# COMBINING KNOWLEDGE-PROCESSING AND SIMULATION TECHNIQUES FOR SYSTEMS MODELING

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## ABSTRACT

Regarding current rapid innovations and applications of information and telecommunication technologies as well as economical requirements, modeling and simulation (M&S) plays an increasingly important role for the planning, development and operation of high-tech products and systems. M&S has to seen as a key technology for multi-facetted analysis of complex systems during their life-cycles. For reasons as accuracy, credibility and cost-effectiveness, the selection of adequate and effective M&S techniques and tools is of significant importance. Regarding these aspects, this paper summarizes the basic methodological modeling approach for effective product and system modeling. In addition, besides a classification of different basic architectures and taxonomies combining knowledge-processing and simulation techniques, the paper describes some practical implementations and experiences.

## 1. INTRODUCTION

Rapid innovations of information and telecommunication technologies, on one hand side, and stringent demands for time-constraint, cost-effective, safe and reliable system development and application, on the other hand, require the use of M&S technology for multiple purposes in all stages of a complex system's life-cycles. Complexity of today's high-tech systems often results from a high degree of distributed subsystems or components, such as in manufacturing & production systems, in traffic control systems or in military systems. System evaluations with respect to different evaluation aspects – e.g. performance, safety, or reliability – require adequate formal, symbolic descriptions of the product's structure and dynamics at different levels of detail. Besides, detailed evaluations sometimes also require a precise modeling of the systems environment, and of the human-system interaction, as well.

This can only be performed by the use of logical or numerical models which adequately represent information and knowledge about the modeled objects. For model implementation and flexible experimentation, computer simulation and knowledge-processing techniques are widely used. Regarding the different restrictions and constraints which have to be considered in applying those techniques, we have to distinguish **different types of problem solving**, e.g.:

- **System analysis** (diagnosis, selection, classification, advise),
- **System synthesis** (construction, configuration, design, planning),
- **Prediction of the system's behavior** (prediction of its dynamic behavior regarding different aspects), and
- **System training** (e.g. operation and maintenance).

For performing those problem solving capabilities efficiently and effectively, different qualities of data, information, or knowledge about a system and its user interaction have to be distinguished and have to be represented adequately, like ([SEV87]):

- **facts** expressing valid propositions,
- **believes** expressing possible propositions, and
- **heuristics** expressing rules of good judgement in situations were valid algorithms do not exist.

The implementation of formal models via simulation techniques mostly requires the numerical or symbolical representation of the modeled system properties, such as structural and behavioral information. The "inference" or problem-solving knowledge is implicitly included in the system knowledge representation while simulation control is primarily a timing and event (or process) scheduling mechanism. In contrast, a knowledge-based system represents system knowledge explicitly and separately from the inference engine. In addition, techniques like predicate logic, production rules, fuzzy logic, semantic nets, constraint propagation, or non-monotonic reasoning can be applied for representation of domain knowledge and for knowledge-processing.

Based on own experience we can say that combining knowledge-processing and classical simulation techniques can significantly enhance and improve representation of data, information and knowledge about a system to be modeled, and flexible and multiple-purpose modeling, as well. Its integration by knowledge-based simulation is a methodological and architectural approach which also addresses those requirements. Knowledge-based simulation has been defined as "... the application of knowledge-based methods within artificial intelligence (AI) to the field of computer simulation. ... Studying how heuristic and fuzzy knowledge might be used in simulation ..." ([FiM91]). That means within a knowledge-based simulation system vague, uncertain and fragmentary information and knowledge can be represented also by those knowledge representation techniques mentioned above and besides classical numerical and functional representation techniques.

## 2. MODEL ENGINEERING – THE SYSTEM MODELING PROCESS

The design and application of models of complex systems requires a stepwise procedure to ensure collaborative model design, implementation, testing, refinement, adoption, and reuse of intermediate results. Based on a more or less informal task description of the modeling aspects, intended usage, and restrictions, system and modeling experts have to present a complete task specification. In the first "modeling" phase, they have to develop a communicative model which serves as specification for the model formalization by a modeling expert in the field. The formalized model is the specification for the model implementation or programming which could be processed by another person. After final verification and validation by modeling and domain experts, the implemented model can be used for its intended purpose.

As already mentioned before in various papers, development and application of M&S is an engineering process – model engineering - performed as a multi-phase process (see Figure 1). It guarantees the effective collaboration between experts in different fields and enables a high degree of flexibility, testability of intermediate results with respect to model validity and correctness, adoption, and reusability. Another reason for subdividing the M&S process into these different phases results from the fact that different types of input and information is required in the different M&S phases, and that different persons input is required: input from the final model user, from the formal model designer and from the model programmer, as well.

## 2. ARCHITECTURES AND TAXONOMIES

The most important arguments for combining or integrating knowledge-processing and traditional simulation methodologies and techniques are:

- adequate representation of domain knowledge and of modeling knowledge (which includes facts, uncertain, vague, and fragmentary information and data);
- separation of domain and problem solving knowledge (especially regarding reusability of these different types of information and knowledge);
- time dependency of domain information and of reasoning mechanisms, as well;
- realization of application and user-oriented model interfaces (e.g. by the implementation of advisory systems or decision support systems);
- enhancement or replacement of "classical" deductive (rule-based) solutions by inductive approaches (e.g. by applying case-based reasoning techniques);
- supporting M&S designers and users in the different phases of a modeling process.

With respect to their user interfaces, the programming environments, and the degree of interaction between knowledge-based and simulation environments, three major categories can be distinguished according to Figure 2 ( [Leh87]):

- **Embedded Simulation system** (Figure 2a): Embedded simulation architectures are characterized by embedding simulation techniques in the knowledge-based system for representation of time-dependent knowledge or of time-dependent reasoning processes.

- **Knowledge-Based Simulator** (Figures 2b, 2c): The characteristics of knowledge-based simulators are the availability of knowledge-representation and -processing techniques besides "classical" numerical techniques for model design and solution. Regarding their architecture and taxonomy, we have to distinguish between interactive co-operative knowledge-based simulators (see Figure 2c) and embedded knowledge-based systems. In contrast to embedded knowledge-based simulators, interactive co-operative architectures do not require a homogeneous programming framework for their implementation.

- **Intelligent Analyst / Modeler's Advisor** (Figures 2d, 2e): Regarding the architectural approaches, we have to distinguish between decision supporting environments (Figure 2d), and intelligent front-ends (see Figure 2e) where the different real system objects are mapped to predefined modeling objects, or components, of a simulation environment.

## 3. EXAMPLES AND EXPERIENCES

The following section presents some examples and briefly describes major features of these knowledge-based modeling and simulation approaches:

- **Embedded Simulation (see Figure 2a):**
  Typical application for embedded simulation is an adequate representation of time-dependent knowledge representation or reasoning by simulation techniques. Examples are realizations of scheduling mechanisms, e.g. in production or in logistic systems. A general requirement for the realization of this architecture is the availability of a homogeneous programming framework for implementation of the knowledge-based system and of the simulation techniques, as well. Some implementations are based on TPROLOG (an extension of PROLOG for discrete systems simulation) or TCPROLOG (a PROLOG extension for time-continuous simulation) .

- **Knowledge-Based Simulator:**
  The characteristics of knowledge-based simulators are extensions of "classical" modeling and simulation techniques by knowledge-representation and -processing techniques.
  Regarding the two different taxonomies, interactive co-operative knowledge-based simulators (see Figure 2c) can be applied for e.g.:
  - Model user support, e.g. for planning simulation experiments or for goal-oriented model adaptation, or for
  - implementation of agent-based simulation. According to most definitions (e.g.[SU00]), autonomous agents can be defined as "distributed computational agents with autonomy". They possess **knowledge and beliefs, intentions and goals, plans and methods** how to achieve them, as well as certain **capabilities** of action and communication. Types of applications of agent-based concepts in the context of co-operating interactive KBS-Simulation are data-collecting agents for a simulation system, such as
    - "Know-bots",
    - "Web-crawlers", or
    - Information-gathering agents in the WWW,
    - autonomous units in Computer Generated Forces (CGF),
    - model agents for representation of social / human / political interactions, or
    - modeling and simulation of traffic and logistic systems based on game theory.

  Embedded knowledge-based systems according Figure 2b are especially used for representation of vague, uncertain, fragmentary, and time-dependent information by those knowledge representation and -processing techniques as mentioned before. Typical applications of this category include automatic, goal-directed model adaptation or design of simulation experiments(e.g. [GC97]). In addition, this approach is used to represent autonomous components of a simulation or simulation federation, e.g. for
  - representation of autonomous entities of the "real world" (example: "automatic pilot" in a flight training simulator [CFK+97]), or
  - migration of agents between computers.

- **Intelligent Analyst / Modeler's Advisor**
  In this category, knowledge-based techniques are used to support model developers and model users in the goal-directed and efficient design of models and their application. Regarding the architectural approaches, we have to distinguish between decision supporting environments (Figure 2d) in which the user can get decision support from the knowledge-based system sharing some data in common with the simulation system. Both systems can be implemented as classification systems or as advisory systems, supporting model designers and users in the different phases of a goal-directed modeling process and the accompanying process of model verification and validation (V&V).
  In contrast, an intelligent front-end (see Figure 2e) maps real system objects of different application domains to modeling objects of a specific modeling or simulation environment. This enables domain experts or users to better understand or specify model inputs and interpret output results without being familiar with the internal structure and functionality of simulation model objects.

## 4. CONCLUSIONS

Rapid technological innovations result in rapid product innovations , in increasing system complexity and distribution, in increasing time-to-markets requirements, and in improving production efficiency. One of the key enabling technologies for future is systems modeling and simulation. The stepwise specification, design, development, operation, and maintenance of complex systems will be enabled and accompanied by permanent use of multi-facetted, hierarchical models and simulations (M&S). Concerning M&S effectiveness and efficiency, improved and new modeling approaches and techniques are required.

This paper deals with combining knowledge-processing and simulation techniques as one approach to coping with future demands. The examples presented and our experiences with concrete applications showed that knowledge-based simulation is one methodological approach which has to be considered as effective to model complex and distributed systems including the situation that data, information and knowledge about the system, its environment and users to be modeled are never complete, certain, or factual.

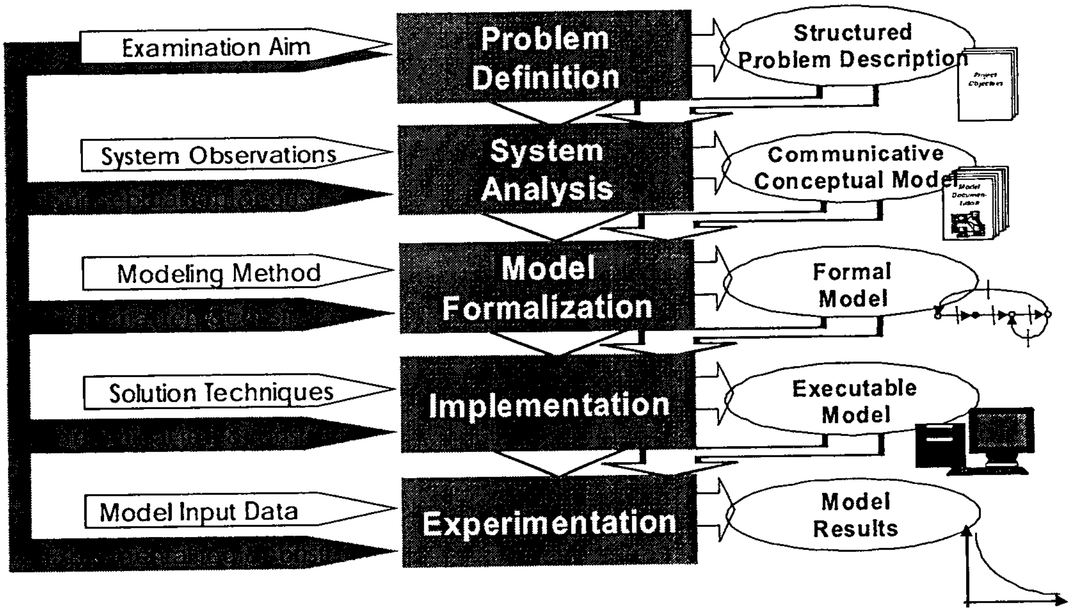

Fig. 1: Model Engineering as multi-phase modeling process [Bra00]

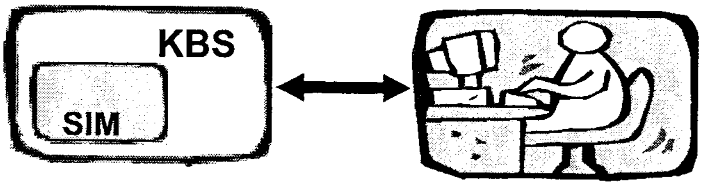

Fig. 2a: Embedded simulation system (SIM)

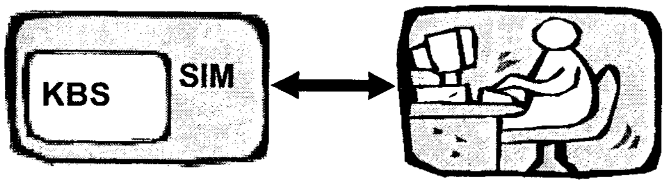

Fig. 2b: Embedded knowledge-based system (KBS)

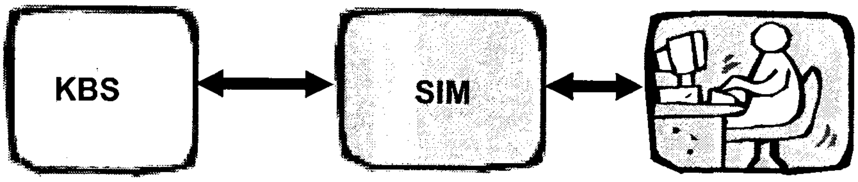

Fig. 2c: Interactive, co-operating KBS

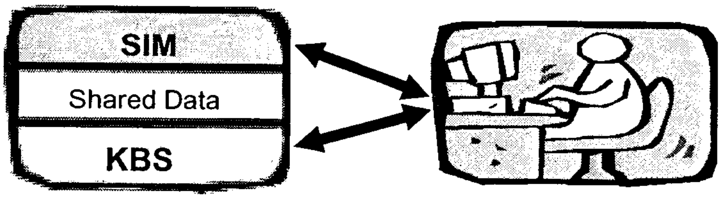

Fig. 2d: Simulation system and knowledge-based system with shared data

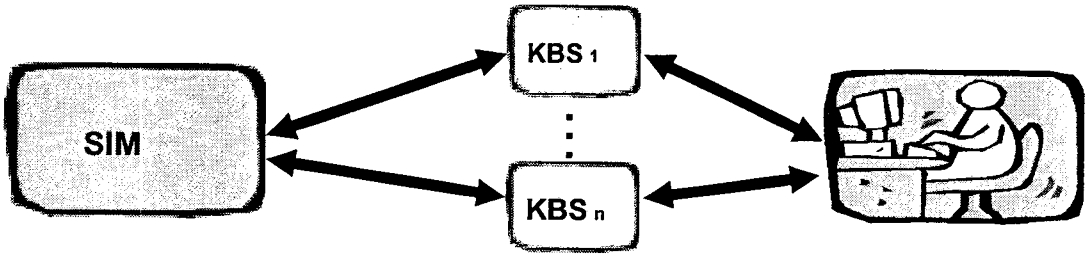

Fig. 2e: KBS's as "intelligent domain-specific front-ends"

**Fig. 2: Architectures and taxonomies of knowledge-based simulation environments**

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