Complex Responsive Processes: The Emergence of Enabling Constraints in the Living Present of a Cyber-Physical Social System

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Keywords: MAPE-K, Cybernetics, Complex Responsive Processes of Relating, Digital Twin, Simulation, Business Process Management, BPM, BPMN, Cyber-Physical Systems, Social Complexity.

Abstract: Contemporary business process modeling is based on predefined constraints where flexibility is built in. Current business challenges result from an increase in data which, are a valuable source for decision taking. Control models from cybernetics could do the job, especially when learning capabilities are added. However, in an agent-based architecture there is something to add: the social component. This position paper aims to advance understanding and practical application of how organizations can effectively utilize the abundance of data in their operational processes while also exploring novel approaches to organizational dynamics and coordination. More in detail, the paper outlines a model that combines socialComplex Responsive Processes (CRP) with a cyber-physical control cycle within a multi-agent simulated business process.

1 INTRODUCTION

In the last few decades, organizations have become considerably more digital. As a result, exponentially more valuable data is created both within the organization, at business partners, and in its environment. With this data, more appropriate decisions can be taken, and learning curves can be accelerated. Mainstream organization theory is based on Systems Thinking, drawing on Kantian philosophy, where the elements of duality are leading, i.e. the rationalist and formative teleology, where action is constrained by given forms. But how can we use these exponentially increased data in operational business processes more dynamically as enabling constraints, and how is the emergence between process actors organized? In this position paper, a model is proposed to harness the possible power of social Complex Responsive Processes of relating (CRP) in combination with a cyber-physical control cycle considering a multi-agent simulated business process.

This position paper is an elaboration on our earlier paper in which the model was presented conceptually. This study has outlined the structure of a self-organized agnostic control cycle for business processes where CRP techniques are applied based on the principles of cybernetics and social science. In this second position paper, the model is taken to a level of applicability. As an example of this, the traditional Beer Game will be modelled as a use case with process modeling standards in a multi-agent system, controlled by inter-agent knowledge sharing and a multi-level control cycle described in this paper.

2 BUSINESS PROCESS MODELING

Business process modeling has been formalized in the last few decades. A good example of formalization is the use of BPMN (Business Process Management Notation) and integration in Process Management Systems. This, however, has led to often inflexible and tightly coupled architectures.

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Willemsen, G., Correia, L. and Janssen, M.
Complex Responsive Processes: The Emergence of Enabling Constraints in the Living Present of a Cyber-Physical Social System.
DOI: 10.5220/0012789400003758

In *Proceedings of the 14th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2024)*, pages 324-331
ISBN: 978-989-758-708-5; ISSN: 2184-2841

2.1 Contemporary Process Models

Organizations are complex systems where learning and knowledge creation is critical for survival. According to Stacey, the learning ability of organizations is constrained; "The mainstream theory of learning and knowledge creation in organizations is a systems theory, and like other systems theories, it implicitly assumes the dual causal structure of Rationalist and Formative Teleology" (Stacey, 2001). These Kantian principles assume predefined constraints and enable the unfolding of already enfolded knowledge by the system. Systems thinking is the foundation for contemporary business process management.

2.2 Business Process Management Systems

The de facto standard for process modeling is BPMN. The idea behind BPMN is that business processes can be modelled by business users where the corresponding execution layer is generated instantly. Currently, many low-coding BPM platforms use the BPMN to feed Business Process Management Systems (BPMS).

2.3 Action or Activity Orientation

An effective and solid BPMS requires a clear architecture that encompasses all functionality in an orchestrated manner to achieve specific business objectives. However, this clear-cut architecture is often missing in organizations. Also, most process models are *activity oriented*. Activity orientation means that complex real-life contexts are harnessed in predefined models. It defines *how* things should be done (while descriptive models describe *what* has been done) (Gotel, Finkelstein, 1996), as the process execution results in process instances, the unique enactment of the process model. The context variability is fitted in the model by decision (split) and join gateways. This presumes that each unique variant of a process instance is deterministic, and the process dynamics is constrained by its process model. To become more effective as an organization, an *action-oriented* process model definition is necessary (Nurcan, 2008).

In an *action-oriented* architecture a connection is made between the knowledge extracted from event data and actions. This enables a context specific management of actions. An *action-oriented* approach can be split into *decision-orientation* or *conversation-orientation*. This should reduce development and transactions costs as the adaptive capabilities increase in a loosely couples process, where decisions drive the adjacent possible action.

2.4 Flexibility in Process Modelling

Most process architecture frameworks presume knowledge of future situations and are not flexible by nature. Nurcan elaborates on process flexibility and identifies the characteristics of a flexible process architecture: posteriori *flexibility by adaptation,* or a priori *flexibility by selection* which are driven by the modeling paradigm. In this paradigm, the decision, conversation, and user experience-oriented approach enable the process executor to instantly adapt to its contextual situation.

A critical characteristic that Nurcan identifies is the flexibility technique, which is only applicable a priori and can be applied in three ways: *late binding, late modeling*, and *case handling*. *Late binding* selects the process patterns that are applicable for the specific instance and composes a process model on the fly. This technique requires a loosely coupled process architecture. *Late modeling* relates to a coarse-grained modeling approach, where the degrees of freedom for process execution are high. For each instance, the details are defined within the higher-level constraints. In the *case handling* technique, the data and flow of a process is combined in a case. This case is state driven, where the appropriate case is selected to achieve the next goal, given the current state. State events will then drive case selection.

3 CYBER-PHYSICAL SOCIAL CONTROL LOOP

When business processes are deployed in real-life environments, an effective control mechanism is essential. Mechanisms from cyber-physical systems control can be integrated with social interaction techniques to support the genuine system dynamics.

3.1 MAPE-K^{ext} Model

In cybernetics, useful control mechanisms can be found. Recently, these mechanisms have been extended with learning capabilities that will support adaptability and context sensitivity.

3.1.1 Cybernetic Control Cycle

A successful *action-oriented* process can adapt itself toward its environment. To become adaptive by nature, the flexibility techniques for process management of Nurcan can be applied. In the control cycle, process parameters will be retrieved from its policies as business rules using the reflexion and rule-based techniques and process patterns are selected from the repository with late binding. These policies and process patterns will then be improved by a learning cycle (Senge, 1990).

In an adaptive process, decisions for process composition and execution are driven by contextual information. To gain grip on organizational processes constituted of temporal actor behavior, control cycles are required (Liu, Barabasi, 2016). These control cycles use knowledge of the environment and the internal state of the system to decide on the actions to be taken. A well-known control cycle process is *MAPE-K*. The *MAPE-K* control cycle consists of five components; the environment is Monitored (M) and Analyzed (A), actions are Planned (P) and Executed (E). All these activities are based on an agent-specific *Knowledge Base* (K or KB) (Kephart et al., 2003). KB includes data such as topology information, historical logs, metrics, symptoms, and policies, which are used by the Monitoring component and deployed by the Execution component.

MAPE-K could be applied to several levels of the processes, both on a central and decentralized level (Weyns et al., 2012). When the *MAPE-K* control is organized on a decentral level, the execution of the subsystem is driven by agent-specific goals which shapes the behavior of higher-level processes. The decentralized process enables the agent to learn, based on its domain specific goals. This MAPE-K loop is modelled as a Markov Decision Process (MDP) using Bayesian learning. Centralized control, on the other hand, will take care of synchronization of these activities (Weyns et al., 2010).

In current research on the *MAPE-K*, attention to the influence of social environmental factors is limited. More specifically, how do environmental factors like the participation of agents in a group influence the perception of environmental data and the evaluation principles of each single agent? Especially when the *MAPE-K* model is applied to distributed control loops with decentralized decision-making, it could be valuable to see how the adaptation rules and results are shared amongst the other agents.

3.1.2 Learning Capabilities

Recent initiatives aimed at fine-tuning the *MAPE-K* model and diving into the characteristics of the KB. Research by Kloes et al. (Kloes et al., 2015) presents a *MAPE-K* extension, where the KB is described with four adaptation mechanisms: the Environment model K^{Env}, System model K^{Sys}, Goal model K^{Goal} and Adaptation model K^{Adapt}. Also, they added two components to enable meta-adaptation: *Evaluation* and *Learning*. Recently, Kloes et al. also added the *Verification* component to this (Kloes et al., 2018). With these extensions, the *MAPE-K* model logic becomes adaptive and applies dynamic, context-specific rules. The first results from this study show that the adaptability of the process improves but should be validated to a higher extent to achieve generic applicability. From now on, the learning extension is referred to as the *MAPE-K*^{ext} model.

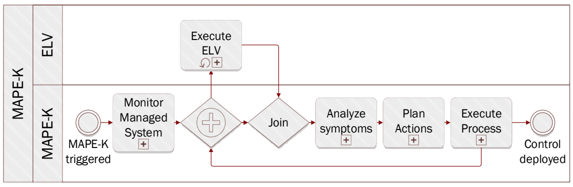

Figure 1: MAPE-K with learning capability.

Within the Knowledge component, two elements are subject to external factors: Knowledge of the *Environment* and Knowledge of *Goal*, while two other elements are internally oriented: Knowledge of the *System* and Knowledge on the *Adaptation* actions. The *MAPE-K*^{ext} model shows how autonomous decision-making techniques in a runtime environment can be used to adapt to continuously changing environments in a quantitative manner. Guards monitor the environment and activate or de-activate specific system- or sub-goals. A guard specifies when an activity can be executed (Ricci et al., 2008). So, these guards are trained to make the system *context sensitive*. In the study of Kloes (Kloes et al., 2018), a model for Goal requirements definition is proposed, where a parent goal can consist of sub-goals. These sub-goals could mutually reinforce and measured as weighted contributors to the parent-goal but can also be exclusive contributors. Together, the joint success rates of the set of sub-goals will determine the total success of the parent-goal and therefore the success of planned actions.

3.2 Social Business Process Interaction

A business process will often rely on a human-machine interaction, where the machines act in a cyber-physical environment while humans behave in a social construct. A complex responsive process approach could integrate both worlds.

3.2.1 Complex Responsive Processes of Relating

Organizations operate in a complex environment, which is characterized by emergence, nonlinearity, and self-organization (Oukharijane et al., 2019). In organization science, the organization, as the locus of attention, has been studied as a *Complex Adaptive System* (CAS), where micro-dynamics of local interactions between the organizational actors result in global patterns. A *MAPE-K^ext^* control cycle is often situated in this organizational context. Although this approach distinguishes the several steps of complexity, the single organizational actor is constituted as a rule-driven agent (Macintoch, MacLean, 2001). Before, we referred to Nurcan who states that an adaptive process should focus on an *action-oriented* agent. However, the full range of human experiences is hardly captured while the environment is perceived as social and complex patterns, in which behavior of a human actor is both physical and cognitive. Complex intelligence, where knowledge is created out of social interaction, includes this human factor, but lacks a suitable integration with the idea of CAS. This has been identified by Stacey et al as *Complex Responsive Processes of Relating* (CRP) (Stacey, 2003), where activity of actors is influenced by the behavior of other actors, individuals, or groups. CRP, however, is taking both perspectives on human interaction and emergence into consideration (Stacey, Griffin, 2005).

According to Homan ((Homan, 2016), p. 495), “the complex responsive process perspective does not assume the [agents] to be more or less mechanistic entities (automatons) reacting in a rule-driven fashion to their neighbors, but endows the [agent] with thoughts, reflections, emotions, anxieties, ambitions, socialization, history, political games, spontaneity, unpredictability, and uncertainty, also understanding (human) interactions with others as intrinsic power relations”. In the CRP setting, actors will search for others to create a critical mass or are complementary in capabilities or skills to overcome uncertainty. These groups are formed around common *themes*, which are shared, repeated, and endure in its values, beliefs, traditions, habits, routines, and procedures (Stacey, 2003).

From the *Social Feedback Theory* (Banisch et al., 2020) we learned that the behavior of the agent is influenced by the group the agent belongs to, from now identified as *trust groups*. Agents perceive their environment through the lens of the group and act, accordingly, based on its dominant logic (Bose et al., 2017). Gergen describes this behavior as *social constructionism* (Gergen, 1999). According to Gergen, relationships in the group and the reality of group members are socially constructed and are limited by culture, history, and human embeddedness in the physical world. Not the individual mind but the relationship becomes the main driver for dynamics. The gesture and response dynamics in group activities are triggered by environmental artifacts and lead to the application and creation of patterns and the disclosure of new artifacts to the environment, which is, as Stacey states, the true source of knowledge creation (Stacey, 2001). So, in the CRP theory, to understand the dynamics of a system, one should focus on the interaction of actors in groups instead of individual behavior (Stacey, 2003).

In the *MAPE-K^ext^* model the focus is set on a mechanistic control loop, as it originated from cybernetics. However, the *MAPE-K^ext^* model is applicable in closed systems with clear constraints and is based on simplified models of reality, which do not represent the living present. When applied to a social system, the subjective pole is missing as agent specific considerations are only partly taken into account. By adding human behavior to the model, the inter-agent dynamics will change, as the closed system is opened, and the process becomes subjective to the adjacent-possible with enabling constraints (Kaufmann, 2016).

By adding the inter-agent dynamics from the CRP theory to *MAPE*-K^ext^ we could increase the learning capabilities of each agent and spread knowledge between trust groups more quickly.

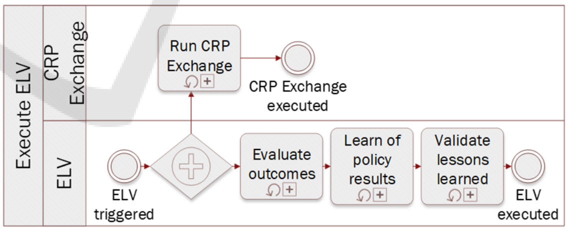

Figure 2: MAPE-K^ext^ with CRP exchange integration.

In this research the feasibility of CRP in the *MAPE-K^ext^* cycle is developed and assessed in simulated business processes. This results in a cyber-physical social model and will be identified as *MAPE-K^ext^ CRP*.

3.2.2 Integration in a BPMS Engine

A business process with a *MAPE-K^ext^ CRP* control cycle can be modelled in BPMN. Also, it is possible to use these BPMN flows in a simulation environment or improves it flexibility by using late binding or late modeling (Patiniotakis et al., 2012).

To model the *MAPE-K^{ext} CRP* in BPMN, the following approach is used:

1. Develop a model to simulate a managed process. This managed process is the operational environment which requires controls for action, more specifically decision taking. Logic will be moved out of the managed process to the *MAPE-K* control loop. As a result, the managed process will become a pure constructor for information processing and/or physical creation.
2. Add a *MAPE-K* control cycle to the managed process to allocate decision making. The *MAPE-K* control cycle will include the logic stored in the KB (K) where context data is stored and monitored (Monitor), analyzed and interpreted with policies (Analyze), translated into behavioral change (Plan), and applied for execution (Execute).
3. Implement an internalized learning process to update the agents KB. The KB contains both contextual information (externalized) and policies (Internalized). This KB will be updated during runtime. As a learning cycle is added to update the agents KB, the internalized policies and rules become dynamic. This learning capability exists of three elements: *Evaluating*, *Learning*, and *Validating* (ELV) to update the KB. This learning on top of *MAPE-K* results in the *MAPE-K^{ext}* model.
4. Add interfacing of agent specific KB data within the agent population. Updating the KB in the *MAPE-K^{ext}* is internalized. However, the learning capabilities of other agents could be valuable to speed up the improvement of a KB. Successful strategies can be shared among agents by updating KB entity records like specific policies of process patterns. Several Agent Based Modelling (ABM) techniques are available to facilitate this data exchange (Pires et al., 2023).
5. Add social bonding between agent cliques. Create groups of agents by adding trust levels. Grouping of agents can be defined in diverse ways i.e., imposed by the modeler, self-organized by agents creating formalized groups or even informal group definition (like influencers). When an agent is part of a group, the trust level between agents improves. This could result in free sharing of KB data between group agents, called *Trust groups* (Hoogendoorn et al., 2008).

This model is based on the ABM principles and detailed with the ODD (Overview, Definition and Details) technique (Grimm et al., 2020).

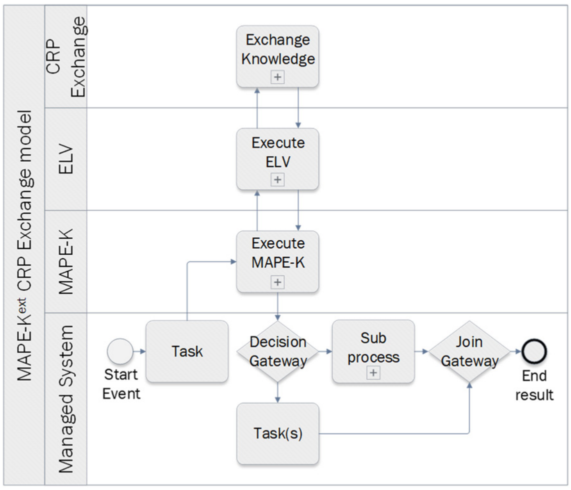

Figure 3: MAPE-K^{ext} CRP model in BPMN.

The managed process will be the locus of control and could be any operational BPMN process, as the *MAPE-K^{ext} CRP* model is agnostic. In BPMN the decomposition of sub models enables an efficient reuse of standardized processes. In the managed process, the *MAPE-K* cycle will be called by embedding the subprocess, while the ELV learning extension process is a subprocess of *MAPE-K*. In this research, the CRP extension will be called from the ELV process. With this process architecture, the *MAPE-K^{ext} CRP* should enable a learning capability that includes inter-agent exchange of knowledge.

4 ENABLING CONSTRAINTS IN THE LIVING PRESENT

4.1 Digital Twin Control Model

In a managed process, the control cycle will take care of the decision making. When the agnostic *MAPE-K^{ext} CRP* model is added to an operational environment, it will be able to generate instance specific process models and becomes adaptive. By integrating this process in a simulation environment, it will function as a *Digital Twin*.

4.1.1 MAPE-K^{ext} CRP Model Architecture

The generic *MAPE-K^{ext} CRP* model is based on four layers. The managed process consists of events, tasks, gateway (decisions or routing elements defined as splits and joins) and possible sub-processes. This is the operational process that is running in its environment and will effectively change the state or phase space. This managed process needs to be a fine-grained model and should take care of achieving a specific objective of the agent.

Within this managed process, one *MAPE-K* sub-process is included. This sub-process monitors the current state of the environment and will define the preferred action to take. This could be a decision to apply a specific policy, which is effectuated in parameter setting or the selection of a process pattern. However, to be able to achieve this, the managed process should be loosely coupled, where process patterns can be selected, defined as a sub-process. This enables agility and late modeling, which results in a high level of adaptability. Knowledge of the events in its environment, policies, and the process patterns available will be stored in the KB.

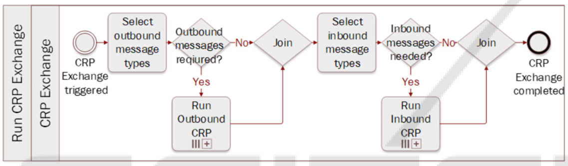

Figure 4: CRP BPMN process flow.

The learning mechanism will be triggered from the *MAPE-K* flow. This learning extension was added to *MAPE-K* by Kloes et al. (Kloes et al., 2018) and is applicable for each *MAPE-K* cycle, just after the monitoring of the managed system and is executed after a change of the process typology or stochastically determined, where the level of randomness can be varied with a system parameter.

This learning process will evaluate the effectiveness of earlier *MAPE-K* decisions and change policies or process patterns when the results are not satisfying. The learning step will search for alternative policies or new process pattern combinations, which will be stored in the KB after verification of the result, based on a meta-simulation of the process during the verification step.

In each cycle of the ELV there is a link to the knowledge of other agents. For each instance, this process will select policies (decisions or parameters) and process patterns that are shared with other agents. This is represented by an outbound process and stimulates the social characteristics of agent behavior. Sequentially, new knowledge is retrieved from others, were new policies and process patterns are stored in the agent's KB while keeping the original source for each acquired knowledge object. This is called the inbound process of the knowledge exchange.

However, knowledge is only shared amongst other agents that belong to the same trust group. Knowledge in the trust groups is ranked and scores of applied knowledge will stimulate or discourage the use of policies and process patterns. During the Verification phase in the ELV cycle, the scores of knowledge of each trust group are taken into consideration.

In addition, this behavior could result in closed trust groups, where access to new knowledge from non-trustees is secluded. To disclose this knowledge, own knowledge is also shared randomly or via social links to non-trustees (for example with a blackboard agent (Szymański et al., 2018) or the attitude formation technique (Pires et al., 2023)) and their knowledge is verified. Based on the outcome of this verification, an improved simulated result will promote the source agent to the trust group.

4.1.2 Real Time Process Simulation

The *MAPE-K^{ext} CRP* model can be modeled as a digital twin of the managed process with the possibility to simulate. This model contains many possible process patterns and stores its relationship with other main process patterns. For this research, the model is agent-based and could contain sub-processes. These sub-processes represent process agents which must achieve a specific task, in this case: Monitoring, Analysis, Planning and Execution in *MAPE-K*, Evaluation, Learning and Verification in the ELV and Outbound and Inbound Exchange in CRP.

The model is linked to the BPMS bi-directionally: process states (events) are retrieved from the managed process to the simulation environment and execution plans are deployed from the *MAPE-K* control cycle to the process orchestration engine. Deployment takes place by pushing the process pattern script to the BPMS. With this, the process flow visualization can be generated in the BPMS and execution in real-time is possible. Based on this bi-directional iteration, a genuine, real-life digital twin is created in which simulation takes place in the living present.

In this research the Anylogic simulation environment is used. Anylogic software supports different paradigms to model large and complex systems (Borshchev, Fillipov, 2004) and could be used to run ABM simulations of complex business processes. With the outcome of these simulations, business process decisions can be underpinned with independent or contingent data. The Anylogic model will be defined as one main process (the *managed* process) that includes a *MAPE-K* sub process, which is decomposed as a separate agent, embedded in the agency of the main process. Also, this *MAPE-K* sub process consists of the Evaluation, Learning and Verification process (ELV) as a sub-sub process. The CRP exchange process will then be another sub process, a part of the ELV cycle and is integrated in the other agent process execution environment.

4.2 Case Studies

To show the practical use of the theoretic *MAPE-K^{ext} CRP* model it will be applied to a real-life business case, to show its usefulness in supporting operational business process decisions.

Traditional business cases are built on predefined, rigid processes. A well-known business case in logistics is the Beer-Game, where the supply chain of beer is modeled with multiple actors, feedback loops, nonlinearities, and time delays. In a beer game simulation, the optimum must be found in the order quantity in a trade off with stock levels and service levels across all stages in a supply chain (Sterman, 1984). Based on this model, extensive research has been performed, including agent-based versions, BPMN, *MAPE-K* and deep reinforcement learning. When the *MAPE-K^{ext} CRP* model is applied to the beer game, it is not intended to prove its added value compared with other beer game improvement techniques. The only objective is to show the applicability of the model in a business case.

In this research, the beer game will be modelled with the *MAPE-K^{ext} CRP* model in several steps; first the late binding process architecture is applied in the traditional beer game; next the *MAPE-K* control cycle and the ELV extension are included; finally, the CRP inter-agent knowledge exchange process is added, where knowledge is shared within trust groups. The analysis is based on the mathematical model described by Edali and Yasarcan (Edali, Yasarcan, 2014).

Comparison of the outcomes should indicate the possible added value of the CRP exchange by its ability to increase knowledge sharing and acceleration of the learning process. In addition, the modification of the agent's Knowledge Base is measured by the number of new, changed, and deleted policies and process patterns. Also, the source of these knowledge base records is reported, as it could origin from the agent itself or a trusted agent. The added value of the MAPE-K^{ext} CRP model is the ability to share knowledge between agents in a controlled manner.

5 CONCLUSIONS

Agent-based models could process operational data in a complex, self-organized way. In cybernetics, many applicable models can be found like the MAPE-K^{ext} control model. However, the exchange of data between agents is limited in these models. And just this inter-agent dynamics seems to have a great potential to accelerate learning and improvement initiatives. In this paper we propose the integration of the MAPE-K model with social complexity CRP techniques. This research investigates the exchange of knowledge between agents to apply in each own MAPE-K^{ext} control cycle. The processes and techniques of knowledge exchange are applied in both managed process and its simulated model. In the final stage of this research, the theoretical model will be applied to an operational simulation model, based on a real-live business case.

6 FURTHER RESEARCH

In this paper, two elements of knowledge exchange are selected as knowledge entities that will be used in the MAPE-K^{ext} control cycle: policies and process patterns. More research must be done on other knowledge entities like topologies, sensors, or effectors.

Also, the requirements for a loosely coupled process architecture are incomplete and should be extended in a more fine-grained manner. This would increase the level of flexibility in process pattern selection and deployment.

The third area of elaboration is the use of trust groups, as this topic has much more depth than used in this research. Using several techniques to create or join trust groups could stimulate the speed and quality of the exchange of knowledge entities. Also, more CRP techniques could be applied to increase the level of inter-agent dynamics.

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