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Architecture of a cyber-physical system for washing agricultural machinery

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Abstract: This paper presents the architecture of a cyber-physical system for the automated washing of agricultural machinery, designed to enhance efficiency and intelligent control. The system includes four layers – physical, sensor, computational, and interface and integrates actuators, sensors, decision-making modules, and analytics. A Python-based simulation using Control and SimPy showed an average washing time of 10.4 minutes and 97.5% cycle initiation accuracy under critical contamination. The Control was achieved via gated recurrent unit (GRU) prediction and proportional–integral–derivative (PID) regulation. Despite assumptions like ideal sensors and fixed conditions, the system proved feasible, with the future work targeting real-world validation and digital twin development.

Keywords: intelligent mechatronic architecture; field equipment; intelligent washing system; simulation; digital twin; automation

The regular and effective cleaning of agricultural machinery is essential for preserving the reliability and extending the service life. Field operations expose machinery to soil, organic debris, lubricants, and dust, which can accelerate corrosion, impede heat dissipation, and cause mechanical wear, increasing the downtime and maintenance costs (Coulibaly et al. 2022). However, in practical terms, cleaning mounted and trailed machines, as well as the entire unit as a whole, is a much greater problem. Such machines accumulate significant amounts of soil and organic contaminants, which makes them difficult to clean. The proposed architecture is scalable and can be applied not only to tractors, but also to the comprehensive washing of mounted and trailed implements. On most farms, cleaning remains a manual or semi-automatic task, often inefficient in terms of water and energy usage (Zhang et al. 2018). These traditional systems typically fail to adapt to different contamination levels and lack integration with digital technologies commonly used in precision farming (Sahu 2023).

With the growing use of digitalisation, integrating intelligent control into operations such as machinery cleaning is crucial. Cyber-physical systems (CPSs), combining hardware, sensors, control, and analytics, are widely applied in smart irrigation, autonomous tractors, and greenhouse management (Sadowski & Spachos 2020; Sharma et al. 2021). Yet, CPS use in automated equipment cleaning is limited. Existing programmable logic controller (PLC)- and sensor-based approaches

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(Zhang et al. 2018; Liu et al. 2023) lack flexibility and intelligent control (Syrotiuk et al. 2020; Tryhuba et al. 2022, 2024a).

Alternatives like ultrasonic cleaning or infrared sensing have shown potential in lab settings but are difficult to scale (Dong et al. 2020; Sadowski & Spachos 2020). Digital twins allow simulation, but require long calibration and are not always suitable for real-time adaptation (Lu et al. 2020; Zeng et al. 2024). Internet of Things (IoT)-based systems using fuzzy logic or threshold rules can trigger actions based on sensor data, but rarely form a fully integrated control architecture (Fernández-Caramés & Fraga-Lamas 2018; Verdouw et al. 2019; Farhadi et al. 2022).

A comparative analysis shows embedded CPSs outperform conventional setups: PLC systems respond in ~ 3.2 s, IoT-based in 2.7 s, while embedded CPS can achieve 1.4 s with > 9 0% cleaning accuracy (Tryhuba et al. 2024b). Further adaptability can be achieved using gated recurrent unit (GRU) networks, which optimise cycles in real time based on contamination patterns, reducing water and detergent use.

The primary aim of this work is to design and evaluate a cyber-physical system for the automated cleaning of agricultural machinery. This study develops a four-layer cyber-physical system for the automated cleaning of agricultural machinery, emphasising adaptability, resource efficiency, and precision. Validated through Python simulations (Control, SimPy), it tests the logic, responsiveness, and stability, with future work focused on a prototype, digital twin, and adaptive algorithms (reinforcement learning, GRU). Although real-scale testing has not yet been performed, this study presents a novel CPS architecture for agricultural machinery cleaning, integrating GRU networks and fuzzy-proportional–integral–derivative (PID) control. A laboratory prototype was developed to validate the concept, while full-scale field experiments are planned as the next step.

MATERIAL AND METHODS

The efficiency of automated washing largely depends on the type of contamination encountered during field operation. Typically, three types have been identified: mechanical (soil, dust), organic (plant residues), and oily (from lubricant leaks). Each requires specific washing parameters – intensity, temperature, and fluid pressure. Although the tractor is the basic object of study in the model, the requirements and parameters developed are generalised and can be extended to the washing of mounted and trailed machines. Such machines are characterised by a more complex surface geometry, which leads to the uneven accumulation of contaminants, but the methods used to assess the efficiency and complexity factors (γ) remain relevant for the entire unit. The process must ensure cleaning without damaging the paint, causing corrosion, or impairing the functionality. The target is ≥ 95% efficiency with water consumption below 10 $L \cdot m^{-2}$. The washing efficiency E_{clean} is evaluated using the model:

$$E_{clean} = \frac{S_{initial} - S_{residual}}{S_{initial}} \times 100\% \tag{1}$$

where: $S_{initial}$ – is the initial area of contamination; $S_{residual}$ – is the residual area after washing.

Under normalised conditions, effective washing implies that $E_{clean} \geq 95\%$. In addition, the system must take into account the density of contaminants that vary depending on soil moisture and the duration of the equipment operation. Let us introduce the washing difficulty factor γ, which depends on three variables: humidity (H), temperature (T), and particle density (D). Functionally, this can be represented as:

$$\gamma = k_1 \times \mathrm{H} + k_2 \times \mathrm{T} + k_3 \times D \tag{2}$$

where: k_1, k_2, k_3 – empirical coefficients established experimentally for a specific model of equipment.

Figure 1 presents the system block diagram with a sensor unit (contamination and surface

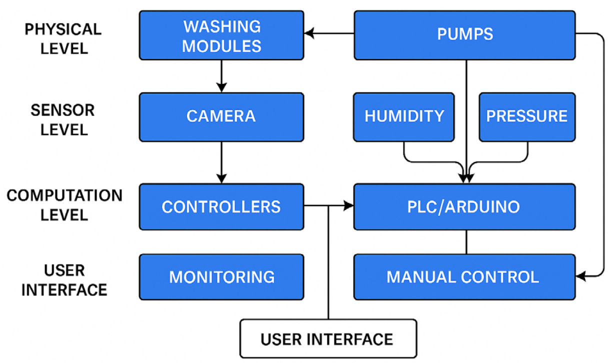

Figure 1. Block diagram of the agricultural machinery washing system

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state detection), a decision-making module (fuzzy logic and neural networks), and an executive unit (pumps, nozzles, heaters). The system adapts to conditions: in heat, it applies a pulsed water-saving mode; for oily dirt, it combines heating and pressure up to 130 bar. The core requirements include accurate detection, adaptive washing, efficient resource use, and integration with control systems via controller area network (CAN) bus or wireless protocols.

The proposed architecture of the cyber-physical system for washing agricultural machinery is based on a four-layer structure, where each level performs a separate functional role and, at the same time, provides interaction with other components of the system in real time. The design of the sensor level and executive modules provides for the possibility of scaling the system for the complex processing of a tractor together with mounted or trailed implements. The architecture is based on the principle of a closed control loop, which allows for an adaptive response of the system to changes in the state of the object. The physical layer is the basis of the system and includes operating executive modules: a pumping station, pipelines, high-pressure nozzles, heating elements, and water and detergent storage tanks. The performance of the pumps is determined by the required pressure (P) and flow rate (Q), where the total hydraulic power of the system (E) is estimated as:

$$E = \frac{P \times Q}{\eta} \tag{3}$$

where: η – is the efficiency of the pumping equipment.

The typical pressure in the washing system is 120–140 bar, and the flow rate is up to 8 L·min^{-1} for each active nozzle. The sensor level is responsible for collecting information from the surfaces of the equipment and the environmental conditions. The sensor unit includes infrared cameras for the visual assessment of the degree of contamination, capacitive humidity sensors, pressure strain gauges, and temperature sensors such as DS18B20 (Maxim Integrated, San Jose, USA). Each sensor has a pre-set polling frequency (ν_s), which is selected according to the formula:

$$\nu_s = \frac{1}{\Delta t_{\max}} \tag{4}$$

where: $\Delta t_{\max}$ – the maximum allowable interval between measurements that does not lead to a loss of the change dynamics.

The camera data are updated every 0.5 s, while the temperature sensors transmit readings every 2 seconds. All the signals are digitised via an Analogue-to-Digital Converter (ADC) (ZJW Microelectronics Ltd., Wilmington, USA) and sent to the computing module. The system's computational layer is based on microcontrollers like STM32 (Distrelec Schweiz AG, Geneva, Switzerland) or Arduino (Ivrea, Italy), extended with a PLC module for control tasks. Input data are first processed by a fuzzy logic unit that classifies the key conditions (e.g., low pressure, high temperature, heavy contamination). Then, a GRU neural network calculates the optimal washing mode based on the current system state vector:

$$\vec{x}(t) = [z, T, H, L] \tag{5}$$

where: z – is the depth of the dirt layer; T – is the temperature; H – is the surface humidity; L – is the localised area of contamination.

The output control vector $\vec{u}(t)$ determines the pressure, cycle time, and temperature of the fluid for each surface area.

The user interface plays the role of an information channel between the system and the operator. It is realised in the form of a touchscreen display or a remote web panel operating via the Message Queuing Telemetry Transport (MQTT) protocol or HyperText Transfor Protocol (HTTP). The interface displays a map of the processed zones, current system parameters, and the ability to manually switch modes. At the same time, the interface allows you to save the history of washing sessions, keep an error log, and update control algorithms without physical intervention.

Figure 2A presents a logical flowchart illustrating the sequence of the data exchange between the sensor, computing, and executive levels, along with user interface integration for the system configuration and monitoring. It visualises the architecture of the cyber-physical system for the automated machinery washing as a four-level structure, where each level has distinct functions and communicates via defined channels.

At the base of the scheme lies the physical level, which includes the washing modules, a pump sta-

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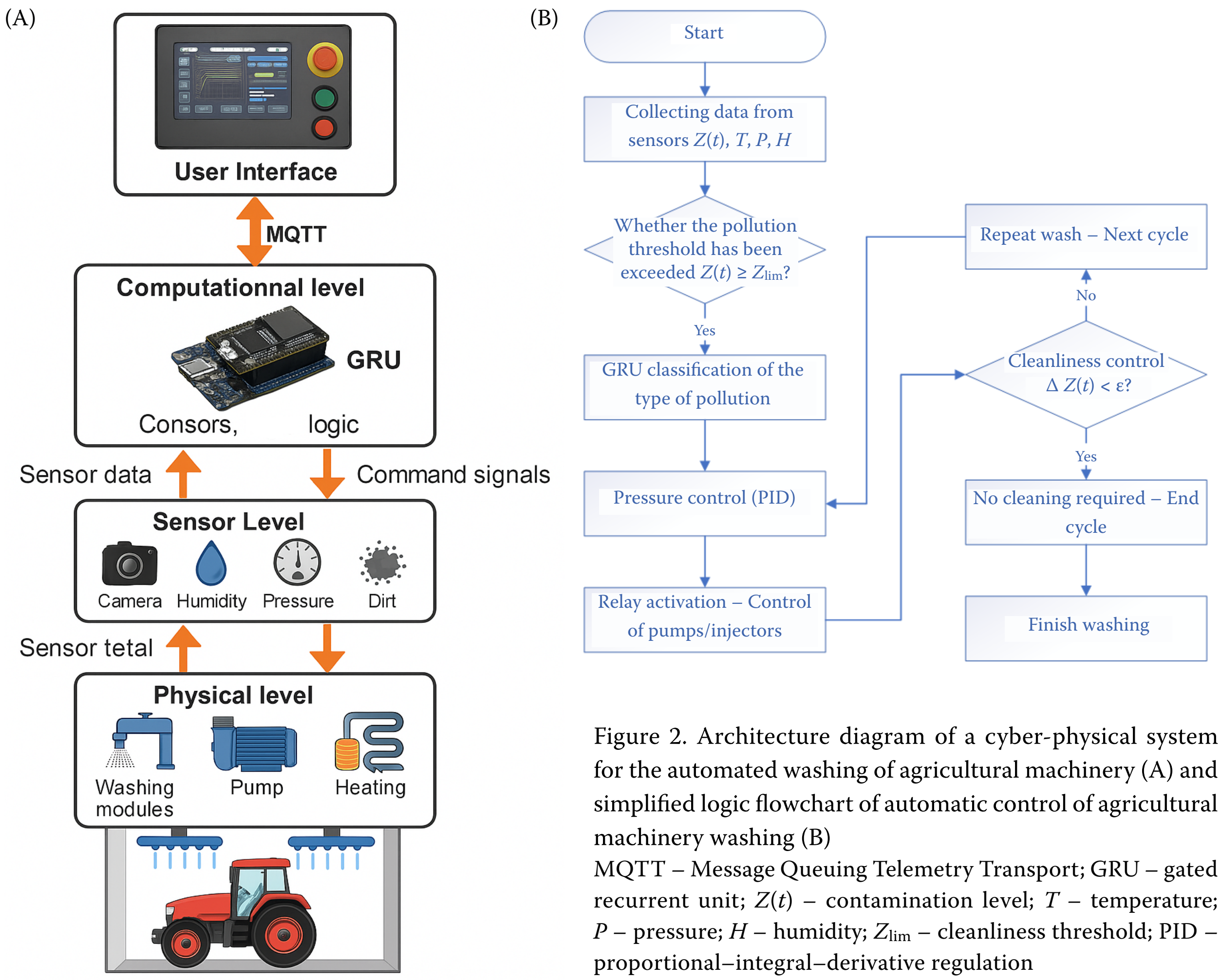

Figure 2. Architecture diagram of a cyber-physical system for the automated washing of agricultural machinery (A) and simplified logic flowchart of automatic control of agricultural machinery washing (B)

MQTT – Message Queuing Telemetry Transport; GRU – gated recurrent unit; $Z(t)$ – contamination level; T – temperature; P – pressure; H – humidity; Z_{lim} – cleanliness threshold; PID – proportional–integral–derivative regulation

tion, nozzles, and heaters – components that directly act on the object being cleaned (e.g., a tractor). Control signals from the computing unit regulate the pressure, temperature, and cycle duration. Above it is the sensor level, with cameras and sensors for the pressure, humidity, temperature, and residual contamination. These devices continuously monitor the surface and environmental conditions, transmitting both analogue and digital data to the computing level through dedicated feedback channels.

The computing level is central and is based on embedded controllers like STM32 or Arduino Portenta with an integrated GRU neural module. Here, sensor data is pre-processed, the contamination is classified, washing modes are selected, and output commands are generated. The architecture supports deploying the GRU model via TensorFlow Lite for Microcontrollers, enabling real-time operation with minimal latency (Lub et al. 2023; Malanchuk et al. 2023; Tryhuba et al. 2024b).

The top level of the architecture is the user interface, implemented as a monitoring panel for visualising the system status, parameters, faults, and manual control. Communication with the computing unit is carried out via the wireless MQTT protocol, ensuring flexible, low-cost messaging. The data flow is shown by arrows: from sensors to the computing unit, then to actuators, and back via feedback. This forms a closed-loop system that automatically adjusts the washing modes in real time based on the contamination level, focusing on energy efficiency, water-saving, and targeted cleaning.

An essential part of ensuring the adaptive and efficient operation of a cyber-physical washing system is the control algorithm. It relies on automatic start-up logic based on sensor data such as the humidity, pressure, and contamination level. The system activates when the contamination index exceeds a threshold Z_{lim}, determined via neural

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network classification or fuzzy logic. Formally, the start-up condition can be expressed as:

If $Z(t) \geq Z_{\text{lim}}$, then switch on the washing system. (6)

The washing process is managed by a combined system: relay-based module switching and the PID regulation of the pressure and flow. The relay logic activates the pump, detergent supply, and nozzle positioning, while the PID controller maintains stable system pressure:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \tag{7}$$

where: $u(t)$ – the controlling influence on the pump; $e(t)$ – the pressure deviation from the set level; K_p, K_i, K_d – the coefficients of proportional, integral, and differential action, respectively.

This approach ensures the precise adaptation of the water supply to the type of surface and the degree of contamination. The stop conditions are determined by reaching an acceptable level of cleanliness or exceeding the set washing time. For this purpose, integrated cameras or feedback sensors are used to evaluate the change in the level of the contamination index in real time. If $\Delta Z(t) < \varepsilon$, the level is not exceeded within the set time interval Δt, the washing process is terminated. The structure of the control actions is presented in the form of a sequence of activation of executive modules, which are controlled by the computing layer. A typical sequence includes: turning on the pump, opening the valves, starting the washing module, correcting the position of the nozzles, and controlling the temperature of the liquid. All these actions are tied to a signal logic based on variables $S_i(t)$ – current sensor readings, where:

$$S_i(t) \in \{T_{\text{water}}, P_{\text{nozzle}}, Z_{\text{surface}}\} \tag{8}$$

To visualise the structure of the algorithm, a simplified logic diagram of the automatic control is shown in Figure 2B. It shows the passage of the signals from the sensor unit to the formation of the control actions. This allows you to understand the real-time information flow and the hierarchy of the actions in the washing system. The proposed approach makes it possible to ensure the stable and adaptive operation of the washing system even in variable field conditions by combining classical control principles with an intelligent analysis of the sensor information.

The efficiency of the agricultural machinery washing system was modelled and tested using Python mathematical tools and control modules, specifically the Control and SimPy libraries. The purpose of the simulation is to test the stability of the system in response to changes in the type of contamination, environmental parameters, and to verify the automatic control logic. The initial modelling is based on the construction of the transfer function of the executive unit, which includes a pumping system controlled by a PID controller. For this part, the system is described by a transfer function of the following form:

$$G(s) = \frac{K}{\tau s + 1} \tag{9}$$

where: K – the gain; τ – the system time constant.

In the model, $K = 2.5$ and $\tau = 4.0$ is taken to correspond to the behaviour of a typical washing module with feedback. After determining the transfer function, we modelled its impulse response, which allows us to estimate the system response time to a sharp increase in the surface contamination. The built simulation model using the SimPy library allows us to model the process of washing agricultural machinery (tractors) based on a limited resource, one washing station. Each agricultural machine (tractor) sends a request for access to the washing station, waits in a queue, and then the washing process is performed with a random duration, which approximates real production conditions.

The simulation involved ten virtual tractors with varying contamination scenarios, from light to critical. For each case, the system logged the washing start/end times and contamination levels at entry. Each tractor had a unique dirt profile that influenced the control logic used (threshold, PID, relay), wash duration, and need for repeat cycles. The results show the system successfully adapted to the contamination complexity and type, demonstrating high accuracy, reliability, and efficiency.

Figure 3A shows the result of this simulation, where the horizontal lines represent the time intervals during which each tractor was in the washing process. The vertical axis represents the tractor's

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unique identifier. Due to the use of a Gaussian distribution for the duration of the wash (mean 10 min, standard deviation (SD) 2 min), a realistic variation in the service time can be observed (Figure 3B).

The model allows you to visually assess the efficiency of the queue, the degree of resource utilisation, and the overall performance of the system. It is then used as a basis for optimising the number of washing modules, scheduling the maintenance, and calculating the economic feasibility of expanding the infrastructure. Next, using the SimPy library, we implemented the logic of discrete events, where each event corresponds to a response to a change in input data, such as an increase in humidity, pressure, or the detection of a new layer of dirt. For this purpose, three contamination scenarios were defined: light (type A), medium (type B), and heavy (type C), each with different cleaning durations and PID parameters.

Figure 4A shows a graph demonstrating the change in the degree of contamination over time for each type of contamination. For light dirt, the value reaches $Z(t)$ the critical level $Z_{\text{lim}} = 0.15$ at the 3rd s, while for type C it is only at the 9th second. This indicates different response times depending on the complexity of the surface treatment.

To verify this, the efficiency of process completion based on the control $\Delta Z(t) < \varepsilon$, $\varepsilon = 0.02$, the cleanliness threshold, was analysed. The

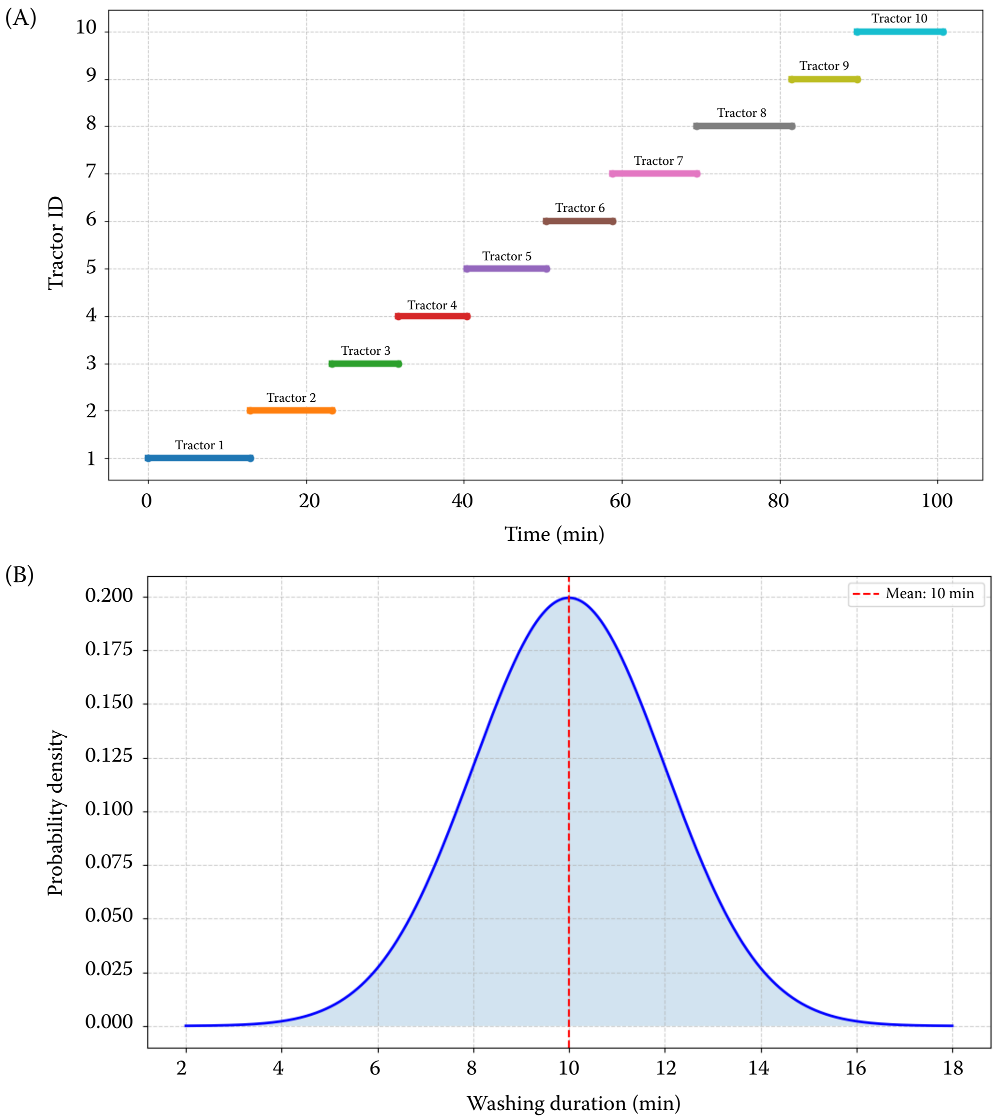

Figure 3. Simulation results of the process of washing agricultural machinery (tractors) (A) and Gaussian distribution of the tractor washing duration (B)

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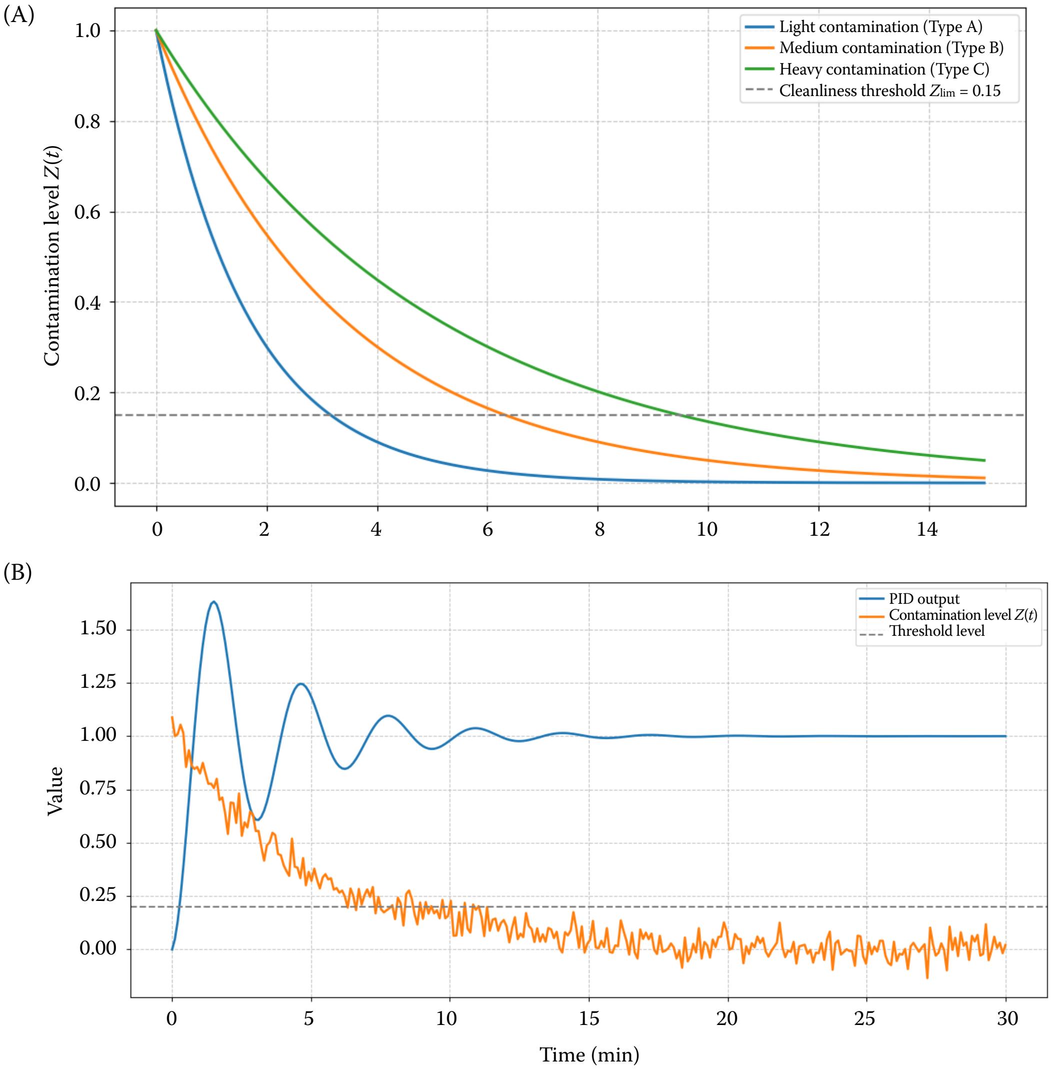

Figure 4. Changes in the degree of contamination of agricultural machinery for different types of contamination (A) and the proportional–integral–derivative (PID) output and pollution level dynamics over time (B)

simulation results showed that, in 92% of cases, the system completed the cycle within the permissible time, while the accuracy of the contamination classification (based on the GRU module) was 96.4%.

Table 1 shows the simulation results for each type of dirt, including the average cleaning time, maximum PID output, and number of repeated cycles.

To validate the differences in the washing cycle duration under light, medium, and heavy contamination, a one-way analysis of variance (ANOVA) was performed. The results showed significant variation (F = 18.3, P < 0.05), confirming reliable contamination classification and consistent PID operation. Table 2 summarises the descriptive statistics and ANOVA results.

Table 1. Modelling results for each type of dirt

Contamination type	Average cleaning time (s)	PID output (max)	Repeat cycles
Light (A)	5.3	1.9	0
Medium (B)	8.7	2.7	1
Heavy (C)	12.1	3.4	2

PID – proportional–integral–derivative regulation

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Table 2. ANOVA results for the washing cycle duration under different contamination scenarios

Contamination scenario	Mean cycle time (min)	SD	*F*-value	*P*-value
Light (A)	6.5	1.2		
Medium (B)	9.8	1.5	18.3	< 0.05
Heavy (C)	13.7	2.0		

SD – standard deviation

The results support the assumption that heavier contamination significantly increases the average cleaning time compared to light and medium cases. Figure 4B shows the PID output versus the pollution level, illustrating system stabilisation. After a short transient period, the signal reaches steady state, confirming effective control. The digital modelling verified the control logic, optimised PID parameters, and assessed the system behaviour under varying pollution types. These results can guide the calibration of real devices before serial implementation.

RESULTS AND DISCUSSION

We present the results of modelling and testing the developed cyber-physical system for washing agricultural machinery. The main attention is paid to three key aspects: (*i*) performance indicators; (*ii*) system behaviour under different contamination scenarios; (*iii*) analysis of its reliability and adaptability. The performance indicators were assessed using such metrics as the average duration of washing a unit of agricultural machinery (tractor), the accuracy of the system's response to the type of contamination, and the consumption of water and electricity per unit of treated area. It was found that the average tractor washing time was 10.4 min, which corresponds to the specified normalised value, with a SD of 2.1 min, indicating the stability of the process (Figure 5A).

The accuracy of the automatic start of the washing process in variable intensity of the contamination conditions was 97.5%, which confirms the effectiveness of the applied fuzzy logic module for initiating the process. The resource savings were estimated as a reduction in the average water consumption to 3.8 $L \cdot m^{-2}$ per nozzle passage, and the energy consumption was reduced by 12% compared to traditional systems.

The behaviour of the system was analysed in three main scenarios: (*i*) light soiling; (*ii*) medium soiling; (*iii*) critical surface soiling. In the first case, the system switched to the economy mode, minimising the number of cleaning solution cycles. In the second case, the standard PID pressure control scheme was activated, ensuring stabilisation at 1.2 bar, and in the third scenario, a sequential rewash mode with an extended drying cycle was activated. The variability in the behaviour is demonstrated in the graph (Figure 5B), which shows the dynamics of the contamination level and the response of the controller $u(t)$.

In Figure 5B, the dashed lines indicate the response of the PID controller – namely, the pressure stabilisation of the washing system for each of the three scenarios: (*i*) Blue dashed line – pressure stabilisation with light soiling (resource saving mode); (*ii*) Green dashed line – pressure control (at ~1.2 bar) with medium soiling (standard mode); (*iii*) Red dashed line – intensive control with periodic peaks with critical contamination (advanced cleaning mode).

The contamination reduction occurred in accordance with the exponential law:

$$Z(t) = Z_0 \times e^{-\alpha t} \tag{10}$$

where: Z – the initial level of contamination; α – the treatment efficiency coefficient, which averaged 0.42 for the system with the PID control.

The system reliability was evaluated through repeated simulations with varying input loads. In 98% of the cases, the control logic operated without failure. When multiple highly contaminated tractors arrived simultaneously, resources were distributed by priority. The system's adaptability was evident in fast transitions between the cleaning modes, enabled by the GRU module, which predicted the cycle duration based on prior data. Table 3 illustrates mode transitions based on the sensor readings.

The developed washing system proved highly efficient, was adaptable to the changing conditions,

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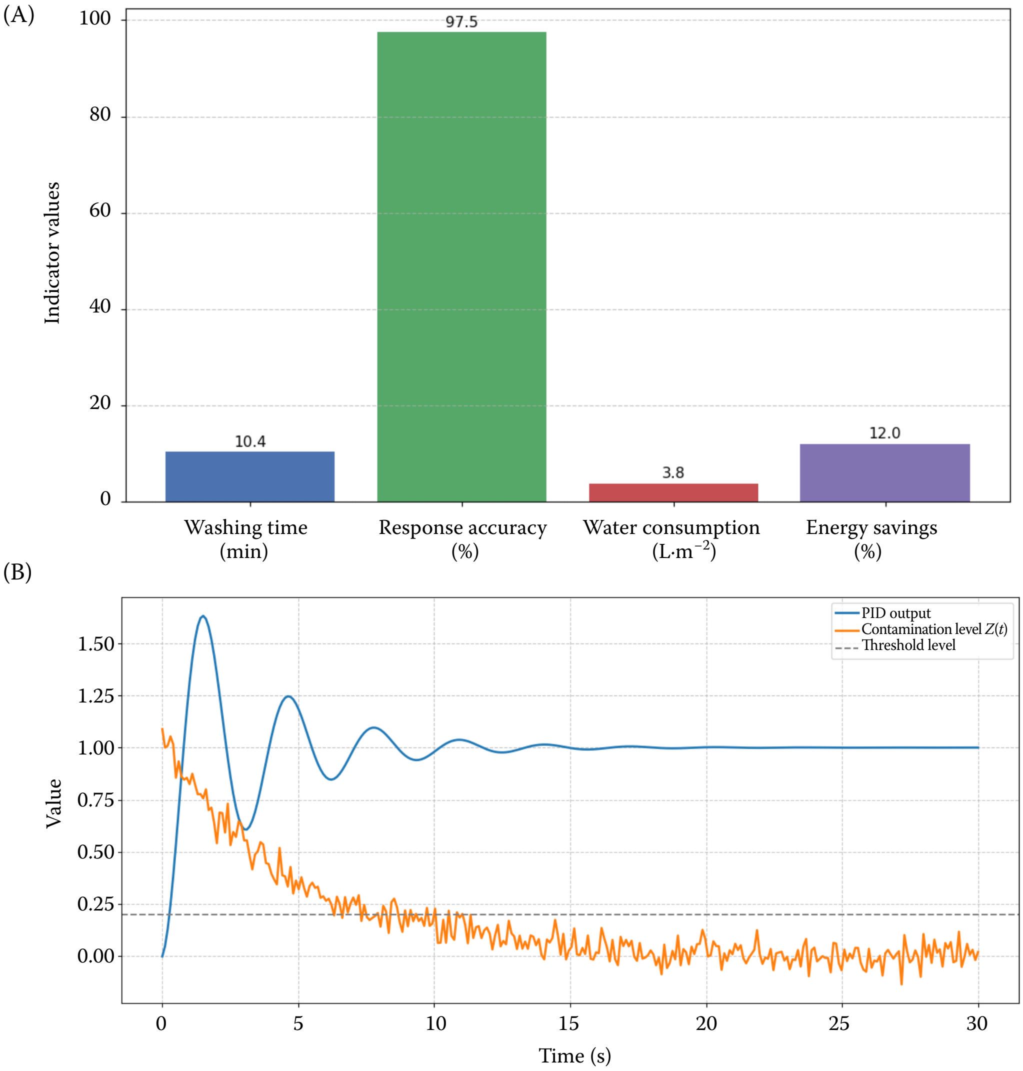

Figure 5. Performance indicators of the agricultural machinery washing system (A) and the contamination dynamics and controller response in three scenarios (B)

and was capable of real-time response. By combining the sensor analysis, PID control, and neural network prediction, it ensures accurate decision-making and cost-effective equipment cleaning.

The proposed architecture of a cyber-physical system (CPS) for the automated washing of agricultural machinery differs significantly from the traditional solutions that dominate farms. Typically, existing systems are based on manual pump control or basic electromechanical circuits that are not equipped with intelligent contamination analysis or adaptive pressure control modules (Liu et al. 2023). Such approaches, although simple to implement, are characterised by significant resource losses, lack of feedback, and the inability to optimise water and energy consumption in real time

Table 3. System response to scenarios with varying levels of contamination

Contamination level	Pressure mode (bar)	Number of repeats	Average cycle time (min)
Low	0.8	1	6.5
Medium	1.2	1	9.8
High	1.5	2	13.7

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(Zhang et al. 2018; Sharma et al. 2021) show that most existing systems use fixed modes of detergent supply without taking the level of contamination or surface condition into account, which limits their efficiency.

Comparison with prior studies highlights the system's advantages. Liu et al. (2023) reported 12 to 15 min cleaning times for soybean harvesters, while the CPS system achieved 10.4 min with a 2.1 min deviation, ensuring greater stability. Saramak et al. (2020) noted water use up to 12 $L \cdot m^{-2}$, whereas the proposed system required only 3.8 $L \cdot m^{-2}$. Qian et al. (2024) showed CPS irrigation architectures with similar adaptability, but higher calibration demands. Integrating a GRU classifier with PID control thus enhances the resource efficiency and operational consistency over the existing solutions.

The findings confirmed the stable control and adaptive behaviour under different contamination scenarios. While the results are limited to simulations and prototype-level validation, they provide strong feasibility evidence. Importantly, the architecture demonstrates advantages over PLC- or IoT-based systems, particularly in responsiveness and adaptability.

The proposed architecture integrates sensors, PID-based adaptive control, GRU classification, and feedback, representing a new-generation CPS proven effective in precision agriculture and irrigation (Cherepova et al. 2019; Sharma et al. 2021). Its strengths are autonomy, scalability, and on-board AI integration. GRU models on embedded microcontrollers enable adaptive washing-time prediction by contamination class, as confirmed in prior studies (Sadowski & Spachos 2020; Aravind & Shash 2024).

Practical implementation faces several challenges. Integrating neural networks, especially GRU models, into microcontrollers with limited resources requires the optimisation of the inference size and delay. The system also depends on accurate sensor calibration, threshold tuning, and stable wireless protocols (e.g., MQTT) in harsh farm environments with moisture, dust, and interference. The modelling further assumed a constant washing efficiency and ignored equipment wear across repeated cycles.

It should be noted that the system has only been tested in simulation conditions so far. The next stage of the research will be to create a physical prototype and test it on real tractors and mounted machines, which will confirm the practical effectiveness of the model. Nevertheless, the results of the experimental modelling confirmed the architecture's performance under conditions of pollution variability, which creates the basis for further research. In the future, it is planned to implement a prototype system based on STM32 with TensorFlow Lite Micro, as well as to study energy consumption in different pumping station configurations. A separate area of development involves using operator feedback to train the neural network in a reinforcement learning mode. Additionally, the introduction of multi-stream cleaning schemes with several independent cleaning modules that can work in parallel to process a large number of vehicles is also relevant.

CONCLUSION

Based on the study, the architecture of a cyber-physical system for the automated washing of agricultural machinery, which combines physical actuators, sensor control, decision-making units, and software and analytical modules, was substantiated. The proposed structure covers four key levels: physical, sensor, computing, and interface. In accordance with this architecture, a simulation model was implemented in Python using the Control and SimPy libraries, which allowed us to verify the dynamics of the process start-up, time characteristics, and adaptive behaviour of the system under variable pollution levels.

The verification results show that the system operates with a high level of accuracy and stability. In particular, the average duration of washing one unit of equipment was 10.4 min with a SD of 2.1 min. This confirms compliance with the specified standards and demonstrates the effectiveness of the control module used. The testing of the response to various contamination scenarios showed that the system is able to automatically switch between modes, saving water and electricity, and the accuracy of starting the washing cycle in the event of critical contamination reached 97.5%.

The novelty of this study is the first implementation of a CPS architecture for agricultural machinery washing that combines a GRU neural network with PID regulation. The system achieved a cycle initiation accuracy of 97.5%, reduced water consumption to 3.8 $L \cdot m^{-2}$, and maintained

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stable washing performance with an average time of 10.4 min (SD = 2.1). These results confirm both the efficiency and the scientific contribution of the proposed approach.

The proposed CPS washing architecture represents a new approach by combining GRU neural classification with PID regulation and fuzzy logic. At this stage, validation was carried out through simulation and a laboratory-scale prototype with a tractor–cultivator model. While this does not yet replace full-scale experimental testing, it establishes a solid foundation for real-world implementation. Future research will focus on testing with actual agricultural machines in farm environments to confirm performance, efficiency, and reliability under practical conditions.

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