Complex Responsive Processes in a Multi-Agent System: A Knowledge Accelerator

Knowledge Sharing in a Self-Adaptive Multi-Agent System based on the principles of Complex Responsive Processes of Relating

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***Abstract*—Complex Responsive Processes (CRP) focus on the interaction between agents, where they exchange knowledge, opinions, experience, and values. In decentralized decision making, this could accelerate the monitoring, analysis, planning and execution process, as defined in a control mechanism like MAPE-K. For Multi-Agent Systems with a decentralized or hybrid architecture the gesture (e.g., agent *expression*) and response dynamics of complex responsive interaction could be valuable to reduce the entropy of a system. Until today, the CRP mechanisms have not been formalized in Multi-Agent decentralized decision making as it lacks a formal model to express inter-agent dialectics. This position paper discloses the area where an extension of the MAPE-K control cycle can be made to include the formalized CRP processes. This extension consists of a set of methods that include the responsive processes of multiple agents and will be used to update the Knowledge base in the MAPE-K model.**

Keywords: Complex Responsive Processes of Relating; MAPE-K; Multi-Agent Systems; Complex Adaptive Systems; Beer Game.

I. INTRODUCTION

In the summer of 1988, the premium beer producer Heineken launched a promising new alcohol-free beer called *Buckler*. After an initial successful market entrance, the sales figures were dropping dramatically since January 1990 and there was a very clear reason why this happened. In a live TV show on New Year's Eve 1989, a famous Dutch comedian claimed that Buckler consumers were "losers" and lack masculinity. Nobody could imagine that this single statement could result in a tremendous loss of market share and even a premature exit of the brand in the Dutch market. The "Buckler-effect" has become a worst-case practice marketing case on Dutch business schools [1].

Demand and supply in logistics are difficult to align as temporal and spatial differences should be bridged. Traditionally, forecasting and planning techniques were powerful mechanisms to control the logistic chain, to bring demand and supply together in the most efficient way [2]. However, situations like the Buckler-effect, or recently the blockage of the Suez Canal by the *Ever-Given* shows that the external factors can suddenly impact the behavior of market players and will have a critical role in decision-making [3].

A marketplace is a place where cooperation or collaboration and competition of players result in dynamic behavior [4][5], which can be characterized as a Complex Adaptive System (CAS) [6] and where Complex Responsive Processes (CRP) [7] occur. The emergent behavior that results from cooperation is difficult to control, and the non-linear characteristics will make predictions about the players' behavior difficult [8], even when information is shared throughout the supply chain. Recently, the use of Multi-Agent Systems (MAS) has gained improved insight in complex behavior in decentralized decision making in logistic processes. However, current models in decentralized, multi-agent collaborative decision processes within supply chains are still not efficient, precise and lead to poor operability [9]. Research in the field of Supply Chain Networks is promising when traditional supply chains are conceptualized as CAS [10]. To achieve a better alignment of demand and supply, more advanced techniques are required, which take the emergent characteristics of the market into account, like the bull-whip effect or social influencing [11]-[13]. The impact of gesture and response dynamics in multi-agent knowledge exchange is lacking at the moment.

In this paper the rationale for research is elaborated, followed by a description of related work. After that, the Multi-Agent Control Cycle structure is clarified and the extended control cycle mechanism will be described. This will be the foundation for a possible further extension of the model into Complex Responsive Processes.

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II. Rationale for research

In multi-agent knowledge creation, each single agent will update its Knowledge Base (KB), for each cycle in runtime. Process patterns, data analysis algorithms, system data or environmental data can be stored in its own knowledge base. This knowledge will then be available for individual agent analysis and decisions. Decentralized decision making in Multi-Agent Systems is a useful resource to challenge complexity. Theories of knowledge sharing in Multi-Agent Systems still lack the emergent behavior of collaborating agents, more specifically the dynamics of the group in open Multi-Agent systems [60]. What happens when we add the exchange of knowledge and dialectics between agents based on trust and group logic to a Multi-Agent System? Or in other words, what is the role of Complex Responsive Processes in a Self-Adapting Multi-Agent System with decentralized decision making? This area of multi-agent behavior needs to be investigated in more detail to understand the emergent characteristics of symbiotic relations between agents. This paper describes the area of research to extend the current Multi-Agent control cycles with dialectical relation between agents. To understand the dialectics between agents, a formal model should be developed that will describe the exchange of gesture and response to support decentralized decisions. The research should result in a clear extension of the MAPE-K model to facilitate the dialectic behavior between multiple agents.

III. Related work

In the last decades, the digitization of markets and the availability of 'big data' enabled a quicker understanding of the space, in which economic decisions are made [14]. For companies to be successful, it has become critical to acquire knowledge from outside the organization [15]-[18], and to have the ability and strength to execute processes based on the capacities to interpret these data [18]-[21]. For companies, like the beer brewer mentioned earlier, the decisions to efficiently sell and distribute their bottles of beer to consumers should be heavily influenced by detailed understanding of their own capabilities and the information of the environment, in which they operate [22]. Recent developments in the knowledge of network dynamics, which can be applied to economic markets as complex systems [23], shows that not only the environment dictates how agents should act but also agents can influence the environment in their own favor [24]. At the same time, the dominant logic can be influenced by tight collaboration. Hence, as Banisch *et al.* [25] demonstrated, the logic of the dominating group could be challenged by the minority and even become the majority themselves, which has been described as the *Social Feedback Theory.* Critical for this domination is the strength of the agents in the group. The stronger the bonds between the agents, the higher the chance that they will become the majority. In economics, this has been labelled as the "bandwagon effect" [26].

Multi-Agent Systems with decentralized decision making can positively contribute to the added value of products and services in the supply chain [27] when they improve the degree of collaboration between them. From an architectural approach, an important principle for a resilient and adaptable supply chain network is *self-organization* [28]. Approaches for self-organization, defined as Self Adapting Systems (SAS), are described by Krupitzer *et al* [29], where a profound taxonomy is proposed. With this taxonomy, SASs are described in a few dimensions: time, level, reason, technique, and adaptation logic. According to Krupitzer *et al*, most approaches are reactive and exclude the impact of the action on its context, which requires further research on proactive and context-altering system architectures.

A recognized system for self-adaptation is the MAPE-K model [29]. Within MAPE-K the adaptation decision criteria are based on models, policies/rules, goals, or utilities. MAPE-K is a useful control model as it is formalized and supports multi-agent abstract state machines [61]. The control mechanisms in MAPE-K will be applied in a centralized, de-centralized or hybrid models. For MAS solutions, the decentralized model is appropriate to support self-adaptation [30]. An external implementation approach for the MAPE-K control loop, which is loosely coupled from the managed system, is superior in most cases [29]. Also, the adaptation decision criteria should be considered, based on models, policies/rules, goals, or utilities. Several models to exchange knowledge about the environment, system, goals and possibilities of adaptations between agents has been developed by Fisch *et al*. [31], where agents can learn from each other in a MAS setting. More work should be done on collaborative data mining and experience exchange.

When we focus on the collaboration between agents, it is important that all agents share the same language. In the last three decades, formal languages have been developed for MAS solutions. However, the acceptance level of MAS languages is still poor, as mainstream development platforms could to the job as well, with only small efforts. [32]. Nevertheless, several agent programming languages could improve the development of MASs and contain valuable concepts to use in MAS architectures. At the time, there is no MAS language that has been adopted as a de facto standard [32].

To be able to describe the formal model, the building blocks should be clarified: 1) MAPE-K model. 2) MAPE-K architecture, 3) Adaptation logic of the knowledge base and 4) The complex responsive processes of relating between agents.

IV. Multi-Agent Control mechanisms

Multi-Agent Systems could be based on human or virtual agents, both capable of autonomous action and interaction with each other. As MAS is developing in the domain of Artificial Intelligence (AI), the semiosis of the human and virtual agents is gaining attention [33][34]. Formal theories of human intention, reasoning and decision making could be valuable to improve the mechanisms in a virtual MAS [35].

A. The MAPE-K model

To gain grip on organizational processes constituted of temporal actor behavior, control cycles are required [36]. These control cycles use knowledge of the environment and the internal state of the system to decide on the actions to be taken. In Multi-Agent Systems (MAS), the knowledge of the environment is embedded in the MAS architecture. A well-known control cycle process for MAS is MAPE-K. The MAPE-K architecture model structures the governance of a MAS system in five components, which constitute the control system. 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) [37]. This KB includes data such as topology information, historical logs, metrics, symptoms, and policies, which are fed by the Monitoring component and updated by the Execution component. MAPE-K could be applied to several levels of the processes, both on a central and decentralized level. Decentralized control is managing the execution of the subsystem for each agent to achieve domain specific goals and will impact the environment [38] and shapes the behavior of higher-level processes. Centralized control on the other hand will take care of synchronization of these activities. Weyns *et al.* [39] describe several patterns for the interaction between centralized and decentralized control.

B. The Frameself Architecture for MAPE-K

The complexity of a distributed Multi-Agent System with MAPE-K control loops will lead to self-adaptation, -deployment and -configuration of information systems. This requires a clear architectural framework, on which agents will act and processes emerge. One of these architectures is the “Frameself” Architecture [40]. This architecture contains a fine-grained model of a MAPE-K loop, including related interfaces, where the environment is monitored, analyzed and changes are planned and implemented, based on an agent-specific knowledge base. As this architecture is fully integrated in the Unified Modelling Language (UML) it gives a clear approach for pragmatic solution. *Frameself* has been developed for Machine to Machine (M2M) behavior, but is suitable for use in a generic MAS context as well. The architecture fully embeds the MAPE-K loop and can be seen as a “mapping” solution from the theoretical to the pragmatic domain. The architecture consists of the five MAPE-K processes, Monitor, Analyze, Plan, Execute and Maintain Knowledge Base, which communicate via web services. The KB is used as a source for information sharing to facilitate process execution and decision making.

When autonomic systems use the MAPE-K architecture to decide in runtime, a detailed understanding is required about what, where, when, how, and with what tools data are collected from the environment. Hence, the way the data are dimensioned, classified, and translated should be clarified before a proper analysis can be done. When these data are analyzed, a suitable benchmark or expectation should be available to evaluate the performance of the system and applicability of business rules [41]. Based on this evaluation, the next operational process configuration is selected. The question raises if the existing rules and processes are appropriate for the state of the system in its context? This requires the need for a meta-adaptation layer, in which higher level evaluation, learning and verification is possible [42].

C. Monitoring

The monitoring process (Figure 1) consist of methods which will scan the environment on relevant events, aggregate, masks and normalize these and creates symptoms which will be send to the Analysis process. Often, these event handlers are also called *receptors*. All methods are managed by the Monitoring manager and knowledge is used from the KB or will be updated by the Knowledge Base Communicator (KBC). The methods used are identified as public (+) or private (-).

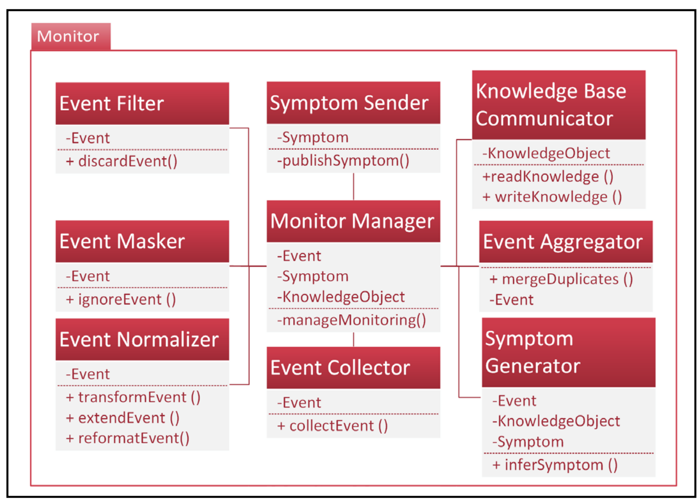

Figure 1. Frameself Monitoring Model.

D. Analysis

The symptom is received from the Monitoring process and a policy is validated and applied with separate methods. The Analysis phase (Figure 2) will take care of the evaluation of environmental phenomena and draw clear conclusions, based on policies. This will lead to the generation of a Request for Change (RfC), which is

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communicated to the Planner process. All knowledge about the policies is interfaced bi-directionally with the KB.

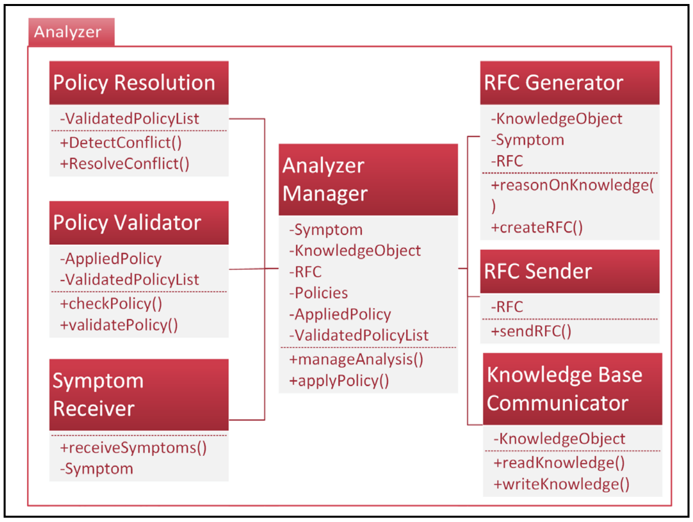

Figure 2. Frameself Analyzing Model.

E. Planning

When the RfC is received, it will be transformed in a policy and interpreted be able to plan the change in the operational system using the KB (Figure 3). When this has been done, the plan will be sent to the Execution process. The Planner Manager method is taking care of the coordination, while the KBC shares the *effectors* and policies to apply.

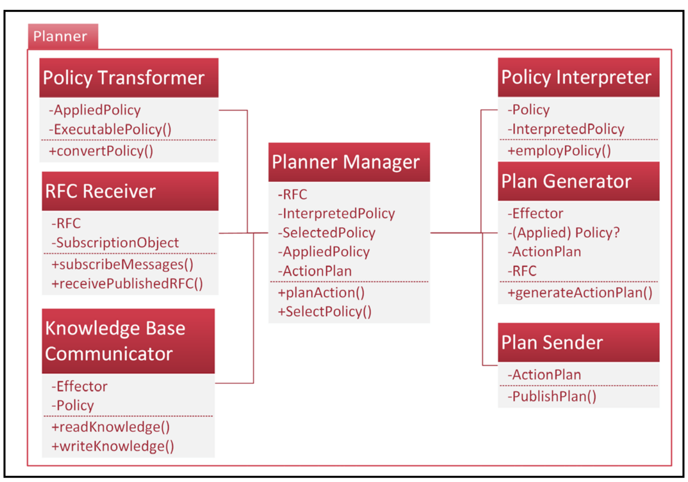

Figure 3. Frameself Planning Model.

F. Execution

After the planning activities have created and a plan is shared to change the operational system, the Execution process will translate the plan into specific actions (interpreted). These actions are embedded in a workflow and the process execution is triggered by the Workflow Engine, scheduled, and dispatched for execution. A process orchestrator method takes care of the monitoring according to the plan. Again, the Executor manager method will take care of a smooth process and the KBC is used for knowledge exchange. The Execution elements are shown in Figure 4.

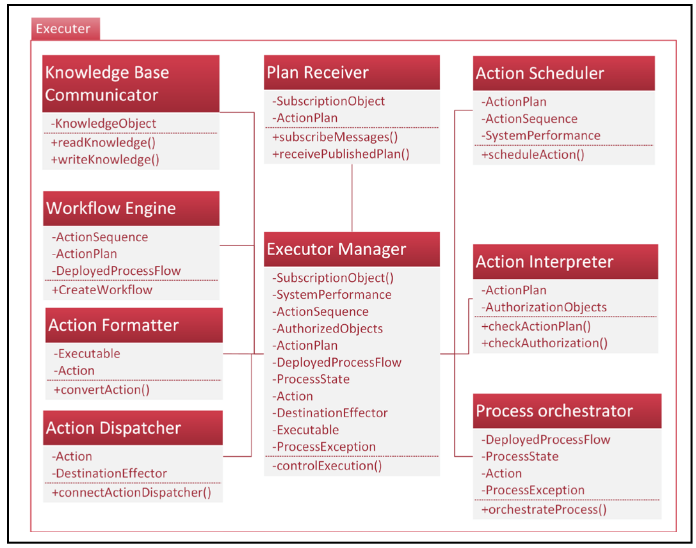

Figure 4. Frameself Execution Model.

G. Knowledge Base

In the KB, entities are created, changed read, and deleted. For each entity, a method is available, to do the job The Frameself architecture does not explicitly define how these methods are used. Also, the dynamics between the MAPE processes and the KB is related to each unique agent (Figure 5). Group learning or exchange of knowledge is not explicitly specified. This area of agent-interconnectedness needs to be studied in more detail.

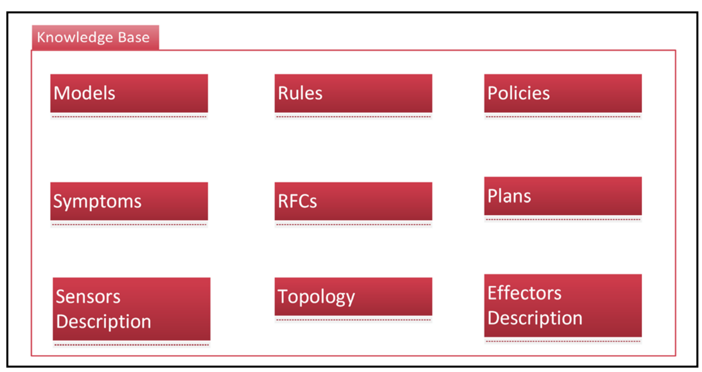

Figure 5. Frameself Knowledge Base Model.

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When autonomic systems use the extended MAPE-K architecture to decide in runtime, a detailed understanding is required about what, where, when, how, and with what tools data are collected from the environment. Hence, the way the data are dimensioned, classified, and translated should be clarified before a proper analysis can be done. And when these data are analyzed, a suitable benchmark or expectation should be available to evaluate the performance of the system and applicability of business rules [41]. Based on this evaluation, the next operational process configuration is selected. But are the existing rules and processes appropriate for the state of the system in its context? This question requires the need for a meta-adaptation layer in which higher level evaluation, learning and verification is possible [42].

V. THE EXTENDED MAPE-K MODEL

In current research on the MAPE-K, attention for the influence of environmental factors is limited. More specifically, how does 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 interesting to see how the adaptation rules and results are shared amongst the other agents.

Recent initiatives aim at fine-tuning the MAPE-K model and dives into the characteristics of the KB. Research by Kloes *et al.* [42] show 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, they also added the Verification component to this [43]. 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.

Within the Knowledge component, two mechanisms are subject to external factors: Knowledge of the Environment and Knowledge of Goal, while two other mechanisms are internal oriented: Knowledge of the System and Knowledge on the Adaptation actions. The Extended MAPE-K [43] 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. So, these guards are trained to make the system context sensitive. In the study of Kloes et al [43], 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.

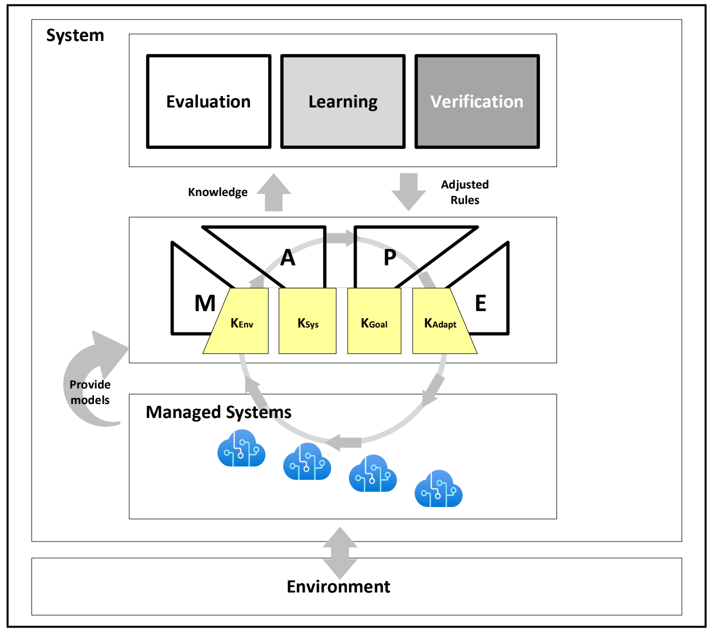

Figure 6. Extended MAPE-K model [43].

Taking notice of the agent driven decisions, how do we integrate the dominant logic of the group [62] in monitoring and adaptation activities in the extended MAPE-K control loop when applied to business processes? Previously, we saw that guards activate or de-activate goals, based on the state of the environment. But how are these guards positioned in the MAS model? Will they be event handlers or connectors that are triggered externally? And what about the data, which are stored in the Logical Operational Environment [45] and analyzed during decision making? These data are applied in the decision-making process, where the environmental-state, (sub)goals and guiding-principles come together [62]. What if the guiding-principles are influenced by the dominant logic of the group? Where do we store and maintain those principles? And how does an agent identify itself with a group, understand their rules of engagement and gain the required trust level? Or in other words, how could the environment be influenced to each actor's own advantage? A complex responsive process view on MAS control-cycles should take these considerations into account.

VI. COMPLEX RESPONSIVE PROCESSES OF RELATING

Organizations operate in a complex environment, which is characterized by emergence, nonlinearity, and self-organization [46][47]. 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 [48][49]. Although this approach distinct the several steps of complexity [50], the single organizational actor is constituted as a rule-driven agent [51]. However, the full range of human experiences is hardly captured [52] while the environment is perceived as social and complex patterns, in which behavior of human actor is both physical and cognitive. Complex intelligence, where knowledge is created out of the social interaction, includes this human factor, but lacks a suitable integration with the idea of CAS [53]. This has been identified by Stacey et al as *Complex Responsive Processes of Relating* (CRP) [54], 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 in consideration [7].

According to Homan [55, 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 [56] to overcome uncertainty. These groups are formed around shared *themes*, which is shared, repetitive and enduring in its values, beliefs, traditions, habits, routines, and procedures [54].

From the Social Feedback Theory [57] we learned that the behavior of the agent is influenced by the group the agent belongs to. Agents perceive their environment through the lens of the group and act accordingly, based on its dominant logic [62]. Gergen describes this behavior as *social constructionism* [58]. 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, according to Stacey [59] the true source of knowledge creation. So, according to the CRP theory, to understand the dynamics of a system, one should focus on the interaction of actors in groups instead of individual behavior [54].

VII. CRP AS ACCELERATOR FOR A SELF-ADAPTING MULTI-AGENT SYSTEM

The effort to include CRP in a MAS system architecture will start with the meta model definition of a MAS. A pragmatic model for MAS architecture is the SARL metamodel [63], which describes the entities that construct the building blocks for a MAS system. Each agent will act in its context, composed of one or multiple spaces. Within this meta model, the interaction model is created, that is derived from the Physical and Social space. The interaction model will group together the several agents and describes the interaction patterns with use of relevant information flows. These information flows are based on the relevant dimensions (descriptions of artifacts) in its environment and influenced by the dominant group logic and semiotics in the system space. Environmental knowledge is perceived through guards and actions are taken to effectuate agent behavior in its environment. This will result in emergent interaction patterns within the Opportunity Space [44].

The adaptive process of a MAS is described by the (extended) MAPE-K model. Environmental events trigger the control cycle, resulting in the execution of the sub-system and a super-system learning cycle (Evaluation, Learning, Verification). Each step in the extended MAPE-K model is probably be influenced by the interaction with other agents and knowledge is shared [42]. The share of knowledge could catalyze the decision-making process in MAS platforms and could be a possible solution to reduce uncertainty in time critical, runtime environments. Also, it will stimulate the coherence of group actions and controllability of MAS behavior. But what elements in the KB are shared and how will this influence the behavior of the agent in the MAPE-K control cycle? Especially the effectiveness and timeliness of the agent's response is an interesting element in knowledge exchange.

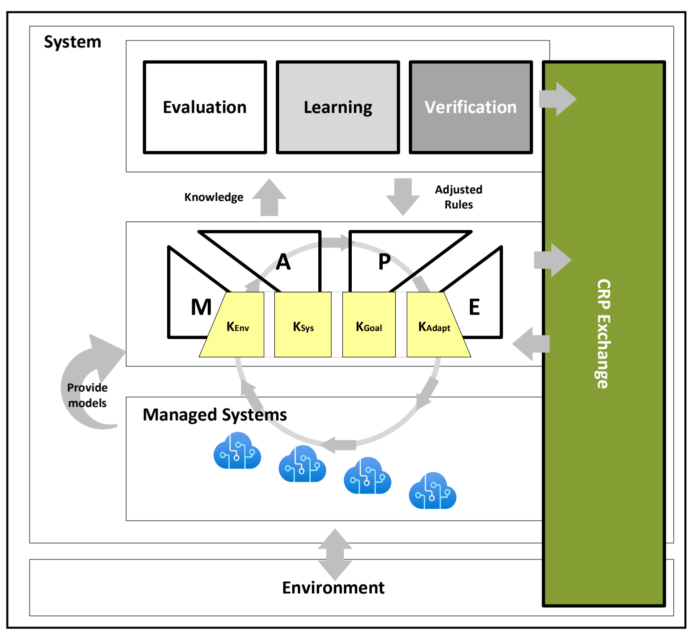

Figure 7. MAPE-K CRP model.

The solution will be a dialectics platform, where groups of agents apply gestures and respond to that. On this platform, a set of formal patterns is available to support these processes. Agents will raise questions and receive feedback from other agents. This will result in dialectics, where new entities are created that could be used in the agent's own knowledge base. Based on this concept, the research should investigate how the meta model and architecture should look like. Also it has to describe the formalize methods for information exchange. This extension can be labelled as the "MAPE-K CRP model", that includes the CRP Exchange of Gesture and Response between agents (Figure 7).

VIII. CONCLUSIONS AND FURTHER WORK

In this position paper the control cycle for Multi-Agent Systems is described, including possible extensions. Current models lack the social dialectics between agents. The instance in which the gesture and response between agents takes place should be added to the model. Further research is required to include social elements of emergent behavior in a Multi-Agent setting. This could accelerate the exchange of knowledge and ability to adapt. The next steps will be the development of the CRP MAPE-K extension architecture and the translation into a meta model including formal methods for development.

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