring of water use across different processes, the cost of sensors and equipment remains significant. Especially when more granular analysis demands high-density data collection, installing numerous devices can drive up costs substantially. [35] illustrates a case study in a beverage production facility, where monitoring at least 18 points (8 production lines and 10 auxiliary facilities) led to an 11% reduction in water consumption. However, the initial capital investment for such sensor networks was substantial, especially in large-scale facilities where various monitoring points are needed to capture a large number of operational parameters critical to production. The installation and ongoing maintenance of a more expansive sensor network constitute a sizable portion of expenditures. To realize higher-resolution insights, the capital and operational costs associated with a wider sensor periphery must be considered.

Therefore, further exploration of disaggregated water data collection methods could help minimize sensor requirements for monitoring purposes. Some algorithms and techniques are discussed and proposed for the residential domain, to disaggregate the water flow within the household scenario [36, 37]. The Semi-supervised clustering model proposed in [37] has an accuracy that varies from 66.7% to 100% regarding different events. Meanwhile, the end-use disaggregation algorithm has certain criteria for data resolution, [38] assessed how the resolution affects the disaggregation model's accuracy for household water activities. 10-seconds resolution shows 93% accuracy and lowest root mean square error while it declined to 89% with a 15-minutes sampling resolution. Although 10 seconds resolution achieved a higher accuracy rate, it is not commercially available yet due to storage challenges.

The industrial environment, however, has significant differences from household water activities. Water demands associated with production and non-production activities may not follow predictable schedules. At the same time, further disaggregation of the extensive plumbing infrastructure is necessitated. Research exploring optimized water management strategies specifically for manufacturing industries remains limited. Dynamic processes and expansive pipe networks present obstacles to high-resolution monitoring. More study is still needed to develop innovative solutions that overcome these complexities faced in industrial settings.

Gap 2: Water quality sensors are expensive and soft-sensing technology is not yet mature enough to be commercialized

Given the variety of water quality attributes monitored within industrial settings, there is a correspondingly wide range of sensor technologies required. Different processing applications and facilities need instrumentation capable of measuring diverse analytes. The cost of typical sensors like conductivity, TSS and COD are generally ranges well above thousands of dollars. As mentioned in Section 3.1, soft-sensing and virtual sensing algorithms are proposed in the academic domain, as a replacement for using cheaper sensors to estimate the targeted parameter's value. However, it has limitations in accuracy, the best model proposed in [28] still presents 25% of mean absolute value error.

Another approach of soft-sensing algorithms is usually case specific – robust model training is required for a new deployment with a sufficiently well-labelled dataset. Such high-quality dataset are typically unavailable and also require extensive pre-processing such as additional manual records and sorting. Additionally, the models trained from one dataset is not expected to able to be directly applied to a different scenario although the input variables remain the same, the final accuracy will likely differ. Nevertheless, it is still worthwhile to explore transfer learning with a more diverse dataset, as this can enhance the algorithm's accuracy and minimize its sensitivity to specific site settings, which is seen as one step closer towards a commercial solution.

Gap 3: Lack of integration of production and wastewater treatment to fine-tune the water-loop

In the industrial sector, a water loop refers to a system that circulates and recycles water within various industrial processes. Although there are literature reviews on how recycled water can enhance the water loop for certain industries [39, 40], there is a lack of studies to model the combination of the production process and wastewater treatments. The level of wastewater contamination is primarily influenced by the production process. Factors such as product type and production schedule play a significant role in determining the degree of contamination, which in turn dictates the necessary treatment methods for the wastewater. While in most wastewater treatment literature, the starting point is the wastewater generated from industrial operations. When in fact, the appropriate treatment method should be selected and applied based on the quality measurements of the wastewater.

By incorporating production-related variables into the model and optimization algorithms, the water cycle - from freshwater input to wastewater and discharge - can be shaped into a fully integrated water loop within the manufacturing process. Furthermore, by reintroducing recycled water back into production, the loop is effectively closed, promoting a more sustainable and efficient system. The value of modeling a closed water loop lies in its ability to help manufacturers precisely optimize water management. It enables fine-tuning of water usage and can even drive adjustments in production processes, ultimately improving overall water efficiency and sustainability.

In summary, this paper has provided a review of the challenges and the state-of-the-art strategies and solutions being employed. Despite the current innovative solutions, there are still several gaps that require additional research and development to ensure the continuous improvement of resource management. This area of study is critical to ensure the sustainability of water management in manufacturing processes.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Claude AI in order to enhance the readability and grammar check. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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