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Leverage analysis in systemic design: Using centrality and structural analysis to understand complexity

Ryan Murphy[a]*, Peter Jones[b]

[a] Memorial University of Newfoundland,

[b] OCAD University,

* Corresponding author e-mail: ryan@systemic.design

Abstract A key component of many systemic design processes is the development and analysis of systems models that represent the issue(s) at hand. Models often take the form of Causal Loop Diagrams in which phenomena are graphed as nodes with connections between them indicating an influencing relationship. Models provide systemic designers with a mechanism for stakeholder collaboration, problem finding, and generative insight, becoming powerful resources for use in visual argument. These functions are valorized in design thinking, but the potential of these models may yet be unfulfilled. We propose the exaptation of techniques from social network analysis and systems dynamics to uncover key structures, relationships, and latent leverage positions of modelled phenomena. We reframe these measures for systemic design and demonstrate their utility in a pilot study. By rethinking logics of leverage, we might make better arguments for change, finding the place to stand from which to move the world.

Keywords: systemic design, leverage, centrality analysis, structural analysis, methodology

1. Introduction

1.1. Systemic design and leverage points

The practice of systemic design offers tools and approaches that can help find leverage in complex systems. Complex systems often produce emergent, counterintuitive behaviour that is difficult to predict by looking at the individual phenomena (Gharajedaghi, 2011). By capturing and illustrating how these phenomena interdepend through models, we may gain the ability to grasp this emergent behaviour. More importantly, we may be able to identify leverage points: places within a system in which a small shift produces big change (Meadows, 1997).

The properties of complex systems (and of how people engage with them) present a number of issues that introduce bias and chance into the process of intervening on systems (Norman & Stappers, 2015). Given a model, systemic designers work through what they observe and interpret, engage in dialogue about what is important, and look for patterns. While some principles and processes exist (cf. Jones, 2014), developing models, identifying leverage points, and designing solutions tends to happen by "muddling through" a problem (Norman & Stappers, 2015; see also Simon, 2008, chapter 2).

Systemic design models vary in type. Designers may create systems thinking or soft operations research (soft OR) models, whose purpose is to describe the system as comprehensively as possible (Forrester, 1994; Checkland, 1985). Models of so-called "soft" systems often take the form of causal loop diagrams (CLDs) in which phenomena are graphed as nodes with connections between them indicating an influencing relationship. Alternatively, designers may quantify the phenomena of a system's variables through systems *dynamics* (Forrester, 1994). These approaches to modelling come with important trade-offs yet to be reconciled in modern methods. Systems thinking models are representative, but their insights may be invalid or inaccurate (Forrester, 1994). On the other hand, systems dynamics models are robustly analytical, but we may be analyzing an ill-developed representation of the problem system (Checkland, 1985). Further, in order to develop representative models, systemic designers must draw on diverse stakeholders (Jones, 2014; Stroh, 2015). The development of recent technologies and practices such as crowdsourcing (participatory systems that involve publics in a collaborative project; Lukyanenko & Parsons, 2012) and data science (a set of techniques and theories that help distill insight from data; Provost & Fawcett, 2013), the collection and organizing of large amounts of data becomes ever easier. This brings us to an important tension (cf. Maass, Parsons, Purao, Storey, & Woo, 2018). Larger, more complex, data-driven models are likely more representative, as they capture more perspectives and nuances than simpler models and as their representations can be tested through the simulations and analysis of systems dynamics. However, these models are also harder to learn, understand, and use (Rossi & Brinkkemper, 1996).

Systemic designers must find ways of balancing the trade-offs between complex representativeness and ease-of-insight. In this paper we illustrate how techniques from graph theory and systems dynamics can be used to take advantage of the structural properties of these models of elements and connections to algorithmically identify leverage points in these models. These techniques promise to help take advantage of big data in systemic design and advance our capacity to muddle through progress on wicked problems (Rittel & Weber, 1973).

In the next subsection, we briefly introduce graph theory. In section 2, we introduce the concepts and metrics of centrality analysis and of structural analysis. In section 3, we relate the metrics from each of these methodologies to applications in systemic design and demonstrate their utility in a pilot study. Section 4 discusses the implications of these ideas, and section 5 concludes the paper.

1.2. The potential of graph theory

A graph is formally defined as a set of vertices and edges. An edge is defined as a pair of vertices, where each vertex in the pair terminates the edge (Ruohonen, 2013, chapter 1). In network analysis vertices correspond with members of the social network and edges with connections between them. In using these concepts in *systems*, we call vertices *elements* (the phenomena of the system) and their edges *connections (how those phenomena influence one another)*. In graph theory, a walk (or a path) is a sequence of elements and their connections that begins at a given element and traverses a given connection to the next element, continuing until a given end element is identified. A walk that returns to the starting element is considered a closed walk and is called a cycle. In systems work, however, this is called a *feedback loop*.

How may we use these concepts to analyze CLDs? Beck, Schoenenberger, and Schenker-Wicki (2012) advance four matrix-based approaches to analyzing systems *dynamics* phenomena as sets of variables. They define four variants of matrices that evaluate the relationships between variables and the system they are structured within. Schoenenberger, Schenker-Wicki, & Beck (2014) return to these methods to examine a systems model of terrorism. Le Blanc (2015) examines the indicators of the United Nations' Sustainable Development Goals as a network of interconnected phenomena, and uses some simple network measures to analyze how these indicators relate to one another. Mohr (2016) builds on Le Blanc's work to introduce several additional measures from social network analysis. Earlier work by the present author (Murphy, 2016) used some social network analysis measures on a CLD as a proof-of-concept to elevate the discussion of leverage points in a systemic design project. Potts, Sartor, Johnson, and Bullock (2017) introduce graph theory analysis methods in their exploration of system of systems engineering architectures. Finally, in a separate line of research, Oliva and other researchers have examined the graph structure of systems dynamics in terms of levels of causality and the nesting of loops (Duggan & Oliva, 2013; Kampmann & Oliva, 2006, 2008; Oliva, 2003, 2004, 2018; Saleh, Oliva, Kampmann, & Davidsen, 2010).

These papers serve as inspiration for the current project. However, none of these projects contextualize the analysis within the discipline of systemic design, nor do they relate their ideas to the search for leverage points. They also leave gaps between centrality and structural analysis. This paper presents three contributions: it brings these methods together for the first time, links this approach to systemic design, and relates the use of these analyses to the search for leverage points.

2. Measures of graph centrality and structure

2.1. Centrality analysis

Social network analysis involves the modelling and measurement of the connections between people and organizations in a directed graph, where people and organizations are represented by nodes and connections are represented by vertices (Carrington & Scott, 2011). By measuring the structure of these networks—say, how densely coupled they are, or how central a given node may be—we can learn important things about the nature of the network as a whole such as who is the "most important" member of the network (though the interpretation of "importance" is something of debate; cf. Freeman, 1979).

We can likewise treat a CLD representing a modelled system as a directed graph of phenomena and their connections, using the algorithms of social network analysis to measure the centrality of the phenomena. This analysis can allow a systemic designer to identify important phenomena quickly and objectively (relative to the structure of the graph) regardless of the size or complexity of the map.

A caveat is that these measures do not supplant one another; researchers in centrality analysis have not determined that there is, say, a *most-central* measure. They examine different—but related—aspects of network structure and therefore offer different utility. It is up to the user of the metrics to examine the measures, the models they are analyzing, and to interpret the results.

2.2. Structural analysis

In addition to centrality, another school of analysis examines the structure of the cycles found in graphs. Known as structural dominance analysis or simply structural analysis, these methods were developed to help analysts partition and test system dynamics models (Oliva, 2004). However, these techniques seem to have been constrained to systems dynamics; their utility to help analyze systems thinking models is therefore untapped.

Structural analysis involves identifying and measuring the structure of feedback loops of the systems as cycles in the model (Oliva, 2004; see also Kampmann, 1996 and Warfield, 1989). By doing so, analysts can develop partitions of the levels and cycles of the graph. Analysis of the level partitions results in a hierarchy of the causal structure of model's phenomena. Analysis of the cycle partition allows the analyst to identify a hierarchical structure of the model’s feedback loops. Both enable the analyst to isolate and understand the causal nature of the model's subsystems (Oliva, 2004). In other words, we may be able to use these measures to illustrate a hierarchy of causality in systemic phenomena.

3. Leverage analysis

3.1. Leverage measures

Table 1 illustrates proposed translations of the techniques of centrality and structural analysis into what we have called "leverage measures" for systemic design.

Table 1. Centrality and structural measures mapped to leverage measures.

	Detail	Original meaning	Leverage measures in systemic design
Degree	The number of connections	Higher connectivity to the rest of the network; influence, access, prestige (Newman, 2010)	Immediate impact, sensitivity, resilience
Indegree	The number of incoming connections	High inward connectivity to the rest of the network; sensitivity to information, influence (Newman, 2010)	Receives change from many other elements; may be highly volatile or highly stable
Outdegree	The number of outgoing connections	High outward connectivity to the rest of the network; rapid communication/high access to the rest of the network, highly infectious (Newman, 2010)	Change in the given phenomena is felt by many other elements; impact, power
Betweenness	Frequency of participation in the shortest path between two other elements	Member has a high degree of control; the network is dependent on the member; bottlenecking, control, influence (Freeman, 1979)	Phenomena is a gateway or bottleneck for change; change strategies must consider how to prevent blocking
Closeness	Average length of the shortest paths between the given vertex and every other vertex in the graph	High visibility to the rest of the network and information spreads easily from this member; independence from the rest of the graph (Freeman, 1979)	Phenomena is highly powerful; likely to be resistant to change, and therefore a key indicator of success or failure
Eigenvector	Connectedness to other well-connected elements	Influence of highly influential elements; influence (Newman, 2010)	High-impact phenomena; likely key phenomena to change in pursuit of a given strategy
Reach	The number of elements within [x] steps of the given element	Quick propagation of information through the network; widely accessible (Hanneman & Riddle, 2005)	The map is highly sensitive to these elements
Reach efficiency	The reach divided by the degree of a given node	Efficient (non-redundant) information spreading; high exposure with limited influence on the given element (Hanneman & Riddle, 2005)	Quickly and efficiently propagate change throughout the rest of the network; is not likely to be highly influenced by the rest of the system
Eccentricity	The distance away of the furthest node	Minimal eccentricity indicates the centre of the graph (Hanneman & Riddle, 2005; Oliva, 2004)	Localization of outcome or intervention; target phenomena “neighbourhoods”
Level partition	Which variables are dependent on which?	Hierarchy of causal structure (Oliva, 2004)	Elements at the “bottom” of the hierarchy are uncontrollable within the system; elements at the top are highly dependent on the rest of the system
Cycle partition	Which other variables share the same set of predecessors/successors?	Illustrates cycle set “dominance” → sub-cycles sets must be understood before their “parents” (but not *that* useful as most elements in models sit in the same cycle set; Oliva, 2004)	Sub-cycle set elements dictate the behaviour of supercycles
Shortest Independent Loop Set (SILS)	A decomposition of the cycle partition showing which loops are included in which	- Illustrates a loop hierarchy - With level partitioning, gives an ordering from simple loops to complex loops Shows isolated loop structures (Oliva, 2004)	- Simple loops are easier to experiment with than more complex loops - Inner loops will influence the behaviour of their containing loops - Isolated structures are more easily manipulated

3.2. A pilot study

we we The model is a CLD representing the system of education curricula change in the Canadian province of Newfoundland and Labrador. It can be found and interacted with online at https://kumu.io/systemicdesign/centrality-and-structural-analysis. The model is not overly complex, containing 30 elements and 49 connections between them. Nonetheless this is a sufficient complexity to make the model difficult to interpret at a glance. A good test of the leverage measures is whether the results make sense and reveal insight based on our experience with the system.

The study artifact & materials

The model is built and maintained on Kumu.io, a web application supporting systems mapping and social network analysis. Kumu.io has implemented the centrality analysis metrics discussed above (except for eccentricity, which remains untested in this pilot study).

Procedure

We first used Kumu's built in algorithms to calculate centrality values for each element for the metrics described above. Second, we followed the procedures detailed by Oliva (2004) to examine the level and cycle partitions of the model. Finally, we reviewed the resulting centrality values, level partitions, and cycle partitions. We present our interpretation of the results according to our experience with the problem domain below.

Results

Structural analysis

As suggested by Oliva (2004), the model's initial level partition was not useful. The partitioning resulted in two levels, of which the bottom included only five of the 30 elements in the model. In no particular order, they are:

- Generational shifts in work
- Innovation learning from outside of the public education system
- Accessible and practical models for innovation education
- Other calls for reform
- Low price of oil

Taken with zero interpretation, this analysis implies that these five phenomena are completely independent forces in the world. For most of the phenomena, however, the opposite is true: "Low price of oil", "Other calls for reform", and "Generational shifts in work" are three phenomena that actually have massive systems behind them, and defining those models was simply outside of the scope of the model—a result of boundary drawing. However, the other two phenomena both deal with injecting innovation learning from outside of the extant system. It makes sense that these do not depend on anything within the system. Their independence may make them a useful point from which to implement a change strategy.

The remaining 25 elements can be decomposed into a shortest independent loop set (SILS) containing 18 separate loops. Of these, the loop inclusion graph is presented below (figure 1). It shows that 13 of the loops are independent, sitting at the same bottom-most level. The remaining five loops form the core structure of the model. These loops are illustrated and labelled in figures 3 through 6.

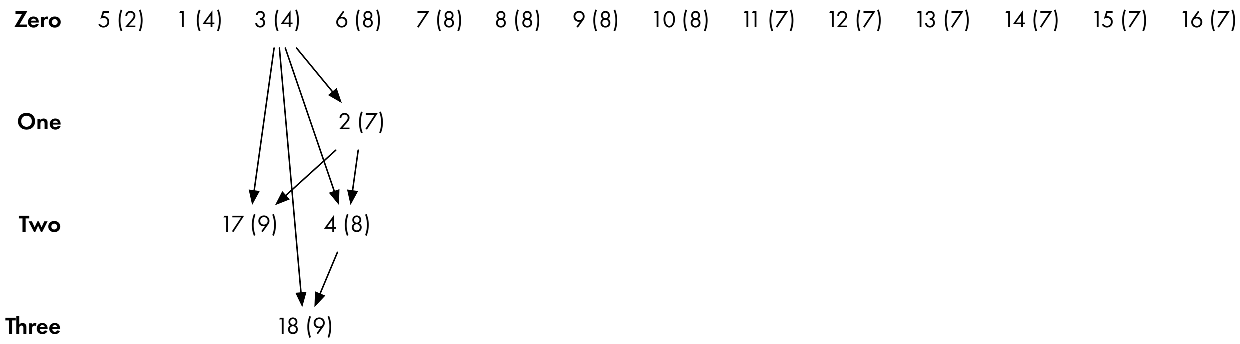

Figure 1. The loop inclusion graph of the innovation education model. Cycle levels are indicated on the left of the diagram.

The core loop of this structure is therefore loop 3—a loop describing how a poor definition of innovation is self-perpetuating. This loop is nested within loops 2, 4, 17, and 18, making it the most contained loop of the model. This is intuitive, as definitions play a major role in how an issue is discussed and, therefore, how policies are made. From a leverage perspective, then, influencing loop 3 means influencing several other key feedback loops of the system.

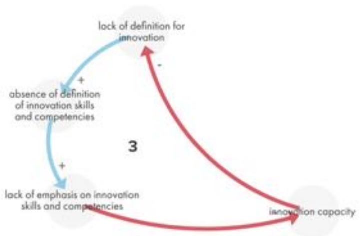

Figure 2. Loop 3: Perpetually poor definition of innovation

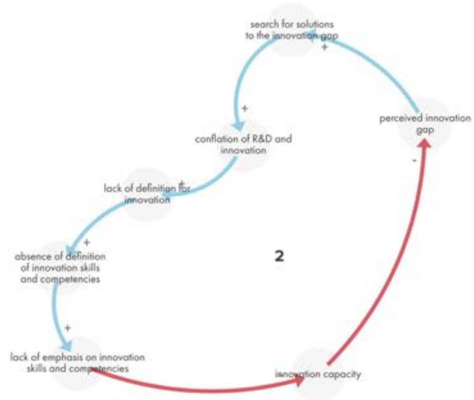

Figure 3. Loop 2: Innovation conflation (with R&D)

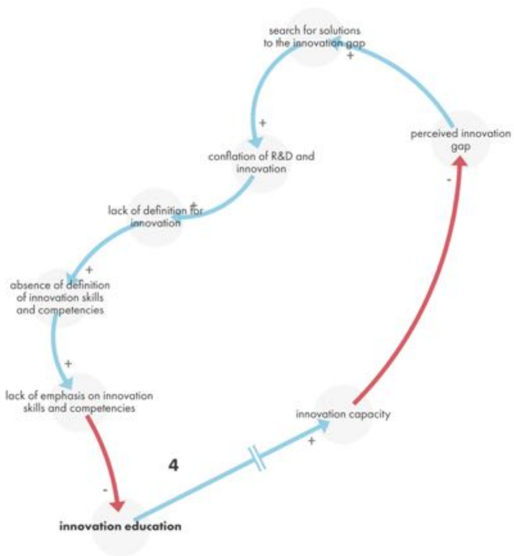

Figure 2. Loop 4: Innovation reinforces innovation

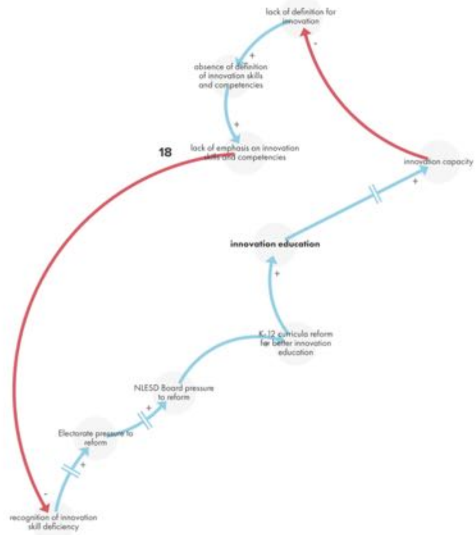

Figure 5. Loop 18: Driving reform

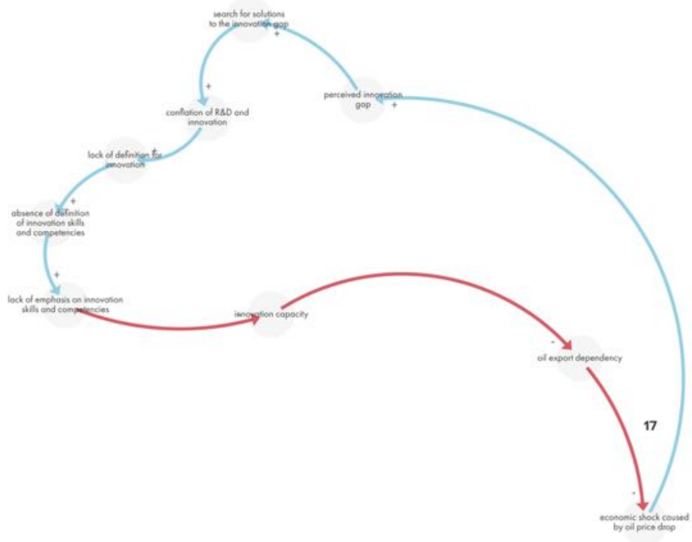

Figure 6. Loop 17: Resource-dependent economy

Centrality analysis

The top three phenomena on each of the centrality indicators is reported in table 2. A full discussion of the implications of these results is outside of the scope of this paper. For now, we provide comment on a few observations on the results of particular metrics below.

Table 2. Ranked results of centrality analysis on phenomena in innovation education, reported in descending order with the highest value items on the left. Values for the respective metric reported in parentheses. Phenomena have been colour-coded for ease of identifying the same phenomena across the table.

Degree	Innovation education (8)	Recognition of innovation skill deficiency (7)	K-12 curricula reform for better innovation education (7)
Indegree	K-12 curricula reform for better innovation education (6)	Innovation education (6)	Recognition of innovation skill deficiency (5)
Outdegree	Innovation capacity (4)	Provincial government pressure to reform (3), Independent actor calls for innovation education reform (3), Austerity limiting new program growth/development (3), Lack of emphasis on innovation skills and competencies (3)	
Betweenness	Innovation capacity (.47)	Innovation education (.454)	Recognition of innovation skill deficiency (.298)
Closeness	Lack of emphasis on innovation skills and competencies (.359)	Innovation capacity (.337)	Innovation learning from outside the public education system (.308)
Eigenvector	Innovation education (.121)	Innovation capacity (.083)	Perceived innovation gap (0.073)
Reach	Lack of emphasis on innovation skills and competencies (0.367)	Innovation capacity (.3)	Recognition of innovation skill deficiency (0.267)
Reach efficiency	Innovation learning from outside the public education system (0.078)	Lack of emphasis on innovation skills and competencies (0.073)	Low price of oil (0.067)

We proposed that high-degree elements would be important indicators of leverage—lead measures of a systemic intervention. Indeed, increased levels of "innovation education", "recognition of innovation skill deficiency", and "K-12 reform for better innovation education" would each be clear signs that change was taking root. Contrast these elements with other components of the system—say, the "need for innovation skills" or the "definition of innovation skills and competencies". These are hand-picked examples, of course, but that the degree measure algorithmically better options is evidence that our proposed definition is appropriate.

We suggested that betweenness indicates a bottleneck. Indeed, "innovation capacity" and "innovation education" reflect bottleneck phenomena in our experience. These phenomena represent our ability to actually practice and teach innovation itself. Since these concepts are fundamental, a change strategy will fail without addressing them. "Recognition of innovation skill deficiency" is third, and it also makes sense that this is a bottleneck. If we knew everything we could about innovation, but fail to notice that we weren't very good at doing it, we would not try to implement reforms to resolve the deficiency.

Last, the eigenvector metric should highlight leverage points in the model. The results here are promising. "Innovation education"—the kernel of the model itself—and "innovation capacity" are the top two results, which are intuitive. The measure also revealed the relative importance of the "perceived innovation gap": whether or not society recognizes that we aren't performing as well on innovation as we should be. This makes sense: alarm that we are failing at innovation is likely to raise awareness and incite change rapidly.

4. Discussion

4.1. Contributions

Leverage analysis is a powerful opportunity for systemic designers. Grafting centrality and structural analysis methods to systemic design is a novel way to gain insight into our wicked or continuous critical problems (Rittel & Webber, 1973; Ozbekhan, 1970). By reframing these techniques using the language of systemic design we hope to motivate more researchers and practitioners to see the potential of these measures for parsing complex systems. Structural analysis adds a rich dimensionality to these otherwise flat and inscrutable diagrams, while centrality analysis offers a quick way of emphasizing structurally important phenomena. Most importantly, these measures help systemic designers do what they are meant to do: interpret the models, with all the experience and domain knowledge they bring, to find strategic opportunities to make change.

A few centrality measures seem especially important. In particular, eigenvector analysis is an intuitive exaptation of the concept of leverage points. It may be that the results of eigenvector analysis should be the first thing that systemic design teams discuss when they move towards strategizing solutions. Identifying potential bottlenecks with the betweenness measure also appears to be a powerful tool in order to ensure that potential bottlenecks are addressed by a change strategy.

The notion of "leverage measures" is a novel concept as a whole. Are there other ways in which we should be measuring the leverage we have on our systems? What principles may be applied in assessing whether a given change strategy has appropriate leverage or not? This is an exciting new idea that deserves further scrutiny and exploration.

4.2. Limitations

First, and most obviously, our proposed metrics deserve further scrutiny than our pilot project. It should be possible to test hypotheses on these ideas. For instance, a modeller or modelling team could examine a domain and develop a model, then assess it with the leverage measures. Expert reviewers could be asked questions (e.g., "What are the key bottlenecks to reform in this issue?") about the domain relating to the proposed leverage measures. After these responses are coded, the reviewers' suggestions could be compared with the results of leverage analysis to see if experts' insights are reflected by the analysis.

Second, the need for interpretation is ever-present. Nonetheless, we can direct what the interpreter interprets. Structural and centrality analysis offers an easy way to provide emphasis, changing what catches the systemic designer's attention.

4.3. Further research

Ontological guidelines for mapping and normalization

The way in which models are researched and designed is not necessarily standardized. Designers may hold different mental models about what is appropriate for a systems model, for the phenomena they are mapping, and for what constitutes a connection between the models. These issues may be alleviated with ontological guidelines or even a strict script for how the real-world problems of systemic design are mapped to systems models.

Explore additional metrics

As discussed earlier in this paper, many more metrics exist dealing with analyzing the structure of graphs. For instance, Borgatti (2005) develops some ideas around how information actually flows in social networks. These ideas may apply to the flows of change between phenomena in systems. Xie, Szymanski, and Liu (2011) profile a set of community detection algorithms used to detect the divisions of social networks into separate social groups. These concepts may relate to new ways to structure and decompose systemic phenomena. Finally, Schoenenberger, Schmid, and Schwaninger (2015) propose a methodology to algorithmically detect different systems archetypes based on the structure of CLDs. This relates directly to the objectives of the current research and should be integrated into the leverage measures framework.

Weighted metrics and algorithms to implement them

It is possible to combine centrality measures. For instance, you can use the Kumu.io algorithms to calculate reach efficiency weighted by eigenvector values. If combined metrics could be clarified and developed with respect to the leverage measures framework, it may be the most powerful way to immediately calculate clear leverage points from a given model. (E.g., eigenvector-weighted reach efficient phenomena may be high-influence high-efficiency intervention points.)

Linking methods

The formal relations and structures emphasized by the methods presented in this paper might be even more useful when embedded in other systemic design methods, such as synthesis maps or Gigamaps (Sevaldson, 2011). Centrality and structural analysis could also find utility in structured dialogic design, where pairwise voting mechanics are already used, providing a semi-quantitative approach to engage stakeholders in modelling complex problems (Jones, 2008).

Systems dynamics vs. systems thinking: from dichotomy to spectrum?

In the introduction, we framed differences between system dynamics and systems thinking as a substantial divide. It may be that these tools can help bridge the gap between the hard, quantitative approaches of systems dynamics and the soft, messy problems of systems thinking. If this is the case, the divide doesn't exist at all—rather work in these two disciplines happens along a spectrum. Choosing the appropriate place on the spectrum to investigate a given problem then becomes a key decision in the systemic design process. This deserves further thought.

5. Conclusion

This paper has served three objectives: to unite different semi-quantitative approaches to analyzing systems, to contextualize these approaches in the discipline of systemic design, and to relate the use of these semi-quantitative methods to the notion of leverage points. Simply by discussing the different aspects structural analysis of systems with respect to systemic design, we hope to have achieved the first and second objectives. By translating different measures from these semi-quantitative approaches into a list of leverage measures, we believe we have achieved the third. Extensive work remains both to critique this work and to extend it. The potential for augmenting the work of systemic design is nonetheless enormous.

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