On the Use of Metaphors for Knowledge Transfer in Agentbased Systems

Béla Pátkai
Production System Design Laboratory
Institute of Production Engineering
Tampere University of Technology
P.O.Box 589, 33101 Tampere, FINLAND
bela.patkai@tut.fi

Seppo J. Torvinen
Production System Design Laboratory
Institute of Production Engineering
Tampere University of Technology
P.O.Box 589, 33101 Tampere, FINLAND
seppo.torvinen@tut.fi

Abstract – **Computational experiments need to be based on a solid methodology, because it is very easy to get lost in the large computational and combinatorial space of possible models. The formulation of such a methodology is strongly influenced by the applied modelling paradigm. Agentbased modelling makes it especially easy to obtain deceiving results mainly because of the complexity inherent in large, heterogeneous, component based systems. The methodology presented in this paper doesn't just involve the computational modelling process, but aims at describing the conceptual implications also, and the interactions of the model with reality and concepts.**

Keywords – agentbased modelling, complex systems, metaphor transfer, scientific method, systems synthesis.

I. INTRODUCTION

As early as in Aristotle's work it was acknowledged that to arrive at conclusions and gather knowledge about the world we have at least two basic methods: the scientific and the rhetorical one. The scientific method has been clearly dominant in the European culture, and the rhetorical one has been typically neglected and considered as undesirable.

As Encyclopedia Britannica puts it, *science is any system of knowledge that is concerned with the physical world and its phenomena and that entails unbiased observations and systematic experimentation.* In general, a science involves a pursuit of knowledge covering general truths or the operations of fundamental laws. However, this pursuit can take many paths.

The first attempt at creating a scientific language was introduced by Galileo, who tried to overcome the limitations of everyday languages, where one linguistic symbol may describe several different objects or events, and one object might have several names ˉ a potential confusion. Instead of a one-to-one association of lingual symbols and objects/events he shifted the emphasis to their measured quantities (and avoided the vague battle to grasp the essence of reality by words). In his scheme of the language of physics, reality is described by physically measurable quantities.

In any scientific endeavor definitions, axioms and theorems have a central role. It is often disputed how we arrive at these mathematical objects. The so-called "transcendental" explanation claims that they are "given", and after deducing theorems from the definitions and axioms we may find some natural phenomena that "match" the mathematical structure[1]. It is easy to see why this is called "transcendental": first comes the idea and reality is derived from it. However, it is common experience that this is not how things happen. Usually the observations and experience of the scientist motivate the measurements and the axioms, definitions are also motivated by them. After a set of axioms, definitions and theorems are set up, this system is used for prediction – the ultimate goal of the whole scientific procedure – and its result can be compared to observations – i.e. reality – and the whole system is due to skeptical criticism and revision. Arecchi calls this procedure as "critical realism" [1] .

An important step in the scientific method is the choice of axioms and definitions, the basic elements of the mathematical language (and its coevolution with observed reality), because this choice is often subjective and depends largely on the decision maker's background and taste. This choice is also referred to as "common sense", warning us that even the most rigorous scientist is prone to make biased decisions during the modelling process. When looking at a problem (i.e. part of physical reality) we have some details and a global picture at hand. In the knowledge gathering process every involved individual has to find an optimum in between the extremes of specificity and generality, and form their "own picture" of the problem (meaning that everybody will have a different optimum depending on their endogenous characteristics).

It is a generally accepted conclusion that follows from these shortcomings or limitations of the scientific process that there is no unique science, only different aspects of reality [2] .

The problem of mapping domain knowledge on computational models is not unique to the area dealt with in this paper. A lot of experience and knowledge is available in the domain of knowledge based systems research, and the methodology proposed in [9] and [10] carries out a similar mapping to the one proposed in the next sections.

The introduction of metaphors to the scientific language [1] aims at providing bridges between the different aspects of reality grasped by different scientific tools. Such a bridge can only be heuristic, making use of its previous compression of knowledge[2] in another environment. In the same time a metaphor – due to its external origin – has the potential of enriching the method with a view of reality not yet captured.

The aim of this paper is to provide an integrating methodology that involves the issues usually neglected or undocumented in modelling, and to introduce it to the realm of agentbased modelling of complex systems.

[1] This way of thinking is associated with german philosopher Immanuel Kant (1724-1804).

[2] These are the schemata of science (i.e. also considered a complex adaptive system) according to Gell-Mann [3] .

II. LIMITATIONS & CHALLENGES OF SYSTEM MODELS AND METHODOLOGIES

The art of handling (i.e. understanding, modelling, simulating, controlling) large, complex, heterogeneous systems is a challenge incomparable to problems modeled by causal mechanistic equations.

One of the important limitations of these endeavors is the Gödel theorem that has shaken mathematics and the belief in unifying formalisms that embrace and perfectly solve a problem area.

The actual consequences are crucially important, because rhetorically formulating it provides an explanation why in practice there have are always been competing theories even in specialized fields. In the next section the metaphoric bridging method provides a way to get around – or at least effectively conceal – this problem, by acknowledging it first and filling in the gaps by rhetoric (despite the pejorative meaning of rhetoric, that has a low respect amongst professionals, because it is very easy to abuse it to cover the gaps instead of bridging them).

The observation of chaos in meteorological calculations by Lorenz has resulted in the unpleasant knowledge of another limitation, i.e. the impossibility of long term prediction of system states. This directly modifies the objectives of the research we do, we are no longer aiming at exact, quantitative forecasts, but use our models in a less direct way to explore possibilities.

The often criticized "reductionist" scientific approach to translate observations to mechanistic equations. In spite of this fashionable criticism no one denies that equation-based analytical models are usually more desirable than "soft" models involving significant uncertainty, fuzziness and the missing of *apparent* causality. The corresponding methodology aiming at minimally an increase in the understanding of such systems – assuming that certain *causes* have a systemic origin, therefore they have to be found in a system theory or system model. As in case of the previous two problems, this can only be achieved by a modification in goals and approach.

III. AGENTBASED MODELLING

Agentbased modelling has a central importance in modelling and representing complex systems. It shouldn't be confused with agent-oriented software engineering, because that is a software development method, while ABM is a modelling method. However, they are not far from each other, since agentbased models are implemented as software. The previously introduced Gaia methodology could therefore be incorporated in the development methodology of agentbased models. The following list includes the main properties of agentbased modelling

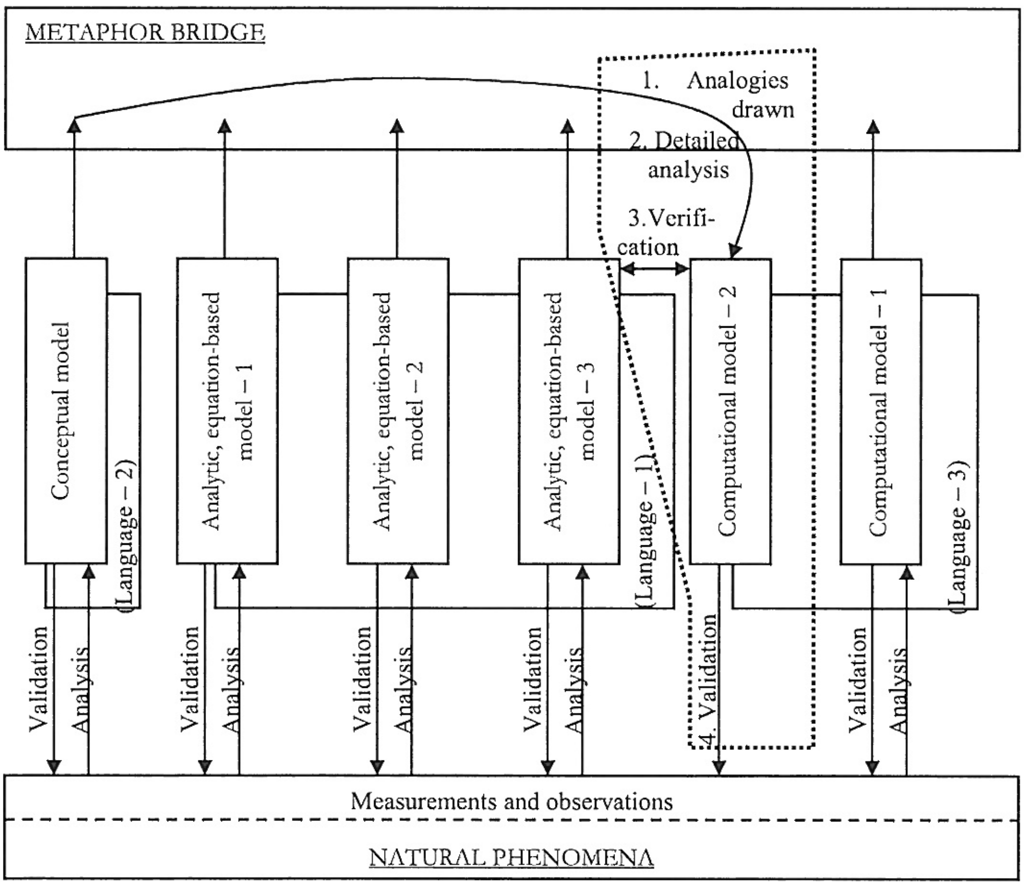

Fig. 1. Transferring knowledge between models by drawing analogies

(ABM):

- it's a bottom-up modeling approach
- agents are the basic entities of the simulation, they have behaviors and actions
- agents are completely independent, i.e. they have their own intelligence, make their own decisions
- the modeled system is typically a large set of agents
- the behavior of the system of agents "emerges" from the basic properties of the agents, and this emergence is the subject of study
- agentbased systems are very close to natural systems, and consequently they are potentially:
    - flexible
    - robust
    - often simpler than manmade systems
    - distributed in space and control
    - evolving
    - learning
- it is very closely related to Complexity Theory, a relatively new and very promising field of research

ABM therefore seems – and is proven – to be a viable alternative of exact mathematical methods for handling high complexity. Various software packages are offered for ABM, e.g. Ascape, AgentSheets, Repast and the earliest one called Swarm.

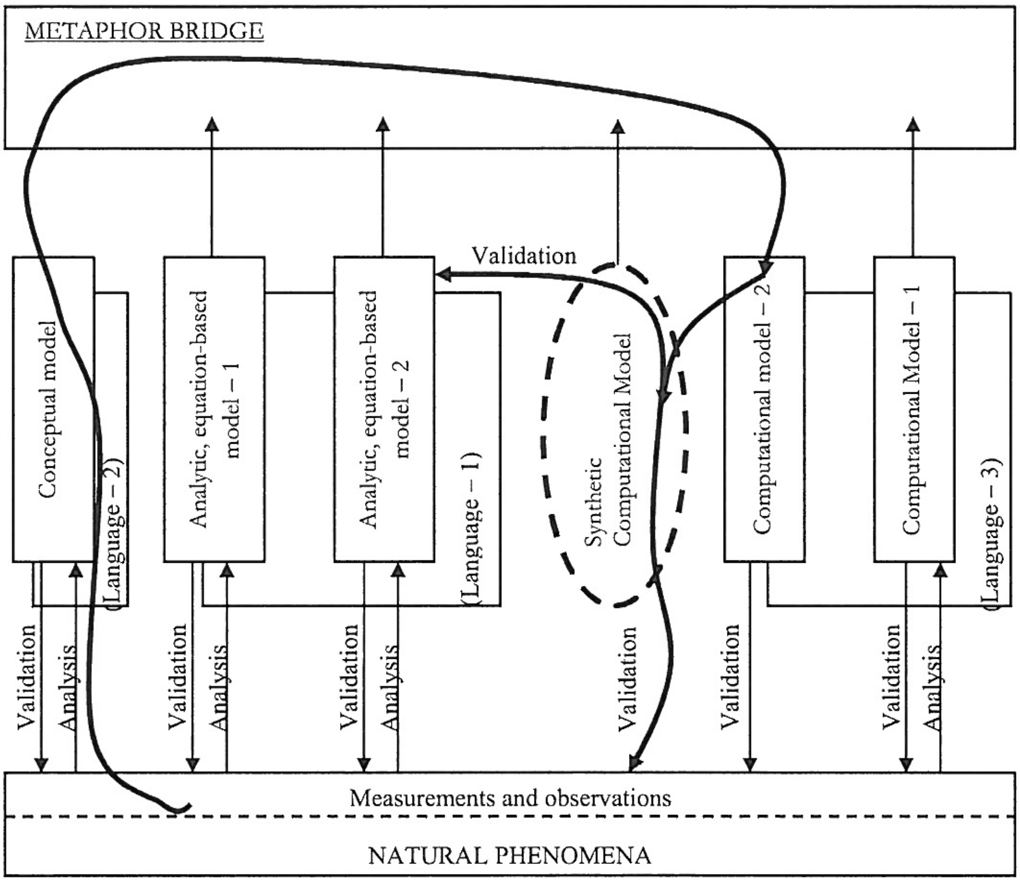

Fig. 2. Computational Synthesis of System Models

IV. AGENTBASED MODELLING SOFTWARE

Agentbased simulation software are the most important for our investigations since they are capable of building synthetic models and incorporating many of the requirements we impose. Most of them are free to use, but this only shows that they are not ready for commercialization yet, so it's not such a good news. To mention some of the other known agentbased simulation software we can list:

- Ascape
- AgentSheets
- Jade
- JAS
- NetLogo
- RePast

- Zeus

V. KNOWLEDGE TRANSFER BETWEEN MODELS BY METAPHORS

In Fig. 1. the knowledge transfer method by metaphors is shown in detail. The basic knowledge that any scientific or computational model can represent is only a segment of reality – as reflected by measurements, observations and models – requires that we fill the gaps between them by our continuous mental– and the corresponding rhetorical models.

Using the scientific language and method observations and measurements are put into a mathematical model, assuming that the experiments are repeatable and reproducible by others. This is satisfies the requirement of objectivity. Part of the process is the validation of the model through numerous experiments that are usually carried out by other parties insuring that no subjective mistakes are generated during experiments and measurements.

The "third" language or symbol system of computation [3] is in many ways related to the language of mathematics, as it can represent equations and solve them with some limitations related to continuity and problem size. However, computation also became a very flexible and multi-purpose tool due to the availability of computing machinery and various modelling approaches make it possible to create models that are not possible to describe by equations. One of these possibilities is agentbased modelling that approaches modelling from an unconventional aspect. Parunak [5] describes the advantages of agentbased modelling and points out that they represent a different aspect of reality, since equation based models represent the relation of observables and agentbased models represent the internal behavior of the modeled individual.

Following the process shown in Fig. 1. we can model reality or natural phenomena (including manmade systems) and exert a varying amount of control over them, depending on the success of the model. Since we know that in case of complex problems none of our models will cover the whole and provide a grip on the controls (or at least find them) we have to make use of different models and either integrate them or use a different one in different circumstances. The knowledge of the possibility about building bridges by rhetoric is not new at all, but its use is mostly unconscious or at least not systematic.

The method for transferring knowledge between different models and even disciplines is not new at all, it has always been part of scientific discourse. The method, however, is described by e.g. Nicolis and Prigogine [5] and by others [1] , in the realm of complex systems where such knowledge transfer is crucial, since we have systems that require us to be approached in a systematic and knowledge integrating manner. In Fig. 1. this algorithm is shown in an area enclosed by dotted line.

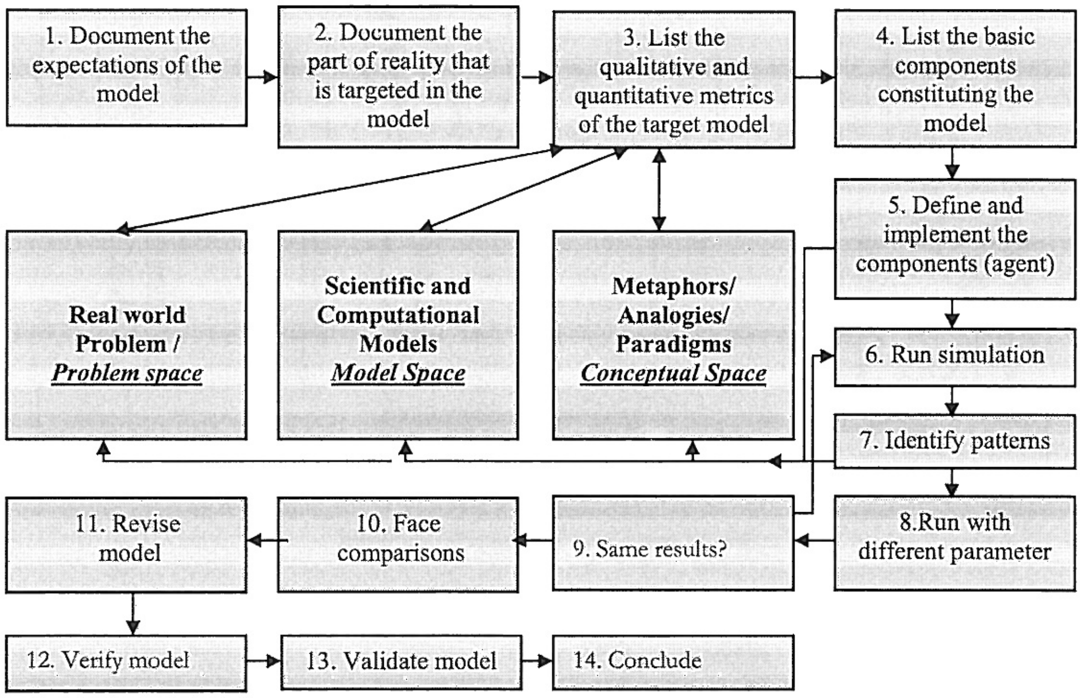

Fig. 3. The computational system model synthesis methodology

VI. AN EXAMPLE OF SUCCESSFUL METAPHORIC KNOWLEDGE TRANSFER

A good example of this knowledge transfer is *evolutionary computation* methods. In case of the "evolution metaphor" the knowledge transfer process is as follows:

1) Darwin observed species and came to assumptions about the basic process of evolution
2) Microbiologists developed analytic methods down to the genetic level and showed how genetic inheritance works, defined such concepts as population genetics, crossover, gene mutation, selection pressure and process.
3) Computer scientists found that some of the problems they face cannot be solved by exact mathematical equations or algorithms, and realized that it is necessary to approach these problems heuristically.
4) Somebody (John Holland et alii) had the idea that looking for better candidate solutions is metaphorically similar to the evolution of species.
5) The evolutionary concepts in (2) were assigned meaning in the realm of computing (bit strings, permutations, etc).
6) The evolutionary algorithm was assembled and it was observed that simulated evolution is able to develop individuals by selection, crossover, mutation, etc.

We have no guarantees, that such a knowledge transfer always works, but the general observation is that interdisciplinary cooperation is mostly very fruitful.

VII. A SYNTHETIC SYTEM MODELLING METHODOLOGY

Synthesis is often regarded as a secondary approach to analysis, not a complementary or equal alternative [5] . However, searching for new structures, new knowledge, virtual and nontrivial systems, and in case we have no other way for the investigation of a mechanism (with possibly explanatory power) synthesis provides a viable alternative (a good example is chemistry).

A characteristic example of synthesis is the modelling of cellular automaton, where we have no analytical knowledge about the emergent phenomena, at most heuristic rules, which were formed on the basis of extensive computational studies[3].

In Fig. 2. a computational synthesis method is shown and explains the idea how agentbased models can fit into a scientific scenario. Model building itself is not science without a methodology that insures the required objectivity, the repeatability of experiments and general applicability. By following the thick arrows in the figure we can see the following steps of the method:

1. identify the basic components of the system
2. formulate a rough conceptual model
3. transform the basic conceptual entities of the model into computational entities by analysis (this is a metaphor translation)
4. define the behavior and interaction pattern of the basic components
5. define/set the initial and boundary conditions
6. select the observable variables
7. run the simulation multiple times with different parameters
8. look for patterns in the system behavior
9. validate the synthetic model by comparing it to real systems, analytical and conceptual models (incl. metaphors)
10. document observed system behavior

By this procedure we have integrated an empirical, synthetic modelling method in a scientific environment. This integration doesn't mean that we have a perfect scientific method, but it is not far from it, because it provides a systematic way of handling computer experiments and uses analytical and rhetorical knowledge to put the model into context, validate it and use it for gaining extra insight into systems.

In Fig. 3. a more detailed view of the empirical methodology is shown from a different aspect.

This methodology helps avoiding some of the trivial problems of agentbased, synthetic, bottom-up modelling. The first step is to put down in written form what we expect of the model, because building in expectations in a model is very easy. By making these intentions "transparent" we admit our skepticism concerning the method. This methodology leads to its applications also, because as it can be expected from the scenario of Fig. 2. we do not expect that such a model will often be able to replace the equation-based, mathematically sound models. Agentbased modelling and synthetic methods have the advantage that they can produce models that would not have been thought of by humans, and by running various open-ended evolutionary simulations many malfunctioning structures can be "explored" as well [8] . This is why the complementarity of such a modelling methodology is emphasized.

VIII. CONCLUSIONS

The proposed methodology for transferring (and deploying) knowledge between agentbased simulation models aims at the integration and documentation of the complete modelling process. Acknowledging the importance of rhetoric tools in the formulation of the problem, definition of the model and carrying out computational experiments motivated us to try to bridge the gap between the "real" modelling process and the often narrow sighted software engineering process, that puts the emphasis on the computational aspects only.

The described "intent transparency", the extensive

[3] Chris Langton introduced the λ parameter that hints whether the cellular automata will be chaotic, repeat a pattern or be random [6] .

documentation and keeping in mind the "big picture" even encourages the investigation of artificial, synthetic systems.

IX. ACKNOWLEDGMENTS

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