Explanatory frameworks in complex change and resilience system modelling

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Abstract

Heterogenous flows across system boundaries continue to pose significant problems for efficient resource allocation especially with respect to long term strategic planning and immediate problems about allocation to address particular resource shortages. The approach taken here to modelling such flows is an engineering change prediction one. This enables margin modelling by producing system models in dependency matrices with different linkage types. Change prediction approaches from engineering design can analyse where these bottlenecks in integrated systems would be so that resources can be deployed flexibility to avoid them and address them when they occur. Current state of the art of margin research can be furthered by identifying margins on multiple levels of system composition. It can usefully be complemented by a category theory based approach which allows representation of variable and constant properties of models under changing conditions, and the identification of flows within models. Category theory is useful for formalising such explanatory frameworks as it can both structure systems and permit analysis of their applications in a complementary way.

Keywords: Category theory, complex systems, explanations, heterogenous, modelling.

1. Explanatory frameworks

Many systems are inherently complex so they must be modelled by complex system models. The models of complex systems are frequently heterogeneous with modelling involving both relationships between various sub-models in larger system models and how models at different levels relate to reality. The modelling of complex systems requires explanatory frameworks to complement formal modelling if such models are to be fully illuminating. The notion of an explanatory framework used here is that of having a general type of framework, which includes and structures the individual explanations of the various parts of a complex system so that they have a high degree of conceptual cohesion. Since explanations are context dependent and interest relative [28] they may include narratives and providing a stipulative definition of what an explanation is would not be appropriate or useful Such explanatory frameworks can broadly be either causal, intentional or teleological or a mixture of these types and within these broad types that these frameworks can take a wide variety of forms. The emphasis here is on the explanatory adequacy of such frameworks in relation to the kinds

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of explanations which are sought in particular cases. It follows that there may not be and indeed need not be a single correct explanatory framework. This paper represents a category theoretical explanation of a highly complex system which is resource allocation in a hospital in the UK National Health Service (NHS). This illustrates the benefits of enabling a flexible modelling approach when it is combines with the mathematically rigorous approach like categories.

Traditionally much of the work on explanatory frameworks for models has been in the philosophy of science literature [26]. Historically, twentieth century philosophy of science was heavily focused on the philosophy of physics. A consequence of this was the causal explanations which dominate physics led to a widespread assumption that causal explanations are paradigmatic ones which should be aspired to. Although in the last forty years or so the philosophy of science has widened its focus from philosophy of physics to serious engagement with the philosophies of biology and cognitive science much of it still either explicitly or implicitly regards explanations of the kind favoured by physics as paradigmatic. Contemporary philosophy of science has increasingly but not fully recognized the increasing diversity and interdisciplinary of current scientific practice with the possible exception of climate and environmental science. However, it has neglected the increasing importance of engineering within science both in terms of ways of thinking about problems and actual scientific practice. This is in itself would not be a problem if this gap in philosophy of science had been filled by philosophy of engineering but to date this has not been substantially the case. Partly due to the success of philosophy of science and the typical disciplinary backgrounds which many philosophers of science have far fewer philosophers have with the challenging of modelling large-scale complex socio-technical systems, which require insight from many different fields including engineering. Of particular relevance here is that the philosophy of modelling systems falls between the philosophies of logic, science and technology belonging partly but not wholly to each of them.

From the perspective of understanding the complex socio-technical systems which are prevalent in engineering the emphasis in contemporary philosophy of science upon explicitly or implicitly regarding explanations of the kind favoured by physics as paradigmatic is both limiting and reductive (see for instance [20]). Crucially complex socio-technical systems are heterogeneous and thus cannot be modelled by a single approach. Instead, different modelling approaches are required for different parts of the system. Such differences in modelling approaches reflects the aspect of model construction that initial subtle variations in perceptions about how best to describe particular systems may result in the final models of these systems being substantially divergent. These variations in perception are a fundamental element of human cognition and at least partially stem from differences in the kinds of expertise possessed. Any adequate epistemological account of modelling has to offer a way of addressing such divergences and potentially incommensurability. One possible way of developing the theory of these systems is through the integrative pluralism approach to multi-scale and multi-formalism sciences in the philosophy of science [23]. Difficulties about model divergence are compounded by the tendency of philosophers to use toy models to make philosophical points. Such an approach gains in conceptual clarity at the expense of considering models which are robust and reliable enough to be scaled up in practice.

Where this problem is particularly acute is in the description and characterization of the behavour of heterogeneous complex systems, where models are frequently reused or adapted to new contexts to reduce the modelling effort. An important aspect of this is the ability to characterize perturbations in models of this kind in robust and reliable ways. Toy models coupled with a focus on causal explanations of physical phenomena do not provide sufficient information to enable this scaling up. As a consequence of these difficulties there are significant gaps and limitations in the current philosophy of science literature about complex heterogeneous system modelling. What is needed is a more philosophically satisfactory explanatory framework for the modelling, description and analysis of such systems. It will be argued that applied category theory provide just such an explanatory framework. A core reason for this is that effective analysis of heterogeneous complex system models requires a robust and reliable process for bringing various models together in ways that enable comparative analysis with applied category theory supplying the tools to perform such integration.

Category theory is mathematically rigorous and thus epistemological constructions correctly built upon it are theoretically rigorous. However, understanding category theory requires some background in algebra and topology with the result that it is not always immediately accessible to all modellers so decisions about the optimal amounts to use can be complicated in practice. Modelling heterogeneous complex systems usually aims to improve overall system efficiency than locally optimizing different parts of the system. The practical need to understand, analyze and improve raises the issue of whether heterogeneous complex systems should be adequately modelled in their full generality and richness using category theory with the attendant complications this brings or whether a simpler and less detailed model would produce greater practical benefits. At present (and for the foreseeable future) it is hard to offer a definitive view on this issue but as will be seen there are a number of heuristics which offer insight into how best to employ category theory.

2. Complex systems

Before considering how complex systems can be modelled it is worth addressing how complexity is conceptualized which has a profound effect on how it can be modelled. Complexity is typically viewed from to different angles: structural complexity, addressing the parts of a system and the connection between them and dynamic complexity of behavior. Simon [31] argues that complex systems are almost decomposable, they can be described in a hierarchical way without fully decomposing into separate parts and therefore the descriptions of complex systems form lattice structures rather than tree structures. The dynamic behavior of complex system is played out on the backcloth of the underlying structural complexity [17]. Approaches such as axiomatic design aim to reduce complexity by reducing the connectivity between parts and the uncertainty associated with processes, for example by introducing an element of periodicity, that is, the periodic resetting of a state [32]. The connectivity between elements is often modeled as dependency structure matrices [12]. An information content or entropy view of complexity takes both the underlaying structure and the uncertainty of dynamic effects into account [16] whereas a notion of a chaotic system focuses on unpredictability [1]. Many complex systems, like the hospital system which is discussed later as an exemplar model, are adaptive systems where the environment of the dynamic system coevolve together [18]. On a short time scale it therefore makes sense to think of a backcloths as a static while on the longer terms both its elements and their connections change [10].

3. Modelling complex systems

Simon states that a complex system is “one made up of a large number of parts that interact in a nonsimple way. In such systems, the whole is more than the sum of the parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole” [30, p.468]. His remark nicely highlights the point that as complex systems are not fully decomposable elements of the system can be part of multiple subsystems. This property of potentially being part of multiple subsystems makes complex systems inherently difficult to model, as decisions have to be taken whether an element is assigned to one or multiple subsystems which in turn profoundly affects the analysis of any model of a complex system.

Before analysing in more detail how flows can be modelled in heterogeneous complex systems it is necessary to step back and look at the nature of modelling itself. It has taken the philosophy of science a surprisingly long time to recognize the importance of models in the scientific process. Models fulfil various different aims [10] however there is a degree of consensus of that models in science are representation of a target system: either a theory, a set of data or a phenomenon. Morgan and Morrison [24] see "models as mediators", where models are autonomous agents in that "(1) [they] function in a way that is partially independent of theory and (2) in many cases they are constructed with a minimal reliance on high level theory" [24, p.43]. Formal notions of isomorphism, partial isomorphism, homomorphism, or other mathematical mappings have been suggested as well as less formal types of similarity such as analogies, similes, or resemblances [27]. In what Toon [33] calls the indirect view of representation the direction of fit is that the target is represented by the model which in turn is specified by the model description. This is different to the direction of fit of models in engineering systems which are brought into being by models and where models typically act as decision making aids [8]. Models are abstraction of reality created for particular purposes and therefore inevitably simplify reality. Scientists are aware that models are simplifications and can often be wrong in significant ways whilst still being useful. Frigg [14] and Toon [33] therefore argue that models can be seen as fictions where all participants play games of make believe inspired by Walton's theory of make believe [35].

4. Heterogeneous flows in system modelling

Conventional modelling and simulation have made huge progress in improving flows for particular conditions. However heterogenous flows across complex system boundaries continues to pose significant problems for efficient resource allocation especially with respect to long term strategic planning and immediate problems about allocation to address particular resource shortages. The approach taken here to modelling such flows is an engineering change prediction one which focuses on systems thinking, systems modelling and margins. Here margins for a nominal unit are understood as the difference between capacity and current need (see Fig. 1).

This approach enables margin modelling by producing system models in dependency matrices with different linkage types [6 and 9]. Figure 2 shows an example of the change propagation model from engineering design applied to modelling the risk from COVID spreading between different government departments. This model is based on a Design Structure Matrix [5 and 7], which indices connection between elements in a matrix with identical row and columns. In Fig. 2 the connection is risk, as the product of likelihood and impact, but interpretation of the connection depends on the context and is thus subject to divergent interpretations of the creator and users of these matrices. Multiple analysis algorithms exist [5] and the Design Structure Matrix can provide straightforward visual impressions of clusters [19].

The modelling and analysis of heterogenous flows raises a number of major issues. A fundamental one is about what appropriate explanatory frameworks there are and how these can be identified. How systems identified as critical are used and the methods employed to alleviate pressure on them is also crucial (particularly in safety critical contexts). Critical flows and links plus which of these need to be considered under what conditions is central to generating models which illuminate aspects of complex system operation. Modelling change propagation is essential for understanding

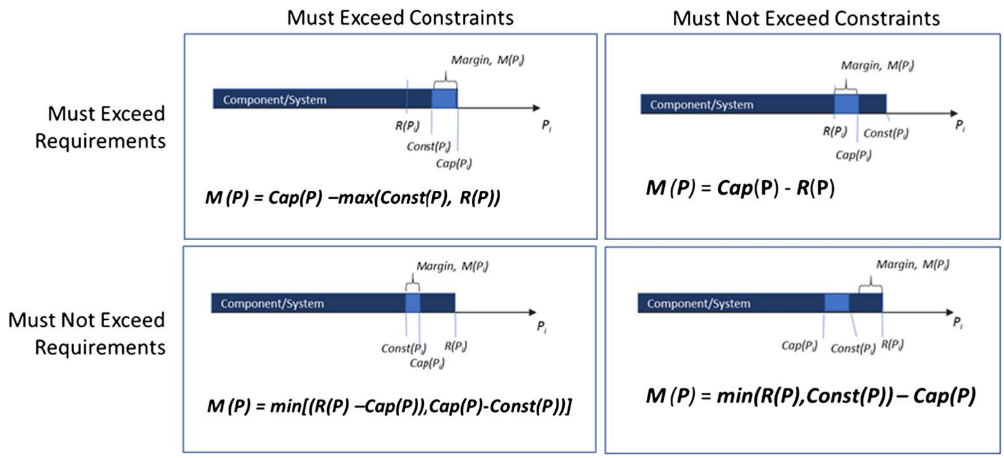

FIGURE 1. Margins as the difference with capability (CAP) or constraints (Const) and requirements (R) from [11].

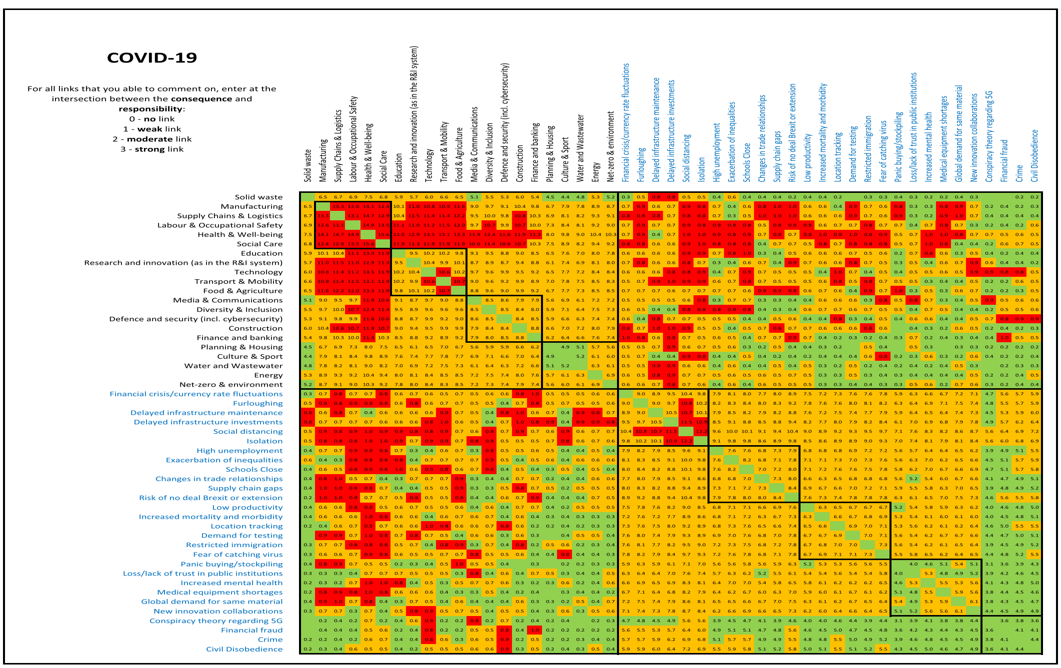

FIGURE 2. Example of a change prediction matrix applied to modelling the connectivity between areas of government linked by common consequences during the COVID pandemic from [6].

the modelling and analysis of heterogenous flows. A frequent motivation for modelling complex systems is to aid decision making so how the state of the system can be used to aid decision making also requires modelling and analysis.

An explanatory framework for a complex modelling should address the question of the difference between what it means to say that a change or outcome is possible and that it is probable. Such an account should be combined with an account of probability which is preferred (such as degrees of subjective belief, a relative frequency interpretation and so on) which is favoured for the appropriate modelling context. The extent to which such an explanatory framework is satisfactory enables the question of whether extensions or modifications of the existing model will suffice for current purposes or whether an entirely different model is needed. In practice remodelling a system is often in practical due to the considerable effort involved in modelling a system, so that models tend to evolve to preferred states. Another important difference is that between an explanatory framework for a model and how algorithms within the model work (especially in situations where the algorithm is black box or has substantial elements of this). The proposal here is to augment the Design Structure Matrix based connectivity models with a category theory approach, where the links can be expressed in a rigorous and nuanced way and hierarchical models or layered models with different information can be connected. The issues about modelling, analysis and explanation just discussed naturally raise the question of whether it is possible to further improve this already effective engineering prediction change approach. An important element of these consideration is the ratio of modelling effort to perceived output. For reasons of scope and focus the methodological improvement which will be considered here is the integration of category theory into this approach. General theoretical aspects and issues will of this integration will be considered along with outlining an application of this to modelling resource allocation and resilience in hospital systems.

5. Applied category theory

In recent years applied category theory has become a rapidly growing area of applied mathematics moving from its origins in computer science system specification and modelling to cover fields as diverse as mapping engineering process flows and epidemiological transmission. Category theory [21] itself has increasingly spread through mathematics from applications in the areas of logic and algebraic topology to probability theory and quantum logic. As a result there is a huge and quickly expanding literature in both pure and applied category theory at varying levels of mathematical sophistication. The focus of this paper is upon the rationale for and benefits of using category theory in an engineering prediction change approach rather than going into full mathematical details. The reason this focus is possible is that like many powerful and general mathematical ways of working the underlying ideas of category theory are simple and intuitive. The basic intuition is that many formally describable structures whether mathematical or having mathematically representable properties can be described as maps. These maps consist of objects and mappings (termed morphisms) between these objects. What gives category theory its power is the generality and flexibility of the concept of a category which is that a category is a collection of objects and maps with every map having a source object and target object. The example category below in Fig. 3 illustrates this and important property of being able to compose maps.

Due to the flexibility of what can count as an object and as a mapping it is possible to move between different levels of mappings thus increasing and decreasing level of detail. What is complex map of objects and mappings at one level can become a single object in a higher level map and that map in turn can become a single object in an even higher level map. This ability to embed mappings into one another becomes useful when modelling and analysing complex systems. In heterogenous complex system flow modelling there is a complicated relationship between a model and its target systems which can be both how the various individual models relate to larger subsystem

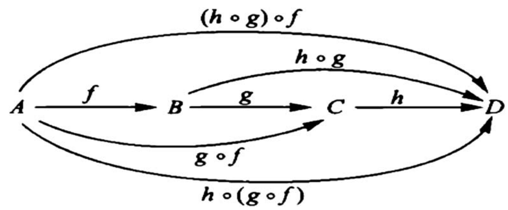

FIGURE 3. Generic description of a category.

and system models, and how models at different levels of the system relate to reality. A key objective of modelling is to enable reality to be related to appropriate models. Such production can be difficult theoretically and practically but applied category theory can offer some assistance as it makes the mappings between various elements and parts of system explicit. Applied category theory can assist in the algebraic construction of modelling requirements and systems models based on analysis of stakeholder requirements and needs. Using this theory a unified model can be superimposed over models with heterogenous structures thereby providing alternative explanations at different levels of abstraction [3].

6. Epistemological gains from category theory

Epistemologically motivating a good mathematical approach is important for achieving good modelling outcomes. Flow modelling in heterogeneous complex systems involves various kinds of truth conditions and probabilistic reasoning. Applied category theory provides a suitable explanatory framework for heterogeneous complex system modelling thereby producing a number of epistemic gains. All these epistemic gains although distinct are related and underpinned by the capacity of category theory to develop a robust and reliable process for the integration of various individual models and submodels within such systems.

Category theory is useful for formalizing explanatory frameworks as it can both structure systems and permit analysis of their applications in a complementary way. This is due to the fact that category theory is about objects and mappings which are relations between objects and therefore it is possible to model the same underlying mathematical structure in a variety of ways depending on what is taken as the objects and the mappings. This flexibility with what are deemed objects and mappings allows the combination of different kinds of models, and discrete and continuous information under one framework plus abstraction from and instantiation into reality through structural descriptions. There are many practical benefits of being able to reuse existing models and connect them together. The varying levels of granularity in system structure and analysis [22] which category theory provides are crucial for specifying the contexts for explanatory frameworks. This specification of contexts enables clear differentiation between an explanatory framework for a model and how computational algorithms within the model function.

A benefit of category theory is that it allows movement between varying levels of abstraction from the system itself to the particular parts of the system by enabling information hiding. In complex systems the ability to focus on information for the purposes of particular decisions is essential for effective decision making. Diagrams play a fundamental role in category theory and therefore are also a modelling technique which lends itself to visualization techniques [19 and 34]. There are various ways of treating the probabilistic reasoning which is important for change prediction in heterogeneous complex system modelling but there are good practical modelling

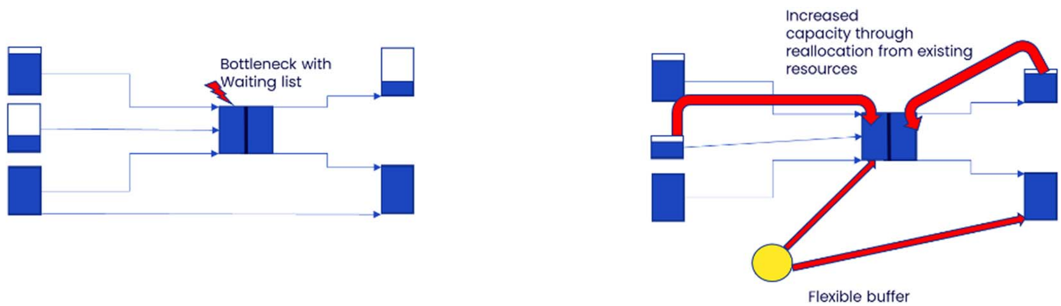

FIGURE 4. Relieving bottlenecks by reallocating resources.

reasons for handling probabilities either directly or indirectly in a standard measure theoretic way which bypasses foundational disputes about what probability actually means. Taking this approach to probabilities fits well with the use of Markov categories [15] which enable synthetic representations of probabilities and the development of computational reasoning frameworks for these probabilities.

One issue of philosophical relevance although not particularly for modelling in practice is what is the nature of the structural connections which category theory develops and presents. For present purposes only a very brief account can be given which places explanations of such structural connections within the broad area of philosophical accounts of structuralism in mathematics and science. Philosophical accounts of structuralism are generally of three major types with these being conceptual structuralism, ontological structuralism and modal structuralism. Conceptual structuralism which regards structures as describing concepts is the least common but arguably the best suited for explaining category theory [2] and has its origins in Dedekind [29]. A major reason for the suitability of conceptual structuralism for accounting for category theory is that it avoids fixed ontological commitments and its flexibility fits well with the purpose relative nature of much representation in category theory.

7. Hospital resource modelling using engineering change prediction

Hospital systems are an important type of heterogenous complex system modelling as they have various patient, staff and equipment flows. Currently and historically many UK hospitals have and had significant staff capacity problems. Expensive agency staff are required to fill capacity gaps which organizationally and financially is not an optimal solution especially in the long term [25]. Staff shortages are a major but not the sole reason for bottlenecks in patient pathways which result in decreased patient satisfaction and missed performance targets for patient outcomes. Bottlenecks result in spare capacity at later points in processes as staff capacity is allocated to cater for patients who do not progress through processes as planned, see Fig. 4.

A holistic modelling approach to hospital resource allocation challenges needs to combine various perspectives produced by empirical studies of patient, staff and equipment flows with ways of modelling that enable integrated system description and analysis. Such a modelling approach needs to take a systematic view of hospital staffing resources, identify the factors affecting short and long term staff capacity and permit the creation of a flexible workforce which can be allocated as required. The problem is that hospitals have a range of different models which represent different

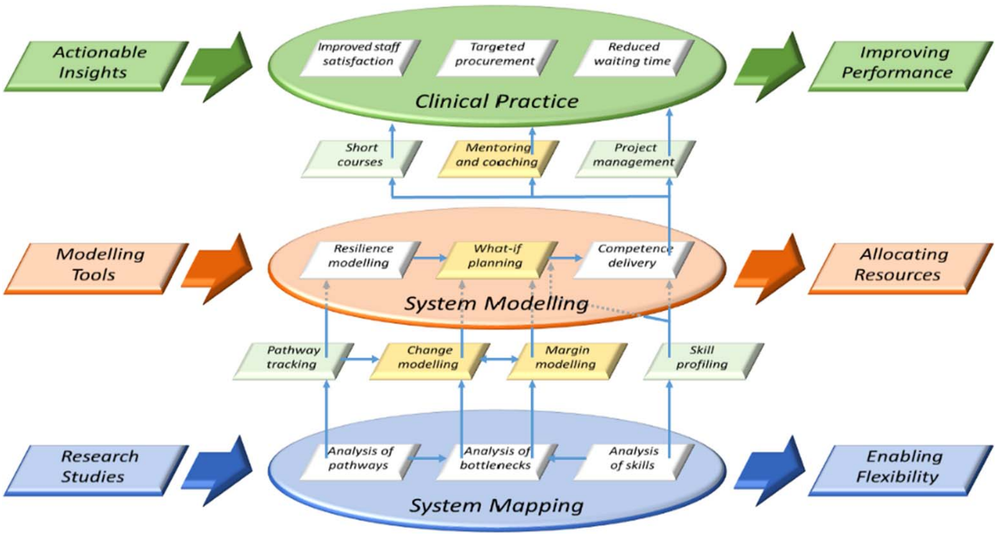

FIGURE 5. Linking system modelling and clinical practice from [7].

perspectives (as the schematic diagram below suggests) and in practice many of these models are incommensurable, see Fig. 5.

Change prediction approaches from engineering design can analyse where these bottlenecks in integrated systems would be so that resources can be deployed flexibility to avoid them and address them when they occur. The focus of such analysis is the interconnections between different elements of the system (such as patient flow and staff flow). Excess demands in the form of changes to one part of the system potentially affect other parts of the system and can make them ineffective or overburden them. For example, if a test cannot be carried out or home care is not available then patients cannot be moved out of a hospital, see Fig. 4. Critical situations often arise when pressure come from multiple sources.

Resilience has collective and individual dimensions. A key element of this is developing and testing operational models for future resilience. Due to the high interdependency small changes can cause knock on effects on multiple parts of the system and avalanches across the system. Whether an element of the system can absorb proposed changes depends on the resource margins that it has. Change prediction approaches can analyse which systems become overloaded due to increased load on multiple systems and show which systems can become change multipliers across a number of systems. Whether a change propagates depends on the margin of an element of the system. Margins have two elements, namely, buffers against uncertainty and excess that is not required to meet current requirements or uncertainty. Excess can be increased either by increasing capability (such as hiring new staff) or by reducing uncertainty. Not all units need to hold their own buffers (see [11]) but they could be supported with flexible resource. This type of analysis can improve the flow in several ways:

•setting up interconnected systems to identify which elements could become bottlenecks and therefore compromise resilience.

•dynamic monitoring of the load on different elements of the system to enable flexible and proactive deployment of resources (such as groups of nurses).

•analysing where new subsystems can be used to disentangle critical patient paths (such as additional scanners or patients advocates).

For modelling using engineering change prediction to be effective in these ways it is essential that a complex heterogeneous hospital system can be analysed and optimized as a whole. The difficulty with doing this is many models in such a system are incommensurable. Applying category theory enables the combination of these different kinds of models into a single hospital system modelling framework through making the mappings between them and the system explicit. It may well not be the case that the use of category theory in this way resolves all potential issues about incommensurably in hospital system models but it should provide workable mappings which enable local and overall resource optimization. Identifying margins on multiple levels of system composition can usefully be complemented by a category theory based approach which allows representation of variable and constant properties of models under changing conditions, and the identification of flows within models [4 and 13].

8. Conclusions

Much complex systems modelling involves considering how both relations between various individual models in larger system models, and how models at different levels relate to reality. For this reason it is often useful to allow the possibility that models are fictions which is a more moderate and pragmatic position than contentious although well-established view in the philosophy of science that all models are fictional. From an engineering systems modelling perspective what is required is not a commitment to all models being fictional as some will clearly describe reality but a commitment to the possibility that a given model and its relationships with other models can be fictional. Models have a similarity to the systems being modelled but this is partial to varying extents and modelling choices can be given a clearly articulated rationale. Fitness for purpose in practice is a pragmatic one, does the model help with making the required decisions.

Another key characteristic of many heterogenous flow modelling problems is that they are too complex for purely analytical reasoning work effectively and thus require efficient representations of probabilistic reasoning. An important aspect of this is that heterogenous flow modelling problems may involve representing perturbations in the models. As a consequence complex system models require the ability to combine analytical and probabilistic reasoning in effective ways with the flexibility to handle model perturbations in robust and reliable ways. Integrating category theory with an engineering change prediction approach assists with handling epistemological complexity through illuminating structural connections in complex system models. Complex systems have emergent properties so that causality is often impossible to show. Such structural connections are generated from the structural descriptions and path mappings which category theory enables. Current philosophy of science heavily foregrounds causal explanations as a paradigmatic scientific explanation sometimes at the expense of appropriately valuing intentional and teleological explanations. Applied category theory offers scope for suitably recognizing and appreciating the value of such explanations in understanding models of heterogeneous complex systems.

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