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Multi-Objective Optimization of IoT-Based Hands-On Learning Using NSGA-II and R-NSGA-II Algorithms

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ABSTRACT

This study aims to optimize Internet of Things-based hands-on learning using a multi-objective approach with Non-dominated Sorting Genetic Algorithm II and Reference Point–based Non-dominated Sorting Genetic Algorithm II. The optimization targets three objectives: learning efficiency, learner engagement, and practical skill improvement. A modeling-based approach is employed, and simulations are conducted to evaluate the effects of key parameters, including the number of Internet of Things devices, practicum duration, and task complexity, on learning outcomes. The results show that Reference Point–based Non-dominated Sorting Genetic Algorithm II achieves higher learning efficiency (0.571) and learner engagement (0.090), producing more balanced solutions across objectives, whereas Non-dominated Sorting Genetic Algorithm II performs better on skill improvement (0.184), particularly for high-complexity tasks. Pareto front visualizations illustrate the distribution of optimal solutions, with Reference Point–based Non-dominated Sorting Genetic Algorithm II demonstrating faster convergence and more consistent solution quality. This study contributes to the design of more efficient, effective, and adaptive Internet of Things-based learning models and provides guidance for educational institutions in selecting optimization methods aligned with specific learning priorities.

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1. INTRODUCTION

IoT (Internet of Things)-based learning has become an increasingly popular method in engineering education, especially in the field of industrial automation and control [1–3]. Hands-on learning involving IoT devices allows learners to apply the theory they have learned in real-life situations, improving their understanding and practical skills [4–6]. However, IoT-based learning implementations often face challenges related to the management of limited resources, such as hardware and software, as well as the time available for each practicum session [7–9]. Therefore, there is a need for a strategy to optimize the use of devices, time, and task complexity to enable learning to run more efficiently and effectively. One way to increase efficiency in IoT-based learning is to implement multi-objective optimization [10–12]. In this context, optimization aims to balance several goals that often conflict, such as learning efficiency, learner engagement, and practical skill improvement. However, managing limited tasks and devices requires a more sophisticated approach. Modeling in multi-objective optimization can play a key role in solving this problem, especially with algorithms such as NSGA-II (Non-dominated Sorting Genetic Algorithm II) and R-NSGA-II (Revised NSGA-II), which can simultaneously optimize multiple objectives.

This modeling not only provides a way to evaluate different learning scenarios but also helps to design optimal scenarios to ensure maximum learning efficiency and high learner engagement. Using a multi-objective optimization algorithm, the model aims to find a solution that optimizes device use, time, and task complexity for each practicum session, with the goal of creating a more efficient and productive learning environment. The research focuses on modeling optimization algorithms for IoT-based learning, comparing NSGA-II and R-NSGA-II in the context of multi-objective optimization. The focus is on developing models that can handle the complexity of hands-on learning and improve learning quality and efficiency. Through this modeling, we hope to contribute to the development of more optimal learning methods using IoT by introducing solutions that can be adjusted for various variables involved in practicum management.

This study aims to develop and apply a multi-objective optimization model in IoT-based hands-on learning using NSGA-II and R-NSGA-II. Although IoT-based learning has been widely applied in engineering education, most studies focus on pedagogical design or technology implementation rather than on optimizing multiple learning objectives simultaneously [11, 13, 14]. Previous works using optimization approaches often address single objectives, such as minimizing time or maximizing device usage, without considering the trade-offs among learning efficiency, engagement, and skill development [11, 15, 16]. Comparative analyses of NSGA-II and R-NSGA-II have also been mostly limited to industrial and engineering problems, leaving their potential in IoT-based educational optimization unexplored [17, 18]. Therefore, this study fills this gap by developing a multi-objective optimization model that applies and compares NSGA-II and R-NSGA-II to determine the optimal configuration of devices, practicum duration, and task complexity to enhance learning efficiency and effectiveness. Specifically, the objectives of this study are to: (1) Implementation of the model to evaluate the influence of various parameters (such as number of devices, practicum duration, and task complexity) on learning efficiency, learner engagement, and skill improvement; (2) Compare the performance of the two multi-objective optimization algorithms (NSGA-II and R-NSGA-II) in optimizing these parameters to achieve the best learning outcomes; (3) Apply a modelling based approach to identify optimal solutions in IoT-based learning management that can overcome the problem of resource and time constraints.

The main contribution of this research is the development of a multi-objective optimization algorithm model for IoT-based learning. By using optimization algorithm modeling, this study provides a more systematic and structured approach to solving hands-on learning problems involving IoT devices. The study also compared two well-known optimization algorithms, NSGA-II and R-NSGA-II, to assess their performance in the context of engineering education optimization. The uniqueness of the proposed approach lies in the application of a multi-objective optimization-based model that addresses real challenges in IoT-based learning and provides a basis for better decision-making to manage limited resources and improve learning quality. Thus, this research is expected to provide new insights and make a significant contribution to the development of more efficient and effective IoT-based education.

2. RESEARCH METHOD

2.1. IoT-Based Hands-On Learning

Internet of Things (IoT)-based hands-on learning is growing in popularity in engineering education due to its ability to provide hands-on, hands-on experience to learners [19–21]. IoT integrates hardware and software, along with connected sensors, to collect data and provide real-time feedback. In the context of engineering education, IoT is used to enrich practicum with simulation and automation of real industrial systems. The main challenges in IoT adoption are the management of a large amount of hardware, difficulties in integrating sensors with educational platforms, and limitations in managing software to support various IoT applications [22–24]. Therefore, optimizing the use of these resources is very important to ensure the learning process remains efficient and effective. Learner involvement in hands-on learning is essential to improve understanding and practical skills. The theory of constructivist learning emphasizes the importance of active involvement of learners in creating knowledge through direct experience [25–27]. In IoT-based practicums, learners not only learn theory but also acquire practical skills directly applied to projects or experiments involving IoT devices.

2.2. Multi-Objective Optimization in Education

Optimization in education aims to strike a balance between various goals that are often conflicting, such as time efficiency, learner engagement, cost, and quality of learning [15, 28, 29]. In the context of IoT-based learning, multi-objective optimization is important because the learning process involves many factors that must be considered simultaneously, such as the number of IoT devices, the duration of the practicum session, and the complexity of the provided material. Multi-objective optimization provides a great advantage because it allows decision-makers to choose solutions that can optimize multiple objectives simultaneously, such as improving learning efficiency, improving learner engagement, and ensuring skill improvement that is appropriate to the material being taught [30–32]. This approach enables the development of more effective learning models that can improve the quality and experience of learners in IoT-based learning.

Several studies have explored optimization approaches in IoT-based learning systems to improve efficiency and learning quality. For instance, resource optimization models have been used to manage IoT device allocation and reduce latency in remote laboratory environments [33], while other works applied reinforcement learning and fuzzy optimization to personalize IoT learning scenarios [16, 34]. However, most of these studies focus on system-level performance or adaptive learning, rather than integrating multi-objective optimization frameworks that simultaneously consider parameters such as device utilization, practicum duration, and task complexity. This research gap highlights the need for a comprehensive optimization model that can balance these multiple objectives to enhance learning efficiency, engagement, and skill development in engineering education.

2.3. NSGA-II and R-NSGA-II algorithms

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is one of the most widely used genetic algorithms to solve multi-objective optimization problems [35–37]. NSGA-II focuses on selection, crossover, and mutation in the evolutionary process to produce optimal solutions that other solutions cannot include without sacrificing any of the objectives [38–40]. The advantage of NSGA-II lies in its ability to produce an optimal Pareto front pareto, i.e., an optimal set of solutions in various objectives, which is very important in an educational context where several variables must be optimized simultaneously [18, 41, 42].

R-NSGA-II (Refined NSGA-II) is a further development of NSGA-II that focuses on improving computing efficiency and improving solution quality [17, 43, 44]. R-NSGA-II introduces refinement in the solution selection and search process to accelerate convergence to the optimal solution while maintaining the diversity of solutions in the search space [44]. The use of R-NSGA-II in the context of IoT-based education is highly relevant, as this algorithm can help design more efficient and effective learning models by accounting for various factors that affect learning outcomes. The comparison between NSGA-II and R-NSGA-II can be examined from several technical aspects, including computational efficiency and solution quality. These two algorithms are used to solve multi-objective optimization problems, but with slightly different approaches. The comparison between NSGA-II and R-NSGA-II is shown in Table 1.

Table 1. The Following Shows The Main Comparisons Between NSGA-II and R-NSGA-II

Aspects	NSGA-II	R-NSGA-II
Algorithmic Approach	Non-dominance selection and sorting-based algorithm with a successive generation approach	Modified algorithms with adaptations for better computing efficiency
Computational Complexity	Moderation, often requiring more iterations to achieve convergence	Tends to be more efficient with lighter computing
Solution Quality	Good in most cases, although sometimes stuck in local solutions	Improve the quality of solutions in more complex conditions
Convergence Speed	Convergence speed is comparatively slower	Faster convergence with fewer generations
Flexibility	Flexible, used in many optimization applications	Focus more on bigger or more complex problems
Scalability	Effective for problems of medium size	Superior in handling problems with many variables

2.4. Research Design

This research design aims to explore and optimize IoT-based learning models using a multi-objective optimization approach with the NSGA-II and R-NSGA-II algorithms. This study aims to improve learning effectiveness, participant engagement, and skill mastery through the use of IoT devices in engineering-based practicums. The experimental approach modeled various learning scenarios, enabling a comprehensive analysis of system performance without being constrained by field data limitations. The research methods used are shown in Figure 1.

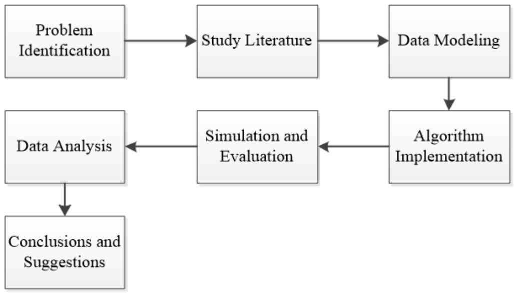


Figure 1. Research Methods

2.5. Experimental Design

This experimental approach is designed to evaluate three main objectives in Internet of Things (IoT)-based learning. The purpose of this design is to ensure that the evaluation process comprehensively measures the cognitive and practical aspects of learning activities. Through this approach, the study systematically identifies key performance indicators that reflect learning efficiency, Learner engagement, and skill improvement under various experimental conditions, as follows: (1) Learning Efficiency: Measured based on how learning can be achieved in a limited time with the number of devices available; (2) Learner Engagement: Evaluate how learners interact and participate in the practicum, taking into account the device load and complexity of the task; (3) Skill Improvement: Seeing how well learners' technical skills develop during practicum, which is affected by the time and complexity of the task.

The experiment is carried out by modeling various scenarios with different combinations of device count, practicum duration, and task complexity. These scenarios are designed to represent realistic conditions that may occur in Internet of Things (IoT)-based hands-on learning environments. The generated scenario data are then used to train and test the NSGA-II and the R-NSGA-II to evaluate their performance in achieving optimal multi-objective solutions.

2.6. Experiment Parameters

This experiment is designed to test various parameters that influence the performance of Internet of Things (IoT)-based learning models. The main parameters include the number of IoT devices, the duration of practicum sessions, the complexity of tasks, and the capacity of IoT devices used during the experiments. Each parameter plays an important role in determining how effectively learners can interact with the system and achieve optimal learning outcomes. The number of IoT devices determines how many units can be utilized simultaneously during the practicum, influencing accessibility and resource allocation. The practicum session time represents the total duration available for learners to complete the assigned tasks. Task complexity refers to the difficulty of a learning activity, which directly affects cognitive load and problem-solving ability. Meanwhile, IoT device capacity indicates how many learners can use a single device concurrently, reflecting scalability and potential for collaboration in the learning environment. For optimization purposes, specific weights are assigned to each learning objective to balance multiple outcomes effectively. Learning efficiency is assigned a weight of 0.4, participant engagement a weight of 0.3, and skill improvement a weight of 0.3. These weight values are used to guide the optimization process toward the most effective and balanced performance of the learning model.

2.7. Model Mathematics Multi-Objective

This multi-objective mathematical model is developed based on three primary variables: the number of Internet of Things (IoT) devices, practicum duration, and task complexity. These variables are selected because they represent the key factors influencing the effectiveness and efficiency of IoT-based hands-on learning environments. A mathematical formulation is constructed to capture the interactions among these parameters and their impact on learning performance, enabling quantitative optimization and comparative analysis across different algorithmic approaches. The mathematical model is as follows: (1) Learning Efficiency (f_1) is used to measure the extent to which practicum devices and time are used efficiently against the complexity of the task. The mathematical model of learning efficiency is shown in Equation 1 [2]; (2) Learner Engagement (f_2) is used to measure learners' participation rate by examining device and time distributions. The mathematical model of learner involvement is shown in Equation 2 [45]; (3) Skill Improvement (f_3) is used to measure the practicum learning outcomes of the tasks performed. Mathematical model of skill improvement as in Equation 3 [46].

$$f_1(x) = \frac{d}{d_{max}} \times \frac{t}{t_{max}} \times \frac{1}{\frac{c}{c_{max}}} \tag{1}$$

$$f_2(x) = (1 - device\_overload) \times \left(1 - \frac{c}{c_{max}}\right) \times \frac{t}{t_{max}} \tag{2}$$

$$f_3(x) = \frac{c}{c_{max}} \times \frac{t}{t_{max}} \times content\_quality \tag{3}$$

Where, d is the device used. t is the practicum session time. c is the complexity of the task. $content\_quality$ is the quality of learning materials. $device\_overload$ be $max\left(0, \frac{students - (d \cdot devices\_capacity)}{students}\right)$

2.8. Implementation of NSGA-II and R-NSGA-II Algorithms

NSGA-II and R-NSGA-II are implemented to optimize the three learning objectives. In their application, both algorithms are used to identify the optimal combination of device count, practicum time, and task complexity that maximizes learning efficiency, learner engagement, and skill improvement. NSGA-II is a genetic-based algorithm used to solve multi-objective optimization problems by performing selection, crossover, and mutation in each generation. Meanwhile, R-NSGA-II is a modification of NSGA-II that integrates data processing techniques and increased computing efficiency in finding optimal solutions. The architectural design of the algorithm used is as shown in Figure 2.

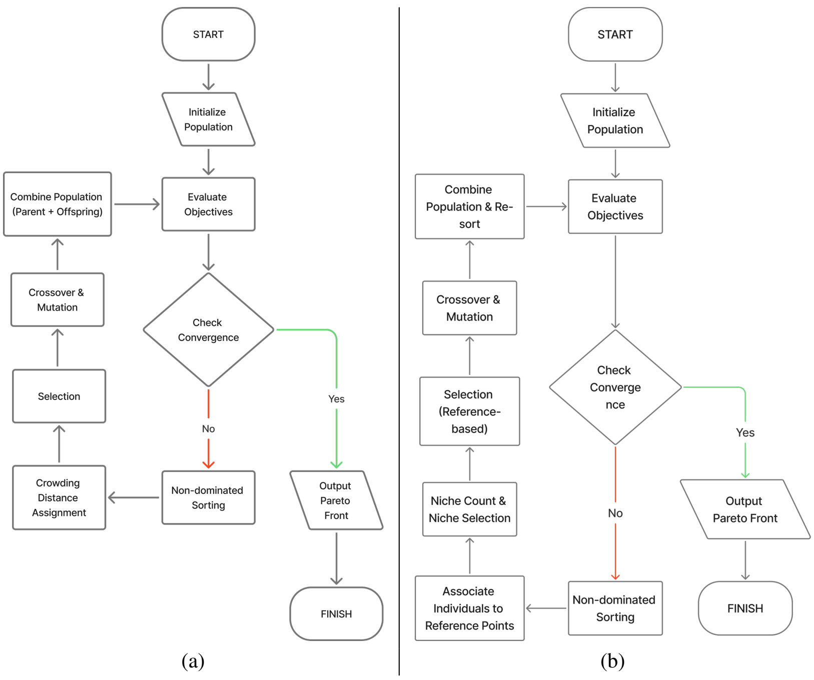


Figure 2. Architectural design (a) NSGA-II and (b) R-NSGA-II

2.9. Simulation Procedure and Result Analysis

The modeling procedure in this experiment is designed to simulate various practical scenarios with full control over the variables being tested. This approach ensures that the simulated conditions reflect realistic situations that might occur in IoT-based practice, while also enabling efficient testing of a range of parameters and scenarios. After running experiments with the NSGA-II and R-NSGA-II algorithms, the results were analyzed by visualizing each algorithm's Pareto Front. The value of optimization goals such as learning efficiency, engagement, and skill improvement is compared to identifying the best solution from each algorithm. The focus of this research is simulation-based optimization, so the results are evaluated quantitatively by comparing the Pareto Front and objective function values. This analysis provides a clear overview of each algorithm's performance and supports conclusions regarding its strengths and performance characteristics. Additional statistical analysis was not included because the primary objective of the study was to evaluate optimization behavior in a controlled simulation, a common practice in model-based multi-objective optimization studies.

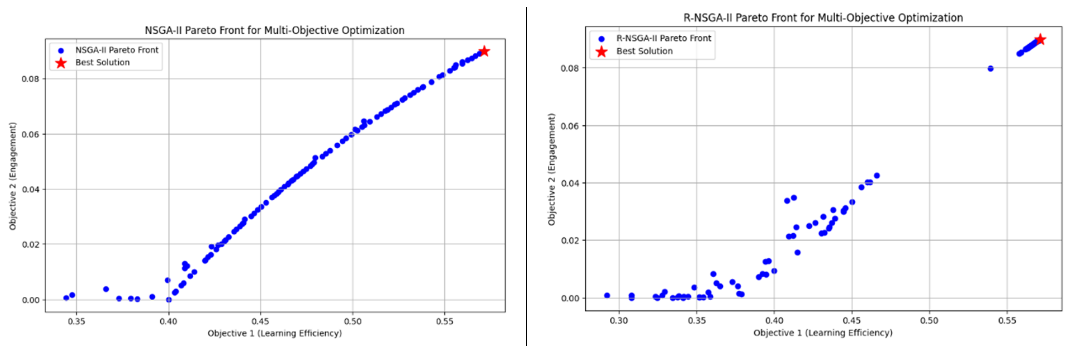
3. RESULT AND ANALYSIS

The results of the experiment are presented using three main indicators: learning efficiency, learner engagement, and skill acquisition. The data obtained from the simulation using the NSGA-II and R-NSGA-II algorithms were compared to evaluate the advantages of each algorithm. The results of the experiment are presented based on three main indicators: learning efficiency, learner engagement, and skill acquisition. These indicators were selected to comprehensively represent the cognitive, affective, and psychomotor aspects of IoT-based hands-on learning. The data obtained from the simulations using NSGA-II and R-NSGA-II were then compared to evaluate the advantages and performance characteristics of each algorithm across various experimental scenarios.

3.1. Pareto Front

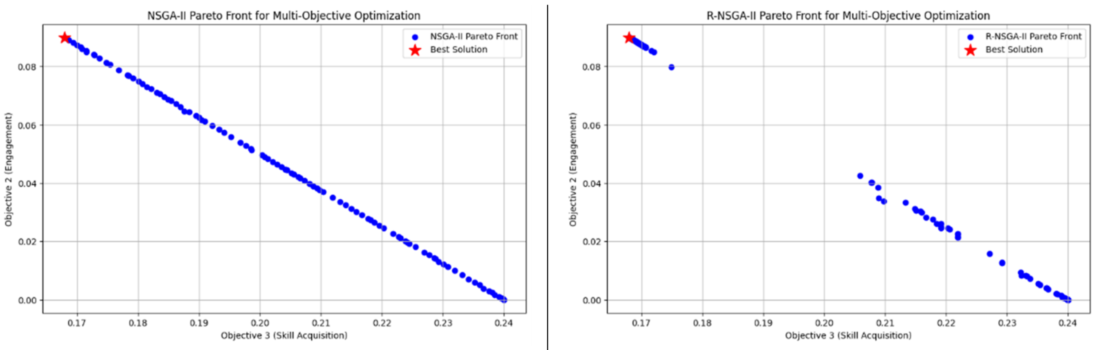
The Pareto Front visualization for both NSGA-II and R-NSGA-II illustrates the distribution of optimal solutions generated from various combinations of decision parameters used in the simulation. These parameters include the number of participants (30), the number of devices (10), the practicum duration (120 minutes), the task complexity level (10), the device capacity (3), and the material quality factor (0.8). The resulting Pareto Front reflects how each algorithm balances the trade-offs between learning effectiveness, time efficiency, and technology accessibility under the defined constraints. This visualization also provides insight into the dominance relationships among the solutions, showing how each algorithm adapts to multi-objective scenarios. Figures 3, 4, and 5 present the complete Pareto Front outcomes for comparison and further analysis.

Based on Figure 3, 4, and 5, Pareto Front data from the NSGA-II and R-NSGA-II algorithms show that both algorithms have produced optimal solutions for three multi-objective goals: time efficiency, learner engagement, and learner skill improvement. NSGA-II demonstrates a more uniform distribution of solutions along the Pareto Front, especially in the trade-off between time efficiency and engagement, although some of its solutions show limitations on skill improvement in certain areas. In contrast, the R-NSGA-II excelled at producing a more well-distributed set of solutions on the Pareto Front across a variety of objective combinations, including the more complex trade-offs between time efficiency and skill. In addition, R-NSGA-II shows better convergence on optimal solutions with higher diversity, especially in scenarios with large conflicts between objectives. Overall, the R-NSGA-II performs better in solution space exploration, while the NSGA-II yields a solution that remains competitive in certain configurations.



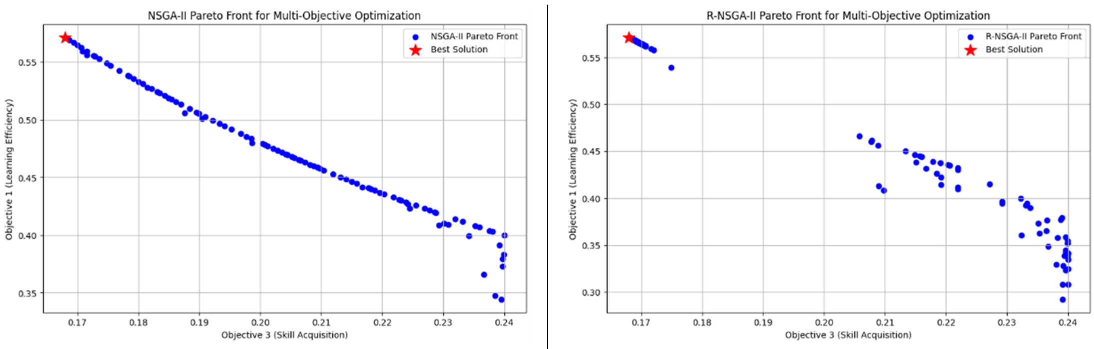
(a) (b)

Figure 3. Graphs of learning effectiveness and participant engagement using (a) NSGA-II and (b) R-NSGA-II



(a) (b)

Figure 4. Participant skill improvement and engagement graphs using (a) NSGA-II and (b) R-NSGA-II



(a) (b)

Figure 5. Graph of skill improvement and learning effectiveness using (a) NSGA-II and (b) R-NSGA-II

3.2. Comparison of Multi-Objective Values

Based on Table 2, the learning efficiency of the NSGA-II algorithm is quite good, but it is lower than that of R-NSGA-II. The R-NSGA-II algorithm significantly improves learning efficiency. This is possible because the direction reference in R-NSGA-II guides the solution toward the optimal region for learning efficiency. In terms of participant engagement, the NSGA-II algorithm yields very low results. This shows that this algorithm pays less attention to factors that affect learner engagement, such as device load management. The R-NSGA-II algorithm does not achieve very high results; it shows more than twice the improvement compared to NSGA-II. This may be related to the algorithm's ability to consider reference preferences in engagement goals. In terms of skill enhancement, NSGA-II yields higher skill improvement than R-NSGA-II. This suggests that these algorithms may be better at exploring solutions that prioritize more complex tasks. Slightly lower than NSGA-II, suggesting that R-NSGA-II may not be as focused on complex tasks when compared to the other two objectives.

Table 2. Data Values The Best Solution for Each Optimization Goal

Algorithm	Learning Efficiency	Participant Engagement	Skill Enhancement
NSGA-II	0.4571407	0.03749942	0.1837504
R-NSGA-II	0.5711987	0.08996204	0.1680019

These results show that NSGA-II is better at upskilling but has significant weaknesses in learning efficiency and learner engagement. This shows that the algorithm focuses more on exploring solutions than on optimal management of resources and time. And R-NSGA-II shows a more balanced performance, especially superior in learning efficiency and learner engagement. This algorithm is more suitable for cases where resource limitations are a major consideration.

3.3. Analyze the Best Solution for Each Algorithm

NSGA-II produces the best solution for upskilling, demonstrating good exploration in supporting project-based learning with high complexity. However, participant involvement is very low, so more attention is needed if learner involvement is the main goal. R-NSGA-II shows the best solution for learning efficiency and participant engagement. This algorithm can consider resources more optimally to produce solutions that support collaborative activities and time efficiency. If the top priority is Upskilling, NSGA-II provides the best solution with a higher value on this goal. If the Priority is a Balance of Efficiency and Participant Engagement, R-NSGA-II is the best choice because the resulting solution is more optimal in learning efficiency and participant engagement. For a solution, ideally using R-NSGA-II with modified preferences to better balance upskilling can be the optimal option, especially for real applications such as IoT-based learning.

3.4. Result Discussion

The discussion of these results focuses on explaining how both algorithms contribute to the decision-making process in optimizing IoT-based learning models. Each algorithm is evaluated based on its ability to meet three optimization goals: learning efficiency, participant engagement, and skill improvement within a controlled simulation environment. Table 3 presents a structured comparison between NSGA-II and R-NSGA-II, highlighting the advantages, limitations, and performance characteristics of each algorithm under various simulation conditions. Comparative analysis shows that NSGA-II excels at generating solutions that maximize skill improvement, particularly in high-complexity scenarios. However, its participant engagement value is relatively low, indicating limitations when applied in collaborative learning environments or under limited-resource conditions. Conversely, R-NSGA-II demonstrates more balanced performance, yielding better results in learning efficiency and participant engagement. This balance stems from a reference-direction mechanism that guides the population toward areas of the solution space that support more even resource allocation and better participant interaction.

Although this study did not use statistical significance tests because the primary research objective was to analyze optimization behavior, not test hypotheses, the comparisons were still supported by quantitative indicators such as the Pareto Front distribution pattern, solution diversity, and objective value summary. These indicators provided sufficient evidence of performance differences among algorithms in simulation-based multi-objective optimization. Advanced quantitative analyses, such as convergence metrics or statistical confidence intervals, can be a development in subsequent studies.

Table 3. Comparison Of NSGA-II And R-NSGA-II Algorithms in Learning Models

Discussion Aspects	NSGA-II	R-NSGA-II
Algorithm Evaluation	The advantage is that it produces the highest skill improvement score.	The advantage is a balance between learning efficiency and engagement.
	The disadvantage is that the participant engagement score is low.	The disadvantage is that the value of skill improvement is lower than that of NSGA-II.
Time Efficiency	Not optimal for conditions with limited time, tend to be more exploratory.	Better at managing time allocation efficiently with directions from references.
Learner Engagement	Low engagement value, less supportive of collaborative learning scenarios.	Providing optimal solutions to increase learner participation in IoT practicums.
Skill Enhancement	Excels in optimizing the mastery of technical skills through high-complexity tasks.	Slightly inferior in skill mastery compared to NSGA-II.
Real Implementation	Suitable for individual projects or IoT-based final projects with a priority for skill mastery.	It is better suited to team-based collaborative learning, with a more equitable allocation of resources.
Practical Applications	Helps determine the optimal complexity to encourage learner skills.	Facilitate the allocation of IoT devices and practicum time for balanced learning.

Based on Table 3, NSGA-II is most suitable for learning scenarios that emphasize improving technical skills, such as individual projects or IoT-based final projects. His ability to explore complex solution areas provides an advantage for tasks with high technical demands. Conversely, R-NSGA-II is better suited for collaborative learning and practical sessions with large numbers of participants, where time efficiency and participant engagement are key. Although the results for skill improvement are slightly lower than those of NSGA-II, this algorithm provides a more stable distribution of solutions, ensuring more even learning outcomes among participants, making it more suitable for adaptive and inclusive IoT-based learning environments.

3.5. Real-World Implementation

The algorithms used in this study can assist engineering education institutions in designing more efficient IoT-based practicum curricula. These algorithms provide data-driven insights that support the development of adaptive learning strategies based on resource availability and learner needs. For example, R-NSGA-II can be used to determine the optimal number of IoT devices for a single practicum session, ensuring that all learners remain actively engaged without compromising time efficiency. By leveraging the R-NSGA-II optimization results, educational laboratories can enhance learner engagement through a more equitable and efficient allocation of learning resources. This approach allows laboratories to identify the most suitable practicum duration and task complexity according to the average capability of the learners. Consequently, the implementation of this algorithm contributes to creating a more balanced, inclusive, and effective learning environment in IoT-based engineering education.

4. CONCLUSION

This research develops and evaluates a multi-objective optimization model for IoT-based hands-on learning using the NSGA-II and R-NSGA-II algorithms. Simulation results show that each algorithm has different advantages depending on learning priorities. NSGA-II excels at optimizing complex, skill-building tasks, making it well-suited to individual learning scenarios or projects that emphasize technical mastery. Conversely, R-NSGA-II demonstrates more balanced performance in learning efficiency and participant engagement, making it a more appropriate choice for collaborative learning in laboratories with time and resource constraints.

Theoretically, this research contributes to the application of optimization models in engineering education by demonstrating that multi-objective evolutionary algorithms can be used to design learning environments that balance efficiency, engagement, and skill improvement. This finding strengthens the idea that optimization approaches can serve as decision-making tools for designing adaptive, scalable IoT-based learning processes. Practically, this research offers insights that can be directly applied by education practitioners, especially in planning IoT-based practicum sessions. R-NSGA-II can be utilized to determine optimal device allocation, efficiently schedule practicum time, and adjust task complexity levels to ensure even participant engagement. Meanwhile, NSGA-II is relevant when the primary goal is to achieve deep mastery of technical skills. Thus, the results of this study can help lecturers and curriculum designers create more effective data-driven learning experiences.

Nevertheless, there are several challenges in applying this model in real-world conditions. Variations in participant abilities, infrastructure limitations, group dynamics, and fluctuations in device availability can affect the performance of a system optimized through simulation. Additionally, the use of optimization algorithms requires adequate digital literacy for educators and institutional support to be integrated into the learning planning process. Further research is suggested to expand the simulation parameters using empirical data from real laboratory sessions, validate the model at a larger class scale, and develop assistive tools or dashboards that enable instructors to easily use the optimization results without requiring advanced computational modeling skills. With further development, this model has the potential to support the creation of a more effective, inclusive, and adaptive IoT-based engineering learning environment.

5. ACKNOWLEDGEMENTS

Collate acknowledgements in a separate section at the end of the article before the references and do not, therefore, include them on the title page, as a footnote to the title or otherwise. List here those individuals who provided help during the research (e.g., providing language help, writing assistance, or proofreading the article, etc.).

6. DECLARATIONS

AUTHOR CONTIBUTION

The contribution to the paper is as follows: Muchamad Wahyu Prasetyo, Aripriharta, Anik Nur Handayani: study conception and design; Muchamad Wahyu Prasetyo: data collection; Muchamad Wahyu Prasetyo, Aripriharta, Anik Nur Handayani: analysis and interpretation of results; Muchamad Wahyu Prasetyo: draft preparation. All authors approved the final version of the manuscript.

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COMPETING INTEREST
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