Research Lab "Multi-Agent Programming Contest 2014"

Final Report

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2.1 MAPC: Contest and Scenario

What is the general scenario? Agents on mars trying to find water in a competitive manner against another team. Explain the concept of zones, gaining points, achievements and also how agents differ from each other. Introduce the notion of *zoning* as the process of finding, forming, defending and destroying a zone. I've put this section first so the later chapters can already rely on the reader knowing what the scenario is about. Furthermore, we can then directly rule out concepts which we are presenting by applying them theoretically onto the scenario/our needs.

2.2 Agent Programming Concepts

2.2.1 BDI.

2.2.2 Formal Methods.$^{\diamond}$

One of the challenges for multi-agent systems is how to make sure that the agent will not behave unacceptable or undesirable? Agents may act in complex production environments, where failure of a single agent may cause serious losses. Formal methods had been used in computer science as a basis to solve correctness challenges. They represent agents as a high level abstractions in complex systems. Such representation can lead to simpler techniques for design and development.

There are two roles of formal methods in distributed artificial intelligence that are often referred to. Firstly, with respect to precise specifications they help in debugging specifications and in validation of system implementations. Abstracting from specific implementation leads to better understanding of the design of the system being developed. Secondly, in the long run formal methods help in developing a clearer understanding of problems and their solutions. [26]

To formalize the concepts of multi-agent systems different types of logics are used, such as propositional, modal, temporal and dynamic logics. In the following several paragraphs these logics, their properties and introduced operators will be briefly discussed. Describing the details of interpretations and models of each individual logic is not the purpose of this report and is left out for further reading.

Propositional logic is the simplest one and serves as a fundament for logics discussed further in this section. It is used for representing factual information and in our case is most suitable to model the agent's environment. Formulas in this logic language consist of atomic propositions (known facts about the world) and truth-functional connectives: $\wedge, \vee, \neg, \rightarrow$ which denote "and" "or" "not" and "implies" respectively. [13]

Modal logic extends propositional logic by introducing two different modes of truth: possibility and necessity. In the study of agents, it is used to give meaning to concepts such as belief and knowledge. Syntactically modal operators

in modal logic languages are defined as $\Diamond$ for possibility and $\Box$ for necessity. The semantics of modal logics is traditionally given in terms of sets of the so-called possible worlds. A world here can be interpreted as a possible state of affairs or sequence of states of affairs (history). Different worlds can be related via a binary accessibility relation, which tells us which worlds are are within the realm of possibility from the standpoint of a given world. In the sense of the accessibility relation a condition is assumed possible if it is true somewhere in the realm of possibility and it is assumed necessary if it is true everywhere in the realm of possibility. [19]

Dynamic logic is also can be referred to as modal logic of action. It adds differen atomic actions to the logic language. In our case atomic actions may be represented as actions that agents can perform directly. This makes dynamic logic very flexible and useful for distributed artificial intelligence systems. Necessity and possibility operators of dynamic logic are based upon the kinds of actions available. [12]

Temporal logic is the logic of time. There are several variations of this logic such as:

- Linear or Branching: single course of history or multiple courses of history.
- Discrete or Dense: discrete steps(like natural numbers) or always having intermediate steps (like real numbers).
- Moment-based or Period-based: atoms of time are points or intervals.

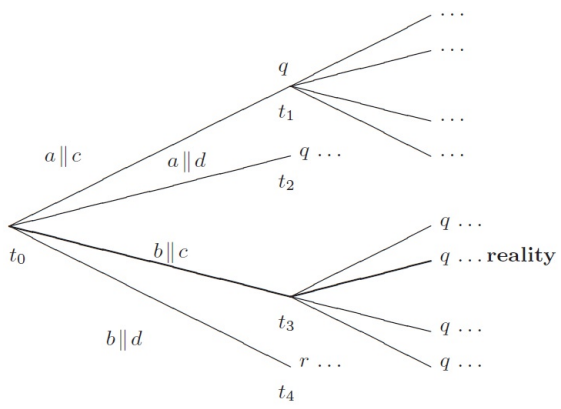
We will concentrate on discrete moment-based models with linear past, but consider both linear and branching futures.

Linear temporal logic introduces several important operators. $p \cup q$ is true at a moment t on a path, if and only if q holds at a future moment on the given path and p holds on all moments between t and the selected occurrence of q. Fp means that p holds sometimes in the future on the given path. Gp means that p always holds in the future on the given path. Xp means that p holds in the next moment. Pq means that q held in a past moment. [26]

Branching temporal and action logic is built on top of both dynamic and linear temporal logics and captures the essential properties of actions and time that are of value in specifying agents. It also adds several specific branching-time operators. A denotes "in all paths at the present moment". The present moment here is the moment at which a given formula is evaluated. E denotes "in some path at the present moment". The reality operator R denotes "in the real path at the present moment". Figure 1 illustrates the example of branching time for two interacting agents.

For modeling intelligent agents quite often used BDI concept, which was described earlier in this report. BDI stands for three cognitive specifications of agents: beliefs, desires, intensions. To model logic of these specifications we will need to introduce several modal operators: Bel for beliefs, Des for desires, Int for intensions and K_h for know how. Considering these operators, for example, the mental state of an agent who desires to win the lottery and intends to buy a lottery ticket sometime, but does not believe that he will ever win can be represented by the following formula: $DesAFwin \wedge IntEFbuy \wedge \neg BelAFwin$.

Fig. 1: An example branching structure of time. (source: [26])



For simplification in future we will consider only those desires which are mutually consistent. Such desires are usually called goals.

It is important to note several important properties of intensions, which should be maintained by all agents[33]:

1. Satisfiability: $xIntp \rightarrow EFp$. This means that if p is intended by x, then it occurs eventually on some path. Intension following this condition is assumed satisfiable.
2. Temporal consistency: $(xIntp \wedge xIntq) \rightarrow xInt(Fp \wedge Fq)$. This requires that if an agent intends p and intends q, then it (implicitly) intends achieving them in some undetermined temporal order: p before q, q before p, or both simultaneously.
3. Persistence does not entail success: $EG((xIntp) \wedge \neg p)$ is satisfiable. This is quite intuitive: just because an agent persists with an intention does not mean that it will succeed.
4. Persist while succeeding. This constraint requires that agents desist from revising their intentions as long as they are able to proceed properly.

The introduced above concepts may be used in each of two roles of formal methods introduced earlier. There are two mostly used reasoning techniques to decide agent's actions: theorem proving and model checking. The first one is more complex in terms of calculations, when the second one is more practical, but it requires additional inputs, though it does not prove to be a problem in several cases.

Considering the practical implementation, the architecture of abstract BDI-interpreter can be described as follows. The inputs to the system are called events, and are received via an event queue. Events can be external or internal for the system. Based on its current state and input events the system selects and executes options, corresponding to some plans. The interpreter continually performs the following: determines available options, deliberates to commit some

options, updates its state and executes chosen atomic actions, after that it updates the event queue and eliminates the options which already achieved or no longer possible.

```
BDI-Interpreter
initialize_state();
do
    options := option-generator(event-queue, B, G, I);
    selected-options := deliberate(options, B, G, I);
    update-intentions(selected-options, I);
    execute(I);
    get-new-external-events();
    drop-successful-attitudes(B, G, I);
    drop-impossible-attitudes(B, G, I);
until quit.
```

As was mentioned above options are usually represented by plans. Plans consist of of the name or type, the body usually specified by a plan graph, invocation condition (triggering event), precondition specifying when it may be selected and add list with delete list, specifying which atomic propositions to be believed after successful plan execution. Intentions in this case may be represented as hierarchically related plans.

Getting back to the algorithm and assuming plans as options, the option generator may look like the following. Given a set of trigger events from the event queue, the option generator iterates through the plan library and returns those plans whose invocation condition matches the trigger event and whose preconditions are believed by the agent.

```
option-generator(trigger-events, B, G ,I)
options := {};
for trigger-event ∈ trigger-events do
    for plan ∈ plan-library do
        if matches(invocation(plan, trigger-event) then
            if provable(precondition(plan), B) then
                options := options ∪ plan;
return options.
```

Deliberation of options should conform with the execution time constraints, therefor under certain circumstances random choice might be appropriate. Sometimes lengthy deliberation becomes possible by introducing metalevel plans into plan library, which form intentions towards some particular plans.

```
deliberate(options)
if length(options) ≤ 1 then return options;
else metalevel-options :=
            option-generator(b-add(option-set(options)));
    selected-options := deliberate(metalevel-options);
    if null(selected-options) then
```

```
        return random-choice(options);
    else return selected-options.
```

Coordination is one of the core functionalities needed by multiagent systems. Especially when different agents autonomous and have different roles and possible actions.

One of the approaches developed by Singh [34] represents each agent as a small skeleton, which includes only the events or transitions made by the agent that are significant for coordination. The core of the architecture is the idea that agents should have limited knowledge about designs of other agents. This limited knowledge is called a significant events of the agent. Events can be of the four main types:

- flexible, which can be delayed or omitted,
- inevitable, which can be only delayed,
- immediate, which agent willing to perform immediately,
- triggerable, which the agent performs based on external events.

These events are organized into skeletons that characterize the coordination behavior of agents. The coordination service is independent of the exact skeletons or events used by agents in a multiagent system.

To specify coordinations a variant of linear-time temporal language with some restrictions is used. For that purpose two temporal operators are introduced: $\cdot$ - before operator, and $\odot$ - the operator of concatenation of two time traces, first of which is finite. Such special logic allows a variety of different relationships to be captured.

Overall, formal methods provide a logic abstraction for multiagent systems. They help to find self-consistent models of agent's behavior. However relatively high complexity do not allow these methods to be implemented in real time systems. Therefore the role of formal methods nowadays is limited to debug, validate and design purposes.

In our project we unfortunately did not apply any formal methods for debugging or validating, mostly because of the limited time for development.

2.2.3 Negotiation and Argumentation.$^{\diamond}$

In multi-agent environment, where each agent has its own beliefs, desires and goals, achieving a common goal usually require some sort of cooperation. It most of the cases it can be achieved through communication and negotiation among groups of agents. Often negotiation is supported by some arguments which help to identify which agent is more suitable for completing certain task. Among them could be better position, better resources for completing the task, importance of current goal and so on. Some arguments can be also used to change the intentions of other agents. This could be the arguments like reserving the node to explore or the enemy to attack and many others. Argumentation is essential when agents don't have the full knowledge about other agents or environment. In such cases

exchanging information helps to develop the consensus and make cooperative decisions.

To negotiate effectively a BDI agent requires the ability to represent and maintain the model of its own properties, such as beliefs, desires, intentions and goals, reason with other agents' properties and be able to influence other agent's properties [18]. These requirements should be supported by the agent programming language we choose for our project.

As was mentioned above, negotiation is performed through communication. Negotiation messages can be of the following three types: a request, response, or a declaration. A response can take the form of an acceptance or a rejection. Messages can also have several parameters for justification or transmitting negotiation arguments. The arguments are produced independently by each agent using the predefined rules, which will be discussed later in this subchapter. Every agent can send and receive messages. Evaluating a received message is the vital part of negotiation procedure. Only the evaluation process following an argument may change the core agents' beliefs, desires, intentions or goals.

There are always several ways of modelling agents for negotiation. Agents can be *bounded* if they do not believe in "false"; *omniscient* if their beliefs are closed under inferences; *knowledgable* if their beliefs are correct; *unforgetful* if they never forget anything; *memoryless* if they do not have memory and they cannot reason about past events; *non-observer* if their beliefs may change only as a result of message evaluation; *cooperative* if they share the common goal [18]. For our project in most of the cases we assumed an agent as knowledgable and memoryless - agents remember only about the current round of negotiation and abolish previous round results when the new round starts. During the zone building process the agents also act as cooperative, since they share the common goal of building a zone.

For every negotiation round an agent needs three types of rules: *argument generation*, *argument selection* and *request evaluation*. We discuss them below.

Argument generation is a process of calculating the arguments for negotiation. An argument may have preconditions for its usage. Only if all preconditions are met, an agent is allowed to use the argument. To check the precondition an agent verifies if it is hold in the agent's current mental state.

In their work Kraus et al. [18] point out six types of arguments, which can be used during negotiation:

1. An appeal to prevailing practice.
2. A counterexample.
3. An appeal to past promise.
4. An appeal to self-interest.
5. A promise of a future reward.
6. A threat.

An appeal to prevailing practice refers to the situation when an agent refuses to perform the requested action, because it contradicts with one of its own goals. In this case the agent, who issued the request may refer to one of the third agent's actions in the similar situation. The algorithm of calculation of the argument

here will be: find a third agent who performed the same action in the past and make sure that this agent had the same goals as the persuadee agent.

A counterexample is similar to appealing to prevailing practice, however in this case the counterexample is taken from the opponent's own history of activities. Here it is assumed that the agent somehow has the access to the persuadee's past history.

An appeal to past promise can be applied only when the a gent is not a memoryless agent. This type of argument is a sort or a reminder to the previously given promise to execute an action is some particular situation. The algorithm of checking if this argument apply is: verify that the persuadee agent is not a memoryless agent, then check if the agent received a request from the opponent in the past with promise of future reward and that reward was the intended action right now.

An appeal to self-interest is a type of argument that convinces the opponent that the performed action will serve towards one of its desires. This argument cannot be applied to knowledgable or reasonable agent, since it can compute the implications by itself. To calculate this argument an agent needs to: verify that the opponent is not a knowledgable or reasonable agent; select one desire the opponent has; generate the list of actions that will lead from the current world state to the opponent's desire fulfillment; check whether the performed action appear in the list. If such opponent's desire is found then the argument is applicable.

A promise of a future reward is a promise given by the agent to the opponent as a condition for the opponent agent to help with executing an action. On order to remember the promise, the opponent naturally should not be a memoryless agent. The calculation algorithm here is: find one opponent's desire, first consider joint desires, trying to find one that can be satisfied with help of the agent; like in self-interest argument generate a list of actions, that lead to the desire fulfillment; out of the resulting list of action select one, which the agent can perform, but the opponent cannot, and which has minimal cost. This action will be offered as a future reward in return to executing requested action right now.

A threat to perform an action that contradicts with opponent's plans in case if the requested action will not be executed can also be a good argument. An algorithm for calculating it includes: find one opponent's desire that is not in agent's desire set, first consider desires with higher preference; find a contradicting action to the desire or like in "appeal to self-interest" find a list of actions needed to satisfy the desire and find an action that undoes effects of one of those actions. This action will then be selected as a threat argument in case if a requested action will not be executed.

An agent can generate several arguments at the same time, but only one of them can be used for every negotiation round. To be able to identify which argument should be used an argument selection rule is required. Kraus et al. [18] proposed to use the argument types in the same order as they were introduced earlier in this subchapter. In this case the weakest argument is selected first and if it will not succeed, then the stronger argument is taken.

Request evaluation rules define how the request is being processed by the agent when it receives one. Request evaluation should end with a response message back to the sender stating either that the argument is accepted and the agent will perform the prescribed action, or that the argument did not persuade the agent to fulfill the request. Also as it was mentioned above during the request evaluation agent's beliefs, desires, intensions or goals can be changed. As an example of such changes in our project can be saboteur switching to zone defending after negotiation with other saboteurs: the beliefs about the zone he has to defend are added and the primary goal is changed to zone defending. Another example is an agent adopting a role of zone coach after negotiation about the best zone: the goal to invite other agents to the newly created zone, regularly check for enemy agents near the zone and so on. Request evaluation always depends on the arguments that are used, the agents participating in the negotiation and the request itself.

For the implementation of negotiation procedures and making collective decisions in our project we mostly used the *bidding* method described in [4]. In this method all the participating in negotiation agents are sending their "bids" to the other agents. These bids contain the appropriate arguments for the current negotiation target. Every agent waits for bids from all other agents and after that performs a comparison of bids: every bid is compared with all other bids. The comparison of two bids includes argument selection and request evaluation at the same time: the arguments are selected one by one in each of two bids and compared until one of the arguments prevail. For the conflict situations when all arguments appear to be the same we assumed that the bid that came from the greatest agent in terms of agent name comparison wins. The agent with the winning bid then fulfills the request: adopts a certain role or performs a prescribed action.

2.2.4 Agent Societies.

2.3 Agent Programming Languages°

We investigated several agent programming languages against their suitability for the Mars-scenario. They were proposed by our supervisors. Our goal was to determine what language we wanted to use for multi-agent programming if any. The following sections present the basic structure of various languages together with examples. These examples are in no relation to the Mars-scenario but are simplified to a minimum to ease understanding. Using the Mars-scenario for examples instead would have meant to either make them complex or to trivialise them to a point where they become too superficial to suit the scenario. section 2.3.1 first introduces the situation calculus. Although not an agent programming language, it serves as a foundation of the logic programming language GOLOG presented in section 2.3.2. It also helps understanding the subsequent section 2.3.3 which summarises the main concepts of FLUX. FLUX is another logic programming language which was partly motivated from the flaws of GOLOG. section 2.3.4 introduces a Java-based agent programming language.

After that, AgentSpeak(L) is presented in section 2.3.5 which is another logic programming language. Jason is an interpreter for this language and is discussed in section 2.3.6. The section focusses mainly on the extensions that Jason adds to AgentSpeak(L). The final section 2.3.7 summarises the previous sections and explains our decision for choosing Jason.

2.3.1 Situation Calculus.°

This section gives a short summary of the situation calculus, which was first introduced by McCarthy and Hayes [25]. The situation calculus is mainly a first-order logic but also uses second order logic to encode a dynamic world [21]. It is a theoretic concept and was consequently not under consideration to be used as an agent programming language to compete in the MAPC. Yet, it is being presented to serve as basis for the later illustrated languages GOLOG and FLUX. The situation calculus consists of the three first-order terms: *fluents*, *actions* and *situations* [25, 7]. Fluents model properties of the world. Actions may change fluents and hence may modify the world. Every action execution creates a new situation. This is because a situation is a history of actions up to a certain point in time starting from the initial situation s_0 [32, 21]. There can only be one initial situation as it models the situation before any action has been executed [27].

Fluents can be evaluated to return a result. As they are situation dependent, the evaluation result may change over time. Fluents are distinguished in *relational fluents* and *functional fluents* [21]. Relational fluents can hold in situations. Their evaluation hence may return either true or false [7]. An example is given in Equation 1. It expresses whether or not the agent p has a coffee in situation s.

$$hasCoffee(p, s) \tag{1}$$

Functional fluents return values instead [21]. As an example, a fluent $location(p, s)$ may return some coordinates (x, y) This then expresses the agent p's location in situation s.

Actions also depend on situations. The reason for this is that certain actions may only be executed when specific fluents hold. As fluents are only modified by actions, their result can be determined by the history of action executions contained in the current situation. Describing when an action is executable is done by *action precondition axioms* [22]. This is expressed by the predicate $Poss(a, s)$ with a being an action. As a recurring example, let us think of the ability to pour an agent p coffee. This must only be possible when p does not already have coffee. Equation 2 illustrates how this can be formalised.

$$Poss(pourCoffee(p), s) \Leftrightarrow \neg hasCoffee(p, s) \tag{2}$$

As mentioned before, the execution of any action must alter the situation: $do(a, s) \rightarrow s'$. Its effects on fluents are described by *action effect axioms*. Equation 3 shows how pouring a coffee to p will result in p having coffee afterwards.

$$Poss(pourCoffee(p), s) \rightarrow hasCoffee\big(p, do(pourCoffee(p), s)\big) \tag{3}$$

In Equation 3, it is unclear whether other fluents are affected by the action execution. For example, reasoning about $location(p, s')$ would not be possible with $do(pourCoffee(p, s)) \rightarrow s'$. This is called the *frame problem* (cf. Hayes [16]). Defining for every fluent how every action does or does not affect it is only a theoretical solution. The reason for that is that the resulting complexity of $\mathcal{O}(A * F)$ would be too high even in most small worlds. A feasible solution to this problem was proposed by Reiter [30]. His approach was to define every effect of all actions only once. Thus, Reiter reduced the complexity to $\mathcal{O}(A * E)$. This solution is known as the *successor state axiom* and is shown in Equation 4.

$$Poss(a, s) \rightarrow \left[F(do(a, s)) \Leftrightarrow \gamma_F^+(a, s) \vee F(s) \wedge \neg\gamma_F^-(a, s)\right] \tag{4}$$

$F(do(a, s))$ means that the fluent F will be true after executing the action a. The first part of the disjunction is $\gamma_F^+(a, s)$ and expresses that the action made the fluent true. $F(s) \wedge \neg\gamma_F^-(a, s)$ as the second part expresses that the fluent had been true before and the action had no influence on it. For a reasonable example, there needs to be a second action which does not influence the fluent given in Equation 1. Therefore, the $sing(s)$ action will be introduced which has no effect on any fluents and can be executed anytime as shown in Equation 5.

$$Poss(sing, s) \Leftrightarrow \top \tag{5}$$

Given Equation 1, 2, 3 and 5 an example can be compiled as done in Equation 6:

$$\begin{aligned} \mathrm{Poss}(a, s) \rightarrow \big[&\mathrm{hasCoffee}(p, \mathrm{do}(a, s)) \\ &\Leftrightarrow [a = \mathrm{pourCoffee}(p)] \\ &\vee\ [\mathrm{hasCoffee}(p, s) \wedge a \neq \mathrm{pourCoffee}(p)]\big] \end{aligned} \tag{6}$$

Equation 6 then formalises that an agent p may only have coffee if it was poured coffee or if it already had coffee and the action was not to pour p a coffee.

2.3.2 GOLOG.°

This section gives a summary of the logic programming language GOLOG. Moreover, its problems in context of the Mars-scenario are shown. If not further specified, all information except for the examples is taken from Levesque et al. [21] who introduced the language. GOLOG builds on the situation calculus. To allow high-level programming, the language adds complex actions like loops, conditions, tests and non-deterministic elements. As an example, a GOLOG program should have a robot pouring other agents coffee until everybody does have coffee. After that, the robot should sing and terminate. Such a program would reuse the fluent of Equation 1, the action precondition axioms of Equation 2 and 5, the successor state axiom of Equation 6 and extend them with the two procedures given in Equation 7 and 8:

$$\begin{aligned} &\textbf{proc } \texttt{main } [\textbf{while } (\exists p)\neg \mathit{hasCoffee}(p) \\ &\qquad\qquad \textbf{do } \texttt{pourSOCoffee}(p) \textbf{ endWhile}]; \\ &\quad \mathit{sing} \textbf{ endProc}. \end{aligned} \tag{7}$$

$$\textbf{proc}\ \texttt{pourSOCoffee}\ (\boldsymbol{\pi} p)\ [\neg \mathit{hasCoffee}(p)\textbf{?};\ \mathit{pourCoffee}(p)]\ \textbf{endProc}. \tag{8}$$

Equation 7 shows the procedure which can be seen as the main method. It loops as long as there exist agents without coffee and tells the robot to pour some agent coffee which is lacking coffee. In the end, the robot sings. Equation 8 allows the robot to non-deterministically choose an agent p to pour coffee by using the π-operator. The ?-operator is similar to the `if`-operator in other programming languages like Java. Due to the non-determinsmic operator, there can be two different resulting situations as shown in Equation 10 with the initial configuration given in Equation 9:

$$\neg \mathit{hasCoffee}(p, s_0) \Leftrightarrow p = \text{Jane} \vee p = \text{John}. \tag{9}$$

$$\begin{aligned} s &= do\Big(\mathit{sing}, do\big(\mathit{pourCoffee}(\text{Jane}), do(\mathit{pourCoffee}(\text{John}), s_0)\big)\Big), \\ s &= do\Big(\mathit{sing}, do\big(\mathit{pourCoffee}(\text{John}), do(\mathit{pourCoffee}(\text{Jane}), s_0)\big)\Big) \end{aligned} \tag{10}$$

Levesque et al. [21] highlight multiple problems with GOLOG. Problems which are relevant when considering to apply GOLOG on the Mars-scneario, are given in this part. One problem is that complete knowledge is assumed in the initial situation. This is not the case for the Mars-scenario and scenarios with unknown worlds that get explored by agents in general.

The second problem is that GOLOG does not offer a simple solution for sensing actions and reactions of agents on sensed actions. Sensing actions are actions by agents that may not modify fluents but the internal knowledge of agents by detecting some properties in the world [35]. This can be seen as a side-effect of GOLOG not being developed for unknown worlds. Again, this would be a feature which is needed for the Mars-scenario.

A third problem is that exogenous actions cannot be handled. Exogenous actions are actions outside of the agent's control. In the Mars-scenario, this e.g. could be the loss of an agent's health due to an enemy agent attacking it.

Thielscher [35] highlights a fourth problem. It arises from GOLOG being *regression-based*. This means that deciding whether an action is executable is only possible after looking at all previous actions and how they might have affected the world. As a result, reasoning takes exponentially longer over time and hence GOLOG does not scale. Due to these problems, GOLOG is unsuitable for a multiple agent-based scenario like the Mars-scenario without considerable modifications and extensions.

2.3.3 FLUX.°

This section gives a summary of the logic programming language FLUX which offers solutions to the earlier shown problems of GOLOG. Except for the examples and if not specified otherwise, the information of this section is taken from Thielscher [35] who first introduced FLUX. This is done by using the *fluent calculus* instead of the situation calculus. Both are similar but the fluent calculus

adds *states*. A state z is a set of fluents $f_1, \ldots, f_n$. In FLUX, it is denoted as $z = f_1 \circ \ldots \circ f_n$. In every situation there exists exactly one state with which the current properties of the world are being described. Yet, the world can be in the same state in multiple situations. FLUX uses *knowledge states* for representing agent knowledge. These are denoted through $KState(s, z)$ meaning that an agent knows that z holds in s. Knowledge states can be incomplete as opposed to knowledge in GOLOG.

The frame problem in the fluent calculus is solved through *state update axioms* as described by Thielscher [36]. The axioms define the effects of an action as the difference between the state before and after the action. This is modelled with ϑ^- for negative and ϑ^+ for positive effects. Both are simply macros for finite states. Due to using states, reasoning is linear in the size of the state representation. That is, after every action execution, the world represented by its fluent is processed. This is called being *progression-based*. Therefore, FLUX can outperform GOLOG as determining whether a property currently holds is only a matter of looking it up in the state. With GOLOG however, the property must be traced back to the initial situation by looking at all action executions and their effects.

Disjunctive and negative state knowledge is modelled through constraints. FLUX uses a constraint solver to simplify these constraints until they are solvable. This is done by using *constraint handling rules* introduced by Frühwirth [15]. Their general form is shown in Equation 11. It consists of one or multiple heads H_m, zero or more guards G_k and one or multiple bodies B_n. The general mechanism is that if the guard can be derived, parts of the constraint matching the head will be replaced by the body and hence get simplified.

$$H_1, \ldots, H_m \Leftrightarrow G_1, \ldots, G_k \mid B_1, \ldots, B_n \tag{11}$$

A FLUX program can be separated into three main parts with the constraint solver building the kernel which is the foundation of a FLUX program. The domain encodings are built on top of this. Included are the initial knowledge state(s), domain constraints, as well as the action precondition and state update axioms. The final part of a FLUX program is the programmer defined intended agent behaviour called strategy. As a trivial example program, the previous example implemented in GOLOG will be transferred into FLUX. This is done by using the logic programming language Prolog in which FLUX is typically implemented (cf. [37, 24]). The example features the domain encodings as well as the strategy.

```
1 perform(sing, []).
2 poss(sing, Z) :- all_holds(hasCoffee(_), Z).
3 state_update(Z, sing, Z, []).
```

Listing 1.1: Defintion of the `sing`-action.

Listing 1.1 shows the definition of the `sing`-action. Empty arrays denoted by `[]` could be replaced by sensed information. They would then effect the outcome of the methods. As this is a trivial example, no sensed information is assumed.

Line 2 is the precondition that singing is only possible in a state where every agent has coffee. As singing should not alter any fluents, the state `Z` in Line 3 is not modified and returned again as `Z`.

```
4  perform(pourCoffee(P), []).
5  poss(pourCoffee(P), Z) :-
6       member(P,[jane,john]),
7       not_holds(hasCoffee(P), Z).
8  state_update(Z1, pourCoffee(P), Z2, []) :-
9       update(Z1, [hasCoffee(P)], [], Z2).
```

Listing 1.2: Definition of the `pourCoffee`-action

The `pourCoffee`-action is defined similarly in Listing 1.2. Line 6 ensures that Prolog will only look for agents that actually exist instead of iterating over memory addresses. The action must modify the state by adding `hasCoffee(P)` to the state as it is done in Line 9. The array after it corresponds to ϑ^-. It is empty in this case as no fluents are removed.

```
10 main_loop(Z) :-
11   poss(sing, Z)
12     -> execute(sing, Z, Z);
13   poss(pourCoffee(P), Z)
14     -> execute(pourCoffee(P), Z, Z1),
15        main_loop(Z1);
16   false.
```

Listing 1.3: Main method which either tells the robot to sing or to pour coffee.

Listing 1.3 models the main method and thus is similar to Equation 7. When singing is possible, the robot will do so and terminate. Else, it will pour someone a coffee and call the main loop again. Line 16 ensures that Prolog will return the false-value `No` if neither of the both actions get triggered at some point.

```
17 init(Z0) :-
18        not_holds(hasCoffee(jane), Z0),
19        not_holds(hasCoffee(john), Z0).
```

Listing 1.4: Initial configuration.

The initial configuration in Listing 1.4 is comparable to Equation 9 but due to Prolog interpreting from top to bottom, the result will be `Z = [hasCoffee(john), hasCoffee(jane)]`.

Schiffel and Thielscher [31] successfully applied FLUX to the gold mining domain. It is a scenario where multiple agents with different roles work together on mining gold in an unknown terrain [31]. The requirements for solving the problems arising from this scenario are comparable to those appearing in the Mars-scenario. Given the former short presentation and this knowledge, it can be said that FLUX could be applied to the Mars-scenario.

2.3.4 Jadex.⊙○

Nowadays a couple of agent frameworks are available for developing multi-agent applications. An overview of existing tools and techniques is given by the European co-ordination action for agent-based computing, namly AgentLink [23]. This section presents Jadex, which is an agent framework focused on the development of goal-oriented agents following the belief-desire-intention model. It aims at bringing middleware and reasoning-centred agent platforms together. For that purpose, Jadex adds a rational reasoning engine to existing middlewares. The most commonly used middleware for Jadex is the *Java Agent Development Framework* (short: JADE) [3]. Jadex integrates agent-theories through object-oriented programming in Java and XML descriptions. Therefore, no new language is introduced. Jadex reuses already existing technologies instead. JADE provides a communication infrastructure, platform services such as agent management and a set of development and debugging tools. It enables the development and execution of peer-to-peer applications which are based on the agent paradigm (autonomous, proactive and social). Agents are identified by a unique name and provide a set of services. They can register and modify their services and/or search for agents providing given services. Additionally they are capable of controlling their life cycle and they can dynamically discover other agents and communicate with them The communication happens by exchanging asynchronous messages via an *agent communication language* (short: ACL). Jadex complies with the standard given by the Foundation for Intelligent Physical Agents (FIPA). FIPA "is an international organization that is dedicated to promoting the industry of intelligent agents by openly developing specifications supporting interoperability among agents and agent-based applications."[11] A FIPA ACL message has a certain structure and parameters. Mandatory parameters are the type of the communicative act, the participants in the communication, the content of the message, the description of the content and the control of the conversation.

Figure 2 depicts an abstract view on a Jadex agent. Every agent may receive messages which trigger internal events that can change his internal knowledge, plans or goals. Interactions with the outside like the environment or other agents happens through the sending of messages. In more detail, beliefs are single facts stored as Java objects which represent the knowledge of an agent. They are stored as key-value pairs. The advantage of storing information as facts is that the programmer has a central place for the knowledge and can query the agent's beliefs. Monitoring of the beliefs is possible too.

The goals are momentary desires of an agent for which the agent engages into suitable actions until it considers the goal as being reached, unreachable, or not wanted any more. Referring to [8], Jadex distinguishes between four generic goal types. A perform goal is directly related to the execution of actions. Therefore, the goal is considered to be reached, when some actions have been executed, regardless of the outcome of these actions. An achieve goal is a goal in the traditional sense, which defines a desired world state without specifying how to reach it. Agents may try several different alternative plans, to achieve a goal of this type. A query goal is similar to an achieve goal, but the desired state is

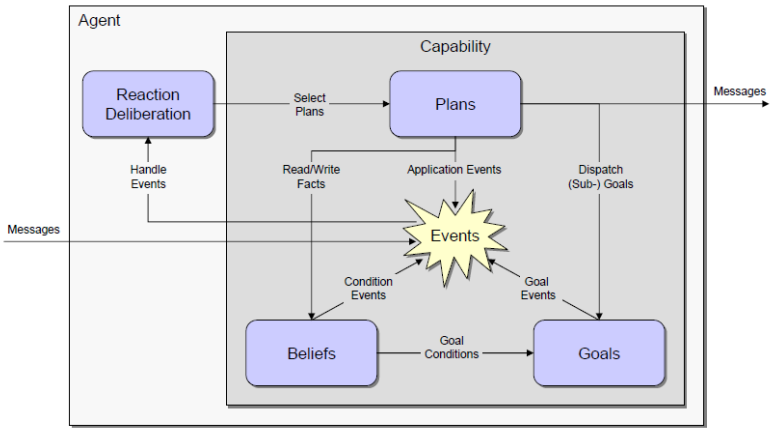


Fig. 2: Jadex abstract agent [28]

not a state of the (outside) world, but in internal state of the agent, regarding the availability of some information the agent wants to know about. For goals of type maintain an agents keep track of a desired state, and will continuously execute appropriate plans to re-establish this maintained state whenever needed. In contrast to goals, events are (per default) dispatched to all interested plans but do not support any BDI-mechanism. Therefore, the originator of an internal event is usually not interested in the effect the internal event may produce but only wants to inform some interested parties about some occurrence. Plans represent the behavioural elements of an agent and are composed of a head and a body part. The plan head specification is similar to other BDI systems and mainly specifies the circumstances under which a plan may be selected, e.g. by stating events or goals handled by the plan and preconditions for the execution of the plan. Additionally, in the plan head a context condition can be stated that must be true for the plan to continue executing. The plan body provides a predefined course of action, given in a procedural language. This course of action is to be executed by the agent, when the plan is selected for execution, and may contain actions provided by the system API, such as sending messages, manipulating beliefs, or creating sub-goals (cf. [10])

Jadex is not based on a new agent programming language. Instead, a hybrid approach is chosen, distinguishing explicitly between the language used for static agent type specification and the language for defining the dynamic agent behaviour. An agent in Jadex consists of two components: An *agent definition file* (short: ADF) for the specification of beliefs, goals, and plans as well as their initial values and on the other hand procedural plan code. The procedural part of plans (the plan bodies) are realized in an ordinary programming language (Java) and have access to the BDI facilities of an agent through an application interface (API). The plan body is a standard Java class that extends a predefined Jadex

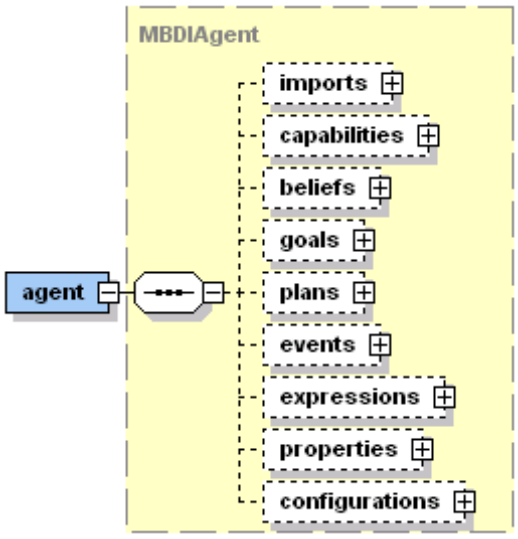


Fig. 3: Jadex top level ADF elements [9]

framework class and has at least to implement the abstract body() method which is invoked after plan instantiation.

```
public class ServeCoffeePlanB1 extends Plan {
   // Plan attributes.

   public ServeCoffeePlanB1() {
       // Initialization code.
   }

   public void body() {
       // Plan code.
   }
}
```

The plan body is associated to a plan head in the ADF. This means that in the plan head several properties of the plan can be specified, e.g. the circumstances under which it is activated and its importance in relation to other plans.

```
<agent xmlns="http://jadex.sourceforge.net/jadex-bdi"
 xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
 xsi:schemaLocation="http://jadex.sourceforge.net/jadex-bdi
                     http://jadex.sourceforge.net/jadex-bdi-2.0.xsd"
 name="CoffeeAgent">

 <plans>
   <plan name="serve">
     <body class="ServeCoffeePlanB1"/>
     <waitqueue>
```

```
11          <messageevent ref="request_serving"/>
12        </waitqueue>
13      </plan>
14    </plans>

16    <events>
17      <messageevent name="request_serving" direction="receive" type="fipa">
18        <parameter name="performative" class="String" direction="fixed">
19          <value>jadex.bridge.fipa.SFipa.REQUEST</value>
20        </parameter>
21      </messageevent>
22    </events>

24    <properties>
25      <property name="debugging">false</property>
26    </properties>

28    <configurations>
29      <configuration name="default">
30        <plans>
31          <initialplan ref="serve"/>
32        </plans>
33      </configuration>
34    </configurations>
35  </agent>
```

There are two types of plans in Jadex. A *service plan* and a *passive plan*. The service plan, as the name indicates, is an instance of a plan which waits for service requests. Therefore a service plan can set up its private event wait queue and receive events for later processing, even when it is working at the moment. In contrast to that, a passive plan is only running when it has a task to achieve. For this kind of plan the triggering event and goals must be specified must be specified in the agent definition file to let the agent know what kinds of events this plan can handle. When an agent receives an event, the BDI reasoning engine builds up the so called applicable plan list which contains all plans that can handle the current event or goal. The candidates are selected and instantiated for execution.

The execution model for Jadex looks like the following:
When an agent receives a message it is placed at a message queue. In the next step the message has to be assigned to a capability, which can handle the message. A suitable capability is found by matching the message against the event templates defined in the event base of each capability. The best matching template is then used to create an appropriate event in the scope of the capability. After that the created event is subsequently added to the agent's global event list. The dispatcher is responsible for selecting applicable plans for the events from the event list. After plans have been selected, they are placed in the ready list, waiting for execution. The execution of plans is performed by a scheduler, which selects plans from the ready list.[28]

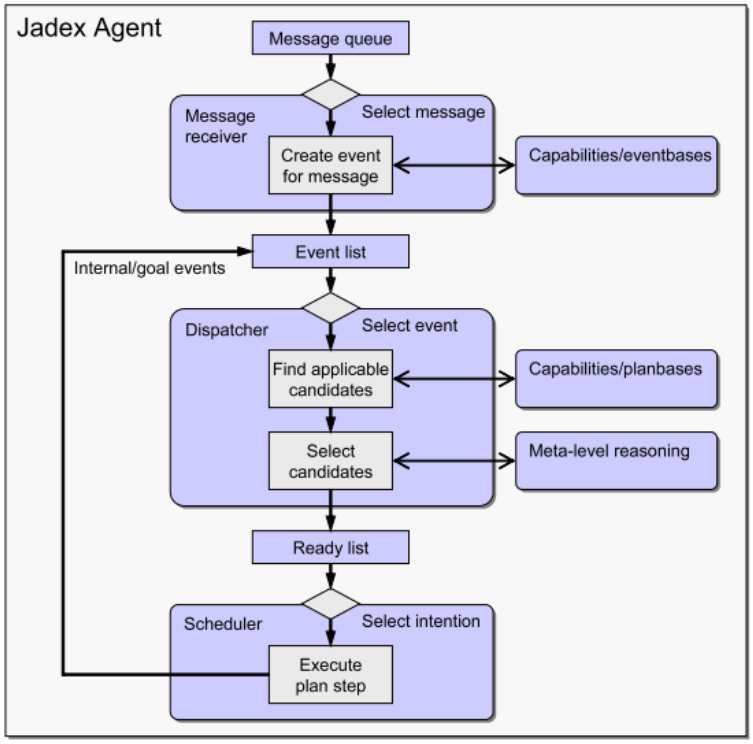


Fig. 4: Jadex execution model [28]

All in all Jadex is a powerful framework that supports easy agent construction with XML-based agent description and procedural plans in Java. Additionally, it offers tool support for development debugging. It comes for example with a BDI-Viewer that allows observing and modifying the internal state of an agent and a logger agent that collects log-outputs of any agent. Judging from this knowledge, Jadex seems suitable for the purpose of competing in the multi-agent programming contest.

2.3.5 AgentSpeak(L).°

This section gives an overview of the general concepts of the logic programming language AgentSpeak(L). The language was developed by Rao [29]. Except for the examples, this section takes its information from the given paper. The idea behind AgentSpeak(L) was to make the theoretic concept of BDI-agents usable in practical scenarios.

The main language constructs are *beliefs*, *goals* and *plans*. Beliefs represent information that an agent has about its environment. A belief `hasCoffee(p)` for example denotes that an agent knows that the person `p` has coffee. In AgentSpeak(L), variables are indicated by using a capital first letter whereas terms with a small first letter are constants.

```
1 ~hasCoffee(jane).
2 ~hasCoffee(john).
```

Listing 1.5: Initial beliefs.

Listing 1.5 shows the initial beliefs an agent has for our earlier introduced example. The tilde expresses that the agent knows that neither `john` nor `jane` has coffee. At any given time, the sum of all current beliefs of one agent are called its *belief base* [5].

Goals can be dividied into *achievement goals* and *test goals*. The first expresses the wish of an agent to reach a state where a belief holds where the second tests whether a belief holds in the current state. Beliefs hold when the agent knows they are true or when the variables can be bound to at least one known configuration. For example, given an achievement goal `!hasCoffee(p)` means that an agent wants to achieve that person `p` has coffee. Similarly, `?hasCoffee(p)` expresses that an agent tests whether `p` has a coffee. Hence, this expression will evaluate to true or false depending on the current agent's knowledge. Achievement goals are comparable to desires. Listing 1.6 shows the initial achievement goal which express that the agent wants to have served everyone coffee.

```
3 !servedCoffee.
```

Listing 1.6: Initial goal.

Events are introduced to allow agents to react on changes in their own knowledge or the world. They can be distinguished into the addition and removal of beliefs or goals. Additions are denoted by a plus- and removals by using a minus-sign in front of the goal or belief:

- `+hasCoffee(p)`: an agent is informed that `p` now has coffee.
- `-hasCoffee(p)`: an agent is informed that `p` no longer has coffee.
- `+!hasCoffee(p)`: an agent is informed that it wants `p` to have coffee.
- `-!hasCoffee(p)`: an agent is informed that it no longer wants `p` to have coffee.
- `+?hasCoffee(p)`: an agent is informed that it should test for the belief.
- `-?hasCoffee(p)`: an agent is informed that it no longer needs to test for the belief.

In order to handle new events, an agent will look for a matching plan.

Plans can be seen as programmer-defined agent instructions. They lead to the execution of actions or the splitting of goals into additional goals. Plans, which an agent wants to execute, are similar to what are called intentions for BDI-agents. The set of plans known to an agent are called the *plan library* [5]. A plan is triggered by events and is context-sensitive. This means that the execution of a plan can be restricted to states in where certain beliefs exist. Listing 1.7 illustrates this by showing when the `sing`-action is being executed. Line 4 is the triggering event of the plan. In this case, an agent will consider executing this plan, when it notices that someone is poured coffee. Hence, this plan is called a *relevant plan*. The underscore denotes an anonymous variable similar to its use in Prolog. Its meaning is that it will match any term. Line 5 is the plan's context. The plan is called an *applicable plan* if the context's beliefs are all known to the agent. In this particular case, the agent must know that there is no person without coffee indicated by the use of the tilde. At last, Line 6 contains the body of the plan. Here, the agent should achieve the goal `sing`. This will trigger a new event which calls the plan in Line 9. As its context is empty, the plan can be executed immediately and evaluates to true as there is no body. Line 7 expresses how the event of someone being poured coffee should be alternatively handled. As AgentSpeak(L) is interpreted from top to bottom, it will only be seen as an applicable plan, if the former relevant plan did not trigger. Therefore, if the agent knew that there was still someone left without coffee, it will want to achieve the `servedCoffee` goal again.

```
4  +hasCoffee(_):
5      ~hasCoffee(_)
6      <- !sing.
7  +hasCoffee(_)
8      <- !servedCoffee.
9  +!sing.
```

Listing 1.7: Events for handling someone being poured a coffee as well as the `sing` plan.

Listing 1.8 contains the plan for serving coffee. It uses a test goal to pick someone without a coffee as shown in Line 11. The person will be bound to the variable `X`. After that, an achievement goal is added to the agent's set of intentions to pour `X` coffee. The plan does not feature any context as this minimal example ensures that the goal `!servedCoffee` will only exist when there actually is a person without coffee.

```
10 +!servedCoffee:
11     <- ?~hasCoffee(X);
12        !pourCoffee(X).
```

Listing 1.8: Definition of the `servedCoffee` plan.

Listing 1.9 shows a plan which states that if an agent receives an event to achieve the goal `!pourCoffee` for some person `X`, it will pour coffee to `X`. Additionally, the knowledge about `X` not having any coffee is removed in Line 16.

```
14 +!pourCoffee(X)
15     <- +hasCoffee(X);
16        -~hasCoffee(X).
```

Listing 1.9: Definition of the `pourCoffee` plan.

AgentSpeak(L) is suitable for multi-agent scenarios as the Mars scenario. Especially when comparing FLUX to the components of AgentSpeak(L) plans, it becomes clear that there are many similarities. A FLUX's action's precondition is similar to a plan's context and the state update axiom is implicitly included in a plan's body. Yet, the state in AgentSpeak(L) does not have to be manually and explicitly modified. Furthermore, a plan's body enables further possibilities like adding new goals. The main difference between FLUX and AgentSpeak(L) is that FLUX is based on fluent calculus. It is hence a more general approach focussing on modelling the change of fluents. AgentSpeak(L) on the other hand was strictly developed as an application for BDI-agents.

2.3.6 Jason.°

This section gives a quick overview of Jason, which is an interpreter for AgentSpeak(L). All information if not marked differently is taken from Bordini et al. [5]. Besides being an interpreter, Jason extends AgentSpeak(L) by several concepts. The most important ones will be discussed in this section.

With Jason, terms can represent more than a constant or a variable. They can be strings, integer or floating point numbers or lists of terms. Therefore, more complex programmatic operations and arithmetic expressions are possible with Jason. Furthermore, Jason introduces annotations. With these annotations, metadata can be added to triggering events and beliefs. This metadata can be accessed programmatically. Listing 1.10 shows the earlier used initial beliefs with added annotations. The `source` annotation is the only one with its meaning predefined by Jason. It expresses the source of the information. If an agent determined something itself, the `source` is `self`. Did the agent receive the information as a perception of the environment, then the `source` will be `percept`. The source can also be a constant identifying a different agent if that agent is the source of this information. With the example given in Listing 1.10, an achievement goal `?~hasCoffee(X)[reliability(Y)]` will bind `X` to `john` and `Y` to `0.3`. The `reliability` has no further meaning unless the value bound to `Y` is used later.

```
1 ~hasCoffee(jane)[source(self)].
2 ~hasCoffee(john)[source(percept), reliability(0.3)].
```

Listing 1.10: Annotation of beliefs in Jason.

Another concept added to AgentSpeak(L) by Jason is called *internal actions*. It was first introduced and implemented by Bordini et al. [6]. Most characteristic for these actions is that they do not affect the environment in which the agents are located in. This means they have no effect on the external world but only on the internal states of the agents as the name suggests. Hence, any effects of internal actions occur immediately after the action execution instead of only after the next environment processing cycle. As a result, internal actions can not only be used within a plan's body but also in its context. Internal actions start with a dot followed by a library identifier, another dot and finally the action name. Bordini et al. [6] implemented various internal actions which are not identified by any explicitly named library. These methods reside in the so called *standard library* and omit the library declaration when being called. An example for this is `.gte(X,Y)` which returns the truth value of `X`$\geq$`Y`. A realisation of the same function outside the standard library could e.g. be called `.math.gte(X,Y)`. The standard library is included in Jason. Furthermore, Jason extends this library by various actions including multiple list operations like sorting or retrieving the minimum. Developers can write additional internal actions in Java or any other programming language which supports the programming framework Java Native Interface.

Arguably, the most important internal action is `.send`. This action enables inter-agent communication as initially proposed and implemented by Vierira et al. [38]. It is similar to KQML performatives which had been introduced in SECTIONXYZ.

```
1 .send(Receiver, Illocutionary_force, Message_content).
2 .send([agent1, agent2], tell, ~hasCoffee(john)).
```

Listing 1.11: Parameters of the internal action `.send` and an example.

In Line 1 of Listing 1.11 the structure of the `.send` action is shown. Line 2 shows example usage of this action. The `Receiver` is the identifying name or a list of identifying names for the agent(s) to which the message should be addressed to. The `Illocutionary_force` is a constant that specifies what all recipients should do with the message. It can be:

- `tell`: add the `Message_content` to the recipient's belief base.
- `untell`: remove the `Message_content` from the recipient's belief base.
- `achieve`: add the `Message_content` as an achievement goal to the recipient.
- `unachieve`: make the recipient remove the achievement goal `Message_content`.
- `tellHow`: `Message_content` is added to the recipient's plan library.
- `untellHow`: `Message_content` is removed from the recipient's plan library.
- `askIf`: asks if `Message_content` is in the recipient's belief base.
- `askOne`: asks for the first belief matching `Message_content`.
- `askAll`: asks for all beliefs matching `Message_content`.

– `askHow`: demand all plans a recipient has that match the triggering event given in the `Message_content`.

Jason automatically processes the messages as needed when a message arrives at an agent. A developer can override Jason's default behaviour if further or different processing is desired. Jason also automatically adds `source` annotations. This allows agents to determine the sender of any received message.

There is special support for defining environments with Jason. Instead of having to do this in AgentSpeak(L), it can be done in Java. For doing so, a developer has to extend the `Environment` class and specify the `getPercepts(String agentName)` and `executeAction(String agentName, Term action)` methods. The first method must return a list of literals restricted to what the agent identified by `agentName` can perceive. When the second method is called, the programmer must specify how the given `action` affects the environment. It returns a boolean to indicate whether the execution was successful. Such an action can fail if for example a repairer agent would try to execute the `attack` action which it cannot according to the Mars-scenario. To call the `executeAction` method from an agent, all it has to do is execute e.g. `attack`. Jason will then call `executeAction(String agentName, Term action)` with the parameters bound to the agent's name and the `attack` action. For the MAPC itself, no fully simulated environment is needed. Instead, it is enough to delegate the actions to the MAPC server and process the server replies by returning the transmitted percepts to the respective agents. Therefore, percepts do not have to be modelled or modified in the environment developed with Jason itself.

Jason also allows running multi-agent systems over networks in a distributed manner. Hence, the workload can be distributed over multiple machines. SACI [17] and JADE are the two fully implemented distributed architectures usable out of the box with Jason [4]. Fernández et al. [14] could not prove the intended performance benefits. The authors tested both SACI and JADE with Jason where one host would run the environment and the other one the agents. They increased both the amount of agents as well as the size of the environment. Fernández et al. [14] saw that with increasing complexity, the system became slower compared to when agents and the environment were run on a single machine. This was due to the added communication cost between the two hosts although connected by Gigabit Ethernet. As a result, a distributed infrastructure with Jason is only advisable, if the workload cannot be handled by one host alone. In our case, replying in time has such an importance that trying to keeping the workload processable by one host alone would be the preferred strategy.

2.3.7 Choice of a programming language.°/⊙

Based on the previous sections, this section summarises why we chose Jason for developing our agents. Generally, we could have started from scratch without using a designated agent programming language. We decided against this idea because of our inexperience with agent programming and artificial intelligence in general. The fear was to overlook difficulties in the beginning which would later

force us to spend more time on fixing mistakes we made in the beginning than on the actual agent development. To prevent this, we were interested in using an already developed and approved agent programming language.

Given the Mars scenario, Jason can be used to implement a suitable multi-agent system. In fact, two teams successfully participated in the 2013 Multi-Agent Programming Contest by using Jason [1]. Yet, there was no competing team using Jadex or FLUX. This is of interest because the scenario of 2013 is comparable to the scenario of 2014 [2]. As the whole team was inexperienced with logical programming prior to this research lab, being able to develop the environment and some operations via internal actions in Java was beneficial. Furthermore, the contest organisers provided a Java library which would simplify the communication with their server. Instead of having to manually compile XML messages and parse the XML server replies, this library allowed simple method calls for server interaction. Thus, deciding against FLUX meant not having to implement the communication with the server ourselves. The library would also have been usable with Jadex. But just like Flux, Jadex does not assist the developer in modelling the environment like Jason does. Jason's support for environments allowed us to focus more on agent programming There, we preferred Jason and Jadex over FLUX, because these two languages are built around BDI, which we found to be a clearer structuring of agents. FLUX on the other hand serves as a quite generic approach to programming multi-agent systems. Besides the support for developing environments, Jason and Jadex are also different in the way how the initial beliefs, goals and plans are being programmed.

The difference lies in the storing of beliefs, goals and plans. In Jadex they are stored in the agent definition file (XML) while in Jason they are stored as facts within the Jason belief base. Another slight difference is that in Jadex plans have to be written in Java whereas in Jason the programmer can use a combination of Java and AgentSpeak with internal actions. We didn't chose Jadex for our research lab because of the overhead that comes with the XML-syntax.

3 Team Organisation and Collaboration Tools$^{\odot/\circ}$

The topic of this section is the team structure as well as the software we used for working together. In the first part of this section, the organisation of the team is shown. It focuses on the distribution of tasks and explains how we worked together. The second part presents what software tools we have used for working together. It also remotely discusses the usefulness of the Jason plugin for our tasks.

At the beginning of the project the team had to define a structure for collaboration. We decided to have a flat hierarchy with all members as part of dynamically built, small development teams. Michael Ruster was selected as a project leader with his role mainly focussed on organisation. He carried out the external communication with the supervisors and contest organisers. The project leader was also responsible for configuring the server and running test simulations together with the organisers of the MAPC as well as running the final simulations.

His leadership followed a democratic management style, so decisions were made by the team as a whole through majority decisions. Once in every week, the team met in person to discuss the current progress and the upcoming course of actions. All meetings were recorded by a minute taker. The minutes logged the attendees, open issues from last meeting, the decisions made in the current meeting as well as a list of assigned tasks to work on until the next meeting. We did not have a designated minute taker but would rotate alphabetically by surname. The person to take the minutes was also the one to present our progress at our weekly meetings with our supervisors. During the weekly team meetings, many of our algorithms were initially developed and discussed. At the end of each meeting, the worked out tasks for the next meeting were assigned to dynamic groups. These groups mainly consisted of two or three people with more people working on tasks we found to be more important. Team members were assigned for a specific task due to personal interest or expertise. In the beginning, we also tried some hacking sessions, but quickly found out that working from home worked best for us. This was advantageous because no fixed timeslots needed to be found. Instead, everybody would work independently when they found the time while staying in contact with the others through chat or voice over IP. The possibility to share the computer screen contents over IP offered by the voice over IP solutions we used, was of great help. Therefore, multiple persons could work on the same code at once with one programming and the others reviewing it real-time. If there was need for reconciliation, for example when tasks of different groups were closely interrelated or dependant on one another, short-termed voice over IP calls were held. To the end of development, the groups diverged mainly into Artur Daudrich and Michael Sewell working on the Java-side of our code and the rest focussing on implementations in AgentSpeak(L). The prior group hence concentrated on implementing background calculations like internally modelling and constructing the graph and environment design. Accordingly, Manuel Mittler, Michael Ruster, Sergey Dedukh and Yuan Sun focussed more on agent programming and developing strategies.

For collaboration on the code, GitHub[1] was chosen as a revisioning system. No team member had any prior experience with GitHub. Some few members had worked with SVN as a revisioning system before. Nevertheless, we decided to use GitHub as it additionally offers a Wiki and an issue tracker. A Wiki is an online collaboration tool which enables users to create and edit hypertext pages within their Web browser (cf. [20]). We used the included Wiki for gathering the minutes of our weekly meetings. GitHub's issue tracker was used for complex problems, ideas or bug reports. It allowed discussions clearly separated by bug or feature. This distinct separation was not given for all bug reports as not all problems were transformed into issues. Instead, many small problems were discussed on our team chat. For this, we used the instant messenger Google Hangouts[2] as all team members already had registered a Google account. The main advantage of Google Hangouts over the issue tracker was that the response time was a lot

[1] `https://github.com/` – last accessed 24.10.2014
[2] `https://www.google.com/+/learnmore/hangouts/` – last accessed 24.10.2014

lower due to its rather informal style. Some were just mentioned and discussed in the Hangouts group chat and then quickly solved after. It was also frequently used for short-dated organisational discussions, which would not have fit well into a ticket. As for voice over IP, we both used Google Hangouts and Skype[3] because some team members preferred one application over the other. Eclipse was chosen as the IDE because all of our team members were familiar with it and a plugin[4] for Jason exists. Besides syntax highlighting for AgentSpeak(L), the plugin also includes a promising mind-inspector for debugging agents and step-based debugging. Unfortunately, we had to find out that the plugin was not of great use for the Mars scenario. This was due to the short time frame per simulation step which for one resulted in each agent receiving a lot of information. Consequently, the mind-inspector often crashed or refreshed the information too fast. Similarly, step-based debugging was not possible because only the current code execution was halted but not the server simulation. As a result, debugging was mainly reduced to analysing log files generated from manually added print statements.

In sum, it can be said that we tried to keep our organisation to a basic form. We made sure that we were able to work well-structured but still quite self-organised and democratic in decision finding to encourage creativity in problem solving. Analogously, we spent little time on deciding what tools to use. Instead, we preferred software most of us had already used before or which was the leading free project for the given task. These approaches allowed us to concentrate on the actual multi-agent system development. It was necessary due to our inexperience and the scant time we had until the competition.

4 Architectural (?) Structure

4.1 Agents

Talk a bit about generalisation e.g. a saboteur is a specialisation of an agent. I.e. both share exploring but the saboteur also knows how and when to attack. Explain what tasks our agents have and where our priorities are.

4.2 Simulation Phases

Explain the general split up into an exploration and a zoning phase. Also mention the parallel aggressive strategy of the saboteurs. Talk about repairers, explorers and inspectors and their special tasks but without going into details abouttheir complete strategy (this is part of the next chapter).

[3] `https://www.skype.com/` – last accessed 24.10.2014

[4] `http://jason.sourceforge.net/mini-tutorial/eclipse-plugin/` – last accessed 24.10.2014

5 Algorithms and Strategies

5.1 General Strategy Overview

This could also be an introductory text which motivates the following subsections.

5.2 Agent Specific Strategies†

Because each of the five different agent types (or *roles*) in the MAPC scenario — Explorers, Repairers, Saboteurs, Sentinels and Inspectors — have different capabilities in terms of the actions they can perform, they must each act according to role-specific strategies and tactics in order for the team to perform well. This section will give a short overview of how different agent types behave differently from each other.

Explorer agents are the only ones who can perform the `probe` action. Vertices must be probed in order to learn their value, which is critical for zoning. Accordingly, an Explorer will spend most of his time seeking out, moving towards and finally probing vertices whose value is not yet known. Since there are 6 Explorers in a team, care must be taken to make sure that multiple Explorers don't move towards the same unprobed vertex, as this is generally a suboptimal usage of their time.

In our implementation, we consider all vertices in the map to be "worthy" of being probed and thus to know their value. However, due to the way our team performs zoning (see section 5.5.2), we prioritize vertices in a specific way which we call "cluster probing". Because our zone calculation algorithm (see section 5.5.1) puts agents around a centre vertex in a circular manner and with a maximum distance of two edges away, and because we want the Explorers' probing to help us with quickly finding and establishing high-value zones, Explorers should avoid probing vertices in e.g. a straight line. Rather, an Explorer's probing pattern should mimic the circular shape of the zone calculation algorithm. Because of this, for probing we prioritize unprobed vertices first by distance, then by the number of edges they share with already probed vertices. The result is that Explorer movement is similar to a spiral pattern (provided the Explorer isn't disturbed by e.g. nearby enemy agents). Explorer agents don't stop this probing pattern until they can no longer find any unprobed vertices.

Repairer agents are the only agents who can perform the `repair` action for restoring health to disabled agents. Because the team loses out on possible points for every disabled agent in the team, to achieve a high score it is essential to quickly repair damaged agents. In our implementation, Repairers' actions are prioritized so that they will attempt to repair any disabled friendly agent in their visibility range, and it is the "job" of the disabled agents to find and move towards the closest friendly repairer. If a Repairer agent is aware of a friendly disabled agent outside of his visibility range, and the Repairer is currently not used for zoning, however, then the Repairer will also move towards the disabled agent.

Saboteur agents are the only agents that can disable enemy agents using the `attack` action. In our implementation, a saboteur's role is very aggressively defined, and is prioritized thusly: if you see a non-disabled enemy, attack it; otherwise find and move towards an enemy you can attack.
Throughout most of our development phase, Saboteur agents were the only agent type we would use the `buy` action for to extend their visibility range once for every Saboteur because we believed that this would give us an offensive edge against other teams. We decided to try out other buying strategies as well, however, by having our agents play matches against copies of themselves, except that the copies used different strategies for buying upgrades. Through this brief, empirical and rather informal testing period, we discovered that a surprisingly simple and novel strategy to buying upgrades actually led to persistently higher scores than our initial approach of buying one visibility range upgrade per Saboteur: by choosing a single Saboteur agent, which we call the *uber-Saboteur*, and allowing him to buy an unlimited (well, limited only by the amount of money available) number of upgrades as needed, we were able to outperform teams using our more conventional approach of upgrade buying. To be more specific, our uber-Saboteur would buy an upgrade whenever no active enemy was within his visibility range and he had the money for it. The kind of upgrade (maximum energy, visibility range, maximum health or strength) depends on the relative improvement that buying that upgrade will bring to the upgrade-specific "module". For example, if the uber-Saboteur has a maximum health of 3 and a visbility range of 1, then increasing the maximum health to 4 would be an improvement of 33 %, while increasing the visibility range from 1 to 2 would be an improvement of 100 % — so the uber-Saboteur will choose to buy an upgrade to the latter.
We also call in Saboteurs to defend a zone if it gets attacked by an enemy agent.

Sentinel agents don't have a unique action that they can perform. Their strength is that they start with a visibility range of 3 by default, which is the highest of all the agent types. This is useful during exploration and to be warned of incoming enemy agents, but we don't use any Sentinel-specific logic in our implementation worth mentioning.

Inspector agents are uniquely able to perform the `inspect` action. We consider it important to inspect every enemy agent once during each match to learn and store that agent's role (it is very important to know which enemy agents are Saboteurs, so that we can avoid them), but once that goal has been achieved, Inspector agents lose most of their importance. Achievement points for performing `inspect` actions are not awarded for inspecting an enemy agent more than once, and `inspect` is not needed to be able to tell if an agent is disabled (the `visibleEntity` percept includes the agent's current state). The only use case for inspecting an enemy agent more than once during a single match is to learn if they have bought any upgrades since the first time they were inspected. But because buying an upgrade for an agent is such a rare occurrence during the actual contest (cf. this year's and the last years' matches), we don't have to re-inspect very often — we could probably just

inspect each enemy agent once to learn their role and then leave it at that. In our implementation, however, we toggle an enemy agent to be ready to be inspected again 50 turns after it was last inspected.

5.3 Exploration*

One precondition of the Agents on Mars Scenario is that all agents start with an empty belief base. Each agent does not know about its local and global environment. Of course every agent gets beliefs about its local environment very quickly by receiving percepts from the server. But the agent still does not know about the global environment. For our strategies it is crucial to have as much information about the overall environment as possible. Just think about finding and building the best global zones or pathfinding. So it is important to store somehow information about the map like vertices, edges between vertices, paths and agent positions. In section 5.3.1 our initial approach with its down- and upsides is described. After that a basic overview over the Distance-Vector-Algorithm and the impact on our map building approach is given in section 5.3.2. Finally this chapter concludes with a description of the second approach we used and sticked to in section 5.3.3

5.3.1 Cartographer Agent*

We decided very early in our development process that we do not want to store information which is needed by every agent in each single agent. The intention behind this decision was to reduce the effort in synchronizing and maintaining data between the single agents. Our initial approach was to install one omniscient pseudo agent we called the "cartographer" agent. The cartographer agent represented a map and had the only purpose to calculate shortest paths between given vertices and to store vertex and edge information like traversing costs, edges between vertices and vertex values. Every agent told the cartographer agent about its environment related beliefs and the cartographer agent stored these beliefs. Environment related beliefs are illustrated in the listing below:

```
1  visibleEntity(<Vehicle>, <Vertex>, <Team>, <Disabled>).
2  position(<Vertex>).
3  visibleVertex(<Vertex>, <Team>).
4  probedVertex(<Vertex>, <Value>).
5  visibleEdge(<VertexA>, <VertexB>).
6  surveyedEdge(<VertexA>, <VertexB>, <EdgeCosts>).
```

Listing 1.12: Map exploration related beliefs

If an agent needed to know a shortest path, it just queried the cartographer agent and got the shortest path as an answer. Or if an agent needs to know if an vertex was already probed or surveyed, it just queried the cartographer. Shortly after implementing this approach, we encountered two major problems, which both resulted in serious performance issues. One problem was that pathfinding, which was done with the help of the Dijkstra-Algorithm, was executed every time

an agent asked for a shortest path. This led to a lot of redundant calculation and processing in the cartographer agent. The second problem was related to communication between agents. To understand the latter problem, one need to know that Jason uses a message box system for communication between agents. This means that every message a sender sends to a receiver is queued in the receivers message inbox. In every Jason lifecycle only one message is processed. Although a Jason lifecycle is a lot shorter than a server lifecycle, still after some execution time the inbox of the cartographer agent was so full, that the processing of messages lagged far behind the receiving of these messages. Both issues resulted in blocked agents, which had been waiting for the response of their queries for rounds.

5.3.2 Distance-Vector Routing-Protocol*

To tackle the problem of repeating calculations of shortest paths, we used the *Distance-Vector Routing Protocol*(short: DV) [40]. DV is a routing protocol based on the Bellman-Ford algorithm [39]. DV can be executed on a network of nodes. The basic idea is that each node informs all of its neighbor nodes about its belief base. The informed node then updates its belief base and informs all of its neighbors also and so on. And some point all information is propagated through the whole network and all nodes have a consistent belief base. To adapt this algorithm to our system, we created node agents. A node agent represents one vertex of the scenario map and holds information about this vertex. To make it easier to address node agents, we named node agents like the vertex they represented. A node agent stores all its neighbors in a neighbor-list belief (`neighbors([<ListOfNeighbors>])`) and all available paths to other vertices as path beliefs (`path(<Destination>, <NextHop>, <Hops>, <CostToNextHop>)`). With regard to exploration and zoning we decided that an node agent also has to store the probed value of the vertex, and if it was already probed or surveyed.

For a better illustration see the following example of the belief base of the node agent `v1`:

- `neighbors([v2, v3]).`
- `probed(true).`
- `probedValue(7).`
- `surveyed(true).`
- `path(v1, v1, 0, 0).`
- `path(v2, v2, 1, 3).`
- `path(v10, v2, 4, 3).`
- `path(v8, v3, 3, 2).`

A query for a shortest path would look like this:

```
1 || .send(v1, askOne, path(v8, NextHop, _, CostToNextHop)).
```

Listing 1.13: Query for shortest path from `v1` to `v8`

After looking up the belief in its belief base the node agent would unify the parameter `NextHop` with `v3` and CostToNextHop with `2` and response to the querying agent.

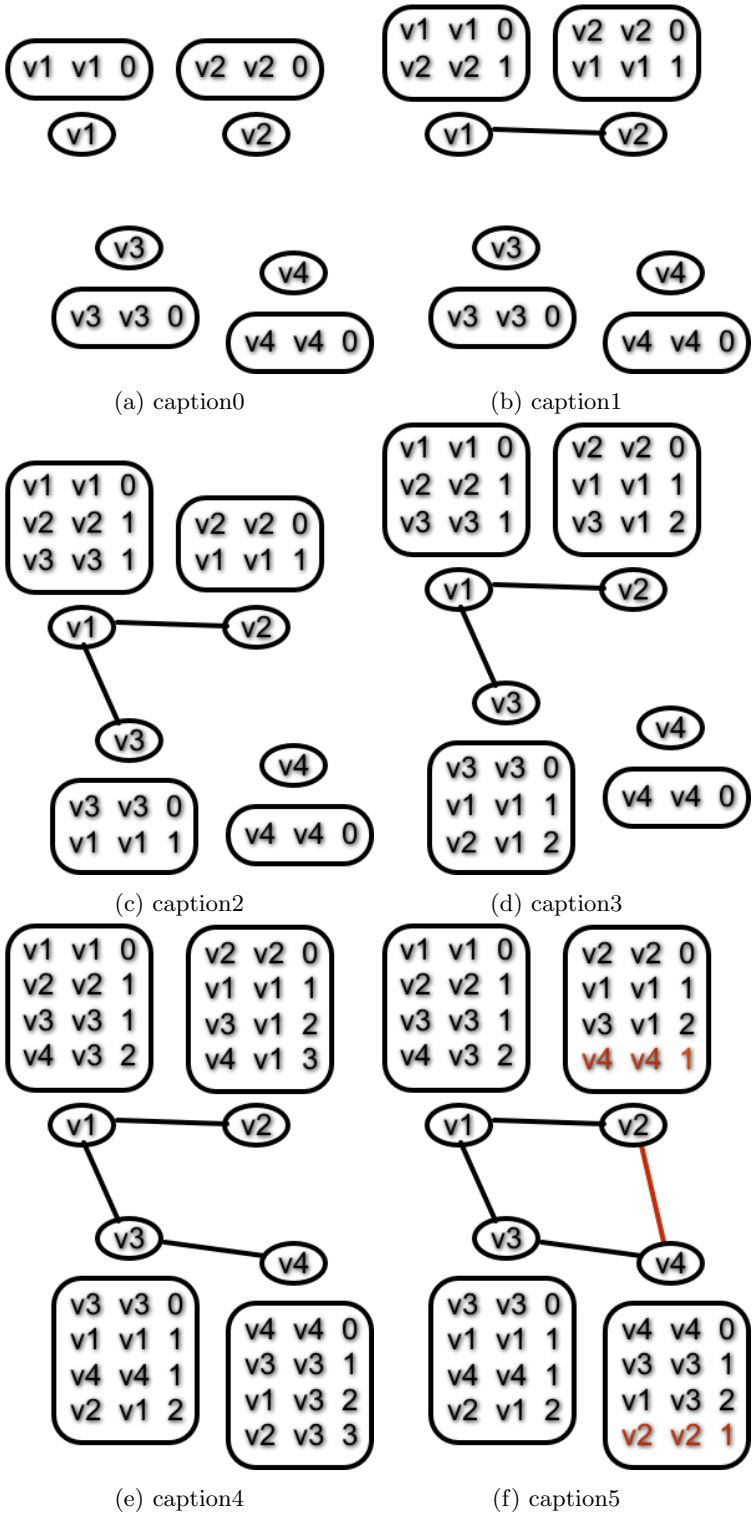
So now we know what information a node agent holds and how it can be addressed. But how does it get its data? How can we assure that it is always the best path we get if we query the node agent? Here the Distance-Vector Routing Protocol comes into play. When an real agent, unlike the virtual node agents, stands on a vertex it gets a lot of beliefs from the server, see Listing 1.12. The `visibleEdge(<VertexA>, <VertexB>)` belief and the `surveyedEdge(<VertexA>, <VertexB>, <EdgeCost>)` belief are showing all connected vertices and hence all neighbors tuples. The real agent informs the respective node agent about its neighbor, who then updates its neighbor-list and adds or updates the path to this neighbor.

```
1  RealAgent:
2  +visibleEdge(VertexA, VertexB) <-
3    .send(VertexA, tell, neighbor(VertexB, 10)).
4
5  +surveyedEdge(VertexA, VertexB, Value) <-
6    .send(VertexA, tell, neighbor(VertexB, Value)).
7
8  NodeAgent:
9  +neighbor(Vertex, Value):
10   path(Vertex, Vertex, Hops, Costs)
11   & Value < Costs
12   <-
13   -path(Vertex, Vertex, Hops, Costs);
14   +path(Vertex, Vertex, 1, Value).
15
16 +neighbor(Vertex, Value):
17   neighbors(List)
18   & <Vertex not in List>
19   <-
20   .abolish(neighbors(_));
21   +neighbors([Vertex|List]);
22   +path(Vertex, Vertex, 1, Value).
```

Listing 1.14: Real agent informs node agent about its neighbor

After updating its belief base the node agent informs all its neighbors about the changes. And these neighbors also inform their neighbors and so on. At some point the belief base of each node agent is consistent and no further broadcasting is needed. Figure 5 demonstrates the procedure for a small set of four neighbor nodes.

What is it? How is it used in our context? What are advantages we gain from it? What is problematic (speed loss)?



(a) caption0 (b) caption1

(c) caption2 (d) caption3

(e) caption4 (f) caption5

Fig. 5: Executing the Distance-Vector Routing Protocol algorithm as described in section 5.3.2 on a small network of four nodes. Each node has a table attached, containing all accessible nodes. The first parameter is the destination node, the second one is the node to pass through and the third parameter shows the overall distance to the destination.

5.3.3 JavaMap*

5.4 Repairing◇

As was already mentioned in scenario description, any agent can get disabled after being attacked by the enemy saboteur. To get disabled in the scenario means to loose all the health points. Naturally, we have implemented several supporting algorithms of avoiding enemy saboteurs when possible and parry when there is a saboteur nearby. However following these algorithms cannot guarantee that the agent will never get disabled, mostly because there not always exists an escape route and not all agents can perform parry action. When an agent gets disabled it looses most of its functionalities: only skip, recharge and goto actions remain active. Additionally repairers even being disabled can perform a repair action, but it costs more energy in this case. Disabled agents also cannot occupy a node and therefore cannot participate in zone building, which is a vital part of getting score points.

In section 5.2 it was said that the primary task of repairer agents is to repair others and they should perform a repair action whenever they see a disabled friendly agent. But the question is how to get the disabled agent to the repairer. In our implementation, every time an agent gets disabled, it sets a high priority goal *getRepaired*. Following the plan of this goal, an agent requests the available repairer and its position from the *MapAgent*. If the returned repairer position is the same the agent's position, then the agents only recharges and waits to get repaired, otherwise the agent simply moves toward the returned repairer position. If there is no repairer available in the reachability range, it means that the graph is not sufficiently explored and the agents then tries to expand the known subgraph by moving to unvisited nodes.

Assignment of agents to their repairers is done inside our Java MapAgent. To be more flexible we decided to perform such assignment on every step. This allows to adapt to constantly changing situation, when agents are moving, some new agent get disabled and some agents get repaired. The assignment itself is done based on the hop distances between agents. First, all the distances between all disabled agents and all repairers is calculated. Then the closest distances are picked and the agents which have this distance between them are assigned to each other. If all repairers are assigned and there are still some unassigned disabled agents, they get assigned to the closest to them repairers. This assigning approach in most of the cases led to fast and effective repairing.

In addition to disabling agents moving to their repairers, repairers can also move towards the assigned to them disabled agents. This behaviour is only possible during the exploration phase of the simulation, because in zoning mode repairers moving somewhere in most of the cases will also mean the zone breakup, which we would like to avoid. We implemented this by making repairers explore the map in the direction of the assigned to them disabled agents, i.e. if the node is not surveyed, they survey, otherwise just go to the assigned disabled agent.

The seeming special case in repairing is when one of the repairers gets disabled. However since even disabled repairer can perform repair action, we decided to

use the standard procedure of assignment even to the disabled agents. The only difference is that the goal to repair have higher priority then the goal to get repaired. This helps to use all the repairers more effective and prevents the situation when all the repairers are disabled and waiting to get repaired.

5.5 Zone Forming°

Zone forming is the most important part in the MAPC Mars scenario [2].It describes the process of agents occupying nodes in a way that they enclose a subgraph. For our approach, zoning takes place after the map exploration phase. This should ensure that enough information about the map has been gathered to calculate high valuable zones close to the agents' current positions. The algorithm for calculating zones and determining which agents have to occupy which nodes is presented in section 5.5.1. Said algorithm is used in the process of finding a zone to build, which is described in section 5.5.2. After a zone that can be build has been found, agents get assigned dedicated roles. These roles determine the agents' duties and tasks throughout the lifecycle of a zone which they are part of. The lifecycle of a zone includes its creation, defence and destruction. Both roles and the lifecycle are featured in the last section 5.5.3.

5.5.1 Zone Calculation†

The graph colouring algorithm used by the MAPC server to determine occupied zones is described in detail in the MAPC 2014 scenario description [2] and will not be explained again here.

Due to the way the server-side colouring algorithm works, placing n agents on the map so that they establish the highest possible zone value per step is anything but straight-forward. Even for $n = 1$, a single agent placed on an articulation point in the graph can establish a high-value zone if there are no enemy agents in either subgraph that it splits the map into. Figure 6 shows an example. To position themselves in an optimally-scoring way, agents *could* run the same algorithm locally to calculate the agent placement that will lead to the highest total sum of zone scores in each step by trying every possible permutation. However, the number of ways to place n agents on k vertices is $C(n + r - 1, r - 1) = \frac{(n+r-1)!}{n!(r-1)!}$, a number that increases rapidly with n and k. In particular, there are $C(28 + 600 - 1, 600 - 1) = 3.75 \times 10^{48}$ ways to place 28 agents on 600 vertices, which were the numbers used in the 2014 competition—far too many to calculate in real-time. Finding an algorithm that calculates high-scoring zones in a limited computation time is one of the major challenges of the MAPC competition.

Our team developed a heuristic algorithm for calculating zones that will be explained below. The goal is to find for every vertex in the graph a placement of agents around that vertex such that:

– All vertices that share an edge with the centre vertex will be included in the zone.

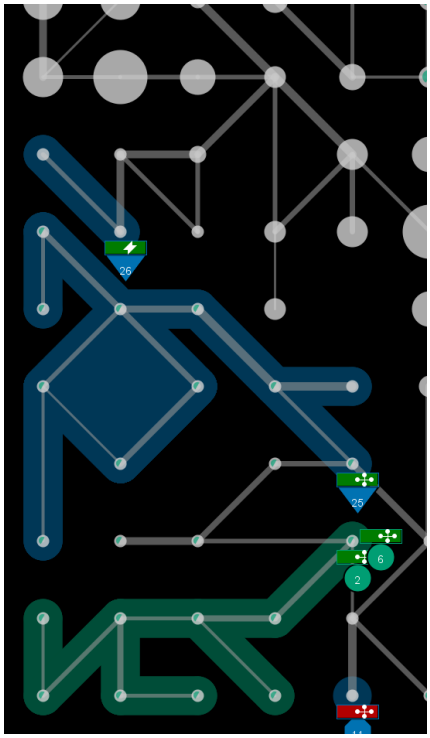


Fig. 6: By occupying an articulation point, a single agent can ostensibly establish a a high-scoring zone—provided that there are no enemy agents inside the subgraph that is split off from the main graph.

– Agents should only be placed on the centre vertex's two-hop neighbours, which are those vertices that are be connected to the centre vertex through a minimum and maximum of two edges.
– The constructed zone's value per agent, that is, the sum of the values of each vertex in the zone divided by the numbers of agents required to establish that zone, should be high. Ideally, it would be maximal, but the heuristic we use doesn't guarantee this.

Figure 7 shows some examples of zones that are found using our heuristic algorithm. Internally, every vertex in the graph is represented by a Java `Vertex` object, and the calculated zone is stored as a field of that object. The steps of the algorithm are best detailed graphically, as in Figure 8.

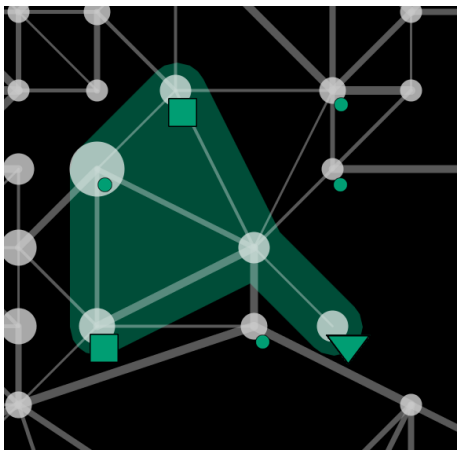
Definition 1. *Let V be the set of vertices and E the set of edges that the system knows about. For any $v \in V$, which we will use to denote the vertex that a zone is centered on, let $V_v^1 \subseteq V$ be the set of one-hop neighbours of v, that is, the set of vertices that share an edge with v: $V_v^1 = \{w|(v,w) \in E\}$. Similarly, V_v^2 denotes the set of two-hop neighbours of v, i.e. the set of vertices that includes exactly those vertices that share an edge with any vertex in V_v^1, excluding those in V_v^1 and v itself: $V_v^2 = \left\{u \middle| (v,w) \in E, (w,u) \in E, u \notin V_v^1 \cup \{v\}\right\}$. Let V_v^{2+} denote the entire two-hop neighbourhood of v: $V_v^{2+} = \{v\} \cup V_v^1 \cup V_v^2$. Additionally, let A_v be an initially empty set that we will use to remember vertices we want to place agents on. A zone and its zone value are defined as specified by the graph colouring algorithm in [2]. Then, the goal of the zone calculation algorithm is to find, for every $v \in V$ in the graph, a set of agent positions $A_v \subseteq V_v^{2+}$ that establish a zone around v so that the zone's value* per agent *is high according to the heuristic used by the algorithm.*

Note that although V_v^1 and V_v^2 start off as defined above, by abuse of notation we will remove vertices from those sets as the algorithm progresses. This does not mean that the structure of the graph has changed. The algorithm for zone calculation is (re)-triggered every time a vertex in the vertex' two-hop neighbourhood (so within the ambit of the zone we're trying to calculate) is discovered during map exploration or changes its known value when it is probed by an Explorer agent, as these are the events that can lead to possible changes in A_v and thus the zone.

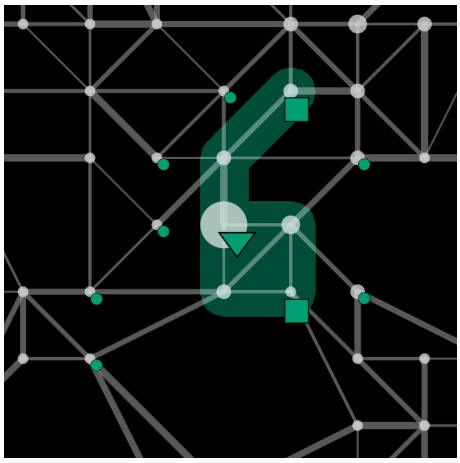
The zone centered around vertex v is is calculated through several steps:

1. Initially, $A_v = \emptyset$, and V_v^1, V_v^2 and V_v^{2+} as defined above. Iterate through every $w \in V_v^2$ and, for every w that is connected to 2 or more vertices in V_v^1, add it to A_v and remove it from V_v^2:

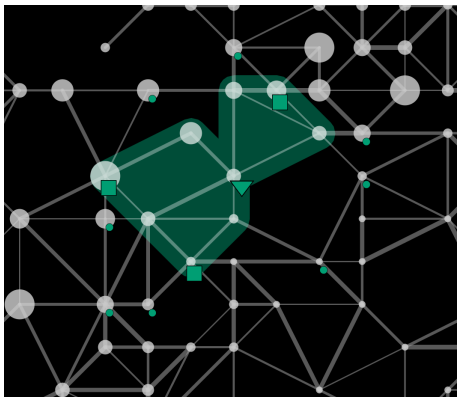
$$\forall w \in V_v^2 : \{(w,u_1),(w,u_2)\} \subseteq E, u_1 \neq u_2, \{u_1,u_2\} \subseteq V_v^1 \\ \rightarrow A_v := A_v \cup \{w\}, V_v^2 := V_v^2 \setminus \{w\} \quad (12)$$



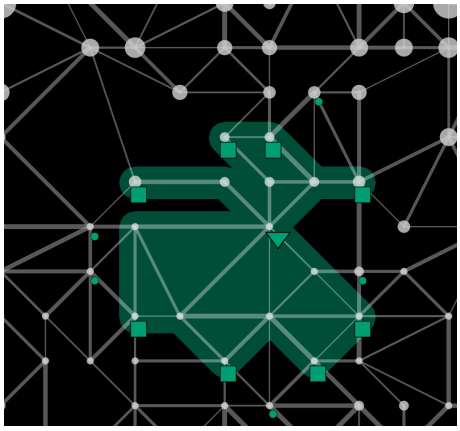
(a) This zone was calculated for a centre vertex that only has a degree of 1, i.e. that is a leaf vertex. Generally, it is preferable to place an agent on the cut vertex that leads to a leaf vertex rather than the leaf vertex itself, as this would establish at least a zone of equal size, and possibly larger.



(b) Here, the centre vertex has a degree of 3, and the calculated zone remains compact with only two additional agents used. A lot of optional agent positions remain.



(c) A zone where the centre vertex has a degree of 5, and the zone uses a total of 4 agents.



(d) A zone where the centre vertex has a degree of 7, and the zone uses a total of 9 agents.

Fig. 7: Four examples of zones calculated by the heuristic algorithm described in section 5.5.1. The green squares and triangles represent the placement of agents, where the triangle is the agent on the center vertex. Vertices marked with a small green circle are optional agent positions that can be used to expand the zone if there are agents left over at the end of the zone building, as described in section 5.5.2. The green-colored area represents the zone that is established by the given agent placement.

2. For every $w \in V_v^2$, if w is connected either directly or through a single one-hop neighbour of v to any $u \in A_v$, remove it from V_v^2:

$$\begin{aligned} &\forall w \in V_v^2 : \exists u \in A_v :\rightarrow V_v^2 := V_v^2 \setminus \{w\} \\ &\forall w \in V_v^2 : \exists u \in A_v : \exists x \in V_v^1 : \{(w,x),(x,u)\} \subseteq E \rightarrow V_v^2 := V_v^2 \setminus \{w\} \end{aligned} \tag{13}$$

   The reasoning behind this is that those vertices in V_v^1 that are neighbours of those in A_v will already definitely be included in the zone, and the vertices we remove this way will not contribute towards our goal of including all one-hop neighbours V_v^1 in the zone for v.
3. In the next step, "bridges" are discovered in the list of remaining two-hop neighbours V_v^2. A *bridge* is considered to be a connected triple of vertices where one of the vertices is directly connected to the other two. If such a bridge exists in V_v^2, all three involved vertices can be included in the zone around v by placing an agent on either end of the of the bridge and leaving out the in-between vertex:

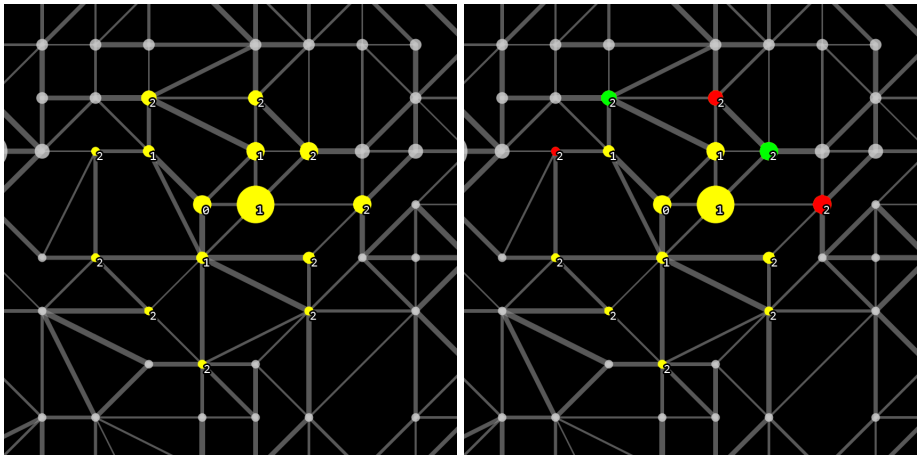
$$\begin{aligned} &\forall w_1, w_2, w_3 \in V_v^2 : (w_1, w_2), (w_2, w_3) \in E \\ &\qquad \rightarrow A_v := A_v \cup \{w_1, w_3\}, V_v^2 := V_v^2 \setminus \{w_1, w_2, w_3\} \end{aligned} \tag{14}$$

   Since three vertices can be captured in the zone for the "cost" of two agents, we consider this a good exchange to make.
4. Next, the algorithm checks if all one-hop neighbours V_v^1 are connected to the agent positions A_v. This is frequently the case, but not always. If a remaining, unconnected one-hop $u \in V_v^1$ is found, we check if it is connected to one or more of the remaining two-hop vertices in V_v^2. If that is the case, we choose the neighbouring two-hop $w \in V_v^2$ with the highest vertex value and add it to the list of agent positions A_v. If no such two-hop vertex is found, we add the unconnected one-hop vertex to the list of agent positions—this is the only case where a one-hop vertex can be added to the list of agent positions:

$$\begin{aligned} &\forall w \in V_v^1 : \neg \exists u \in A_v : (w,u) \in E \\ &\quad \rightarrow \begin{cases} A_v := A_v \cup \{x\}, V_v^2 := V_v^2 \setminus \{x\} & \text{if } \exists x \in V_v^2 : (x,w) \in E \\ A_v := A_v \cup \{w\} & \text{else} \end{cases} \end{aligned} \tag{15}$$

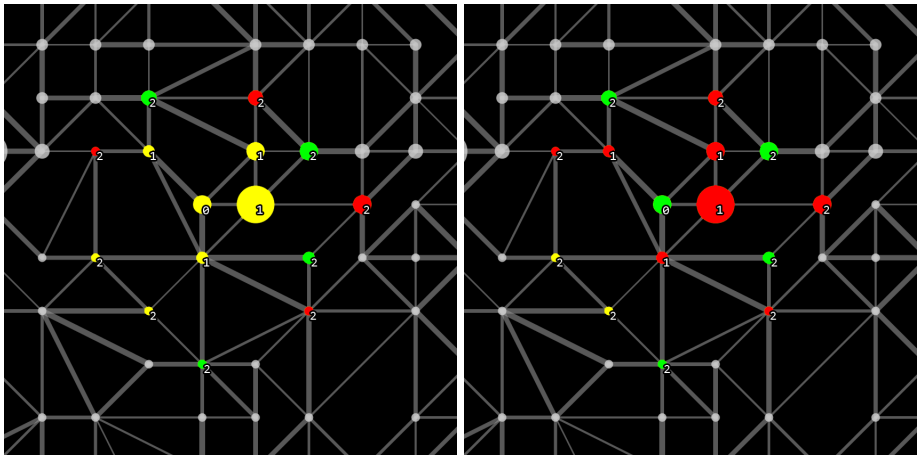
5. Finally, we include the center vertex v in the list of agent positions: $A_v := A_v \cup \{v\}$. Any vertices that remain in V_v^2 are saved as additional agent positions that could be used to extend the zone by otherwise idle agents, but unlike the vertices in A_v vertices are not required to establish the initial smallest zone that we calculated.

While we consider our algorithm to find zones of acceptably high zone values per agent, it can easily be shown to be suboptimal. For one, it only considers vertices within the two-hop neighbourhood of the centre vertex, and it is not difficult to think of possible graph structures where a different agent placement would lead



(a) Before zone calculation.

(b) After finding multiply-connected vertices in V_v^2 and removing their neighbouring two-hops.



(c) Finding bridges.

(d) After zone calculation.

Fig. 8: The zone calculation algorithm shown in four steps. Vertices are coloured differently according to their current state as the algorithm progresses. Green vertices are vertices that an agent must be placed on, so those in A_v. Red vertices are those where placing an agent would be redundant because it does not help with the goal of including all one-hop neighbours V_v^1 in the zone. Yellow vertices denote notes where agents could be placed to extend the zone, but are not considered optimal agent positions in the eyes of the algorithm. Numbers shown next to vertices represent their edge distance from the centre vertex v.

to a better zone. For example, if one of the remaining yellow vertices in Figure 8d were an articulation point whose inclusion in the list of agent positions would add more than that single vertex to the zone, this would probably be a good vertex to place an agent on, yet this would not be discovered by our heuristic algorithm.

5.5.2 Zone Finding Process.°

This section explains how agents decide on what zones should be built. Each zone finding process can end successfully or fail for any individual agent. If it failed, the agent is not going to be a part of a zone and a new zone finding process is started. The first part of this section covers what changes are made so that with every failed zone finding process a successful one becomes likelier. If a zone finding process ended succesfully, the most valuable zone known to the agents will be built. This is ensured through agent communication which is presented in the last part of this section. Agents start looking for zones when they have finished the exploration phase. As explained in section 5.3, explorer agents do not only survey but probe as well. Hence, other agents may finish the exploration phase earlier. Furthermore, zones can be broken up at any time forcing the agents to start looking for a new zone again. As a result, the zone finding process is in fact asynchronous. Problems arising from this are mainly dealt with throughout the actual building of zones which is illustrated in section 5.5.3.

In the beginning, all agents have to centrally register themselves when they are ready for zone building to indicate this availability. Next, each agent uses the algorithm presented in section 5.5.1 to determine the best zone in its neighbourhood. The algorithm uses a range parameter k which indicates the k-hop-neighbourhood up to which the algorithm will look for the best not yet built zone. This range starts at 1 and is incremented every time the agent finishes a zone finding process without being part of a zone afterwards. As a result, it is more probable for an agent to find a zone with a high per agent score which has not been build yet. Thus, it is also likelier for the agent to be part of a zone, because throughout every zone finding process only the most valuable zone is going to be built. The range has a maximum to ensure that an agent will not look for zones too far away from it. When a zone is broken up, the range will be reset, which is covered by section 5.5.3.

After every agent interested in building a zone has determined the best zone in its neighbourhood, all such agents must send their best zone to all other agents. This is because all agents ready to build a zone should know about and hence only try to build the best globally, not yet built zone. At any time, every agent may only know about one zone. This zone will be the best zone an agent is aware of at the moment. Zones are being compared by their per agent score. A higher score indicates a better zone. Before building any zone, the agents will have to wait until the information about their best zone has reached all other agents. This is ensured by the agent having to wait for all other agents to reply to him. Therefore, when an agent receives information about a zone, it has two options. One is to reply with a simple acknowledgement message expressing that it had

received the message. The other is to reply with its own zone in case that its zone is better. Agents may not reply with information about a better zone if it is not their own. This is to prevent duplicate messages. Otherwise, multiple agents could reply with the same zone of which they had been informed about by the same agent. Whenever an agent receives information about a better zone, it replaces its former knowledge about the best zone with the new one. Agents which are not interested in building a zone but receive information about a zone simply ignore the message but reply with an acknowledgement. This way, the sender will still be able to determine when every agent has processed the sent information. In case the zone calculation algorithm did not return any zone to an agent, this agent has to ask all other agents for a zone. It will accept the first reply containing zone information as its new best zone because it is better than no zone. The agent will then continue similar to the earlier presented behaviour and wait until it received replies from all other agents. After an agent has received all replies, it may start building a zone as illustrated in the next subsection.

5.5.3 Zone Building Roles and the Lifecycle of a Zone.°

This subsection describes the two roles exclusive to zone building. It covers the roles' associated tasks and duties throughout the lifecycle of a zone as well as the lifecycle itself. These roles are those of a *coach* and a *minion*. Each zone is built by one coach and a varying amount of minions. Minions are agents which are dedicated to build a zone by obeying their coach's orders. Every agent may only be part of one zone at a time. The roles are assigned when the zone finding process has ended and a concrete zone is about to be built. Agents keep either of these roles until the zone is broken up or they have to leave it. The roles regulate the agents' behaviour throughout the time they spend in a zone.

Before looking at border cases, an ideal case of a zone lifecycle is presented. There, the zone finding process described in section 5.5.2 ends with all agents knowing about the same best zone. This zone was found by one agent which will then become the zone's coach. Next, the coach informs the agents which will be part of the zone where to go to. On receipt of this message, the agents become minions and move to their designated node. The coach will also have to move to its node, which happens to be the centre node of the zone. Furthermore, the coach will unregister itself and all its minions to indicate their unavailability to build any other zone. In a zone, minions serve no other purpose than to occupy their designated node. If a minion becomes disabled, it has to move towards a repairer agents. Due to this, it has to leave its node. Therefore, the zone can no longer exist in its original form. In such a case, a minion has to inform its coach about its departure. The coach must then tell all its other minions that the zone can no longer be maintained. Consequently, all affected agents drop their role and restart looking for zones as illustrated in section 5.5.2.

In reality, the zone finding process is asynchronous. Therefore, it is likely that some agents start looking for a zone when others have nearly finished. As a result, there can be multiple groups of agents with different knowledge about which zone would currently bring the highest score per agent. Each group could

then be expecting a different agent to become a coach. This interferes with the assumptions that each agent may only be in one zone and have only one role at a time. To solve this problem, coaches do not only inform their minions about where to move to. Instead, they also transmit the per agent score of the zone they want to build together with this agent. Any agent can then compare the received zone score with the zone it wanted to build before. If it is higher, it must inform the coach of its former zone or its minions if it had been the coach itself. In case that the proposed zone's score is lower than the zone the agent intended to form, it must inform the coach who just proposed the new zone. Said coach will then have to inform all its minions that its zone is not going to be built.

Besides coaches and minions, there are also other agents who might be looking for a zone but will not be part of the one which will be built. Such an agent will have to start a new zone finding process. Prior to that though, it will look for any highly valuable node in its surrounding which is not yet occupied by anyone and move there. The range to look for such a node is the same as the range for finding a zone in the agent's neighbourhood presented in section 5.5.1. It is increased after every zone finding process which does not result in a zone where the agent is part of. The idea is that with a wider range, the probability to find a highly valuable zone increases. Additionally, the agent will likelier move farther away from its position in case it is not part of the zone to be built. This should further ensure that zones are only proposed multiple times as best zones if they have a very high per agent score.

We assume due to our zone calculation algorithm that a node within a zone will be occupied by at most one agent. Then, any enemy agent close to a zone endangers it. This is because a zone may not spread across an enemy inside of it [2]. Moreover, enemy saboteur agents can disable agents inside a zone, which similarly destroys the zone in its original form [2]. Hence, coaches check once per step whether an enemy agent is close to the zone. If this is the case, the coach broadcasts a message to all saboteur agents to come and defend the zone. Saboteur agents which are not already defending a zone bid for this. The saboteur agent closest to the zone's centre will win the bidding. It then moves towards the enemy to disable it. If the coach detects in a next step that the enemy moved away from the zone, it will cancel the zone defence. The coach does so by using another broadcast as it does not know which saboteur agent was selected to defend the zone.

Explorer agents will still be probing when the first agents start looking for zones. Therefore, the most valuable zones may change with more and more nodes being probed. To prevent that agents build a zone once and stay there for ever if no agents attack them, zones will be split up periodically. The periodic trigger is linked to the overall steps of the simulation and not the lifetime of each zone respectively. Consequently, agents from different zones will have to restart looking for a zone at the same time. In addition to allowing new zones to be build which take the information of the newly probed nodes into account, this also allows for agents to start the zone finding process in a less asynchronous fashion.

6 Implementation Details

6.1 BDI in AS(L) and Jason

Or in general: how did we implement what we had learnt from our scientific background?

6.2 Information Flow

Who gets what information how and when? How do we communicate with the server?

6.3 Lifecycle of one Step

Maybe illustrate what happens within one step and how we prevent multiple actions to be executed in one step.

7 Discussion and Conclusion

7.1 Competition results$^{\odot}$

The competition took place on two dates (15th and 17th of September) and each team had to play three times against all other teams. Each simulation consisted of a total of 400 steps and the team with the highest score at the end got three points for a victory. The overall score is the sum over all 400 step scores. The score per step is composed of points for zones plus achievement points. Since the strategy of team "MaKo" was to extensively buy upgrades for the artillery agent", most of the earned achievement points were consumed and therefore did not count towards the step score. Figure Figure 9 shows the progress of achievement points over time. As one can see, the achievement points of team "MaKo" go up and down due to the buying actions whereas the the points of the other team increase constantly. It looks like that this is a huge drawback because achievement points earned at some point count into every future step score. But compared to the number of points awarded for zones, this is only a minor fraction of the step score. As it can be seen in figure Figure 10 the spending of achievement points paid off since our upgraded saboteur agents hindered the enemy agents from building high valued zones. It was worth spending the achievement points for the purpose of attacking and disturbing the other team because the amount of potential zone points they would have earned without being attacked, is probably much higher than the amount of achievement points team "MaKo" spent for upgrades. At the end of the tournament team "MaKo" scored second with a total of 18 points. The winner 2014 was, for three times in a row now, the team from the USFC. The final results are shown in Table 1. Statistics of all the individual games can be found in the appendix.[reference here!!!!]

Team "MaKo" lost every second game against each opponent due to the fact that for some reason the repairer agents weren't able to repair. The reason behind

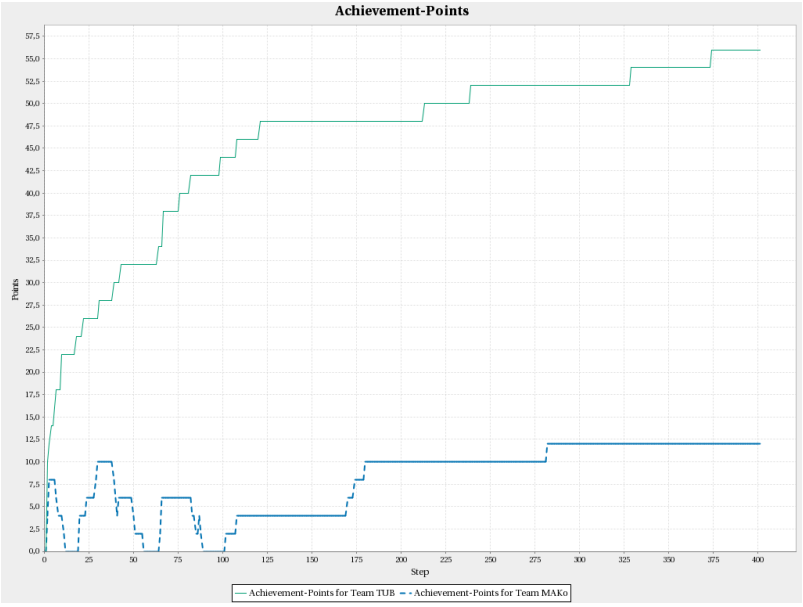


Fig. 9: MAPC 2014 result

Table 1: The results of the 2014 MAPC. Each team played three matches against every other team, and winning a match awarded 3 points.

Pos.	Team name	Score	Difference	Points
1	SMADAS-UFSC	1180662 : 654624	526038	33
2	MAKo	617086 : 776868	-15782	18
3	TUB	904874 : 872399	32475	15
4	TheWonderbolts	711001 : 1014669	-303668	15
5	GOAL-DTU	653178 : 748241	-95063	9

this was not obvious to the team. Summarizing the matches, team "MaKo" was capable of exploring the map, building local optima zones, dealing with disabled agents and attacking the opponent. A thing that could be improved is the zoning behaviour. Due to the fact that zones were broken up on a regular basis, zones with a high value sometimes were discarded even when there was no need to do that. Also no handling of edge cases has been implemented which could improve zoning in the sense that the actual number of agents needed to build that zone could be less than the number calculated by our algorithm. But the general idea regarding small zone forming was good. Because one big zone is easy to disturb, having some small high value zones was quite effective to not provide the enemy with an easy target. Like already mentioned a strategy that worked out well, was the approach to upgrade the visibility range and the strength of one saboteur agent significantly. In all matches the it was able to disable enemy agents many

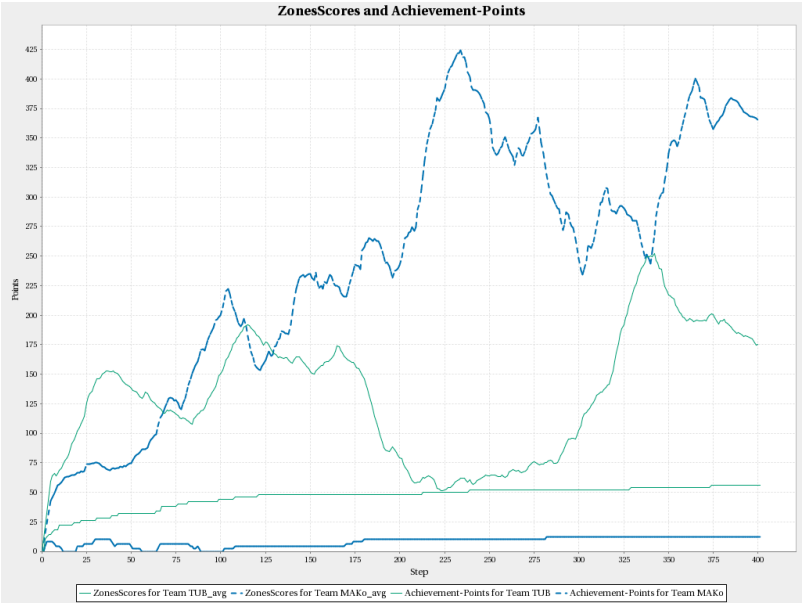


Fig. 10: MAPC 2014 result

times and therefore disturb zones and keep the enemy repairers busy, which kept them away from building zones.

7.2 Lessons learned⊙

None of the "MaKo" team member had experience with Jason as a programming language before the research lab. The first thing that caused problems was that Jason was quite slow, especially when it comes to communication between agents. Since agents most times needed some information from others and could not continue with their reasoning until this information was given, communication was a extreme bottleneck. Extreme delay was observed when the group tried to exchange information about the graph. The first approach was to communicate everything that an agent perceives, while exploring the graph, to every other agent. The reason behind this was to have every agent store the full knowledge about the until then explored (sub-)graph. This course of action was quickly discarded, because agents were not able to do actions while processing all the incoming messages. The next attempt to reduce communication was to implement a so called "cartographer" agent. The purpose of this agent was to have an additionally agent in the background that gathers all the information about the map that all 28 agents perceive. With that cartographer agent the amount of communication was reduced and agents could act like intended, because now they just sent their percepts to the cartographer agent and they had not to deal with incoming messages of the other 27 agents. The drawback of this approach revealed when

it came to querying the cartographer agent for information, for instance when an agent wanted to know if a vertex was already surveyed or how he could reach given vertex. Like it was noticed before, processing the received messages is quite slow and so it happened that the cartographer agent was not able to handle messages in time. It occurred that agents asked about some specific vertex which the cartographer agent should have known about (because some other agent already informed him about that particular vertex) and they got no answer due to the fact that the cartographer agent hadn't processed the message yet. That's why this approach was also discarded. The next idea, which worked in the end, was to use a Java object, the so called "map agent", for the purpose of storing and processing graph information. Internal actions were used to obtain the required information about the graph. For instance the internal action "getBestHopToVertex" calculates the shortest path and returns, for a given target node, the next vertex where the agent has to go to. Another issue that arose initially during the contest was that if a Term in Jason contains a dash, it is interpreted as a Number. We observed this during our first match against a team that had a dash in its name. The result was that we were not able to distinguish between friendly and enemy agents. We immediately fixed it, so that in the next matches we took this possibility of having a dash in the team name into account.

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