Development and Validation of a Soil pH Monitoring Algorithm

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ABSTRACT

In the context of the ongoing digitalization in engineering education, this study presents the development and validation of a soil pH monitoring algorithm. Laboratory tests were performed on soils treated with various additives to monitor the pH trends over a 14-day period. These empirical results served as the foundation for designing a simulation that models the observed dynamics of the soil behavior. The simulation algorithm supports the core learning in the "Soil Mechanics" module by providing a structured view of how the pH varies over time. According to an expert evaluation, it achieved 97% accuracy (88 out of 90 points), confirming both its technical validity and educational relevance. The resulting simulation algorithm can be tailored for different instructional and research applications. These findings underscore the importance of integrating experimental data into digital learning environments and demonstrate the potential of such approaches to enhance applied learning, particularly in settings where the access to laboratories is limited.

Keywords-pH sensor; soil monitoring; biopolymer; simulation algorithm; digital learning

I. INTRODUCTION

The integration of theoretical knowledge and practical skills is an essential part of the modern education. Traditional learning methods often overlook the rapidly changing demands of the industry, which can negatively impact the training of specialists. This highlights the importance of digital methods that bridge the gap between theory and practice in engineering education [1]. Such tools can enhance the interaction between teachers and students, as well as boost the accessibility of educational resources [2]. Interactive simulations and modeling tools have demonstrated their effectiveness in improving students' understanding of technical concepts, thereby advancing the engineering education. Virtual reality (VR) and 4D modeling help students understand the complex construction project scheduling [3]. The project "Skope" initiative highlights the role of AR/VR platforms in promoting sustainable construction skills [4]. Remote laboratories expand the access to physical equipment using Virtual Network Computing (VNC) and video conferencing tools [5]. Additionally, VR-based environments improve the spatial and procedural learning in construction education [6].

In Kazakhstan, the national strategies highlight the digital transformation in education, promoting the integration of advanced technologies into the academic environments [7].

However, despite the ongoing efforts, engineering education often remains dependent on traditional laboratory-based methods. Simulation-based approaches offer flexible and scalable alternatives that help address these limitations. Interactive digital platforms have proven to enhance the learning outcomes and promote the development of key skills, underscoring the importance of educational technologies in soil science and related fields. For instance, authors in [8] describe an IoT-enabled system for real-time monitoring of the pH and electrical conductivity in hydroponic environments, while authors in [9] demonstrate the use of machine learning and remote sensing techniques to predict the soil quality. In Kazakhstan, a digital educational platform is being developed to promote practice-oriented learning in civil engineering. The pH testing simulation is included in the Soil Mechanics module of engineering education.

Soil pH is a fundamental parameter influencing a wide range of soil properties and processes [10]. There are various direct and indirect methods for measuring the pH. The potentiometric method, for example, involves mixing soil with distilled water or calcium chloride ($CaCl_2$) and measuring the pH using a glass electrode and pH meter. The solid-state electrode method utilizes reliable sensors for field testing [11], whereas the spectrophotometric method relies on dye indicators and light absorption. The $CaCl_2$ method provides more stable readings, especially in saline or moisture-variable soils.

The objective of this study is to investigate how different environmentally friendly additives affect the soil pH over time and to create a simulation algorithm that replicates the soil pH testing process based on observed trends. Over a period of two weeks, pH measurements were regularly recorded from soil samples treated with microorganisms and biopolymers. Using experimental data, a simulation algorithm was developed and validated with Python. The purpose was to transform physical, practice-based procedures into a structured digital format.

II. METHODS AND MATERIALS

A. Educational and Experimental Setting

Two groups of students, Group A and Group B were given different but complementary roles. Group A, comprising 20 participants, was divided into two subgroups of 10. They carried out the entire laboratory process, including the preparation of the soil samples modified with biopolymers and microorganisms, and measured the pH using both stationary and digital sensors under controlled conditions. The tasks involved reviewing relevant documentation, preparing soil samples modified with biopolymers and microorganisms, developing procedures for sensor calibration and placement, and performing systematic pH measurements.

Besides providing empirical observations, Group A participated in the verification of the algorithm by comparing its output with trends observed during physical testing. Group B, which did not participate in the laboratory phase, was involved in the subsequent evaluation of the Python-based simulation. Figure 1 provides an overview of the research workflow.

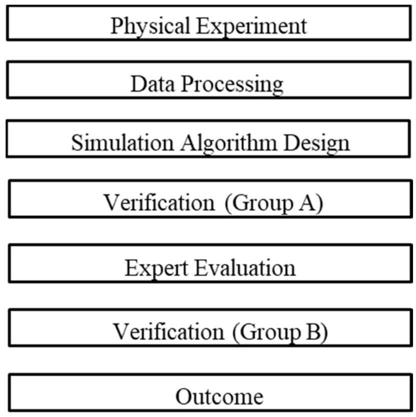

Fig. 1. Workflow of experimental and simulation stages.

B. Physical Experiment (Group A)

1) Soil Treatment

Twelve soil samples modified with natural polymers and microorganisms were used in the experiment, along with two untreated control samples. Studies were conducted under standard laboratory conditions [12]. Table I shows the physical characteristics of the soil. The soil composition consists of 60.794% sand, 19.193% silt, and 15.609% clay. During the practical sessions, each subgroup worked with seven soil samples: three prepared by students with biopolymer additives (chitosan), three pre-treated with microorganisms due to their complexity, and one untreated control. Figure 2 displays the mixing materials.

TABLE I. PHYSICAL CHARACTERISTICS OF SOIL

Soil characteristic	Value
Specific gravity, g/cm3	2.538
Maximum dry density, g/cm3	2.031
Optimum water content, %	10.194
Sand-sized fraction (75 μm–2 mm), %	60.794
Silt-sized fraction (5–75 μm), %	19.193
Clay-sized fraction (<5 μm), %	15.607
Liquid limit (LL) %	23.251
Plastic limit (PL) %	1.190
Plasticity Index (PI) %	22.061

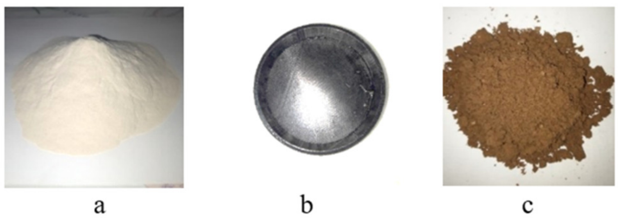

Fig. 2. Materials for mixing: *a* – biopolymer, *b* – mixing bowl, *c*– sand with fine friction.

Polymer exhibits properties, such as biocompatibility and the ability to bind to various substances [13]. Chitosan is actively used to improve the soil structure by increasing the particle cohesion and enhancing the soil's strength characteristics. Using additives that are environmentally safe and biodegradable makes it a promising material for sustainable technologies [14]. The soil was mixed with chitosan at a ratio of 2 g per 100 g using a pre-dissolved aqueous solution. The gradual mixing ensured uniformity and prevented the lump formation. The stabilization facilitated the effective interaction between the chitosan and soil particles. The additives enhance the cohesion among the soil particles, boosting strength, and are considered environmentally sustainable options [15]. Regular pH monitoring maintains optimal conditions for the microbial activity, supporting the treatment's effectiveness.

2) Testing Procedure

The stationary sensor, constructed from wear-resistant polycarbonate and ABS, measured the pH, temperature, and moisture using two sensitive probes. The calibration was performed with pH-buffer powder. The measurements were repeated under consistent conditions, and the averages were used to minimize the random and human errors. Data were collected at three points for each sample. For the digital sensor connected to a personal computer, the pH and temperature were recorded every 30 min over a 14-day period. The pH values from each sample type were documented in a structured table. For each soil type (unmodified, biopolymer-modified, and microorganism-modified), separate tables were created to show the measurement conditions, sensor type (stationary or digital), and pH results. The tabulated data served as a foundational dataset for algorithm training and simulation development.

3) Grading and Feedback of Practice Task (Group A).

At the end of the experiment, both subgroups of Group A submitted structured reports summarizing their practical work results. The evaluation framework, as shown in Table II, includes five key indicators. These criteria ensure a systematic and objective assessment of the practical tasks completed.

TABLE II. PRACTICAL WORK EVALUATION CRITERIA

Criterion label	Criteria	Explanation
C1	Accuracy of measurements and use of equipment	To evaluate the sensor calibration, measurement accuracy, and proper equipment operation.
C2	Adherence to scientific methodology	To evaluate the methodological accuracy, procedural compliance, and data quality.
C3	Correctness of data interpretation	To assess students' skills in data interpretation, pattern recognition, and conclusion formulation.
C4	Quality of presentation of results	To assess the clarity and logic of data visualization and result presentation.
C5	Group work and interaction	Assessment of teamwork, roles, and communication.

C. Simulation Algorithm Design

Based on the analysis of the experimental data and the applied pH sensor methodology, an initial algorithm was developed to simulate the pH measurement process. This algorithm provides a technical foundation for developing an interactive simulation, emphasizing the ease of use, intuitive navigation, visualization of different soil types, interaction with interface elements (such as drag-and-drop tools, substance selection, and parameter adjustment), and compatibility with both mobile devices and personal computers. Figure 3 illustrates the main steps of the algorithm.

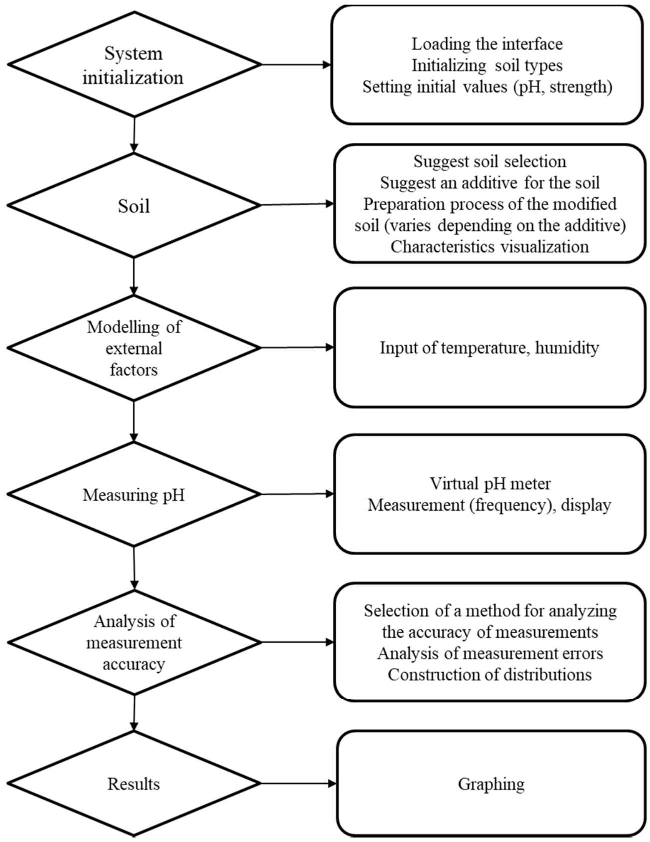

Fig. 3. Algorithm of simulation.

The algorithm introduced in this study can be used to support one of the educational simulations planned for the digital learning platform described above. A Python-based prototype was developed to verify the algorithm's logic and accuracy before developing the full simulation. The prototype utilized the Matplotlib library, specifically the pyplot, patches, and animation modules, to generate dynamic visualizations based on real experimental data. An additive layer was animated to grow gradually with each frame, illustrating the cumulative effect of treatment over the 14-day observation period. Meanwhile, a side table was updated automatically to display the corresponding pH values for each day, strengthening the connection between the time and soil pH response.

D. Evaluation of the Simulation Algorithm

1) Verification by Group A

Following the practical experiment and testing of the Python-based algorithm, Group A submitted anonymous feedback to evaluate the algorithm's logic and structure. Anonymity was maintained to minimize the bias and encourage honest feedback, particularly when students evaluate tools developed with instructor input. Each item was scored using a 5-point Likert scale, and the mean value and Standard Deviation (SD) were calculated for each item (see Table III).

TABLE III. VERIFICATION AND EVALUATION QUESTIONNAIRE FOR GROUP A

№	Statement	Evaluation objective	Response scale
1	The visualization in the prototype corresponds to the stages of the real experiment.	Verification of simulation-to-practice alignment	1-5
2	The algorithm helps to better understand the pH measurement process.	Educational value	1-5
3	The interface and simulation stages are clear without additional explanation.	Ease of use	1-5
4	The simulation results reflect the pH changes observed in the practical lesson.	Model accuracy	1-5
5	This format can be used for online learning as a substitute for the real experiment.	Applicability in an educational platform	1-5

2) *Expert Evaluation*

The algorithm and its prototype implementation were reviewed by three domain experts. One is a soil science specialist with practical experience in the pH monitoring of treated soils. The second specializes in developing digital educational tools and designing algorithms. The third expert has a background in geotechnical engineering and environmental soil analysis. Their combined feedback helped verify both the technical accuracy of the model and its appropriateness for integration into an educational simulation environment. To gather structured feedback on the algorithm's performance, a five-point Likert scale was used, where 1 indicated "strongly disagree" and 5 indicated "strongly agree."

3) *Evaluation by Group B*

To assess the effectiveness of the simulation algorithm developed for soil pH testing, the four-level evaluation model by Donald Kirkpatrick was applied and adapted for a digital learning setting [16]. The assessment focused on Group B, which consisted of 27 undergraduate civil engineering students, who did not take part in the physical laboratory phase. All responses were gathered anonymously. Group B represented a target user group for whom the simulation could serve as a primary tool for understanding the pH testing procedures. Their feedback was used to evaluate the usability, clarity, and user engagement (Level 1 – Reaction). Data were gathered utilizing standardized questionnaires that included both closed and open-ended questions, enabling the identification of user perceptions and the perceived effectiveness of the simulation algorithm. To assess both the cognitive outcomes and behavioral transfer from the simulation, Levels 2 and 3 (learning and behavior) of Kirkpatrick's evaluation model were integrated into a unified approach. This method maintains reliability while optimizing efficiency (Table IV). The behavioral application (Level 3) was evaluated using a series of delayed items within the same survey. Closed and open-ended questions were used to gather data on the long-term retention and practical relevance. No grades were given, as the focus was on assessing the simulation algorithm's practical usefulness rather than the user performance.

TABLE IV. EVALUATION CRITERIA FOR GROUP B

№	Question	Category	Scale (1–5)
1	How satisfied are you with the simulation overall?	General satisfaction	
2	The simulation helped me understand the pH testing process.	Perceived usefulness	
3	The interface was clear and easy to navigate.	Interface usability	
4	I found the structure of the simulation logical and well-organized.	Interface structure	
5	The simulation kept me engaged throughout the task.	Engagement	
6	I felt actively involved in the experiment, despite the digital format.	Cognitive Engagement	
7	I experienced no technical difficulties while using the simulation.	Technical reliability	
8	I would recommend using this simulation in future educational courses.	Overall perception	
Open-ended questions			
9	What aspects of the simulation did you find most helpful?		Not scored
10	What would you improve in the simulation?		Not scored
11	Did you face any difficulties or challenges?		Not scored

III. RESULTS AND DISCUSSION

A. *Assessing the Impact of pH*

The control sample (unmodified soil) had a stable pH of 7. In the samples treated with microorganisms (additive 1), the initial pH values showed acidic conditions; however, by day 7, the pH increased to 6.5 (Figure 4).

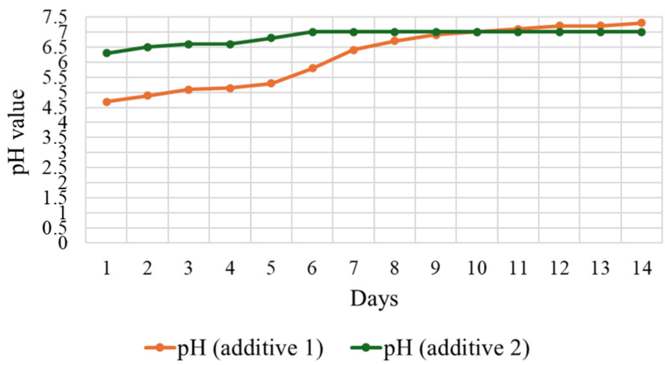

Fig. 4. Results of soil pH test.

This shift indicates biochemical activity, where microorganisms use urea and calcium salts, producing alkaline byproducts, such as calcium carbonate. These substances neutralize the soil acidity and support the bio-cementation while enhancing the pH balance. Ten days after starting the soil modification, the measurements showed that the pH continued to rise to 7.0. This level indicates a neutral environment, which is ideal for most microbial processes, particularly those involving the mineralization of organic matter and the precipitation of calcium. The steady increase in the pH throughout the experiment reflects ongoing biochemical reactions involving microorganisms that keep activating cementation processes in the soil. Additive 2 (biopolymer) initially lowered the pH of the sand slightly. This occurs because the amino groups of chitosan interact with water, releasing hydrogen ions that reduce the pH of the medium. Since the sand started with a neutral medium, the pH change caused by the polymer was not very noticeable. The sensor readings varied within an acceptable error range (±0.1–0.2), confirming the reliability of the collected data.

B. Instructor-based Performance Assessment Results

Both subgroups demonstrated satisfactory performance and skills. Although the results differed slightly among the subgroups, each was able to accurately interpret the data and present their findings. Overall, both groups drew valid conclusions from the experiment data (Figure 5).

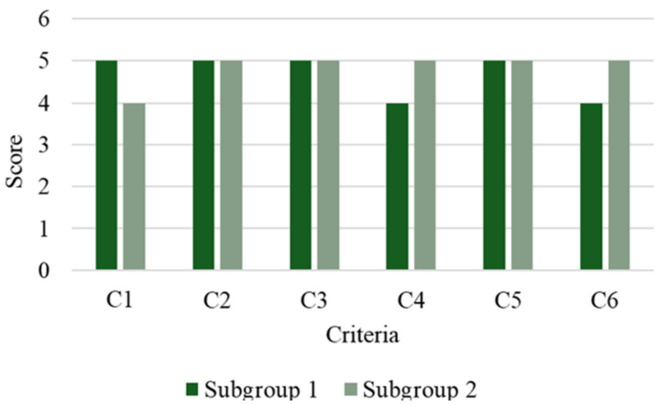

Fig. 5. Score for Group A.

C. Results of Verification of the Simulation Algorithm

1) Results of Simulation Verification (Group A)

The final evaluation results for Group A are shown in Table V, which presents the average values and SDs for each item related to verifying the simulation and its perceived effectiveness. The items (Q1–Q5) align with the indicators listed in Table III. The quantitative analysis consistently indicated positive evaluations of the simulation's accuracy and perceived educational value.

TABLE V. RESULTS OF VERIFICATION BY GROUP A

Question number	Mean score	SDs
Q1	4.50	0.51
Q2	5.00	0.00
Q3	4.50	0.51
Q4	4.45	0.51
Q5	4.65	0.49

The statement "The algorithm helps to better understand the pH measurement process" received unanimous approval (mean value = 5.00, SD = 0.00). Other items scored between 4.45 and 4.65, with SD being scored under 0.51, indicating low variability and strong agreement among the participants. The quantitative analysis of the responses confirmed consistent positive evaluations of the simulation's accuracy.

2) Expert Evaluation of the Simulation Algorithm

Experts evaluated six key criteria related to the algorithm's accuracy, completeness, usability, and educational relevance. The evaluation results show a high level of agreement and satisfaction with the algorithm across all criteria. A score of 4 indicates that the algorithm is mostly effective but requires minor revisions. The results are summarized in Table VI.

TABLE VI. RESULTS OF VERIFICATION BY EXPERTS

Accuracy of operations		Expert 1	Expert 2	Expert 3
Completeness	Inclusion of relevant scenarios	5	5	5
Educational alignment	Support of curriculum goals and key scientific concepts	5	5	5
Logical structure	Coherence and clarity of algorithm logic	5	5	5
Interface clarity	Intuitiveness and clarity of the user interface	5	5	4
Ease of use	Simplicity and ease of interaction	5	4	5
Correctness	Accuracy of operations	5	5	5

The necessary adjustments were reviewed with the experts after the evaluation and were taken into consideration. Overall, the evaluation results support the algorithm's functionality and its alignment with the educational goals. These findings confirm the algorithm as an effective and pedagogically appropriate tool in engineering education.

3) Evaluation of the Simulation Algorithm (Group B)

The Level 1 (Reaction) results demonstrate how well the simulation algorithm achieved a stable, user-friendly, and educationally valuable experience (Figure 6).

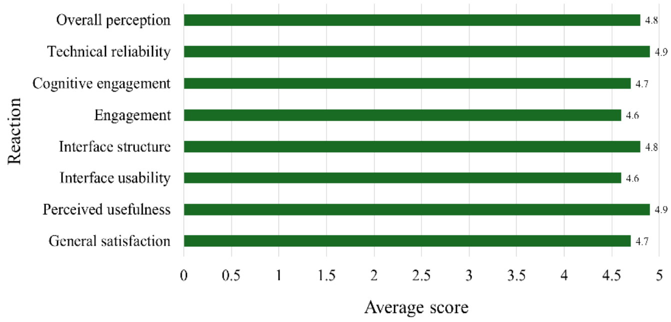

Fig. 6. Results of verification by group B.

The highest average scores were reported for technical reliability and perceived usefulness, both at 4.9, demonstrating that the algorithm operated smoothly without interruptions. The interface structure and overall perception also received high ratings of 4.8, emphasizing the clarity and educational effectiveness of the algorithm-based design. The algorithm's capacity to maintain engagement was reflected in the scores of 4.6 and 4.7 for two related items, while the interface usability was rated at 4.6. Overall, students rated their satisfaction at 4.7 and endorsed the simulation for future implementation. These results demonstrate that the simulation algorithm fulfilled the technical requirements and effectively promoted active learning within a digital setting. Level 2 (Learning) results showed high self-assessed outcomes from 27 students: 4.8 for understanding the pH procedure, 4.6 for error recognition, and 4.8 for interpreting the experimental data, demonstrating the algorithm's effectiveness in improving subject knowledge. Level 3 (Behavior) outcomes indicated a successful knowledge transfer, with scores of 4.6 for completing academic tasks, 4.5 for interdisciplinary applications, and 4.7 for confidence in performing laboratory procedures. These ratings imply that the simulation algorithm not only supported the learning retention, but also facilitated the practical application of skills across various educational contexts. The analysis of simulation logs showed that 96% of users (26 out of 27) completed the algorithm-driven procedure without any omissions or structural errors.

IV. CONCLUSION

The experimental results exhibited different pH change patterns depending on the additive type. The soils treated with microorganisms (additive 1) experienced a steady rise in the pH—from strongly acidic (pH 4.7) to slightly alkaline (pH 7.3) over 14 days—reflecting ongoing biochemical activities, like urea hydrolysis and calcium carbonate formation. This continuous increase indicates sustained microbial action and a strong potential for successful biocementation. In contrast, the biopolymer-modified samples (additive 2) exhibited a quicker and smaller change in the pH, reaching neutral (pH 7.0) by day 6 and staying stable afterward. This indicates the immediate but limited buffering capacity of the polymer, likely due to short-term interactions between functional groups and the soil solution. The unmodified soil maintained a steady pH of 7.0, acting as a reliable control. The consistent readings across different sensor types confirmed the dataset's reliability, which was then used to create a time-dependent simulation algorithm that mimics the observed modification patterns. This study converts empirical soil behavior into a validated simulation algorithm, establishing a foundation for teaching tools in engineering education. It connects the practical experimentation with educational technology, ensuring both scientific accuracy and teaching value.

DATA AVAILABILITY STATEMENT

The corresponding author may provide access to the student-generated dataset upon a reasonable request.

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