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A Utility-based Optimization Model for Allocating Student Teams to Community Projects

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Abstract

Participation in community-based projects provides students with invaluable benefits, including gaining practical experience and developing a sense of connection and belonging within the community. Nevertheless, the projects to which students are assigned can significantly influence their overall experience in this form of learning. Rather than relying on an approach that randomly assigns students to projects and often results in a mismatch between student preference and assigned project, we propose an optimization model to allocate community-based projects to students. The students provided a ranking of their project preference and 89 percent of all students received either their first or second choices. The optimization modeling approach not only streamlines the student-to-project allocation process for project coordinators but also ensures a consistent consideration of all relevant variables.

Keywords: Community-based research, project allocation, discrete optimization

1. Introduction

Community-based research (CBR) is a collaborative approach that involves the active participation of community members, organizations, and researchers in all stages of the research process, with the aim of addressing community needs and improving public health (Israel et al., 1998). In CBR, community members or organizations take part from the outset, particularly in identifying the research needs and questions (Strand et al., 2003), while, researchers, including faculty and students, ensure that the research is rooted in the real concerns and priorities of the community (Cummins et al., 2010). Students are involved in CBR through community engagement, service-learning, and project-based learning. These approaches not only grant students opportunities to actively participate in research, but also enable them to contribute to community development and enhance their skills. The implementation of project-based learning (PBL) in community-based projects has been shown to improve students' collaboration and communication skills (Sagala et al., 2019). PBL involves exploration of knowledge as students work on a project over an extended period of time, providing opportunities for students to gain professional experience with real-world projects (Bakar et al., 2019; Kokotsaki et al., 2016).

CBR offer numerous advantages for both researchers and the communities involved. This research methodology has been shown to be effective for translating research findings into community solutions (Tapia et al., 2022). Furthermore, CBR promotes co-learning where researchers gain insights about the research project from the expertise of community members, while community members develop skills in conducting research (Israel et al., 1998). Students who are integral to the research team also derive benefits from engaging in community-based projects. This involvement enhances their awareness of community issues, fosters community collaborations, and refines their research skills and methods (Dunbar et al., 2013). Despite these benefits, CBR also presents challenges, such as ethical dilemmas between community desires with respect to research design and methods and outsider researchers scientific rigor (Minkler, 2005). Additionally, early career researchers engaging in CBR face challenges due to competing demands on their time and resources (Lowry & Ford-Paz, 2013). These challenges underscore the complexity of conducting research in community settings and highlight the importance of addressing ethical, methodological, and resource-related issues to ensure the validity and impact of CBR.

Assigning students to community-based projects presents a challenging task, demanding careful consideration of multiple factors to align students with projects matching their skills, interests, and the community's needs. Sax (2004) suggests that student interaction across diverse backgrounds has a lasting positive impact beyond college years. However, balancing personalities and ensuring effective collaboration among students can be a challenge. The assignment of students to projects should be transparent and free from any personal biases from decision makers. Nevertheless, project coordinators often rely on random assignments or allow students to choose projects themselves (Ramotsisi et al., 2022). While these approaches may accommodate students' preferences, there is a need for a standardized approach that considers important decision criteria. To assign students to community-based projects, optimization models can be utilized to ensure an efficient and effective allocation process. These models facilitate the matching of students to projects by considering their skills, preferences, and project requirements, while also addressing logistical constraints such as project capacity and student availability.

The rest of the paper is organized as follows. **Section 2** gives a brief account of related work. **Section 3** describes the student-project allocation problem. **Section 4** describes the mathematical optimization model. Result and analysis are presented in **Section 5**. Finally, the conclusions and future work are discussed in **Section 6**.

2. Related Literature

Student involvement in community-based projects has been shown to have a positive impact on students' development and learning outcomes across various disciplines. For instance, Arantes do Amaral and Lino dos Santos (2018) found that CBR offered students rich and meaningful experiences, despite the challenges they faced in coordinating with community partners. Johan et al. (2022) suggested that learning for students should extend beyond the classroom, emphasizing that community-based learning stands as a powerful tool for students' development. al Makmun and Nuraeni (2018) demonstrated that community projects effectively improved student's communication, social awareness, and leadership skills, further supporting the positive impact of community-based projects on students' holistic development. Moreover, the benefits of community-based projects extend beyond students to faculty members. Wagner et al. (2015) emphasized that engagement in learning communities provides faculty members with opportunities to collaborate with colleagues, foster positive relationships with learners, and develop a sense of connectedness with their academic institution. MacGregor and Smith (2005) outline how learning community programs have become locations for faculty and staff development, indicating the role of community-based projects in fostering professional growth among faculty members.

In community-based projects, precise scheduling, resource allocation, and strategic coordination are essential for successful implementation. According to Perry et al. (2006), the tasks assigned to students play a central role in influencing their engagement. To allocate students properly to projects, Todd and Magleby (2005) proposed assigning students based on their interest levels, as it may lead to greater motivation. This approach aims to align students with projects that resonate with their passions, potentially improving their engagement throughout the project duration. Additionally, Robinson (2012) highlighted the impact of power dynamics within student-tutor relationships on student engagement, emphasizing the importance of considering student perspectives in the allocation process.

To address the student-project allocation problem, optimization techniques have been widely explored in the literature. Various approaches such as genetic algorithms (Sanchez-Anguix et al., 2019), simulated annealing (Chown et al., 2018), fuzzy logic (Paunović et al., 2019), and integer programming Anwar and Bahaj (2003) have been proposed to efficiently allocate students to projects. These techniques aim to achieve fair and efficient assignments by considering preferences of both students and projects, workload balance, and capacity constraints (Manlove et al., 2018; Paunović et al., 2019; Sanchez-Anguix et al., 2019). Additionally, multi-objective optimization has been utilized to increase resource utilization, decrease project duration, and minimize project cost (Bibi et al., 2014). Furthermore, the use of discrete optimization has been proposed to find allocations that incorporate both efficiency and fairness considerations (Magnanti & Natarajan, 2018). The student-project allocation is a complex problem, and various optimization techniques have been applied to address its different aspects. For instance, the use of stable marriage algorithms has been explored to achieve stable matching solutions based on student-project preferences (Modi et al., 2018), Moreover, the integration of preference lists over (student, project) pairs has been proposed to enhance the allocation process (El-Atta & Moussa, 2009). Additionally, the application of multi-criteria decision support systems has been suggested to assist in the allocation of students to groups (Weitz & Jelassi, 1992).

In this study, we propose a discrete optimization model for assigning selected students to community-based projects based on their preferences in a transparent and unbiased manner.

3. Problem Description

In this study, community members identified 6 projects and will serve as mentors to the selected students. Interested students applied to be part of the program by providing information about their background, why they are interested in working on community projects and their CV. A total of 42 students applied to the program and the applicants were interviewed and then the top 19 applicants were selected. These 19 students comprised of 14 undergraduate and 5 high school students **(see Figure 1)** from a range of majors such as environmental studies, computer science, product design, philosophy, politics, and economics.

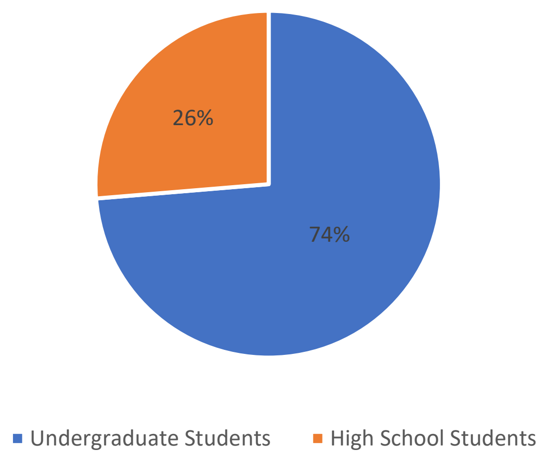

Figure 1: Program participants by educational level

The selected students were given detailed information about all the projects and then provided a ranking of their project preference, ranking them from 1, their most preferred, to 6, their least preferred. **Figure 2** shows the preference ratings provided by the students. In previous years, students were randomly assigned to projects, leading to instances where some did not find their allocated projects interesting (Bello et al., 2023). Consequently, this mismatch often resulted in a drop in project satisfaction levels by the end of the program. To address this issue, we have implemented a discrete optimization model aimed at resolving these challenges in student-project allocation.

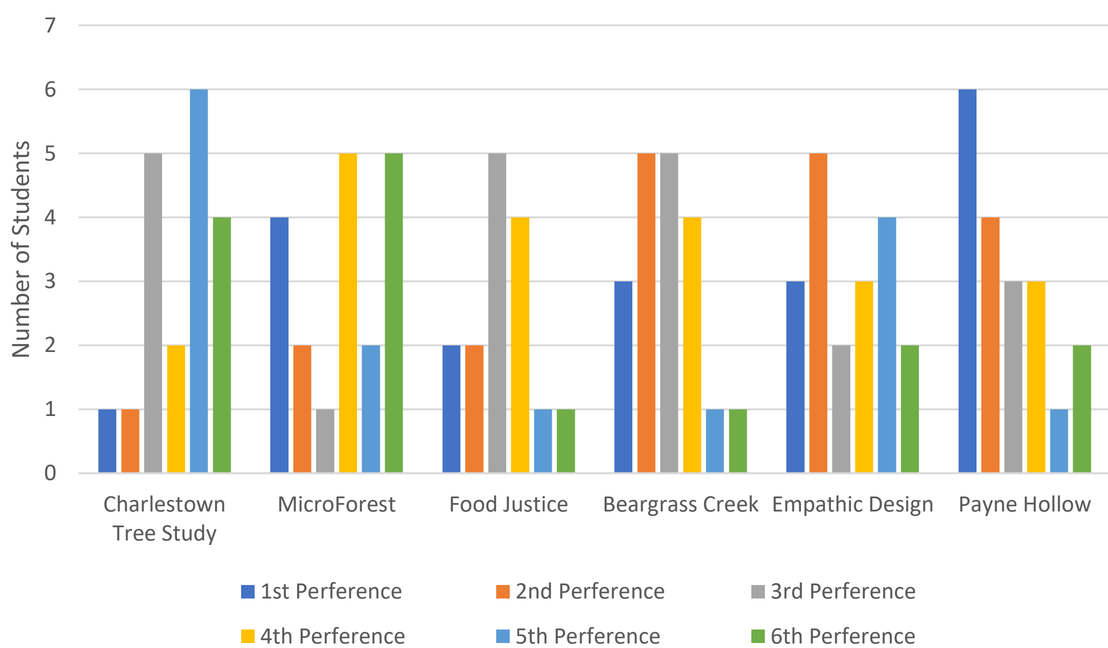

Figure 2: Preference ratings by selected students

Each project requires specific skills, such as programming, data analysis, GIS etc. A student is assigned to a project only if they meet or exceed the required skill set. Furthermore, if a student is selected after the interview stage but fails to meet the program requirements which include not being a master's student, being above the age of 16, being a US citizen, and being available for the entire 8-week program, they will not be assigned to any project.

4. Mathematical Model

Sets:

S: set of all students, indexed by *s*

P: set of all projects, indexed by *p*

I: set of all skills/attributes, indexed by *i*.

Decision Variable:

$$X_{sp} = \begin{cases} 1, & if\ student\ s\ is\ assigned\ to\ project\ p \\ 0, & otherwise \end{cases}$$

Model Parameters:

$U_{sp} = Utility\ of\ project\ p\ for\ student\ s$

$R_p = maximum\ number\ of\ students\ allowed\ on\ any\ project\ p$

$N_p = minimum\ number\ of\ students\ allowed\ on\ any\ project\ p$

$$G_{is} = \begin{cases} 1, & if\ a\ student\ s\ has\ skill\ i \\ 0, & otherwise \end{cases}$$

$$F_{ip} = \begin{cases} 1, & if\ project\ p\ requires\ skill\ i \\ 0, & otherwise \end{cases}$$

$$E_s = \begin{cases} 1, & if\ student\ s\ possess\ all\ four\ requirements\ for\ selection \\ 0, & otherwise \end{cases}$$

Objective Function:

In the student-project assignment problem, students express their project preferences through ranking, which are then translated into utility values. The highest-ranked project for a student receives a utility value of *Y*, while subsequent preferences are assigned decreasing values, with the next ranked project being *Y-1* and the lowest ranked project is given a utility value of 1. The objective of our optimization model is to maximize the overall utility derived from assigning students to projects as shown in Eq. (1)

$$Max\ Z = \sum_{s \epsilon S} \sum_{p \epsilon P} U_{sp} X_{sp} \tag{1}$$

Constraints:

Constraint (2) ensures that every student is assigned to only one project.

$$\sum_{p \epsilon P} X_{sp} = 1;\ \forall s \epsilon S \qquad (2)$$

Constraints (3) and (4) ensure that the number of students assigned to a project stays within the allowed range, defined by both a maximum and a minimum permissible number.

$$\sum_{s \epsilon S} X_{sp} \leq\ R_p;\ \forall p \epsilon P \qquad (3)$$

$$\sum_{s \epsilon S} X_{sp} \geq\ N_p;\ \forall p \epsilon P \qquad (4)$$

Constraint (5) ensures that a student is only assigned to a project if the skills possessed by the student meets or exceeds the skills required by the project.

$$\sum_{i \epsilon I} (G_{is}\ \times\ F_{ip}) \geq\ X_{sp};\ \forall s \epsilon S, \forall p \epsilon P \qquad (5)$$

If a student does not meet all the four requirements for selection ($E_s = 0$), constraint *(6)* restricts the assignment of that student to any project.

$$X_{sp} \leq\ E_s;\ \forall s \epsilon S, \forall p \epsilon P \qquad (6)$$

5. Model Implementation and Analysis

The model was implemented in LINGO 19.0. The data were placed in an EXCEL spreadsheet file, and OLE function was used to access the data. It takes the model 0.14 seconds to run, while it took an expert several hours to assign students to projects manually.

From the LINGO solution report, the optimal solution to the student-project allocation problem is as follows: assign students 1, 5, and 9 to project 1; assign students 2, 16 and 17 to project 2; assign students 10, 18, and 19 to project 3; assign students 3, 6, and 11 to project 4; assign students 4, 7, and 15 to project 5; assign students 8, 12, 13 and 14 to project 6. This assignment resulted in a maximum utility value of 106. It is noteworthy that a utility value of 114 would have indicated that every student was allocated their first choice; however, this was not the case. 89 percent of all students were either assigned their first or second choices. Importantly, all constraints were satisfied.

All students were successfully assigned to a project, and the allocations are shown in **Figure 3**. The model assignment and expert assignment both saw the majority of students being assigned to their first-preferred projects. However, there was a discrepancy wherein the model assigned a student to their fifth-preferred project, resulting in the expert assignment having a higher total utility value of 109, in contrast to the model's total utility value of 106. **Table 1** shows the project assignment made by the expert in comparison to those made by the model. There was a 79% match in the assignment using both methods.

In certain instances, the model outperformed the expert assignment. For instance, student 13 was assigned to their third-preferred project by the expert, whereas the model placed the same student in their first-preferred project. The expert assignment was also better in some cases. This indicates that further refinement of the constraints or the utilization of advanced optimization techniques could enhance the model's performance.

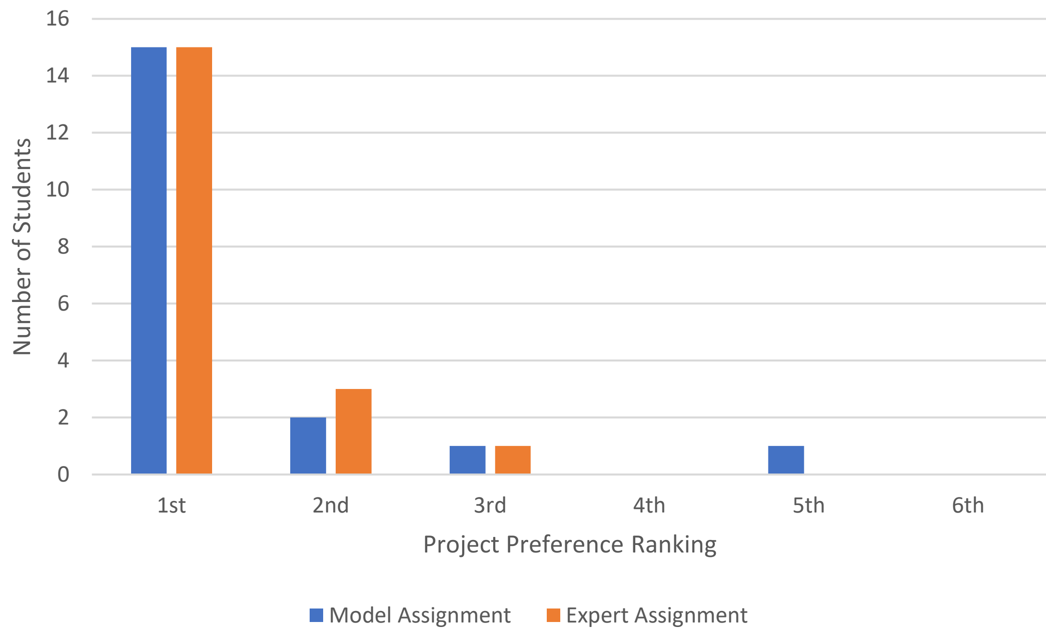

Figure 3: Projects allocated to students using the model and expert.

Table 1: Comparison between the model assignment and the expert assignment

Student No.	Assigned Project (Model)	Assigned Project (Expert)	Match
1	Charlestown Tree Study	Charlestown Tree Study	Yes
2	Micro Forest	Micro Forest	Yes
3	Beargrass Creek	Payne Hollow	No
4	Empathic Design	Empathic Design	Yes
5	Charlestown Tree Study	Charlestown Tree Study	Yes
6	Beargrass Creek	Beargrass Creek	Yes
7	Empathic Design	Empathic Design	Yes
8	Payne Hollow	Payne Hollow	Yes
9	Charlestown Tree Study	Food Justice	No
10	Food Justice	Beargrass Creek	No
11	Beargrass Creek	Beargrass Creek	Yes
12	Payne Hollow	Payne Hollow	Yes
13	Payne Hollow	Charlestown Tree Study	No
14	Payne Hollow	Payne Hollow	Yes
15	Empathic Design	Empathic Design	Yes
16	Micro Forest	Micro Forest	Yes
17	Micro Forest	Micro Forest	Yes
18	Food Justice	Food Justice	Yes
19	Food Justice	Food Justice	Yes

6. Conclusions and Future Work

This paper presents an optimization model designed to solve the allocation of projects to students, taking into consideration the constraints outlined by a community-based research program. The model demonstrated successful application in a case study involving 19 students, proving to be computationally efficient. Subsequent efforts will concentrate on extending the application of this model to a larger student cohort in a new case study. Additionally, post-surveys will be employed to gather feedback from students regarding their experience working on their assigned projects.

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