

General Morphological Analysis as a Basic Scientific Modelling Method

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Abstract: General Morphological Analysis (GMA) is a method for structuring a conceptual problem space – called a morphospace – and, through a process of existential combinatorics, synthesising a solution space. As such, it is a basic modelling method, on a par with other scientific modelling methods including System Dynamics Modelling, Bayesian Networks and various types graph-based “influence diagrams”. The purpose of this article is 1) to present the theoretical and methodological basics of morphological modelling; 2) to situate GMA within a broader modelling theoretical framework by developing a (morphological) model representing different modelling methods, and 3) to demonstrate some of the basic modelling techniques that can be carried out with GMA using dedicated computer support.

Keywords: General morphological analysis; morphological modelling; modelling theory; analysis and synthesis; existential combinatorics

1. Introduction

This article is about General Morphological Analysis (GMA) as a basic, conceptual (non-quantified) modelling method. As such, it can be compared with a wide range of other scientific modelling methods, including System Dynamics Modelling (SDM), Bayesian Networks (BN) and various forms of “influence diagrams”. As will be shown, all of these modelling methods are based on variations among a common set of components and properties, and are developed through the same iterative process involving cycles of *analysis* and *synthesis* (Ritchey, 1991, 2012). Indeed, these variations in modelling properties can themselves be modelled morphologically.

Firstly, the theoretical and methodological foundations of GMA as a modelling method are presented. This will include the task of providing a general operational definition of a (scientific) model, in order to identify its components and properties. Next, GMA will be situated within a wider modelling theoretical framework by developing a morphology of modelling methods, which will allow for the systematic identification, classification and comparison of different such methods. The construction of this morphological (meta-) model will also serve as an *example* of how to “build” morphological models in general. The meta-model also gives us a graphical representation of how a given modelling method can be transformed into another by altering one or more of its parametric values. Finally, a number of GMA modelling techniques will be demonstrated that have been made possible by the introduction of dedicated computer support in the early 1990’s.

We begin by discussing the basic nature of a “scientific model”, in order to identify those modelling properties by which to create a morphospace of modelling methods.

2. What is a scientific model?

The notion of a *model*, like that of a *system* or a *theory*, belongs to a class of concepts which essentially encompass an unbounded domain. The open-ended nature of these concepts makes it difficult to give them both an all inclusive and a precise definition (cf. Portides, 2014; Koperski, 2016). From the perspective of the philosophy of science it is understandable to opt for an all-inclusive

account, and we often find the concept of a *model* being based on the notion of “representation”, e.g. a model is a (mathematical, symbolic or conceptual) representation of the thing being modelled. This is certainly all inclusive, but is only a *nominal* designation. For our present purposes a “real” or operational definition needs to be put forward – even if it is not “all-inclusive” – in order to better clarify how models are actually developed and *how they do their work*, i.e. their *means* of representation.

Here, the notion of a (scientific) model is defined on the basis of 1) its components and structure (variables and links) and 2) its method of generation (analysis and synthesis). There is nothing essentially new in this operational description, but since we claim that GMA is a fundamental modelling method itself, with its own unique place in the menagerie of such methods, a review of these formal principles is warranted. (The following text is a further development of work appearing in Ritchey 2011a & 2012).

The following criteria are posited as necessary and sufficient for at least a *minimal definition* of a scientific model. (At this point I am going to drop the “scientific” qualifier and ask that this be understood.) The two criteria are:

- A. A model must contain two or more (mental) constructs that can serve as variables which can support a range of states or values – otherwise called the variable’s *domain* or *value range* (since we are not necessarily working with directed mathematical functions here, these two terms are interchangeable). Such variables represent those aspects of reality (or abstract system) one wants to treat, and which make up the dimensions of the *modelling space* to be developed. We shall call these variables the model’s *parameters*. [The term *parameter* is being used here in its broader “systems science” sense, as being *one of a set of factors that defines a system and determines its behaviour, and which can be varied in an experiment* – including a *Gedankenexperiment*.]
- B. One must be able to establish relationships (e.g. causal, statistical, logical, modal, normative) between the different parameters, such that each parameter is “connected to” (i.e. constrained or influenced by) at least one of the other parameters.

The development of these two components (variables and connective links) into a model is essentially an iterative process of analysis and synthesis. In the analysis phase, variables and their respective domains are formulated which represent the model’s initial *problem space*. In the synthesis phase, connective relationships between parameters are defined which *bind* the modelling space and determine its topological properties. It also constrains the total modelling space in order to produce a solution or outcome space.

Thus the basic framework for a model is an internally connected, n-dimensional conceptual space which goes under a number of different names depending on the nature of the model, its area of application and the *properties of the space to be emphasised*: e.g. parameter space, configuration space, state space or phase space, or, in the case of GMA, a *morphospace*.

At this point we need to distinguish between so-called *static* and *dynamic* models. (These terms are used somewhat differently in different modelling contexts, but are here generalised.) In *dynamic models*, the variables have explicitly defined, specified domains; and the connective links between variables are connections between their respective domains. This means that the modelling space can be manipulated by treating one or more of the model’s variables as “independent”, varying its values (as inputs) and realising the results on the remaining “dependent” variables (as outputs). This is what we usually think of as a proper “model” in science. Included here are SDM, BN and GMA.

In *static models*, the variables are treated as black boxes and only an overall (graphic) connective structure is indicated. No dynamic input-output variability is obtainable. Indeed, this is why such “models” are often referred to as diagrams, charts or graphs. Included here are flow charts, classical influence diagrams and so-called system dynamics (SD) diagrams. Although we are primarily concerned with *dynamic models*, we will include *static models* in the meta-model in order to mark out the interface between these two basic modelling types.

It is interesting to note that this general operational definition of a model is quite similar that of an *experiment*. In experimental research the aim is to design an environment by which one is able to manipulate designated (“independent”) variables in order to examine the effect on the remaining (“dependent”) variables. Thus the very definition of an experiment involves the identification of variables and a “set up” that both creates and allows one to examine the (e.g. causal) connections between such variables. In this sense, dynamic models in general can be regarded as *conceptual experiments* or *thought experiments* (although this is only one aspect of the notion of thought experiments; see e.g. Sorensen, 1992). This is why we have often referred to morphological models as *conceptual laboratories*.

3. A morphology of modelling methods

On the basis of this operational definition of a model, we will proceed to develop a theoretical morphospace by which we can identify and compare a range of different modelling methods, including GMA itself. The development of this *meta-model* will also serve as a procedural example of how to create a (relatively simple) morphological model.

We begin with the analysis phase of defining the parameters (i.e. variables and their respective domains) which represent the meta-model’s initial “problem space”. Note that variables in morphological models consist of *discrete category variables*. There are no metric relationships or numerical calculations involved. Even if a variable in a morphospace may *look like* a magnitude or interval scale variable (e.g. age, weight, income bracket), they are nonetheless treated as discrete categories and assessed as such. The only scaling property utilised in classical morphological modelling is “rank order”. (Some extended forms of GMA allow for the use of probabilities or other numeric relationships but, as we shall see, this in effect is a shift into another modelling type.)

For the purposes of this (meta-) model, we employ the following five parameters (further developed from Ritchey, 2012):

P1. Variable type: Are the domains of the variables (a) continuous, (b) discrete or (c) unspecified (black boxes)?

P2. Directionality of connective links: Are the connections between the variables (a) *directed* (asymmetric) or (b) *non-directed* (symmetric)?

P3. Quantification of connectivity: Are the relationships of connectivity between the variables (a) *quantified* or (b) *non-quantified*?

P4. Cyclic relationships: Does the model allow for (a) *cyclic connectivity* (closed loops, circular feedback) between the variables, or is the model (b) *acyclic*.

P5. Type of connectivity: What is the nature of the connective relationships between variables? For instance, are they (a) *mathematical/functional*, (b) *probabilistic*, (c) *non-causal* (e.g. logical, modal, normative), or (d) *unspecified* (or *quasi-causal*).

First of all, one may ask why just these five particular parameters have been chosen to represent the basic properties of the meta-model. They were chosen because 1) we have to start somewhere and 2) they make up some of the simplest and fundamental operational properties that can be identified (note that P1 is given, and P2, 3 & 4 are basic parameters in mathematical graph theory, the *skeletal form* of a modelling theory). A more complete morphology could certainly treat a wider range of modelling properties, including the distinctions between e.g. different scaling types; open vs. closed modelling contexts; hierarchical vs. non-hierarchical variable structure; the distinction between different types of uncertainty; and whether or not mereological (whole-part) interactions and self-reference is accounted for. However, the present five variables will provide a relatively broad field of modelling methods which will give a first illustration of how GMA can be situated within such a meta-modelling framework.

These variables thus make up the parameters of a morphospace as shown in Figure 1. This 5-dimensional space contains 96 (= 3 x 2 x 2 x 2 x 4) *formal configurations* or *potential morphotypes*, each represented by one condition selected under each of the parameters. This represents the model's total problem space. The specific configuration shown in Figure 1 (dark cells) represents the modelling properties of one particular modelling type – in this case a *morphological model*.

[Note that this morphological (meta-) model is unusually small. A “normal” scenario, strategy or policy model will typically have 7-12 parameters and a problem space of between 50,000 and several million configurations. See the examples used to describe GMA modelling techniques below.]

Variable type	Directedness of connections	Quantification of connections	Cyclicity of connections	Nature of connections between variables
Continuous variables	Directed connections	Quantified connections	Cyclic connections	Causal: deterministic (mathematical-functional)
Discrete variables	Undirected connections	Non-quantified connections	Acyclic connections	Causal: probabilistic
Black-box variables (Unspecified domains)				Non-causal: (e.g. logical/modal/normative)
				Unspecified connections

Figure 1: Morphological model of modelling types, consisting of five modelling properties. One configuration is shown (black) representing *morphological models*.

In this morphospace, all of the (category) variables can be considered to be *rank-ordered* on the basis of *increasing information requirements concerning the properties they represent*. For instance, a specified variable domain represents more information than that of an unspecified one. Likewise, directed vs. non-directed connections, quantification vs. non-quantification, cyclic vs. acyclic connections, and the hierarchy of types of connective properties, can all be thought of as representing rank order relationships of increasing information content.

However, this rank order is a double-edged sword: on the one hand it shows how different modelling methods represent *increasing information about the modelling target*; on the other hand, it also shows what is *required from the modelling target* – what information is *necessary* – in order that a given modelling method can *be successfully applied*. Thus a System Dynamics Model is not “better” than an influence diagram if the knowledge available about the modelling target is only sufficient to warrant an influence diagram. Here we must instead speak of the “applicability” of a

given modelling type *vis á vis* the quantity and quality of the (empirical) information available concerning the object to be modelled (for a detailed discussion see Ritchey, 1991; 2012).

Furthermore, modelling methods employing connective links involving not only logical and empirical categories, but also modal logical categories (necessity, possibility, contingency) and normative relationships are in fact quite information laden. Modelling policy-driven problems necessarily involves “subjective” information, e.g. values, motivations and ideologies. In this sense, it is difficult to ascribe a simple measuring rod concerning the quantity and quality of information.

The next step in the analysis-synthesis cycle of the modelling process is to identify which pairs of variables directly influence each other, and then to scrutinise all of their pair-wise combinations of values, in order to weed out incompatible or mutually inconsistent value pairs. This is called a Cross-Consistency Assessment (CCA) and is performed on a cross-consistency matrix (Figure 2). (Leibniz called this process “synthesis by combinatorics”; Zwicky called it the “principle of contradiction and reduction”. In mathematics it is called “existential combinatorics”. For a detailed discussion of the CCA process, see Ritchey, 2015.)

CCA is based upon the insight that there may be numerous pairs of conditions in the morphospace that are mutually incompatible. For instance, “black-box variables” are intrinsically incompatible with “mathematical/functional” connections between variables, since a “black-box variable” has no domain by which to support such a connection. To the extent that a particular pair of values is incompatible, or indeed is a blatant contradiction, then *all those configurations containing this pair of values would also be internally inconsistent*. Here there is no reference to *causality* or *direction* but only to (mutual) consistency, which is why only a “half-matrix” is required for the assessment.

		Variable type			Directedness		Quantification		Cyclicality	
		Continuous	Discrete	Black-box	Directed	Undirected	Quantified	Non-quantified	Cyclic	Acyclic
Directedness	Directed									
	Undirected									
Quantification	Quantified									
	Non-quantified	1								
Cyclicality	Cyclic									
	Acyclic									
Nature of connections	Causal: deterministic			4	5		6			
	Causal: probabilistic						7			
	Non-causal									
	Unspecified	2	3							

Figure 2: The Cross-Consistency Assessment for the morphological meta-model. Constrained value pairs are shown in shaded, numbered cells.

The CCA is normally based on three types of inconsistencies: 1) purely logical contradictions; 2) empirical constraints and 3) normative constraints (relationships ruled out on e.g. ethical or political grounds). Since the present model consists of purely analytical concepts, the pair-wise assessments are “logical” and based on principles of contradiction.

The combinatoric reduction of the problem space creates a *solution space* which, with proper computer support, can be treated as an inference model. The CCA process also serves as a check on the integrity and clarity of the concepts being employed, since ambiguous or otherwise poorly defined concepts are immediately exposed and are difficult to assess in a distinct manner. Indeed, one of the functions of the CCA is to serve as an initial “garbage detector”.

Figure 2 shows the CCA for the morphospace in Figure 1. Out of necessity, this CCA was carried out solo by the author. This is not the ideal situation. Such an assessment should be carried out in a group setting with modelling specialists representing different competencies and traditions, and where dialogue and a collective learning process can be established. In any event, I chose to be extremely tolerant and only constrained those combinations of values which represent blatant logical contradictions – i.e. “contradictions in terms” (marked by the shaded, numbered cells). All the rest of the configurations were allowed survive. (The reader may want to scrutinise and adjust these assessments.)

The deleted pairs of conditions concern the following (by the numbered cells):

(1): Variables with “continuous domains” would not employ “non-quantified connections”, as this would render these domains useless and render the variables equivalent to “black-boxes”.

(2) & (3): Variables with both continuous and discrete specified domains would not employ “un-specified connections”, for the same reason as above (1).

(4): Black-box variables are intrinsically incompatible with “mathematical/functional” connections between variables, since a “Black-box variable” has, by definition, no domain by which to support such connections.

(5) & (6): Models employing mathematical/functional connections must, by definition, be quantified and have (functional) direction.

(7): Models based on probabilistic connections are – by definition – quantified.

These seven pair-wise exclusions reduce the problem space from 96 *formal configurations* to 44 possible modelling types (shown in Table 2, below). Thus, beyond the given analytical contradictions, everything else is considered (at least) *possible*. One might suspect that some of these possible theoretical modelling types would be of marginal utility or only represent slight modelling variations. Others may seem just plain weird. However, as we all know, “weird” things can sometimes lead to interesting discoveries.

Note that there is no generally agreed upon nomenclature for all of these 44 possible modelling types. Some are clearly distinguishable (like SDM, BN and GMA) while others may denote broad or vague categories of models such as “influence diagrams”. One of the main purposes, and results, of collective morphological modelling is to develop a common “domain terminology”, which would include at least an attempt to assign names to these types. Since I have performed this (first-cut) CCA alone, I have not attempted to tackle this problem. (The reader might like to try to identify other known modelling types and/or consider names for others not-so-well-known.)

As far as GMA goes, it is significant that we find it at the “bottom” (I would rather use the word “base”) of the list of *dynamic models* (Table 2), with only a *special type* of GMA, in the form of an “acyclic” tree, containing less information. Thus, as represented within our defined parameter space, morphological models are the “simplest”, but also the most flexible, of the dynamic modelling types.

4. Examples of modelling types

The first step is to test this (meta-) model by plugging into it a number of more or less well established modelling types. Five such (recognised) modelling types are chosen in Table 1.

Modelling type	Variable type	Directedness of connections	Quantification of connections	Cyclicity	Nature of connections between variables
System Dynamics Model (SDM)	Continuous	yes	yes	yes	Mathematical
Bayesian Network model (BNM)	Discrete	yes	yes	no	Probabilistic
Morphological model (GMA)	Discrete	no	no	yes	Non-causal
Weighted, directed, cyclic graph	Black-box	yes	yes	yes	Unspecified
Non-quantified, non-directed tree	Black Box	no	no	no	Unspecified

Table 1: Five of the 44 possible modelling types represented in the meta-model.

We begin by looking at the two extremes or *boundary cases* represented by the meta-model (Figure 3). The black configuration at the top shows the properties of System Dynamics Models (SDM) and the light shaded configuration at the bottom shows the properties of a “Non-quantified, undirected tree” in graph theory. These two modelling types have no common attributes in the morphospace and a transformation from a graphic tree to a SDM would require a significant augmentation of information – the most significant being the shift from black-box variables to variable involving continuous functions, and thereby a shift from unspecified connections to mathematical-functional one.

Variable type	Directedness of connections	Quantification of connections	Cyclicity of connections	Nature of connections between variables
Continuous variables	Directed connections	Quantified connections	Cyclic connections	Causal: deterministic (mathematical-functional)
Discrete variables	Undirected connections	Non-quantified connections	Acyclic connections	Causal: probabilistic
Black-box variables (Unspecified domains)				Non-causal: (logical/modal/normative)
				Unspecified (quasi-causal)

Figure 3: The two extreme configurations of the meta-model, a System Dynamics Model (black) and a “non-quantified, undirected tree” in graph theory (light shaded).

Figure 4 compares Morphological Models (light blue) and Bayesian Networks (gray). Here we see that both modelling types employ discrete variable ranges but that they are otherwise disjoint. However, in this case the shift between modelling types is relatively easy: Once the possibility of applying probability distributions between conditionally dependent variables is established, this automatically implies a shift to both directed and quantified connections. The only change of structure required beyond this is turning the GMA’s cyclic network into an acyclic BN tree. Indeed, in

working with social-technical and policy driven modelling, the most common modelling progression is just from GMA and BN, which can be appreciated by looking at the modelling steps of these two modelling types in Figure 5. For a real example, see De Waal & Ritchey (2007).

Variable type	Directedness of connections	Quantification of connections	Cyclicity of connections	Nature of connections between variables
Continuous variables	Directed connections ↑	Quantified connections ↑	Cyclic connections ↓	Causal: deterministic (mathematical-functional)
Discrete variables	Undirected connections ↑	Non-quantified connections ↑	Acyclic connections ↓	Causal: probabilistic ↑
Black-box variables (Unspecified domains)				Non-causal: (logical/modal/normative) ↑
				Unspecified (quasi-causal)

Figure 4. Transformative steps in moving from a morphological model to a Bayesian Network. The solid arrows are assigned changes; the dotted arrows are concomitant.

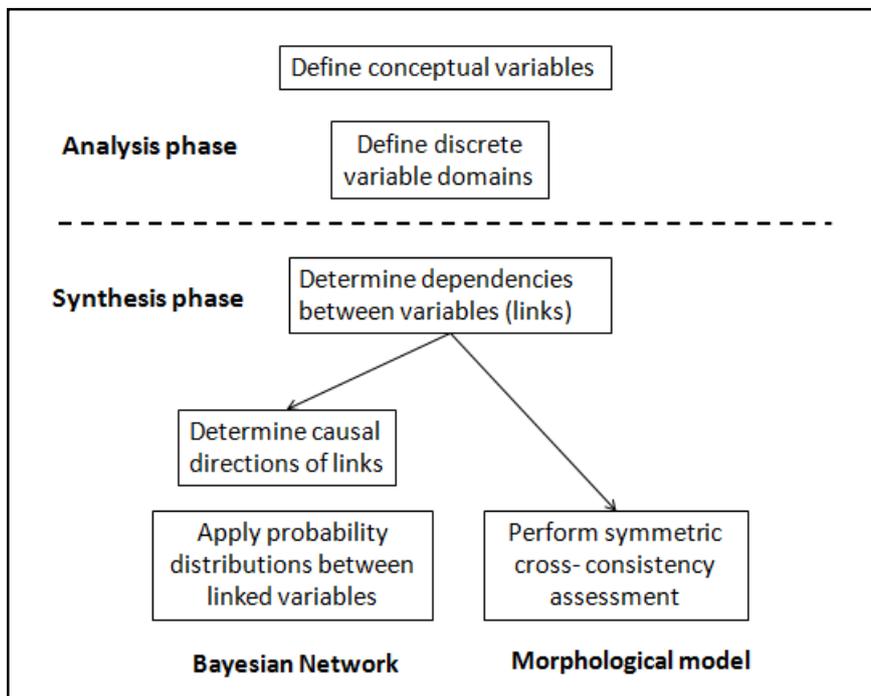


Figure 5. Comparative steps in developing Bayesian Networks and Morphological models.

	#	Name	Variable domain type	Directionality	Quantification	Cyclicity	Type of connections
Dynamic models	1	System Dynamics Model	Continuous	Directed	Quantified	Cyclic	Math/function
	2		Continuous	Directed	Quantified	Acyclic	Math/function
	3		Continuous	Directed	Quantified	Cyclic	Probabilistic
	4		Continuous	Directed	Quantified	Acyclic	Probabilistic
	5		Continuous	Non-directed	Quantified	Cyclic	Probabilistic
	6		Continuous	Non-directed	Quantified	Acyclic	Probabilistic
	7		Continuous	Directed	Quantified	Cyclic	Non-causal
	8		Continuous	Directed	Quantified	Acyclic	Non-causal
	9		Continuous	Non-directed	Quantified	Cyclic	Non-causal
	10		Continuous	Non-directed	Quantified	Acyclic	Non-causal
	11		Discrete	Directed	Quantified	Cyclic	Math/function
	12		Discrete	Directed	Quantified	Acyclic	Math/function
	13		Discrete	Directed	Quantified	Cyclic	Probabilistic
	14	Bayesian Network	Discrete	Directed	Quantified	Acyclic	Probabilistic
	15		Discrete	Non-directed	Quantified	Cyclic	Probabilistic
	16		Discrete	Non-directed	Quantified	Acyclic	Probabilistic
	17		Discrete	Directed	Quantified	Cyclic	Non-causal
	18		Discrete	Directed	Quantified	Acyclic	Non-causal
	19		Discrete	Directed	Non-Quantified	Cyclic	Non-causal
	20		Discrete	Directed	Non-Quantified	Acyclic	Non-causal
	21		Discrete	Non-directed	Quantified	Cyclic	Non-causal
	22		Discrete	Non-directed	Quantified	Acyclic	Non-causal
	23	General Morphological Model	Discrete	Non-directed	Non-Quantified	Cyclic	Non-causal
	24		Discrete	Non-directed	Non-Quantified	Acyclic	Non-causal
Static models	25		Black-box	Directed	Quantified	Cyclic	Probabilistic
	26		Black-box	Directed	Quantified	Acyclic	Probabilistic
	27		Black-box	Non-directed	Quantified	Cyclic	Probabilistic
	28		Black-box	Non-directed	Quantified	Acyclic	Probabilistic
	29		Black-box	Directed	Quantified	Cyclic	Non-causal
	30		Black-box	Directed	Quantified	Acyclic	Non-causal
	31		Black-box	Directed	Non-Quantified	Cyclic	Non-causal
	32		Black-box	Directed	Non-Quantified	Acyclic	Non-causal
	33		Black-box	Non-directed	Quantified	Cyclic	Non-causal
	34		Black-box	Non-directed	Quantified	Acyclic	Non-causal
	35		Black-box	Non-directed	Non-Quantified	Cyclic	Non-causal
	36		Black-box	Non-directed	Non-Quantified	Acyclic	Non-causal
	37	Weighted, directed cyclic graph	Black-box	Directed	Quantified	Cyclic	Unspecified
	38		Black-box	Directed	Quantified	Acyclic	Unspecified
	39		Black-box	Directed	Non-Quantified	Cyclic	Unspecified
	40		Black-box	Directed	Non-Quantified	Acyclic	Unspecified
	41		Black-box	Non-directed	Quantified	Cyclic	Unspecified
	42		Black-box	Non-directed	Quantified	Acyclic	Unspecified
	43		Black-box	Non-directed	Non-Quantified	Cyclic	Unspecified
	44	Non-quantified, undirected tree	Black-box	Non-directed	Non-Quantified	Acyclic	Unspecified

Table 2. List of 44 possible modelling types in the meta-model’s solution space, sorted by *variable domain type* and rank-ordered information content. Five modelling types are identified by name.

5. Modelling Techniques with Computer-Aided GMA

In much the same way that dedicated computer support revolutionised mathematical Modelling and Simulation (M&S), it likewise revolutionised morphological modelling. In this context it is a curious fact that the *technically simpler* morphological modelling procedure was given dedicated computer support only decades after it began to be developed for System Dynamics Modelling, and some years after that for Bayesian Networks. While there are interesting historical and scientific-sociological reasons for this, it is not pertinent to the present work (see Ritchey, *in preparation*).

As discussed above, dedicated computer support allows us to treat morphological problem spaces – synthesised by combinatorial procedures – as (“what-if”) input-output models. Here we present examples of different forms that such models can take and demonstrate how they can be treated.

As with all “dynamic” models – and especially with morphological models which are quite “visual” – it is difficult to demonstrate their dynamic features on paper. We can only show individual “snapshots” of given configurations. Note also that these examples are presented in order to demonstrate *modelling technical principles*, not to elaborate on the *content* of the studies involved. If the reader is interested in this content, the articles in which they appear can be downloaded from the designated URLs.

5.1 Simplex models

We begin by describing a typical, “simple” (or simplex) model in order to demonstrate its basic features and principles. Figure 6 is an *organisational structure* model developed for the Swedish National Defence Research Agency in preparation for a major organisational change in the late 1990’s (Ritchey, 2011a). It contains seven parameters which together generate $6 \times 6 \times 6 \times 6 \times 4 \times 6 \times 6 = 186,624$ distinct *simple configurations* – i.e. consisting of a single value given under each parameter.

At this point we need to distinguish between two main types of “parameters”: i.e. those whose domains consist of mutually exclusive values, or Boolean OR-lists; and those consisting of non-mutually exclusive values, or Boolean AND-lists. Both of these types of parameters can be employed in morphological models as long as they are properly defined, such that the logical relationships between dependent parameters are treated properly. Most morphological models concerning policy-driven problems are hybrids in this manner, although “pure” OR-list models are also common (see below). It depends on the nature of the problem and the goals to be obtained.

Some feel that only models consisting exclusively of OR-lists, or “true variables”, are appropriate for “real” scientific models. However, in the case of social-organisational, policy-space modelling, this restriction is misplaced. Firstly, the possibility of including variables representing concurrent conditions significantly enhances GMA’s flexibility and breadth of applications – for instance allowing the inclusion of concurrent goals or other independent properties. Secondly, such AND-lists are actually sets of *mutually exclusive binary parameters*. Their representation as a single list of concurrent properties is a short-cut which “saves parameter space” and allows for more complex relationships without having to create excessively large and visually difficult modelling spaces.

Organisation TYPE	Dominant leadership culture	Buyer structure	Dominate product/ service	Co-operation strategies	Main employee incentive	Employee profile
Official state agency	Bureaucratic hierarchy	Ministry dominated	Process + method support	Outside help when needed	Money	Life-long service
Government owned enterprise	Strong scientific leadership	Military and material dominated	Soft studies	Joint ventures	Managerial career	Career researcher
Academy (à la university)	Marketing division leadership	Defence Industry	Hard studies	Consultant purchasing	Pleasure in one's work	Development engineer
Trade institute	Umbrella management	Civilian agencies	Basic research	Mediator only	Educational motivation	"Consultant"
Consultant firm	Gate-keeping	Private markets (national)	Testing, construction		Titles, specialist career	Entrepreneur
"Learning organisation"	Skunk-works (ad hoc/rati)	International markets	Second opinion		Organisation gives status	Elite troops

Figure 6. Organisational structure model with Organisational type and Leadership culture designated as drivers (red).

Another issue concerns the distinction between independent variables and dependent variables. With morphological models this is an open question: any of the variables can be designated (temporarily) as either/or. More specifically, the user examines the solution space of the model by *choosing* alternative input variables (or drivers) on order to scrutinize the resultant outputs. The models are completely flexible in this context.

Thus the organisational structure model in Figure 6 is a mix of OR-lists (the first two variables “Organisation type” and “Dominant leadership culture”) and AND-lists (the rest of the variables). The first two variables have been temporarily designated as the independent variables or “drivers”, and the rest are treated (temporarily) as dependent. The red cells under the first two parameters have been selected as inputs, and the cluster of dark blue cells is the output along the remaining parameters. The red “dot” in the “Bureaucratic hierarchy” cell tells us that this was the only other “Leadership culture” value available for an “Official state agency”. (Note that inputs, outputs and other properties of these computer supported models are colour coded – which can be applied in the PDF version of this article, but not to the paper version.)

Thus any combination of drivers/inputs can be designated, giving these models great flexibility. For instance, Figure 7 shows the organisational consequences from a completely different perspective – i.e. from that of employee types and incentives. Here there are significantly different organisational requirements.

Organisation TYPE	Dominant leadership culture	Buyer structure	Dominate product/ service	Co-operation strategies	Main employee incentive	Employee profile
Official state agency	Bureaucratic hierarchy	Ministry dominated	Process + method support	Outside help when needed	Money	Life-long service
Government owned enterprise	Strong scientific leadership	Military and material dominated	Soft studies	Joint ventures	Managerial career	Career researcher
Academy (à la university)	Marketing division leadership	Defence Industry	Hard studies	Consultant purchasing	Pleasure in one's work	Development engineer
Trade institute	Umbrella management	Civilian agencies	Basic research	Mediator only	Educational motivation	"Consultant"
Consultant firm	Gate-keeping	Private markets (national)	Testing, construction		Titles, specialist career	Entrepreneur
"Learning organisation"	Skunk-works (ad hoc/rati)	International markets	Second opinion		Organisation gives status	Elite troops

Figure 7. The organisational structure from the perspective of a given employee type and incentive.

5.2 Duplex models

The preceding model is called a *simplex model*, which means that the model’s dimensions (parameters) belong to a single context or structural idea – in this case those conforming to an integrated organisational structure. However, GMA is especially suitable for pitting one type of structure against another – for instance a scenario model pitted against a strategy or organisational structure model. (For GMA’s special application to scenario modelling, see e.g. Ritchey, 2009, 2011b.) When we link such structures together we call this a *duplex* (or multiplex) model.

The idea behind a duplex model is that we can treat one of the modelling contexts as a coherent set of input conditions and the other as a set of output conditions – i.e. we are looking for compatibility not simply between different parameters within a morphospace, but between two different – albeit

mutually dependent -- morphospaces. This is illustrated by in the following duplex model representing the relationship between, on the one hand, an organisation's *resource structure* and, on the other hand, the *demands placed upon this structure* by various stressor events (scenarios).

The model in Figure 8 was developed for the Swedish National Rescue Services Board as a prototype and proof-of-concept for a computer-based instrument for evaluating Rescue Services' preparedness for accidents involving hazardous materials (i.e. "chemical accidents"). The instrument should allow any municipal Rescue Service to measure and test their *preparedness resources* against *responses* required for different types of chemical accidents under different conditions; and further to show what types of improvements in preparedness resources would result in improved responses. A more detailed account of this summary is available in Ritchey *et. al.* 2002.

The resource-response evaluation instrument is made up of two inter-linked fields: a general preparedness *Resource field* and a scenario specific *Response field* (Figure 8). The *Resource field* is general, in that any and all rescue services – from part-time organisations in small municipalities to large metropolitan organisations – can be described within it. These preparedness resources are defined by five parameters on the left side of the model.

The *Response field* (the three rightmost columns) describes possible responses that a rescue service can make within a set of critical time periods as *defined by a specific accident scenario* (either based on an actual case or on a well defined "possible scenario"). The accident scenario given in this example was the actual case of a freight train accident involving the release of a poisonous, pressurised gas (ammonia) which was released into the air in 30 minutes. In this particular case, the model concerns these first 30 minutes of the rescue operation.

There are two ways to apply the evaluation model. The first way is to determine *what level of response to a given accident scenario is attainable for a given resource profile*. That is, we use the *Resource field* as "input", and the *Response field* as "output". This is shown in Figure8, where the input (red) represents the preparedness resources of a medium sized Rescue Service in a small Swedish city (year 2001).

Resource field					Response field		
PLANNING/ PLANS	TRAINING AND EDUCATION	PERSONNEL AVAILABLE	EQUIPMENT AVAILABLE	LEADERSHIP LEVEL	RESPONSE to chemical release	RESPONSE: Information to public	RESPONSE: Affected people
Full preparedness plan	Broad co-op. training	11 or more	Special equipment for specific case	Level 4	Reduce by least 80% within 15 min	Warn involved within 5 min	Help many within 30 min
Response plan for specific case	Training for specific case	8-10	Base equipment for specific case	Level 3	Reduce by least 80% within 30 min	Warn involved within 30 min	Help some individuals within 15 min
Standard routine for specific case	Base education + regular training	5-7	Less than base equipment for specific case	Level 2	Reduce by less than 50% within 15 min	No warning within 30 min	Help some individuals within 30 min
Standard routine for general case	Base education only	4 or less		Level 1	Reduce by less than 50% within 30 min		No help within 30 min
Only alert plan					No measures within 30 min		

Figure 8. Given a rescue service's preparedness profile (red), what response can be achieved given the specific scenario represented by the response field (blue)?

In order to establish what improvements in preparedness would result in an improved response profile, the configurations are “frozen”, and preparedness recourses are successively raised until the desired response profile is achieved (light blue cells) as shown in Figure 9.

PLANNING/ PLANS	TRAINING AND EDUCATION	PERSONNEL AVAILABLE	EQUIPMENT AVAILABLE	LEADERSHIP LEVEL	RESPONSE to chemical release	RESPONSE: Information to public	RESPONSE: Affected people
Full preparedness plan	Broad co-op. training	11 or more	Special equipment for specific case	Level 4	Reduce by least 80% within 15 min	Warn involved within 5 min	Help many within 30 min
Response plan for specific case	Training for specific case	8-10	Base equipment for specific case	Level 3	Reduce by least 80% within 30 min	Warn involved within 30 min	Help some individuals within 15 min
Standard routine for specific case	Base education + regular training	5-7	Less than base equipment for specific case	Level 2	Reduce by less than 50% within 15 min	No warning within 30 min	Help some individuals within 30 min
Standard routine for general case	Base education only	4 or less		Level 1	Reduce by less than 50% within 30 min		No help within 30 min
Only alert plan					No measures within 30 min		

Figure 9. New parameters values are chosen in the Resource field (light blue cells) in order to see how response can be improved. In this case, one higher degree of planning, training and equipment will maximize the response to the chemical release as such.

The second way to apply the instrument is to run it “backwards”, so to speak, i.e. determine *what resources would be required* in order to realise a *desired level of response* (Figure 10). Here we use the *Response field* as input (red) and the *Resource field* as output (blue). This mode of use is more suited for the task of municipal planning, e.g. in dialogue with political decision-makers.

PLANNING/ PLANS	TRAINING AND EDUCATION	PERSONNEL AVAILABLE	EQUIPMENT AVAILABLE	LEADERSHIP LEVEL	RESPONSE to chemical release	RESPONSE: Information to public	RESPONSE: Affected people
Full preparedness plan	Broad co-op. training	11 or more	Special equipment for specific case	Level 4	Reduce by least 80% within 15 min	Warn involved within 5 min	Help many within 30 min
Response plan for specific case	Training for specific case	8-10	Base equipment for specific case	Level 3	Reduce by least 80% within 30 min	Warn involved within 30 min	Help some individuals within 15 min
Standard routine for specific case	Base education + regular training	5-7	Less than base equipment for specific case	Level 2	Reduce by less than 50% within 15 min	No warning within 30 min	Help some individuals within 30 min
Standard routine for general case	Base education only	4 or less		Level 1	Reduce by less than 50% within 30 min		No help within 30 min
Only alert plan					No measures within 30 min		

Figure 10. Given a response level (red), what preparedness resources would be required (blue)?

5.3 Overlay models

In contrast to the duplex model presented above, overlay models utilize a common set of parameters – i.e. a common morphospace – by which two *concepts* can be (commonly) defined and linked. Examples of such dual concepts are:

- *Scenario-Strategy models*: e.g. scenarios of external stressors vs. organisational strategies for dealing with different scenarios
- *Knowledge management models*: e.g. knowledge resource bases for different tasks vs. knowledge required in order to carry out a task.

In such a model, the dual concepts are each linked, separately, to a *commonly defined morphospace* by which both concepts can be expressed. This saves parameter space and allows for more complex models. The example presented here is a prototype scenario-strategy overlay model developed for the Swedish Ministry of the Environment in order to evaluate and redesign an Extended Producer Responsibility (EPR) system in Sweden. The purpose of the study was to formulate 1) a range of *contextual environmental scenarios* by which to test and stress 2) alternative EPR *organisational strategies*. The study was reported in Stenström & Ritchey (2004).

The common morphospace by which to define these two concepts consisted of the following set of parameters.

1. Dominant consumer behaviour concerning willingness to buy environmentally
2. Dominant consumption patterns concerning total consumption vs. private import
3. Dominant household sorting behaviour
4. The scope of a national environmental policy
5. Price levels: raw material prices vs. recycled material prices
6. Technological developments in reduced material usage
7. Technological development concerning material recycling
8. EU import/export directives

Figure 11 shows the scenario and strategy alternatives as they are linked to these 8 common parameters. One scenario is selected (“Current development – pessimistic”) which then shows the indicated scenario configuration and the EPR strategy best able to cope with it.

Scenarios ----->				<----- Strategies for					
Contextual environmental SCENARIOS	Dominant consumer behaviour	Dominant consumption patterns (Total & private import)	Dominant household sorting behaviour	National environmental policy	Price levels: Raw material vs. recycled material	Tech development: material usage	Tech development: material recycling	EU directives import/export	Alternative EPA organisational STRATEGIES
World ecological crisis	Will buy environmentally; willing to pay more	Total - UP Private - UP	Positive on ideological basis	Advanced holistic econ. & policy	Raw - high Recyc - high	Much less material than at present	Very fast development	More open than at present	Strategy A
Raw material crisis	Will buy environmentally; but not pay more	Total - DOWN Private - UP	Will sort by reward	Advanced but fragmented	Raw - low Recyc - high	Somewhat less material than at present	Fast development	Status quo	Strategy B
Current development - pessimistic	Will not buy environmentally	Total - UP Private - DOWN	Will sort if forced to	Advanced but only voluntary	Raw - high Recyc - low	About same as at present	Marginal development	More restrictive than at present	Strategy C
Current development - optimistic		Total - DOWN Private - DOWN	Will not sort	Lowest EU- adaption	Raw - low Recyc - low				No adequate strategy
Greenhouse nightmare									
Batman: High-tech solutions									
Radical dematerialization									
Green paradise									

Figure 11: Single scenario selected, showing the scenario’s attributes and the best available strategy.

Similarly, Figure 12 shows the strategy parameter being used as a driver, showing that Strategy “C” covers five of the scenarios. Finally, Figure 13 shows how opposite “corners” of a parameter pair can be selected to identify extreme conditions which, in this case, results in a scenario for which there is no adequate strategy.

Contextual environmental SCENARIOS	Dominant consumer behaviour	Dominant consumption patterns (Total & private import)	Dominant household sorting behaviour	National environmental policy	Price levels: Raw material vs. recycled material	Tech development: material usage	Tech development: material recycling	EU directives import/export	Alternative EPA organisational STRATEGIES
World ecological crisis	Will buy environmentally; willing to pay more	Total - UP Private - UP	Positive on ideological basis	Advanced holistic econ. & policy	Raw - high Recyc - high	Much less material than at present	Very fast development	More open than at present	Strategy A
Raw material crisis	Will buy environmentally; but not pay more	Total - DOWN Private - UP	Will sort by reward	Advanced but fragmented	Raw - low Recyc - high	Somewhat less material than at present	Fast development	Status quo	Strategy B
Current development - pessimistic	Will not buy environmentally	Total - UP Private - DOWN	Will sort if forced to	Advanced but only voluntary	Raw - high Recyc - low	About same as at present	Marginal development	More restrictive than at present	Strategy C
Current development - optimistic		Total - DOWN Private - DOWN	Will not sort	Lowest EU- adaption	Raw - low Recyc - low				No adequate strategy
Greenhouse nightmare									
Batman: High-tech solutions									
Radical dematerialization									
Green paradise									

Figure 12. Selected Strategy C covers five of the designated scenarios.

Contextual environmental SCENARIOS	Dominant consumer behaviour	Dominant consumption patterns (Total & private import)	Dominant household sorting behaviour	National environmental policy	Price levels: Raw material vs. recycled material	Tech development: material usage	Tech development: material recycling	EU directives import/export	Alternative EPA organisational STRATEGIES
World ecological crisis	Will buy environmentally; willing to pay more	Total - UP Private - UP	Positive on ideological basis	Advanced holistic econ. & policy	Raw - high Recyc - high	Much less material than at present	Very fast development	More open than at present	Strategy A
Raw material crisis	Will buy environmentally; but not pay more	Total - DOWN Private - UP	Will sort by reward	Advanced but fragmented	Raw - low Recyc - high	Somewhat less material than at present	Fast development	Status quo	Strategy B
Current development - pessimistic	Will not buy environmentally	Total - UP Private - DOWN	Will sort if forced to	Advanced but only voluntary	Raw - high Recyc - low	About same as at present	Marginal development	More restrictive than at present	Strategy C
Current development - optimistic		Total - DOWN Private - DOWN	Will not sort	Lowest EU- adaption	Raw - low Recyc - low				No adequate strategy
Greenhouse nightmare									
Batman: High-tech solutions									
Radical dematerialization									
Green paradise									

Figure 13. New high-tech material processes, combined with lagging development of recycling technology, identifies conditions for which there is no adequate strategy.

6. Conclusions

General Morphological Analysis is a dynamic “conceptual” (non-quantified, non-causal) modelling method which can be employed for structuring and investigating the total set of relationships contained in multi-dimensional, non-quantifiable, problem complexes. It is a basic scientific modelling method, developed along the same lines as other scientific models: i.e. through the identification of variables and variable links, and through iterative cycles of analysis and synthesis.

We have shown that the technical properties of scientific models *in general* can be treated as variables in a morphospace of modelling methods. Such a meta-model identifies 44 different modelling types, including morphological models themselves. These modelling types can be ranked and compared on the basis of different relative *levels of information* which they require in order to be successfully applied to a given modelling target.

GMA is shown to be a suitable method for structuring and modelling those types of social/organisational structures and processes which, by their very nature, are not applicable to formal mathematical (causal deterministic) or probabilistic (stochastic) methods. This includes complex policy-driven processes (a.k.a. *wicked problems*, see Rittel & Webber, 1973; Ritchey, 2011a) in which one must work with modal categories and normative constraints rather than deterministic and probabilistic constraints.

Fritz Zwicky, the method's modern pioneer, called morphological modelling "totality research" which, in an "unbiased way attempts to derive all the solutions of any given problem". It may help us to discover new relationships or configurations, which may not be so evident and which we might have overlooked by less systematic methods. Importantly, it encourages the identification and investigation of boundary conditions, i.e. the limits and extremes of different contexts and factors.

GMA also has definite advantages for scientific communication and for group work. As a process, the method demands that parameters, conditions and the issues underlying these be clearly defined. Poorly defined parameters become immediately evident when they are cross-referenced and assessed for internal consistency. Such assessments simply cannot be made until the morphospace is well defined and the working group is in agreement about what these definitions mean. This is a form of "garbage detection" that is especially important for policy analysis, futures studies and social/cultural modelling.

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