

PART V

MULTI-LEVEL NETWORKS

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As Johnson, Fortune and Bromley state in their chapter “Almost all social systems have many levels of organization, from micro to macro levels, and multi-level structure is fundamental to their dynamics. Part-whole structures play a major role in multi-level systems, where intermediate wholes may themselves be parts in higher level structures.”

But what is really meant here by ‘multi-level’? Patrick Beutement defines it in broad terms in Chapter 20 (Employment of Tools and Models Appropriate to Complex, Real-world Situations). He says that these levels are certainly *not* hierarchies of homogenous entities in a reductionist breakdown (as in parts of a machine where subsystems and sub-subsystems have fixed and predictable properties and relationships), nor even fractal self-similarities.

Instead, he draws on Cohen and Stewart’s view¹ that these multi-levels of networks are so dissimilar that phenomena, information and activities at one level may have little meaning or equivalence at another. The reason for this is that the emergent properties of one level can be the influences on another level and as such, those emergent properties are hidden from the level that generates them.

Indeed, even the term ‘level’ is misleading as it implies hierarchy. For example, take the nervous, endocrine, immune and autonomic systems of mammals. They are distinct and operate concurrently within the bodies of creatures yet no one of them is at the top or the bottom, nor are they bounded and disjoint, there is overlap and inter-twingling of functionality throughout.

To address these, Beutement’s chapter first provides a model of practice, and a framework for judging appropriateness of tools based on that model (with three examples of the framework in use). The chapter then offers a critique of two sets of example tools: examining the applicability of autonomous agents and multi-agent systems to a range of situations; and explaining how to employ multi-modal, multi-level influence networks to bring about ongoing change. Finally, the chapter presents a list of principles of practice, drawn from experience in the field, to be used to inform real-world decision- and policymaking. Beutement asserts that, to employ the multi-level networks approach in analysis, modelling or as a practical tool, one must take account of the fact that they:

- *Are made up of a number of heterogeneous network structures* each of which have distinct characteristics (not defined by humans) and that function differently;

- *Exist at many different scales and rates* – from micro to macro (such as from the virus to human societies), and over timescales from the immediate to the geological;
- *Are inter-dependent, yet loosely coupled, and interact via a variety of modes* (for example, using chemical or electrical signalling; by passing information in a number of forms; or through exchanging resources or by modifying the environment, as in stigmergy);
- *Have modes of interaction that are not homogenous* between all networks. Instead, there is a ‘soup’ of signalling in which they exist from which networks use the modes which are appropriate to their scale and function (and all other modes are ignored or are transparent);
- *Have effects and influences which extend and may cascade beyond the immediate bounds* of the networks’ structures and may occur ‘up’, ‘down’ or ‘sideways’. For example, the firing of synapses in the brain releases neurotransmitters (hormones) which may affect other organs, the whole body or even social behaviours beyond the person’s body – such as the reaction to a shock making the person feel ill and anxious and so causing concern for relatives;
- *Have transitions between the networks which can be emergent* in that activity within one network may generate emergent phenomena which may be inputs to other networks (for example, the processes within the mitochondria in cells are driven in a manner which seems largely decoupled from the activities of the whole organism – yet there *are* cross-network influences, even though the mitochondria will not be ‘aware’ of their source²);
- *Exchange information, much of which will be unknowable or unobservable* by human beings and/or our sensing devices, partly owing to the vast range of types of ‘information’;
- *They exist regardless of whether or not humans can detect them.* It is not relevant to their functioning whether or not we can identify and label the network structures, their nature, bounds or influences – indeed, science tries to find those bounds and categorize them.

This implies that, for real-world applications, research methods and tools should at least consider these characteristics of multi-level networks – though, in practice, this list is very exacting and demanding. In Johnson, Fortune and Bromley’s chapter (Multilevel Systems and Policy) they take a pragmatic approach and present a simple tool for bounding what might otherwise be an unmanageable research task.

Johnson et al. indicate that anything that impacts on what is of particular interest will be included in the representation of the system and its environment. Thus:

- Anything the system can control directly is inside the system;
- Anything else that affects the system or its elements but cannot be controlled by the system is in the system environment;
- Everything else is outside the representation of the system.

Johnson et al. then develop the defined ‘system’ through taxonomic aggregation techniques. These are of the form of reductionist decompositions – an approach which would be at odds with Érdi³ who would claim that there still remains the issue of bound-

ing the depth of decomposition that is appropriate – which Johnson et al. then address. For example, in a health system, can one stop at the patient? What about the role of the epidemic that is bringing the patient to the doctor's door (and of bacteria that caused it)? Cohen and Stewart would also point out that each subsystem is itself distinct and bounded without any ambiguous blurring. The tool to apply here is, of course, expert judgement which can be the final arbiter of whether an item is included or not.

As any system is dynamic (even a dead one is decaying), Johnson et al. then examine the traffic through the system using the taxonomy as a backdrop. This technique enables the researcher to begin to identify patterns of, for example, conflict in the use of resources, or overloads, blockers or enablers. Dynamic phenomena, such as beneficial or damaging oscillations may also be evident.

However, even within these bounds, if results are to be valid and insights relevant to practice there is a but, and it is a big but . . . how to obtain suitable data which spans these heterogeneous multi-levels of networks for use in research work.⁴ This is a significant issue. Is the data needed observable, detectable and meaningful – is its significance something that we can even begin to appreciate? Johnson et al. attack this issue, showing the value of using micro-data from synthetic micropopulations which, within the context of the system under investigation, can be derived from detailed models.

Finally, a rich model of multi-level systems is developed based on a Formal System Model (the FSM)⁵ and Johnson et al. use this to analyse one aspect of the current crisis in the United Kingdom's National Health Service – that of a resource clash between emergency and social care. The analysis shows clearly that the mismatch between the responsibilities and scope of authority of both systems generates mal-adapted behaviour – one symptom of which is patients unable to be admitted to hospital wards. Finally, they recommend that agent-based modelling be employed to explore alternative arrangements which could inform policy.

In Palit, Banerjee and Mukherjee's chapter (Complex Scenarios in Socio-Economic Data: A Comprehensive Analytical study), they start by stating that "Complex systems are those which are composed of many particles, or objects, or elements of same or different kinds. The elements may interact with each other in a more or less complicated manner by various nonlinear couplings. The global human society, especially the economy, with its numerous participants – managers, employers and consumers, its financial systems, its capital goods, its natural resources, and its traffic probably form the most complex system in our world."

They go on to show that, when comparing countries, their GDP (Gross Domestic Product) and population dynamics are key indicators. To analyse these, the team employed three nonlinear tools: recurrence rate, mean conditional recurrence (MCR), and complex networks (CN). These analyze country level GDP and population data, and have successfully validated the derived results with the standard conclusions based on general theories of economics as follows:

- Recurrence rate is used to show how two non-identical systems get synchronized through their phase spaces;
- MCR detects the driver and response system in synchronized states; and
- CN reflects the overall scenarios of the complex systems by its various statistical measures.

To address the challenge of obtaining relevant data (mentioned above), the whole data are collected from a data centre in NASA's Earth Observing System Data and Information System hosted at Columbia University and are downscaled projected based on Special Report on Emissions Scenarios (SRES).

An important part of Palit et al.'s chapter is clarifying the nature of the types of synchronization that can occur between non-identical systems at different levels. This clarity is necessary as it determines the complex influences that the systems may have on each other. They cite three important ones: Complete Synchronization (CS), Generalized Synchronization (GS) and Phase Synchronization (PS). Obviously though, if there is no direct synchronization there will be little effect – though influence may still manifest itself through intermediate, indirect or underlying routes. In the chapter, the synchronization tools have been applied in a number of ways, such as to analyze the worldwide population data so as to verify whether the population data of a particular year is synchronized with that of the previous years.

As part of Palit et al.'s analysis the nature of the phase space and how it is reconstructed is examined in detail. A number of nonlinear tools are described and a food web example is employed to show their utility. In addition, measures such as bifurcation and sensitivity analysis are discussed. Palit et al. then raise an important issue: “constructing a proper model for a complex phenomenon and observing their nonlinear behaviour is one of the efficient ways to predict the long term dynamics of the system. However, if the parameters and variables of the system are not properly taken, [the] mathematical model does not reflect the real scenario”. One might add that, at the limit, Gödel's Incompleteness Theorem⁶ may make the model misleading unless expert judgement is applied.

To address this they cite the 'Takens Model' which is used to construct attractor spaces which are topologically equivalent to given attractors. They then go on to describe how to construct a recurrence plot and to show how these are used to develop phase synchronization indicators. Between countries, these form networks of influences and socio-economic GDP networks are then analysed in the chapter.

Following this, standard network analysis tools (such as degree distribution) are employed to derive an important insight – that the GDP network is scale free and so there are huge differences between the GDP characteristics of countries across the globe. These GDP networks are then further analysed for their: small-world properties (which shows that they are a small world); transitivity or clustering (which indicates a recent reduction in the tendency to form cliques); assortativity (where it is shown that there are mixed types of association); and centrality (which shows that high GDP countries tend to be involved with low-GDP countries).

In conclusion, Palit et al. summarize the value of using the analysis tools associated with complex multi-level networks to investigate real-world issues – in this case of economic and population data. The results are striking and insightful and are an excellent case study of what can be achieved by using the tools of complexity science in an appropriate way.

The last chapter in this Multi-Level Networks Section of the Handbook is from Michael Gabbay. His chapter (Leadership Network Structure and Influence Dynamics) describes a quantitative methodology for the analysis and modelling of leadership networks which leverages research in complex systems, in particular nonlinear dynamical systems theory and network science. A prototype software package, PORTEND, is introduced which implements the methodology using data from expert analysts in order

to help assess policy and factional outcomes with respect to the internal dynamics of a system of political actors.

Gabbay starts by highlighting the importance of being able to understand, if one is going to negotiate effectively with them, the dynamics of leadership groups and of their networks of allegiances and inter-dependencies.

He then introduces a software package called PORTEND (Political Outcomes Research Tool for Elite Network Dynamics). This integrates quantitative techniques from nonlinear systems theory and network science to aid the analysis of policy and factional outcomes with respect to the internal dynamics of a system of political actors. The political actors may be individual leaders or organizations within a government or movement. The outcomes of concern may be policy decisions, winning and losing factions, the positions of individuals, or the potential for issues to cause dissension or factional realignment.⁷

His case study involves Iran and he obtains relevant data⁸ from a survey of two experts in Iranian matters. They not only gave information about the characteristics of fifteen leaders but also provided data under the following headings:

- Liberalism (LIB): The proper role for Western culture, Islam, media sources, and democratic institutions.
- Economic Reform (ECON): Whether economic policies should benefit the current elites or a wider set of interests.
- Arab States (ARAB): Whether Iran's peers in the Arab world are potential allies or enemies.
- Syrian Regime (SYR): Whether the Assad regime in Syria should be supported.
- US/Israel (USISR): The extent to which Iran should confront the US and Israel.
- Nuclear Issues (NUKE): The extent to which Iran should develop nuclear technology.
- IRGC Influence (IRGC): The appropriate role for the Islamic Revolutionary Guard Corps (IRGC).

As part of this analysis the experts generated an influence network indicating the nature and strength of connections between the various actors selected. From this and the other data collected it was possible to generate a matrix of the range of attitudes to a topic for each actor. Plots of these opinions of graphs showed various degrees of clustering of opinions from which one could infer that certain actors were aligned in their opinions (which might indicate which actors would be compatible within coalitions on that matter). Further analysis was applied using Principal Components Analysis (PCA) which seeks to represent a data matrix by a series of coordinate vectors, known as principal components (PCs), each of which corresponds to a pattern of covariation in the data. PORTEND then applies a network analysis tool and displays the results in the visualizations shown in Gabbay's chapter.

He then describes the Nonlinear Social Influence Simulation built into the tool. In the model, an actor's position changes under the influence of two separate forces: the 'self-bias force' and the 'group influence force'. For example, for self-bias force, each actor is assumed to come to the debate with an initial issue position given by his natural preference (also called the natural bias) which reflects the actor's underlying beliefs, attitudes, and worldview pertinent to the issue. The group influence force is the total force acting to

change an actor's position due to the persuasive efforts of the other actors in the group. It is assumed to operate in a pairwise manner so that an actor – the message receiver – experiences a persuasive 'coupling force' from another actor – the message sender – to whom he is connected (and vice versa). The results of the simulation in respect to one actor are described in detail.

Gabbay completes his chapter by discussing possible further research. One area could involve the investigation of whether automated content analysis of actor rhetoric could be a viable input source for either the structural analysis or the simulation. Another area could be extending the social influence model to a multidimensional issue space in order to allow issues to trade off against each other. Additionally, complexity research on adaptive networks could be used to develop an issue-network coevolution model in which both issue positions and network ties would interact and change dynamically, thereby explicitly modelling alliance formation processes, a capability not present in the current model.

In summary, the chapters in this Multi-Level Networks Section of the Handbook provide pragmatic examples of the use of such networks as an analytical approach. The Section:

- Defines the nature and characteristics of multi-level networks.
- Illustrates the range of tools and techniques that are available to represent different areas of real-world phenomena, to analyse them and support decision-making.
- Examines some of the issues which could inhibit the use of the approach (such as the need for relevant data) and offers solutions and insights.
- Provides a number of 'industrial weight' case studies to illustrate that this approach has real relevance to policy makers and those seeking to tackle real-world global challenges.

NOTES

1. Cohen, J. and Stewart, I. (2000) *The Collapse of Chaos. Discovering Simplicity in a Complex World*, London: Penguin Books.
2. See Lane, N. (2005) *Power, Sex, Suicide: Mitochondria and the Meaning of Life*, Oxford: Oxford University Press, and especially the work by Dr Peter Mitchell on 'proton pumping' cited in this book.
3. Erdi, P. (2008) *Complexity Explained*, pp.328–351, Berlin: Springer-Verlag.
4. As Dr Robert Myers said in the panel discussion (on the Complexity of Global Change) at ECCS Complex'09 "... there is no shortage of irrelevant data, but a serious lack of relevant information" (see: http://www2.warwick.ac.uk/fac/cross_fac/complexity/newsandevents/events/archive/2009/eccs09/publicsession, accessed 13 August 2017).
5. Readers may wish to compare the FSM with Stafford Beer's Viable Systems Model (VSM), for example, at: https://en.wikipedia.org/wiki/Viable_system_model, which places emphasis on viability within the wider environment and therefore on the adaptive and self-regulatory capabilities of the parts of the system.
6. For a detailed discussion of the Incompleteness Theorem see Hofstadter, D.R. (1983) *Gödel, Escher, Bach: an Eternal Golden Braid*, London: Penguin Books.
7. A related technique is by Howard, N., Bennett, P. and Bryant, J. (2001) 'Drama Theory and Confrontation Analysis'. In Rosenhead J.V. and Mingers J. (eds), *Rational Analysis for a Problematic World Revisited: Problem Structuring Methods for Complexity, Uncertainty and Conflict*, London: Wiley. Also see so-called 'Ripeness Theory', Zartman, I. William (2002) *Power and Negotiation* (edited by I. William Zartman and Jeffrey Z. Rubin), Ann Arbor: University of Michigan Press.
8. Readers may wish to consider how the validity of such data (and hence of the outputs of a model) can be established given that the publicly stated and privately held views of all of us are usually different.