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Multi-perspective modelling of complex phenomena

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Abstract This conceptual paper discusses the limitations of a single-perspective hierarchical approach to modelling and proposes multi-perspective modelling as a way to overcome them. As it turns out, multi-perspective modelling is primarily a new methodology, using existing modelling techniques but extending the modelling hierarchy with a new epistemological level which integrates the different perspectives. The methodology will be presented in some detail, and its use will be demonstrated by analyzing an example taken from a socio-political context.

Keywords Multi-perspective modelling · Complex systems modelling · Aspect models · Bridge models

1 Introduction

As evidenced from the growing number of publications on social simulation and rising research interests, modelling and simulation is increasingly applied to the study of social phenomena. The domain of 'social systems' deals with higher levels of objective complexity (Bailly and Longo 2003) in comparison with the artificial and physical systems which have traditionally benefited the most from modelling and simulation as a method of inquiry. Hence, the '*complexity*' paradigm emerged to deal with the new class of systems. In this paper we will look at multi-perspective modelling to address the problems that come with modelling complex systems.

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The remainder of this paper will first set the stage by providing a background on modelling complex phenomena. Following that, it will introduce multi-perspective modelling as a way to overcome some of the problems of traditional reductionist modelling, and show where it fits into the modelling hierarchies as defined by Zeigler (Zeigler et al. 2000) and Klir (1985). We will interpret perspectives as (theoretical) positions from which we look at the world, providing both a deliniation of the system and a way to decompose it, a definition general enough to encompass levels in the sense of Lane (2006). The paper continues with a formalization of multi-perspective models. Following that, an example taken from a socio-political context will be analyzed within the extended framework; the example shows how different levels can be integrated in a single model. The paper ends with a discussion of the results and directions for further work.

2 Modelling complex phenomena

A common way to understand systems is to impose on them a hierarchical structure by isolating parts and defining relations between them; parts are further aggregated into higher level parts in a way that aims to minimize the relations between formed composite parts (Wimsatt 2000). For example, from a structural perspective we may decompose a technical system like the International Space Station (ISS) into a hierarchy of parts and subparts. The same could be done from a functional perspective. This approach has proved to be tremendously successful. In fact, it was so successful that it has led people to claim that hierarchy is the '*architecture of complexity*' (Simon 1962) and apply it to non-technical systems as well. Simon furthermore argues that by decomposing systems in a hierarchical way, our depiction of reality does not suffer too much, and hence he refers to systems that can be modeled this way as '*nearly-decomposable*'. According to this vision, it is possible and even desirable to analyze all systems like 'Chinese boxes', where an entity contains smaller entities, with the latter smaller entities containing even smaller entities, and so forth. From Simon onwards, hierarchy theory developed as a sub-field of systems theory and has had a broad influence in modelling (Pattee 1973). Hence, current modelling and simulation approaches inherited a strong reductionist world view. For instance, the DEVS formalism (Zeigler et al. 2000) uses atomic and composite models to represent systems.

As non-technical systems usually have higher complexity than technical systems, they are often studied at different levels, each level corresponding to a specific time and space scale. This led Lane to point out that different types of hierarchy exist (Lane 2006), of which the *level hierarchy* accounts for this case. Sometimes, the levels correspond to different scientific domains, like for example sociology and psychology, where one level corresponds to aggregates composed of units that are (at least partly) described by the lower level. Similarly, in a medical context the levels could be the body, the organs, the tissues making up these organs, and the individual cells making up the tissues. Again, each level consists of elements described at the lower level, but not fully defined by that level.

Yet another type of system occurs when a given element can be part of different hierarchies at the same time. For example, in a social system the unit of behavior could be the individual, who can at the same time be part of a family, a company, a neighborhood, a religious group. Each of these different ecosystems can be described by its own (level) hierarchy, but all these hierarchies share the same low-level element, the individual in this case. This situation is referred to as a *tangled hierarchy* (Lane 2006).

When studying such systems, one has to set boundaries; one has to select amongst the different ecosystems or levels the parts that will be modeled. By doing so one adopts, at least implicitly, a theoretical perspective. The concept of a partitioning frame (Winther 2006) posits the existence of a *de facto* theoretical unit guiding the investigation and decomposition of a given system of interest. It is often neglected that when decomposing a system from a single perspective, the resulting hierarchical decomposition on a system is a simplifying abstraction that comes at a cost in terms of model expressiveness and richness (Agazzi 1991; Levins 2006), and that, by not explicitly recognizing the chosen perspective, one tends to overlook the limitations imposed by it. This may be of little consequence when one is modelling engineered systems like the aforementioned ISS, because such systems are a result of a design process that adopted the very same principles and hence resulted in systems that are clearly hierarchical, with a well-defined whole/part structure. In such cases perspectives have clear boundaries and their interactions are few, so usually the constraints they pose will be acceptable.

In contrast, modelling social systems as simple hierarchies will fail to answer all questions one might pose or lead to answers that are inaccurate. This is because the system's decomposition has necessarily lost relations between elements occurring in the real world; relations outside the partitioning frame, which will not be brought back to life when the behavior of the reconstructed system is studied: the latter system can only be a straightforward composition of lower level behaviours.

3 Overcoming the problems of single-perspective reductionism

The problem of modelling complex systems as a compositional hierarchy has already been posed in various ways. For instance, Lane showed the qualitative difference between inclusion and level hierarchies (Lane 2006). As an example, in systems biology, Uhrmacher discussed the difficulty of representing complex multi-level biological systems (Uhrmacher et al. 2007) using hierarchical modeling. By adding an organizational level hierarchy to the classic compositional hierarchy of DEVS (through ports and variables that apply throughout the composed model), her approach tackles some of the problems of reductionism; it sticks, however, to the unique decomposition paradigm. Dalle and colleagues (Dalle et al. 2008) proposed to enrich hierarchical modeling by introducing shared components in DEVS hierarchical models. However, Dalle's approach is not meant to model complex systems (e.g., social systems) that exhibit the tangled hierarchies that are common to such systems (Lane 2006).

Prevalent modeling approaches in social simulation are also not immune from the issue stated here. To tackle complexity, modularity is commonly seen as a desirable feature, and complex models are built by coupling sub-models which are each responsible for part of the total system's behavior. To understand such coupled models, the property of being 'closed under coupling' is a very important one. It states that any composite model is equivalent to a corresponding atomic ('flattened') model expressed in the same formalism: no 'magic' results from composing lower level models (Zeigler et al. 2000). The standard methodology when creating a complex model is thus to decompose it into smaller and smaller parts until reaching a given unit of behavior generation. This decomposition effort is only possible through the adoption of an implicit or explicit theoretical perspective. Thus, ultimately, such models cannot be other than inclusion hierarchies, like 'Chinese boxes'.

A core tenet of the *complexity paradigm* is the departure from the above type of reductionism (Morin 1990). It emphasizes that, by analyzing a (natural) system into (artificial) parts, significant properties of the system will be irremediably lost (Mikulecky 2001). We understand complexity as a relational property between the observed system and the observer who partitions the system in a *de facto* imperfect way. The practical problem thus becomes not reductionism *per se*, but rather our misguided assumption that the parts of a system form an objective reality, instead of being the result of a certain abstraction or theoretical perspective imposed on the system. A parallel can be drawn with the role of theories, as in the following quote taken from (Popper 1959): "*Theories are nets cast to catch what we call 'the world': to rationalize, explain, and to master it. We endeavor to make the mesh finer and finer*."

4 Multi-perspective modelling

Before introducing a way to make the "mesh finer and finer" without weaving a new net, we will have a quick look at the modelling relation as defined by Rosen (2000), Mikulecky (2001). This modelling relation represents a bridge between two worlds: the natural world in which we live and which we try to understand, and the 'inner (mental) world' which represents our perceptions of the former (see also Rosen 1991, 2000). In the modelling relation, our perceptions of the world are called the *formal system*, because when performing the modelling task we somehow formalize the outside world. It is important to note, however, that whenever we conceptualize anything at all, we are defining such a formal system, no matter how imprecise (Mikulecky 2001). In contrast one may refer to the natural world as the *natural system*. The relationships between both worlds are depicted in Fig. 1, which contains both Rosen's and more specific terms that apply to modelling and simulation. In this figure, the conceptualization step is represented as *encoding*; it results in a formal system. The inverse step is shown as *decoding*; it interprets the formal system and tries to explain or predict the natural world on the basis of our understanding of the formal system. In simulation modelling, the encoding step corresponds to the construction of a simulation model; the decoding step corresponds to analysis and validation. Whereas the natural system evolves through *causality*, the formal system evolves through *implication* by following the rules that were defined during the formalization step. In simulation terms, the phenomena occurring in the natural system are modeled as events taking place in the model, causing the latter to evolve along a path that reflects the natural system's evolution.

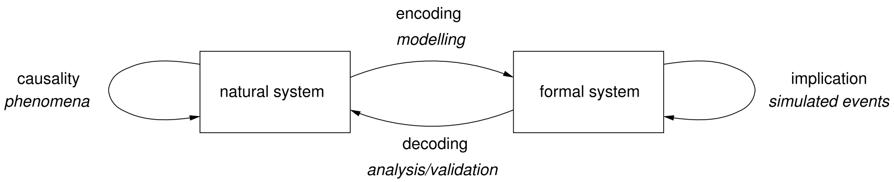


Fig. 1 Modelling simple phenomena

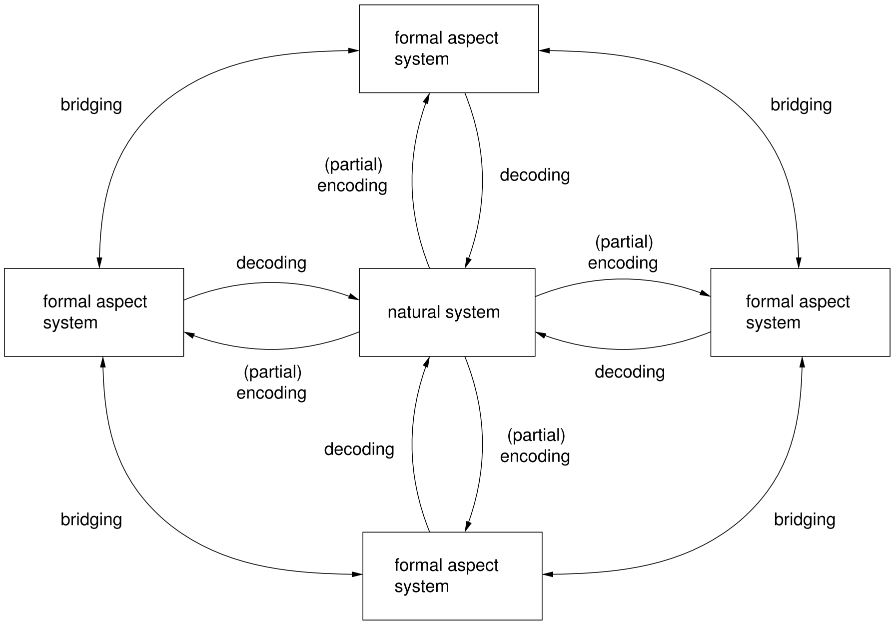


Fig. 2 Modelling complex phenomena through multiple perspectives

Now if the phenomena we try to model are complex, a reductionist formal system can only be partially successful in describing the natural system (Agazzi 1991; Mikulecky 2001). By describing a natural system as a collection of perspectives, though, where each perspective is associated with a unique formal system (having a unique decomposition) as shown in Fig. 2, we can model a system in an inherently 'richer' way by having multiple non-isomorphic decompositions that may influence each other. Such multi-perspective models can indeed capture the tangledness of the systems that result when we observe the world from different perspectives. As Morin puts it (Morin 1990), "we must found the idea of a complex system on a non-hierarchical concept of the whole" (Morin 1990). In a similar way, Levins (2006) proposes the robustness methodology, which, in a sort of triangulation, invites to analyze and model systems with multiple conceptually independent tools, thus improving accuracy of the models by relating the outcomes obtained from different perspectives.

The relation between complexity and multiple perspectives has been acknowledged by various authors. Kaufmann has stated that the number of possible theoretical perspectives and the resulting alternative decompositions of a system are an indication of its complexity (Kauffman 1970). Wimsatt's notions of descriptive and interactional system complexity further strengthen this view (Wimsatt 1972). His notion of *descriptive complexity* refers to the property of a system allowing various alternative and non-isomorphic decompositions, while *interactional complexity* refers to the amount of cross-cutting relations (with the action of defining them indicated as *bridging* in Fig. 2) between those alternative system decompositions (Wimsatt 1972). Wimsatt provides some examples at both extremes of descriptive and interactional complexity: a piece of granite decomposed into subregions of roughly constant chemical composition and crystalline form, under the perspectives of electrical conductivity, thermal conductivity, and density, is descriptively simple. If the system is decomposed according to each of these perspectives, the resulting models will be isomorphic. At the other extreme, a differentiated multi-cellular organism decomposed under anatomical, physiological, biochemical, etc., perspectives is descriptively and interactionally complex; the resulting model structures are non-isomorphic. Descriptive and interactional simplicity often characterize engineered systems, while descriptive and interactional complexities characterize evolved systems.

5 Connecting aspects

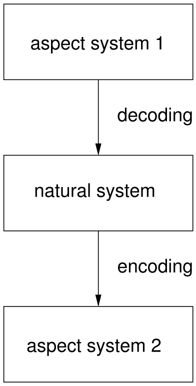
Compared to single-perspective modelling, building multi-perspective models requires additional effort: the management of alternative system perspectives as well as the identification of the bridges between them. These tasks are key to realizing the additional power of multi-perspective modelling. With aspect models covering different perspectives of the same natural system, the central question becomes how to connect the resulting non-isomorphic aspect models.

Different perspectives may correspond to the levels of a level hierarchy (Lane 2006), but they might also come from different theoretical perspectives at the same level. Either way, relations result from two components in the two decompositions sharing a common referent, like a parameter in one perspective being an observable variable in another perspective, or an atomic model in the first perspective having an aggregation/disaggregation relation with a coupled model in the second perspective, such that the atomic model constrains the structure of the coupled model, and the coupled model's components' outputs are used in the transition functions of the atomic model.

As an example, consider a single natural system and two formal systems (A and B) that each give a partial description (explanation) of the phenomena in the natural system. Now assume that in A we have a notion p, that might be implicit or explicit. Explicit means that we have defined p in our theory, but we are not able to predict its value inside A. Since we cannot predict it inside A, we can only fix its value or make it a parameter of the model.[1] Implicit means that p is not even present in the model, but

[1] The existing theory doesn't say anything about how the parameter may obtain its value; such knowledge is simply not present within the perspective. It does say, however, what are the results of changes in p's value for the aspect being modeled.

Fig. 3 Bridging involves decoding and encoding steps



its effects are still accounted for when computing A's outputs. Now if we have such a p, we might be able to predict its value using outputs from model B representing another perspective. Or, if there are no such outputs, we might know that there exist variables inside B that could be used to derive a value for p in A. In that case we could change B to add an observable variable β and create a *bridge model* that uses β to compute a value for p. Doing so will improve the quality of A's prediction of the value α, which can be validated. The term bridge model was chosen to indicate that they represent a theory about the relations between values in different aspect models. Bridge models are *not* a theory about the system under consideration, as such theories belong to the domain of the individual aspect models. Hence, bridge models cannot have inputs other than those that connect to some aspect model's output, nor outputs other than those that connect to some aspect model's input(s).

In order to identify common variables and relations we have to identify the terms p in A that we know to have a relationship with observable variables β in B. If p is implicit, it has to be made explicit first; if it is already explicit, it has to be made an input of A. Similarly for β, which might have been implicit at first, but has to be made into an output of B. The relation between the new input(s) and output(s) will usually be defined empirically. Note that in determining the variables and relations (which must have referents in the natural system whose behavior we can observe) we have to go to a decode/encode cycle as defined by the modelling relation (see Fig. 3, which represent the part of Fig. 2 that corresponds to a single bridge model). This decode/encode cycle avoids a problem noted by Agazzi: "…, a single term, used in two different disciplinary contexts, receives, within the two, different meanings and refers to different types of objects" (Agazzi 1991). Still, finding references and creating the bridge models involves transdisciplinary experts that are able to identify which properties of objects in one aspect model control (or are controlled by) other properties of other objects in another aspect model. Alternatively, statistical methods and data mining may be employed to find predictive relationships between variables belonging to different domains (Zwick 2004; Klir 1975, 1976). Whereas the former method would result in explanatory bridge models, the latter results in just predictive models.

Fig. 4 Extended modelling hierarchy that includes aspect-models

source system	What are the inputs of the system, what are the (observed) variables.
data system	What is the input/output relation of the system
generative system	What states and state transitions explain the system's behaviour
structure system	What are the system's components and how are they connected
multi–aspect system	What are the relevant perspectives and how do they interrelate
metasystem	How does the system evolve over time

6 Extending the modelling hierarchy

To clarify the position defended in this paper and to see how multi-perspective modelling relates to traditional simulation modelling, we place our discussion in the context of a very general yet powerful system concept that Klir and Zeigler independently proposed in the late 70's and the early 80's as "*epistemological system categories*" and "*levels of system specification*" respectively. These two concepts are essential components of the integrative system frameworks introduced by these authors and presented in detail in Klir (1985), Zeigler et al. (2000). The epistemological categories of a system framework are the classes of system it can represent. System categories are also called epistemological levels, because at each level, new knowledge is gained on the system of interest, which was not known at the lower levels. An overview of the various epistemological levels is given in Fig. 4. Note that this figure already includes the level of multi-aspect systems that will be introduced later.

In the context of an inductive system framework (Klir 1985), epistemological categories emerge from examples observed in reality. New examples or areas of interest that cannot be fully supported in the existing categories should lead to the definition of new categories. In this section, the category of '*multi-aspect systems*' will be added to Zeigler and Klir's frameworks. Aspect systems were already mentioned in Fig. 2, and are in fact also an explicit part of Zeigler's System Entity Structures (SES). However, when building models with DEVS, one aspect is chosen as the modeller's perspective; the other aspects are '*pruned*'. Hence, aspect models are no longer part of the epistemological levels defined by Zeigler's framework (Zeigler et al. 2000). To understand how aspect systems relate to the other categories, we will first describe the levels in some detail.

Basically, a system is "*conceived as a set of variables together with a relation recognized among their state sets*" (Klir 1985). System categories are implicitly defined by the type of relations that can be defined between their variables. The most basic system category defined by Klir is the '*source system*'; this level of system specification is referred to in Zeigler's framework as the *observation frame*. This category determines a system's boundary by defining its input and output variables, with their state and support sets. Thus defined, the source system embodies both the object of study as well as the pragmatic orientation and the theoretical perspective selected by the investigator, and can be radically different depending on the choices made.

Once the source system in known and defined, supplementing it with data brings about the next system category: the *data system*. This level consists in a collection of input/output pairs indexed by the support set, which, in modelling and simulation, is always *time*. Building a data system is a routine activity in modelling and simulation, as it is used to derive model parameters and because this is the only way of performing quantitative validation of simulation experiments.

The core of modelling and simulation occurs at the next category, that of '*generative systems*'. A simulation model can actually be defined as a data generation device. Time invariant functions are specified using the predefined observational variables and new internal variables which operationalize a theoretical language. Zeigler rightfully calls this level the *state transition level*. All simulation modelling paradigms and languages provide concepts and constructs to specify the state transition mechanism governing the dynamics of the system. The specification of a generative system depends on the source system that was previously defined for it. In cellular automata, each cell is a generative system (a finite state automaton) characterizing the relation between input variables (the state of neighboring cells) and one output variable (the state of the cell itself) over time. In agent based modelling, the modeller chooses a certain level of granularity, and defines (through behavioral rules) a mechanism that amounts to a generative system.

The next system category is the *structure system* level. This level specifies how systems defined in lower categories (generally generative systems) can be integrated in a compositional fashion. Cellular automata, coupled DEVS models, multi-agent models, and system dynamic models are all structure systems. They all specify relations between lower level model components.

Whereas most modelling stops at this level, Klir defines yet higher levels, which he calls *metasystems*, *meta-metasystems*, etc. (Klir 1976). The latter system categories are used to model evolving systems by specifying transitions between structure systems.

The proposal we make is to add a level that specifically addresses the limitations of adopting a single perspective. The new level is intended to be used to integrate different perspectives into the same model, and would allow us to model problems that, due to their complexity, cannot be solved within a unique theoretical framework (for example, a model that needs to integrate psychological and sociological perspectives in the same model). It should be noted here that a organizational level of the problem domain may be modeled by means of a perspective, but perspectives are not limited to represent organizational levels; they can also used to represent alternative decompositions corresponding to different theoretical or pragmatical perspectives at a comparable level of organization. In Yilmaz and Ören's taxonomy of multi-models (Yilmaz and Ören 2005), the proposed multi-perspective models fit in the class of multi-aspect model. Simulating such systems would amount to simulating the different perspectives in parallel, and allowing them to influence each other. While Vangheluwe (Vangheluwe and de Lara 2002) provides a platform for metamodelling, he doesn't define an epistemological basis for the interaction between the different models. Nevertheless, his platform might prove very useful for building multi-perspective models using the methodology outlined in this paper.

The new category of *multi-aspect system* specifies how generative or structure systems defined in different perspectives may be integrated into a multi-perspective system specification. To this end, two types of models will be distinguished: *aspect models* and *bridge models*. An aspect model is a model of a system according to a given perspective; it is a regular generative or structure model, in the sense that it has well defined observable input and output variables, and it is modeled according to a theory relevant to the problem being investigated. A multi-aspect system contains a finite number of such aspect models and defines the relations between them. To integrate the aspect models, bridge models are introduced. A bridge model maps outputs from one or more aspect models to some input in another aspect model. Bridge models play the same role as do the *bridge principles* of Nagel (1961) and Hempel (1965) in theory reduction; as bridge models reason about the relations between different theoretical or pragmatic frameworks, they are indeed at the meta-level when compared to the lower levels. This has important implications for the methodology of building such models: one could say that aspect models specify all of the pre-theorized knowledge in the multi-perspective model, while bridge models represent the not-yet theorized part of the models. As will be shown in the section about methodology, bridge models can only be understood through decoding and encoding steps which relate the models through their common referent (which is part of the natural system being modeled). This extra decoding/encoding step is what distinguishes this layer from the preceding one, the structure system.

7 Formalization of multi-perspective models

Our formalization of multi-perspective models will be derived from the standard formalization of coupled models in DEVS (Zeigler et al. 2000), which defines a coupled model as a tuple containing a set of input events and a set of output events, two sets containing subcomponents and their names, three sets containing external input couplings, external output couplings, and internal couplings. In multi-perspective models, the subcomponents will be separated in two distinct sets: aspect models and bridge models.

The different aspect models to be connected in a multi-perspective model are regular DEVS models, where the interaction between the different sub-models is done through bridge models. Hence, the dynamics of each aspect are modeled as before, and connection points must be defined to allow the various models to influence each other where necessary. Sometimes the different aspect models can be connected directly, the output of one aspect model providing an input for another aspect model, but usually this will not be the case and some transformation has to take place. These transformations (see also Fig. 2) are taken care of by the bridge models, which are DEVS models as well. Bridge models are communication paths between aspect models; their inputs are connected to the outputs of aspect models, while their outputs influence the aspect models though the latter's inputs.

As will be shown in their formalization, multi-perspective models do not introduce any new syntax to the definition of DEVS. They merely add a semantic distinction between two types of models (the aforementioned aspect models and bridge models). Making this distinction allows us to specify methodological constraints to how the models are used and how they can be interconnected. The resulting multi-perspective models still have the important property of being closed under coupling, which means that current simulation platforms can deal with them.

The constraints on how models can be connected are not intended to limit the modeller in any way. Instead, they are meant to provide guidelines for modellers to define proper interfaces between the models that implement the various theoretical perspectives, and as such they are used to support the proposed methodology. This aspect will be highlighted in the next section.

We can now define a multi-perspective model as follows:

$$MPM = \langle X, Y, A, B, EIC, EOC, IC \rangle$$

where:

$X =$ the set of inputs of the multi-perspective model,
$Y =$ the set of outputs of the multi-perspective model,
$A =$ the set of aspect models, each one being a regular DEVS model,
$B =$ the set of bridge models, each one being a regular DEVS model,
$EIC = \{(ei, i) \mid ei \in X, i \in \bigcup_{s.X \mid s \in A}\}$ (i.e., the set of external input couplings),
$EOC = \{(o, eo) \mid o \in \bigcup_{s.Y \mid s \in A}, eo \in Y\}$ (i.e., the set of external output couplings),
$IC = \{(o, i) \mid i \in \bigcup_{s.X \mid s \in A \cup B}, o \in \bigcup_{s.Y \mid s \in A \cup B}\}$ (i.e., the set of internal couplings).

The couplings between models are subject to the following constraints:

– any aspect model's input can only be connected to a single source:

$$\forall (x, i), (y, i) \in EIC \cup IC : x = y$$

– any bridge model's input can only be connected to a single source:

$$\forall (x, i), (y, i) \in IC : x = y$$

– any output of the multi-perspective model can only be connected to a single source:

$$\forall (x, o), (y, o) \in EOC : x = y$$

– all aspect models' inputs must be connected either an external input or to a bridge model's output:

$$\forall a \in A,\ i \in a.X : \exists(\_, i) \in EIC \vee \exists(o_b, i) \in IC \mid b \in B \wedge o_b \in b.Y$$

– all bridge models' inputs must be connected to an aspect model's output:

$$\forall b \in B,\ i \in b.X : \exists(o_a, i) \in IC \mid a \in A \wedge o_a \in a.Y$$

– all outputs of the multi-perspective model must be connected to an aspect model's output:

$$\forall o \in Y : \exists(o_a, o) \in EOC \mid a \in A \wedge o_a \in a.Y$$

Most of the above constraints are the result of one not being able to obtain a value by connecting two outputs. Some others are the result of the constraints posed in Sect. 5, which states that bridge models are theories about relations between aspect models, and should not have external inputs or outputs of their own.

While the formalization given above assumes regular DEVS models as its component models, it should be realized that modelling system from different perspectives might well result in the need to share components between perspectives. This would be possible by basing the formalization upon extended DEVS (Dalle et al. 2008), instead of regular DEVS.

As the reader will note, nothing was said about the time base of the individual aspect models. This is in line with DEVS, where time is implicit as and assumed to be consistent between the sub-models in a hierarchical model. The same restriction holds for the different aspect models as well. Since the literature on complex systems clearly states that the various perspectives might be defined using different time scales, further research will need to define some extension of the formalism that allows for the mapping of different time bases.

8 Applying multi-perspective modelling to a socio-political problem

An example model is presented in this section to clarify the ideas discussed previously. Let us consider analyzing a conflict opposing two communities (ethnic, political or religious) with a third actor, an armed policing force playing a peace keeping role. The goal of the study could be, for example, to compare different policing tactics in order to discover the one that is most effective in reducing the total count of violent actions.

The first question faced when designing a model for this conflict would be to decide the appropriate level of description. A modeller with social mechanist or methodological individualist tendencies would consider describing the system at the lowest level where individuals interact. A sociological realist would be satisfied with modelling laws occurring at the societal level. In between these two, there could be many possible levels of description. Practical questions such as the granularity of data, the availability of theories, or the availability of computational power can help decide this issue. Literature search can reveal that collective action literature is clearly relevant to this problem. For example, a theoretical framework based on diffusion theory was proposed in Myers and Oliver (2008) to predict the size and severity of protest and riot events. This theory offers an explanation at the aggregate level. At the individual level, we could make the hypothesis that stress and emotions are the important drivers of behavior in this context. Emotional appraisal theory (Lazarus 1991) is relevant to model how agents interpret their environments and react to it.

From this short analysis, one can see that the conflict may be considered from two distinct and non-isomorphic perspectives which in this case correspond to two distinct levels of description. The two levels use distinct underlying theories. One of the theories can be more complete than the other to describe some aspects of the problem. For example, the low level model accounts for a peace keeping (police) force, which is not present in the collective action model. The alternative decompositions can be seen in the SES ontology depicted on Fig. 5.

From the *aggregate collective action* perspective, the conflict system consists of two communities. Each community is further decomposed into two collective actions which they can use as means of expression. These collective actions are ‘peaceful protest’ and ‘violence’. Each of those collective actions is modeled with the Opposing Forces Diffusion model (OFD) as an underlying theory (Myers and Oliver 2008).

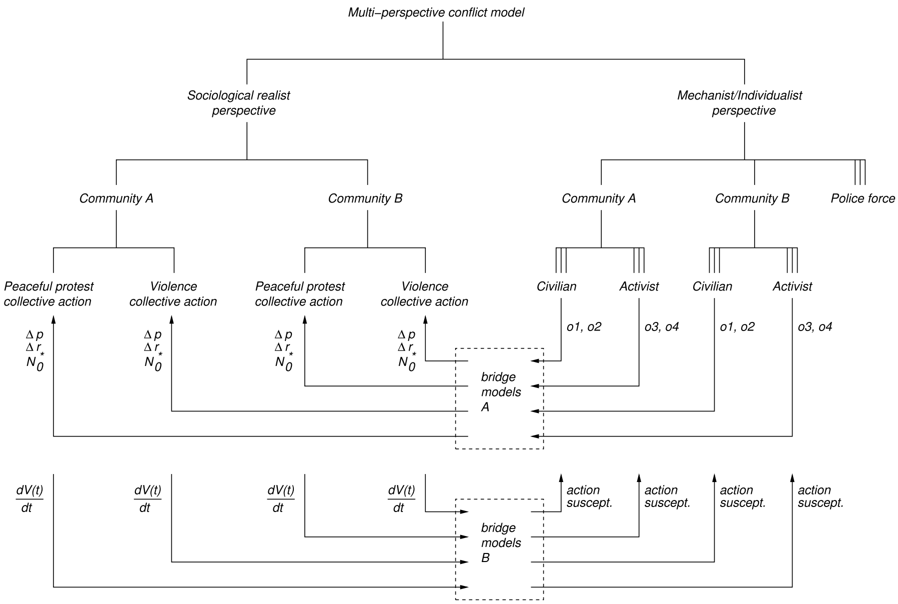


Fig. 5 A multi-perspective conflict model

In each of the collective action models, a provocation and a repression rate of adoption are defined as input variables, along with the initial proportion of adopters of those modes of expression. The OFD model is a theoretical and explicative model. Its theoretical grounding and straightforward parameter interpretation make it a good candidate for simulation. But, being an explicative model, the OFD model parameters are estimated a posteriori in face of available data; in comparison, a predictive model is supposed to generate the data on the basis of these parameters. In addition, we want the parameters to change dynamically as a result of interactions and interpretation by agents, like the influence of the policing force (which, in this perspective, is part of the environment). As we will see below, bridge models will dynamically provide the required parameters on the basis of information obtained from the other perspective.

In Myers and Oliver (2008), *provocation* (P) and *repression* (R) are formalized as two similar logistic functions representing the proportions of adopters of the two competing ideologies. The intensity of collective actions depends on the size of the difference between P and R, when $P > R$ as in the following equations:

$$P^*(t) = \frac{1}{1 + \frac{1-N_0^*}{N_0^*} e^{-pt}}$$

$$R^*(t) = \frac{1}{1 + \frac{1-N_0^*}{N_0^*} e^{-rt}}$$

Table 1 Observation frame for collective action OFD

Name	Type	Range	Meaning
N_0^*	input	0..1	initial proportion of adopters
Δp	input	0..1	provocation rate of adoption
Δr	input	0..1	repression rate of adoption
$\frac{dV(t)}{dt}$	output	0..1	event probability at time t

Table 2 Observation frame for Civilian

Name	Type	Range	Meaning
action susceptibility	input	0..1	willingness to take action
actions (o1-04)	output	$S_C \times S_A \times S_P$	agent actions

where N_0^* represents the initial proportion of adopters in the population and p and r represent the provocation and repression ideologies' infectiousness, respectively. Event probability at any instant is obtained by:

$$\frac{dV(t)}{dt} = P^*(t) - R^*(t)$$

In the *mechanistic* perspective, the conflict system is decomposed into four subcomponents: the two communities, the policing force, and the terrain through which they interact. Each community is composed of *Civilian* agents, and *Activist* agents. The Civilian agent represents an individual of the general population in one community, who can be in states such as: 'inactive', 'demonstrating', and 'rioting'. The Activist agent represents a more active individual of the population who can be in states such as: 'inactive', 'provocation', 'violence'. The transitions between these states are governed by the emotions elicited by an emotional appraisal module in each agent. The policing force is composed of *Reconnaissance patrol* agents, *Combat patrol* agents, and *Crowd control* agents, each with their own specified behavior, derived from miliary rules of engagement. The terrain is modeled as a lattice where each cell has parameters reflecting the symbolic value of each location for each community, the visibility it allows for the policing force agents, the density of populations from the communities, etc. It also contains state variables being updated depending on what is currently occurring in each location. The behavior of the agents is determined by local interactions and by a parameter related to the global state of the conflict ('action susceptibility' in Table 2), which is again derived from the other perspective through a set of bridge models.

Based on the decomposition given in Fig. 5, an observation frame can be built for this system. Tables 1 and 2 show the observation frames for the collective action OFD model and a civilian agent respectively. Data can be collected about the conflict to set initial parameters for the model. The initial parameters of the OFD model could be estimated with numerical regression techniques on historical data as shown in Myers and Oliver (2008). Such data on conflicts are available in databases such as the Upsala Dataset on Armed Conflicts (Data on Armed Conflict n.d.). After that, an appropriate formalism is chosen to specify the models. For this example, all models were specified in the DEVS formalism.

Bridge models define the relations between the aspect models. Adapting provocation (p) and repression (r) rates as a result of micro-level outcomes requires hypotheses regarding how, for example, a violence act will have a future effect on the adoption of the violent provocation ideology in both the source population and the target population. The collective action literature has numerous references on the effect of prior actions on future collective behavior. One clear fact is that policing style influences the evolution of conflicts. For example, G. Marx analyzed different police behaviours and their effect on crowds (Marx 1970). Newman and Lynch show the role of vengeance as an ideology fueling violence in feuding societies (Newman and Lynch 1987). Assumptions on the influences between peaceful and violent ideologies within a community or between opposing communities can be diverse. The specification of these assumptions can be done in the bridge models.

Outputs from the low level models with relevance to the collective action models can be listed as follows:

(o1) Effective crowd control: a peaceful demonstration did not escalate to rioting,
(o2) Rioting: a peaceful demonstration escalated to rioting,
(o3) Failed violence act: the police force was able to stop violence act,
(o4) Successful violence act: activist successfully perpetrated a violence act.

The above values are the inputs to a set of bridge models A represented in Fig. 5; they are mapped to a certain effect (null, positive, or negative) on the Peaceful Protest and Violence collective actions through their provocation and repression rates p and r. For example, we assumed that a successful (o4) violence act by an activist group affiliated to Community 1 has the following effects:

- strengthens provocation ideology for peaceful demonstrations in Community 1,
- does not have any effect on the repression ideology for peaceful demonstration in Community 1,
- strengthens provocation ideology for violent behavior in Community 1,
- does not have any effect on the repression ideology for violent behavior in Community 1,
- does not have any effect on the provocation ideology for peaceful demonstration in Community 2,
- strengthens repression ideology for peaceful demonstrations in Community 2,
- strengthens provocation ideology for violent behavior in Community 2,
- does not have any effect on the repression ideology for violent behavior in Community 2.

Whenever the bridge model calculates new values for p and r, a new value of N_0^* is derived from these as follows:

$$N_0^* = \frac{1}{1 + \frac{\frac{1-N}{N} e^{-pt} - \frac{1-N}{N} e^{-rt}}{e^{-pt} - e^{-rt}}}$$

Once the bridge models are built, the overall model representing the conflict according to two perspectives (also corresponding to levels of organizations) is obtained. In our case, the resulting model is a coupled DEVS model containing two aspect models, each represented as a classical DEVS model, and two bridge models, also DEVS models, responsible of encoding and decoding values from one perspective to another. An earlier account of this work focusing on the models themselves can be found in (forthcoming).

9 Conclusions and further research

This paper has shown some of the limitations of single perspective hierarchical modelling and has proposed multi-perspective modelling as a solution, with motivations taken from system theory, philosophy of science, and modelling and simulation practice.

Multi-aspect systems have been shown to form a specific system category, in between structure systems and meta-systems. It is argued that the syntax of the current generative modelling formalisms is expressive enough to create multi-perspective models. Consequently, a formalization was provided based upon DEVS coupled models, specifying Aspect and Bridge models with constraints managing their interactions. These constraints are chiefly methodological. This is in line with our proposal itself, which is *de facto* a methodological extension of an existing modelling paradigm. The extension is to clarify the way in which multiple perspectives can interact in a meaningful way in an integrated model.

A first definition of a corresponding methodology is given, inspired by Klir's systems approach, Rosen's modelling relation, and the logical empiricists' bridge principle concept. The methodology explains why notions from one modelling perspective must be decoded through the natural system and re-encoded into another perspective's formal system. An example application of the methodology on conflict simulation is given.

Future work includes further investigation on the nature of bridge models and their relation with data mining and statistical techniques. Applicability of the approach to modelling styles other than DEVS will also be studied.

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