MARS – A next-gen multi-agent simulation framework

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Abstract

The usage of Individual Based Modelling (IBM) or Agent Based Modelling (ABM) in ecological science is well accepted for 25 years now. However a lot of experience on when and how to use IBM has been collected over time (Filatova et al., 2013; Grimm, 1999; Huston et al., 1988) as well as new approaches, methods and technologies in computer science have emerged (Bellifemine et al., 2008, 2007; Grimm et al., 2006, 2010; Le et al., 2008; Ralha et al., 2013; Vigueras et al., 2013).

Together with these improvements, new obstacles and problems have arisen in the various domains of ecological science. Some of the major challenges are the integration of different models and almost arbitrary data into combined simulation models (Thiel-Clemen, 2013), execution performance of simulations and the need for large scale scenarios, while at the same time be able to visualize the simulation.

The coupling of ecological, social, economic and political systems creates a huge complexity to the overall model and simulation. Creation and usage of multi-agent based simulation systems has proven to be a great tool to explore and investigate such models (Le et al., 2008; Ralha et al., 2013).

The MARS Group (Multi Agent Research and Simulation) of the Hamburg University of Applied Sciences is developing a distributed and highly scalable framework for use in research and education. MARS is not a single program, but consists of a multitude of processes and tools chained together to provide an approach to most if not all of today’s simulation requirements. In our presentation the current state of development is demonstrated. Future research and development topics as well as concrete scenarios will also be shown.

# Introduction

The usage of Individual Based Modelling (IBM) or Agent Based Modelling (ABM) in ecological science is well accepted for 25 years now. During this time a lot of experience on when and how to use ABM has been collected (Filatova et al., 2013; Grimm, 1999; Huston et al., 1988), as well as new approaches, methods and technologies in computer science have emerged (Bellifemine et al., 2008, 2007; Grimm et al., 2006, 2010; Le et al., 2008; Ralha et al., 2013; Vigueras et al., 2013).

Together with these improvements, new obstacles and problems have arisen in the various domains of ecological science. The coupling of ecological, social, economic and political systems creates a huge complexity to the overall model and simulation. Some of the major challenges are the integration of different models and almost arbitrary data into combined simulation models (Thiel-Clemen, 2013), execution performance of simulations meeting the need for large scale scenarios, while at the same time being able to visualize the simulation’s results.

Creation and usage of multi-agent based simulation systems has proven to be a great tool to explore and investigate such models (Le et al., 2008; Ralha et al., 2013).

The MARS Group (Multi Agent Research and Simulation) of the Hamburg University of Applied Sciences is developing a distributed and highly scalable framework for use in research and education. MARS is not a single program, but consists of a multitude of processes and tools chained together to provide an approach to most if not all of today's simulation requirements. ~~In this paper we present an overview of relating literature and results (Chapter 2), the current state of development of the MARS SYSTEM (Chapter 3) and first results from prototypic implementations (Chapter 4). The last chapter features a discussion as well as future research and development topics. TODO: Update!~~

# Requirements for modern simulation systems

TODO: Short overview

## Modularity and Reusability

As shown by findings, such as Liu et al. (2007),  almost every ecosystem today is tightly coupled with its neighboring economic or social systems and thus these need to be taken into account when watching the evolution of that ecosystem. Filatova et al. (2013) go even further by demanding that the corresponding aspects of ecological systems like economy, social systems and bio-physical dynamics need to be integrated into the representation of a heterogeneous landscape representation.

One of the most important requirements resulting from this circumstances is the integration of existing models with each other. This can only be done if models ,or even better, their parts, are designed in a modular and reusable manner. The idea is to connect and integrate domain specific models from domain specific experts to create a new super model of a certain domain (or, alternatively, focus on different compositions). If for example one would want to create a large scale model of the ecosystem of a national park in south Africa, it would be very helpful, if one could use already existing models of certain components, such as animal behaviors, weather, land erosion and so on. Another aspect that could profit from modular and reusable models is comparison. If it was easy to integrate most of the models available, you could run models[[1]](#footnote-1) directly next to each other, consuming the same data, allowing for example to perform real-time digression analyses.

Actually integrating models turns out to be extremely difficult, since each group of scientists working on a model tends to use another, individual, paradigm, architecture, programming language, data format. A good solution should address this problem.

## Information Integration

Of huge importance in simulation is data. It is needed for nearly all tasks from generation of hypotheses, over simulation initialization and calibration to validation. Unfortunately, the data, that is being collected, has a tremendous heterogeneity in terms of temporal and spatial resolution, reference formats, completeness and error margins. To be viable in a simulation, this data has to be integrated. It must be carefully corrected, the resolutions have to be aligned, the error must be treated.

Furthermore the relevant data of all the available must be singled out and connected. Since we focus on spacially explicit simulations, a special point is also to link data without any further reference together to establish a common context. For example we are might be designing a model for an animal species in a wildlife reserve somewhere in Africa. For one concrete simulation it might be necessary to include weather data for the whole region, topology data of the general landshape, as well as a rough overview of vegetation types and population metrics for certain species in that area.

A simulation framework should assist domain experts with all the steps involved: GIS imports, data collection and analysis and possibly transformation.

These dimensions target the difficulty when technically connecting different models. A more functional view has been made by Liu et al. (2007) who take a look at the complexity of coupled human and natural systems. Their integration efforts aim at taking interdisciplinary research on a broader scale into account, as well as exceeding local and temporal boundaries when modelling certain ecological system.

## Ease of use

To be useful for and accepted by experts of other domains than computer science, a simulation system should also be as accessible as possible. There are two aspects that we want to emphasize in this context. One is the ever important question of usability of the general toolset. The other is the nature of the means provided by the simulation system to model the actual questions.

## Scalability

Although it should always be the goal of a modeler, to design everything as simple as possible, some things are inherently computationally intensive. There are several scenarios that, often in combination, prohibit simulation execution on a single computer within reasonable time frames.

First of all the agents themselves are becoming more complex, in order to replicate natural behavior. This is especially true for animated objects, such as for example animals or humans. To come close to the real world, the modeler might need to use computationally expensive techniques, such as learning or planning algorithms, path-finding, collision avoidance and others, often even in use simultaneously. And the more models are integrated, the more of those techniques are likely to occur.

As the field of multi agent systems research matures, the applications get also bigger, resulting in a larger number of agents. Imagine for example a checkers or draughts-like discrete environment with size ten by ten fields filled with one agent per field. Accordingly, the system has to handle about 100 agents. Now, if the length of the sides is only doubled, the computational effort increases fourfold, in the three-dimensional case even eightfold[[2]](#footnote-2).

The real world areas of interest are steadily growing larger, further intensifying this problem. This is especially true, when a model is used to forecast future developments of its real world counterpart. Initially mostly used for the understanding of system dynamics, the technique of agent based modeling is likely to be used increasingly for prognosis on a large scale, as well. The area of interest may be for example the entire Kruger national park, or in our recent case the Abdoulaye forest (Pereki, 2012). TODO: References!

Of course it may sometimes be possible to avoid the problem by extrapolating from a sample set of agents to the bigger scenarios. But that would in return diminish the factor that sets apart MAS from other simulation techniques: the ability to track individual agent’s actions and states. Also, depending on the system, some desirable emergent properties of the real system (for example lane formation in crowd simulation scenarios) are only achievable with a realistic density of agents.

The most promising solution to really solve this problem, as opposed to avoiding it, is to make the simulation system scalable across multiple computers. Research budgets are not limitless, so we think it is important to target commodity hardware or rentable compute clouds. Scalability thus by our definition means not only “still running on multiple computers” but a more strict definition. We mean the definition of horizontal scalability or scaling-out: The computation speed of a single simulation run increases by a **constant** factor per added compute node.

## Summary

The discussion today circles around the fields of model re-usage (Holst (2013)), model integration (Filatova et al. (2013), Le et al. (2008), Liu et al. (2007), Villa (2001)), which makes distributed, parallel, scalable simulation execution (Cicirelli et al. (2010), Wang et al. (2009), Wang et al. (2012), Bellifemine et al. (2007), Thiel (2013), Vigueras et al. (2013)) necessary and raises the question of spatial-temporal information integration (Thiel-Clemen (2013), Filatova et al. (2013)).

# Related work

Villa (2001) proposes his Integrating Modeling Architecture (IMA) to mitigate these problems. He singles out three characterizing dimensions for connecting different models:

* **Representation** A unified semantic relating to the depiction of space, time and behavior in every respective model is needed.
* **Domain** A clear distinction between the domain spaces of each sub-model must be made. In particular this relates to the input and output parameters, which are valid for each sub-model.
* **Scale** Data, which is exchanged between models, must be compatible or translated in space and time dimensions

A huge number of MAS frameworks and domain specific implementations have been created over the past years. Since we strive to create yet another framework, it makes perfect sense to look at the previous work and evaluate their capabilities and usefulness.

## Simulation Frameworks

### JADE

One of the most famous frameworks is JADE (Bellifemine et al., 2007), which allows executing a simulation distributed across several JADE container processes or just locally in a single container. JADE was developed in Java to create a reference implementation of the FIPA agent specification ([http://www.fipa.org)](http://www.fipa.org/). Mengistu et al.(2008) extensively investigated the performance of JADE. Their findings show that JADE has significant performance issues in the fields of communication and agent migration due to the usage of the LDAP protocol and slow message transport services. JADE’s Lookup-Directory-Service also is measured to be slow, which is caused by not using local caching on the respective nodes. Mengistu et al. (2008) propose improvements to both mechanisms and present promising results from experiments they conducted. However a more recent investigation of JADE’s performance seems appropriate, given that the paper is almost 6 years old.

### GAMA

GAMA (Amouroux et al., 2007) is a modeling and simulation framework, which is based on RepastJ. It features a nice model description language, called GAML, which allows nonprogrammers to create complex models. GAMA is written in JAVA and thus executable on all java enabled systems. A very strong feature of GAMA is its visualization feature, especially when it comes to using GIS data. An easy import function allows to quickly create a scenario’s environment and visualization from a GIS file and thus allows for a quick integration of that kind of data. These features make GAMA very accessible.

The downside of GAMA is, that it’s not possible to distribute the system and that it does not scale well across multiple CPU cores. In fact when testing GAMA, it actually used only just up to 4 cores while running on a 24-core machine. While testing I found GAMA to have a performance threshold around 80.000 agents, with one simulation step taking more than 800ms on the aforementioned machine.

### WALK

Also from 2013 comes a solution with a strong focus on evacuation scenarios, which has been developed here at the Hamburg University of Applied Sciences and is called WALK (Thiel, 2013). It features a dynamic (re)partitioning and distribution of agents across several compute nodes and is thus capable of running simulations with hundreds of thousands agents on commodity hardware. In fact Thiel (2013) showed in his final tests that WALK can run a 300.000 agent random walk simulation in near real time. Also remarkable about WALK is, that its agents pass the RiMEA tests and thus provide a pretty good behavior. As a recent addition Stefan Münchow added support for leadership models and social behavior to the agents implemented in WALK. These additions show very promising results and create a very high interest in re-using the agent implementation from WALK in the new system whenever human agents are explored.

### Vigueras

Another interesting architecture (Vigueras et al., 2013) proposes an almost completely asynchronous, distributed simulation execution to implement interactive simulations, which may be visualized in near real-time. The only time Vigueras et al.(2013) synchronize the execution of their agents is, when they happen to act or move beyond the boundaries of their respective environment patch.

When it comes to visualization of the simulation Vigueras et al.(2013) utilize visualization nodes (VS) that also act asynchronously on the distributed nodes. Each VS has a camera-style definition of its field of view and may thus only ask those nodes for information containing parts of the environment, which is in that field of view. This is very contrary to other visualization approaches (e.g. GAMA, NetLogo), since it does not attempt to visualize the whole simulation at once.

Considering the amount of agents and the sheer size of simulated space in our upcoming scenarios, this approach might become very valuable.

# Focus on scalability

As a consequence of the former considerations we come to the conclusion, that there are some simulation systems that really fit the general-purpose character and support the modeler with for example GIS integration. The same tools also offer advanced modeling solutions, such as a domain specific language (GAMA, NetLogo). Other tools on the other hand excel at the distribution but are crafted for the special model they implement (WALK, Vigueras). Also, most systems examined, which claim to be scalable, in fact are limited in this area (e.g. GAMA).

As discussed above, there are many reasons, why a quasi-standard simulation system that, most importantly, combines a general-purpose approach with full-fledged horizontal scalability would be desirable. Other reasonable features should be the facilitation of model creation and integration as well as information integration (Thiel-Clemen, 2013). Letting computer science professionals translate the model can bridge the process of model creation from domain experts to simulation. However, agent based models with viable size for real world scenarios are not possible without a system, which computes them in reasonable time frames.

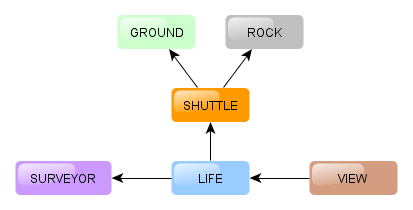
For those reasons we decided to design a completely new framework instead of building upon or augmenting an existing one. After giving a brief overview of how the simulation component fits within the whole planned tool chain, the focus of this paper will be on our ideas regarding the scalability aspects.

# MARS Overall Architecture

## Overview

The system’s components on the top-level are shown in Picture 1. MARS is divided into three parts, whereas the top-level components are assigned as follows:

* **Data Integration**: GROUND, ROCK and SHUTTLE
* **Simulation**: LIFE
* **Analysis & Visualization**: VIEW and SURVEYOR



Picture 1: General system overview

Following is a description of what each component’s purpose is and how they interact.

### GROUND

MARS GROUND is the component responsible for all interaction with geo-data. It encapsulates the connection and interaction with Geoserver (<http://geoserver.org/>), which it utilizes to import, edit and export geo-data. GROUND further solves the problem of different projections, formats and scales on heterogeneous get-data.

TODO: Rasterdaten, Polygone, Vektoren

### ROCK

MARS ROCK holds all data that is not optimally representable in GIS formats. This is especially true for data that changes depending on time. Examples would be the population of a country. TODO: ask Jan, also: especially point data

### SHUTTLE

This part of the system integrates the data from GROUND and ROCK behind a unified interface, so that the user is not able to tell from which technical source the data originates. It includes also graphical and other sub components, that support a user with the compilation of data necessary for a simulation model. A real novelty is also, that the data TODO: spatial and temporal data intersected, crossreferencing

## LIFE Architecture

## Layers & Agents

## Communication

## Agent Shadowing

Assuming an architecture where agents live in three dimensional layers each distributed across one or more container nodes, the problem of synchronization and communication arises, when it comes to agent interaction or movement across the boundaries.

Specifically whenever an agent wants to communicate (that is call a method) with another agent, it first has to check whether the desired agent is present locally or remotely and, if remotely, obtain a reference through which it may perform the actual communication.

If agents may move around their environment or are moved by a load balancing partitioning mechanism, it may well happen, that an agent crosses the virtual border of a container node’s part of the layer and thus has to be moved to another container node instance. If that happens the communication reference of that agent has to be updated, whenever another agent holding an old reference wants to communicate.

### Concept

Agent Shadowing is the depiction of an agent living on layer A1 drawn onto layer A2, where it is not actually instantiated, but instead is represented by a stub-like object as in remote communication concepts like RPC/RMI.

In RPC/RMI each agent’s methods are callable by third parties through its stub object. Usually a stub just provides the capabilities to establish an interface-bound communication with the remote object. If the remote reference changes, in classic RPC/RMI the stub simply becomes useless since its reference is not updated. The protocol then has to notice the broken link and re-establish a new one.

A shadow agent stub (SAS) is extended by the ability to hold cached attributes like its position or any other attribute. Both, the attributes and the remote reference, may be updated by the real agent object whenever a change occurs. These updates may be delivered via multicast when in LAN to reduce the amount of traffic. The initial remote references can be provided when the overall system is initiated since some kind of distribution information has to be provided at that state.

This results in each container node containing the full environment as well as all 10.000 agents, but with the difference, that only 5.000 agents are really instantiated (and thus have to be computed). The other 5.000 agents are only instantiated as SASs and thus do not contain any agent behavior logic. An increase in container nodes would reduce the amount of agents per node that have to be actively computed, while the memory footprint per node would also potentially decrease, assuming that a SAS consumes less RAM than a full fledged agent.

### Hypotheses:

1. This data-binding mechanism significantly reduces the amount of (duplicated) network communication / traffic between agents, because heavily used attributes may be cached in SAS.
2. Lookup of remote references is not necessary anymore, since each agent is virtually present at each container node and may be accessed through its usual interface, with the stub-object binding taking care of the remote reference[[1]](file:///E:/Master/Shadow%20Agents/ShadowAgents.docx#_ftn1).
3. Distribution of agents is transparent to the programmer.
4. No single-point-of-failure since no central directory for lookup or routing is necessary. Furthermore if a container node crashes, its state might be recreated by another node.
5. Massive traffic resulting from multiple simultaneous SAS updates, can be reduced by aggregating these updates into one large batch update.
6. The system is limited by the maximum amount of RAM per node .
7. This limitation can be compensated by introducing lazy loading of SASs, utilizing potential locality of agent interaction and a garbage collection for SASs which have been unused for too long[[2]](file:///E:/Master/Shadow%20Agents/ShadowAgents.docx#_ftn2).

# Outlook

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1. For example with competing hypotheses or simply older versions of the same model. [↑](#footnote-ref-1)
2. In practice, unless one is doing climate simulation (which is definitely not our focus), cases where the simulation area’s border lengths are all equal to each other are very unlikely. In most cases the height dimension, although present, is going to remain constant. It can of course still be influential, when the air is of interest (e.g. when simulating flying animals). [↑](#footnote-ref-2)