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Leverage analysis

A method for locating points of influence in systemic design decisions

Abstract

Many systemic design processes include the development and analysis of systems models that represent the issue(s) at hand. In causal loop diagram models, phenomena are graphed as nodes, with connections between them indicating a control relationship. Such models provide mechanisms for stakeholder collaboration, problem finding and generative insight and are powerful resources when presenting a visual argument. These functions are valued in design thinking, but the potential of these models may yet be unfulfilled. We introduce the notion of "leverage measures" to systemic design, adapting techniques from social network analysis and systems dynamics to uncover key structures, relationships and latent leverage positions of modelled phenomena. We demonstrate their utility in a pilot study. By rethinking the logics of leverage, we can make better arguments for change and find the place from which to move the world.

Keywords**:** systemic design, leverage points, centrality analysis, structural analysis, social network, causal loop diagrams.

Introduction

The practice of systemic design offers tools and approaches that can help find leverage for change decisions anticipated to produce a desired impact within complex system problems. Complex social systems, as any complex systems, often produce emergent, counterintuitive behaviour that is impossible to predict by examining the parts or the individual phenomena (Forrester, 1971). By using models to capture and illustrate how these phenomena interdepend on one another, we may gain the ability to grasp such emergent behaviour. More importantly, we may be able to identify leverage points, the places within a system where a small shift produces a big change (Meadows, 1997). In pursuit of better ways to find leverage, we offer the following three contributions: We highlight how tools from graph theory (the mathematical study of structured relations between objects; Ruohonen, 2013) may be useful in the analysis of systemic design models. We bring together several such tools under a unified approach in what we call "leverage analysis" and introduce a set of leverage measures and their definitions for analysing systemic design models. Finally, we demonstrate how these tools may be used to explore the logics of leverage in a pilot study.

Why do leverage points matter? To demonstrate the physical principles of a simple lever, Archimedes famously said, "Give me a place to stand, and with a lever I shall move the whole world" ("Archimedes," n.d.; cf. Tzetzes & Kiessling, 1826, for an earlier Greek version). In truth, the place he would have needed to stand is about 3.8 trillion light years away (or 40x the size of the observable universe),[1] but his statement was nonetheless *moving*. More importantly, it is an excellent illustration that the choice of where to act *from* is as significant as the choice to take action. In fact, the choice of where to stand may matter more than the force applied in the act itself.

Systems scientists have developed several approaches to defining and cataloguing sociotechnical complexity in large-scale social systemic contexts. Many refer, for example, to the concept of "wicked problems," proposed by Rittel and Webber in *Dilemmas in a General*

Theory of Planning (1973), in which they articulated ten observations consistent with "wicked" or intractable, irreducible problems that resist solutions or linear resolutions. Problems of a "wicked" nature have been described as messes (Ackoff, 1997), ill-structured problems (Mitroff, et al, 1982) and continuous critical problems (Özbekhan, 1969). Özbekhan (1970) developed a comprehensive – though, he admits, incomplete – list of 49 such problems for the *Predicament of Mankind* prospectus for the Club of Rome,[2] building on the list of 28 documented in the earlier cited work. These problematic contexts all are conceived as sharing the following common attributes: their irreducibility into component issues, their continuous and adaptive configuration over time, their intractability to problem-solving approaches and so on.

Despite our best efforts and intentions, no matter what actions we take, wicked problems often appear to be unyielding. Challenges such as ending homelessness, preventing climate change and eliminating discrimination all fall in this class of problem, as do many more at every scale, industry and locale. Countless individuals and organisations – also of every scale, industry and locale – have attempted to tackle these problems, but progress seems to happen at a rate disproportionate to effort. When it comes to wicked problems, moving towards solutions is akin to moving the Earth – there is a clear need to find leverage in order to ensure our efforts are effective and efficient.

Finding leverage in systemic design

The practitioners of systemic design hope to offer tools and approaches that could help us find leverage. Systemic design has contributed hybrid practices that combine the formal modelling of complex systems thinking with the investigative and creative capacities of design thinking (Jones, 2014). Indeed, systems thinkers have often asked, "Why, often despite our best efforts, have we been unable to achieve a certain goal or solve a particular problem?" (Stroh, 2015, p. 92), a direct inquiry into the apparent lack of success by the other efforts described above. Using the processes of systemic design, wicked problems can be understood through more coherent narratives because hybrid visualisations and strategic interventions can be modelled as well as designed and tested.

The properties of complex systems (and of how people engage with them) nonetheless present a number of issues that introduce bias and chance into the process of intervening in systems (Norman & Stappers, 2015). Systemic design tools produce models, and "all models are wrong" (Box, 1976). Further, while some principles and processes exist (Jones, 2014), developing models, identifying leverage points and designing solutions tends to happen by "muddling through" a problem (Norman & Stappers, 2015; see also Simon, 1996).

Systemic design models vary in type. Designers may create systems thinking 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. Within systemic design, synthesis maps (Jones & Bowes, 2017) are used for visualising complex social systems that incorporate models and formalisms, as well as GIGAmaps, wherein systems are mapped out generatively and described across many complex layers and scales (Sevaldson, 2011). Alternatively, designers may quantify the phenomena of a system's variables through techniques from system *dynamics* (these techniques are also known as "hard" or "semi-structured" approaches; Forrester, 1994). These models may then be interpreted and used to identify points of potential leverage, the "places within a complex system . . . where a small shift in one thing can produce big changes in everything" (Meadows, 1997, p. 1).

The discipline of systemic design, and the use of modelling, is particularly suited to finding and emphasizing leverage points as these points are frequently counterintuitive. As Meadows (1997) argues, they may not only be hard to identify and isolate in a system, but stakeholders are often working to address leverage points by pushing them in the wrong direction. Systemic designers work with stakeholders to understand the whole system and reveal its counterintuitive structures and dynamics, and the resulting models (e.g. CLDs) provide a way to visually argue the significance of the discovered leverage points and the directions in which these phenomena should be pushed.

The different approaches to modelling come with important trade-offs which are yet to be reconciled in modern methods. Systems thinking models are representative, but their insights may be invalid or inaccurate (Forrester, 1994). Also, system dynamics models are robustly analytical, but we may be analysing an ill-developed or reductive representation of the problem system (Checkland, 1985). Further, in order to develop representative models, systemic designers must draw on diverse stakeholders to ensure that perspectival variety and appropriate representations are legitimated (Jones, 2014; Stroh, 2015). Due to the development of recent technologies and practices such as crowdsourcing (participatory systems that involve publics in collaborative projects; Lukyanenko & Parsons, 2012) and data science (a set of techniques and theories that help distil insight from data; Provost & Fawcett, 2013), the collection and organising of large amounts of data has become commonplace. This brings us to an important tension (see Maass et al., 2018). Larger, more complex data-driven models are likely to be 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 representational validity and what we might call 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 systemic design models' elements and connections to algorithmically identify leverage points in these models. These techniques make it easier to take advantage of big data in systemic design and advance our capacity to muddle through wicked problems (Rittel & Webber, 1973).

In the next subsection, we briefly introduce graph theory. In section two, we introduce the concepts and metrics of centrality analysis and of structural analysis and their applications in systemic design. In section three, we demonstrate their utility in a pilot study. Section four discusses the implications of these ideas and presents our conclusions.

The potential of graph theory

For the purposes of this paper, we present a simplistic discussion of the formalisms of graph theory to help the reader understand the workings of leverage analysis. We avoid delving into the explanation and justification of the formal concepts, choosing instead to refer the reader to sources where these concepts have been demonstrated in analytical disciplines. The technical details of the implementation of these concepts have been well-defined in these papers, and our goal is to map their utility to productive directions in systemic design.

A graph is formally defined as a set of vertices and edges and can be seen as a relationship between a node (vertex) and its connecting edges. An edge is defined as a pair of vertices where each vertex in the pair terminates the edge (Ruohonen, 2013). In network analysis, vertices correspond with the members of the social network, and edges with the connections between them. Using these concepts in *systems*, we call vertices *elements* (the phenomena of the system) and their edges *connections* (how these 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 science, however, a cycle is called a *feedback loop*.

The formalism of a graph as a pair of sets of vertices and edges allows us to represent a graph in matrix form in what is called an adjacency matrix, where each column and row represent the elements of a system. The number "1" in a column-row intersection indicates that there is a directed connection from the row element of the intersection to the column (Oliva, 2004). "0" indicates no such connection exists. We will return to the concept of the adjacency matrix in the next section, when it becomes useful in partitioning system models, that is decomposing models into useful subcomponents and their relationships.

How may we use these concepts to analyse CLDs? Beck et al. (2012) propose four matrix-based approaches to analysing systems *dynamics* phenomena as sets of variables. They define four variants of matrices that evaluate the relationships between the variables and the system they are structured within. Schoenenberger et al. (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 analyse how these indicators relate to one another. Mohr (2016) builds on Le Blanc to introduce several additional measures from social network analysis. Earlier work by one of the present authors (Murphy, 2016) use 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 et al. (2017) introduce graph theory analysis methods in their exploration of systems engineering architectures. Finally, in a separate line of research, Oliva and other researchers examine 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 et al., 2010).

These papers serve as inspiration for the current project. However, none of these projects contextualise 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.

Background: Graph centrality and structure

We start by explicating the most common and relevant centrality measures and models for structural analysis. This elementary background can be considered minimally necessary for understanding the potential applications of network and centrality analysis in complex social systems.

Centrality analysis

Graph theory can be explored through its relevance to multiple adjacent disciplines via the study of social networks. Based on theoretical origins in formal sociology (Carrington & Scott, 2011), social network studies aim to understand the shape and characteristics of social structures composed of individuals and their relations. Sociologists interested in the complex divisions within American minority communities turned to network analysis as a way of mapping the network of social relations in these communities. Systems scientist John Warfield conducted policy research by employing interpretive structural modelling (digraph influence maps) for social network analysis in complex social domain analysis. A significant early study describes the modelling of community assets in underprivileged urban communities in Dayton, Ohio (Fitz & Troha, 1977). This led to what is now known as social network analysis (Carrington & Scott, 2011). Warfield's (1974) interpretive structural modeling (ISM) algorithm was further developed for use as the network modeling methodology for the multi-stakeholder decision-making process known as Interactive Management. Today, the process is convened as Structured Dialogic Design, a multiple-facilitator decision-making process using the ISM algorithm in a web-based system employed in systemic design practice.

Social network analysis involves the modelling and measurement of the connections between people and organisations in a directed graph, where people and organisations 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 make important observations about the nature of the network as a whole. Based on the representations of behaviour in the network, social network analysis also enables scoping out very specific data-supported attributes of individuals, allowing researchers to determine central figures, gatekeepers and other roles of importance in the network (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 allows 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.

Many types of centrality analysis exist (see Newman, 2010, for a comprehensive resource on network analysis). Below, we profile a set of key centrality formalisms relevant to our applications to examine networks of phenomena. Each formalism is offered with a reference for further information. The reference is not necessarily the origin of the measure, nor is it the definitive resource, as centrality measures are well-documented, and extensive literature exists describing these formalisms in various ways. The list of formal types below is also not intended to be a complete set; a key direction for further research is to continue exploring available formal models to evaluate their utility to systemic design problems.

It is crucial to note that these measures do not supplant one another; researchers in centrality analysis have not determined that there is, say, a *most-central* measure. Each measure examines different but related aspects of a network structure and therefore offers different uses. It is up to the user of the metrics to examine the measures and the models they are analysing and to interpret the results. The challenge of interpretation becomes, we might say, a design problem.

Degree (Newman, 2010)

Degree centrality is a simple measure of the number of connections: How many edges does the vertex have? As a basic measure of importance, a vertex with a higher degree is more connected to the rest of the network than an element of a lower degree. For directed edges, there are two sub-variants of degree: indegree (the number of incoming connections) and outdegree (the number of outgoing connections). In social networks, the *indegree* is a good indicator of popularity, representing a high number of people who communicate to the given member. *Outdegree* is an indicator of gregariousness, showing someone who communicates to a large number of people in the network. See Figure 1 for an illustration of degree, indegree, and outdegree centrality.

Betweenness (Freeman, 1979)

Betweenness measures how often a given vertex lies on the shortest path between two other elements. It is calculated by counting the number of shortest paths from vertex a to vertex b in a network, dividing the number of those paths that pass through the given vertex by the total and then summing those values for all possible pairs of nodes in the network.

In a social network, a high betweenness is a good indicator that the given member has ready access and possibly extensive control over the network. Such members might serve the function of gatekeepers by regulating access to higher-status members. Consider how gatekeepers can halt the spread of a rumour: To stop a rumour from spreading with minimal effort, we should intervene on members of the network with high betweenness values.

Closeness (Freeman, 1979)

How close is a given vertex to every other vertex in the graph? Closeness is the reciprocal of the average length of the shortest paths between the given vertex and every other vertex in the graph.

High closeness is an indication of the network's dependence on the given member. An example of a family is illustrative: The member that the family depends on is likely to have a high closeness value. This is also an indication of communication efficiency: In an extended family, if you want to propagate news, you tell a grandparent as they are probably close to all the aunts and uncles as well as the grandchildren and cousins.

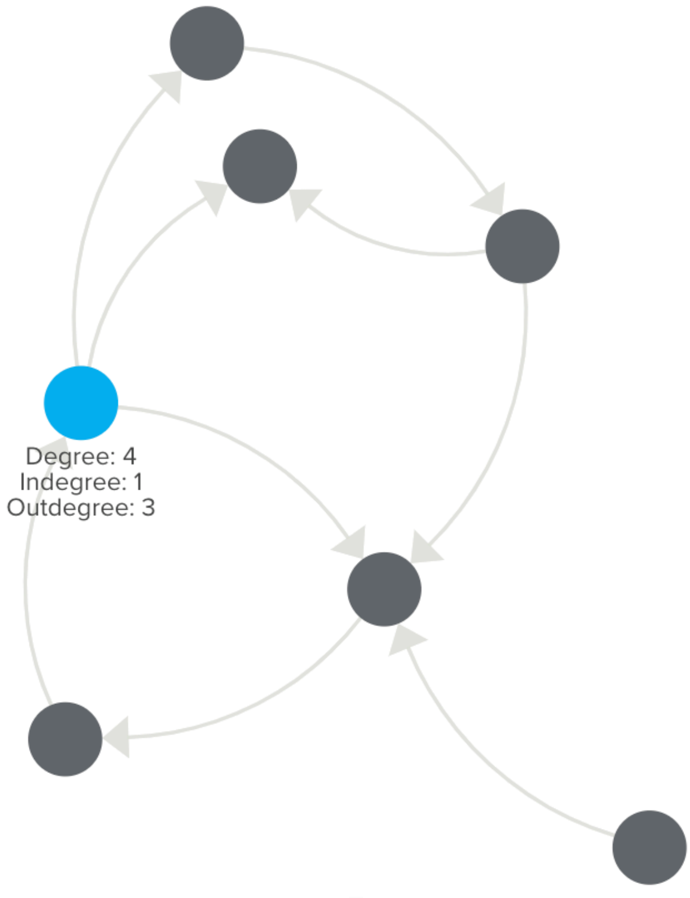

Figure 1. A simple network illustrating the degree, indegree and outdegree measures.

Eigenvector (Newman, 2010)

A vertex that is well-connected by any metric may seem to have high centrality, but it may be well-connected to weakly-connected elements. Eigenvector centrality recognises that not all neighbouring vertices are equivalent in terms of centrality and assesses whether the given vertex is well-connected *to other well-connected elements*.

Eigenvector centrality is found by summing the relative eigenvector centrality scores of all the neighbours of an element; it is therefore calculated iteratively as an estimate.

As eigenvector centrality is an indicator of how well-connected a given element is to other well-connected elements, it is a potent measure of importance. Indeed, Google's famous PageRank algorithm implements eigenvector centrality (Newman, 2010, p. 707).

However, eigenvector centrality suffers a problem in directed graphs. According to Newman (2010), it only measures strong connectivity and hence may not be a good indicator of implicit leverage: "Only vertices that are in a strongly connected component of two or more vertices, or the out-component of such a component, can have non-zero eigenvector centrality" (p. 172).

This fact is relevant to our analysis of CLDs and shall be discussed as we further apply these metrics to systemic design.

Reach (Hanneman & Riddle, 2005)
Reach is the proportion of the network within *k* steps of a given vertex; by convention, *k* is usually 2.

How much of the network is within the "reach" of a given element? In a social network, a member with high reach is likely to be capable of quickly spreading information. Reachability is also a good indicator of potential (undiscovered) leverage as a vertex with higher reach than others has a larger directed network in which influence can be exerted.

Reach efficiency (Hanneman & Riddle, 2005)
Reach efficiency is calculated by dividing the reach of a vertex by its size (the degree of the vertex plus one, in order to count itself in the size).

How efficiently can a given vertex reach the rest of the network? High reach efficiency is an indication that the member can connect with much of the network with little effort. If a member of a network only has redundant contacts – people they already know, or those they can reach through different parallel connections – then this member will have low reach efficiency.

Eccentricity (Hanneman & Riddle, 2005; Oliva, 2004)
A vertex's eccentricity is the length of the longest of the shortest paths to every other vertex in the graph. In other words, how far away is the furthest vertex, at minimum? Eccentricity has several properties. The vertex with the smallest eccentricity is in the "centre" of the graph, and the eccentricity value of that vertex is said to be the graph's radius.

A high relative eccentricity, in other words, indicates a substantial distance from the graph's centre. A member's minimal centrality indicates proximity to the centre of the network – membership, perhaps, in the clique that holds the broader group together.

Notes on centrality metrics
As has been discussed, we can use the above metrics to calculate the centrality or "importance" of elements by assessing how a given element is connected to the rest of the graph (Freeman, 1979). All of the above measures are relative per-element metrics. That is, they provide values to a given member based on how they relate to the rest of the network. It is possible to use network analysis to measure the network as a whole (e.g. the number of elements/connections in the model may be a potent indicator of its complexity). However, as our interest is in determining which phenomena are the most important leverage points in a systems model, we will leave examining the system itself outside of the scope of the present research.

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, this method was developed to help analysts partition and test system dynamics models (Oliva, 2004). Recall that systems dynamics models use rate and equation modelling drawn from real-world data. Due to the nature of the phenomena modelled with systems work, it can be challenging to actually measure and integrate these real-world measures into a model. Oliva's motivation was to find a way to decompose dynamics models such that what the data designers had access to could be used in the best way possible. However, these techniques have been constrained to systems dynamics; therefore, their utility to help analyse systems thinking models remains untapped.

Structural analysis involves identifying and measuring the structure of systems' feedback loops 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, enabling them 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. We further note three powerful methods described by Oliva (2004) for analysing influence and intervention in systems dynamics as these methods might be applicable in resolving design decisions for complex social phenomena.

Level partitioning

Level partitioning helps analysis by identifying levels of influence in a complex structure by using a reachability matrix (a matrix whereby an entry of "1" in a row/column intersection indicates that the vertex represented by the row can reach (via a walk) the vertex represented by the column). A reachability matrix can then be partitioned into blocks grouping the vertices that depend on the same variables. Then, we can identify variable "levels" that correspond to reach or influence across a network.

Importantly, the variables in a feedback loop are at the same level because – by the definition of a feedback loop – there is no causal precedence, and thus all phenomena represented by this loop cause one another.

In systems dynamics, level partitioning results in a clear hierarchy of the causal structure captured by the model. This technique allows us to specify the dependency of variables on each other. Variables at the top level are often outcome variables, while those at the bottom-most level are the least embedded, but often the highest-impact ones, within the complex causality of a system.

Cycle partitioning

Cycle partitioning addresses the lack of specificity in defining related vertices within feedback loops. We can partition the reachability matrix defined above by grouping together vertices that share the same set of predecessors and successors; these variables are a cycle set. This cycle partition is a strongly connected graph – it is possible to walk from each variable to every other variable.

A cycle set is not that useful on its own. In many system models, due to the nature of the system, main cycle sets account for a large proportion of the modelled variables. Because, as described above, all variables in this set are at the same level, the set does not give us new knowledge until its structure is further analysed.

Two graph theory concepts are useful for this analysis (in the context of the present research). The first is a geodetic circuit. A circuit is a cycle in which vertices may be repeated (whereas, in a cycle, vertices cannot repeat). A geodetic circuit is the shortest possible circuit in which two given vertices participate. The second concept is an independent loop set (ILS): a set of loops beginning with a given loop and adding a new loop to the set if and only if the candidate loop contains an edge not yet included in the loops of the set. Oliva (2004) expands this model by only considering the geodetic circuits of the graph as candidates for the loop set. This modified version is called the shortest independent loop set (SILS). These loop sets can yield high-potential design options for intervention, redesign or, if warranted, integration with other defined problem sets.

Considerations for leverage analysis

How can we translate the above measures and techniques into useful tools for analysing soft social systems in systemic design proposals? It is necessary to consider some disclaimers before we begin.

First, there is a difference between the domains normally used for social network analysis and the messy (unstructured and unstructurable) problems of systemic design. For instance, models of social networks show the flows of communication or connection between people and organisations. Systemic design models often show flows of "change" through pathways, human activity journeys and complex processes. Network analysis reveals the potential for change through communicative action between participants in the network. But centrality is not a measure of change or flow in the social system. Change and activity are complex multicausal phenomena and obviously have no standard measurement unit. For example, how does a shift in police violence against racialised people influence how racialised people perceive the justice system? We know that it does, but characterising the connection between these phenomena further is a complex task. Thus, we should be cautious when we use network analysis techniques to examine the target phenomena of systemic design in social systems.

Second, there may be a role for the weighting and thresholds of connections and elements. The degree of change in one element may be very slow, for instance, while in another it may be very fast; an investment of time, effort, and resources in changing one phenomenon may be disproportionately costly to an investment in another. These intricacies are difficult to model. Finding ways to do so may be worthy of future research.

Ultimately, we cannot eliminate the role of interpretation from these models. We can, however, help systemic design studies and system maps parse complex models, identify potential key phenomena and ensure completeness. With these concerns in mind, in the following section we translate the centrality and structural analysis techniques discussed above into what we call *leverage measures* for application in systemic design.

Leverage Measures

Table 1 illustrates the proposed translations of the techniques of centrality and structural analysis into leverage measures for systemic design. A more robust discussion of each measure follows.

Table 1. Centrality and Structural Measures Mapped to Leverage Measures

	Definition	**Systems function**	**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 or influence from many other nodes; may be highly volatile or highly stable.
Outdegree	The number of outgoing connections.	High outward connectivity to the rest of the network; rapid communication and access to the network, highly “contagious” (Newman, 2010).	Change in the given phenomena is felt by many other nodes in the network; high 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).	Phenomenon is a gate point or a bottleneck; change strategies must consider bypasses or strategies to prevent blocking.

	Definition	Systems function	Leverage measures in systemic design
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, information spreads easily from this node; independence from the rest of the graph (Freeman, 1979).	High-closeness nodes hold cohesion and power; likely to be resistant to change, and therefore a central locus to enable success or a failure point for change strategy.
Eigenvector	Connectedness to other well-connected elements.	Influence of highly influential elements; influence (Newman, 2010).	High-impact nodes and pathways; likely key points of leverage 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 (Warfield, 2001; Hanneman & Riddle, 2005).	The measure is highly sensitive to deeper-placed elements that exhibit reach across the network. Reachability was Warfield's (2001) simplest effective measure of complexity in onterpretive structural modelling, a digraph network model.
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 measure of the furthest node.	Minimal eccentricity indicates the centre of the graph (Hanneman & Riddle, 2005; Oliva, 2004).	Localisation of outcome or intervention; target "neighbourhoods" of salient phenomena.
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-cycle sets must be understood before their "parents" (Oliva, 2004).	Sub-cycle set elements dictate the behaviour of supercycles.
Shortest independent loop set	A decomposition of the cycle partition showing how loops are embedded within loop sets.	Illustrates a loop hierarchy. With level partitioning, shows 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.

Analysis pilot study

Can leverage analysis support policymakers and "changemakers" (Rahman et al., 2016) in their pursuit of systemic change? To explore the utility of these measures, we conducted a pilot study using an existing model of an education system (Murphy, 2016). That model was previously used to identify opportunities for education system change in the Canadian province of Newfoundland and Labrador. The model was a CLD[3] that represented the system of education curricula changes. It was built to provide strategic information for a change strategy whose purpose was to introduce innovation skills into the public-school systems at all levels of formal education. (Thus, the model contains many references to innovation. These references can likely be swapped by any other curricular goal, and the system will be structurally equivalent.)

As with most sociotechnical systems (Emery & Trist, 1960; Gharajedaghi, 2011), the forces influencing curriculum outcomes in the Newfoundland and Labrador education system were quite dynamic. Moreover, outside of the established players (e.g. teachers' unions and government ministries), many of the actors of the system had limited resources with which to stage an intervention. Changemakers should therefore strive to root their strategies – theories of change (see Annie E. Casey Foundation, 2004) – in changes that yield important shifts for the economy of efforts required. In the case of the *Innovation Education* project, the actors sought to identify the best way to cultivate innovation skills as part of the Newfoundland and Labrador public education outcomes.

A model of the system was developed through secondary research. The model was not overly complex, containing 30 elements and 49 connections between them. Nonetheless, this was sufficient complexity to make the model difficult to interpret at a glance. A small organisation might be able to use the model to inform change strategies, but this use requires intuitive, substantial interpretation of the model structure and dynamics. Such interpretation can be difficult, even for those practiced in systems (Sterman, 2009). Leverage analysis measures present an opportunity to augment that intuitive interpretation. As an exploration of the utility of these measures, we examine the model developed for Murphy (2016) with the leverage analysis measures described above. We then interpret the results and discuss whether the proposed measures provided the expected results.

Study apparatus

The model is built and maintained on Kumu (http://kumu.io), a web application supporting systems mapping and social network analysis. Kumu has implemented the centrality measures discussed above (except for eccentricity, which remains untested in this pilot study). Unfortunately, Kumu's implementation of these algorithms is not public, so we cannot report on the exact approach to calculating relative centrality values used in the pilot study. For exploratory purposes, however, the results are still provided, and as the measures are relative to the structure of the modelled system, the analyses possible through Kumu will suffice to illustrate the ideas presented above.

Procedure

We first used Kumu's built-in algorithms to calculate the 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.

Analysis results

Structural leverage analysis

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 were as follows:

- 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.

As suggested by Oliva (2004), the model's initial level partition was not useful. Taken for granted, 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 emerge from massively complex systems and histories, and defining such models was simply outside of the scope of the model, a result of boundary framing. 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 SILS containing 18 separate loops. The loop inclusion graph for these 18 separate loops is presented below (Figure 2). It shows that 13 of the loops are independent, located at the same bottommost level. The remaining five loops form the core structure of the model. These loops are illustrated and labelled in Figures 3 to 6.

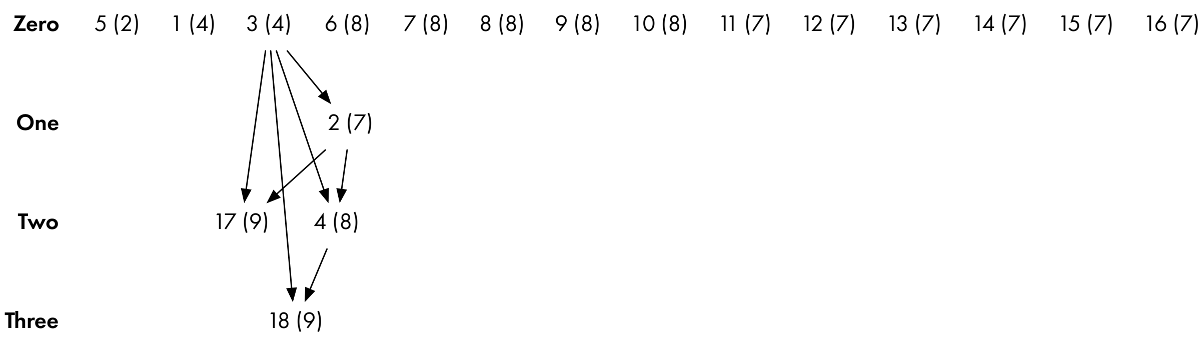

Figure 2. The loop inclusion graph of the innovation education model. Cycle levels are indicated on the left of the diagram.

The core loop of this structure is therefore loop 3 (Figure 3), a loop describing how a poor definition of innovation is self-perpetuating. This loop is nested within loops 2 (Figure 4), 4 (Figure 5), 17 (Figure 7) and 18 (Figure 8), 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.

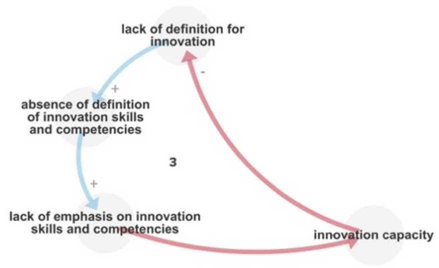

Figure 3. Loop 3: Perpetually poor definition of innovation.

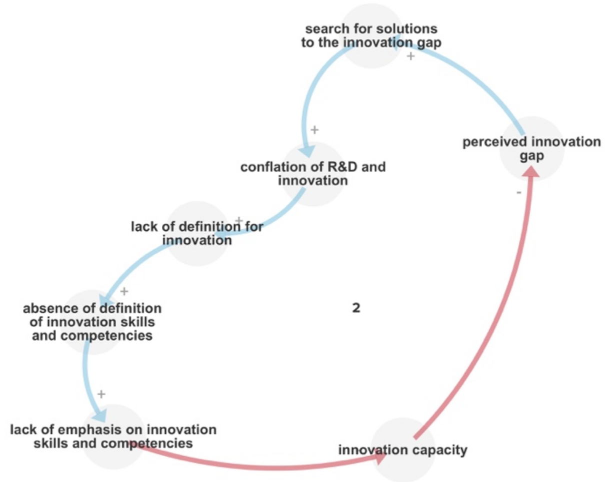

Figure 4. Loop 2: Innovation conflation (with R&D).

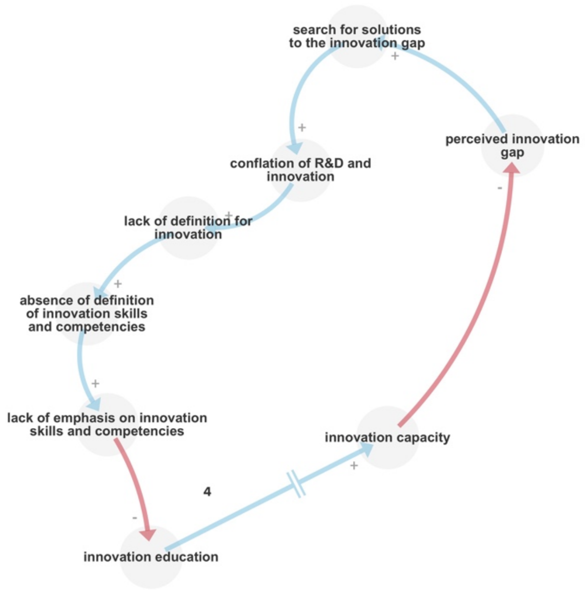

Figure 5. Loop 4: Innovation reinforces innovation.

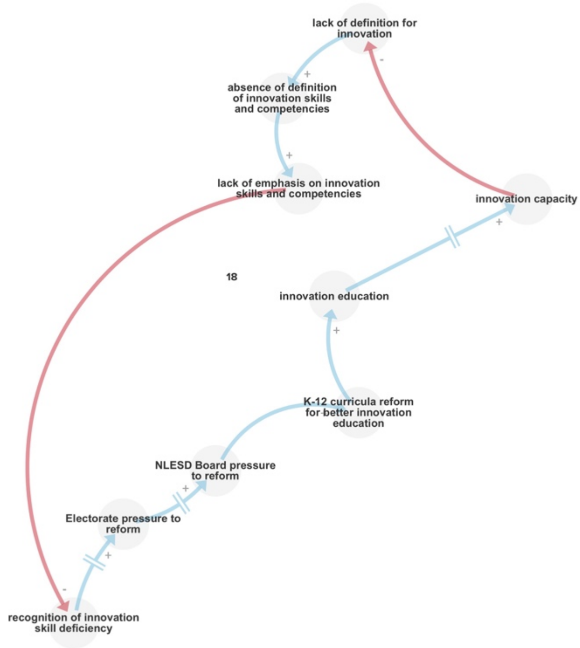

Figure 6. Loop 18: Driving reform.

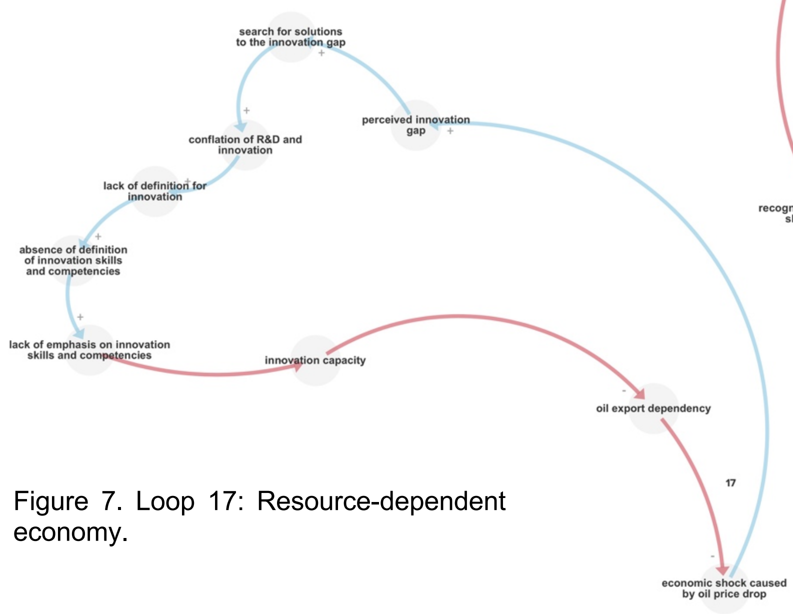

Figure 7. Loop 17: Resource-dependent economy.

Centrality leverage analysis

The top three phenomena on each of the centrality indicators are reported in Table 2. We provide comments on a few of the results of particular metrics below.

Table 2. Ranked results of centrality leverage analysis of phenomena in innovation education. Note: The results are 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 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 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 signals of change, lead indicators of systemic effects. Indeed, the results seem to demonstrate this notion. Increased levels of “innovation education,” “recognition of innovation skill deficiency” and “K-12 reform for better innovation education” would each be a clear sign that change was taking root. This could be contrasted with, say, the “need for innovation skills” or the “definition of innovation skills and competencies.” These are hand-picked examples, of course, but the fact that the measure ranked these elements highly is a qualitative (if weak) indication that our hypothesized understanding of degree measures was accurate. The third element, “K-12 reform for better innovation education”, is particularly apt. In Newfoundland and Labrador, the education system is regularly criticized for being slow to change (Fagan, 1995). If reform were to actually take place, it is an obvious sign that progress is taking root.

We suggested that betweenness would indicate a bottleneck. Indeed, “innovation capacity” and “innovation education” were clear winners, and, again, this reflects a qualitative truth of the system. These phenomena represent our ability to actually practice the skills themselves and then to teach them to students. Since these concepts are fundamental to both defining what innovation is and to teaching it, we must ensure we have the appropriate capacities in place. "Recognition of innovation skill deficiency" is ranked third, and it also makes sense that this is a bottleneck. If we knew about innovation only in the abstract but failed to notice that we were ineffective because of inexperience, we might not even try to implement reforms to resolve the deficiency.

We proposed that high closeness values would show resilience, which should be reflected in phenomena that are slow or difficult to change. Interestingly, while we would argue that the top two phenomena on this measure clearly reflect this tendency, the third-ranked phenomenon – "innovation learning from outside the public education system" – is less intuitive. This phenomenon should be easy and quick to introduce into the system as it does not depend on the other systemic factors that we have mapped; arguably, anyone can start an initiative that, for example, provides innovation learning to teachers or students. To explain this inconsistency, we returned to the original definitions of closeness as discussed by Freeman (1979). Note that closeness also indicates *independence from the rest of the graph*. Indeed, as described above, this notion of extra-curricular innovation learning is systemically independent. It is not controlled by any public entity nor influenced by any other part of the system. Thus, the results of this pilot study prompt us to refine our definition of closeness as a leverage measure. High closeness elements may be resilient and therefore difficult to change, as we suggested earlier. "Lack of emphasis on innovation skills and competencies" and "innovation capacity" are both phenomena that may be slow to show results, even if a high level of program activity is occurring throughout the educational system. However, high closeness elements may also be independent forces, uninfluenced by the rest of the system. This insight is practically useful. In the case of "innovation learning from outside the public education system," this independence is double-edged: it is easy for anyone to introduce extra-curricular innovation lessons, but it may be difficult for that initiative to integrate with the rest of the system (e.g. it could be challenging for such an initiative to gain legitimacy or scale and therefore it may fail to reach many teachers or students).

The eigenvector metric should highlight the "most favorable" leverage points in the model: phenomena which, if changed a little, would trigger a cascade of impacts throughout the rest of the system. The results of the pilot study reflect this conceptualisation of an eigenvector measure. "Innovation education," the kernel of the model itself, and "innovation capacity" are the top two results. Indeed, if an actor could directly influence either of these phenomena, it is intuitive that the rest of the mapped system would respond powerfully to these changes. The difficulty, of course, is that these are significant and complex programs in themselves, and it would be a challenge for any actor to act on them directly. The metric's third-ranked phenomenon is the "perceived innovation gap," whether or not society recognises that we are not performing as well on innovation as we should be. Indeed, alarm and agreement across the system that we are failing at innovation is likely to raise awareness and incite change rapidly. Instead of beginning a campaign to encourage innovation learning by engaging directly with schools or departments of education, an actor might instead start by emphasizing a region's innovation weaknesses in the public discourse.[4] By increasing recognition of the gap, other actors may align to help solve the problem, yielding multiplicative returns on effort. In sum, eigenvector analysis shows high-yield opportunities for leveraged action within the system. While the first two elements were somewhat obvious, the third was not, demonstrating the potential usefulness of this measure to a systemic design team looking to create change in this system.

We proposed that reach measures should emphasise the phenomena that the mapped system is sensitive to; a change in high-reach phenomena will propagate to other phenomena across the system. The phenomenon "lack of emphasis on innovation skills and competencies" is ranked first by this measure. This phenomenon represents awareness-raising. Thus, the more society knows about innovation skills, the more it will consider their importance. Intuitively, this is a phenomenon that the rest of the system is sensitive to: if innovation skills are suddenly recognised in, say, public examinations, via a prolific scholarship, other phenomena in the system are likely to change to adapt. This argument extends to "innovation capacity" and "recognition of innovation skill deficiency" as well.

Finally, we suggested that reach efficiency would highlight elements that are points of efficient impact: that is, that shifts in highly reach-efficient phenomena would be observed more rapidly in other phenomena in the system than shifts in phenomena with low reach efficiency. The first two results reflect an accurate assessment of this idea. "Innovation learning from outside the public education system" should be easy to implement (systemically speaking) but have broad impact. The "lack of emphasis on innovation skills and competencies" likewise represents a phenomenon that should be easy to influence – a press campaign, for example, profiling how to practice innovation skills – and, if successful, would result in ripple effects throughout the system. The third choice, "low price of oil," is blatantly incorrect, but it is hard to fault the algorithm (the modeller simply underconceptualised the issue and failed to sufficiently model the relational complexity of oil prices). One possible approach to deal with this issue in general is to only calculate centrality leverage analysis on the elements of each level of the model (as indicated by level partitioning). This would prevent confusion by interpreting the results of these metrics based on elements with only outward connections.[5]

Discussion and conclusion

Leverage analysis presents a powerful opportunity for systemic designers to form stronger design proposals for complex system interventions as it provides a quantitative, analytical rationale for intervention decisions based on empirical observations (or at least transparently sourced data). The value is not that the methodology provides a "quantitative" analysis as such, as we are not advocating a positivist or reductive approach to independent analysis of complex systems. Qualitative, knowledgeable judgments are, in fact, required to select the appropriate nodes and data and to ascertain scores that assign values in the measures. The value for decision making is that graph modelling reveals the strengths and weaknesses in an analysis based on comparable reference models, enabling policy or advising teams to make well-supported claims for investment within change programs.

Contributions to systemic design

As a methodology adapted from "hard" systems dynamics and graph theory, leverage analysis can be introduced into qualitative and critical systems approaches as a way to examine the space for design options. Cultivating centrality and structural leverage analysis methods within systemic design accelerates a group's ability to gain insight into wicked or continuous critical problems. Conventional CLDs often fall far short of constructing effective arguments as they depend entirely on the skill of the modeller in identifying appropriate variables and drawing out critical relationships for possible action.

CLDs are customarily used to argue for a salient reinforcing dynamic interpreted as significant or problematic by stakeholders. We know from research on group decision-making dysfunctions that stakeholders acting on interests commonly manifest the *erroneous priorities effect* (Christakis & Dye, 2008), whereby individuals search and advocate for preferred outcomes rather than efficient leverage to achieve those outcomes. Erroneous priorities are resolved by using structural leverage analysis to demonstrate the higher impact of demonstrated points of leverage. Drawing on stakeholder knowledge, we can assess reachability, reach efficiency leverage, highly connected betweenness barriers or high-impact eigenvector relationships within a social system network. Leverage analysis reduces the risk of significant design-program investment as we can determine the relative contribution of impact between options.

By reframing these techniques as relevant to systemic design, we hope to motivate more researchers and practitioners to see the potential of these measures for analytically parsing complex system problems. Structural leverage analysis adds a rich dimensionality to these otherwise flat and inscrutable CLDs, while centrality leverage analysis offers a quick way of emphasising 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 for desired change in order to achieve preferred future outcomes.

On a related front, leverage measures offer a new way for systemic designers to take advantage of emerging technologies. At a big data scale, data-driven modelling would be difficult to do using conventional systemic design mapping. Leverage measures offer systemic designers modern ways to parse, reframe and restructure their models, including the "big" ones.

A side-effect of the use of leverage measures is the requirement to digitalise models. Many systemic design models and GIGAmaps are captured and presented in static form, meant to represent a comprehensive understanding of complexity but not necessarily to enable ongoing, dynamic work with the model. Leverage analysis mandates an action-oriented representation of the system, potentially enabling new representations and entrees to decision analysis in design and action research.

At the same time, these measures re-centre the purpose of models in systemic design work. At the beginning, we discussed some of the challenges of systemic design, such as the tensions between "hard" and "soft" modelling approaches and between the representativeness of simple models and the ease of generating insights from them. Conventional models are perhaps most useful in visual arguments. Presenting the complexity of a problem to stakeholders is an effective way that allows them to see their own contributions to the problem's complexity, to align decisions around a common consensus for action and to help stakeholders observe the unseen dynamics that cause the problem to persist and escalate.

To share models with stakeholders, however, we must often simplify, extract or otherwise reduce complexity in order to gain ease-of-insight, especially for model users new to systemic design logics. Leverage measures allow us to call this reductive tendency into question by emphasising the importance of the whole system and the integrity of its metadata – that is, the structure of the system used in leverage analysis. Using both leverage analytics and designerly visualisations may be the best way to stand between these core problems of systemic design and to "muddle through" their trade-offs.

The pilot study we conducted helped to refine the measures we have proposed. By running structural and centrality leverage analyses and critically examining the results in a system we are familiar with, we were able to check our earlier definitions against real-world phenomena. This resulted in some alterations; we present a final set of leverage measures below (Tables 3 and 4).

Discussion of analysis formalisms

A few centrality leverage measures seem especially important to note. 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 step that systemic design teams discuss when they move towards strategising 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. Reachability and reach efficiency are useful in demonstrating the potential speed of change in a network and the range of options or actors touched by a change proposal. Many directed graphs demonstrate path-dependency, and reach across the entire set of paths and cycles is critical in any change proposal.

The notion of leverage measures in general is an underdeveloped approach, worth further application in systemic design studies. Are there other, better ways for measuring the leverage we have in a well-bounded social system? What principles may be applied in assessing whether a given change strategy has appropriate leverage or not? Ought there to be leverage thresholds for investing in change proposals, whereby a low-leverage, "first order" policy or project might be scrutinised for its systemic effects before approval or award? This is an exciting development that deserves further exploration in design action research. Below, we briefly discuss the implications of each of the leverage measures we have translated for systemic design and summarise the measures in Tables 3 and 4.

Level partitioning
Elements at the first level of the causal hierarchy are dependent on everything else. These elements may therefore be difficult to influence deliberately, even if they have high values according to other metrics. Elements at the lowest levels are the most external. These are likely more tractable to intervention opportunities.

Cycle partitioning and the SILS
What phenomena are inseparable from which feedback loops? Used in combination with loop inclusion and further level partitioning techniques, cycle partitioning can reveal the feedback structure of the model. Core feedback loops – those contained within all of the others – are likely the most important to influence. Likewise, loop hierarchies isolated from one another may be experimented with differentially.

Degree
A high-degree phenomenon is likely to be an important signal in the system. Systemic designers may hypothesise how high-degree phenomena should change according to a given intervention and set up lead indicators to determine whether or not the intervention is having the systemic impact they thought it would. Phenomena with high indegree may be particularly useful "signal" phenomena, and the rapidity of change in these phenomena may be an indication of the system's overall volatility. High-outdegree phenomena conversely influence many others, and outdegree is therefore a rudimentary measure of potential impact or power.

Betweenness
High-betweenness phenomena are liable to be gateways for change. These bottlenecks must be accounted for in change strategies as substantial impact may be dampened by a lack of foresight or engagement with these phenomena.

Closeness
High closeness values indicate resilience or independence. High-closeness phenomena are not likely to change easily in response to events elsewhere in the system, nor will changes in these phenomena easily propagate elsewhere. These phenomena may therefore be important barriers to resolve as part of a change strategy. They are also key lag indicators of systemic change as they aggregate shifts happening elsewhere in the system.

Eigenvector
What influences the influential? Eigenvector analysis reveals high-impact phenomena. These are potentially the true leverage points in the system, as, by definition, the impact made on high-eigenvector phenomena will influence other high-impact phenomena.

Reach
The system itself is sensitive to elements with high reach values. Changes implemented in these phenomena are likely to influence the rest of the system, if shallowly.

Reach efficiency
Efficient impact. Change propagates from high-reach-efficiency elements without redundancy. It may be strategic to target several reach-efficient elements that are eccentric to one another.

Eccentricity

Eccentricity may be most valuable relative to the goal phenomena of the systemic design project. Where in the system are these goals? If goal phenomena are highly eccentric, perhaps it would be best to remodel the system with an eye for phenomena close to the goal.

Alternatively, when identifying opportunities for intervention, it may be worth taking eccentricity into account with other measures. A phenomenon that seems more powerful but is far away from the centre could be less strategic than a "weaker" one that is close to the heart of the system.

Table 3. Structural Leverage Measures and Their Use in Interpreting Systemic Design Models.

	Description	**Use in systemic design**
Level partition	Which phenomena are dependent on which?	Use level partitioning to detect the phenomena that are uncontrollable from within the system (those at the bottom of the hierarchy) and those that are highly dependent on the system (top of the hierarchy).
Cycle partition	Which other phenomena share the same set of predecessors/successors?	Use cycle partitioning to differentiate core phenomena and feedback loops from broader phenomena and feedback loops: - Sub-cycle phenomena and inner loops likely dominant the behaviour of supercycle phenomena and outer loops. - Simple loops are easier to experiment with; isolated structures are more easily manipulated without interference from the rest of the system.
Shortest independent loop set	A decomposition of the cycle partition showing which loops are included in which.	

Table 4. Centrality Leverage Measures and Their Use in Interpreting Systemic Design Models.

	Description	**Use in systemic design**
Degree	The number of connections	Changes to high-degree phenomena will translate more quickly to more phenomena; high-degree phenomena are more sensitive to changes throughout the system.
Indegree	The number of incoming connections	High-indegree phenomena receive change from many other elements; they are indicators of systemic change and representative of the system's volatility.
Outdegree	The number of outgoing connections	Changes to high-outdegree phenomena are felt by many other elements.
Betweenness	Frequency of participation in the shortest path between two other elements	High-betweenness phenomena are gateways or bottlenecks for change; change strategies must consider how to address these gateways.
Closeness	Average length of the shortest paths between the given vertex and every other vertex in the graph	High-closeness phenomena are resilient or independent, resisting change coming from elsewhere in the system; likewise, the system may resist change coming from these phenomena.
Eigenvector	Connectedness to other well-connected elements	High-eigenvector phenomena are powerful; these are good candidates for leverage across the rest of the system.
Reach	The number of elements within [x] steps of the given element	High-reach phenomena connect deeply to the rest of the system; change in these phenomena will be felt by other relatively disconnected elements.

Reach efficiency	The reach divided by the degree of a given node	High-reach-efficiency phenomena quickly and efficiently propagate change throughout the rest of the network.
Eccentricity	The distance away of the furthest node	High-eccentricity phenomena are far away from others, implying localisation of outcome or intervention; eccentricity may be used to structure and target "neighbourhoods" of phenomena that are structurally close together.

The pilot study also helped demonstrate the practical utility of leverage measures to systemic design decisions for intervention planning or change programs. These measures can provide important strategic insights for a team intent on creating change in a complex problem. For example, the following steps provide a potential approach to using these analyses in developing a high–leverage change strategy:

- Adapt network analysis and present findings from leverage analysis along with other systems research for design program decision making and for planning best-value and highest-impact interventions.
- Reformat centrality formalisms into visualisations that present the decision options for possible interventions while maintaining data-set validity for further reference.
- Conduct structural leverage analysis to detect levels, subset and superset structures and feedback loops in the system.
- Conduct centrality leverage analysis, particularly eigenvector, betweenness, closeness and reach efficiency values, for mapped phenomena.
- Find high-eigenvector phenomena at core structural locations in the system (e.g. at low levels and in inner loops). These relationships are powerful discriminators of leverage and, if they can be influenced, may yield significant change effects across the system.
- Find reach-efficient nodes (functions) that influence those high-eigenvector nodes as directly as possible. Develop strategies to change these reach-efficient functions that will lead to change in the targeted high-eigenvector nodes.
- Identify high-betweenness and high-closeness phenomena and map their potential influence on the reach-efficient and high-eigenvector phenomena identified by analysis or research. Develop a strategy to prevent these bottlenecks and resistant phenomena from impeding the planned interventions or change program.

Limitations

Clearly, these proposed metrics deserve further scrutiny beyond our pilot project. It should be possible to test hypotheses on these ideas. For instance, a modeller or a modelling team could examine a domain and develop a model and then assess it with the leverage measures. Expert reviewers could be asked questions (e.g., "Which 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, as the pilot study demonstrated, the need for interpretation is ever-present. The results of these analyses cannot be accepted without critical examination and stakeholder consultation. In other words, these techniques do not present systemic designers with the ability to craft a high-leverage change strategy at the touch of a button. 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.

Further research

A number of remaining issues deserve attention in future research.

Ontological guidelines for mapping and normalisation

The way in which models are researched and designed is not necessarily standardised. Designers, decision makers and stakeholders will hold varying mental models regarding the appropriate choices and value assignments for any social system or model. Experience and knowledge will vary, often widely, relevant to the phenomena under analysis. These issues may be alleviated with ontological guidelines (essentially, multistakeholder perspective selection) or even a defined script for guiding the selection of systemic design proposals within system models.

Guidelines for design, interpretation and use

While we have done our best to provide plain guidance on leverage measures, this format is still not ideal for practitioner consumption. Work must be done to translate these ideas into practice.

Explore additional metrics

As discussed earlier in this paper, many more metrics exist that deal with analysing 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 et al. (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 et al. (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, the Kumu algorithms can be employed 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 based on 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 emphasised by the methods presented in this paper might be even more useful when embedded in other systemic design methods, such as synthesis maps (Jones & Bowes, 2017) or Gigamaps (Sevaldson, 2011). Synthesis maps in particular build visualisations and system narratives from multiple representations and formalisms based on evidence or stakeholder data. Mapping leverage along timelines or strategic pathways would significantly increase the effectiveness of synthesis maps developed for policy and planning scenarios. Visual presentation of centrality and structural leverage analysis would also be useful in structured dialogic design (SDD). SDD (Christakis & Bausch, 2006) is a mixed-methods approach to engage high-variance, multiple-organisation stakeholders in dialogue, using software based on Warfield’s algorithms to present acyclic graphs to identity leverage within complex problem systems (Jones, 2018). SDD uses pairwise voting to form progressive structural models that display a collectively-voted influence map as a representation of the group’s decision making. Additional centrality analysis techniques have often been considered in the 50 years of dialogic design practice, and the integration of network visualisation could provide significant new value.

Systems dynamics versus 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, a divide does not 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.

Conclusion

This paper has served three objectives: to unite different analytical approaches in order to understand modelled systems, to contextualise these approaches in the discipline of systemic design and to articulate these formalisms as leverage measures in order to develop effective change strategies for complex problems. Simply by discussing the different aspects of structural and centrality leverage analysis of systems with respect to systemic design, we hope to have achieved the first and second objectives. By translating different measures from these 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 methodological contribution and effectiveness of systemic design is, nonetheless, considerable.

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References

Ackoff, R. L. (1997). Systems, messes and interactive planning. *The Societal Engagement of Social Science, 3*, 417–438.

Annie E. Casey Foundation. (2004). *Theory of change: A practical tool*. Retrieved from https://www.aecf.org/m/resourcedoc/aecf-theoryofchange-2004.pdf

Archimedes. (n.d.). In *Wikiquote*. Retrieved March 31, 2018, from https://en.wikiquote.org/wiki/Archimedes

Beck, M., Schoenenberger, L. K., & Schenker-Wicki, A. (2012). How managers can deal with complex issues: A semi-quantitative analysis method of causal loop diagrams based on matrices. SSRN Electronic Journal. doi:10.2139/ssrn.2573718

Borgatti, S. P. (2005). Centrality and network flow. *Social Networks*, *27*(1), 55–71. https://doi.org/10.1016/j.socnet.2004.11.008

Box, G. E. P. (1976). Science and statistics. *Journal of the American Statistical Association*, *71*(356), 791–799. https://doi.org/10.2307/2286841

Carrington, P. J., & Scott, J. (Eds.). (2011). Introduction. In *The SAGE handbook of social network analysis* (pp. 1–8). London: Sage.

Checkland, P. (1985). From optimizing to learning: A development of systems thinking for the 1990s. *The Journal of the Operational Research Society*, *36*(9), 757–767. https://doi.org/10.2307/2582164

Christakis, A. N., & Bausch, K. C. (2006). *How people harness their collective wisdom and power to construct the future in co-laboratories of democracy*. Greenwich, CN: Information Age.

Christakis, A. N., & Dye, K. C. M. (2008). The Cogniscope: Lessons learned in the arena. In P. M. Jenlink & B. H. Banathy (Eds.), *Dialogue as a collective means of design conversation* (pp. 187-203). New York: Springer.

Duggan, J., & Oliva, R. (2013). Methods for identifying structural dominance. *System Dynamics Review, 29*. Retrieved from https://ssrn.com/abstract=2892735

Emery, F. E., & Trist, E. L. (1960). Socio-technical systems. In C.W. Churchman & M. Verhurst (Eds), *Management science, models and techniques* (Vol. 2, pp. 83–97). London: Pergamon Press.

Fagan, L. P. (1995). Performance accountability in the Newfoundland school system. *Canadian Journal of Education/Revue canadienne de l'éducation*, *20*(1), 65-76.

Fitz, R., & Troha, J. (1977). Interpretive structural modeling and urban planning. *Proceedings of the International Conference on Cybernetics and Society*, *USA*, 297-302.

Forrester, J. W. (1971). Counterintuitive behavior of social systems. *Technological Forecasting and Social Change, 3*, 1–22.

Forrester, J. W. (1994). System dynamics, systems thinking, and soft OR. *System Dynamics Review*, *10*(2–3), 245–256. Retrieved from http://onlinelibrary.wiley.com/doi/10.1002/sdr.4260100211/abstract

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, *40*(1), 35–41. https://doi.org/10.2307/3033543

Freeman, L. C. (1979). Centrality in social networks conceptual clarification. *Social Networks*, *1*(3), 215–239.

Gharajedaghi, J. (2011). *Systems thinking: Managing chaos and complexity: A platform for designing business architecture* (3rd ed). Burlington, MA: Morgan Kaufmann.

Hanneman, R. A., & Riddle, M. (2005). Ego networks. In *Introduction to social network methods*. Riverside, CA: University of California, Riverside. Retrieved from http://faculty.ucr.edu/~hanneman/nettext/C9_Ego_networks.html

Jones, P. H. (2014). Systemic Design Principles for Complex Social Systems. In G. S. Metcalf (Ed.), *Social Systems and Design* (pp. 91–128). Japan: Springer. https://doi.org/10.1007/978-4-431-544784_4

Jones, P. H. (2018). Contexts of co-creation: Designing with system stakeholders. In P. Jones and K. Kijima (Eds.), *Systemic Design: Theory, Methods and Practice*, *8*, 3-52. Tokyo, Japan: Springer.

Jones, P. H., & Bowes, J. (2017). Rendering systems visible for design: Synthesis maps as constructivist design narratives. *She Ji: The Journal of Design, Economics, and Innovation, 3*(3), 229–248.

Kampmann, C. E. (1996). Feedback loop gains and system behavior. *System Dynamics Review, 28*(4), 370-395. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1002/sdr.1483

Kampmann, C. E., & Oliva, R. (2006). Loop eigenvalue elasticity analysis: Three case studies. *System Dynamics Review (Wiley)*, *22*(2), 141–162. https://doi.org/10.1002/sdr.333

Kampmann, C. E., & Oliva, R. (2008). Structural dominance analysis and theory building in system dynamics. *Systems Research & Behavioral Science*, *25*(4), 505–519. https://doi.org/10.1002/sres.909

Le Blanc, D. (2015). Towards integration at last? The sustainable development goals as a network of targets. *Sustainable Development*, *23*(3), 176–187.

Lukyanenko, R., & Parsons, J. (2012). Conceptual modeling principles for crowdsourcing. *Proceedings of the 1st International Workshop on Multimodal Crowd Sensing*, November 2012, 3–6. https://doi.org/10.1145/2390034.2390038

Maass, W., Parsons, J., Purao, S., Storey, V. C., & Woo, C. (2018). Data-driven meets theory-driven research in the era of big data: Opportunities and challenges for information systems research. *Journal of the Association for Information Systems*, *19*(12), 1253–1273. https://doi.org/10.17705/1jais.00526

Meadows, D. (1997). Leverage points: Places to intervene in a system. *Whole Earth, 91*(1), 78–84.

Mitroff, I. I., Mason, R. O., & Barabba, V. P. (1982). Policy as argument – A logic for ill-structured decision problems. *Management Science, 28*(12), 1391–1404.

Mohr, J. (2016, September 2). A toolkit for mapping relationships among the Sustainable Development Goals (SDGs). Retrieved January 20, 2018, from https://blog.kumu.io/a-toolkit-for-mapping-relationships-among-the-sustainable-development-goals-sdgs-a21b76d4dda0

Murphy, R. J. A. (2016). *Innovation Education* (MRP). OCAD University, Toronto, ON. Retrieved from http://openresearch.ocadu.ca/id/eprint/1344/

Newman, M. (2010). *Networks: An introduction*. Oxford, UK: Oxford University Press.

Norman, D. A., & Stappers, P. J. (2015). DesignX: Complex sociotechnical systems. *She Ji: The Journal of Design, Economics, and Innovation*, *1*(2), 83–106. https://doi.org/10.1016/j.sheji.2016.01.002

Oliva, R. (2003). Model calibration as a testing strategy for system dynamics models. *European Journal of Operational Research*, *151*(3), 552–568. https://doi.org/10.1016/S0377-2217(02)00622-7

Oliva, R. (2004). Model structure analysis through graph theory: Partition heuristics and feedback structure decomposition. *System Dynamics Review*, *20*(4), 313–336. https://doi.org/10.1002/sdr.298

Oliva, R. (2018). Formalization of model partition heuristics through graph theory. *System Dynamics Society*. Retrieved August 5, 2019, from https://www.systemdynamics.org/assets/conferences/2001/papers/Oliva_1.pdf

Özbekhan, H. (1969). *Toward a general theory of planning*. Philadelphia, PA: University of Pennsylvania.

Özbekhan, H. (1970). *The predicament of mankind: A quest for structured responses to growing world-wide complexities and uncertainties* (Original proposal to the Club of Rome). Geneva, Switzerland: The Club of Rome. Retrieved from http://quergeist.net/Christakis/predicament.pdf

Potts, M., Sartor, P., Johnson, A., & Bullock, S. (2017). Hidden structures: Using graph theory to explore complex system of systems architectures. *International Conference on Complex Systems Design & Management*, December 2017. Retrieved from https://seis.bristol.ac.uk/~sb15704/papers/CSDM_2017.pdf

Provost, F., & Fawcett, T. (2013). *Data science for business*. Sebastopol, USA: O'Reilly Media.

Rahman, R., Herbst, K., & Scheu, T. (2016). What is a changemaker? Retrieved August 4, 2016, from https://www.fastcompany.com/3062483/what-is-a-changemaker

Rittel, H. W., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences*, *4*(2), 155–169. Retrieved from http://link.springer.com/article/10.1007/BF01405730

Rossi, M., & Brinkkemper, S. (1996). Complexity metrics for systems development methods and techniques. *Information Systems*, *21*(2), 209–227.

Ruohonen, K. (2013). *Graph theory* (J. Tamminen, K.-C. Lee, & R. Piché, Trans.). Retrieved from http://math.tut.fi/~ruohonen/GT_English.pdf

Saleh, M., Oliva, R., Kampmann, C. E., & Davidsen, P. I. (2010). A comprehensive analytical approach for policy analysis of system dynamics models. *European Journal of Operational Research*, *203*(3), 673–683. https://doi.org/10.1016/j.ejor.2009.09.016

Schoenenberger, L., Schenker-Wicki, A., & Beck, M. (2014). Analysing terrorism from a systems thinking perspective. *Perspectives on Terrorism*, *8*(1). Retrieved from http://www.terrorismanalysts.com/pt/index.php/pot/article/view/323

Schoenenberger, L., Schmid, A., & Schwaninger, M. (2015). Towards the algorithmic detection of archetypal structures in system dynamics. *System Dynamics Review*, *31*(1/2), 66–85. https://doi.org/10.1002/sdr.1526

Sevaldson, B. (2011). GIGA-Mapping: Visualisation for complexity and systems thinking in design. *Nordes*, *0*(4). Retrieved from http://nordes.org/opj/index.php/n13/article/view/104

Simon, H. A. (1996). *The sciences of the artificial* (3rd ed.). Cambridge, MA: MIT Press.

Sterman, J. D. (2009). *Business dynamics: Systems thinking and modeling for a complex world*. Boston: Irwin/McGraw-Hill.

Stroh, D. P. (2015). *Systems thinking for social change: A practical guide to solving complex problems, avoiding unintended consequences, and achieving lasting results*. Chelsea, VT: Chelsea Green Publishing.

Tzetzes, J., & Kiessling, G. (1826). *Chiliades [Thousands]*. Lipsiae: F.C.G. Vogel.

Warfield, J. N. (1974). *Structuring complex systems*. Columbus, OH: Battelle Memorial Institute.

Warfield, J. N. (1989). *Societal systems: Planning, policy, and complexity*. New York: Wiley.

Warfield, J. N. (2001). *Measuring complexity*. Fairfax, VA: Integrative Sciences.

Xie, J., Szymanski, B. K., & Liu, X. (2011). SLPA: Uncovering overlapping communities in social networks via a speaker-listener interaction dynamic process. *ArXiv:1109.5720 [Physics]*. Retrieved from http://arxiv.org/abs/1109.5720

Notes

[1] For some attempts at calculating where Archimedes would have needed to stand, see the following discussion on Reddit: https://www.reddit.com/r/theydidthemath/comments/3zvuap/request_archimedes_once_said_give_me_a_place_to/

[2] Özbekhan's prospectus to the Club of Rome, *The Predicament of Mankind*, was the basis for later proposals, even though his proposal was rejected. Instead, Meadows et al.'s world model analysis was accepted by the Club of Rome, which resulted in the well-known *Limits to Growth*.

[3] The CLD developed and analysed in this study can be found and interacted with online at https://kumu.io/systemicdesign/centrality-and-structural-analysis

[4] Interestingly, this is the effect of the University of Toronto Impact Centre's *Narwhal Report*, which provides year-over-year comparisons of Canadian start-up business successes (https://www.impactcentre.ca/narwhal/).

[5] We thank Dr. W. Kubiak for this suggestion.