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Automation and Optimization of Engineering Design Team Selection Considering Personality Types and Course-Specific Constraints

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Automation and Optimization of Engineering Design Team Selection Considering Personality Types and Course-Specific Constraints

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Optimal team selection in introductory and capstone mechanical design courses is vital to the success of the project, and, as such, many studies have been conducted to determine the means of generating ideal design teams. This work seeks to employ multiple areas of design team theory, including the use of Myers-Briggs Type Indicators (MBTI) for personality assessment and the capability for students to be placed in teams with respect to certain course-specific constraints, including project preference and teaming constraints, in order to automate the optimization of design team selection. Various test cases are shown that indicate the weighted multi-objective Mixed-Integer Linear Programming approach can quickly select optimal design teams consisting of diverse personality types, and can also assign students to preferred projects. This work serves as the first step toward a downloadable design team selection software package that will be made freely available to design researchers and educators.

Introduction

Oregon State University is home to one of the largest mechanical engineering design groups in the country, which has historically focused on undergraduate design education that combines both computational and hands-on design skills. As such, Oregon State University's department of mechanical engineering offers multiple undergraduate design courses, including two large project-based courses: a junior-level introductory course, and a multi-term senior-level capstone course. In the junior course, students have been placed on design teams considering MBTI personality types for more than twenty years; however, the instructor and the teaching assistants have always performed this team selection process manually. Similarly, in the senior capstone course, students are introduced to a breadth of available research or industry-sponsored projects, and then are placed on teams depending on students' ranking of their interest in each project. This process has also been performed manually by the instructor, which allows for the consideration of various constraints (e.g., students with previous experience on a certain project should get priority to work on said project).

The work presented in this paper builds on the capability of an existing project selection algorithm developed by Kirkwood [1]. This framework utilizes a user-defined objective and constraints that can be solved using mixed-integer linear programming methods, and is currently run on a web-based optimization server such that the user does not need their own optimization software capability to perform team selection. Future work will include the development of a local optimization environment, such that the team selection software is standalone.

This work also seeks to expand on the existing Comprehensive Assessment for Team-Member Effectiveness (CATME) system [2] – an online tool that instructors and students can use to facilitate teaming and explore teaming success using evaluative measures [3,4]. Unlike

this black-box tool, the method proposed in this work allows instructors to choose course-specific constraints, including ensuring students are placed on the same or different teams, and allowing for project preference to influence team selection. By developing standalone software, the current work would enable the inclusion of subsequent constraints – such as maximizing diversity based on experience – that are deemed necessary on an instructor-by-instructor and course-by-course basis.

As the current professors of design courses at Oregon State University, the authors' intent is to automate the selection of design teams for both the junior-level introductory design course and the senior capstone design course such that both MBTI personality types and other course-specific constraints are considered, in addition to a series of realistic constraints. This work serves as the preliminary step in creating a freely accessible software application that design course instructors at other schools can use to automate team selection.

Motivation

The motivation for automating design team selection is twofold: we seek to speed up the process of creating design teams by removing the need for manual sorting, while ensuring that the resulting teams have a high likelihood of performing optimally. Optimality in team selection can be determined in many ways, but generally it is estimated by the success of the resulting project and the satisfaction of the team members [5].

Many researchers have hypothesized that utilizing MBTI personality types to strategically select students for engineering design teams will lead to more successful teams. This concept was refined and tested over many years by Douglass Wilde at Stanford University [5,6], and has been shown to be key to the success of many additional student engineering design teams [7–12]. Using years of data from design teams at Stanford, Wilde showed that teams developed using MBTI considerations performed "qualitatively and quantitatively better" than teams that are selected without accounting for the personality types of the team members [5]. It should be noted that it is not the intent of this work to explore the validity of these claims, or to suggest that teams developed considering MBTI personality types are superior. Rather, the MBTI method is used here due to its acceptance in design engineering teaming, and, in the future, new algorithms for team selection can be employed instead of MBTI.

The Myers-Briggs Type Indicator (MBTI) [13] is a psychometric assessment – a series of questions – that aims to enable users to better understand themselves by establishing certain personality traits within individuals. Based on the Jungian model of personality types, completion of the MBTI assessment results in the selection of one of two opposing traits, of which there are four in total, leading to sixteen (2^4) possible outcomes represented by a four-letter string. These dichotomies are depicted in Fig. 1.

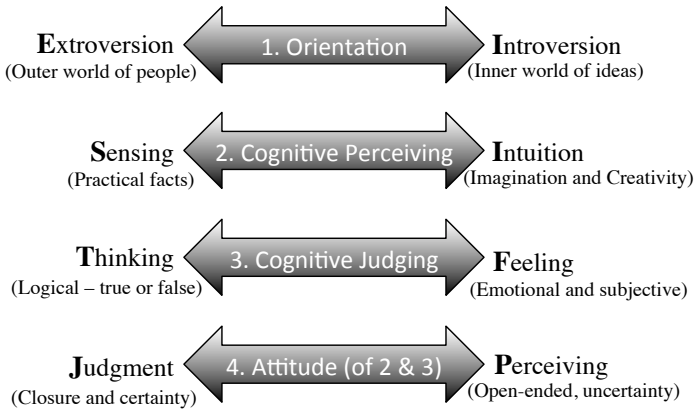

Fig. 1: The Four Dichotomies of the MBTI [11]

The dichotomies shown in Fig. 1 represent opposing sides of different personality traits. The first, called "Orientation", describes whether a person is generally more extroverted or introverted in their daily lives. The second, called "Cognitive Perceiving", indicates whether a person is more likely to sense facts in a practical way, or intuit facts creatively. The third dichotomy is "Cognitive Judging", which indicates how a person approaches making judgments – either more logically ("Thinking") or more subjectively ("Feeling"). The last dichotomy describes the attitude the user has with respect to the second and third dichotomies, whether they are more likely to judge (and seek certainty) or perceive (and seek open-endedness). Particular values of these dichotomies are more likely to be held by engineering students; for example, in Oregon State's junior-level introductory design class in 2013, the students were three times as likely to be Thinkers than Feelers (dichotomy 3), and the Judging students outnumber Perceiving students (dichotomy 4) eleven-to-one.

ISTJ Practical, realistic, responsible	ISFJ Considerate, thorough, friendly	INFJ Conscientious, committed, organized	INTJ Competent, independent, skeptical
ISTP Tolerant, flexible, efficient	ISFP Sensitive, observant, kind	INFP Idealistic, curious, adaptable	INTP Logical, conceptual, analytical
ESTP Spontaneous, engaged, pragmatic	ESFP Generous, outgoing, friendly	ENFP Optimistic, enthusiastic, imaginative	ENTP Inventive, ingenious, outspoken
ESTJ Realistic, decisive, practical	ESFJ Cooperative, loyal, appreciative	ENFJ Persuasive, empathetic, sociable	ENFJ Commanding, forceful, decisive

Fig. 2: The Sixteen Personality Types of the MBTI [14]

The full range of MBTI personality types is shown in Fig. 2. In this work, the optimization algorithm for design team selection includes an objective that maximizes the diversity of the

MBTI characteristics of the team, while incentivizing the selection of a leader (or leaders) on each team. A leader is considered to be either:

a) A single student with an MBTI personality type that includes EN (**E**xtroverted I**N**tuitor), corresponding to a leadership score of 1; or
b) Two students, each with an MBTI personality type that includes IN (**I**ntroverted I**N**tuitor) and EF (**E**xtroverted **F**eeler), corresponding to a leadership score of 0.1 and 0.9, respectively.

An EN personality is generally creative, social, and logical, and capable of seeing "the big picture" [11]– all traits that make strong leaders. The leadership role can be divided amongst two students, one IN and one EF, where the intuitive ideas of the IN can be related to the group by the extroverted and relatable nature of the EF. The algorithm presented in this work uses a multi-objective approach (Eq. (1)) that incentivizes the selection of a single EN leader, or the combination of two IN and EF leaders.

The remaining members of each team are chosen such that there is significant quantitative distance between the MBTI attributes of the members. That is, each student reports not only their four-character MBTI type, but also the percentage of each dichotomous pair they received (i.e., 35% I vs. 65% E). The pairwise difference between each attribute is calculated for all the members of a potential team, and the objective function maximizes this difference to ensure variance in personality types. The use of a diversity metric for personality types enforces the collaboration of more varied teammates, capitalizing on diverse strengths and thought processes, and approaches the multi-disciplinary aspect of traditionally successful design teams (despite teammates in these courses having nearly identical academic backgrounds).

The selection of cognitively diverse design teams has been shown to increase the likelihood of success of the team and the course project. One early example was discussed by Wilde [5], who used MBTI personality types to select diverse design teams at Stanford, and many of these teams were successful in taking prizes at the national Lincoln Foundation Design Competition. When Wilde took a leave for a year and was not enforcing the use of MBTI diversity in design team selection, the design teams performed significantly worse in the national competition than they had during years with structured MBTI diversity. A similar result was seen at the University of California – San Diego, where half of the senior design teams were assigned at random and the other half used MBTI traits to select cognitively diverse teams. Though the cognitively diverse teams reported that they felt their team lacked cohesion, the industry sponsor objectively determined the teams with diverse MBTI traits to be more creative [6].

This work combines the use of traditional leadership MBTI traits and MBTI cognitive diversity with the capability for students to work on projects for which they have a preference. Each student is given a presentation or a written description of the various research and industry-led projects available for their capstone design course, and then students rank each project in descending order from 1 to M, where M is the number of projects. An optimal design team is one that has an EN leader or an IN-EF leader pair, has sufficient cognitive diversity amongst all of the team members, and includes students who have all rated their assigned project as highly favorable. The current optimization method also considers constraints on team selection, including students who must not be placed on the same team or students who must be placed on the same team.

Method

The method presented in this paper seeks to automate and optimize the selection of student design teams (for an introductory or capstone mechanical design course) while accounting for both the personality indicators of individual students and the availability of design projects for each team. Using the project-selection algorithm developed by Kirkwood [1] as a foundation, the current work expands on the capability of previous design team selection tools by using a multi-objective optimization approach, allowing for the selection of both project (based on student preference) and teammates (based on MBTI personality types), while enforcing multiple realistic constraints.

Multi-objective Optimization Formulation

The optimization algorithm is formulated as follows, given in negative null form.

Minimize the objective function:

$$\left(\text{Project Term}\right) + w_1\left(\text{Leadership Penalty}\right) - w_2\left(\text{Diversity Term}\right) \quad (1)$$

where:

$$\text{Project Term} = \sum_{i=1}^{N}\sum_{j=1}^{M}\left[\left(\text{Rank}_{\text{Project } i,j}\right)\left(Binary_{\text{On Project? } i,j}\right)\right] \quad (2)$$

$$\text{Leadership Penalty} = \sum_{j=1}^{M}\left(\text{Flag}_{\text{MBTI}} \times \text{Flag}_{\text{Penalty}} \times N \times Binary_{\text{Penalty } j}\right) \quad (3)$$

$$\text{Diversity Term} = \sum_{j=1}^{M}\sum_{i=1}^{N}\left[\left(\text{Distance}_{i,j}\right)\left(\text{PersonToProject}_{i,j,k}\right)\right] \quad (4)$$

subject to:

$$TeamSize = x \quad (5)$$

$$Binary_{\text{Prevent}(i,i)} = 0 \quad (6)$$

$$Binary_{\text{Prevent}(i,j)} = 0 \quad (7)$$

$$Binary_{\text{MustAssign}(i,j)} = 1 \quad (8)$$

$$Binary_{Major\ \text{Assignment}(i,j)} = 1 \qquad (9)$$

In the objective function given in Eq. (1), the coefficients w_1 and w_2 are used to weight the impact of the Leadership Penalty and the Diversity Term on the overall objective evaluation. For courses that do not require the selection of various projects, the Project Term simply goes to zero.

The Project Term given in Eq. (2) indicates whether or not the algorithm has met the students' preferences in assigning projects. It is formulated as the sum, for the number of

students N across the number of projects M, of the ranks that each student selected for each project multiplied by a binary factor indicating whether or not a student has been assigned to a particular project. The best possible evaluation of the Project Term is equal to the number of students in the class, indicating that for every student in the class, each student has been assigned to their first-ranked project.

The Leadership Penalty term (Eq. (3)) ensures that each team has an appropriate leader or pair of leaders based on MBTI personality types. The indicators Flag_{MBTI} and $\text{Flag}_{Penalty}$ are user-defined for modularity, where each is equal to 1 if MBTI data is available for the class and if the user would like a penalty to enforce the selection of leaders for each team, respectively. $Binary_{Penalty}$ is a check used to see if there is a leader or pair of leaders on each team, and is equal to 1 if a true value is returned. A true value, in this case, indicates that there is exactly one "Extroverted Intuitor" (EN), or both an "Introverted Intuitor" (IN) and an "Extroverted Feeler" (EF) on each team. The maximum leadership score achievable for a team is 1.1, indicating that there is both an IN and EF on the team. The value N (the number of students in the class) is used to scale the Leadership Penalty term such that its value is relevant for the scope of the team selection problem. The Diversity Term is a negative portion of the objective function, as we seek to maximize the diversity of the resulting design teams. This term considers the lower half of a symmetric matrix $\text{Distance}_{i,j}$, which consists of the pairwise Euclidian distances between each students' MBTI indicators. That is, each student reports the percentage value for each of his or her MBTI attributes (e.g., 35% E and 65% I, 10% S and 90% N, etc.), and the distance between each student's personality types is calculated using these percentages:

$$\text{Distance} = \sqrt{\left(f1_i - f1_{i+1}\right)^2 + \left(f2_i - f2_{i+1}\right)^2 + \left(f3_i - f3_{i+1}\right)^2 + \left(f4_i - f4_{i+1}\right)^2} \qquad (10)$$

where $f1$, $f2$, $f3$, and $f4$ represent the percentage values for each student's four MBTI functions. This value is multiplied by the $\text{PersonToProject}_{i,j,k}$ matrix, a linear binary model that represents the assignment of each student to each project in a pairwise (student-to-student) fashion. The method of converting what would have been a polynomial binary model to a linear binary model was developed by Kuo et al. [15] specifically for modeling the maximization of group diversity.

There are five equality constraints enforced throughout the optimization, which can vary depending on the course's specific parameters. The first, Eq. (5), is a constraint on the size of the design team, limiting the team size to a user-defined value x. The second constraint, Eq. (6), allows for students to select other student(s) that they would not like to work with; the 0-value of this constraint enforces that these students will not be placed on the same team. This constraint is enabled in order to avoid potential social conflicts on the resulting design teams, particularly in those situations where students know from previous experience that their placement with other specific students led to a negative course experience. The third constraint, Eq. (7), specifies those students that should not be assigned to certain projects, with a value of zero indicating that none of these flagged students have been selected to work on these particular projects. This constraint allows the instructor to fine-tune the team selection in order to dissuade students from working on projects outside their areas of expertise, for example. The fourth constraint, Eq. (8), is essentially the opposite of the third constraint (Eq. (7)) in that it specifies that particular students must be assigned to certain projects, and returns a value of one if true. This constraint is often employed when students

previously discussed with the instructor that there is a particular project they have had experience with prior to the start of the course. The last constraint, Eq. (9), designates that the team selection includes a suitable distribution of underrepresented majors on each design team, with a value of one indicating that each team has a required number of team members from underrepresented majors. For example, a potential project in lean manufacturing will benefit from the inclusion of multiple industrial and manufacturing engineers on that team, and the user can specify such a constraint in team selection. This constraint is specifically designed for the senior capstone class in the School of Mechanical, Industrial, and Manufacturing Engineering at Oregon State University, where Mechanical Engineering students generally outnumber the students in Industrial and Manufacturing Engineering.

Language and Solver

The current version of the team selection algorithm presented in this work uses an internet-based solver, the Network Enabled Optimization System (NEOS) [16]. NEOS is an online optimization server that uploads user-developed optimization inputs and allows for the selection of different types of optimization solvers in order to quickly solve large-scale optimization problems. The input files, which contain the objective, input matrices, and constraint matrices are written in AMPL, a programming language specifically designed for linear optimization that capitalizes on traditional algebraic notation for ease of computation [17]. Given the type of optimization problem presented in this work, a mixed-integer linear programming solver is selected in NEOS. In the future, this problem will be implemented in a local optimization-ready environment, such that the resulting software will be standalone, and therefore can be easily downloaded and used by design researchers and course instructors.

Results

Two test cases are shown; the first case is representative of the junior-level introductory course, where every team is working on the same project and the objective is to maximize cognitive diversity (hence, no project selection term in the objective). The second test case is representative of the team selection for the senior-level capstone course, which includes both project selection and cognitive diversity objectives. Both cases use a class size of 36 students. Each design team is constrained to have only four team members, as it has been found both in the authors' experience as well as in the literature that design team "success and satisfaction can be more confidently guaranteed for quartets" than teams of other sizes [5]. For the second test case, there are 14 available projects; only nine will be selected (e.g., nine teams of four). The current design teams at Oregon State use Wilde's 20-attribute MBTI questionnaire, based on the less counseling-driven Keirsey Temperament Sorter [6], and as such, the results for cognitive diversity were based on results from a questionnaire of this length.

Test Case 1: Cognitive Diversity and Leadership Objectives

The results of the first test case – the junior-level introductory course that does not include variation in projects – are shown in Tables 1 and 2. The left column shows the results when only the leadership objective was considered, and the right column shows results for when both the leadership and cognitive diversity objectives were considered.

Table 1: First Test Case, Leadership Results

Leadership Objective Only		**Leadership & Diversity Objectives**	
Leaders		**Leaders**	
Team 1	1	Team 1	1.1
Team 2	1	Team 2	1.1
Team 3	1	Team 3	1
Team 4	1.1	Team 4	1.1
Team 5	1	Team 5	1
Team 6	1.1	Team 6	1
Team 7	1	Team 7	1
Team 8	1.1	Team 8	1
Team 9	1.1	Team 9	1.1

Table 1 shows that regardless of the inclusion of the maximization of diversity, all teams were able to meet the leadership objective, that is, all teams have a value of either 1 or 1.1. These values correspond to the inclusion of 1) a single EN leader (score of 1), 2) a single EN leader (score of 1) and an EN leader (score of 0.1), 3) the combinatory leadership of an IN (0.9) and an EF (0.1), or 4) the combinatory leadership of an IN (0.9) and two EFs (0.1).

Table 2: First Test Case, Maximizing Diversity Results

Leadership Objective Only		**Leadership & Diversity Objectives**	
Diversity		**Diversity**	
Team 1	21.14	Team 1	21.52
Team 2	15.74	Team 2	19.82
Team 3	20.54	Team 3	23.54
Team 4	18.88	Team 4	24.76
Team 5	22.08	Team 5	18.58
Team 6	21.04	Team 6	19.26
Team 7	13.36	Team 7	20.32
Team 8	19.7	Team 8	22.72
Team 9	22.18	Team 9	21.54
	174.66		**192.06**

Table 2 shows the difference in diversity, given by the Euclidian distance between the percentages of each MBTI characteristic of each of the four team members, when the objective is focusing on diversity maximization and when it is not. In the left column, there is considerable diversity (i.e., distance) in that the leadership objective is satisfied, so there has already been some consideration made for placing different personality types on different teams. The right column shows how this result is improved when the maximization of diversity is considered in conjunction with the leadership objective.

Test Case 2: Project Rank, Cognitive Diversity and Leadership Objectives

The results of the second test case – the senior-level capstone course that includes both variation in projects and cognitive diversity/leadership objectives – are shown in Tables 3–6. The furthest left column shows the results when only the project rank was considered, the center column shows the results when both the project rank and a leadership role was enforced, and the right column shows results for when project rank, the leadership objective and the maximization of cognitive diversity objective were considered.

Table 3: Second Test Case, Project Selection

Ranking only		**Ranking & Leadership**		**Ranking, Leadership, & 0.4 Diversity**	
Project Selected		**Project Selected**		**Project Selected**	
Project 1	0	Project 1	0	Project 1	1
Project 2	1	Project 2	1	Project 2	1
Project 3	1	Project 3	1	Project 3	0
Project 4	1	Project 4	1	Project 4	1
Project 5	1	Project 5	1	Project 5	1
Project 6	0	Project 6	0	Project 6	0
Project 7	1	Project 7	1	Project 7	1
Project 8	1	Project 8	1	Project 8	1
Project 9	1	Project 9	0	Project 9	0
Project 10	0	Project 10	0	Project 10	0
Project 11	1	Project 11	1	Project 11	1
Project 12	0	Project 12	0	Project 12	0
Project 13	1	Project 13	1	Project 13	1
Project 14	0	Project 14	1	Project 14	1

Table 3 shows the different projects that were selected for each of the different sets of active objectives. It should be noted that the inclusion of all three objectives (right-hand column) caused the algorithm to select different projects than in either of the other two cases.

Table 4: Second Test Case, Major Inclusion Constraint Results

Ranking only		**Ranking & Leadership**		**Ranking, Leadership, & 0.4 Diversity**	
Major		**Major**		**Major**	
Project 2	1	Project 2	1	Project 1	2
Project 3	1	Project 3	1	Project 2	0
Project 4	3	Project 4	3	Project 4	3
Project 5	0	Project 5	0	Project 5	0
Project 7	2	Project 7	1	Project 7	1
Project 8	1	Project 8	2	Project 8	1
Project 9	1	Project 11	2	Project 11	2
Project 11	2	Project 13	1	Project 13	1
Project 13	2	Project 14	2	Project 14	3

Table 4 shows that regardless of the objective applied, the constraint of having a certain number of underrepresented majors involved on particular teams was always satisfied. The algorithm behavior will change significantly as the parameters of this constraint – specifically how many underrepresented majors are enrolled in the class – change from term to term.

Table 5: Second Test Case, Leadership Objective Results

Ranking only		**Ranking & Leadership**		**Ranking, Leadership, & 0.4 Diversity**	
Leaders		**Leaders**		**Leaders**	
Project 2	1.1	Project 2	1.1	Project 1	1.1
Project 3	1.1	Project 3	1.1	Project 2	1.2
Project 4	2	Project 4	1.1	Project 4	1.1
Project 5	1.9	Project 5	1	Project 5	1
Project 7	1	Project 7	1	Project 7	1
Project 8	0.1	Project 8	1.1	Project 8	1
Project 9	0.1	Project 11	1	Project 11	1
Project 11	1	Project 13	1	Project 13	1
Project 13	1.1	Project 14	1	Project 14	1

Table 5, as with Table 2, shows that the leadership objective has been met for all three objective cases. However, it should be noted that for the project rank, leadership, and cognitive diversity objective case (right-hand column), one team has a leadership metric of 1.2, indicating they may have too many students who will take on a leadership role, potentially leading to dissonance within the group. However, this should be investigated on a case-by-case basis, as certain combinations of EN, IN, and EF leaders may not create leadership issues within the team.

Table 6: Second Test Case, Cognitive Diversity Results

Ranking only		**Ranking & Leadership**		**Ranking, Leadership, & 0.4 Diversity**	
Diversity		**Diversity**		**Diversity**	
Project 2	21.1	Project 2	21.1	Project 1	23.34
Project 3	22.22	Project 3	22.22	Project 2	19.42
Project 4	21.62	Project 4	22.08	Project 4	22.08
Project 5	19.56	Project 5	19.38	Project 5	19.38
Project 7	15.98	Project 7	19.44	Project 7	19.44
Project 8	15.62	Project 8	20.74	Project 8	19.16
Project 9	19.12	Project 11	16.58	Project 11	16.58
Project 11	16.58	Project 13	17.62	Project 13	20.84
Project 13	20.86	Project 14	18.86	Project 14	23.04
	172.66		**178.02**		**183.28**

Table 6 shows how the inclusion of the leadership and cognitive diversity objectives helps to create teams with an increased distance between MBTI parameters, likely leading to more harmonious, successful student design teams.

Concluding Discussion

In this work, we presented an algorithm that can be used to optimize the selection of engineering design teams that accounts for both the student preference of individual projects, as well as personality types amongst teams members. Previous work explored the selection of design teams with respect to Meyers-Briggs Type Indicator data to ensure a variation in personality types and leadership potential. These teams have been shown to be more successful in completing their projects, to be more creative, and to have a better overall opinion of their team's capabilities. In addition, students whose project preference has been considered during the team selection process feel more engaged and driven to succeed. The automated systems developed in this work allows for both of these attributes to be considered simultaneously, theoretically leading to more successful, satisfied engineering design teams.

The algorithm presented in this work has been shown to be capable of selecting design teams that balance project preference and cognitive diversity, all while establishing leadership roles on each team and operating within the defined constraints of major representation, enabling certain students to avoid being placed on the same team, etc. Immediate future work includes refinement of the algorithm such that it can be employed during the 2015–2016 academic year.

This work is a first step in enabling engineering design professors and professionals to perform optimal design team selection in an easy-to-use, automated way. While the algorithm has been used this year to develop teams in the junior-level class, current empirical evidence from the instructor suggests that design teams are as successful as those of previous years that were placed manually. However, our intent is to test the design teams developed using this algorithm throughout the next few years at Oregon State in order to ensure that our design

teams are harmonious and successful. During that time, we intend to refine the algorithm to be able to accommodate various constraints, and to allow for the increase in diversity of each team with respect to gender and other qualities. The goal of this project is to deploy the algorithm in a software application that can automatically create design teams while considering project preference and personality types, but is readily alterable to accommodate varying goals and constraints for different users and courses.

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