Scaffolding Training on Digital Manufacturing: Prepare for the Workforce 4.0

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Abstract

In this Work-in-Progress paper, scaffolding training for Workforce 4.0 was described. The onset of Industry 4.0, also known as the fourth industrial revolution, will add new challenges to the shortage of skilled labor, such as CNC programmers and machinists. Like any new technology, new job categories are emerging that require new skill sets, presumably not replacing the current workforce but rather reinventing it. Some projections claim that between 75 and 375 million workers globally may need to change their occupational categories by 2030 due to a sizable amount of employment being automated or digitized.

Within a vertically integrated project program of New York University, a systematic training scheme was developed for training undergraduate students with the xArm educational robot, as mentioned in our previous ASEE publication. The goal of the training is to lay the technical foundations for undergraduate students who have no experience in robotics for their future careers in Workforce 4.0. By the end of the training, the students should be ready to solve open-ended problems in automated production lines.

The overall training lasts 12 weeks in total, there are no pre-requisite courses for the training, and it is open to all STEM majors. 16 students participated in the training. The training scheme has been divided into two major blocks: the first block is foundational training, and the second block is advanced training. In the foundational training, the first week is to understand fundamentals by reviewing at least five research papers. The second week is to work on the mechanical assembly of the xArm robots. Robotic kinematics is introduced from the third to the fifth week. In the advanced training, the students were then divided into two specialized groups based on their own interests: Computer Vision (CV) and Natural Language Processing (NLP). There is a seminar about the Robotic Operation System (ROS). The final week is to assess training outcomes. Collaborative teams are formed to build a mini version of a production line using xArm robots, a conveyor belt, and selected sensors. An end-of-course learning assessment survey indicated that students self-reported an improved understanding of the course topics.

1. Introduction and Background

The fourth industrial revolution introduced the integration of digital technologies into the manufacturing process to increase productivity and efficiency. As part of Industry 4.0, the manufacturing industry is being digitally transformed to produce smarter products, gadgets, processes, and connected facilities [1-3], which is widely recognized as the fourth industrial revolution. Cyber-Physical Systems (CPS) is a key component of this revolution, as are a variety of disruptive technologies, such as the Internet of Things (IoT) [4], Big Data [5], Cloud Computing [6], Artificial Intelligence (AI) [7], virtual and augmented reality[8], collaborative robots [9, 10], and additive manufacturing [11].

The phrase "digital manufacturing technologies" (DMTs) describes the use of smart, digital, autonomous, and intelligent technologies, including sensor, cloud, distributed, and additive manufacturing, in modern industry. This new wave of industrialization is anticipated to improve the quality of work by fostering an environment that gives workers more autonomy for self-development and problem-solving. The workers are expected to make strategic decisions and find adaptable solutions to engineering problems promptly. For example, in an automated system involving industrial robots, Workforce 4.0, a new breed of skilled workers can play a more creative and active role.

The production environment is changing as a result of the adoption of these disruptive technologies, which will also change the working practices, job descriptions, and skills required. [12]. In fact, a PwC report [13] shows the adoption of Industry 4.0 in the manufacturing sector will increase the degree of digitalization from 33% in 2015 to 72% in 2020 for industrial companies on a global scale. As a result, more advanced technology will be used in the industry, which boosts the demand for more qualified workers as well as new employment positions. Industry 4.0 will alter 8 – 9% of the labor demand by 2030, producing new employment that didn't exist before [14]. According to recent data, Industry 4.0 technology would inevitably result in substantial worker shortages [15]. Therefore, it is essential to prepare for skill requirements in early college education.

In the context of undergraduate engineering at New York University, the students normally take course modules to acquire essential skillsets for manufacturing industries. A vertically integrated project (VIP) program course provides an alternative route for students to experience first-hand knowledge about digital manufacturing through a project-based and step-by-step learning process.

This study aims to implement a systematic training scheme, specifically tailored to undergraduates, to develop both their interests and enhance their skillsets in the digital manufacturing process. Several 6-DoF robotic arms were used for training; the students could assemble and implement the robotic arms. The scheme was developed using the theory of constructivism. The list of skills has been scaffolded into four major modules: mechanical assembly, robotic kinematics, Computer Vision (CV), and Natural Language Processing (NLP). Mechanical assembly and robotic kinematics are the foundational skills while the CV and NLP are the advanced skills. The study helps to address a research question: *How to develop and implement a scaffolded group training scheme for learning digital manufacturing technology for undergraduate students?*

2. Experimental methods

2.1 Training Equipment

Two different types of educational robotic arms were used in this study. They are shipped in parts with detailed instructions. The Jetson Nano-powered robotic arm was used for object detection. The Raspberry Pi-powered robotic arm was used for voice control.

(a) Jetson Nano-powered 6-DoF robotic arm

(b) Raspberry Pi-powered 6-DoF robotic arm

(c) Conveyor belt

Figure 1. The three major components required for the robotic training, (a) shows Jetson Nano robotic arm by Yahboom Robotics [16], (b) shows the Raspberry Pi-powered robotic arm by Hiwonder [17], (c) shows conveyor belt by Dobot [18].

2.2 Training Scheme

The overall training lasted 12 weeks in total (**Figure 2**) in Fall 2022. 16 students participated in the training. The students have a wide range of knowledge backgrounds. 90% of the students were in their second year of study, while 10% of the students were in their first year. The majority of students had backgrounds in Python programming as well as motor control. The training was conducted under the program of vertically integrated projects and there are no prerequisites to take the training.

The training scheme was divided into two major blocks: the first block was foundational training, and the second block was advanced training. In the foundational training, the first week was to understand fundamentals by reviewing at least five research papers. In the second week, students were assigned to work on the mechanical assembly of the xArm robots. Robotic kinematics were introduced from the third to the fifth week. In the advanced training, the students were then divided into two specialized groups based on their own interests: CV and NLP. There was a seminar about the Robotic Operation System (ROS). The final week was to assess training outcomes.

The students were mentored by two senior students (group leaders) who have been trained by instructors in the previous semester. The senior students gave presentations, organized group activities, and led the group discussions.

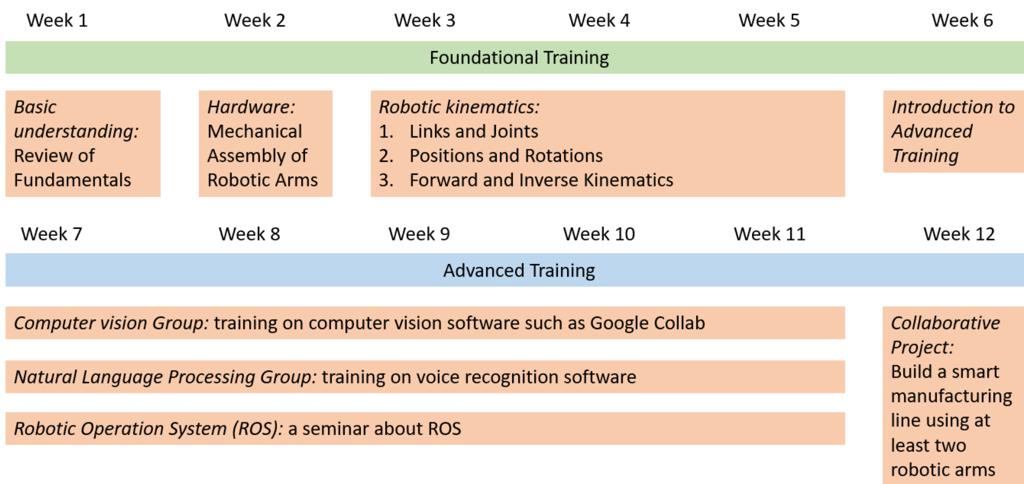


Figure 2. Detailed training scheme across 12 weeks.

2.3 Training Evaluation

Engineering notebooks were used for assessing individual learning progress. What was included in the notebook are event date/time, bullet points, and pictures describing weekly progress. This allowed the instructor to track the progress asynchronously and provide formative feedback. Also, the students attended weekly meetings to update their progress, reflections, and future steps. At the beginning of Week 12, the students were assigned into smaller groups of 5 to work on designing, assembling, and operating the manufacturing line. The training evaluation includes the following criteria:

- Task 1: Could robotic arm 1 be activated by the voice module?
- Task 2: Could robotic arms 2 and 3 pick up the cube and place the cube back on the line?
- Task 3: Could robotic arm 4 detect the color of the object and sort it in terms of red, blue, yellow, and green?
- Task 4: Could the Conveyer belt run at an optimal speed, so the robotic collaboration happens in time sequence?

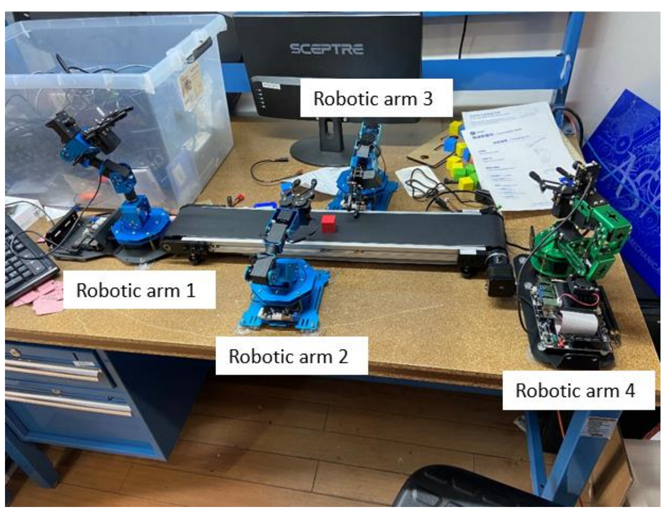


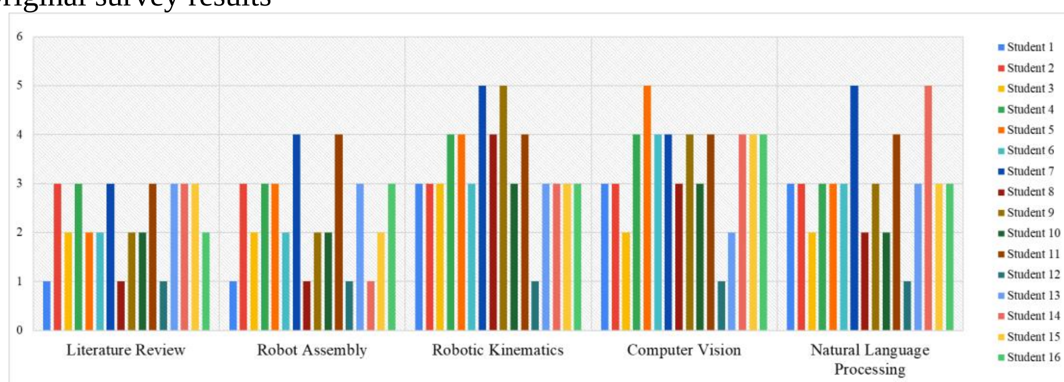
Figure 3. Proposed collaborative robotic team training

3. Results and Discussion

The Week 12 training evaluation shows most of the students were able to complete Tasks 1 —3. The student was not able to complete Task 4 on time as they were having difficulty operating the robots and the conveyer belt in the correct time sequence. One of the future improvements for the training scheme would be to add one more module to the advanced training block of the training scheme: the collaborative robot. The module would cover five different levels of collaboration: fenced robot, co-existence, sequential collaboration, cooperation, and responsive collaboration.

An end-of-semester survey was administered to the students for learning evaluation. 16 students responded to the survey. Figure 4 (a) shows the quantitative survey results indicating the level of difficulty of each training module (Likert scale, 1 indicates the student feels the training module is easy to follow while 5 indicates the student feels the training module is very hard to follow). Taking 3 as the level when students start to feel the learning curve, Figure 4 (b) shows the processed results based on the percentage of students. 70% of the students rated 3 and above on the modules of *Computer Vision*, and *Natural Language Processing* in terms of learning difficulty. This result was consistent with the training scheme in **Figure 2**, as both modules were listed as advanced training modules. However, over 90% of students rated 3 and above on the module of *Robotic Kinematics*, which was in the foundation training in **Figure 2**. This indicates more training time and support should be allocated to the module of *Robotic Kinematics* for students to fully comprehend the learning information.

(a) Original survey results



(b) Processed survey results

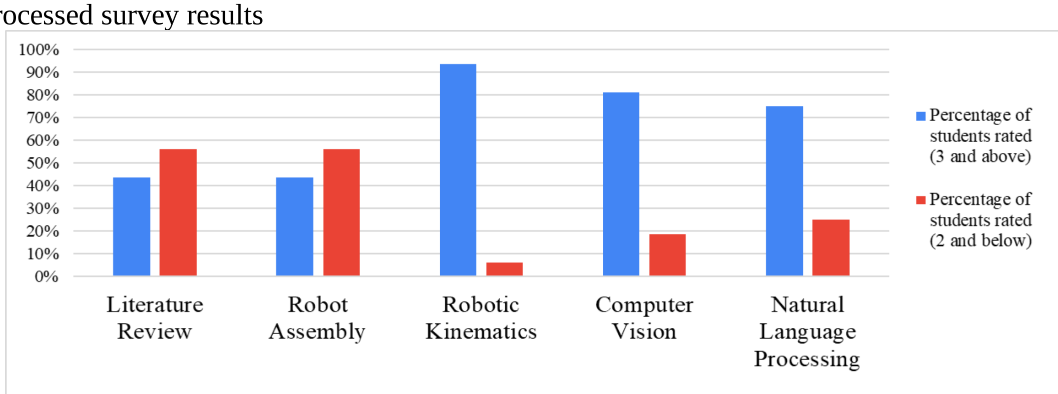


Figure 4. Quantitative analysis of the training feedback

15 of 16 students felt their understanding of robotic arms has been greatly improved. Six students reported that the CV module was the most helpful to their personal development. One question from the end-of-training survey asks, “Please reflect upon your participation in the robotic training. Were your expectations met? Why or why not?” Student A responded, *“Yes, they were met because I had the opportunity to build an arm and also spend time learning to code it.”* Student B responded, *“As I participated in the robotic training, I was excited to learn about how I could incorporate a computer vision algorithm into the robot for in-person testing. Overall, I found the training to be very helpful in achieving this goal.”*

In this study, only one survey was conducted at the end of the semester. During the semester, the instructor has also arranged one-on-one appointments with the students to monitor their self-learning progress. According to the students’ verbal feedback, most of them have developed self-motivation on learning robotic operation through this collaborative learning opportunity. The students were able to meet the objective together by asking questions, explaining their personal opinions, and justifying their reasons. Compared to traditional instructor-led robotic classes, this could potentially improve the students’ self-esteem and motivation via knowledge exchange of member-member and member-mentor [19].

The training scheme developed in this paper would be generalizable when the class pool has students meeting the following requirements: Complete at least one semester of engineering school; Have pre-knowledge about automation; Have pre-knowledge about Python and Linux; Have a basic understanding of machine learning. In the future, the number of student participants would ideally be at least 30.

4. Conclusion and Future Work

A weekly-based training program was implemented in a hands-on, project-based course, which allows undergraduate students to build foundational skillsets for operating robotic arms in a collaborative setting. Preliminary results indicated that students self-reported improved understanding of the course topics. They were able to reflect on their learning throughout the modules and found the CV module to be the most helpful to their personal development. Future improvements would be to provide more customized training for students. A pre-knowledge survey would be administered before conducting the training to assess their experience of robotic operations. Beginners will spend more time on foundational training while medium-to-advanced robotic users would participate in advanced training from Week 2. Therefore, by the end of Week 12, all the students would feel more confident to work on the final project of collaborative robots. In addition, a new module called “collaborative robot” should be added to the advanced training block to enhance students’ understanding of sequential operation. This could help to address the new research question in the next study: How would individualized training help to benefit students’ robotic learning?

4. References

[1] M. A. K. Bahrin, M. F. Othman, N. H. N. Azli, and M. F. Talib, "Industry 4.0: A review on industrial automation and robotic," *Jurnal teknologi,* vol. 78, no. 6-13, 2016.

[2] M. Ghobakhloo, M. Fathi, M. Iranmanesh, P. Maroufkhani, and M. E. Morales, "Industry 4.0 ten years on: A bibliometric and systematic review of concepts, sustainability value drivers, and success determinants," *Journal of Cleaner Production,* vol. 302, p. 127052, 2021.

[3] K. Rojko, N. Erman, and D. Jelovac, "Impacts of the Transformation to Industry 4.0 in the Manufacturing Sector: The Case of the US," *Organizacija,* vol. 53, no. 4, pp. 287-305, 2020.

[4] L. Georgios, S. Kerstin, and A. Theofylaktos, "Internet of things in the context of industry 4.0: An overview," 2019.

[5] M. O. Gokalp, K. Kayabay, M. A. Akyol, P. E. Eren, and A. Koçyiğit, "Big data for industry 4.0: A conceptual framework," in *2016 international conference on computational science and computational intelligence (CSCI),* 2016: IEEE, pp. 431-434.

[6] G. Aceto, V. Persico, and A. Pescapé, "Industry 4.0 and health: Internet of things, big data, and cloud computing for healthcare 4.0," *Journal of Industrial Information Integration,* vol. 18, p. 100129, 2020.

[7] R. S. Peres, X. Jia, J. Lee, K. Sun, A. W. Colombo, and J. Barata, "Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook," *IEEE Access,* vol. 8, pp. 220121-220139, 2020.

[8] P. Fraga-Lamas, T. M. Fernandez-Carames, O. Blanco-Novoa, and M. A. Vilar-Montesinos, "A review on industrial augmented reality systems for the industry 4.0 shipyard," *Ieee Access,* vol. 6, pp. 13358-13375, 2018.

[9] P. Poór, T. Broum, and J. Basl, "Role of collaborative robots in industry 4.0 with target on education in industrial engineering," in *2019 4th international conference on control, robotics and cybernetics (CRC),* 2019: IEEE, pp. 42-46.

[10] H. Alasti, "Turning a Legacy Robot to Collaborate to Fit in Industry 4.0 Demands," in *2021 ASEE Virtual Annual Conference Content Access*, 2021.

[11] U. M. Dilberoglu, B. Gharehpapagh, U. Yaman, and M. Dolen, "The role of additive manufacturing in the era of industry 4.0," *Procedia manufacturing,* vol. 11, pp. 545-554, 2017.

[12] S. Fareri, G. Fantoni, F. Chiarello, E. Coli, and A. Binda, "Estimating Industry 4.0 impact on job profiles and skills using text mining," *Computers in industry,* vol. 118, p. 103222, 2020.

[13] R. Geissbauer, J. Vedso, and S. Schrauf, "Industry 4.0: Building the digital enterprise," ed, 2016.

[14] E. Paris and S. Washington, "Skill Shift Automation and the Future of the Workforce," *Company, Tech. Rep.*, 2018.

[15] A. Grenčíková, M. Kordoš, and V. Navickas, "The impact of industry 4.0 on education contents," *Business: Theory and Practice,* vol. 22, no. 1, pp. 29-38, 2021.

[16] L. Shenzhen Yahboom Technology Co. "Yahboom DOFBOT AI Vision Robotic Arm with ROS Python programming for Raspberry Pi 4B 8GB/4GB." https://category.yahboom.net/collections/r-robotics-arm/products/dofbot-pi (accessed.

[17] H. C. Ltd. "Hiwonder ArmPi FPV AI Vision Raspberry Pi ROS Robotic Arm with Python Open Source." https://hiwonder.hk/products/hiwonder-armpi-fpv-ai-vision-raspberry-pi-ros-robotic-arm-with-python-open-source?variant=39341129203799 (accessed.

[18] Dobot. "DOBOT Conveyor Belt Kit." https://www.dobot.nu/en/product/dobot-conveyor-belt-kit/ (accessed.

[19] E. Rienovita, M. Taniguchi, M. Kawahara, Y. Hayashi, and Y. Takeuchi, "Implementation of Interactive Peer Learning Environment Enhances Learners‟ Self-Esteem and Self-Efficacy," *International Journal of Learning Technologies and Learning Environments,* vol. 1, no. 1, pp. 1-24, 2018.