Using A Modularity Analysis to Determine Tool and Student Roles within Makerspaces

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Abstract

Student use of makerspaces can vary greatly, with some students confidently using the space throughout their academic career and others quickly losing interest or never participating. Many of the potential roadblocks are nuanced or unpredictable and can only be discerned when multiple makerspace design parameters are evaluated in reference to each other. This preliminary investigation models the makerspaces as a network of actors (students and tools) connected by individual student-equipment interactions. This representation allows for a modularity analysis to be performed, a tool primarily used by ecologists to study mutualistic networks in nature and investigated here for its potential to understand and design the makerspace from a systems-perspective. The modularity analysis can highlight the different roles, for example what are great introductory or stepping stone tools, that the students and tools play within and their respective contributions to the larger makerspace. The results suggests that the analysis has the potential to support makerspace decision-makers with information such as: which students act as recruiters for and which are not fully using a makerspace (enabling them to potentially be connected), which tools have low usage rates and potentially discourage students from the space versus, and how students navigate the overall space to identify enhancements.

Keywords

Makerspaces; modularity analysis; network design; engineering education

Introduction

Makerspaces are a powerful new tool in the engineering educators' toolbox, a growing body of empirical data demonstrates their benefits to learning, but more needs to be done to ensure they meet their full potential. This paper presents novel makerspace network analysis techniques to measure the underlying network structure that leads to successful and impactful makerspace functioning. The proposed analyses will model the makerspace as a network of interactions between tools and students. The resultant network-level understanding has the potential to *empower* educators to 1) identify and remove previously undiscovered hurdles for students who underutilize the space, 2) design an effective space using limited resources, 3) understand the impact of new tools or staff, and 4) create learning opportunities such workshops and curriculum integration that increase student return rates.

Makerspaces provide a multitude of opportunities to enhance the existing engineering curriculum, allow students to learn through pursuing their own passion projects, and can create communities for students. To ensure positive impacts to students, much more research is needed to improve these spaces making them effective for all students. Network analysis enables problem understanding and solution generation at a systems level. A systems-level analysis of a network of industries, for example, (as opposed to designing each industry individually) was able to reduce the overall environmental impact of all industries in the network without increasing the cost of the network (thereby maintaining profits) [1-3]. Similar system-analyses of water distribution networks and power grids have also resulted in designs that reduced raw material usage, improved use of available resources, and reduced economic damages following disruptions [4-8].

Modeling and analyzing makerspaces as networks is expected to similarly maximize student impact (use of available resources) and increase the stability and longevity of the educational space. The modeling approach will provide a completely new perspective, highlighting new techniques for constructing and operating a makerspace in the most productive way possible.

Prior Work on Makerspaces

There have been a number of studies of academic and non-academic makerspaces that guide this research but generally limited empirical data demonstrating impact to students. In a paper touting the promise of makerspaces for education, Martin identifies three elements essential to consider in determining potential affordances: 1) digital tools, including rapid prototyping and low-cost microcontrollers; 2) community infrastructure, including events; and 3) the maker mindset, aesthetic principles, a failure-positive approach, collaboration and habits of mind [9]. Wilczynski identified best practices for those planning new campus spaces: the importance of user training, the need for a clear definition of its mission, proper staffing, promoting collaboration, alignment with student work schedules, and attention to creating a maker community on campus [10]. While not focused exclusively on makerspaces, a study of collaborative co-working spaces found that a student-led organizational structure, access to the latest technology, and possibly partnerships with for-profit makerspaces were important for growing and sustaining these spaces [11]. In an informal interview study of five new makerspace users at Tufts, O'Connell [12] found that accessibility led to changes in perception for participants with regard to making in general and seeing themselves as makers. Similar access-related themes such as ease of entry, initial orientation to the space, and the physical arrangement of the space have been identified by early efforts to apply ethnographic techniques to study makerspaces [13].

The research on barriers to students' participation in makerspaces remains limited. Still, some key barriers have been identified in the literature on best practices for makerspaces, and on creating inclusive environments. Work on best practices for makerspaces indicates that training and mentorship are essential, and a lack of training and mentorship are barriers [14]. Students sometimes do not feel qualified to enter the space [15]. Students may have difficulty finding the makerspace or knowing that the space exists. Strategic placement of makerspaces in high traffic locations may assist [16]. Individuals face fear of criticism and fear of failure [17]. Spaces that are loud, dusty, and disorganized can deter potential makers [17]. Narrow definitions of what is making, which do not include the more nontechnical creative areas like arts and crafts, has been identified in studies [14, 15, 18]. Gender imbalances in makerspaces can discourage women [18]. Many other barriers likely exist that research has yet to identify. The current work provides another avenue for identifying barriers.

The proposed network modeling technique is reminiscent of actor-network theory (sociology of translation) from sociology [19], which has recently been applied by Braga and Guttmann to networks of knowledge exchanges between students [20] and by Biermeier to study emerging properties in curriculums [21]. Lord *et al.* reframed the examination of persistence in engineering education by expanding the pipeline and pathway metaphor into an ecosystem. The ecosystem approach suggests more complex aspects of a system be recognized by offering a holistic understanding of educational experiences [22]. Lord *et al.* argue that the ecosystem approach offers insights into contextual factors such as multiple influential actors, gatekeepers, power relations, tacit knowledge, knowledge transmission, and disciplinary cultures. Much like this paper, we plan to apply network analysis techniques to makerspaces to provide richer insights.

A survey measuring student participation in makerspaces and students' self-efficacy for design related tasks [23] was deployed at Georgia Tech. The results of the study showed that students who are voluntary involved (not class-related) in the makerspaces, have statistically significant greater confidence, motivation, and expectation of success to complete design tasks and also lower levels of anxiety for design tasks [24-27]. This work also demonstrates that early engagement in the makerspace with a 3d printed project increases student voluntary (non-class related) participation later. A second qualitative study has shown that recurring catalysts (described by students) for engaging with a makerspace included friends, design classes, research projects, becoming shop hands/prototyping instructors, staff, and tours [15, 28]. Certain equipment like 3D printers and laser cutters are very commonly found in university makerspaces. Other equipment like computer stations and whiteboards are far less common but may serve critical roles in the spaces [29]. These pieces of equipment may be very important for students' pathways into and through the spaces. Identifying with confidence those things that are "gateway" tools for the makerspace, especially when they are not obvious high-traffic items, is critical to improving student usage and return rates. Better understanding what aspects of a makerspace, especially relating to those tools and resources that are already present, can be better utilized to engage students has the potential to further increase these types of beneficial student reported feelings related to being a confident engineer.

Modularity Network Analysis

The modularity analysis is a network analysis technique often employed by ecologists to study ecosystems. Biological ecosystems have evolved over millions of years, creating complex networks of actors whose interactions create intricate thriving and resilient communities. Characteristics from biological ecosystems have been translated to human networks, imparting beneficial characteristics such as resilience, stability, and sustainability [2, 3, 7, 30-33]. Bio-inspired power grids, water distribution networks, and industrial resource networks have all used an analogy with biological ecosystems coupled with network analysis and graph theory modeling techniques to gain structural and functional properties of ecosystems. A makerspace inherently seeks to support interactions between students and space that are *mutually beneficial*, a concept that is derived from the field of ecology and implies that interactions promote the well-being of both parties. A biological ecosystem primarily composed of these interactions is called a mutualistic network [34]. Applying the biological analogy to makerspaces enables both a modularity analysis to be performed and potential biological inspiration to be applied, improving both our understanding and the design of makerspaces.

Research Questions

The modularity analysis conducted in this study is the first of its kind to be applied to makerspace design, but not for all human networks. *Guimerà 2005* used the same modularity analysis for the global air transportation network and was able to conclude the number of nonstop connections and shortest path flights for each city have distributions that are scale free [35]. The identification of air travel roles of each city showed the potential for engineering more efficient networks and better connecting communities that are poorly connected. The disproportionate role of some communities in the transmission of infectious diseases such as severe acute respiratory syndrome could also be determined by this analysis.
A modularity analysis for makerspaces has the goal of promoting student involvement and social networking on engineering projects involving fabrication. The research questions that must be answered to support this goal are as follows:

1. Can modularity analysis describe which groups of students are most effectively navigating large portions of a makerspace? What cohorts are these?
2. Can cohorts of students be analyzed to determine which activities such as class projects, pop-up classes, and club involvement are most effective in promoting student use of a makerspace?
3. Can modularity analysis describe which tools are effective entry points into the maker space? Which tools need to be invested in monetarily or with training to promote colonization of students to new and more advanced areas in the makerspace?

Methods

Analyze Texas A&M University makerspace-student interaction data

The dataset used here is from Texas A&M University and portrays the nature of what a larger dataset would look like for a centrally located makerspace. Data was collected by coordinators in the makerspace and authors did not participate in this process. The data recorded includes general access authorizations, specialty training certificates, fabrication requests, and equipment reservations. Over 4000 students were granted general access to the makerspace at Texas A&M in the three semesters before spring 2020. As a result, this dataset offers a uniquely current and sizeable foundation for this preliminary investigation into makerspace design.

The data used does have some limitation: equipment reservations are limited to senior design teams and the equipment list covers only the reservation of storage spaces, build spaces, and workbenches. High-resolution tool-use data collection is set to begin spring of 2020 at Texas A&M, including details that will remove some of these limitations.

Because of these limitations a hypothetical dataset was created to reflect student-tool interactions. This hypothetical dataset is guided by current data and engineering curriculum for Texas A&M, so the results are reasonable. These results present a picture of the design advice modularity analyses will be able to provide once additional data is available.

Hypothetical student-tool network creation

A hypothetical-realistic dataset of student-tool interactions is used here as a proof of concept on informing makerspace design by student-tool interactions. While the data used in this paper is hypothetical, it is based on data that could be available for research once the study is approved by the internal review board. The current Texas A&M University data contains current login data, equipment use data, and the student curriculum flowchart.

Login data includes student name, a global identifier, semester classification, and a reason for requesting access to the central makerspace. Currently, the reason for access and the equipment used is not specific enough for this analysis, but if the current work shows that this data is highly useful, it can be added and an interval review board approval will be completed. A global identifier allows for future tracking of the interactions of a student with the space. These login details allow the filtering of data by cohort. The equipment use data makes the hypothetical student-tool use data created reasonable for Texas A&M. As a proof of concept, the results from the hypothetical dataset are not meant to be accurate, but instead are intended to portray how a modularity analysis could inform value-creating design decisions in a makerspace. The standard student curriculum flowchart for Texas A&M, describing when classes should generally be taken in the undergraduate program, also informs the hypothetical-realistic dataset. A total of 100 students and 23 tools (the list of tools included can be found in Table 2) was deemed sufficient to conduct a modularity analysis capable of producing non-obvious makerspace design advice. This assumption is based on a modularity analysis done by ecologists Oleson and Bascompte on plant-pollinator networks where the authors found nested and modular structures developed for networks larger than 50 species [36]. The 23 tools include things such as general computing and printing, hand tools, electronics, benches, lathes, mills, and senior design workstations.

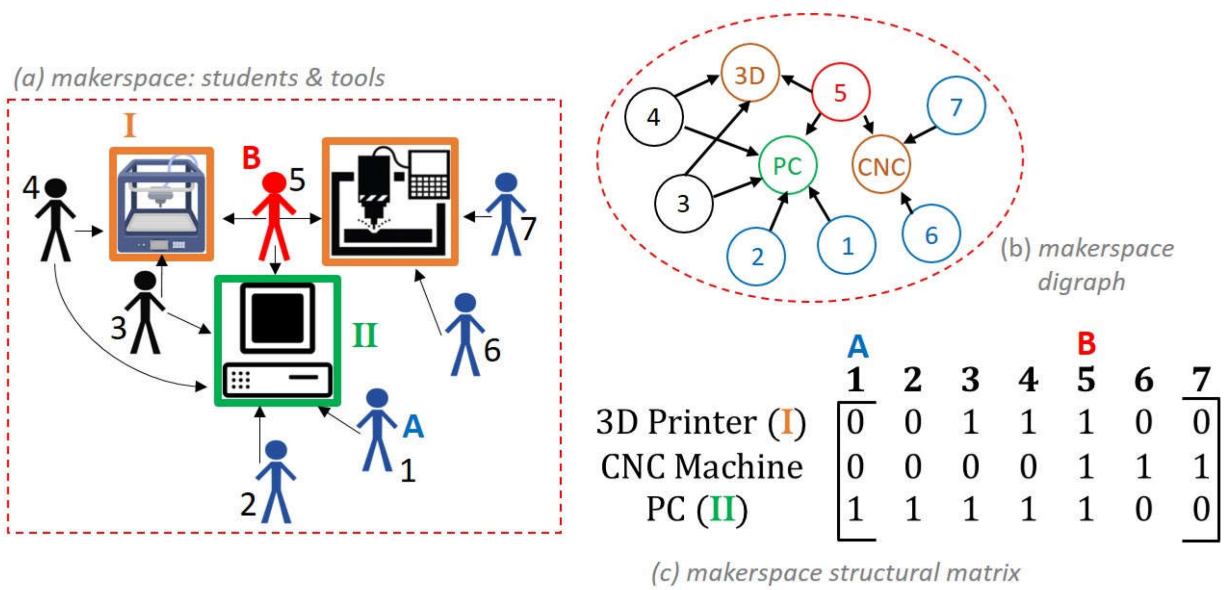

Figure 1: A small-scale representation of the makerspace network (a), the resultant digraph made of the interactions between students and tools in the space (b), and the documentation of interactions into a binary structural matrix (c).

The modularity analysis in this study uses a binary matrix, like the one shown in Figure 1c, to describe the student-tool interactions of the network (shown in Figure 1a and b). The hypothetical makerspace data is depicted in this matrix by listing tools and students as the rows and columns respectively. The cells in the matrix are filled as zeros if there is no interaction and ones if there is an interaction between a student and tool. Additional data about student cohorts such as semester, major, and gender are used to filter the students into cohorts to provide multiple perspectives of the *roles* played by each cohort. This single data structure serves as the input for all calculations made in the modularity analysis.

Modularity analysis

The two main values calculated in the modularity analysis are inter-module connectivity (*c*) and intra-module degree (*z*). These values depict the *role* students and tools act out in a makerspace. The values *c* and *z* are depicted in graphs filtered by student cohorts, showing the *roles* played by each cohort.

There are many types of modularity algorithms inspired from simulated annealing that have been used in a span of situations from plant-pollinator networks to global air travel [35, 36]. The algorithms used in this study are from the *renetcarto* package in R version 0.2.4 [37]. These algorithms are used for bipartite and unweighted networks, meaning the network can be separated into two groups (tools and students here) and the interactions are then logged as a Boolean value of 1 or 0. Equations 1-3 are from *rnetcarto:*

$$M = \sum_{s=1}^{N_m} \left(\frac{I_s}{I} - \left(\frac{k_s}{2I} \right)^2 \right) \tag{1}$$

Where N_M is number of modules in the network, I_s is number of links between tools and students within module *s*, *I* is number of links in the network, and k_s is the sum of degrees of all tools/students in *s*.

$$z = \frac{k_{is} - \bar{k}_s}{SD_{ks}} \tag{2}$$

$$c = 1 - \sum_{t=1}^{N_m} \left(\frac{k_{it}}{k_i} \right)^2 \tag{3}$$

Where k_{is} is number of links of *i* to other tools/students in its own module s, $\bar{k}_s$ and SD_{ks} are average and standard deviation of within-module *k* of all tools/students in *s,* k_i is degree of species *I*, and k_{it} is number of links from *i* to tools/students in module *t*.

The *rnetcarto* package assigns the network into modules, needed to solve Eq. 1. Calculating modularity does not directly inform makerspace design decisions, but it describes the degree to which modules dominate the network. Modularity (M, Eq. 1) is on a scale of 0-1, where completely random networks have a modularity of zero and networks that display high modularity (dense communities of interaction that have few interactions with other communities in the network) have a modularity of one. In this study, a module is a community of students and tools that are highly connected but may not often interact with other communities of students and tools. Equation 2 calculates the intra-module degree (*z*), serving as the y-axis in the results. Equation 3 calculates the inter-module connectivity (*c*) and serves as the x-axis in the results.

Intra-module degree (*z*) is the tools/students' standardized number of links to other tools/students in the same module. This contrasts with inter-module connectivity (*c*), which is the level to which the tools/students are linked to other modules. A combination of the *c* and *z* values determines the role of each tool/student in the network.

Following the modularity analysis, the *z-c* graph was created for freshmen students. Filtering for the freshmen students requires the selection of the appropriate class parameter stored with each student's global identifier. This was the only filter used in this case study. Alternative cohorts of students that could be used to filter the data in a modularity analysis include gender, major, and/or club affiliation.

Results and Discussion

The modularity (*M*, Eq. 1) of the student-tool network was 0.297 with a total of 4 modules (N_M =4) of varying size. This *M* value is on the lower end of the range (0-1) indicating that the hypothetical makerspace network is structured closer to a completely random network (M=0) than a highly connected network of unique community groups (M=1). The four module roles classified in this study are ultra-peripherals (low *z* and *c*), connectors (low *z* and high *c*), peripherals (low *z* and moderate *c*), and connector hubs (high *z* and *c*). The boundary values for these roles were set according to prior studies done on plant-pollinator networks and airport networks using the *rnetcarto* package [36-38]. These studies are similar to student-tool networks in that both network groups are unweighted and bipartite networks. The boundary values are: are ultra-peripherals (z<2.5 and c<0.05), connectors (z<2.5 and c>0.62), peripherals (z<2.5 and 0.05<c<0.62), and connector hubs (z>2.5 and c>0.3).

The results indicate that the modularity role of a student or tool can tell a lot about how it is being used. A student in an *ultra-peripheral* role has a minimal number interaction across the entire makerspace, only one or two interactions total. Highly specialized tools, which require extensive training and certifications, are also expected to be ultra-peripherals (seen in Table 2). *Peripherals* are tools and students that interact primarily within a module, promoting further interactions within their immediate design space. They have slightly more interactions than ultra-peripherals, but do not connect modules together. Student c*onnectors* can be thought of as students that successfully navigate the entire makerspace, participating in many distinct design modules and often bringing new students with them into the makerspace for the first time. Tools in the *connector* role (seen in Table 2) can serve as launching points to other modules, but may not necessarily promote further student interaction with tools in that module. Separating students into cohorts informs on how to move makerspace users from ultra-peripherals and peripherals to connectors, better connecting the makerspace and promoting student-student interactions by enhancing soft skills. Students that fulfill the connector role are more likely to feel confident in all types of makerspace tasks, and because the design process is often a team activity, connector students are more likely to act as mentors to others. *Connector hubs* can be thought of as launching pads for the makerspace, made up of the most general nodes in the space. These are tools that get students in the door and make them more comfortable navigating the space into more challenging design areas. Connector hubs are more likely to be tools that have reduced access requirements and provide high value to students in their class work and extracurricular pursuits. Table 1 shows a distribution relative abundance of the modularity roles for the students and tools in the hypothetical makerspace.

Table 1: Distribution of students and tools in the hypothetical makerspace network between the four modularity roles (ultra-peripheral, peripheral, connector, and connector hub).

	Tools	**Students**
Ultra-peripheral	4.3%	21%
Peripheral	56.6%	54%
Connector	8.7%	25%
Connector hub	30.4%	0%

The results of the makerspace modularity analysis separated the students and tools into 4 modules, with a modularity value (M, Eq. 1) of 0.297 for the makerspace. Table 1 shows a diversification of the students and tools within the hypothetical makerspace into different roles. Table 2 shows the 23 tools organized into their four different modular roles. The relative abundance of tools to students (23 to 100 respectively) is partially responsible for the two groups occupying largely different roles. This is because the makerspace interaction network is bipartite (every interaction is between a student and tool – no tool-tool or student-student interactions are allowed in the hypothetical makerspace network used in this study), where students interact directly with tools. With only 23 tools available to 100 students, the tools will experience far more interaction per tool than the students. Tools for this reason would generally express larger z and c values. The role of connector hubs, for example 3D printers are usually the main attraction of a makerspace to engineering students, involve a high number of connections to actors throughout the space resulting in a high intra-modular degree (z). Most of the students in the hypothetical makerspace never have high enough intra-modular degrees to reach this role, while 29.2% of the tools in the network are highly connected enough to classify as connector hubs.

Table 2: The 23 tools of the hypothetical makerspace, arranged in their 4 module roles as determined by Eqs. 1-3.

Ultra-peripherals	**Peripherals**		**Connectors**	**Connector Hubs**
CNC metal	CNC Wood	Soldering iron	CAD station	Specialty print
	Water jet	Protomat S103	Protolaser S	General comp.
	Band saw	CNC vinyl		Hand tools
	Drill press	3D printer (high quality)		Electronics bench
	Fluids workbench	Welding		Lathe
	Rolling cabinet	3D printer (standard)		Mill
	Basement locker			Senior design workbench

Figure 2 displays the inter-module connectivity (*c*) versus the intra-module degree (*z*) for all 23 tools and 100 students in the hypothetical makerspace. These two axes determine the *role (ultra-peripherals, peripherals, connectors, and connector hubs)* of each student and tool interacting in the makerspace environment. Figure 3 displays only the 100 students in the makerspace, a subset of the same dataset used in Figure 2. Freshmen students are highlighted in orange (only 7 of the 24 orange data points are visible because there are multiples of identical students within the population data - students with identical tool use patterns often occurs when they only use one or two tools). This is possible because Texas A&M University already tracks how many semesters the students using the makerspace had attended the university, enabling the hypothetical dataset here to realistically determine this information. The average inter-module connectivity (*c*) value is 0.12 for freshmen students compared to 0.39 for the entire population of students, suggesting that freshmen are much less connected to the makerspace at large when compared to their more experienced classmates. This result is not unexpected, freshmen represent the student body that has the fewest number of course or design group related opportunities motivating use of the space. The average the *z* value is –0.34 for freshmen students compared to –0.37 for the entire population of students. The similarity of these two values suggest that freshmen are just as likely to interact within a module as is the entire population of students.

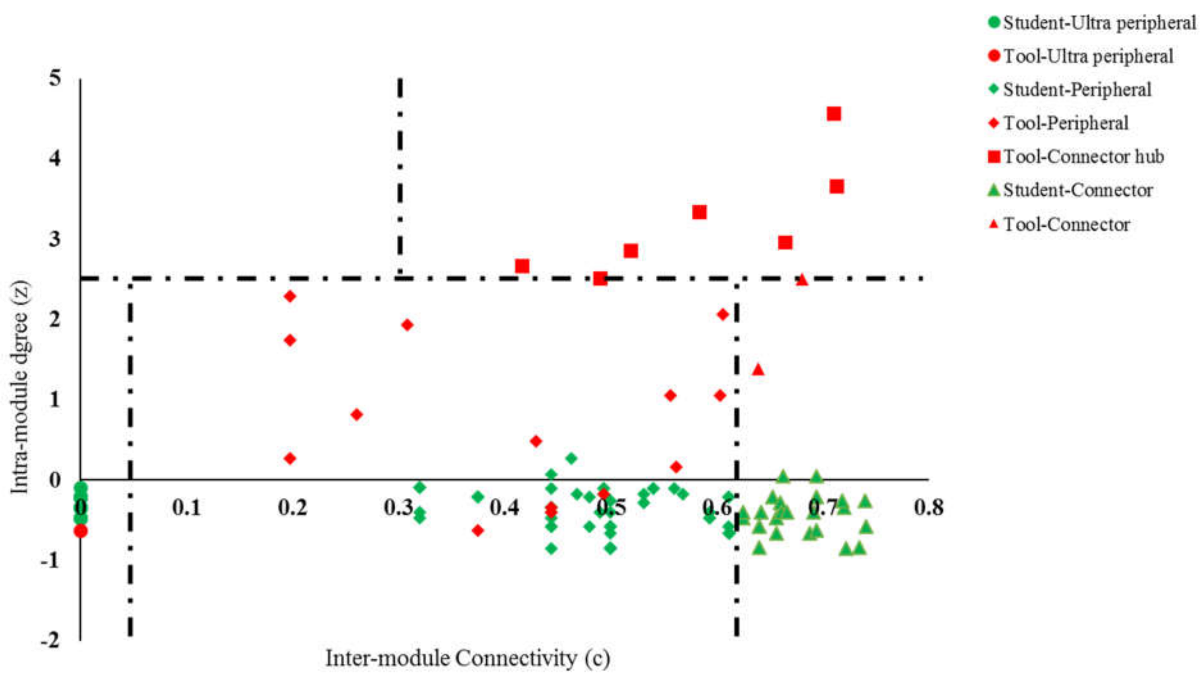

Figure 2: The intra-modular degree (*z*) vs the inter-module connectivity (*c*) is shown for 23 tools (red icons) and 100 students (green icons). The results highlight the four discovered modularity roles (ultra-perifpherals, peripherals, ocnnectors, and connector hubs) of the analyzed makerspace tools and student users – indicated with dashed lines.

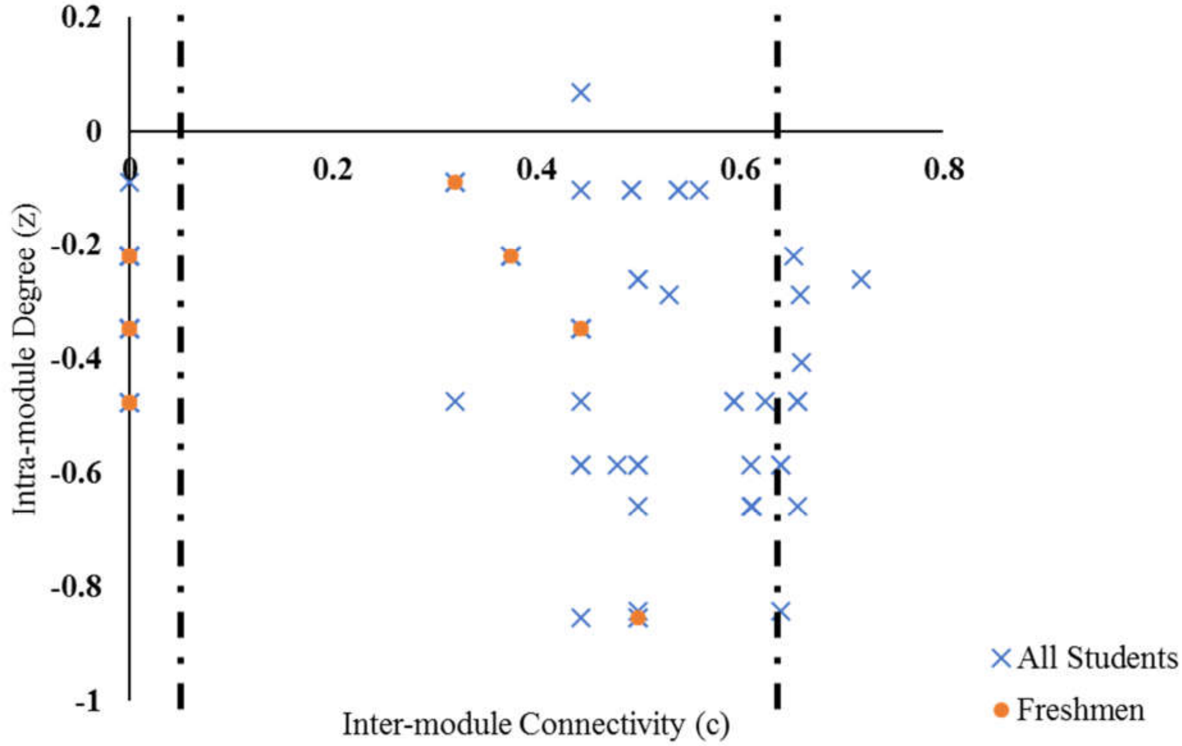

Figure 3: The modularity roles of 24 freshmen (orange circles) vs. all 100 students (blue crosses), highlighting the effect of filtering the intra-module degree (*z*) vs the inter-module connectivity (*c*) of makerspace students. The results highlight the four discovered modularity roles (ultra-perifpherals, peripherals, ocnnectors, and connector hubs) of the analyzed makerspace tools and student users – indicated with dashed lines.

Recognizing the *role* of a tool can help promote cost effective makerspace design. Understanding which tools are the *connector hubs* can provide a foundation for bringing new students into the makerspace. The connector hub tools in the hypothetical makerspace network used here are general computing and printing, hand tools, electronics, bench, lathe, mill, and senior design workstation. Two main takeaways from the set of tools used in the hypothetical makerspace here is that they either require no advanced skills or are required tools for classes in the engineering curriculum. *Connector* tools in a makerspace may be promising candidates to move toward *connector hubs* because of the relative ease to increase their use in the curriculum. For example, students may initially spend significant amounts of time in the makerspace using the whiteboards completing group projects or homework, and while they are there, they see a tool they would like to learn to use and a staff member with time to teach them. Only two *connector* tools exist in our hypothetical makerspace: the Protolaser S and the CAD station. These are tools students are required to use early in the engineering curriculum and then often voluntarily use later on for group design projects. Over 60% of the tools in our hypothetical makerspace fall into the *peripheral* or *ultra-peripheral* categories, as seen in Table 1. Examples of these tools include a CNC wood machine, soldering iron, bandsaw, waterjet, drill-press, and welding torch. Tools in the *peripheral* or *ultra-peripheral* categories require more extensive training and either do not or rarely show up in the curriculum as mandatory. Moving these tools into *connector hub* roles may require things such as more available faculty or TAs in the design area or an increased focus on using these tools in the curriculum. Streamlining safety certifications to use specialized tools may also help with such a shift.

Makerspace designers may want to consider the roles identified through a modularity analysis when purchasing equipment. The department that owns our hypothetical makerspace, if they wanted to further promote skills with CNC machines, the modularity analysis indicates that investing more in their current wood and vinyl CNC machines would be the most beneficial route, as the metal CNC was the only *ultra-peripheral* tool of the three. This *ultra-peripheral* status means that more makerspace-supporting resources such as curriculum changes and dedicated faculty help would be necessary before justifying a financial investment in additional metal CNC machines.

The results of a modularity analysis can help recognize how students navigate the makerspace in a way that identifies enhancements for involving underrepresented groups and teamwork. Figure 2 shows that the students have a much lower average z value than tools, largely a result of the bipartite network structure of the makerspace. Despite this, there is a large variation in inter-module connectivity (c). Every student identified by the modularity analysis as being in an *ultra-peripheral* role, and therefore having few interactions with tools, was also a freshman. This confirms that the actors in an *ultra-peripheral* role correspond with the logically appropriate actors in a makerspace. None of the students found in the modularity analysis to have *connector* roles were freshmen, pointing toward upper classmen as being pivotal to helping students colonize new modules in the makerspace. The average inter-module connectivity value for freshmen was more than three times *lower* than the average of the total set of 100 students. Future work will use real data collected from Texas A&M University, including identifiers for each student, to perform similar filters as the freshman filter used to create Figure 3, determining how other cohorts of students navigate the makerspace.

Conclusions

The modularity analysis of a hypothetical-realistic makerspace suggests its potential to support makerspace decision makers in improvements as a space grows, as well those creating a space from scratch. While more work needs to be done to fully understand the potential impact that a modularity analysis can have for both the creation and use of makerspaces, the analysis here was able to identify those areas where tool investment, curriculum planning, safety certifications, and faculty support could be best implemented based on the goals for the overall space. The modularity analysis found for the hypothetical makerspace investigated here that core course involvement is paramount to introducing students to new tools and areas within the space. The modularity results also show that the undergraduate classification (freshmen vs. others) is a valid way to sample interactions in the makerspace. Cohort filtering presents a rich method for gaining layered perspectives on how to promote the activities of all students. For example in the space modeled, filtering for freshmen students confirmed that none of these students were actively using the entire makerspace. Using more nuanced cohorts, such as semester, major, and gender, in future work will help determine which makerspace activities (e.g. course-connected projects and popup classes) are most effective at moving students from peripheral roles (a student who only ever uses one tool in the space) to connectors (a student who successfully navigates the entire makerspace and introduces new students to the makerspace) with many tool interactions across the makerspace. Many interactions across the makerspace leads to more opportunities for students to learn as they learn how to use new tools, teach and interact with other students, and work on new projects in the space. Future work will also determine if the suggestions make based on this hypothetical data will change when real individual-tool data is made available at Texas A&M University.

References

[1] Y. Lu, B. Chen, K. Feng, and K. Hubacek, "Ecological network analysis for carbon metabolism of eco-industrial parks: a case study of a typical eco-industrial park in Beijing," *Environmental Science & Technology,* vol. 49, no. 12, pp. 7254-64, Jun 16 2015.

[2] A. Layton, B. Bras, and M. Weissburg, "Industrial Ecosystems and Food Webs: An expansion and update of existing data for eco-industrial parks and understanding the ecological food webs they wish to mimic," *Journal of Industrial Ecology,* vol. 20, no. 1, pp. 85–98, 2016.

[3] A. Layton, B. Bras, and M. Weissburg, "Designing Industrial Networks Using Ecological Food Web Metrics," *Environmental Science & Technology,* vol. 50, no. 20, pp. 11243-11252, 2016.

[4] M. Chertow and D. R. Lombardi, "Quantifying economic and environmental benefits of co-located firms," *Environmental Science & Technology,* vol. 39, no. 17, pp. 6536-6541, 2005.

[5] H.-S. Park, E. R. Rene, S.-M. Choi, and A. S. F. Chiu, "Strategies for sustainable development of industrial park in Ulsan, South Korea--from spontaneous evolution to systematic expansion of industrial symbiosis," *Journal of Environmental Management,* vol. 87, no. 1, pp. 1-13, Apr 2008.

[6] J. J. Reap, "Holistic biomimicry: A biologically inspired approach to environmentally benign engineering," Ph.D., Mechanical Engineering Georgia Institute of Technology, Atlanta, GA, 2009.

[7] V. Panyam, H. Huang, K. Davis, and A. Layton, "Bio-Inspired Design for Resilient Power Networks," *Applied Energy,* vol. 251, 2019.

[8] T. Dave and A. Layton, "Designing Ecologically-Inspired Robustness into a Water Distribution Network," *Journal of Cleaner Production,* vol. 254, no. 1, p. 120057, 2020.

[9] L. Martin, "The Promise of the Maker Movement for Education," *Journal of Pre-College Engineering Education Research,* vol. 5, no. 1, pp. 30-39, 2015.

[10] V. Wilczynski, "Academic Maker Spaces and Engineering Design," presented at the 122nd ASEE Annual Conference & Exposition, Seattle, WA, June 14-17, 2015.

[11] J. Myers, "Creating Collaborative Spaces at the University of Arizona: Ways to Encourage Interdisciplinary Research and Ideas," College of Architecture, University of Arizona, 2015.

[12] B. O'Connell, "Going from Curious to Maker: New User Experiences in a University Makerspace," in *VentureWell OPEN 2015 National Convention*, Washington, DC, 2015, p. 1.

[13] M. Penney *et al.*, "'Making' an Impact: An Ethnographic Approach to University Maker Spaces," in *American Society for Engineering Education Annual Conference*, New Orleans, LA, 2016.

[14] Intel/Harris_Poll, "MakeHers: Engaging girls and women in technology through making, creating, and inventing," intel2014, Available:

https://www.intel.com/content/www/us/en/technology-in-education/making-her-future-report.html.

[15] M. Tomko, "Developing One's "Toolbox of Design" through the Lived Experiences of Women Students: Academic Makerspaces as Sites for Learning " PhD Dissertation, Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA, 2019.

[16] B. Levy *et al.*, "MAKER: How to Make a University Maker Space," presented at the American Society for Engineering Education Annual Conference, New Orleans, LA, 2016.

[17] V. Bean, N. M. Farmer, and B. A. Kerr, "An exploration of women's engagement in Makerspaces," *Gifted and Talented International,* vol. 30, no. 1-2, pp. 61-67, 2015/07/03 2015.

[18] S. Faulkner and A. McClard, "Making change: Can ethnographic research about women makers change the future of computing?," presented at the Ethnographic Praxis in Industry Conference, 2014.

[19] M. Callon, "The sociology of an actor-network: The case of electric vehicle," in *Mapping the dynamic of science and technology*, M. Callon, J. Law, and A. Rip, Eds. London: Palgrave Macmillan, 1986, pp. 19-34.

[20] M. Braga and G. Guttmann, "The Knowledge Networks in a Makerspace: the Topologies of Collaboration," *International Journal of Science and Mathematics Education,* vol. 17, no. 1, pp. 13-30, 2019/06/01 2019.

[21] M. A. Biermeier, "Inspired by Reggio Emilia: Emergent Curriculum in Relationship-Driven Learning Environments," *National Association for the Education of Young Children,* vol. 70, no. 5, 2015.

[22] S. M. Lord, M. W. Ohland, R. A. Layton, and M. M. Camacho, "Beyond pipeline and pathways: Ecosystem metrics," *Journal of Engineering Education,* vol. 108, no. 1, pp. 32-56, 2019.

[23] A. R. Carberry, H.-S. Lee, and M. W. Ohland, "Measuring Engineering Design Self-Efficacy," *Journal of Engineering Education,* vol. 99, no. 1, pp. 71-79, 2010/01/01 2010.

[24] R. Morocz, "Classifying and Characterizing University Maker Space Users: A Foundation," M.S., Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA, 2016.

[25] R. Morocz *et al.*, "Relating Student Participation in University Maker Spaces to their Engineering Design Self-Efficacy," presented at the ASEE's 123rd Annual Conference & Exposition, New Orleans, LA, 2016.

[26] E. Hilton, "Approaches for the Development of Early Stage Design Skills " Ph.D. Ph.D. Thesis, Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA, 2019.

[27] E. Hilton, M. Tomko, A. Murphy, R. Nagel, and J. Linsey, "Impacts on Design Self-Efficacy for Students Choosing to Participate in a University Makerspace," presented at the The 5th International Conference on Design Creativity, Bath, UK., 2018.

[28] M. Tomko, M. Alemán, R. Nagel, W. Newstetter, and J. Linsey, "Changing the Narrative Around Making: Understanding Women's Pathways into University Makerspaces," *Journal of Engineering Education,* in review.

[29] T. Barrett *et al.*, "A Review of University Maker Spaces," presented at the American Society for Engineering Education Annual Conference, Seattle, WA., 2015.

[30] A. Layton, B. Bras, and M. Weissburg, "Ecological Principles and Metrics for Improving Material Cycling Structures in Manufacturing Networks," *Journal of Manufacturing Science and Engineering,* vol. 138, no. 10, pp. 101002-1 – 101002-12, 2016.
[31] J. Reap and A. Layton, "Lessons from Living Systems for the Development of Sustainable Industrial Resource Networks," *Journal of Energy Challenges and Mechanics,* vol. 4, no. 1, pp. 1-10, 2017.
[32] C. Brehm and A. Layton, "Designing eco-industrial parks in a nested structure to mimic mutualistic ecological networks," *Procedia CIRP,* vol. 80, pp. 590-595, 2019.
[33] T. Dave and A. Layton, "Bio-inspired design for resilient water distribution networks," *Procedia CIRP,* vol. 80, pp. 275-280, 2019.
[34] D. H. Boucher, S. W. James, and K. H. Keeler, "The ecology of mutualism," *Annual Review of Ecology and Systematics,* vol. 13, pp. 315-347, 1982.
[35] R. Guimerà, S. Mossa, A. Turtschi, and L. A. N. Amaral, "The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles," *PNAS,* vol. 02, no. 22, pp. 7794-7799, 2005.
[36] J. M. Olesen, J. Bascompte, Y. L. Dupont, and P. Jordano, "The modularity of pollination networks," *PNAS,* vol. 104, no. 50, pp. 19891-19896, 2007.
[37] G. Doulcier and D. Stoufer, "Rnetcarto: Fast Network Modularity and Roles Computation by Simulated Annealing," ed. GitHub, 2015.
[38] R. Guimera, M. Sales-Pardo, and L. A. Nunes Amaral, "Module identification in bipartite and directed networks," *Physical Review E,* vol. 76, p. 036102, 2007.