Supporting Agent-Oriented Designs with Models of Macroscopic System Behavior

(Extended Abstract)

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ABSTRACT

The purposeful development of MAS, particularly when addressing complex, decentralized application architectures, demands the ability to anticipate the effects of agent coaction. Sophisticated design and modeling tools support the development of individual agent models and their arrangement in organizational structures. However, only limited support is available to pre-estimate the qualitative, macroscopic system properties that rise from agent (inter-)action. Here, we propose a *systemic* modeling level that allows to describe the qualitative macroscopic dynamics of MAS by modeling the impact of exhibiting agent behaviors on parts of the agent population as well as environment elements. We discuss the systematic derivation of these models from established design models / notations and outline how these models can be used to anticipate the qualitative dynamics of MAS as well as to validate MAS implementations.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems*

General Terms

Design

Keywords

Decentralized Coordination, System Dynamics

1. INTRODUCTION

An integral part of Agent-Oriented Software Engineering (AOSE) methodologies [3] are tailored notations that support the utilization of agent technology concepts in application development contexts. The utilized modeling levels typically address either microscopic agent designs, e.g. the specification of agent internal reasoning, or the organizational structures of agent populations. However, when conceiving complex, decentralized coordination schemes within MAS, developers have to anticipate the effects of agent coaction to pre-estimate whether MAS designs are capable of meeting given requirements, i.e. to show adaptation. Complex dynamics may also be unintentionally designed [6].

Here, we propose the integration of *systemic* modeling techniques in AOSE practices [3] to bridge the gap between microscopic agent designs and the qualitative macroscopic MAS dynamics. Systemic modeling techniques address the macroscopic description of complex systems by describing the causal relations between system elements and system variables [8]. Systemic and agent-based modeling techniques are typically treated as opposing approaches and it is particularly difficult to link them exactly. We argue that systemic descriptions of MAS can be systematically transferred from agent-based application designs and that these allow developers to examine the qualitative space of potential application dynamics. This approach does not allow for precise parameter predictions, but enables developers to estimate the dynamical modes, e.g. steady states and oscillations, that designed implementations are capable to exhibit [6].

2. SYSTEMIC MODELING OF MAS

The here proposed, systemic description level extends the prominent *Causal Loop Diagrams* (CLD) [8], a graph-based notation which denotes system variables as nodes that are linked via causal relations. System variables describe the accumulative values of system qualities and the causal relations indicate their rates of change [8]. The unambiguous modeling (see [7] for a discussion of complications) of MAS applications is facilitated by a refinement of system variables and the types of causal relations. We utilize the generic *role* and *group* concepts to describe macroscopic MAS states. Roles characterize agent activities / behaviors and groups partition MAS in agent sets that share characteristics [5].

A so-called *Agent Causal Behavior Graph* (ACBG) is denoted by: $ACBG :=< V_{ACBG}, E_{ACBG} >$, where V_{ACBG} is a set of nodes and E_{ACBG} is a set of directed edges between nodes ($E_{ACBG} \subseteq V_{ACBG} \times V_{ACBG}$). Four node types describe the macroscopic observable state of a MAS by the number of current role activations ($r_{(x)}$), the number of active groups ($g_{(x)}$), the size of specific groups ($gs_{(x)}$) the accumulative values of environment elements ($e_{(x)}$). An

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additional node type allows to denote influences on rates ($ra_{(x)}$). The causal interdependencies between these nodes describe positive or negative influences and that are either *direct* ($e_{(d+/-)}$), e.g. caused by inter-agent communication, or *mediated* ($e_{(m+/-)}$) by coordination mechanisms, e.g. shared environments. Connections between MAS nodes ($r_{(x)}$,$g_{(x)}$,$gs_{(x)}$,$e_{(x)}$) describe causal relations, i.e. increases in originating variables of positive influences enforce that the values of connected variables increase in subsequent time steps. Negative relations describe changes in opposite directions [8]. Connections from rate-nodes have only additive / subtractive influences. E.g. the number of agents adopting a *producer* role will positively influence the rate of *production*, i.e. an increase of producers increases this rate proportionally. However, this rate contributes only additively to the amount of produced subjects (cf. [7]).

3. SUPPLEMENTING AGENT-ORIENTED DESIGNS WITH SYSTEMIC MODELING

Systemic models highlight the *causal* structure that underlies MAS designs. They reveal non-linear influences and cyclic dependencies (feedback cycles) that are inherently present within microscopic agent / environment designs.

3.1 Deriving Systemic Models

The systematic derivation of systemic MAS models from AOSE designs requires (1) the identification of the system variables and (2) their causal influences. The designs of the agent(s), environment(s) and MAS organization(s) (cf. figure 1, A) provide input to the identification of ACBG nodes (cf. figure 1, B). ACBG *role* nodes can be identified in the agent design models, which describe the role changing behavior of agents, e.g. via *AUML* Sequence Diagrams. ACBG *group membership* and *group size* nodes can be identified by the optional consideration of organizational models that describe which organizational structures partition the MAS, e.g. following [1]. Finally, the environment models indicate which environment variables / elements are present.

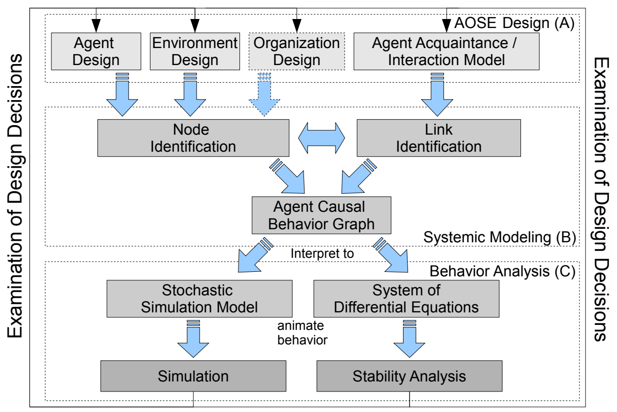

Figure 1: Examination of qualitative dynamics.

The identified nodes describe the number of agents / environment elements. ACBG links are identified by searching design models for the influences that trigger increases / decreases of the system variables, i.e. cause agents to adopt roles or leave groups. The identification of direct links within agent models is architecture specific, these are triggered by agent internal processing. Direct inter-agent links typically originate from agent interactions. Models of the agent acquaintance / interactions (e.g. GAIA: acquaintance diagram, Prometheus: system overview diagram [3]) highlight which agent types interact. These interactions can be related to ACBG nodes by tracing back the affected agent internal elements. Mediated links are identified by examining which agent activities interact with MAS environment(s).

3.2 Examining Qualitative Dynamics

The identification of the causal structure of application designs facilitates the anticipation of dynamic system properties. Their manual examination is assisted by the derivation of simulations and/or mathematical models (cf. figure 1 (C)). Our experiences show that stochastic simulation models, e.g. stochastic process algebra (cf. [2]), are appropriate for the qualitative simulation of ACBGs. The accumulative values of system variables can be represented by numbers of active processes and rate of stochastic process interactions allow to express average system causalities. The derivation of differential equations [8] allows qualitative prediction of steady states and oscillations using stability analysis [4].

4. CONCLUSIONS

We propose the application of systemic modeling levels to examine the implications of agent-oriented application designs. The presented modeling approach has been successfully applied to check MAS designs as it allows to identify unexpected dynamical behaviors, i.e. oscillations and steady states, in valid MAS designs. These initial applications comprise the detection of unexpected interdependencies of agent workloads and the initial design of a resource allocation algorithm that showed a surprising *absorbing* behavior of agent roles, due to an insufficient communication of resource demands. Ongoing work addresses guidelines to the interpretation of systemic models and tool support to their alignment / derivation with established AOSE notations [3].

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