Complex Systems Research and Evaluation in Engineering Education

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Abstract

The purpose of this theory-to-practice paper is to discuss complex systems research needs within engineering education. We provide a comprehensive definition of complex systems educational research (Hilpert & Marchand, under review; Jacobson et al., 2016) and an overview of methods specific to the approach (Hollenstein, 2013; Koopsman & Stavalomsis, 2016; Strogatz, 1994). After this, we delineate a research-based framework that can be used to develop and conduct complex systems research and evaluation. We identify two areas within the field of engineering education where complex systems research can be useful: 1) educational research focused on student interaction and cognition and 2) assessment and evaluation of collaboratives such as grant funded projects and communication/publication networks. We discuss existing literature in these spaces, and then outline the critical research needs for engineering education. We address each of these critical needs with an eye on theory as well as methodological and analytic techniques that can be used to design and conduct complex systems research and evaluation in engineering education settings and contexts. The result is a set of specific guidelines that researchers can use to move complex systems research forward in engineering education. This material is based upon work supported by the National Science Foundation under Grant Number NSF DUE #1245018 and partial support was also provided by the National Institute of General Medical Sciences, Grant No. P20GM109025.

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Definition of Complex Systems Research

Complex systems research in education is focused on the complex, emergent, and dynamic interactions among people, tasks, and settings (Hilpert & Marchand, under review). Complex systems are collections of micro-level variables (often referred to as agents, components, or elements) that interact to produce macro-level patterns and outcomes (Kauffman, 1993). Complexity is the mutually causal, multiple interactions among components of a system (Mitchell, 2009). Emergence is the arisal of non-reducible, macro level patterns from micro level interaction among systems components (Holland, 2000). Dynamics is change in micro level variables in relation to each other, or in relation to the macro level, across time (Richardson et al., 2014). Complex systems are considered interaction-dominant, as opposed to component-dominant, because the focus of analysis is on the dynamic interaction among system components as opposed to the replication of components and their nomothetic relationships (Holden, Van Orden, Turvey, 2009).

In contrast to mechanical systems that presuppose linear mechanisms, complex systems assume nonlinear relationships among variables and multiple levels of analysis. Whereas mechanical systems are often described using stable, left-to-right style diagrams that portray their underlying causal mechanism, a complex system contains an underlying network structure, with mutually causal relationships among system components that produce emergent patterns at a higher level of analysis (Mitchell, 2009). The network structure implies self-organizing properties, meaning there is little centralized control and system homeostasis is produced through bottom-up interaction of system components (Dale, et al., 2014). The complexity of a system, which is often measured as a balance between ordered and random interaction of system micro components, is the necessary condition for the dynamic emergence of self-organization at the macro level (Mitchell, 2009). Complex systems research is focused on the processes of stability and change in a system, the critical values and initial conditions that lead to stability and change, and system response to perturbation (Koopsman, 2016).
For example, recently researchers have begun to examine educational phenomena including classroom learning (Conner et al., 2015; Hilpert & Husman, 2016), student-to-teacher interaction (Hollenstein, 2013; Pennings & Mainhard, 2016), student collaborative groups (Hilpert, 2016; Stamovlosis, 2016), and student cognition and engagement (Skinner et al., 2008; Stamovlosis & Sideridis, 2014) from a complex systems perspective. Moreover, complex systems thinking has found its way into the evaluation literature as well, including the examination of how educational innovations diffuse among educators and practitioners (Borrego, et al., 2010), the establishment of faculty to faculty collaborative networks (Borrego & Newsander, 2008), publications networks for research and teaching (Madhavan, et al., 2011), institution to institution networks (Berggren et al., 2003) for initiating and examining cultural, institutional, and faculty change, and innovative methods for assessing research collaboratives (Marchand & Hilpert, 2017). In each of these examples, key features of complex systems such as emergent relationships between multiple levels of analysis, underlying network structures of information sharing and collaboration, and dynamic mutually causal change have provided new research insights.

What these studies have to offer is unique conclusions about the adaptivity and functioning of a bounded system. Much education research, both at large and within engineering education, is dominated by a deductive-nomothetic paradigm that seeks to provide evidence for the replicability of linear structures, mediating and moderating effects, or test interventions. Other qualitative approaches provide their own unique insights as well. Complex systems research offers researchers methods for analyzing the complex, dynamic, and emergent qualities of systems, allowing for conclusions about how adaptive a systems is, how well information flows through a system, and under what conditions a system is likely to undergo shifts in behavior that influence its functioning. Complex systems research, and the conclusions that can be drawn from it, can complement existing research but require that researchers understand the methodology (theory, philosophy, and assumptions of research), method (techniques and procedures to gather evidence), and practice (analytic techniques and takeaways) related to the approach (i.e. Harding, 1987; Schwandt, 2001; Twining, Heller, Nussbaum, & Tsai, 2017).

**Complex Systems Research Methodology and Method**

Because complex systems are interaction-dominant, they require research methods that account for the dynamic interplay among variables. Any system that competes, collaborates, or interferes contains dynamic interplay that produces non-linear behavior (Strogatz, 1994); accordingly, nonlinear methods, or a combination of qualitative, linear, and nonlinear methods, are used in educational research to study complex systems (i.e. Hilpert & Marchand, under review; Jacobson, et al., 2016; Koopsman & Stavalomsis, 2016). In contrast to the use of linear statistical techniques (i.e. Fisher, 1925) which assume independent observations, homogeneity of variance, and an underlying normal distribution, nonlinear techniques can be used to study sequential dependence, highly variable change, and underlying power law distributions. Hilpert and Marchand (under review) categorize the nonlinear techniques useful for complex systems research into three categories: time series analysis, nonlinear dynamical modeling, and network analysis. Koopsman and Stavalomsis (2016) and Jacobson and colleagues (2016) also contain descriptions and examples of these techniques in educational contexts.

Typically the goal of complex systems research is to produce evidence for adaptive system functioning, or evidence for stability and change within systems and the conditions and critical values that produce stability or change. For example, nonlinear time series analysis is often used to test the change in complexity hypotheses (CICH; Sleimen-Malkoun, et al., 2015), where time series signals are analyzed to produce evidence for the deterministic, random, and stochastic characteristics of a data stream (Gao, et al., 2007; Riley & van Orden, 2005). Results can be used to determine if a system is losing complexity, or becoming overly ordered or overly complex in its dynamic interplay. Or, nonlinear dynamic modeling (of both simulated or observed data) may be used to produce evidence for attractor states (Hollenstein, 2013;
Strogatz, 1994), which are the tendency for systems to settle into patterned homeostasis. Both nonlinear time series analysis and nonlinear dynamic modeling can be used to determine if there are critical values or contextual factors that produce attractor states, or phase transitions between attractor states. Additionally, network analysis can be used to model the underlying network structure of a bounded system, producing evidence for endogenous and exogenous effects, and well as influence and selection effects, among system components (Lusher, et al., 2014; Krackhardt, 1987). Below we discuss some relevant complex systems approaches and the application of related analytic techniques to research and evaluation in engineering education.

Complex Systems Research Domains in Engineering Education

Engineering education is a broad field of study, replete with its own cultural value system and ways of conducting research. It is probably reasonable to suggest that the prevailing research paradigms in engineering education are largely characterized by deductive-nomothetic, phenomenological, and critical perspectives. However, despite the predominance of these approaches, within the larger milieu of engineering education much work is devoted to the study of complex, emergent, and dynamic phenomena but investigated using methods that do not assess these characteristics. Complex systems research approaches are uniquely positioned to provide improved understanding in two engineering education domains: 1) educational research focused on classroom interaction/learning and student cognition, and 2) evaluation and assessment of collaboratives such as grant funded projects and communication/publication networks.

Many research, evaluation, and assessment pursuits in engineering education target interaction-dominant phenomena, and thus may also lend themselves to complex systems approaches. These methods don’t serve to replace existing research traditions and paradigms, but rather complement them by providing new insights and forms of evidence that can be used for improved understanding and decision making (i.e. Carver & Schiere, 2001; Davis & Sumara, 2006). There are a variety of domains where complex systems thinking can provide new insights and ways of thinking about research. Below we examine some possibilities by focusing on existing research where elements of complex systems have been incorporated, or show promise for examination using complex systems methodologies. Each section begins with a discussion of the interaction-dominant nature of the domain, and is followed by a brief discussion of existing research or examples relevant to engineering education.

Educational research. Educational phenomena such as classroom learning and interaction, student collaboration, and motivation, cognition, and engagement (Ohland, et al., 2008; Benson, Kirn, & Faber, 2013; Felder & Brent, 2016; Vogt, 2008) all contain central features of interaction-dominant complex systems. These features include complex, dynamic qualities that produce emergent outcomes (Kaplan, et al., 2012; Mitchell, 2009; Richardsen, et al., 2014). Research conducted within learning environments (i.e. classrooms, laboratories, etc.) necessarily involves the interaction of settings, tasks, teachers, and students (Schwab, 1971) and the study of motivation and engagement involves competing intraorganismic and extraorganismic factors (Deci & Ryan, 2002). Because cooperation, competition, and interference are ever present features of these areas of study, changes in any system variables results in changes to another and so on that reverberate throughout the learning context or the organism under study creating dynamic change. Many engineering studies suggest that teacher to student and student to student interaction produce complex, dynamic outcomes.

For example, Shekhar and colleagues (2015) demonstrate the conditions under which Research Based Instructional Strategies (RBIS) (i.e. strategies that have demonstrated evidence of improved student engagement) can lead to different forms of student resistance and disengagement in engineering contexts. Husman and Hilpert (2016) show how different aggregate levels of engagement within engineering classroom contexts can shift the direction and strength of motivational influence and student desire to
pursue a career in engineering. Brown and colleagues (2014) demonstrate the role of peer networks and social capital in interactive engineering classrooms. And Hilpert and Husman (2016) developed a measure of interactive engagement that describes the complex and adaptive ways students rely upon the social and intellectual capital of their peers to develop innovative solutions to engineering problems. These studies provide points of leverage for complex systems research to be integrated into studies of classroom interaction and collaboration, instructional strategy use, and how environment shapes student learning.

Similar to the nature of learning environments, motivation, affect, and engagement are widely accepted to be composed of complex combinations of self-organizing physiological and psychological substratum (Ellis & Newton, 2000; Fried, et al., 2016; Reeve, 2014). The study of goal directed behavior (Kirn & Benson, 2013), academic engagement (Ohland, et al., 2008), and affective/ motivated perceptions of academic tasks and achievement related pursuits (Carberry, Lee, & Ohland, 2010; Nelson, et al., 2015; Villanueva et al., 2016) are all areas of research common in engineering education with underlying dynamic complexity that have not been thoroughly examined in engineering contexts. One common strand in these studies is that the unique qualities of engineering culture and context are important to student perceptions and motivational expression (i.e. Benson & Kirn, 2013), suggesting a complex and dynamic interaction between context and learner that shapes the emergence of relevant affective and motivational processes related to learning and knowledge construction in engineering education. The underlying stability of student affect/ motivation and engagement, the environmental factors that contribute to its dynamic change over time, and the meaningful levels of analysis and time frames of study are all points of leverage for future research.

**Evaluation and assessment.** The establishment of faculty collaborative networks for research and teaching (Madhavan, et al., 2011) and the diffusion of educational innovations among engineering education faculty (Borrego, et al., 2010) possess underlying network structures that are the hallmark of complex systems (Lusher, et al., 2012). Mutually causal network structures create the push and pull that produces nonlinear dynamic change. What is not well understood are how these network structures develop, spread, and exceed the initial boundaries of the founding collaborative group. Evaluation approaches rooted in complex systems research methods can provide useful information about the spread of information among collaborative partners, offering insight into how interactions that take place during the course of collaboration contribute to the quality of products derived from collaborations (Welch, Feeney, & Siciliano, 2016). Moreover, complex systems approaches to the evaluation of the diffusion of innovation amongst faculty or research collaborations move the focus from discrete products or outcomes to the creation of human and social capital from whence emerges new knowledge (Bozeman, Dietz & Gaughan, 2001).

Collaborative work in the classroom, on grants, and across institutions offers unique demands, particularly as much work in engineering education and other STEM fields brings together faculty and students from multiple disciplines (Borrego & Newswander, 2008). Developing networks of actors from diverse disciplinary groups may pose challenges due to specific localized definitions and meaning of terms, paradigmatic differences in research philosophy and approaches, and discipline-specific norms for conducting scholarly inquiry. Such differences often constitute a significant barrier to effective cross-disciplinary scholarship. A shared language among collaborators is needed to coordinate ideas and action when individuals interact to solve a problem (Molinari, et al., 2009). Creation of successful interdisciplinary research teams that lead to information-information interaction (Qin, et al., 1997) require explicit attention to the development of competencies needed for such a collaborative (Gebbie et al., 2008). When members work together successfully to develop shared conceptual and methodological frameworks, they transcend any one disciplinary perspective (Stokols et al., 2008).

These qualities of collaboration inherently draw upon complex systems concepts in that the underlying structure of the collaborative is a network, actors within a network interact in a dynamic ways
around research and innovation, and hallmarks of successful and sustainable collaborations are emergent, shared goals. Typical evaluation designs take a component-centered approach and apply designs that measure anticipated outcomes (e.g., student performance, grant submissions) prior and subsequent to the educational innovation or formation of collaboration. While these designs may be somewhat useful for measuring a change in discrete, bounded outcomes they provide limited utility for understanding socially embedded learning and change processes. Traditional evaluation designs provide no evidence for how ties between actors (e.g., instructors or collaborators) form around the innovation or collaboration, whether particular attributes of actor in the system are related to the development of networks, or how patterns of dynamic change within the innovation or collaboration may be variable and when the system is particularly open to change (accelerating growth, etc.) (Bozeman et al., 2001).

The number and type of funding mechanisms for collaboration that are designed to support engineering education practice and research is on the rise (National Science Board, 2016; Xian & Madhavan, 2012). For instance, multi-country and institution collaboratives have formed to reform engineering education (e.g., Berggren et al., 2003); faculty and students from colleges of education & engineering have formed research collaboratives to address particular issues in engineering and STEM (Lohani, et al. 2004); and centers and institutes have emerged to support outreach and science in engineering education (Bozeman & Boardman, 2004; Brophy, et al., 2008). These collaboratives offer a second point of entry for complex systems research and evaluation in engineering education to take hold. Complex systems approaches lead to evaluation that is designed to provide evidence of system functioning and information diffusion. This evidence can be used to make changes to a program to disrupt maladaptive patterns that might limit collaborative growth or spread of innovation; enhance and further support systems with adaptive functioning; and track how changes amongst system components lead to desirable emergent properties or how adjustments to environment (e.g., more funds or support) influence the interaction of system components.

Critical Research Needs for Complex Systems Research

The success of complex systems research in engineering education hinges on several critical research needs for any given project or evaluation. Alignment of methodology and method not only requires understanding the philosophical and theoretical nature of complex systems (methodology), but also addressing the practical concerns of research context, data collection, and analysis (method). These concerns include consideration of factors such as the appropriate context for research, the identification of system critical variables, possible methods for data collection, and tools and software for analyzing data. The following sections outline aspects of complex systems research that need to be considered within the context of engineering education in order for complex systems research to gain traction. We provide accessible examples of complex systems research from the natural sciences to illustrate each of the critical needs. In the discussion/conclusion we relate these examples to education research to demonstrate their application to engineering education.

Context of Educational Systems. To produce findings that can be leveraged by stakeholders, use inspired educational problems (i.e. Stokes, 1997; Sloane, 2006) should be researched that are likely to produce context specific conclusions relevant to practitioners in engineering education. Furthermore, complex systems research is inherently an interaction-dominant approach. Interaction-dominant systems in education (i.e. those related to classrooms and research collaboratives) are open, biological, thermodynamic systems that exchange heat, matter, and information. Although they have natural boundaries (i.e. in the same way that organs are composed of cells) there is no place where the diffusion of energy, matter, or information stops. Thus, researchers must make theoretically driven choices about the contextual boundaries of a given system, often based on use-inspired and feasibility needs. For example, when a person is ill and winds up in the hospital, cardiac monitoring of heart activity, or electrocardiography, is used to continuously assess a patient's condition by drawing conclusions about
their cardiac rhythm. The monitor will be used under some conditions and not others, depending upon severity of the patient's condition, risk assessment, and the feasibility and cost of using the monitor. Contextual factors drive the use-inspired decisions about what data to collect and when. Also of interest is the notion that the heart is a system critical variable worth monitoring, as opposed to some other measure taken from the body (which is a complex system). This illustrates our next critical need: choosing system critical variables that provide evidence of holistic system functioning.

**Critical System Variables.** Critical systems variables and/or appropriate families of indicators must be specified to satisfy the demands of system modeling and produce meaningful outcomes. Although complex systems research is not deductive, it is reductive in the sense that researchers have to make choices about what variables may provide the best evidence for system functioning. Because interaction-dominant systems are open, researchers not only have to place arbitrary contextual boundaries on the system, but also choose system critical variables at the center of a system that are subject to its push and pull. For example, overly ordered or overly random characteristics of a heart rhythm allow for robust conclusions about the complex functioning of the body. Taking dynamic, times series measures of system critical variables can provide evidence of how a complex system is functioning, without having to know the entire system. For example, in the famous Lorenz system, convention can be modeled using three system critical variables: fluid viscosity/thermal conductivity, temperature difference between top and bottom of a vessel, and deviation of linear change in temperature. Each of these variables has their own dynamics, and certain parameter values produce chaotic solutions (i.e. to coupled differential equations) with smooth attractor states indicative of stable functioning. Interestingly, Takens (1981) showed how a measuring a single variable from the center of a convention system can be used to recover the smooth attractor state produced by all three variables by reconstructing the phase space. Although Taken’s work simplifies the measurement demands for studying Lorenz systems, the example leads us to the next critical need: methods for gathering data at proper granularity to capture phenomena of interest.

**Methods for Systems Data Collection.** Because the underlying structure of a complex system is a mutually causal network, and the push and pull of components within a network produce dynamic behavior over time, new methods for data collection that can assess 1) the underlying network structure of a bounded system and 2) the dynamic behavior of system critical variables over time, are required to move complex systems research forward. Methods that can produce adequate data to routinely monitor and assess psychological and human systems must be developed and validated. For example, social physics researchers from the media lab at the Massachusetts Institute of Technology have developed sociometric badges (see Petland, 2014) that can used for experience sampling for social networks. About the size of a cell phone, the badges provide finely grained information about social networks in physical spaces (i.e. organizations and collaborative groups) that emerge through human interaction. Worn around the neck, they provide real-time data about face-to-face interaction, human to computer interaction, physical proximity, speech characteristics, nonverbal cues, physical activity, and conversation analysis. The badges are specifically designed for longitudinal social network data collection, and have been used primarily to study teamwork and organizational behavior. Novel solutions to improved data collection such as these, however, place increasing demands on data analysis and modeling, our final critical need.

**Tools for Data Analysis and System Modeling.** Off-the-shelf tools for analyzing complex systems data must be developed and vetted for completing complex systems projects. Although there are a variety of software packages for analyzing and modeling data using linear statistics, there are relatively few options available for complex systems researchers in education that can be used to examine nonlinear data. This trend may be partly due to the fact that many researchers in the natural sciences “speak math” and thus do much of their analysis using matlab or other general mathematics suites, but there are many popular software packages offered to researchers in these spaces (e.g. Anylogic, 2016). Also, there are a variety of packages available in R that can be used for nonlinear analysis such as time series analysis, dynamic modeling, and network analysis, certainly too many to provide an exhaustive account here.
However, the development of new software packages that make it easier for researchers to analyze nonlinear data specific to education research would almost certainly help complex systems research become more widespread in educational research contexts. One example is time series analysis software that has been developed by the researchers at the Center for Cognition, Action, and Perception at the University of Cincinnati (CAP, 2016). Using Matlab code and a basic GUI, they have produced software specific to their own purposes that can conduct batched time series analysis. For example, patients with and without Parkinson’s may participate in a lab study, their gross motor movements measured by body sensors during the study. The CAP software can conduct batched time series analyses of the sensor data streams, preparing it for hypothesis testing about statistical differences between qualities of the time series between study groups.

Discussion

To conclude, we will provide some examples of how the illustrations described in the critical needs section above are being translated into complex systems research in engineering education. Similar to the heart monitoring example, Villanueva and colleagues (2014; 2016) have taken skin response measures to examine students’ emotional states during a laboratory examination activity. Their work is an example of how researchers are conducting complex systems research to understand student motivation and emotion. They integrate salivary and survey measures with the galvanic skin response data collection. They are also developing their own algorithms to examine the qualities of the signals. Analyzing the time series skin response data in conjunction with the survey and salivary data allows them to draw conclusions at multiple levels of analysis: 1) the underlying biophysical substrata of the cognitive system and 2) how students are experiencing and regulating their emergent emotional states.

Similar to the Lorenz system example, Hilpert and colleagues (2013, 2014) have used differential equation modeling to produce simulations of how students plan for a future career in engineering as they enter young adulthood. Their work is an example of how dynamic modeling can be used to examine students planning, self-regulation, and problem solving. They integrate interviews, surveys, and student drawings of timelines of their lives to produce dynamic models for how students’ goals shift with regard to 1) what they value in the future and when and 2) gender differences in these shifts that influence work life balance and motivation in the present. Instead of focusing on stable components of a cognitive system, these researches assume an interaction-dominant system of cognition, demonstrating how dynamic shifts in future goals shape adaptive or maladaptive functioning.

Similar to the social physics network example, Martinez and colleagues (2003) drew upon multiple data sources, including questionnaires, interviews, and computer log files to evaluate computer supported collaborative learning projects in an engineering course with social network analyses, yielding the insight that collaborative learning was characterized by sharing information. The network approach allowed evaluators to understand social roles and structural patterns related to participation, which could then be used formatively to intervene when collaboratives were not functioning optimally. Researchers interested in the growth and change of Engineering Education Research (EER) as a field also applied network mapping of large scale data with time-series analyses to document the development and impact of research collaborations (Madhavan et al., 2011). Madhavan and colleagues introduced a tool called iKNEER that could be applied to publication and presentation data and to illustrate impact, showed how a specific conference fostered the growth of academic networks.

These are examples of how complex systems research is beginning to take shape in engineering education. In education research at large, the approach is also gaining some momentum, but has been an important paradigm for some time. Davis and Sumara (2006) provide a wonderful description of complexity research in education, detailing an extensive review of the methodological underpinnings. More recently, Jacobson and colleagues (2016) have provided a theoretical framework for complex
dynamic systems research in educational psychology. And Koopsman and Stavamolsis (2016) have edited an excellent book that contains examples of empirical complex systems research in education. These resources may be useful for engineering education researchers interested in further exploration. By utilizing methodological approaches that assume underlying complex systems, conducting research in engineering education domains focused on interaction-dominant phenomena, and meeting critical data collection and analysis needs, complex systems research can provide important insights for the engineering education community.

References


Hilpert, J. & Marchand, G. Complex Systems Research in Educational Psychology. (Theoretical Article Under Review)


I. Villanueva, A. Raikes, N. Ruben, S. Schaefer, and J. Gunther. The use of physiological tools to identify changes in affective responses for graduate students recently admitted into a scientific discipline. 2014 FIE Conference under the ‘Student Beliefs, Motivation, and Persistence Through the College Years’ session, Madrid, Spain (2014).


Qin, J., Lancaster, F. W., & Allen, B. (1997). Types and levels of collaboration in interdisciplinary research in the sciences. JASIS, 48(10), 893-916.


