The Future of Engineering Education
2024 Annual Conference & Exposition
Oregon Convention Center
Portland, OR . June 23 - 26, 2024
ASEE
Paper ID #41894

Developing Computational Intelligence Curriculum Materials to Advance Student Learning for Robot Control and Optimization

Dr. Tingjun Lei, Mississippi State University

Dr. Tingjun Lei is currently a Postdoctoral Research Fellow in the Department of Electrical and Computer Engineering at the Mississippi State University (MSU). He received his Ph.D. degree in electrical and computer engineering with the Department of Electrical and Computer Engineering, Mississippi State University, Mississippi State, MS, USA., in 2023, his M.S. degree in electrical and computer engineering from the New York Institute of Technology, Old Westbury, NY, USA, in 2016, and the B.S. degree in intelligent transportation engineering from Shanghai Maritime University, Shanghai, China, in 2014. He was Graduate Teaching Assistant for ECE1013 Foundations in ECE, ECE1022 Foundations in Design, ECE4713/6713 Computer Architecture, and ECE4753/6753 Introduction to Robotics at the undergraduate level and as a guest lecturer delivered graduate-level courses, ECE 8743 Advanced Robotics and ECE8833 Computational Intelligence. He received the ECE Best Graduate Researcher Award from the Department of Electrical and Computer Engineering, Mississippi State University in 2023. He received the Research Travel Award from Bagley College of Engineering, Mississippi State University in 2023. His two papers have been selected and featured as cover articles on Intelligence & Robotics Journal. He won six oral and poster presentation awards at multiple conferences. Dr. Lei received the Best Paper Award in 2022 International Conference on Swarm Intelligence. Dr. Lei serves as Youth Editorial Board Member of Intelligence and Robotics. Dr. Lei has served on the technical program committee for numerous international conferences, such as IEEE-CEC, IEEE-IJCNN, ICSI, and PRIS, etc. Dr. Lei has extensively published journal and conference papers in robotics, intelligent systems, and engineering education areas. His research interests include engineering education, robotics and autonomous systems, human robot interaction, deep learning, intelligent transportation systems, and evolutionary computation.

Timothy Sellers, Mississippi State University

Timothy Sellers received the B.S. degree in robotics and automation technology and applied science in electro-mechanical engineering from the Alcorn State University, Lorman, MS, USA in 2020. He is currently pursuing a Ph.D. degree in the Department of Electrical and Computer Engineering at Mississippi State University, Mississippi State, MS, USA. He is currently a Graduate Teaching Assistant for Senior Design II (ECE4542/ECE4522) and was for Advance Circuits (ECE3434) at the undergraduate level and as guest lecturer delivered graduate-level courses, Advanced Robotics (ECE 8743) and Computational Intelligence (ECE 8833). He received the ECE Outstanding Teaching Assistant Award from the Department of Electrical and Computer Engineering, Mississippi State University in 2021. He received the Research Travel Award from Bagley College of Engineering, Mississippi State University in 2024. He has also received the Bagley College of Engineering Student Hall of Fame award in 2024. He won three poster presentation awards at multiple conferences. Mr. Sellers has served on the technical program committee for numerous international conferences and journals, such as IJMLC, ICSI, and PRIS, etc. He has extensively published journal and conference papers in engineering education and robotics fields. His research interests include engineering education, robotics and autonomous systems, human robot interaction, deep learning, and computational intelligence.

Prof. Chaomin Luo, Mississippi State University

Dr. Chaomin Luo (Senior Member, IEEE) holds a Ph.D. degree in electrical and computer engineering from the Department of Electrical and Computer Engineering at the University of Waterloo, Canada in 2008. He also earned an M.Sc. degree in engineering systems and computing from the University of Guelph, Canada in 2002, and a B.Sc. in electrical engineering from Southeast University. Currently, he is an Associate Professor in the Department of Electrical and Computer Engineering at Mississippi State University. His research interests include engineering education, intelligent systems, control and automation, robotics, and autonomous systems. He is Associate Editor in 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2019). He is Tutorials Co-Chair in the 2020 IEEE

Symposium Series on Computational Intelligence. Dr. Luo was the recipient of the Best Paper Awards in IEEE International Conference on Information and Automation, International Conference on Swarm Intelligence, and SWORD Conference. His research interests include Robotics, Autonomous Systems, and Control and Automation. Dr. Luo is an IEEE senior member, INFORMS, and ASEE member. Dr. Luo is active nationally and internationally in his research field. He was the Program Co-Chair in 2018 IEEE International Conference on Information and Automation (IEEE-ICIA'2018). He was the Plenary Session Co-Chair in the 2021 and 2019 International Conference on Swarm Intelligence, and he was the Invited Session Co-Chair in the 2017 International Conference on Swarm Intelligence. He was the General Co-Chair of the 1st IEEE International Workshop on Computational Intelligence in Smart Technologies (IEEE-CIST 2015), and Journal Special Issues Chair, IEEE 2016 International Conference on Smart Technologies (IEEE-SmarTech), Cleveland, OH, USA. He was Chair and Vice Chair of IEEE SEM - Computational Intelligence Chapter and was a Chair of IEEE SEM - Computational Intelligence Chapter and Chair of Education Committee of IEEE SEM. He has organized and chaired several special sessions on topics of Intelligent Vehicle Systems and Bio-inspired Intelligence in reputed international conferences such as IJCNN, IEEE-SSCI, IEEE-CEC, IEEE-CASE, and IEEE-Fuzzy, etc. He has extensively published in reputed journals and conference proceedings, such as IEEE Transactions on Industrial Electronics, IEEE Transactions on Neural Networks and Learning Systems, IEEE Transactions on SMC, IEEE Transactions on Cybernetics, IEEE-ICRA, and IEEE-IROS, etc. Dr. Luo serves as Associate Editor of IEEE Transactions on Cognitive and Developmental Systems, International journal of Robotics and Automation, and Associate Editor of International Journal of Swarm Intelligence Research (IJSIR).

Prof. Zhuming Bi, Purdue University

Zhuming Bi (Senior Member, IEEE) received the Ph.D. degree from the Harbin Institute of Technology, Harbin, China, in 1994, and the Ph.D. degree from the University of Saskatchewan, Saskatoon, SK, Canada, in 2002. He has international work experience in Mainland China, Hong Kong, Singapore, Canada, UK, Finland, and USA. He is currently a professor of Mechanical Engineering with Purdue University Fort Wayne, Fort Wayne, IN, USA. His current research interests include robotics, mechatronics, Internet of Things (IoT), digital manufacturing, automatic robotic processing, and enterprise information systems. He has published 6 research books and over 180 journal publications in these fields.

Prof. Gene Eu Jan, Tainan National University of the Arts

Gene Eu Jan (M'00) received the B.S. degree in electrical engineering from National Taiwan University, Taipei, Taiwan, in 1982 and the M.S. and Ph.D. degrees in electrical and computer engineering from the University of Maryland, College Park, MD, USA, in 1988 and 1992, respectively. He has been a Professor with the Departments of Computer Science and Electrical Engineering, National Taipei University, New Taipei City, Taiwan since 2004, where he also served as the Dean of the College of Electrical Engineering and Computer Science from 2007 to 2009. Currently, he is the president of Tainan National University of the Arts. He has published more than 270 articles related to parallel computer systems, interconnection networks, path planning, electronic design automation, and VLSI systems design in journals, conference proceedings, and books.

Developing Computational Intelligence Curriculum Materials to Advance Student Learning for Robot Control and Optimization

Tingjun Lei[1], Timothy Sellers[1], Chaomin Luo[1], Zhuming Bi[2], and Gene Eu Jan[3]
[1]Department of Electrical and Computer Engineering, Mississippi State University
[2]Department of Civil and Mechanical Engineering, Purdue University Fort Wayne
[3]National Taipei University, and Tainan National University of the Arts

Abstract
The integration of nature-inspired intelligence in computational intelligence curricula, particularly for robot path planning optimization, represents a significant advancement in both research and education realms. This study introduces a unique pedagogical approach that combines sparrow-dissection and scaffolding with flipped learning (SDS-FL) and ongoing project-based methods. This approach is implemented in a graduate-level course where students explore various nature-inspired algorithms such as particle swarm optimization, genetic algorithms, and bat algorithms, provided with source codes for practical application and adaptation. The flipped classroom model ensures pre-class preparation, enabling students to build foundational knowledge independently. In-class sessions are then focused on collaborative project work and discussions, fostering problem-solving, critical thinking, and analytical skills. This hybrid teaching method, promoting active engagement and practical application, is evaluated for its effectiveness through various assessments, including homework, exams, and feedback surveys. The positive outcomes from this innovative pedagogical approach affirm its success in enhancing students' understanding and application of nature-inspired intelligence in computational intelligence, making the learning process more dynamic and impactful.

1 Introduction

The field of engineering education places a significant emphasis on shaping students into proficient experts. To achieve this, a wide range of teaching techniques, including flipped-based [1–4], inquiry-based [5–8], collaborative [9–11], and differentiated learning [7, 12–14], have been explored and integrated. Each technique contributes its own unique aspect to the educational process, thereby enriching the learning experience for students in engineering.

Flipped classroom models in engineering education have demonstrated notable impacts on student achievement and engagement. Lo and Hew conducted a meta-analysis covering 29 interventions with over 5,000 students, revealing significant improvements in student achievement with the flipped model compared to traditional lectures, especially when classes began with a brief review [1]. Chiquito *et al.* [2] observed positive effects on student grades in a second-year engineering course, particularly among female students, and an increase in exam attendance. Li *et al.* [3] enhanced online engineering education through a flipped classroom in a Massive Open Online

Courses (MOOC), using a deep learning model to predict student performance, highlighting the importance of middle and final course stages. Additionally, Jo *et al.* [4] found that integrating gaming elements in flipped classroom online lectures increased student participation and interest. Each study showcases the flipped classroom's potential in improving learning outcomes, though their specific contexts limit the broader applicability of these findings.

Inquiry Learning focuses on fostering student curiosity and investigative skills, promoting active knowledge acquisition through questioning and exploration. Xenofontos *et al.* [5] investigated student engagement with graphing tasks in a computer-supported environment, emphasizing the positive effects of retrospective action and the importance of offering students a choice of variables. However, the study's small sample size of 51 students limits its generalizability. Notaroš *et al.* [6] integrated MATLAB-based instruction into an electromagnetics course, receiving positive feedback despite initial challenges due to students' limited MATLAB experience . The assessment was constrained to qualitative feedback and improvements in the Electromagnetics Concept Inventory, as program changes at Colorado State University (CSU) restricted a quantitative evaluation of the impact on student grades. Kollöffel and Jong focused on the impact of virtual lab inquiry learning in electrical circuit education, noting improvements in students' conceptual understanding and procedural skills, although their study faced questions about ecological validity [7]. Lastly, Dong and Guo studied the effects of collaborative project-based and inquiry-based learning in undergraduate computer networking, observing positive impacts on students' understanding, especially in teamwork environments [8]. They discussed strategies for integrating inquiry-based learning effectively but noted limitations related to remote collaboration difficulties and time constraints in projects. Each of these studies highlights both the potential benefits and challenges of implementing inquiry-based and collaborative learning methods in diverse educational contexts.

Collaborative Learning highlights the importance of group interactions, enriching comprehension through the exchange of collective ideas. Foldnes compared the effectiveness of the flipped classroom model with traditional lectures, focusing on two flipped classroom implementations [9]. The study found no significant difference in student exam scores with the first implementation without cooperative learning. However, the second implementation, which incorporated cooperative learning activities, showed significantly higher student scores, suggesting the flipped classroom's enhanced effectiveness when combined with cooperative learning. Martin-Gutierrez *et al.* [10] implemented augmented reality (AR) in an electrical engineering course, creating an engaging and interactive learning environment. While students found AR tools beneficial for understanding and task performance, the study mainly evaluated immediate feedback, leaving questions about long-term impact and adaptability in different academic settings open. Lastly, Hadfield-Menell *et al.* [11] proposed cooperative inverse reinforcement learning (CIRL) for aligning autonomous system behaviors with human values. Their theoretical approach, focusing on collaborative goals and communicative actions, suggests Partially Observable Markov Decision Process (POMDP) solutions but lacks practical application and real-world validation. Each study contributes to understanding the nuances of effective learning strategies, emphasizing the importance of context and implementation in educational outcomes.

Differentiated Learning adapts educational methods to accommodate the varied needs and learning styles of students. Meneskse *et al.* [12] evaluated the Differentiated Overt Learning

Activities (DOLA) framework in engineering education, confirming the Integrated Cognitive Antisocial Potential (ICAP) hypothesis that interactive activities enhance learning more effectively than other types. Their study, while supporting the effectiveness of interactive and constructive activities, was limited to short-term results and did not explore long-term retention or broader applicability. Zervoudakis *et al.* [13] developed a particle swarm optimization-based clustering algorithm for student classification in differentiated instruction. This method effectively grouped students with similar characteristics, aiding in class management, but the study mainly focused on the algorithm's technical efficiency rather than its practical educational application. Kolloffel and Jong's study in electrical engineering education compared traditional instruction with inquiry learning in a virtual lab [7]. They observed significant improvements in conceptual understanding and procedural skills in the virtual lab setting, especially in complex problem-solving. However, the study's quasi-experimental design and focus on vocational engineering students may limit its applicability to broader educational contexts. Finally, Cheng *et al.* [14] meta-analysis assessed the effectiveness of flipped classroom strategies across various studies. They found a significant positive impact on student learning outcomes, with variations across disciplines like mathematics, science, and engineering. Despite favorable results, the study's reliance on existing literature limits its scope in addressing diverse educational settings and long-term effects. Each study contributes to the understanding of effective learning strategies, highlighting the importance of context-specific implementation and the need for further research in diverse educational environments.

While flipped classrooms, inquiry learning, collaborative learning, and differentiated instruction offer valuable approaches to education, they may not fully address the unique challenges of integrating nature-inspired intelligence into computational intelligence education. These methods prioritize active learning, group interactions, and accommodating diverse learning styles, but they lack the structured guidance needed for students to grasp complex algorithms effectively. In contrast, our proposed approach of sparrow-dissection and scaffolding (SDS) integrated with flipped learning and project-based methods offers a hands-on, structured framework for students to comprehend and apply nature-inspired intelligence models. By providing guided exploration and practical application, our approach addresses the specific challenges of integrating these advanced concepts into the curriculum.

In this research, a pedagogy of sparrow-dissection and scaffolding (SDS)[15, 16] integrated with a flipped learning and a milestone on-going project-based method is developed to assist students to comprehend, create, and implement nature-inspired intelligence models for robot path planning optimization and control. In our graduate-level Computational Intelligence curriculum, we introduce students to various nature-inspired intelligence methods such as particle swarm optimization (PSO), genetic algorithms (GA), and bat algorithms (BA) [17, 18]. These methods are provided along with their source codes, serving as a 'sparrow' for students to dissect and explore how nature-inspired intelligence can be applied to optimize robot path planning. Working collaboratively with students, we guide them through the process of revising and customizing the provided source codes for the purpose of robot path planning.

The integration of a pedagogy of SDS with a flipped learning and milestone-driven project-based method in our Computational Intelligence curriculum is specifically tailored to the unique nature of the content and learning goals of the course. Nature-inspired algorithms, such as PSO, GA, and

BA, require a deep understanding of their underlying principles and practical application for optimizing robot path planning. By utilizing a pedagogy of sparrow-dissection, students are provided with source codes to dissect and explore these algorithms, facilitating a hands-on and experiential learning approach that is crucial for comprehending complex concepts in computational intelligence. Furthermore, the flipped learning model empowers students to engage with course materials at their own pace, enabling them to build a solid foundation in nature-inspired intelligence methods before engaging in collaborative projects. The project-based approach, integrated with multiple milestones, not only reinforces students' understanding of the algorithms but also cultivates problem-solving, critical thinking, and collaborative skills essential for success in engineering practice. Thus, these pedagogical approaches are selected for their suitability in promoting active engagement, deep comprehension, and practical application of nature-inspired algorithms in the context of robot path planning, aligning closely with the goals and objectives of the course.

Integrating flipped learning and a project-based approach with multiple milestones can establish a dynamic and captivating learning environment. Within this flipped classroom model, students receive nature-inspired intelligence algorithm materials before class, including reading assignments and online resources. This pre-class preparation empowers students to review these materials at their own convenience, enabling them to build a solid foundation in nature-inspired intelligence methods. These ongoing projects, integrated with the flipped learning pedagogy, serve a dual purpose. They not only aim to improve students' comprehension of nature-inspired intelligence algorithms for robot path planning but also to nurture and sharpen their problem-solving, critical thinking, and problem analysis skills. During in-class time, we utilize flipped learning activities to introduce and discuss these ongoing projects. We provide project guidelines and objectives, and we organize students into groups to collaborate on projects related to nature-inspired intelligence algorithms for robot path planning. We also elaborately design and provide various practice exercises after each lecture. This hybrid pedagogy empowers students to take ownership of their learning in nature-inspired intelligence algorithms, build problem-solving skills and connect these algorithms to practice in robot path planning. It promotes active engagement, critical thinking, and collaborative learning, making the educational experience more dynamic and meaningful for students.

In computational intelligence education the emphasis on nature inspired algorithms arises from their inherent advantages over traditional optimization techniques. These algorithms, drawing inspiration from natural phenomena or biological processes, demonstrate robustness, adaptability, and scalability, making them well-suited for solving complex optimization problems encountered in robotics planning and other domains. Their interdisciplinary nature aligns seamlessly with the diverse topics covered in computational intelligence classes, offering students a comprehensive understanding of intelligent systems and their practical applications. Hence, the incorporation of nature-inspired algorithms into the curriculum underscores their efficacy, versatility, and relevance in advancing computational intelligence and optimization studies.

2 Description of the Course and Project Design

The course ECE 8833, titled "Computational Intelligence", serves as a Technical Elective for students majoring in electrical engineering, computer engineering, and robotics and mechatronic systems engineering. The course involves two 75-minute lectures per week. In light of advancements in faster computing hardware and more affordable memory chips, computational intelligence, a subset of “soft computation”, is gaining significance in various engineering and non-engineering disciplines, such as robotics and embedded systems [19, 20, 20–26].

This course explores fundamental structures in computational intelligence techniques, encompassing the theory, design, application, and development of biologically and nature-inspired computational paradigms. The three primary pillars of Computational Intelligence — Neural Networks, Fuzzy Systems, and Evolutionary Computation — are thoroughly addressed [27, 28]. It is important to note that this course diverges from traditional, theory-centric engineering courses. Instead, it delves deeply into specific and practical topics drawn from computational intelligence techniques that are highly beneficial for engineering applications.

The emphasis is on supporting students to build the skills to undertake engineering projects, ensuring they can meet specified requirements through the application of computational intelligence techniques as follows:

- Utilize computational intelligence-based algorithms to simulate a robot’s movement in an environment, showcasing how biological models enable efficient navigation from start to target while avoiding obstacles and minimizing path cost. Visualize the trajectory and clearly articulate the path planning algorithm and its computational model in reports.
- Experiment with modifying given algorithms to explore diverse computational strategies for path planning, including heuristic searches, genetic algorithms, or neural networks. Analyze the efficiency of generated paths, compare them with the shortest paths, and discuss observations to enhance understanding.
- Apply AI algorithms on simpler models initially before tackling complex scenarios involving obstacles, dynamic environments, or varying conditions. This step is essential for grasping the fundamentals of computational intelligence in path planning effectively.
- Develop both flowcharts and pseudocode based on provided algorithms, elucidating computational intelligence methods in path planning. Understand and elaborate on the logic behind AI algorithms employed for navigation.
- Explore different facets of computational intelligence, such as varying heuristics, learning parameters, or network structures, to observe their impact on pathfinding. Document outcomes and visually represent generated paths while discussing insights derived from experimentation.

3 The Project Description and Consideration

3.1 Advanced Optimization in Computational Intelligence

Optimization methodologies are fundamental to computational intelligence, enabling the development and refinement of systems and designs in electrical engineering to achieve maximum efficiency and functionality. The process involves selecting the best possible solution from a set of alternatives under a given set of constraints. Optimization algorithms, which are at the heart of computational intelligence, are broadly classified into deterministic and stochastic categories, each with unique characteristics and applications. These algorithms follow a specific sequence of operations that lead to a predictable outcome, making them suitable for problems where a guaranteed solution is preferred. Linear programming (LP) is designed to optimize a linear objective function subject to linear constraints. The general form of an LP problem can be expressed mathematically as:

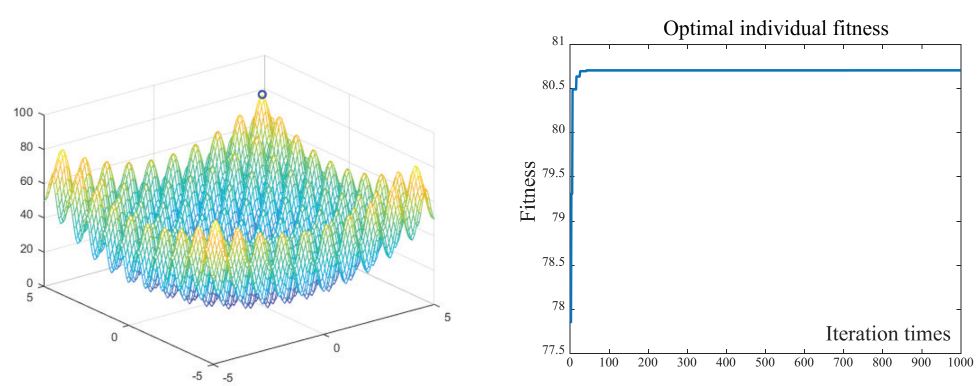
$$\begin{aligned} \text{maximize or minimize} \quad & f(\mathbf{x}) && (1) \\ \text{subject to} \quad & \mathbf{A}\mathbf{x} \leq \mathbf{b}, && (2) \\ & \mathbf{x} \geq 0 \quad (2) && (3) \end{aligned}$$

Nature-inspired optimization algorithms leverage biological behaviors through mathematical models to address complex engineering challenges. These algorithms are pivotal in computational intelligence due to their adaptability and efficiency. Cuckoo Search (CS) algorithm utilizes a brood parasitism behavior of cuckoos along with Lévy flights for effective search space exploration. The position update of a cuckoo i is mathematically expressed as:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \otimes \text{Lévy}(\lambda), \tag{4}$$

where $x_i^{(t)}$ represents the current position, $x_i^{(t+1)}$ is the new position, α denotes the step size, and Lévy(λ) represents the Lévy flights characterized by a Lévy distribution. This mechanism facilitates both local and global searches in the problem space. Ant Colony Optimization (ACO) is inspired by the pheromone trail-laying behavior of ants in finding the shortest paths. The probabilistic decision of an ant k to move from node i to node j is given by:

$$P_{ij}^k = \frac{\tau_{ij}(t)^\alpha \cdot \eta_{ij}^\beta}{\sum \tau_{il}(t)^\alpha \cdot \eta_{il}^\beta}, \tag{5}$$



(a) (b)

Figure 1: Illustration of the example optimization data plots for the different algorithms discussed int he course.

where $\tau_{ij}(t)$ is the pheromone concentration on the path, η_{ij} is the heuristic desirability of the path, and α and β are parameters that control the relative importance of pheromone versus heuristic information. The pheromone update rule is:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t), \tag{6}$$

with ρ representing the pheromone evaporation rate, and $\Delta\tau_{ij}(t)$ being the pheromone deposited, which depends on the quality of the solution. Evolutionary Computing (EC) encompasses a spectrum of algorithms based on the Darwinian principles of natural selection. The EC operates through genetic operators as follows:

$$I_{selected} = \text{Selection}(I_i, f(I_i)), \tag{7}$$

$$I_{offspring} = \text{Crossover}(I_{parent1}, I_{parent2}), \tag{8}$$

$$I_{mutated} = \text{Mutation}(I_{offspring}, p_m), \tag{9}$$

where I_i represents an individual in the population, $f(I_i)$ is the fitness function, $I_{parent1}$ and $I_{parent2}$ are individuals selected for reproduction, and p_m is the mutation probability. This process is iterated to evolve the population toward optimal solutions. These algorithms are adept at solving diverse optimization problems in electrical engineering, such as system design, parameter optimization, and resource distribution, by exploiting complex and dynamic search landscapes.

3.2 Traveling Salesman Problem (TSP)

The Traveling Salesman Problem (TSP) is a renowned optimization challenge that involves determining the shortest possible route through a set of cities, visiting each city exactly once and returning to the origin [29]. Mathematically, for a set of n cities with a distance d_{ij} between each pair of cities i and j, the TSP seeks to minimize the total travel distance:

$$\min \sum_{i=1}^{n} d_{\pi(i)\pi(i+1)} \tag{10}$$

where $\pi(i)$ represents the i-th city in the permutation of cities, and $\pi(n+1) = \pi(1)$ to ensure return to the starting city. The TSP is classified as NP-hard, indicating the absence of a polynomial-time solution for all instances. Cuckoo Search can be adapted for TSP, with each nest representing a potential route. The new routes are generated using the Lévy flight mechanism, which swaps city positions within a route. The fitness of each nest is evaluated by the total route length:

$$\text{Fitness} = \sum_{i=1}^{n} d_{\pi(i)\pi(i+1)} \tag{11}$$

ACO's incremental solution construction and pheromone-based learning are well-suited for TSP. Each ant constructs a tour by choosing the next city based on pheromone concentration and heuristic value, usually the inverse of the distance:

$$P_{ij}^{k} = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{l \in \text{allowed}_k} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}]^{\beta}} \tag{12}$$

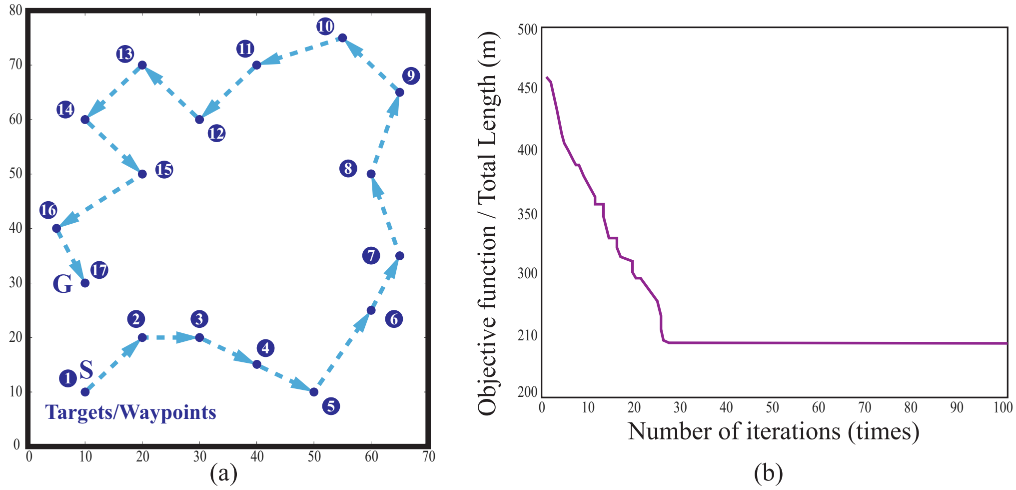


Figure 2: Illustration of the example TSP solution Utilizing the ACO methodology. (a) depicts the route taken through the different cities to fine a solution. (b) illustrates the how the objective function decreases at the number of iteration increases.

where P_{ij}^k is the transition probability, $\tau_{ij}(t)$ the pheromone concentration, $\eta_{ij} = 1/d_{ij}$ the heuristic desirability, and allowed$_k$ the set of yet-to-visit cities for ant k. EC, particularly Genetic Algorithms, applies a population of solutions to evolve routes for TSP. Each individual in the population represents a tour. The selection, crossover, and mutation operators generate new routes, favoring shorter distances:

$$\text{Fitness}(I_i) = \frac{1}{\sum_{i=1}^{n} d_{I_i(I_i+1)}} \tag{13}$$

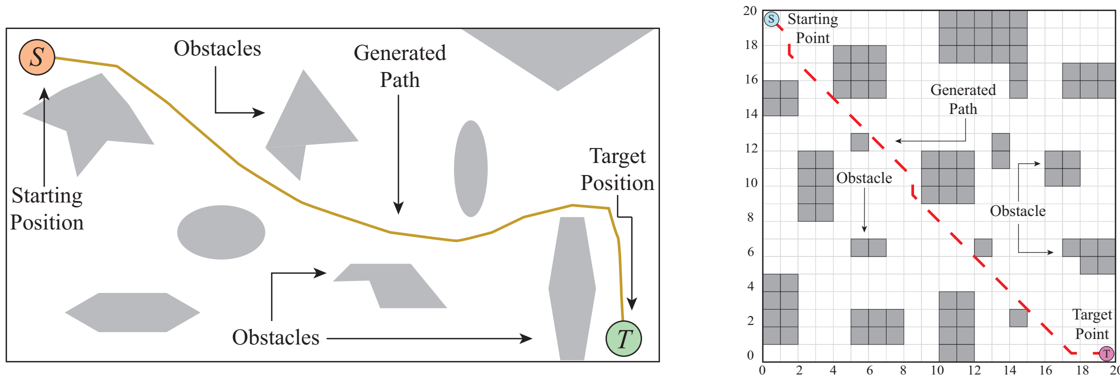
Here, I_i denotes the i-th city in the individual's sequence, with the fitness function inversely related to the route length, encouraging minimization of travel distance.These algorithms provide feasible and efficient solutions for TSP, particularly useful for large-scale problems where exhaustive search methods are impractical.

3.3 Path Planning Using Optimization Algorithms

Path planning is a fundamental aspect of robotics and autonomous systems, involving the determination of an optimal path from a starting point to a destination while avoiding obstacles. Three advanced algorithms, Cuckoo Search, ACO, and GAs from Evolutionary Computation, are adapted for efficient path planning [30, 31]. Cuckoo Search algorithm, inspired by the brood parasitism of cuckoo species, can be efficiently utilized in path planning. Each nest represents a unique path, and new paths are generated through Lévy flight behavior, enabling a broad search capability and avoidance of local optima. The fitness of each path is evaluated based on the length and obstacle avoidance, defined as:

$$\text{Fitness} = \alpha \cdot \text{Length} + \beta \cdot \text{Obstacle Avoidance} \tag{14}$$

where α and β are weighting factors for length and obstacle avoidance, respectively. ACO, mimicking the trail-laying behavior of ants, is well-suited for path planning in complex



(a) (b)

Figure 3: Homework assignment pertaining to path planning and navigation algorithms based on evolutionary computation optimization. The goal is to traverse the obstacle environment from the starting point (S) to the target point (T). (a) illustrates the optimization algorithms are utilized to navigate robot to reach from the starting point (S) to the target (T). (b) depicts the optimization algorithms are utilized to apply within a grid based environment. The red dotted line is the final trajectory generated by ACO algorithm.

environments. Ants explore paths and deposit pheromones, guiding subsequent ants towards more promising paths. The transition probability for an ant to move from point i to point j is given by:

$$P_{ij}^k = \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}]^\beta}{\sum_{l \in \text{allowed}_k} [\tau_{il}(t)]^\alpha \cdot [\eta_{il}]^\beta} \tag{15}$$

where $\tau_{ij}(t)$ represents the pheromone level, and η_{ij} is the heuristic information, typically the inverse of the distance or cost associated with the path. Genetic Algorithms, a subset of Evolutionary Computation, apply principles of natural selection and genetics to path planning. Each individual in the population represents a potential path, with genetic operators used to evolve towards optimal solutions. The fitness function, promoting shorter and feasible paths, is defined as:

$$\text{Fitness}(I_i) = \frac{1}{\gamma \cdot \text{Length}(I_i) + \delta \cdot \text{Feasibility}(I_i)} \tag{16}$$

where I_i denotes an individual path, and γ and δ are weighting factors for the path length and feasibility, respectively. These algorithms provide robust and flexible frameworks for path planning in various applications, from autonomous vehicles to robotic manipulators, offering efficient solutions in complex and dynamic environments.

4 The Project based Pedagogy Infused with Self-Assessment Method

Our teaching methodology adopts the Sparrow-Dissection and Scaffolding (SDS) approach, integrated with flipped learning strategies, to segment the comprehensive course content into smaller, interrelated sub-projects, as detailed in Table 1. This modular structure is distinct from traditional project-based learning, offering a more granular and interconnected educational journey. Each sub-project is autonomously significant while also laying the groundwork for the following modules, thereby ensuring a progressive and cohesive learning experience, as shown in

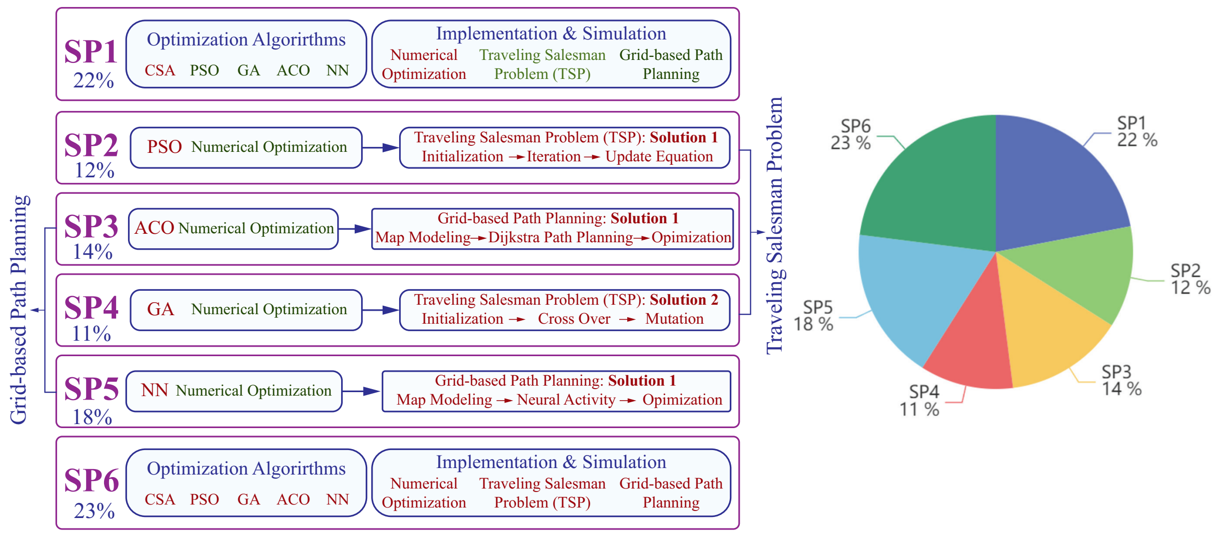


Figure 4: The proposed method is explained in detail regarding the sub-projects in Table 1. The dark red in the figure indicates the key points of the sub-project (including creating flowcharts, programming and answering questions, *etc.*), while the light blue content refers to the related content. Among them, there are connections in each sub-project, and students not only understand the computational intelligence algorithm but also have hands-on experiments (such as using them for robot path planning).

Figure 4. This approach is specifically tailored for in-depth engagement with graph-based path planning methods. The initial module, or Sub-Project 1, plays a critical role. It not only introduces students to the course framework but also initiates the step-by-step development of skills and knowledge. This gradual progression, moving from foundational concepts to more complex applications, is designed to deepen students' comprehension and practical skills in graph-based techniques for robot path planning. Our course materials, including visual aids like Figure 5, specifically illustrate the application of these graph-based models in the context of robot navigation. This structured and phased approach aims to build a comprehensive understanding, preparing students for the final project that encapsulates all the learned concepts.

The sub-projects listed in Table 1 provide a structured approach to evaluate student progression in advanced computational algorithms, with a focus on MATLAB code implementation for robotic navigation. These projects involve the development of written reports and participation in interviews with the instructor, which aid in cultivating a deeper practical and theoretical understanding. Beginning with SP1, students are introduced to MATLAB code involving various advanced algorithms, including the Ant Colony Optimization (ACO) in SP2, Cuckoo Search (CS) in SP3, Genetic Algorithms in SP4, and Neural Networks in SP5. In these projects, students are engaged in tasks like constructing flowcharts, coding algorithms, and adjusting parameters to optimize the performance of these sophisticated path planning methods.

Each sub-project is designed to highlight a specific facet of computational intelligence in path planning, offering students an opportunity to tackle different challenges and develop solutions for robotic navigation. They explore the balance between computational efficiency and the effectiveness of these algorithms in diverse scenarios. The final project (SP5) represents a

Table 1: The descriptions of the sub-projects

Sub-Project	Objective	Tasks
SP1: Distribution and exercise of sample MATLAB code	• Students are provided with MATLAB source code that encompasses a range of graph-based algorithms. • The task for students is to fully comprehend and execute the given MATLAB code. • At this phase, the instructor's role involves defining the project requirements, analyzing the context, and identifying any design constraints. • A project plan should be formulated and followed, ensuring that the overarching design goals are achieved.	**22%**
SP2: Analysis of Particle Swarm Optimization in Path Planning	• Students are required to create a detailed flowchart of the Particle Swarm Optimization algorithm, utilizing block diagrams and schematics for clarity. • Students are tasked with developing code that implements the PSO algorithm, aimed at efficient path planning. • Students are provided with opportunities to experiment with various parameters of the PSO algorithm, enhancing their understanding of its impact on performance.	**12%**
SP3: Exploration of Ant Colony Optimization for Path Planning	• Students are tasked to diagram the ACO process, illustrating how pheromone trails are used to find optimal paths. • Development of a simulation using the ACO algorithm is required, with an emphasis on real-time path optimization in dynamic environments. • An analysis project is included where students modify pheromone evaporation rates and other ACO parameters to observe changes in path efficiency.	**14%**
SP4: Genetic Algorithms for Optimized Path Planning	• Creation of schematics illustrating the crossover and mutation processes in Genetic Algorithms as applied to path planning. • Students are to develop a path planning solution using Genetic Algorithms, focusing on evolutionary strategies for optimal route finding. • An exploration task where students adjust genetic operators like mutation rates to study their impact on path efficiency and robustness.	**11%**
SP5: Neural Networks in Adaptive Path Planning	• Students will prepare a conceptual diagram illustrating the architecture of neural networks used in path planning. • Implementation of a neural network-based path planning model, with a focus on training the network for complex environment navigation. • Students are encouraged to experiment with different network topologies and learning rates to observe variations in pathfinding effectiveness.	**18%**
SP6: Final Project: Demonstration, Report, and Presentation	• Students are expected to compile a final submission including comprehensive, well-commented code, along with a report that details the integration process and explains the choice of algorithms. • The effectiveness of the final integrated navigation system must be demonstrated, either through simulated environments or actual field testing, highlighting its proficiency in diverse scenarios. • A critical aspect of the project is the performance evaluation, where students compare the efficiency and effectiveness of their system with conventional navigation methods.	**23%**

culmination of all the learned concepts, where students are required to integrate and demonstrate the efficacy of their comprehensive navigation system, benchmarking it against standard navigation algorithms. This final task not only consolidates their learning but also showcases their capabilities in applying advanced computational techniques to address complex navigation challenges.

5 Course Assessment and Project Evaluation

The self-assessments, tailored to gauge learning outcomes, are intricately linked with ABET standards, functioning crucially in the overall ABET assessment procedure. Conducted before the semester concludes, these assessments not only provide a basis for instructors to improve teaching methods and fine-tune course designs but also play a pivotal role in validating the quality of learning and academic success in this course. In this course, students engage with six specific questions outlined in Table 1, with corresponding ABET outcomes referenced in parentheses.

- Question 1 - "I can understand and use knowledge of mathematics including advanced topics such as differential and integral calculus, linear algebra, discrete math, and differential equations in nature-inspired intelligence methodologies for optimizing robot path planning and enhancing motion control." (Outcome (*a*): An ability to apply knowledge of mathematics, science, and engineering principles to electrical engineering, *i.e*. Knowledge of mathematics encompasses advanced topics typically including differential and integral calculus, linear algebra, complex variables, discrete math, and differential equations.)
- Question 2 - "I can apply formal engineering design methodology to perform the design, experiments and construction of the nature-inspired intelligence methodology for robot path planning, and motion control projects based on experimental test data and interpretation, as well as to analyze and interpret data relating to nature-inspired intelligence methodology for robot path planning, and motion control projects that resolve electrical system problems" (Outcome (*b*): An ability to design and conduct experiments, as well as to analyze and interpret data relating to electrical systems.)
- Question 3 - "I can understand and design basic nature-inspired models for robot path planning and motion control with assigned a sequence of projects such as ACO and CS for optimization, TSP, and robot path planning, and work to meet the final goals." (Outcome (*c*): An ability to design electrical systems, components, or processes to meet desired needs).
- Question 4 - "I can understand structures and models of nature-inspired intelligence for robot path planning and profoundly understand some important nature-inspired intelligence methodologies such as ACO and CS models, and can also identify, formulate, and solve the issues raised in assigned nature-inspired robot path planning and motion control projects" (Outcome (*e*): An ability to identify, formulate, and solve electrical engineering problems).
- Question 5 - "I have effective communication skills in the context of a collaborative, multi-disciplinary design activity in the project". (Outcome (*g*): An ability to communicate effectively).

- Question 6 - “I can create professional documentation in connection with the assignments and design project of nature-inspired intelligence methodology for robot path planning, and motion control”. (Outcome (*g*): An ability to communicate effectively).

The outcomes of the assessment questionnaire are displayed in Table 2 and visually depicted in Figure 5. Based on the results in Table 2, most students predominantly indicate either “strong agreement” or “agreement” with statements aligning with ABET outcomes (*a*), (*b*), (*c*), (*e*), and (*g*). Evidently, the percentages for “strong agreement” in this course are notably higher for outcomes b, c, and e compared to the instructor’s experience in teaching other courses. This implies a potential positive influence of the implemented pedagogies on these particular outcomes. In terms of communication skills, specifically in writing and oral presentation corresponding to ABET outcome (*g*), a noteworthy observation is the presence of “disagreement”. Some graduate students express discomfort with their oral and written presentation abilities, despite the provision of training in this class and other related curricula.

Of particular note is the remarkable surge in “strongly agree” responses, especially for Question 3, reaching an impressive 83.3%, surpassing the typical rate. Question 3 is closely tied to the capacity to design electrical systems, components, or processes to meet specific needs, as illustrated in Figure 5. Moreover, in comparison to the instructor’s past experience teaching the course using a traditional project-based method (without sub-projects, sparrow-dissection, scaffolding (SDS), flipped learning (SDS-FL) protocol, and interview sessions for reflection and adjustments), the current course demonstrates higher percentages for both “strongly agree” and “agree” with 97.6% in total. This suggests that the integrated approach of project-based pedagogy and the SDS-FL mechanism in this course is significantly more effective than previous models.

In relation to Questions 1 and 2, we observe substantial “strongly agree” percentages at 71.4% and 69.0%, aligning with Outcomes a and b, respectively. These outcomes emphasize the “ability to apply knowledge of mathematics, science, and engineering principles to electrical engineering”, encompassing advanced topics like differential and integral calculus, linear algebra, complex variables, discrete math, and differential equations. Additionally, Outcome (*b*), which relates to the “ability to design and conduct experiments, as well as to analyze and interpret data relating to electrical systems”, similarly receives high “strongly agree” responses. There are minimal “neutral” percentages of 4.8% each in Questions 1 and 2, corresponding to Outcomes a and b, respectively. Analysis of interview and survey comments reveals that some students attribute this to a lack of sufficient background in programming and mathematics, particularly in discrete math and differential equations.

The marginally lower “strongly agree” percentages for Questions 2 and 4, in contrast to Question 3, stem from the heightened efficacy of nature-inspired intelligence methodologies in the context of designing robot path planning and motion control projects. This methodology encompasses the application of electrical system design principles to meet the specific requirements of nature-inspired intelligence for robot path planning and motion control. This not only contributes to a more resilient learning experience but also underscores the nuanced effectiveness of these methodologies in the given context.

Outcome (*g*), assessed through Question 5, evaluates communication capabilities during the final project presentation and teamwork. In this context, 7.1% of students express “disagreement”, while 9.5% express “neutral”, as noted in Question 6, aligning with Outcome (*g*). The requirement for high-quality written documentation is a crucial aspect of this project-based class. However, students often face challenges in acclimating to technical writing, resulting in a 9.5% “disagreement” rate and an 11.9% “neutral” rate in Question 6, linked to Outcome (*g*). This evaluation is vital for the development of professional documentation related to ongoing assignments and the design project focusing on nature-inspired intelligence for robot path planning. Given the inherent challenges in oral and technical writing communication skills in milestone reports and final project report for graduate students studying nature-inspired intelligence for robotics, 40.5% and 33.3% of students express “strong agreement” for Questions 5 and 6, respectively, both tied to Outcome (*g*).

Conducting interviews and interactions with students within the SDS-FL protocol plays a pivotal role in elevating the quality of teaching. Processes like crafting reflection reports and engaging in interviews with the instructor about sub-projects have emerged as crucial tools in empowering students. This empowerment is clearly reflected in their adeptness at assuming responsibility for self-regulation cycles related to problem-solving. Noteworthy, this approach has enhanced various facets including forethought, self-motivation, execution, exploration, discovery, and the mastery of artificial intelligence techniques.

In our endeavor to enhance the quality of teaching, we meticulously utilized both quantitative data and qualitative feedback, particularly drawn from student interviews, to inform and refine our pedagogical practices. Quantitative data encompassed metrics such as student performance, assessment results, and engagement levels, offering a broad understanding of areas needing improvement. Meanwhile, student interviews provided invaluable qualitative insights into the nuances of their learning experiences. These interviews served as a direct avenue for students to express their thoughts, concerns, and preferences regarding teaching methods and materials. By analyzing these interviews, we identified specific areas of improvement, tailored teaching strategies to accommodate diverse learning needs, and addressed communication challenges. For instance, if students expressed difficulties with certain mathematical concepts, such as differential equations, we adjusted our teaching approach accordingly, incorporating more accessible explanations and supplementary materials. Moreover, interviews guided the implementation of targeted interventions, such as workshops to improve communication skills, based on students’ expressed discomfort. This iterative process of gathering feedback through interviews allowed us to continuously assess the effectiveness of our interventions and refine our teaching approaches for maximum impact on student learning experiences. Ultimately, the integration of insights from student interviews into our pedagogical practices played a pivotal role in elevating the quality of teaching and fostering a more enriching learning environment for our students.

Examining students’ performance across various aspects such as homework assignments, Q&A sessions, exams, self-assessment surveys, and feedback provided in the official university course evaluation, in conjunction with a comparative analysis against the instructor’s prior teaching experiences, underscores the pronounced effectiveness of the hybrid SDS-FL pedagogy. This approach has demonstrably contributed to fostering a profound understanding of nature-inspired intelligence models.

Table 2: The Questionnaire of Students for Assessment of Learning Quality

Questions and ABET Outcomes	Survey				
	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Q1- (*a*)	71.2%	23.9%	4.9%	0%	0%
Q2 - (*b*)	69.0%	26.2%	4.8%	0%	0%
Q3 - (*c*)	83.3%	14.3%	2.4%	0%	0%
Q4 - (*e*)	64.3%	35.7%	0%	0%	0%
Q5 - (*g*)	40.5%	42.9%	9.5%	7.1%	0%
Q6 - (*g*)	33.3%	45.3%	11.9%	9.5%	0%

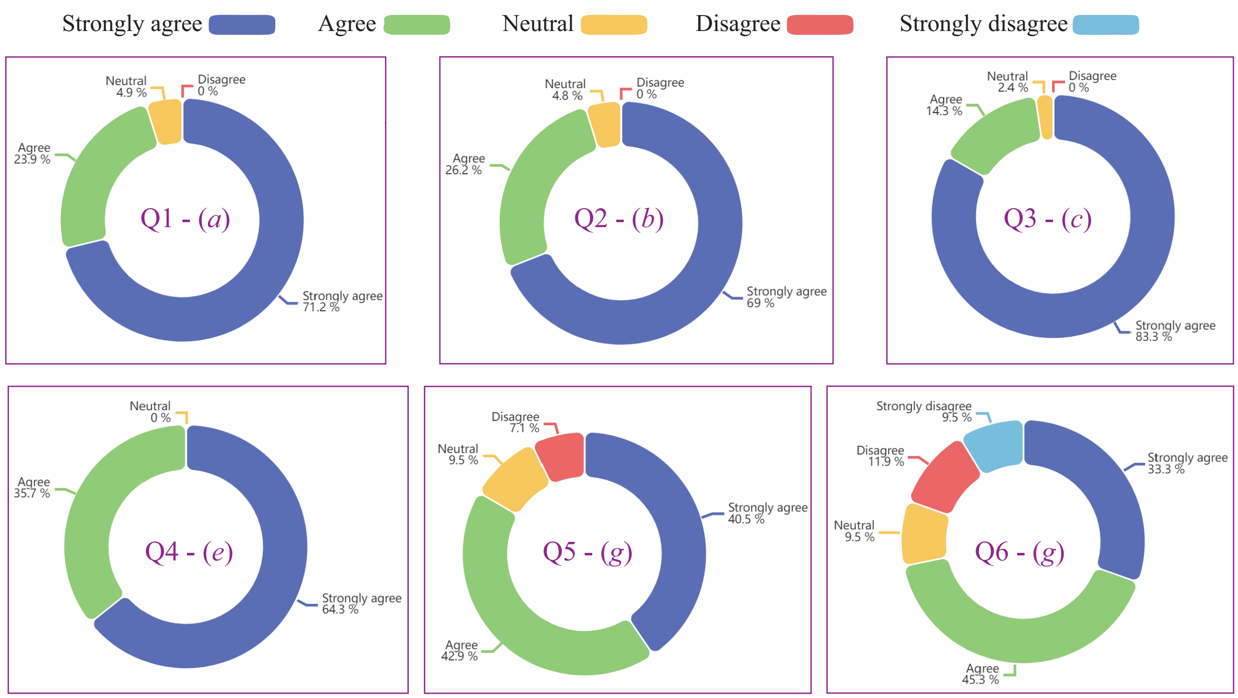


Figure 5: The illustration of the assessment of learning quality results.

6 Conclusion

This paper describes an innovative teaching method that combines sparrow-dissection and scaffolding with flipped learning (SDS-FL), specifically designed for robot path planning and motion control projects. This adapted project-based approach focuses on teaching nature-inspired intelligence methodologies. The method breaks down the project into smaller, manageable segments, enabling students to progressively design, implement, debug, and operate efficient nature-inspired intelligence methods. Each segment concludes with students submitting milestone reports and participating in interviews, fostering self-motivated learning. The paper details the evaluation process of this approach, which includes various milestone assignments, reports, presentations, and activities. A comprehensive assessment was conducted to measure students' understanding and comfort with the nature-inspired intelligence methodologies for robot path planning and motion control, both before and after the project. Feedback was collected after each milestone to gain insights into the students' experiences with the implementation and application of these methodologies. The results, gathered from students' self-assessment questionnaires, demonstrate that the SDS-FL integrated pedagogy effectively meets the learning objectives of an advanced robotics course. This approach has been shown to significantly enhance students' self-motivation, reflection, performance, and exploration, as well as their overall understanding of artificial intelligence and robotics techniques.

References

[1] C. K. Lo and K. F. Hew, "The impact of flipped classrooms on student achievement in engineering education: A meta-analysis of 10 years of research," *Journal of Engineering Education*, vol. 108, no. 4, pp. 523–546, 2019.

[2] M. Chiquito, R. Castedo, A. P. Santos, L. M. López, and C. Alarcón, "Flipped classroom in engineering: The influence of gender," *Computer Applications in Engineering Education*, vol. 28, no. 1, pp. 80–89, 2020.

[3] C. Li, K. Zhao, M. Yan, X. Zou, M. Xiao, and Y. Qian, "Research on the big data analysis of MOOCs in a flipped classroom based on attention mechanism in deep learning model," *Computer Applications in Engineering Education*.

[4] J. Jo, H. Jun, and H. Lim, "A comparative study on gamification of the flipped classroom in engineering education to enhance the effects of learning," *Computer Applications in Engineering Education*, vol. 26, no. 5, pp. 1626–1640, 2018.

[5] N. A. Xenofontos, T. Hovardas, Z. C. Zacharia, and T. de Jong, "Inquiry-based learning and retrospective action: Problematizing student work in a computer-supported learning environment," *Journal of Computer Assisted Learning*, vol. 36, no. 1, pp. 12–28, 2020.

[6] B. M. Notaroš, R. McCullough, S. B. Manić, and A. A. Maciejewski, "Computer-assisted learning of electromagnetics through matlab programming of electromagnetic fields in the creativity thread of an integrated approach to electrical engineering education," *Computer Applications in Engineering Education*, vol. 27, no. 2, pp. 271–287, 2019.

[7] B. Kollöffel and T. De Jong, "Conceptual understanding of electrical circuits in secondary vocational engineering education: Combining traditional instruction with inquiry learning in a virtual lab," *Journal of engineering education*, vol. 102, no. 3, pp. 375–393, 2013.

[8] J. Dong and H. Guo, "Effective collaborative inquiry-based learning in undergraduate computer networking curriculum," in *2013 ASEE Annual Conference & Exposition*, 2013, pp. 23–463.

[9] N. Foldnes, "The flipped classroom and cooperative learning: Evidence from a randomised experiment," *Active Learning in Higher Education*, vol. 17, no. 1, pp. 39–49, 2016.

[10] J. Martín-Gutiérrez, P. Fabiani, W. Benesova, M. D. Meneses, and C. E. Mora, "Augmented reality to promote collaborative and autonomous learning in higher education," *Computers in human behavior*, vol. 51, pp. 752–761, 2015.

[11] D. Hadfield-Menell, S. J. Russell, P. Abbeel, and A. Dragan, "Cooperative inverse reinforcement learning," *Advances in neural information processing systems*, vol. 29, 2016.

[12] M. Menekse, G. S. Stump, S. Krause, and M. T. Chi, "Differentiated overt learning activities for effective instruction in engineering classrooms," *Journal of Engineering Education*, vol. 102, no. 3, pp. 346–374, 2013.

[13] K. Zervoudakis, K. Mastrothanasis, and S. Tsafarakis, "Forming automatic groups of learners using particle swarm optimization for applications of differentiated instruction," *Computer Applications in Engineering Education*, vol. 28, no. 2, pp. 282–292, 2020.

[14] L. Cheng, A. D. Ritzhaupt, and P. Antonenko, "Effects of the flipped classroom instructional strategy on students' learning outcomes: A meta-analysis," *Educational Technology Research and Development*, vol. 67, pp. 793–824, 2019.

[15] M. Alibali, "Does visual scaffolding facilitate students' mathematics learning? evidence from early algebra," *Retrieved February*, vol. 13, p. 2016, 2006.

[16] K. E. Hogan and M. E. Pressley, *Scaffolding student learning: Instructional approaches and issues.* Brookline Books, 1997.

[17] T. Lei, C. Luo, T. Sellers, and S. Rahimi, "A bat-pigeon algorithm to crack detection-enabled autonomous vehicle navigation and mapping," *Intelligent Systems with Applications*, vol. 12, p. 200053, 2021.

[18] T. Sellers, T. Lei, C. Luo, G. E. Jan, and J. Ma, "A node selection algorithm to graph-based multi-waypoint optimization navigation and mapping," *Intelligence & Robotics*, vol. 2, no. 4, pp. 333–54, 2022.

[19] W. Zhao, R. Lun, C. Gordon, A.-B. Fofana, D. D. Espy, M. A. Reinthal *et al.*, "A privacy-aware kinect-based system for healthcare professionals," in *2016 IEEE International Conference on Electro Information Technology (EIT).* IEEE, 2016, pp. 0205–0210.

[20] C. Luo, M. F. Anjos, and A. Vannelli, "Large-scale fixed-outline floorplanning design using convex optimization techniques," in *2008 Asia and South Pacific Design Automation Conference*. IEEE, 2008, pp. 198–203.

[21] T. Lei, T. Sellers, C. Luo, L. Cao, and Z. Bi, "Digital twin-based multi-objective autonomous vehicle navigation approach as applied in infrastructure construction," *IET Cyber-Systems and Robotics*, vol. 6, no. 2, p. e12110, 2024.

[22] L. Wang, C. Luo, J. Cai *et al.*, "A variable interval rescheduling strategy for dynamic flexible job shop scheduling problem by improved genetic algorithm," *Journal of Advanced Transportation*, vol. 2017, 2017.

[23] T. Lei, P. Chintam, D. W. Carruth, G. E. Jan, and C. Luo, "Human-autonomy teaming-based robot informative path planning and mapping algorithms with tree search mechanism," in *2022 IEEE 3rd International Conference on Human-Machine Systems (ICHMS).* IEEE, 2022, pp. 1–6.

[24] L. Wang, C. Luo, M. Li, and J. Cai, "Trajectory planning of an autonomous mobile robot by evolving ant colony system," *International Journal of Robotics and Automation*, vol. 32, no. 4, pp. 1500–1515, 2017.

[25] Y. Fu, C. Luo, and Z. Bi, "Low-rank joint embedding and its application for robust process monitoring," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13, 2021.

[26] W. Zhao, R. Lun, C. Gordon, A.-B. M. Fofana, D. D. Espy, A. Reinthal *et al.*, "Liftingdoneright: A privacy-aware human motion tracking system for healthcare professionals," *International Journal of Handheld Computing Research (IJHCR)*, vol. 7, no. 3, pp. 1–15, 2016.

[27] T. Lei, C. Luo, S. X. Yang, D. W. Carruth, and Z. Bi, "Bio-inspired intelligence-based multi-agent navigation with safety-aware considerations," *IEEE Transactions on Artificial Intelligence*, 2023.

[28] D. Short, T. Lei, D. W. Carruth, C. Luo, and Z. Bi, "A bio-inspired algorithm in image-based path planning and localization using visual features and maps," *Intelligence & Robotics*, vol. 3, no. 2, pp. 222–41, 2023.

[29] T. Lei, T. Sellers, S. Rahimi, S. Cheng, and C. Luo, "A nature-inspired algorithm to adaptively safe navigation of a Covid-19 disinfection robot," in *Intelligent Robotics and Applications: 14th International Conference, ICIRA 2021, Yantai, China, October 22–25, 2021, Proceedings, Part III 14.* Springer, 2021, pp. 123–134.

[30] T. Lei, T. Sellers, C. Luo, D. W. Carruth, and Z. Bi, "Graph-based robot optimal path planning with bio-inspired algorithms," *Biomimetic Intelligence and Robotics*, p. 100119, 2023.

[31] P. Chintam, T. Lei, B. Osmanoglu, Y. Wang, and C. Luo, "Informed sampling space driven robot informative path planning," *Robotics and Autonomous Systems*, p. 104656, 2024.