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RESEARCH

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Reduction of greenhouse gas emissions by optimizing the textile dyeing process using digital twin technology

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Abstract

Owing to global warming and pollution concerns, reducing the environmental footprint of the textile and fashion industry has received considerable attention. Within this industry, the dyeing and finishing processes contribute significantly to greenhouse gas emissions and water pollution. This study introduces an innovative approach to address these challenges by leveraging digital twin technology to optimize the textile dyeing process. A smart analysis module was developed to continuously monitor and analyze the dyeing parameters in real time to implement control actions to automatically reduce the process duration. Integrated with this module, a digital twin of the dyeing machine enabled the real-time monitoring of energy consumption and process parameters. A case study comparing the traditional dyeing process with the optimized process was conducted. The results showed that dyeing time was reduced by ~ 17.5% without compromising dyeing quality. Energy consumption and greenhouse gas emissions were also reduced by ~ 12.1% when using the optimized process. This study offers a practical and sustainable option for textile dyeing, particularly for small and medium-sized enterprises.

Keywords: Textile dyeing, Digital twin technology, Greenhouse gas emissions, Sustainability, Process optimization

Introduction

In recent years, the global environmental crisis, driven by global warming and rapidly changing climates, has brought sustainability to the forefront of the textile and fashion industries (Diabat et al., 2014; Roy et al., 2020). The fashion and textile industry is widely recognized as one of the primary contributors to global pollution (Desore & Narula, 2018). Estimations indicate that the fashion industry alone contributes ~ 10% of global carbon emissions, whereas dyeing and finishing processes within textile production are responsible for ~ 20% of global water pollution (European Parliament, 2020). While the textile industry is not typically energy-intensive, the manufacturing of final products involves a lengthy process chain that consumes a significant amount of energy (Hasanbeigi & Price, 2012). Notably, the dyeing and finishing processes, which are wet processes, consume substantial energy through steam and water; thus, these processes are the largest energy and water consumers in the textile industry (Farhana et al., 2022). Consequently, the dyeing and finishing processes constitute the largest emitters of greenhouse gases (2021) within the garment value chain (Sharpe et al., 2022).

Numerous studies are underway to develop eco-friendly dyeing methods that can mitigate the energy, water, and pollution associated with the dyeing processes. One such innovation is supercritical carbon dioxide dyeing, an anhydrous dyeing technique that eliminates the need for water as a carrier by employing supercritical CO_2 at high temperatures and pressures to dissolve the dyes. Additionally, this method reduces dyeing time because of the high dispersion of supercritical CO_2 (Banchero, 2020). Furthermore, this approach saves energy because the drying process is not required (Kim et al., 2019). However, note that this method faces challenges when dyeing hydrophilic fibers due to the hydrophobic nature of CO_2. Moreover, its practical implementation is challenging due to its relatively high initial setup costs (Goñi et al., 2021).

Another eco-friendly dyeing technique is cold pad-batch dyeing, which is particularly suitable for dyeing cellulosic textiles using reactive dyes. This method involves impregnating textiles with a dye at temperatures nearly equivalent to room temperature, thereby eliminating the need for high-temperature dyeing. Dyeing is achieved by passing textiles through a dye bath and pressing them through a dye padder. This process minimizes water and energy consumption (Khatri et al., 2011). However, this process is time-consuming and has potential limitations related to uneven dyeing (Khatri et al., 2014).

Dyeing with bio-dyes is an alternative approach to synthetic dyes, which contribute to water pollution. Bio-dyes go beyond the use of natural plant and animal pigments by identifying the color genes produced by natural organisms, transforming them into microorganisms, incubating them, and utilizing them as dyes (CORDIS, 2022). The dyeing process using bio-dyes involves no chemicals and generates no toxic waste. Nevertheless, bio-dyes have certain limitations in terms of color fastness and consistency (Saxena & Raja, 2014).

These alternative dyeing methods are limited by the selection of dyes suitable for the dyeing process and the variety of textiles that can be dyed. Furthermore, substantial investment is required to establish and manage facilities for these new processes. Notably, the textile industry primarily comprises small- and medium-sized enterprises (SMEs) (Vajnhandl & Valh, 2014). Thus, implementing alternative dyeing methods is challenging. Therefore, techniques that can be applied to SMEs without significant investments must be developed. Furthermore, these techniques should afford a concurrent reduction in energy consumption and wastewater generation. In this regard, this study developed a smart analysis module tailored to SMEs.

In this study, we aimed to address the environmental challenges faced by the textile and fashion industry, with a particular focus on the dyeing and finishing processes, which contribute significantly to greenhouse gas emissions and water pollution. The primary objective was to optimize the textile dyeing process using digital twin technology. In particular, we targeted cotton fibers, a widely used natural material with a complex reactive dyeing process and the highest incidence of dyeing defects. A smart analysis module was developed to continuously monitor and analyze the dyeing parameters in real-time, allowing the dyeing time to be reduced automatically. This module was integrated with a digital twin of the dyeing machine, allowing real-time monitoring of energy consumption and process parameters. Finally, the effectiveness of the smart analysis module and digital twin in reducing energy consumption and GHG emissions was validated through a case study.

Methods

Development of a smart analysis module for dyeing process optimization

As shown in Fig. 1, the dyeing process can be divided into pretreatment, dyeing, and washing stages. Different types of dyeing assistants and dyes are incorporated according to the process, and the dyeing characteristics vary depending on the method and quantity of the dyeing. Dyeing conditions such as the pretreatment conditions of the fabric, dye recipe, dyeing temperature, and dyeing time significantly affect the bonding and reaction rate between the dye and the fiber. In addition, the color of the dyed fabric depends on the amount of dye adsorbed. In general, the color of the dyeing outcome is determined after completing the dyeing process and not during the process. In contrast, real-time measurement technology for monitoring the dyeing behavior based on data collected during the dyeing process is primarily employed at the laboratory level (Kim et al., 2022).

Measuring and analyzing factors, such as pH, during the pretreatment process enables the identification of the optimal endpoint for washing, thereby conserving water by reducing the number of wash cycles. Moreover, during the dyeing process, energy consumption can be reduced by monitoring and analyzing factors such as the exhaustion rate and pH. These data help determine the ideal time for adding dyeing assistants and completing the process, thereby reducing the overall dyeing time. Similarly, in the post-dyeing washing phase, water consumption can be minimized by monitoring pH and chromaticity, reducing the number of wash cycles.

Figure 2 shows the development of a data-collection device for measuring the dyeing parameters. This device was designed to capture real-time data on dye- exhaustion rates, chromaticity, and pH levels. The data-collection device for dyeing parameters comprises (1) a circulation pump responsible for extracting the dye liquor from the dyeing machine and recirculating it, (2) a spectroscopic analyzer for measuring the spectrum and reflectance of the dye liquor, (3) a pH sensor for measuring the pH of the liquor, and (4) a thermosensitive valve, which safeguards the pH sensor from high-temperature dye liquors. Finally, a communication controller was used to collect the measured data.

Data regarding the exhaustion rates and chromaticity were obtained through the real-time analysis of the spectrum and reflectance of the dye liquor. In particular, by measuring the dye-exhaustion rates, various dyeing parameters, such as the dyeing time (min), dyeing speed (%/min), and compatibility index, could be determined. Consequently, optimal conditions for the washing process were established by comparing the color difference (ΔE) between the target and batch colors using information from chromaticity measurements. the concept of color difference is a way to measure and quantify how similar or different two colors are by taking into account factors like their brightness (L^*), redness or greenness (a^*), and yellowness or blueness (b^*), with ΔE representing the overall difference between the target and batch colors; this information is crucial for establishing the ideal conditions for a dyeing process, based on how closely the batch matches the target color, and it's determined by analyzing the spectral and reflective properties of the dye liquor in real-time, as

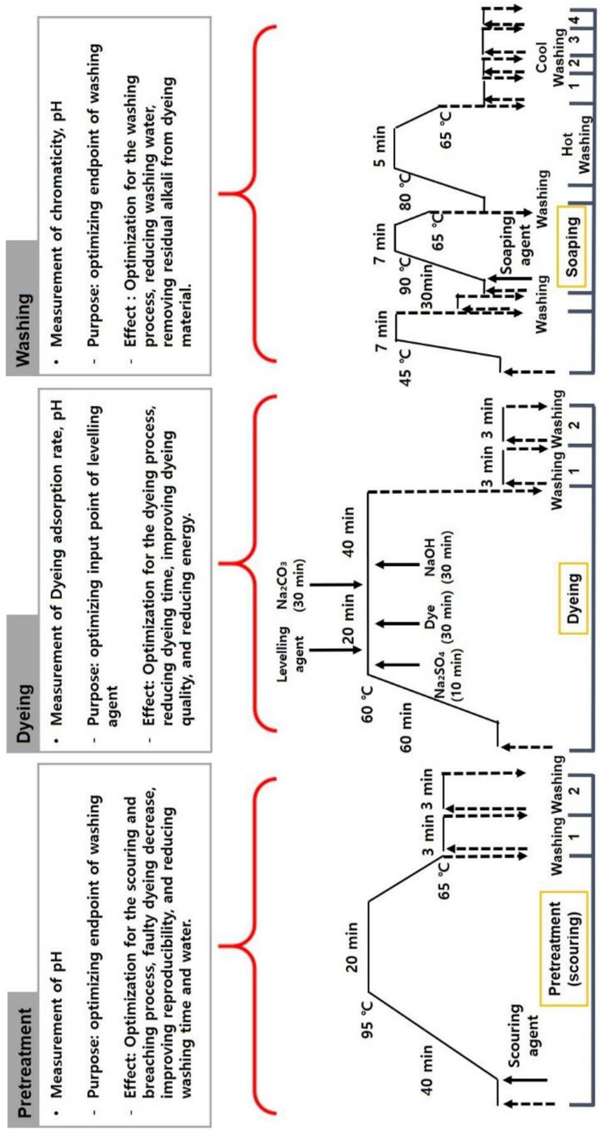

Fig. 1 Overview of the dyeing process

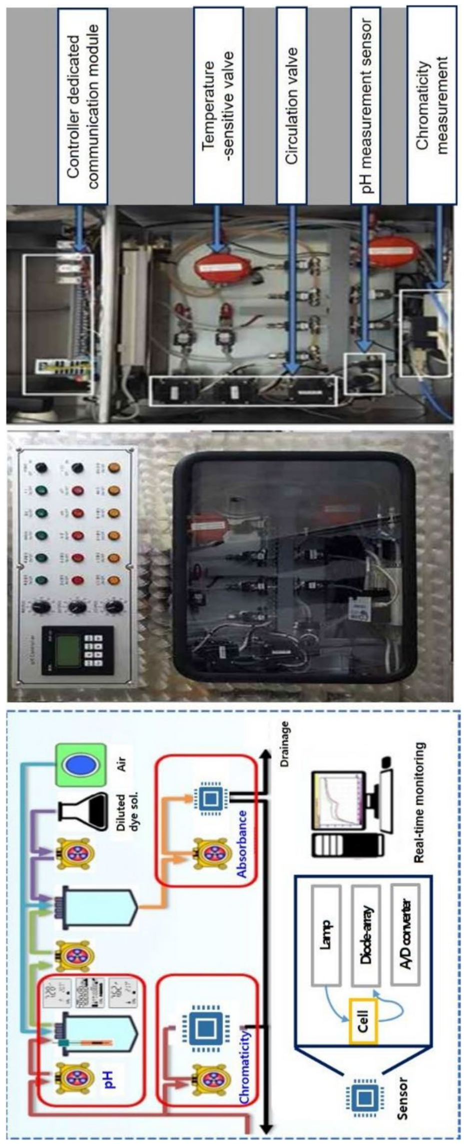

Fig. 2 Developed device for collecting dyeing parameters

well as monitoring dye-exhaustion rates and various dyeing parameters like time and speed. The pH measurement sensor was linked to a thermos-sensitive valve, which automatically halted dye-liquor circulation when the dyeing temperature surpassed 80 °C, protecting the measurement sensor.

The dyeing process using reactive dyes is illustrated in Fig. 3. During the adsorption phase, dye molecules adhere to the cotton fabric, and Glauber's salt is introduced to enhance the interaction between the fiber and the dye, thereby increasing dye adsorption within the fiber (Ahmed, 2005). This step is referred to as the primary exhaustion. Subsequently, after adsorption onto the fiber surface, the dye diffuses into the fiber, which swells due to water, and re-adsorbs onto the surface of the amorphous region (Peters & Inggamells, 1973). At this stage, some of the hydroxyl groups (OH) in the fibers dissociate in water and ionize the fiber surface, leading to electrostatic repulsion with the dye-containing anions. Glauber's salt, acting as a dyeing assistant, mitigates the electrostatic barrier between the fiber and dye, thereby overcoming the repulsion and facilitating the action of van der Waals forces (Burkinshaw, 1995). This also reduces the solubility of the dyes. Therefore, Glauber's salt aids dye access to the fiber surface and enhances dye adsorption. In the subsequent reaction phase, the exhausted dye molecules and fibers were covalently bonded upon adding an alkali. Simultaneously, the dye molecules in the liquor are adsorbed onto the fibers, and the newly exhausted dye molecules are fixed by covalent bonds (Huang & Yu, 1999; Peters & Inggamells, 1973). This step is known as secondary exhaustion.

The addition of alkali increases the amount of O- within the fiber, leading to fixation. However, increasing the amount of O- in water can also trigger hydrolysis of the dyes (Benz, 1961). Consequently, adding an appropriate alkali concentration is crucial because the pH of the dye liquor changes depending on the type and quantity of the alkali, and a higher pH accelerates the reaction. Optimal results can be achieved by adding an alkali at the point where the primary exhaustion equilibrium is reached after introducing Glauber's salt, facilitating a reaction between the dye and fiber during the maximum adsorption phase, enhancing fixation efficiency, and achieving more uniform dyeing. Adding alkali immediately upon reaching the exhaustion equilibrium point can expedite the process by reducing unnecessary time consumption.

In this study, an algorithm was developed to control the dyeing process by analyzing real-time exhaustion rate data. In the graph of the collected exhaustion rate data, the primary exhaustion equilibrium occurred when the dye molecules were optimally adsorbed onto the fiber. However, some of the maximally adsorbed dye molecules desorbed from the fiber over time, slightly decreasing the adsorption rate. Hence, based on the current time point 't,' the algorithm calculates the slope (Eq. 2) of a simple linear regression (Eq. 1) for the exhaustion rate data collected at times 't,' 't – 1,' 't – 2,' and 't – 3.' The algorithm identifies the time point 't' when the slope turns negative as the point for alkali injection. The same method was used to determine the endpoints of the dyeing process.

$$\widehat{y} = \beta_0 + \beta_1 x, \tag{1}$$

$$\beta_1 = \frac{\sum_{t-3}^{t}(x-\overline{x})(y-\overline{y})}{\sum_{t-3}^{t}(x-\overline{x})^2}, \tag{2}$$

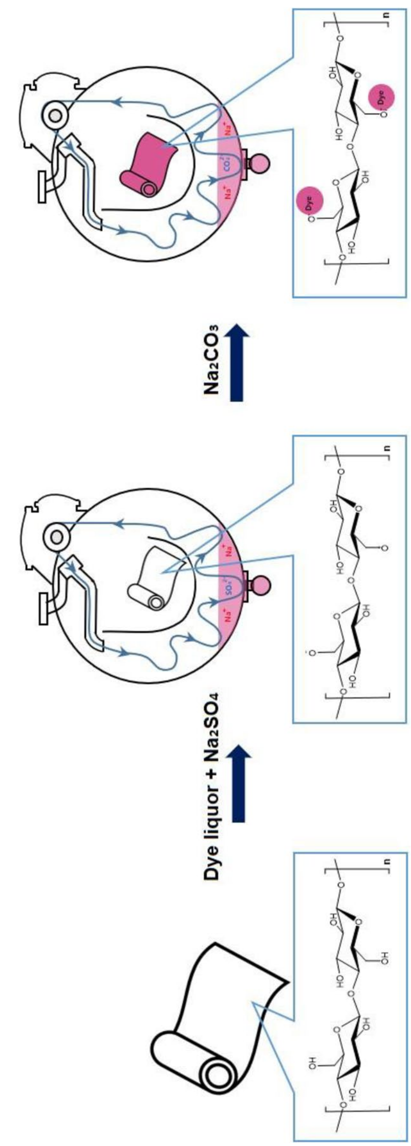

Fig. 3 Schematic diagram of the dyeing process using reactive dyes

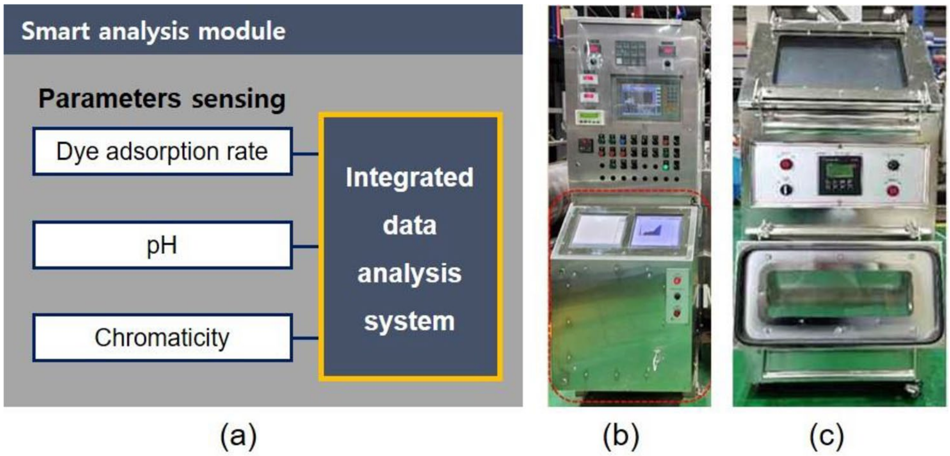

Fig. 4 Smart analysis module (**a**) structure, (**b**) all-in-one, and (**c**) standalone

where, $\widehat{y}$, β_0, and β_1 are the predicted value of y, intercept, and slope. And $\overline{x}$, and $\overline{y}$ are the mean of the independent and dependent variables.

As depicted in Fig. 4a, a data-collection device for dyeing variables and a smart analysis module were developed. This automatically controllable device was combined with an integrated data analysis system for sensing and measuring dyeing parameters and subsequently analyzing data to calculate the timing of the assistant injection and the washing endpoint. Both integrated and standalone smart analysis modules were developed. The integrated type (Fig. 4b) can be installed in the control devices of various dyeing machines. The standalone type (Fig. 4c) can be connected to the dyeing machine and dye liquor–circulation line.

Development of a digital twin system for real-time monitoring

Digital twin technology is pivotal in developing smart factories (Kim et al., 2020; Lu et al., 2020; Qi & Tao, 2018). A digital twin is a virtual representation of a physical system that continually updates itself using data obtained from its physical counterparts (Schleich et al., 2017; VanDerHorn & Mahadevan, 2021). In manufacturing, a digital twin is not limited to simulation. Instead, it can monitor, control, diagnose, and even predict the behavior of the physical system (He & Bai, 2021; Negri et al., 2017). Various manufacturing sectors have embraced digital twin technology, with major companies, such as Lockheed Martin, Siemens, and GE, integrating it into their production processes (Zhang & Zhu, 2019). Nevertheless, few studies have focused on applying digital twin technology in the traditional textile and apparel industries (Alam et al., 2023; Kim et al., 2020; Zhang et al., 2022). While some research on digital twin technology has focused on textile dyeing, current research has primarily considered the digital twin as part of the implementation methodology for a service-oriented platform (Park et al., 2019). In this study, we introduced a digital twin architecture designed for real-time monitoring of the dyeing process and its implementation.

Architecture

To precisely replicate the operational features of the 3D model and a pilot dyeing machine, we constructed an architecture that connects the workstation, server, and pilot machine, as depicted in Fig. 5. A program for interfacing big data was developed and connected to facilitate the collection and processing of various machine data, including the real-time status, measurement, quality, and macro and micro data, all in a standardized format. The web application server (WAS), which functions as an open-source platform for web and application services, and the relational database management system (RDBMS), which is dedicated to constructing the digital twin and linking macro data, are vital components of this architecture. Additionally, the remote dictionary server (Redis) enables the digital twin to animate machine operations in real time, whereas the big data acquisition (DAQ) server functions as a server for collecting and storing raw data.

Implementation

To enable the real-time monitoring of the dyeing process, we implemented a digital twin for the dyeing machine based on the architecture described above, as shown in Fig. 6. This digital twin was seamlessly integrated into a database, allowing the collection and monitoring of real-time data, including parameters such as electricity consumption, steam consumption, water consumption, nozzle pressure, pump speed, dyeing temperature, pH behavior, chromaticity, and exhaustion rate. Specific elements were incorporated for the direct control (Table 1).

Case study

A case study was conducted to validate the effectiveness of the smart analysis module and digital twin system in reducing energy consumption and GHG emissions. To conduct this case study, a smart analysis module was installed in a dyeing machine (iSMART1H30, Dong-a Dyeing Machinery, Korea) at a pilot plant. The dyeing machine and integrated smart analysis module were linked to the implemented digital twin. The real-time monitoring of the dyeing process was performed using the digital twin. Dyeing was conducted using both the current and new processes, employing identical materials and conditions. Subsequently, key parameters, such as the dyeing time, dyeing quality, energy consumption, and GHG emissions, were compared.

The textile used for dyeing was a 100% cotton knit fabric (Single 30S, Woosung Dyetech, Korea). Dyeing was conducted using Glauber's salt and alkali, with anhydrous sodium sulfate (Na_2SO_4) and anhydrous sodium carbonate (Na_2CO_3) as specific chemicals. A bifunctional reactive dye (Sunfix Red S3B, Ohyoung, Korea) was used. The dyeing conditions included a liquor ratio of 20:1 and a dye concentration of 1.0% owf (on the weight of fabric). The dyeing process is shown in Fig. 7. First, a 15 kg sample, dyes, and 50 g/L of Glauber's salt are added at 30 °C. After maintaining this mixture for 10 min, the temperature was gradually increased at a rate of 1 °C/min until it reached 60 °C. In the current process, 20 g/L of alkali was added at 60 °C, and the dyeing was completed in a 40 min reaction step. In contrast, in the new process, the smart analysis module controls the timing of the alkali addition and the endpoint of the dyeing process.

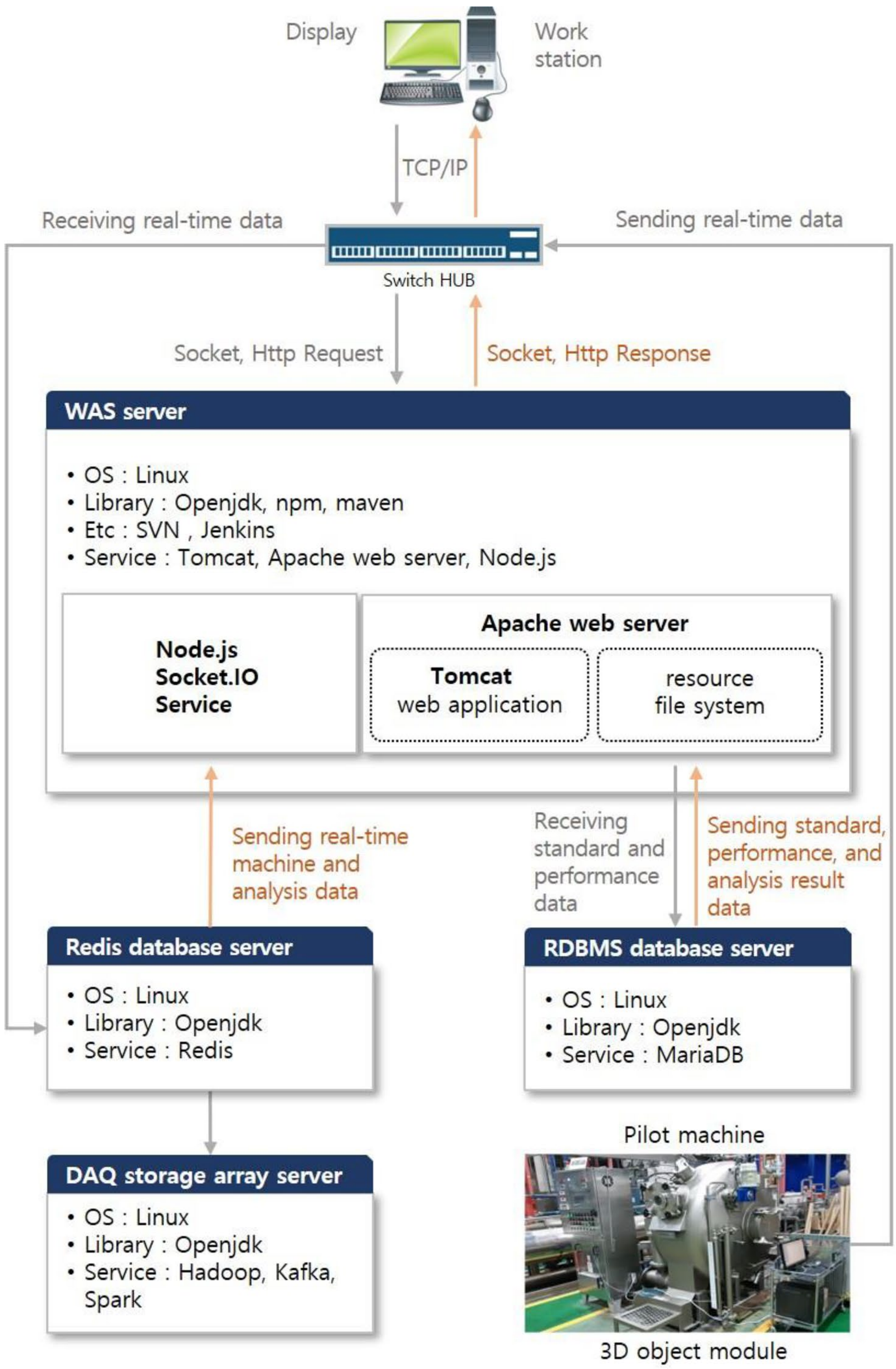

Fig. 5 Architecture of the digital twin

The dyeing quality was evaluated by measuring the color difference and washing fastness. The color difference between samples dyed using the current and new processes was compared; ΔEcmc was calculated following KS K ISO 105-J03:2009. ΔEcmc is the

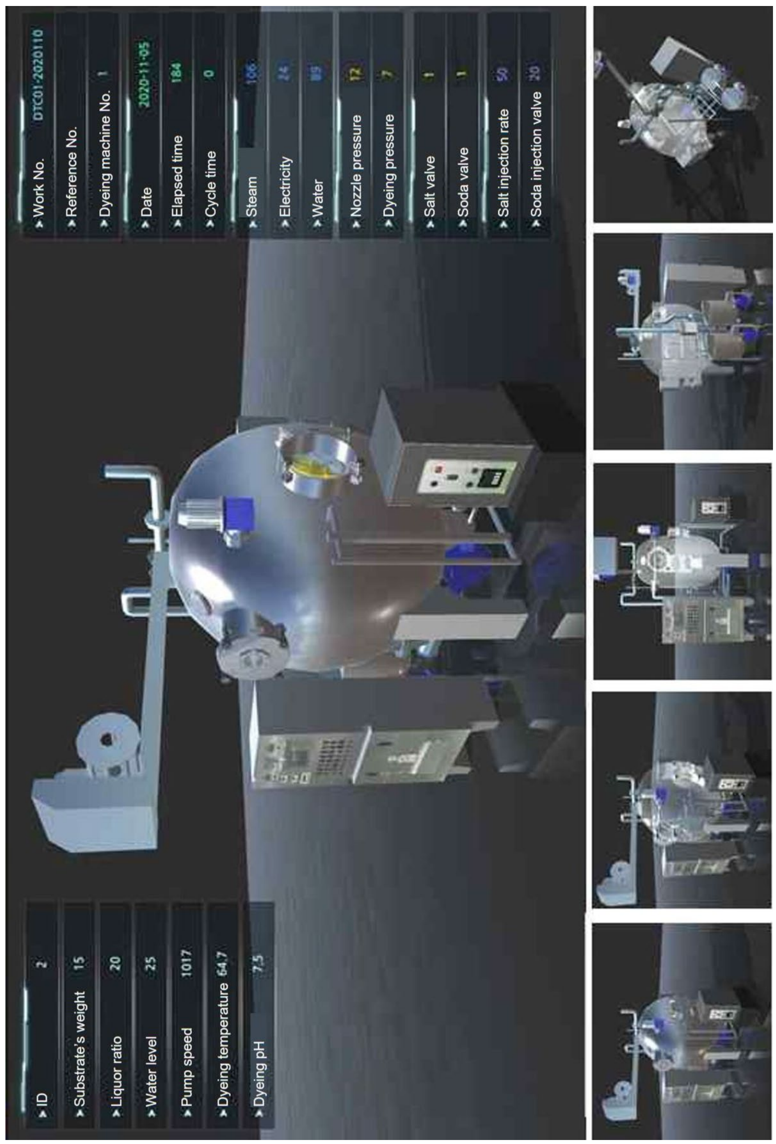

Fig. 6 Implementation of digital twin

Table 1 Real-time monitoring items of dyeing machine

Items	Monitoring	Control	Input/output[a]
Electricity consumption	○	–	DI
Steam consumption	○	–	DI
Water consumption	○	○	AI
Nozzle pressure	○	–	AI
Internal pressure	○	○	AI
Pump speed	○	○	AI
Reel speed	○	○	AI
Dyeing temperature	○	○	AI
pH behavior	○	○	AI
Acid valve for pH	○	○	DI/DO
Alkaline valve for pH	○	○	DI/DO
Chromaticity	○	–	–
Exhaustion rate	○	–	–
Glauber's salt injection behavior	○	–	AI
Glauber's salt injection valve	○	–	DO
Soda injection behavior	○	○	AI
Soda injection valve	○	○	DO

[a] *DI* digital input, *DO* digital output, *AI* analog input

color difference formula recommended as a standard by the color measurement committee (CMC) of the society of Dyers and Colorists of Great Britain. In particular, ΔEcmc uniformly measures color differences based on the CIELAB color space, and has been adopted and widely used as a standard by the British Standard, AATCC test method, and ISO. Measurements were conducted using a CM700d device (Konica Minolta, USA), operating within a wavelength range of 400–700 nm, utilizing D65/10 (without regular reflection) as the light source and applying CMC (2:1), primarily used for textile products. Washing fastness tests were performed on samples dyed with both processes, following KS K ISO 105-C06:2010 and A2S standards (washing temperature: 40 ± 2 °C; washing time: 30 min; ECE standard detergent). Finally, the results were compared.

Electricity and steam consumption during the current and new dyeing processes were monitored using a digital twin. GHG emissions were calculated based on Korea's 2021 GHG emissions factors (Table 2) by employing the IPCC 2006 guidelines for national greenhouse gas inventories to estimate indirect GHG emissions (Eggleston et al., 2006). The primary GHG considered were CO_2, CH_4, and N_2O, and their emissions were converted to carbon dioxide equivalents (CO_2eq) according to Eq. (3).

$$Emissions_{GHG} = \sum_{fuel} Fuel\ Consumption_{fuel} \times Emission\ Factor_{GHG,fuel}. \tag{3}$$

Results and Discussion

The exhaustion behavior of the current and new processes based on exhaustion rate data collected every 3 min using the dyeing parameter collection device was analyzed (Fig. 8). The results highlighted differences between both processes. In the current process, alkali

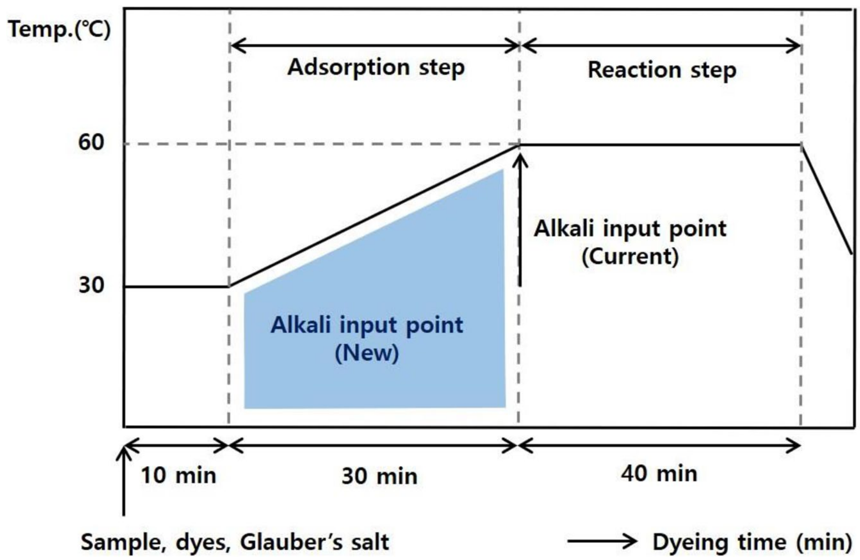

Fig. 7 Dyeing using the current and new processes of cotton knit fabric with reactive dye

was added 40 min after starting the dyeing process. Conversely, the new process, aided by a smart analysis module, automatically introduces an alkali solution 24 min after the start of dyeing. Following the reaction step, the dyeing process was completed in 80 min for the current process and 66 min for the new process using the smart analysis module. Therefore, the new process reduced the dyeing time by 14 min compared with the current process. Additionally, after the dyeing process, the exhaustion rates of the current and new processes were 83.90% and 86.81%, respectively. These results demonstrate that the new process has a better exhaustion behavior, despite the reduced dyeing time. The primary exhaustion process may result in decreased the exhaustion rate after reaching equilibrium due to the free migration of the dye. However, the new process quickly identifies the equilibrium point and adds alkali through the smart analysis module, resulting in reduced dyeing time and improved exhaustion behavior.

Subsequently, we compared the dyeing qualities of the current and new processes. The comparison of the color difference between samples dyed with the current and new processes revealed no substantial differences, as the ΔEcmc (2:1) value was 0.31, which was less than 1. Additionally, washing fastness tests conducted on samples dyed using both processes showed no noticeable differences in washing fastness, with the samples achieving a rating of 4–5 grade for the color change and staining (cotton and wool) (Table 3). The results show that there are no significant differences in dyeing quality between the

Table 2 Greenhouse gas emissions factor (Greenhouse Gas Inventory & Research Center of Korea, 2021)

Items	Data sources	Unit	Emissions factor			
			CO_2 ($kgCO_2$/unit)	CH_4 ($kgCH_4$/unit)	N_2O (kgN_2O/unit)	Total ($kgCO_2eq$/unit)
Electricity	Consumption	MWh	474.7	0.0125	0.0100	478.1
Steam	Consumption	TJ	35,396	0.6534	0.0661	35,970

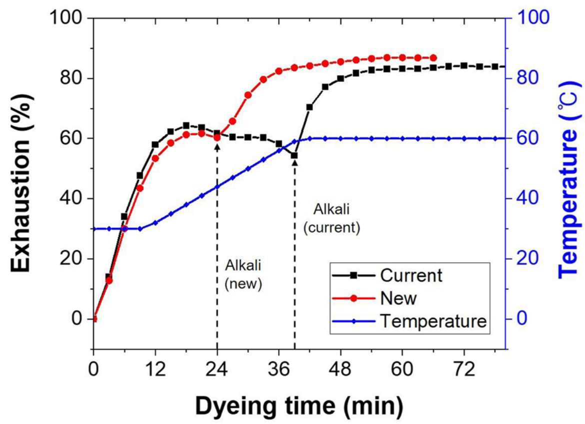

Fig. 8 Exhaustion behavior of the current and new dyeing processes

Table 3 Washing fastness of the current and new processes

Process	Washing fastness (grade)		
	Color change	Color staining	
		Cotton	Wool
Current	4–5	4–5	4–5
New	4–5	4–5	4–5

samples dyed using the current and new processes, despite the reduction in dyeing time. This confirms that the developed smart analysis module is capable of reducing unnecessary time consumption while maintaining dyeing quality in the reactive dyeing process.

The energy consumption and GHG emissions of the current and new processes are presented below, as monitored by the digital twin. Electricity consumption for both processes was 2.5 kWh and 2.2 kWh, respectively, representing a reduction of ~ 12.0% in electricity consumption when using the new process compared to the current process. Similarly, steam consumption for both processes was 27.2 kg and 23.9 kg, respectively, reducing by ~ 12.1% in steam consumption for the new process. When converting energy consumption data into GHG emissions, the GHG emissions for the current and new processes were 3.534 $kgCO_2eq$ and 3.107 $kgCO_2eq$, respectively. Consequently, the new process reduced GHG emissions by ~ 12.1% compared with the current process. This reduction was achieved by reducing the total dyeing time, which resulted in a reduction in the operating time of the dyeing machine. The new process reduces the dyeing time by 17.5% compared with the current process, resulting in a reasonable reduction of ~ 12.1% in total energy consumption and GHG emissions.

Conclusions

In this study, we developed a smart analysis module to reduce energy consumption and GHG emissions during the dyeing process. The smart analysis module enhances the dyeing process by continuously sensing and analyzing the parameters of the dye liquor and then automatically adjusting the process based on this analysis. Additionally, we implemented a digital twin to monitor the dyeing process and integrated it into a smart analysis module. This integrated system was installed on a dyeing machine in a pilot plant, and a case study was conducted with dyeing performed under both current and new processes, utilizing identical materials and conditions.

The new process reduced the dyeing time by ~ 17.5% compared with the current process. The ΔEcmc (2:1) value obtained from samples dyed using the current and new processes was 0.31, indicating no significant difference in color quality between the two processes. Furthermore, testing revealed no notable disparity in washing fastness between samples dyed using the current and new processes, achieving a rating of 4–5 grade for color change and color staining.

Regarding energy consumption, the current process required 2.5 kWh of electricity and 27.2 kg of steam, while the new process required 2.2 kWh of electricity and 23.9 kg of steam. In terms of GHG emissions, the current process emitted 3.534 $kgCO_2eq$, whereas the new process emitted 3.107 $kgCO_2eq$. Consequently, the integrated digital twin system reduced by ~ 12.1% the energy consumption and GHG emissions during the dyeing process.

The smart analysis module developed in this study was designed as a modular system for easy installation in existing dyeing machines in factories. Therefore, this module can be readily applied to SMEs without difficulty. Meanwhile, this module was optimized for dyeing process using reactive dyes. In future research, our objective is to further reduce wastewater generation by minimizing the number of washing cycles through analysis of pH and chromaticity data collected during the washing process. Additionally, we aim to enhance the optimization of the dyeing process by collecting data on the dyeing parameters and analyzing it as big data.

Abbreviations

GHG	Greenhouse gases
SMEs	Small- and medium-sized enterprises
WAS	Web application server
RDBMS	Relational database management system
Redis	Remote dictionary server
DAQ	Data acquisition
CMC	Color measurement committee

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Author contributions
MK was a major contributor in writing the manuscript. JYS conceptualized and reviewed the entire research. SL drafted the manuscript. HL developed the digital twin system. SCK developed the smart analysis module. SH designed the entire research and performed the experiment. SR designed the entire research and drafted the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
Not applicable.

Declarations

Ethics approval and consent to participate
Not applicable

Competing interests
The authors declare that they have no competing interests.

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