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DriniChlor: Towards a Data-driven and Adaptive Chlorination Process in Drinking Water Treatment Systems

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Abstract

This study presents the development of an automated system for the management and monitoring of water quality using the *Python* programming language, focusing on optimising chlorine dosage in water disinfection processes. The proposed module, named *DriniChlor*, utilises sensors to measure key water parameters such as temperature, dissolved oxygen, and turbidity. The collected data were analysed in real-time to determine the optimal chlorine dosage, ensuring maximum safety and efficiency. The integration of such technologies offers an innovative approach that not only improves water quality but also reduces operational costs and environmental impact. Results indicate that the system is effective in enhancing water treatment processes and is suitable for application in various treatment plants. This development represents a significant step toward the use of automated technologies for the sustainable management of water resources.

Keywords

Process control engineering, Python, automated water treatment system, chlorine dosage optimisation

1 Introduction

Modern engineering calculations are hard to imagine without a flexible and efficient programming language. *Python* is such a language – it is open-source, free, easy to learn, and simple to use.[1] *Python* code that is specialised and optimised for specific applications can be easily reused across projects through modular *Python* packages. The flexibility and portability of the language, combined with its intuitive syntax and extensive open-source libraries, make *Python* an appealing tool for scientific computation in chemistry and chemical engineering. Its accessibility across major operating systems allows researchers to execute and share code seamlessly, promoting reproducibility and interdisciplinary collaboration. The interpretive nature of *Python* further simplifies algorithmic development, offering a balance between computational power and user-friendliness.[2,3]At the same time, the amount and value of data are increasing significantly, along with advancements in data analysis and information extraction techniques.[4] Scientists are increasingly developing programs that automate and simplify scientific tasks, especially in fields such as chemical engineering.[5]

Monitoring water quality aims to provide regular information on drinking water safety and to assess the efficiency of treatment and disinfection processes in line with national regulations. With population growth, the demand for safe water has also increased, encouraging the integration of automatic control systems in water treatment facilities.[6] Chemical processes, being dynamic in nature, require continuous monitoring of parameters such as temperature, NTU, electrical conductivity, and pH.[7,8]

Water resource management requires close cooperation with technology to ensure the sustainable and equitable use of water resources.[9] Every industrial chemical process aims for the economic production of a specific product through various processing stages, where equipment plays a crucial role in the economic performance of the process.[10] The use of sensors in water treatment plants is essential for the development of a Python-based module that enables real-time reading and processing of parameters such as chlorine, DO, temperature, and NTU. The collected data is analysed and visualised using *Matplotlib* to ensure efficient monitoring (see Fig. 1). A functional implementation of this module, named *DriniChlor*, has been developed by the author and is available as open-source code for download on *GitHub*.[11]

The goal is to adjust the chlorine dosage in real time based on temperature changes, replacing current practices that use a fixed dose. This approach increases efficiency and reduces environmental impact, thereby enhancing sustainability in modern water treatment.

2 State of the field

Recent advances in water treatment technologies have increasingly focused on automation, data-driven control, and intelligent monitoring systems. The integration of digital tools and programming languages such as *Python* has allowed for the development of flexible, open-source platforms capable of processing real-time sensor data for water quality assessment.

Modern systems typically combine sensors for temperature, DO, NTU, and residual chlorine, providing continuous feedback to optimise disinfection and operational efficiency.

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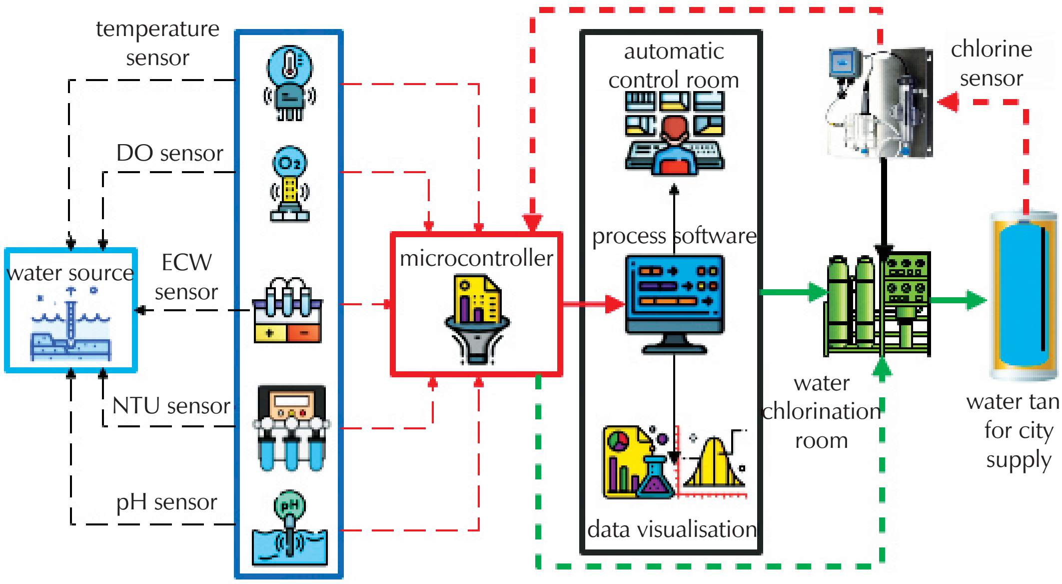

Fig. 1 – Automated system for optimising chlorine dosing in drinking water based on physicochemical parameters (source: own study)
Slika 1 – Automatizirani sustav za optimizaciju doziranja klora u vodi za piće na temelju fizikalno-kemijskih parametara (izvor: vlastito istraživanje)

Several studies have highlighted the importance of real-time data visualisation and adaptive control in minimising chlorine consumption and by-product formation, thereby improving sustainability and reducing environmental impact.

Despite these advances, most existing applications remain limited to static or semi-automated control schemes, lacking fully integrated solutions that combine sensor analytics, predictive algorithms, and real-time decision support.

Therefore, there is a growing need for modular and adaptive systems capable of linking physical measurements with algorithmic intelligence to achieve optimised chlorine dosing and sustainable water treatment operations.

3 Functionality

3.1 SCADA/PLC integration and control implementation

3.1.1 System architecture

The implementation integrates online analysers for turbidity (AMI Turbitrace, ISO 7027 compliant), pH (AMI pH/Redox), and auxiliary transmitters for DO and temperature with a PLC/RTU and the *DriniChlor* software module (*Python*). Fig. 2 (block diagram) summarises the data path:

Sensors/Analysers → (4–20 mA or RS-485/Modbus RTU) → PLC/RTU → (OPC-UA/Modbus TCP) → SCADA HMI & DriniChlor → (analog 4–20 mA/DO) → Chlorine dosing actuator.

The analysers provide (i) measurement outputs (4–20 mA or Modbus registers), (ii) alarm relays (fault/maintenance), and (iii) service interfaces (USB/logger). The PLC aggregates signals and enforces interlocks; SCADA displays process status; *DriniChlor* computes the recommended CDW and writes it to the PLC when Auto mode is enabled.

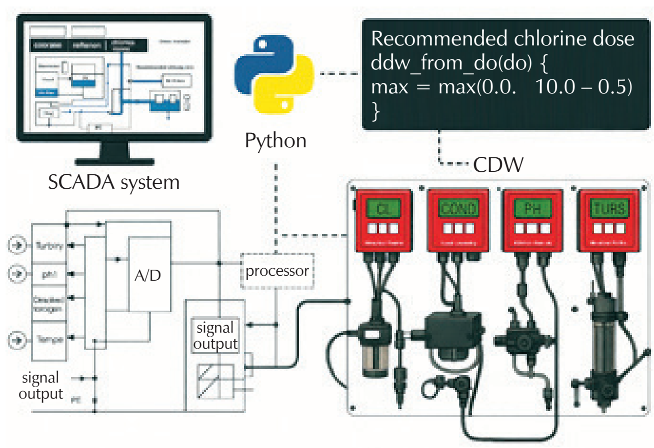

Fig. 2 – System architecture and experimental integration of the *DriniChlor* adaptive chlorination control system with SCADA and online analysers (source: own study)
Slika 2 – Arhitektura sustava i eksperimentalna integracija adaptivnog sustava za kontrolu kloriranja *DriniChlora* sa SCADA-om i mrežnim analizatorima (izvor: vlastito istraživanje)

3.1.2 Implementation snippet (Modbus TCP → PLC)

The following *Python* implementation demonstrates the communication workflow between the *DriniChlor* module and a PLC/SCADA system using the Modbus TCP protocol. A dedicated I/O session is established through the modbus_session class, which manages reading and writing of process variables (NTU, DO, temperature, and flow) from the analyser network.

The function combine_cdw() (Fig. 3) computes the recommended chlorine dose (CDW_rec) as a weighted combination of empirical sub-models for dissolved oxygen, temperature, and turbidity, incorporating safety constraints such as minimum/maximum limits and rate-of-change restriction.

Once calculated, the optimised set-point is written back to the PLC *via* write_cdw_setpoint(), where it is processed by the internal PID loop to generate the corresponding 4–20 mA control signal for the chlorine dosing pump.

This implementation provides a practical interface between the *DriniChlor* computational algorithm and industrial automation infrastructure, ensuring reliable real-time data exchange and adaptive process control consistent with SCADA/PLC communication standards (Modbus TCP, OPC-UA).

```python
from drinichlor.modbus_io import modbus_session
from drinichlor.chlorine_controller import combine_cdw

with modbus_session(host="192.168.x.xx", port=502, unit=1, endian=">f") as io:
    pv = io.read_process_values()                # NTU, DO, Temp, Flow
    sp = combine_cdw(do=pv["do"], tempC=pv["temp"], ntu_in=pv["ntu"],
                     w_do=0.4, w_temp=0.3, w_ntu=0.3,
                     sp_min=0.5, sp_max=5.0, rate_limit=0.2, last_sp=None)
    io.write_cdw_setpoint(sp) # PLC PID drives 4–20 mA to the dosing pump
```

Fig. 3 – *Python* code snippet showing Modbus TCP communication between the *DriniChlor* module and the PLC for real-time chlorine dosage control (source: own study)

Slika 3 – Isječak *Python* koda koji prikazuje Modbus TCP komunikaciju između *DriniChlora* modula i PLC-a za upravljanje doziranjem klora u stvarnom vremenu (izvor: vlastito istraživanje)

3.2 Installing the DriniChlor package

DriniChlor is a *Python*-based library developed to optimise chlorine dosing in drinking and technical water by integrating physicochemical parameters such as temperature, DO, and NTU. The package can be installed directly from the Python Package Index (PyPI) and imported into any *Python* environment. Once installed, the module provides functions for real-time data acquisition, CDW, and adaptive control based on process variables. Detailed installation and user documentation are available in the project's official repository.[11]

3.3 Formulation and implementation of chlorine dosage algorithms based on physicochemical indicators

Formulas for CDW based on DO and NTU have been developed to optimise the water disinfection process. However, these formulas may vary depending on specific conditions and are not universal. The following empirical formula was developed by the author to illustrate the inverse dependence of chlorine demand on DO, as suggested by trends reported in the literature.[12,13]

$$C_{DO} = \max(0.1 - 0.5 \times DO) \quad (1)$$

10 g l^{-1} is the maximum chlorine concentration that might be required for water disinfection, 0.5 is a factor indicating how rapidly chlorine is consumed based on the level of DO, and DO is the concentration of dissolved oxygen in water, usually measured in mg l^{-1}.

This simplified empirical model (Eq. (1)) was used to illustrate the relationship between dissolved oxygen concentration and chlorine consumption in drinking water. This formula was conceptually developed following the methodological principles described in the California State Water Resources Control Board (2018) guidelines, which provide practical examples of chlorine dosing under diverse water quality conditions.

This suggests that, for every 1 mg l^{-1} increase in DO, the chlorine dose is reduced by 0.5 mg l^{-1}, reflecting that water with higher DO may require less chlorine for disinfection.

Similarly, for NTU and temperature, an empirical expression can be proposed as:

$$\text{CNTU, temp} = \max(0, 5 + 0.2 \times (\text{NTU\_outlet} - \text{NTU\_inlet}) - 0.1 \times \text{temp}) \quad (2)$$

NTU_outlet and NTU_inlet represent the turbidity levels at the inlet and outlet of the treatment system, respectively. The coefficient 0.2 is an empirical factor indicating the effect of turbidity variation on chlorine demand, while 0.1 represents the inverse influence of temperature.

This simplified empirical model was developed by the author to illustrate how combined variations in turbidity and temperature can influence chlorine consumption in water treatment systems. Although this equation is not directly adopted from existing standards, it is conceptually based on relationships described in the Standard Methods for the Examination of Water and Wastewater[12] and on the kinetic considerations of chlorine reactions discussed in WHO Guidelines for Drinking-Water Quality[13]. These studies emphasise that both particle load turbidity and temperature significantly affect chlorine demand and reaction kinetics in aqueous systems.

Therefore, Eq. (2) is introduced as a demonstrative, data-driven approximation, designed for educational and analytical purposes, and intended to be calibrated with real experimental or field data in future work. For practical applications, it is recommended to consult local standards and scientific literature for specific guidance on chlorine dosing depending on water parameters.

Formulas for chlorine dosing based on parameters such as DO and NTU have been developed to optimise the water disinfection process. These formulas are based on various studies and practices in the field of water treatment.

For example, a study by *Hua and Reckhow*[14], explores the factors that influence disinfection by-product formation during chlorination, including the impact of parameters like DO and NTU.

Additionally, the *Standard Methods for the Examination of Water and Wastewater* of the American Public Health Association (APHA) provide detailed guidance on chlorine dosing procedures based on various water parameters. It is important to note that these formulas and guidelines are the result of extensive studies and practices in the field of water treatment. However, they may vary based on the specific conditions of the water being treated. It cannot be stated that this research is universal for all water processing industries, whether public drinking water plants or sectors of the chemical and food industries that use water as a raw material in their production processes.

In our study, we identified such an adaptation of these formulas, which have been implemented in code to reflect specific conditions and to optimise the process for specific water treatment scenarios.

3.4 Summary and practical applications

The *Python*-based *DriniChlor* toolbox represents a practical example of integrating water quality monitoring with predictive control algorithms to optimise chlorine dosage in water treatment processes. This system combines real-time data acquisition from sensors with analytical models that determine the optimal chlorine dose based on key physicochemical parameters – temperature, DO, and NTU.

By automating the analysis of these parameters, the toolbox enhances operational efficiency, ensures consistent disinfection quality, and contributes to a more sustainable management of chemical consumption and environmental protection. The system's modular design allows it to be adapted for both laboratory simulations and industrial-scale treatment plants.

Temperature and DO are closely interrelated factors that significantly influence the efficiency of chlorination. As temperature increases, water's capacity to retain dissolved oxygen decreases due to the reduced solubility of oxygen molecules. In contrast, at lower temperatures, water can hold higher levels of DO, enhancing its oxidative capacity. This interplay directly affects the chemical reactions between chlorine and organic or microbial contaminants during the disinfection process.[15,16] At higher temperatures (above 20 °C), chlorine reacts faster with pollutants and microorganisms, achieving more rapid disinfection but also increasing the rate of chlorine decay. Therefore, slightly higher doses may be needed to maintain sufficient residual chlorine throughout the process. Conversely, at lower temperatures (below 10 °C), reaction kinetics slow down, requiring longer contact times or higher chlorine concentrations to achieve equivalent disinfection efficiency.[17,18]

Continuous monitoring of DO and temperature enables dynamic adjustment of chlorine dosage through the *DriniChlor* adaptive model, ensuring the right balance between disinfection effectiveness and chemical economy. In this way, the system contributes to safer, cost-effective, and environmentally sustainable water treatment operations.

4 Optimising chlorine dosing: avoiding underchlorination and overchlorination

Achieving a careful balance between the amounts of chlorine applied and environmental conditions – including temperature and DO concentration – is crucial. When temperatures are high and chlorine dosing is not adjusted accordingly, underchlorination may occur, where the chlorine level is insufficient to eliminate microorganisms, thereby compromising drinking water safety.[14]

Conversely, overchlorination occurs when the amount of chlorine exceeds the actual needs of the water, often due to neglecting temperature or low contamination levels. This not only results in unnecessary costs but can also lead to the formation of harmful by-products such as trihalomethanes (THMs) and haloacetic acids (HAAs), which have potentially carcinogenic effects.[19]

5 Scientific contribution

This research advances the field by developing an intelligent monitoring system in *Python* that integrates real-time data on temperature, DO, and NTU to optimise chlorine dosing (see Fig. 4). The system visually assesses the impact of temperature on chlorine reactivity and automates dosage adjustments based on environmental conditions.

Through experimental validation and case studies, this study demonstrates that chlorine efficiency can be maximised by correlating sensor data with disinfection response curves. This approach offers a practical, real-time solution for dynamic chlorine control in both surface and groundwater treatment processes. Therefore, the use of automated systems that measure temperature and DO in real time-such as the one implemented in the *EngineeringTool* platform – is essential for optimal chlorination management. These systems enable immediate decision-making for accurate chlorine dosing based on measured environmental parameters.

The impact of temperature on the optimisation of chlorine dosing in treated drinking water: In the water disinfection process, it is crucial that chlorine dosing is continuously aligned with changing environmental conditions, particularly water temperature. Water temperature directly influences the amount of chlorine required to ensure thorough and effective disinfection. This is due to the significant role that temperature plays in the chemical reactions of chlorine with organic and inorganic constituents present in water.

Dynamic chlorine dosing based on temperature: When the temperature of the water changes, the chlorine dose required for effective disinfection must also adjust accordingly. By installing a temperature sensor at the inlet of the treatment plant, it becomes possible to continuously monitor the water temperature and automatically regulate the amount of chlorine added. This automatic chlorine dosing adjustment ensures consistent disinfection throughout the treatment process, avoiding both underchlorination and overchlorination.

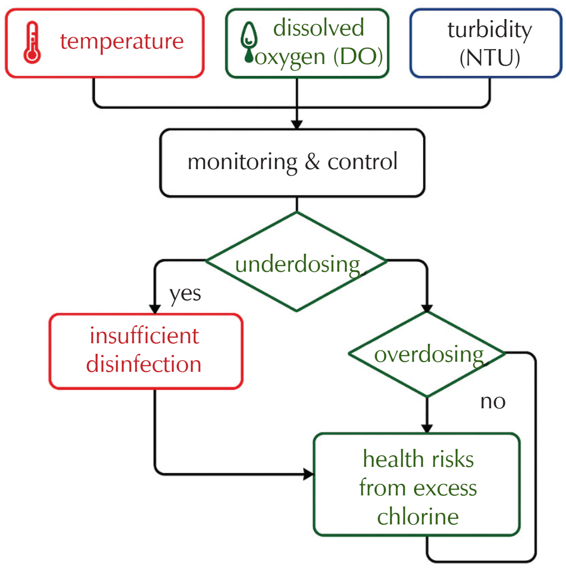

Fig. 4 – Flowchart of the *DriniChlor* engineering system, developed through the *EngineeringTool* interface, for determining the optimal chlorine dose in water (source: own study)

Slika 4 – Dijagram toka inženjerskog sustava pod nazivom *DriniChlor*, razvijenog putem sučelja *EngineeringTool*, za određivanje optimalne doze klora u vodi (izvor: vlastito istraživanje)

5.1 Benefits of temperature-controlled CDW

This approach offers several key advantages:

Chlorine savings: By adjusting chlorine levels based on temperature, chlorine consumption is optimised, using only the necessary amount for effective disinfection. This reduces chlorine overuse and lowers treatment costs.

Improved disinfection efficiency: Since chlorine dosing is always adapted to the current water temperature, the disinfection process achieves maximum effectiveness. At higher temperatures, chlorine reacts more rapidly with organic matter and microorganisms, resulting in a shorter required contact time for effective pathogen inactivation. However, due to the lower solubility and higher volatility of chlorine at elevated temperatures, a slightly higher initial dose may sometimes be necessary to maintain the desired residual chlorine concentration throughout the treatment process.[15,17]

Conversely, at lower temperatures, chlorine reactions occur more slowly, but the chemical remains more stable in solution. Therefore, a lower dosage can be used without compromising disinfection performance, reducing the risk of overchlorination and the formation of disinfection by-products.[18,20]

Effect on control of other parameters: This system can also be integrated with DO and NTU sensors to create a comprehensive dosing scheme that addresses all aspects of water quality. High temperatures are often associated with lower DO levels, which can also affect the required chlorine dosage. In this way, an intelligent water treatment system is established – one that automatically monitors and adjusts key water quality parameters (see Fig. 5).

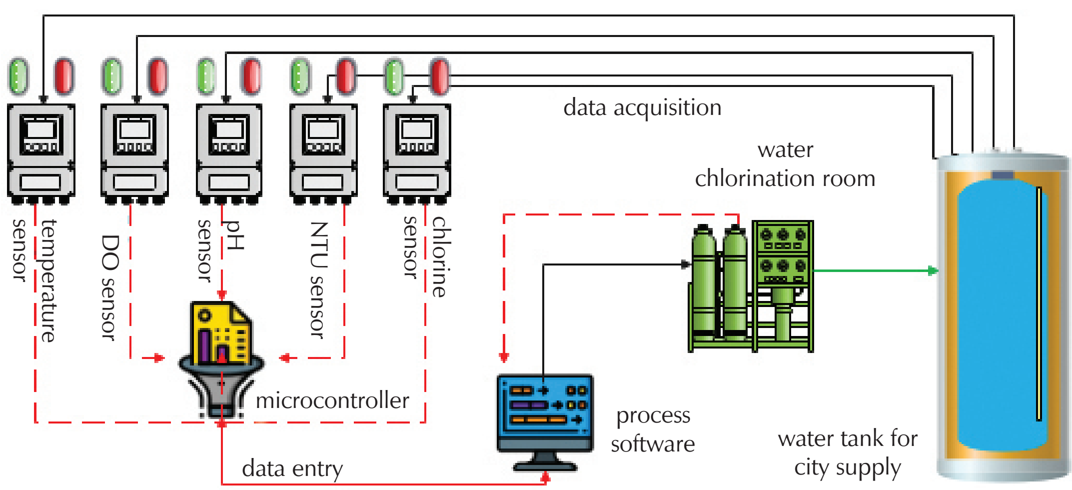

Fig. 5 – *DriniChlor* architecture in an automated system for chlorine dosing based on the physicochemical parameters of drinking water (source: own study)

Slika 5 – Arhitektura *DriniChlora* u automatiziranom sustavu za doziranje klora na temelju fizikalno-kemijskih parametara vode za piće (izvor: vlastito istraživanje)

5.2 Engineering tool for monitoring surface and groundwater quality: the DriniChlor system

In this research, a modular architecture based on the *Python* programming language was developed for modelling and simulating the behaviour of sensors used in water treatment systems. The Sensor class represents a virtual unit capable of reading, storing, analysing, and predicting data related to key physicochemical parameters of water such as DO, temperature, and NTU. The main objective of this model is to calculate and optimise the chlorine dosage required for effective disinfection, based on the real-time conditions of the water.

The *__init__* constructor initialises each Sensor object by assigning it a unique name and creating an empty list to store values obtained during the system's operation. The read_value() method generates simulated readings using a uniform distribution in the range [0, 14], representing possible sensor data (*e.g.*, DO in mg l^{-1}). These values are stored for subsequent analysis and serve as the foundation for prediction algorithms and process control. The model incorporates several analytical functions for determining the recommended chlorine level.

The first function estimates chlorine dosage as a function of DO concentration. It is modelled as a simple linear regression, in which each 1 mg l^{-1} increase in DO reduces chlorine demand by 0.5 mg l^{-1}, due to improved oxidative efficiency under higher DO conditions.

A second function determines the chlorine dosage as a function of water temperature. As temperature increases, chlorination kinetics improve, allowing for reduced dosage. For each 1 °C increase, chlorine requirement decreases by approximately 0.3 mg l^{-1}.

A third, more complex function considers the interaction between turbidity and temperature. The difference between outlet and inlet NTU represents filtration efficiency, while temperature has an inverse effect on chlorine demand. For every 1 NTU increase, the chlorine dose increases by 0.2 mg l^{-1}; for every 1 °C rise, the chlorine dose decreases by 0.1 mg l^{-1}.

The *predict_next()* method implements a simple moving average algorithm to predict the next measurement based on the last five recorded values. When insufficient data are available, the most recent value is used. This predictive mechanism stabilises the analytical results and improves the system's ability to handle sensor noise and unexpected measurement deviations (see the code in Fig. 6 and Appendix A). By combining these analytical and predictive modules, the system ensures robust control and adaptive decision-making in real time.

5.3 Engineering tool for monitoring surface and groundwater quality: the DriniChlor system

Our *Python* toolbox *DriniChlor* is an advanced tool for monitoring and optimising water quality. *DriniChlor* integrates specialised sensors and scientific algorithms to determine the optimal amount of chlorine for disinfection, based on parameters such as temperature and DO. The

```
class EngineeringTool(tk.Tk):
    def __init__(self):
        super().__init__()
        self.title("Monitoring Chlorine, Temperature, DO, and NTU")
        self.geometry("1600x800")

        self.chlorine_sensor = Sensor("Chlorine")
        self.do_sensor = Sensor("DO")
        self.temp_sensor = Sensor("Temperature")

        frame_graph = ttk.Frame(self)
        frame_graph.pack(side=tk.TOP, fill=tk.BOTH, expand=True)

        self.fig_chlorine, (self.ax_chlorine,
                            self.ax_do_temp_ntu) = plt.subplots(2, 1, figsize=(10, 8))
        self.canvas_chlorine = FigureCanvasTkAgg(self.fig_chlorine, master=frame_graph)
        self.canvas_chlorine.get_tk_widget().pack(side=tk.LEFT, fill=tk.BOTH, expand=True)

        frame_command = ttk.Frame(self)
        frame_command.pack(side=tk.BOTTOM, fill=tk.X)

        self.ntu_inlet_entry = ttk.Entry(frame_command)
        self.ntu_inlet_entry.pack(side=tk.LEFT, padx=10)
        self.ntu_inlet_entry.insert(0, "NTU Inlet")

        self.ntu_outlet_entry = ttk.Entry(frame_command)
        self.ntu_outlet_entry.pack(side=tk.LEFT, padx=10)
        self.ntu_outlet_entry.insert(0, "NTU Outlet")

        self.temp_entry = ttk.Entry(frame_command)
        self.temp_entry.pack(side=tk.LEFT, padx=10)
        self.temp_entry.insert(0, "Temperature")
```

Fig. 6 – Sensor class for measuring and calculating chlorine levels based on water quality parameters (source of code: own study)

Slika 6 – Klasa senzora za mjerenje i izračunavanje razine klora na temelju parametara kvalitete vode (izvor koda: vlastito istraživanje)

```python
class Sensor:
    def __init__(self, name):
        self.name = name
        self.values = []

    def read_value(self):
        value = np.random.uniform(0, 14)
        self.values.append(value)
        return value

    def determine_chlorine_level_by_do(self, do_level):
        return max(0, 10 - 0.5 * do_level)

    def determine_chlorine_level_by_temp(self, temp_level):
        return max(0, 8 - 0.3 * temp_level)

    def determine_klor_level_by_ntu_temp(self, ntu_inlet, ntu_outlet, temp_level):
        ntu_diff = ntu_outlet - ntu_inlet
        klor_level = max(0, 5 + 0.2 * ntu_diff - 0.1 * temp_level)
        return klor_level

    def predict_next(self):
        return np.mean(self.values[-5:]) if len(self.values) >= 5 else self.values[-1]
```

Fig. 7 – Engineering control panel architecture of the *DriniChlor* system implemented in *Python* (source of code: own study)
Slika 7 – Arhitektura inženjerske upravljačke ploče *DriniChlor* sustava implementirana u *Pythonu* (izvor koda: vlastito istraživanje)

use of *DriniChlor* enables dynamic and automated chlorine dosing, avoiding losses, underchlorination, and overchlorination. This is achieved through sensor technology and advanced analytical models that can analyse real-time data and adapt water treatment processes efficiently. This tool also assists in combining data from other important parameters, such as NTU and dissolved oxygen, to ensure a comprehensive and integrated treatment process. By using this integrated approach, *DriniChlor* improves water quality, reduces treatment costs, and minimises environmental impacts.

With the use of this platform, it is possible to ensure that every phase of the water treatment process is fully optimised for the specific conditions of the water and environment. This approach guarantees that the treated water is safe and of high quality for both consumption and industrial use. *DriniChlor* represents an innovative solution in the field of environmental engineering and water resource management. The overall system communication and data acquisition architecture, illustrating the integration between sensors, analysers, PLC/RTU, SCADA, and the *DriniChlor Python* platform, is presented in Appendices B and C.

5.3.1 Implementation in the DriniChlor control environment

The *DriniChlor Python* toolbox (Fig. 7) is an advanced engineering tool for real-time monitoring and optimisation of chlorine dosage. It integrates specialised sensors and scientific algorithms to determine the optimal amount of chlorine required for disinfection, considering parameters such as temperature, dissolved oxygen, and turbidity.

This modular integration enables automated dosing control, avoiding underchlorination and overchlorination, while minimising operational costs and chemical waste. The system can be expanded to incorporate additional process variables (*e.g.*, pH, conductivity, or flow rate) to provide a comprehensive and adaptive framework for sustainable water treatment. By using this approach, each phase of the treatment process is continuously optimised to match specific hydraulic and environmental conditions, ensuring safe, stable, and cost-effective operation.

5.4 CDW in four phases with *DriniChlor*: Avoiding over- and under-chlorination and optimising costs in water treatment

Groundwater typically contains lower microbiological loads compared to surface water due to natural filtration occurring as water flows through soil and rock layers. Bacterial communities in groundwater are less variable and less influenced by seasonal changes, while hydraulic factors such as the thickness of the vadose zone significantly contribute to the reduction of pathogenic microorganisms.[20,21]

In contrast, surface waters are highly exposed to anthropogenic and climatic contamination, especially during summer when high temperatures and rainfall create optimal conditions for microbiological growth.[22] The high concentration of microorganisms and organic substances in surface water necessitates higher chlorine doses, often resulting in excessive formation of disinfection by-products such as trihalomethanes (THMs), which pose health risks to consumers.[23] By comparison, groundwater is more easily disinfected and generates lower levels of THMs due to its lower organic and microbial content, though some organic matter may still form during treatment.[24]

Therefore, in chlorination processes, it is essential to assess the type of source water: the optimal chlorine dosage must be determined by considering the physicochemical and microbiological composition to ensure effective disinfection while minimising risks from disinfection by-products.

In treatment plants processing surface or groundwater for human consumption, particularly in cold climate areas where water temperatures range between 0 and 10 °C (Phase I), the CDW should not be constant but rather determined based on the average values of water temperature and DO concentration. In this range, the standard DO concentration is 5 mg l^{-1}. Compared to this reference, CDW should be approximately 50 % lower if based on DO, and about 30 % lower if based on temperature. In cases where NTU and microbial load are low, a dose of 5 mg l^{-1} CDW is sufficient. However, if NTU or pathogenic organisms are elevated, chlorination should begin at 8 mg l^{-1} and be gradually reduced to 5 mg l^{-1}. This strategy is critical to balance public health protection and prevent overchlorination.

At 10 °C (Phase II), the difference between the recommended chlorine dose based on DO *vs.* temperature is only 0.49 %, representing an optimal point for harmonising all parameters (temperature, NTU, DO, and CDW). Between 10 and 14 °C, CDW should range from 5.5 to 3.64 mg l^{-1} and be primarily determined based on DO. In this range, chlorination may be reduced by 0–0.55 mg l^{-1} when DO-based dosing is applied.

When the temperature ranges between 15 and 20 °C (Phase III), CDW should be primarily determined based on temperature, maintaining a dose between 2 and 3.45 mg l^{-1}. At 20–25 °C (Phase IV), CDW should be within 1.5 and 2 mg l^{-1}, and at this stage, NTU becomes the most influential factor. During the winter season, when temperatures drop below 15 °C, chlorine is often overdosed. However, rather than determining CDW based solely on one parameter (either temperature or DO), a combined average of DO, temperature, and NTU is preferred. For instance, a guiding value of 5 mg l^{-1} in the 5–10 °C interval is suggested – see the Fig. 8 and Appendix D.

CDW should be based on dynamic analysis of the water's physicochemical conditions, avoiding both under- and over-chlorination. This approach not only enhances public health protection but also contributes to the economic optimisation of chlorine use in water systems across Kosovo.

6 Economic analysis of chlorine dosage optimisation in high-capacity water treatment plants

The optimisation of chlorine dosage in water treatment systems represents a crucial aspect in terms of technological efficiency and economic resource management. The findings of this research indicate that the use of a controlled dosage methodology, dependent on parameters such as temperature, DO, and NTU, can lead to significant economic savings in the operation of high-capacity plants.

Instead of applying a fixed dose for water disinfection, the dynamic adjustment of CDW according to current water conditions allows for a substantial reduction in unnecessary chlorine use. This directly results in decreased operational costs related to the purchase and administration of chlorine, as well as avoiding maintenance costs caused by overdosing, such as pipeline corrosion and equipment damage. Moreover, the risk of forming harmful secondary products like trihalomethanes is reduced, thereby lowering the costs of subsequent treatments needed to ensure water quality.

From a macroeconomic perspective, plants that implement this model can achieve more sustainable financial management of the disinfection process, creating an optimal balance between public health protection and expenditure efficiency. This approach not only enhances service quality but also strengthens the capacity of institutions to operate

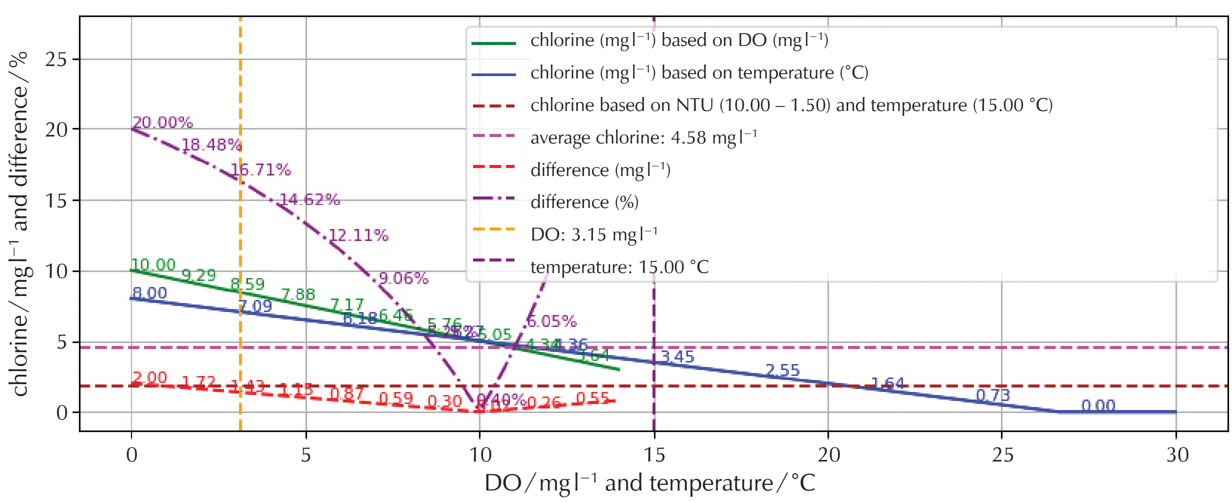

Fig. 8 – Variation of CDW and relative differences as a function of DO, temperature, and NTU (source: own study)
Slika 8 – Varijacija CDW-a i relativne razlike kao funkcija DO, temperature i NTU-a (izvor: vlastito istraživanje)

Table 1 – Phase-based dynamic chlorine dosage strategy in drinking water based on temperature, DO, and NTU (source: own study)
Tablica 1 – Strategija dinamičkog doziranja klora temeljena na fazama u vodi za piće na temelju temperature, otopljenog kisika i NTU-a (izvor: vlastito istraživanje)

Phase Faza	Water temperature / °C Temperatura vode / °C	Dominant parameter Dominantni parametar	Recommended CDW / mg l^{-1} Preporučeni CDW / mg l^{-1}	Comment / Dosing strategy Komentar / Strategija doziranja
Phase 1	0 – 10	Average temperature + DO	5 mg l^{-1} (under good conditions) 8 mg l^{-1} (if NTU or pathogenic microorganisms are high)	CDW is based on the average; ≈ 50 % less compared to DO alone, ≈ 30 % less compared to temperature
			Gradual decrease to 5 mg l^{-1}	Start with 8 mg l^{-1} → decrease over time to 5 mg l^{-1}
Phase 2	10	All parameters balanced	≈ 5 mg l^{-1}	Difference between DO- and temperature-based CDW is only 0.49 % – optimal point
Transition phase: dosing moves from DO-dominant to temp-dominant	10 – 14	DO	5.5 – 3.64 mg l^{-1}	Difference in CDW between DO and temperature: 0.49 – 5 % → chlorine saving of 0–0.55 mg l^{-1}
Phase 3	15 – 20	Temperature	2 – 3.45 mg l^{-1}	CDW depends on temperature, applied during spring and autumn
Summer range: higher turbidity levels require CDW based on NTU	20 – 25	NTU	1.5 – 2 mg l^{-1}	CDW depends on turbidity; used during the summer season
Phase 4	Below 15	Average DO + NTU + temp	5 mg l^{-1}	Applied during winter; avoids both underchlorination and overchlorination by balancing all parameters

under higher standards of control and budgetary transparency (see Fig. 9).

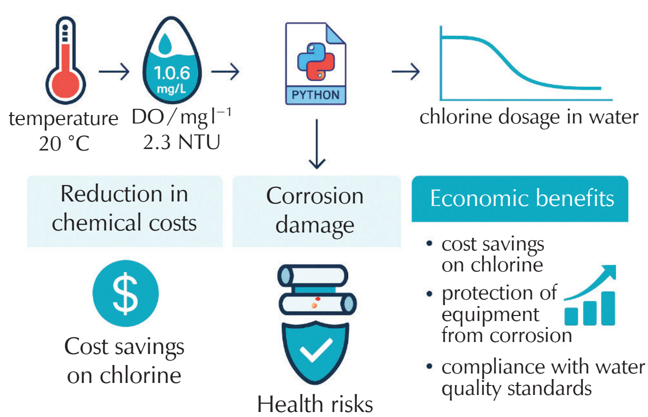

Fig. 9 – Economic and technological optimisation of CDW using *DriniChlor Python* application based on real-time water quality parameters -temperature, DO, NTU (source: own study)
Slika 9 – Ekonomska i tehnološka optimizacija CDW-a primjenom *DriniChlor Python* aplikacije na temelju parametara kvalitete vode u stvarnom vremenu – temperatura, otopljeni kisik, NTU (izvor: vlastito istraživanje)

7 Conclusion

The development of an automated system for monitoring and managing water quality, such as the proposed *DriniChlor* module, represents a significant step toward improving water treatment processes. By utilising modern technologies, advanced sensors, and analytical algorithms, this system not only ensures accurate and real-time control of key water parameters, but also contributes to the optimisation of the water disinfection process, reducing both costs and environmental impact.

The dynamic adjustment of chlorine dosage based on temperature, DO, and NTU is an innovative approach that ensures safety, efficiency, and sustainability in water treatment. This solution can serve as a model for improving existing practices in water treatment plants, and pave the way for similar applications in the management of water resources.

At a time when water resources are under increasing pressure due to growing demand and climate change, the development of such systems is essential to ensure sustainable and safe access to clean water for all.

List of abbreviations
Popis kratica

DriniChlor – *Python*-based automated system for adaptive chlorine dosing in drinking-water treatment
– automatizirani sustav temeljen na *Pythonu* za adaptivno doziranje klora u obradi pitke vode

CDW – chlorine dosage in water
– doziranje klora u vodi

DO – dissolved oxygen
– otopljeni kisik

NTU – nephelometric turbidity unit
– nefelometrijska jedinica zamućenja

PLC – Programmable Logic Controller
– programabilni logički upravljač

SCADA – Supervisory Control and Data Acquisition
– nadzorni sustav za upravljanje i prikupljanje podataka

THMs – trihalomethanes
– trihalometani

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APPENDIX

Appendix A – Parametric diagram of CDW in relation to temperature and DO/NTU
Dodatak A – Parametarski dijagram CDW-a u odnosu na temperaturu i DO/NTU

Temperature / °C Temperatura / °C	DO / mg l^{-1}	NTU / mg l^{-1}	CDW / mg l^{-1}	Based on Na temelju
0 – 10	5 (standard)	low	5	DO, temperature, NTU
0 – 10	>5	increase	8 → 5 gradual	DO, NTU
10	–	–	≈ 5	harmonisation
10 – 14	variable	–	5.5 – 3.64	DO
15 – 20	–	–	2 – 3.45	temperature
20 – 25	–	high	1.5 – 2	NTU

Appendix B – System architecture (from sensors to SCADA & *DriniChlor*)
Dodatak B – Arhitektura sustava – od senzora do SCADA i *DriniChlor* sustava

Subsystem Podsustav	Components / Connections Komponente / Priključci	Communication / signal Komunikacija / Signal	Integration description Opis integracije
Process sensors Procesni senzori	– temperature (Pt100) – dissolved oxygen (DO) – turbidity (NTU) – flowmeter (L/s)	4–20 mA analogue signals	Primary measurement devices for process parameters in water treatment.
Transmitter / analyser Odašiljač / Analizator	– SWAN AMI Turbitrace (turbidity) – SWAN AMI pH/Redox – SWAN AMI DO – Additional alarm relay or 0–10 V optional output	RS-485 Modbus RTU or 4–20 mA	Converts raw sensor data into standardised industrial signals for PLC acquisition.
PLC / RTU & SCADA system PLC / RTU i SCADA sustav	– PLC/RTU module with DI, AI, DO, PID interlocks – SCADA interface for data logging and visualisation	Modbus RTU (RS-485) OPC-UA / Modbus TCP (Ethernet)	Centralised control logic for process automation and data transmission to *DriniChlor*.
DriniChlor (*Python* platform) *DriniChlor* (*Python* platforma)	– PC / Server with *Python* runtime – *DriniChlor* algorithm and visualisation HMI	Modbus TCP / OPC-UA	Adaptive chlorine dosing calculation, HMI display, and logging of measured data.
Optional Interfaces Dodatna sučelja	– USB data logger – dedicated alarm relay – additional analogue/digital I/O	Local or network connection	Provides extended monitoring, redundancy, and local data storage in panel units.

Appendix C – Signals and interfaces
Dodatak C – Signali i sučelja

Tag	Source Izvor	Type Tip	Range / scaling Raspon / skaliranje	Register (example) Registar (primjer)
NTU	AMI Turbitrace	AI / Float	0–30 NTU	30001–30002
DO	DO transmitter	AI / Float	0–10 mg l^{-1}	30021–30022
Temp	RTD conv.	AI / Float	0–40 °C	30031–30032
Flow	Flowmeter	AI / Float	0–100 l s^{-1}	30041–30042
CDW_SP	PLC set-point	AO / Float	0–5 mg l^{-1}	40001–40002 (write)

Note: The presented register addresses and data ordering (endianness) are illustrative. Practical implementation must follow the specific Modbus register mapping and byte order defined in the PLC or analyser technical manuals.

Appendix D – Comparison of the required chlorine dose as a function of DO, temperature, and NTU for optimising water disinfection
Dodatak D – Usporedba potrebne doze klora kao funkcije otopljenog kisika, temperature i NTU-a za optimizaciju dezinfekcije vode

No.	Variable parameter Varijabilni parametar	Value (unit) Vrijednost (jedinica)	Chlorine based on DO / mg l^{-1} Klor na temelju otopljenog kisika / mg l^{-1}	Chlorine based on temp. / mg l^{-1} Klor na temelju temperature / mg l^{-1}	Chlorine based on NTU + Temp. / mg l^{-1} Klor na temelju NTU-a i temperature / mg l^{-1}	Difference from average / mg l^{-1} Razlika od prosjeka / mg l^{-1}	Difference / % Razlika / %
1	DO	10.0 mg l^{-1}	9.00	–	–	4.42	96.52
2	DO	9.0 mg l^{-1}	8.00	–	–	3.42	74.67
3	DO	8.0 mg l^{-1}	7.59	–	–	3.01	65.71
4	DO	7.0 mg l^{-1}	6.88	–	–	2.30	50.22
5	DO	6.0 mg l^{-1}	5.88	–	–	1.30	28.38
6	DO	5.0 mg l^{-1}	4.59	–	–	0.01	0.22
7	DO	4.0 mg l^{-1}	2.59	–	–	−1.99	−43.45
8	DO	3.15 mg l^{-1}	1.15	–	–	−3.43	−74.89
9	temp.	5.0 °C	–	7.35	–	2.77	60.48
10	temp.	10.0 °C	–	5.09	–	0.51	11.14
11	temp.	15.0 °C	–	2.55	2.55	−2.03	−44.32
12	temp.	20.0 °C	–	1.64	–	−2.94	−64.19
13	temp.	25.0 °C	–	0.73	–	−3.85	−84.06
14	temp.	30.0 °C	–	0.00	–	−4.58	−100.00

Data Availability Statement

All code for *DriniChlor* is available for download: https://github.com/ValdrinBeluli/DriniChlor/tree/main

Installation in development mode:

```
git clone https://github.com/username/DriniChlor.git
cd DriniChlor
python -m pip install -e .
```

Modelling the Relationship between DO, NTU, and Chlorine Demand

SAŽETAK

DriniChlor: Prema podatkovno vođenom i adaptivnom procesu kloriranja u sustavima za obradu pitke vode

Valdrin M. Beluli [a,b]

Ovo istraživanje predstavlja razvoj automatiziranog sustava za upravljanje i praćenje kvalitete vode pomoću programskog jezika *Python*, s naglaskom na optimizaciju doziranja klora u vodi za procese dezinfekcije. Predloženi modul, nazvan *DriniChlor*, koristi se senzorima za mjerenje ključnih parametara vode poput temperature, otopljenog kisika i zamućenosti. Prikupljeni podatci analiziraju se u stvarnom vremenu da bi se odredila optimalna doza klora, čime se osigurava maksimalna sigurnost i učinkovitost. Integracija takvih tehnologija nudi inovativan pristup, koji ne samo da poboljšava kvalitetu vode već i smanjuje operativne troškove te utjecaj na okoliš. Rezultati pokazuju da je sustav učinkovit u unaprjeđenju procesa obrade vode i prikladan za primjenu u različitim postrojenjima. Taj razvoj predstavlja značajan korak prema primjeni automatiziranih tehnologija za održivo upravljanje vodnim resursima.

Ključne riječi
Inženjerstvo upravljanja procesima, Python, automatizirani sustav za obradu vode, optimizacija doziranja klora

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