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# Development of a sensor-integrated fuzzy logic-based decision support system for real-time classification and management of textile wastewater

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A prototype wastewater treatment system integrated with a fuzzy logic-based decision support model was developed to characterize, classify, and assess the reuse potential of textile wastewater. Unlike conventional approaches that treat all effluent streams uniformly, this study presents a selective management strategy based on real-time pollution load classification to enable cost-effective and sustainable reuse. A total of 132 samples from various textile processes were analyzed for color, total suspended solids (TSS), pH, conductivity, and temperature. The results indicated that approximately 58% of the wastewater was suitable for membrane treatment and reuse. Sensor data from a jet dyeing machine fed a fuzzy logic inference system that determined wastewater treatability in real-time, automatically routing streams to either the drain or the treatment system. The prototype, consisting of pretreatment units and a reverse osmosis (RO) module, achieved 30–60% treatment efficiencies depending on color intensity and salinity. In dyeing trials with the recovered water, $\Delta E$ values (0.16–0.76) remained below the threshold ($\Delta E < 1$), confirming reuse viability. In addition, content analyses of the treated water were performed, and the results confirmed that the recovered water met the necessary quality criteria for reuse in textile dyeing processes. This study demonstrates that data-driven classification significantly optimizes the volume of water requiring treatment compared to non-selective strategies, offering a practical pathway for circular water management in the textile industry.

**Water impact**

This study advances circular water management in the textile industry by shifting from maximum pollutant removal to fuzzy logic-based real-time wastewater classification. The developed fuzzy logic prototype identifies treatable streams with 58% reuse potential and achieves a recovered water cost of €0.38 per $m^3$. Successful integration into industrial dyeing processes demonstrates a practical pathway for large-scale wastewater reuse and more resilient water supplies.

## Introduction

Global freshwater scarcity has become a critical challenge, as nearly 97.5% of the Earth's water resources are saline and unsuitable for direct consumption.[1–3] Although desalination technologies have expanded worldwide, their high energy demand and brine disposal challenges constrain large-scale economic sustainability.[4–6] Consequently, attention has shifted toward industrial wastewater recovery and reuse, particularly in water-intensive sectors such as textile manufacturing.

In recent years, it has been reported that nearly 20% of global freshwater pollution originates from textile wet-processing operations.[7] Textile wet processes include desizing, scouring, bleaching, mercerization, reduction, dyeing, printing, and finishing.[8] The characteristics of wastewater generated during dyeing processes vary depending on the type of dyes and chemicals used.[9] These wastewaters typically contain a complex mixture of acids, alkalis, dyes, hydrogen peroxide, starch, surfactants, dispersing agents, and metal salts.[10] Due to inefficiencies in dyeing operations, a significant portion of dyes (approximately 10–20%) fails to fix onto the fabric and is released directly into the wastewater.[11] Consequently, around

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50 000 tons of textile dyes are discharged into the environment annually, causing severe water contamination worldwide.[11,12] Textile effluents are therefore characterized by high color intensity (chroma), elevated chemical oxygen demand (COD) and biochemical oxygen demand (BOD), as well as the presence of numerous non-biodegradable organic compounds.[13,14] The main pollutants in textile wastewater are unfixed dyes and various dyeing auxiliary chemicals.[15] The characteristic properties of untreated textile wastewater are presented in Table 1. However, the high variability in pollution loads (*e.g.*, pH, color, salinity) makes it difficult for conventional, static treatment plants to operate efficiently, often leading to over-treatment or failure to meet reuse standards.

Conventional wastewater treatment methods often lack the flexibility to handle the dynamic nature of textile effluents. To address this limitation, recent research has increasingly focused on integrating data-driven modeling with systems optimization. For instance, Masud *et al.* (2024) highlighted the potential of using data-driven classification to advance sustainable resource management from concentrated wastewater sources.[17] Similarly, the transition from static treatment protocols to dynamic, real-time decision support systems is becoming a critical area of research for industrial water reuse. Considering the growing importance and complexity of water-related challenges, advanced computational tools—often referred to as artificial intelligence (AI) in broader literature—have emerged as promising solutions for process control.[18] In recent decades, numerous studies have demonstrated that data-driven models can effectively substitute traditional statistical approaches in estimation and forecasting tasks.[17,19] While these techniques have been successfully applied in controlled environments, their implementation for real-time stream segregation (source separation) using rule-based decision support in full-scale industrial settings remains limited.[20–22]

Conventional wastewater treatment methods have several limitations, including high operational costs and energy consumption. Therefore, in recent years, advanced computational modeling techniques—such as artificial neural networks (ANN) and fuzzy logic (FL)—have emerged as promising tools for the optimization of wastewater treatment processes.[11,23–25]

AI-based approaches are increasingly being applied in both the textile industry and general wastewater treatment, leading to significant advancements in process optimization and pollutant removal efficiency.[11,26–28,30]

Unlike studies focusing solely on pollutant removal efficiency, this study addresses the 'classification-optimization' problem in wastewater management. A fuzzy logic-based decision support system was developed to function as an intelligent classifier, optimizing the trade-off between treatment costs and water recovery rates. By validating this system against conventional non-selective strategies using real-time sensor data from 132 industrial batches, it is demonstrated a scalable methodology for circular water management in the textile industry.

**Table 1** Typical concentration ranges and standard limits of water pollutants in the textile industry[16]

| Parameter | Range |
|---|---|
| pH | 6–10 |
| Temperature (°C) | 35–45 |
| BOD (mg $L^{-1}$) | 80–6000 |
| COD (mg $L^{-1}$) | 150–12 000 |
| Total suspended solids (mg $L^{-1}$) | 15–8000 |
| Total dissolved solids (mg $L^{-1}$) | 2900–3100 |
| Chlorine (mg $L^{-1}$) | 1000–6000 |
| Free chlorine (mg $L^{-1}$) | <10 |
| Sodium (mg $L^{-1}$) | 70% |
| Trace metals (mg $L^{-1}$) | |
| Fe | <10 |
| Zn | <10 |
| Cu | <10 |
| AS | <10 |
| Ni | <10 |
| B | <10 |
| F | <10 |
| Mn | <10 |
| V | <10 |
| Hg | <10 |
| $PO_4$ | <10 |
| Co | <10 |
| Oil and grease (mg $L^{-1}$) | 10–30 |
| TNK (mg $L^{-1}$) | 10–30 |
| $NO_3$-N (mg $L^{-1}$) | <15 |
| Free ammonia (mg $L^{-1}$) | <10 |
| Sulfate (mg $L^{-1}$) | 600–1000 |
| Silica (mg $L^{-1}$) | <15 |
| Total Kjeldahl nitrogen (mg $L^{-1}$) | 70–80 |
| Color (Pt–Co) | 50–2500 |

## Materials and methods

### Wastewater characterization

A drum-type jet dyeing machine with a fabric capacity of 600 kg, operating at a liquor ratio of 1 : 5, was used in this study. A total of 132 wastewater samples were collected from different textile wet-processing operations, including scouring, bleaching, desizing, reactive dyeing, disperse dyeing, acid dyeing, as well as washing and neutralization baths following these processes (Table 2). Detailed recipes of all 132 baths are provided in the SI.

The wastewater from the jet machine was first manually analyzed in the laboratory. Laboratory measurements were carried out using the following instruments: a TSS sensor based on optical turbidity measurement (measurement range: 0–4000

**Table 2** Types and numbers of wastewater baths analyzed

| Bath type | Number of baths |
|---|---|
| Scouring/bleaching | 11 |
| Desizing | 3 |
| Reactive dyeing | 12 |
| Disperse dyeing | 3 |
| Acid dyeing | 2 |
| Soap washing | 15 |
| Reductive washing | 1 |
| Acid washing | 1 |
| Rinsing | 45 |
| Neutralizing | 34 |
| Enzymatic processes | 5 |


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NTU, corresponding to 0–4500 mg $L^{-1}$ total suspended solids); a color sensor with a measurement range of 0–500 Pt–Co; a portable pH meter (Seven2Go S2-FK, Mettler Toledo) with a measurement range of 0–14 and an accuracy of ±0.01; a portable conductivity meter (Seven2Go S3-FK, Mettler Toledo) capable of measuring conductivity (0.010 μS $cm^{-1}$ to 500 mS $cm^{-1}$), TDS (0.01 mg $L^{-1}$ to 300 g $L^{-1}$), salinity (0–42 psu), and temperature (−5 to +105 °C); and a DR3900 Vis spectrophotometer (Hach Lange) operating in the wavelength range of 320–1100 nm. The data obtained from these instruments were used to evaluate the treatability potential of the wastewater.

To enable real-time wastewater characterization, online pH, conductivity, TSS, temperature, and color sensors were installed on the wastewater outlet line of the jet dyeing machine. The analysis results were used to generate data for fuzzy logic modeling. A fuzzy logic–based decision system, using sensor data, controlled an actuator valve at the jet wastewater outlet to direct the effluent either to the drain or to the treatment prototype.

### Fuzzy logic models

Based on the basic working mechanism of the fuzzy logic method, treatment decisions were made using water characteristics (color, TSS, conductivity, temperature, and pH), and the Mamdani and Sugeno methods were applied in the fuzzy inference stage.

Fuzzy logic was selected due to its robustness against noisy sensor data and its ability to incorporate expert knowledge, making it suitable for real-time industrial wastewater management applications. This method provides flexibility in making real-time decisions regarding whether wastewater streams should be directed to the drain or the treatment prototype.[11,23–25]

The selection of wastewater streams to be directed to the treatment prototype was determined based on laboratory analysis results, inputs from project partners, and expert evaluations. Subsequently, a fuzzy logic decision model was developed in accordance with these findings.

After the system installation, online data were collected to conduct sensor accuracy tests, verify whether the system operated in accordance with the fuzzy logic model, and evaluate the test results for necessary corrections and improvements. The online monitoring of the data collected from the system was managed through a cloud-based platform.

### Treatment prototype

The treatment prototype consists of a 5-ton capacity wastewater collection tank; a roughing filter, activated carbon filter, and sand filter used in the pre-treatment stage; a reverse osmosis system as the main treatment unit; electronic control and monitoring panels; mechanical and electrical connection equipment; water and energy meters; and pH, conductivity, TSS, temperature, and color sensors.

The specifications of the devices used in the installation of the treatment prototype are as follows:

- Roughing filter: 100 micron basket type, 316 stainless steel
- Sand filter: mixed media containing coarse sand, fine sand, and anthracite (20–2000 microns (μ))
- Activated carbon filter: granular coconut shell-based, iodine number: 1050 mg $g^{-1}$, surface area (BET $N_2$): 1100 $m^2$ $g^{-1}$, apparent density: 0.52 g $cm^{-3}$, adsorber fill density: 450 kg $m^{-3}$
- Reverse osmosis system: capacity: 3 $m^3$ $h^{-1}$, maximum operating pressure: 16 bar, Toray Brackish water membrane
- pH sensor: Endress + Hauser online measurement sensor, wide measurement range: 0–14 pH, accuracy: ±0.01
- Conductivity sensor: online conductivity meter (E+H), measurement range: 0.010 μS $cm^{-1}$–500 mS $cm^{-1}$, TDS Range: 0.01 mg $L^{-1}$–300 g $L^{-1}$, resistance range: 0.00–100.00 MΩ·cm, salinity: 0.00–42.00 psu, temperature range: −5–+105 °C (depending on the electrode)
- Total suspended solids (TSS) sensor: measurement method: optical, measurement range: turbidity: 0–4000 NTU; SS: 0–4500 mg $L^{-1}$, power supply: 12 V DC, signal output: 4–20 mA Modbus RS485, 0–5 V, pressure resistance: 0–2 bar @25 °C, operating temperature range: −10–50 °C, custom-made
- Temperature sensor: operating temperature range: −50–500 °C, type: Pt-100
- Color sensor: measurement range: 0–500 Pt–Co, IP68/ output: RS485, material: 316 L stainless steel; sapphire, power supply: 10–26 V DC, custom-made

### Fabric dyeing

After the system was put into operation, laboratory dyeing experiments were conducted using the recovered water. Three dyeing experiments were conducted in the study: one using conventional process water and the other two using two different batches of recovered water treated at different times. To evaluate the water quality, dyeing tests were carried out by dyeing 95 g $m^{-2}$ 100% viscose woven fabrics in black and gray, and 95 g $m^{-2}$ 100% cotton woven fabric in cream. The CIEL*a*b* values of the dyed fabrics are presented in Table 3.

In addition, both the recovered water and the conventional process water were analyzed, with the latter serving as a reference benchmark to evaluate the suitability of the recovered water for fabric dyeing.

## Results and discussion

### Wastewater treatment

The results obtained from 132 wastewater samples collected from the baths are presented in Table 4. Considering the overall treatment efficiency, it was estimated that 66 of the 132 baths were suitable for treatment. In this case, it was assumed that

Table 3 CIEL*a*b* values of the dyed fabrics

| | L* | a* | b* | C* | h |
|---|---|---|---|---|---|
| Black | 11.76 | 0.71 | −0.73 | 1.02 | 314.42 |
| Gray | 76.32 | −0.53 | −0.37 | 0.65 | 214.85 |
| Beige | 63.61 | 2.87 | 6.06 | 6.70 | 64.64 |

approximately 50% of the water consumed had the potential to be treated for reuse.

### Fuzzy logic rules

The ranges for the membership function bases for the five parameters used in wastewater characterization were determined as shown in Table 5.

Based on the data presented in Table 5 and the defined membership functions, the fuzzy logic rules established are shown in Table 6.

### System validation: Sensor accuracy and decision verification

To ensure the reliability of the fuzzy logic decision support system, a two-stage validation process was conducted. First,

Table 4 Characterization of wastewater from jet dyeing processes

| Bath/parameter | Mean | SD | Median | Range |
|---|---|---|---|---|
| **Desizing ($n$ = 3)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 77 | 110.04 | 17 | 10–204 |
| Color (Pt–Co) | 741.67 | 1098.62 | 129 | 86–2010 |
| pH | 6.50 | 1.13 | 7.11 | 5.19–7.19 |
| Conductivity (μS $cm^{-1}$) | 882 | 473.47 | 712 | 517–1417 |
| **Neutralizing ($n$ = 34)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 23.59 | 17.95 | 17 | 1–77 |
| Color (Pt–Co) | 536.09 | 950.65 | 210 | 27–4510 |
| pH | 6.02 | 1.44 | 5.59 | 4.18–9.71 |
| Conductivity (μS $cm^{-1}$) | n.a.[a] | n.a. | 921 | 197–≥3999 |
| **Scouring/bleaching ($n$ = 11)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 339 | 427.98 | 134 | 41–1426 |
| Color (Pt–Co) | 2392.27 | 2675.05 | 1336 | 312–9200 |
| pH | 10.43 | 1.91 | 10.55 | 7.46–12.57 |
| Conductivity (μS $cm^{-1}$) | n.a. | n.a. | 1472 | 445–≥3999 |
| **Enzymatic processes ($n$ = 5)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 43.4 | 24.60 | 41 | 15–76 |
| Color (Pt–Co) | 438.2 | 237.43 | 364 | 293–858 |
| pH | 4.97 | 0.14 | 4.99 | 4.79–5.14 |
| Conductivity (μS $cm^{-1}$) | 907.8 | 205.84 | 907 | 594–1156 |
| **Reactive dyeing ($n$ = 12)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 46.75 | 35.39 | 34 | 10–108 |
| Color (Pt–Co) | 7906.92 | 10564.91 | 3607.5 | 235–37 350 |
| pH | 10.45 | 0.45 | 10.54 | 9.25–11.07 |
| Conductivity (μS $cm^{-1}$) | n.a. | n.a. | n.a. | ≥3999 |
| **Disperse dyeing ($n$ = 3)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 143.67 | 33.29 | 152 | 107–172 |
| Color (Pt–Co) | 1991.67 | 381.32 | 1955 | 1630–2390 |
| pH | 4.29 | 0.37 | 4.4 | 3.87–4.59 |
| Conductivity (μS $cm^{-1}$) | 902 | 121.24 | 882 | 792–1032 |
| **Acid dyeing ($n$ = 2)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 31.5 | 26.16 | 31.3 | 13–50 |
| Color (Pt–Co) | 241.5 | 88.39 | 241.5 | 179–304 |
| pH | 4.76 | 0.30 | 476 | 4.55–4.97 |
| Conductivity (μS $cm^{-1}$) | 1010 | 72.12 | 1010 | 959–1061 |
| **Soap washing ($n$ = 15)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 30.27 | 16.68 | 34 | 1–51 |
| Color (Pt–Co) | 1381.13 | 1838.56 | 760 | 92–7270 |
| pH | 7.93 | 0.68 | 7.92 | 6.67–9.26 |
| Conductivity (μS $cm^{-1}$) | n.a. | n.a. | 1234 | 540–≥3999 |
| **Reductive washing ($n$ = 1)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 14 | n.a. | 14 | 14 |
| Color (Pt–Co) | 166 | n.a. | 166 | 166 |
| Conductivity (μS $cm^{-1}$) | n.a. | n.a. | n.a. | ≥3999 |
| **Acid washing ($n$ = 1)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 14 | n.a. | 14 | 14 |
| Color (Pt–Co) | 146 | n.a. | 146 | 146 |
| pH | 6.87 | n.a. | 6.87 | 6.87 |
| Conductivity (μS $cm^{-1}$) | 528 | n.a. | 528 | 528 |
| **Rinsing ($n$ = 45)** | | | | |
| Total suspended solids (mg $L^{-1}$) | 45.18 | 67.11 | 25 | 1–408 |
| Color (Pt–Co) | 1388.9 | 2296.6 | 426 | 32–11 400 |
| pH | 9.25 | 2.13 | 10.22 | 3.4–11.9 |
| Conductivity (μS $cm^{-1}$) | n.a. | n.a. | 2074 | 545–≥3999 |

SD: Standard Deviation. [a] n.a.: not available.


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Table 5 Membership function bases used for wastewater characterization

| | Bad (1. Area) | Medium (2. Area) | Good (3. Area) |
|---|---|---|---|
| Color (Pt–Co) | >1000 | 500–1000 | 0–500 |
| Total suspended solids (mg $L^{-1}$) | >1000 | 300–1000 | 0–300 |
| Conductivity (μS $cm^{-1}$) | >10 000 | 4.000–10 000 | 0–3999 |
| Temperature (°C) | >60 | 40–60 | 0–40 |
| pH | <4/>13 | 4–6/10–13 | 6–10 |

Table 6 Fuzzy logic rules

| Rule number | Color (Pt–Co) | Total suspended solids (mg $L^{-1}$) | Conductivity (μS $cm^{-1}$) | Temperature (°C) | pH | Decision |
|---|---|---|---|---|---|---|
| 1 | Bad | Medium | Good | Good | Medium | Drain |
| 2 | Medium | Good | Good | Good | Good | Treatment prototype |
| 3 | Bad | Good | Good | Good | Medium | Drain |
| 4 | Bad | Medium | Good | Good | Good | Drain |
| 5 | Medium | Good | Good | Bad | Good | Drain |
| 6 | Medium | Good | Good | Good | Good | Treatment prototype |
| 7 | Medium | Good | Good | Bad | Good | Drain |
| 8 | Good | Good | Good | Good | Medium | Treatment prototype |
| 9 | Good | Good | Good | Good | Good | Treatment prototype |
| 10 | Good | Good | Good | Good | Bad | Treatment prototype |
| 11 | Medium | Medium | Medium | Medium | Medium | Drain |
| 12 | Good | Good | Medium | Good | Good | Treatment prototype |
| 13 | Medium | Medium | Bad | Good | Good | Drain |
| 14 | Medium | Bad | Medium | Bad | Medium | Drain |
| 15 | Good | Medium | Medium | Medium | Medium | Treatment prototype |

the accuracy of the online sensors was verified by comparing real-time measurements with standard laboratory analyses. Simultaneous samples were collected from the prototype inlet, and parameters (Color, TSS, conductivity, pH, and temperature) were analyzed. As shown in Table 7, the sensor readings demonstrated a high degree of consistency with the laboratory results, confirming that the data fed into the fuzzy logic model was reliable for industrial monitoring.

Following sensor validation, the decision-making capability of the fuzzy logic model was tested under real-time operating conditions. The system continuously monitored various dyeing and washing baths, classifying them as either "suitable for treatment" (directed to the treatment tank) or "unsuitable" (directed to the drain). These automated decisions were cross-verified against expert evaluations based on the defined rule base. As presented in Table 8, the system correctly classified 100% of the tested batches, successfully separating high-

Table 7 Comparison of real-time sensor measurements *vs.* standard laboratory analysis

| | Sensor test results | | | | | Laboratory test results | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Test no | Color (Pt–Co) | Total suspended solids (mg $L^{-1}$) | Conductivity (μS $cm^{-1}$) | pH | Temperature (°C) | Color (Pt–Co) | Total suspended solids (mg $L^{-1}$) | Conductivity (μS $cm^{-1}$) | pH | Temperature (°C) |
| 1 | ≥2000 | 758 | ≥3999 | 12.21 | 60 | ≥5000 | 796 | ≥3999 | 12.11 | 60 |
| 2 | 1492 | 277 | 1754 | 11.72 | 60 | 1519 | 268 | 1802 | 11.57 | 60 |
| 3 | ≥2000 | 652 | 2194 | 11.26 | 55 | ≥5000 | 645 | 2131 | 11.12 | 58 |
| 4 | ≥2000 | 789 | 2100 | 11.28 | 54 | 4994 | 795 | 2056 | 11.18 | 56 |
| 5 | ≥2000 | 569 | 1292 | 10.22 | 50 | ≥5000 | 584 | 1325 | 10.35 | 50 |
| 6 | 1885 | 152 | 2905 | 8.56 | 55 | 1926 | 186 | 3012 | 8.65 | 58 |
| 7 | 873 | 22 | 995 | 7.55 | 55 | 921 | 53 | 1054 | 7.64 | 57 |
| 8 | 1108 | 216 | 2412 | 10.51 | 56 | 1124 | 304 | 2532 | 10.62 | 55 |
| 9 | 1783 | 19 | 3250 | 7.87 | 47 | 1802 | 29 | 3269 | 7.91 | 50 |
| 10 | 1993 | 21 | 2985 | 7.28 | 45 | 2038 | 54 | 2994 | 7.35 | 50 |
| 11 | ≥2000 | 985 | ≥3999 | 6.61 | 55 | ≥5000 | 1026 | ≥3999 | 6.74 | 50 |
| 12 | 1462 | 138 | 2740 | 6.02 | 85 | 1498 | 265 | 2804 | 6.12 | 80 |
| 13 | 670 | 73 | 1186 | 6.77 | 70 | 695 | 152 | 1178 | 6.98 | 70 |
| 14 | 1097 | 54 | 3302 | 10.01 | 110 | 1128 | 78 | 3365 | 10.15 | 85 |

Table 8 Validation of the fuzzy logic decision model against expert evaluation

| | Sensor test results | | | | | Fuzzy logic decision | Are the results accurate? |
|---|---|---|---|---|---|---|---|
| Bath | Color (Pt–Co) | Total suspended solids (mg $L^{-1}$) | Conductivity (μS $cm^{-1}$) | pH | Temperature (°C) | Treatment prototype/drain | Yes/no |
| Rinsing | 1812 | 526 | 1965 | 6.41 | 80 | Drain | Yes |
| Desizing | 756 | 123 | 1523 | 6.12 | 80 | Drain | Yes |
| Rinsing | 423 | 63 | 964 | 6.78 | 70 | Drain | Yes |
| Scouring/bleaching | 1263 | 126 | 1365 | 10.45 | 80 | Drain | Yes |
| Rinsing | 459 | 84 | 1230 | 9.74 | 80 | Drain | Yes |
| Neutralizing | 409 | 59 | 854 | 6.01 | 50 | Treatment prototype | Yes |
| Scouring/bleaching | 212 | 15 | 825 | 6.52 | 55 | Treatment prototype | Yes |
| Reactive dyeing | ≥2000 | 963 | 2635 | 6.41 | 80 | Drain | Yes |
| Rinsing | ≥2000 | 965 | 2563 | 6.96 | 60 | Drain | Yes |
| Rinsing | 1697 | 569 | 1136 | 10.14 | 60 | Drain | Yes |
| Neutralizing | 1833 | 412 | 1302 | 8.45 | 50 | Drain | Yes |
| Reactive washing | ≥2000 | 746 | 2965 | 8.63 | 80 | Drain | Yes |
| Reactive washing | ≥2000 | 254 | 3012 | 9.25 | 80 | Drain | Yes |

pollution loads (*e.g.*, reactive dyeing, desizing) from recoverable streams (*e.g.*, neutralization, antiper), thereby preventing membrane fouling risks while maximizing recovery.

### Treatment performance

An image of the prototype system installed in the facility is shown in Fig. 1.

Rather than treating all wastewater streams to the same standard, the proposed system enables selective treatment based on pollution load, thereby reducing unnecessary energy and operational costs.

Based on the observations, the treatment efficiency of the installed system was found to range between 30% and 60%, depending on the color and salinity of the bath and the treatment pressure. Under optimal conditions, with a 60% treatment efficiency, 58 liters of 100 liters of water can be treated, of which approximately 35 liters can be recovered. Additionally, using daily data from the water and energy meters, cost calculations were performed as shown in Table 9.

The formulas for the values calculated in Table 9 are as follows:



Fig. 1 Prototype wastewater treatment system installed in the facility.

$$\mathrm{TE} = \frac{\text{Amount of recovered water } (m^3)}{\text{Daily amount of wastewater sent for treatment } (m^3)} \times 100$$

$$\mathrm{SEC_{treat}} = \frac{\text{The amount of energy used in treatment (kWh)}}{\text{Amount of wastewater } (m^3)}$$

$$\mathrm{SEC_{product}} = \frac{\mathrm{SEC_{treat}}\ (\text{kWh } m^{-3})}{\mathrm{TE}}$$

All cost calculations were performed based on a fixed exchange rate of TRY/EUR = 41.12 for March 2025.

$$\text{Unit Cost (€ per } m^3) = \text{Recovered water energy consumption} \times 0.061 \text{ € per kWh}$$

According to the report published by the Ministry of Environment, Urbanization and Climate Change (2021), the membrane energy consumption of treated water is in the range of 1.5–3 kWh $m^{-3}$, while in this project, the results varied between 2.5 and 10 kWh $m^{-3}$, with an average of 6.14 kWh $m^{-3}$.[29] However, a review of the literature indicates that this value represents only the membrane energy consumption; in order to achieve such values, pre-treatment systems must also be applied. The total energy consumption of combined pre-treatment + membrane systems has been reported to range between 14 and 40 kWh $m^{-3}$.[29]

In this regard, the average recovered water cost of approximately €0.445 per $m^3$ obtained using the developed system represents a substantial reduction compared to the minimum cost of €1.02 per $m^3$ reported in previous literature.

### Comparative efficiency analysis

To validate the operational necessity of the fuzzy logic decision model, a comparative evaluation was conducted against two alternative management strategies using a dataset of 132

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Table 9 Treatment efficiency and approximate cost of the produced water

| Day | TE (%) | $SEC_{treat}$ | $SEC_{product}$ | Unit cost (€ per $m^3$) |
|---|---|---|---|---|
| 1 | 43% | 2.14 | 4.98 | 0.361 |
| 2 | 56% | 2.36 | 4.21 | 0.305 |
| 3 | 83% | 2.12 | 2.55 | 0.185 |
| 4 | 63% | 2.5 | 3.97 | 0.288 |
| 5 | 71% | 4.17 | 5.87 | 0.426 |
| 6 | 67% | 3.67 | 5.48 | 0.397 |
| 7 | 62% | 3.84 | 6.19 | 0.449 |
| 8 | 31% | 2.33 | 7.52 | 0.545 |
| 9 | 57% | 5.26 | 9.23 | 0.669 |
| 10 | 33% | 2.82 | 8.55 | 0.619 |
| 11 | 63% | 2.56 | 4.06 | 0.295 |
| 12 | 65% | 6.84 | 10.52 | 0.763 |
| 13 | 70% | 3.8 | 5.43 | 0.393 |
| 14 | 55% | 3.61 | 6.56 | 0.476 |
| 15 | 49% | 3.47 | 7.08 | 0.513 |
| **Mean** | **58%** | | **6.14** | **0.445** |

TE: treatment efficiency. $SEC_{treat}$: specific energy consumption – treatment (kWh $m^{-3}$). $SEC_{product}$: specific energy consumption – product (kWh $m^{-3}$).

wastewater bath samples: (i) non-selective treatment and (ii) a simple threshold-based rejection rule.

In the non-selective treatment scenario, all wastewater streams are directed to the treatment system regardless of their pollution level. According to the experimental results, the fuzzy logic model classified approximately 58% of the total wastewater as suitable for treatment and reuse (Table 10). Therefore, treating all streams would require an increase in treatment capacity of approximately 72% compared to the fuzzy-based selective approach. This increase would directly lead to higher energy consumption, increased operating costs, greater space requirements, and an elevated risk of membrane fouling due to high salinity (*e.g.*, conductivity >4000 μS $cm^{-1}$) and the processing of concentrated dye baths.

In contrast, the simple threshold method applies a decision rule based on only a single parameter (*e.g.*, color >1000 Pt–Co → rejection). Although this approach reduces the treatment volume, it evaluates wastewater quality using a single parameter and does not account for the combined effects of conductivity, total suspended solids, temperature, and pH. As a result, streams with acceptable color but high salinity can still be directed to the treatment process, increasing the risk of membrane fouling. Conversely, the method lacks the flexibility to evaluate boundary states through multi-parameter interaction. Consequently, the threshold-based strategy provides a less balanced recovery potential compared to the fuzzy inference system.

In contrast to the single-parameter threshold approach, the proposed fuzzy logic model simultaneously integrates color, total suspended solids, conductivity, temperature, and pH through a multi-parameter rule base. This structure enables balanced decision-making by considering the combined pollution load instead of isolated boundaries. As a result, the system maximizes water recovery by excluding streams that are not economically or technically suitable for treatment. These findings demonstrate that the multi-parameter fuzzy inference system provides a clear operational advantage in industrial textile wastewater management compared to both non-selective treatment and strict heuristic threshold rules.

The fuzzy logic–based selective approach pre-filters the pollution load entering the treatment unit. For example, water with high conductivity and/or high total suspended solids (SS) is classified as "drain" by the fuzzy logic system. This reduces stress on the membranes. Compared to the conventional non-selective "treat everything" approach, this strategy extends membrane cleaning intervals, enhances long-term system sustainability, and lowers operational costs while ensuring that the quality of the recovered water consistently meets the stringent requirements for textile dyeing processes.

### Fabric dyeing

The characterization of the conventional process water used in the facility showed that the pH was 7.7 ± 1, TSS was 0 ± 2 mg $L^{-1}$, and the color value was 3 ± 3 Pt–Co. The characterization of the reverse osmosis outlet (recovered water) used in the facility showed that the pH was 10 ± 1, TSS was 4 ± 2 mg $L^{-1}$, and the color value was 22 ± 3 Pt–Co. The results of the recovered water and conventional water are presented in Table 11.

For the dyeing experiments, recovered waters obtained from the facility at different times were labeled as recovered water 1 and recovered water 2. The TSS and color values of the recovered waters were within the range of the conventional process water used in the facility; however, pH adjustments were made using caustic soda or phosphoric acid to bring the pH within the reference range.

Black, gray, and beige colors were dyed using both the conventional process water and the recovered waters. The $\Delta E$ values of the black and gray fabrics dyed with recovered water 1 were found to be 0.16 and 0.24, respectively. The $\Delta E$ value

Table 10 Comparison of wastewater selection methods and their recovery rates

| Selective method | Samples suitable for treatment/recycling (Qty) | Samples drained (Qty) | Recovery rate (%) |
|---|---|---|---|
| Non-selective | 132 | 0 | 100.00% |
| Threshold (color <1000) | 89 | 43 | 67.42% |
| Fuzzy logic | 76 | 56 | 57.58% |

Table 11 Analysis results of water samples taken from different stages

| Sample name | WB | SFI | ROI | ROO | CPW |
|---|---|---|---|---|---|
| Color (Pt–Co) | 663 | 361 | 419 | 22 | <10 |
| Total suspended solids (mg $L^{-1}$) | 87 | 66 | 47 | 4 | 2 |
| Conductivity (μS $cm^{-1}$) | ≥3999 | ≥3999 | ≥3999 | ≥3999 | ≥3999 |
| pH | 10.31 | 9.76 | 10.11 | 10.6 | 7.6 |
| Temperature (°C) | 60 | 60 | 60 | 60 | 60 |

WB: washing bath. SFI: sand filter inlet. ROI: reverse osmosis inlet. ROO: reverse osmosis outlet (recovered water). CPW: conventional process water.

of the beige fabric dyed with recovered water 2 was measured as 0.76. Since all $\Delta E$ values were below the acceptable limit of 1, the dyeing processes were considered successful.[31]

Spectrophotometric analyses showed no noticeable color difference between fabrics dyed with the recovered water and fabrics dyed with the conventional process water, indicating that the recovered water can be safely used in production processes. Based on these results, the recovered water from the prototype system was directed to the facility's standard water reservoir, which is expected to further reduce the $\Delta E$ values.

### Generalizability of the decision support system

Although this study was conducted at a single textile facility, the proposed fuzzy logic framework is designed to be adaptable. The membership functions (*e.g.*, limits for conductivity or color) can be recalibrated to suit the specific effluent characteristics of different textile sub-sectors, such as denim or knitwear production. The core contribution—using real-time sensor data to drive selective treatment decisions—is a scalable methodology that can be applied to other industries with variable wastewater streams, provided that the sensor array is adjusted to the relevant pollutants of concern.

## Conclusions

In this study, a prototype wastewater treatment system integrated with a sensor-based fuzzy logic decision model was developed and its performance for textile wastewater management was evaluated. Characterization of 132 wastewater samples collected from different processes revealed that key parameters such as color, total suspended solids (TSS), pH, and conductivity are effective indicators for classifying wastewater and determining its reuse potential. The developed fuzzy logic model contributed to process optimization by making real-time decisions on whether or not the wastewater should be directed to the treatment prototype.

The proposed approach focuses on real-time classification and selective treatment of wastewater streams, rather than aiming for maximum pollutant removal, thus providing more efficient and cost-effective reuse strategies.

The treatment efficiency of the prototype system, consisting of pre-filtration, activated carbon, sand filters, and a reverse osmosis (RO) unit, ranged from 30% to 60% depending on the color intensity and salinity of the wastewater. After treatment, approximately 58% of the total wastewater was found to be suitable for reuse. While the reverse osmosis unit effectively reduces salinity, long-term closed-loop recirculation may lead to the gradual accumulation of monovalent ions; however, in the present system, the treated water is partially blended with conventional process water, mitigating excessive ionic build-up. Therefore, periodic blow-down or fresh water make-up may be required to maintain conductivity levels within the optimal range, particularly for sensitive dyeing recipes. In dyeing experiments conducted with treated water, $\Delta E$ values were found to be 0.16, 0.24, and 0.76, indicating that the color difference is acceptable. This demonstrates that the recovered water can be safely used in place of conventional process water in dyeing operations.

The findings demonstrate that integrating a sensor-based monitoring system with a fuzzy logic model provides an effective, low-cost, and sustainable solution for wastewater reuse in the textile industry. By combining intelligent monitoring with decision-making and physical flow management, the developed system illustrates how water research and technology can support practical industrial reuse and circular water management strategies. Furthermore, the system contributes to minimizing environmental impacts by reducing freshwater consumption and supporting sustainable production goals in line with circular economy principles.

## Author contributions

Hulya Kıcık: writing – review & editing supervision; project administration; funding acquisition. Ayse Ceren Sen: writing – original draft; investigation; visualization; validation. Osman Erdem Kestioglu: conceptualization; methodology; software; formal analysis; resources; data curation.

## Conflicts of interest

There are no conflicts to declare.

## Data availability

The data supporting the findings of this study are included within the article and its supplementary information (SI). Additional data are available from the corresponding author upon reasonable request.

Supplementary information is available. See DOI: https://doi.org/10.1039/d6ew00015k.

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