Engineering hierarchical complex systems: an agent-based approach
The case of flexible manufacturing systems

Gildas Morvan\textsuperscript{1,2}, Daniel Dupont\textsuperscript{1,3}, Jean-Baptiste Soyez\textsuperscript{1,4}, and Rochdi Merzouki\textsuperscript{1,4}

\textsuperscript{1} Univ. Lille Nord de France, 1bis rue Georges Lefèvre 59044 Lille cedex, France
\textsuperscript{2} LGI2A, U. Artois, Technoparc Futura 62400 Béthune, France. email: first.name.surname@univ-artois.fr
\textsuperscript{3} HEI, 13 rue de Toul 59046 Lille Cedex, France. email: first.name.surname@hei.fr
\textsuperscript{4} LAGIS, EC-Lille, Avenue Paul Langevin BP 48 59651 Villeneuve D’ascq cedex, France

Abstract. This article introduces a formal model to specify, model and validate hierarchical complex systems described at different levels of analysis. It relies on concepts that have been developed in the multi-agent-based simulation (MABS) literature: level, influence and reaction. One application of such model is the specification of hierarchical complex systems, in which decisional capacities are dynamically adapted at each level with respect to the emergences/constraints paradigm. In the conclusion, we discuss the main perspective of this work: the definition of a generic meta-model for holonic multi-agent systems (HMAS).

Keywords: multi-level multi-agent based simulations, formal models, hierarchical systems

1 Introduction

Engineering a complex system such as a flexible manufacturing system (FMS) is a challenging problem. The target system is complex, holonic, relies on distributed decisional processes, and must be adaptive, \textit{i.e.}, robust to perturbations and easily reconfigurable.

To solve these problems, proposed solutions\textsuperscript{1} take advantage of system

\begin{itemize}
    \item complexity, distributing the control in system components that embody primitive cognitive capacities, \textit{e.g.}, be able to be identified, to communicate, to react to environmental changes,
    \item holonic structure, using dedicated meta-models and conception methodologies.
\end{itemize}

\textsuperscript{1} \textit{E.g.}, heterarchical\textsuperscript{3} or semi-heterarchical\textsuperscript{25} control, holonic multi-agent systems (HMAS)\textsuperscript{26,31} or intelligent product based concepts\textsuperscript{24}.
An important tool in the design, simulation and validation of such solutions has been multi-agent-based simulation (MABS). This article introduces a formal model to specify, model and validate hierarchical complex systems. It takes inspiration from two trends in MABS research:

– the formalization of interaction models,
– multi-level modeling, where interacting agents are ontologically distributed among multiple layers of organization.

The article is organized as follows:

– in the section 2, the two trends of MABS research cited above, multi-level modeling and formal modeling, are introduced,
– the section 3 presents a generic formal model for multi-level MABS,
– an abstract implementation of this model, focusing on the specification of hierarchical multi-agent systems (MAS), in which decisional capacities are dynamically adapted at each level with respect to the emergences/constraints paradigm, is proposed in the section 4,
– the conclusion (section 5) summarizes our contributions and perspectives.

2 Two trends in MABS research

2.1 Multi-level modeling

A level represents a point of view on the system, and its relations to other points of view [16]. While this concept seems important to understand complex systems [3], it generally remains abstract: implementations tend to constraint this definition, in particular the relations between levels. Therefore, a multi-level model integrates knowledge on different levels and their relations. Multi-scale are multi-level models characterized by hierarchical relations in levels [7,12,19,23]. A level may represent, according to the context, a spatio-temporal extent, a position in a decision hierarchy, etc. Let consider these two examples.

1. The system is characterized by processes that have different spatio-temporal extents. Two types of relations can be commonly found in such models:
   – scaling, i.e., computing macroscopic (resp. microscopic) variables from microscopic (resp. macroscopic) processes,
   – grouping and degrouping (or aggregation and disaggregation) [6,20,26], i.e., defining a process at a level as a group (resp. part) of processes (resp. a process) at an other level.

2. Levels are characterized by decisional capacities; relations represent the emergence of new capacities and the constraint over existing capacities [15,17].

A level is often viewed as a level of organization. This concept is closely related to the notion of holon [6]. This aspect is discussed in the section 5.

2 The presentation focuses on the influences → reaction model (IRM). Other approaches such as IODA [10] or based on DEVS [18] are not described.
3 Multi-level approaches have proven useful in many domain such as statistics [8], chemistry [9,11], physics [28], hydrology [26] or biology [33].
2.2 The influences → reaction model

The influences → reaction model (IRM) has been developed to address issues raised by the classical vision of action in Artificial Intelligence as the transformation of a global state [5]:

- simultaneous actions cannot be easily handled,
- the result of an action depends on the agent that performs it but not on other actions,
- the autonomy of agents is not respected.

Basically, it decomposes action in two phases: agents and environment (micro level) produce a set of influences, then the system (at macro level) reacts to influences; e.g., detects and solves influence conflicts such as in the platform Jaak[^4]. As [13] notes, "the influences [produced by an agent] do not directly change the environment, but rather represent the desire of an agent to see it changed in some way". Thus, reaction computes the consequences of agent desires and environment dynamics. In recent years, variants of IRM have been developed to handle specific situations [13,16,36,37]. This presentation focuses on the influence reaction model for simulation (IRM4S) [13].

Let $\delta(t) \in \Delta$ be the dynamic state of the system at time $t$:

$$\delta(t) = \langle \sigma(t), \gamma(t) \rangle,$$

where $\sigma(t) \in \Sigma$ is the set of environmental properties and $\gamma(t) \in \Gamma$ the set of influences, representing system dynamics. The state of an agent $a \in A$ is characterized by its physical state $\phi_a \in \Phi_a$ with $\Phi_a \in \Sigma$ (e.g., its position) and its internal state $s_a \in S_a$ (e.g., its beliefs).

The evolution of the system from $t$ to $t + dt$ is a two-step process:

1. agents and environment produce a set of influences $\gamma'(t) \in \Gamma'$,
2. the reaction to influences produces the new dynamic state of the system.

An agent $a \in A$ produces influences through a function $Behavior_a : \Delta \mapsto \Gamma'$. This function is decomposed into three functions executed sequentially:

$$p_a(t) = Perception_a(\delta(t)),$$

$$s_a(t + dt) = Memorization_a(p_a(t), s_a(t)),$$

$$\gamma'_a(t) = Decision_a(s_a(t + dt)).$$

The environment produces influences through a function $Natural_\omega : \Delta \mapsto \Gamma'$:

$$\gamma'_\omega(t) = Natural_\omega(\delta(t)).$$

[^4]: [http://www.janus-project.org/Jaak](http://www.janus-project.org/Jaak)

[^5]: the sets of producible influence sets and influences produced at $t$ are denoted respectively $\Gamma'$ and $\gamma'(t)$ to point out that the latter is temporary and will be used to compute the dynamic state of the system at $t + dt$. 

Then the set of influences produced in the system at $t$ is:

$$\gamma'(t) = \{\gamma(t) \cup \gamma'_a(t) \cup \bigcup_{a \in A} \gamma'_a(t)\}. \quad (6)$$

After influences have been produced, the new dynamic state of the system is computed by a function $\text{Reaction} : \Sigma \times \Gamma' \mapsto \Delta$ such as:

$$\delta(t + dt) = \text{Reaction}(\sigma(t), \gamma'(t)). \quad (7)$$

3 A generic meta-model for multi-level MABS

In this section, a generic meta-model for multi-level MABS, called IRM4MLS, is presented. This model has the following interesting properties:

- any valid instance can be simulated \[27\],
- simulation scheduling is logically distributed by level,
- complexity of simulation algorithm can be optimized according to model structure.

3.1 Specification of the levels and their interactions

A multi-level model is defined by a set of levels $L$ and a specification of the relations between levels. Two kinds of relations are specified in IRM4MLS: an influence relation (agents in a level $l$ are able to produce influences in a level $l' \neq l$) and a perception relation (agents in a level $l$ are able to perceive the dynamic state of a level $l' \neq l$), represented by directed graphs denoted respectively $< L, E_I >$ and $< L, E_P >$, where $E_I$ and $E_P$ are two sets of edges, i.e., ordered pairs of elements of $L$. Influence and perception relations in a level are systematic and thus not specified in $E_I$ and $E_P$ (cf. eq. 8 and 9).

E.g., $\forall l, l' \in L^2$, if $E_P = \{ll'\}$ then the agents of $l$ are able to perceive the dynamic states of $l$ and $l'$ while the agents of $l'$ are able to perceive the dynamic state of $l'$.

The in and out neighborhood in $< L, E_I >$ (respectively $< L, E_P >$) are denoted $N^-_I(l)$ (resp. $N^+_I(l)$) and are defined as follows:

$$\forall l \in L, N^-_I(l) \text{ (resp. } N^+_I(l)) = \{l\} \cup \{l' : l' \in E_I \text{ (resp. } E_P)\}, \quad (8)$$

$$\forall l \in L, N^+_I(l) \text{ (resp. } N^-_I(l)) = \{l\} \cup \{l' : ll' \in E_I \text{ (resp. } E_P)\}, \quad (9)$$

E.g., $\forall l, l' \in L^2$ if $l' \in N^+_I(l)$ then the environment and the agents of $l$ are able to produce influences in the level $l'$; conversely we have $l \in N^-_I(l')$, i.e., $l'$ is influenced by $l$.

---

6 The dynamic aspects of the meta-model, i.e., simulation algorithms, are not described here. An exhaustive presentation can be found in \[16\].

7 The notion of level is here similar to the notion of brute space in the MASQ meta-model \[29\].
3.2 Agent population and environments

The set of agents in the system at time $t$ is denoted $A(t)$. $\forall l \in L$, the set of agents belonging to $l$ at $t$ is denoted $A_l(t) \subseteq A(t)$. An agent belongs to a level iff a subset of its physical state $\phi_a$ belongs to the state of the level:

$$\forall a \in A(t), \forall l \in L, a \in A_l(t) \text{ iff } \exists \phi_a^l (t) \subseteq \phi_a(t) \subseteq \sigma^l (t).$$ (10)

Thus, an agent belongs to zero, one, or more levels. As notes [29, p. 815], the physical state of an agent in a level, i.e., its body, is "the manifestation of an agent in the environment and allows others to perceive it." An environment can also belong to multiple levels (cf. fig. 1).

3.3 Action modeling

The dynamic state of a level $l \in L$ at time $t$, denoted $\delta^l(t) \in \Delta^l$, is a tuple $< \sigma^l(t), \gamma^l(t) >$, where $\sigma^l(t) \in \Sigma^l$ and $\gamma^l(t) \in \Gamma^l$ are the sets of environmental properties and influences of $l$.

The influence production step takes into account the influence and perception relations between levels:

$$\forall a \in A_l, \text{Behavior}_a^l : \prod_{l \in N^l_p(t)} \Delta^l_{lp} \mapsto \prod_{l \in N^l_i(t)} \Gamma^l_{il}. (11)$$

Once influences have been produced, interactions between levels do not matter anymore. Thus, the reaction function defined in IRM4S can be re-used:

$$\text{Reaction}^l : \Sigma^l \times \Gamma^l \mapsto \Delta^l, (12)$$

where $\text{Reaction}^l$ is the reaction function proper to each level.

4 Engineering hierarchical complex systems with IRM4MLS

4.1 The emergence/constraint paradigm

In many MABS, processes are considered on the following 2-level relative hierarchy:
Arrows represent causality relations between levels. Dashing suggests that they are generally not explicitly defined but emerge from interactions between entities. A contrario, a multi-level approach considers these relations explicitly. In engineering applications, a level may rather represents a position in a decision hierarchy (cf. section 2.1). Two kinds of relation may be distinguished in such systems: emergence of new capacities and constraint over existing capacities [14].

Let consider an example in the domain of FMS engineering. In a case study on automated guided vehicle (AGV) control presented in [17] (cf. section 4.4), the model relies on the following relations:

Macro agents (representing a set of "trapped" AGVs) emerge from micro agent interactions when an interaction pattern defined as a deadlock is detected, and then constraint their behaviors to solve it. While the notions of emergence and constraint were informally defined in [17], formal definitions in the context of IRM4MLS are given in the following.

4.2 IRM4MLS implementation

Let $L$ be a hierarchy and $\{\mu, M\} \subseteq L$ two hierarchically coupled levels, $\mu$ referring to the micro level and $M$ to the macro level. Thus, $A_\mu$ (respectively $A_M$) denotes the agents of the micro-level (resp. macro-level). The emergence/constraint paradigm supposes that $E_I \supseteq \{\mu M, M \mu\}$.

\[
\forall l \in L, \gamma^l(t) = \{\gamma^l(t), \gamma^M_\omega, \gamma^\mu_\omega, \bigcup_{a \in A_M} \gamma^M_a(t), \bigcup_{a \in A_\mu} \gamma^\mu_a(t)\}. \tag{13}
\]

An emergence $e$ at the level $M$ is an influence that has the following properties:

- $e$ belongs to the macro-level but not to the micro-level:
  \[
  e \in \Gamma^M \text{ but } e \notin \Gamma^\mu, \tag{14}
  \]

- $e$ cannot be produced by the behavior of an agent or the environment of $M$:
  \[
  \forall t, e \notin \bigcup_{a \in A_M} \text{Behavior}^M_a(\delta(t)) \cup \text{Natural}^M_\omega(\delta(t)), \tag{15}
  \]

with $\delta(t) = \langle \delta^M(t), \delta^\mu(t) \rangle$. 

Emergent influences generally determine the life-cycle (creation, evolution, destruction) of agents at the macro-level.

A constraint over an influence \(i\), denoted \(\neg i\), is the special kind of influence that has the following properties:

- \(\{i, \neg i\}\) belongs to the micro-level but not to the macro-level:
  \[
  \{i, \neg i\} \subseteq \Gamma^\mu \text{ but } \{i, \neg i\} \notin \Gamma^M,
  \]  
  (16)

- \(\neg i\) cannot be produced by the behavior of an agent or the environment of \(\mu\):
  \[
  \forall t, \neg i \notin \bigcup_{a \in A_\mu} Behavior^\mu_a(\delta(t)) \cup Natural^\mu_\omega(\delta(t)),
  \]  
  (17)
  
  with \(\delta(t) = < \delta^M(t), \delta^\mu(t) >\),

- \(\neg i\) inhibits \(i\):
  \[
  \text{if } \{i, \neg i\} \subseteq \gamma^\mu(t) \text{ then } \quad \text{Reaction}^\mu(\sigma^\mu(t), \gamma^\mu(t)) = \text{Reaction}^\mu(\sigma^\mu(t), \gamma^\mu(t) \setminus \{i\}).
  \]  
  (18)

### 4.3 Conception of hierarchical systems

The approach described below can be viewed as a semi-heterarchical control one and takes advantage of complexity and hierarchical (not yet holarchical) organization of the system, distributing the control by level. Heterarchical control methods rely on self-organization principles and therefore assume that the system is able to achieve its goals and is easily reconfigurable, i.e., that the normal functioning mode emerges from the interactions between system components (products, machines, simulated entities, etc.) that embody limited cognitive capabilities (cf. introduction). However, the trajectory of such systems may lead to non desired attractors.

The proposed methodology is presented in the fig. 2. The system is designed iteratively in a two-step process.

1. From an initial specification of the system, a model of the system in normal functioning mode, is defined and verified, i.e., that system components have the necessary cognitive capacities to perform their tasks.
2. From non desired attractors exhibited by the simulation of the model, the control strategy may be designed and validated. However, it is likely that the specification of the system has be modified to do so, e.g., because a new decisional level is needed.

The notion of influence is very general and therefore, may have many possible meanings. In this case, let

---

\(^8\) Self-organized systems are generally characterized by the use of environment as a communication medium to carry local informations as well as positive and negative feedbacks.
– $\gamma_l(t)$ be the capacities of each agent of a level $l$ at time $t$, i.e., the tasks they can perform at the moment,
– $\gamma_l(t)$ the actual affectation of tasks to agents; the only cognitive capacity required for agents is to expose services they may provide.

Thus, Reaction $l$ is a task assignment algorithm that computes $<\sigma_l(t), \gamma_l(t)>$ from $<\sigma_l(t), \gamma_l(t)>$. Note that the hierarchical nature of the system allows to decompose the specification of the system $S$ by level:

$$S = \{\gamma_l(\delta_l) : \forall l \in L, \forall \delta_l \in \Delta\},$$

i.e., task assignments for all functioning modes.

That design should lead to the definition of reaction functions that control goal affectations. If such a function cannot be defined, then the system design is not valid and must be redefined. This process is iterated until a solution is found (cf. fig. 2).

4.4 Case study: AGV deadlocks in gradient field-based FMS

The main functionalities of an intelligent transportation system (ITS) are: (1) transport assignment, (2) routing, (3) gathering traffic information, (4) collision avoidance, (5) deadlock avoidance [38].

Gradient field-based approaches, where AGV trajectories are computed from gradient fields, allow to implement efficient ITS in FMS [31,32]. A dedicated task assignment algorithm is generally used to ensure functionality 1, while functionalities 2–4 rely on AGV and shop self-organization properties. Thus, an AGV has two cognitives capabilities: sense attractive or repulsive force fields and emit a repulsive force field. Similarly, a shop is able to emit attractive fields to require products to process and give back the result to the system. A known problem of gradient field-based approaches is that a group of AGVs may be trapped in local minima that lead to a system deadlock [30,32,39]. However, this issue can be easily addressed by hierarchical control methods that compute explicit trajectories $^9$.

$^9$ Readers interested in general, i.e., not gradient-field based approaches, deadlock avoidance techniques in FMS may refer e.g., to [11,40].
The first design of the system is presented in fig. 3(a): a task assignment algorithm affects goals to AGVs (statically, a signal to maximize) and shops (dynamically, products to process). The deadlock avoidance functionality is not explicitly programmed but is supposed to emerge from mediated interactions between AGVs and shops. Various researches have shown that such a solution may reduce the number of deadlock occurrences but not eliminate it: routing is not deadlock avoidance 10. A new system architecture is then designed (cf. fig. 3(b)): if a deadlock (reified by an emergence) is observed by a deadlock solving algorithm, constraints over signal sensing and emission are computed to solve it 10.

5 Conclusion

In this article, we have presented a formal model for MABS and its implementation to engineer hierarchical complex systems. Two types of influences have been distinguished in this approach: emergence, that basically triggers a new system behavior when a specific pattern is detected (in the previous short example of gradient field-based FMS, the detection of a deadlock triggers the modification of AGV repulsive signal emission) and constraint, that, as its name suggests, constraints decisional capacities of system entities to solve a situation.

The main advantage of this approach lies in the multi-level and simulation capabilities of IRM4MLS, to model a system in which decisional capacities are distributed in its components and evolve along time to meet user’s goals and to simulate a model whiteout bias and temporal deadlocks11. Its main drawback is the strict hierarchical organization in levels.

Holonic multi-agent systems (HMAS) can be viewed as a specific case of multi-level multi-agent-systems (MAS), the most obvious aspect being the loosely

---

10 Practical aspects of this approach are discussed in 17. E.g., AGVs embody the deadlock solving algorithm, becoming multi-level agents. This problem has been an important motivation in the development of IRM4MLS.

11 Simulation properties of IRM4MLS may be exploited to explore model behavior using, e.g., the polyagent concept 22,21. Such an approach may be used to determine fail probabilities of system components or control strategies.
hierarchical organization of levels. However, from a methodological perspective, differences remain: thus, most of holonic meta-models focus on organizational aspects (cf. e.g., 2, 3, 5, 34). An important issue towards a generic meta-model for HMAS would be to define a holon with respect to IRM4MLS concepts: a holon cannot be defined with IRM4MLS first class abstractions (level, agent or environment), as it represents a multi-level entity. This situation is the main perspective of this work.

Acknowledgments

Authors would like to thank Daniel Jolly (LGI2A, Université d’Artois, Béthune France) and Alexandre Verreme (HEI, pôle recherche Ingénierie et Sciences du Vivant, Lille France) for their help and support. Jean-Baptiste Soyez is funded by the InTrade project[12].

References

1. Banaszak, Z., Krogh, B.: Deadlock avoidance in flexible manufacturing systems with concurrently competing process flows. IEEE Transactions on Robotics and Automation 6(6), 724 – 734 (1990)
2. Bendriss, S., Ben Abdelhafid, A., J.Boukachour, Boudebous, D.: Meta-modèle de référence holonique pour la gestion de la traçabilité du produit dans la chaîne logistique. In: 5ème Colloque International Conception et Production Intégrées - CPI’2007 (2007)
3. Duffie, N.: Heterarchical control of highly distributed manufacturing systems. International Journal of Computer Integrated Manufacturing 9(4), 270–281 (1996)
4. Ezpeleta, J., Tricas, F., f. Garcia-Valles, Colom, J.: A banker's solution for deadlock avoidance in fms with flexible routing and multiresource states. IEEE Transactions on Robotics and Automation 18(4), 621 – 625 (2002)
5. Ferber, J., Müller, J.P.: Influences and reaction: a model of situated multiagent systems. In: 2nd International Conference on Multi-agent systems (ICMAS-96), pp. 72–79 (1996)
6. Gaud, N., Galland, S., Gechter, F., Hilaire, V., Koukam, A.: Holonic multilevel simulation of complex systems: Application to real-time pedestrians simulation in virtual urban environment. Simulation Modelling Practice and Theory 16, 1659–1676 (2008)
7. Gil Quijano, J., Hutzler, G., Louail, T.: Accroche-toi au niveau, j’enlève l’échelle: Éléments d’analyse des aspects multiniveaux dans la simulation à base d’agents. Revue d’Intelligence Artificielle 24(5), 625–648 (2010)
8. Goldstein, H.: Multilevel Statistical Models. Wiley Series in Probability and Statistics, Wiley-Blackwell, 4th revised edition edn. (2010)
9. Horstemeyer, M.: Practical Aspects of Computational Chemistry Methods, Concepts and Applications, chap. Multiscale Modeling: A Review, pp. 87–135. Springer (2010)

[12] http://www.intrade-nwe.eu
10. Kubera, Y., Mathieu, P., Picault, S.: Interaction-oriented agent simulations: From theory to implementation. In: Proceeding of the 2008 conference on ECAI 2008: 18th European Conference on Artificial Intelligence. pp. 383–387. IOS Press (2008)
11. Lucia, A.: Multi-scale methods and complex processes: A survey and look ahead. Computers & Chemical Engineering 34(9), 1467 – 1475 (2010), selected papers from the 7th International Conference on the Foundations of Computer-Aided Process Design (FOCAPD, 2009, Breckenridge, Colorado, USA.
12. McGregor, S., Fernando, C.: Levels of description: A novel approach to dynamical hierarchies. Artificial Life 11(4), 459–472 (2005)
13. Michél, F.: The IRM4S model: the influence/reaction principle for multiagent based simulation. In: AAMAS ’07: Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems. pp. 1–3. ACM, New York, NY, USA (2007)
14. Morin, E.: Method: Towards a Study of Humankind, vol. 1. Peter Lang Pub Inc (1992)
15. Morvan, G., Jolly, D., Veremme, A., Dupont, D., Charabidze, D.: Vers une méthode de modélisation multi-niveaux. In: Actes de la 7ème Conférence de Modélisation et Simulation MOSIM, Paris, France. vol. 1, pp. 167–174 (2008)
16. Morvan, G., Veremme, A., Dupont, D.: IRM4MLS: the influence reaction model for multi-level simulation. In: Multi-Agent-Based Simulation XI. No. 6532 in Lecture Notes in Artificial Intelligence, Springer (2011)
17. Morvan, G., Veremme, A., Dupont, D., Jolly, D.: Modélisation et conception multi-niveau de systèmes complexes : stratégie d’agentification des organisations. Journal Européen des Systèmes Automatisés 43, 381–406 (2009)
18. Müller, J.P.: Towards a formal semantics of event-based multi-agent simulations. In: David, N., Sichman, J. (eds.) Multi-Agent-Based Simulation IX, Lecture Notes in Computer Science, vol. 5269, pp. 110–126. Springer Berlin / Heidelberg (2009)
19. Müller, J.P., Ratzé, C., Gillet, F., Stoffel, K.: Modeling and simulating hierarchies using an agent-based approach. In: Proceedings of the MODSIM 2005 International Congress on Modelling and Simulation. pp. 1631–1638 (2005)
20. Navarro, L., Flacher, F., Corruble, V.: Dynamic level of detail for large scale agent-based urban simulations. In: Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2011). pp. 701–708 (2011)
21. Parunak, H.: Pheromones, probabilities and multiple futures. In: Multi-Agent-Based Simulation XI, Lecture Notes in Artificial Intelligence, vol. 6532, pp. 44–60. Springer (2011)
22. Parunak, H., Brueckner, S.: Concurrent modeling of alternative worlds with polyagents. In: Multi-Agent-Based Simulation VII, pp. 128–141. Lecture Notes in Computer Science, Springer (2007)
23. Ratzé, C., Gillet, F., Müller, J.P., Stoffelb, K.: Simulation modelling of ecological hierarchies in constructive dynamical systems. Ecological Complexity 4(1–2), 13–25 (2007)
24. Sallez, Y., Berger, T., Deneux, D., Trentesaux, D.: The lifecycle of active and intelligent products: The augmentation concept. International Journal of Computer Integrated Manufacturing 23(10), 905–924 (2010)
25. Sallez, Y., Berger, T., Raileanu, S., Chaabane, S., Trentesaux, D.: Semo-heterarchical control of FMS: From theory to application. Eng. Appl. Artif. Intell. 23, 1314–1326 (2010)
26. Servat, D., Pierre, E., Treuil, J., Drogoul, A.: Virtual Worlds, chap. Towards Virtual Experiment Laboratories : How Multi-Agent Simulations Can Cope with
27. Soyez, J.B., Morvan, G., Merzouki, R., Dupont, D., Kubiatk, P.: Modélisation et simulation multi-agents multi-niveaux. Submitted to Studia Informatica Universalis (2011)

28. Steinhauser, M.: Computational Multiscale Modeling of Fluids and Solids Computational Multiscale Modeling of Fluids and Solids. Springer (2008)

29. Stratulat, T., Ferber, J., Tranier, J.: Mosa: towards an integral approach to interaction. In: AAMAS '09: Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems. pp. 813–820. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC (2009)

30. Ueda, K., Kitob, T., Fujii, N.: Modeling biological manufacturing systems with bounded-rational agents. CIRP Annals - Manufacturing Technology 55(1), 469–472 (2006)

31. Ueda, K., Markusb, A., Monostorib, L., Kalsc, H., Arai, T.: Emergent synthesis methodologies for manufacturing. CIRP Annals - Manufacturing Technology 50(2), 535–551 (2001)

32. Ueda, K., Vaario, J., Ohkura, K.: Modelling of biological manufacturing systems for dynamic reconfiguration. CIRP Annals - Manufacturing Technology 46(1), 343–346 (1997)

33. Uhrmacher, A.M., Ewald, R., John, M., Maus, C., Jeschke, M., Biermann, S.: Combining micro and macro-modeling in devs for computational biology. In: Proceedings of the 39th conference on Winter simulation: 40 years! The best is yet to come. pp. 871–880. WSC '07, IEEE Press, Piscataway, NJ, USA (2007)

34. Van Brussel, H.: Holonic manufacturing systems, the vision matching the problem. In: Proc. of First European Conf. on Holonic Manufacturing Systems (2007)

35. Van Brussel, H., Wyns, J., Valckenaers, P., Bongaerts, L., Peeters, P.: Reference architecture for holonic manufacturing systems: Prosa. Computers in Industry 37(3), 255–274 (1998)

36. Weyns, D., Holvoet, T.: Multi-Agent System Technologies, chap. Model for Simultaneous Actions in Situated Multi-agent Systems, pp. 105–118. No. 2831 in Lecture Notes in Artificial Intelligence, Springer-Verlag Berlin Heidelberg (2003)

37. Weyns, D., Holvoet, T.: A formal model for situated multi-agent systems. Fundamenta Informaticae 63(2–3), 125 – 158 (2004)

38. Weyns, D., Holvoet, T., Schelfhout, K., Wielemans, J.: Decentralized control of automatic guided vehicles: applying multi-agent systems in practice. In: Companion to the 23rd ACM SIGPLAN conference on Object-oriented programming systems languages and applications. pp. 663–674. OOPSLA Companion ’08, ACM, New York, NY, USA (2008)

39. Weyns, D., N.Boucké, Holvoet, T.: Gradient field-based task assignment in an agv transportation system. In: Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems. pp. 842–849. AAMAS ’06, ACM, New York, NY, USA (2006)

40. Yoo, J.W., Sim, E., Cao, C., Park, J.W.: An algorithm for deadlock avoidance in an agv system. The International Journal of Advanced Manufacturing Technology 26, 659–668 (2005)